A Graphical Interface for Structured Prompting with Large Language Models

ALEX ASCH, UCSD, USA
REI IKEDO, UCSD, USA
BOWEN BOTHELLO, UCSD, USA
YANHUA SHI, UCSD, USA

ACM Reference Format:
Alex Asch, Rei Ikedo, Bowen Bothello, and Yanhua Shi. 2026. A Graphical Interface for Structured Prompting with Large Language Models. In *Proceedings of the 15th PLATEAU Workshop on Programming Languages and Human-Computer Interaction (PLATEAU '25).* 9 pages. https://doi.org/XX.XXXX/XXXXXXX.XXXXXXX

1 Abstract

When users interact with LLM systems, they generally utilize purely text-chat-based interfaces. These require users to rely on their own recall ability or to use cumbersome scrolling and text-based search to inspect parts of prior usage. Additionally, a purely scrolled text interface renders no visible information about the general flow or path of the conversation, or overall chain of discovery to attain a solution. This provides a poor interface for adding additional contextual data, which would have been beneficial for improving prompt accuracy. In this paper, we design a tree-based user interface for LLM interaction, and perform an experimental pilot study that shows the impact of this new prompting framework. The results of our pilot study showed that participants generally felt that the visual interface promoted a more interactive, iterative approach to studying. Furthermore, they reported that the node structure promoted a more intuitive navigation process between topics that closely mapped to their mental models for brainstorming style tasks.

1.1 General Terms

LLM, Interfaces

1.2 Keywords

LLM interface, Prompt Engineering,

2 Introduction

There exist a variety of techniques for improving prompt design in order to facilitate more useful LLM responses (such as role assignment, Chain-of-Thought (CoT), few-shot, etc.) [2, 6]. These techniques are not immediately obvious to most users [12], and as such there are some approaches that have been explored for helping users leverage these techniques. These approaches include establishing frameworks for prompting [2], delivering training and assessing common pitfalls [3, 12], and also leveraging software tools which can optimize prompt text for users [8, 9, 11]. These

Authors' Contact Information: Alex Asch, UCSD, San Diego, CA, USA; Rei Ikedo, UCSD, San Diego, CA, USA; Bowen Bothello, UCSD, San Diego, CA, USA; Yanhua Shi, UCSD, San Diego, CA, USA.

PLATEAU '25, Boston, MA

https://doi.org/XX.XXXX/XXXXXXX.XXXXXXX

are all in service of conveying these techniques and best prompting practices to users. Our project would be juxtaposed with these in that it is attempting to make these techniques available to users in an intuitive visual way as part of the LLM interface itself such that it might promote development of intuition regarding these techniques without requiring explicit training or knowledge of a specific framework.

University students are the demographic of interest, as one of their main goals is studying for their courses. While studying with peers can be helpful for reflecting on material, such support is not always available and furthermore peers from other departments may lack the domain knowledge required to provide feedback on concepts being explored. As such, we propose that our visually interactive LLM interface could help fulfill the role of an on-demand interactive study partner and tutor in a more intuitive way than a simple text input box typical of many popular LLM tools currently available. CoT is a technique used to improve LLM prompting efficacy, and we posit that university students would be able to benefit from the composite nature of this technique in a natural way via the interface design being a visual mind map. In addition, students could benefit from more interactive LLM use which can better engage them mentally with study material rather than passively. This can give students the dual benefit of tapping into the psychological "cognitive looping" effect (a concept from sociocultural cognition theory which emphasizes the importance of iterative feedback on learning), while also leveraging the more effective CoT prompting method in an intuitive way as facilitated by the visual mind map interface.

The findings of our pilot study were promising. Participants noted that the interface supported clearer lines of reasoning compared to the traditional ChatGPT interface, which participants described as a "wall of text." The node-based structure appeared to improve the organization of information and allowed participants to more easily follow and revisit lines of thought. In particular, participants appreciated the ability to traverse between nodes when finishing a topic or when deciding that a particular direction was not useful. Moving up and down between nodes was reported as a common interaction, and traversal indicators helped participants keep track of the progression of ideas. Participants also highlighted the prompt refinement nudges as an important feature that made the system feel more interactive and conversational. Rather than receiving a single, complete response, users were encouraged to iteratively refine their prompts and explore alternative directions, which appeared to promote deeper engagement with the material. Finally, participants suggested that the graphical user interface was particularly well suited for exploratory or brainstorming-style tasks. The branching structure and visual organization of ideas appeared to align with how participants approached studying or learning about new topics, and the interface was therefore perceived as more natural than a traditional linear chat interface when engaging in exploratory learning.

