When AI Joins the Brainstorm: Impacts of Generative Language Models on Collaborative Divergent Thinking

Completed Research Paper

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Abstract

Divergent thinking is the key mechanism for generating creative ideas. In collaborative ideation, it leads to the generation of a wide range of creative ideas. But this process can be challenging due to fear of judgment, idea fixation, and the influence of group dynamics. In this paper, we explore how integrating generative language models as an AI peer impacts collaborative divergent thinking. We conducted a randomized controlled experiment (N=96) with four conditions, varying two factors: the structure of idea sharing (live vs. round-based), and the presence of an AI peer generating ideas using a Generative Language Model. Using a mixed-methods approach, we assessed creative fluency, idea elaboration and originality, collaboration, and participants' experience. Results show that AI agents generated more original ideas than human participants, but that exposure to these ideas decreased participants' fluency and originality. Round-based interaction also strengthened collaboration, while decreasing individual fluency.

Keywords: Generative AI, Originality, Human-AI Collaboration, Divergent Thinking, Computer-Supported Collaborative Work

Introduction

Ideation, the process of generating new ideas, is at the core of design thinking and innovation processes, forming the basis for developing creative solutions to wicked problems (von Thienen et al., 2014). Effective ideation benefits from the collaboration of diverse team members and their capacity to generate uncommon ideas, especially during the early phases of innovation (Edmondson and Harvey, 2018; Palazzo et al., 2012). It can be described as the succession of two mechanisms: divergent and convergent thinking (Guilford, 1967; Parnes, 1967). Divergent thinking is the generation of diverse and original ideas, and convergent thinking is the evaluation and selection of the previously generated ideas. These two phases complement each other. They play different roles and research suggest that they may be more effective when explicitly separated (Wang et al., 2023; Zhu et al., 2019). In this paper, we focus on divergent thinking.

Brainstorming is a well-established method for fostering divergent thinking and collaboration (Osborn, 1963). Traditionally, brainstorming activities have been conducted using physical media such as paper, white-boards, or basic online collaboration tools like Google Docs or Microsoft Word (White et al., 2010). Although these approaches facilitate the exchange of ideas, they also present several limitations. First, the lack of anonymity can hinder participation, as individuals may be reluctant to share unconventional ideas due to fear of judgment or criticism (Cooper et al., 1998; Kang et al., 2013). Second, when participants struggle to produce original ideas, it can reinforce psychological phenomena such as idea fixation, whereby individuals tend to elaborate only on existing suggestions rather than exploring novel directions (Kohn and Smith, 2011). Finally, divergent thinking can be framed as a distributed cognitive process (Hollan et al., 2000; Rogers and Ellis, 1994). Under this lens, the process of generating ideas is not isolated within individuals but emerge through interactions with external structures, the environment, and other participants, evolving over time as earlier contributions influence subsequent developments. Thus, the timing and structure of idea sharing—whether immediate or delayed—can significantly shape the creative dynamics of the group. Valued in Human-Computer Interactions (HCI) and Computer-Supported Collaborative Work (CSCW), this theoretical approach informs the design of digital environments and artifacts that support divergent thinking, and, more generally, ideation. Recent advancements in digital platforms, Generative Artificial Intelligence (GenAI), and in particular Generative Language Models (GLMs) have created new opportunities to structure and enhance collaborative divergent thinking, with the hope to overcome the limitations described previously. For instance, general brainstorming platforms can strengthen collaboration by preserving participants' anonymity. Moreover, AI-driven brainstorming platforms can enhance creativity through automatic idea reformulation (La Scala et al., 2025a) and generating diverse, unexpected suggestions (Haase and Hanel, 2023; Shaer et al., 2024a; Stevenson et al., 2022). Such systems have the potential to stimulate broader exploration, reduce fixation effects, and increase the novelty of the ideas produced (La Scala et al., 2025a; La Scala et al., 2025b; Memmert and Bittner, 2024). Finally, structuring the ideation process and managing the interactions between participants offer additional means to support creativity.

However, despite the promising capabilities, research on the use and impact of GenAI-supported brainstorming platforms remains scarce. Key questions persist regarding how these systems affect the *collaboration*, *participants' experiences*, and *creativity* of outcomes during collective ideation processes. In this paper, we contribute to addressing these gaps by investigating the following overarching research question:

RQ: *How do the structure of collaboration and the integration of an AI peer influence divergent thinking during group ideation processes?*

To explore this question, we examine four key dimensions of the ideation task (1) the creative fluency of participants (i.e., the number of ideas generated), (2) the elaboration and originality of the ideas produced, (3) the co-construction processes between participants and the AI peer, (4) and participants' overall user experience.

We introduce and study a novel digital platform designed to support collaborative brainstorming by integrating GenAI. The platform offers two modes of idea exchange: a round-based process, where ideas are shared collectively after each phase, and a live process, where ideas are immediately visible to all participants. It also features an *AI peer* that generates divergent ideas to counteract idea fixation, and it preserves participant anonymity to promote more open and uninhibited contributions.

Through this work, we aim to provide new insights into the design of AI-augmented collaborative ideation systems and to advance understanding of how GenAI can foster creativity, collaboration, and innovation across educational and professional contexts.

Collaboration Systems for Divergent Thinking

Recent advancements in digital tools and virtual environments have driven a significant amount of research in CSCW, in co-located, hybrid, or remote settings. The topic of collaborative ideation has received the attention of researchers and designers, which have proposed approaches and systems drawing on various techno-social lenses.

