

Generative AI and Creativity: A Systematic Literature Review and Meta-Analysis

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Generative artificial intelligence (GenAI) is increasingly used to support a wide range of human tasks, yet empirical evidence on its effect on creativity remains scattered. Can GenAI generate ideas that are creative? To what extent can it support humans in generating ideas that are both creative and diverse? In this study, we conduct a meta-analysis to evaluate the effect of GenAI on the performance in creative tasks. For this, we first perform a systematic literature search, based on which we identify $n = 28$ relevant studies ($m = 8214$ participants) for inclusion in our meta-analysis. We then compute standardized effect sizes based on Hedges' g . We compare different outcomes: (i) how creative GenAI is; (ii) how creative humans augmented by GenAI are; and (iii) the diversity of ideas by humans augmented by GenAI. Our results show no significant difference in creative performance between GenAI and humans ($g = -0.05$), while humans collaborating with GenAI significantly outperform those working without assistance ($g = 0.27$). However, GenAI has a significant negative effect on the diversity of ideas for such collaborations between humans and GenAI ($g = -0.86$). We further analyze heterogeneity across different GenAI models (e.g., GPT-3.5, GPT-4), different tasks (e.g., creative writing, ideation, divergent thinking), and different participant populations (e.g., laypeople, business, academia). Overall, our results position GenAI as an augmentative tool that can support, rather than replace, human creativity—particularly in tasks benefiting from ideation support.

1 INTRODUCTION

Generative artificial intelligence (GenAI) refers to a class of machine learning technologies that have the capability to generate new content that resembles human-created output, such as images, text, audio, and videos [21]. GenAI can thus support various human tasks such as writing, software development, composing lyrics, and academic research, often at a performance similar to that of humans [6, 11, 26, 28, 50, 72]. On top of that, Generative AI has also become a valuable tool in creative industries—spanning graphic design, advertising, fashion, writing, and visual arts [36, 59].

Yet, empirical evidence on the benefits of GenAI for creative performance is scattered, and the theoretical arguments are often inconsistent or even contradictory. On the one side, cognitive research argues that creativity is an inherently human trait [1, 51]. One common issue in practice is that GenAI models often lack the tacit knowledge required for systematic, compositional reasoning such as multi-step problem solving to generate ideas perceived as creative, especially in real-world tasks from businesses. Similarly, GenAI is likely to reproduce ideas seen during training rather than ideating novel ideas [30]. Hence, simply by means of the training data of GenAI, the generated ideas may also be less diverse than those of humans [16]. On the other side, there is early evidence suggesting that outputs from GenAI are perceived as being creative [65]. For example, several studies find benefits from GenAI in creative tasks, but these findings are typically limited to specific creative tasks (e.g., story writing, ideating business models) [16, 39, 64, 72]. This may suggest that GenAI can generally improve creativity, but it is often unclear how well the results generalize across domains.

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Here, we perform a meta-analysis to evaluate the effect of GenAI on creative performance.¹ For this, we focus on different outcomes, namely: (i) how creative GenAI is; (ii) how creative humans augmented by GenAI are; and (iii) the diversity of ideas by humans augmented by GenAI.² To this end, we analyze the following **research questions (RQs)**:

- **RQ1:** *How creative are ideas generated by GenAI (compared to humans without GenAI support)?*
- **RQ2a:** *How creative are ideas generated by humans when supported by GenAI (compared to humans without GenAI support)?*
- **RQ2b:** *How diverse are ideas generated by humans when supported by GenAI (compared to humans without GenAI support)?*

To answer the above research questions, we first perform a systematic literature search and then conduct a meta-analysis. Overall, we retrieved $n = 691$ studies for inclusion, and eventually identified $n = 28$ studies with empirical results ($m = 8214$ participants). We then calculated the standardized effect size via Hedges' g and computed a random-effects meta-analysis. We further analyzed heterogeneity across different GenAI models (e.g., GPT-3.5, GPT-4), different tasks (e.g., creative writing, ideation, divergent thinking), and different participant populations (e.g., laypeople, business, and academia) to provide a general but differentiated understanding of the effect of GenAI on creativity.

2 METHODS

In this section, we describe our data collection to identify relevant studies and statistical analysis.

2.1 Search Strategy

Search databases: We followed the PRISMA 2020 framework [45] for systematic literature reviews. To identify relevant studies, we searched the following databases: (i) Web of Science, (ii) SSRN, and (iii) arXiv. Our search includes non-peer-reviewed studies to reflect the rapidly evolving nature of GenAI research and to capture recent advances. Our search was limited to publications in the English language from the past five years, which is loosely aligned with the emergence of foundational models such as GPT and BERT. The knowledge cutoff of our search was May 2, 2025.

Search query: Our search query was intentionally broad to include various ways to relate to GenAI technology and creativity. Overall, our search query was inspired by Schemmer et al. (2022) [52], which we adapted to our research question, namely, creativity:

Search query

```
TITLE("creativity" OR "creative" OR "ideation" OR "idea")
AND
("AI" OR "Artificial Intelligence" OR "LLM" OR "Large Language Models")
```

Inclusion/exclusion: The process for inclusion/exclusion in our systematic literature review is shown in Figure 1 (based on the format of the PRISMA 2020 Flowchart [46]). Literature screening, eligibility checks, and final inclusion were performed by one person (the first author). In the identification phase, $n = 691$ publications were identified by our search query, out of which $n = 96$

¹Code and data are available via our Git at <https://github.com/SM2982/Meta-Analysis-LLMs-Creativity.git>.

²We also considered a fourth outcome, namely, the diversity of ideas generated by humans with GenAI support. Yet, our literature search did not return a sufficient number of empirical studies for this outcome. Hence, we refrain from analyzing this outcome. However, we identify this gap as a promising opportunity for future research, which we elaborate on in the discussion section.

duplicate publications were removed manually. Out of the remaining $n = 595$ publications, both the title and abstract were screened for inclusion in the assessment of eligibility. Here, $n = 516$ publications were excluded due to a lack of fit (e.g., a focus on legal studies).

Subsequently, $n = 79$ records were assessed for eligibility. Studies were eligible if they:

- (1) The study design was aimed at comparing (a) the creativity performance of humans versus GenAI or (b) the creative performance of humans with vs. without GenAI support. The study further followed a between-subject experiment design, which is crucial to make rigorous statistical comparisons.
- (2) The study had to report sufficient statistics (e.g., the group means and standard deviations or equivalent statistics) that allow for computation of standardized effect size Hedges' g . In cases where such statistics were not directly reported, we examined whether the publication was accompanied by raw data, either in supplementary materials or associated repositories, that would enable us to reconstruct the necessary statistics. However, if these data were not accompanied by clearly documented analysis scripts and/or the reconstruction would have required substantial interpretation or rewriting of the original code, the study was excluded based on insufficient raw data.
- (3) The study had to measure creative performance using an established measurement dimension (e.g., novelty [60], originality [40], diversity [47, 56]).

