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Human–AI Collaboration as a Strategic Capability in the Creative Economy

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Abstrak

The rapid advancement of artificial intelligence (AI), particularly generative systems, has transformed its role from a supportive tool into an active participant in organizational processes, especially within the creative economy where value creation is increasingly co-produced. Despite this shift, existing literature remains fragmented across strategic management, AI capability, and human–AI interaction, lacking an integrated framework that explains how human–AI collaboration systematically drives value creation. This study aims to conceptualize human–AI collaboration as a firm-level strategic capability by addressing this theoretical gap. Adopting a conceptual and integrative approach, the study synthesizes insights from dynamic capabilities, AI capability research, and creativity and innovation literature to develop a multidimensional framework. The proposed model conceptualizes Human–AI Collaboration Capability (HACC.) as comprising cognitive augmentation, generative co-creation, adaptive orchestration, and value attribution capability, operating through an iterative collaboration cycle that links micro-level interaction processes to macro-level strategic outcomes. The study contributes by extending capability theory toward distributed cognition and hybrid agency, offering a process-oriented explanation of value creation, and providing a foundation for future empirical research in AI-enabled organizational contexts.

Keywords

human–AI collaboration; dynamic capabilities; hybrid intelligence; creative economy; generative AI; value creation

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1. Introduction

The rapid advancement of artificial intelligence (AI), particularly generative and learning-based systems, has fundamentally reshaped the role of technology within organizations. Rather than functioning solely as an instrument for automation or efficiency enhancement, AI is increasingly positioned as an active participant in organizational processes, influencing decision-making, creativity, and strategic outcomes (Raisch & Krakowski, 2021; Berente *et al.*, 2021; Dwivedi *et al.*, 2023; Krakowski *et al.*, 2023). This transformation reflects a broader shift in which technology evolves from a passive infrastructure into an embedded co-actor that contributes to knowledge production and value creation mechanisms.

In the context of the creative economy, this transformation is particularly significant. Creative processes—traditionally grounded in human cognition, intuition, and cultural interpretation—are now increasingly mediated by AI systems capable of generating ideas, producing content, and exploring complex solution spaces at scale (Kakatkar *et al.*, 2020; Dellermann *et al.*, 2019). As a result, creativity is no longer exclusively human-driven but emerges through iterative interactions between human agents and algorithmic systems (Jarrahi, 2018; Seeber *et al.*, 2020). This shift suggests that creative outputs are increasingly co-produced, where AI contributes generative variation while humans provide contextual interpretation and meaning-making.

Such developments challenge long-standing assumptions in strategic management and innovation research. Traditional perspectives conceptualize creativity as an outcome of individual cognition and organizational context (Anderson *et al.*, 2014; Woodman *et al.*, 1993), while technological systems are treated as enabling tools rather than active contributors. However, recent studies indicate that AI not only enhances human cognition but also reshapes how opportunities are identified, evaluated, and exploited, thereby influencing the very foundations of competitive advantage (Krakowski *et al.*, 2023; Duan *et al.*, 2019).

Despite the growing importance of AI in shaping organizational outcomes, existing research has predominantly approached AI as a technological resource or capability that firms deploy to improve efficiency, decision quality, or performance (Mikalef & Gupta, 2021; Wamba *et al.*, 2024; Keding, 2021). From this perspective, AI is conceptualized as an input into organizational processes rather than as a collaborative entity that actively participates in them. Similarly, the digital transformation literature has emphasized the integration of digital technologies into business models and operations (Vial, 2019; Verhoef *et al.*, 2021; Bharadwaj *et al.*, 2013), yet it has paid limited attention to the relational dynamics between human actors and intelligent systems.

Parallel to this, the dynamic capabilities literature provides a robust framework for understanding how firms achieve sustained competitive advantage through processes of sensing, seizing, and transforming (Teece *et al.*, 1997; Eisenhardt & Martin, 2000; Teece, 2007). These frameworks emphasize learning, resource orchestration, and strategic renewal as central mechanisms of adaptation (Zollo & Winter, 2002; Pavlou & El Sawy, 2011). However, they are largely grounded in a human-centric view of cognition and decision-making, assuming that organizational capabilities emerge primarily from human interpretation and action. In AI-enabled environments, this assumption becomes increasingly problematic, as intelligent systems actively participate in pattern recognition, knowledge generation, and strategic recommendation processes (Raisch & Krakowski, 2021; Berente *et al.*, 2021).

At the same time, emerging research on human–AI interaction introduces the concept of hybrid intelligence, where humans and AI systems collaborate to achieve outcomes that exceed the capabilities of either acting alone (Dellermann *et al.*, 2019). Studies have explored AI as a teammate in collaborative environments (Seeber *et al.*, 2020), as well as its implications for decision-making structures, control mechanisms, and organizational coordination (Shrestha *et al.*, 2019; Kellogg *et al.*, 2020). These perspectives highlight the importance of interaction, trust, and distributed agency in shaping human–AI collaboration (Glikson & Woolley, 2020). However, this stream of research remains largely disconnected from strategic management theory, particularly from capability-based perspectives.

This fragmentation across research streams reveals a critical theoretical gap. On one hand, strategic management literature lacks a framework that incorporates AI as an active collaborator within capability development. On the other hand, research on human–AI collaboration has not been sufficiently integrated into broader theories of competitive advantage and value creation. As a result, there is limited understanding of how organizations can systematically leverage human–AI interaction as a source of sustained strategic advantage.

The creative economy provides a particularly relevant context for addressing this gap. Industries such as digital media, design, marketing, and content creation are characterized by high levels of creativity, symbolic value, and rapid innovation (Nambisan *et al.*, 2017; Yoo *et al.*, 2010). These industries are also among the earliest adopters of AI-driven tools, making them ideal settings for examining how human–AI collaboration reshapes value creation processes. In such environments, the ability to integrate human intuition with AI-generated insights may constitute a critical organizational capability.

Building on these observations, this study advances the argument that human–AI collaboration should be conceptualized as a strategic capability rather than merely a technological application. This perspective shifts the focus from AI as a standalone resource toward AI as part of a relational system involving human cognition, organizational processes, and technological affordances (Faraj *et al.*, 2018). By adopting this view, the study aligns with relational and process-oriented perspectives on digital innovation, which emphasize interaction and co-evolution as central mechanisms of value creation.

Accordingly, this paper addresses the following research question:

How can human–AI collaboration be conceptualized as a strategic capability that drives value creation in the creative economy?

To answer this question, the study integrates insights from dynamic capability theory, AI capability research, and creativity and innovation literature. It develops a conceptual framework that positions human–AI collaboration as a multi-dimensional capability encompassing cognitive augmentation, generative co-creation, adaptive orchestration, and value attribution. Through this framework, the study contributes to strategic management literature by extending capability-based perspectives to account for distributed cognition and hybrid agency.

By reframing AI as a co-creative partner embedded within organizational capabilities, this study not only advances theoretical understanding but also provides a foundation for future empirical research. It offers a new lens for examining how firms can design, manage, and leverage human–AI interaction to achieve sustained competitive advantage in the evolving landscape of the creative economy.