A variety of professional online tools have been designed to facilitate teamwork, many of which offer features that specifically support group ideation activities. Platforms such as FigJam[1] and Miro[2] provide collaborative environments that replicate the experience of using a physical whiteboard. Other tools emphasize different aspects of collaboration: for instance, SpeakUp (Holzer et al., 2013) leverages anonymity through a flexible messaging platform optimized for short, interactive sessions. Similarly, Wooclap offers functionalities tailored to efficiently manage brainstorming processes, particularly in educational contexts[3].

Experimental setups have also been designed and studied to foster collaboration in ideation and co-design. Shi et al. (2017) proposed an immersive environment which was shown to improve group discussions by supporting the visual organisation of ideas. Similarly, by combining paper-based collaboration and a central digital system, Geyer et al. (2012) proposed a novel way to blend traditional, paper-based, collaboration workflows with the flexibility of digital mediation. They also suggest that this flexibility may benefit idea exploration and reinterpretation, which in turns may lead to more creative outcomes.

Collaborative ideation research underscores a balance between the advantages of social interaction and the cognitive challenges inherent in group settings. Live brainstorming facilitates real-time idea exchange among participants; however, it often encounters obstacles such as production blocking, evaluation apprehension, and social loafing, which can diminish both the quantity and diversity of ideas generated (Diehl and Stroebe, 1987; Hymes and Olson, 1992). To address these issues, round-based approaches like brain- writing have been developed, wherein participants independently generate ideas in parallel before sharing them with the group. This method has been shown to enhance the quality and originality of ideas compared to traditional face-to-face brainstorming sessions (Heslin, 2009; Paulus and Yang, 2000). Brown and Paulus (2002), Korde and Paulus (2017), and Paulus et al. (2015) showed that alternating solitary and group brainstorming lead to a greater number of high-quality ideas. Recent studies have further explored the integration of large language models (LLMs) into the ideation process, demonstrating that AI-augmented brainwriting can support both divergent and convergent thinking stages, leading to improved creative outcomes (Shaer et al., 2024b). However, to our knowledge, no study has yet investigated the impact of timing and structure when incorporating AI agents on group creativity.

Supporting Divergent Idea Generation with Artificial Agents

The capabilities of GenAI, and in particular GLMs, have progressed significantly over the last decade. This new capacity opened the path to new applications and greatly improved direct interaction with these models powering numerous chatbots.

With the emergence of human-AI collaboration, the paradigm has expanded both the scope of collaboration technologies and the conceptual framework for understanding human-AI interaction (Wang et al., 2020). Human-AI collaboration has been explored to foster ideation through multiple modalities. For instance, the generation of visual cues to augment human creativity in design (Davis et al., 2024; Kim, 2024).

When tasked with the generation of ideas, GLMs can generate creative ideas, often outperforming humans (Haase and Hanel, 2023; La Scala et al., 2025a; Shaer et al., 2024a; Stevenson et al., 2022). They can offer context-specific, useful, and creative input, thereby enhancing the overall ideation process (Harwood, 2023). Building on these findings, recent studies have explored new forms of collaboration with conversational agents to support ideation in journalism (Petridis et al., 2023), complex problem solving (Memmert, 2024; Memmert and Bittner, 2024), and engineering (Farah et al., 2025; Kharrufa et al., 2024; Marques et al., 2024). GLMs can also help individuals in the ideation process, providing valuable suggestions and insights (Heyman et al., 2024; Memmert, 2024; Memmert and Bittner, 2024).

[1] https://www.figma.com/figjam/brainstorming-tool/

[2] https://miro.com/fr/modeles/brainstorming/

[3] https://www.wooclap.com/en/brainstorming-tool/

Despite these advancements, it appears that systems which have utilized AI-based agents to impersonate virtual and artificial peers in collaborative ideation activities have not been thoroughly studied. More generally, research on human-AI collaboration in group settings appears to be in its early stages.

Intervention Design

This research is part of a larger project aiming to design models of collaboration supported by digital tools to support and structure efficient ideation processes (see Farah et al. (2025), La Scala et al. (2025a), and La Scala et al. (2025b)). In this framework, we designed the ideation board as a web application integrated into the Graasp [4] open-source learning experience platform (Gillet et al., 2022). This application is open source, and its code can be found in (La Scala, 2024). With this system, groups have the possibility to include a virtual AI peer who contributes to the ideation process. The AI peer is powered by OpenAI's GPT-4o model (OpenAI, 2024). The prompt for the AI peer contains the problem statement (i.e., the main challenge or topic the group is working on), the other participants' ideas, and instructions to generate a new idea.

Ideas are short texts (limited to 200 characters) that participants write down on the ideation board to propose solutions or elements of solutions to their problem statement. These ideas are anonymous. Participants can also build on each others' ideas. When doing so, the text is simply appended below the parent idea.

In the round-based condition, the idea generation phase unfolds in a series of rounds. In each round, the app presents to each participant all the ideas the group generated in the preceding rounds. Consequently, the first round does not include any pre-existing ideas. In the live condition, the ideas are shared in real time. When present, the AI peer automatically generates new ideas. In round-based condition, the AI peer will generate two ideas during each round. These ideas will be marked as "AI-generated" and have a particular border color to be clearly identified in the UI. In the live condition, each time that three ideas are submitted in the ideation board by users, the AI peer submits one of its own ideas. The AI peer can only generate initial ideas and cannot build on another idea. The number of generated ideas for each condition was chosen on the basis of previous experiments which showed that each participant generate about two ideas per round of similar length, for a total of about six ideas. The AI peer was designed to follow the pace of the group in live collaboration, and thus, generate only ideas when enough ideas had been submitted by the participants. Therefore, considering groups of three to four students, we would have 18 to 24 students' ideas, assuming a similar fluency in live and round-based collaboration, and thus we set the AI peer throughput to one idea for every three participants' ideas. After the end of the divergent thinking phase, the users are shown an interface where all the ideas of their group are visible. Additional details and screenshots can be found in La Scala et al. (2025a) and La Scala et al. (2025b).

