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From Knowledge Assets to Epistemic Capital: Human–AI Collective Intelligence in Organizations

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ABSTRACT
As organizations increasingly integrate artificial intelligence into decision-making and knowledge work, traditional notions of knowledge assets are no longer sufficient to explain how value is created, sustained, and leveraged. This paper advances a conceptual shift from knowledge assets to epistemic capital, defined as the collectively produced, context-sensitive, and action-oriented capacity to generate, validate, and apply knowledge within human–AI systems. We argue that epistemic capital emerges not from isolated human expertise or standalone AI capabilities, but from their dynamic interaction within organizational settings. Building on theories of collective intelligence, organizational knowledge, and socio-technical systems, the paper conceptualizes Human–AI Collective Intelligence as an epistemic infrastructure through which organizations accumulate, transform, and deploy epistemic capital. The framework highlights key dimensions of epistemic capital including epistemic diversity, validation mechanisms, interpretability, and governance and explains how these dimensions shape the quality of organizational decision-making. By reframing Human–AI collaboration as a process of epistemic capital formation rather than mere knowledge management or automation, this study offers a theoretical foundation for understanding intelligence as a strategic organizational resource. The paper contributes to research on organizational intelligence, AI-enabled decision-making, and knowledge-based theory of the firm, while providing implications for the design, governance, and ethical deployment of Human–AI systems in modern organizations.

Keywords: *Epistemic Capital; Human–AI Collective Intelligence; Organizational Decision-Making; Knowledge Assets; Hybrid Intelligence Systems; Organizational Knowledge; Socio-Technical Systems; AI Governance; Collective Cognition; Strategic Decision-Making.*

1. Introduction

Contemporary organizations operate in environments characterized by increasing complexity, uncertainty, and informational abundance. Strategic and operational decisions are no longer constrained by data scarcity; rather, they are challenged by information overload, fragmented knowledge sources, and rapidly shifting contexts (Ajmal & Suleman, 2015a). While knowledge has long been considered a critical organizational resource, traditional conceptions of *knowledge assets*—as static, codified, and human-centered repositories—are increasingly insufficient for explaining how organizations generate decision quality and competitive advantage in the age of artificial intelligence (AI). The growing integration of AI into organizational decision-making fundamentally reshapes how knowledge is produced, validated, and mobilized, calling for a conceptual rethinking of organizational intelligence (Trunk et al., 2020).

AI systems now play an active role in sensemaking, prediction, pattern recognition, and recommendation generation across organizational domains. However, empirical and conceptual research consistently emphasizes that AI does not replace human judgment but rather transforms it through hybrid configurations of human and machine intelligence (Trianni et al., 2023; Bhattacharjee, 2025). These configurations—often described as *human–AI collective intelligence*—emerge when humans and AI systems interact as complementary cognitive agents, combining human contextual understanding, ethical reasoning, and tacit knowledge with AI's capacity for large-scale data processing and analytical consistency (Trunk et al., 2020; Bolisani et al., 2025). Despite growing interest in such hybrid systems, existing organizational and information systems literature tends to frame AI primarily as a tool for efficiency, automation, or decision support, rather than as a constitutive element of organizational knowledge itself (Ajmal & Suleman, 2015b).

This instrumental framing limits theoretical progress in understanding how value is created through human–AI interaction. Knowledge management research, for instance, continues to focus on knowledge capture, storage, and sharing, even as AI systems actively shape what counts as relevant knowledge, how evidence is weighted, and which alternatives are rendered visible to decision-makers (Aljuwaiber, 2025). Similarly, studies on AI-enabled decision-making often emphasize performance outcomes or adoption barriers, such as trust, transparency, and ethical concerns, without sufficiently theorizing the underlying epistemic dynamics of hybrid decision systems (Booyse & Scheepers, 2023). As a result, the literature lacks a unifying conceptual lens capable of explaining how organizations accumulate, sustain, and govern knowledge-based value in human–AI collectives (Ajmal, et al., 2025).

To address this gap, this article proposes a conceptual shift from *knowledge assets* to *epistemic capital*. Unlike knowledge assets, which are typically treated as discrete, ownable, and static resources, epistemic capital refers to the collectively generated capacity of an organization to produce, validate, integrate, and apply knowledge for action. Epistemic capital is inherently relational, dynamic, and processual, emerging from interactions among human actors, AI systems, organizational structures, and governance mechanisms. Recent research on hybrid collective intelligence supports this view, demonstrating that decision quality depends not merely on the availability of information, but on how diverse epistemic inputs are elicited, aggregated, interpreted, and legitimized within socio-technical systems (Trianni et al., 2023).

