



Reframing Innovation in the Age of Artificial Intelligence: A Human–AI Innovation Dynamics Model

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Abstrak

The rapid advancement of artificial intelligence, particularly generative AI, is fundamentally transforming how innovation is conceived and executed within organizations, yet existing research remains limited by human-centric, linear, and static conceptualizations of innovation processes. This study addresses this gap by developing a conceptual framework that explains how human–AI collaboration reshapes the dynamics of innovation. Adopting a theory synthesis approach, the study integrates insights from innovation theory, knowledge-based perspectives, hybrid intelligence, and co-creation literature to construct the Human–AI Innovation Dynamics Model. The model conceptualizes innovation as an interaction-based, iterative, and co-adaptive process driven by continuous exchanges between human cognition and AI-generated outputs. It further identifies key mechanisms, including iterative co-creation and iteration depth, as well as moderating and boundary conditions that influence innovation outcomes. The study contributes to the literature by reconceptualizing AI as a co-creative agent, extending dynamic capability theory toward interaction-based systems, and advancing the notion of distributed creativity. The framework provides a foundation for future empirical research and offers strategic implications for organizations navigating AI-enabled innovation environments.

Keywords

human–AI collaboration; innovation dynamics; generative artificial intelligence; co-creation; dynamic capability; distributed creativity

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1. Introduction

The rapid advancement of artificial intelligence (AI), particularly generative AI, is fundamentally transforming how innovation is conceived, developed, and realized within organizations. Traditionally, innovation has been understood as a human-centered process grounded in cognitive creativity, experiential knowledge, and organizational learning (Amabile & Pratt, 2016; Nonaka, 1994). However, recent developments in AI technologies have significantly altered this paradigm by enabling machines to actively participate in ideation, problem-solving, and creative production processes (Dellermann *et al.*, 2019; Raisch & Krakowski, 2021; Dwivedi *et al.*, 2023). As a result, innovation is no longer solely a human-driven activity but increasingly emerges from dynamic interactions between human cognition and algorithmic intelligence.

Emerging evidence suggests that generative AI does not merely enhance human creativity but fundamentally reshapes cognitive processes by introducing probabilistic and large-scale generative mechanisms that expand beyond human associative limits (Brynjolfsson *et al.*, 2023; Eloundou *et al.*, 2023). In this context, AI acts not only as a productivity-enhancing tool but as a co-creative agent capable of generating novel alternatives, recombining knowledge elements, and influencing decision-making trajectories. This shift signals a transition from bounded rational creativity toward statistically augmented ideation systems, thereby transforming the epistemic foundations of innovation processes.

Despite the growing recognition of AI's role in organizations, existing research has largely conceptualized AI as a tool for automation, efficiency enhancement, or decision support (Brynjolfsson *et al.*, 2017; Davenport *et al.*, 2020). Even more advanced perspectives tend to frame AI as an organizational capability that improves performance outcomes (Mikalef & Gupta, 2021; Dwivedi *et al.*, 2021). While these perspectives provide important insights, they remain limited in explaining how innovation itself evolves when AI becomes an active co-creator rather than a passive instrument. In particular, current literature lacks a comprehensive theoretical framework that captures the dynamic, iterative, and co-creative nature of innovation processes in human–AI collaborative systems.

At the same time, foundational theories of innovation emphasize that innovation is inherently dynamic, involving continuous cycles of exploration, recombination, and knowledge integration (March, 1991; Fleming, 2001; Nambisan *et al.*, 2017). These processes are traditionally driven by human cognition and organizational learning mechanisms (Grant, 1996; Argote, 2012). However, the integration of AI introduces new dynamics that challenge these assumptions. AI systems can generate vast numbers of alternatives, accelerate iteration cycles, and enable large-scale recombination of knowledge elements in real time (Brynjolfsson *et al.*, 2023; Huang & Rust, 2021). Consequently, innovation processes are no longer linear or solely human-controlled but evolve into co-adaptive systems characterized by continuous feedback loops between human judgment and machine-generated outputs.

This transformation is particularly salient in the context of the creative economy, where value creation increasingly depends on originality, symbolic meaning, and experiential differentiation (Arnould & Thompson, 2005; Throsby, 2008). In such environments, innovation is closely tied to creative processes that are socially and culturally embedded. While co-creation has long been recognized as a key mechanism of value creation in marketing and service systems (Prahalad & Ramaswamy, 2004; Vargo & Lusch, 2008), the emergence of AI as a co-creative agent introduces a qualitatively different form of collaboration that extends beyond human-to-human interaction. Creativity thus becomes a distributed phenomenon shaped by interactions among human actors, digital technologies, and algorithmic systems (Leonardi, 2011).

Against this backdrop, a critical gap emerges in the literature. Although prior research has examined innovation dynamics, human–AI collaboration, and co-creation as separate

streams, it has yet to fully integrate these perspectives into a unified framework that explains how innovation processes are reconfigured in AI-enabled environments. In particular, existing theories remain limited by their reliance on human-centric assumptions, linear process models, and static conceptualizations of technological roles. As AI increasingly assumes generative and decision-making functions, there is a need to reconceptualize innovation as an interaction-based, iterative, and hybrid process driven by continuous collaboration between human and artificial agents.

Accordingly, this study addresses the following research question: How does human–AI collaboration reshape the dynamics of innovation processes in contemporary organizations?

To answer this question, this paper develops a Human–AI Innovation Dynamics Framework that conceptualizes innovation as a multi-stage, iterative process emerging from the interaction between human cognitive capabilities and AI generative systems. Unlike prior studies that focus on static relationships between AI adoption and performance outcomes, this framework emphasizes the processual and interactional mechanisms through which innovation unfolds. Specifically, the model integrates insights from innovation theory, knowledge-based perspectives, and co-creation literature to explain how ideation, generation, selection, and refinement processes are fundamentally reconfigured in human–AI collaborative contexts.

The novelty of this study lies in three key contributions. First, it reconceptualizes AI from a supportive tool into an active co-innovator, thereby extending existing perspectives on digital innovation and artificial intelligence in management (Raisch & Krakowski, 2021; Nambisan *et al.*, 2017). Second, it introduces a dynamic, stage-based model of innovation that explicitly incorporates iterative feedback loops and co-adaptive mechanisms between human and AI agents, addressing the lack of process-oriented explanations in current literature. Third, it integrates both enabling and constraining mechanisms, recognizing not only the potential of AI to enhance exploration and speed but also risks such as cognitive dependency and the potential dilution of originality.

