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Value Ownership in Human–AI Co-Creation: A Multi-Level Framework of Distributed Agency and Ethical Tensions

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Abstrak

The increasing integration of generative artificial intelligence into creative and organizational processes challenges traditional assumptions about value creation, authorship, and ownership. In human–AI co-creation contexts, value emerges through iterative interactions between human cognition and algorithmic generation, leading to ambiguity in contribution, attribution, and ownership. Despite growing research on artificial intelligence and digital transformation, existing literature remains fragmented, lacking an integrative framework that explains how value ownership is constructed across multiple levels. This study aims to address this theoretical gap by developing a process-oriented conceptual framework that integrates perspectives from ethics, ownership theory, and co-creation. Using an integrative analytical approach, the study conceptualizes human–AI collaboration as a dynamic system characterized by distributed agency, iterative interaction loops, and multi-level value attribution mechanisms. The proposed model identifies key ethical tensions—authorship ambiguity, value attribution uncertainty, responsibility diffusion, and authenticity erosion—and positions them within an ethical paradox system. The study contributes by reconceptualizing ownership as a multi-dimensional and relational construct while providing a structured framework for analyzing how value is generated, interpreted, and allocated in human–AI systems, offering directions for future empirical research.

Keywords

human–AI co-creation; value ownership; distributed agency; ethical paradox; value attribution; sociotechnical systems

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1. Introduction

The emergence of generative artificial intelligence (AI) is reshaping the fundamental logic of creativity, value creation, and ownership in contemporary digital economies. Rather than merely supporting human productivity, AI systems are increasingly capable of generating novel content, proposing ideas, and influencing creative direction, thereby challenging long-standing assumptions that position creativity as an exclusively human-centered capability grounded in intentionality, experience, and contextual judgment (Amabile, 2020). Recent developments further indicate that generative AI shifts the locus of novelty toward data-driven recombination processes, raising critical questions about how creativity is conceptualized and evaluated in hybrid human–machine environments (Dwivedi *et al.*, 2023; Tredinnick & Laybats, 2023).

This transformation has accelerated the rise of human–AI collaboration (HAC) as a dominant paradigm in creative and knowledge-intensive work. Within this paradigm, creativity is no longer confined to individual actors but emerges from iterative interactions between human cognition and algorithmic generation (Raisch & Krakowski, 2021; Wu *et al.*, 2021). AI systems contribute through large-scale pattern recognition and probabilistic recombination, while human actors provide contextual framing, evaluation, and meaning attribution. This interdependence creates a distributed creative process in which value is co-produced rather than individually generated, marking a shift toward hybrid systems of agency and cognition (Faraj *et al.*, 2018; Benbya *et al.*, 2021).

In organizational contexts, the integration of AI into creative workflows is no longer limited to automation but increasingly involves augmentation and co-creation. Firms embed AI into ideation, design, and content production processes to expand creative search spaces and accelerate innovation outcomes (Haefner *et al.*, 2021; Berente *et al.*, 2021). This development aligns with broader transformations in digital and platform-based economies, where technological infrastructures mediate interactions between creators, consumers, and intelligent systems (Nambisan *et al.*, 2019; Parker *et al.*, 2017). Consequently, creative outputs are increasingly shaped by sociotechnical configurations in which human and algorithmic contributions are deeply intertwined.

However, this shift introduces a fundamental tension concerning value ownership in human–AI co-creation. Traditional frameworks of ownership assume a direct and identifiable relationship between creator and output, typically grounded in legal notions of authorship and economic entitlement. In AI-mediated environments, this relationship becomes fragmented, as outputs are generated through complex interactions involving users, developers, training data, and platform infrastructures (Gervais, 2020; Abbott, 2020). The resulting ambiguity challenges existing assumptions about who owns value, how contributions are recognized, and how benefits should be distributed across actors (Al-Busaidi *et al.*, 2024; Gaidartzi *et al.*, 2025).

Beyond legal considerations, value ownership in human–AI systems also raises critical ethical concerns. The deployment of AI in creative processes introduces issues related to fairness, accountability, transparency, and legitimacy, particularly when algorithmic systems operate as opaque “black boxes” (Floridi *et al.*, 2018; Mittelstadt *et al.*, 2016; Adadi & Berrada, 2018). In such contexts, responsibility becomes diffused across multiple actors, complicating the attribution of accountability when outcomes produce unintended consequences or societal harm (Bender *et al.*, 2021; Raji *et al.*, 2020). As a result, ownership is no longer solely a legal construct but also an ethical and socio-technical phenomenon shaped by institutional arrangements and technological design.

At the same time, market dynamics and consumer perceptions further complicate the construction of value in human–AI co-creation. Empirical research shows that individuals exhibit varying levels of trust, acceptance, and resistance toward AI-generated outputs depending on perceived authenticity, transparency, and task context (Glikson & Woolley, 2020; Longoni *et al*., 2019; Castelo *et al*., 2019). In creative domains, where originality and emotional expression are highly valued, the involvement of AI can both enhance perceived novelty and undermine perceived authenticity. These divergent perceptions directly influence how value is interpreted, legitimized, and ultimately attributed.

The role of digital platforms adds another layer of complexity to value ownership. Platforms function as intermediaries that structure interactions, control access to AI systems, and regulate how value is captured and distributed. In platform-based ecosystems, value is co-created through networked participation but is often appropriated asymmetrically by platform operators, reflecting broader dynamics of data-driven capitalism and algorithmic governance (Kenney & Zysman, 2016; Nieborg & Poell, 2018). This asymmetry highlights the need to examine ownership not only at the level of individual contribution but also within broader systems of control and intermediation.

Despite the rapid expansion of research on artificial intelligence, creativity, and digital transformation, existing literature remains fragmented. Prior studies tend to examine technological capabilities, ethical principles, or organizational implications in isolation, without sufficiently addressing how these dimensions interact to shape value ownership in distributed human–AI systems (Jobin *et al*., 2019; Morley *et al*., 2020; Dwivedi *et al*., 2023). Moreover, AI is often conceptualized either as a tool or as a disruptive force, overlooking its emerging role as an active participant in co-creation processes.

This fragmentation reveals a critical theoretical gap: the absence of an integrative framework that explains how value is co-created, interpreted, and allocated across multiple levels in human–AI collaboration. Addressing this gap requires moving beyond static and single-level perspectives toward a processual and multi-level understanding of ownership that incorporates ethical, organizational, and technological dimensions simultaneously.

In response, this study develops a conceptual framework that explains how value ownership is constructed in human–AI co-creation systems. Specifically, the paper aims to (1) identify the key ethical tensions emerging from human–AI collaboration, (2) analyze the multi-level dynamics of value ownership across individual, organizational, platform, and societal contexts, and (3) propose an integrative model linking human input, AI generative processes, interaction mechanisms, and ownership allocation outcomes. By doing so, this study contributes to the literature on AI in management and the creative economy by offering a theoretically grounded and analytically rich perspective on one of the most pressing issues in the age of generative AI.

2. Theoretical Foundations: Ethics, Ownership, and Co-Creation

The increasing integration of artificial intelligence into creative and organizational processes necessitates a re-examination of foundational theoretical domains that have traditionally evolved in parallel rather than in conjunction. In particular, ethics, ownership, and co-creation have been extensively developed within distinct scholarly traditions, each offering partial insights into how value is generated, governed, and distributed. However, the emergence of human–AI collaboration introduces a qualitatively different context characterized by distributed agency, hybrid authorship, and algorithmically mediated interaction. As such, understanding value ownership in this setting requires an integrative theoretical perspective that bridges these domains into a coherent analytical framework.

Rather than treating ethics as a normative overlay, ownership as a legal construct, and co-creation as a processual mechanism, this study positions them as interdependent dimensions of a unified system in which value is simultaneously produced, evaluated, and allocated. This integrative approach aligns with sociotechnical perspectives that emphasize the co-evolution of human and technological elements in shaping organizational and economic outcomes (Faraj *et al.*, 2018; Benbya *et al.*, 2021).

2.1 Ethics of Artificial Intelligence and Normative Legitimacy

The ethical discourse surrounding artificial intelligence has expanded significantly in response to the increasing societal and organizational impact of algorithmic systems. Foundational frameworks emphasize principles such as fairness, accountability, transparency, and beneficence as essential guidelines for the responsible development and deployment of AI (Floridi *et al.*, 2018; Jobin *et al.*, 2019). These principles aim to ensure that AI systems align with societal values while minimizing harm and unintended consequences.

However, subsequent scholarship highlights the limitations of principle-based approaches, arguing that high-level ethical guidelines alone are insufficient to address the complexities of real-world AI systems (Mittelstadt, 2019; Whittlestone *et al.*, 2019). In practice, ethical outcomes are shaped not only by abstract principles but also by the ways in which AI systems are designed, implemented, and embedded within organizational and social contexts (Morley *et al.*, 2020). This perspective shifts the focus from "what ethics should be" to "how ethics is enacted," emphasizing the performative and context-dependent nature of AI ethics.