Human–AI collective intelligence can thus be understood as an epistemic infrastructure through which epistemic capital is formed and mobilized. AI systems contribute analytical breadth, speed, and consistency, while humans provide contextual grounding, normative judgment, and sensemaking capabilities (Ajmal, Islam & Islam, 2024a). However, this epistemic co-production is not neutral. Studies highlight risks of epistemic injustice, bias amplification, and over-reliance on algorithmic outputs, particularly when AI systems shape whose knowledge is recognized and whose is marginalized within organizational decision processes (Nihei, 2022). These findings

underscore that epistemic capital is not only a technical or cognitive resource, but also a socio-political one, shaped by power relations, governance structures, and ethical frameworks.
Moreover, empirical work across organizational domains—including strategy, human resources, and knowledge-intensive industries—shows that the effectiveness of human–AI systems depends on how organizations design feedback loops, human-in-the-loop mechanisms, and learning processes that allow epistemic capital to evolve over time (Bolisani et al., 2025; Trunk et al., 2020). Without such mechanisms, AI may exacerbate existing decision-making limitations rather than enhance organizational intelligence. Consequently, understanding human–AI collaboration as a process of epistemic capital formation provides a more robust theoretical foundation for analyzing both the benefits and risks of AI integration.
Against this backdrop, the present article develops a conceptual framework that reconceptualizes organizational decision-making as an epistemic capital process enacted through human–AI collective intelligence. By synthesizing insights from collective intelligence theory, organizational knowledge research, and AI-enabled decision-making studies, the article advances three contributions. First, it reframes intelligence as a form of capital that is collectively produced rather than individually possessed. Second, it positions human–AI collective intelligence as the primary mechanism through which epistemic capital is accumulated and deployed in modern organizations. Third, it highlights key dimensions—such as epistemic diversity, validation practices, interpretability, and governance—that shape the quality and sustainability of epistemic capital. In doing so, the article lays the groundwork for future empirical research and offers theoretical guidance for the responsible design and governance of human–AI systems in organizational contexts.

2. Literature Review

2.1. Knowledge Assets and Organizational Decision-Making

The concept of knowledge as a strategic organizational resource has long been central to management and organization theory. Traditional knowledge-based views of the firm conceptualize knowledge as an asset that can be created, stored, transferred, and leveraged to achieve competitive advantage (Ahmed, Ajmal & Haq,2024b). Within this paradigm, organizations invest in knowledge management systems to codify expertise, improve knowledge sharing, and enhance decision-making efficiency. However, recent studies argue that this asset-based view increasingly fails to capture the dynamic, distributed, and interactive nature of knowledge production in digitally mediated environments (Bolisani et al., 2025).
As organizational contexts grow more complex and data-intensive, decision-makers face not a lack of information but an overabundance of heterogeneous, uncertain, and sometimes contradictory knowledge inputs. Trunk et al. (2020) emphasize that strategic decision-making under uncertainty requires not only access to information but also the ability to interpret, contextualize, and integrate diverse forms of knowledge. This insight challenges static notions of knowledge assets and points toward more process-oriented understandings of organizational intelligence.
Moreover, empirical research on AI-supported knowledge management highlights that AI systems do not merely store or retrieve knowledge but actively participate in shaping how knowledge is constructed and applied. AI-driven tools increasingly synthesize information, generate insights, and recommend actions, thereby influencing managerial cognition and organizational learning processes (Aljuwaiber, 2025; Bolisani et al., 2025). These developments

suggest that knowledge in modern organizations is no longer solely a human-held asset but an emergent property of socio-technical systems.

2.2. Artificial Intelligence in Organizational Decision-Making

The integration of AI into organizational decision-making has expanded rapidly across domains such as strategy, finance, human resources, and operations. AI technologies—including machine learning, natural language processing, and predictive analytics—enhance organizations' ability to process large datasets, identify patterns, and generate decision alternatives at unprecedented speed and scale (Bhattacharjee, 2025). Empirical evidence indicates that AI can improve decision efficiency, reduce cognitive load, and support data-driven management practices (Bolisani et al., 2025).

However, the literature consistently cautions against viewing AI as an autonomous decision-maker. Trunk et al. (2020) demonstrate that AI systems often amplify existing decision-making challenges, such as bias, overconfidence, and misinterpretation, if not carefully integrated into human workflows. Similarly, Booyse and Scheepers (2023) identify organizational barriers to AI-driven decision-making, including lack of trust, transparency concerns, regulatory constraints, and resistance linked to power and control.

These findings underscore the importance of human judgment in AI-enabled decision contexts. Rather than replacing human decision-makers, AI systems reshape decision processes by redistributing cognitive tasks between humans and machines. This redistribution creates new dependencies and responsibilities, increasing the need for human oversight, ethical reflection, and contextual interpretation (Bhattacharjee, 2025). Consequently, the effectiveness of AI in organizations depends less on technological sophistication alone and more on how AI is embedded within broader organizational decision architectures.

