Generative AI and the Creativity-Diversity Paradox: Designing Organizations for Individual Innovation and Collective Pluralism

Aditya Tripathi

Abstract

Generative artificial intelligence (GenAI) can increase individual productivity and creative performance while simultaneously narrowing the diversity of ideas available to groups and organizations. This quality-weighted integrative review synthesizes recent evidence from top peer-reviewed articles published recently. The evidence indicates that GenAI raises the performance floor, accelerates idea generation, and supports less experienced users, but can also concentrate collective search around similar concepts. Expertise, task stage, collaboration modality, metacognitive engagement, and organizational capabilities moderate these effects. Integrating creativity research with innovation-management evidence, the paper develops a design architecture centred on human-led problem framing, selective AI roles, differentiated prompting, expertise-sensitive deployment, dual quality-diversity metrics, and active governance. The central contribution is to treat individual creativity and collective diversity as distinct, jointly managed organizational outcomes.

Keywords: Generative AI, Creativity, Idea Diversity, Human–AI Collaboration, Innovation Management

Corresponding author (s):
ITM School of Business and Leadership, ITM University, Gwalior, Madhya Pradesh, India- 475001
Email: aditya.tripathi@itmuniversity.ac.in

1. Introduction

Generative artificial intelligence (GenAI) has moved rapidly from experimentation to routine use in knowledge-intensive and creative work. Evidence from professional writing, customer support, artistic production, and employee creativity shows that GenAI can reduce effort, improve output quality, and expand the immediate set of options available to individuals. In a randomized experiment with professionals, Noy and Zhang (2023) found that ChatGPT reduced task-completion time by 40% while increasing output quality by 18%. Large-scale workplace evidence similarly shows that AI assistance can raise productivity, with especially large gains among less experienced workers (Brynjolfsson et al., 2025). In creativity-focused settings, Lee and Chung (2024) found that ChatGPT improved idea creativity across experiments, while Zhou and Lee (2024) documented substantial productivity and value gains after artists adopted text-to-image GenAI.

These individual benefits, however, create an organizational problem that cannot be understood by examining average performance alone. Doshi and Hauser (2024) showed that AI-assisted stories were judged more creative while becoming more similar to one another. Meincke et al. (2025) reached a comparable conclusion in brainstorming: assistance can improve the apparent quality of individual ideas while reducing diversity in the pooled idea set. More recent large-scale evidence indicates that humans retain substantially greater variability and stronger upper-tail creative performance than large language models (Wang et al., 2026), while cross-model comparisons show that different LLMs themselves generate unusually homogeneous creative responses (Wenger & Kenett, 2026). An organization can therefore improve average employee output while unintentionally weakening the heterogeneity on which exploration and breakthrough innovation depend.

This paper conceptualizes that tension as the creativity-diversity paradox and asks how organizations can capture individual augmentation without allowing common models, prompts, and workflows to compress collective search. It contributes by integrating recent evidence across disciplines and extending the empirical paradox into an organizational design problem using the distinction between AI applications that replace, reinforce, or reveal organizational activities (Gama & Magistretti, 2025).

2. Review of Literature

2.1 Individual Creative Augmentation

Recent research provides strong evidence that GenAI can augment creative performance, although the size and nature of the gain depend on the task and on how the system is used. Lee and Chung (2024) found that ChatGPT improved creativity relative to unaided work and conventional web search, particularly for incrementally novel ideas. On standardized divergent-thinking tasks, current generative models can equal or exceed average human performance (Hubert et al., 2024; Koivisto & Grassini, 2023). In artistic production, Zhou and Lee (2024) reported a 25% increase in creative productivity and a 50% increase in artwork value after adoption, while also observing declining average content and visual novelty. The emerging pattern is therefore not simple technological superiority; it is a redistribution of creative performance in which AI raises the floor while potentially compressing the range.

Innovation-management research helps explain why these gains occur. Bouschery et al. (2023) position transformer-based language models as members of hybrid innovation teams and propose an AI-augmented Double Diamond in which models enlarge problem and solution spaces through summarization, insight generation, and ideation. Jia et al. (2024) likewise show that AI can augment employee creativity when technology absorbs more codified components while employees retain higher-order problem solving.

Collaboration modality and human cognition are decisive boundary conditions. Chen and Chan (2024) found that using an LLM as a sounding board benefited nonexperts, whereas allowing the model to act as a ghostwriter could harm experts through anchoring. Hou et al. (2025) similarly show that GenAI affects ideation and implementation differently and that user expertise conditions these effects. Sun et al. (2025) add a metacognitive boundary condition: employees who actively monitor, question, and regulate their thinking are better positioned to convert LLM assistance into creative gains. Thus, augmentation is strongest when AI extends human search while leaving meaningful cognitive work for the person.