In this stage, publications were excluded due to (i) insufficient study design ($n = 34$) (ii) insufficient statistics ($n = 15$), and (iii) insufficient creativity measurement ($n = 4$). Cases with ambiguity were resolved through discussion until consensus was reached (based on Author #1 together with Author #2 and Author #3).

We contacted the corresponding authors from 15 publications via e-mail to address two of the above reasons for exclusion, namely, (ii) insufficient statistics and (iv) insufficient data reporting. If no response was received after the initial contact, a follow-up e-mail was sent to maximize the inclusion of eligible studies. As a result, we obtained sufficient additional information for inclusion from four studies ($n = 4$). All studies that did not elicit a response were excluded.

Given the novel scope of the research question and the evolving terminology in the field, we recognized the possibility that the search strategy might overlook relevant studies. To address this, the authors manually included two additional studies that met all eligibility criteria but were not captured by the original database query.

In total, we identified $n = 28$ publications that met the eligibility criteria for inclusion in our meta-analysis. Several of these publications reported multiple experiments or included multiple outcome measures related to creativity and diversity. As a result, the 28 studies correspond to a total of 127 effect size estimates.

2.2 Data Collection

The $n = 28$ studies that met the inclusion criteria were recorded in our database. Our database capturing all relevant study features and outcomes is deposited in our GitHub.

An overview of the extracted dimensions is summarized in Table 1, which serves as the basis for exploring heterogeneity in creative performance across various study and task characteristics. Specifically, we extracted study-level data of metadata (title, author, abstract, publication date, source). We further provide details about the experimental design (GenAI type, GenAI model, task type, creativity measurement, evaluator), participant characteristics (professional domain, recruitment source), and outcome statistics (means, SD , SE , m_{total} , m_{control} , $m_{\text{treatment}}$, F -value, standardized β , and $SE - \beta$). We discuss the dimensions in the following.

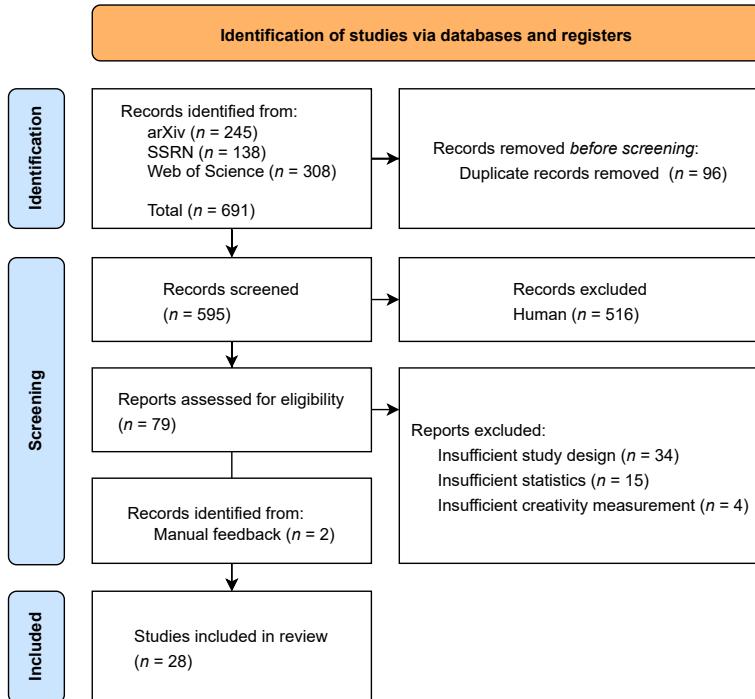


Fig. 1. PRISMA flow chart.

The **task type** reflects the notion that different creative tasks tap into distinct aspects of creativity (and thus different cognitive processes), such as compositional skills, imaginative reasoning, or divergent thinking (i.e., the ability to generate multiple, varied ideas in response to an open-ended prompt). The studies in our analysis employ a variety of creative tasks, each targeting different dimensions of creative cognition. For example, the so-called *alternate uses task* (AUT) [27] asks participants to generate unconventional uses for everyday objects (e.g., “a brick”), which assesses originality. The so-called *consequences task* (CT) [67] involves imagining outcomes of improbable scenarios (e.g., “What would happen if people could fly?”), which taps into imaginative thinking and hypothetical reasoning. The so-called *divergent association task* (DAT) [33] requires listing unrelated words (e.g., “apple”, “justice”, “galaxy”). *Forward flow* (FF) measures [25] the conceptual distance between sequential thoughts in open-ended responses, reflecting the natural flow of creative ideation. Finally, other studies rely upon creative writing tasks such as composing a short story or poetry to challenge narrative creativity, but also business ideation tasks (e.g., coming up with a new business model).

Prior work has suggested that creative performance comprises multiple dimensions [40]. Hence **creativity measurements** can be obtained in subjective (e.g., human ratings) or objective (e.g., via metrics from natural language processing such as semantic distance or cosine similarity [22]) ways. Subjective assessments commonly rely on scales such as perceived creativity, originality, or novelty—terms that show some overlap conceptually but are occasionally operationalized as distinct constructs [35]. For example, *creativity* is often perceived as a combination of novelty and effectiveness, *originality* refers to how uncommon or unique an idea is, and *novelty* emphasizes newness or unfamiliarity. These dimensions may be interpreted differently by human raters,

depending on context and individual experience. Hence we also coded the identity of the **evaluator**. For example, self-assessments may introduce bias due to over- or underestimation of one's creative performance, in contrast to expert ratings. Rule-based or AI-based evaluations offer standardization and scalability but may miss nuanced judgment or (tacit) domain knowledge.

In cases where studies reported multiple measurements per experiment, we prioritized evaluations of creative performance by experts over self-assessments. When multiple experiments were reported within a single study, each experiment was included separately, with one outcome measurement per experiment. Creative performance was encoded using the most conceptually appropriate metric available—ideally an overall creativity score (if available) or, alternatively, measures of originality or novelty before using any other measurement.³

Table 1. Extracted dimensions.