2.3. Human–AI Collective Intelligence

In response to the limitations of purely automated or purely human decision systems, scholars increasingly adopt the concept of *human–AI collective intelligence*. Collective intelligence refers to the enhanced problem-solving capacity that emerges when multiple cognitive agents interact effectively. Trianni et al. (2023) extend this concept to hybrid systems, showing that human–AI collectives can outperform either humans or machines alone in complex, open-ended decision domains.

Hybrid collective intelligence leverages the complementary strengths of humans and AI: humans contribute contextual understanding, ethical reasoning, and tacit knowledge, while AI contributes scalability, consistency, and analytical rigor (Trianni et al., 2023). Empirical case studies demonstrate that such systems are particularly effective when they promote epistemic diversity, avoid herding effects, and incorporate mechanisms for aggregating and validating heterogeneous inputs.

Nevertheless, the literature also highlights risks associated with hybrid intelligence systems. Nihei (2022) introduces the concept of epistemic injustice in human-centered AI, arguing that AI systems can marginalize certain forms of human knowledge or systematically disadvantage specific groups if epistemic assumptions remain unexamined. This concern reveals that collective intelligence is not merely a technical configuration but a deeply epistemic and ethical phenomenon shaped by power relations and institutional norms.

2.4. Epistemic Dimensions of Human–AI Systems

While research on AI and collective intelligence has grown substantially, relatively few studies explicitly address the epistemic foundations of human–AI collaboration. Existing work tends to focus on performance outcomes, adoption challenges, or ethical principles, leaving the underlying processes of knowledge validation, credibility assignment, and sensemaking under-theorized (Nihei, 2022; Trunk et al., 2020).

The notion of epistemic capital offers a promising lens for addressing this gap. Epistemic capital shifts attention from knowledge as a static object to knowledge as a collectively generated capacity for justified belief and informed action. In hybrid decision systems, epistemic capital emerges through continuous interaction between human judgment and algorithmic output, mediated by organizational structures and governance practices (Trianni et al., 2023).

Research on knowledge-driven decision-making supports this view, showing that AI outputs require human interpretation and contextual adjustment to become actionable knowledge (Bolisani et al., 2025). Without human-in-the-loop mechanisms, AI-generated insights risk being misapplied or over-trusted, undermining decision quality. Thus, epistemic capital depends not only on data or algorithms but on institutionalized practices of validation, learning, and accountability.

2.5. Governance, Ethics, and the Sustainability of Epistemic Capital

A growing body of literature emphasizes that governance and ethical considerations are central to the sustainability of human–AI collective intelligence. Booyse and Scheepers (2023) highlight that trust, transparency, and ethical alignment are critical enablers of AI adoption in organizational decision-making. Similarly, Nihei (2022) argues that fairness and diversity must be embedded at the epistemic level of AI system design to prevent systemic injustice.

These studies suggest that epistemic capital is not neutral or evenly distributed; it is shaped by organizational power dynamics, access to AI tools, and institutional decision rights. As AI systems increasingly influence what knowledge is visible and actionable, organizations must actively govern epistemic processes to ensure inclusivity, accountability, and adaptability. Failure to do so may result in epistemic fragility, where decision systems become efficient but brittle, opaque, or ethically misaligned.

2.6. Synthesis and Research Gap

In summary, prior research establishes that (1) traditional knowledge asset frameworks are insufficient for AI-mediated organizations, (2) AI reshapes rather than replaces human decision-making, and (3) human–AI collective intelligence offers significant potential for improving decision quality. However, the literature lacks a unifying theoretical construct that explains how knowledge-based value is accumulated, sustained, and governed in hybrid systems.

This gap motivates the present study's focus on epistemic capital. By integrating insights from organizational knowledge theory, AI-enabled decision-making, and collective intelligence research, this article advances a conceptual framework that positions epistemic capital as the foundational resource of human–AI collective intelligence in organizations.

3. Conceptual Framework and Model Development

3.1. From Knowledge Assets to Epistemic Capital

Traditional organizational theories conceptualize knowledge as an asset—something that can be owned, stored, transferred, and leveraged for competitive advantage. While this perspective has been influential, it presupposes relative stability in knowledge structures and clear boundaries between knowledge producers and users. In AI-enabled organizations, these assumptions no longer hold. Knowledge is continuously generated, recombined, filtered, and reinterpreted through interactions between human actors and intelligent systems (Trunk et al., 2020; Bolisani et al., 2025).