A central challenge in this domain is the opacity of algorithmic systems. Many AI models, particularly those based on deep learning architectures, operate as black boxes, limiting users' ability to understand or explain how outputs are generated (Adadi & Berrada, 2018; Arrieta *et al.*, 2020). This lack of explainability complicates the attribution of responsibility, as decision-making processes are distributed across multiple actors, including developers, users, organizations, and the AI system itself (Kroll *et al.*, 2017; Raji *et al.*, 2020).

In the context of human–AI co-creation, ethical considerations extend beyond system performance to encompass issues of legitimacy and recognition. The integration of AI into creative workflows raises questions about fairness in credit allocation, transparency in authorship, and the legitimacy of algorithmic contributions (Ryan & Stahl, 2020). Moreover, recent research highlights the ethical risks associated with generative AI, including bias amplification, misinformation, and the erosion of human agency (Bender *et al.*, 2021; Weidinger *et al.*, 2021). These concerns underscore the need for an ethical framework that accounts for the dynamic and interactive nature of human–AI collaboration.

2.2 Ownership and Authorship in the Age of Artificial Intelligence

Ownership has traditionally been conceptualized as a mechanism for allocating rights, responsibilities, and economic incentives. In creative industries, ownership is closely tied to authorship, which assumes a clear and identifiable creator responsible for producing an original work. This assumption, however, is fundamentally challenged by the emergence of AI systems capable of generating content autonomously or semi-autonomously (Gervais, 2020; Abbott, 2020).

Legal scholarship has extensively debated whether AI can be recognized as an author. Dominant perspectives argue that AI lacks intentionality, consciousness, and moral agency, and therefore cannot hold ownership rights (Bridy, 2012; Guadamuz, 2017). However, alternative viewpoints suggest that the increasing autonomy and generative capacity of AI systems challenge anthropocentric models of authorship and may necessitate the development of new legal categories or hybrid frameworks (Yanisky-Ravid, 2017; Chesterman, 2020).

Beyond legal considerations, ownership also has an economic dimension related to value capture. In human–AI co-creation, value is generated through iterative interactions involving multiple stakeholders, including users, developers, data providers, organizations, and platform operators. This distributed process complicates the attribution of ownership, as contributions are often intertwined and difficult to isolate (Al-Busaidi *et al.*, 2024; Gaidartzi *et al.*, 2025).

From this perspective, ownership is better understood as a negotiated construct rather than a fixed allocation. It reflects not only formal legal entitlements but also informal recognition, perceived contribution, and institutional arrangements. This view aligns with emerging discussions on intellectual property in AI contexts, which emphasize the need for relational and multi-actor frameworks to address the complexity of algorithmically generated outputs (Kirakosyan, 2024).

2.3 Co-Creation and Distributed Agency

The concept of co-creation originates from service-dominant logic and innovation studies, where value is seen as emerging from interactions among multiple actors rather than being produced by a single entity (Nambisan, 2017; Nambisan *et al.*, 2019). In digital environments, co-creation is facilitated by platforms that enable collaboration among users, firms, and technologies, transforming value creation into a networked and interactive process (Yoo *et al.*, 2012; Parker *et al.*, 2017).

The integration of AI into these processes introduces a new dimension in which non-human agents actively participate in value creation. Human–AI co-creation can therefore be conceptualized as a form of distributed agency, where creative input and decision-making are shared between human and machine actors. AI systems contribute through pattern recognition, generative capabilities, and large-scale data processing, while humans provide contextual interpretation, goal orientation, and evaluative judgment (Amabile, 2020.

This configuration aligns with sociotechnical system theory, which emphasizes the interdependence of human and technological elements in shaping outcomes (Faraj *et al.*, 2018). It also resonates with distributed cognition theory, where cognitive processes extend beyond individuals to include tools, artifacts, and environments. In this sense, creativity in human–AI systems emerges not from isolated actors but from iterative interactions within a network of interdependent components (Wu *et al.*, 2021).

However, the distribution of agency introduces significant challenges related to accountability and control. As AI systems become more actively involved in creative processes, it becomes increasingly difficult to determine who is responsible for the outcomes. This issue is further complicated by the opacity of AI systems and the complexity of their interactions with human users (Berente *et al.*, 2021; Dwivedi *et al.*, 2023). Consequently, co-creation in human–AI systems requires a rethinking of traditional assumptions about agency, responsibility, and authorship.

2.4 Integrating Ethics, Ownership, and Co-Creation

While ethics, ownership, and co-creation each provide valuable insights, their integration is essential for understanding value ownership in human–AI collaboration. Ethics offers a normative framework for evaluating fairness and legitimacy, ownership provides a mechanism for allocating rights and value, and co-creation explains the processes through which value is generated.

The intersection of these domains reveals a set of inherent tensions. First, ethical principles of fairness and transparency may conflict with economic incentives for value capture, particularly in platform-based ecosystems characterized by power asymmetries (Kenney & Zysman, 2016; Nieborg & Poell, 2018). Second, the distributed nature of co-creation challenges the feasibility of assigning clear ownership, leading to ambiguity and contested claims. Third, the increasing role of AI as an active participant raises questions about the boundaries of agency and the legitimacy of non-human contributions.

These tensions can be understood as forming a paradoxical structure, where competing yet interdependent logics coexist without clear resolution. This aligns with broader organizational theory on paradox, which suggests that such tensions must be managed rather than resolved (Smith & Lewis, 2011). In the context of human–AI co-creation, this implies that value ownership cannot be fully determined through static rules but must be continuously negotiated across contexts and interactions.

Therefore, an integrative framework is needed to capture the dynamic and multi-level nature of value ownership in human–AI systems. Such a framework must account for the interplay between ethical norms, economic incentives, technological capabilities, and social perceptions. By synthesizing these dimensions, this study aims to provide a more comprehensive theoretical foundation for understanding how value ownership is constructed, contested, and legitimized in the age of artificial intelligence.

3. Human–AI Co-Creation: From Tool Use to Agency Distribution

The role of artificial intelligence in creative and knowledge work has evolved from a purely instrumental function toward a more complex configuration in which AI actively participates in the generation and shaping of outputs. Earlier perspectives positioned AI as a tool designed to enhance efficiency and support human decision-making. However, advances in generative models demonstrate that AI systems can propose ideas, generate alternatives, and influence creative trajectories, thereby transforming the nature of interaction between human actors and technological systems (Raisch & Krakowski, 2021; Berente *et al.*, 2021).

This shift reflects a fundamental transition from tool-based interaction to distributed agency. In traditional models of creativity, agency is assumed to reside within human actors who possess intentionality, judgment, and contextual awareness. In contrast, human–AI co-creation redistributes elements of agency across both human and machine actors. AI contributes through pattern recognition, probabilistic generation, and large-scale recombination of knowledge, while humans provide contextual framing, evaluation, and meaning attribution (Amabile, 2020). Rather than replacing human agency, AI reconfigures it into an interdependent system where outcomes emerge from interaction.

3.1 Reconfiguration of Agency in Human–AI Systems

The notion of agency in human–AI collaboration is best understood as relational rather than individual. Agency does not reside exclusively within a single actor but emerges through interactions among humans, algorithms, and technological infrastructures. This perspective aligns with sociotechnical system theory, which emphasizes that organizational outcomes are co-produced by human and technological elements operating in tandem (Faraj *et al.*, 2018; Benbya *et al.*, 2021).

In this configuration, AI systems function as computational agents that expand the creative search space by generating a wide range of potential solutions. At the same time, human actors retain control over goal definition, interpretation, and final decision-making. This asymmetry is critical: while AI can influence the direction of creativity, it does not possess intrinsic intentionality or awareness. Consequently, agency in human–AI systems is distributed but not equivalent, creating a dynamic balance between augmentation and control.

Importantly, the perception of agency also plays a significant role in shaping interaction. Empirical research shows that users often interpret AI-generated outputs as contributions rather than passive responses, particularly when systems exhibit adaptive or generative capabilities (Oh *et al.*, 2018; Muller *et al.*, 2020). This perception transforms interaction into a collaborative process, where users alternate between directing the AI and responding to its outputs. As a result, creativity becomes dialogical rather than unilateral.

3.2 The Human–AI Co-Creation Loop

At the core of human–AI collaboration lies an iterative co-creation loop that structures the interaction between human and machine actors. This loop can be conceptualized as a cyclical process consisting of three primary phases: initiation, generation, and evaluation.

The first phase, human initiation, involves the formulation of prompts, constraints, or objectives that guide the AI system. This stage reflects the locus of intentionality, where human actors define the problem space and establish the direction of the creative process.

