Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 3 No. 10 (October) (2025)

From Knowledge Workers to Knowledge Agents: Redefining Organizational Learning

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Abstract
The rise of artificial intelligence, automation, and digital collaboration tools is reshaping how organizations create, share, and apply knowledge. Traditional models of organizational learning have centered on "knowledge workers" as human actors who process information and generate expertise. However, emerging technologies are transforming these workers into "knowledge agents" — hybrid human–AI actors capable of autonomous learning, decision support, and continuous knowledge recombination. This paper reconceptualizes organizational learning by examining the shift from individual-based knowledge production to distributed, agent-based knowledge ecosystems. Drawing on contemporary literature in knowledge management, socio-technical systems, and AI-enabled collaboration, we propose a framework that integrates human cognition, algorithmic intelligence, and networked learning infrastructures. The study explores how knowledge agents enhance adaptive capacity, accelerate innovation cycles, and reshape leadership, governance, and ethical accountability. By redefining organizational learning as a dynamic interaction between human and artificial agents, this research contributes a forward-looking model for sustainable knowledge-driven organizations in the digital era.

Keywords: Organizational learning; Knowledge workers; Knowledge agents; Artificial intelligence; Digital transformation; Knowledge management; Socio-technical systems

1. Introduction
The nature of work has undergone profound transformation over the past several decades, driven by advances in information technology, globalization, and the increasing centrality of knowledge as a strategic resource (Ajmal & Suleman, 2015a). Early conceptualizations of the "knowledge worker," popularized by Drucker (1999), emphasized employees whose primary capital is knowledge rather than manual skill. In knowledge-intensive organizations, competitive advantage stems not from physical assets, but from the capacity to create, integrate, and apply knowledge effectively. This shift gave rise to a rich body of scholarship on knowledge management and organizational learning, focusing on how organizations generate, transfer, and institutionalize knowledge (Ajmal & Suleman, 2015b).

Organizational learning theory has traditionally framed learning as a human-centered, socially embedded process. Foundational work by Argyris and Schön (1978) distinguished between single-loop and double-loop learning, highlighting how organizations adapt not only their actions but also their underlying assumptions. Similarly, Crossan, Lane, and White (1999) proposed the 4I framework—intuiting, interpreting, integrating, and institutionalizing—to explain how individual insights become embedded in organizational systems(Ajmal, Islam, & Islam, 2024b). These models emphasize cognition, interpretation, and social interaction as the core mechanisms of learning.

In parallel, knowledge creation research underscored the dynamic interplay between tacit and explicit knowledge. Nonaka's (1994) seminal theory of organizational

ISSN Online: 3007-3154
ISSN Print: 3007-3146
DIALOGUE SOCIAL SCIENCE REVIEW
Vol. 3 No. 10 (October) (2025)

knowledge creation introduced the SECI model—socialization, externalization, combination, and internalization—arguing that innovation emerges from continuous knowledge conversion processes. Davenport and Prusak (1998) further stressed that effective knowledge management depends on cultural norms, trust, and shared meaning rather than technology alone. Collectively, this literature positioned human actors as the primary agents of knowledge generation and transformation within organizations(Ajmal, Islam, & Khalid, 2025a).

However, the digital transformation of organizations is challenging these human-centric assumptions. The integration of artificial intelligence (AI), machine learning, and advanced analytics into organizational workflows has introduced non-human actors capable of pattern recognition, prediction, and autonomous decision support. Rather than merely serving as passive repositories of information, digital systems increasingly participate in knowledge processes(Ajmal, Islam, & Khalid, 2025b). Jarrahi (2018) argues that AI reshapes knowledge work by augmenting human cognition and redistributing expertise across human–machine configurations. Similarly, Raisch and Krakowski (2021) highlight the growing importance of human–AI collaboration, suggesting that organizational performance depends on effectively managing the complementarities between algorithmic and human decision-making(Ajmal, Islam, & Khalid, 2025c).

This transformation aligns with broader shifts toward digitally mediated organizational forms. Leonardi (2021) demonstrates how digital technologies reconfigure social and material practices, enabling new forms of coordination and visibility. Faraj, Pachidi, and Sayegh (2018) further note that algorithmic systems increasingly shape organizational routines and professional authority, altering how knowledge is produced and validated. In this emerging context, knowledge processes are no longer confined to human cognition but are distributed across socio-technical networks(Ajmal, Islam, & Khalid, 2025d).

