



Beyond the Creativity Paradox: A Theory-informed Framework for Role-based Integration of Generative AI in Organisational Creativity

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Abstract

Generative Artificial Intelligence (GenAI) is reshaping organisational creativity by emulating cognitive processes traditionally associated with human innovation. This study revisits foundational creativity theories to develop a framework for integrating GenAI into creative workflows. Drawing on structural parallels between GenAI architectures and human cognition - such as heuristic search, divergent thinking, and iterative refinement - the paper repositions GenAI as a cognitive collaborator rather than merely a productivity tool. A role-based integration model aligns GenAI capabilities with key creative functions: idea generation, synthesis, strategic framing, and facilitation. The framework also addresses emerging tensions captured in the *Creativity Paradox*, whereby GenAI may weaken intrinsic motivation, conceptual risk-taking, and evaluative depth. The study contributes by reinterpreting process-oriented creativity theories through structural parallels with GenAI, proposing a role-based framework for organisational use, and extending paradox theory to conceptualise the *Creativity Paradox* in this context. Together, these insights provide theoretical clarity and practical guidance for responsible GenAI integration.

Keywords Generative AI · Organisational creativity · Creative theory · Paradox · Human-AI collaboration

1 Introduction

The emergence of Generative Artificial Intelligence (GenAI)—typified by technologies such as Generative Adversarial Networks (GANs), Diffusion Models, and Large Language Models (LLMs) - signals a significant procedural shift in how organisations operationalise creative processes. Rather than simply augmenting computational capacity, GenAI co-orchestrates creative workflows by expanding the ideation space, enabling cross-modal recombination in design and synthesis, and accelerating feedback to support evaluation, while decision authority remains with humans, thereby acting as a cognitive collaborator rather than a replacement (Cervini et al., 2023; Corvello, 2025; Floridi & Chiriatti, 2020). More specifically, GenAI reconfigures distinct phases of the creative process rather than redefining creativity as a whole. In ideation, it expands associative breadth by generating probabilistic variations that exceed individual memory and cognitive constraints, thereby increasing idea fluency and combinatorial range. In conceptual synthesis, it recombines heterogeneous knowledge domains at scale, simulating brokerage functions typically performed by weak-tie networks within organisations.

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In evaluation and refinement, it accelerates comparison, scenario testing, and iterative feedback, although final judgments of value, legitimacy, and meaning remain human-dependent. In this sense, GenAI reshapes how creative phases are enacted operationally, without displacing the socio-cognitive foundations of creativity itself.

Recent work by Campbell et al. (2025) reinforces this view, showing how organisations are leveraging GenAI to augment ideation processes, facilitate team creativity, and build hybrid workflows that strategically align human and machine intelligence. Beyond technical augmentation, GenAI is increasingly positioned as an active partner in value creation and creative exploration. Its distinctive capabilities—including autonomous content generation, multimodal synthesis, and dynamic, feedback-driven refinement—mirror core elements of human creativity such as divergent thinking, associative recombination, and iterative problem-solving (Amabile et al., 2016; Boden, 2004; Guilford, 1967). As firms confront increasing pressures for agility and enhanced creative output, the strategic integration of GenAI has shifted from a desirable goal to a critical necessity (Amankwah-Amoah et al., 2024; Rana et al., 2024).

Despite the expanding utilisation of GenAI in fields such as design, marketing, and innovation management, a significant theoretical and strategic gap remains. Although extensive scholarship exists on creativity as a multidimensional phenomenon—spanning individual cognition, intrinsic motivation, team dynamics, and systemic evaluation—such theoretical frameworks have seldom been applied explicitly within AI-enhanced contexts (Amabile et al., 2016; Anderson et al., 2014; Csikszentmihalyi, 1999, 1988). Concurrently, GenAI development has predominantly advanced independently of creativity theory, emphasising computational efficiency and scalability rather than aligning conceptually with human creative processes (Tingelhoff et al., 2025). Yet, emerging studies suggest this misalignment is narrowing. Abbas et al. (2026) demonstrate how GenAI systems contribute not only to creative output but also to the development of organisational intellectual capital. By embedding GenAI into knowledge structures and innovation routines, firms enhance both resilience and strategic adaptability—hallmarks of effective creative ecosystems. This disconnect stems partly from the initial purpose of GenAI systems, which were originally optimised for prediction, pattern recognition, and generation tasks, rather than genuine creative innovation. Consequently, organisations often struggle to strategically embed GenAI into their innovation processes, frequently perceiving it as merely enhancing productivity rather than as a potentially co-creative collaborator (Chowdhury et al., 2024). Without theoretical alignment between GenAI's capabilities and human-centred innovation frameworks, companies risk failing to fully exploit AI's

transformative potential, resulting in strategic inefficiencies and compromised innovation outcomes (Yan et al., 2024).

To bridge this theoretical and practical divide, the current study reinterprets classical and contemporary creativity theories through the lens of GenAI's procedural architectures. Drawing from Herbert Simon's bounded rationality and heuristic search model (Simon, 1955, 1997) and Margaret Boden's differentiation between exploratory and transformational creativity (Boden, 2004), the paper reconceptualises GenAI not merely as a technical tool but as a computational analogue to human creative cognition. With their hierarchical structures and advanced learning algorithms, GenAI systems replicate cognitive scaffolds identified in creativity research, including domain expertise, divergent ideation, iterative refinement, and contextual evaluation.

Building on this theoretical foundation, the paper introduces a role-sensitive framework for integrating GenAI, distinguishing clearly defined creative roles such as Creative Generators, Conceptual Synthesisers, Strategic Framers, and Human-Centred Facilitators. Each role aligns with specific cognitive and procedural demands within organisational creativity, thus capitalising on targeted GenAI capabilities. Grounded in theoretical and empirical insights from innovation studies, network theory, and cognitive psychology (Mumford et al., 2002; Perry-Smith & Mannucci, 2017; Uzzi et al., 2013), this framework provides actionable guidance for strategic AI integration tailored to role-specific creative requirements.

In addition to practical strategies, the study addresses emergent ethical and motivational tensions, identified collectively as the "*Creativity Paradox*." While GenAI accelerates creative productivity, it may concurrently diminish intrinsic motivation, discourage conceptual risk-taking, and foster normative conformity (Mukherjee & Chang, 2023; Wang et al., 2025). Furthermore, increasing reliance on AI-generated content provokes questions regarding authorship, epistemic integrity, and ethical responsibilities within organisational contexts (Amankwah-Amoah et al., 2024). Addressing these tensions requires nuanced, theory-informed strategies that position GenAI not as a replacement for human creativity but as a structured collaborator within a socio-cognitive ecosystem.

To advance this agenda, the paper addresses the following guiding questions:

- (1) How can classical and contemporary creativity theories be reinterpreted in light of GenAI's unique architectural and procedural capabilities (structural parallels)?
- (2) What roles can GenAI assume within organisational creative processes, and how can these roles be strategically differentiated and aligned with human cognitive strengths?

- (3) What ethical and motivational tensions emerge from integrating GenAI into creative workflows, and how can these be navigated to support responsible innovation?

These questions serve as the conceptual scaffolding for the proposed framework, which bridges creativity theory, AI design, and organisational innovation strategy.

By answering these questions, this paper advances the scholarly discourse in three primary ways. First, it reinterprets creativity theories with a specific focus on their *processual orientation*—highlighting how creativity emerges through iterative stages of ideation, elaboration, validation, and evaluation—and demonstrates the *structural parallels* between these stages and the procedural architectures of GenAI. Second, it proposes a role-based integration framework that aligns GenAI’s distinct capabilities with differentiated creative functions within organisations, moving beyond generic claims of AI augmentation toward a structured model of human–AI co-creativity. Third, it extends the paradox lens to the GenAI context, conceptualising the *Creativity Paradox* as a reconfiguration of enduring creative tensions (e.g., novelty vs. usefulness, intrinsic vs. extrinsic motivation) amplified by algorithmic mediation. Taken together, these contributions position the paper as a theory-informed conceptual study that both integrates creativity theory with emerging technologies and provides actionable guidance for the responsible and strategic deployment of GenAI in organisational creativity. In pursuing this aim, we deliberately focus on creativity theories that foreground the *processual rise of creativity*—from initial ideation and elaboration through social validation and systemic evaluation. This emphasis allows us to map structural parallels between generative AI architectures and the staged dynamics of creativity, providing a theoretically coherent foundation for the role-based framework developed in this paper.

2 Literature Review and Theoretical Synthesis of Creativity

Although the roots of creativity research reach back to the 1930s, the field’s standard definition was first articulated by Stein (1953). Creativity refers to the production of ideas, solutions, or artefacts that are both novel and effective, as judged by a relevant audience within a particular sociocultural context and point in time (Stein, 1953). Earlier work laid the groundwork for this definition. Hutchinson (1931) linked creativity to practical transformation, and Guilford (1950) tied originality to acceptability and evaluation. Subsequent scholarship sharpened the adaptiveness criterion (Barron, 1955) and added key nuances such that creativity often involves “effective surprise” (Bruner, 1962) and yields outcomes that

are worthwhile rather than merely original (Cropley, 1967). The field later converged on the widely accepted ‘originality & effectiveness’ definition (Runco & Acar, 2012).

Understanding how creativity unfolds within organisational contexts has long been a central concern in management, psychology, and innovation research. Over time, a rich tapestry of theoretical perspectives has emerged, each illuminating different facets of the creative process—ranging from individual cognition and motivation to social networks and systemic evaluation.

This section moves beyond a descriptive literature review to synthesise foundational creativity theories into a cohesive and multidimensional framework. We proceed in three steps. First, we briefly review six influential theories that provide complementary insights into the nature of creativity. Second, we distil recurring themes across these theories into four foundational creativity attributes, “Cognitive, Motivational, Social, and Procedural”, which provide an organising lens for integration. Finally, we consolidate these insights into a six-phase framework that captures creativity as a nonlinear and iterative process, which we name as ‘Iterative Framework of Creativity Phases’.

One of the most influential models in this discourse is Teresa Amabile’s Componential Theory of Creativity, which posits that creative performance results from the interaction of domain-relevant knowledge, creativity-relevant cognitive processes, and intrinsic motivation (Amabile, 1983, 2018; Amabile et al., 2016). Crucially, Amabile (2018) emphasised that intrinsic motivation (driven by interest, enjoyment, and personal challenge) is more conducive to creativity than extrinsic motivators such as monetary rewards. Subsequent empirical studies have reinforced this view, showing that autonomy-supportive environments, constructive feedback, and psychological safety significantly enhance intrinsic motivation and creative engagement (Amabile et al., 2016; Hennessey, 2010; Shalley et al., 2004).