The urgency of this research is underscored by the rapid diffusion of generative AI across industries, where organizations increasingly rely on AI for creative tasks, product design, and strategic decision-making. Without a clear theoretical understanding of how human–AI interactions shape innovation processes, firms risk mismanaging the balance between human expertise and algorithmic capabilities. This is particularly critical in knowledge-intensive and creative sectors, where innovation quality and authenticity are key determinants of competitive advantage (Huang & Rust, 2018; Rust, 2020).

This study contributes to the literature in several important ways. Theoretically, it advances innovation research by proposing a multi-level, interaction-based framework that bridges gaps between innovation dynamics, human cognition, and AI capabilities. It also contributes to the emerging literature on human–AI collaboration by offering a structured explanation of how co-creation processes influence innovation outcomes. Practically, the model provides guidance for managers in designing organizational systems that effectively integrate human and AI capabilities, emphasizing the importance of balancing automation with human judgment. From a policy perspective, the findings highlight the need for new approaches to workforce development, governance, and capability building in AI-driven innovation ecosystems.

In sum, this paper argues that innovation in the age of artificial intelligence is no longer a purely human endeavor but a collaborative, evolving process shaped by the continuous interplay between human cognition and machine intelligence. Understanding this transformation is essential for advancing both theory and practice in management, innovation, and the creative economy.

2. Theoretical Foundations

2.1 Innovation as a Dynamic and Recombinative Process

Innovation has long been conceptualized as a dynamic, iterative, and path-dependent process rather than a static outcome. Foundational work by March (1991) highlights the fundamental tension between exploration and exploitation, where organizations must balance experimentation with efficiency. This duality is further extended by recombination theory, which posits that innovation emerges through the integration and reconfiguration of existing knowledge elements (Fleming, 2001). Such perspectives emphasize that novelty is not created *ex nihilo*, but through structured variation and recombination processes embedded within organizational systems.

Complementing this view, the knowledge-based perspective conceptualizes innovation as the result of knowledge integration and application across distributed organizational units (Grant, 1996; Kogut & Zander, 1992). Nonaka's (1994) theory of knowledge creation further enriches this understanding by emphasizing the dynamic interaction between tacit and explicit knowledge through iterative conversion processes. Collectively, these perspectives converge on the notion that innovation is a continuous learning process shaped by knowledge flows, organizational routines, and environmental adaptation (Argote, 2012).

However, contemporary digital environments challenge these traditional assumptions. Digital technologies, particularly AI, enable large-scale, real-time recombination of knowledge elements, thereby accelerating innovation cycles and expanding the scope of exploration (Nambisan *et al.*, 2017; Yoo *et al.*, 2010). This shift suggests that innovation processes are no longer bounded by human cognitive limitations but are increasingly shaped by computational augmentation. As a result, innovation evolves into a socio-technical system characterized by distributed cognition and continuous feedback between human and technological actors.

2.2 Human–AI Collaboration and Hybrid Intelligence

The increasing integration of artificial intelligence into organizational processes has led to the emergence of hybrid intelligence, defined as the collaborative interaction between human and machine intelligence (Dellermann *et al.*, 2019). Unlike traditional automation, which replaces human tasks, hybrid intelligence emphasizes complementarity, where humans contribute contextual judgment, intuition, and ethical reasoning, while AI provides computational power, scalability, and pattern recognition capabilities.

Recent research highlights that AI is progressively shifting from a supporting role toward an active participant in decision-making and innovation processes (Raisch & Krakowski, 2021). In particular, AI systems now perform cognitive functions traditionally associated with humans, including idea generation, prediction, and problem-solving (Dwivedi *et al.*, 2023). This transformation challenges the traditional division of labor between humans and machines and necessitates a reconfiguration of collaboration mechanisms.

Within this context, AI can assume multiple functional roles. As an augmentor, AI enhances human performance by improving efficiency and analytical capabilities (Brynjolfsson *et al.*, 2017). As a recommender, it guides decision-making through predictive analytics (Davenport *et al.*, 2020). More critically, as a generator, AI produces novel ideas and creative outputs through generative models, thereby directly contributing to innovation processes (Dwivedi *et al.*, 2023; Brynjolfsson *et al.*, 2023).

Despite these advancements, existing research remains fragmented and predominantly outcome-oriented, focusing on performance improvements rather than underlying interaction mechanisms. Consequently, there is limited theoretical integration between hybrid intelligence and innovation dynamics. This gap highlights the need for a process-oriented

perspective that explains how continuous interactions between humans and AI reshape innovation structures and outcomes.

2.3 Creativity, Co-Creation, and Distributed Agency

Creativity has traditionally been conceptualized as an individual cognitive process driven by intrinsic motivation, domain expertise, and creative thinking capabilities (Amabile & Pratt, 2016). However, contemporary research increasingly recognizes creativity as a socially embedded and collaborative phenomenon, where ideas emerge through interactions among individuals, teams, and networks (Anderson *et al.*, 2014; Zhou & Shalley, 2003).

The concept of co-creation extends this perspective by emphasizing that value is jointly created through interactions among multiple actors, including firms, customers, and stakeholders (Prahalad & Ramaswamy, 2004; Vargo & Lusch, 2008). This shift reflects a broader transition from firm-centric to network-centric models of innovation, where value creation is distributed across ecosystems.

In digital contexts, creativity becomes increasingly mediated by technological artifacts that shape how ideas are generated, shared, and refined (Leonardi, 2011). The integration of AI further intensifies this transformation by introducing a non-human actor capable of generating content, proposing alternatives, and influencing decision-making processes. As a result, creativity evolves into a distributed and hybrid phenomenon, where agency is shared between human cognition and algorithmic systems.

This reconceptualization challenges traditional creativity theories, which primarily focus on human actors. It suggests that innovation should be understood as emerging from socio-technical interactions rather than isolated cognitive processes. By incorporating AI into the co-creation paradigm, this study extends existing frameworks and provides a foundation for understanding creativity in AI-enabled environments.

2.4 Toward an Integrative Perspective

Taken together, the literatures on innovation dynamics, human–AI collaboration, and co-creation provide valuable but fragmented insights into how innovation processes operate. Innovation theory emphasizes recombination and learning, hybrid intelligence highlights human–AI complementarity, and co-creation research underscores distributed value creation. However, these perspectives have not been fully integrated into a unified framework that captures the interactional and iterative nature of innovation in AI-enabled contexts.

This study addresses this gap by synthesizing these theoretical streams into an integrative perspective that conceptualizes innovation as a dynamic, interaction-based process emerging from continuous collaboration between human and artificial intelligence. This synthesis forms the foundation for the conceptual framework developed in the following sections.

