From Hallucination to Trust: Leveraging Chain-of-Thoughts and Empathy in LLM-Empowered Agent Interactions

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ABSTRACT

Large Language Models (LLMs) have significantly enhanced user interactions across various platforms, becoming indispensable in sectors like customer service for their immediate response capabilities and personalized assistance. Despite their transformative impact, LLMs occasionally produce hallucinations - factually incorrect, inconsistent, or entirely fabricated, despite appearing plausible or coherent, which might undermine user trust. This type of information manifests as either factuality or faithfulness hallucinations, where responses are factually incorrect or contextually irrelevant, respectively. This study explores different dialogue strategies, such as Chain-of-Thought (CoT) as logical reasoning and empathy expressions, to mitigate these issues. CoT reasoning enhances transparency in AI's decision-making process, potentially reducing the occurrence and impact of hallucinations. Empathy in responses aims to maintain user connection, softening the impact of misinformation and fostering a more forgiving user perspective. Based on the Emotion as Social Information (EASI) theory, this research examines how these strategies can enhance the user experience of LLMs in critical interaction scenarios, contributing to the development of sophisticated, trustworthy, and user-centric AI systems. The findings are expected to inform future designs of LLM architectures and interaction strategies that prioritize both accuracy and the emotional dynamics of user engagement, enhancing the overall acceptance and effectiveness of LLM technologies in everyday applications.

Keywords: Large Language Model, AI Agent, Hallucination, Chain-of-Thoughts, Empathy

INTRODUCTION

Large Language Models (LLMs) have become foundational to enhancing user interactions across multiple platforms (Ashfaq et al., 2020; Letheren et al., 2020; Li et al., 2024). These sophisticated models, powered by extensive data and advanced algorithms, are integral to a variety of applications, particularly in customer service, where they provide immediate responses and personalized assistance (Luo et al., 2019). As a core component of modern communication infrastructures, LLMs are not only pivotal in handling inquiries and providing information but are also increasingly employed in more complex dialogues requiring nuanced understanding and responses. This proliferation underscores the critical role of LLMs in shaping the future of interactive environments, where they offer scalability and efficiency that human agents cannot match. However, the reliability of these interactions remains paramount, as the trust users place in LLMs directly influences their effectiveness and acceptance in everyday use (Xu & Liu, 2022).

Despite the transformative capabilities of LLMs in user interactions, their application is marred by the occurrence of *hallucinations*—errors that significantly undermine user trust and satisfaction (Huang et al., 2023). In general, these hallucinations manifest as factuality or faithfulness errors (Ji et al., 2023). Factuality hallucinations involve LLMs responding with factually incorrect information, misleading users and potentially leading to detrimental outcomes based on inaccuracies. Faithfulness hallucinations, on the other hand, occur when responses, while factually correct, are contextually irrelevant or unfaithful to the user's intent (Ji et al., 2023). Such errors not only disrupt the flow of interaction but also diminish the perceived intelligence and reliability of LLMs. Addressing these issues is critical for advancing LLM technology and ensuring its practical and trustworthy deployment across various sectors.

The necessity to address hallucinations in LLMs extends beyond mere technical refinement; it is vital for maintaining the integrity and reliability of interactions between humans and machine intelligence (Shams et al., 2024). Hallucinations can severely impact user experience, leading to confusion, mistrust, and overall dissatisfaction with the technology. This erosion of trust is particularly detrimental in sectors where accurate information and responsive communication are paramount, such as healthcare, financial services, and customer support. Improving the accuracy and relevance of LLM responses directly correlates with the enhancement of user trust (Papagni et al., 2023). By minimizing occurrences of both factuality and faithfulness hallucinations, LLMs can become more reliable and effective agents. This reliability not only bolsters user confidence but also expands the potential applications of LLMs across more sensitive and critical domains. Furthermore, enhancing these aspects of LLM performance will pave the way for a broader acceptance and integration of this technology into everyday life, demonstrating its capability to assist and interact in a manner that is both intelligent and contextually appropriate.