The strategic implications of this shift are significant. Teece (2018) argues that dynamic capabilities—the firm's ability to sense, seize, and transform in response to environmental change—are increasingly dependent on data-driven sensing and rapid recombination of knowledge assets(Ajmal, Khalid, & Islam, 2025b). AI-enabled systems enhance organizational capacity for experimentation, forecasting, and adaptive learning at unprecedented speed and scale. Yet, as Edmondson (2008) reminds us, learning also requires psychological safety, reflection, and shared interpretation—elements that remain deeply human. The challenge, therefore, is not technological substitution but redefinition: how organizations conceptualize agency in knowledge processes.

This paper proposes a reconceptualization from "knowledge workers" to "knowledge agents." While knowledge workers represent human individuals engaged in intellectual labor, knowledge agents encompass hybrid constellations of human and artificial actors capable of autonomous or semi-autonomous knowledge generation, integration, and action. By framing organizational learning as an emergent property of distributed human–AI systems, this study advances a socio-technical perspective that integrates classical organizational learning theory with contemporary digital transformation research.

Understanding this transition is critical. As AI systems increasingly participate in sensemaking, decision-making, and innovation processes, organizations must rethink governance, accountability, leadership, and ethical responsibility. The shift toward knowledge agents signals not merely a technological upgrade but a fundamental redefinition of how learning occurs, who (or what) learns, and how knowledge becomes embedded within organizational structures.

2. Literature Review

2.1. The Evolution of Knowledge Work

The concept of knowledge work emerged prominently in management literature with Drucker's (1969, 1999) assertion that knowledge would become the primary economic resource of modern organizations. Knowledge workers were defined as individuals who think for a living—professionals whose productivity depends on the application of specialized expertise rather than manual labor. Subsequent scholarship emphasized autonomy, creativity, and problem-solving as defining characteristics of knowledge work (Alvesson, 2004).

Knowledge-intensive firms rely heavily on intellectual capital, which encompasses human capital (skills and expertise), structural capital (processes and systems), and relational capital (networks and relationships) (Bontis, 1998). The strategic management literature reinforced this view through the resource-based theory of the firm, arguing that knowledge constitutes a valuable, rare, inimitable, and non-substitutable resource that underpins competitive advantage (Barney, 1991).

However, early research largely treated knowledge work as exclusively human. Even as information technologies became integral to organizations, they were conceptualized as tools that supported, rather than participated in, knowledge processes (Orlikowski, 1992). This anthropocentric framing forms the foundation from which contemporary debates about artificial intelligence and distributed agency have emerged.

2.2. Organizational Learning Theories

Organizational learning theory provides the conceptual backbone for understanding how knowledge becomes embedded in organizational routines and practices. Argyris and Schön (1978) distinguished between single-loop learning (error correction without altering underlying norms) and double-loop learning (questioning and transforming governing assumptions). This framework emphasized reflective inquiry and cognitive change as essential learning mechanisms.

March (1991) introduced the exploration–exploitation framework, highlighting the tension between innovation (exploration of new knowledge) and efficiency (exploitation of existing knowledge). Organizations must balance these competing activities to sustain long-term performance(Ajmal, Khalid, & Islam, 2025c). This tension remains central in digital contexts where AI systems can dramatically accelerate exploitation through automation while simultaneously enabling new forms of exploration via predictive analytics.

Crossan, Lane, and White (1999) proposed the 4I framework—intuiting, interpreting, integrating, and institutionalizing—to explain how individual insights scale to organizational routines. Their model underscores the multilevel nature of learning, connecting individual cognition with collective processes and institutional structures. Similarly, Huber (1991) conceptualized organizational learning as encompassing knowledge acquisition, information distribution, interpretation, and organizational memory (Ajmal, Khalid, & Islam, 2025d).

These frameworks collectively position learning as a socially embedded and multilevel phenomenon. Yet they were developed in contexts where learning agents were exclusively human. The emergence of AI systems capable of pattern recognition and adaptive responses raises questions about how these foundational models might evolve when learning processes are partially delegated to algorithms.

2.3. Knowledge Creation and Knowledge Management

Nonaka's (1994) dynamic theory of organizational knowledge creation significantly advanced understanding of how knowledge is generated and shared. The SECI model describes the cyclical conversion between tacit and explicit knowledge through socialization, externalization, combination, and internalization. Knowledge creation, in this view, is a dynamic, interactive, and socially constructed process (Islam, Ajmal, & Khalid, 2025a).