To further clarify the theoretical positioning of this study, Table 1 synthesizes key literature streams, highlighting their core contributions and limitations. This synthesis demonstrates how prior research, while rich in insights, remains fragmented and insufficient to explain innovation dynamics in human–AI collaborative contexts.

Table 1. Synthesis of Theoretical Foundations in Innovation and Human–AI Research

Theoretical Stream	Key Scholars	Core Focus	Key Contribution	Limitation
Innovation as Dynamic Process	March (1991); Fleming (2001); Nambisan <i>et al.</i> (2017)	Exploration–exploitation, recombination, digital innovation	Explains innovation as iterative and knowledge-driven process	Assumes human-driven processes; lacks AI integration

Theoretical Stream	Key Scholars	Core Focus	Key Contribution	Limitation
Knowledge-Based View	Grant (1996); Nonaka (1994); Kogut & Zander (1992)	Knowledge creation and integration	Highlights role of knowledge flows and learning	Limited to human and organizational cognition
Hybrid Intelligence (Human–AI Collaboration)	Dellermann <i>et al.</i> (2019); Raisch & Krakowski (2021)	Human–AI complementarity	Explains division of cognitive roles between humans and AI	Focuses on performance outcomes; lacks process explanation
AI Capability & Digital Innovation	Dwivedi <i>et al.</i> (2023); Brynjolfsson <i>et al.</i> (2023)	Generative AI, automation, augmentation	Shows AI as generator and decision agent	Lacks integration with innovation theory
Creativity Theory	Amabile & Pratt (2016); Zhou & Shalley (2003)	Individual creativity and cognition	Identifies drivers of creative output	Human-centric perspective
Co-Creation & Service-Dominant Logic	Prahalad & Ramaswamy (2004); Vargo & Lusch (2008)	Value co-creation	Emphasizes collaborative value creation	Limited to human actors
Digital & Socio-Technical Systems	Yoo <i>et al.</i> (2010); Leonardi (2011)	Technology-mediated processes	Shows role of digital artifacts in shaping innovation	Does not fully capture AI agency

Source: Developed by the author

As shown in Table 1, prior research provides strong theoretical foundations for understanding innovation, knowledge creation, and collaboration. However, these perspectives remain largely fragmented and insufficient to explain the structural transformation introduced by artificial intelligence. In particular, most frameworks either assume human-dominant processes or treat technology as a passive enabler rather than an active participant. This gap underscores the need for an integrative framework that captures innovation as a dynamic, interaction-based system involving both human and AI agents.

3. Conceptual Gap

Despite substantial advances across innovation theory, human–AI collaboration, and creativity research, a critical gap persists in explaining how innovation processes are fundamentally reconfigured in the presence of artificial intelligence. Existing theoretical perspectives provide important but partial explanations, often constrained by three dominant limitations: (1) reliance on implicitly linear or stage-based models of innovation, (2) human-centric assumptions in cognitive and creative processes, and (3) static conceptualizations of organizational capabilities. These limitations collectively hinder a comprehensive understanding of innovation as it unfolds within human–AI collaborative systems.

3.1 The Persistence of Linear and Stage-Based Innovation Models

A central limitation of prior research lies in its continued reliance on linear or sequential representations of innovation. Classical frameworks, such as the exploration–exploitation model (March, 1991) and knowledge conversion theory (Nonaka, 1994), acknowledge the dynamic nature of innovation but still implicitly assume ordered transitions between stages. Even contemporary digital innovation literature often conceptualizes innovation as a progression enabled by technological infrastructures (Yoo *et al.*, 2010; Nambisan *et al.*, 2017).

However, the emergence of generative AI fundamentally disrupts this logic. AI systems are capable of simultaneously generating, evaluating, and recombining ideas across multiple stages of the innovation process, effectively collapsing the boundaries between ideation, development, and refinement (Brynjolfsson *et al.*, 2023; Dwivedi *et al.*, 2023). This simultaneity transforms innovation into a recursive and non-linear system characterized by rapid iteration cycles and parallel processing of alternatives.

Consequently, existing linear models are insufficient for capturing the fluid and interconnected nature of innovation in AI-enabled environments. A new conceptualization is required—one that reflects the recursive, multi-directional, and continuously evolving structure of human–AI interaction.

3.2 Human-Centric Bias in Innovation and Creativity Theories

A second limitation concerns the persistent human-centric bias embedded within innovation and creativity theories. Foundational perspectives consistently position humans as the primary agents of cognition, creativity, and decision-making (Amabile & Pratt, 2016; Grant, 1996). Even within collaborative frameworks, non-human elements are typically treated as tools or enablers rather than active contributors.

This assumption becomes increasingly problematic in the context of AI-enabled systems. Contemporary AI technologies perform cognitive functions traditionally associated with human intelligence, including pattern recognition, predictive reasoning, and generative ideation (Dellermann *et al.*, 2019; Raisch & Krakowski, 2021). In particular, generative AI introduces a new form of creative agency, where machines actively produce novel alternatives and influence decision-making trajectories (Dwivedi *et al.*, 2023).

This shift aligns with the notion of distributed cognition, where cognitive processes are no longer confined to individuals but are distributed across human and technological actors. As a result, innovation must be reconceptualized as an emergent outcome of interactions between human cognition and algorithmic systems, rather than as a purely human-driven phenomenon.

3.3 Static Conceptualization of Capabilities in Dynamic Environments

A third limitation lies in the static treatment of organizational capabilities. While the dynamic capabilities framework emphasizes adaptability and resource reconfiguration (Teece, 2007), it remains grounded in a firm-centric and human-driven perspective. Capabilities are typically conceptualized as organizational attributes that are developed, deployed, and controlled by human actors.

In AI-enabled contexts, however, capabilities are increasingly co-constructed through continuous interaction between human expertise and machine learning systems. AI systems learn from human input, adapt to feedback, and shape subsequent decision-making processes, creating an ongoing feedback loop that dynamically reshapes both human and technological capabilities (Mikalef & Gupta, 2021).

This interaction suggests that capabilities should be understood not as static resources but as emergent properties of socio-technical systems. Such a perspective requires a shift from viewing capabilities as organizational assets toward understanding them as evolving outcomes of human–AI co-adaptation.

3.4 Fragmentation Across Theoretical Streams

Beyond these limitations, a broader issue lies in the fragmentation of existing research. Innovation theory, human–AI collaboration, and co-creation literature have largely developed in parallel, with limited theoretical integration. Innovation research focuses on processes and outcomes, hybrid intelligence literature emphasizes complementarity, and co-creation theory

highlights value generation through interaction (Prahalad & Ramaswamy, 2004; Vargo & Lusch, 2008).