Study design

To answer our research questions, we carried out a randomized controlled experiment in a co-design work- shop during the ideation phase of digital innovation projects.

Participants

The digital innovation projects formed part of a 14-week, semester-long Bachelor-level course on information systems design (6 ECTS), involving 108 students (75 male, 33 female) enrolled in economics (63), data science (35), or sports and economics (10) programs. A total of 96 students provided informed consent to participate in the research component of the workshops. Students who did not consent still participated fully in all workshop activities, but no data were collected from them, ensuring their course experience remained unaffected. To maintain the integrity of both research and teaching, the respective teams operated independently; the teaching team had no access to information regarding students consent status. Ethical approval for the study was granted by the university's Ethical Commission. Students worked in self-organized groups of up to five members (23 groups in total) to design and evaluate a prototype of a digital innovation aimed at addressing a challenge aligned with one of the United

[4] https://graasp.org/

Nations Sustainable Development Goals (SDGs)[5]. Throughout the course, students were instructed to follow a structured design thinking process, progressing through the stages of empathizing, defining, ideating, prototyping, and testing.

Workshop Session

On week 6 of the semester (during the ideation phase), we created a 2-hours long brainstorming activity where students used the ideation board to generate ideas for their prototype. Prior to the session, each group submitted a problem statement to the instructors. Students were not given specific instructions about pre-brainstorming preparation; they were allowed to conduct preliminary brainstorming sessions. However, they knew this particular class session would be dedicated entirely to brainstorming. To investigate the effects of the two experimental factors—collaboration modality and the presence of an AI peer—groups were assigned to one of four experimental conditions:

1. Live collaboration without AI peer ("*Live*")
2. Round-based collaboration without AI peer ("*Rounds*")
3. Live collaboration with AI peer ("*Live AI*")
4. Round-based collaboration with AI peer ("*Rounds AI*")

Each condition took place in a separate classroom, with groups distributed accordingly. In each room, a facilitator was present to introduce the session, prevent in-between group interaction, and provide support if needed. The brainstorming activity began with a brief introduction and consent collection. Students then engaged in a 15-minute ideation phase to propose and discuss ideas, followed by a 5-minute voting phase on ideas, to select the best idea(s). Within each group, one student was designated as responsible for progressing through the activity on the platform. Each student could access only their own group's workspace. The session concluded with a short post-activity questionnaire.

Data collection

Data were gathered from students participating in the study, encompassing both human and AI-generated contributions. Specifically, all ideas created by students were recorded alongside relevant metadata, including author identifiers and timestamps of submission. Likewise, all ideas suggested by the AI peer were logged with corresponding metadata. Furthermore, to assess the usability and perceived effectiveness of the system, participants completed a post-activity questionnaire, which incorporated the Short User Experience Questionnaire (S-UEQ) as well as open questions to capture students' perceptions of key aspects of the collaborative ideation process.

Analysis and Results

In this section, we present our analysis and its results. We first analyzed the outcome of the task using key quantitative indicators: fluency, elaboration, and originality. We examined the collaboration between the participants and finally analyzed their experience with the system and the activity.

Divergent Thinking Outcome: Fluency, Elaboration, and Originality

Our statistical analysis for the fluency, elaboration, and originality are conducted with a Bayesian framework (Lindley, 1990). As stated by Kruschke (2021), we chose to conduct Bayesian analysis for two main reasons. First, its flexibility in specifying models that are appropriate for the data, such as the creative fluency which is better modeled with a negative binomial distribution. Second, the ability to generate estimates and credible intervals for effect sizes gives us a precise and quantified argument to support our hypothesis. In this study, the lack of prior knowledge on the potential effects of the AI peer or the collaborative condition makes this information crucial to estimate the probabilities of having either a negative or a positive hypothesis when we could not devise an appropriate hypothesis a priori. The robustness of the obtained estimates of parameter values and their credible intervals also contribute to the reliability of our results.

[5] https://sdgs.un.org/goals

For each of the three dependent variables analyzed in this section – fluency, elaboration, and originality – we designed a simple model for which we inferred the parameters. Each model is characterized by a mean $\mu_{c,a}$ for which we established a normal prior distribution $\mu_{c,a} \sim N(\bar{y}, s)$, based on the sample's mean $\bar{y}$, and the sample's standard deviation s.

With c the index variable for the collaborative condition (live or round-based), and a the index variable for the agent condition (no AI peer or with AI peer).

Although the study investigates collaborative ideation, analyses were conducted at the individual level for the fluency, and idea level for the elaboration and originality. This decision reflects both our research focus on individual idea generation within groups and the limited number of groups available, which constrained statistical power for reliable group-level or multilevel modeling.

All Bayesian models were fitted using No-U-Turn Sampler (NUTS), with 4 chains, 1000 samples per chain, and a warm-up (burn-in) period of 1000 samples.

Prior to the analysis, two independent raters evaluated the relevance of each idea using the prompt: "*To what extent does the idea reflect how well the idea is connected with or appropriate for the objectives, requirements, or challenges of the problem statement?*" All the ideas that were deemed irrelevant by a score of 1 on the relevance scale by at least one rater were filtered out. A few contributions were marked as non-idea, to identify the responses that were not a valid creative contribution. For example, these responses could be comments indicating appreciation for an idea (e.g. "*I agree*", "*I like it*"), misunderstanding (e.g. "*I did not understand*"), or questions (e.g. "*How can we achieve this?*"). This led to a final pool of N = 582 ideas.