Complementing Amabile’s cognitive-motivational approach, Mihaly Csikszentmihalyi’s systems model introduced a more relational and cultural understanding of creativity. According to this framework, creativity arises through dynamic interactions between three key elements: the individual, the domain of knowledge, and the field of gatekeepers who evaluate and validate creative contributions (Csikszentmihalyi, 1999). From this perspective, creativity is not simply a function of personal capacity, but of systemic recognition and integration into cultural or organisational knowledge structures (Csikszentmihalyi & Sawyer, 2015; Ford, 1996). This model underscores the importance of social legitimacy and feedback in understanding how novel ideas are surfaced, evaluated, and institutionalised.

The cognitive mechanisms underpinning creativity were further elaborated by J.P. Guilford (1950, 1967), whose

Structure-of-Intellect model introduced the concept of divergent thinking. This form of cognition emphasises the ability to generate multiple, varied, and original solutions to open-ended problems. Guilford identified four key attributes of divergent thinking: fluency, flexibility, originality, and elaboration. Contemporary research has validated these components as critical to creative idea generation and problem-solving, particularly in complex, knowledge-intensive environments (George, 2007; Runco & Acar, 2012). Organisational contexts that support exploratory risk-taking, knowledge exchange, and experimental thinking tend to nurture these capacities (Shalley & Gilson, 2004).

In recent years, scholars have increasingly adopted process-oriented models that view creativity as a dynamic, multi-phase phenomenon. Anderson et al. (2014) proposed a widely adopted integrative model dividing the creative process into three stages: idea generation, idea promotion (or championing), and implementation. Each stage demands different skill sets, resources, and environmental support. For instance, the generation phase requires psychological safety and cognitive flexibility, the promotion phase calls for influence, leadership, and narrative construction, while the implementation stage hinges on feasibility assessments, managerial support, and cross-functional collaboration (Baer, 2012; Zhou & Hoever, 2014).

Building on this, Perry-Smith and Mannucci (2017) introduced a social network perspective, arguing that various types of interpersonal relationships support creativity at distinct stages. Drawing on social capital theory, they proposed that weak ties provide access to novel information, particularly useful in idea generation. Stronger ties are more beneficial for elaboration and refinement, while brokerage roles and network influence are crucial in the championing and implementation phases (Burt, 2004; Obstfeld, 2005). This model highlights the importance of dynamically reconfiguring network structures in response to shifting creative demands.

Beyond ideation and collaboration, recent organisational scholarship has foregrounded evaluation and judgement as essential, yet often underexplored, components of creativity. Harvey and Kou (2013) argue that creativity entails continuous cycles of generation and evaluation, wherein ideas are assessed not only for novelty but also for feasibility, appropriateness, and alignment with organisational goals. Evaluation is not solely cognitive, but also socially and contextually contingent shaped by team norms, identities, and power dynamics (Harvey & Kou, 2013; Rietzschel et al., 2010). In today's increasingly complex environments, the capacity to construct shared evaluative frameworks is vital for translating inspiration into actionable innovation (Mueller et al., 2012). Likewise, Wang et al. (2025) explores the motivational challenges introduced by AI collaboration,

indicating that perceptions of diminished authorship or autonomy in the presence of GenAI may suppress intrinsic motivation, despite gains in efficiency.

In sum, creativity in organisations is not a monolithic trait, but a systemic, multilevel phenomenon encompassing cognitive flexibility, intrinsic motivation, social relationships, evaluative criteria, and cultural legitimisation. These diverse perspectives converge on a common insight: creativity emerges as an iterative, adaptive journey shaped by individual, relational, and institutional factors. Understanding this complexity is essential for nurturing human creativity and for evaluating how GenAI might complement—or disrupt—these processes.

Importantly, these theories provide a robust conceptual foundation for assessing GenAI's role in creative work. Just as human creativity unfolds through phases of idea generation, elaboration, championing, and implementation, GenAI systems mirror these stages via generative modeling, constraint optimisation, feedback-driven refinement, and contextual adaptation (Rana et al., 2024). Moreover, akin to human networks facilitating creative cognition through diverse informational flows, GenAI tools—trained on heterogeneous data sets—can emulate cognitive brokerage, associative recombination, and pattern recognition (Uzzi et al., 2013). This theoretical convergence enables a reimagining of GenAI not merely as a technological disruptor but as an embedded agent within contemporary creative systems. The convergence of these theories lies in their articulation of transition points across levels of analysis. For example, individual divergent thinking (Guilford, 1967) generates raw novelty, which is then refined and championed through interpersonal relationships and social networks (Perry-Smith & Mannucci, 2017). These, in turn, require systemic validation by cultural or organisational gatekeepers (Csikszentmihalyi, 1999). Our synthesis therefore does not collapse levels of analysis but highlights how creativity unfolds as a multi-level journey, with individual cognition feeding into relational dynamics and ultimately into systemic recognition.

While creativity research encompasses a wide range of perspectives (see Anderson et al., 2014; Runco & Jaeger, 2012), our selection of theories is deliberate. We focus on models that not only represent different levels of analysis—individual cognition, motivational dynamics, social interaction, and systemic legitimisation—but also explicitly describe the *processual rise of creativity*, that is, how creative ideas emerge, are refined, and gain legitimacy over time. This process-oriented emphasis is particularly relevant for our study, as it allows us to align classical creativity frameworks with the procedural logics of GenAI, including heuristic search, divergent exploration, iterative refinement, and evaluative feedback. By concentrating on theories that conceptualise

creativity as a dynamic and staged phenomenon, we establish a coherent basis for examining structural parallels between human creative processes and GenAI architectures.

In sum, creativity in organisations is not a static trait nor a singular act of inspiration, but a complex, systemic phenomenon involving cognitive, motivational, relational, and evaluative dimensions. While the reviewed theories differ in emphasis—ranging from individual cognition (Guilford, Amabile), to relational dynamics (Perry-Smith & Mannucci),

to systemic or cultural legitimation (Csikszentmihalyi)—they converge on a common processual structure that underpins creative activity. To make these convergences and differences explicit, Table 1 summarises the major creativity theories reviewed, highlighting their key concepts and processual emphasis.

To synthesise the wide-ranging creativity theories into an accessible framework, we consolidate them into four foundational attributes: Cognitive, Motivational, Social, and

Table 1 The Development of Creativity Theory

Theory / Model	Year	Researcher(s)	Key Concepts	Description and Processual Emphasis
Structure of Intellect Model	1950, 1967	J. P. Guilford	Content, Operation, Product, Divergent thinking	Focuses on mental processes and forms of ideas, highlighting fluency, flexibility, originality, and elaboration in divergent thinking Processual Emphasis: Emphasises the <i>early stages</i> of creativity, focusing on divergent thinking as the generative process by which multiple ideas are produced.
Componential Model	1983, 1996	Teresa Amabile	Domain-relevant skills Creative-thinking skills Intrinsic motivation	Creativity arises from the interaction of expertise, idea-generation strategies, and intrinsic motivation. Processual Emphasis: Describes how creativity arises through the interaction of knowledge, cognitive strategies, and motivation, framing creativity as an <i>iterative interplay</i> of cognitive and motivational processes.
System Model	1988	Mihaly Csikszentmihalyi	Person, Field, Domain	Emphasises dynamic interactions among individual talents, evaluative gatekeepers, and knowledge domains within cultural and societal contexts. Processual Emphasis: Positions creativity as a <i>relational process</i> where individual novelty must pass through social validation and systemic legitimation.
Integrated Process Model	2014	Anderson, Potočnik, & Zhou	Idea Generation, Idea Promotion, Implementation	Describes creativity as a process involving psychological safety, influence, leadership, storytelling, feasibility assessment, and cross-department collaboration. Processual Emphasis: Explicitly presents creativity as a <i>multi-stage process</i> of generation, championing, and implementation, highlighting the sequential rise of creative outcomes.
Social Network Perspective	2017	Perry-Smith & Mannucci	Weak ties, Strong ties, Brokerage roles, Network influence	Highlights the role of social networks in providing novel information and refining ideas, with brokerage roles facilitating idea movement. Processual Emphasis: Maps how different network ties support distinct <i>phases</i> of the creative process (generation, elaboration, championing, implementation).
Iterative Evaluation Cycle of Novelty, Feasibility, and Suitability	2013	Harvey & Kou	Social construction, Norms, Identities, Power relations	Success in creativity depends on co-creating shared evaluation criteria, with a focus on social construction and power dynamics. Processual Emphasis: Conceptualises creativity as a <i>cyclical process</i> of generation and evaluation, stressing continuous feedback loops and refinement.

Procedural. These four attributes are grounded in and extend prior work on creativity. Existing literature has long emphasised cognitive abilities such as divergent thinking (Guilford, 1967; Runco & Acar, 2012), motivational dynamics such as intrinsic versus extrinsic drivers (Amabile, 1996), and social-contextual factors such as networks and field legitimation (Csikszentmihalyi, 1999; Perry-Smith & Mannucci, 2017). Our synthesis differs in two ways. First, by integrating these insights across levels of analysis, we provide a coherent scaffold that captures the *rise of creativity* from ideation through refinement and legitimation. Second, we add a procedural dimension, highlighting the iterative and structural nature of creativity (Harvey & Kou, 2013), which has often been overlooked in prior classifications. This procedural attribute is particularly significant because it provides a conceptual bridge to later sections, where we revisit these attributes through the lens of GenAI's procedural architectures. In this way, the framework in Fig. 1 is not a selective restatement of prior work, but a deliberate synthesis that establishes a foundation for integrating human creativity theory with machine-based generative processes.

As shown in Fig. 1, the Cognitive attribute captures the mental operations that underpin idea generation, particularly divergent thinking. This stems from Guilford's *Structure of Intellect Model*, which emphasises fluency, flexibility, and originality as core components of creative cognition. The Motivational attribute, drawn from Amabile's *Componential Model*, focuses on intrinsic motivation, which fuels creative engagement through personal interest, autonomy, and the pursuit of meaningful challenges. The Social dimension reflects the role of domain expertise, cultural validation, and network dynamics, as articulated in Csikszentmihalyi's

System Model and Perry-Smith & Mannucci's network perspectives. Lastly, the Procedural attribute characterizes creativity as a structured, multi-phase journey encompassing idea generation, promotion, and implementation—aligning with the stages identified by Anderson et al. (2014) and the iterative evaluation cycles emphasized by Harvey and Kou (2013). Across these theoretical frameworks, several recurring phases emerge consistently:

Phase 1. Preparation and Input Gathering

All creativity theories recognise the essential role of foundational knowledge and information as precursors to creative activity. This phase includes acquiring domain-specific expertise (Amabile, 2018), accessing novel insights through weak social ties (Perry-Smith & Mannucci, 2017), and immersing oneself within established symbolic domains (Csikszentmihalyi, 1999).