The second phase, AI generation, involves the production of outputs based on learned representations and probabilistic modeling. Unlike traditional tools, AI systems generate multiple variations, often introducing novel combinations that extend beyond the user's initial expectations. This capability expands the creative search space and enables exploration of alternative possibilities (Wu *et al*., 2021).

The third phase, human evaluation and refinement, involves selecting, modifying, and interpreting AI-generated outputs. In this stage, human actors apply judgment, contextual knowledge, and aesthetic criteria to determine the value and relevance of outputs. This evaluative function is central to maintaining human oversight within the system.

These phases are not linear but recursive. The output of one cycle becomes the input for the next, creating a continuous feedback loop in which creativity emerges through iteration rather than single-step production. This process reflects a form of distributed cognition, where cognitive processes are extended across human and technological components (Faraj *et al*., 2018).

3.3 3Opportunities and Cognitive Risks in Co-Creation

The distributed nature of human–AI co-creation introduces both opportunities and risks. On one hand, AI enhances creativity by expanding the range of possible solutions and accelerating ideation processes. By generating diverse alternatives, AI enables users to explore novel directions that may not emerge through human cognition alone (Haefner *et al*., 2021; Dwivedi *et al*., 2023).

On the other hand, reliance on AI-generated outputs can introduce cognitive biases that affect decision-making. Research in behavioral science suggests that algorithmic suggestions can anchor human judgment, leading to over-reliance and reduced critical evaluation (Logg *et al*., 2019; Castelo *et al*., 2019). This phenomenon, often referred to as automation bias, may limit originality and depth, particularly in complex creative tasks.

Moreover, the perceived authority of AI systems can influence user behavior. When users attribute high competence to AI, they may accept outputs without sufficient scrutiny, thereby shifting control away from human actors. Conversely, low trust in AI may lead to underutilization of its capabilities, reducing the potential benefits of collaboration (Glikson & Woolley, 2020). These dynamics highlight the importance of balancing augmentation with critical oversight.

3.4 Organizational and Platform Embeddedness of Co-Creation

Human–AI co-creation does not occur in isolation but is embedded within organizational and platform contexts that shape how interactions unfold. Organizations increasingly integrate AI into workflows, creating hybrid systems in which human and machine roles are formally defined and coordinated (Benbya *et al*., 2021; Shrestha *et al*., 2019). These systems require new forms of governance, including task allocation, performance evaluation, and accountability structures.

At the same time, digital platforms provide the infrastructure through which human–AI interactions are mediated. Platforms influence access to AI tools, control data flows, and determine how outputs are distributed and monetized (Parker *et al.*, 2017; Nambisan *et al.*, 2019). As a result, agency is not only distributed between humans and AI but also shaped by platform architectures and governance mechanisms.

This creates a multi-actor system in which agency is layered across individuals, organizations, and platforms. Platform operators, for example, may exert indirect control over creative processes through algorithm design and interface constraints, even though they are not directly involved in content creation. This layered distribution of agency complicates the attribution of responsibility and ownership.

3.5 External Perception of Agency and Value

The distribution of agency in human–AI co-creation extends beyond internal processes to include external stakeholders, particularly consumers. Perceptions of agency influence how outputs are evaluated, valued, and legitimized in the marketplace.

Research indicates that consumers attribute varying degrees of agency to AI depending on context and task characteristics (Longoni *et al.*, 2019; Glikson & Woolley, 2020). In creative domains, where authenticity and emotional expression are central, the involvement of AI may reduce perceived authenticity if the system is seen as the primary creator. Conversely, when AI is perceived as a supportive collaborator, human contribution remains central to value perception (Castelo *et al.*, 2019).

These perceptions have direct implications for value creation. The same output may be evaluated differently depending on whether it is perceived as human-created, AI-generated, or co-created. This suggests that value is not inherent in the output itself but is socially constructed through interpretation and attribution processes.

Synthesis: From Tool Use to Distributed Agency

The transition from tool use to distributed agency represents a fundamental shift in how creativity and value creation are conceptualized in the digital era. Human–AI co-creation is not merely an extension of existing processes but a reconfiguration that redistributes roles, responsibilities, and control across multiple actors.

This section establishes the mechanism through which value is generated in human–AI systems: an iterative, interaction-driven process characterized by distributed agency, cognitive interdependence, and contextual embedding. Understanding this mechanism is essential for addressing the subsequent question of how value is attributed and ownership is constructed, which becomes the focus of the following section.

4. The Ethical Tensions in Human–AI Co-Creation

The emergence of human–AI co-creation introduces a set of ethical tensions that fundamentally challenge established assumptions about creativity, responsibility, and value. Unlike traditional creative processes, where authorship and ownership can be clearly attributed to identifiable individuals or organizations, human–AI collaboration operates within a distributed system in which contributions are intertwined, iterative, and often inseparable. This condition gives rise to a complex configuration of ethical tensions that cannot be understood as isolated dilemmas but rather as an interconnected system of contradictions embedded within the co-creation process itself.

Rather than framing these issues as discrete problems to be resolved, this study conceptualizes them as an ethical paradox system, where competing yet interdependent principles, such as fairness, efficiency, transparency, and innovation: coexist and continuously interact. This perspective aligns with broader organizational theory on paradox, which suggests that tensions in complex systems are persistent and must be managed rather than eliminated (Smith & Lewis, 2011). In the context of human–AI collaboration, ethical tensions emerge not as anomalies but as inherent features of distributed agency and sociotechnical interaction.

The table systematizes the ethical tensions by linking each tension to its underlying source, normative concern, and implications for value ownership. This structured breakdown complements the conceptual figure by making the analytical distinctions explicit and comparable.

Table 1. Ethical Tensions in Human–AI Co-Creation and Their Implications for Value Ownership

Ethical Tension	Underlying Source	Core Ethical Concern	Implication for Value Ownership
Authorship Ambiguity	Distributed and hybrid contribution structure	Recognition and credit allocation	Blurred authorship weakens clear ownership claims
Value Attribution Uncertainty	Iterative and interdependent generation	Fairness in value distribution	Difficulty in proportionally assigning ownership
Responsibility Diffusion	Multi-actor involvement and system opacity	Accountability and liability	Ownership detached from responsibility
Authenticity Erosion	Algorithmic generation and recombination	Legitimacy and originality	Reduced perceived legitimacy of ownership claims

Source: Author's conceptualization

Table 1 clarifies how each ethical tension contributes to the instability of value ownership in human–AI co-creation systems. By explicitly mapping tensions to their sources and ownership implications, Table 1 supports the analytical argument that ownership ambiguity is not a single issue but the cumulative effect of interrelated ethical dynamics.

4.1 Authorship Ambiguity

One of the most immediate tensions concerns the ambiguity of authorship in AI-mediated creative processes. Conventional frameworks define authorship based on intentionality, originality, and creative control, assuming a clear and identifiable human creator. However, in human–AI co-creation, this assumption becomes problematic as AI systems generate substantive components of the output based on learned representations and probabilistic processes (Gervais, 2020; Abbott, 2020).

The human actor provides prompts, constraints, and contextual framing, yet the AI system produces variations that may extend beyond the user's initial conception. As a result, authorship becomes distributed across multiple layers of contribution, including training data, algorithmic design, and user interaction. This fragmentation challenges the notion of singular authorship and raises questions about whether AI should be considered a contributor, a tool, or an intermediary entity.

From an ethical perspective, authorship ambiguity creates tensions in recognition and credit allocation. Attributing authorship solely to human actors may obscure the role of AI, while recognizing AI as an author introduces unresolved questions about agency, rights, and responsibility. Furthermore, generative AI systems often rely on large-scale datasets that incorporate prior human knowledge, making each output a recombination of collective contributions rather than a discrete act of creation (Bender *et al.*, 2021). Consequently, authorship shifts from a fixed designation to a negotiated and context-dependent construct.

4.2 Value Attribution Uncertainty

Closely linked to authorship ambiguity is the uncertainty surrounding value attribution. In traditional production systems, value is typically assigned based on identifiable contributions and measurable inputs. In contrast, human–AI co-creation involves iterative and interdependent processes in which contributions are continuously reshaped through interaction.

AI systems can generate multiple alternatives, enhance efficiency, and improve output quality, yet these contributions are embedded within dynamic processes that blur the boundaries between human and machine input. At the same time, human actors contribute through interpretation, refinement, and contextualization, which are less visible but critical to the final outcome.

This complexity creates uncertainty in determining how value should be distributed among stakeholders, including users, developers, organizations, and platform providers (Al-Busaidi *et al.*, 2024; Gaidartzi *et al.*, 2025). The challenge is not merely technical but also normative: different actors may apply distinct criteria for evaluating contribution, such as effort, expertise, or creative control.

