Workplace Everyday-Creativity through a Highly-Conversational UI to Large Language Models

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We explore everyday co-creativity for collaborative human-AI teams in workplaces via a conversational user interface to a large language model. Previous short papers explored human-AI team-creativity methods such as framing and reframing. This experiment examines aspects of brainstorming. We demonstrate divergent thinking (idea generation) and convergent thinking (summarization and classification) between a human and a conversatioanl AI agent. We observed that creativity emerges in the hybrid interstitial conversational space between human and AI.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **Empirical studies in collaborative and social computing**; **Collaborative interaction**; • **Computing methodologies → Artificial intelligence**.

Additional Key Words and Phrases: Human-centered AI, Co-creativity, Generative AI, Large language model, Conversational UI

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1 INTRODUCTION

We describe a recent case study in human-AI co-creativity, through team-creativity methods between a human and a conversational large language model (LLM). We are interested in "everyday" creativity, such as answering questions and creating solutions to problems, that knowledge workers face many times each day. Creativity studies have used expressions such as "small-c creativity" [15], "mundane creativity" [5], or "P-creativity" [1] to describe these quotidian instances. Consistent with Glăveanu's proposal of *distributed creativity* and Kantosalo's and Takala's conception of creativity as performed by a *collective of human and AI* [11], we explore human-AI collaborations in everyday team-creativity work. We hope to understand possibilities for human-AI co-creativity in ordinary workplace collaborations.

To begin our exploration, we examined team-creativity practices [21, 30], and we chose brainstorming as familiar method that is used in many institutions. Earlier work examined methods of framing [18] and reframing [19] in analogy-based design. For our experiment, we chose a more structured form of brainstorming (e.g., [9]) as a task that most teams perform on a regular basis.

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Common stages in brainstorming include divergent thinking (idea generation) and convergent thinking (idea summarization and categorization) [17]. These phases often correspond to higher-level goals of exploration and optimization, as have been discussed in AI [22, 28], HCAI [7, 20], HCAI-oriented design [29], CHI [12, 31] as well as influential critiques of AI planning approaches [27].

2 BRAINSTORMING WITH THE AI

In this study, we used a highly-conversational user interface (UI) to the Llama2 large language model (LLM), similar to [23] Each conversational turn by the AI was "tuned" to be brief, humble, and helpful, through prompt design and some intermediate software between the UI and the LLM. Conversations with the AI took place in an internal group chat application on a company-internal server.

Figure 1 shows excerpts from an informal, one-user dialog during the divergent thinking phase of the brainstorming activity. The human proposes a business problem as the topic of brainstorming at Figure 1A. The AI proposes "a few brainstorming ideas" at Figure 1B. While these ideas may not be brilliant, we believe they are plausible and potentially useful.

Good brainstorming partners should be able to critique ideas and collect new suggestions [3]. Figure 1C-E shows a series of such interactions. The human objects to the fourth idea that the AI had proposed. The AI offers alternative ideas that the human "could consider" (Figure 1D), but insists that its original idea continues to have merit (Figure 1E). The conversation continues on the right side of Figure 1F-G, with a second human objection, and a second set of AI-proposed alternatives. Ultimately, the human rejects all of those alternatives, and the problematic item as well at Figure 1H.

Brainstorming can also involve a sudden expansion of the scope of a topic or a question. In Figure 1J, the human asks the AI a more open-ended question, and the AI responds at Figure 1K.

We also note that the work of the human and the AI moved between exploratory activities (divergent thinking, Figure 1A-B, D, G, J-K) and optimization activities (critical and convergent thinking, Figure 1C, F, H). These fluid changes in focus – within the broader context of brainstorming – appear to be related to Schön's analyses of designers' reflective practice [24] as constantly developing and emerging through conversations with the design materials [25]. If designer collectives (i.e., of human and AI [11]) can move from divergent to convergent and back again – from exploration to optimization and back again – then these observations call into question the binary distinctions that have been discussed between exploration and optimization [7, 12, 20, 22, 28, 29, 31]. Further study may show that exploration and optimization are in some cases simple alternations in focus within a single holistic activity.

Figure 2 shows additional convergent thinking operations, in which the human has requested a summary and categorization of the accepted ideas at Figure 2A, and then requests that the AI move an idea from one category to another at Figure 2C. The AI first performs a critical thinking task at Figure 2B, and performs more of a secretarial task, responding to the human's instruction at Figure 2D.