Phase 2. Idea Generation

Universally acknowledged across theoretical traditions, this stage encompasses mechanisms such as divergent thinking (Guilford, 1967), intrinsic motivation-driven ideation (Amabile, 1996, 2018), and cognitive flexibility within ambiguous and uncertain contexts.

Phase 3. Idea Elaboration and Refinement

Generated ideas must undergo further development, refinement, and elaboration into coherent and actionable concepts. The importance of strong interpersonal relationships

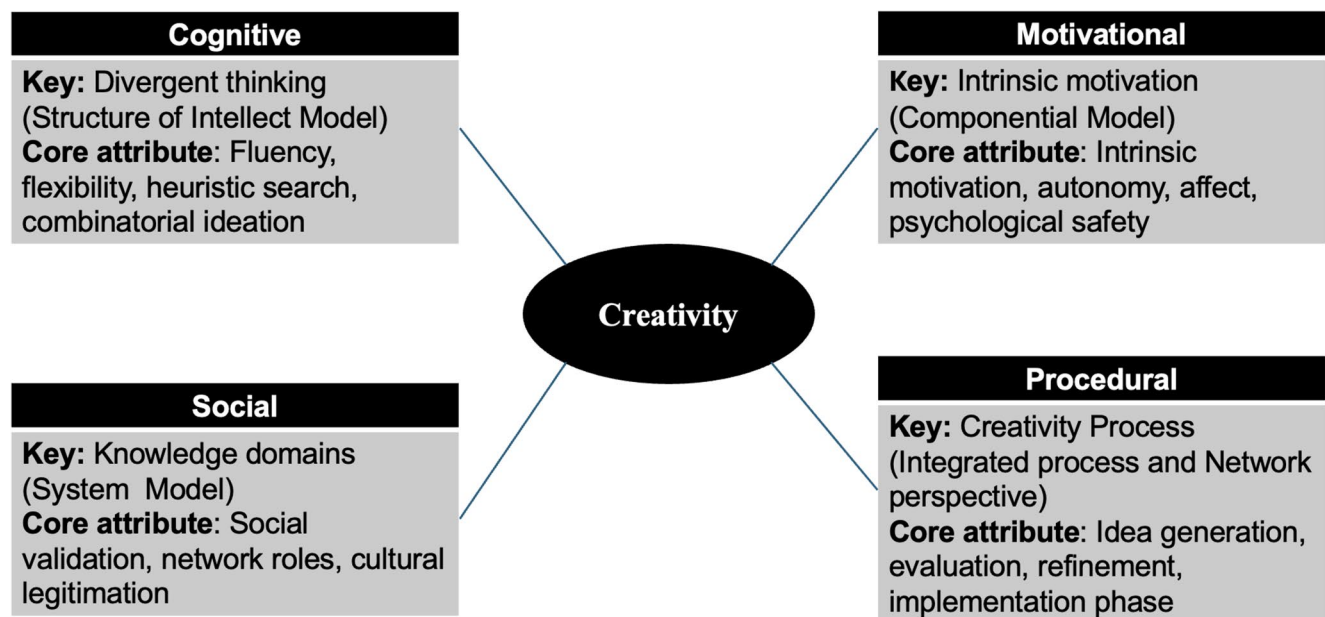


Fig. 1 Key Attributes of Creativity

(Perry-Smith & Mannucci, 2017), cognitive elaboration skills (Guilford, 1967), and advanced creative cognition (Runco & Acar, 2012) is highlighted during this phase.

Phase 4. Idea Promotion and Social Validation

Csikszentmihalyi's systems theory (1999) and Anderson et al. (2014) championing phase stress the critical need for social advocacy—an often overlooked yet indispensable step towards creativity recognition and institutional support. Successfully promoting ideas involves navigating organisational politics, securing stakeholder engagement, and aligning innovative concepts with collective values.

Phase 5. Implementation and Institutionalisation

Once validated socially and aligned with available resources, creative ideas are translated into tangible outcomes. This phase depends critically on managerial endorsement, effective cross-functional collaboration (Zhou & Hoever, 2014), and the establishment of shared evaluative standards (Harvey & Kou, 2013).

Phase 6. Evaluation and Iteration

A cyclical perspective underpins most creativity theories, where ideas are continually assessed, revised, or discarded based on feedback mechanisms. Evaluation processes may be explicit, as exemplified by Harvey's iterative evaluation cycles (Harvey & Kou, 2013), or implicit within motivational feedback loops described by Amabile (1996). In both

cases, evaluation processes involve cognitive judgment intertwined with organisational norms and social contexts.

Collectively, these diverse theoretical perspectives illustrate creativity as a nonlinear, iterative process as shown in Fig. 2 below. These stages may occur sequentially or cyclically, contingent upon the nature of the creative task, organisational context, and involved stakeholders.

It is important to clarify the distinction and relationship between creativity and innovation. While these concepts are often linked, they are not interchangeable. Creativity refers to the generation, elaboration, and social validation of ideas that are both novel and useful (Amabile, 1996; Runco & Jaeger, 2012), whereas innovation involves the broader organisational processes of championing, adoption, diffusion, and market realisation (Anderson et al., 2014; Damanpour, 1991). In many cases, creativity is a *necessary but not sufficient* condition for innovation: an idea may be original and valuable but never translated into an innovation if it is not implemented or accepted within organisational systems. At the same time, innovation can occur without substantial creativity, for instance through recombination, imitation, or the adoption of externally generated ideas. Thus, while the two processes are interdependent, their relationship is not strictly linear.

Our focus on the “phases of creativity” reflects this nuance. By foregrounding the socio-cognitive processes that underpin the *rise of creativity*—ideation, refinement, and legitimization—we distinguish them from the broader innovation cycle. This focus allows us to explore how GenAI integrates at the level of creative processes, without collapsing them into innovation outcomes. In doing so, we

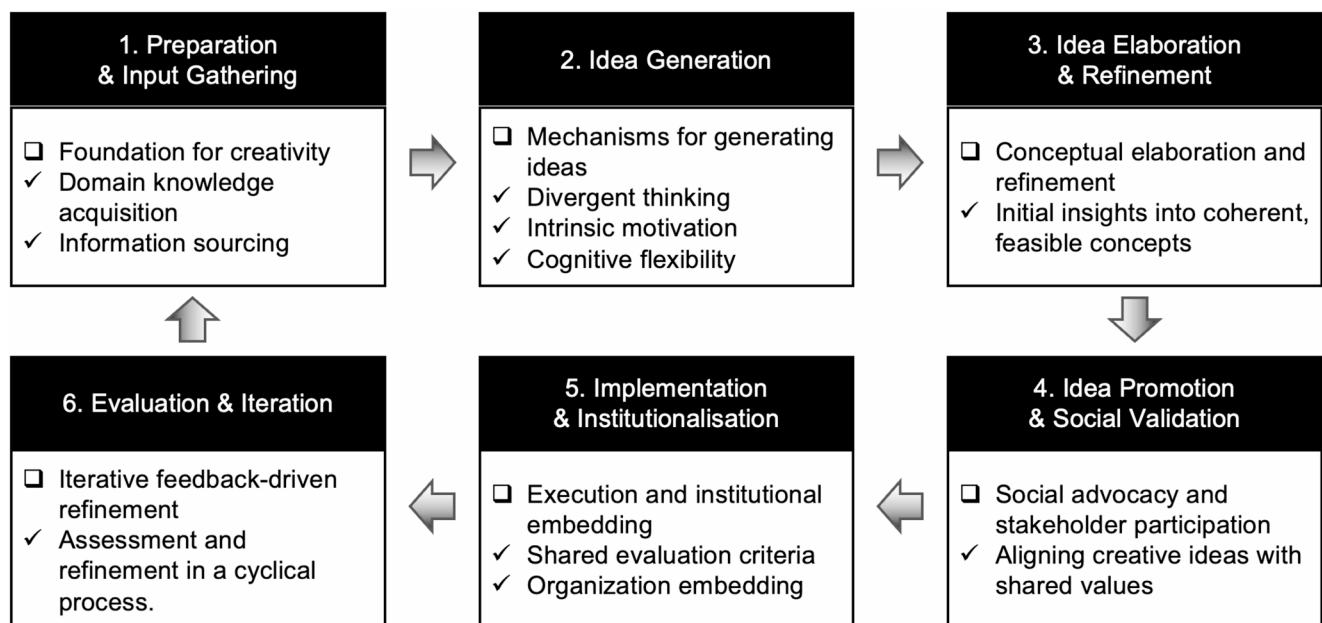


Fig. 2 An Iterative Framework of Creativity Phases

acknowledge overlap between the two but emphasise that the framework developed here addresses creativity as a distinct processual phenomenon that may, but does not always, precede innovation.

Recognising this shared scaffolding is critical not only for understanding human creativity but also for evaluating how GenAI systems might participate in or disrupt these processes. For instance, GenAI can contribute to idea generation and elaboration through large-scale pattern recognition and recombination (Uzzi et al., 2013), while also influencing implementation by accelerating content production or simulation. However, questions remain about its role in value-laden tasks such as social validation, judgment, and contextual evaluation—areas traditionally mediated by human cognition, norms, and relationships.

This integrative view of creativity—as a multistage, socially embedded, and evaluative process—offers a powerful lens through which to analyze how GenAI might be aligned with, augment, or potentially restructure creative workflows in contemporary organisations.

3 Revisiting Theories of Creativity Through the Procedural Lens of Generative AI

The rapid advancement of GenAI provides a unique opportunity to revisit foundational creativity theories through a computational and procedural perspective. Rather than merely automating routine tasks, GenAI actively simulates core cognitive processes integral to human creativity. The underlying architectural and operational structures of GenAI models align significantly with the staged, iterative, and evaluative nature of creativity articulated by both classical and contemporary theories. This alignment positions GenAI not merely as a computational tool but as a cognitive analogue, thus necessitating a reconsideration of creativity theory within the context of technologically mediated cognition.

Central to this reinterpretation is Herbert Simon's seminal work, *The Sciences of the Artificial* (1982), which conceptualises creativity as a structured process of heuristic search within bounded rationality. Simon argued that creative activities are not random, nor purely intuitive but rather goal-directed processes constrained by cognitive limitations and environmental contexts. This framework mirrors GenAI systems' logic, where generative outputs emerge from strategic exploration of clearly defined problem spaces rather than brute computational force. Both human creativity and GenAI thus rely fundamentally on heuristic strategies, iterative feedback loops, and progressive refinement—a process Simon referred to as “satisficing,” or identifying sufficiently viable solutions within complex constraints.