Ethically, this uncertainty raises questions about equity and justice. If value is disproportionately captured by certain actors—particularly platform operators or technology providers—the system may reinforce existing power asymmetries in digital economies. Moreover, the opacity of AI processes limits the ability of participants to fully understand how value is generated, further complicating fair distribution (Weidinger *et al.*, 2021).

4.3 Responsibility Diffusion

A third critical tension arises from the diffusion of responsibility in human–AI collaborative systems. In traditional contexts, responsibility for creative outputs can be assigned based on clearly defined roles and decision-making authority. However, in human–AI co-creation, decision-making is distributed across multiple actors, including AI systems that operate without direct human oversight at every stage.

This distribution complicates accountability, particularly when AI-generated outputs lead to unintended or harmful consequences. For example, biases embedded in training data may be reflected in outputs, or generative systems may produce misleading or inappropriate content. When such outcomes occur, responsibility may be attributed to multiple actors, including developers, users, organizations, and platform operators.

The problem is further intensified by the opacity and complexity of AI systems. Users may rely on outputs without fully understanding how they are generated, while developers may not anticipate all possible applications or risks (Raji *et al.*, 2020). This creates a gap between action and accountability, where responsibility is diffused across the system rather than clearly assigned.

From an ethical standpoint, responsibility diffusion challenges existing frameworks that rely on clear lines of accountability. Addressing this issue requires moving toward models of shared or distributed responsibility that reflect the collaborative nature of human–AI systems (Ryan & Stahl, 2020).

4.4 Authenticity Erosion

The fourth tension concerns the erosion of authenticity in creative outputs. Authenticity has long been a central value in creative industries, associated with originality, emotional expression, and human experience. The integration of AI into creative processes challenges this notion by introducing algorithmically generated elements that may not reflect genuine human intention.

As generative AI systems become more sophisticated, distinguishing between human-created and machine-generated content becomes increasingly difficult. This blurring of boundaries can undermine perceptions of authenticity, particularly in domains where consumers value personal expression and originality.

At the same time, perceptions of authenticity are not static. Research suggests that consumer attitudes toward AI-generated content vary depending on context, familiarity, and perceived role of AI in the creative process (Longoni *et al.*, 2019; Castelo *et al.*, 2019). When AI is perceived as a supportive collaborator, human authenticity may remain intact. However, when AI is perceived as the primary creator, the legitimacy of the output may be questioned.

This tension also raises issues related to transparency and disclosure. Creators may need to communicate the extent of AI involvement to maintain trust and legitimacy, yet excessive transparency may reduce perceived value. Thus, authenticity becomes a negotiated construct shaped by both technological and social factors.

4.5 Human–AI Co-Creation as an Ethical Paradox System

Taken together, these four tensions—authorship ambiguity, value attribution uncertainty, responsibility diffusion, and authenticity erosion—form an interconnected system of ethical contradictions that define human–AI co-creation. Rather than operating independently, these tensions reinforce and amplify one another. For example, ambiguity in authorship contributes to uncertainty in value attribution, which in turn complicates the assignment of responsibility. Similarly, concerns about authenticity influence how value is perceived and distributed.

The figure conceptualizes ethical tensions in human–AI co-creation as a paradox system rather than a set of isolated dilemmas. It highlights how authorship, value attribution, responsibility, and authenticity mutually reinforce one another within distributed agency conditions.

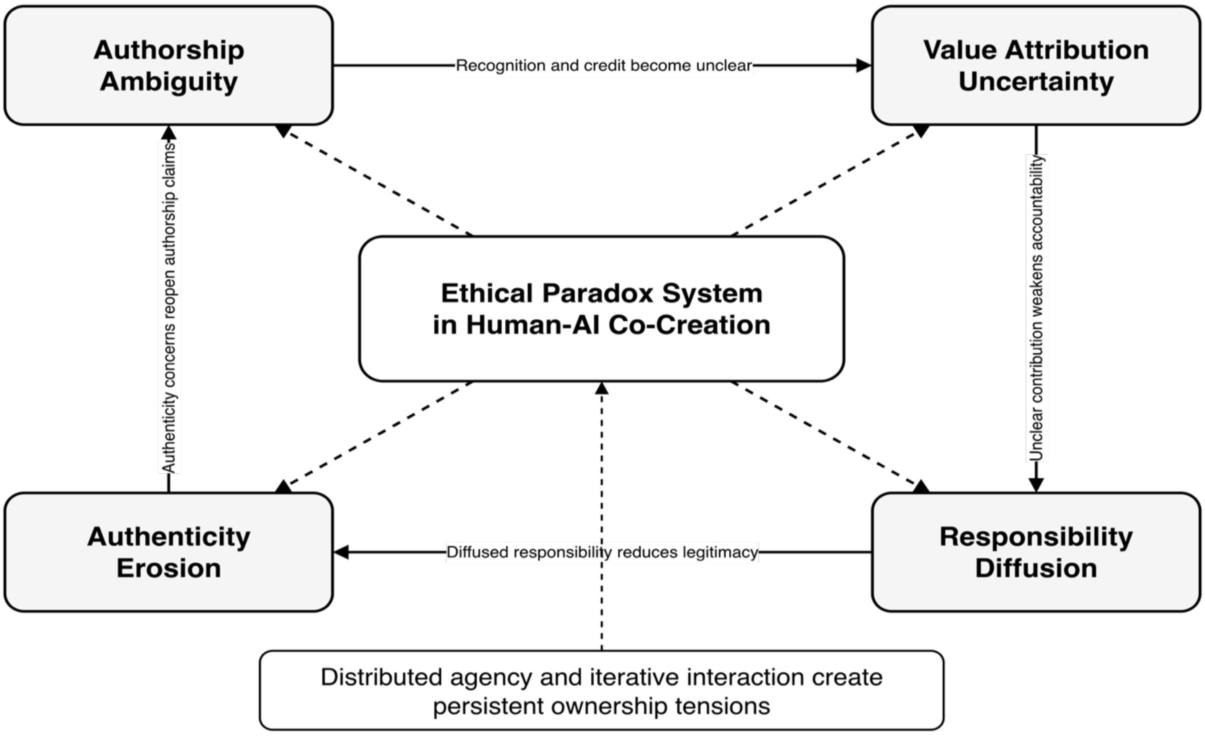

Figure 1. Ethical Paradox System in Human–AI Co-Creation
Source: Author's conceptualization

As illustrated in Figure 1, the ethical tensions surrounding human–AI co-creation operate as an interconnected paradox system. The figure supports the article's argument by showing that authorship ambiguity, value attribution uncertainty, responsibility diffusion, and authenticity erosion do not arise independently; instead, they mutually reinforce one another under conditions of distributed agency and iterative interaction.

This interconnectedness supports the conceptualization of human–AI collaboration as an ethical paradox system, in which competing principles coexist without straightforward resolution. The tension between fairness and efficiency, transparency and usability, or innovation and control cannot be fully eliminated but must be continuously balanced.

Importantly, this paradoxical structure highlights the limitations of static ethical frameworks. Instead of seeking definitive solutions, organizations and policymakers must develop adaptive approaches that can navigate these tensions in context-specific ways. Such approaches should recognize the distributed and dynamic nature of human–AI systems, where ethical considerations are embedded within ongoing processes of interaction and value creation.

By framing ethical tensions as a system rather than a set of isolated issues, this section provides a critical foundation for understanding how value is interpreted and attributed in human–AI co-creation. This, in turn, sets the stage for the multi-level analysis of value ownership and the development of an integrative conceptual model in subsequent sections.

5. Value Ownership in Human–AI Systems: A Multi-Level Perspective

Understanding value ownership in human–AI co-creation requires moving beyond conventional single-actor frameworks toward a multi-level perspective that captures the distributed and emergent nature of value creation. In traditional economic and legal models, ownership is typically defined as the right to control, use, and benefit from an asset. However, in human–AI collaborative systems, value does not originate from a single source but emerges through iterative interactions among multiple actors embedded within sociotechnical and platform-based environments.

The table delineates how value ownership is constructed differently across analytical levels by specifying actors, value sources, and ownership forms. It provides a structured comparison that complements the multi-level framework by making cross-level distinctions explicit and analytically tractable.

Table 2. Multi-Level Dimensions of Value Ownership in Human–AI Co-Creation

Level	Primary Actors	Source of Value Contribution	Dominant Form of Ownership	Key Mechanism of Ownership Construction
Individual	Users, creators	Cognitive input, interpretation, prompt design	Interpretive and symbolic ownership	Meaning-making and evaluative judgment
Organizational	Firms, teams	Resource integration, workflow orchestration	Economic ownership and value capture	Control over processes, contracts, and outputs
Platform	Platform providers, AI developers	Infrastructure, data control, algorithmic mediation	Intermediated and asymmetrical ownership	Governance rules, access control, monetization
Societal	Institutions, regulators, public	Norms, legitimacy frameworks, cultural expectations	Legitimated and institutional ownership	Legal recognition and social acceptance

Source: Author's conceptualization

Table 2 strengthens the analytical clarity of the multi-level perspective by explicitly differentiating how ownership is constructed at each level. By aligning actors, value sources, and ownership forms, Table 2 supports the argument that value ownership is not uniform but varies systematically depending on the locus of control, interpretation, and legitimacy within the human–AI ecosystem.

