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Creativity in the Age of Artificial Intelligence: A Hybrid Human–AI Co-Creation Framework

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Abstrak

The rapid advancement of generative artificial intelligence (AI) has transformed creative work by shifting creativity from an individual cognitive activity to a hybrid, interactional process involving both human and algorithmic agents. Despite extensive research on creativity and computational systems, existing theories remain fragmented, largely treating human and machine creativity as separate domains and failing to capture their dynamic integration. This study addresses this theoretical gap by reconceptualizing creativity as a distributed, iterative, and hybrid process emerging from human–AI co-creation. Adopting a conceptual and integrative analytical approach, the study synthesizes insights from creativity theory, computational creativity, human–AI interaction, and digital innovation literature to develop a unified theoretical framework. It further introduces a process-oriented Human–AI Creative Co-Creation Model that explains how creative outcomes emerge through stages of intent formation, generative expansion, evaluation, and iterative refinement. The study contributes to theory by redefining creativity as a system-level phenomenon characterized by hybrid agency and co-evolutionary interaction, while offering implications for future empirical research on measuring and managing creativity in AI-mediated environments.

Keywords

human–AI co-creation; hybrid creativity; distributed creativity; generative artificial intelligence; computational creativity; digital innovation

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1. Introduction

The rapid advancement of generative artificial intelligence (AI) has fundamentally transformed the landscape of creative work, shifting the role of technology from a passive instrument to an active participant in the creative process. Unlike earlier digital systems that primarily enhanced efficiency or supported execution, contemporary AI systems—particularly large language models and generative design tools—are capable of producing novel content, suggesting ideas, and engaging in iterative collaboration with human users (Dwivedi *et al.*, 2023; Nah *et al.*, 2023; Doshi & Hauser, 2024). This transformation reflects not merely a technological improvement but a structural shift in how creativity is enacted, distributed, and evaluated.

Emerging evidence suggests that generative AI does not simply accelerate creative processes but actively reshapes cognitive pathways by externalizing associative thinking and redistributing cognitive effort between human and machine agents (Chen & Chan, 2024; Zhou & Lee, 2024). In this context, creativity becomes increasingly mediated by algorithmic systems that expand ideation spaces while simultaneously influencing the direction and structure of creative exploration. As a result, the boundaries between human cognition and computational generation become progressively blurred, raising critical questions about the nature, ownership, and locus of creative agency.

Traditional theories of creativity have predominantly conceptualized creativity as an inherently human capability grounded in cognitive processes such as divergent thinking, associative reasoning, and domain-specific expertise (Guilford, 1950; Mednick, 1962; Runco & Jaeger, 2012). Foundational frameworks, including the componential theory of creativity (Amabile, 1983) and the investment theory of creativity (Sternberg & Lubart, 1996), emphasize individual-level attributes such as intrinsic motivation, knowledge, and cognitive style. Even more integrative perspectives, including cultural and distributed approaches, continue to position humans as the primary locus of creative generation (Glăveanu, 2014; Hennessey & Amabile, 2010). While these perspectives have significantly advanced the understanding of creativity, they offer limited explanatory power in contexts where non-human agents actively participate in generating creative outputs.

Parallel to developments in creativity research, the field of computational creativity has examined the extent to which machines can exhibit creative behavior, generate artifacts, and simulate aspects of human creativity (Boden, 1998; Colton & Wiggins, 2012; Jordanous, 2012). Advances in machine learning and generative models have significantly enhanced these capabilities, enabling systems to produce outputs that meet conventional criteria of creativity, such as novelty and usefulness (Hertzmann, 2018; Elgammal *et al.*, 2017). More recent work demonstrates that large language models can exhibit both individual and collective forms of creativity comparable to human performance in certain tasks (Lu *et al.*, 2023; Kang & Zhang, 2023). However, much of this literature treats machine creativity as an isolated phenomenon, focusing on whether machines can be considered creative rather than examining how creativity emerges through interaction with human agents.

Recent advances in human–AI collaboration challenge this dichotomy by introducing the concept of hybrid or collaborative intelligence, where humans and AI systems jointly contribute to problem-solving and creative production (Dellermann *et al.*, 2019; Seeber *et al.*, 2020; Wilson & Daugherty, 2018). In such contexts, AI is no longer a passive tool but a co-creative partner capable of shaping ideation, expanding the solution space, and influencing decision-making processes (Rezwana & Maher, 2023; Yuan *et al.*, 2022). Empirical evidence suggests that generative AI enhances individual creativity while simultaneously reducing the diversity of collective outputs, indicating complex trade-offs within co-creative systems (Doshi & Hauser, 2024). These findings highlight that creativity increasingly emerges from iterative interactions between human cognition and algorithmic generativity rather than from isolated individual effort.

At the same time, this transformation introduces fundamental theoretical tensions that challenge existing creativity frameworks. First, the distinction between augmentation and substitution becomes blurred, as AI systems both enhance and potentially replace human creative contributions (Raisch & Krakowski, 2021). Second, the distribution of agency becomes increasingly complex, as algorithmic systems influence human decision-making through suggestion, filtering, and generative outputs (Amershi *et al.*, 2019; Seeber *et al.*, 2020). Third, the notion of originality is contested, given that AI-generated outputs are based on large-scale recombination of existing data rather than intentional innovation (Floridi & Chiriatti, 2020; Epstein *et al.*, 2023). Finally, creativity shifts from an individual attribute to a distributed phenomenon emerging from interactions among humans, machines, and socio-technical systems (Faraj *et al.*, 2018; Yoo *et al.*, 2012).

Despite the growing body of research on AI and creativity, a critical gap remains in conceptualizing creativity as a fundamentally hybrid process. Existing studies tend to adopt fragmented perspectives, examining either human creativity or machine creativity in isolation, thereby overlooking the systemic interdependencies that characterize human–AI co-creation (Nambisan *et al.*, 2019; Li *et al.*, 2024). Moreover, the implications of hybrid creativity for the broader creative economy—where value is increasingly generated through symbolic, cultural, and experiential outputs—remain underexplored (Florida, 2002; Howkins, 2001; Potts, 2011).

Addressing this gap, this paper aims to reconceptualize creativity in the context of human–AI collaboration by developing a theoretical framework that captures the dynamic, iterative, and distributed nature of co-creative processes. Specifically, this study seeks to answer two research questions: (1) How should creativity be defined in the context of human–AI co-creation? and (2) How do interactions between human cognition and algorithmic generativity reshape the nature of creative processes and outcomes?

The contributions of this paper are threefold. First, it critically examines the limitations of existing creativity theories in accounting for AI-mediated creative processes. Second, it integrates insights from creativity research, computational creativity, and human–AI interaction to propose a redefined conceptualization of creativity as a hybrid phenomenon. Third, it introduces a process-oriented model of human–AI co-creation that explains how creative outputs emerge through iterative interactions between human and artificial agents. By doing so, this study advances a more comprehensive and future-oriented understanding of creativity in the age of artificial intelligence and provides a foundation for subsequent empirical and theoretical development.

2. Theoretical Foundations

2.1 Classical Theories of Creativity: Individual-Centric Foundations

The study of creativity has historically been rooted in psychological and cognitive traditions that conceptualize creativity as an individual capability. Early foundational work by Joy Paul Guilford (1950) positioned creativity as a function of divergent thinking, emphasizing fluency, flexibility, originality, and elaboration as core dimensions. This perspective was further extended by associative theories, which framed creativity as the ability to connect remote ideas in novel ways (Mednick, 1962). These early frameworks established creativity as a cognitive process grounded in mental operations and individual problem-solving abilities.

Subsequent theoretical developments expanded this perspective by incorporating motivational and contextual factors. The componential theory of creativity highlights the interaction between domain-relevant skills, creativity-relevant processes, and intrinsic motivation in generating creative outcomes (Amabile, 1983). Similarly, the investment theory of creativity conceptualizes creative individuals as those who pursue unconventional ideas that may initially be undervalued but later gain recognition (Sternberg & Lubart, 1996). These frameworks reinforce the notion that creativity is fundamentally driven by individual-level characteristics.

More recent perspectives have attempted to broaden the scope of creativity by integrating social and cultural dimensions. Cultural and systems-based approaches argue that creativity emerges through interactions between individuals, domains, and social fields, rather than solely from isolated cognition (Glăveanu, 2014; Hennessey & Amabile, 2010). In parallel, models such as the Four-C framework distinguish between different levels of creativity, ranging from everyday creativity (mini-c) to eminent creativity (Big-C) (Kaufman & Beghetto, 2009). Despite these advancements, a common assumption persists: humans remain the primary agents of creative production.