However, these perspectives have not been systematically combined to explain how innovation processes are structurally transformed when AI becomes an active participant. This fragmentation limits the explanatory power of existing frameworks and prevents a holistic understanding of innovation in AI-enabled environments.

3.5 Toward an Interaction-Based and Iterative Innovation Model

Addressing these limitations requires a fundamental reconceptualization of innovation processes. Specifically, three theoretical shifts are necessary.

First, innovation must be understood as an interaction-based system, where outcomes emerge from continuous exchanges between human and AI agents rather than from isolated actions. This perspective shifts the analytical focus from individual actors to relational dynamics.

Second, innovation processes must be conceptualized as iterative and recursive, incorporating feedback loops that continuously refine and reshape ideas. This contrasts with linear models and reflects the real-time, adaptive nature of human–AI collaboration.

Third, artificial intelligence must be recognized as a co-agent in the innovation process. Rather than being treated as a tool or infrastructure, AI should be conceptualized as an active participant that contributes to ideation, influences decision-making, and shapes innovation outcomes.

3.6 Summary of the Conceptual Gap

In summary, existing theories are limited by linear assumptions, human-centric bias, and static conceptualizations of capabilities. These limitations prevent a comprehensive understanding of innovation in AI-enabled environments. This study addresses this gap by proposing a Human–AI Innovation Dynamics Model that conceptualizes innovation as a multi-stage, iterative, and interaction-based process driven by continuous collaboration between human and artificial intelligence.

To illustrate the proposed reconceptualization, Figure 1 presents the Human–AI Innovation Dynamics Model, which captures the interaction-based, iterative, and co-adaptive nature of innovation processes in AI-enabled environments.



Figure 1. Human–AI Innovation Dynamics Model: An Interaction-Based and Iterative Framework
Source: Developed by the authors.

As shown in Figure 1, innovation emerges from a multi-stage process involving human ideation, AI-driven generative expansion, human selection and framing, and iterative co-creation loops. These stages are interconnected through feedback mechanisms that enable continuous refinement and adaptation. The model also incorporates key moderating and mediating variables, including human judgment, interaction intensity, and dynamic capability, which collectively shape innovation outcomes in terms of novelty and usefulness.

4. Proposed Framework

4.1 Human–AI Innovation Dynamics Model

Building on the conceptual gaps identified in the previous section, this study proposes the Human–AI Innovation Dynamics Model, which conceptualizes innovation as an interaction-based, iterative, and co-adaptive process emerging from continuous collaboration between human cognition and artificial intelligence.

Unlike traditional linear models, the proposed framework positions innovation as a recursive system in which human and AI agents jointly contribute to idea generation, evaluation, and refinement through ongoing feedback loops. This perspective shifts the analytical focus from sequential stages toward interaction dynamics, emphasizing how innovation outcomes are shaped by the intensity, structure, and quality of human–AI collaboration.

As illustrated in Figure 1, the model consists of four interconnected process stages—human ideation, AI generative expansion, human selection and framing, and iterative co-creation—culminating in innovation outputs. These stages are embedded within a system of feedback loops and co-adaptive mechanisms that continuously reshape both human cognition and AI outputs over time.

4.2 Core Process Stages of Human–AI Innovation

The innovation process begins with human ideation, where individuals draw upon prior knowledge, domain expertise, and contextual understanding to define problem spaces and initiate creative exploration (Amabile & Pratt, 2016). This stage plays a critical role in framing the direction of innovation, as it determines the initial conditions that guide subsequent interactions with AI systems.

Following this, AI generative expansion significantly broadens the scope of idea generation. Leveraging large-scale data processing and probabilistic modeling, AI systems generate diverse alternatives and novel combinations that extend beyond human cognitive constraints (Brynjolfsson *et al.*, 2023; Dwivedi *et al.*, 2023). This stage enhances exploratory capacity and increases the diversity of potential innovation pathways.

However, the abundance of AI-generated outputs necessitates human selection and framing, where individuals evaluate, filter, and reinterpret generated alternatives based on strategic goals, contextual relevance, and value considerations (Grant, 1996; Davenport *et al.*, 2020). This stage highlights the continued importance of human judgment in transforming raw ideas into meaningful and actionable innovations.

The process then evolves into an iterative co-creation loop, where human and AI agents engage in continuous cycles of generation, evaluation, and refinement. In this stage, human feedback informs AI outputs, while AI-generated alternatives reshape human thinking. This recursive interaction reflects a co-adaptive system in which both agents evolve over time, reinforcing each other's capabilities (Dellermann *et al.*, 2019; Raisch & Krakowski, 2021).

Ultimately, these interactions lead to innovation outputs, which are evaluated based on two key dimensions: novelty and usefulness (Fleming, 2001; Amabile & Pratt, 2016). Importantly, outputs are not final endpoints but feed back into the system, influencing future ideation and reinforcing the dynamic nature of the innovation process.

4.3 Underlying Mechanisms: Feedback, Reinforcement, and Co-Adaptation

Beyond the observable stages, the proposed framework is driven by three underlying mechanisms that explain how innovation evolves over time.

First, feedback loops connect outputs to earlier stages, enabling continuous learning and refinement. These loops ensure that insights generated during the innovation process are reintegrated into subsequent cycles, enhancing both efficiency and effectiveness.

Second, reinforcement effects emerge through repeated interactions between human and AI agents. Successful patterns, ideas, and decision strategies are strengthened over time, as AI systems learn from human inputs and humans adapt their cognitive approaches based on AI-generated insights.

Third, the model emphasizes co-adaptation, where both human cognition and AI systems evolve through interaction. AI systems continuously adjust their outputs based on feedback, while humans refine their problem-solving strategies in response to AI capabilities. This co-evolutionary dynamic transforms innovation into a living system rather than a static process.

4.4 Key Variables in Human–AI Innovation Dynamics

To operationalize the proposed framework, the model identifies key variables across three analytical dimensions: inputs, processes, and outputs.

At the input level, two core variables shape the innovation process. Human creativity reflects the ability of individuals to generate original and meaningful ideas, influenced by expertise, intrinsic motivation, and cognitive flexibility (Amabile & Pratt, 2016). AI capability, on the other hand, captures the technological capacity of AI systems to generate, analyze, and recombine information, including both generative and predictive functionalities (Mikalef & Gupta, 2021).