Dimensions	Values
GenAI type	text-to-text (T2T), text-to-image (T2I)
GenAI model	GPT-4o, GPT-4, GPT-4all, GPT-3.5-turbo, GPT-3.5, GPT-3, Claude, SparkDesk, Qwen, Dou Bao, alpaca, bing, dolly, koala, oa, stablelm, vicuna, not disclosed (n.d.); <i>optional:</i> multiple models
Participants	academia, business, laypeople, not disclosed
Task type	alternate uses task (AUT), consequences task (CT), divergent associations task (DAT), forward flow (FF), creative writing, creative problem solving, creative thinking, divergent thinking, ideation product, ideation item usage, ideation research proposal, ideation business concepts, ideation other
Recruitment source	university, Prolific, Mturk, public, company
Creativity measurement	creativity scale, originality scale, novelty scale, semantic distance, cosine similarity, creative problem-solving scale, flexibility score
Evaluator	self-assessed, laypeople, expert, rule-based, AI

2.3 Statistical Analysis

Hedges' g : For each comparison, we extracted reported Cohen's d or calculated it based on reported statistics [10]. When effect sizes were not directly reported, we converted other statistical measures (e.g., t -values, F -values, means and standard deviations) to Cohen's d using widely accepted conversion formulas [3, 17, 48, 49], which are documented in our project repository. To adjust for potential upward bias in small samples, we applied Hedges' g correction [38]. We report one effect size per individual experiment across all included studies to ensure statistical independence. We further report 95% confidence intervals (CIs).

Random-effects model: As we expect large heterogeneity regarding treatment, task, and measurement across studies, we chose to estimate a random-effects model as recommended by Cochrane [13]. Pooled effect sizes were estimated under the random-effects model using the DerSimonian-Laird estimator [14] to account for the expected between-study heterogeneity. We calculated 95% confidence intervals (CIs) to indicate the expected range of true effects across settings.

³To examine potential heterogeneity across different conceptualizations of creative performance, we conducted exploratory subgroup analyses based on the specific constructs used—namely, creativity, originality, and novelty. However, these analyses revealed no substantial heterogeneity. This may be due to the high conceptual overlap among the constructs of creativity, originality, and novelty, which are often used interchangeably in both academic and applied contexts. We thus omitted the analysis for space but the reproducibility code is available for interested readers in our repository.

Variability (I^2 statistic): The variability in effect sizes across studies was quantified using the I^2 statistic, Cochran's Q test, and by estimating the between-study variance (τ^2) via Jackson's method [32].

Heterogeneity analysis: To further explore potential sources of heterogeneity, we conducted subgroup analyses, such as comparing creativity across participants with different backgrounds (e.g., academic vs. business). As a robustness check, we also performed meta-regression analyses [62], which yielded results consistent with the subgroup analyses. For reasons of space, detailed meta-regression results are provided in our GitHub repository.

Bias assessment: Risk of bias was assessed using the Cochrane Risk-of-Bias 2.0 tool [57], with judgments recorded for selection, performance, detection, and reporting bias. Publication bias was evaluated through Egger's regression test [19] and the trim-and-fill procedure [18] for comparisons including at least ten studies. These analyses revealed no substantial concerns regarding bias; we thus included full results in our GitHub for brevity.

Implementation details: All analyses were implemented in R (version 4.2.3) using the `metafor` package (version 4.8-0). Influence diagnostics were conducted via the `influence()` function from the `metafor` package, and leave-one-out sensitivity analyses [63] were used to assess the robustness of pooled estimates. Codes are available in our repository for reproducibility.

ID	HAI ID	CP ID	CD ID	Title	GenAI model	Participants	#Participants (<i>m</i>)	Task type	GenAI type	Recruitment source	Creativity measurement	Evaluator
1	HAI01 R12			A Confederacy of Models: a Comprehensive Evaluation of LLMs on Creative Writing [23]	GPT-4, GPT-3.5, bing, claudie12, koala, vicuna, oa, bard, GPT-4all, stablelm, dolly, alpaca	Academia	5	creative writing	T2T	University	creativity scale	Expert
2	HAI02 R6			AI Delivers Creative Output but Struggles with Thinking Processes [70]	GPT-3.5, GPT-4, GPT-4o	Laypeople	162		T2T	Public	novelty scale	Human
3	HAI03 R1 CP01 R6			An empirical investigation of the impact of ChatGPT on creativity [39]	GPT-3.5	Laypeople	1701	ideation item usage, ideation product, ideation other creative interpretation	T2T	Mturk/Prolific	creativity scale	Expert
4	HAI04 R1			Artificial Creativity? Evaluating AI Against Human Performance in Creative Interpretation of Visual Stimuli [24]	GPT-4	Not disclosed	256		T2T	Prolific	creativity scale	Human
5	HAI05 R1			Artificial muses: Generative Artificial Intelligence Chatbots Have Risen to Human-Level Creativity [34]	GPT-3, Copy.Ai, Alpa.ai, Studio, YouChat	Academia	100	AUT	T2T	Prolific	creativity scale	Human
6	HAI06 R1			Best humans still outperform artificial intelligence in a creative divergent thinking task [37]	GPT-3.5, GPT-4, Copy.Ai	Not disclosed	256	AUT	T2T	Prolific	creativity scale, semantic distance	Human
7	HAI07 R1			Can LLMs Generate Novel Research Ideas? A Large-Scale Human Study with 100+ NLP Researchers [54]	claude-3.5-sonnet	Academia	49	ideation research ideas	T2T	Public	novelty scale	Expert
8	HAI08 R2 CP02 R1			Creative and Strategic Capabilities of Generative AI: Evidence from Large-Scale Experiments [43]	GPT-4, Bard	Not disclosed	1250	creative writing	T2T	Prolific	creativity scale	Human
9	HAI09 R4			Creativity and AI [8]	GPT-3.5, GPT-4o	Not disclosed	80	creative writing, ideation product	T2T	Prolific	creativity scale	Human
10	HAI10 R1 CP03 R3			Establishing the importance of co-creation and self-efficacy in creative collaboration with artificial intelligence [41]	n.d.	Academia	96	creative writing	T2T	Prolific	creativity scale	Expert
11	HAI11 R1 CD03 R1			Evaluating Creative Short Story Generation in Humans and Large Language Models [31]	60 models	Academia	59	creative writing	T2T	Prolific	creativity scale	Expert
12	CP04 R1			Generative AI Adoption in Human Creative Tasks: Experimental Evidence [73]	GPT-3.5	Academia	246	ideation other	T2T	University	creativity scale	Human
13	CP05 R2 CD01 R2			Generative artificial intelligence enhances creativity but reduces the diversity of novel content [16]	GPT-4	Not disclosed	293	creative writing	T2T	Prolific	novelty scale, cosine similarity	Expert / Rule-based
14	HAI12 R1			How AI Ideas Affect the Creativity, Diversity, and Evolution of Human Ideas: Evidence From a Large, Dynamic Experiment [2]	GPT 3.5	Not disclosed	844	AUT	T2T	Public	originality score	Rule-based
15	HAI13 R1			How AI Outperforms Humans at Creative Idea Generation [7]	GPT-4	Business	10	ideations of new products	T2T	Prolific	creativity scale	Human
16	CP06 R1 CD02 R1			How Experience Moderates the Impact of Generative AI Ideas on the Research Process [15]	GPT-4	Academia	310	ideation research proposal	T2T	University	novelty scale, cosine similarity	Self-assessed
17	CP07 R1			If ChatGPT can do it, where is my creativity? generative AI boosts performance but diminishes experience in creative writing [42]	GPT-4o, GPT-4-turbo	Academia	266	creative writing	T2T	Prolific	flexibility score	Human
18	CP08 R1			Interactions with generative AI chatbots: unveiling dialogic dynamics, students' perceptions, and practical competencies in creative problem-solving [55]	Dou Bao	Academia	80	creative problem solving	T2T	University	CPS scale	Rule-based
19	HAI14 R1 CP09 R1 CD04 R2			Large Language Model in Creative Work: The Role of Collaboration Modality and User Expertise [9]	GPT-4	Business	355	ideation business concepts	T2T	Prolific	creativity scale	Human
20	CP10 R1			Large Language Model in Ideation for Product Innovation: An Exploratory Comparative Study [71]	GPT-3.5-turbo	Laypeople	90	ideation product	T2T	Mturk	novelty scale	Human
21	HAI15 R52			Large Language Models show both individual and collective creativity comparable to humans [58]	GPT-3.5, GPT-4, Claude, Qwen, SparkDesk	Academia	467	Divergent Thinking, problem solving, creative writing	T2T	University	novelty scale, originality scale	Human
22	HAI16 R1			One Does Not Simply Meme Alone: Evaluating Co-Creativity Between LLMs and Humans in the Generation of Humor, 1082–1092 [68]	GPT-4o	Academia	562	ideation meme content	T2T	Prolific	creativity scale	Human
23	HAI17 R1 CP11 R1			Revolution or inflated expectations? Exploring the impact of generative AI on ideation in a practical sustainability context [20]	GPT-4	Business	56	ideation other	T2T	Company	novelty scale	Expert
24	CP12 R2			The Crowdless Future? How Generative AI Is Shaping the Future of Human Crowdsourcing [5]	GPT-4	Business	125	ideation business concepts	T2T	Public	novelty scale	Expert
25	HAI18 R5			The current state of artificial intelligence generative language models is more creative than humans on divergent thinking tasks [29]	GPT-4	Academia	151	AUT / CT / DAT	T2T	Prolific	semantic distance	AI
26	HAI20 R2			The Language of Creativity: Evidence from Humans and Large Language Models [44]	GPT-3	Not disclosed	50	creative writing	T2T	Prolific	creativity scale	Human
27	HAI21 R3			We're Different, We're the Same: Creative Homogeneity Across LLMs [66]	22 models	Not disclosed	102	AUT / FF / DAT	T2T	Prolific	semantic distance	Rule-based
28	HAI22 R2			Writing, creativity, and artificial intelligence. ChatGPT in the university context [12]	20 models	Academia	193	ideation item usage, creative thinking	T2T	University	originality score	Rule-based