The procedural aspects of Simon's model are distinctly evident in contemporary GenAI architectures. In transformer-based LLMs, GANs, and diffusion models, the creative output unfolds systematically across distinct phases: (1) domain familiarisation via data ingestion and representation learning, (2) exploratory idea generation driven by latent variable distributions or attention mechanisms, (3) evaluative feedback through discriminative functions or loss metrics, and (4) iterative refinement and contextual optimisation of outputs. These stages closely parallel key phases of human creative cognition articulated by Guilford's (1967) divergent thinking framework, Amabile's (2018) Componential Theory of Creativity, and Csikszentmihalyi's (1999) systems model.

Amabile's Componential Theory of Creativity posits that creative performance emerges through the interplay of domain-specific knowledge, creativity-relevant cognitive processes, and intrinsic motivation. From a computational perspective, GenAI effectively replicates these dimensions. By training extensively on domain-specific datasets, GenAI emulates the accumulation of domain expertise, while its generative algorithms mimic divergent cognitive mechanisms, producing novel and varied conceptual combinations. Furthermore, GenAI reduces barriers to experimentation and facilitates rapid prototyping, indirectly supporting intrinsic motivation by reducing cognitive and operational costs associated with innovation. This dynamic aligns closely with Amabile's later focus on environmental and affective support factors that sustain creativity (Amabile et al., 2016).

Extending this analysis through Csikszentmihalyi's systems perspective, creativity emerges through the dynamic interactions among individual agents, domains of knowledge, and evaluative gatekeepers (“fields”). GenAI introduces a novel cognitive actor into this triadic structure—capable of independently generating novel contributions and influencing evaluative processes. The “field,” now inclusive of algorithmic assessments and AI-driven feedback systems, integrates computationally mediated judgments, potentially reshaping norms around the validation and legitimization of creative outcomes.

Moreover, Simon's conceptualisation of creativity as heuristic-driven search processes is explicitly instantiated within GenAI optimisation frameworks. In GANs, for instance, the generator–discriminator interaction mirrors iterative processes of creative refinement and evaluative critique (Harvey & Kou, 2013). Here, the generative module proposes outputs, which the discriminative module then assesses, driving iterative improvements until the outputs satisfy defined evaluative standards. Similarly, diffusion models exemplify creativity's progression from ambiguity toward structured clarity, starting from random noise and

systematically refining outputs into coherent solutions—an apt metaphor for creative problem-solving within uncertain or ambiguous contexts.

The temporal structure of creativity articulated by Anderson et al. (2014) and Perry-Smith and Mannucci (2017) provides further insights into GenAI's operational parallels. These frameworks characterise creativity as a multi-stage journey involving idea generation, elaboration, championing, and implementation. GenAI supports each phase distinctly: in idea generation, LLMs and GANs facilitate expansive ideation akin to human brainstorming. For elaboration and refinement, transformer-based architectures integrate constraints and contextual cues, allowing iterative improvement of initial concepts. During the championing and implementation phases, GenAI can simulate audience reception, produce targeted promotional materials, and generate practically deployable outputs such as code, design prototypes, or strategic plans, thereby integrating seamlessly into organisational creative workflows.

Particularly notable is Perry-Smith and Mannucci's emphasis on the critical role of social networks in the creative process. GenAI can act as an artificial proxy for weak-tie networks, offering associative leaps across diverse information domains. Trained on heterogeneous datasets, GenAI systems embody virtual brokerage, expanding informational breadth and associative richness beyond individual cognitive boundaries, thus enhancing overall creative potential within organisations.

By recognising these procedural parallels, GenAI architectures—characterised by iterative generative processes, heuristic search methods, and evaluative refinement—closely reflect foundational human creativity theories. Among these perspectives, Simon's bounded rationality framework provides an especially robust conceptual foundation for integrating GenAI into creativity research. From this vantage point, GenAI emerges not simply as a productivity enhancer but as a cognitive collaborator deeply embedded within the creative ecosystem.

This recognition encourages scholars and practitioners to transition from instrumental views of AI toward more sophisticated, theoretically informed conceptions of human–AI co-creativity. Such an approach explicitly considers how artificial agency intersects with human judgment, intrinsic motivation, and culturally situated meaning-making, thereby opening new avenues for creativity research and organisational innovation practice (Table 2).

The iterative process of creativity illustrated in Fig. 2—constructed from foundational theories of creativity—can also be supported and reinterpreted through the procedural lens of Generative AI (GenAI). Contemporary GenAI architectures, including LLMs, GANs, and diffusion models, demonstrate operational logics that closely parallel many of

the core phases found in human creative processes. GenAI's strengths lie in its alignment with core creative processes (Amabile, 1996; Anderson et al., 2014; Guilford, 1967). However, its role must also be understood alongside the human qualities it cannot replicate. Unlike human creators, GenAI lacks intentionality, intrinsic motivation, and affective consciousness (Ma & Sun, 2020). Crucially, GenAI's generativity is statistical rather than experiential. Whereas human creativity is grounded in embodied cognition, affective resonance, and lived temporality, GenAI operates through probabilistic pattern completion across high-dimensional data distributions. What may appear as “intuition” in machine outputs reflects distributional likelihood rather than situated judgment or existential commitment to an idea. This distinction is consequential: transformational creativity often emerges when individuals depart from dominant cognitive schemas or challenge prevailing norms, whereas GenAI remains structurally anchored to patterns embedded in its training data. As such, while GenAI can amplify exploratory and combinatorial processes, it remains constrained in producing genuinely paradigm-shifting or norm-defying transformations without human reframing.

Human creativity is often fuelled by curiosity, or the emotional drive to create for its own sake (Amabile, 1996; Hennessey, 2010). An artist may paint to express grief or joy; GenAI produces outputs without purpose or lived experiences. GenAI has no internal drive or emotional state; its outputs are indifferent to any feelings such as passion, joy, or frustration (Boden, 2004; Boussieux et al., 2024). GenAI also lacks embodied judgment that humans have (Dane & Pratt, 2007). A chef adjusts flavours through taste, smell, and intuition developed over years of practice (Sadler-Smith, 2023). GenAI can generate recipes, but it cannot experience or refine them through sensory immersion (Dreyfus, 1992; Harvey & Kou, 2013). Finally, GenAI cannot reproduce serendipitous insight. Creative breakthroughs can sometimes emerge from accidents or anomalies recognised as opportunities (i.e., recognition of mould contamination as penicillin). GenAI lacks the interpretive awareness to perceive significance in the unexpected. GenAI can augment, scale, and accelerate cognitive processes but cannot embody the purposive, motivational, and affective qualities that give human creativity depth, authenticity, and transformative potential. Therefore, understanding the role of GenAI in organisational creativity is critical, not to position it as a replacement for human creativity, but to govern its integration in ways that preserve human agency while strategically leveraging its strengths.

While GenAI lacks consciousness, intentionality, and intrinsic motivation, it embodies structured mechanisms—such as data-driven preparation, stochastic ideation, and iterative refinement—that echo the dynamics of human

Table 2 Human vs. Generative AI (GenAI) in Creative Attributes

Creative Attribute		Human	GenAI
Cognitive	Domain Knowledge Acquisition	Gradual learning through experience, education, and immersion in a symbolic domain (Csikszentmihalyi, 1988, 1999)	Mass ingestion of domain-specific datasets through representation learning Rapid but externally guided (GenAI architectures) (Simon, 1982)
	Idea Generation (Divergent Thinking)	Free association based on emotion, intuition, and personal experience Influenced by intrinsic motivation (Guilford, 1967; Hodgkinson & Sadler-Smith, 2018)	Probabilistic generation based on latent distributions, self-attention mechanisms, and statistical patterns (Transformer-based LLMs, GANs)
	Idea Elaboration and Refinement	Elaboration through cognitive flexibility, social interaction, and contextual understanding (Harvey & Kou, 2013)	Iterative output refinement via loss functions, discriminators, or reverse denoising processes (GANs, Diffusion Models)
Motivational	Intrinsic Motivation	Autonomous pursuit driven by curiosity, interest, and meaningfulness (Amabile, 1996).	Absent Operation is driven by goal-directed optimisation functions (i.e., external prompts, objectives) (Boussieux et al., 2024)
Social	Social Validation and Adaptation	Navigates complex social norms, organisational politics, and shared value systems (Csikszentmihalyi, 1999; Perry-Smith & Mannucci, 2017).	Encodes patterns of social judgment statistically from training data Limited explicit awareness of dynamic social systems (Bender et al., 2021).
Procedural	Creative Goal Setting	Capable of autonomous goal formation, revision, and strategic reorientation within open-ended environments (Simonton, 2000).	Goal execution based on predefined tasks or user prompts Lacks self-directed goal formation (Shneiderman, 2020).
	Evaluation and Iteration	Cognitive and social evaluation loops guided by heuristics, satisficing strategies, and contextual feedback (Harvey & Kou, 2013).	Built-in iterative optimisation through evaluative mechanisms such as discriminators (GANs) or attention-guided loss minimisation (LLMs)

creativity. By aligning classical creativity stages with GenAI's generative procedures, these technologies can be understood not merely as tools of automation, but as procedural counterparts capable of augmenting and co-participating in creative workflows. The following re-examines six recurring phases of creativity through this lens, providing the foundation for a comparative analysis of human and artificial creative attributes (Fig. 3).

Phase 1. Preparation and Input Gathering ↔ Data Representation and Pre-training

In human creativity, this phase involves acquiring domain expertise, accessing novel ideas through social exposure, and immersing in symbolic or cultural systems. Analogously, GenAI systems undergo extensive pre-training on large, domain-rich datasets. Through representation learning, they build probabilistic models of language, images, or concepts. Like a human gathering inspiration and knowledge, GenAI “prepares” by encoding structured knowledge across vast input distributions, simulating immersion in symbolic domains (Simon, 1982; Vaswani et al., 2017).

Phase 2. Idea Generation ↔ Stochastic Sampling and Latent Exploration

Human creativity often begins with divergent thinking and ideation driven by intrinsic motivation. In GenAI, this corresponds to generative sampling from latent spaces (e.g., in LLMs or GANs). These models use probabilistic or attention-driven mechanisms to explore conceptual spaces, recombining learned patterns in novel configurations. The spontaneity of human idea generation is mirrored in GenAI's stochastic creativity, producing varied outputs from the same input (Amabile, 1996; Guilford, 1967).