At the process level, the effectiveness of human–AI collaboration is determined by interaction dynamics. Interaction intensity refers to the frequency and depth of engagement between human and AI agents, influencing the extent of knowledge exchange and refinement. Iteration depth captures the degree to which ideas undergo repeated cycles of generation and evaluation, reflecting the recursive nature of innovation processes.

At the output level, innovation outcomes are conceptualized along two dimensions. Innovation novelty refers to the originality and uniqueness of outputs, while innovation usefulness reflects their practical value and alignment with user or market needs (Fleming, 2001; Amabile & Pratt, 2016). Together, these dimensions capture the dual criteria of successful innovation.

4.5 Integrative Logic of the Model

Taken together, the Human–AI Innovation Dynamics Model provides an integrative framework that captures the multi-level, processual, and interaction-based nature of innovation in AI-enabled environments. By linking stages, mechanisms, and variables, the model moves beyond static representations and offers a dynamic explanation of how innovation emerges from continuous collaboration between human and artificial intelligence.

This integrative perspective serves as the foundation for the development of formal propositions in the next section, where the relationships among key constructs are articulated and positioned for empirical testing.

To enhance the empirical readiness of the proposed framework, Table 2 presents the key constructs, conceptual definitions, analytical roles, and possible measurement indicators. This operational mapping clarifies how the Human–AI Innovation Dynamics Model can be translated into future empirical research, particularly using structural equation modeling approaches.

Table 2. Proposed Constructs and Measurement Indicators for the Human–AI Innovation Dynamics Model

Construct	Role in Model	Conceptual Definition	Possible Measurement Indicators	Theoretical Basis
Human Creativity	Input variable	The individual capability to generate original, meaningful, and contextually relevant ideas.	Domain expertise; intrinsic motivation; cognitive flexibility; originality of initial ideas; ability to frame problems creatively.	Amabile & Pratt (2016); Anderson <i>et al.</i> (2014); Zhou & Shalley (2003)
AI Capability	Input variable	The technological capacity of AI systems to generate, analyze, predict, and recombine information for innovation purposes.	Generative capacity; predictive accuracy; data-processing ability; recombination capacity; responsiveness to prompts.	Mikalef & Gupta (2021); Dwivedi <i>et al.</i> (2023); Brynjolfsson <i>et al.</i> (2023)
AI Generative Expansion	Process variable	The extent to which AI broadens the range, diversity, and novelty of potential ideas or solutions.	Number of generated alternatives; diversity of outputs; novelty of AI suggestions; speed of idea expansion; unexpected recombinations.	Fleming (2001); Dwivedi <i>et al.</i> (2023); Brynjolfsson <i>et al.</i> (2023)
Human Selection and Framing	Process variable	The human ability to evaluate, filter, contextualize, and assign meaning to AI-generated outputs.	Relevance assessment; strategic fit; contextual interpretation; feasibility evaluation; ethical judgment.	Grant (1996); Davenport <i>et al.</i> (2020); Raisch & Krakowski (2021)
Interaction Intensity	Process variable	The frequency, depth, and responsiveness of exchanges between human and AI agents during innovation activities.	Frequency of interaction; depth of prompt refinement; responsiveness to AI outputs; continuity of feedback; collaborative engagement.	Dellermann <i>et al.</i> (2019); Dellermann <i>et al.</i> (2020); Raisch & Krakowski (2021)
Iteration Depth	Mediating process variable	The extent to which ideas undergo repeated cycles of generation, evaluation, modification, and refinement.	Number of refinement cycles; degree of revision; feedback integration; progressive improvement; learning from prior outputs.	March (1991); Nambisan <i>et al.</i> (2017); Garud <i>et al.</i> (2013)
Iterative Co-Creation	Mediator	The collaborative process through which human and AI agents jointly transform initial ideas into refined innovation outputs.	Human feedback to AI; AI-driven idea modification; mutual adjustment; co-development of solutions; repeated human–AI refinement.	Prahalad & Ramaswamy (2004); Vargo & Lusch (2008); Dellermann <i>et al.</i> (2019)
Human Selective Judgment	Moderator	The human evaluative capability to determine which AI-generated outputs are useful, meaningful, ethical, and strategically relevant.	Critical evaluation; contextual judgment; domain-based filtering; ethical consideration; avoidance of overreliance on AI.	Grant (1996); Jarrahi (2018); Raisch & Krakowski (2021)

Construct	Role in Model	Conceptual Definition	Possible Measurement Indicators	Theoretical Basis
Dynamic Capability	Moderator	The organizational ability to sense, seize, and reconfigure resources to support effective human–AI innovation.	Opportunity sensing; resource reconfiguration; process adaptability; learning capability; AI integration capability.	Teece (2007); Mikalef & Gupta (2021); Vial (2019)
Balanced Human–AI Collaboration	Boundary condition	The degree to which human and AI contributions are proportionally integrated in the innovation process.	Complementarity of roles; balance between automation and human judgment; avoidance of AI dominance; human oversight; collaborative fit.	Dellermann <i>et al.</i> (2019); Raisch & Krakowski (2021); Wilson & Daugherty (2018)
Innovation Novelty	Output variable	The degree to which innovation outputs are original, unique, and meaningfully different from existing solutions.	Originality; uniqueness; radicalness; divergence from existing ideas; perceived newness.	Fleming (2001); Amabile & Pratt (2016); Anderson <i>et al.</i> (2014)
Innovation Usefulness	Output variable	The extent to which innovation outputs are practical, feasible, valuable, and aligned with user or market needs.	Practical value; feasibility; market relevance; user benefit; strategic usefulness.	Amabile & Pratt (2016); Vargo & Lusch (2008); Huang & Rust (2021)
Innovation Performance	Final outcome	The overall effectiveness of innovation outcomes in generating organizational, market, or creative value.	Innovation quality; implementation success; competitive value; creative performance; organizational impact.	Nambisan <i>et al.</i> (2017); Teece (2007); Mikalef & Gupta (2021)

Source: Developed by the author based on innovation theory, human–AI collaboration, dynamic capability, and co-creation literature.

As presented in Table 2, the proposed model can be operationalized through input, process, moderating, mediating, and output constructs. This structure enables future empirical studies to test not only direct relationships between human creativity, AI capability, and innovation outcomes, but also the mechanisms through which human–AI collaboration produces innovation. In particular, iteration depth and iterative co-creation serve as process mechanisms, while human selective judgment and dynamic capability function as boundary conditions that shape the effectiveness of AI-enabled innovation.