To address this limitation, the present framework adopts epistemic capital as its core construct. Epistemic capital is defined as the *collectively produced organizational capacity to generate, validate, integrate, and apply knowledge for decision-making*. Unlike knowledge assets, epistemic capital is not reducible to databases, expertise repositories, or individual competencies. Instead, it emerges from ongoing epistemic processes embedded within socio-technical systems. This reconceptualization aligns with research showing that decision quality depends less on information availability and more on how knowledge claims are evaluated, contextualized, and legitimized in practice (Trianni et al., 2023).

Epistemic capital is therefore dynamic, relational, and cumulative. It grows when organizations improve their ability to align AI-generated insights with human judgment, organizational goals, and ethical standards. Conversely, it erodes when epistemic processes become opaque, biased, or poorly governed.

3.2. Human–AI Collective Intelligence as an Epistemic Infrastructure

The framework positions human–AI collective intelligence as the primary mechanism through which epistemic capital is formed and mobilized. Human–AI collective intelligence refers to hybrid cognitive systems in which humans and AI act as interdependent epistemic agents, each contributing distinct but complementary capabilities (Trianni et al., 2023).

AI systems contribute computational scalability, pattern recognition, probabilistic reasoning, and the ability to synthesize vast amounts of heterogeneous data. Human actors contribute contextual understanding, domain expertise, ethical reasoning, and interpretive sensemaking. Prior research consistently demonstrates that neither humans nor AI alone are sufficient for high-quality decision-making in complex, uncertain environments (Trunk et al., 2020; Bhattacharjee, 2025). Instead, intelligence emerges from their interaction.

Within the proposed framework, human–AI collective intelligence functions as an epistemic infrastructure—a set of processes, tools, and practices that structure how knowledge is produced and used. This infrastructure determines which data are considered relevant, how models are trained and interpreted, how outputs are validated, and how decisions are ultimately justified. As such, collective intelligence is not merely an operational configuration but a foundational epistemic condition for organizational decision-making.

3.3. Core Dimensions of Epistemic Capital

Building on the literature, the framework identifies four interrelated dimensions through which epistemic capital is constituted in human–AI collective intelligence systems.

3.3.1 Epistemic Diversity

Epistemic diversity refers to the variety of perspectives, knowledge sources, and cognitive approaches involved in decision-making. Research on collective intelligence emphasizes that diverse inputs improve problem-solving and reduce the risk of herding or systematic error (Trianni et al., 2023). In human–AI systems, diversity arises not only from human actors with different expertise but also from the use of multiple models, data sources, and analytical approaches.

AI systems can both enhance and constrain epistemic diversity. While they enable the integration of large-scale and heterogeneous data, they may also reinforce dominant patterns or biases embedded in training data. Consequently, epistemic capital increases when organizations actively design for diversity at both the human and algorithmic levels (Nihei, 2022).

3.3.2 Knowledge Validation and Credibility Mechanisms

A defining feature of epistemic capital is the presence of robust mechanisms for validating knowledge claims. AI-generated outputs do not possess intrinsic epistemic authority; their credibility depends on human interpretation, contextual evaluation, and institutional trust (Bolisani et al., 2025). Human-in-the-loop practices, peer review of AI recommendations, and feedback mechanisms are therefore essential components of epistemic capital formation.

Studies show that organizations lacking clear validation structures are more likely to over-rely on AI outputs or dismiss them entirely, both of which undermine decision quality (Trunk et al., 2020; Booyse & Scheepers, 2023). Epistemic capital is strongest when validation processes balance algorithmic evidence with human judgment and accountability.

3.3.3 Interpretability and Sensemaking

Interpretability refers to the extent to which AI outputs can be understood, explained, and meaningfully integrated into human sensemaking processes. Without interpretability, AI systems risk becoming epistemically opaque, limiting users' ability to assess assumptions, uncertainties, and implications (Bhattacharjee, 2025).

Sensemaking is a distinctly human activity that involves constructing coherent narratives from ambiguous information. Epistemic capital increases when AI systems support, rather than replace, human sensemaking—by providing explanations, uncertainty estimates, and scenario comparisons. Conversely, opaque systems weaken epistemic capital by reducing trust and inhibiting learning (Booyse & Scheepers, 2023).

3.3.4 Governance and Ethical Alignment

Finally, epistemic capital is shaped by governance structures that regulate how knowledge is produced and used. Governance includes policies, norms, and accountability mechanisms that address issues such as fairness, transparency, responsibility, and power distribution in decision-making (Nihei, 2022).

Ethical misalignment—such as biased models or exclusion of certain knowledge holders—constitutes a form of epistemic risk that can erode organizational intelligence. Research on AI ethics highlights that epistemic injustice can arise when AI systems systematically privilege certain perspectives over others (Nihei, 2022). Effective governance mitigates these risks and ensures that epistemic capital remains sustainable over time.