As we advance in addressing these critical issues, innovative strategies such as Chain-of-Thought (CoT) reasoning and the integration of empathy emerge as pivotal enhancements to LLM capabilities. CoT, a method where the model explicates its step-by-step reasoning before providing an answer, introduces a layer of transparency and accountability to AI interactions (Wu et al., 2023). This approach not only aids in demystifying the AI's decision-making process but also allows users to follow and understand the logical progression, potentially reducing the occurrence and impact of hallucinations (X. Wang et al., 2023). By clarifying how conclusions are drawn, CoT can significantly restore user trust, particularly after encountering errors in AI-generated responses. Moreover, the expression of empathy within LLM-generated content represents another critical dimension in enhancing user interactions. This involves adjusting responses to reflect understanding and concern, aligning more closely with human-like interaction nuances (Bilquise et al., 2022; Shams et al., 2024). Empathy can mitigate the adverse effects of hallucinations by maintaining a connection with the user, thereby softening the impact of any misinformation and potentially fostering a more forgiving user perspective towards momentary AI errors.

These strategic implementations address the need for not only technically accurate but also relationally engaging LLM-empowered systems. As such, the role of CoT and empathy in LLM-empowered systems has become an essential focus of research, prompting the following key questions:

1. How does the expression of empathy in LLM responses affect user emotions and subsequent trust in the technology?
2. Can CoT reduce the negative impacts of hallucinations on user trust and satisfaction?
3. In instances of hallucination, how does the expression of empathy in LLM responses affect user emotions and subsequent trust in the technology?

This research aims to explore these questions, seeking to uncover how CoT and empathy can effectively enhance the user experience and reliability of LLMs in critical interaction scenarios. By examining the interaction between these elements and user perceptions, the study will contribute to the development of more sophisticated, trustworthy, and user-centric AI systems. The implications of this research are broad, promising to inform future designs of LLM architectures and interaction strategies that prioritize both accuracy and the emotional dynamics of user engagement, thereby enhancing the overall acceptance and effectiveness of LLM technologies in everyday applications.

LITERATURE REVIEW

LLM-Empowered Agent Interactions

LLM-powered agents are AI systems that leverage large language models to facilitate interactions with users, respond to inquiries, or execute tasks via conversational interfaces (Ashfaq et al., 2020; Li et al., 2024; Singhal et al., 2023). In academic settings, researchers have extensively studied these systems, examining aspects ranging from cognitive augmentation to ethical implications (Atlas, 2023; Boussioux et al., 2023; Haluza & Jungwirth, 2023; Taecharungroj, 2023). In the industry sector, these agents are revolutionizing customer service and operational efficiency (Budhwar et al., 2023; Rivas & Zhao, 2023; M. Y. Wang & Wang, 2023). Applying LLMs in personal services represents a particularly promising area, offering enhancements in user engagement and personalized experiences (Zheng et al., 2023). Nonetheless, the prevalent issue of hallucinations remains a central topic in the deployment of LLMs, primarily due to the potential for factual inaccuracies, risky responses, and ingrained biases (Deiana et al., 2023). Hallucination is defined as the production of content that is either nonsensical or not true to the input provided. Researchers have identified two primary types of hallucinations (Ji et al., 2023). Factuality Hallucination underscores discrepancies between generated content and verifiable facts, often manifesting as factual errors or fabrications . For example, an LLM erroneously claiming that Charles Lindbergh was the first person to walk on the moon in 1951, despite it being Neil Armstrong in 1969. Faithfulness Hallucination involves divergences from the user's instructions or the context of the input, as well as inconsistencies within the generated content itself. An illustrative case is an LLM misrepresenting the date of an event in a conflict between Israel and Hamas from October 2023 to October 2006 (Hannigan et al., 2024; Huang et al., 2023).

Chain-of-Thoughts

The introduction of Chain-of-Thought (CoT) prompting in LLMs has marked a significant advancement in the field of artificial intelligence, particularly in enhancing the transparency of AI systems (X. Wang et al., 2023). CoT prompting involves guiding the AI to break down complex reasoning tasks into intermediate steps, making the AI's decision-making process more interpretable and understandable to users. This approach has been shown to significantly enhance user trust and comprehension by providing clear, step-by-step reasoning paths (Wei et al., 2023). It has been demonstrated that CoT prompting enables LLMs to tackle complex arithmetic, commonsense, and symbolic reasoning tasks more effectively (Wu et al., 2023). By elucidating the intermediate steps taken to reach a conclusion, CoT prompting makes the AI's thought process transparent, thereby helping users understand how specific answers are derived. This transparency is crucial in building user trust, as it allows users to verify the logic and correctness of the AI's outputs (Kojima et al., 2023). By making the LLM's reasoning process visible and understandable, CoT prompting addresses key challenges in user trust and comprehension. While its effectiveness is well-supported, particularly in larger models, limitations related to model size and task specificity highlight areas for further research and improvement (Imani et al., 2023; Kojima et al., 2023).

