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ChatGPT and Me: Collaborative Creativity in a Group Brainstorming with Generative AI

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Introduction

The emergence of generative AI (genAI), exemplified by ChatGPT, offers unprecedented opportunities to the education system. However, as this technological advancement gains momentum, concerns surrounding hallucination [1, 2] and academic integrity [3, 4] have been raised, casting doubt on its applicability in educational contexts. These pivotal concerns revolve around ensuring factual accuracy, especially in learning scenarios when the primary objective is to provide accurate factual information. Yet, it is crucial to recognize that this objective, in line with some of the established education frameworks like Bloom's taxonomy [5, 6], represents merely a fraction of the learning objectives necessary for effective educational experiences. When learning activities are designed to empower students to analyze, evaluate, or create new ideas based on factual information, fostering students' creativity becomes a core issue [7, 8]. For example, in group brainstorming settings, the quantity or novelty of the ideas become crucial metrics to track [9, 10].

Building upon this perspective, our paper explores a novel application of genAI in collaborative learning, specifically in the domain of group brainstorming. In this learning scenario, the emphasis lies in encouraging students to apply their factual knowledge creatively without stringent concerns about correctness. Employing statistical analysis and natural language processing (NLP), we investigate the influence of ChatGPT on the creative ideation process within student groups, utilizing real student data from a graduate-level product engineering class. Specifically, our exploration is guided by the following two key research questions:

- **RQ #1:** Are product design ideas generated with ChatGPT perceived as more creative by students than those generated between students without ChatGPT?
- **RQ #2:** Are the ideas produced with ChatGPT more similar to each other than those generated by students without ChatGPT?

This paper not only introduces a use case of genAI in an educational context, but also pioneers the investigation into its impact on the creative group ideation process. By posing and addressing these research questions, we contribute to a deeper understanding of how genAI can shape and enhance collaborative learning experiences, particularly in fostering creativity among students.

Background

Creative ideation with AI

The discourse surrounding the integration of AI in collaboration and co-creation during a creative ideation process is gaining traction within collaboration engineering communities. For example, [11] conducted a comprehensive survey of 65 collaboration researchers around the world. It elicited diverse perspectives on the evolving role of AI in team collaboration, emphasizing the need for a systematic understanding of team, task, and work practice design in the context of human-AI collaboration. Furthermore, it calls for AI systems that can proactively capture, adjust, and coordinate their responses according to complex contextual nuances, similarly raised by other recent works [12, 13, 14, 15, 16].

While the present state of AI, including genAI, may not fully embody the ideal envisioned by these works, it is crucial to recognize that genAI's generation capability, empowered by large training data and pre-trained models, stands as a pivotal element in realizing this envisioned design. Therefore, understanding the effects of genAI on the creative ideation process or output cannot be overlooked. Although works such as [4, 17] suggested the idea of applying ChatGPT for group brainstorming and creative ideation sessions, a quantitative assessment of the effects of incorporating ChatGPT in these contexts remains unexplored. A study by [18] summarized students' survey responses after incorporating ChatGPT into their brainstorming sessions. However, they did not include any statistical analysis, raising concerns about the generalizability of their findings on ChatGPT's impact on students' cognitive stimulation and the risk of free riding. This paper aims to bridge the gap by quantitatively analyzing the effects of incorporating ChatGPT, providing valuable insights into the potential of genAI in fostering and enhancing collaborative creativity.

Generative AI in Education

There are also various prevailing use cases of ChatGPT in the field of education, which include utilizing ChatGPT as a virtual assistant to support instructors' teaching activities such as grading, doubt-solving, and plagiarism checking [19]. Beyond these instructional roles, it also serves as a virtual student, contributing to test question answering and performance evaluations across diverse domains such as medicine, law, engineering, and others. Despite the growing number of applications that integrate ChatGPT and other large language models in educational settings, their impact on student learning outcomes or experiences remains largely unexplored. More quantitative analyses are urgently needed to comprehensively understand their implications.

As one example of these applications, the efficacy of ChatGPT as a virtual tutor is explored due to its capabilities to perform relevant tasks, such as personalized tutoring, automated essay grading, and interactive, adaptive learning within the broader context of general education [20]. Similarly, ChatGPT has the potential for integration into the engineering education domain, but one must emphasize the importance of asking the right questions to obtain the best possible responses from large language models to avoid ChatGPT's potential for hallucination when applied to unfamiliar contexts [21]. Despite these valuable contributions to the general educational landscape, no prior work has extensively explored the impact of ChatGPT on the creative ideation process or brainstorming.

