Journal of Creativity 35 (2025) 100105

Contents lists available at ScienceDirect

Journal of Creativity

journal homepage: www.elsevier.com/locate/yjoc

Artificial Intelligence and the creative process: Does AI-creativity extend beyond divergent thinking?

Christian Byrge [a], Erik E. Guzik [b,*], Christian Gilde [c]

[a] Vilnius University, Business School, Lithuania
[b] University of Montana, College of Business, United States
[c] University of Montana Western, Business Department, United States

ARTICLE INFO

Keywords:
Creative problem solving
Future problem solving
Artificial intelligence
Ai
AGI
convergent thinking
divergent thinking
creative process

ABSTRACT

While several recent studies have demonstrated the impressive creative performance of Artificial Intelligence (AI) on divergent thinking tasks, there is currently insufficient research and understanding of how AI performs on convergent thinking and discernment activities, essential components of the human creative process. Creative problem-solving methods, in particular, present an intriguing means of researching AI's capacity to identify problems within ambiguous situations, while also generating relevant, useful solutions that respond to authentic, real-world issues in a meaningful way. This paper examined the performance of three separate AI entries generated by GPT-4o as compared with 68 human team entries from students in grades 7–9 within the competitive World Solutions Challenge offered by the Future Problem Solving Program International (FPSPI). The three entries were blind-scored by trained human evaluators for measures of effectiveness, impact, humaneness, creative strength, and development of action plan. Though all three AI entries scored in the top 15 % for all measures, including achieving the top scores for effectiveness, impact, humaneness, development of action plan, and overall performance, the AI entries were not found to be significantly different than the student control group on the measure of creative strength. The results suggest that AI models like GPT-4 may approach human-like abilities on certain aspects of creative performance during a more comprehensive creative process than divergent thinking alone, providing new insight into the current creative strengths—and limitations—of existing AI models.

1. Introduction

An important body of recent research suggests that the latest versions of generative artificial intelligence (GAI), including large language models (LLMs), match or exceed human test results on a range of cognitive tasks, including creative thinking. Guzik et al. (2023) found GPT-4 to be in top 1 % for measures of originality and fluency using the standardized Torrance Tests of Creative Thinking (TTCT). Koivisto and Grassini (2023) observed higher mean originality for AI responses as compared to a human control group. Haase and Hanel (2023) tested recent AI tools, such as GPT-3, and found AI to perform at or above human levels on a battery of Alternative Use Tasks (AUT). Hubert et al. (2024) also found GPT-4 to be more original and elaborate than humans using a test battery consisting of the AUT, Consequences Task, and Divergent Associations Task.

Research into the advanced divergent thinking abilities of AI has been especially surprising, as some studies have demonstrated that the latest LLMs perform at or above human levels on an array of divergent thinking (DT) tasks (Cropley, 2023; Koivisto & Grassini, 2023). One of the more interesting results is that GPT-4 performed at a higher level than most human test-takers on tasks that required high levels of inquiry and imagination, such as the "Asking Questions" and "Just Suppose" tasks of the TTCT (Guzik et al., 2023) and in the "Imagine humans no longer needed sleep" consequences task (Hubert et al., 2024).

Certainly, as critics have noted, not all recent research into the creative performance of AI has shown LLMs to outperform human participants on creative tasks or specific creative capacities (Bangerl et al., 2024; Koivisto & Grassini, 2023; Carolus et al., 2025). Further, many recent studies into AI-creativity have lacked necessary evaluator training and rigor, which has likely influenced assessment results (Yarbrough, 2016; Silvia et al., 2008). And though often neglected in current research of AI-based creativity, the actual assessment of

* Corresponding author at: 32 Campus Drive, Missoula, MT 59812, United States.
E-mail address: erik.guzik@umontana.edu (E.E. Guzik).

https://doi.org/10.1016/j.yjoc.2025.100105
Received 12 March 2025; Received in revised form 4 August 2025; Accepted 5 August 2025
Available online 6 August 2025
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creativity—whether human or AI-based—has overwhelmingly depended on the application of synthetic tests with widely available public data, particularly those tests reliant on the measurement of semantic distance or divergent idea production using well-known prompts like the AUT, and may therefore not fully capture the complexity of the creative process (Baer, 2011; Beaty et al., 2022; Kwon et al., 2022), or perhaps simply express the training of AI models on vast data sets that included such prompts.