2. Theoretical Foundations

2.1 Dynamic Capabilities Perspective

The dynamic capabilities perspective has long served as a central theoretical lens for explaining how firms achieve and sustain competitive advantage in rapidly changing environments. It conceptualizes capabilities as the firm's ability to integrate, build, and reconfigure internal and external resources in response to environmental shifts (Teece *et al.*, 1997; Eisenhardt & Martin, 2000). Subsequent developments have elaborated the microfoundations of dynamic capabilities, emphasizing processes such as sensing opportunities, seizing them through resource mobilization, and transforming organizational structures to maintain strategic alignment (Teece, 2007; Zollo & Winter, 2002).

At its core, this perspective assumes that organizational capabilities are grounded in human cognition, managerial judgment, and organizational learning processes. Concepts such as absorptive capacity, managerial cognition, and learning routines highlight the central role of human actors in interpreting information and orchestrating strategic responses (Pavlou & El Sawy, 2011; Barreto, 2010). In this sense, capabilities are viewed as emergent properties of coordinated human action embedded within organizational routines.

However, this human-centric assumption becomes increasingly insufficient in AI-enabled environments. As organizations adopt advanced AI systems capable of pattern recognition, predictive analytics, and decision support, the locus of cognition is no longer exclusively human. AI systems actively contribute to sensing environmental signals, generating insights, and even shaping strategic recommendations (Raisch & Krakowski, 2021; Berente *et al*., 2021). This introduces a form of distributed cognition, where decision-making is jointly enacted by human and artificial agents.

Recent research on digital transformation further highlights that capabilities in contemporary organizations are deeply intertwined with digital infrastructures and data-driven processes (Warner & Wäger, 2019; Vial, 2019). Yet, even these extensions often treat technology as an enabling layer rather than as an active participant in capability enactment. As a result, existing dynamic capability frameworks do not fully capture how capabilities evolve when cognitive and analytical functions are shared between humans and AI systems.

This limitation suggests the need to extend the dynamic capabilities perspective toward a hybrid cognition view, where sensing, seizing, and transforming activities are co-constructed through interaction between human expertise and algorithmic intelligence. Such an extension provides a more accurate representation of capability development in AI-driven organizational contexts.

2.2 Artificial Intelligence as Organizational Capability

Parallel to the development of dynamic capabilities theory, a growing body of research conceptualizes AI as a strategic organizational capability. This literature defines AI capability as a firm's ability to deploy AI technologies, manage data resources, and develop analytical competencies to enhance decision-making and performance (Mikalef & Gupta, 2021; Wamba *et al*., 2024). Empirical findings consistently show that AI capability contributes to organizational creativity, innovation outcomes, and firm performance, particularly when supported by complementary assets such as data-driven culture and digital infrastructure (Keding, 2021).

From this perspective, AI is primarily treated as a resource that enhances existing organizational processes. This aligns with broader digital strategy frameworks, which emphasize the role of information technologies in shaping competitive advantage (Bharadwaj *et al*., 2013; Verhoef *et al*., 2021). However, such an instrumental view limits the theoretical understanding of AI's role in organizations, as it reduces AI to a tool that augments human capabilities rather than recognizing its interactive and transformative potential.

Recent studies begin to challenge this perspective by demonstrating that AI reshapes organizational structures, decision-making processes, and sources of competitive advantage. For instance, AI systems can redistribute decision authority, influence strategic choices, and alter coordination mechanisms within organizations (Shrestha *et al*., 2019; Kellogg *et al*., 2020). Furthermore, AI-driven insights may extend beyond human intuition, enabling new forms of opportunity recognition and strategic positioning (Krakowski *et al.*, 2023).

Despite these advances, the AI capability literature remains limited in its treatment of human–AI interaction. While it acknowledges the importance of integrating AI into organizational processes, it does not fully theorize how AI and human capabilities co-evolve through continuous interaction. Consequently, the relational and processual dimensions of AI-enabled value creation remain underexplored.

This gap becomes particularly critical in contexts where value creation depends on creativity and innovation. In such environments, the effectiveness of AI is not determined solely by its technical performance but by how it interacts with human cognition in processes of ideation, evaluation, and refinement. This suggests that AI capability alone is insufficient to explain value creation, and that interaction quality between human and AI must be considered as a central construct.

2.3 Human–AI Collaboration and Hybrid Intelligence

The emerging literature on human–AI collaboration provides important insights into how humans and intelligent systems interact within organizational settings. The concept of hybrid intelligence emphasizes the complementary strengths of humans and AI, suggesting that superior outcomes are achieved when both collaborate rather than operate independently (Dellermann *et al.*, 2019). Humans contribute contextual understanding, ethical reasoning, and creative interpretation, while AI provides computational power, scalability, and pattern recognition capabilities (Jarrahi, 2018).

Empirical research has explored various forms of human–AI interaction, including AI as a teammate in collaborative tasks, AI-assisted decision-making, and algorithmically mediated work processes (Seeber *et al.*, 2020; Faraj *et al.*, 2018). These studies highlight that effective collaboration depends on coordination mechanisms, trust, and role clarity between human and AI agents (Glikson & Woolley, 2020). In addition, AI introduces new forms of agency, where decision-making is distributed across human and machine actors (Murray *et al.*, 2021; Shrestha *et al.*, 2019).

From a theoretical standpoint, this research aligns with relational perspectives on technology, which view technological systems as active participants in organizational processes rather than passive tools (Faraj *et al.*, 2018). This perspective emphasizes that outcomes are shaped by ongoing interactions between human and technological actors, suggesting that value creation is inherently processual and co-constructed.

However, despite its relevance, the human–AI collaboration literature remains largely disconnected from strategic management theory. In particular, it lacks a clear articulation of how interaction-level dynamics can be aggregated into firm-level capabilities. Without such integration, it is difficult to assess the strategic implications of human–AI collaboration or its contribution to sustained competitive advantage.

This limitation indicates the need to bridge micro-level interaction dynamics with macro-level capability development, thereby positioning human–AI collaboration as a firm-level strategic construct.

2.4 Creativity and Innovation in Digital Contexts

Creativity and innovation are central to value creation in the creative economy, where firms compete not only through efficiency but also through originality, symbolic meaning, and cultural relevance (Anderson *et al.*, 2014; Woodman *et al.*, 1993). Traditional theories of organizational creativity emphasize the role of individual traits, social context, and organizational structures in shaping creative outcomes, while innovation is often framed as the balance between exploration and exploitation (March, 1991; Benner & Tushman, 2003).

The emergence of digital technologies has significantly transformed these processes. Digital innovation is characterized by recombination, modularity, and rapid experimentation, enabling organizations to generate and test new ideas at scale (Yoo *et al.*, 2010; Nambisan *et al.*, 2017). In this context, AI introduces a new dimension to creativity by enabling the generation of novel content, designs, and solutions that extend beyond traditional human cognitive boundaries.

This development raises fundamental questions about the nature of creativity in AI-enabled environments. If AI systems can independently generate ideas, the distinction between human creativity and machine-generated outputs becomes increasingly blurred. Moreover, the value of creative outputs depends not only on novelty but also on interpretation, meaning, and market acceptance, which remain deeply human-centered processes.