Education context & dataset description

To address our research questions, we conducted a multistage analysis of data collected from a graduate-level product engineering course at a large private university in the western region of the United States during the spring semester of 2023. For a two-week time period, a cohort of 33 students was randomly assigned to 8 brainstorming groups, comprising 3 to 5 students per group. The weekly task involved generating and submitting 10 product ideas based on specific user scenarios (see Table 1). The exercises aimed to give students hands-on experience in applying various product engineering techniques while adapting to subtle changes in user requirements. To this end, the two provided user scenarios were designed to be similar, with only slight variations in the user requirements.

Table 1: Discussion topic for each week

Week	User scenario for group brainstorming
Week 1	Product ideas to prevent the spread of COVID for customers that must go outside for required activities but are always willing to keep a minimal social distance from others
Week 2	Product ideas to prevent COVID-19 for customers who go outside and cannot maintain the required social distance

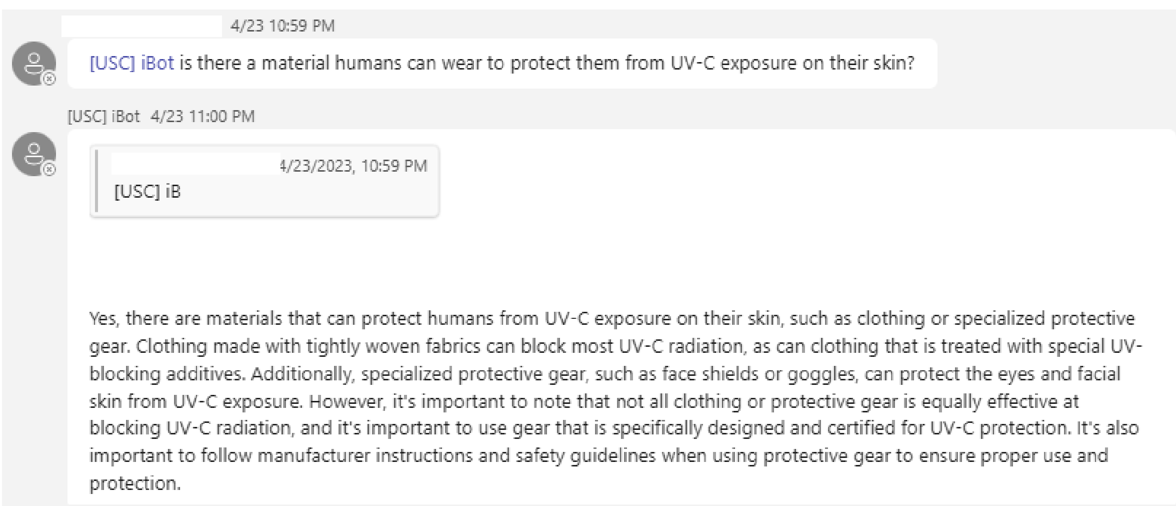


Figure 1: Example of a student prompting ChatGPT in a group chat. ChatGPT was assigned the user name `iBot`

Each group was assigned to its designated group chat in Microsoft Teams, in which they were free to discuss, share, and ideate. In half of the groups (designated as G_A), ChatGPT was introduced, allowing students to directly prompt ChatGPT within the group chat, with responses posted in the same chat (Figure 1). Conversely, the remaining groups (designated as G_B) did not have access to ChatGPT during their brainstorming sessions. Additionally, the chats of G_B were monitored to ensure that ChatGPT was not used outside of their group discussions. At the end of each week, four larger groups were formed by combining randomly selected groups from both G_A and G_B. These larger groups (designated as G_{comb}) were asked to discuss and select the top 5 most creative ideas from their collective pool of 20 product ideas. Each of the chosen ideas had to be attributed to its origin, requiring each group in G_{comb} to specify whether it originated from G_A or G_B. Within G_{comb}, we use each group's selection of the top 5 creative product ideas to understand the impact of ChatGPT on a group's creative ideation process. An overall summary of our dataset is provided in Table 2.