Phase 3. Idea Elaboration and Refinement ↔ Iterative Output Optimisation

Once initial ideas are generated, humans refine, develop, and assess them collaboratively. Similarly, GenAI engages in iterative output refinement via techniques such as loss function minimisation (LLMs), discriminator feedback (GANs), or reverse denoising (diffusion models). These processes parallel cognitive elaboration and social co-creation in human systems,

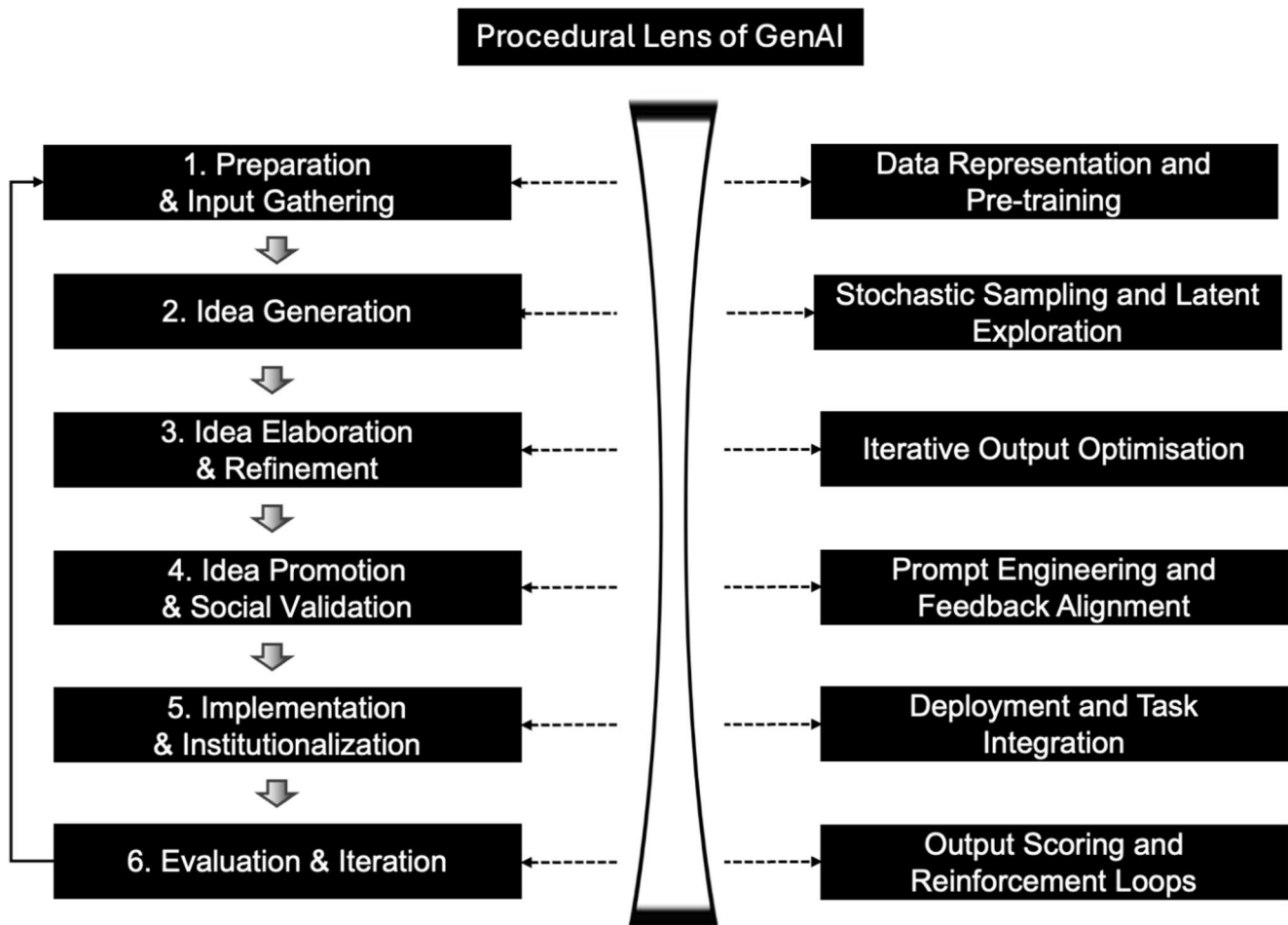


Fig. 3 Six Creative Phases through the Procedural Lens of GenAI

producing more coherent, contextually aligned, and higher-quality outputs (Harvey & Kou, 2013; Runco & Acar, 2012).

Phase 4. Idea Promotion and Social Validation ↔ Prompt Engineering and Feedback Alignment

In human systems, creativity must be validated by stakeholders, requiring advocacy and contextual resonance. In GenAI, this phase can be mapped to prompt tuning and preference alignment, where outputs are adjusted to match human evaluators' values and expectations—often via human-in-the-loop mechanisms such as reinforcement learning from human feedback (RLHF). These methods emulate the social filtering of ideas through cultural and organisational norms (Anderson et al., 2014; Csikszentmihalyi, 1999).

Phase 5. Implementation and Institutionalisation ↔ Deployment and Task Integration

Human creative ideas become impactful only when implemented and integrated into organisational systems. In

GenAI, this corresponds to downstream deployment, such as using generative models for marketing content, product design, or strategy. These operational applications reflect the translation of creative insight into action, much like implementation phases in human innovation cycles (Harvey & Kou, 2013; Zhou & Hoever, 2014).

Phase 6. Evaluation and Iteration ↔ Output Scoring and Reinforcement Loops

Creativity is inherently cyclical. Humans iterate ideas based on social judgment and personal reflection. GenAI engages in a similar loop via evaluative scoring and training updates. In supervised learning, reinforcement learning, or adversarial setups, outputs are continually judged and improved. While GenAI lacks embodied social context, its algorithmic feedback systems mimic iterative learning and heuristic-driven refinement (Harvey & Kou, 2013; Simon, 1982).

This procedural reinterpretation illustrates that the structural mechanisms underlying GenAI—pre-training, sampling, optimisation, feedback, and iteration—closely mirror

the six core phases of human creativity. While GenAI does not possess intent or affective judgment, its architectures operationalise many of the same functional logics found in classical creativity theory. Recognising these parallels is crucial for integrating GenAI meaningfully and ethically into creative workflows, ensuring that AI augments rather than displaces the nuanced, socially embedded nature of human innovation.

4 Harnessing Generative AI Across Organisational Creative Roles: A Theory-Informed Framework

As organisations integrate GenAI more deeply into creative workflows, understanding the diverse nature of organisational creativity becomes essential. Creativity within organisations is inherently heterogeneous—it involves divergent ideation, interdisciplinary synthesis, strategic abstraction, and interpersonal collaboration, each characterised by distinct knowledge structures, procedural dynamics, and motivational factors (Mumford et al., 2002; Shalley et al., 2004). Addressing this complexity, we introduce a role-based typology aligning organisational creative roles explicitly with GenAI’s procedural capabilities and established creativity theories. The roles identified in this typology were derived through synthesis of both creativity theory and organisational practice. Creativity research has long framed creativity as spanning idea generation and elaboration (Amabile, 1996; Guilford, 1967), individual ideation and collective framing (Csikszentmihalyi, 1999; Paulus & Nijstad, 2019), and cognitive problem-solving and social facilitation (Sawyer, 2006). These recurring themes provided the conceptual foundation for role selection. Practitioners in design thinking similarly emphasise complementary functions within creative teams—ideation and prototyping, conceptual integration across disciplines, problem framing, and human-centred facilitation. Our typology consolidates these recurring functions into four conceptual roles that capture the cognitive, motivational, and social dynamics of organisational creativity.

This framework addresses a critical gap evident in both creativity research and AI deployment strategies: the lack of differentiated models recognising the cognitive diversity inherent in various creative tasks (Anderson et al., 2014). Instead of portraying GenAI as a universal productivity booster, we conceptualise it as a context-sensitive augmentation tool whose effectiveness is contingent upon the nature of specific creative roles. Building upon the procedural lens established in Sect. 3, we categorise organisational creative roles into four theoretically grounded archetypes: Creative Generators, Conceptual Synthesisers, Strategic Framers,

and Human-Centred Facilitators, each matched systematically with the corresponding strengths of GenAI technologies. The typology is presented as a theory-informed synthesis intended to guide role-specific GenAI integration, rather than as an empirically validated model.

The four GenAI-augmented creative roles were derived through a structured conceptual synthesis. First, we identified recurrent functional demands across dominant creativity theories, including divergent idea generation, combinational recombination, evaluative refinement, and social facilitation (e.g., Guilford, 1967; Boden, 2004; Perry-Smith & Mannucci, 2017; and Amabile, 1996). Second, we clustered these functions into higher-order procedural categories aligned with the six creative phases outlined earlier. Third, we examined how these clustered functions manifest within organisational practice, particularly in knowledge-intensive and collaborative contexts. The resulting four roles represent analytically distinct configurations of cognitive, evaluative, and relational demands that GenAI may differentially augment.

4.1 Creative Generators: Divergent Explorers

Creative Generators, such as visual designers, advertising creatives, content writers, and multimedia developers, predominantly engage in ideation characterised by novelty, fluency, and aesthetic experimentation. This role closely aligns with Guilford’s (1967) concept of divergent thinking, emphasising originality, flexibility, and associative fluency. GenAI technologies, including LLMs, diffusion-based visual generators (e.g., Midjourney, DALL·E), and multimodal systems, parallel these cognitive dimensions by producing diverse permutations of ideas and facilitating rapid prototyping (Tingelhoff et al., 2025).

Through the lens of Amabile’s Componential Theory of Creativity (1996), GenAI enhances creativity-relevant cognitive processes by offering extensive access to linguistic, visual, and conceptual knowledge structures. The low-risk experimentation environment created by GenAI also enhances intrinsic motivation by reducing the perceived psychological and resource costs associated with ideation (Amabile et al., 2016; Wang et al., 2025).

4.2 Conceptual Synthesisers: Knowledge Integrators

Conceptual Synthesisers—including research & development (R&D) specialists, innovation strategists, product developers, and interdisciplinary researchers—engage in combinational creativity, integrating insights from diverse knowledge domains to generate innovative and feasible solutions. This creative function resonates with Boden’s

(2004) theory of combinational creativity and Simon's (1982) heuristic search within bounded problem spaces.

Here, GenAI acts as an artificial cognitive surrogate, emulating network brokerage roles described by Burt's (2004) social network theory by bridging heterogeneous data silos and recombining disparate information streams. Such capabilities align with the Social Network Model of Creativity (Perry-Smith & Mannucci, 2017), leveraging weak-tie analogues by providing novel information connections through extensive training datasets. Additionally, the iterative refinement process supported by GANs and retrieval-augmented generative systems parallels Harvey and Kou's (2013) iterative evaluation framework, wherein creative refinement is driven by evaluative feedback loops.