Critically, even these expanded frameworks provide limited explanatory power in contexts where non-human agents actively participate in generating creative outputs. The increasing integration of AI into creative processes challenges the anthropocentric bias embedded in classical theories. While extended cognition perspectives suggest that tools can become part of cognitive systems, traditional creativity theories have not fully accounted for intelligent systems that actively generate, transform, and influence ideas. As a result, classical frameworks, while foundational, require theoretical extension to remain relevant in AI-mediated environments.

2.2 Computational Creativity: From Simulation to Generative Systems

Parallel to psychological theories, the field of computational creativity has explored whether machines can exhibit creative behavior and produce outputs that meet established criteria of creativity. Early work by Margaret Boden (1998) categorized creativity into combinational, exploratory, and transformational forms, providing a foundational framework for understanding how computational systems generate novelty. This perspective reframed creativity as a process that could, in principle, be simulated through algorithmic operations.

Subsequent research advanced this field by developing formal criteria for evaluating machine creativity, including novelty, value, and surprise (Ritchie, 2007; Jordanous, 2012). Frameworks proposed by Colton and Wiggins (2012) emphasized the importance of evaluating both the creative process and the resulting artifact, suggesting that systems could be considered creative if they demonstrate autonomy, intentionality, and evaluative capabilities. These developments marked a shift from philosophical debates about machine creativity toward more operational and measurable approaches.

Recent advancements in machine learning, particularly deep learning and generative models, have significantly expanded the capabilities of computational systems. Technologies such as generative adversarial networks, diffusion models, and large language models enable AI systems to produce complex outputs across domains including visual art, music, and text (Elgammal *et al.*, 2017; Brown *et al.*, 2020). Empirical findings indicate that such systems can achieve levels of creativity comparable to human performance in certain tasks, both individually and collectively (Lu *et al.*, 2023; Kang & Zhang, 2023).

However, despite these advancements, computational creativity research has largely treated machine creativity as an independent phenomenon. The primary focus has been on whether machines can be considered creative rather than on how creativity emerges through interaction with human users. This limitation becomes increasingly problematic in contemporary contexts, where AI systems are rarely used in isolation but are embedded within interactive workflows involving continuous human input, interpretation, and evaluation. Consequently, computational creativity provides important insights into generative mechanisms but remains insufficient for explaining hybrid creative processes.

2.3 Human–AI Collaboration: Toward Hybrid Intelligence

Recent developments in artificial intelligence have shifted the focus from automation toward collaboration, giving rise to the concept of hybrid intelligence. Rather than replacing human capabilities, AI systems are increasingly designed to complement and extend human cognition (Dellermann *et al.*, 2019; Wilson & Daugherty, 2018). This perspective reflects a broader transformation in digital innovation research, where value is generated through the integration of human and technological capabilities rather than through substitution alone.

In human–AI collaborative settings, AI systems function as active participants in creative processes by generating alternatives, identifying patterns, and expanding the space of possible solutions (Rezwana & Maher, 2023; Yuan *et al.*, 2022). Human actors, in turn, contribute contextual understanding, interpretive judgment, and evaluative filtering. This complementarity forms the foundation of hybrid intelligence systems, where optimal outcomes emerge from the interaction between human intuition and machine computation.

Empirical research demonstrates that human–AI collaboration can enhance creative performance by increasing idea diversity and accelerating ideation processes (Doshi & Hauser, 2024; Chen & Chan, 2024). At the same time, it introduces new complexities, including shifts in cognitive effort, changes in authorship perception, and the risk of over-reliance on algorithmic suggestions (Amershi *et al.*, 2019; Seeber *et al.*, 2020). These dynamics highlight that collaboration with AI is not neutral but actively reshapes how creativity is performed and experienced.

Importantly, human–AI collaboration challenges traditional distinctions between tools and agents. As AI systems become more autonomous and generative, they exhibit characteristics traditionally associated with creative actors. This transformation necessitates a reconceptualization of agency, where creativity is no longer attributed solely to human intention but emerges from negotiated interactions between human and artificial agents.

2.4 Creativity as a Distributed and Socio-Technical Process

Building on both creativity theory and human–AI collaboration, emerging perspectives conceptualize creativity as a distributed process embedded within socio-technical systems. This view aligns with research in digital innovation and organizational theory, which emphasizes the interdependence between technological infrastructures and social practices in shaping outcomes (Faraj *et al.*, 2018; Yoo *et al.*, 2012).

From this perspective, creativity is not confined to individual cognition but emerges from interactions among multiple agents, including humans, algorithms, platforms, and data infrastructures. Digital technologies act as mediators that influence how ideas are generated, transformed, and evaluated. Importantly, this mediation extends beyond functional support to actively shaping the direction and structure of creative processes.

The concept of distributed creativity (Glăveanu, 2014) becomes particularly salient in this context, as it highlights how creative outcomes emerge from networks of interaction rather than from isolated individuals. In human–AI systems, this distributed nature is further amplified by the role of algorithmic systems, which introduce new forms of generativity, constraint, and influence.

Moreover, digital platforms play a critical role in enabling and structuring distributed creativity. Platform-based ecosystems facilitate large-scale collaboration and real-time interaction, allowing creative processes to unfold across geographically dispersed and technologically mediated environments. This platformization of creativity introduces new dynamics of coordination, control, and value creation, further reinforcing the need to conceptualize creativity as a socio-technical phenomenon.

2.5 Toward a Hybrid Understanding of Creativity

Synthesizing the above perspectives reveals a fundamental gap in existing theories. Classical creativity research emphasizes human cognition, while computational creativity focuses on machine capabilities. Human–AI collaboration research bridges these domains but often lacks a unified conceptual framework that captures the interactive and co-creative nature of hybrid systems.

Human–AI co-creation introduces a hybrid mode of creativity that integrates human intuition, contextual reasoning, and symbolic interpretation with algorithmic generativity, scalability, and pattern recognition. This integration challenges traditional definitions of creativity and calls for a reconceptualization that accounts for both human and artificial contributions.

Furthermore, this shift has significant implications for broader domains such as innovation management, digital entrepreneurship, and the creative economy. As creativity becomes increasingly mediated by AI, value is generated not only through individual ingenuity but through the effective orchestration of human–AI interaction (Nambisan *et al.*, 2017; Raisch & Krakowski, 2021). This perspective aligns with co-creation theories, where value emerges from interaction rather than from isolated production.

In light of these developments, creativity must be understood as a dynamic, relational, and hybrid phenomenon. This requires moving beyond dichotomous perspectives that separate human and machine creativity and toward integrative frameworks that capture the complexity of co-creative systems. The following section builds on this foundation by identifying key conceptual tensions that define the nature of creativity in human–AI collaboration.

To synthesize the diverse theoretical perspectives discussed, Table 1 provides an integrative overview of the key theoretical streams that inform the reconceptualization of creativity in human–AI contexts. The table highlights how each perspective contributes distinct assumptions, analytical focus, and limitations, thereby establishing the need for a hybrid and interactional framework.

Table 1. Theoretical Streams Informing Human–AI Hybrid Creativity

Theoretical Stream	Core Assumptions	Analytical Focus	Key Contributions	Limitations in AI Context	Theoretical Stream
Classical Creativity Theory	Creativity is an individual cognitive capability rooted in human traits and motivation	Divergent thinking, intrinsic motivation, domain expertise	Establishes foundational understanding of creativity as novelty and usefulness	Anthropocentric; does not account for non-human agents	Classical Creativity Theory
Computational Creativity	Creativity can be simulated through algorithmic and generative processes	Machine-generated outputs, novelty, and evaluation criteria	Demonstrates that AI can produce creative artifacts	Treats machine creativity as isolated from human interaction	Computational Creativity
Human–AI Collaboration	Creativity emerges through collaboration between humans and intelligent systems	Interaction between human judgment and AI-generated suggestions	Introduces hybrid intelligence and co-creative dynamics	Lacks unified framework for explaining creativity as a process	Human–AI Collaboration

Theoretical Stream	Core Assumptions	Analytical Focus	Key Contributions	Limitations in AI Context	Theoretical Stream
Distributed Creativity	Creativity is a socio-technical phenomenon emerging from interactions among multiple actors	Networks, systems, and contextual influences	Expands creativity beyond individuals to systems and environments	Does not fully incorporate algorithmic agency as an active contributor	Distributed Creativity
Hybrid Creativity (Emerging Perspective)	Creativity is a dynamic, iterative, and hybrid process involving human and AI co-evolution	Interaction, feedback loops, and co-creation processes	Integrates human cognition and AI generativity into a unified framework	Still underdeveloped and requires empirical validation	Hybrid Creativity (Emerging Perspective)

Source: Author's synthesis based on creativity theory, computational creativity, human–AI collaboration, and socio-technical perspectives.