Table 2: A basic statistic on groups in the dataset

Group number in G_{comb}	Total number of students	Number of students from G_A	Number of students from G_B
1	9	5	4
2	7	3	4
3	9	5	4
4	8	4	4

Quantitative analysis & discussion

Student: what are some ideas to prevent covid-19 that are not yet on the market?

ChatGPT: Here are some potential product ideas to prevent COVID-19 that are not yet on the market: A self-cleaning water bottle that uses **UV-C light to sanitize** the inside of the bottle, ensuring that it remains free of germs and viruses.

…

Submitted idea #1: A portable **UV-C light sanitizer** that can be used to disinfect surfaces like doorknobs, shopping carts, and other high-touch areas. The device could be small enough to fit in a purse or backpack and could be charged via USB.

Submitted idea #2: A self-cleaning phone case that uses **UV-C light** to disinfect the phone when it is placed inside. Could also apply for other things that require cases such as iPads, computers, etc

….

Figure 2: Comparison of ChatGPT's response and the final product ideas generated

As only groups in G_A had access to ChatGPT during their brainstorming sessions, we categorized all product ideas submitted from groups in G_A as ideas generated with ChatGPT. Although the chat logs from the groups in G_A indicate that members relied heavily on ChatGPT to generate their initial ideas, the 10 product ideas selected from G_A were not mere replicas of ChatGPT's responses. Instead, these ideas contained enhancements and modifications to the original responses from ChatGPT, highlighting the collaborative aspect of the ideation process between ChatGPT and students within G_A.

Figure 2 illustrates the difference between ChatGPT's response and the group's submitted product ideas. For example, when ChatGPT suggested applying UV-C light to sanitize a water bottle, the group expanded this idea to a more general use case, proposing portable sanitizer or phone cases. Though the underlying technology remained the same, the students not only extended the use cases but also incorporated additional features, such as specifying the size of the sanitizer. In contrast, all ideas generated from G_B are ideas generated solely from student discussions, as ChatGPT did not take any role in contributing to the brainstorming sessions in G_B.

Research question #1: Perceived creativity

To gauge the perceived creativity of the ideas among student groups, we measure the ratio (R_A) of product ideas originating from G_A among the top 5 ideas selected in G_{comb}. Since both groups in G_A and G_B generated 10 product ideas before being merged into the larger groups in G_{comb}, any deviation of $E[R_A]$ from 0.5 across our dataset would indicate a statistically significant difference in the perceived creativity between the ideas generated with ChatGPT and those created solely by the students.

Before statistically validating this hypothesis, we must confirm whether any significant variation in R_A stems from group-wise or week-wise differences in our dataset. For example, students once placed in G_{comb} might lean towards voting for their original ideas from G_A or G_B. Given the uneven distribution of students from G_A and G_B in most groups of G_{comb} (as shown in Table 2), such bias towards their original ideas could potentially impact R_A. To assess the influence of group-wise and week-wise factors on R_A, we conduct a linear regression with R_A as the dependent variable and a week number ($w \in 1, 2$), a group number of G_{comb} ($g \in 1, 2, 3, 4$), and the ratio of students from G_A in each group in G_{comb} (s_{ratio}) as independent variables. Note that w and g are categorical variables, while $0 \leq s_{ratio} \leq 1$. The resulting linear regression model suggests that w, g, and s_{ratio} are statistically insignificant, with p-values of 0.444, 0.397, and 0.411, respectively. This result suggests that there are no statistically significant linear variations of R_A resulting from these factors, allowing us to disregard any group-wise or week-wise variation when validating our hypothesis that $E[R_A] \neq 0.5$.

To statistically validate whether $E[R_A] \neq 0.5$ in our dataset, we employ the Wilcoxon signed-rank test implemented in SciPy[1]. The test indicates strong statistical significance that $E[R_A] \neq 0.5$ (p-value of 0.012). Furthermore, over the two weeks, $E[R_A]$ is 0.725, suggesting that, on average, 3.625 product ideas selected in G_{comb} are ideas generated with ChatGPT. This outcome highlights a preference for and a higher level of perceived creativity in the product ideas generated with ChatGPT compared to those created solely from student discussions.