Participant's Creative Fluency

We explored how the different factors may have influenced how fluent the participants where during the activity. We define the fluency as the number of ideas generated in a given period of time.

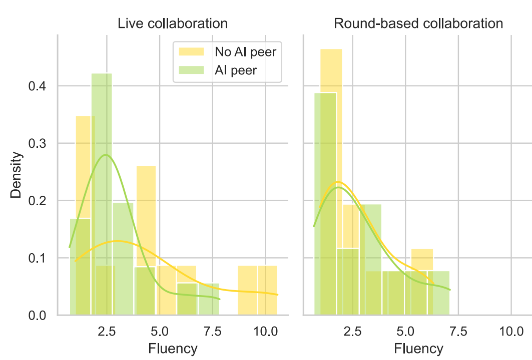

Figure 1. Distribution of the Fluency of the Participants (Number of Ideas Generated in 15 Minutes)

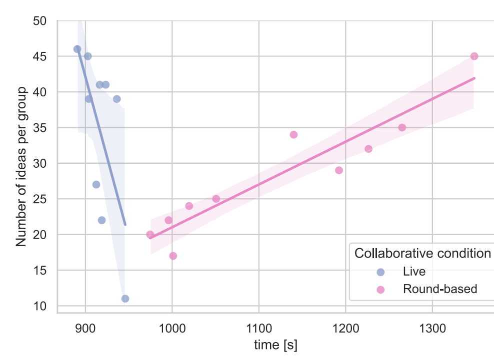

Figure 2. The Correlation Between the Time and the Number of Ideas Generated Is Very Strong in *Round-Based* Collaboration

We explored the influence of time on the number of ideas generated by group. As shown in Fig. 2, the correlation between the time and the number of ideas generated is very strong in *round-based* collaboration (Pearson *(N = 10): r(8) = 0.94,* $p^{***} < 0.001$*)*. The relationship is unclear for *live* collaboration (Pearson *(N = 9): r(7) = −0.65, p = 0.059)*. Interestingly, we observe that the groups in *round-based* collaboration exceeded the suggested time limit, while the others completed the activity not long after the limit. The longest *live* activity took 16 minutes and 46 seconds, while the shortest *round-based* took 16 minutes and 15 seconds.

We normalized the number of ideas generated $N_{ideas,i}$ for each participant i by the time of the activity for their group t_{group} to obtain their fluency y_i (expressed in number of ideas per 15 minutes), following equation (1).

$$y_i = \frac{N_{ideas,i}}{t_{group}} * 15min \qquad (1)$$

The distributions of fluency in each condition is shown in Fig. 1. Participants in live and no AI peer condition reach much higher fluency than any other condition. We modeled the distribution of the fluency with a Negative Binomial distribution as shown in equation (2). We set the prior distribution of α with a weakly informed half normal distribution $\alpha \sim HalfNormal(2)$.

$$y_i \sim NegativeBinomial(\mu_{c,a}, \alpha) \qquad (2)$$

The effect size d_{agent} between conditions with AI peer and no AI peer was 0.16 (HDI 94%: [-0.37, 0.67]) in round-based collaboration, and -0.61 (HDI 94%: [-1.22, -0.07]) in live collaboration, the latter suggesting a strong negative effect. The effect size $d_{collaboration}$ of round-based collaboration was -0.04 (HDI 94%: [-0.52, 0.45]) with an AI peer, and -0.79 (HDI 94%: [-1.39, -0.26]) without any AI peer, which also suggest a strong negative effect of the round-based collaboration when no AI was present.

Participants Elaboration

Following our analysis of the fluency, we analyzed how elaborated were the ideas given by the participants and compared this variable across condition. We computed the elaboration score of each idea by counting the number of words after removal of the stopwords using NLTK (Bird et al., 2009) and the stop words corpus provided with it. We modeled the distribution of the elaboration e_j, for each idea j, with a normal distribution as shown in equation (3). We set the prior distribution of σ with a weakly informed uniform distribution $\sigma \sim Uniform(10^{-2}, 10)$.

$$e_j \sim N(\mu_{c,a}, \sigma) \qquad (3)$$

In both conditions, the effect sizes of the AI peer are close to zero (round-based collaboration: d_{agent} = -0.01, HDI 94%: [-0.26, 0.26]; live collaboration: d_{agent} = 0.05, HDI 94%: [-0.19, 0.3]) which suggests no effect on the elaboration of the participants.

Ideas' Originality

In divergent thinking tasks, assessing the originality of ideas is a central objective. To evaluate this, we employed a two-pronged approach combining automated and human judgment. First, we conducted an automatic evaluation using the Open Creativity Scoring with Artificial Intelligence (OCSAI), introduced by Organisciak et al. (2023). OCSAI is a Large Language Model (LLM) fine-tuned on human-rated responses to improve the reliability and scalability of creativity assessment, particularly in divergent thinking contexts. In idea generation tasks such as online brainstorming, OCSAI enables automated scoring of originality beyond simple semantic distance, supporting more consistent and objective evaluation of creative output. However, because OCSAI was specifically developed and validated for responses to the Alternative Use Task (AUT), its applicability to other open-ended tasks remains uncertain. To address this limitation, we supplemented the automated analysis with human evaluation. Two human raters independently assessed the originality and relevance of 680 ideas using predefined rating scales. These scales were adapted from prior work by Shaer et al. (2024a), initially designed with five levels. To enhance rating granularity, we added two intermediate levels, resulting in a seven-point scale.