3.4. Epistemic Capital and Organizational Decision Quality

The framework proposes that epistemic capital mediates the relationship between human–AI collective intelligence and organizational decision quality. Decision quality is understood not merely in terms of efficiency or accuracy, but as the degree to which decisions are informed, justified, adaptable, and ethically defensible.

Empirical studies show that organizations with well-designed human–AI systems achieve superior outcomes when they emphasize learning, feedback, and accountability rather than automation alone (Bolisani et al., 2025; Trunk et al., 2020). From an epistemic capital perspective, these outcomes result from stronger collective capacities to evaluate evidence, revise beliefs, and adapt decisions as conditions change.

Thus, the proposed model suggests that investments in AI yield sustainable decision advantages only when accompanied by organizational practices that cultivate epistemic capital.

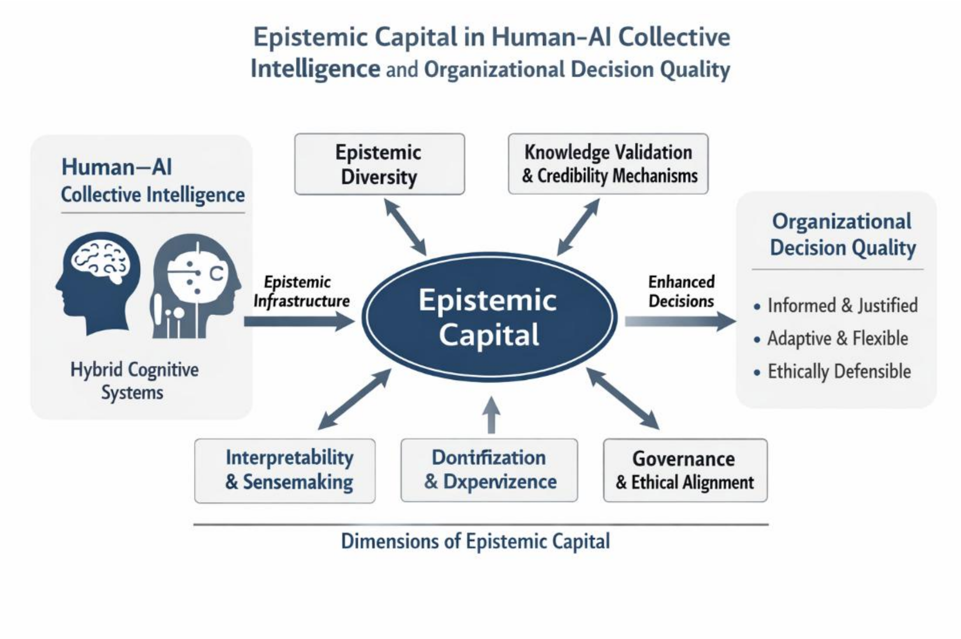

Figure 1: Conceptual Model

4. Model Explanation: Epistemic Capital in Human–AI Collective Intelligence

4.1. Overview of the Conceptual Model

The proposed model conceptualizes Epistemic Capital as the central theoretical construct that links Human–AI Collective Intelligence to Organizational Decision Quality. The model positions human–AI collective intelligence not merely as a technological configuration but as an epistemic infrastructure—a socio-technical system through which organizations generate, validate, and apply knowledge. Epistemic capital emerges from this infrastructure and determines the quality, adaptability, and legitimacy of organizational decisions.

Unlike traditional models of AI-enabled decision-making that emphasize efficiency or automation, this framework foregrounds the epistemic processes underlying decision outcomes. It argues that decision quality is contingent on how well organizations cultivate epistemic capital through structured interaction between human judgment and artificial intelligence (Trunk et al., 2020; Trianni et al., 2023).

4.2. Human–AI Collective Intelligence as Epistemic Infrastructure

At the left side of the model, Human–AI Collective Intelligence represents hybrid cognitive systems in which humans and AI function as interdependent epistemic agents. Prior research demonstrates that AI excels at large-scale data processing, pattern recognition, and probabilistic inference, while humans contribute contextual understanding, moral reasoning, and interpretive sensemaking (Bhattacharjee, 2025; Trunk et al., 2020).

The model conceptualizes this hybrid arrangement as an epistemic infrastructure because it structures:

- What information is collected and analyzed,
- How knowledge claims are generated,
- How uncertainty is represented,
- Who validates and authorizes decisions

Trianni et al. (2023) show that such hybrid systems outperform isolated human or machine intelligence in complex, open-ended domains precisely because intelligence emerges from interaction rather than delegation. However, the model emphasizes that this interaction alone does not guarantee high-quality decisions; it must be epistemically productive. That productivity is captured by the concept of epistemic capital.