This shift fundamentally challenges the assumption that ownership can be clearly assigned based on identifiable contributions. Instead, ownership becomes a layered and negotiated construct shaped by interactions across different levels of analysis. Moreover, value ownership in this context cannot be reduced to legal entitlement alone; it encompasses economic control over value capture and symbolic recognition of contribution. In other words, ownership operates simultaneously across legal, economic, and socio-cultural dimensions.

From a strategic perspective, value ownership in digital environments is increasingly determined by control over critical resources such as data, algorithms, and network access, rather than traditional asset ownership (Kenney & Zysman, 2016; Nambisan *et al.*, 2019). This reconfiguration underscores the need for a multi-level framework that captures how ownership is constructed, contested, and legitimized across interconnected systems.

5.1 Individual Level: Cognitive Contribution and Interpretive Ownership

At the individual level, value ownership has traditionally been associated with authorship and direct creative contribution. In human–AI co-creation, however, the notion of the "creator" becomes more complex due to the interdependence between human input and AI-generated output.

Human actors initiate the creative process by defining prompts, objectives, and contextual boundaries, while AI systems generate alternatives that expand the solution space. Although AI contributes to output generation, human actors retain a critical role in interpreting, selecting, and assigning meaning to these outputs. This evaluative function suggests that ownership at the individual level is not solely based on production but also on interpretation and contextualization.

This perspective aligns with the idea of interpretive ownership, where value is derived from the ability to frame meaning and relevance rather than merely generate content. As AI systems become more sophisticated, the visibility of human contribution may decrease, potentially weakening traditional claims to authorship. At the same time, new forms of creative labor—such as prompt engineering and AI curation—emerge, redefining the basis of individual ownership in distributed creative systems (Muller *et al.*, 2020).

5.2 Organizational Level: Resource Control and Value Capture

At the organizational level, ownership is closely linked to the ability of firms to capture value from co-created outputs. Organizations integrate AI into workflows to enhance productivity, expand creative capabilities, and accelerate innovation processes (Benbya *et al.*, 2021; Berente *et al.*, 2021). In doing so, they establish structures that govern how human and AI contributions are coordinated and how resulting value is appropriated.

Firms typically assert ownership through formal mechanisms such as employment contracts, intellectual property policies, and internal governance frameworks. However, the integration of AI introduces additional complexities. Organizations often rely on third-party AI systems, raising questions about the extent to which they can claim ownership over outputs generated using external technologies. Similarly, employees may independently use AI tools, creating potential tensions between individual and organizational claims.

From an economic perspective, firms seek to maximize value capture by controlling key resources, including proprietary data, algorithmic capabilities, and distribution channels. This aligns with broader trends in digital transformation, where competitive advantage is increasingly driven by the ability to orchestrate technological and human resources within integrated systems (Haefner *et al.*, 2021; Dwivedi *et al.*, 2023). However, the distributed nature of human–AI co-creation means that value often extends beyond organizational boundaries, challenging firm-centric models of ownership.

5.3 Platform Level: Intermediation, Control, and Asymmetry

The platform level introduces a critical dimension to value ownership by mediating interactions between creators, AI systems, and consumers. Digital platforms provide the infrastructure through which human–AI co-creation occurs, including access to tools, data, and markets. In doing so, they play a central role in shaping how value is generated, distributed, and captured.

Platforms exert control through governance mechanisms such as terms of service, data policies, and algorithmic design. These mechanisms determine how users interact with AI systems and how outputs are monetized. As a result, platform operators often capture a significant portion of the value generated within the ecosystem, even when they are not directly involved in the creative process (Parker *et al.*, 2017; Nieborg & Poell, 2018).

This dynamic reflects the logic of platform economies, where network effects and data accumulation create asymmetries in power and value distribution (Kenney & Zysman, 2016). In human–AI co-creation, these asymmetries are further amplified by the opacity of algorithmic systems and the dependence of users on platform-provided tools.

Moreover, platforms influence the degree of autonomy and transparency available to users. Limited transparency may obscure the contributions of AI systems, while restrictive policies may constrain users' claims to ownership. Consequently, platforms function not only as intermediaries but also as active participants in the construction of value ownership.

5.4 Societal Level: Norms, Legitimacy, and Collective Value

At the societal level, value ownership is shaped by broader institutional, cultural, and regulatory contexts. Legal frameworks define formal ownership rights, but societal perceptions of legitimacy play an equally important role in determining how ownership is recognized and accepted.

In human–AI co-creation, societal attitudes toward AI influence whether machine-generated contributions are considered legitimate sources of value. Cultural norms surrounding authenticity, originality, and creativity affect how outputs are evaluated and how ownership claims are interpreted. These norms are not static but evolve over time as AI becomes more embedded in everyday practices.

The concept of data-driven capitalism provides a useful lens for understanding value extraction at this level. Organizations and platforms often derive value from user interactions and data, transforming them into economic assets without direct compensation to contributors (Zuboff, 2015). In human–AI systems, this dynamic extends to creative outputs, where value may be generated collectively but captured selectively.

Regulatory developments further shape the societal dimension of ownership. Governments and international bodies are increasingly exploring frameworks to address intellectual property, data rights, and AI accountability (Novelli *et al.*, 2024). However, these frameworks often lag behind technological advancements, creating gaps and uncertainties that affect how ownership is defined and enforced.

5.5 Ownership as a Multi-Dimensional and Multi-Level Construct

The analysis across individual, organizational, platform, and societal levels demonstrates that value ownership in human–AI co-creation is inherently multi-dimensional and relational.

Ownership is not a static attribute assigned to a single actor but an emergent outcome shaped by interactions across multiple levels.

The figure organizes value ownership as a multi-level construct rather than a single legal claim. It clarifies how ownership emerges through individual interpretation, organizational value capture, platform control, and societal legitimacy.

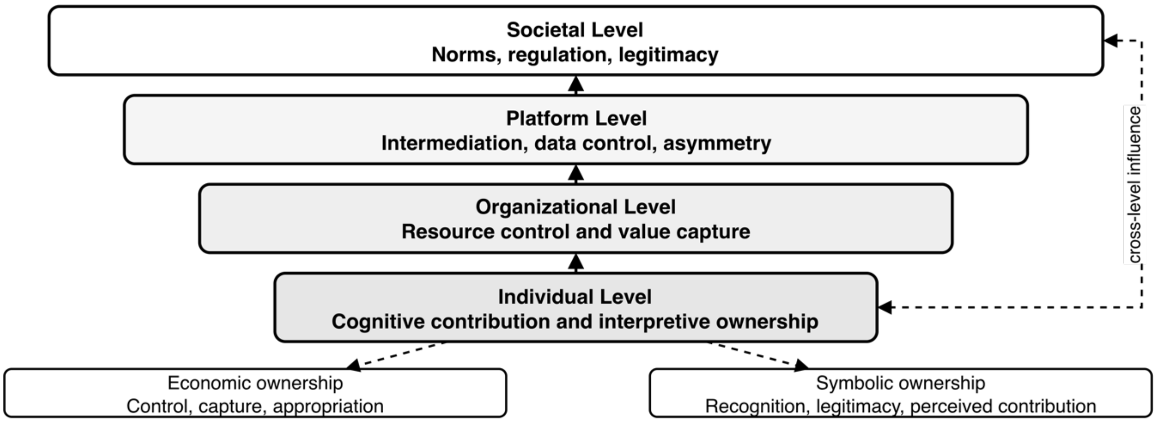

Figure 2. Multi-Level Framework of Value Ownership in Human–AI Co-Creation
Source: Author's conceptualization

The framework articulated in Figure 2 clarifies that value ownership is constructed across nested and mutually influencing levels of analysis. Figure 2 supports the article's argument by showing that ownership cannot be reduced to individual authorship or legal entitlement, because economic control and symbolic recognition are shaped by organizational, platform, and societal conditions.

At the individual level, ownership is linked to cognitive and interpretive contributions. At the organizational level, it is associated with resource control and value capture. At the platform level, it is shaped by intermediation and power asymmetries. At the societal level, it is influenced by norms, legitimacy, and regulatory frameworks.

Importantly, these levels are deeply interconnected. Platform policies influence organizational strategies, which in turn shape individual behavior. Societal norms and regulations affect how ownership is perceived and legitimized across all levels. This interconnectedness reinforces the need to conceptualize ownership as both an economic and symbolic phenomenon.