Our aforementioned findings uncovered while attempting to address our research question could be generalized beyond university students to many other demographics undergoing some learning process. Industry professionals upskilling, health professionals keeping up-to-date on the latest techniques, K-12 students, and so on. Furthermore, this style of visual interface could be generalized to broader LLM usage, not just studying related tasks, since chain-of-thought is a more effective prompting technique which can help more generalist users of LLMs who can benefit from a methodical decomposition of their prompt response.

3 Methods

3.1 Platform Design

We implement a platform in which users are able to prompt an LLM in an exploratory fashion, creating a tree rooted at a parent, which is their initial prompt. From there, we generate 3-5 child nodes, each proposing a certain potential path the user could explore, with a title on the topic of the node, and an input body, where the user can further prompt down that branch of the tree, which then reiterates the above prompting process. In addition to this, we add side leaf nodes for each selected and prompted node, in which users can then submit text and re-prompt, to generate new leaf nodes from the parent node, to further clarify intent about the question. We persist the overall tree, and allow drag-and-drop rearrangement and navigation of the overall platform as well. Through this, the user is intended to explore idea paths in their pursuit of a problem, rather than to obtain a one-shot answer, or a linear chain of prompt refinement. An example screenshot of the interface is included in Figure 1.

In terms of LLM prompting, we believe we will see benefits from this approach by having a reined-in system prompt, and user-generated external data. By forcing the model via system prompt to ask clarifying questions of the user, and add a tree of previous ideas to each prompt, we effectively make the prompt more robust and well-defined, which is generally accepted to increase prompt accuracy using additional information. By using a tree node structure with a limited amount of generated text, and only immediate context in prompt, we are able to avoid the context window explosion problem that is frequently seen with long-running chat LLMs.

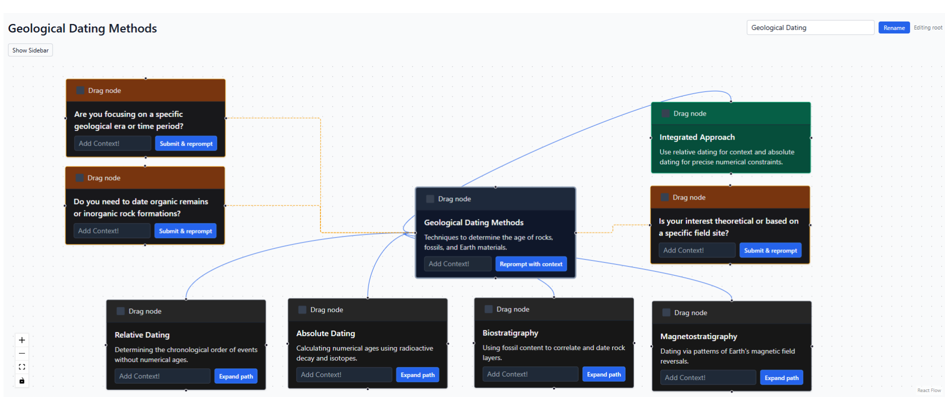

Fig. 1. Example Screenshot of our Platform Interface

3.1.1 Technologies. We implement our platform as a session-based webapp using Node.js with React. We implement our prompt tree nodes using React Flow, and currently only support one chat per session. For the choice of LLM, we chose Gemini, as for the experiment, we needed free access to a more robust model (to support our detailed system prompt), which the Gemini API allowed us to use albeit with a daily limit on prompts.

3.2 Study Design

3.2.1 Conducting the Study. We carried out a small pilot usability study of our visual LLM interface. Four participants completed a task pertaining to studying a given concept, leveraging the visual LLM interface to assist them while performing a think-aloud process throughout. For recruitment, we asked classmates and friends on campus to participate in our pilot study.

Participants first completed a brief demographic pre-survey to capture background information, such as their level of experience with LLM tools, perceived efficiency when using LLMs for tasks, and familiarity with visualization or mind-mapping tools. This served to provide individual participant context as well as a record for potential confounding variables. We conducted 30-minute sessions with each participant individually. At the start of each session, we first provided brief training on the usage of our LLM interface platform, going over topics including initial node creation, how to expand branching paths, and how to enter text into re-prompt suggestion nodes.