4.3. Epistemic Capital as the Central Mediating Construct

At the core of the model lies Epistemic Capital, defined as the *collectively produced organizational capacity to generate, validate, integrate, and apply knowledge for action*. Epistemic capital differs fundamentally from knowledge assets. Whereas knowledge assets are static, ownable, and often codified, epistemic capital is dynamic, relational, and processual (Bolisani et al., 2025).

The model treats epistemic capital as a mediator between human–AI collective intelligence and organizational decision quality. This means that AI investments improve decision outcomes only to the extent that they enhance epistemic capital. Without epistemic capital, AI may increase speed or volume of outputs while degrading understanding, trust, or ethical legitimacy (Booyse & Scheepers, 2023).

4.4. Dimensions of Epistemic Capital

The model specifies four interdependent dimensions through which epistemic capital is formed.

4.4.1 Epistemic Diversity

Epistemic diversity refers to the inclusion of multiple perspectives, knowledge sources, and cognitive approaches in decision-making. Research on collective intelligence consistently finds that diversity reduces systematic error and improves problem-solving in uncertain environments (Trianni et al., 2023).

In human–AI systems, epistemic diversity arises from:

- Heterogeneous human expertise,
- Multiple data sources,
- Different AI models and analytical approaches.

However, AI systems can also suppress diversity by reinforcing dominant patterns embedded in training data. Nihei (2022) warns that such dynamics may produce epistemic injustice, where certain forms of knowledge are systematically excluded. The model therefore treats epistemic diversity as a designed property of epistemic capital, not an automatic outcome of AI adoption.

4.4.2 Knowledge Validation and Credibility Mechanisms

The second-dimension concerns how knowledge claims are evaluated and legitimized. AI outputs do not possess inherent epistemic authority; their credibility depends on human interpretation, organizational norms, and institutional accountability (Bolisani et al., 2025).

Human-in-the-loop mechanisms, peer review of AI recommendations, and feedback loops are essential for transforming AI outputs into reliable organizational knowledge. Trunk et al. (2020) show that without such validation mechanisms, organizations either over-trust AI or disregard it entirely, both of which undermine decision quality. In the model, robust validation processes are a core component of epistemic capital.

4.4.3 Interpretability and Sensemaking

Interpretability refers to the extent to which AI outputs can be understood, explained, and integrated into human reasoning. Sensemaking is the human process of constructing meaning from ambiguous or complex information. Together, these processes ensure that AI supports rather than replaces human judgment (Bhattacharjee, 2025).

Opaque AI systems weaken epistemic capital by limiting users' ability to question assumptions, assess uncertainty, and learn from outcomes. Booyse and Scheepers (2023) identify lack of transparency as a major barrier to AI adoption in organizational decision-making. In the model, interpretability strengthens epistemic capital by enabling reflective judgment and organizational learning.

4.4.4 Governance and Ethical Alignment

The final dimension emphasizes that epistemic capital is shaped by governance structures and ethical norms. Governance determines who has decision authority, how accountability is assigned, and how epistemic risks—such as bias or exclusion—are managed (Nihei, 2022).

Ethical misalignment represents a form of epistemic failure, as it undermines trust and legitimacy even when decisions are technically efficient. The model therefore integrates governance and ethics directly into epistemic capital, rather than treating them as external constraints. Sustainable epistemic capital requires alignment between technical capabilities, organizational values, and societal expectations.

4.5. Organizational Decision Quality as the Outcome

On the right side of the model, Organizational Decision Quality represents the outcome of epistemic capital formation. Decision quality is conceptualized not only in terms of accuracy or efficiency, but also as:

- **Informed and justified** (based on credible knowledge),
- **Adaptive and flexible** (responsive to change),
- **Ethically defensible** (aligned with values and norms).

Empirical studies show that organizations achieve these outcomes when AI systems are embedded in learning-oriented, accountable, and human-centered decision architectures (Bolisani et al., 2025; Trunk et al., 2020). The model thus explains why similar AI technologies can produce radically different outcomes across organizations: the difference lies in epistemic capital, not computational power.

5. Discussion

5.1. Reinterpreting Organizational Intelligence Through Epistemic Capital

This article set out to reconceptualize organizational intelligence in the context of AI-enabled decision-making by shifting the analytical focus from *knowledge assets* to *epistemic capital*. The conceptual framework developed and explained in this study suggests that the value of human–AI collective intelligence does not primarily lie in automation, efficiency gains, or computational superiority, but in the organization's capacity to cultivate epistemically robust decision processes. This reframing responds directly to longstanding concerns in the literature that AI adoption often outpaces theoretical understanding of how knowledge is produced, validated, and governed in hybrid systems (Trunk et al., 2020; Bhattacharjee, 2025).