Since criteria for evaluating creative product ideas vary based on context [22, 23], we suggest the

[1] https://scipy.org/

linguistic differences between the ideas generated in G_A and G_B as one potential factor behind the difference in the perceived creativity. To analyze the linguistic properties of the generated ideas, we initially apply text pre-processing via SpaCy[2] to lemmatize and remove stopwords from all ideas reported from G_A and G_B. Upon text pre-processing, the ideas generated with ChatGPT, on average, contain 14.92 words, while student-generated ideas use 10.5 words. This difference is statistically significant at the 0.001 level, indicating that the ideas generated with ChatGPT are generally longer and contain more descriptive components.

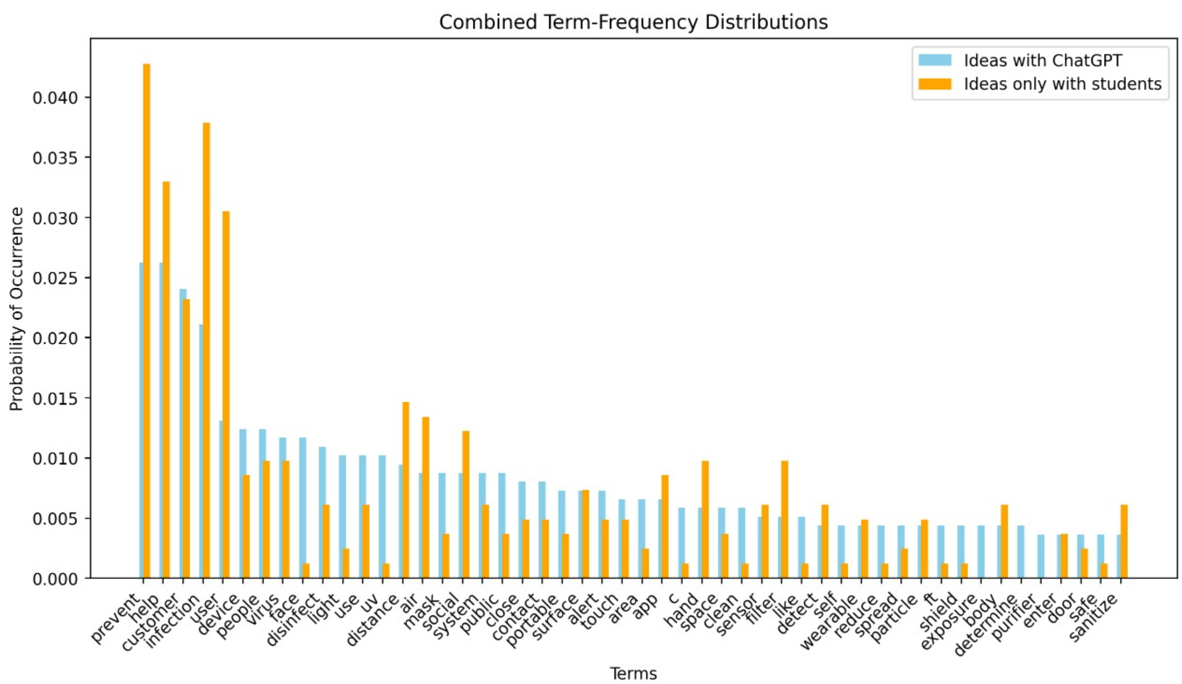


Figure 3: Term-frequency distributions of ideas generated in G_A and G_B (Visualized for top 50 commonly occurring terms)

Furthermore, we compared the term-frequency distributions of the words used in the product ideas generated from G_A and G_B (Figure 3). For each term used in both sets of ideas, the term-frequency distribution computes the probability of its occurrence within each set of ideas. The resulting distributions additionally reveal significant distinctions in word usage patterns between the groups in G_A and G_B. Over the course of two weeks, the groups in G_A employed 573 unique words to express their ideas, a substantial contrast to the 376 unique words utilized by the groups in G_B. This apparent difference is also quantified through the Jensen–Shannon divergence (ranging between 0 and 1) between these two term-frequency distributions, yielding a calculated value of 0.4094. These outcomes once again affirm the markedly descriptive nature of ideas generated with ChatGPT. While we refrain from attributing these identified disparities exclusively to ChatGPT, we posit it as a plausible factor contributing to the increased level of perceived creativity in ideas generated with ChatGPT. Exploring the direct relationship between these divergent linguistic patterns and the perceived creativity level of genAI-driven ideas beckons as an intriguing avenue. Yet, recognizing the need for a more systematic and targeted

[2]https://spacy.io/

research approach, we deliberately defer this nuanced investigation to our future endeavors.