Participants then spent roughly 15 minutes exploring a topic to answer a question we gave them about a subject they had indicated in the survey as having a low level of familiarity with. Our intention was that the topic would be novel to them so as to avoid any prior knowledge on a subject undermining the use of the LLM platform as a study aid. Since participants indicated geology as a topic of low familiarity, we used the following question: “Give a brief summary of how the layers of the ground can indicate the time period in which they were formed.” Participants were also encouraged to write notes to summarize their learning on the topic.

Participants observed the think-aloud protocol while researching the topic. We collected audio recordings of the think-aloud sessions along with observational notes documenting user behaviors and strategies related to navigating the visual interface, as well as screen recordings to preserve the mind map layout and navigation choices performed by each participant. We also recorded audio responses to a post-task interview with questions aimed at assessing perceived usefulness, challenges, and overall usability. The interview was semi-structured to allow for exploration of novel themes or suggestions that participants might raise.

3.2.2 Data Analysis. We carry out a thematic analysis of think-aloud transcripts and interview responses, leveraging Braun & Clarke’s six-phase framework for this process. Our analysis is inductive rather than adhering to a pre-existing theoretical framework so as to afford us some flexibility to evolve and explore our understanding of the problem space based on new or unexpected themes in the data.

Multiple researchers first independently code a portion of the data, and then we later cross-check our codes for consistency. Data from our background pre-survey will be leveraged to contextualize our findings and serve as a record of any potential confounding variables. Furthermore, textual LLM interaction logs and researcher notes on observed user navigation behavior will be used to help support the construction of our memos and themes.

4 Results

We recruited four undergraduate Computer Science majors at UCSD (two men and two women) with varying levels of LLM usage experience, to participate in our pilot study. After performing thematic analysis we found that the following themes emerged.

4.1 Visualizing Chains of Reasoning

Four out of four participants mentioned that the visual node structure helped them understand how ideas were connected. Instead of reading large blocks of text, the visual layout allowed them to quickly scan the reasoning paths and relationships between concepts. This structure helped participants see how different ideas were connected and how the exploration process developed over time. One participant, P2, described the experience as similar to “opening multiple tabs while researching a topic,” which helped them follow different ideas more easily. She explained that the connections between nodes made it easier to track different lines of thought compared to reading a long conversation in a chat interface. This sentiment is also evidenced by P1’s interview quote: "It’s nice having the pretty well-defined line between like, alright, this is what you were talking about first, like, we went over here...". Moreover, both P1 and P2 contrasted the visual LLM interface with the "wall of text" structure that a more conventional LLM interface such as ChatGPT provides, which necessitates cumbersome scrolling and a lack of visual distinctions between topic.

4.2 Exploration with Multiple Paths

All participants appreciated the ability to explore multiple directions from a single topic. The branching structure allowed them to follow different lines of reasoning and explore related concepts during the learning process. Participants mentioned that this structure supported a more exploratory style of thinking, where they could gradually move from one concept to another. Both P1 and P2 mentioned how the more visually distinctive interface seemed to naturally map to their mental processes of exploratory studying a novel topic. This is highlighted in P2's quote that "I do like this sort of mind map style better, because it's a lot more related to how my brain works and how I study". P1 similarly likened the interface as akin to a brainstorming session in that "it's definitely a bit more organic, I'd say, like, closer to… you know, like, how you'd get a bunch of friends drawing on a chalkboard."

However, participants P3 and P4 reported that choosing between multiple branches could sometimes feel confusing, especially when the topic was completely unfamiliar to them. When they did not yet understand the terminology or the relationships between concepts, deciding which branch to explore next became more difficult.

4.3 Revisiting and Comparing Previous Nodes

Three of the participants emphasized the importance of revisiting previously explored nodes. They mentioned that being able to return to earlier nodes would help them compare ideas, trace back what they had learned, and continue their exploration process. Revisiting previous nodes was also useful for understanding how different concepts were related. P1 took on a sort of sequential approach which embodied this concept in that he would move on from one branch to the next "if I feel like I've gone through most of that line of reasoning" to go back up the tree and move on to the next branch. P2 similarly mentioned how the interface allowed her to quickly move between topics after she deemed them to not be relevant, "what I thought branched into something that might have helped me, didn't actually, so let me go back. What did I have before? Okay, maybe… maybe that was the wrong direction, so let me keep going back".