Economic ownership refers to the ability to capture and appropriate value, while symbolic ownership relates to recognition, legitimacy, and perceived contribution. In human–AI co-creation, both dimensions are critical, as they determine not only who benefits from value creation but also whose contributions are acknowledged.

By framing ownership as a multi-level and multi-dimensional construct, this section provides a critical bridge between the ethical tensions identified earlier and the conceptual model developed in the next section. It establishes that ownership is not merely an endpoint of production but an emergent outcome of complex sociotechnical interactions.

6. Proposed Conceptual Framework: Human–AI Value Co-Creation and Ownership Model

Building on the preceding analysis, this section introduces the central theoretical contribution of the study: the Human–AI Value Co-Creation and Ownership Model. The model conceptualizes human–AI collaboration as a processual and multi-stage system in which value is generated through iterative interaction and subsequently translated into ownership outcomes across multiple levels.

Rather than treating value creation and ownership as separate phenomena, the proposed framework integrates both within a single analytical architecture. This reflects the argument that ownership is not merely an ex-post legal assignment but an emergent outcome embedded within the co-creation process itself. In this sense, ownership is continuously constructed through interaction, evaluation, and attribution mechanisms.

The model adopts a process perspective, recognizing that value emerges over time through recursive interactions rather than discrete events (Garud *et al.*, 2010; Faraj *et al.*, 2018). It consists of six core components—Human Input, AI Generative Process, Interaction Loop, Output Creation, Value Attribution Mechanism, and Ownership Allocation Outcome—supported by three moderating variables: Trust, Transparency, and Regulation.

6.1 Human Input: Intentionality and Boundary Setting

The co-creation process begins with human input, which includes intention, contextual framing, domain knowledge, and goal specification. Human actors define the problem space by formulating prompts, constraints, and creative directions that guide the AI system.

From a theoretical perspective, human input represents the locus of intentionality and interpretive authority within the system. Even as AI contributes to generation, humans retain control over purpose and meaning, aligning with sociotechnical perspectives that position human actors as central in shaping outcomes (Faraj *et al.*, 2018; Benbya *et al.*, 2021).

Importantly, human input functions not only as an initiating force but also as a boundary-setting mechanism. Structured inputs constrain the range of possible outputs, while open-ended inputs expand the creative search space. This dual role influences the trajectory of the entire co-creation process.

6.2 AI Generative Process: Algorithmic Expansion of Possibilities

The second component is the AI generative process, in which the system produces outputs based on learned representations, probabilistic modeling, and large-scale pattern recognition. Unlike traditional tools, AI systems do not merely execute predefined instructions but actively generate novel combinations of information.

This generative capability introduces a degree of algorithmic agency, as outputs may extend beyond the explicit intentions of the human user (Berente *et al.*, 2021). However, this agency is structurally bounded by model architecture, training data, and system parameters. As such, the AI generative process simultaneously acts as a source of innovation and a constraint on possible outcomes.

Within the model, this component represents the expansion phase of value creation, where the creative search space is broadened through algorithmic recombination (Wu *et al.*, 2021).

6.3 Interaction Loop: Iterative Co-Creation Dynamics

At the core of the framework lies the interaction loop, which captures the iterative and recursive nature of human–AI collaboration. Rather than a linear sequence, co-creation unfolds through continuous cycles of input, generation, evaluation, and refinement.

In this loop, human actors respond to AI-generated outputs by selecting, modifying, and reinterpreting them, which in turn informs subsequent inputs. This creates a feedback-driven system in which creativity emerges through ongoing interaction rather than one-time production.

The interaction loop operationalizes the concept of distributed agency, where influence shifts dynamically between human and AI actors across iterations (Raisch & Krakowski, 2021). It also reflects principles of distributed cognition, where cognitive processes are extended across human and technological components (Faraj *et al.*, 2018).

The intensity and duration of this loop vary across contexts, influencing both the quality of outputs and the perceived contribution of each actor. As such, the interaction loop serves as the mechanistic core linking input and output within the co-creation process.

6.4 Output Creation: Hybrid Artifact Formation

The outcome of the interaction loop is output creation, where a final or intermediate artifact is produced. This output may take various forms, including text, images, designs, or strategic decisions.

Crucially, the output is not attributable to a single actor but represents a hybrid artifact resulting from the interaction between human and AI contributions. This hybrid nature complicates the identification of discrete inputs and challenges traditional notions of authorship and ownership.

From a theoretical standpoint, output creation represents the transition point at which potential value becomes observable. However, value is not inherent in the output itself; it emerges through subsequent processes of interpretation, use, and exchange.

6.5 Value Attribution Mechanism: Interpretation and Evaluation

Following output creation, the framework introduces the value attribution mechanism, which determines how value is interpreted, evaluated, and assigned among actors. This mechanism operates across multiple levels, including individual perception, organizational assessment, and market evaluation.

Value attribution is influenced by factors such as perceived contribution, expertise, effort, and legitimacy. In human–AI systems, these factors become more complex due to the opacity of AI processes and the distributed nature of contributions (Weidinger *et al.*, 2021).

Importantly, value attribution is not purely objective but involves subjective judgment and negotiated interpretation. Different stakeholders may apply distinct criteria, leading to variation in how value is perceived and distributed. This aligns with the ethical tensions identified earlier, particularly value attribution uncertainty and authorship ambiguity.

Within the model, this component serves as the critical bridge between co-creation and ownership, translating interaction outcomes into evaluative judgments.

6.6 Ownership Allocation Outcome: Distribution of Rights and Recognition

The final component of the framework is the ownership allocation outcome, which represents the distribution of rights, economic benefits, and symbolic recognition among actors.

Ownership in human–AI co-creation may take multiple forms, including:

1) Exclusive ownership by a single actor
2) Shared ownership among participants
3) Platform-mediated ownership governed by predefined rules

In many cases, ownership is fragmented, reflecting the distributed nature of contributions. This outcome is shaped by the value attribution mechanism, as perceived contribution directly influences ownership claims.

From a theoretical perspective, this component reinforces the argument that ownership is not a static legal assignment but a socio-technical construct emerging from interaction, interpretation, and institutional context (Gaidartzi *et al.*, 2025; Al-Busaidi *et al.*, 2024).

6.7 Moderating Variables: Trust, Transparency, and Regulation

The model incorporates three moderating variables that influence the relationships between core components:

Trust affects how human actors engage with AI systems and how they evaluate outputs. Higher trust increases reliance on AI contributions and may enhance acceptance of shared ownership (Glikson & Woolley, 2020).

Transparency influences the visibility of AI processes and the extent to which users understand how outputs are generated. Greater transparency improves value attribution accuracy and supports accountability (Rai, 2020; Arrieta *et al.*, 2020).

Regulation provides the institutional framework within which ownership is defined and enforced. Legal clarity reduces ambiguity and facilitates consistent ownership allocation (Novelli *et al.*, 2024).

These moderators interact with the core components, shaping the strength and direction of relationships within the model.

6.8 Synthesis and Figure Positioning

Taken together, the Human–AI Value Co-Creation and Ownership Model conceptualizes co-creation as a dynamic, multi-stage system that integrates production, evaluation, and allocation processes. The framework emphasizes that ownership is not an endpoint but an emergent property of interactions that unfold over time.

The model integrates value creation and ownership allocation into a single processual architecture. It positions ownership as an emergent outcome of iterative human–AI interaction, value attribution, and institutional moderation.

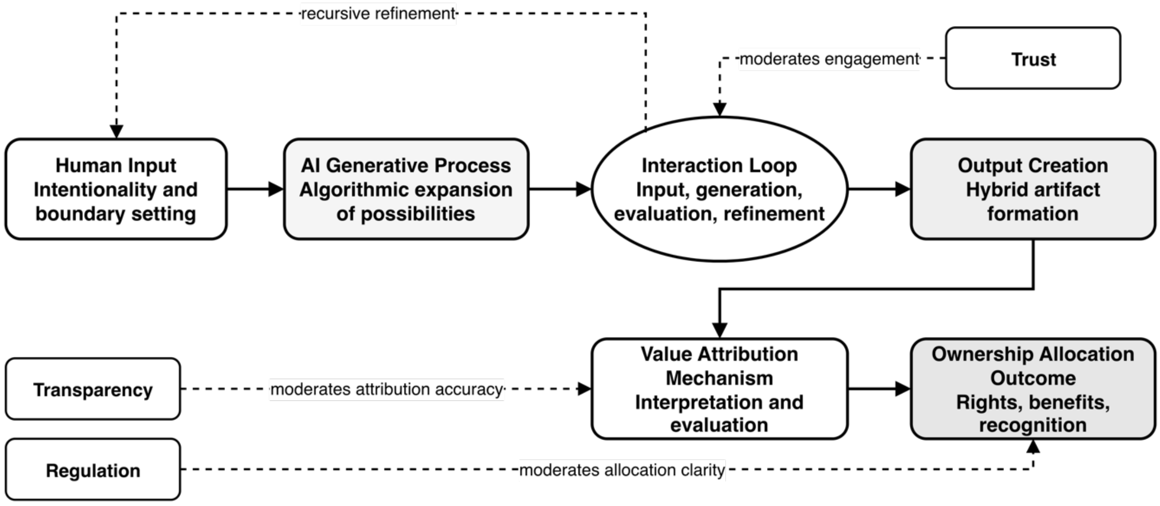

Figure 3. Human–AI Value Co-Creation and Ownership Model
Source: Author's conceptualization

Figure 3 reorients the analysis toward the full mechanism through which value ownership emerges in human–AI systems. It shows that ownership allocation is not a final legal step detached from production, but a processual outcome shaped by human input, AI generation, iterative interaction, hybrid output formation, value attribution, and moderating conditions such as trust, transparency, and regulation.