Researching and identifying the relative strengths of AI-creativity vis-à-vis human creativity, however, remains an important area of inquiry in creativity research, the need for which goes beyond philosophical, or even perhaps epistemological, debate on whether AI can 'truly' be creative (Boden, 2009). As a form of technology, AI holds the practical potential to contribute to human betterment in myriad ways: through economic development and innovation, new theoretical understandings and definitions of creativity, and, perhaps most importantly, more effective development of human creative abilities, which has itself been woefully neglected in the past.

Along these lines, recent research has explored the notion of co-creation between humans and AI (Vear & Poltronieri, 2022). Indeed, in some studies, AI has been shown to be equal to or surpass human scores on at least one indicator of creative ability—and vice-versa. For example, Bangerl et al. (2024) found humans to produce more original and diverse ideas, but AI chatbots produced more elaborate and detailed ideas. Stevenson et al. (2022) compared human performance to GPT-3 performance and found humans scored higher on originality, surprise, and flexibility, while GPT-3 scored higher for usefulness across testing runs.

Given such results, recent research has also explored how AI can assist humans during phases of the creative process. For example, Urban et al. (2024) found that ChatGPT can help improve creative performance and advance creative self-efficacy when working on complex creative tasks. In another study, Doshi and Hauser (2023) found that humans using AI as a tool wrote more novel and useful stories (appropriate, feasible, publishable) than those who did not use AI. Comparing three different test groups, Dell'Acqua et al. (2023) discovered that a group of management consultants with access to and training in the use of OpenAI's GPT-4 performed more creatively compared to a second group with access to, but no training, in GPT-4. The worst performing group had no access to GPT-4.

A particularly novel aspect of the study by Dell'Acqua et al. (2023) was that they went beyond evaluating divergent thinking and included additional steps of the creative process, including idea evaluation, idea selection, and prototype description by human co-creators. Indeed, based on dual process models of creativity (Allen & Thomas, 2011; Sowden et al., 2015), the creative process, as is well known, has been proposed to involve an interplay between divergent and convergent thinking, building on Guilford's Structure of Intellect (SOI) model of human intelligence in important ways (Guilford, 1956).

Within these models, creative thinking is believed to comprise two primary components: the generation of novel ideas through divergent thinking and the assessment of their originality and relevance through convergent thinking (Cropley, 2006; Goldschmidt, 2016). Brophy (1998), for example, has argued that a full process of creative thinking involves alternating between close-ended convergent evaluation and open-ended divergent ideation. According to this view, to master the creative process, any agent–human or AI– must demonstrate proficiency in both constituent elements of creative thinking (divergent and convergent) to be deemed "creative."

Motivated by such previous research, this paper investigated AI's ability to work through an entire creative process, including phases of divergent and convergent thinking, without any human contribution to the final product. It focused specifically on AI's creative problem solving abilities, as judged by trained human evaluators, during a global creative problem solving competition involving teams of students from grades 7–9. In so doing, this study sought to evaluate the potential creative abilities of AI in a way that went beyond the analysis of the divergent production of ideas using limited tests like the AUT. Simply, this study asked: if provided an open-ended, real-life scenario, scored by trained evaluators, would AI be deemed creative?

2. Method

The study utilized standard definitions of creativity to examine AI's creative performance. Such definitions have highlighted product differentiation and effectiveness as key markers of creative ability. These definitions, for example, have suggested that creative output must be new and useful (Runco & Jaeger, 2012), surprising (Acar, Burnett & Cabra, 2017), unique and valuable (Harrington, 2018), and original and appropriate (Runco, 2023). While these definitions include a concept of novelty (new, unique, original, etc.), they also emphasize the need for the assessed output to be relevant and effective (useful, valuable, appropriate, etc.). That is, for a product to be considered creative, it is not enough to be different, original, or unique—the differentiated product must be relevant and appropriate to the task at hand (that is, the proposed solution must fit the problem presented).