P3 suggested adding a history panel on the left side that would allow users to track which nodes they had explored. She mentioned that the GUI could not only be used as a learning path but also as a notebook for tracking learning progress and organizing notes about the topic. P1 similarly expressed a desire to more clearly view or perhaps archive the mind map's older nodes for later reference.

4.4 Reliance on System Generated Suggestions

P3 and P4 mentioned that they relied heavily on the LLM-generated suggestions when deciding which branch to explore next. These suggestions often guided and influenced the direction of their learning process. In many cases, participants followed the suggested nodes because they provided possible directions for further exploration. However, when the topic was completely unfamiliar to them, some participants reported that it was difficult to determine which suggestion would be the most useful. One participant also mentioned that once they selected "No" when the system asked about a suggested path (for example, "Are you interested in this path?"), the node would disappear and there was no way to return to it later. This made it harder to reconsider earlier options during the exploration process.

Conversely, P1 and P2 felt that rather than being reliant on the suggested re-prompting nodes, they felt that it incorporated a more interactive element to the interface. P1 described how "it seems to replicate a bit more of, like, a conversation". P2 took this sentiment even further and mentioned that "I didn't try it because I didn't want to, but I don't know what the output would have looked like if I had just typed the question in, as opposed to typing just a single idea". She expressed how she did this explicity because she did not want to be given an entire answer to a question right away and would rather engage in a more interactive or iterative approach to searching about the assigned topic. She expressed that the re-prompting question nodes helped to facilitate this form of cyclical engagement.

So, although participants had different levels of visual learning preference and levels of experience with LLM tools, several common themes emerged across the interviews.

5 Limitations

This study has several limitations related to participant diversity, prototype design, and study methodology. First, the participant pool in this pilot study was relatively small and homogeneous. The study involved only four participants, all of whom were undergraduate Computer Science majors at UCSD. Although we attempted to reduce bias by asking participants to explore topics outside of their existing knowledge domains, some bias may still remain. Participants with technical backgrounds may have stronger analytical skills and may be more comfortable interacting with experimental interfaces than the general population. In addition, all participants were university students within a similar age group. In real-world scenarios, potential users may include people from different age groups and educational backgrounds, whose learning styles and levels of digital literacy may differ significantly. Second, the prototype interface used in this study had several usability limitations. Participants reported issues related to navigation, node organization, and the lack of a history feature for revisiting previously explored branches. Some participants also mentioned that once a suggested path was rejected, it could not easily be revisited. These design limitations may have influenced how participants interacted with the system and may have affected their evaluation of the interface. Third, the study was conducted in a short experimental session in which participants explored a new topic for a limited period of time. Real learning processes often occur over longer periods and involve repeated interaction with learning tools. Therefore, the results of this study mainly reflect short-term exploratory usage rather than long-term learning behavior. Although there are some limitations, the study still provides preliminary findings into how mind-map-based interfaces may support exploratory learning and knowledge organization. Future work could address these limitations by improving the interface design and conducting studies with larger and more diverse participant populations.

6 Discussion

The findings from this pilot study suggest that a mind map interface may support exploratory learning by providing a visual structure that helps users organize and navigate information more easily. Compared with traditional text-heavy interfaces, the mind map visualization presents information with less text and more visual connections between concepts. This visual representation may help users quickly understand relationships between ideas without reading large amounts of plain text. Participants were able to explore different branches of a topic and gradually build a broader understanding of unfamiliar subjects. The visual representation of relationships between concepts appeared to encourage users to follow different paths and discover related ideas during the exploration process. Compared with traditional linear information presentation, the mind map structure may reduce cognitive load by allowing users to see relationships between concepts at a glance. This tool may help learners understand how ideas are connected and support knowledge organization during exploratory learning tasks. Participants in the study also reported that the branching structure encouraged them to explore topics more freely rather than following a fixed path. Our observations suggest that a mind map interface could be useful for learning environments that emphasize exploration and discovery, such as self-directed learning or topic exploration. While the current prototype is still limited, the results indicate that visual knowledge structures may play a role in supporting exploratory learning processes.