Research question #2: Similarity of ideas

As the language generation capability of ChatGPT is rooted in its pre-trained large language model, one can reasonably anticipate linguistic similarities in its responses when presented with similar prompts. In the context of our study, where most students in G_A initiated their product idea generation through interactions with ChatGPT, a natural hypothesis is that the ideas resulting from this process across all groups within G_A would exhibit similar linguistic patterns and contents. Therefore, in this section, we examine the linguistic similarities among students' prompts, ChatGPT's response, and the resultant ideas within groups in G_A.

To measure linguistic similarity, we apply term frequency and inverse document frequency (TF-IDF) [24] from NLP, which generates a vector of term importance for a given text. Among various text vectorization methods available, we specifically opt for TF-IDF due to its inherent intuitive interpretability [25]. Throughout our investigation, we transform prompts, responses, and resultant ideas from each group in G_A into a single TF-IDF vector. Similar to the previous section, text pre-processing has been applied prior to generating TF-IDF vectors. Subsequently, we use the cosine distance, which ranges from 0 to 1, between TF-IDF vectors to measure their linguistic similarity.

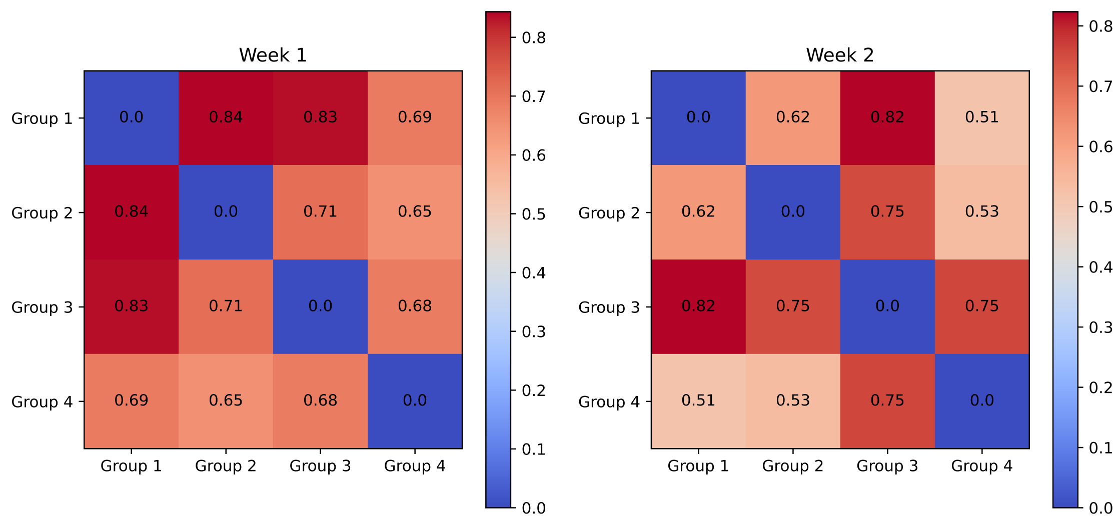


Figure 4: Comparison of the pairwise Cosine distance between TF-IDF vectors of students' prompts to ChatGPT in G_A

When measuring linguistic similarity among the prompts given to ChatGPT and its responses, we exclusively analyze the groups within G_A as only they were given access to ChatGPT. As illustrated in Figures 4 and 5, the pairwise Cosine distance between TF-IDF vectors for prompts and responses across each week reveals distinct linguistic patterns between the groups in G_A. Even when presented with identical user scenarios, these groups formulated linguistically dissimilar prompts, resulting in correspondingly diverse responses from ChatGPT. However, Groups 1, 2, and 4 exhibited relatively high linguistic similarity in both their prompts and