The 2023 World Solutions Challenge (WSC), offered by the Future Problem-Solving Program International (FPSPI) (Torrance, 1976; Torrance & Torrance, 1978), was chosen for the experiment due to its focus on several steps of the creative process, including divergent steps to generate challenges, solutions, and evaluation criteria, as well as convergent steps to select an underlying problem, rank solution ideas, and develop an elaborate and relevant action plan. Of note, the WSC offered a unique opportunity to test AI using an open-ended task that depended on the application of an entire creative process, not just the divergent production of ideas, thereby extending in important ways recent research with focus on open-ended versus close-ended problem solving (Raz et al., 2024). Further, utilizing a form of the Consensual Assessment Technique, trained evaluators scored entries for a range of indicators of creative ability, including not only a measure of Creative Strength, but also Effectiveness and Impact (described in detail below).

Based on the work of E. Paul Torrance, FPSPI has been designed to encourage participants to develop creative solutions for problems for which there are no existing solutions (Terry et al., 2008). Participating teams are given a scenario based on an open-ended, real-world challenge (e.g., climate change, global warming, genetic engineering). The scenario is often referred to as a fuzzy situation, an example of a 'wicked problem' for which there is no one, obvious solution. Teams are instructed to work through the scenario using a six-step creative problem-solving process, an adaptation of the Osborn-Parnes Creative Problem-Solving Model (Osborn, 1953; Parnes, 1967). Specifically, the Future Problem-Solving process includes the following steps: (1.) Identify challenges; (2.) Select an underlying problem; (3.) Produce solution ideas; (4.) Select criteria; (5.) Apply criteria; and (6.) Develop an action plan.

The theme for the 2023 WSC focused on the following basic prompt: "How will emerging uses of artificial intelligence (AI) impact how we work, live, play, and learn in the future?" (Future Problem Solving, 2023). Participants were asked to think of solutions to challenges touching on the following general themes, and ultimately develop a detailed, novel, impactful, and effective action plan:

1. How can AI be best used to assist humans?
2. How will human and machine decision-making be balanced?
3. What is the best way to balance labor between humans and AI tools?
4. How can misinformation in AI be prevented?
5. What should be considered when lawmakers create regulations about AI?
6. Who owns AI-generated content? If AI makes a biased decision, who is to blame? (Source: Future Problem Solving, 2023)

3. Procedure

Given evaluator availability and time constraints, FPSPI allowed the study to submit a maximum of three AI-generated responses to the WSC for scoring. OpenAI's GPT-4o model was utilized to create the three submissions. Each of the three submissions was created in a separate session, with the default temperature setting of 0.7. The study provided each GPT-4o session with an exact copy of the challenge, including all instructions and details provided to human teams. The study also provided each session with an exact copy of the six-step creative problem-solving method suggested by FPSPI to apply for solving the challenge. The output generated by GPT-4o for evaluation was copied to the FPSPI submission system without making any changes. The submission system allowed for an abstract of up to 150 words and an Action Plan of up to 1000 words.

The control group was made up of 68 human team submissions for the same WSC. These teams consisted of students from grades 7–9 from seven countries. Student teams were given the same details about the challenge and six-step creative problem-solving method. The submitted work was not timed.

Each submission was blind-scored using a variation of the Consensual Assessment Technique (CAT) (Amabile, 1982) by FPSPI-trained evaluators (there were a total of 32 evaluators participating in the WSC). The three AI booklets were assigned the competition codes WSC403, WSC406, and WSC409, following the naming convention provided to human teams. Evaluators were not told about the three AI submissions. Evaluators used a rubric-based assessment consisting of the following criteria (Future Problem Solving, 2023;):

A. Effectiveness, scored from 1 to 10.
B. Impact, scored from 1 to 10.
C. Humaneness, scored from 1 to 10.
D. Creative Strength, scored from 1 to 10.
E. Development of Action Plan, scored from 1 to 20.