7. Research Propositions and Future Research Agenda

Building on the proposed Human–AI Value Co-Creation and Ownership Model, this section develops a set of research propositions that translate the conceptual relationships into analytically testable statements. These propositions are grounded in prior literature on human–AI collaboration, algorithmic decision-making, trust, and organizational AI integration, and aim to guide future empirical validation of the model.

Rather than treating value creation and ownership as independent constructs, the propositions emphasize the processual linkages between human input, AI contribution, interaction dynamics, and ownership outcomes. In doing so, they reflect the underlying argument of this study that ownership is an emergent result of iterative co-creation processes rather than a predetermined assignment.

7.1 Human Input and AI Contribution

The first set of propositions examines how the relative contributions of human actors and AI systems influence perceptions of authorship and ownership.

P1: *The greater the relative contribution of AI in the generative process, the lower the perceived clarity of authorship.*

As AI systems generate increasingly substantive and unpredictable outputs, distinguishing between human and machine contributions becomes more difficult, leading to ambiguity in authorship attribution (Bender *et al.*, 2021; Crawford & Calo, 2016).

P2: *The specificity and structure of human input positively influence perceived ownership by increasing the visibility of human contribution.*

Structured prompts, constraints, and iterative refinements make human involvement more explicit, strengthening ownership claims by enhancing perceived intentionality and control.

7.2 Interaction Loop and Value Attribution

The second group of propositions focuses on the role of iterative interaction in shaping value attribution.

P3: *Higher levels of iterative interaction between human and AI actors increase the perceived legitimacy of shared ownership.*

When users actively engage in refining AI-generated outputs, the resulting artifact is more likely to be perceived as co-created rather than machine-generated (Oh *et al.*, 2018; Muller *et al.*, 2020).

P4: *The opacity of the interaction process negatively affects the accuracy of value attribution.*

Limited understanding of how AI generates outputs reduces the ability of actors to assess contributions, leading to uncertainty in value distribution (Adadi & Berrada, 2018; Rai, 2020).

7.3 Value Attribution and Ownership Allocation

The third set of propositions links value attribution mechanisms to ownership outcomes.

P5: *Perceived contribution is positively associated with ownership claims in human–AI co-creation.*

Actors who are perceived to contribute more significantly: whether through input, refinement, or interpretation, are more likely to assert and be granted ownership rights.

P6: *Divergence in value attribution criteria across stakeholders increases the likelihood of contested ownership outcomes.*

Different actors, including users, organizations, and platforms, may apply distinct evaluative criteria, leading to conflicting ownership claims and negotiation processes (Whittlestone *et al*., 2019; Ryan & Stahl, 2020).

7.4 Moderating Effects of Trust, Transparency, and Regulation

The model incorporates three moderating variables that shape the relationships between co-creation processes and ownership outcomes.

P7: *Trust in AI positively moderates the relationship between AI contribution and perceived legitimacy of co-created outputs.*

Higher levels of trust reduce resistance to AI involvement and increase acceptance of shared authorship (Glikson & Woolley, 2020).

P8: *Transparency positively moderates the relationship between interaction processes and value attribution accuracy.*

Greater visibility into AI processes enables more informed evaluation of contributions and improves perceived fairness (Rai, 2020; Arrieta *et al*., 2020).

P9: *Regulatory clarity positively moderates the relationship between value attribution and ownership allocation outcomes.*

Clear legal and institutional frameworks reduce ambiguity and facilitate consistent ownership assignments (Novelli *et al*., 2024).

The table consolidates the research propositions by mapping each relationship in the conceptual model to its corresponding theoretical logic. This structured overview enables clearer interpretation of how process components translate into testable claims.

Table 3. Mapping of Conceptual Relationships and Research Propositions in Human-AI Co-Creation

Proposition & Conceptual Relationship		Key Constructs Involved	Theoretical Rationale
P1	AI contribution → authorship clarity	AI contribution, authorship perception	Higher AI involvement obscures identifiable authorship
P2	Human input structure → ownership perception	Human input, perceived ownership	Structured input increases visibility of human contribution
P3	Interaction intensity → shared ownership	Iterative interaction, ownership form	Repeated engagement legitimizes co-creation
P4	Process opacity → attribution accuracy	Transparency, value attribution	Limited explainability reduces evaluation accuracy
P5	Perceived contribution → ownership claim	Contribution perception, ownership claim	Greater perceived input strengthens ownership assertion
P6	Divergent evaluation criteria → ownership conflict	Stakeholder perspectives, attribution	Different valuation logics create contested ownership
P7	Trust moderates AI contribution → legitimacy	Trust, AI role, legitimacy perception	Trust increases acceptance of AI involvement
P8	Transparency moderates interaction → attribution	Transparency, interaction process	Visibility improves fairness in value assessment
P9	Regulation moderates attribution → ownership	Regulation, ownership allocation	Legal clarity stabilizes ownership outcomes

Source: Author's conceptualization

Table 3 strengthens the analytical coherence of the research agenda by explicitly linking each proposition to its underlying conceptual relationship and theoretical justification. By organizing the propositions in this way, Table 3 clarifies how the abstract model is operationalized into empirically testable statements and ensures consistency between theoretical constructs and proposed hypotheses.

7.5 Future Research Directions

The propositions outlined above open several promising avenues for future research that extend beyond immediate empirical validation.

First, empirical testing of the proposed model is essential. Quantitative approaches such as structural equation modeling can be used to examine relationships between human input, AI contribution, and ownership perceptions. Experimental designs may also be employed to manipulate levels of AI involvement and transparency, allowing for causal inference. Complementary qualitative studies, including interviews and case analyses, can provide deeper insights into how actors negotiate ownership in practice.

Second, future research should explore contextual variations across industries and task types. The dynamics of human–AI co-creation may differ significantly between domains such as marketing, design, journalism, and software development. In highly creative domains, authenticity concerns may play a more prominent role, while in technical domains, efficiency and accuracy may dominate value attribution.

Third, cross-cultural investigations are needed to understand how societal norms influence perceptions of authorship, authenticity, and ownership. Cultural differences in attitudes toward technology and creativity may lead to variation in how AI contributions are interpreted and legitimized.

Fourth, the role of digital platforms as governance actors warrants deeper examination. Platform design, data policies, and revenue-sharing mechanisms can significantly influence value attribution and ownership outcomes. Future studies should investigate how platform governance structures shape power asymmetries and value distribution in human–AI ecosystems (Parker *et al.*, 2017; Nieborg & Poell, 2018).

Fifth, interdisciplinary research integrating management, law, and ethics is essential for developing comprehensive frameworks. Legal scholars can contribute to understanding intellectual property implications, while ethicists can explore normative dimensions of fairness and accountability in distributed systems.

Finally, longitudinal research is needed to capture how human–AI collaboration evolves over time. As users become more familiar with AI technologies and regulatory frameworks mature, perceptions of ownership and value may shift. Tracking these changes can provide valuable insights into the long-term implications of AI integration in creative and organizational contexts.

8. Discussion and Implications

The findings of this study provide a comprehensive re-examination of how value ownership is constructed in human–AI co-creation systems. By integrating perspectives from ethics, ownership theory, and co-creation, the study advances a multi-level and process-oriented understanding of value creation in digitally mediated environments. Rather than viewing ownership as a static outcome, the analysis demonstrates that ownership is continuously shaped through iterative interactions, evaluative processes, and institutional contexts.

8.1 Theoretical Implications

From a theoretical standpoint, this study makes three primary contributions.

First, it reconceptualizes ownership as a distributed and multi-dimensional construct. Traditional models assume a clear relationship between creator and output, grounded in individual authorship and legal entitlement. In contrast, this study demonstrates that ownership in human–AI systems emerges from interactions among multiple actors and operates across legal, economic, and symbolic dimensions. This reconceptualization extends existing ownership theory by incorporating relational and process-based elements that reflect the realities of sociotechnical systems (Gaidartzi *et al*., 2025; Al-Busaidi *et al*., 2024).