Existing research acknowledges the role of digital technologies in enabling creativity but does not fully account for the implications of AI as a generative and interactive actor. As a result, there is a need to reconceptualize creativity and innovation as outcomes of human–AI co-creation, where value emerges from the interaction between human interpretation and machine-generated variation.

3. Conceptual Gap and Problem Framing

The preceding discussion suggests that research on artificial intelligence, dynamic capabilities, and organizational creativity has evolved along largely independent trajectories. Each stream provides valuable insights into specific aspects of value creation, yet their separation limits the ability to fully explain how organizations generate and sustain advantage in environments increasingly shaped by intelligent technologies. This limitation becomes particularly salient in the creative economy, where value emerges not from isolated resources, but from the interaction between human interpretation, technological systems, and market meaning.

Within the dynamic capabilities literature, capability development continues to be conceptualized as a process grounded in human cognition, organizational routines, and managerial judgment. Sensing, seizing, and transforming are predominantly framed as human-driven activities, even when supported by digital infrastructures (Teece, 2007; Pavlou & El Sawy, 2011; Warner & Wäger, 2019). While such perspectives remain analytically powerful, they provide only a partial account of contemporary organizational contexts, where AI systems actively participate in pattern recognition, insight generation, and decision support (Raisch & Krakowski, 2021; Berente *et al.*, 2021). As cognition becomes increasingly distributed, the assumption of human-centered capability formation appears progressively constrained.

A similar boundary can be observed in the literature on AI capability. Existing research has established that firms benefit from deploying AI in conjunction with data resources and organizational competencies (Mikalef & Gupta, 2021; Wamba *et al.*, 2024). However, this line of inquiry tends to privilege a resource-based logic, emphasizing deployment, utilization, and performance outcomes. Less attention has been directed toward the mechanisms through which AI interacts with human actors to shape the underlying processes of value creation. Yet emerging evidence indicates that AI does not merely enhance decision-making efficiency but can alter how opportunities are identified, evaluated, and pursued (Krakowski *et al.*, 2023), suggesting that its role extends beyond that of an enabling asset.

Research on human–AI collaboration offers a different perspective by foregrounding interaction, coordination, and shared agency. Studies of hybrid intelligence and algorithmically mediated work demonstrate that outcomes are often co-produced through iterative exchanges between humans and intelligent systems (Dellermann *et al.*, 2019; Seeber *et al.*, 2020; Faraj *et al.*, 2018). These contributions highlight the importance of trust, role configuration, and interaction design in shaping collaborative effectiveness (Glikson & Woolley, 2020; Kellogg *et al*., 2020). Nevertheless, this stream remains primarily focused on interaction-level phenomena. The question of how such interactions accumulate into stable, organization-level capabilities remains insufficiently theorized.

The creativity and innovation literature presents a further layer of complexity. Traditional models continue to locate creativity within human cognition and social context, even as digital technologies expand the scope for recombination and experimentation (Anderson *et al*., 2014; Yoo *et al*., 2010; Nambisan *et al*., 2017). The growing use of generative AI challenges this orientation by introducing systems capable of producing novel content independently of direct human input. In such settings, creative outcomes are no longer solely attributable to human agency but emerge from ongoing interplay between human interpretation and machine-generated variation. Existing frameworks, however, provide limited guidance for understanding this shift.

Taken together, these perspectives point toward an unresolved tension in the literature. On one hand, strategic management research continues to emphasize human-driven capability development. On the other, advances in AI and digital technologies increasingly distribute cognitive and creative functions across human and artificial agents. What remains underdeveloped is a conceptual account that connects these developments, explaining how interaction between human and AI can be organized, stabilized, and leveraged as a source of sustained value creation.

Addressing this limitation requires moving beyond the treatment of AI as either a supporting tool or a standalone capability. Instead, it becomes necessary to consider the relational structures through which human and artificial intelligence jointly contribute to organizational outcomes. From this perspective, value creation is not located within a single actor or resource, but within patterns of interaction that integrate human judgment, algorithmic processing, and organizational coordination (Faraj *et al*., 2018).

Building on this line of reasoning, the present study develops a conceptualization in which human–AI collaboration is understood as a firm-level capability. This perspective allows capability development to be reframed as an inherently interactive process, where cognition, creativity, and decision-making are co-constructed across human and technological domains. In doing so, it provides a foundation for integrating insights from dynamic capability theory, AI capability research, and creativity literature into a coherent framework for understanding value creation in the creative economy.

4. Conceptualization: Human–AI Collaboration as a Strategic Capability

4.1 Defining Human–AI Collaboration Capability

Building on the identified theoretical tensions, this study conceptualizes HACC as a firm-level strategic capability that enables organizations to systematically integrate and leverage interactions between human cognition and artificial intelligence in value-creating processes.

Human–AI Collaboration Capability refers to the organizational ability to purposefully structure, coordinate, and refine interactions between human actors and AI systems in order to generate, evaluate, and realize value, particularly in contexts characterized by high levels of creativity, uncertainty, and rapid change.

This definition departs from existing conceptualizations in two important ways. First, it moves beyond the instrumental view of AI as a technological resource by recognizing AI as an active participant in organizational processes (Raisch & Krakowski, 2021; Berente *et al*., 2021). Second, it extends the dynamic capabilities perspective by incorporating distributed cognition, where sensing, interpretation, and decision-making are jointly enacted by human and artificial agents rather than residing solely within managerial cognition (Pavlou & El Sawy, 2011).

Importantly, HACC is not reducible to AI capability alone (Mikalef & Gupta, 2021), nor to human expertise. Instead, it emerges from the quality, structure, and repeatability of interaction between the two. In this sense, the locus of capability shifts from individual components to the relational architecture that governs how human and machine intelligence are combined.

4.2 Positioning HACC within the Dynamic Capabilities Framework

To establish its theoretical grounding, HACC can be situated within the logic of dynamic capabilities, which conceptualizes competitive advantage as arising from the firm's ability to sense opportunities, seize them, and transform its resource base (Teece, 2007).

HACC extends this framework by embedding hybrid cognition into each stage.

In the sensing phase, AI systems enhance the organization's ability to identify patterns, detect weak signals, and process large-scale data beyond human cognitive limits (Duan *et al.*, 2019; Wamba *et al.*, 2024). Human actors, in turn, interpret these signals within broader strategic and contextual frameworks. Sensing thus becomes a co-constructed process.

In the seizing phase, decision-making is shaped through interaction between algorithmic recommendations and human judgment. AI contributes probabilistic assessments and scenario generation, while humans provide contextual reasoning, ethical evaluation, and strategic intent (Shrestha *et al.*, 2019; Jarrahi, 2018). Seizing therefore reflects a hybrid decision architecture.

In the transforming phase, organizations reconfigure routines, structures, and workflows to embed continuous human–AI interaction (Warner & Wäger, 2019). This involves designing governance mechanisms, redefining roles, and establishing feedback loops that allow learning to occur across both human and technological domains.