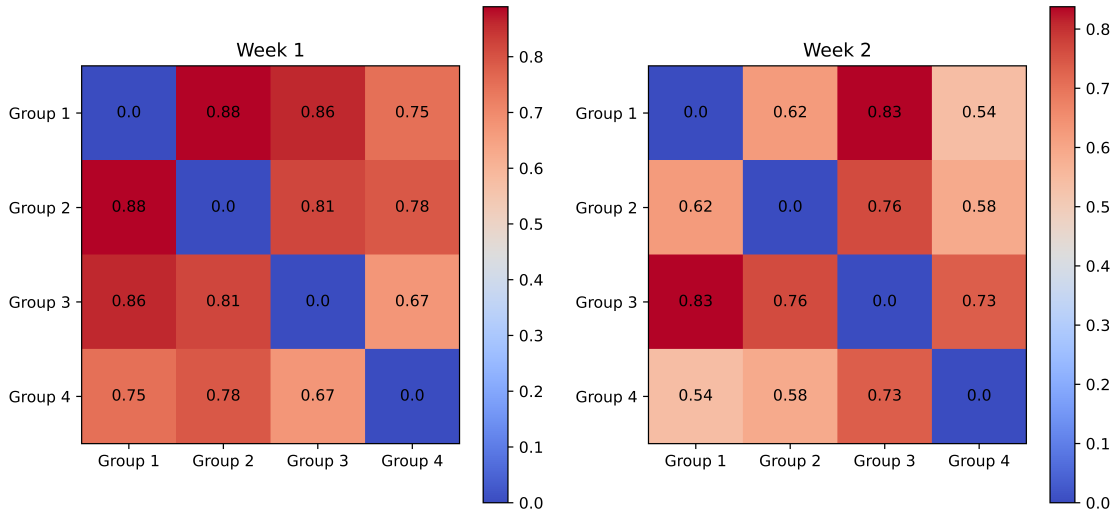
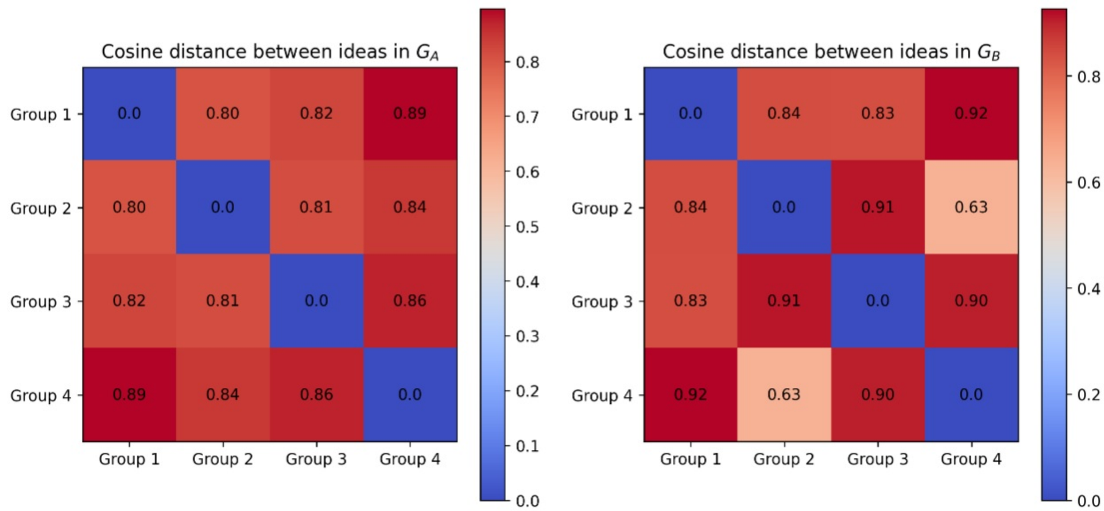


Figure 5: Comparison of the pairwise Cosine distance between TF-IDF vectors of ChatGPT's responses in G_A