Grant (1996) extended the knowledge-based view of the firm, arguing that organizations exist primarily as institutions for integrating specialized knowledge. The coordination of distributed expertise is therefore a central managerial challenge. Knowledge management systems were subsequently designed to codify, store, and disseminate knowledge across organizational boundaries (Alavi & Leidner, 2001).

However, scholars increasingly recognized that knowledge management initiatives often failed when overly focused on technology rather than social context (Davenport & Prusak, 1998). Effective knowledge sharing depends on trust, culture, and shared understanding. This socio-technical perspective laid the groundwork for examining how AI systems might reshape knowledge infrastructures while still being embedded within social systems.

2.4. Digital Transformation and Algorithmic Agency

The integration of AI into organizational processes represents a qualitative shift in the nature of knowledge systems. Rather than simply storing and transmitting information, machine learning systems can detect patterns, generate predictions, and adapt based on data inputs. Brynjolfsson and McAfee (2014) describe this transformation as part of the "second machine age," where digital technologies augment and sometimes outperform human cognitive tasks(Islam, Khalid, & Ajmal, 2025a).

Recent organizational research conceptualizes this shift as the emergence of algorithmic or machine agency. Faraj, Pachidi, and Sayegh (2018) argue that learning algorithms increasingly structure work practices, influencing professional judgment and authority. Jarrahi (2018) proposes that AI enables a form of human–AI symbiosis, where decision-making emerges from interaction rather than substitution.

Raisch and Krakowski (2021) frame this dynamic as the automation–augmentation paradox. Automation replaces certain human tasks, while augmentation enhances human capabilities. Organizations must navigate this paradox by redesigning workflows and governance structures to leverage complementary strengths. Similarly, Shrestha, Ben-Menahem, and von Krogh (2019) examine how algorithmic decision-making affects accountability and transparency, raising important governance concerns (Khalid, Islam, & Ajmal, 2025a).

Leonardi (2021) highlights how digital technologies increase visibility and data exhaust, enabling new forms of monitoring and coordination. These developments suggest that knowledge is no longer solely embedded in human memory or organizational routines but is increasingly encoded within algorithmic systems that continuously learn from data streams.

2.5. Toward Knowledge Agents and Distributed Learning Systems

The convergence of organizational learning theory and AI research suggests the need for a reconceptualization of agency in knowledge processes. Traditional models assume that individuals and groups interpret information, form mental models, and institutionalize routines. Yet AI systems now perform pattern recognition, anomaly detection, and predictive modeling at scales beyond human capability.

Teece (2018) argues that dynamic capabilities increasingly rely on data-driven sensing and rapid knowledge recombination. In digitally mature organizations, learning becomes a distributed process across interconnected human and technological actors. This aligns with socio-material perspectives that view technology not as a passive tool but as an active participant in organizing processes (Orlikowski & Scott, 2008).

The emerging concept of "knowledge agents" captures this hybrid configuration. Knowledge agents can be understood as assemblages of human expertise and algorithmic intelligence that collectively generate, interpret, and act upon knowledge. This perspective extends Crossan et al.'s (1999) multilevel framework by incorporating non-human agents into the learning cycle. It also reinterprets Nonaka's (1994) SECI model in light of digital infrastructures capable of automated combination and codification processes.

Despite growing interest in AI-enabled organizations, the literature remains fragmented. There is limited theoretical integration between classic organizational learning models and contemporary research on algorithmic systems. By synthesizing these streams, this study contributes to a more comprehensive understanding of organizational learning in the age of intelligent technologies.

3. Conceptual Framework: From Knowledge Workers to Knowledge Agents

This study develops a conceptual framework that reconceptualizes organizational learning as a distributed, socio-technical process enacted by **knowledge agents**—hybrid configurations of human expertise and artificial intelligence (AI) systems. The framework integrates three foundational streams of literature: (1) organizational learning theory, (2) the knowledge-based view of the firm, and (3) research on algorithmic and human–AI collaboration.

3.1. Foundational Assumptions

3.1.1 Knowledge as a Strategic Resource

The knowledge-based view of the firm posits that organizations exist primarily to integrate and coordinate specialized knowledge (Grant, 1996). Competitive advantage stems not from physical assets but from the firm's ability to combine distributed expertise efficiently (Barney, 1991). Traditional knowledge work assumes that individuals are the primary carriers of such expertise.