Originality was evaluated in response to the following prompt: *"To what extent does the idea reflect how original and creative the idea is, breaking away from the conventional or existing solutions to the problem statement?"*. And relevance was rated based on the prompt: *"To what extent does the idea reflect how well the idea is connected with or appropriate for the objectives, requirements, or challenges of the problem statement?"*

For subsequent analysis, we normalized the originality on a scale ranging from 0 to 1. We examined the Pearson correlations among the different raters (rater 1, rater 2, and OCSAI). We first observed a moderate positive correlation between the two human raters ($r = .45$, $p^{***} < .001$). The correlation of each rater with OCSAI was higher (for rater 1: $r = .57$, $p^{***} < .001$, and for rater 2: $r = .62$, $p^{***} < .001$). Finally, we took the mean score of the two human raters for each idea and found a fairly high correlation with OCSAI (r = .70, p*** < .001). Fig. 3 shows the scores of the raters compared to OCSAI.

For the AI peer to have an effect on the originality of the participant, AI-generated ideas should be at least as original as those generated by the participants. In our sample, the originality means, medians, and standard deviations are respectively $\bar{o}_{AI} = 0.64$, $\tilde{o}_{AI} = 0.64$, $s_{oAI} = 0.12$, with $N = 156$ for AI-generated ideas, and $\bar{o}_{hum} = 0.44$, $\tilde{o}_{hum} = 0.44$, $s_{ohum} = 0.16$, with $N = 426$ for human-generated ideas. Figure 4 compares the distribution of originality based on the nature of their author. We performed a Shapiro-Wilk test on each sample that showed evidence of non-normality for the human-generated ideas ($W_{AI} = 0.98$, $p = .014$ and $W_{hum} = 0.99$, $p^{**} = 0.001$). Therefore, we conducted a non-parametric Mann-Whitney U test with the alternative hypothesis that the originality of the AI-generated ideas was greater than the originality of the human-generated ideas. The test showed a significant difference ($U = 56620$, $p^{***} < .001$) between the origin of the ideas of the AI and those of the participants. Finally, we examined the difference of originality of human-generated ideas between the different conditions. We assumed the originality would be distributed normally and we built the model described in equation (4). We set the prior distribution of σ with a weakly informed uniform distribution $\sigma \sim \text{Uniform}(10^{-2}, 10)$.

$$o_j \sim N(\mu_{c,a}, \sigma) \qquad (4)$$

The effect size d_{agent} between conditions with AI peer and no AI peer was -0.17 (HDI 94%: [-0.44, 0.10]) in live collaboration, which suggest no significant effect. However, in round-based collaboration, the effect size was -0.24 (HDI 94%: [-0.51, 0.01]), which provides a quantitative argument that the presence of an AI agent lead the participants to generate slightly less original ideas in this condition.

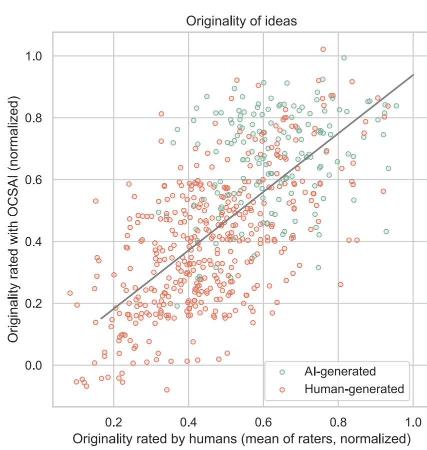

Figure 3. Each Dot Represent a Single Idea. Given That the Ratings Take Discrete Values, Random Jitter Was Added to Facilitate the Visual Appreciation of the Density. We Can See the Strong Correlation (R = .7, P* < .001) Between the Evaluation Made by OCSAI And the Mean of the Two Human Raters**

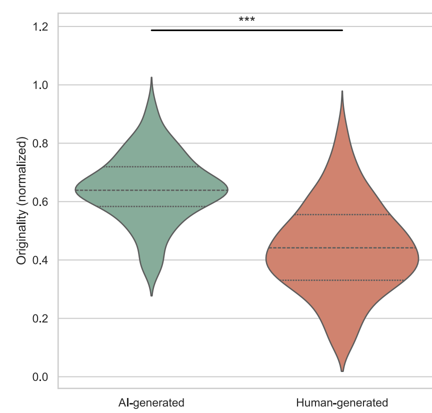

Figure 4. AI-Generated Ideas Are Significantly More Original Than Human-Generated Ones

Collaboration Between Participants

During this task, the participants had the possibility to build on each other's ideas, using a dedicated button. Doing so would append the new text to the idea that was built upon. This feature is an explicit way to collaborate through the system. Therefore, we used this interaction as a proxy to assess collaboration during the task. We built directed graphs of ideas where each node is an idea, and the edges represent the co-construction of idea. For each idea, we computed the number of outgoing edges and reported their distribution in 5. An example of these graphs is shown in Fig. 6.

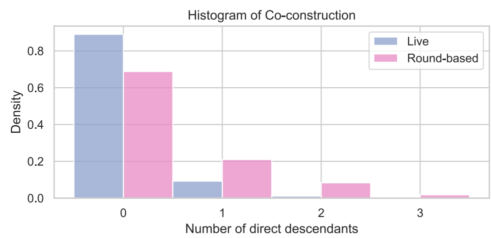

Figure 5. Proportion of Ideas With 0, 1, 2, or 3 Direct Descendants. In Live Collaboration, Very Few Ideas Have at Least One Descendant. The Round-Based May Have Favored the Elaboration of Ideas Based on Peers' Ones