2.2 Collective Homogenization and Portfolio Risk

The strongest evidence for collective homogenization comes from studies that distinguish the quality of an individual output from the diversity of a population of outputs. Doshi and Hauser (2024) demonstrate this divergence directly: access to GenAI improved evaluations of individual stories but reduced collective novelty. Meincke et al. (2025), reanalysing brainstorming experiments, found that ChatGPT assistance reduced the diversity of the pooled idea set even when average creativity increased. Their experiments provide a vivid illustration of shared-model convergence: independently assisted participants repeatedly arrived at overlapping toy concepts, including the same "Build-a-Breeze Castle" idea.

At a broader scale, Wang et al. (2026) compared thousands of humans with more than 200,000 LLM observations and found substantially greater variability among humans, particularly in the high-creativity tail. Wenger and Kenett (2026) likewise show that the issue is not confined to one model: responses from multiple LLMs resemble one another more strongly than human responses do. These findings suggest that the principal organizational risk is not necessarily low average quality, but concentration of the search distribution. A portfolio of polished proposals may still be strategically weak if the proposals occupy the same conceptual neighbourhood.

Evidence from real-world innovation reinforces that interpretation. In an open innovation challenge, Boussioux et al. (2024) found that human crowds produced more novel solutions than standard human-AI configurations, although human-AI solutions performed well on value and overall quality. Importantly, differentiated search instructions that pushed successive AI outputs away from earlier ones improved novelty without sacrificing value. This makes homogenization a design risk rather than an unavoidable technological outcome. The evidence also reveals a surface-quality/portfolio-diversity decoupling: fluency, coherence, and perceived creativity can improve even as collective search breadth declines (Doshi & Hauser, 2024; Meincke et al., 2025; Zhou & Lee, 2024).

2.3 Organizational Capabilities and Cognitive Moderators

A capability perspective clarifies why the same technology produces different innovation outcomes across organizations. Gama and Magistretti (2025), drawing on the technological-organizational-environmental framework, distinguish enabling capabilities required for effective AI adoption from enhancing capabilities created or transformed after adoption. They also classify AI applications according to three strategic intents: replace, reinforce, and reveal. Replace applications substitute or automate existing activities; reinforce applications augment existing processes and employee capabilities; reveal applications use AI to uncover patterns, opportunities, or possibilities that would otherwise remain hidden. For creativity-intensive work, this taxonomy implies that the organizational objective should rarely be indiscriminate replacement. Reinforce and reveal configurations preserve a meaningful human contribution while exploiting machine scale.

Expertise further complicates the picture. Brynjolfsson et al. (2025) find particularly large productivity gains among less experienced workers, whereas Chen and Chan (2024) show that experts may be harmed when fluent model output anchors their work. Jia et al. (2024), however, demonstrate that augmentation can also favour skilled employees when AI extends rather than substitutes for their problem-solving capacity. Zhao et al. (2025) similarly show that AI-enabled job non-routinization can stimulate creativity through challenge and hindrance appraisals. Expertise therefore matters through the role assigned to AI and the cognitive demands retained by the employee.

Organizational dependence can also accumulate over time. Glickman and Sharot (2025) show that human-AI feedback loops can alter human judgements and amplify biases when users are unaware of AI influence. Although their study is not a creativity experiment, the mechanism is relevant because repeated exposure to similar AI-generated frames can normalize particular assumptions and search directions. Mariani and Dwivedi (2024) accordingly identify agency, governance, and biased innovation as central issues in GenAI-enabled innovation management, while Kumar et al. (2025) show that ethical leadership and perceived information characteristics condition GenAI adoption and firm outcomes. Organizational incentives and governance therefore shape whether GenAI becomes an exploratory resource or a shortcut toward convergence.

3. Research Objectives and Review Questions

The paper has three objectives: (1) to explain how GenAI improves individual productivity and creative performance; (2) to identify why the same systems can reduce the diversity of collective idea pools; and (3) to derive organizational design practices that preserve both individual augmentation and collective pluralism. The review is guided by three questions: What recent evidence supports creativity and productivity gains from GenAI? Through what mechanisms and boundary conditions does GenAI generate convergence? How should organizations configure work, human-AI collaboration, prompting, evaluation, and governance so that AI expands rather than replaces heterogeneous human search?

4. Methodology

This study uses a quality-weighted integrative literature review because the focal problem spans multiple disciplines and research designs, including randomized experiments, field studies, observational analyses, creativity assessments, and innovation-management research. Candidate studies were identified from the existing evidence base and refined through targeted searches and verification of publisher records, scholarly indexes, and DOI metadata using combinations of “generative AI,” “large language model,” “ChatGPT,” “creativity,” “idea diversity,” “homogenization,” “human-AI collaboration,” “employee creativity,” and “innovation.” The temporal window was restricted to 2023–2026.