3 DISCUSSION: THE LOCUS OF CREATIVITY

Unlike projects that elicit creative outputs from generative AI models [2, 16], we pursue the concept of co-creativity as a *process* that is distributed [5] between the two parties of a human-AI collective [11]. We propose that creativity emerges through interaction, in the hybrid space between human and AI (see e.g., [14]). For example, the human framed the problem space in Figure 1A, and the AI proposed ideas into that frame in Figure 1B. Within a more critical subframe, the pattern repeated in Figure 1C-D and again in Figure 1F-G. An even stronger example is the exchange that begins

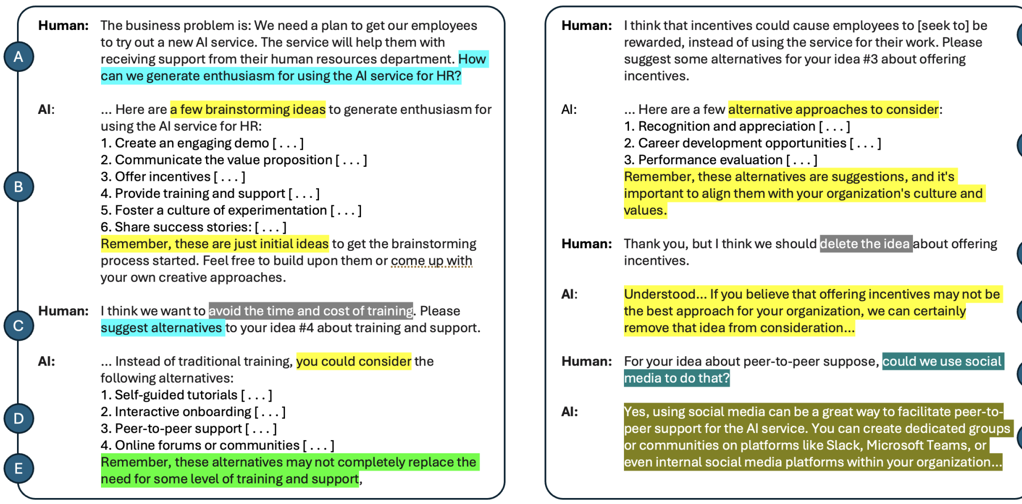

Fig. 1. Divergent thinking between human and AI. Y*ellow-highlighted text* shows AI's humble (rather than oracular) conversational moves, including responsiveness to human correction. *Blue-highlgithed text* shows divergent thinking requests. *Grey-highlighted text* shows critical and convergent thinking. *Green-highlighted text* shows persistence of one idea. *Teal-colored text* shows a request for "blue-sky" speculation, answered by *mustard-highlighted text*. **A.** Human begins the brainstorming with a request for divergent thinking. **B.** AI provides divergent ideas. **C.** Human criticizes one idea and requests alternative. **D.** AI proides alternatives. **E.** AI presists with one idea. **F.** Human makes a second request for alternatives. **G.** AI provides alternatives. **H.** Human rejects an idea. **I.** AI complies. **J.** Human requests "blue-sky" speculation. **K.** AI complies.

in Figure 1D with the AI's suggestion for peer-to-peer support, which the human picks up again at Figure 1I. The human asks the AI to pursue the topic of Figure 1D, and the AI responds with a further series of novel suggestions.

4 CONCLUSION

Glăveanu proposed that creativity could be distributed among persons [5], as a more focused version of the concept of distributed cognition [8]. While their emphasis was on the *social* distribution of cognition and creativity, researchers also showed how objects and record-keeping systems were also involved in the distribution of knowledge [6], and in some cases of action [13]. Scholars such as Jordanous, Kantosalo, and Takala extended this line of thinking into the partial equivalence of human and AI in creativity ([10]; see also [4, 26]) and the necessary co-participation of human and AI in co-creativity [11]. In this paper, we have applied that theorizing to the practical case of human-AI brainstorming, where we have demonstrated that creativity emerges not from one party or the other, but rather through the interaction of diverse human and AI actions.

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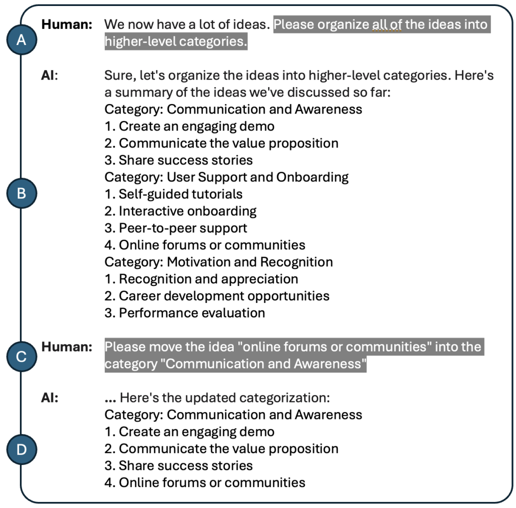

Fig. 2. Convergent thinking, summarizing, organizing, and selecting between human and AI. **A.** Human requests a curated, structured summary of collective work. **B.** AI provides the summary. **C.** Human requests to modify the structure of the summary. **D.** AI confirms the modification.

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