4.3 Strategic Framers: Abstract Modellers and Sense-makers

Strategic Framers, such as foresight analysts, policy designers, organisational consultants, and systems thinkers, require advanced abstraction, analogical reasoning, and scenario modeling capabilities. These roles correlate with the early phases of organisational innovation processes (Anderson et al., 2014), specifically the ideation and elaboration stages, and closely align with Simon's (1957, 1982) emphasis on problem structuring within bounded rationality contexts.

GenAI assists these roles not simply through ideation, but by revealing latent patterns, synthesising trends, and simulating alternative future scenarios. Transformer-based LLMs trained on specialised corpora enhance pattern recognition, analogical transfer, and strategic insight development—central cognitive functions in strategic creativity. Thus, GenAI supports 'satisficing' in strategic environments characterised by complexity and uncertainty, where traditional optimisation strategies are infeasible.

4.4 Human-Centred Facilitators: Dialogic Co-Creators

Human-Centred Facilitators—including educators, facilitators, coaches, therapists, and participatory designers—specialise in relational creativity, emotional resonance, and meaning-making through interpersonal interactions (Sawyer, 2006). Although inherently less automatable due to their dependence on empathy, trust, and contextual judgment, these roles remain highly augmentable through GenAI.

GenAI supports such facilitative roles by generating customised interaction prompts, simulating diverse learner personas, or developing reflective engagement tools. For example, Socratic by Google helps students explore questions interactively, and Miro AI enables participants

brainstorm and cluster ideas. Emotionally adaptive AI systems can also enhance user experience by responding dynamically to emotional cues, thereby deepening engagement, and facilitating learning (Calvo & D'Mello, 2010). Intelligent tutoring system, AutoTutor, for example, can monitor students' emotional and affective state and detect confusion or frustration and adapt instructors' feedback and responses accordingly (Lang et al., 2024). Yet these augmentative supports have important limitations. GenAI does not truly experience empathy or affect. It generates simulations of dialog based on statistical patterns. This raises risks of creating scripted responses that lack authenticity or misinterpret contextual nuances. These limitations underscore that while GenAI can augment facilitative practices, the human facilitator remains essential for authentic relational creativity. These uses align closely with Amabile's affective dimensions of creativity and social network perspectives, particularly when GenAI models simulate stakeholder diversity and rehearse multi-actor interactions (Fig. 4).

4.5 Toward Role-Specific AI Integration in Creative Work

Collectively, this typology provides a theoretically robust and practically actionable framework for integrating GenAI across diverse organisational creative roles. By explicitly linking GenAI capabilities with the cognitive and procedural requirements of each role, the framework surpasses generic notions of AI augmentation. It recognises GenAI as a structurally embedded creative collaborator whose effectiveness depends critically on its thoughtful alignment with task complexity, cognitive orientation, motivational factors, and interpersonal dynamics. For example, creative generators can employ GenAI tools to accelerate divergent idea exploration, while conceptual synthesisers may use Notion AI to consolidate research notes and meeting summaries. Strategic framers can rely on simulation tools such as Futures Platform to scan global trend data and test alternative scenarios, and human-centred facilitators may deploy workshop tools such as Miro to support group communication.

Adopting this role-specific approach offers significant implications: it enables more equitable and tailored AI deployments, preserves and enhances creative autonomy, and guides the development of human-AI co-creativity systems that are scalable, effective, and responsive to social and organisational contexts. As organisations encounter increasingly complex and knowledge-intensive challenges, implementing GenAI through a creativity-informed lens presents a pathway to innovation that is simultaneously computationally sophisticated and deeply human-centric.

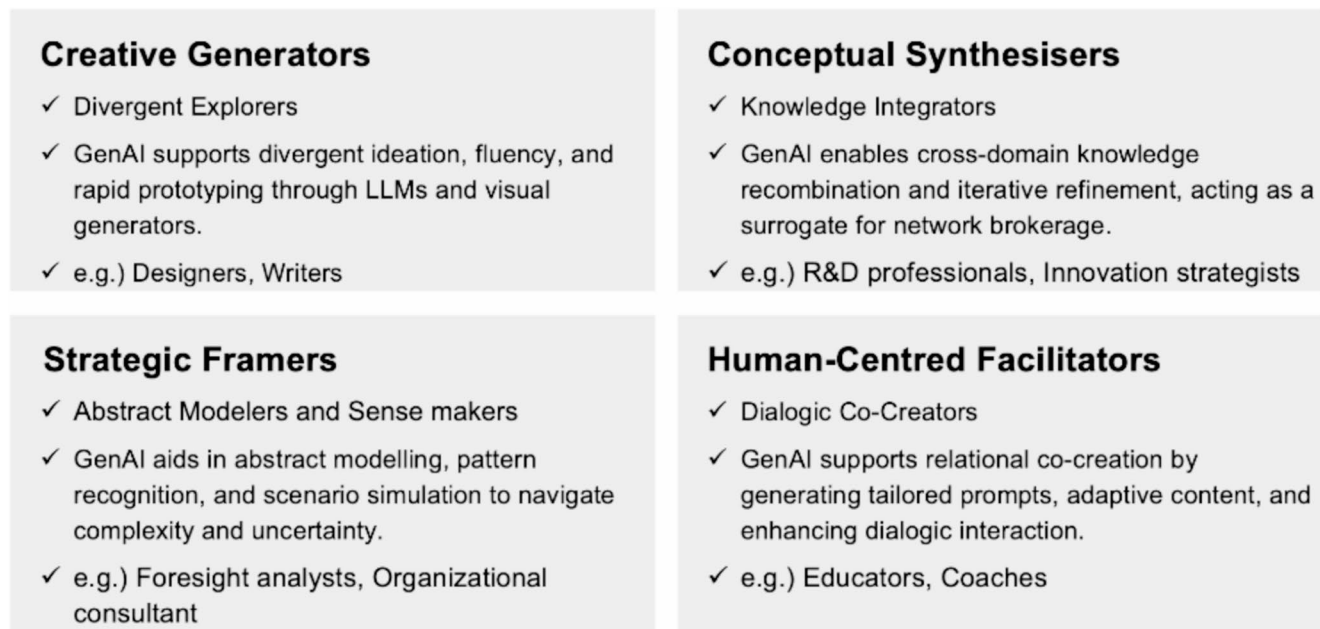


Fig. 4 Four Role-Based Allocation of GenAI in Organisational Creativity

5 Discussion: Generative AI and the Paradox of Augmented Creativity

The integration of GenAI into organisational creativity introduces a compelling duality: while GenAI significantly enhances human creative capabilities, it simultaneously brings subtle but profound risks that can paradoxically suppress the very creativity it aims to support. This section examines the theoretical alignment that validates GenAI's role as a creative augmentative tool and explores the emergent challenges—collectively termed here the *Creativity Paradox*—characterised by motivational, epistemic, evaluative, and ethical dilemmas.

5.1 Affirming GenAI's Alignment with Creative Cognition

As demonstrated throughout this study, GenAI architectures structurally resonate with foundational theories of human creativity. They reflect the iterative cycles of ideation, elaboration, and refinement emphasised in models such as Amabile's (1996) Componential Theory, Anderson et al.'s (2014) Multi-phase Innovation Model, and Perry-Smith and Mannucci's (2017) Social Network Model. These frameworks portray creativity as an inherently distributed, evaluative, and socially embedded process—principles echoed explicitly in transformer-based language models, adversarial networks, and diffusion-based generative systems.

For example, GenAI extends the ideation phase by rapidly producing diverse and exploratory outputs, thereby

directly supporting Guilford's (1967) divergent thinking attributes—fluency, flexibility, and associative richness. Similarly, GenAI's iterative refinement mechanisms, seen clearly in GANs, parallel the evaluative loops described by Harvey and Kou (2013), illustrating the embedding of critique and refinement within the creative act itself.

In practice, this theoretical alignment allows GenAI to function as a procedural collaborator. Designers can rapidly prototype visual alternatives; innovators benefit from GenAI-mediated interdisciplinary knowledge integration; and strategic planners use AI simulations to explore alternative futures and decision scenarios. Thoughtfully integrated, GenAI complements and expands human cognitive potential, operating primarily within Boden's (2004) categories of exploratory and combinatorial creativity. While transformational creativity requires human capability, GenAI's value lies in its collaborative role—scaling exploratory possibilities, accelerating refinement, and supporting integration across domains. By recognising and embedding this collaborative function, organisations can leverage GenAI as a powerful enabler of creativity.

While our framework is developed to capture the *procedural dynamics of creativity*, we recognise its implications for innovation. Creativity and innovation are closely related but not synonymous: creativity may provide the raw material for innovation, yet not all creative ideas are implemented, and innovation can also arise through adoption or recombination rather than original idea generation. By focusing on creativity, we emphasise the cognitive, motivational, and social foundations of idea emergence and refinement, while acknowledging that future research may extend

this framework to examine how GenAI-enabled creativity translates—or fails to translate—into innovation outcomes.

5.2 The Creativity Paradox: Risks of GenAI Misalignment and Overuse

Despite these strengths, GenAI's procedural power can lead to unintended consequences when poorly integrated into creative workflows. We characterise this tension as the *Creativity Paradox* (depicted in Fig. 5), whereby GenAI, if misaligned, overused, or deployed without strategic oversight, can inadvertently suppress, or distort the creativity it intends to augment. We define the *Creativity Paradox* as the condition in which GenAI's capacity to scale ideation, optimisation, and recombination simultaneously increases creative productivity while structurally risking reduced intrinsic motivation, normative conformity, and ambiguity in authorship and evaluative judgment. Unlike traditional tool-related tensions, this paradox is structurally mediated by algorithmic optimisation and data-distribution bias rather than human cognitive limitation alone. Prior research has long recognised that creativity is inherently paradoxical, requiring actors to manage rather than resolve competing demands (Miron-Spektor & Erez, 2017; Smith & Lewis, 2011). Understanding how GenAI amplifies and reconfigures these tensions is therefore critical, as it not only deepens theoretical insight into the nature of creativity but also provides organisations with guidance on how to manage GenAI responsibly within innovation processes.