Second, the study advances co-creation theory by integrating the concept of non-human agency. While prior literature has emphasized value co-creation among human actors, the inclusion of AI as an active participant introduces a new layer of complexity. The notion of distributed agency highlights that value is not solely generated by human intention but emerges from interactions between human cognition and algorithmic processes (Raisch & Krakowski, 2021; Berente *et al*., 2021). This contribution aligns with and extends sociotechnical and service-dominant logic perspectives by incorporating intelligent systems as operant resources within value creation processes.

Third, the study introduces the concept of an ethical paradox system in human–AI co-creation. By identifying interrelated tensions—authorship ambiguity, value attribution uncertainty, responsibility diffusion, and authenticity erosion—the study moves beyond fragmented discussions of AI ethics. It demonstrates that these tensions are not isolated but form a dynamic system of competing logics that must be continuously managed rather than resolved. This perspective contributes to organizational theory by applying paradox thinking to the domain of AI-mediated creativity, offering a more nuanced understanding of how ethical considerations shape value ownership.

In addition, the proposed conceptual model contributes to the literature by providing a processual framework that links value creation mechanisms to ownership outcomes. By integrating human input, AI generative processes, interaction dynamics, and value attribution mechanisms, the model offers a structured approach for analyzing how ownership emerges in complex systems. This bridges a critical gap in existing research, which has often treated value creation and ownership as separate phenomena.

8.2 Managerial Implications

The findings of this study have significant implications for organizations integrating AI into creative and knowledge-intensive work.

First, organizations must develop explicit governance frameworks that define roles, contributions, and ownership rights in human–AI collaboration. The ambiguity surrounding authorship and value attribution can lead to internal conflicts, legal risks, and reputational challenges if not proactively addressed. Establishing clear guidelines for how AI-generated outputs are recognized and attributed is essential for maintaining fairness and organizational coherence.

Second, firms should invest in transparency and explainability mechanisms. As the study highlights, opacity in AI processes undermines trust and complicates value attribution. By enhancing explainability—through interface design, documentation, or process visibility—organizations can improve collaboration quality and strengthen the legitimacy of co-created outputs (Rai, 2020).

Third, organizations must rethink capability development and role design. The emergence of roles such as prompt engineers, AI curators, and hybrid creators indicates a shift in the nature of creative labor. Firms need to develop competencies that enable employees to effectively interact with AI systems, balancing augmentation with critical oversight.

Fourth, managers should be aware of cognitive risks associated with AI reliance, such as automation bias and reduced critical evaluation. Designing workflows that encourage iterative engagement and human judgment is essential to preserve creativity and avoid over-dependence on algorithmic outputs (Logg *et al.*, 2019).

Finally, organizations must recognize that value creation increasingly extends beyond firm boundaries. Collaboration with external platforms and AI providers requires strategic consideration of how value is shared and captured within broader ecosystems.

8.3 Policy and Regulatory Implications

At the policy level, the study highlights the need for adaptive and forward-looking regulatory frameworks that address the unique challenges of human–AI co-creation.

Existing intellectual property and liability frameworks are largely based on assumptions of singular authorship and clearly defined responsibility. These assumptions are increasingly inadequate in contexts characterized by distributed agency and hybrid outputs. Policymakers must therefore explore new approaches that account for multi-actor contributions and algorithmically mediated processes (Novelli *et al.*, 2024).

In particular, regulatory frameworks should address three key areas. First, authorship and ownership definitions must be revisited to reflect the realities of AI-assisted creation. Second, accountability mechanisms should be designed to manage responsibility diffusion across developers, users, and organizations. Third, platform governance requires attention, as platforms play a central role in shaping value distribution and may reinforce power asymmetries if left unregulated (Kenney & Zysman, 2016; Nieborg & Poell, 2018).

Moreover, transparency requirements and disclosure standards may be necessary to ensure that users and consumers are aware of the role of AI in content creation. Such measures can enhance trust while supporting more informed evaluation of value.

8.4 Integrative Reflection

Taken together, the findings underscore that human–AI co-creation represents not merely a technological shift but a fundamental transformation in how value, agency, and ownership are conceptualized. The integration of AI into creative processes reconfigures the relationships between actors, redistributes control, and introduces new forms of ethical and economic complexity.

The multi-level framework and conceptual model developed in this study provide a foundation for understanding these dynamics, emphasizing that value ownership is an emergent property of interaction rather than a predetermined allocation. This perspective invites a rethinking of foundational assumptions in management, innovation, and digital economy research.

9. Conclusion

The growing integration of generative artificial intelligence into creative and organizational processes has introduced a fundamental challenge to existing assumptions about how value is created, attributed, and owned. In contexts where human cognition and algorithmic generation interact iteratively, the traditional linkage between creator, contribution, and ownership becomes increasingly fragmented. Addressing this problem, the present study developed an integrative conceptual framework to explain how value ownership is constructed in human–AI co-creation systems, with particular emphasis on the interplay between distributed agency, ethical tensions, and multi-level value attribution mechanisms.

The analysis demonstrates that value ownership in human–AI collaboration cannot be adequately explained through conventional models grounded in singular authorship or clearly bounded production processes. Instead, value emerges through recursive interaction loops between human input and AI generative processes, and is subsequently shaped by interpretive and evaluative mechanisms that operate across individual, organizational, platform, and societal levels. The most significant insight lies in the articulation of human–AI co-creation as an ethical paradox system, characterized by interrelated tensions—authorship ambiguity, value attribution uncertainty, responsibility diffusion, and authenticity erosion—that do not resolve independently but co-evolve within the same sociotechnical environment. By integrating these tensions into a process-oriented model, the study advances a more comprehensive understanding of how ownership is not merely assigned but constructed through ongoing interaction and negotiation.

From a theoretical perspective, the study contributes by extending ownership theory beyond its traditional legal-economic boundaries toward a distributed and multi-dimensional construct encompassing economic control, symbolic recognition, and relational legitimacy. It also advances co-creation theory by incorporating non-human agency, thereby reconceptualizing value creation as a dynamic outcome of human–algorithm interaction rather than purely human collaboration. Furthermore, the introduction of an ethical paradox framework situates AI-related ethical challenges within a broader organizational context, highlighting the need to manage persistent tensions rather than seek definitive resolutions. These contributions collectively bridge fragmented streams of literature in management, information systems, and AI ethics, offering a unified lens for analyzing value ownership in digitally mediated environments.

The implications for practice and policy are equally significant. Organizations must move beyond ad hoc adoption of AI tools toward deliberate governance structures that clarify roles, enhance transparency, and ensure equitable value distribution. The findings underscore the importance of developing capabilities that enable meaningful human oversight while leveraging the generative potential of AI. At the policy level, the analysis points to the limitations of existing intellectual property and accountability frameworks, emphasizing the need for adaptive regulatory approaches that reflect the distributed and evolving nature of authorship and ownership in AI-mediated systems. Addressing these challenges is critical not only for organizational effectiveness but also for maintaining trust and legitimacy in increasingly algorithm-driven economies.

Several limitations provide opportunities for further refinement and empirical exploration. The conceptual nature of the framework necessarily abstracts from the diversity of technological configurations and industry-specific contexts in which human–AI co-creation occurs. Variations in AI capability, domain complexity, and institutional environments may influence how value and ownership are constructed in practice. In addition, the framework emphasizes generalized interaction dynamics and does not fully capture cultural and contextual differences in how authorship and legitimacy are perceived. These limitations do not diminish the explanatory value of the model but instead highlight the complexity of the phenomenon and the need for context-sensitive investigation.

Future research should build on this foundation by empirically examining the proposed relationships using mixed-method approaches, including quantitative modeling of interaction dynamics and qualitative analysis of real-world co-creation practices. Comparative studies across industries and cultural settings would deepen understanding of how norms and institutional factors shape ownership perceptions. Further inquiry into platform governance, algorithm design, and transparency mechanisms is essential to uncover how structural conditions influence value attribution and distribution. Longitudinal research will also be critical in capturing how human–AI collaboration evolves over time as technologies mature and regulatory frameworks adapt.

Ultimately, the question of who owns value in the age of artificial intelligence cannot be resolved through existing paradigms that assume stable boundaries between creators, tools, and outcomes. Human–AI co-creation reconfigures these boundaries in ways that demand new theoretical and practical approaches to agency, responsibility, and legitimacy. By offering an integrative and process-oriented framework, this study provides a foundation for rethinking value ownership in an increasingly intelligent and interconnected digital economy, while opening pathways for future scholarship to refine, test, and extend this emerging field of inquiry.

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