Table 1 illustrates that existing theories provide partial and fragmented explanations of creativity when considered in isolation. Classical approaches emphasize human cognition, while computational perspectives focus on machine generativity. Human–AI collaboration introduces interaction but lacks conceptual integration, and distributed creativity expands the system view without fully incorporating algorithmic agency. The emerging hybrid perspective bridges these gaps by positioning creativity as a dynamic and interactional process. This synthesis underscores the necessity of moving toward an integrative framework that captures the co-evolutionary nature of human–AI creativity, which is further elaborated in the following section.

3. Conceptual Tensions in Human–AI Co-Creation

The emergence of human–AI co-creation fundamentally challenges the foundational assumptions of creativity theory by introducing a set of conceptual tensions that cannot be fully explained within existing frameworks. While prior research has largely treated creativity as either a human-centered cognitive process or a machine-driven generative capability, contemporary creative practices increasingly reflect hybrid interactions between human cognition and algorithmic systems (Dwivedi *et al.*, 2023; Li *et al.*, 2024). These interactions are not merely additive but transformative, producing new dynamics that reshape how creativity is generated, evaluated, and distributed.

Rather than viewing these tensions as contradictions to be resolved, this study conceptualizes them as constitutive dimensions of hybrid creativity—interdependent forces that define the structure and behavior of human–AI co-creative systems. Building on this perspective, four core tensions are identified: (1) augmentation versus substitution, (2) human agency versus algorithmic influence, (3) originality versus recombinative generation, and (4) individual versus distributed creativity. Together, these tensions provide an analytical foundation for reconceptualizing creativity in hybrid environments.

3.1 Augmentation versus Substitution

A central tension in human–AI co-creation concerns whether AI functions as an augmentative tool that enhances human creativity or as a substitutive agent that replaces human contribution. The augmentation perspective emphasizes that AI expands human creative capacity by accelerating ideation, increasing the diversity of alternatives, and enabling exploration beyond cognitive constraints (Dellermann *et al.*, 2019; Wilson & Daugherty, 2018). Empirical evidence supports this view, demonstrating that generative AI enhances individual creative output, particularly in tasks involving idea generation and content production (Doshi & Hauser, 2024; Chen & Chan, 2024).

However, this augmentation logic is inherently unstable. The same generative capabilities that enhance creativity can also enable AI systems to independently produce outputs that meet conventional standards of novelty and usefulness. Advances in generative models have demonstrated that AI can produce artifacts that are increasingly indistinguishable from human-created outputs (Hertzmann, 2018; Sun *et al.*, 2025). This introduces the possibility of substitution, where human creative input becomes less necessary in certain domains.

This tension reflects the broader automation–augmentation paradox, where technologies designed to enhance human capabilities simultaneously reduce the need for human involvement (Raisch & Krakowski, 2021). In creative contexts, this paradox manifests as a trade-off between efficiency and engagement. While AI enables rapid production and idea expansion, it may also reduce deep cognitive involvement, potentially leading to a decline in exploratory thinking and creative ownership.

Recent studies further suggest that reliance on AI-generated outputs may anchor users to algorithmically suggested solutions, limiting divergence and reinforcing dominant patterns (Bender *et al.*, 2021; Epstein *et al.*, 2023). Thus, augmentation and substitution are not mutually exclusive but dynamically intertwined, creating a shifting balance that depends on how AI is integrated into creative workflows.

3.2 Human Agency versus Algorithmic Influence

A second tension concerns the distribution of agency within human–AI co-creation. Classical creativity theories assume that humans are the primary agents responsible for generating, evaluating, and selecting creative ideas (Amabile, 1983; Sternberg & Lubart, 1996). In contrast, human–AI collaboration introduces algorithmic systems that actively shape these processes by generating suggestions, filtering options, and structuring the creative search space (Amershi *et al.*, 2019; Seeber *et al.*, 2020).

This shift does not eliminate human agency but transforms it. Human actors remain responsible for initiating prompts, interpreting outputs, and making final decisions. However, AI systems increasingly influence these decisions through embedded biases, probabilistic patterns, and interface design. This creates a form of algorithmic influence, where decision-making is co-shaped by human intention and machine-generated suggestions.

Importantly, this influence is often subtle and implicit. Algorithmic outputs can guide attention, frame alternatives, and shape preferences without explicit awareness, thereby redistributing agency within the interaction process. As a result, creativity becomes a negotiated outcome rather than a purely intentional act.

The concept of hybrid intelligence suggests that optimal outcomes emerge from balanced collaboration between human judgment and machine computation (Dellermann *et al.*, 2019). However, achieving this balance is inherently challenging, as increased reliance on AI may lead to cognitive offloading and reduced critical engagement (Jarrahi, 2018). Consequently, the tension between human agency and algorithmic influence highlights the need to reconceptualize creativity as a shared and dynamically negotiated process of control and contribution.

3.3 Originality versus Recombinative Generation

Originality has long been regarded as a defining criterion of creativity, typically operationalized as the production of ideas that are both novel and useful (Runco & Jaeger, 2012). Classical theories emphasize the role of divergent thinking and associative processes in generating original ideas (Guilford, 1950; Mednick, 1962). However, the emergence of generative AI challenges this notion by introducing systems that produce outputs through large-scale recombination of existing data.

From a computational perspective, creativity can be understood as the recombination and transformation of prior knowledge structures (Boden, 1998; Wiggins, 2006). Generative AI systems exemplify this process by producing outputs that reflect statistical patterns in training data while introducing variations perceived as novel. Empirical research indicates that such outputs can achieve high levels of perceived creativity, even when they are fundamentally recombinative (Doshi & Hauser, 2024; Sun *et al*., 2025).

This raises a fundamental ambiguity: if novelty is defined in terms of recombination, then AI-generated outputs qualify as creative. However, if originality requires intentionality, contextual understanding, and meaning-making, then human contribution remains indispensable. This distinction becomes particularly salient in creative domains where symbolic interpretation and cultural relevance play a central role.

Moreover, concerns have been raised regarding the potential homogenization of creative outputs, as reliance on shared datasets may lead to convergence rather than divergence in creative expression (Epstein *et al*., 2023; Floridi & Chiriatti, 2020). This suggests that AI may simultaneously expand and constrain creativity, depending on how novelty is conceptualized and evaluated.

Thus, the tension between originality and recombination reflects a deeper epistemological challenge: whether creativity should be defined by the process of generation or by the interpretation and meaning assigned to the output.

3.4 Individual Creativity versus Distributed Creativity

The final tension concerns the locus of creativity. Traditional frameworks conceptualize creativity as an attribute of individuals, emphasizing personal traits, cognitive abilities, and domain expertise (Amabile, 1983; Sternberg & Lubart, 1996). In contrast, contemporary perspectives increasingly recognize creativity as a distributed phenomenon that emerges from interactions among individuals, tools, and social contexts (Glăveanu, 2014).

Human–AI co-creation extends this perspective by introducing non-human agents as active participants in the creative process. In such systems, creativity is not located within a single actor but emerges from the interplay between human cognition, algorithmic processes, and socio-technical infrastructures (Faraj *et al*., 2018; Yoo *et al*., 2012). This distributed view aligns with knowledge-based and digital innovation theories, which emphasize recombination, interaction, and networked value creation (Nambisan *et al*., 2017).

The shift toward distributed creativity has profound implications for authorship, ownership, and value attribution. In hybrid systems, creative outputs are co-produced by multiple agents, making it increasingly difficult to assign credit to a single source. This complexity is further amplified by digital platforms, where algorithms mediate visibility, engagement, and recognition.

Furthermore, distributed creativity challenges traditional evaluation criteria that prioritize individual originality. Instead, creativity may need to be assessed at the system level, considering the effectiveness of interactions between human and AI components. This perspective aligns with co-creation theory, where value emerges from interaction rather than isolated production (Prahalad & Ramaswamy, 2004; Ramaswamy & Ozcan, 2018).

3.5 Synthesis of Conceptual Tensions

Taken together, these four tensions reveal that creativity in human–AI co-creation cannot be adequately explained through existing theoretical lenses that prioritize either human cognition or machine capability. Instead, creativity must be understood as a dynamic, relational, and hybrid phenomenon characterized by continuous negotiation between competing forces.

The tension between augmentation and substitution reflects the evolving role of AI in creative work. The tension between human agency and algorithmic influence underscores the redistribution of control within co-creative systems. The tension between originality and recombination challenges established criteria for evaluating creativity. Finally, the shift from individual to distributed creativity redefines the locus of creative activity.

Importantly, these tensions do not represent problems to be resolved but rather structural conditions that define hybrid creativity. Their coexistence creates a complex system in which creativity emerges through interaction, adaptation, and co-evolution between human and artificial agents.