Table 2. Overview of studies included by the structured literature review on GenAI and creativity. The columns HAI, CP, and CD note the identification number of each study in the different meta-analyses across the different outcomes (HAI: creative performance of human vs GenAI; CP: creative performance in human-GenAI collaboration; CD: creative diversity in human-GenAI collaboration). The “R X” value provided for each study reports how many observations from each study were included in the corresponding meta-analysis (e.g., R3 means that 3 individual studies from the paper were included in the meta-analysis as separate observations).

3 RESULTS

We first summarize key characteristics of the included studies, and afterward, we answer our research questions. Note that all analyses are reported at the effect size level (i.e., 127 observations with effect sizes for 28 studies).

3.1 Descriptive Summary

Study settings: The studies vary in which outcomes are analyzed. The majority of studies ($n = 21$) measure creative performance between humans versus GenAI (with $m = 4582$ human participants), which is later relevant for **RQ1**. In contrast, $n = 12$ studies focus on creative performance between humans and human-GenAI collaboration ($m = 2798$; **RQ2a**), and $n = 4$ studies focus on creative diversity between humans and human-GenAI collaboration ($m = 1017$; **RQ2b**).

GenAI models: The capabilities of the GenAI model also determine how well it excels with creative tasks. In the included studies, *GPT-4* is the GenAI model that is used most frequently (37 of 127; 29.6%), followed by *GPT-3.5* (25, 20.0%). Other GenAI models appear in fewer than 11% of studies, which, on the one hand, reflects the state-of-the-art performance of GPT-4 in many tasks, but, on the other hand, implies that the findings may not generalize across all GenAI models but are subject to the specific choice (see our discussion in Section 4.3).

Task type: The majority of experiments involve tasks aimed at testing *creative writing* to assess creativity (48 of 127 tasks; 38%), followed by *creative problem solving* (25; 20%) and the alternate uses test (12, 10%). In contrast, only a few studies investigate business-oriented ideation tasks (fewer than 15%).

Participants: The choice of the participant sample determines whether findings later generalize only to laypeople or even to people with domain expertise. Here, the primary participant pool stems from an *academic* background, accounting for over two-thirds of all observations (85 of 127; 67%), whereas *laypeople* (14; 11%) and business professionals (9; 7%) appear far less frequently. Of note, 19 studies do not even disclose the background of their participants or include participant pools with mixed backgrounds.

3.2 RQ1: Comparing the Creative Performance of Human vs. GenAI

In **RQ1**, we aim to answer: *How creative are ideas generated by GenAI compared to humans without GenAI support*, we first execute the random-effects model on the studies comparing (a) the creativity performance of humans versus GenAI. Here, out of the 127 observations, only 100 are relevant as they perform such a comparison.

Pooled effect: The pooled effect based on our random-effects meta-analysis corresponds to a Hedges' $g = -0.048$ (95% CI: [−0.257, 0.161]; $p = 0.653$). The forest plot is shown in Figure 2. The overall heterogeneity is large ($I^2 = 98.90\%$; $\tau^2 = 1.08$). While the results hint toward a slight disadvantage toward GenAI, the effect sizes show no statistically significant difference between GenAI and human-only conditions across studies.

Each study contributes less than 1.1% weight, so the finding is not dominated by any single experiment. Nevertheless, we performed a leave-one-out sensitivity analysis. Here, the sequential deletion keeps the pooled estimate between $g = -0.083$ and $g = -0.024$, and with each 95% CI: still overlapping with zero and the I^2 staying above 98%. This shows that the results do not hinge on a single study but corroborate our general finding that there is no or only a negligible difference in the creative performance of humans vs. GenAI.