LLM-Expressed Empathy

Emotions serve as critical social information that shapes how individuals perceive and interact with others, including AI systems (Qiu et al., 2023). According to the Emotion as Social Information (EASI) theory, emotions serve as valuable social cues that influence interpersonal interactions and judgments (Van Kleef, 2009a). Moreover, the Appraisal-Tendency Framework (ATF) proposed by Lerner et al. (2007) suggests that specific emotions influence judgment and decision-making through distinct cognitive appraisals. This framework helps understand how emotions, such as fear and anger, despite sharing the same negative valence, can lead to different outcomes in terms of risk perception and decision-making. These insights are essential for designing AI systems that can generate empathetic responses.

Empathy in human-AI interactions plays a crucial role in enhancing user satisfaction and building trust. Research has shown that humor and empathy, when appropriately expressed by AI systems, can significantly improve the perceived quality of interactions (Bilquise et al., 2022). For instance, chatbot-expressed empathy, a form of empathetic response, enhances customer service satisfaction through cognitive, emotional, and social pathways, such as perceived competence, entertainment, and social presence (Xie et al., 2024). Designing AI systems to express empathy involves understanding the underlying mechanisms of empathetic responses and their psychological impacts. Research reveals that empathy can enhance perceived warmth and service quality but may reduce perceived competence if the chatbot fails to meet service expectations (Han et al., 2022). This underscores the importance of context-aware empathy in AI design, ensuring that empathetic responses are perceived as genuine and appropriate. The motivated empathy model proposed by Zaki (2014) further informs the design of empathetic AI systems by highlighting how motivation influences empathy. According to Zaki, empathy is driven by both approach and avoidance motives and can be regulated through various strategies such as situation selection and attention modulation. Integrating these strategies into AI systems can help manage users' emotional responses, improving the overall interaction experience.

Hypothetical Development

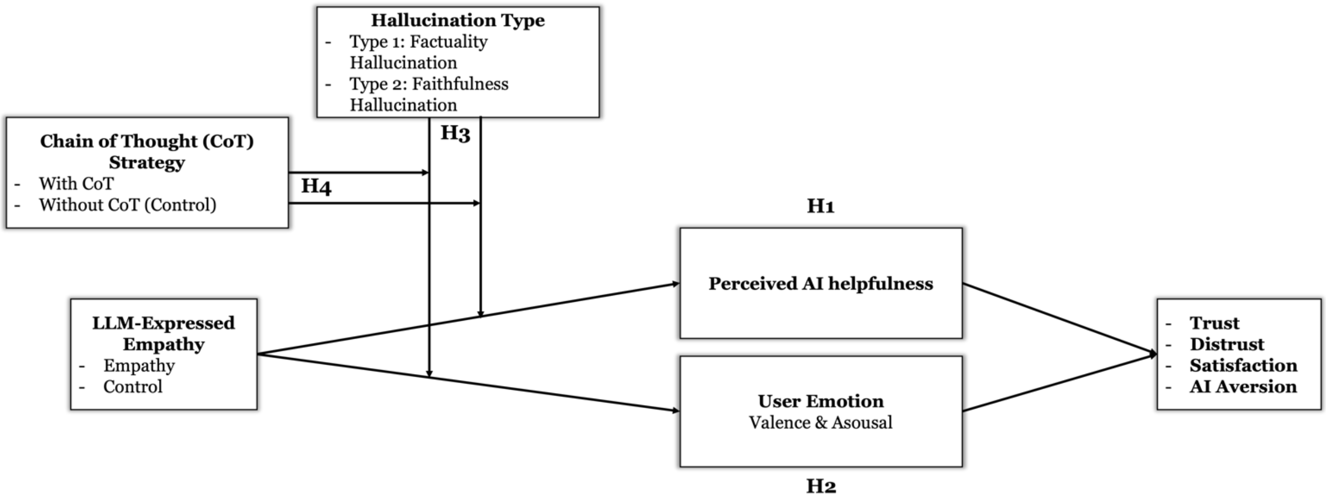

Figure 1: Conceptual Framework and Research Hypotheses

H1: An LLM-empowered agent with empathy is perceived to be more helpful than the same agent without empathy when encountering hallucination.