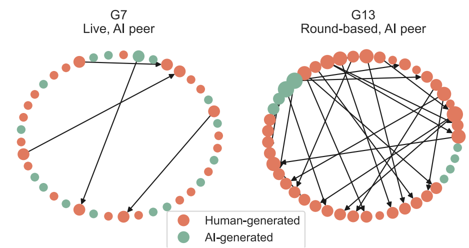

Figure 6. These Graphs Are Examples of Groups Building on Each Other. In the Live Condition, Most Groups Exhibit Very Few Explicit Links Between Their Ideas

We observed that in the round-based condition, the number of direct descendants k is slightly larger (in live condition: $\bar{k}_{live} = 0.13$, $s_{klive} = 0.41$; in round-based condition: $\bar{k}_{round} = 0.43$, $s_{krounds} = 0.72$). A non-parametric Mann-Whitney U test showed a significant difference between the two distributions, assuming the ideas in the round-based condition would have a greater amount of descendants than those in the live condition ($U = 45686.5$, $n_{live} = 356$, $n_{round} = 324$, $p^{***} < .001$). This result provide evidence for a stronger co-construction of ideas in the round-based condition.

Finally, we also hypothesized that the participants would tend to build more on the most original ideas, but the Pearson correlation between the number of direct descendants and the originality was weak ($r = -.09$, $p^{*} = 0.03$, $N = 582$).

User Experience

To complete our analysis, we collected quantitative and qualitative data on the user experience. We asked the participants to fill the short version of the User Experience Questionnaire (UEQ-S) (Hinderks, 2017). The UEQ-S is designed to evaluate the hedonic and pragmatic qualities of a system. When used with our system, we observed a significant difference between condition with the AI peer and without any AI peer. The scores with the agent are significantly higher, as shown in Fig. 7. We did not find any difference between the collaborative conditions.

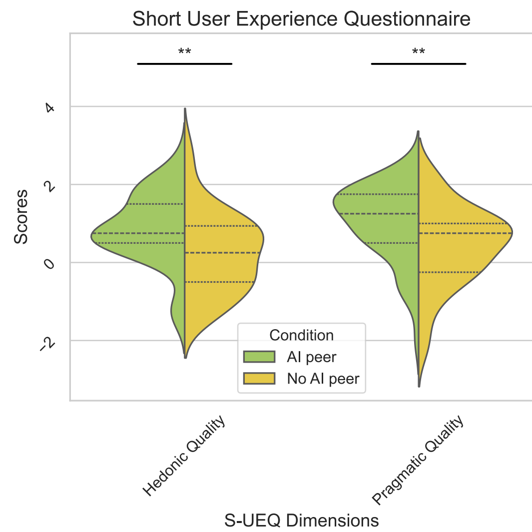

Figure 7. According to the Hedonic and Pragmatic Scores Provided by the UEQ-S, Collaborating with an AI Peer Significantly Improved the User Experience

To better understand participants' experience with the system, we analyzed the qualitative responses to the open-ended question about the user experience: "*Do you think this application influenced your group ideation process? Why?*" Overall, we collected 99 responses, with 54 participants reporting a positive impact of the ap- plication on the brainstorming activity, 35 reporting a neutral or no impact, 3 reporting a negative impact, and 7 not responding. We removed simple "*yes*" or "*no*" responses without explanation, leaving 63 responses for analysis. Based on qualitative analysis methods used in similar studies (Baysden et al., 2022; Szolin et al., 2023), we adopted a coding approach inspired by Braun and Clarke's thematic analysis procedure (Braun and Clarke, 2012). This process involved: (1) two researchers carefully reviewing all responses to understand the content; (2) agreeing on codes and applying them to each response; (3) identifying themes based on the codes and common data features; (4) discussing and reviewing these themes with other researchers; (5) defining and naming the final themes; and (6) conducting the data analysis.

Theme	Collaboration Dynamics	System Interface	AI Relevance	Process Integration
Reducing Social Barriers in Group Discussions	14	6	0	0
Enhancing Group Knowledge and Idea Generation	5	9	2	0
Improving Idea Visualization and Organization	3	6	1	0
Limited or Negative Impact for Some Participants	4	3	1	9
Total	**26**	**24**	**4**	**9**

Table 1. Theme Category Association

We found four themes as follows: reducing social barriers in group discussions, enhancing group knowledge and idea generation, improving idea visualization and organization, and limited or negative impact. The themes were then organized into four categories concerning the aspects of the experiment that participants commented on. The categories are the following: collaboration dynamics (impact on group interactions), system interface (time constraints and design elements), AI relevance (AI-peer impact), and process integration (activity fit within the project workflow). The Table 1 below summarizes these themes by categories, with the number of responses associated with each combination. We then discuss the themes with relevant quotes for illustration.

Reducing Social Barriers in Group Discussions

One of the key themes that emerged from the analysis was the ability of the system to remove social barriers in group discussions. A total of 20 responses highlighted this aspect, emphasizing how the application helped facilitate idea-sharing, especially in unfamiliar groups. For example, one participant noted that the tool was "*very useful for debriefing and generating ideas in a group, especially at the beginning when members do not know each other well*" (P14, Live AI). Others appreciated the ability to express ideas freely without fear of judgment, as one participant stated, "*You can suggest many ideas without being afraid of saying something silly, and it helps refine and develop them further*" (P33, Rounds AI). Anonymity was seen as an important factor in encouraging participation. For example, one participant shared, *"[...] every- one was able to share their idea anonymously and had no hesitation in submitting it*" (P94, Live). Another echoed this, saying, "*The anonymous aspect of the app allows group members to fully open up and share ideas without fear of being judged*" (P68, Live).