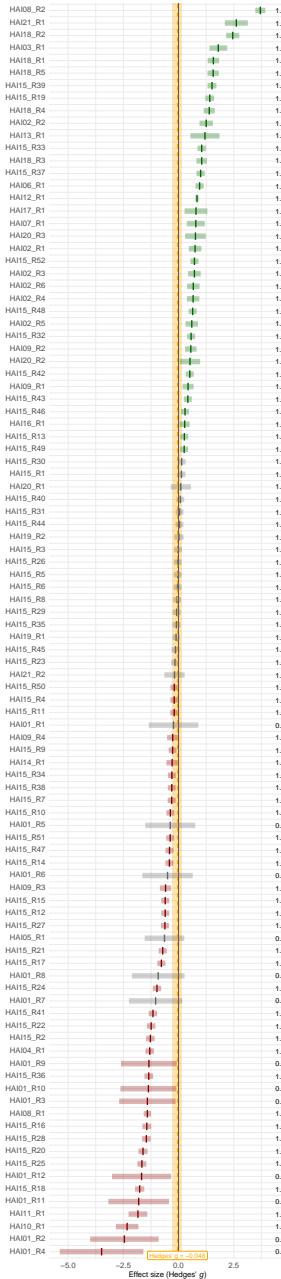


Fig. 2. Pooled effect comparing the creative performance of humans vs. GenAI (RQ1). The forest plot summarizes the Hedges' g effect sizes and 95% confidence intervals for a direct comparison between humans vs. GenAI (treatment: GenAI vs. control: human alone). Out of the 127 observations, 100 observations (participants $m = 4582$) compare differences in creative performance between humans and GenAI, and are thus included in the comparison. Each line is one estimate (the weight is shown at the right). The overall effect size of $g = -0.048$ indicates no statistically significant difference. The vertical line at $g = 0$ corresponds to a null effect; observations to the left favor the human control, and observations to the right favor GenAI. The bars are the estimated effect sizes, and the whiskers are 95% CIs. The orange dashed line is the mean pooled effect size and the orange shaded area is its 95% CI.

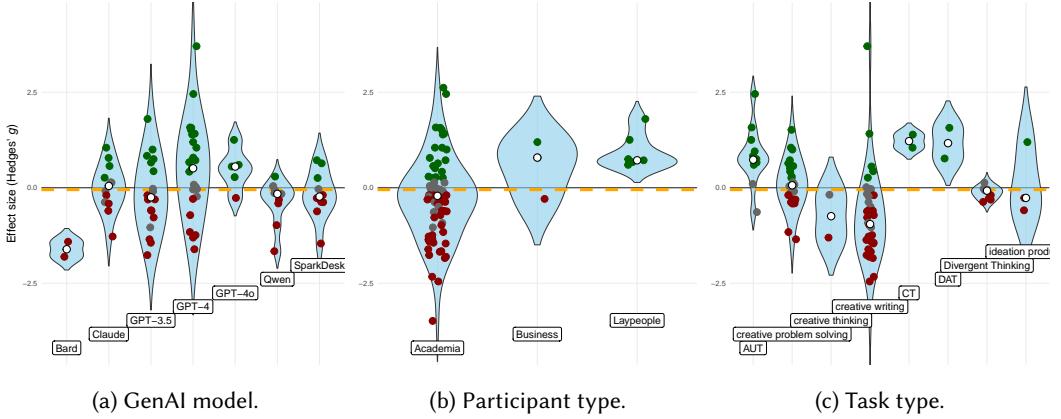


Fig. 3. Heterogeneity analysis for RQ1 (creative performance of humans vs. GenAI). Violin plots show the distribution of observation-level Hedges' g for the comparison in creative performance between human vs. GenAI conditions. The comparison is stratified by (a) GenAI model, (b) participant background, and (c) task type. Subgroup analyses are reported only for categories with a sufficient number of observations to support meaningful comparisons. The widths reflect the density of effect sizes; the dashed line corresponds to $g = -0.048$ with no overall difference.

3.2.1 Heterogeneity Analysis. GenAI model (Figure 3a): As expected, a key determinant for creative performance is the choice of the GenAI model. The model *GPT-4* performs the strongest, with distribution centered slightly above zero. A meta-regression confirms the positive effect for *GPT-4* ($g = 0.499$; 95% CI: [0.132, 0.865]; $p = 0.008$). For comparison, the effect for other models often overlaps with zero and has wide tails, which implies both non-significant coefficients and substantial within-model variability.

Participants (Figure 3b): *Laypeople* appear to be constantly outperformed by GenAI ($g = 0.918$; 95% CI: [0.202, 1.630]; $p = 0.012$). The distribution of laypeople is right-skewed and centered above zero. While academics show a small but significant pro-human difference ($g = -0.223$; 95% CI: [-0.445, -0.001]; $p = 0.049$), the results for participants with business background remain inconclusive ($g = 0.539$; 95% CI: [-0.579, 1.660]; $p = 0.345$). This suggests that the background of participants (and thus their domain expertise) is a moderator that explains the gap in creative performance between humans and GenAI.

Task type (Figure 3c): Violin shapes show modes above zero for *AUT* and *CT* tasks. The *AUT* favors GenAI ($g = 0.855$; 95% CI: [0.358, 1.350]; $p < 0.001$), as do *CT* tasks ($g = 1.220$; 95% CI: [0.016, 2.420]; $p = 0.047$). By contrast, creative-writing tasks favor humans ($g = -0.717$; 95% CI: [-1.010, -0.424]; $p < 0.001$), a pronounced left-shift for creative writing. Other categories (e.g., creative problem solving, divergent thinking) are non-significant, highlighting task-specific effects. The violin plot has a broad overlap for the remaining categories, echoing the task-specific moderator coefficients.

3.2.2 Robustness. Funnel plot & Egger's test: Egger's mixed-effects regression detects significant funnel asymmetry ($z = -3.363$; $p = 0.001$), indicating the presence of small-study or publication bias. The **trim-and-fill adjustment** therefore imputes 24 missing studies on the right of the funnel and shifts the random-effects estimate to ($g = 0.364$, 95% CI: [0.131; 0.596]; $p = 0.002$), implying that bias-correction would reverse the direction of the overall effect in favor of GenAI.

Influence diagnostics: All influence metrics (studentized residuals, DFFITS, Cook's D , hat values, cov.r) remain well below critical cut-offs, except for one potential outlier; removing this

study lowers τ^2 only modestly (to 0.93) and leaves the pooled effect virtually unchanged, confirming that no single study drives the results.

3.3 RQ2a: Benefit of Human-GenAI Collaboration for Creative Performance

In RQ2a, we answer: *How creative are ideas generated by humans when supported by GenAI (compared to humans without GenAI support)?* Here, we restrict our analysis to 21 observations where studies report effect sizes aimed at understanding the effect of human-GenAI collaboration.

Pooled effect: The pooled effect based on our random-effects meta-analysis amounts to Hedges' $g = 0.273$ (95% CI: [0.018, 0.528]; $p = 0.036$). The forest plot is shown in Figure 4. Again, heterogeneity is substantial ($Q_{20} = 232.17$; $p < 0.001$; $I^2 = 94.11\%$; $\tau^2 = 0.3261$). This result indicates a small but statistically significant positive effect of GenAI support on the creativity of human-generated ideas, meaning that humans augmented with GenAI are more creative than humans without.