The discussion highlights that epistemic capital provides a unifying construct capable of integrating disparate research streams on knowledge management, collective intelligence, and AI-enabled decision-making. By conceptualizing intelligence as a form of capital, the model emphasizes accumulation, depreciation, and sustainability of decision-making capability—dimensions that are largely absent from existing instrumental or technology-centric accounts of AI in organizations (Bolisani et al., 2025).

5.2. Human–AI Collective Intelligence as an Epistemic, Not Merely Technical, System

One of the central insights emerging from the model is that human–AI collective intelligence functions as an epistemic infrastructure, rather than a neutral technical system. While prior research has established that hybrid human–AI systems outperform either humans or machines alone in complex environments (Trianni et al., 2023), this study advances the argument by explaining *why* such systems succeed or fail: their effectiveness depends on how well they generate epistemic capital.

This perspective helps explain mixed empirical findings in the AI adoption literature. Organizations deploying similar AI technologies often experience divergent outcomes—ranging from improved strategic decision-making to increased opacity, bias, and mistrust (Booyse & Scheepers, 2023). The present framework suggests that these differences arise not from the technology itself, but from variation in epistemic diversity, validation practices, interpretability, and governance. In other words, AI does not inherently enhance intelligence; it amplifies existing epistemic strengths and weaknesses within organizations.

5.3. Epistemic Capital and Decision Quality Under Uncertainty

The discussion further clarifies the relationship between epistemic capital and organizational decision quality. Traditional decision-making models often equate quality with accuracy or efficiency. In contrast, the epistemic capital framework broadens this understanding to include justification, adaptability, and ethical defensibility. This broader conception is particularly salient in environments characterized by uncertainty, ambiguity, and contested values—conditions under which AI systems are increasingly deployed (Trunk et al., 2020).

Empirical research shows that AI-generated insights require human sensemaking to become actionable knowledge (Bolisani et al., 2025). The discussion reinforces this finding by arguing that interpretability and validation are not auxiliary concerns but core epistemic functions. When organizations lack these functions, AI outputs may be fast and sophisticated yet epistemically fragile—leading to overconfidence, blind automation, or post hoc rationalization of decisions. Epistemic capital thus acts as a buffer against such failure modes by sustaining reflective judgment and learning over time.

5.4. Ethical and Governance Implications

A key contribution of this article lies in integrating ethics and governance directly into the epistemic core of human–AI systems, rather than treating them as external constraints. Prior work on AI ethics often focuses on compliance, fairness metrics, or regulatory frameworks (Nihei, 2022). While essential, such approaches risk overlooking how ethical failures originate at the epistemic level—through biased data, exclusion of certain knowledge holders, or unchallengeable algorithmic authority.

The epistemic capital framework highlights that ethical misalignment constitutes a form of epistemic degradation. When certain perspectives are systematically excluded or when AI outputs are treated as epistemically superior to human judgment, organizations experience epistemic injustice, which undermines trust and long-term decision legitimacy (Nihei, 2022). This discussion suggests that ethical governance should therefore be evaluated not only in normative terms, but also in terms of its impact on epistemic capital accumulation and sustainability.

6. Theoretical Implications

First, this study advances organizational knowledge theory by reconceptualizing knowledge from a static asset to a dynamic form of epistemic capital. Traditional knowledge-based views of the firm largely treat knowledge as a resource that can be stored, transferred, and leveraged for competitive advantage. While influential, such perspectives struggle to account for the fluid, interactive, and AI-mediated nature of contemporary knowledge production. By introducing epistemic capital as a collectively generated capacity for knowledge creation, validation, and application, this article extends knowledge theory toward a process-oriented and relational epistemology that better reflects how organizational intelligence operates in hybrid human–AI environments (Bolisani et al., 2025; Trunk et al., 2020). This shift enables scholars to theorize not only what organizations know, but how they come to know, justify, and revise decisions over time.

Second, the article contributes to collective intelligence theory by explicitly articulating the epistemic mechanisms underlying human–AI collective intelligence. Prior research demonstrates that hybrid systems can outperform purely human or purely artificial systems, particularly in complex and uncertain domains (Trianni et al., 2023). However, much of this literature remains outcome-oriented, offering limited theoretical explanation for why such performance differences emerge. By positioning epistemic capital as the mediating construct between collective intelligence and decision quality, this study provides a deeper theoretical account of collective cognition, emphasizing epistemic diversity, validation, and sensemaking as foundational mechanisms. This contribution strengthens collective intelligence theory by grounding it in epistemic processes rather than aggregation or computational efficiency alone.