5. Proposition Development

Building on the Human–AI Innovation Dynamics Model and its operationalization in Table 2, this section develops a set of theoretically grounded propositions that explain how innovation outcomes emerge from the interaction between human creativity and artificial intelligence. The propositions capture direct effects, mediating mechanisms, and moderating conditions, providing a comprehensive structure for future empirical testing.

5.1 Direct Effects in Human–AI Innovation

Human creativity serves as the foundational input in the innovation process, shaping how problems are defined and how initial ideas are framed. Creativity theory suggests that individuals with higher levels of domain expertise, intrinsic motivation, and cognitive flexibility are more capable of generating original and meaningful ideas (Amabile & Pratt, 2016). In the context of human–AI collaboration, this capability determines the quality of initial ideation, which subsequently influences the effectiveness of AI-generated expansion.

At the same time, AI capability significantly enhances the breadth and diversity of idea generation. Generative AI systems can process vast amounts of data and recombine knowledge elements to produce a wide range of alternatives beyond human cognitive constraints (Dwivedi *et al.*, 2023; Brynjolfsson *et al.*, 2023). From an innovation perspective, such diversity is critical for exploratory search and recombination processes (March, 1991; Fleming, 2001).

Furthermore, the intensity of interaction between human and AI agents plays a crucial role in shaping innovation outcomes. Higher interaction intensity enables continuous feedback, refinement, and knowledge recombination, leading to greater novelty in outputs (Nambisan *et al.*, 2017; Dellermann *et al.*, 2019).

Based on these arguments, the following propositions are advanced:

P1: *Human creative capability positively influences the quality of initial ideation.*

P2: *AI capability positively influences idea diversity through generative expansion.*

P3: *Interaction intensity between human and AI positively affects innovation novelty.*

5.2 Mediating Mechanism: Iterative Co-Creation

While both human creativity and AI capability contribute to innovation, their effects are not direct but are realized through the process of iterative co-creation. This process involves continuous cycles of idea generation, evaluation, and refinement, where human and AI agents collaboratively transform raw ideas into meaningful innovation outcomes.

Iterative co-creation functions as a transformation mechanism that converts AI-generated outputs into contextually relevant and strategically aligned innovations. Without such iteration, the potential value of AI-generated ideas may remain unrealized. This aligns with the broader view of innovation as a recursive and learning-based process (Garud *et al.*, 2013; Nambisan *et al.*, 2017).

Moreover, iteration depth—capturing the extent of repeated refinement cycles—enhances the quality of innovation outcomes by allowing for progressive improvement and integration of feedback. This suggests that the effectiveness of AI capability depends on the extent to which organizations engage in iterative co-creation processes.

Accordingly, the following propositions are formulated:

P4: *Iterative co-creation mediates the relationship between AI capability and innovation performance.*

P5: *Iteration depth positively influences innovation quality by enhancing refinement processes.*

5.3 Moderating Effects: Human Judgment and Dynamic Capability

Despite the generative power of AI, not all outputs are valuable or relevant. Human selective judgment plays a critical role in evaluating, filtering, and contextualizing AI-generated ideas. This aligns with the knowledge-based view, which emphasizes the importance of human expertise in interpreting and applying knowledge (Grant, 1996).

Human judgment determines which ideas are retained, refined, or discarded, thereby influencing the usefulness of innovation outcomes. In this sense, it acts as a moderating mechanism that strengthens the relationship between AI-generated outputs and their practical value.

At the organizational level, dynamic capability further shapes the effectiveness of human–AI collaboration. Firms with strong dynamic capabilities are better able to integrate, reconfigure, and leverage both human and AI resources to support innovation (Teece, 2007). Such capabilities enable organizations to adapt collaboration processes, manage feedback loops, and continuously improve innovation outcomes.

Thus, the following propositions are advanced:

P6: *Human selective judgment positively moderates the relationship between AI-generated outputs and innovation usefulness.*

P7: *Dynamic capability positively moderates the relationship between human–AI collaboration and innovation performance.*

5.4 Boundary Condition: Balanced Human–AI Collaboration

The effectiveness of human–AI collaboration is contingent upon the balance between human and AI contributions. Over-reliance on AI may lead to cognitive dependency and reduced originality, while excessive reliance on human cognition may limit exploration and scalability (Raisch & Krakowski, 2021).

A balanced collaboration leverages the complementary strengths of both agents—human intuition and contextual understanding alongside AI’s computational and generative capabilities. Such complementarity enhances both novelty and usefulness, leading to superior innovation performance.

Therefore, the following proposition is proposed:

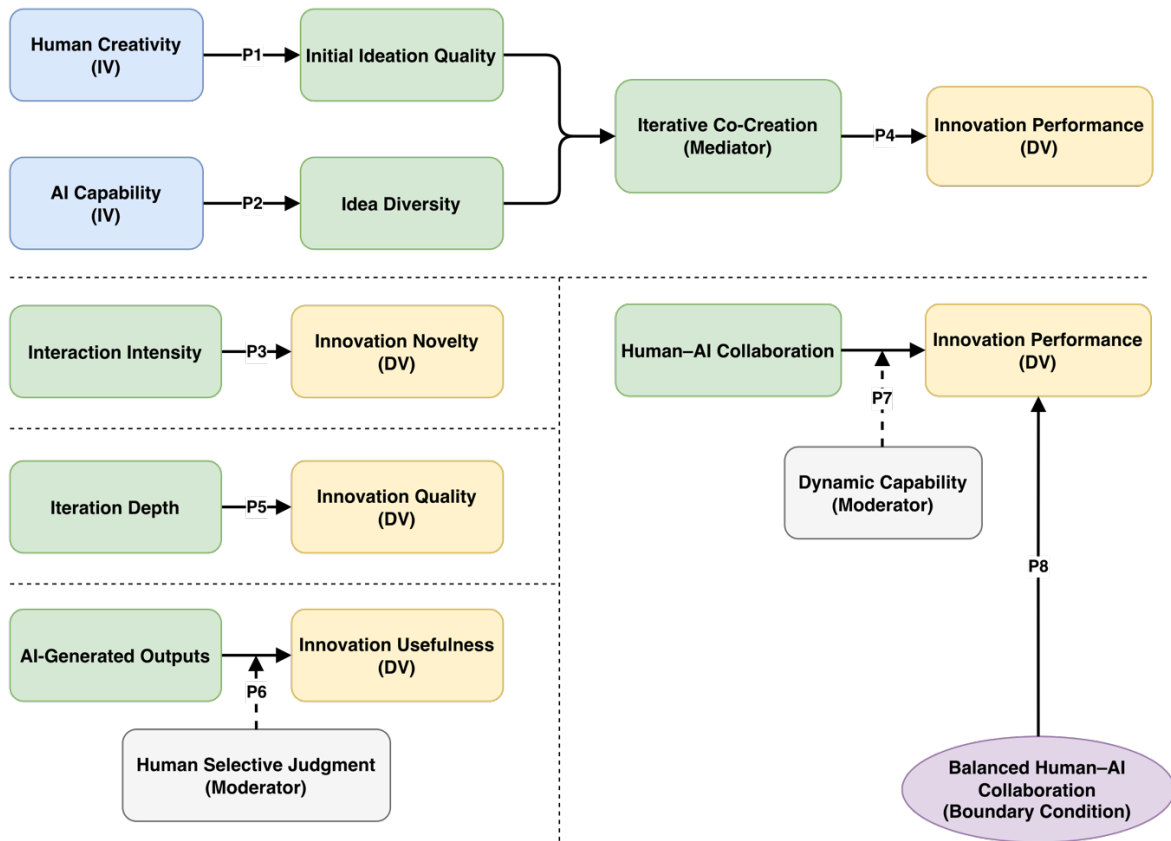
P8: *Balanced human–AI collaboration leads to higher innovation performance compared to AI-dominant or human-dominant processes.*