By articulating these tensions, this study establishes a conceptual foundation for redefining creativity in the context of human–AI collaboration. The following section builds on this foundation to propose a revised definition of creativity that reflects its distributed, iterative, and hybrid nature.

To consolidate the conceptual tensions identified in the preceding discussion, Table 2 presents a structured synthesis of the four core tensions that define human–AI co-creation. This table clarifies the opposing dimensions, underlying dynamics, and their implications for understanding creativity as a hybrid and interactional process.

Table 2. Core Conceptual Tensions in Human–AI Co-Creation

Conceptual Tension	Opposing Dimensions	Core Dynamics	Implications for Creativity	Key Risk
Augmentation vs Substitution	AI enhances human creativity vs AI replaces human contribution	AI expands ideation while simultaneously automating creative tasks	Creativity shifts between empowerment and displacement of human input	Over-reliance on AI reducing human engagement
Human Agency vs Algorithmic Influence	Human control and intention vs AI-driven suggestions and constraints	Decision-making is co-shaped by human judgment and algorithmic output	Creativity becomes a negotiated outcome rather than purely intentional	Loss of critical thinking due to cognitive offloading
Originality vs Recombinative Generation	Novel, intentional ideas vs recombination of existing data patterns	AI generates outputs through probabilistic recombination while humans assign meaning	Redefinition of originality from creation to interpretation	Homogenization of creative outputs
Individual vs Distributed Creativity	Creativity as individual capability vs system-level emergent property	Creativity emerges from interactions among humans, AI, and socio-technical systems	Shift from individual authorship to co-created value systems	Ambiguity in authorship and ownership

Source: Author's conceptualization.

Table 2 demonstrates that creativity in human–AI contexts is structured by interdependent tensions rather than linear processes. Each tension reflects a shift from traditional human-centered assumptions toward hybrid and system-level dynamics. These tensions do not operate independently; instead, they interact to shape how creativity is generated, evaluated, and distributed.

To synthesize the conceptual tensions identified, Figure 1 presents a multidimensional view of human–AI creative co-creation. It positions hybrid creativity at the intersection of two shifts: from human-driven to AI-driven contribution and from individual to distributed creativity. The four tensions represent the key structural forces shaping how creativity is generated, evaluated, and organized in AI-mediated environments.

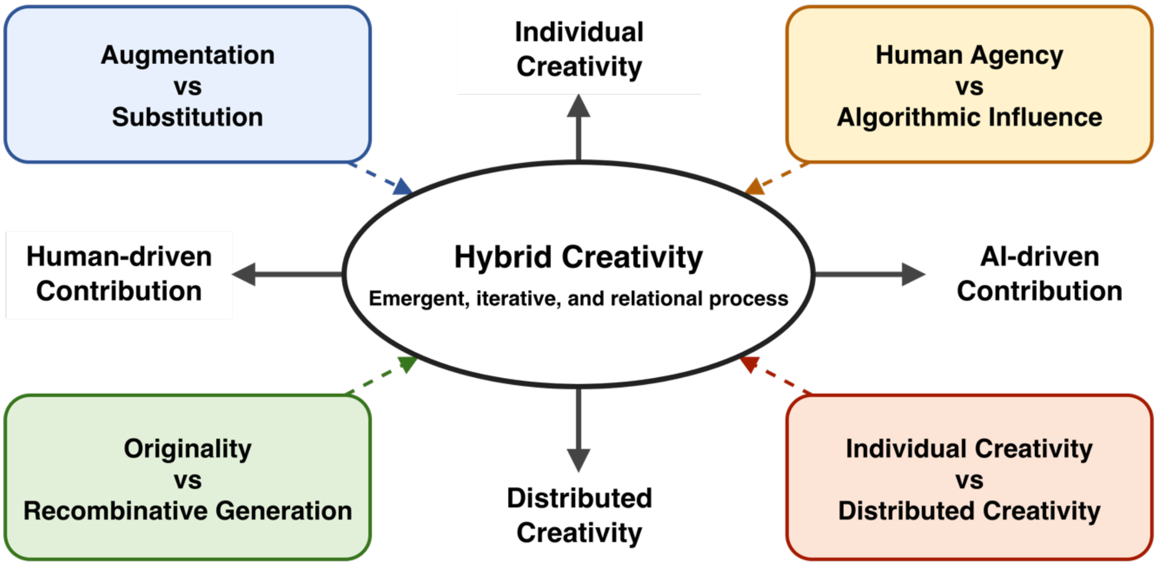

Figure 1. Conceptual Tensions in Human–AI Creative Co-Creation
Source: Author's conceptualization based on the synthesis of creativity theory, computational creativity, human–AI collaboration, and socio-technical perspectives.

Figure 1 shows that creativity in human–AI contexts is shaped by interacting tensions rather than a single linear process. The horizontal axis represents the shift from human-driven to AI-driven contribution, while the vertical axis reflects the transition from individual to distributed creativity. The four tensions surrounding the center highlight key dynamics in co-creation: augmentation versus substitution, human agency versus algorithmic influence, originality versus recombinative generation, and individual versus distributed creativity. Together, these dimensions frame hybrid creativity as an emergent and relational process.

4. Redefining Creativity: Toward a Hybrid and Interactive Paradigm

4.1 Critique of Traditional Definitions of Creativity

The dominant definition of creativity has long been framed as the production of ideas that are both novel and useful (Runco & Jaeger, 2012). This definition has achieved widespread acceptance due to its simplicity and cross-disciplinary applicability. Rooted in early psychological traditions, it reflects the influence of divergent thinking (Guilford, 1950) and associative processes (Mednick, 1962), while subsequent theoretical developments have reinforced its relevance in organizational and applied contexts (Amabile, 1983; Sternberg & Lubart, 1996).

Despite its enduring utility, this definition becomes increasingly inadequate in the context of human–AI co-creation. First, the notion of novelty is destabilized by the generative mechanisms of AI systems. Generative models produce outputs through large-scale recombination of existing data patterns rather than through intentional deviation from established norms (Boden, 1998; Wiggins, 2006). While such outputs may be perceived as novel, their underlying process raises questions about whether recombination alone constitutes genuine originality (Floridi & Chiriatti, 2020).

Second, the criterion of usefulness assumes a stable evaluative framework in which human actors assess the value of creative outputs. However, in human–AI collaborative environments, evaluation is increasingly mediated by algorithmic systems, platform dynamics, and feedback loops (Amershi *et al*., 2019; Seeber *et al*., 2020). This shifts the locus of evaluation from purely human judgment to a socio-technical process in which value emerges through interaction.

Third, traditional definitions implicitly assume that creativity is an attribute of individuals. Even when acknowledging contextual influences, classical theories maintain a human-centered perspective that positions individuals as the primary source of creative production (Hennessey & Amabile, 2010; Glăveanu, 2014). This assumption becomes untenable in environments where AI systems actively generate, shape, and influence creative outputs.

Fourth, existing definitions conceptualize creativity as an outcome rather than a process. Human–AI co-creation, however, is characterized by iterative cycles of prompting, generation, evaluation, and refinement, where creativity emerges through continuous interaction rather than discrete moments of insight (Rezwana & Maher, 2023; Yuan *et al*., 2022). As such, reducing creativity to a final output obscures the dynamic mechanisms through which it is produced.

Taken together, these limitations indicate that the traditional definition of creativity, while effective in human-centered contexts, lacks the conceptual scope necessary to capture the complexities of hybrid creative systems. A redefinition is therefore required to account for the distributed, iterative, and interactive nature of contemporary creativity.

4.2 Proposed Definition: Creativity as a Hybrid and Distributed Process

In response to these limitations, this study proposes a reconceptualization of creativity:

> *Creativity is a distributed, iterative, and hybrid process that emerges from dynamic interactions between human cognition and algorithmic generativity, resulting in contextually meaningful and evaluatively recognized outputs.*

This definition introduces several critical conceptual shifts.

First, creativity is reconceptualized as distributed rather than individual. Drawing on distributed creativity theory and socio-technical perspectives, this view recognizes that creative outcomes emerge from interactions among multiple agents, including humans, algorithms, platforms, and data infrastructures (Glăveanu, 2014; Faraj *et al*., 2018). Creativity is thus not located within a single actor but is an emergent property of a system.

Second, creativity is understood as iterative rather than episodic. In human–AI co-creation, creative production unfolds through repeated cycles of interaction, where outputs are continuously refined through feedback loops (Rezwana & Maher, 2023). This processual perspective aligns with knowledge creation theory, which emphasizes continuous transformation and interaction as the basis of innovation (Nonaka *et al*., 2000).