Through this integration, HACC reframes dynamic capabilities as not purely human-driven processes, but as outcomes of coordinated interaction between human and artificial intelligence. Competitive advantage, therefore, derives not only from resource possession, but from the organization's ability to orchestrate hybrid intelligence.

4.3 Core Dimensions of Human–AI Collaboration Capability

To further specify the construct, HACC is conceptualized as a multi-dimensional capability comprising four interrelated dimensions. These dimensions represent distinct but interconnected mechanisms through which human–AI interaction contributes to value creation.

1) Cognitive Augmentation

Cognitive augmentation refers to the enhancement of human analytical and interpretive processes through AI-enabled data processing and pattern recognition.

AI systems extend cognitive capacity by rapidly analyzing complex and large-scale data, identifying patterns that may not be immediately observable to human actors (Duan *et al.*, 2019). This allows organizations to operate under conditions of uncertainty with greater informational depth. However, AI-generated insights require human interpretation to be strategically meaningful. Human actors contextualize outputs, evaluate relevance, and integrate them into broader decision frameworks (Jarrahi, 2018).

Thus, cognitive augmentation is not a substitution mechanism but a complementary one, where value emerges from the interaction between machine-generated insight and human judgment.

2) Generative Co-Creation

Generative co-creation captures the role of AI as an active contributor to ideation and creative processes.

Unlike traditional technologies, generative AI systems are capable of producing novel content, alternatives, and design variations at scale, significantly expanding the exploration space available to organizations (Dellermann *et al.*, 2019). This enables a shift from linear creativity toward iterative and combinatorial processes.

However, novelty alone does not constitute value. AI-generated outputs require human evaluation, selection, and refinement to become meaningful innovations. This reflects the interplay between exploration and exploitation, where AI expands possibilities while humans provide direction and coherence (March, 1991).

Generative co-creation therefore represents a mechanism through which creativity is co-produced, rather than individually generated.

3) Adaptive Orchestration

Adaptive orchestration refers to the organization's ability to structure and continuously adjust the interaction between human and AI agents.

Effective collaboration requires more than technological integration; it depends on how tasks are allocated, how authority is distributed, and how feedback is managed (Kellogg *et al.*, 2020; Seeber *et al.*, 2020). Organizations must determine when AI should generate, when humans should evaluate, and how iterative cycles are coordinated.

This dimension reflects the orchestration logic within dynamic capabilities, where competitive advantage depends on the firm's ability to reconfigure resources in response to changing conditions (Teece, 2007). In the case of HACC, the key resource is not AI itself, but the interaction architecture between human and AI systems.

Adaptive orchestration ensures that collaboration remains aligned with strategic objectives while maintaining flexibility in dynamic environments.

4) Value Attribution Capability

Value attribution capability refers to the organization's ability to assign meaning, legitimacy, and ownership to outputs generated through human–AI collaboration.

In the creative economy, value is shaped not only by functionality but also by symbolic meaning and consumer perception (Nambisan *et al.*, 2017). When outputs are co-created by humans and AI, ambiguity arises regarding authorship, originality, and authenticity.

Consumer responses to AI-generated content depend on how such outputs are framed and communicated (Puntoni *et al.*, 2021; Huang & Rust, 2021). Organizations must therefore actively construct narratives that clarify the role of human creativity while leveraging the generative power of AI.

Value attribution becomes critical because value creation is not complete until it is recognized and accepted in the market.

To clarify the conceptual structure of Human–AI Collaboration Capability, Table 1 summarizes its core dimensions, definitions, and theoretical foundations. This synthesis highlights how each dimension contributes to the overall capability while drawing from distinct but complementary literature streams.

Table 1. Dimensions of Human–AI Collaboration Capability and Their Theoretical Foundations

Dimension	Definition	Theoretical Foundation	Role in HACC
Cognitive Augmentation	Enhancement of human judgment through AI-driven data processing and pattern recognition	AI capability, decision-making theory (Duan *et al.*, 2019; Jarrahi, 2018)	Expands analytical capacity and improves interpretation
Generative Co-Creation	Collaborative generation of ideas through interaction between human creativity and AI-generated variation	Creativity theory, exploration–exploitation (March, 1991; Dellermann *et al.*, 2019)	Broadens idea space and supports novelty creation
Adaptive Orchestration	Organizational ability to structure and coordinate human–AI interaction processes	Dynamic capabilities, coordination theory (Teece, 2007; Kellogg *et al.*, 2020)	Stabilizes interaction into repeatable capability
Value Attribution Capability	Ability to assign meaning, legitimacy, and market recognition to co-created outputs	Consumer perception, symbolic value (Nambisan *et al.*, 2017; Puntoni *et al.*, 2021)	Translates outputs into recognized value

Source: Author's conceptualization based on integrated literature

As shown in Table 1, the four dimensions of HACC represent distinct yet interdependent mechanisms that collectively enable value creation. While each dimension draws on different theoretical foundations, their integration forms a higher-order capability that operates across cognitive, creative, organizational, and market domains.

4.4 Integrative Conceptualization

Taken together, these four dimensions suggest that Human–AI Collaboration Capability is a higher-order, process-oriented construct that operates across cognitive, creative, organizational, and market domains.

Rather than functioning as a discrete capability, HACC acts as a meta-capability that integrates and enhances other organizational capabilities, including innovation capability and strategic flexibility. Its effectiveness depends on the alignment between human expertise, technological systems, and organizational processes within a coherent interaction structure.

This integrative perspective shifts the basis of competitive advantage from isolated resources to relational capability configurations. In AI-enabled environments, firms do not compete solely on the basis of technological sophistication or human talent, but on their ability to combine both into a repeatable and scalable system of value creation.

By conceptualizing human–AI collaboration in this manner, the study provides a theoretically grounded framework for understanding how organizations can leverage hybrid intelligence as a strategic capability in the creative economy.

To provide an integrated view of the construct developed in this study, Figure 1 presents the conceptual framework of HACC. The figure synthesizes the core dimensions of HACC, the underlying human–AI collaboration cycle, and the resulting strategic outcomes within the creative economy context.

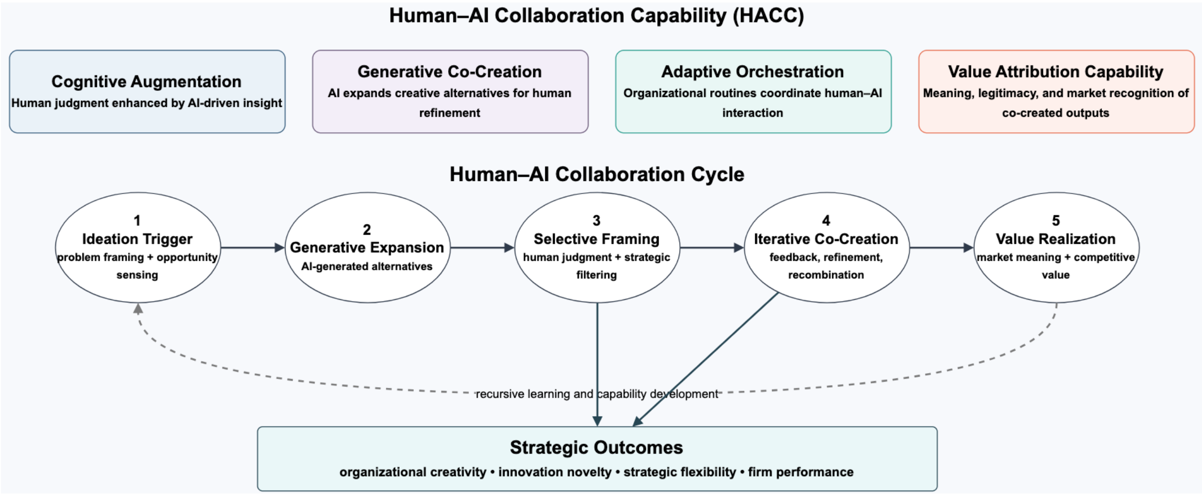

Figure 1. Conceptual Framework of Human–AI Collaboration Capability and the Collaboration Cycle in the Creative Economy
Source: Developed by the author