5.5 Integrative Model Perspective

Taken together, the proposed relationships form a coherent theoretical model that explains how innovation emerges from the interaction between human creativity and AI capability. The model integrates direct effects (P1–P3), mediating mechanisms (P4–P5), moderating conditions (P6–P7), and boundary effects (P8), providing a comprehensive framework for understanding human–AI innovation dynamics.

Importantly, this structure aligns with a PLS-SEM analytical approach, enabling future research to test complex relationships involving mediation and moderation. This not only strengthens the theoretical contribution of the model but also enhances its empirical applicability in diverse organizational contexts.

To provide a clear representation of the proposed relationships, Figure 2 presents the structural proposition map of the Human–AI Innovation Dynamics Model. The figure illustrates the direct effects, mediating mechanisms, moderating influences, and boundary conditions underlying the proposed theoretical framework.



Legend: IV = Independent Variable; DV = Dependent Variable; dashed arrows indicate moderating effects.

Figure 2. Structural Proposition Map of Human–AI Innovation Dynamics
Source: Developed by the author

As shown in Figure 2, the model specifies multiple relational paths linking human creativity and AI capability to innovation outcomes. Iterative co-creation functions as the central mediating mechanism, while interaction intensity and iteration depth capture key process dynamics influencing novelty and performance. The model further incorporates human selective judgment and dynamic capability as moderating conditions, highlighting the role of human and organizational factors in shaping the effectiveness of AI-enabled innovation. Balanced human–AI collaboration is positioned as a boundary condition that ensures optimal integration between human and algorithmic contributions.

6. Discussion

6.1 Theoretical Advancement: Reframing Innovation in the Age of AI

This study advances innovation research by fundamentally reframing innovation as an interaction-based, iterative, and co-adaptive process emerging from continuous collaboration between human cognition and artificial intelligence. While prior research has acknowledged the dynamic nature of innovation (March, 1991; Nambisan *et al.*, 2017), it has largely remained anchored in human-centric and stage-based assumptions. The proposed Human–AI Innovation Dynamics Model challenges these assumptions by demonstrating that innovation is no longer a sequence of activities performed by human actors, but a recursive system shaped by ongoing exchanges between human and algorithmic agents.

A key theoretical contribution lies in shifting the unit of analysis from isolated actors to interaction dynamics. Rather than viewing innovation as the outcome of individual creativity or organizational routines, this study conceptualizes it as an emergent property of socio-technical systems. This perspective aligns with and extends digital innovation research by

explicitly incorporating AI as an active co-creative agent rather than a passive technological enabler (Raisch & Krakowski, 2021; Dwivedi *et al.*, 2023). In doing so, the study responds to recent calls for more integrative frameworks that capture the complexity of innovation in digitally mediated environments.

Furthermore, this study extends the dynamic capability framework by reconceptualizing capabilities as co-evolving properties of human–AI systems. Traditional views emphasize organizational abilities to sense, seize, and reconfigure resources (Teece, 2007), but remain grounded in human-driven processes. In contrast, the present model highlights that capabilities increasingly emerge from continuous interaction between human expertise and AI systems, where both agents adapt and influence each other over time. This shift transforms dynamic capability from a firm-level construct into a distributed and interaction-based phenomenon, offering a more nuanced understanding of capability development in AI-enabled contexts.

Another significant contribution lies in integrating creativity and co-creation theory within a human–AI framework. While creativity research has traditionally focused on individual cognition (Amabile & Pratt, 2016) and co-creation literature has emphasized collaborative value creation among human actors (Prahalad & Ramaswamy, 2004; Vargo & Lusch, 2008), this study extends both perspectives by incorporating AI as a co-creative participant. As a result, creativity is reconceptualized as a distributed process spanning human and artificial agents, where innovation emerges through iterative cycles of interaction, recombination, and refinement.

Taken together, these contributions position the study as a theory-building effort that bridges fragmented literatures and offers a unified framework for understanding innovation in the age of artificial intelligence. By moving beyond linear, human-centric, and static perspectives, the study provides a more comprehensive and realistic representation of contemporary innovation processes.

6.2 Managerial Implications: Designing Adaptive Human–AI Innovation Systems

Beyond its theoretical contributions, the proposed framework offers important managerial implications for organizations seeking to leverage AI in innovation processes. A central implication is the need to move beyond viewing AI as a standalone tool and instead design organizational systems that enable effective human–AI collaboration.

First, organizations must rethink how innovation teams are structured by developing hybrid human–AI systems. Rather than separating technological and creative roles, firms should integrate AI into innovation workflows as an active participant. This requires clear role differentiation, where humans focus on problem framing, contextual interpretation, and strategic judgment, while AI contributes to idea generation, pattern recognition, and rapid exploration (Dellermann *et al.*, 2019; Raisch & Krakowski, 2021). Such integration enhances complementarity and enables organizations to fully exploit the strengths of both human and artificial intelligence.

Second, the findings highlight the growing importance of new skill sets for human–AI collaboration. In particular, employees must develop capabilities in prompting, interpretation, and evaluation. The ability to effectively guide AI systems through well-structured inputs determines the quality and relevance of generated outputs, while critical evaluation skills ensure that AI-generated ideas are filtered and contextualized appropriately (Davenport *et al.*, 2020; Dwivedi *et al.*, 2023). This suggests that organizations must invest in capability development that goes beyond technical proficiency, emphasizing cognitive and interactional skills.