During each round of scoring, an overall score was calculated based on the composite of the five criteria, with a maximum possible score of 60. The top booklets went on to subsequent scoring rounds, receiving a maximum of three rounds of scoring. A rank was assigned to each booklet during each round of evaluation relative to the other booklets within the assigned round (1 designated as best ranking). For each submission, evaluators also submitted an overall "quality term" to further distinguish between entries and top submissions (Exemplary, Outstanding, Very Good, Proficient, Developing), and provided overall comments as part of each booklet evaluation.

4. Results

All three AI booklets received the full three rounds of evaluation. In terms of individual results, one of the three AI entries, WSC403, received the top overall average score from evaluators, while WSC406 received the third highest average score. In addition, all three AI booklets scored in the top 3 for Humaneness and Effectiveness, and in the top 5 for Impact and Action Plan. Descriptive statistics and associated box plots are displayed in Table 1 and Fig. 1.

Table 1
Statistical Comparison of Student and AI Results.

Measure	Student ($n = 68$) $M \pm$ SD	AI ($n = 3$) $M \pm$ SD
Effectiveness	4.80 ± 2.45	8.78 ± 0.38
Impact	4.90 ± 2.43	8.67 ± 0.88
Humaneness	5.13 ± 2.44	8.67 ± 0.58
Creative Strength	4.98 ± 2.46	7.56 ± 1.35
Development of Action Plan	9.61 ± 5.28	17.11 ± 1.68
Total Score	29.42 ± 14.69	50.78 ± 4.07

Because the two groups were unbalanced in size (68 vs 3) and Levene's tests indicated heterogeneous variances on most measures, Welch's unequal-variance *t*-test, a variation of Student's *t*-test, was adopted as the primary significance test.

Significance tests showed AI teams outperformed student teams on *Effectiveness, Impact, Humaneness, Development of Action Plan, and Total Score*, with large effect sizes ($|d| \geq 1.44$). The advantage of AI entries on the measure of *Creative Strength* trended in the same direction, but did not reach conventional significance ($p = .06361$). See Table 2 for the full set of results.

Given the small AI sample as noted above, basic robustness checks were also completed, including permutation tests and bootstrap confidence intervals, each of which supported the previously reported statistical differences. See Table 3.

Overall Ranks and assignment of Quality Terms were also compared across the two groups, and again showed statistical differences between the student and AI submissions. AI entries were more likely to be ranked higher—and rated qualitatively better—than student team entries. AI entries clustered near ranks 1–2 and attracted more high-end quality labels (e.g., "Exemplary"), whereas student entries spanned the full rank range and were more often tagged "Developing" or "Proficient." See Figs. 2& 3.

5. Discussion

The purpose of this study was to move beyond testing AI for divergent thinking ability alone, expanding AI creativity research into additional, relevant aspects of the creative process. Toward this end, GPT-4o was tested for its potential to work through both divergent and convergent steps of the creative process to solve a real-life challenge in a format often referred to as a "wicked problem". The capacities demonstrated by GPT-4o in this study hold relevance to a more complete understanding of AI-creativity and its potential application—capacities which this research suggests likely extend beyond divergent production and performance on simpler, more synthetic, tests like the AUT. The following discussion therefore focuses on three main points: (1) Extension of AI-creativity beyond divergent thinking; (2) Utilization of AI-creativity as an element in the co-creation processes; and (3) Contribution to new, emerging understandings of creativity—both AI- and human-based.

6. AI-Creativity beyond divergent thinking

Lazar et al. (2022) have suggested that problem-understanding, and solution criteria are essential to recognize an idea as suitable for the problem. Haase and Hanel (2023) have argued that because these steps call for human skills, AI chatbots remain assistants to human idea generation, incapable of completing the entire creative problem-solving process. Boussioux et al. (2024) have noted that AI systems, by their very design, may be restricted by their training data and constrained to searching for less novel solutions based on this past training.