Third, creativity is defined as hybrid, integrating human and artificial contributions. Human actors provide contextual understanding, interpretive judgment, and symbolic meaning, while AI systems contribute generative capacity, scalability, and pattern recognition (Dellermann *et al*., 2019; Chen & Chan, 2024). The resulting creative output is neither purely human nor purely machine-generated but reflects a synthesis of both.

Fourth, the definition emphasizes dynamic interaction as the core generative mechanism. Creativity is not a static attribute but a relational process shaped by ongoing exchanges between human intention and algorithmic output. This interaction introduces co-evolutionary dynamics, where both human inputs and AI outputs adapt over time.

Fifth, creativity remains tied to contextual meaning and evaluation, acknowledging that outputs must be recognized as valuable within specific social, cultural, or organizational contexts (Runco & Jaeger, 2012). However, this evaluation is no longer exclusively human-driven but is co-mediated by socio-technical systems, including algorithmic filtering and platform-based metrics.

This redefinition shifts the analytical focus from "who creates" to "how creativity emerges," thereby providing a more robust framework for understanding creative processes in AI-mediated environments.

4.3 Implications of the New Definition

The proposed reconceptualization has significant implications for theory, practice, and the broader understanding of creativity.

First, it fundamentally challenges the assumption that creativity is an individual attribute. By framing creativity as distributed, this perspective shifts attention from personal traits and cognitive abilities to the configuration of interaction systems. Creative capability becomes a function of how effectively individuals engage with AI systems and socio-technical environments.

Second, the redefinition reframes creativity as an interactive process rather than a static outcome. This has important implications for measurement and evaluation. Traditional metrics that focus on final outputs may fail to capture the iterative dynamics of co-creation. Instead, process-oriented approaches that examine interaction patterns, feedback loops, and co-evolution of ideas become more relevant.

Third, the hybrid nature of creativity introduces complexity in authorship, ownership, and accountability. As outputs are co-produced by humans and AI, it becomes increasingly difficult to attribute credit to a single source. This raises critical questions for intellectual property frameworks and professional identity in creative work (Epstein *et al.*, 2023; Formosa *et al.*, 2025).

Fourth, the redefinition highlights the importance of designing systems that support effective human–AI collaboration. Organizations must move beyond viewing AI as a tool and instead develop capabilities for orchestrating hybrid creative processes. This includes designing interfaces, workflows, and governance mechanisms that facilitate meaningful interaction between human and artificial agents (Amershi *et al.*, 2019; Dellermann *et al.*, 2019).

Fifth, this perspective contributes to a broader reconceptualization of value creation in the digital economy. Creativity becomes a function of interaction rather than isolated production, aligning with co-creation theory where value emerges through engagement and collaboration (Prahalad & Ramaswamy, 2004; Ramaswamy & Ozcan, 2018). In this context, AI acts not only as a productivity tool but as a co-creator that reshapes the mechanisms through which value is generated.

Finally, redefining creativity as a hybrid and distributed process provides a theoretical foundation for integrating creativity research with digital innovation and management theory. It positions human–AI co-creation as a central mechanism through which innovation occurs in contemporary organizations and creative industries (Nambisan *et al.*, 2017; Raisch & Krakowski, 2021).

To integrate the theoretical foundations, conceptual tensions, and proposed reconceptualization, Figure 2 presents an integrated framework of hybrid creativity in human–AI co-creation. The framework illustrates how foundational theories inform key tensions, which in turn shape the emergence of hybrid creativity and its manifestation in co-creative processes.

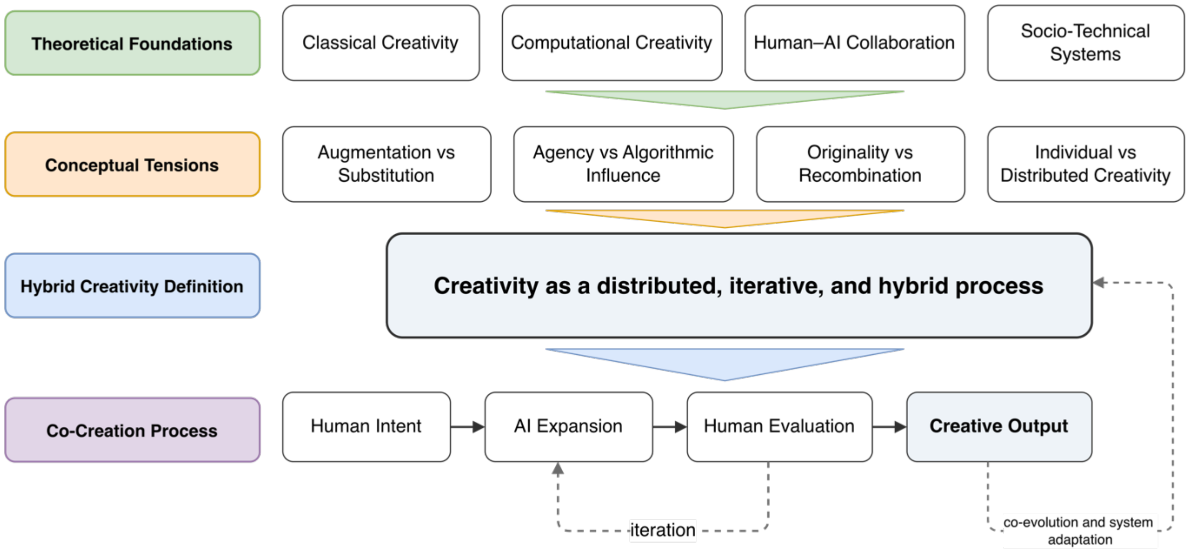

Figure 2. Integrated Framework of Hybrid Creativity in Human–AI Co-Creation
Source: Author's conceptualization Author's conceptualization based on the integration of creativity theory, computational creativity, human–AI collaboration, and socio-technical perspectives.

Figure 2 shows that hybrid creativity emerges from the interaction between theoretical foundations, structural tensions, and process dynamics. Foundational theories provide the conceptual basis, while tensions define the conditions under which creativity operates. These elements converge in the redefinition of creativity as a hybrid process, which is operationalized through the co-creation model. The framework highlights that creativity is not a static attribute but a system-level phenomenon shaped by continuous interaction and co-evolution.

5. Proposed Conceptual Model: Human–AI Creative Co-Creation

Building on the reconceptualization of creativity as a distributed, iterative, and hybrid process, this section introduces the Human–AI Creative Co-Creation Model, a process-oriented framework that explains how creative outcomes emerge through structured yet adaptive interactions between human cognition and algorithmic generativity. The model integrates insights from creativity theory, computational creativity, and human–AI collaboration to articulate the mechanisms through which hybrid creativity unfolds.

Rather than conceptualizing creativity as a linear sequence or a static attribute, the model positions it as a dynamic co-evolutionary process, in which human and artificial agents continuously interact, adapt, and reshape each other's contributions. This perspective aligns with socio-technical and knowledge-creation theories that emphasize interaction, feedback, and iterative transformation as core drivers of innovation (Nonaka *et al.*, 2000; Faraj *et al.*, 2018).

5.1 Process Model: A Co-Creation Pipeline

The proposed model conceptualizes human–AI creativity as a multi-stage process consisting of five interconnected phases: (1) human intent formation, (2) AI generative expansion, (3) human evaluation and framing, (4) iterative co-creation loop, and (5) creative output emergence. While these stages are analytically separated for clarity, in practice they operate recursively and dynamically.

Figure 3 presents the Human–AI Creative Co-Creation Model, illustrating how creativity emerges through iterative interactions between human cognition and algorithmic generativity. The model highlights a process-based structure in which human intention, AI-driven expansion, and evaluative refinement interact dynamically to produce creative outcomes.

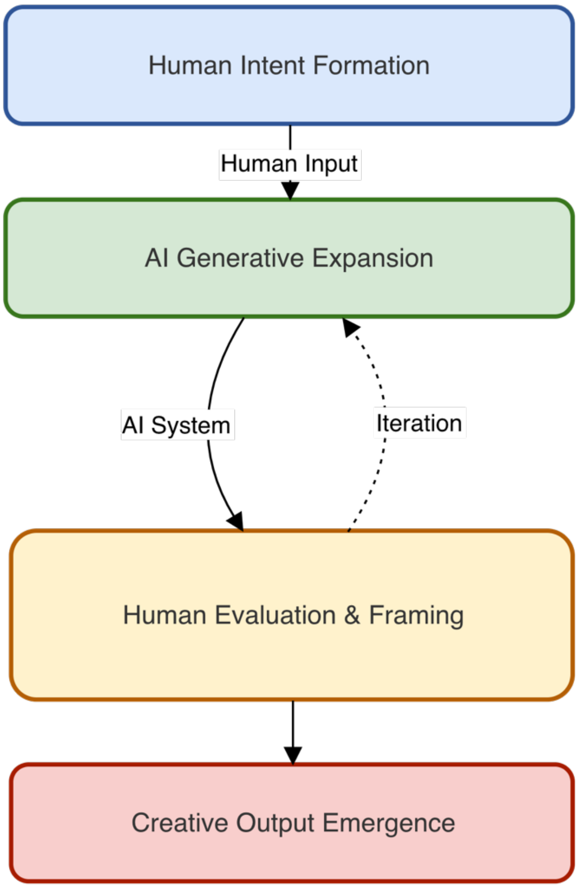

Figure 3. Human–AI Creative Co-Creation Process Model
Source: Author's conceptualization based on the integration of creativity theory, human–AI collaboration, and digital innovation perspectives.