As illustrated in Figure 1, HACC is conceptualized as a higher-order capability composed of four interrelated dimensions: cognitive augmentation, generative co-creation, adaptive orchestration, and value attribution capability. These dimensions operate through an iterative collaboration cycle consisting of ideation, expansion, selective framing, co-creation, and value realization.

The model further highlights the recursive nature of human–AI interaction, where learning and capability development continuously feed back into subsequent cycles. Through this mechanism, organizations transform hybrid intelligence into strategic outcomes, including organizational creativity, innovation novelty, strategic flexibility, and firm performance.

5. Process Model: The Human–AI Collaboration Cycle

To operationalize HACC, this study develops a process model that explicates how value emerges through iterative interactions between human cognition and artificial intelligence. Rather than conceptualizing collaboration as a static configuration of resources, the model frames human–AI interaction as a dynamic and recursive cycle through which organizations generate, refine, and realize value over time.

This process-oriented perspective builds on the dynamic capabilities tradition, which emphasizes continuous adaptation and learning (Teece, 2007; Pavlou & El Sawy, 2011), while also aligning with digital innovation research that highlights recombination and iterative experimentation as core mechanisms of value creation (Yoo *et al.*, 2010; Nambisan *et al.*, 2017). Within this framework, human–AI collaboration is understood as an evolving system in which outputs are progressively shaped through repeated cycles of interaction.

The proposed model consists of five interrelated stages that collectively describe how hybrid intelligence is enacted in organizational contexts. These stages are analytically separable but empirically intertwined, forming a recursive cycle rather than a linear sequence.

5.1 Ideation Trigger

The process begins with the emergence of an ideation trigger, which defines the initial problem space or opportunity domain. This trigger may originate from human intuition, prior experience, or strategic intent, but it can also be informed by AI-driven insights derived from large-scale data analysis.

Human actors play a critical role in framing the problem by interpreting signals and defining boundaries for exploration. At the same time, AI systems contribute by identifying patterns, anomalies, or emerging trends that may not be immediately visible to human cognition (Duan *et al.*, 2019). The ideation trigger thus reflects a co-constructed sensing process, where both human judgment and machine intelligence contribute to the identification of opportunities.

Importantly, the quality of this stage influences subsequent outcomes, as it shapes the direction and scope of the creative search process.

5.2 Generative Expansion

Following the initial trigger, the process moves into a phase of generative expansion, in which AI systems produce a wide range of potential ideas, alternatives, or solutions. Generative AI significantly broadens the exploration space by enabling rapid recombination of knowledge elements and probabilistic generation of novel outputs.

This stage reflects the exploratory dimension of innovation, where diversity of options increases the likelihood of identifying valuable opportunities (March, 1991). AI's capacity for large-scale variation allows organizations to move beyond the cognitive constraints of human ideation, introducing possibilities that may not emerge through traditional creative processes.

However, this expansion is not inherently strategic. While AI excels at generating alternatives, it lacks contextual understanding and evaluative judgment. As such, generative expansion must be complemented by human interpretation to ensure relevance and coherence.

5.3 Selective Framing

The selective framing stage represents the critical transition from exploration to strategic evaluation. At this stage, human actors interpret, assess, and refine the outputs generated by AI systems, applying contextual knowledge, organizational priorities, and ethical considerations.

This process aligns with the seizing function in dynamic capabilities, where organizations determine which opportunities to pursue and how to allocate resources (Teece, 2007). AI may provide probabilistic recommendations or comparative analyses, but the final evaluation remains embedded in human judgment (Shrestha *et al.*, 2019).

Selective framing is particularly important because it filters the abundance generated during the expansion phase, transforming raw variation into strategically meaningful alternatives. Without effective framing, the value of generative processes remains unrealized.

5.4 Iterative Co-Creation

Following selection, ideas enter a phase of iterative co-creation, where human and AI agents engage in continuous cycles of refinement, feedback, and recombination. This stage represents the core mechanism of HACC, as it embodies the ongoing interaction through which value is progressively shaped.

Humans contribute direction, contextual adjustment, and evaluative judgment, while AI provides speed, variation, and computational support (Dellermann *et al.*, 2019; Seeber *et al.*, 2020). Through repeated interaction, outputs evolve beyond their initial forms, reflecting both human intentionality and machine-generated variation.

This process resonates with digital innovation logic, where value emerges through recombination and modular refinement rather than one-time creation (Yoo *et al.*, 2010). It also reflects adaptive orchestration, as organizations continuously adjust the balance between human input and AI contribution to improve outcomes.

Iterative co-creation therefore represents not a discrete stage but a dynamic interaction loop that refines both the output and the collaboration itself.

5.5 Value Realization

The final stage involves the realization of value, where co-created outputs are translated into organizational and market outcomes. In the creative economy, value is not determined solely by functional performance but also by meaning, authenticity, and consumer perception (Nambisan *et al.*, 2017).

Outputs generated through human–AI collaboration must be positioned, communicated, and legitimized in ways that resonate with stakeholders. Consumer responses to AI-assisted or AI-generated content depend on perceptions of originality, trust, and authorship (Puntoni *et al.*, 2021; Huang & Rust, 2021). As a result, value realization is both a substantive and interpretive process.

This stage highlights that value creation is incomplete until outputs are recognized and accepted in the market, reinforcing the importance of value attribution within the broader HACC framework.

5.6 Recursive Feedback and Capability Development

A defining feature of the model is its recursive nature. Insights generated during value realization feed back into subsequent cycles, informing future ideation, guiding generative processes, and refining evaluation criteria.

This feedback loop reflects the transforming dimension of dynamic capabilities, where organizations learn from experience and reconfigure processes over time (Pavlou & El Sawy, 2011; Warner & Wäger, 2019). Through repeated cycles, human–AI collaboration becomes more structured, efficient, and strategically aligned.

Importantly, this recursive process does not only improve outputs but also strengthens the underlying capability itself. HACC evolves through use, as organizations accumulate experience in coordinating human and AI contributions.