In this context, this study provides new evidence that LLMs may hold heretofore unrecognized abilities that are integral to the creative process. As noted earlier, creativity is conventionally defined as the generation of output (product) that is not just original or different, but also relevant and useful. The evaluation of AI's output within this study is therefore worth reviewing in detail. Perhaps of greatest relevance, the measures of *Effectiveness* and *Impact* of the AI entries were scored by evaluators to be significantly higher than the control group. AI models like GPT-4o therefore seemingly hold the capacity to not only generate unique and differentiated output, but also potentially effective and impactful solutions to open-ended problems. As such, this research provides new insight that generative AI engines, such as GPT-4o, demonstrate an ability to work through an entire creative process, such as forms of creative problem-solving, and utilize effective convergent thinking capacities.

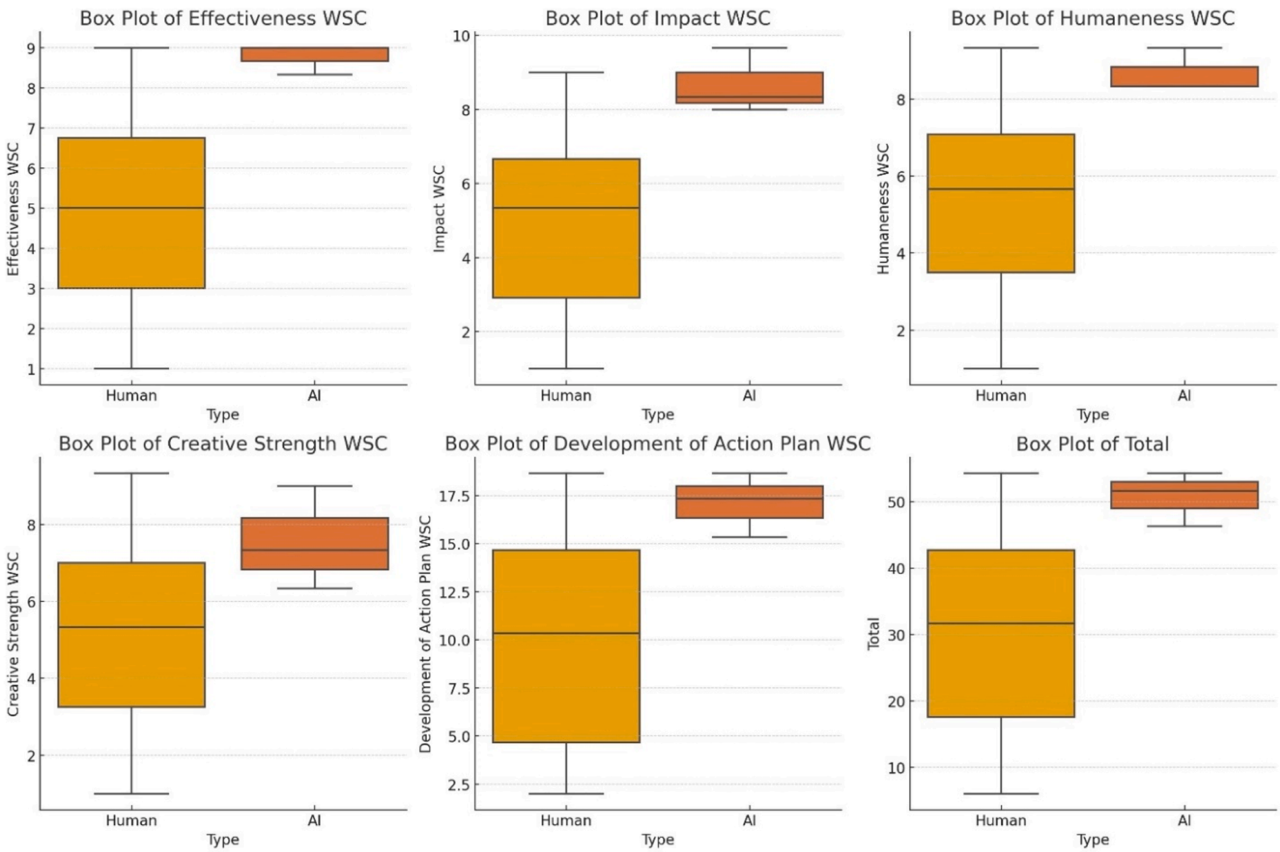

Fig. 1. Box Plot Comparison of Student and AI Results.

Table 2
Significance Testing.

Measure	t	df	*P*	Cohen's *d*
Effectiveness	–10.71	14.18	< 0.00001	–1.65
Impact	–6.41	3.55	.00453	–1.57
Humaneness	–7.94	6.29	.00017	–1.47
Creative Strength	–3.10	2.63	.06361	–1.06
Development of Action Plan	–6.46	4.10	.00270	–1.44