7 Related Work

There has been research into the concept of improving the visual interactive experience of LLM prompting [1, 4, 7, 13], through the use of standard UI techniques. This could be exhibited through the addition of buttons, which either hold static pre-written prompt additions the user could select to improve their inquiry, or dynamic buttons, with which an LLM determines the best extensions of their initial inquiry to improve their final generated prompt [1]. There is also the possibility to include other visual user experience elements such as multiple choice options or drop-down menus to provide further contextual information and control towards prompt generation [4]. Our own project's aim would be to leverage our more interactive LLM UI in such a way that it would incorporate a more iterative or dialogic CoT approach [2, 6], which would help users benefit from enhanced specificity of their prompts [13] while also making them implicitly more involved in the back-and-forth thought process to improve their mental engagement and thus retention of study material they are using the LLM to review.

Additionally, there is a focus on explainability in AI and turning prompting tricks like CoT into usable interactive UI elements [13], or a dynamic UI context framework with prompt based UI elements [1]. Combining these existing implementations with the frameworked approach of human-AI collaboration as outlined in [10], we observe that increased explainability of model prompting "tricks" like CoT through UI elements can contribute to user understanding, meeting the design goal of usability driving explainability. Our work looks to contribute to this idea, by exposing framework tooling adaptively to the user, contributing to the HCAI model of usability through explainability, and extending on previous work done in CoT visibility.

8 Future Work

Due to the semi-structured nature of our interviews we were able to engage in an unexpected line of questioning with P2 with regards to the desire she expressed to have the LLM withhold certain information from her in order to better facilitate an engaging study session. Both P1 and P2 indicated through their interview responses that they valued the interactivity that the prompt refinement suggestions offered, and while information withholding was not an initial component of our design that we considered during the development of the LLM platform we believe that it could be well suited for facilitating studying and learning. Professional human tutors are typically trained to guide students to answers, which is something that students such as P2 may not wish to be given right away when they are attempting to study and learn. As such, if we were to continue this project we may want to investigate ways that we might incorporate this into our design by perhaps adjusting prompt text sent to the API to include explicit requests to not be given full answers, and to perhaps incorporate hint nodes or even follow-up questions the LLM could pose as a way to draw out student cognitive engagement. This could align well with the Chain-of-Thought (CoT) techniques in that an LLM response may be portioned into multiple steps, with only the initial steps revealed to the user and the rest obfuscated until a sufficient "productive failure" has been performed by the student. Productive failure is a teaching technique by which a student is given a question and spends at least 30 minutes attempting to solve it before being given instruction on how to solve it, and this has been shown to have a significantly positive effect on learning outcomes [5]. As such, we believe that incorporating this sort of information obfuscation could be a means of leveraging both CoT prompting in an intuitive way as well as the productive failure teaching strategy.

9 Conclusion

This paper presents a different way of prompting and visualizing a LLM through a node-based interface rather than the standard text-chat-based designs. This node-based interface allows users to branch out from an initial prompt by treating it as a tree root, with paths to explore branching off from it for further discovery on the topic. Our intent for this design is to benefit users who are intending to do exploratory research into concepts as a means of growing their knowledge on a subject. In this study we conducted think-aloud sessions with four participants in which they explored a topic utilizing our branch-based LLM interface platform. They also provided responses to a post-task semi-structured interview to further explain their thoughts on how they perceived and utilized the interface. From this pilot study we uncovered several themes through our thematic analysis of the participant data collected. These themes are as follows:

Chains of Reasoning All four participants indicated an improved understanding of how ideas within a subject are connected to each other due to the layout's visual depiction of branching exploration paths. Two of the participants preferred this design choice to the "wall of text" structure of more conventional LLM interfaces.

Path Exploration Every participant expressed appreciation for the ability to explore multiple directions from a single topic. This design benefitted what was described as an exploratory style of thinking. Furthermore, two participants likened the branching nature of the LLM interface to mental mapping and brainstorming sessions. In contrast, there were two participants who considered the branching paths confusing in certain circumstances.

Ability to Revisit Nodes Three of the participants emphasized the importance of being able to revisit previously explored nodes. In particular, by being able to access these nodes, the participants were able to compare ideas, trace back what they had learned, continue their exploration process, and understand how different concepts were related.

Reliant on Generated Suggestions Half of the participants indicated that they relied heavily on the LLM-generated suggestions to decide the direction of their exploration. The other half considered the communication as more of an interactive conversation which facilitated a form of cyclical engagement.