Figure 3 illustrates creativity as a process emerging from iterative interaction between human and AI contributions. The process begins with human intent formation, followed by AI-driven expansion of ideas, and continues with human evaluation and framing. These stages are connected through a feedback loop, indicating that creative development is iterative rather than linear. The final output emerges from this continuous interaction, reflecting a hybrid integration of human judgment and algorithmic generation.

1) Human Intent Formation

The creative process begins with human intent formation, where individuals define goals, constraints, and contextual meaning. This stage reflects classical creativity theories that emphasize intrinsic motivation, domain knowledge, and problem framing as key drivers of creativity (Amabile, 1983; Sternberg & Lubart, 1996). Human actors contribute elements that remain difficult for AI systems to replicate, including contextual awareness, cultural understanding, and symbolic interpretation.

Importantly, intent formation is not merely an initial step but a structuring mechanism that shapes the entire co-creative process. The way prompts are formulated determines how the AI system interprets and generates outputs. This aligns with knowledge-based perspectives, where creativity emerges from the recombination of knowledge within a defined problem space (Grant, 1996; Nonaka *et al.*, 2000).

In human–AI systems, intent formation also introduces an asymmetry: while humans initiate the process, the translation of intent into machine-interpretable inputs (e.g., prompts) inherently constrains and frames subsequent generative possibilities. Thus, creativity at this stage is both enabled and bounded by how human intention is encoded.

2) AI Generative Expansion

Following intent formation, AI systems perform generative expansion by producing multiple candidate ideas, designs, or textual outputs. This stage reflects the computational creativity paradigm, where creativity is operationalized through combinational and exploratory mechanisms (Boden, 1998; Wiggins, 2006).

Generative AI systems significantly expand the ideation space by leveraging large-scale data and probabilistic modeling, enabling the rapid production of diverse outputs (Brown *et al.*, 2020; Dwivedi *et al.*, 2023). Empirical evidence indicates that such systems can enhance ideation diversity and creative productivity (Doshi & Hauser, 2024).

However, generative expansion is not neutral. The outputs are shaped by training data, model architecture, and embedded biases, which influence both the range and direction of generated ideas (Bender *et al.*, 2021; Epstein *et al.*, 2023). As a result, AI contributes not only to the quantity of ideas but also to their directionality and structure, effectively guiding the creative search space.

This stage highlights a critical shift: creativity is no longer limited by human cognitive constraints but is expanded through algorithmic generativity, albeit within the boundaries defined by data and model design.

3) Human Evaluation and Framing

In the third stage, human actors engage in evaluation and framing, where AI-generated outputs are selected, interpreted, and refined. This stage reintroduces human judgment as a central component of creativity, consistent with theories that emphasize evaluation as a key determinant of creative value (Runco & Jaeger, 2012).

Evaluation in this context is not merely a filtering process but an act of meaning construction. Human actors assign relevance, contextualize outputs, and align them with broader goals and constraints. This aligns with socio-cultural perspectives that emphasize the role of interpretation and domain-specific standards in creativity (Glăveanu, 2014).

However, human evaluation is increasingly mediated by algorithmic influence. Interface design, ranking mechanisms, and feedback loops shape how outputs are perceived and selected (Amershi *et al.*, 2019; Seeber *et al.*, 2020). Consequently, evaluation becomes a co-mediated process, where human judgment and algorithmic structure interact.

This stage is critical because it determines which ideas are retained, transformed, or discarded, thereby shaping the trajectory of the creative process.

4) 5Iterative Co-Creation Loop

At the core of the model lies the iterative co-creation loop, where human and AI agents continuously interact through cycles of prompting, generation, evaluation, and refinement. This stage represents the defining characteristic of hybrid creativity.

Unlike traditional creative processes, which are often conceptualized as linear or stage-based, human–AI co-creation is inherently recursive and adaptive. Human inputs evolve in response to AI outputs, while AI outputs are shaped by updated prompts and contextual cues. This creates a co-evolutionary dynamic in which both human cognition and algorithmic generation adapt over time.

Human–AI interaction research demonstrates that iterative engagement enhances creative outcomes by enabling deeper exploration and progressive refinement (Rezwana & Maher, 2023; Yuan *et al.*, 2022). This aligns with learning and knowledge-creation theories, which emphasize feedback loops and continuous adaptation as drivers of innovation (Nonaka *et al.*, 2000).

Importantly, this loop also reflects the tension between augmentation and substitution identified in Section 3. While iteration can enhance creativity, excessive reliance on AI may reduce human engagement, highlighting the need for balanced interaction.

5) Creative Output Emergence

The final stage involves the emergence of creative output, where ideas crystallize into artifacts that are recognized as creative within a given context. These outputs may take various forms, including designs, texts, products, or experiences.

In this model, creative output is not attributable to a single actor but emerges from the interaction between human and AI contributions. This aligns with distributed creativity perspectives, where outcomes are understood as products of systems rather than individuals (Glăveanu, 2014; Faraj *et al.*, 2018).

Evaluation of these outputs is inherently contextual, influenced by social, cultural, and market factors. In the creative economy, value is often determined not only by intrinsic qualities but by audience reception, platform dynamics, and symbolic meaning (Florida, 2002; Potts, 2011).

Thus, creative output is both a process outcome and a socially constructed phenomenon, shaped by interactions that extend beyond the immediate human–AI system.

5.2 Key Characteristics of the Model

The Human–AI Creative Co-Creation Model is defined by three core characteristics that distinguish it from traditional models of creativity.

First, the model is iterative, emphasizing continuous interaction rather than discrete stages. Creativity unfolds through repeated cycles of engagement, enabling progressive refinement and adaptation.

Second, the model is non-linear, reflecting the complex and dynamic nature of creative processes. Stages may overlap, repeat, or occur simultaneously, depending on the interaction between human and AI agents (Yoo *et al.*, 2012).

Third, the model is co-dependent, highlighting the interdependence between human and AI contributions. Humans provide direction, interpretation, and contextual meaning, while AI provides generative capacity and scalability. This co-dependence aligns with the concept of hybrid intelligence, where value emerges from integration rather than substitution (Dellermann *et al.*, 2019).

5.3 Propositions for Future Empirical Research

To enable empirical validation, the model generates a set of testable propositions that capture the relationships between human–AI interaction and creative outcomes.

P1: *Human–AI collaboration increases ideation diversity compared to human-only creative processes.*

This proposition is supported by evidence that generative AI expands the range of possible ideas beyond human cognitive constraints (Doshi & Hauser, 2024).

P2: *Human agency moderates the influence of AI-generated content on creative outcomes.*

The impact of AI depends on the degree of human control, interpretation, and engagement in the co-creative process (Amershi *et al*., 2019; Seeber *et al*., 2020).

P3: *Iterative interaction between humans and AI positively influences the perceived creativity of outputs.*

Repeated cycles of generation and refinement enhance alignment with contextual goals and increase perceived originality (Rezwana & Maher, 2023).

P4: *Human–AI co-creation reduces clarity of authorship attribution.*

As outputs emerge from distributed processes, it becomes increasingly difficult to assign creative ownership to a single actor (Dwivedi *et al*., 2023).

P5: *Hybrid creativity shifts evaluation criteria from individual originality to system-level effectiveness.*

Creative value increasingly reflects the performance of the human–AI system rather than individual contribution (Raisch & Krakowski, 2021; Nambisan *et al*., 2017).

6. Discussion

6.1 Theoretical Implications

This study contributes to a fundamental reconceptualization of creativity by shifting its locus from an individual cognitive attribute to a hybrid, distributed, and interactional process. Traditional creativity theories have long emphasized individual cognition, intrinsic motivation, and domain expertise as primary drivers of creative output (Amabile, 1983; Sternberg & Lubart, 1996). However, the findings of this study demonstrate that in the context of human–AI co-creation, creativity increasingly emerges from interactions between human cognition and algorithmic systems rather than from isolated individuals.