Total Score	–7.24	4.91	.00085	–1.47

Table 3
Additional Tests.

Measure	Student Mean	AI Mean	Permutation p	95 % Bootstrap CI (Student – AI)	Mixed p
Effectiveness	4.80	8.78	.00270	–4.66 to –3.28	< 0.001
Impact	4.90	8.67	.00780	–4.80 to –2.83	< 0.001
Humaneness	5.13	8.67	.00950	–4.34 to –2.78	< 0.001
Creative Strength	4.98	7.56	.07509	–3.97 to –1.26	.01135
Development of Action Plan	9.61	17.11	.00970	–9.49 to –5.46	< 0.001
Total Score	29.42	50.78	.00330	–27.61 to –14.12	< 0.001

Of note, while GPT-4o performed at a level that matched student participants in terms of *Creative Strength*, it did not *outperform* these students on this particular measure. That is, the *Creative Strength* of the

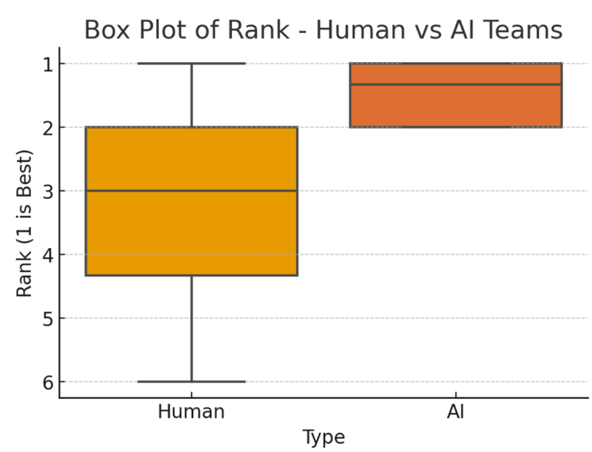

Fig. 2. Comparison of Student and AI Ranking.

AI submissions did not score significantly higher than that of student participants. These results could indicate a potential weakness of the creative performance of current LLMs, or possible limitations of existing AI models based on complex semantic pattern-matching and generation—a potential limitation that might be further exposed as testing is extended beyond the evaluation of divergent thinking to include a more complete assessment of the creative process. In this regard, additional research is required to further assess the abilities of current AI models as involving a more complete creative process.