No single study contributes more than 5.1% weight, indicating that the positive performance advantage is not driven by any single experiment. Nevertheless, we performed a leave-one-out sensitivity analysis. Sequential deletion keeps the pooled effect between $g = 0.204$ and $g = 0.343$. Across these iterations of the leave-one-out sensitivity analysis, the lower bound of the 95% CI ranged from -0.0179 to 0.1198 , meaning that omitting certain studies can yield a CI that just crosses zero. The I^2 remained above 91%, confirming that the positive performance effect is stable yet accompanied by persistent heterogeneity.

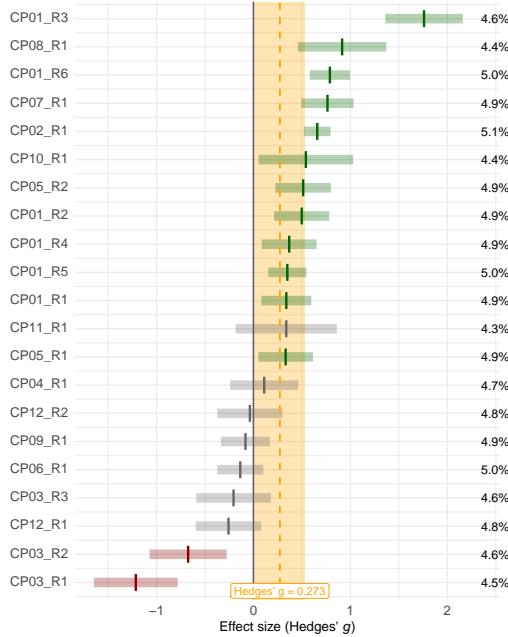


Fig. 4. Pooled effect of the benefit from Human-GenAI collaboration on creative performance (RQ2a). The forest plot summarizes the Hedges' g effect sizes and 95% confidence intervals (treatment: human-GenAI collaboration versus control: human alone). Out of the 127 observations, $n = 21$ observations (participants $m = 2798$) quantify differences in creative performance between humans and human-GenAI collaboration. Each line is one estimate (the weight is shown at the right). The overall effect size of $g = 0.273$ indicates a modest performance gain from GenAI assistance. The vertical line at $g = 0$ corresponds to a null effect; points to the right favor the GenAI-assisted collaboration. The bars are the estimated effect sizes, and the whiskers are the 95% CIs. The orange dashed line is the mean pooled effect size and the orange shaded area is its 95% CI.

3.3.1 Heterogeneity Analysis. GenAI model (Figure 5a): The plot shows a higher median and thicker right tail for GPT-3.5 relative to GPT-4, which is also confirmed in a meta-analytic regression ($g = 0.587$; 95% CI: [0.280, 0.893]; $p < 0.001$). Interestingly, GPT-3.5 contributes larger performance gains, whereas GPT-4 shows no detectable deviation from the overall mean ($g = 0.089$; 95% CI: [-0.223, 0.401]; $p = 0.577$).

Participants (Figure 5b): The distribution of effect sizes for *laypeople* is right-skewed and centered above zero, point to a benefit from collaboration ($g = 0.654$; 95% CI: [0.237, 1.070]; $p = 0.002$). The distribution of the effect sizes for *academia* ($g = -0.057$; 95% CI: [-0.480, 0.367]) and *business* ($g = -0.021$; 95% CI: [-0.581, 0.540]) cluster around the grand mean, indicating that participant expertise moderates outcomes asymmetrically. In other words, laypeople seem to benefit from co-creation with GenAI, while domain experts do not.

Task type (Figure 5c): A wide and mostly right-shifted violin is found for *ideation-product* tasks ($g = 0.743$; 95% CI: [0.128, 1.360]; $p = 0.018$) where human-GenAI teams show a better creative performance than the human-only condition. The effect sizes for tasks aimed at *creative writing* overlap with zero ($g = 0.048$; 95% CI: [-0.412, 0.508]). The same pattern is found for the other ideation tasks.

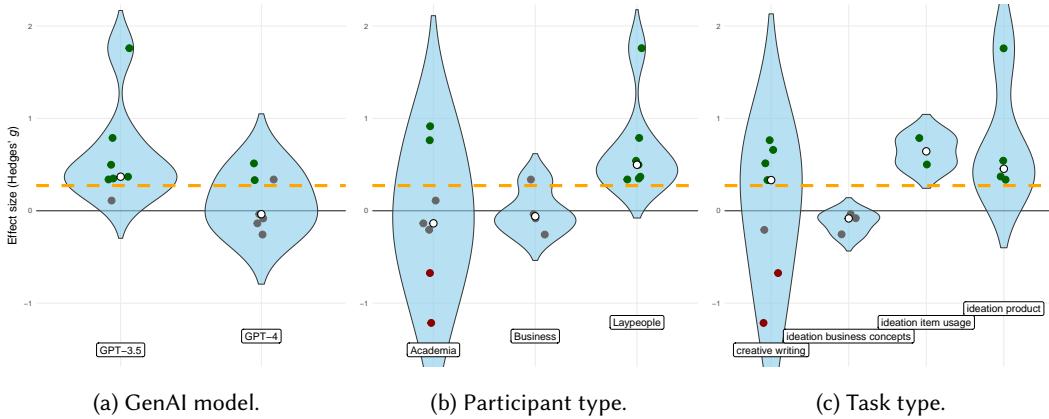


Fig. 5. Heterogeneity analysis for RQ2a (creative performance of humans+GenAI vs. humans only). Violin plots show the distribution of observation-level Hedges' g for the benefit in creative performance of human-GenAI collaboration over a human-only condition. The comparison is stratified by (a) GenAI model, (b) participant background, and (c) task type. Subgroup analyses are reported only for categories with a sufficient number of observations to support meaningful comparisons. The widths reflect the density of effect sizes; the dashed line corresponds to $g = 0$ with no overall difference.

3.3.2 Robustness. Funnel plot & Egger's test: Egger's regression detects no funnel asymmetry ($z = -0.624; p = 0.533$), suggesting the absence of small-study or publication bias. The **trim-and-fill procedure** imputes zero missing studies; the bias-adjusted estimate remains essentially unchanged at $g = 0.273$, (95% [0.018, 0.528]), corroborating the robustness of the performance benefit. **Influence diagnostics:** One observation shows a high studentized residual ($r = 2.933$), but its removal reduces τ^2 only from 0.3261 to 0.2271 and leaves g within the original confidence limits. All other influence metrics (DFFITS, Cook's D , hat values, cov.r) remain below conventional thresholds.