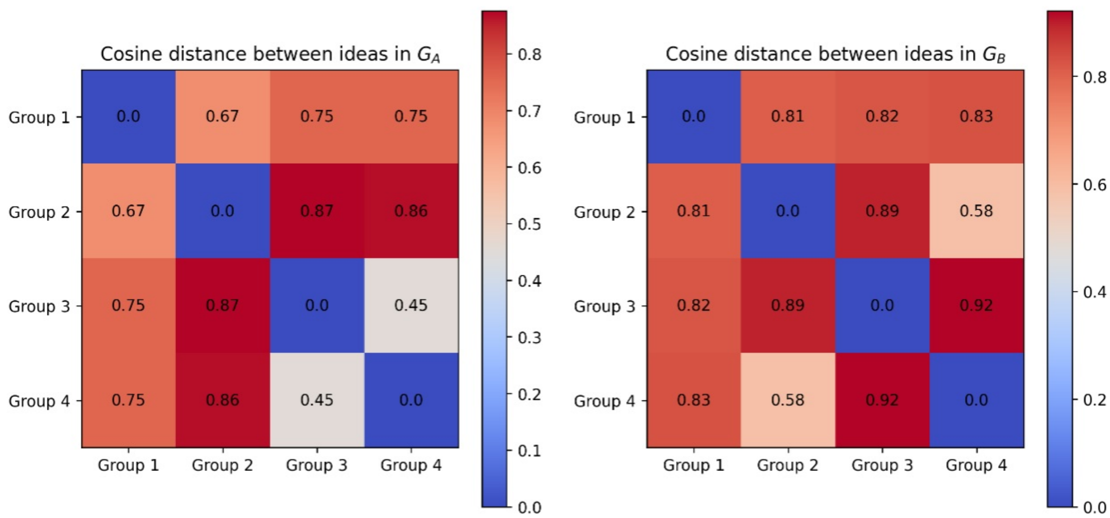
responses. Upon closer examination, we found that this similarity stemmed from all three groups exploring concepts related to masks or UV-C light in their design tasks, resulting in similar interaction patterns with ChatGPT. Despite this anomaly, the observed variability in linguistic patterns underscores the pivotal role of prompting in guiding the creative ideation process.

In assessing the similarity among product ideas generated with ChatGPT, we employ NLP once again as our analytical tool. For each week, we consolidate the 10 product ideas from each group within both G_A and G_B into a single TF-IDF vector. Subsequently, we analyze the distribution of all pairwise Cosine distances between the TF-IDF vectors of ideas within G_A and compare it with that of G_B. A smaller pairwise distance between the TF-IDF vectors within G_A compared to that of G_B will signify the presence of similar or homogeneous product ideas among groups in G_A.

As shown in Figures 6a and 6b, the pairwise distances of TF-IDF idea vectors within both G_A and G_B consistently fall within the range of 0.8 to 0.92 throughout both weeks. Subsequent statistical validation on the distribution differences in the pairwise Cosine distances between G_A and G_B using t-tests reveals no statistical significance (p values of 0.9624 and 0.3375 for weeks 1 and 2, respectively). This statistical insignificance implies that the linguistic divergence among ideas generated with ChatGPT resembles, with statistical equivalence, the linguistic distinctions between the ideas created within G_B. This result indicates that generating product ideas based on ChatGPT's responses does not inherently lead to more homogeneous or similar ideas. Rather, it hints at the nuanced interplay between the responses generated by ChatGPT and the intricate human interpretations in shaping the ideation process. Although more systematic experiments and analysis are warranted, the outcome implies that, despite the assistance of ChatGPT, human input continues to be a pivotal factor in generating diverse ideas.



(a) Week 1



(b) Week 2

Figure 6: Comparison of the pairwise Cosine distances among TF-IDF vectors of idea between G_A and G_B for Week 1 and Week 2

Conclusion

Based on the analyses above, we statistically validated that product ideas conceived with the assistance of ChatGPT are indeed perceived to be more creative compared to those solely originating from students. While a systematic investigation of the root causes behind this perceptual difference remains a subject for future investigation, our present finding identifies the differences in the linguistic patterns used in expressing these ideas as one potential reason. Notably, the ideas generated with ChatGPT tend to be more lengthy and detailed, potentially explaining this difference in the perception. Furthermore, we quantitatively confirmed that even when student groups collaborate with identical ChatGPT settings, the resulting product ideas demonstrate a similar degree of linguistic diversity as those found in ideas generated solely by the students.

While this paper introduced an application of genAI in the context of group brainstorming, it merely scratched the surface of a much broader landscape filled with more complex questions. To comprehensively unravel the intricate relationship between human creativity and genAI, further systematic research is needed. For example, as highlighted in [26], creative ideas, particularly within the domain of engineering, require exploring the nuanced interplay of various components, such as a person, a product, and a process. Thus, a deeper investigation into the effect of genAI on these individual components will be critical for a more holistic understanding. Furthermore, in our case, ChatGPT served as a reactive agent, requiring a student's initial conversation or prompt to trigger its responses. However, reactive chatbots are often perceived merely as a tool by their users [27], thereby limiting the full potential of genAI in fostering the creative ideation process. Aligned with the growing interest in proactive chatbots in the context of education [28, 29], additional research endeavors are warranted to explore the impact of proactive genAI-based chatbots on the creative ideation process.

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