7. AI-Creativity as an element of co-creation

Results suggest that AI will likely continue to impact human

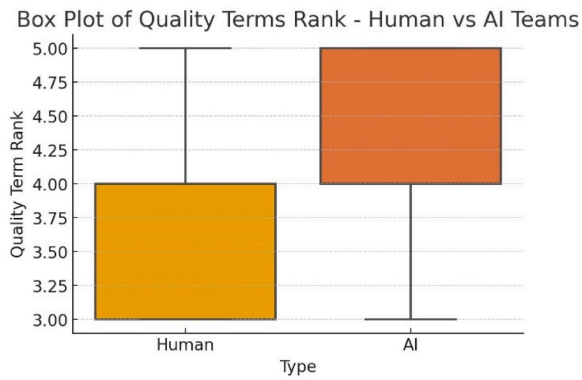

Fig. 3. Comparison of Student and AI Quality Terms.

creativity in complex ways, serving as both a potential complement and substitute for human creativity. In short, as past studies have indicated, AI-creativity might support and/or displace human creativity in complicated and perhaps even contradictory ways. For example, previous research highlighted potential concerns with AI-creativity replacing human creativity (Caporusso, 2023; Fisher, 2023). In contrast, Vinchon et al. (2023) proposed AI being a collaborative agent in creative work and suggested that humans will still play an integral role in the start and conclusion of the creative process. In the present study, though the authors did in fact initiate the creative process by sharing the FPSPI World Solutions Challenge instructions with GPT-4o (more on this below); the LLM performed and completed the entire creative process, including the development of a detailed, effective action plan, without any human contribution. And, according to the competition's human judges, the AI entries matched or exceeded the abilities of the student teams in the control group.

The practical significance of these results is worth considering. Focusing on the far end of the complement-substitute spectrum, there might certainly be good reason for replacing human creativity with AI creativity in specific situations or for specific problems. Perhaps AI can solve problems that are not intrinsically motivating for humans to solve; or maybe AI can solve the problems that urgently require a solution in situations where human team members are already pushed to their very-human limits. Extending on what may be deemed a utilitarian argument, there may also be important benefits of AI creativity related to scalability, efficiency and cost-effectiveness (Boussioux et al., 2024). Even so, such arguments must acknowledge that humans derive immense intrinsic value from being creative (Acar et al., 2021; Keenan-Lechel et al., 2023) and the enjoyment (and hence utility) of being in a state of creative flow (Csikszentmihalyi, 1999). In short, even from a basic value perspective, humans may prefer to be creative even if AI can do it better, faster or cheaper.

As noted earlier, in a co-creative approach, both humans participants and AI serve as important actors within the creative process (Vear & Poltronieri, 2022). On one hand, humans need to learn how to use AI tools creatively and understand their potential limitations. For example, even though AI may produce more novel ideas, it may also lead to less diverse ideas (Dell'Acqua et al., 2023; Doshi & Hauser, 2023). It might likewise perform relatively lower on factors of creative ability, such as flexibility vis-à-vis originality and fluency (Guzik et al., 2023). As such, competencies in creative prompt engineering may be crucial (Battle & Gollapudi, 2024; Zamfirescu-Pereira et al., 2023) for the success of human-AI co-creative processes, as well as learning new strategies to engage with LLMs, such as forceful interactive prompting (Goes et al., 2023) or independent and differentiated searching (Boussioux et al., 2024). On the other hand, AI tools likely need to be developed further to better support human creativity (Davis et al., 2017; Deshpande et al., 2023) by facilitating collaboration and exploration, making it more enjoyable to engage with the tool, and increasing human expressiveness and satisfaction with the outcome (Cherry & Latulipe, 2014).

Educational initiatives like FPSPI are not simply about winning challenges and competitions. Rather, these initiatives are designed to give students the necessary creative skills and creative self-efficacy to approach future problems and challenges (Volk, 2008). As such, FPSPI and similar creativity programs may benefit from the integration of AI as a new type of mentor and guide to assist, support and challenge students during both divergent and convergent steps of creative problem-solving. Extending this line of thinking, AI-creativity might offer an array of advantages for human teams tasked with developing creative output.

To provide specific examples, LLM chatbots, with their less judgmental approach (Wieland et al., 2022), could be effective members of human teams especially during brainstorming sessions to overcome social barriers of creativity, such as groupthink, and cognitive barriers, such as cognitive fixedness (Hubert, 2024). This partnership of AI's ability to draw on vast amounts of information in new ways combined with the human ability of self-awareness and situational mindfulness may be particularly valuable for mini-C and little-C creativity (Habib et al., 2023). In this context, AI-creativity as a co-creator might present an important new tool to help develop human creativity in useful ways. Despite impressive gains in research of human creativity during the past half-century, still today relatively few training-, educational-, and productivity programs exist to develop this essential human ability.