5.7 Integrative Mechanism

Taken together, the Human–AI Collaboration Cycle provides a mechanism-level explanation of how HACC operates. It demonstrates that value creation in AI-enabled environments is not the result of isolated actions or static resources, but of coordinated, iterative interactions between human and artificial intelligence.

By linking cognitive augmentation, generative co-creation, adaptive orchestration, and value attribution into a unified process, the model explains how organizations transform hybrid intelligence into sustained strategic advantage. In this sense, HACC functions as a dynamic and evolving system, where competitive advantage arises from the organization's ability to continuously refine and scale human–AI interaction.

6. Propositional Development

Building on the conceptualization of HACC and its underlying process mechanisms, this section develops a set of theoretical propositions that specify how HACC contributes to value creation in the creative economy. Rather than treating HACC as a monolithic construct, the propositions articulate how its dimensions and interaction dynamics influence key organizational outcomes.

Building on the conceptual framework and process model developed in the preceding sections, Figure 2 presents the propositional model of Human–AI Collaboration Capability and its relationships with strategic outcomes. The figure specifies the hypothesized relationships among the core collaboration mechanisms, intermediate outcomes, and firm-level performance.

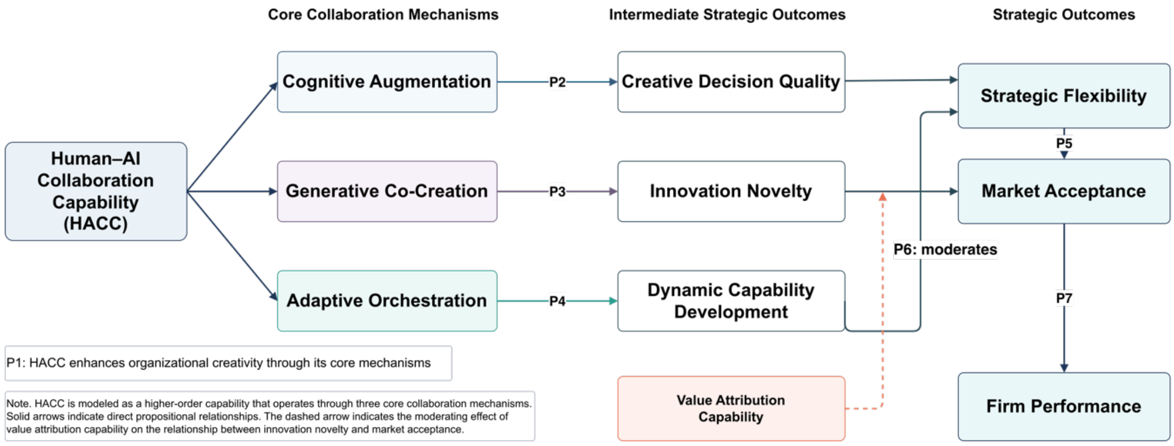

Figure 2. Propositional Model of Human–AI Collaboration Capability and Strategic Outcomes
Source: Developed by the author

As shown in Figure 2, HACC operates through three core collaboration mechanisms—cognitive augmentation, generative co-creation, and adaptive orchestration—which influence intermediate strategic outcomes, including creative decision quality, innovation novelty, and dynamic capability development. These intermediate outcomes subsequently contribute to strategic flexibility and market acceptance, which in turn drive firm performance.

In addition, value attribution capability is modeled as a moderating factor that shapes the relationship between innovation novelty and market acceptance. This highlights the importance of meaning construction and legitimacy in translating co-created outputs into market-recognized value.

The structure of the model reflects a multi-stage value creation process, where HACC functions as a higher-order capability that exerts its influence indirectly through interconnected mechanisms and outcomes.

6.1 HACC and Organizational Creativity

Organizational creativity reflects the capacity to generate ideas that are both novel and useful within a given context (Woodman *et al*., 1993; Anderson *et al*., 2014). In environments characterized by rapid change and symbolic competition, creativity becomes a central driver of differentiation.

HACC enhances organizational creativity by combining human interpretive capabilities with AI-enabled generative processes. While human actors contribute contextual understanding, cultural sensitivity, and meaning-making, AI systems expand the range of potential ideas through large-scale recombination and pattern recognition (Jarrahi, 2018; Dellermann *et al*., 2019). This interaction transforms creativity from an individual cognitive activity into a distributed and iterative process.

Importantly, the contribution of HACC lies not only in increasing idea quantity but in reshaping the structure of the creative search process itself. By enabling broader exploration and faster iteration, human–AI collaboration increases the likelihood of generating high-quality creative outcomes.

Proposition 1 (P1)
Human–AI Collaboration Capability is positively associated with organizational creativity.

6.2 Cognitive Augmentation and Creative Decision Quality

Creative processes often involve ambiguity, incomplete information, and competing alternatives. Under such conditions, decision quality depends on the ability to interpret signals, evaluate options, and align choices with strategic intent.

Cognitive augmentation enhances this process by integrating AI-driven analytical capabilities with human judgment. AI contributes by identifying patterns, simulating scenarios, and reducing informational uncertainty (Duan *et al.*, 2019), while human actors provide contextual interpretation and normative evaluation (Jarrahi, 2018; Shrestha *et al.*, 2019).

The effectiveness of this interaction depends on the degree to which AI insights are meaningfully integrated into human decision-making processes. When such integration occurs, organizations are better positioned to make informed and contextually appropriate creative decisions.

Proposition 2 (P2)
Cognitive augmentation positively influences creative decision quality by strengthening the integration of AI-generated insights with human contextual judgment.

6.3 Generative Co-Creation and Innovation Novelty

Innovation novelty refers to the extent to which outputs depart from existing solutions and introduce new combinations or meanings. It is typically associated with exploratory search and variation (March, 1991).

Generative co-creation expands the search space by enabling AI systems to produce diverse alternatives at scale. This increases the probability of identifying novel configurations that would be unlikely to emerge from human cognition alone (Dellermann *et al.*, 2019). However, novelty is not solely a function of generation. Human actors play a critical role in selecting, refining, and recombining AI outputs into coherent innovations.

This interaction creates a dual mechanism: AI enhances variation, while humans ensure direction and relevance. The resulting balance between exploration and guided refinement strengthens the novelty of innovation outcomes.

Proposition 3 (P3)
Generative co-creation positively influences innovation novelty by expanding the range of alternatives while enabling human-guided refinement.

6.4 Adaptive Orchestration and Dynamic Capability Development

Dynamic capabilities depend on the organization's ability to repeatedly sense opportunities, seize them, and transform resources in response to change (Teece, 2007). In AI-enabled environments, these processes require coordination between human and technological actors.

Adaptive orchestration facilitates this coordination by structuring interaction patterns, allocating tasks, and embedding feedback loops within organizational routines (Kellogg *et al.*, 2020; Seeber *et al.*, 2020). Through this process, human–AI collaboration becomes stabilized and repeatable, transforming interaction into capability.

This suggests that HACC contributes to dynamic capability development not merely through resource deployment, but through the institutionalization of hybrid interaction processes.

Proposition 4 (P4)
Adaptive orchestration positively influences dynamic capability development by embedding human–AI interaction into repeatable sensing, seizing, and transforming routines.