This shift extends creativity theory in three significant ways. First, it reframes creativity as a processual and relational phenomenon, rather than a static outcome. While prior literature has acknowledged the importance of interaction and context (Glăveanu, 2014), the present study advances this perspective by explicitly integrating algorithmic agents into the creative process. Creativity is thus conceptualized as an emergent property of dynamic interaction systems, aligning with socio-technical and distributed cognition frameworks (Faraj *et al*., 2018; Yoo *et al*., 2012).

Second, the study introduces the notion of hybrid agency, where creative outcomes are co-produced through negotiated interactions between human intention and algorithmic influence. This challenges the anthropocentric bias of classical theories and extends the concept of agency beyond human actors. In doing so, the study contributes to the growing literature on human–AI collaboration, which emphasizes the co-evolution of human and machine capabilities (Dellermann *et al*., 2019; Seeber *et al*., 2020). Importantly, hybrid agency is not merely a combination of human and machine inputs but a reconfiguration of control, decision-making, and creative responsibility.

Third, this study contributes to the theoretical integration of creativity research with innovation and digital transformation literature. By positioning human–AI co-creation as a mechanism of knowledge recombination and expansion, the model aligns with knowledge-based theories of the firm and dynamic capability perspectives (Nonaka *et al*., 2000; Teece, 2007). AI systems expand the exploration space through generative capabilities, while human actors provide evaluative judgment and contextual framing. This interaction enhances both exploratory and exploitative dimensions of innovation, thereby extending existing frameworks of digital innovation (Nambisan *et al*., 2017; Nambisan *et al*., 2019).

Furthermore, the study contributes to computational creativity literature by shifting the focus from machine autonomy to relational creativity, where the creative value of AI emerges through interaction rather than isolation. This perspective addresses a critical limitation in prior research, which has often evaluated machine creativity independently of human engagement (Boden, 1998; Colton & Wiggins, 2012).

Taken together, these contributions establish a theoretical bridge between creativity, human–AI interaction, and innovation research, providing a more comprehensive framework for understanding creative processes in the age of artificial intelligence.

6.2 Managerial Implications

The findings of this study have important implications for managerial practice, particularly in how organizations design and manage creative processes in AI-enabled environments. A central insight is that organizations must move beyond viewing AI as a tool for efficiency and instead treat it as a co-creative partner that actively shapes ideation and decision-making.

First, organizations should focus on designing co-creative systems rather than merely adopting AI technologies. The effectiveness of human–AI collaboration depends not only on technological capability but on how interaction is structured. Systems that provide transparency, user control, and iterative feedback mechanisms are more likely to enhance creativity and trust (Amershi *et al.*, 2019; Muller & Weisz, 2022). This implies that the design of interfaces and workflows becomes a critical determinant of creative performance.

Second, firms need to develop capabilities for orchestrating hybrid creativity. This involves training employees not only to use AI tools but to collaborate with them effectively. Evidence suggests that individuals achieve higher creative outcomes when they engage with AI as a co-creator rather than as a passive assistant (Chen & Chan, 2024; Cui & Wu, 2024). Consequently, skill requirements shift from purely technical proficiency to include interpretive, interactional, and critical thinking capabilities.

Third, managerial strategies must account for the iterative nature of co-creation. Unlike traditional workflows, human–AI creativity unfolds through continuous cycles of generation and evaluation. Organizations should therefore design processes that support experimentation, iteration, and learning, rather than linear execution. This requires a cultural shift toward embracing uncertainty and adaptive problem-solving.

Fourth, governance mechanisms must address issues of agency, accountability, and bias. As AI systems increasingly influence creative decisions, organizations must ensure that human oversight is maintained and that algorithmic biases are identified and mitigated (Bender *et al.*, 2021; Epstein *et al.*, 2023). This includes establishing clear guidelines for the responsible use of AI and defining roles within co-creative processes.

Finally, organizations should recognize that the integration of AI does not automatically enhance creativity. The benefits of human–AI collaboration depend on how effectively interaction is designed and managed. Poorly structured collaboration may lead to over-reliance on AI, reduced human engagement, and homogenization of outputs. Therefore, creativity in AI-enabled environments must be actively cultivated rather than passively assumed.

6.3 Implications for the Creative Economy

The reconceptualization of creativity as a hybrid and distributed process has profound implications for the structure and dynamics of the creative economy. Traditionally, creative industries have been organized around individual creators and firms that generate and monetize symbolic and cultural products (Florida, 2002; Howkins, 2001). However, the integration of AI into creative processes is transforming both value creation and value capture mechanisms.

First, the creative economy is shifting from individual production to collaborative value creation systems. Human–AI co-creation enables the production of content at scale while maintaining contextual relevance, thereby lowering barriers to entry and democratizing creative production. This aligns with broader trends in digital innovation, where value is generated through interaction and recombination rather than isolated creation (Nambisan *et al.*, 2017).

Second, value creation is increasingly based on interaction rather than ownership. In hybrid systems, creative value emerges from the interplay between human input and AI-generated output. This challenges traditional notions of authorship and intellectual property, as creative outputs cannot be easily attributed to a single actor (Dwivedi *et al.*, 2023). As a result, new frameworks for assigning value and credit are required.

Third, the creative economy is becoming more platform-mediated and data-driven. AI systems rely on large datasets and are often embedded within digital platforms that shape how creative outputs are distributed and consumed. These platforms introduce new dynamics of visibility, engagement, and control, where algorithmic curation plays a central role in determining success.

Fourth, human–AI collaboration enhances innovation capacity and productivity within creative industries. By expanding ideation spaces and accelerating production cycles, AI enables the development of new products, services, and experiences (Corvello *et al.*, 2025). At the same time, it introduces risks of homogenization, as shared datasets and algorithmic patterns may lead to convergence in creative outputs (Epstein *et al.*, 2023).

Finally, these transformations highlight the need for new institutional and policy frameworks. Issues related to intellectual property, ethical use of AI, and the protection of creative labor become increasingly important as AI assumes a more active role in creative production. Policymakers must therefore balance the benefits of technological advancement with the need to preserve diversity, fairness, and human contribution in the creative economy.

6.4 Integrative Reflection

Taken together, the findings of this study indicate that human–AI co-creation represents not merely a technological enhancement but a structural transformation in the nature of creativity itself. Creativity is no longer confined to individual cognition but is increasingly embedded within hybrid systems that integrate human insight with algorithmic capability.

This transformation requires a shift in both theoretical and practical perspectives. From a theoretical standpoint, it necessitates moving beyond human-centered models toward relational and system-level frameworks. From a practical standpoint, it demands new approaches to designing, managing, and evaluating creative processes.

Ultimately, understanding creativity in the age of artificial intelligence requires recognizing that value emerges not from isolated actors but from the quality of interaction between human and machine intelligence. This insight provides a foundation for future research and practice aimed at harnessing the full potential of human–AI collaboration.

7. Future Research Agenda

The reconceptualization of creativity as a distributed, iterative, and hybrid process opens a broad and multi-dimensional research agenda. While this study provides a conceptual foundation and a process-oriented model of human–AI co-creation, advancing the field requires systematic empirical validation, theoretical refinement, and contextual expansion. Future research must move beyond descriptive exploration toward rigorous, multi-level investigation of hybrid creative systems.

7.1 Empirical Validation of Human–AI Co-Creation

A primary direction for future research is the empirical validation of the proposed Human–AI Creative Co-Creation Model and its associated propositions. Although emerging studies suggest that generative AI enhances individual creativity (Doshi & Hauser, 2024), systematic testing of the mechanisms underlying hybrid creativity remains limited.

Quantitative research designs can operationalize key constructs such as human agency, AI reliance, interaction intensity, and ideation diversity. Structural equation modeling and multilevel analysis may be employed to examine how these variables influence creative outcomes across individual and team levels. This approach aligns with broader calls in digital innovation research to empirically investigate hybrid intelligence systems (Dellermann *et al.*, 2019; Nambisan *et al.*, 2017).

Experimental methods offer additional opportunities to isolate causal relationships. Controlled experiments comparing human-only, AI-only, and human–AI collaborative conditions can provide insights into how different configurations affect creativity, originality, and performance. Prior findings indicate that while AI enhances individual output, it may reduce collective diversity, suggesting nuanced and context-dependent effects (Doshi & Hauser, 2024).

Complementing quantitative approaches, qualitative methods such as process tracing and longitudinal case studies can capture the iterative and dynamic nature of co-creation. These approaches are particularly valuable for examining how human and AI contributions evolve over time and how creative decisions are negotiated within hybrid systems.