Enhancing Group Knowledge and Idea Generation

Another key theme that emerged was the system's role in enhancing group knowledge by allowing participants to build on each other's ideas and generate new ones. Sixteen participants highlighted how the tool helped them expand on existing ideas, while 18 noted its ability to foster new ones. For instance, one participant explained that the activity provided a "*mental reset*," allowing them to revisit previous thoughts while also generating new ideas: "*The activity allows us to reset mentally and build on our existing ideas while also proposing new ones*." (P46, Rounds AI). Several participants said that reading others' contributions helped deepen and expand their own thinking. For instance, one shared, "*Reading my colleagues' responses helped me find new ideas and expand on the ones I had already proposed*." (P49, Live AI), while another added, "*It allowed us to propose many ideas quickly and directly react to and be inspired by others' responses*." (P59, Rounds). The tool also supported idea comparison and alignment. As one participant put it, "*It allowed us to bring ideas together and see if we had similar ones*." (P48, Live AI). Others appreciated how it helped evaluate and refine group input, noting: "*It helped us gather, compare, and assess ideas*." (P4, Rounds AI), and "*We were able to reflect and suggest ideas we hadn't previously thought of. As a result, we came up with different ideas*." (P60, Rounds).

Improving Idea Visualization and Organization

Another important theme that emerged was the visual organization of ideas, with 10 participants highlighting how the tool helped them better see and keep track of their thoughts. One participant noted that it allowed them to "*lay out all our ideas in a single visual*" (P24, Rounds AI). Others appreciated how the system recorded and grouped ideas in one place, making them easily accessible: "*Ideas were gathered in a single document without prior discussion, and everything was stored somewhere*." (P27, Live AI). Another participant mentioned that the tool helped structure the creative process: "*The application helped control and organize the creative workflow*." (P44, Rounds AI). Additionally, some found the visual aspect useful for identifying key ideas, as one participant explained: "*I could clearly see the ideas in black and white, which helped me better identify the group's key concepts*." (P2, Rounds AI).

Limited or Negative Impact for Some Participants

The final theme that emerged focused on participants who reported little or no benefit, and in some cases, a negative experience, from using the tool. A common reason was that their group had already brainstormed before using the tool. One participant shared, *"[...] we had already brainstormed well before today. But I think it would have been useful if we hadn't done that*." (P40, Live AI). Another agreed, saying, "*It might have been useful if we didn't have an in-person brainstorming session before. For sure, it makes it faster because of the timer, but that also gave me a bit of anxiety*." (P39, Live AI).

The timer and word limit were seen as drawbacks. One participant said, *"[...] it pushes us to really think for a short time and generate ideas (even if not always relevant). But the pressure can backfire, we have so little time that it's easy to get stuck on one idea while stressing about not finding others.*" (P84, Rounds). Another commented, "*I prefer to defend my idea in front of my classmates and develop my arguments. The 200-character limit was too restrictive for me.*" (P19, Rounds AI). Some participants noted that the tool wasn't necessary for groups that already communicated well. For example, one said, "*[...] we already communicate a lot in our group, so it wasn't really needed*" (P89, Live). Others suggested it might work better in different group settings, such as with unfamiliar peers: "*I would have preferred doing it with people from other groups to share ideas we might not have thought of ourselves.*" (P72, Rounds), and "*If the group already knows each other and communicates well, it doesn't add much. But if the members are unfamiliar, it can be a good idea.*" (P76, Rounds). Finally, a few participants pointed out that the tool only works if everyone is engaged. One participant noted, "*The same ideas were generated. There was very little reaction to the proposals. Some people wrote exactly the same idea.*" (P50, Live AI).

Findings and Contributions

In this section, we will discuss the principal findings of this study along their implications and state our contributions. The section will conclude with a discussion of the limitations of this study.

AI Agents Can Outperform Humans in Generating Original Ideas

With their extensive human-like capabilities, generative AI models are increasingly evaluated on tasks that were reserved to humans so far. The ability to come up with original ideas is one of them. Previous research have explored the capacity of GLMs to generate original ideas, and found that they have reached human-like capabilities in this area (Haase and Hanel, 2023; Stevenson et al., 2022). Our findings align with these research and provide new evidence that GLMs can outperform humans for the generation of short text expressing original ideas as a response to an open and goal-oriented problem statement.

Therefore, seeding collaborative ideation processes with original ideas, as we propose with our system, is first attempt to use the originality of GLMs at our advantage in collaborative ideation.

AI Peers May Disrupt the Divergent Thinking Process

Our results suggest that integrating AI peers can disrupt the divergent thinking process.

First, in live collaboration, we observed a marked decrease in creative fluency when an AI peer was present. Since this effect only occurred in live collaboration, we hypothesize that it was triggered by AI-generated ideas appearing on the shared board during the activity. These contributions were clearly identifiable as AI- generated and may have diverted participants' attention, thereby interrupting their own thought processes. This phenomenon aligns with the well-documented effect of production blocking, or productivity loss, which is known to impair fluency in ideation tasks (Brown and Paulus, 2002; Diehl and Stroebe, 1987; Paulus et al., 1995).

This interpretation is further supported by the absence of a similar effect in round-based collaboration. In this setting, the exchange of ideas among participants—including the AI peer—occurred only at predefined intervals, leaving intervening periods free for individual reflection, discussion, and idea generation.

However, in the round-based condition, we observed a slight reduction in originality. This decline may be explained by increased social loafing, potentially triggered by the highly original contributions of the AI peer. As argued by Elshan et al. (2025), social loafing in human–AI teams is more likely when the AI is perceived as highly competent for the task at hand. Under such conditions, participants may defer responsibility to the AI, thereby reducing their own engagement with the task.

Taken together, these findings suggest the need to explore alternative interaction mechanisms for integrating GLM-based AI agents into collaborative divergent thinking tasks, or ideation more broadly. In our study, AI peers introduced more disruption than benefit in this context.