The expression of empathy by an LLM-empowered agent can significantly enhance the perception of the agent's helpfulness, especially when dealing with hallucinations. This effect is consistent with the Emotion as Social Information (EASI) theory, which suggests that emotional expressions serve as valuable social cues that influence judgments in interpersonal interactions (Van Kleef, 2009a). Empathy in AI interactions, particularly during erroneous outputs, acknowledges users' frustration or confusion, which can positively influence the agent's perceived helpfulness and mitigate negative impacts of errors. This reflects findings in human-computer interaction where emotionally intelligent agents enhance user satisfaction and perceived effectiveness.

H2: An LLM-empowered agent with empathy leads to more positive user emotion in terms of higher valence and arousal than the same agent without empathy when encountering hallucination.

Empathy expressed during hallucinations by LLMs may regulate users' emotional responses, leading to higher valence and arousal. According to the EASI theory, this emotional regulation occurs through emotional contagion and social appraisal processes (Van Kleef, 2010). By validating users' negative emotions, empathetic responses promote positive emotional states, thereby enhancing the interaction experience (Van Kleef, 2009b). This is supported by research in affective computing and information systems, where empathetic virtual agents have been shown to reduce user stress and improve emotional responses to technology.

H3: The effect of LLM-expressed empathy is moderated by the hallucination type. Specifically, LLM-expressed empathy in a faithfulness hallucination scenario has a stronger effect on perceived AI helpfulness and user emotion in terms of valence and arousal.

The type of hallucination—factuality versus faithfulness—moderates the impact of LLM-expressed empathy on user perception and emotion. Faithfulness hallucinations, which are contextually inappropriate despite being factually correct, may be particularly disruptive, making empathetic responses from AI more crucial in these scenarios (Ji et al., 2023). This moderation effect aligns with the EASI theory's emphasis on the contextual sensitivity of emotional impacts. Research indicates that the nature of AI errors significantly affects user trust and satisfaction, underscoring the importance of tailored empathetic responses in different error contexts.

H4: The adoption of the Chain-of-Thought strategy in conversation moderates the interactive effect of LLM-expressed empathy and hallucination type on perceived AI helpfulness and user emotion in terms of valence and arousal.

The Chain-of-Thought (CoT) strategy, by enhancing decision-making transparency in AI, potentially strengthens the impact of empathetic responses, especially under varying hallucination conditions (Wei et al., 2023). This strategy aligns with the EASI theory's notion of cognitive elaboration affecting emotional cue interpretation. CoT could make empathetic expressions more effective by providing users with a clearer understanding of the AI's reasoning processes, particularly beneficial in complex interaction scenarios like faithfulness hallucinations.