7.2 Cross-Cultural and Contextual Variations in Hybrid Creativity

Creativity is inherently embedded in cultural and contextual environments, and the emergence of human–AI co-creation raises important questions about how these contexts shape hybrid creative processes. Existing research demonstrates that cultural norms influence both the production and evaluation of creativity (Glăveanu, 2014; Hennessey & Amabile, 2010), yet the role of AI in mediating these dynamics remains underexplored.

Future research should investigate how human–AI co-creation operates across diverse cultural settings. For instance, cultures that emphasize individual originality may respond differently to AI-generated content compared to those that prioritize collective or incremental innovation. Similarly, perceptions of authorship, authenticity, and creative value may vary significantly when AI is involved (Dwivedi *et al.*, 2023).

Contextual factors beyond culture are also critical. Differences across industries—such as design, marketing, journalism, and software development—may shape how AI is integrated into creative workflows. Research should explore how domain-specific knowledge structures interact with AI capabilities to influence creative outcomes.

Additionally, the role of data localization and training datasets warrants further investigation. Since AI systems are trained on culturally embedded data, their outputs may reflect dominant cultural patterns, potentially reinforcing biases or limiting diversity (Epstein *et al.*, 2023). Understanding these dynamics is essential for developing inclusive and context-sensitive co-creative systems.

7.3 Re-examining Originality in Hybrid Systems

The tension between originality and recombination identified in this study presents a critical avenue for future research. While AI systems can generate outputs that appear novel, their reliance on existing data raises questions about the nature and measurement of originality.

Future research should systematically compare human-generated, AI-generated, and hybrid outputs to assess differences in perceived creativity, originality, and value. Experimental studies can examine how audiences evaluate these outputs, including perceptions of authenticity, emotional resonance, and symbolic meaning (Zhou & Lee, 2024; Sun *et al*., 2025).

Moreover, research should investigate the conditions under which hybrid outputs are perceived as more creative than either human-only or AI-only outputs. This includes examining the role of human intervention in enhancing originality and the extent to which AI contributes to or constrains creative diversity.

Advancing this line of inquiry requires developing new measurement frameworks that go beyond traditional criteria of novelty and usefulness. Such frameworks should incorporate process-based indicators, interpretive dimensions, and socio-technical influences to capture the complexity of hybrid creativity.

7.4 Longitudinal Dynamics of Human–AI Co-Creation

Another critical direction involves adopting longitudinal approaches to study how human–AI co-creation evolves over time. Creativity is inherently dynamic, and the iterative nature of human–AI interaction suggests that both processes and outcomes change through repeated engagement.

Longitudinal studies can examine how individuals and organizations adapt to AI over time, how patterns of interaction evolve, and how creative capabilities develop. For example, repeated interaction with AI may lead to increased efficiency but also potential dependency, affecting both the quality and diversity of creative outputs (Jarrahi, 2018).

From a strategic perspective, such studies can explore how hybrid creativity contributes to organizational learning and capability development. The ability to effectively integrate AI into creative processes may become a key dynamic capability, enabling firms to sustain competitive advantage in digital environments (Teece, 2007).

Additionally, longitudinal research can capture shifts in norms, practices, and expectations related to creativity. As AI becomes more deeply embedded in creative work, perceptions of authorship, value, and originality are likely to evolve, requiring continuous theoretical adaptation.

7.5 Multi-Level and Interdisciplinary Approaches

The complexity of human–AI creativity necessitates multi-level and interdisciplinary research approaches. Future studies should integrate perspectives from psychology, information systems, management, design, and cultural studies to develop a more comprehensive understanding of hybrid creativity.

At the individual level, research can explore cognitive and behavioral changes associated with AI collaboration, including shifts in creative self-efficacy and decision-making processes. At the team level, studies can examine how collaboration structures and interaction patterns influence collective creativity. At the organizational level, research can investigate how firms design and govern co-creative systems.

Furthermore, interdisciplinary approaches can enrich theoretical development by integrating insights from fields such as ethics, law, and sociology. Issues related to intellectual property, algorithmic bias, and creative labor require cross-disciplinary perspectives to fully understand their implications.

7.6 Toward a Research Program on Hybrid Creativity

Taken together, these directions suggest the need for a coordinated research program focused on hybrid creativity. Such a program should aim to develop:

1) Validated measurement frameworks for assessing creativity in human–AI systems
2) Process-based models that capture interaction dynamics over time
3) Context-sensitive theories that account for cultural and domain variation
4) Design principles for effective human–AI collaboration
5) Policy frameworks addressing ethical and economic implications

By advancing research along these dimensions, scholars can move beyond fragmented studies toward a cohesive and empirically grounded understanding of creativity in the age of artificial intelligence.

8. Conclusion

This study set out to address a fundamental gap in creativity research: the inadequacy of existing theories to explain how creativity unfolds in the context of human–AI co-creation. While traditional frameworks have long conceptualized creativity as an individual, cognitively driven phenomenon, the rapid advancement of generative artificial intelligence has transformed creative work into a hybrid, interactive, and system-level process. In response, the primary objective of this study was to reconceptualize creativity by developing a theoretically grounded framework that captures the distributed, iterative, and co-evolutionary dynamics between human cognition and algorithmic generativity.

The findings advance this objective by demonstrating that creativity in contemporary digital environments cannot be fully understood through dichotomous perspectives that separate human and machine contributions. Instead, creativity emerges from the interaction between human intention, contextual interpretation, and algorithmic expansion of possibilities. By identifying four core conceptual tensions—augmentation versus substitution, human agency versus algorithmic influence, originality versus recombinative generation, and individual versus distributed creativity—this study reveals the structural conditions that define hybrid creative systems. These tensions are not anomalies but constitutive elements of a new creative paradigm, highlighting that creativity is increasingly shaped by negotiation, interdependence, and co-evolution between human and artificial agents.

The study's primary theoretical contribution lies in redefining creativity as a distributed, iterative, and hybrid process, thereby extending classical creativity theory beyond its anthropocentric foundations. This reconceptualization integrates insights from computational creativity, human–AI interaction, and innovation research, offering a unified framework that captures the mechanisms through which creative value emerges in socio-technical systems. The proposed Human–AI Creative Co-Creation Model further operationalizes this perspective by articulating a process-oriented structure in which creativity unfolds through stages of intent formation, generative expansion, evaluation, and iterative refinement. In doing so, the study contributes to theory building by shifting the analytical focus from individual output to interactional processes, and from isolated cognition to system-level dynamics.

Beyond its theoretical implications, the study offers important insights for managerial practice and policy development. It highlights that organizations must move beyond viewing AI as a tool for efficiency and instead cultivate capabilities for orchestrating human–AI co-creation. Effective integration of AI into creative processes requires deliberate design of interaction systems, attention to human agency and oversight, and mechanisms to mitigate algorithmic bias. At a broader level, the study underscores the need for updated institutional and policy frameworks that address emerging challenges related to authorship, intellectual property, and the valuation of creative work in AI-mediated environments. As creativity becomes increasingly embedded in platform-based and data-driven ecosystems, the governance of hybrid creativity becomes a critical concern for both organizations and policymakers.

At the same time, this study is not without limitations. As a conceptual investigation, it does not empirically test the proposed model or propositions, and therefore its claims remain to be validated through quantitative and qualitative research. Additionally, while the framework integrates multiple theoretical perspectives, it necessarily abstracts from domain-specific variations in creative practice, which may influence how human–AI co-creation unfolds in different contexts. However, these limitations do not diminish the study's contribution; rather, they reflect the exploratory nature of theory development in an emerging field and point to opportunities for further refinement and empirical grounding.

Future research should build on this foundation by systematically testing the proposed model across different contexts, employing experimental, longitudinal, and multi-level methodologies to capture the dynamics of hybrid creativity. Comparative studies examining human-only, AI-only, and hybrid creative processes can further clarify the conditions under which co-creation enhances or constrains creativity. In addition, research exploring cultural, institutional, and domain-specific variations will be essential for developing more context-sensitive theories of human–AI interaction. Finally, interdisciplinary approaches that integrate insights from management, information systems, psychology, and ethics will be critical for addressing the broader implications of AI in creative work.

In conclusion, this study demonstrates that the rise of generative artificial intelligence represents not merely a technological advancement but a paradigm shift in the nature of creativity itself. Creativity is no longer confined to individual minds but is increasingly produced within hybrid systems that integrate human insight with algorithmic capability. Understanding this transformation requires a fundamental shift toward relational, process-oriented, and system-level perspectives. By articulating this shift and providing a conceptual foundation for human–AI co-creation, this study contributes to a more comprehensive and future-oriented understanding of creativity, positioning it as a central mechanism of value creation in the evolving digital economy.

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