Round-based Collaboration Increases Co-construction but Decreases Creative Fluency

Our system offered the possibility to the participants to build on each other's ideas. When doing so, they would simply see the text they would type being appended to the existing idea. This mechanism gave us the possibility to see the extent to which the participants would deliberately choose to co-construct ideas, which we assume to be an indicator of strong collaboration.

We hypothesized that round-based collaboration would provide a better opportunity for co-constructing ideas. During each round, the participants would have a window of time in which they are not interrupted by the apparition of new ideas. They can take this time to examine the existing ideas and pick one to build upon. While they could still talk to each other, this approach may have been an incentive to reduce spurious interactions during each round and leave some time to each other for generating new ideas.

The benefits of such interaction are recognized by the participants themselves. As reported above, having the possibility to expand other's ideas helped them develop their ideas and inspired them.

Nevertheless, this increase in co-construction costs to the fluency of the participants. Time spent reading and thinking about others' ideas is not used to generate and write new ideas. We only observed this effect when no AI peer was present. We believe that the blocking effect of the AI described above may have shadowed the effect of collaborative condition, leading to equivalent fluency in both conditions.

The Presence of an AI Agent Improved the User Experience

Based on the scores obtained with the S-UEQ, we found that the participants seemed to have a significantly better experience when having the AI peer taking part to the task. Due to the novelty of GenAI and GLMs, their application to new context may create an attractive effect that influence positively the user experience. This novelty effect has been documented with new applications or deployment of technologies (Koch et al., 2018; Rutten and Geerts, 2020).

However, we also believe that the S-UEQ would have been able to capture this effect, as it would mainly improve the hedonic quality of the system. Participants may consider the system as more interesting, inventive, or exciting because of its novelty. But in our case, we also captured a significant increase of the pragmatic quality of the system, which suggests that the participants found a real benefit of the AI peer, beyond its mere novelty.

Using GLMs to Automatically Assess Idea Originality

To evaluate the originality of the ideas produced by the participants, we combined two methods to increase the objectiveness and robustness of our analysis: human-raters and automatic evaluation using a fine-tuned GLM.

To conduct the automatic analysis, we used the work Organisciak et al., OCSAI (Organisciak et al., 2023). This GLM was fine-tuned for evaluating the originality of answers to the Alternative Use Task (AUT), a widely use psychology task for evaluating creativity (Guilford, 1967).

This approach gave us the opportunity to study the reliability of this method on another set of tasks. In its original paper, OCSAI's reliability was assessed for the AUT. Here, we showed that this approach is relevant for evaluating the originality of short ideas generated as answers to a variety of open, goal-oriented problem statements. The correlation between the ratings obtained from OCSAI with the mean of the human raters was fairly high ($r = .70$, $p^{***} < .001$). As proposed by Organisciak et al. (2023), GLMs "*look more like our best alternative: multiple trained judges.*" They can be used as "*an extra judge, that hews closer to a panel of multiple raters with less inter-response variability than seen with individual raters.*" This study extends the validity and relevance of this approach, and in particular of OCSAI.

Limitations

As with any study, this one has limitations.

Our analyses were restricted to the participant and idea levels, where the sample size was adequate to detect moderate effects. This approach does not fully capture group effects. We adopted it because our focus was on how collaboration shapes individual idea generation, and because the limited number of groups in our dataset reduced statistical power for group-level or multilevel models. We also pooled all participants, without considering individual characteristics such as demographics, psychological traits, or attitudes. Data collection relied solely on our system, which allowed efficient gathering during a single workshop but excluded interactions outside the platform. Since participants could also talk during the activity, unrecorded exchanges may have influenced outcomes. Future research could address these limitations by (1) examining how individual characteristics moderate the findings, (2) recruiting larger group samples and applying group-level or multilevel models, and (3) restricting communication to digital channels or recording group interactions. Such work would provide a richer and more ecologically valid account of how creativity emerges from group interaction.

It is worth noting that participants chose their problems days in advance, which may have led them to enter the session with pre-formed ideas. In fact, one group engaged in prior brainstorming. We hypothesize that our system might be more effective in genuine "*cold-start*" scenarios, where participants encounter the problem for the first time during the activity.

Finally, the study investigated a specific Human-AI collaboration model (the AI peer) in a single experimental context (one class at a Swiss university), thereby reducing the overall generalizability of the findings.

Conclusion

This study examined how collaboration structure and AI integration influence divergent thinking in group ideation. Our experiment with 96 students across 23 groups revealed several key contributions.

First, AI peers based on GLMs generated ideas with significantly higher originality than human participants, demonstrating their potential as valuable collaborators. However, AI integration also led to reduced creative fluency in live collaboration and a modest decrease in originality in round-based interactions, highlighting potential trade-offs.

Second, the round-based interaction model fostered more co-construction of ideas than live interaction. This structured approach created space for reflection and building upon existing ideas, though it may have also encouraged participants to defer to AI suggestions, resulting in some social loafing.

Third, participants experienced an enhanced user experience when collaborating with AI peers. While participants may not have fully identified this effect, the collaboration system supported engagement and positive perceptions of the ideation process.

These findings have practical implications for the design of AI-augmented collaborative systems. Beyond generating ideas, AI peers could actively pose reflective questions or offer prompts that guide participants toward unexplored creative avenues. Such strategies could more effectively stimulate original thinking and deeper cognitive engagement with the problem space.

In conclusion, this research advances our understanding of AI-augmented collaborative ideation by demonstrating that both interaction structure and AI integration shape creative outcomes. As AI technology evolves, these insights provide guidance for designing collaborative systems that foster innovation in educational and professional contexts.

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