10 Appendix

10.1 Platform Code Repository

The LLM platform code repository, as well as setup instructions can be found here: https://github.com/aasch2020/LLM-GUI.git

10.2 Post-task Interview Questions

The list of questions used to carry out our semi-structured interviews are as follows:

(1) How does this experience compare to how you normally study or use LLMs?
(2) How does your approach to using this visual mind map interface compare to your use of a typical plain text-input LLM interface?
(3) How well would you say that this mind map format reflects your thought process when studying and learning new material?
(4) Can you recall any recent events where you were using an LLM and had any particular challenges with the interface structure?

(5) What was your initial impression of the interface? Did this impression shift at all throughout the duration of the tasks?
(6) Can you think of any specific situations or tasks where you would find this type of LLM interface useful to you? Anywhere you would not?
(7) Did the visual positioning of the mind map nodes have any effect on your mental organization of concepts?
(8) What did you think of the branching structure of the mind map and its decomposition of concepts into subtopics?
(9) Can you recall a moment during the tasks when you felt that the visual interface had a noticeable effect on your studying of the material?

References

[1] Ian Drosos, Jack Williams, Advait Sarkar, Nicholas Wilson, Sean Rintel, and Payod Panda. Dynamic prompt middleware: Contextual prompt refinement controls for comprehension tasks. In *Proceedings of the 4th Annual Symposium on Human-Computer Interaction for Work*, CHIWORK '25, New York, NY, USA, 2025. Association for Computing Machinery.
[2] Yao-Yang Liu, Zhen Zheng, Feng Zhang, Jin-Cheng Feng, Yi-Yang Fu, Ji-Dong Zhai, Bing-Sheng He, Xiao Zhang, and Xiao-Yong Du. A comprehensive taxonomy of prompt engineering techniques for large language models. *Frontiers of Computer Science*, 20(3):2003601, 2025.
[3] Qianou Ma, Weirui Peng, Chenyang Yang, Hua Shen, Ken Koedinger, and Tongshuang Wu. What should we engineer in prompts? training humans in requirement-driven llm use. *ACM Trans. Comput.-Hum. Interact.*, 32(4), August 2025.
[4] Stephen MacNeil, Andrew Tran, Joanne Kim, Ziheng Huang, Seth Bernstein, and Dan Mogil. Prompt middleware: Mapping prompts for large language models to ui affordances, 2023.
[5] Lauren E. Margulieux, James Prather, Masoumeh Rahimi, and Gozde Cetin Uzun. Leverage biology to learn rapidly from mistakes without feeling like a failure. *Computing in Science & Engineering*, 25(2):44–49, 2023.
[6] Douglas C. Schmidt, Jesse Spencer-Smith, Quchen Fu, and Jules White. Towards a catalog of prompt patterns to enhance the discipline of prompt engineering. *Ada Lett.*, 43(2):43–51, June 2024.
[7] Maddalena Torricelli, Mauro Martino, Andrea Baronchelli, and Luca Maria Aiello. The role of interface design on prompt-mediated creativity in generative ai, 2024.
[8] Zhijie Wang, Yuheng Huang, Da Song, Lei Ma, and Tianyi Zhang. Promptcharm: Text-to-image generation through multi-modal prompting and refinement. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, New York, NY, USA, 2024. Association for Computing Machinery.
[9] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, brian ichter, Fei Xia, Ed Chi, Quoc V Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh, editors, *Advances in Neural Information Processing Systems*, volume 35, pages 24824–24837. Curran Associates, Inc., 2022.
[10] Wei Xu, Marvin J. Dainoff, Liezhong Ge, and Zaifeng Gao. Transitioning to human interaction with ai systems: New challenges and opportunities for hci professionals to enable human-centered ai. *International Journal of Human–Computer Interaction*, 39(3):494–518, 2023.
[11] Mert Yuksekgonul, Federico Bianchi, Joseph Boen, Sheng Liu, Zhi Huang, Carlos Guestrin, and James Zou. Textgrad: Automatic "differentiation" via text, 2024.
[12] J.D. Zamfirescu-Pereira, Richmond Y. Wong, Bjoern Hartmann, and Qian Yang. Why johnny can't prompt: How non-ai experts try (and fail) to design llm prompts. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery.
[13] Runtao Zhou, Giang Nguyen, Nikita Kharya, Anh Totti Nguyen, and Chirag Agarwal. Improving human verification of llm reasoning through interactive explanation interfaces, 2026.