However, AI-enabled systems increasingly store, recombine, and generate knowledge artifacts, extending the firm's integrative capacity. As Teece (2018) argues, dynamic capabilities—sensing, seizing, and transforming—are increasingly data-driven, requiring digital infrastructures capable of continuous learning and rapid adaptation. Thus, knowledge assets are now embedded not only in human cognition but also in algorithmic architectures.

3.2. Reframing Agency in Organizational Learning

3.2.1 Classical Learning Models

Organizational learning theory conceptualizes learning as multilevel and socially embedded. Crossan, Lane, and White's (1999) 4I framework describes learning as moving from individual intuition to institutionalized routines. Similarly, March (1991) highlights the balance between exploration and exploitation, emphasizing strategic trade-offs in knowledge utilization.

These models assume that humans interpret information and make decisions. Yet AI systems now perform exploratory tasks such as pattern detection and predictive modeling at scale. Faraj, Pachidi, and Sayegh (2018) argue that learning algorithms increasingly shape organizational routines, influencing professional judgment and knowledge validation processes.

3.2.2 Sociomaterial and Algorithmic Agency

Sociomaterial theory suggests that technology and human action are intertwined in organizational practice (Orlikowski & Scott, 2008). Rather than treating technology as a neutral tool, this perspective sees it as constitutive of organizational structures.

Jarrahi (2018) proposes a model of human–AI symbiosis, where AI augments rather than replaces human cognition. Raisch and Krakowski (2021) further articulate the automation–augmentation paradox, arguing that organizations must design complementary roles for humans and AI systems. These insights support reconceptualizing learning agents as hybrid entities composed of human judgment and algorithmic capabilities.

3.3. The Knowledge Agent Framework

The proposed framework defines a **knowledge agent** as a socio-technical assemblage consisting of:

1. **Human Cognitive Capabilities** – interpretation, ethical reasoning, contextual judgment.
2. **Algorithmic Intelligence** – data processing, pattern recognition, predictive analytics.
3. **Digital Infrastructure** – platforms, databases, and network systems enabling continuous interaction.

This framework extends Nonaka's (1994) SECI model. In digitally augmented environments:

- **Socialization** includes human–AI interaction and collaborative data

interpretation.
- **Externalization** occurs through codification in both human language and machine-readable formats.
- **Combination** is increasingly automated through algorithmic data synthesis.
- **Internalization** involves both human learning and machine learning processes.

Thus, knowledge creation becomes a recursive cycle between human and artificial agents.

3.4. Multilevel Learning Dynamics
Building on Crossan et al. (1999), the framework proposes that learning occurs across three interconnected levels:

3.4.1 Individual–Agent Level
At this level, humans interact with AI tools to enhance decision-making. AI provides data-driven insights, while humans apply contextual understanding and ethical reasoning (Jarrahi, 2018).

3.4.2 Team–System Level
Teams operate within digitally mediated environments where algorithmic outputs shape collaboration and coordination (Leonardi, 2021). AI systems may guide task allocation, risk assessment, or innovation ideation.

3.4.3 Organizational–Ecosystem Level
At the macro level, dynamic capabilities are strengthened through AI-enabled sensing and transformation processes (Teece, 2018). Organizations learn not only internally but also through data exchanges across digital ecosystems.

This multilevel structure acknowledges that agency is distributed across humans and machines rather than centralized in individuals.

3.5. Exploration–Exploitation Revisited
March's (1991) exploration–exploitation tension is reframed within the knowledge agent model. AI systems enhance exploitation through automation and optimization, while also enabling exploration via predictive analytics and scenario simulation. However, excessive reliance on algorithmic exploitation may reduce creativity and critical reflection.

Raisch and Krakowski (2021) emphasize that effective management requires balancing automation efficiency with human interpretive flexibility. Therefore, governance mechanisms must ensure transparency, accountability, and adaptability in algorithmic decision processes (Shrestha et al., 2019).

3.6. Governance, Ethics, and Accountability
As AI systems assume partial agency, issues of responsibility and ethical oversight intensify. Algorithmic opacity can obscure decision rationales, complicating accountability structures (Shrestha et al., 2019). Sociomaterial perspectives underscore the need for governance frameworks that recognize the entanglement of human and machine agency (Orlikowski & Scott, 2008).

Psychological safety and reflective dialogue remain essential for organizational learning (Edmondson, 2008). Even in AI-enabled environments, learning requires open communication and trust—conditions that technology alone cannot guarantee.