3.4 RQ2b: Effect of Human-GenAI Collaboration on Creative Diversity

In RQ2b, we aim to answer: *How diverse are ideas generated by humans when supported by GenAI compared to humans without GenAI support.* Here, we analyze all studies comparing the creative performance of humans with vs. without GenAI support in regard to creative diversity. Note that creative diversity is measured only in a few studies (i.e., we have 6 observations with effect sizes), because of which the meta-analytic results below are subject to a small sample size.

Pooled effect: As shown in Figure 6, the effect of human-AI collaboration on diversity yields a pooled Hedges' $g = -0.863$ (95% CI: [-1.328, -0.398], $p < 0.001$). Still, heterogeneity is severe ($Q_5 = 51.69; p < 0.001; I^2 = 93.70\%; \tau^2 = 0.310$). Each study carries roughly 16% to 17% weight. Nevertheless, we find a consistent and statistically meaningful reduction in idea diversity when GenAI joins the team.

Robustness: We again performed a leave-one-out sensitivity analysis. Sequential deletion keeps the pooled estimate between $g = -0.655$ and $g = -0.952$; every 95% CI excludes zero, and I^2 never falls below 78.21%. The diversity-reducing effect is therefore robust to the removal of any single study, albeit heterogeneity persists.

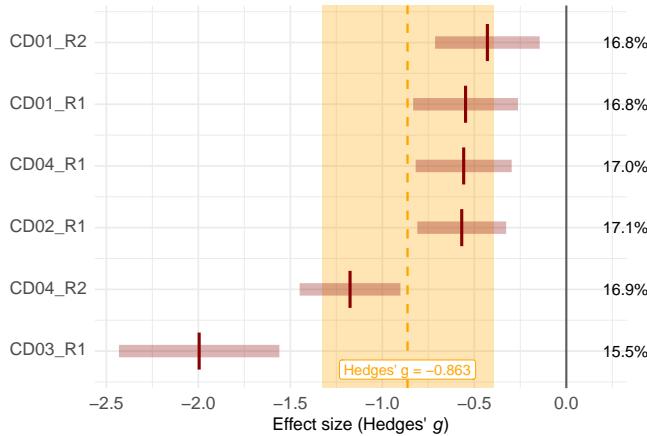


Fig. 6. Pooled effects (RQ2b). Forest plot summarizing the Hedges' g effect sizes and 95% confidence intervals for creative diversity at the observation level (treatment: human-GenAI vs. control: Human alone), across six individual experiments from four studies. Out of the 127 observations, $n = 6$ observations (participants $m = 1017$) quantify differences in creative diversity between human and human-GenAI collaboration. Each line is one replication's estimate (the weight is shown at the right). The overall effect size of $g = -0.863$ indicates that GenAI assistance leads to ideas that are less diverse. The vertical line at $g = 0$ marks the null; points to the right favor the GenAI-assisted treatment. The bars are the estimated effect sizes, and the whiskers are the 95% CIs. The orange dashed line is the mean pooled effect size and the orange shaded area is its 95% CI.

3.4.1 Heterogeneity Analysis. Due to the small sample size and limited variation in experimental designs across studies, we restrict our focus to the following subgroup analysis around participants (i.e., we cannot perform subgroup analyses for GenAI models or task types as above).

Participants. Compared with laypeople samples, academic cohorts show a stronger reduction in diversity ($g = -1.260$; 95% CI: $[-2.340, -0.187]$; $p = 0.021$), while business populations exhibit a non-significant shift ($g = -0.866$; 95% CI: $[-1.930, 0.197]$; $p = 0.110$). Participant background thus moderates the magnitude of the negative diversity effect.

3.4.2 Robustness. Funnel plot & Egger's test: Egger's test and trim-and-fill were not executed due to the number of studies. **Influence diagnostics.** One outlier (study #4) shows a studentized residual of -3.662 and Cook's $D = 0.766$, excising it lowers τ^2 from 0.310 to 0.067 and Q_E from 51.69 to 17.87, but the pooled effect remains negative and significant ($g = -0.656$; 95% CI: $[-0.913, -0.398]$). Thus, although the outlier inflates heterogeneity, it does not alter the conclusion.

4 DISCUSSION

4.1 Summary of Key Findings

The fragmented state of the literature in human-GenAI co-creativity research raises two central questions: *How creative are the ideas generated by GenAI? And to what extent can GenAI support humans in producing ideas that are both creative and diverse?* For our meta-analysis, we screened 691 records and finally included 28 studies (with $m = 8214$ participants) comparing creative performance along three dimensions: (i) how creative GenAI is, (ii) how creative human-GenAI collaboration is vs. human-only performance, and (iii) the effect of human-GenAI collaboration on idea diversity.

RQ	Description	Hedges' g	Supported?
RQ1	Creative performance of GenAI (compared to human)	-0.05 (ns)	✗
RQ2a	Creative performance of human-GenAI (compared to human only)	0.27*	✓
RQ2b	Diversity of ideas in human-GenAI (compared to human only)	-0.86***	✓

Table 3. **Key findings from our meta-analysis.** Reported are Hedges' g for each analysis. ✓ indicates $p < 0.001$, ✗ indicates non-significant. Significance levels: ***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

Finding for RQ1: Parity rather than super-human creativity. GenAI matches the average human creative output ($g \approx -0.05$; see Table 3). A moderate advantage ($g \approx 0.499$) emerges only for specific GenAI models and is largely attributable to a subset of studies using GPT-4. Hence, any observed superiority is tied to specific models, rather than being a general property of LLMs. This result is also in line with studies explicitly comparing the creative performance of different models, such as GPT-3 and GPT-4 [37]. Nevertheless, with the growing number of research using recent LLMs with reasoning capabilities, we may observe a gradual shift in average performance benchmarks.

Finding to RQ2a. Modest but robust gains from collaboration. Human-GenAI teams deliver a small yet robust boost in creative performance ($g \approx 0.27$) that holds across different models, tasks, and participant backgrounds. While our meta-analysis focused on comparing human-GenAI collaboration with human-only performance (rather than contrasting human-GenAI teams with GenAI-only outputs), recent studies examining the latter report no significant performance gains from adding humans to GenAI-generated content [39]. Together, humans using GenAI therefore show higher creative performance than humans without GenAI support.

Finding to RQ2b. Decrease in idea diversity. Collaboration with GenAI is associated with a significant decrease in idea diversity (pooled $g \approx -0.86$), indicating a potential homogenization effect of the AI. This finding strengthens the impression that collaboration with LLMs might improve individual performance while showing detrimental effects on group-level [16]. It remains unclear whether this effect generalizes beyond GPT-4 and text-based tasks, as the analysis aimed at understanding RQ2b was based on limited data.