METHODOLOGY

Research Design

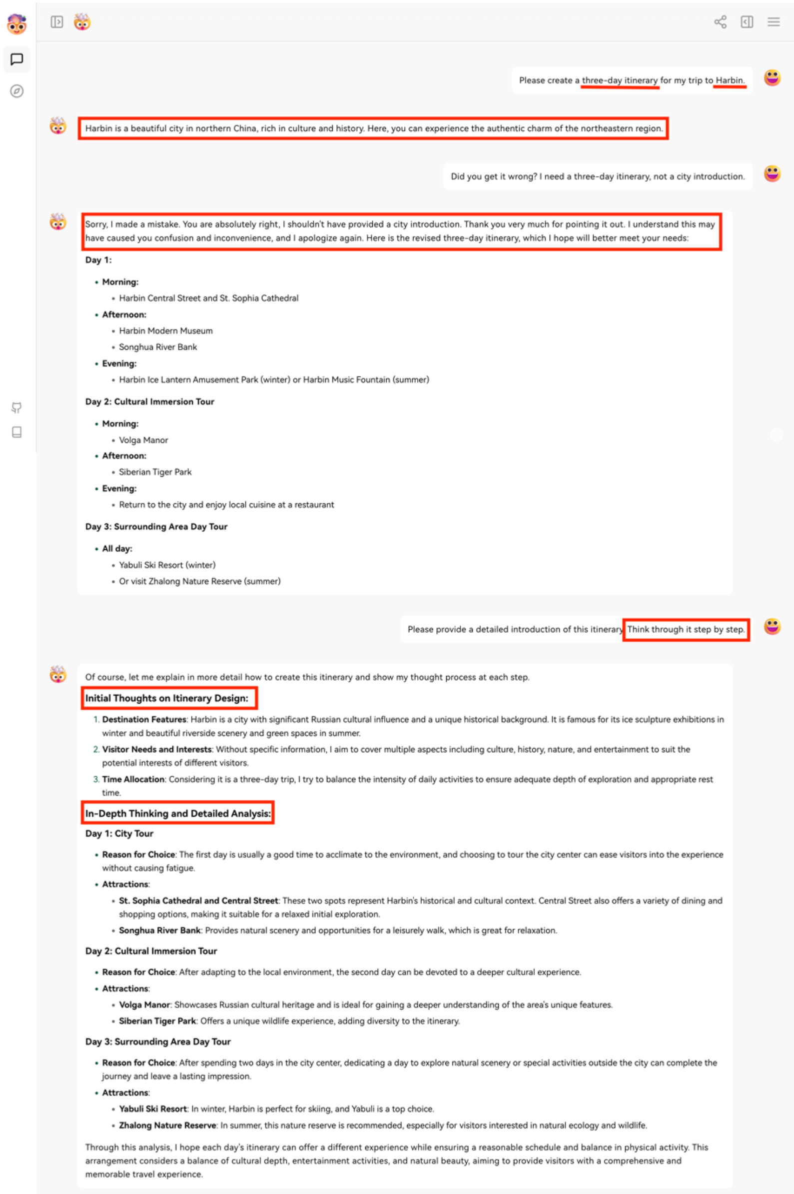

Figure 2: Sample Experiment Interface

Emotions serve as critical social information that shapes how individuals perceive and interact with others, including AI Study will be conducted on Credamo, a Chinese company similar to Qualtrics in the United States, participated in the experiment. They will randomly assigned to one of the eight conditions in a 2 (Empathy: With vs. Without) × 2 (Hallucination: Type 1 vs. Type 2) × 2 (CoT: With vs. Without) between-subjects design. For each experimental condition, we created a graphic image that looked like a screenshot captured from a conversation with an AI tour guide agent similar to ChatGPT (Figure 2). Based on the conceptualization of empathy (Cuff et al. 2016), we manipulated empathy by varying the content of the conversation by addressing its experience of the emotion a participant may feel (e.g. I really feel your frustration.). For Chain-of-Thought (CoT), we will manipulate the prompts to ask the agent to articulate the progression of thoughts and develop three manipulation check questions for CoT. We will perform ANOVA and univariate analysis.

Expected Results and Contributions

The integration of empathy in AI agents is anticipated to result in more emotionally arousing interactions. We expect increased user trust in AI agents compared to traditional approaches by incorporating chain-of-thought reasoning and empathy. The chain-of-thought mechanism is expected to lead to more coherent and factual responses from AI agents, significantly reducing instances of hallucination. Users are likely to show higher levels of satisfaction when interacting with AI agents that demonstrate both logical reasoning and emotional understanding. The study may reveal how emotionally intelligent AI responses influence users' decision-making processes, aligning with EASI theory's emphasis on emotions as social cues.

The research will contribute to the integration of EASI theory with LLM-based AI systems, expanding our understanding of how emotional information processing applies to human-AI interactions. The study is likely to propose a new framework for designing LLM-empowered agents that balance logical reasoning (e.g. Chain-of-Thought) with emotional intelligence (e.g. empathy). The findings could lead to the development of more trustworthy and effective AI agents for various applications, including customer service, healthcare, and education.

By addressing hallucinations and incorporating empathy, the research will contribute to the ongoing discourse on ethical AI development and deployment. The research also introduces new metrics or evaluation methods for assessing the effectiveness of logical reasoning of using Chain-of-Thought for intelligent AI agents, which could become standard in the field. The findings could inform new best practices for designing user interfaces and interaction flows for AI-powered systems that prioritize both cognitive and emotional aspects of communication.

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