A strict publication-quality screen was then applied. Only peer-reviewed journal articles published in top journals classified were retained. The synthesis proceeded in four stages. First, studies were coded into individual augmentation, collective diversity, human and task moderators, or organizational capabilities. Second, findings were compared across domains to distinguish robust patterns from context-specific effects. Third, apparent contradictions were interpreted as boundary conditions rather than averaged away; for example, evidence that models can outperform the average human was considered alongside evidence that humans retain greater variance and stronger exceptional outcomes. Fourth, the findings were translated into an organizational design architecture that links AI role, user expertise, task stage, prompting, evaluation, and governance. Because the review is integrative rather than a preregistered systematic review, it does not claim exhaustive coverage; its purpose is a focused, transparent, quality-screened synthesis of decision-relevant recent evidence.

5. Results and Discussion

5.1 GenAI Raises the Performance Floor and Expands Search Capacity

The first result is that GenAI augmentation is real, but its organizational value is best understood as raising the performance floor and expanding search capacity rather than replacing human creative advantage. Noy and Zhang (2023) and Brynjolfsson et al. (2025) demonstrate gains in speed, productivity, and quality in professional work. Creativity-specific studies likewise show strong average performance: Lee and Chung (2024) report increased idea creativity, Hubert et al. (2024) report superior GPT-4 performance on several divergent-thinking measures, and Koivisto and Grassini (2023) show that AI can outperform the average human while the best human ideas remain competitive.

Bouschery et al. (2023) help translate these results into innovation-process design. Their AI-augmented Double Diamond positions the model as a scalable partner for enlarging problem and solution spaces before humans undertake convergent evaluation. This is consistent with Gama and Magistretti’s (2025) distinction between replacing human activities and reinforcing or revealing innovation capability. For creativity-intensive work, the strongest use case is not wholesale replacement but selective reinforcement of search and execution while preserving human ownership of framing, interpretation, and judgement.

5.2 The Creativity-Diversity Paradox Is a Portfolio-Level Search Problem

The second result is that average improvement can coexist with portfolio deterioration. Doshi and Hauser (2024), Meincke et al. (2025), Wang et al. (2026), and Wenger and Kenett (2026) converge on the same strategic concern: AI-assisted or AI-generated outputs can be individually strong while exhibiting lower variation across a group. Zhou and Lee (2024) report a related pattern in visual art, where productivity and value rise while average novelty declines. The relevant unit of analysis for an organization is therefore not only the individual idea but the distribution of alternatives produced by the organization.

This distinction changes how creative performance should be governed. Ten polished ideas occupying the same conceptual neighbourhood may be less valuable than a smaller set of genuinely distinct alternatives. Boussioux et al. (2024) provide an important countermeasure: differentiated search prompts that intentionally move new AI outputs away from previous solutions can recover novelty without sacrificing value. The strategic objective should therefore be to preserve search breadth while exploiting AI's ability to improve speed and quality. Homogenization is partly a property of model-generated central tendencies, but it is also produced by shared prompts, common workflows, and evaluation systems that reward fluency and speed without measuring portfolio diversity.

5.3 Expertise, Task Stage, and Metacognition Should Determine AI's Role

The third result is that there is no universally optimal level of AI involvement. Chen and Chan (2024) show that nonexperts can benefit from an LLM sounding board while experts may suffer when the model becomes a ghostwriter. Hou et al. (2025) show that ideation and implementation should be treated as different creative stages, and Jia et al. (2024) support a division of labour in which AI handles more codified work while humans retain higher-order problem solving. Zhao et al. (2025) further demonstrate that AI-enabled job non-routinization can operate through both challenge and hindrance pathways, emphasizing the need to consider tacit knowledge and work design.

Metacognition provides another decisive boundary condition. Sun et al. (2025) find that GenAI is more valuable for employees who actively monitor and regulate their thinking. This suggests that organizations should train users not merely to write better prompts but to diagnose what they know, identify what the model may be omitting, compare alternative routes, and deliberately revise strategy when outputs converge. Combined with evidence on human-AI feedback loops (Glickman & Sharot, 2025), the implication is that passive reliance should be treated as a capability risk: repeated acceptance of fluent model outputs can gradually shape human judgement and narrow subsequent search.

5.4 An Organizational Design Architecture for Creativity and Pluralism

The integrated evidence supports five complementary design principles. First, preserve human-led problem framing and at least some independent ideation before AI exposure. This creates a heterogeneous starting pool before model suggestions introduce a common anchor. Second, differentiate the role of AI. Following Gama and Magistretti (2025), organizations should use "replace" mainly for codified, low-discretion tasks and favour "reinforce" or "reveal" roles in creativity-intensive work. For experienced employees, AI should often function as challenger, critic, search partner, or rapid synthesizer rather than default ghostwriter (Chen & Chan, 2024).