Third, the model underscores the importance of governance in AI-enabled innovation. As AI assumes a more active role in creative and decision-making processes, organizations must establish mechanisms to balance autonomy and control. This includes mitigating risks such as cognitive dependency, ensuring transparency and explainability, and maintaining human oversight in critical decision points (Huang & Rust, 2021). Governance frameworks must also address emerging challenges related to authorship, accountability, and intellectual property in AI-assisted innovation.

Finally, the study highlights the need for organizations to transition toward adaptive and co-evolutionary innovation systems. Innovation processes should be designed to support continuous feedback, iterative experimentation, and learning. By enabling co-adaptation between human and AI agents, organizations can enhance both the speed and quality of innovation, leading to more sustainable competitive advantage.

6.3 Future Research Directions: Toward Empirical and Multi-Level Exploration

While the proposed model provides a comprehensive conceptual framework, it also opens several avenues for future research. A primary direction involves empirical validation using structural equation modeling approaches, particularly PLS-SEM. The constructs and relationships outlined in this study provide a clear foundation for testing direct, mediating, and moderating effects within human–AI innovation systems.

Experimental research designs also offer promising opportunities to examine causal mechanisms underlying human–AI collaboration. By comparing human-only, AI-dominant, and hybrid systems, future studies can identify optimal configurations of interaction intensity, iteration depth, and role balance. Such approaches would provide deeper insights into how different collaboration structures influence innovation outcomes.

In addition, there is a need for industry-specific investigations to explore how human–AI innovation dynamics vary across contexts. The role of AI may differ significantly between creative industries, technology-driven sectors, and service environments, suggesting that contextual factors play a critical role in shaping innovation processes. Understanding these variations would enhance the generalizability and applicability of the proposed framework.

Future research may also benefit from adopting multi-level and longitudinal perspectives. Innovation is inherently dynamic, and capturing how human–AI interactions evolve over time requires examining processes at individual, team, and organizational levels. Such approaches would provide a more comprehensive understanding of how co-adaptation and feedback mechanisms develop and stabilize within innovation systems.

6.4 Integrative Insight

Overall, this study demonstrates that innovation in the age of artificial intelligence cannot be adequately explained through traditional frameworks that separate human creativity from technological capability. Instead, innovation must be understood as an emergent, interaction-based phenomenon shaped by continuous collaboration between human and AI agents. This perspective not only advances theoretical understanding but also provides a foundation for future empirical research and practical application in AI-driven innovation environments.

7. Conclusion

This study set out to address a fundamental gap in contemporary innovation research: the lack of a coherent theoretical explanation for how innovation processes are reconfigured when artificial intelligence evolves from a supporting tool into an active co-creative agent. Specifically, it aimed to explain how human–AI collaboration reshapes the dynamics of innovation within organizations. By developing the Human–AI Innovation Dynamics Model,

the study reconceptualizes innovation as an interaction-based, iterative, and co-adaptive process, moving beyond traditional linear and human-centric frameworks that have dominated prior literature.

The findings advance existing knowledge by demonstrating that innovation in AI-enabled environments is not simply accelerated or enhanced, but structurally transformed. Unlike prior perspectives that treat AI as a capability or infrastructure (e.g., Davenport *et al.*, 2020; Mikalef & Gupta, 2021), this study positions AI as a co-creative agent that actively participates in ideation, recombination, and evaluation processes. The model further reveals that innovation outcomes are shaped not only by the presence of AI but by the quality of interaction between human and artificial agents, mediated through iterative co-creation and moderated by human judgment and organizational capabilities. This insight extends foundational theories of innovation (March, 1991; Nambisan *et al.*, 2017) by introducing a recursive and interactional logic that better reflects the realities of AI-driven innovation systems.

From a theoretical standpoint, the study contributes in three significant ways. First, it reframes innovation as an emergent property of socio-technical interaction systems, thereby shifting the analytical focus from individual or organizational actors to relational dynamics. Second, it extends the dynamic capability perspective by conceptualizing capabilities as co-evolving outcomes of human–AI interaction, rather than static firm-level attributes (Teece, 2007). Third, it integrates creativity and co-creation theories by incorporating AI as a non-human agent, advancing the notion of distributed creativity in which innovation emerges through continuous interplay between human cognition and algorithmic generation. Together, these contributions offer a unified framework that bridges previously fragmented streams of research and opens new avenues for theory development.

The study also carries important managerial and policy implications. For organizations, it highlights the necessity of designing innovation systems that enable effective human–AI collaboration, emphasizing the importance of balancing human judgment with algorithmic capabilities. Firms must invest not only in AI technologies but also in developing human competencies such as critical evaluation, contextual interpretation, and adaptive learning. At the same time, governance mechanisms must be established to mitigate risks associated with over-reliance on AI, including cognitive dependency, lack of transparency, and ambiguity in authorship and accountability. From a policy perspective, the findings underscore the need for frameworks that support workforce transformation, ethical AI deployment, and capability development in increasingly AI-driven economies.

Despite these contributions, the study is not without limitations. As a conceptual paper, it does not provide empirical validation of the proposed relationships, and the model remains to be tested across different organizational and industry contexts. Additionally, while the framework captures key mechanisms of human–AI interaction, it does not fully account for contextual variables such as cultural differences, regulatory environments, or sector-specific dynamics that may influence innovation processes. These limitations, however, do not diminish the value of the study; rather, they highlight opportunities for further inquiry and refinement.

Future research should therefore focus on empirically testing the proposed model using approaches such as PLS-SEM to examine the relationships among constructs, including mediation and moderation effects. Experimental studies could provide deeper insights into causal mechanisms by comparing different configurations of human–AI collaboration, while longitudinal research would be particularly valuable in capturing the evolution of co-adaptive processes over time. Moreover, industry-specific investigations are needed to understand how the dynamics identified in this study manifest across diverse contexts, from creative industries to technology-intensive sectors. Such research would not only validate but also extend the applicability of the proposed framework.

In conclusion, this study argues that innovation in the age of artificial intelligence is no longer a human-centric endeavor but a collaborative, evolving process shaped by the continuous interaction between human and machine intelligence. By offering a theoretically grounded and integrative framework, the study provides a foundation for rethinking innovation in contemporary organizations and contributes to a broader understanding of how socio-technical systems drive value creation. As artificial intelligence continues to permeate organizational life, developing robust theories that capture its transformative role in innovation will be essential for both academic advancement and practical impact.

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