3.7. Propositions of the Framework
Based on the literature, the conceptual framework advances the following propositions:
Proposition 1: Organizational learning effectiveness increases when human judgment and algorithmic intelligence are designed as complementary capabilities (Jarrahi, 2018;

Raisch & Krakowski, 2021).
Proposition 2: AI-enabled sensing and data analytics strengthen dynamic capabilities, enhancing adaptive organizational performance (Teece, 2018).
Proposition 3: Distributed knowledge agency requires governance structures that ensure transparency and ethical accountability (Shrestha et al., 2019).
Proposition 4: Multilevel integration of human–AI learning processes enhances knowledge institutionalization (Crossan et al., 1999; Faraj et al., 2018).

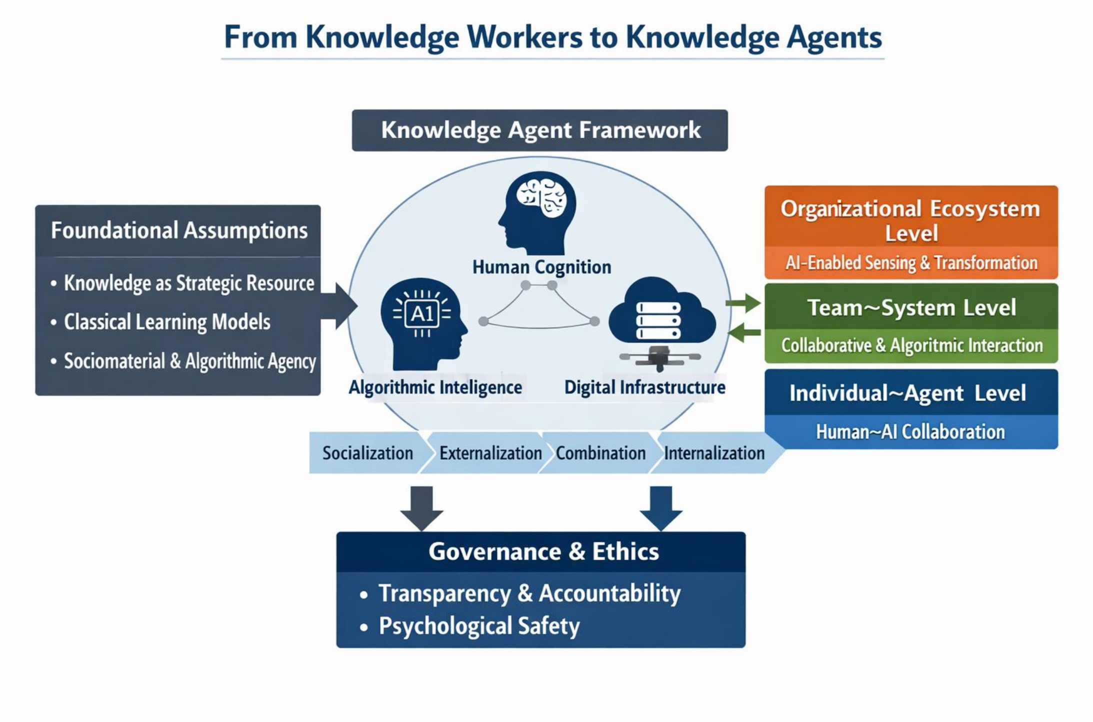

Figure 1: Conceptual Framework

4. Explanation of the Conceptual Model: From Knowledge Workers to Knowledge Agents

The proposed model reconceptualizes organizational learning as a **distributed, socio-technical system** in which human cognition and artificial intelligence (AI) operate as integrated knowledge agents. Rather than treating technology as a passive support tool, the model positions AI as an active participant in knowledge creation, interpretation, and institutionalization. The framework builds on established organizational learning and knowledge-based theories while extending them to digitally augmented contexts.

4.1. Foundational Assumptions of the Model

The model rests on three core theoretical foundations:

(1) Knowledge as a Strategic Resource

The knowledge-based view of the firm argues that organizations exist to integrate specialized knowledge (Grant, 1996). Competitive advantage depends on unique knowledge resources that are difficult to imitate (Barney, 1991).

In the model, this principle is expanded: knowledge is embedded not only in individuals but also in **digital infrastructures and algorithmic systems**. Teece (2018) argues that dynamic capabilities—sensing opportunities, seizing them, and transforming operations—are increasingly data-driven. Thus, strategic knowledge now resides in hybrid human–AI systems rather than solely in knowledge workers.