As a process, co-creation is certainly not new to creativity (Sawyer, 2007). In practice, many creatives depend on the novel and useful contributions of those humans they work with, including teammates, customers, users, investors, colleagues, friends, family, co-founders, leaders and subordinates. Even those individuals that may seek to create alone, like artists, musicians, writers, and inventors, are often guided, influenced, and inspired by others from the environments in which they operate, blurring the lines between individual creative work and co-creative processes. More research is needed to better understand who will benefit—and how—from the new human-AI co-creative opportunities.

8. Toward new understandings of creativity

Given the performance of LLMs during the creative process and its potentially value to creative co-creation, it is worth revisiting what is meant by the terms creative and creative process, acknowledging how intertwined these terms are with the human experience. Indeed, the latest research into the creativity of AI has triggered a necessary debate about how to better understand human creativity, including how it differs from the AI generative process and output.

Runco (2023), for example, has suggested the need for intentionality and authenticity as required elements of true creativity. He has therefore proposed the concept *artificial creativity* as a means of differentiating the output of human creativity from that generated by AI, due to the latter's inability to be authentic and demonstrate intent. According to this view, two identical ideas, one created by AI, the other by a human, might each be original, surprising and valuable. However, according to this proposed definition of creativity, only the idea developed by a human could count as creative.

A focus on intentionality is extremely important and valuable, and certainly worthy of additional discussion. First, this new definition pushes conceptions of creativity further into the realm of process, itself a key contribution. Yet, including intentionality as an essential condition for a true creative process may nevertheless be problematic as it relates to human and AI creativity. As one example, human intention is an integral component of many non-creative acts, including derivative copying and conscious duplication, which seems to muddy the theoretical waters of defining what it means to be creative. Further, many creative individuals (including, for example, musicians, apprentices, students, and employees) respond to the direction and instruction of others (their producers, superiors, teachers, and clients) as a precursor to their creative work. Despite the apparent lack of initiative and originating intent by these individuals, their resultant work nevertheless seems to fall under the notion of "creative" if such work produces original, surprising and valuable results.

This is not to diminish the role of intentionality in the creative process. That intent may serve as a possible component of human creativity seems warranted and seemingly underpins, for example, the creative process as described by Wallas (1926), von Helmholtz (1896), and Isaksen et al. (1994). As Henri Poincare (1908) phrased it, "Invention is discernment, selection." One might imagine that choice and intention are infused in different ways into the creative process, including the definition of the creator's objectives, research, idea generation, new connections and associations, acceptance, elaboration, verification, and so on. Beyond simple divergent thinking, then, the creative process includes different stages of decision-making and evaluation. However, the results of this study suggest that AI can make this series of choices during the creative process in a way that leads to what humans define as a creative, relevant, impactful, humane, and well-developed action plan.

Surprisingly little is known about how AI produces its creative ideas, beyond the use of complex semantic analysis and the resultant language sequencing and (re)generation of data on which it has been trained. AI does not require the metacognitive and affective processes that are utilized by humans to produce novel and valuable ideas (Chatterjee, 2022). AI creativity, perhaps by necessity and design, is driven by its own unique set of algorithmic processing and stepwise sequencing to generate novel solutions to unclear problems—that is, AI likely leverages its own, unique creative process (or processes). In this sense, AI creativity may be no less complicated than human creativity. Such considerations might provide a new way to better understand creativity—and how the process of AI-creativity differs from the process of human creativity in terms of the unique constituent elements—and current limitations—defining each.

Funding

This research did not receive any type of grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Christian Byrge: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Erik E. Guzik:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization. **Christian Gilde:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Thank you to the Future Problem Solving Program International (FPSPI) for their participation in this research.

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