Third, design interaction protocols for contrast rather than convenience. Boussioux et al. (2024) show that differentiated prompting can improve novelty, while Bouschery et al. (2023) suggest that models can be productively located at multiple points in the innovation process rather than allowed to dominate it. Teams can require alternative framings, cross-model comparison, or explicit search for solutions that differ from earlier outputs. Fourth, separate individual quality evaluation from collective diversity evaluation. A dual dashboard should track familiar outcomes such as time saved, quality, acceptance rates, and employee capability, while also tracking portfolio indicators such as semantic similarity, thematic duplication, concentration around common mechanisms, and the proportion of ideas generated before versus after AI exposure.

Fifth, embed these practices in active governance. Mariani and Dwivedi (2024) identify organizational design and agency as central issues in GenAI innovation, while Kumar et al. (2025) show that ethical leadership conditions adoption outcomes. Governance should therefore specify where human judgement is non-delegable, require verification for consequential claims, and periodically compare AI-assisted portfolios across teams for convergence. Because feedback loops can shape human judgement over time (Glickman & Sharot, 2025), periodic AI-free review and independent expert challenge are useful safeguards. The goal is not maximal AI use; it is an architecture in which machine scale and human heterogeneity remain complementary.

6. Conclusion and Implications

This review shows why organizational discussions of GenAI, and creativity must distinguish individual performance from collective diversity. At the individual level, recent evidence is strongly supportive: GenAI can increase speed, productivity, idea quality, and access to creative capability, often with especially large benefits for less experienced users. At the collective level, however, the same technology can compress variation. The strongest recent studies show that AI-assisted ideas can become more similar, that multiple LLMs are comparatively homogeneous, and that humans retain greater variance and exceptional upper-tail performance.

For managers, the implication is to design for augmentation rather than substitution. Employees should retain ownership of problem definition, interpretation, judgement, and final selection; AI should be used selectively as an idea expander, sounding board, execution aid, or opportunity-revealing tool. The replace-reinforce-reveal taxonomy provides a practical way to decide where automation is appropriate and where human cognitive contribution should be protected. Teams should generate some ideas independently, then use AI to challenge or expand them, and organizations should compare idea pools for diversity rather than evaluating proposals only one at a time.

The theoretical implication is that GenAI functions simultaneously as a productivity technology, a search technology, and a coordination force. By making high-quality outputs easier to produce, it can democratize creative performance; by exposing many people to similar representations and solution patterns, it can also narrow organizational search. The central contribution of this paper is therefore to treat creativity and diversity as distinct but interdependent outcomes. Sustainable advantage is most likely when organizations deliberately raise individual capability while preserving the pluralism of human perspectives that produces genuinely differentiated innovation.

7. Limitations and Future Research Directions

This review is integrative rather than systematic and intentionally prioritizes recent evidence that were published in top outlets; it may therefore omit relevant lower-ranked or emerging studies. The literature also evolves quickly as model capabilities change. Future research should examine long-term organizational exposure, compare prompting and multi-model regimes in field settings, validate portfolio-level diversity measures, and test whether independent pre-AI ideation protects minority or unconventional perspectives. Additional work should also examine when the replace, reinforce, and reveal roles produce different creativity-diversity trade-offs across expertise levels, industries, and stages of innovation.

Table 1. Organizational Design Architecture for Preserving Creativity and Collective Pluralism

Design problem	Evidence-based rationale	Recommended architecture	Illustrative metric
Protect independent framing	Common AI suggestions can anchor users and compress idea pools.	Require initial problem framing and some pre-AI ideation before model exposure.	Pre-/post-AI idea share; semantic spread
Match AI role to task	AI can replace codified work, reinforce human capability, or reveal new opportunities.	Use replace for low-discretion tasks; favour reinforce/reveal for creative work.	Human ownership; quality; task-stage performance
Differentiate by expertise	Novices often gain from structure; experts can be anchored by ghostwriting.	Use AI as scaffold for novices and challenger/sounding board for experts.	Gains by expertise; override/revision rate
Design for contrast	Shared models and prompts increase convergence; differentiated search can recover novelty.	Require contrasting alternatives, cross-model comparison, and explicit distance from prior ideas.	Semantic similarity; thematic concentration
Govern quality and diversity	Fluent outputs can improve while portfolio diversity declines; feedback loops can shape judgement.	Use a dual dashboard, periodic AI-free review, verification, and independent expert challenge.	Quality/productivity plus portfolio-diversity indicators

Note. Synthesized from Bouschery et al. (2023), Boussioux et al. (2024), Chen and Chan (2024), Doshi and Hauser (2024), Gama and Magistretti (2025), Glickman and Sharot (2025), Hou et al. (2025), Kumar et al. (2025), Meincke et al. (2025), and Sun et al. (2025).

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