Third, this research extends AI and decision-making theory by challenging instrumental and automation-centric views of AI in organizations. Much of the existing literature conceptualizes AI as a decision-support tool that improves speed, accuracy, or efficiency. In contrast, the epistemic capital framework theorizes AI as an epistemic actor whose value depends on how it reshapes knowledge validation, interpretability, and governance. This perspective explains why AI adoption often produces uneven or paradoxical outcomes across organizations, even when similar technologies are deployed (Booyse & Scheepers, 2023). Theoretically, the study reframes AI not as a substitute for human judgment but as a catalyst that amplifies epistemic strengths or weaknesses embedded in organizational structures.

Fourth, the study makes a significant contribution to AI ethics and governance theory by integrating ethical considerations directly into the epistemic core of organizational decision-making. Existing AI ethics frameworks often focus on normative principles such as fairness, accountability, and transparency as external constraints on technology. This article advances theory by showing that ethical failures are fundamentally epistemic failures—arising from biased knowledge production, exclusion of perspectives, or unchallengeable algorithmic authority. Drawing on the concept of epistemic injustice, the framework theorizes governance and ethics as constitutive dimensions of epistemic capital rather than supplementary controls (Nihei, 2022). This integration provides a more robust theoretical bridge between epistemology and AI ethics.

Finally, the article contributes to organizational decision theory by broadening the conceptualization of decision quality. Traditional decision theory often emphasizes rationality, optimization, or performance outcomes. In contrast, the epistemic capital perspective theorizes decision quality as multidimensional—encompassing justification, adaptability, learning capacity, and ethical defensibility. This reconceptualization aligns decision theory more closely with the realities of decision-making under uncertainty, where correctness cannot be fully evaluated ex ante and where legitimacy and revisability are central concerns (Trunk et al., 2020).

Theoretically, this contribution positions epistemic capital as a foundational construct for understanding intelligent action in modern organizations.

7. Practical Implications

First, the findings of this study suggest that organizations should rethink AI initiatives as epistemic investments rather than purely technological deployments. Many AI projects fail to deliver sustained value because they prioritize automation and efficiency while neglecting how knowledge is interpreted, validated, and applied in practice. Managers should therefore assess AI systems based on their contribution to epistemic capital—namely, whether they enhance collective understanding, improve justification of decisions, and support learning over time. Prior research shows that organizations benefit most from AI when human judgment remains central and AI outputs are embedded within reflective decision processes (Trunk et al., 2020; Bolisani et al., 2025).

Second, the framework highlights the importance of designing for epistemic diversity in human–AI systems. Practically, this means assembling decision teams with heterogeneous expertise, combining multiple data sources, and avoiding reliance on a single algorithmic model. Organizations should treat diversity not only as a social value but as a strategic epistemic resource that improves decision robustness under uncertainty. Empirical studies on hybrid collective intelligence demonstrate that diverse human–AI inputs reduce herding effects and improve problem-solving outcomes in complex environments (Trianni et al., 2023). Managers can operationalize this insight by encouraging pluralistic modeling approaches and cross-functional human oversight.

Third, the model underscores the need for institutionalized knowledge validation mechanisms. AI-generated recommendations should not be treated as final answers but as inputs into structured validation processes, such as peer review, human-in-the-loop verification, and post-decision feedback. Organizations lacking such mechanisms are more likely to experience either blind trust in AI or complete resistance to its use, both of which undermine decision quality (Booyse & Scheepers, 2023). Practically, firms should formalize roles and responsibilities for reviewing AI outputs, documenting assumptions, and learning from decision outcomes.

Fourth, interpretability and sensemaking emerge as critical practical priorities. Managers and system designers should favor AI solutions that provide explanations, uncertainty indicators, and scenario comparisons rather than opaque predictions. Interpretability enables decision-makers to integrate AI insights into their mental models, fostering trust and informed judgment (Bhattacharjee, 2025). From a practical standpoint, investments in explainable AI interfaces and user training are not optional add-ons but essential components of epistemic capital formation.

Fifth, the framework has direct implications for AI governance and ethics in organizations. Ethical failures in AI systems often stem from epistemic shortcomings, such as biased data, exclusion of stakeholder perspectives, or unchallengeable algorithmic authority. Organizations should therefore embed ethical oversight within epistemic governance structures, ensuring transparency, accountability, and inclusivity in decision processes (Nihei, 2022). Practically, this involves establishing governance bodies that oversee not only compliance but also epistemic fairness—monitoring whose knowledge is included, how credibility is assigned, and how disagreements are resolved.

Finally, the study suggests that senior leaders should evaluate organizational performance not only in terms of decision speed or efficiency but also in terms of epistemic resilience—the organization's ability to adapt decisions as conditions change and new knowledge emerges. AI systems that optimize short-term outcomes while weakening learning capacity may erode long-term strategic intelligence. By focusing on epistemic capital, organizations can develop decision systems that are not only faster, but also more robust, adaptable, and ethically defensible in the face of uncertainty (Trunk et al., 2020).

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