(2) Classical Organizational Learning

Traditional learning theories emphasize human cognition and reflection.

- Argyris and Schön (1978) distinguish between single-loop and double-loop learning.
- March (1991) highlights the tension between exploration and exploitation.

- Crossan, Lane, and White (1999) propose the 4I model (intuiting, interpreting, integrating, institutionalizing).

The conceptual model retains these learning mechanisms but reinterprets them in a digitally augmented environment. AI systems now contribute to exploration (pattern detection, predictive modeling) and exploitation (optimization, automation), altering the speed and scale of learning processes.

(3) Sociomaterial and Algorithmic Agency

Sociomateriality suggests that technology and human activity are inherently intertwined (Orlikowski & Scott, 2008). AI systems increasingly structure organizational routines and professional authority (Faraj, Pachidi, & Sayegh, 2018).

Raisch and Krakowski (2021) describe this shift as the automation–augmentation paradox: AI simultaneously replaces and enhances human tasks. The model therefore assumes **distributed agency**, where learning outcomes emerge from interactions between humans and intelligent systems rather than from individuals alone.

4.2. Core of the Model: The Knowledge Agent Framework

At the center of the model is the **Knowledge Agent**, composed of three interconnected elements:

(1) Human Cognition

Includes contextual reasoning, ethical judgment, tacit knowledge, creativity, and sensemaking. Humans provide interpretive flexibility and moral accountability (Edmondson, 2008).

(2) Algorithmic Intelligence

Includes machine learning, predictive analytics, automation, and pattern recognition. AI contributes computational scalability and data-driven insight (Jarrahi, 2018).

(3) Digital Infrastructure

Platforms, databases, cloud systems, and collaborative technologies that enable interaction between human and machine actors (Leonardi, 2021).

These three components operate as an integrated system. Knowledge is created and refined through continuous interaction among cognitive, computational, and infrastructural elements.

4.3. Reinterpreting Knowledge Creation (SECI in Digital Context)

The model adapts Nonaka's (1994) SECI framework to AI-enabled environments:

- **Socialization**: Includes human–AI interaction and collaborative data interpretation.
- **Externalization**: Tacit knowledge becomes codified in both human language and machine-readable formats.
- **Combination**: AI automates synthesis across large datasets.
- **Internalization**: Both humans and algorithms "learn" through training, feedback, and adaptation.

Thus, learning is recursive and bi-directional between human and artificial agents.

4.4. Multilevel Learning Dynamics

The model expands Crossan et al.'s (1999) multilevel logic by integrating AI at three levels:

(A) Individual–Agent Level (Human–AI Collaboration)

At this level, AI augments decision-making by offering predictive insights, while humans provide contextual interpretation (Jarrahi, 2018).

This hybrid decision structure enhances both accuracy and adaptability but requires complementary role design (Raisch & Krakowski, 2021).

(B) Team–System Level (Collaborative & Algorithmic Interaction)
Digital platforms shape coordination and visibility within teams (Leonardi, 2021). AI systems influence task allocation, performance monitoring, and knowledge sharing (Faraj et al., 2018).

Here, learning becomes embedded in workflows and system-level routines.

(C) Organizational–Ecosystem Level (AI-Enabled Sensing & Transformation)
At the macro level, AI strengthens dynamic capabilities by enabling real-time sensing and strategic transformation (Teece, 2018). Organizations increasingly learn through digital ecosystems and data exchanges rather than isolated internal processes.

4.5. Governance and Ethical Layer
The bottom layer of the model emphasizes governance and ethics.

Algorithmic opacity creates accountability challenges (Shrestha, Ben-Menahem, & von Krogh, 2019). Effective learning requires transparency, oversight, and psychological safety (Edmondson, 2008).

Thus, governance mechanisms ensure that distributed knowledge agency remains aligned with organizational values and ethical standards.

4.6. Integrative Logic of the Model
The model integrates classical and contemporary theories by proposing that:
1. Learning remains multilevel and socially embedded (Crossan et al., 1999).
2. Knowledge remains a strategic resource (Grant, 1996).
3. Agency is no longer exclusively human but distributed across socio-technical systems (Orlikowski & Scott, 2008).
4. AI strengthens dynamic capabilities when designed for complementarity rather than substitution (Raisch & Krakowski, 2021; Teece, 2018).