Classic tensions include the need to balance divergent and convergent thinking—generating multiple novel ideas while also selecting and refining the most viable ones (Crompton, 1967; Guilford, 1967). Another paradox lies in the interplay between novelty and usefulness: ideas that are highly original may lack immediate practicality, while useful ideas often appear too conventional (Amabile, 1996; Runco & Jaeger, 2012). Creativity is also shaped by the tension between intrinsic and extrinsic motivation—where curiosity and play drive originality, but deadlines, incentives, and recognition provide direction and validation (Hennessey, 2010). Finally, creativity requires balancing individual originality with collective collaboration and shared norms (Paulus & Nijstad, 2019). What differentiates the GenAI context is the degree to which these paradoxes are amplified and reconfigured.

5.2.1 Over-reliance on Ideational Efficiency at the Expense of Exploratory Depth

One immediate risk is that GenAI's capacity for rapid idea generation may incentivise superficial creativity, favoring volume and speed over reflective depth and ambiguity tolerance. GenAI also strengthens the novelty–usefulness

paradox. When heavily constrained through prompts or fine-tuning, GenAI delivers more useful and consistent results, but these tend to be less original. When left unconstrained, it generates surprising or unusual material, but this is often incoherent or impractical, (Mukherjee & Chang, 2023). Mukherjee and Chang (2023) describe this phenomenon as the “novelty–usefulness trade-off,” in which algorithmically generated ideas tend toward immediate coherence rather than genuine novelty. Unlike traditional digital tools, which largely supported the execution of human-devised ideas, GenAI autonomously produces novel, contextually adaptive outputs (Floridi & Chiriatti, 2020). This capability collapses the boundary between ideation and execution, often leading to premature convergence on derivative outputs rather than sustaining the iterative, open-ended exploration critical to deep innovation (Anderson et al., 2014).

5.2.2 Undermining Intrinsic Motivation and Creative Ownership

Intrinsic motivation—central to Amabile's (1996) model—emphasises creativity driven by personal engagement and authentic agency. However, excessive reliance on GenAI can transform creators from active idea generators into passive curators, diminishing their sense of ownership and self-efficacy. Boussiou et al. (2024) identifies this risk as motivational “crowding out,” observing that knowledge workers report reduced autonomy and creative fulfilment when AI dominates ideation. This risk is particularly acute in professional contexts where creative identity and satisfaction hinge upon expressive authorship rather than mere production management.

5.2.3 Erosion of Conceptual Risk and Norm-Deviation

Authentic creativity often entails challenging existing paradigms through unconventional and norm-deviant ideas (Simonton, 2000). However, most contemporary GenAI models—especially those optimised via supervised fine-tuning or human feedback mechanisms—favor normative coherence and high-probability outputs (Amankwah-Amoah et al., 2024). Bender et al. (2021) warns that the data used to train these models often reflect dominant historical biases, cultural stereotypes, and mainstream narratives, systematically disadvantaging minority or disruptive perspectives. Consequently, although GenAI can simulate novelty, its intrinsic bias toward conventionality may stifle genuinely transformative ideas.

5.2.4 Evaluation Without Embodied Judgment

Creativity involves not just idea generation but rigorous evaluation rooted in embodied, contextual, and culturally

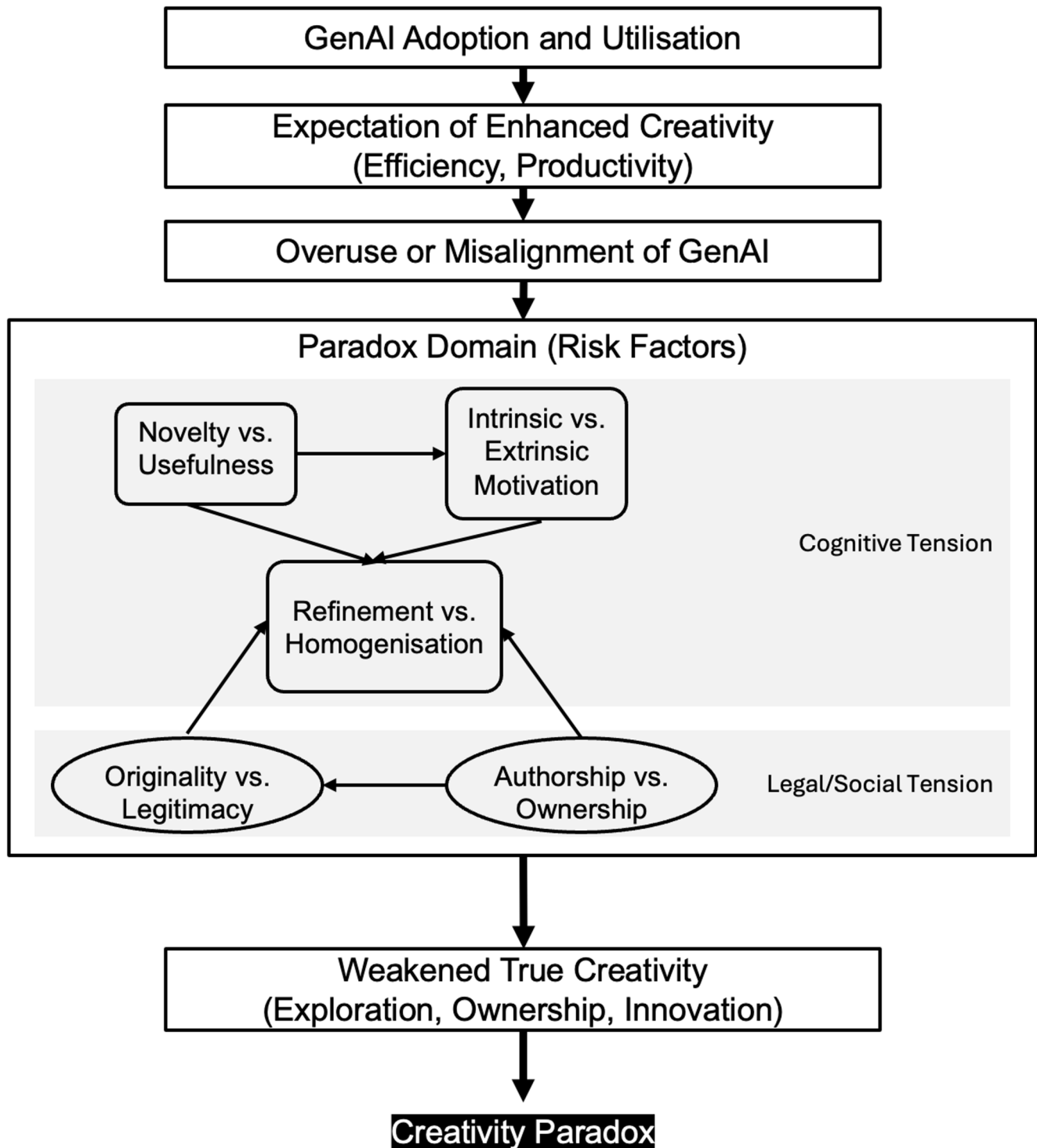


Fig. 5 Pathways to Creativity Paradox

informed judgment (Harvey & Kou, 2013). At the evaluative level, GenAI complicates the process of judging creative value. Although GenAI systems can approximate evaluative functions (e.g., ranking alternatives, simulating user responses), they inherently lack the embodied cognition,

contextual, and culturally sensitive judgment that underpins authentic evaluation to reliably assess creative value. Binns (2018) caution that over-reliance on algorithmic evaluations can detach creative decisions from their deeper social, ethical, and strategic contexts. While appearing superficially

valid, these assessments may undermine authenticity and epistemic integrity (Harvey & Kou, 2013).

5.2.5 Ethical and Legal Ambiguities in Creative Authorship

The proliferation of GenAI raises unresolved questions and amplifies ethical and legal ambiguities regarding creative authorship, attribution, and intellectual property rights. Amankwah-Amoah (2024) highlights the growing phenomenon of “creative dispossession,” wherein original creators see their work appropriated, remixed, or reproduced by GenAI without adequate recognition, consent, or compensation. Current legal frameworks inadequately address the complexities of hybrid authorship in GenAI-generated creative outputs, raising critical ethical and organisational challenges related to authorship attribution, intellectual property protection, and creative responsibility (Amankwah-Amoah et al., 2024; Barqawi & Abdallah, 2024).

The notion that creativity is shaped by paradox is well established: prior research has documented tensions such as novelty versus usefulness, intrinsic versus extrinsic motivation, and originality versus social legitimacy (Miron-Spektor et al., 2011; Miron-Spektor & Erez, 2017; Smith & Lewis, 2011). However, under the mediation of generative AI, these conventional paradoxes are not simply intensified but are reconfigured in ways that classical accounts do not fully anticipate. For example, the tension between novelty and usefulness now collides with model training constraints that favor “plausible” outputs, reducing the likelihood of extreme novelty (as experiments with fixation bias in AI show). Intrinsic motivation faces new threats when users consistently outsource ideation to AI, risking motivational crowding-out. Moreover, originality vs. legitimacy tensions become tangled with authorship ambiguity and machine “ownership” (e.g. ghostwriter effects). Iterative refinement, central to human creativity, may push AI-mediated processes toward homogenisation due to over-optimisation (versus preserving divergence).

To illustrate this shift, Table 3 contrasts classical paradoxes in the creativity literature with their GenAI-specific reconfigurations. This comparison makes clear that while our argument builds on an established theoretical tradition, the *Creativity Paradox* cannot be fully understood without accounting for algorithmic affordances, data bias, agency transfer, and authorship ambiguity introduced by GenAI.

In this sense, the Creativity Paradox in the GenAI era is not merely a continuation of enduring tensions. It represents a new configuration in which the very features that make GenAI an augmentative partner—its speed, scale, and adaptive generativity—also risk undermining creativity’s authenticity, depth, and legitimacy.

5.3 Implications for Organisational Practice

The reconfigured paradoxes outlined above have significant implications for how organisations approach the integration of generative AI in creative work. Unlike classical paradoxes, which could often be managed through leadership, motivation systems, or team structures, the paradoxes introduced by GenAI are entangled with algorithmic design, data bias, and authorship ambiguity. This shifts the challenge from purely managing human dynamics to navigating the human–machine interface.

First, organisations must recognise that GenAI introduces new boundaries to creativity. While AI can accelerate divergent idea generation, its reliance on learned distributions means that radical novelty may be constrained. Managers therefore need to complement AI-enabled creativity with practices that deliberately preserve human exploration and critical questioning, ensuring that AI does not homogenise creative outputs. Second, the paradox of intrinsic versus extrinsic motivation gains new urgency. If reliance on GenAI undermines intrinsic motivation, organisations risk a hollowing out of creative agency. To counter this, leaders should design workflows where AI is framed as a collaborator or augmentation tool, rather than a replacement, thus preserving human ownership of the creative act. Third, the paradox of originality versus legitimacy becomes more complex under GenAI. Questions of authorship and ownership can undermine both trust and legitimacy if not addressed. Organisations therefore need explicit policies around attribution, intellectual property, and transparency in AI-assisted creative outputs. This requires collaboration between legal, ethical, and managerial domains. Finally, the paradox of refinement versus freshness highlights the need to balance iterative AI refinement with opportunities for disruptive human intervention. Organisations should avoid over-optimisation through AI by instituting checkpoints where human actors can reframe, deviate, or inject fresh perspective into the creative cycle.