6.5 HACC and Strategic Flexibility

Strategic flexibility refers to the ability of firms to adapt to environmental changes by reconfiguring resources and exploring alternative courses of action (Zhou & Wu, 2010). In the creative economy, such flexibility is essential due to rapidly shifting consumer preferences and technological developments.

HACC enhances strategic flexibility by enabling organizations to generate multiple strategic options, evaluate them efficiently, and iteratively refine them through human–AI interaction. AI supports rapid exploration, while human actors maintain interpretive coherence and strategic alignment.

Through this mechanism, firms become better equipped to respond to uncertainty without sacrificing direction, thereby improving their adaptive capacity.

Proposition 5 (P5)
Human–AI Collaboration Capability is positively associated with strategic flexibility.

6.6 Value Attribution Capability and Market Acceptance

In the creative economy, value is shaped not only by functional performance but also by perceived authenticity, legitimacy, and meaning (Nambisan *et al.*, 2017). When outputs are co-created by humans and AI, ambiguity may arise regarding authorship and originality.

Value attribution capability enables organizations to frame and communicate co-created outputs in ways that enhance legitimacy and consumer trust. By clarifying the role of human creativity and AI contribution, firms can influence how outputs are perceived and evaluated (Puntoni *et al.*, 2021; Huang & Rust, 2021).

This suggests that the effectiveness of generative processes depends not only on production but also on interpretation and communication.

Proposition 6 (P6)
Value attribution capability positively moderates the relationship between generative co-creation and market acceptance of creative outputs.

6.7 HACC and Firm Performance

Firm performance in the creative economy depends on the ability to generate differentiated offerings, adapt to changing conditions, and achieve market acceptance. Prior research indicates that AI capability contributes to performance when supported by complementary organizational resources (Mikalef & Gupta, 2021; Wamba *et al.*, 2024).

HACC extends this logic by emphasizing the integration of human and AI capabilities within value creation processes. Through its effects on creativity, innovation novelty, strategic flexibility, and market acceptance, HACC contributes to performance through multiple, interrelated pathways.

Rather than exerting a direct effect, HACC operates as a higher-order capability that influences performance through mediating mechanisms embedded in organizational processes.

Proposition 7 (P7)
Human–AI Collaboration Capability positively influences firm performance through its effects on organizational creativity, innovation novelty, strategic flexibility, and market acceptance.

6.8 Integrated Propositional Logic

Taken together, these propositions position HACC as a meta-capability that connects cognitive processes, creative dynamics, organizational coordination, and market interpretation into a unified system of value creation.

The logic unfolds sequentially yet interactively. Cognitive augmentation and generative co-creation shape internal processes of idea generation and evaluation. Adaptive orchestration stabilizes these processes into repeatable routines, enabling capability development. Value attribution translates co-created outputs into market acceptance, completing the value creation cycle. Through these interconnected mechanisms, HACC enables organizations to transform hybrid intelligence into sustained competitive advantage.

This integrated structure not only provides a coherent theoretical framework but also offers a basis for empirical testing using quantitative, qualitative, or mixed-method approaches.

To provide a structured overview of the proposed relationships, Table 2 summarizes the key propositions, their underlying mechanisms, and expected outcomes. This table complements Figure 2 by explicitly linking each proposition to its theoretical rationale.

Table 2. Summary of Propositions and Theoretical Logic

Proposition & Relationship		Underlying Mechanism	Expected Outcome
P1	HACC → Organizational Creativity	Integration of human interpretation and AI-generated variation	Increased idea generation and creative quality
P2	Cognitive Augmentation → Creative Decision Quality	AI-supported analysis combined with human judgment	Improved decision accuracy and contextual relevance
P3	Generative Co-Creation → Innovation Novelty	Expansion of exploration space through AI-generated alternatives	Higher level of novelty in outputs
P4	Adaptive Orchestration → Dynamic Capability Development	Structuring and stabilization of human–AI interaction routines	Enhanced organizational adaptability
P5	HACC → Strategic Flexibility	Generation and evaluation of multiple strategic options	Greater responsiveness to environmental change
P6	Value Attribution moderates (Innovation → Market Acceptance)	Framing and legitimizing co-created outputs	Increased consumer trust and acceptance
P7	HACC → Firm Performance (via mediators)	Indirect effect through creativity, innovation, and flexibility	Improved firm-level outcomes

Source: Author's conceptualization

Table 2 demonstrates that HACC influences firm performance through a multi-stage and interrelated process. Rather than exerting direct effects, the capability operates through intermediate mechanisms that connect cognitive processes, creative dynamics, and market interpretation into a coherent system of value creation.

7. Discussion

7.1 Theoretical Contributions

This study contributes to the literature by advancing a relational and process-oriented perspective on artificial intelligence within strategic management. By conceptualizing HACC as a firm-level capability, the study extends existing theoretical frameworks in three important ways.

First, it revisits the dynamic capabilities perspective by challenging its implicit assumption of human-centered cognition. While prior work has emphasized sensing, seizing, and transforming as outcomes of managerial judgment and organizational routines (Teece, 2007; Pavlou & El Sawy, 2011), the present study suggests that these processes are increasingly co-constructed through interaction between human and artificial agents. This shift introduces the notion of distributed cognition into capability theory, where analytical and interpretive functions are no longer confined to human actors but are shared with AI systems (Raisch & Krakowski, 2021; Berente *et al.*, 2021). In doing so, the study provides a conceptual extension that better reflects the realities of data-intensive and AI-enabled organizational environments.

Second, the study reframes AI capability by moving beyond an instrumental, resource-based view toward a relational capability perspective. Existing research has largely focused on how firms deploy AI to enhance performance (Mikalef & Gupta, 2021; Wamba *et al.*, 2024). In contrast, this study emphasizes that the strategic value of AI depends on how it is integrated with human cognition through structured interaction processes. Competitive advantage, therefore, does not stem from AI alone, but from the organization's ability to orchestrate human–AI collaboration as a repeatable and scalable mechanism of value creation. This perspective aligns with relational views of digital innovation (Faraj *et al.*, 2018) while providing a clearer connection to capability-based theory.

Third, the study contributes to the creativity and innovation literature by reconceptualizing creativity as a co-creative and distributed process. Traditional models position creativity within individuals or social systems (Anderson *et al.*, 2014), whereas the present framework highlights the role of generative AI in expanding the space of possible ideas. Creativity is thus reframed as an emergent outcome of iterative interaction between human interpretation and machine-generated variation. This shift provides a more comprehensive understanding of how novelty is produced in digitally mediated environments.

Taken together, these contributions position HACC as a higher-order capability that integrates cognition, creativity, and coordination into a unified framework. Rather than treating technology and human agency as separate domains, the study emphasizes their interdependence as the foundation of contemporary value creation.

7.2 Managerial Implications

The findings of this study carry important implications for managers operating in environments characterized by rapid technological change and increasing reliance on AI.

First, organizations need to move beyond viewing AI as a tool for automation and instead recognize it as a collaborative partner in value creation processes. This shift requires rethinking organizational design to facilitate interaction between human and AI agents, rather than simply embedding AI into existing workflows. Managers must consider how tasks are allocated, how decisions are structured, and how human judgment and AI outputs are integrated.