Heterogeneity in our findings. Our heterogeneity analysis reveals three key insights. First, GenAI performs better on simple, standardized creativity tests—such as the alternative uses task (AUT) and consequences task (CT)—than on more complex, elaborative tasks like creative writing. Second, creative performance varies by model: newer models outperform older ones when generating ideas without human involvement, but, in human-AI collaboration, GPT-3.5 consistently improves creative output, while GPT-4 shows no significant added benefit. Third, laypeople particularly benefit from collaborating with GenAI, yet they tend to be outperformed when directly competing against it.

4.2 Implications

Practical implications: Our research suggests substantial potential for organizations to integrate GenAI into creative workflows—but only by pairing it with employees to enhance ideation processes. These benefits also imply a shift in individual creative potential: as GenAI can augment human creativity, especially lower innate creative capabilities might be compensated [16]. Yet, the observed gains in creativity could come at a cost, namely, due to reduced idea diversity. As a result, users collaborating with GenAI tend to produce more homogeneous outputs in some settings. This trade-off is especially problematic in contexts where ideational breadth is essential, such as where companies search for “out-of-the-box” ideas or in open innovation and crowd ideation tasks [4].

Thus, while human-GenAI teaming may suffice for boosting individual creativity, practitioners will need to be careful when scaling GenAI use with the intention of promoting collective creativity.

Further, current GenAI models often tend to recombine familiar elements [39] across contexts rather than generating radically novel ideas, which may lead to more incremental innovation. This highlights the importance of human agency in co-creation processes to counteract potential convergence effects—where repeated exposure to similar outputs leads to reduced variability—and highlights the need for human-GenAI systems that actively support diversity.

Theoretical implications: Our study reveals that the creative impact of GenAI is highly contingent on contextual factors. A high between-study heterogeneity $I^2 > 80\%$ demonstrates that creativity augmentation cannot be treated as a general affordance of GenAI alone. However, the effectiveness mechanisms of GenAI in creativity remain unclear. Importantly, our heterogeneity analysis identifies only the choice of the GenAI model as a consistent moderator that explains higher creativity levels.

Given that the benefit from human-GenAI collaboration in creative tasks is robust for both laypeople and domain experts, it is likely that the performance gain is due to a generic facilitation mechanism (e.g. faster drafting and broader ideation, reduced cognitive load) rather than task-specific benefits from augmentation. Previous evidence indicates that co-creation tasks are particularly beneficial for human-GenAI collaboration when there are inherent synergies between humans and GenAI systems, allowing each to leverage their respective strengths—unlike in many analytical, decision-making contexts [35].

4.3 Limitations

Our meta-analysis has limitations due to the current state of research and technological progress. First, some of the included studies are not yet peer-reviewed. Nevertheless, we still chose to include them to provide a timely synthesis of empirical findings, including recent ones. Second, the findings depend on the choice of GenAI models. Given the fast-evolving capabilities of GenAI, it is likely that newer models, including improved reasoning capabilities or different fine-tuning strategies, may yield different outcomes. Third, many studies use simple, well-known tasks for benchmarking, such as the so-called alternative uses test, which asks participants to generate creative uses for common objects. Such tasks may have been part of the training data in GenAI models, which is a known issue in GenAI research [61] and underscores the need for devising novel tasks that preserve experimental rigor while minimizing overlap with model training data.

4.4 Future Research

To guide future work, we identified salient gaps around the use of GenAI for creativity systems in HCI/CSCW research based on our structured literature review and propose three key research directions.

Research direction 1: More relevant, real-world-inspired study designs: The majority of studies focus on simplified creativity tasks such as the alternative uses test (AUT) [69]. While these tasks draw on established scales from psychological research to assess creativity, they fall short of capturing the complexity of real-world settings that involve creative thinking. In contrast, there are only a few studies that test GenAI in real-world situations such as work settings (e.g., [9]), or with creative tasks beyond text, such as images, audio, or code.

Future studies could focus on more realistic scenarios for a higher ecological validity and further explore context-sensitive moderators for more targeted creativity interventions. For example, to enhance relevance to CSCW and HCI applications in business contexts, future studies could investigate settings where tacit knowledge plays a critical role, or where creative tasks must account for specific organizational contexts—such as operational constraints or strategic alignment.

One promising direction would be to examine how GenAI can support ideation in tasks like developing new business models that align with a company's brand strategy or existing capabilities of that company. Moreover, all of the existing studies were performed at a single time point; thus, longitudinal designs are needed to examine how collaboration patterns and creativity effects evolve over time—especially as users gain fluency in leveraging GenAI within creative tasks.

Research direction 2: Understand psychological mechanisms: Existing research has primarily focused on the outcomes of GenAI-assisted creativity, typically through rigorous A/B experiments. Yet, prior research has largely overlooked the underlying psychological mechanisms that drive the effects. For example, it is unclear whether gains in GenAI-assisted creativity come from broader ideation (e.g., generating more ideas due to increased speed or reduced distractions), deeper engagement (e.g., more intensive thinking due to reduced cognitive load), or heightened motivation (e.g., playful interaction with the system).

To develop a more nuanced understanding of human-GenAI co-creation, future work should explore potential psychological mediators and moderators, such as cognitive effort, user agency, trust, task framing, and participants personality traits. Uncovering such cognitive processes is relevant to identifying how human and machine capabilities can be combined to foster synergistic collaboration. Ultimately, such insights could inform frameworks with a notion of ‘appropriate reliance’ (see [53] for an overview on the notion of appropriate reliance in AI advice), that is, when it is most beneficial for an idea to originate from the human, the GenAI system, or through their collaboration.

Research direction 3: Explore CSCW/HCI design choices to elicit creative thinking: The majority of studies identified in our literature review rely on relatively naive GenAI setups—often based on simple one-shot prompts (e.g., as in [37]) or by providing participants with unmodified, off-the-shelf LLMs (e.g., as in [39]). In contrast, studies that devise and compare different design choices are largely absent. Future studies could thus explore more elaborate workflows (e.g., critique-refine, suggestions-refine) that reflect an iterative creation process. Eventually, this could help to integrate GenAI tools into creativity systems through effective, user-friendly interfaces that allow for natural interactions, as well as to build GenAI agents that are effective at supporting creative thinking tasks.

5 CONCLUSION

Our meta-analysis shows that GenAI and humans show similar creative performance on average, with moderate advantages emerging mainly for GPT-4. In contrast, human-GenAI collaboration shows small but consistent gains in creative output across tasks and contexts. However, collaboration with GenAI reduces the diversity of ideas, indicating a risk of creative outputs that could become more homogeneous. Our meta-analysis also highlights important gaps in the literature, which provide interesting avenues for future research to understand psychological mechanisms of human-GenAI augmentation and identify drivers for how GenAI systems can successfully elicit creative thinking.

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Data Availability. Code, data, and outputs are available via our Git at <https://github.com/SM2982/Meta-Analysis-LLMs-Creativity.git>.