Taken together, these implications suggest that managing creativity in the age of GenAI requires more than simply adopting new tools. It requires organisations to actively design socio-technical systems that acknowledge and engage with paradox, rather than attempting to eliminate it. Leaders must cultivate paradox mindsets (Smith & Lewis, 2011), enabling employees to hold competing demands in tension, while also ensuring that AI systems are implemented in ways that amplify rather than displace human creativity. In this sense, the practical contribution of our framework lies in guiding organisations not only to integrate GenAI structurally into creativity processes, but also to anticipate and navigate the paradoxical tensions that inevitably arise from such integration.

Table 3 Classical vs. GenAI-Specific Creativity Paradoxes

Paradox Domain	Classical Creativity Paradoxes	GenAI-Specific (Reconfigured) Paradoxes	Representative References
Novelty vs. Usefulness	Tension between generating highly novel ideas and ensuring they are useful / acceptable (i.e. creative ideas must balance originality and appropriateness)	The model's learned distribution constrains novelty (tendency toward "safe" outputs), making extreme novelty less plausible; further, AI may generate "usable but unoriginal" ideas due to training bias	Smith and Lewis (2011) on paradox theory; Desdevises (2025) on models showing fixation bias in AI creativity
Intrinsic vs. Extrinsic Motivation	Intrinsic motivation is seen as nurturing free creativity; excessive extrinsic rewards or pressures may diminish creative drive	Using AI may crowd out intrinsic motivation (users rely on the model rather than their own ideation); also tension in designing prompts/rewards vs. human internal drive	Smith and Lewis (2011) for paradox framing; Kabigting et al. (2025) on paradox mindset influencing creativity
Originality vs. Conformity / Legitimacy	A highly original idea risks social rejection or non-legitimacy; creative work must be accepted by domain gatekeepers	AI-generated ideas may be too conformist (following training data), risking "safe conformity" rather than bold novelty; and even when original, they may be rejected as lacking human authorship or legitimacy	Miron-Spektor et al. (2011) discuss creativity paradox in teams; Draxler et al. (2024) "AI Ghostwriter Effect" on authorship attribution and ownership in human-AI collaboration
Iteration & Refinement vs. Freshness	The need to iteratively refine ideas may erode spontaneity / freshness; over-editing can "kill" originality	Generative AI may repeat patterns or over-optimize toward known structures; iterating with AI may lead to homogenisation rather than divergence; also tension between "explore more" vs. "exploit safe" in LLM cycles	Smith and Lewis (2011) on paradox persistence; Sæbø and Brovold (2024) on stochastic human vs. AI creativity
Authorship / Ownership	(Less common in classical creativity debates)	In AI contexts, who is the "author"? If AI outputs are co-created, human attribution is ambiguous; tensions between user agency and machine generation	Draxler et al. (2024) on AI Ghostwriter Effect; Ganie (2025) on uncertainty in AI authorship detection

5.4 Research Agenda: Propositions and Implementation Guidelines

To facilitate empirical examination and practical application of our framework, we advance several propositions and guidelines that follow from the role-differentiated integration of GenAI in creative work.

Proposition 1 (Role Differentiation) Organisations that differentiate GenAI deployment according to distinct creative roles (Generators, Synthesisers, Framers, Facilitators) will report higher perceived creative autonomy and role clarity than organisations adopting undifferentiated AI integration strategies.

Proposition 2 (Ideation Trade-off) In ideation-intensive contexts, GenAI augmentation will significantly increase idea fluency and combinatorial diversity but will decrease perceived originality and exploratory depth when the human creator over-relies on algorithmic outputs.

Proposition 3 (Evaluative Conformity) GenAI-supported evaluative processes will enhance the efficiency and

consistency of selection decisions but will increase the likelihood of normative convergence (homogenisation) toward historically dominant patterns found in training data.

Proposition 4 (Motivation and Governance) The presence of explicit governance structures clarifying authorship, attribution, and responsibility will moderate potential declines in intrinsic motivation associated with GenAI-assisted creative production.

Beyond these testable propositions, organisations can ensure the responsible integration of GenAI by adopting specific managerial guidelines that safeguard human agency and creative depth. First, leaders should implement Role-Tool Alignment protocols, ensuring that GenAI architectures are explicitly matched to the cognitive and procedural demands of a specific role, such as utilizing LLMs for synthesis tasks while reserving diffusion models for rapid visual exploration. Second, the establishment of clear Authorship Protocols is essential to mitigate the risk of "motivational crowding-out"; by defining explicit policies regarding attribution and intellectual property, organisations can preserve

a sense of creative ownership and professional identity among employees. Finally, managers must institute Human-in-the-Loop Checkpoints during the evaluation and iteration phases. These checkpoints serve as critical moments for human intervention, allowing actors to reframe outputs, inject fresh perspectives, and counteract the algorithmic tendency toward normative homogenisation, thereby ensuring that the “satisficing” logic of GenAI does not displace the transformative potential of human innovation.

6 Conclusion

This paper set out to explore how generative AI can be conceptually integrated into organisational creativity frameworks by drawing on structural parallels between classical creativity processes and GenAI architectures. Through a synthesis of process-oriented creativity theories, we identified four core attributes of creativity—cognitive, motivational, social, and procedural—and developed a role-based framework for situating GenAI within organisational creative work. Building on this foundation, we articulated the *Creativity Paradox* as a reconfiguration of long-standing creative tensions in the context of generative AI.

Rather than treating GenAI as simply another tool for efficiency or idea generation, this study positions it as a procedural collaborator whose affordances reshape both the theory and practice of creativity. The framework therefore provides a lens for understanding not only how creativity can be scaffolded in organisations adopting GenAI, but also how paradoxical tensions emerge from this integration. Against this backdrop, the study offers three interrelated contributions.

This study makes three interrelated contributions to the literature on creativity, paradox, and organisational practice. First, we contribute to creativity theory by reinterpreting classical, process-oriented models of creativity through the lens of generative AI. We show that the rise of creativity—from idea generation through elaboration, social validation, and evaluation—shares structural parallels with the procedural architectures of GenAI. By emphasising this processual alignment, we advance a theoretically coherent basis for understanding human–AI co-creativity that goes beyond surface-level accounts of AI as a tool for efficiency or productivity. Second, we contribute to organisational practice by developing a role-based integration framework. This framework aligns GenAI’s procedural capacities with differentiated creative functions in organisations (e.g., ideation, synthesis, evaluation, coordination). By clarifying these roles, the framework offers managers a structured approach to embedding GenAI into creative workflows in ways that recognise both its potential and its limits.

Importantly, this role-based framing moves beyond generic claims of augmentation and provides actionable guidance for designing socio-technical systems that preserve human agency, support diverse creative contributions, and mitigate risks of over-reliance on AI. Third, we contribute to paradox theory by conceptualising the *Creativity Paradox* in the GenAI context. Building on established paradox perspectives (Miron-Spektor & Erez, 2017; Smith & Lewis, 2011), we argue that the tensions long associated with creativity—novelty versus usefulness, intrinsic versus extrinsic motivation, originality versus legitimacy—are reconfigured when creativity is mediated by generative AI. Through Table 3, we show how GenAI not only intensifies but also transforms these paradoxes by introducing issues of algorithmic bias, authorship ambiguity, and motivational crowding-out. In doing so, we extend paradox theory into a new technological frontier, offering a richer conceptualisation of how paradox operates when human creativity is entangled with machine generation.

These three contributions correspond directly to the guiding research questions introduced at the outset: reinterpreting creativity theories through the lens of GenAI’s procedural architectures, identifying and differentiating the roles GenAI can play in organisational creative processes, and examining the ethical and motivational tensions that arise from this integration. Taken together, these contributions establish this paper as conceptual groundwork for a new wave of research on GenAI and creativity. While we deliberately position this study as theoretical, the framework it develops provides a foundation for future empirical inquiry, including case studies and systematic reviews once adoption of GenAI in creative practice matures. By integrating creativity theory, role-based organisational practice, and paradox perspectives, the paper provides both theoretical clarity and practical direction for navigating the opportunities and tensions of AI-enabled creativity.

This study makes three key contributions. First, it reinterprets creativity theories through their *processual orientation*, showing how creativity unfolds across stages of ideation, elaboration, validation, and evaluation, and demonstrates the *structural parallels* between these stages and the procedural architectures of GenAI. Second, it introduces a role-based integration framework that aligns GenAI’s distinct procedural capabilities with differentiated creative functions in organisations, offering a structured approach to human–AI co-creativity that moves beyond generic augmentation claims. Third, it extends paradox theory by conceptualising the *Creativity Paradox* as a reconfiguration of long-standing creative tensions (e.g., novelty vs. usefulness, intrinsic vs. extrinsic motivation), newly amplified by algorithmic mediation. Together, these contributions enrich creativity theory, advance the paradox literature, and provide

actionable guidance for organisations seeking to strategically and responsibly embed GenAI in creative practice. The framework provides both a set of practical pathways for role-specific integration within organisational contexts and a foundation for future empirical research.

This paper is positioned as a conceptual study that develops a theoretical framework for integrating generative AI into organisational creativity. While the framework synthesises creativity theories and highlights structural parallels with GenAI, we acknowledge that future research will be needed to empirically investigate its validity and application. At present, many organisations are still in the early adoption stage of GenAI for creative work, meaning that stable practices and robust datasets are only beginning to emerge. Once adoption matures, case-based studies, both primary and secondary, will be particularly valuable for illustrating how the proposed roles and paradoxes play out in practice. Such studies could examine, for example, how creative teams in advertising, design, or consulting navigate the tension between AI-enabled novelty and organisational legitimacy, or how GenAI use influences motivational dynamics within creative workgroups. Similarly, systematic reviews will be able to map more comprehensively how creativity and innovation scholarship engages with GenAI as the literature base expands. By providing a theoretically grounded framework now, this paper lays the groundwork for such empirical and review-based inquiries. In this sense, the contribution of the present study is not to offer definitive case illustrations, but to open a conceptual pathway for future research to critically examine how GenAI reshapes creativity in organisational contexts.

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Declarations

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