Second, the development of competitive advantage increasingly depends on building capabilities rather than acquiring technologies. Investing in AI infrastructure alone is insufficient; firms must develop the organizational routines and competencies required to effectively coordinate human–AI interaction. This includes training employees to interpret AI outputs, fostering data-driven cultures, and establishing processes that enable iterative learning.

Third, adaptive orchestration emerges as a critical managerial challenge. Organizations must continuously adjust how human and AI contributions are balanced across different tasks and stages of value creation. This involves defining appropriate levels of autonomy for AI systems, maintaining human oversight, and ensuring accountability in hybrid decision environments (Kellogg *et al.*, 2020).

Fourth, managers in the creative economy must actively manage value attribution. As AI-generated content becomes more prevalent, issues of authenticity, originality, and trust become increasingly important. Firms must carefully frame the role of AI in creative outputs to ensure that they are perceived as legitimate and meaningful by consumers (Puntoni *et al.*, 2021; Huang & Rust, 2021).

Overall, the study suggests that managerial focus should shift from technology adoption to interaction design—how human and AI capabilities are combined to create value.

7.3 Policy Implications

At a broader level, the study highlights several implications for policymakers concerned with digital transformation and the development of creative industries.

First, there is a growing need to support the development of hybrid competencies that integrate technical and creative skills. Traditional education and training systems often treat these domains separately, whereas effective human–AI collaboration requires their convergence. Policymakers should therefore promote interdisciplinary programs that combine data literacy, AI understanding, and creative problem-solving.

Second, the increasing role of AI in creative processes raises questions related to authorship, ownership, and accountability. Existing regulatory frameworks are not fully equipped to address outputs generated through human–AI collaboration. Clear guidelines are needed to define intellectual property rights and ensure fair distribution of value in co-created outputs.

Third, innovation ecosystems should be designed to facilitate collaboration between technology developers, creative professionals, and organizations. Such ecosystems can accelerate the diffusion of human–AI collaboration practices and enhance the competitiveness of creative industries in global markets.

7.4 Future Research Directions

While this study provides a conceptual framework for understanding human–AI collaboration as a strategic capability, several avenues for future research remain open.

One important direction involves empirical validation of the proposed construct. Future studies can develop measurement scales for HACC and test the relationships outlined in the propositional model using quantitative methods such as structural equation modeling or experimental designs.

Another direction concerns contextual variation. The effectiveness of human–AI collaboration may differ across industries, organizational sizes, and cultural settings. Comparative studies could provide insights into how contextual factors influence the development and impact of HACC.

Longitudinal research would also be valuable in examining how HACC evolves over time. As organizations gain experience with AI systems, the nature of interaction, coordination, and learning may change, leading to different patterns of capability development (Warner & Wäger, 2019).

Finally, there is a need to explore micro-level mechanisms underlying human–AI interaction, such as trust formation, role negotiation, and decision authority. Understanding these processes can provide deeper insights into how collaboration is enacted in practice and how it contributes to organizational outcomes (Glikson & Woolley, 2020).

8. Conclusion

This study addressed a central question emerging at the intersection of artificial intelligence, creativity, and management: how value ownership is constructed and allocated in human–AI co-creation systems where contributions are distributed, iterative, and often opaque. Existing literature has examined AI as a technological capability, a source of ethical concern, or a driver of organizational change, yet has not sufficiently explained how these dimensions converge to shape ownership outcomes in collaborative human–machine environments. The objective of this study was therefore to develop an integrative conceptual framework that explains the process through which value is co-created and subsequently translated into ownership across multiple levels of analysis.

The analysis demonstrates that human–AI co-creation fundamentally destabilizes traditional assumptions of singular authorship and linear value creation. The most significant finding lies in conceptualizing this phenomenon as an ethical paradox system structured around four interdependent tensions: authorship ambiguity, value attribution uncertainty, responsibility diffusion, and authenticity erosion. These tensions do not operate in isolation but are mutually reinforcing, emerging through iterative interaction loops that blur the boundaries between human intention and machine generation. In contrast to prior studies that treat AI as either a tool or a threat, this study advances a processual perspective in which AI acts as a co-creative participant within a sociotechnical system. By integrating human input, AI generative processes, interaction dynamics, and value attribution mechanisms into a single framework, the study shows that ownership is not a post hoc legal assignment but an emergent outcome embedded within the co-creation process itself.

The theoretical contributions of this study are threefold. First, it extends ownership theory by reconceptualizing ownership as a distributed and multi-dimensional construct that encompasses legal rights, economic value capture, and symbolic recognition. Second, it advances co-creation theory by incorporating non-human agency, thereby offering a more comprehensive account of how value is generated in digitally mediated environments. Third, it integrates ethical considerations into the core of value creation, positioning ethics not as an external constraint but as a constitutive element in how ownership is legitimized and contested. These contributions collectively bridge gaps between management, information systems, and AI ethics literature, providing a unified lens for analyzing human–AI collaboration.

The study also offers important implications for practice and policy. For organizations, the findings highlight the need to design governance mechanisms that clarify roles, manage distributed agency, and ensure transparent value attribution in AI-assisted creative processes. Firms must move beyond implicit assumptions of ownership and develop explicit frameworks that address authorship, accountability, and value sharing. For platform operators, the analysis underscores the importance of addressing structural asymmetries in value capture and enhancing transparency in algorithmic systems. At the policy level, the study points to the inadequacy of existing legal frameworks in addressing hybrid authorship and calls for adaptive regulatory approaches that account for the evolving nature of AI-mediated production.

Notwithstanding these contributions, the study is subject to limitations that open avenues for further inquiry. As a conceptual analysis, it does not provide empirical validation of the proposed relationships, and its abstraction may not fully capture variations across industries, technologies, or institutional contexts. The framework also assumes a generalized form of human–AI interaction, whereas in practice the degree of autonomy and integration of AI systems may differ significantly. These limitations, however, do not detract from the study's value but instead highlight the complexity of the phenomenon and the need for continued empirical and theoretical development.

Future research should focus on empirically testing the proposed model across diverse creative and organizational settings, employing both quantitative and qualitative approaches to capture the dynamics of co-creation and ownership. Comparative studies across cultural and regulatory environments would provide deeper insights into how societal norms influence perceptions of value and legitimacy. Further investigation is also needed into the role of platforms as mediators of ownership, particularly in relation to data governance and revenue distribution. Interdisciplinary research that integrates management, law, and ethics will be critical in developing more robust frameworks capable of addressing the multifaceted challenges posed by human–AI collaboration.

In conclusion, the question of value ownership in the age of artificial intelligence cannot be resolved within existing paradigms that assume clear distinctions between creators, tools, and outputs. Human–AI co-creation reconfigures these distinctions, producing a new landscape in which ownership is negotiated, distributed, and continually redefined. By offering a theoretically grounded and integrative framework, this study contributes to advancing a more nuanced understanding of value ownership that reflects the realities of an increasingly intelligent and interconnected economy, and provides a foundation for future scholarship and practice in navigating this transformation.

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