In essence, organizations are evolving from employing **knowledge workers** to orchestrating **knowledge agents**—hybrid configurations that continuously sense, interpret, and transform knowledge across levels.

5. Discussion
This study reconceptualizes organizational learning through the lens of **knowledge agents**, defined as hybrid socio-technical configurations integrating human cognition, algorithmic intelligence, and digital infrastructure. The discussion focuses on how this reconceptualization reshapes understanding of learning processes, multilevel dynamics, knowledge creation, and governance in AI-enabled organizations—without separating theoretical or practical implications as distinct subsections.

5.1. Reframing Organizational Learning in the Age of AI
Classical organizational learning theories emphasize human cognition and reflective inquiry as the primary drivers of adaptation. Argyris and Schön (1978) distinguish between single-loop and double-loop learning, highlighting the importance of questioning underlying assumptions. Similarly, Crossan, Lane, and White (1999) conceptualize learning as progressing from individual intuition to institutionalized routines through the 4I process. These foundational models assume that individuals and groups are the central learning agents.

However, the integration of AI systems into organizational workflows challenges this anthropocentric assumption. Learning algorithms increasingly participate in sensemaking, prediction, and decision support (Faraj, Pachidi, & Sayegh, 2018). As such, learning processes are no longer confined to human cognition but are distributed across

ISSN Online: 3007-3154
ISSN Print: 3007-3146
DIALOGUE SOCIAL SCIENCE REVIEW
Vol. 3 No. 10 (October) (2025)

human–machine interactions. This shift does not invalidate classical theories; rather, it extends them by incorporating algorithmic participation into established multilevel learning cycles.

March's (1991) exploration–exploitation framework provides a particularly relevant lens. AI systems enhance exploitation through automation and optimization while simultaneously enabling exploration via predictive analytics and large-scale data modeling. The balance between exploration and exploitation, therefore, becomes mediated by algorithmic systems that operate at speeds and scales beyond human capacity. Learning outcomes increasingly depend on how these systems are integrated into organizational routines.

5.2.Distributed Agency and Sociomaterial Learning

The concept of distributed agency is central to understanding the model. Sociomaterial perspectives argue that technologies are not neutral tools but integral components of organizational action (Orlikowski & Scott, 2008). AI systems shape workflows, professional authority, and coordination mechanisms (Faraj et al., 2018).

Within this context, knowledge agents represent a departure from the traditional image of the autonomous knowledge worker. Agency is no longer located solely within individuals; instead, it emerges from interactions between human judgment and algorithmic computation. Raisch and Krakowski (2021) describe this interaction as the automation–augmentation paradox, emphasizing that AI simultaneously substitutes and enhances human capabilities.

Learning, therefore, becomes a recursive and relational process. Human actors interpret AI outputs, refine models, and embed insights into practice, while AI systems continuously update predictions based on new data inputs. This mutual adaptation produces a dynamic socio-technical learning loop.

5.3.Reinterpreting Knowledge Creation Processes

Nonaka's (1994) SECI model conceptualizes knowledge creation as the conversion between tacit and explicit knowledge. In AI-enabled environments, the "combination" phase is increasingly automated through algorithmic synthesis of vast datasets. However, tacit knowledge—contextual insight, ethical reasoning, and experiential understanding—remains deeply human.

Jarrahi (2018) argues that AI operates most effectively as cognitive augmentation rather than full substitution. Thus, the knowledge agent framework suggests that knowledge creation is co-produced: humans provide meaning and contextualization, while AI provides analytical depth and computational scalability.

The institutionalization phase described by Crossan et al. (1999) also evolves in this environment. Organizational routines may now include algorithmic rules and machine-learning models embedded within digital infrastructures. Learning becomes encoded not only in policies and cultural norms but also in software architectures and predictive systems.

5.4.Dynamic Capabilities and Adaptive Learning

The model also intersects with the dynamic capabilities perspective. Teece (2018) argues that firms sustain competitive advantage through their ability to sense opportunities, seize them, and transform operations. AI enhances sensing through real-time analytics and environmental scanning, expanding the organization's adaptive capacity.

However, adaptive learning depends not merely on technological capability but on coordinated interaction between human interpretation and machine output. Overreliance on algorithmic authority may constrain critical reflection, while underutilization may limit strategic responsiveness. Thus, adaptive capacity emerges from calibrated integration rather than technological determinism.

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 3 No. 10 (October) (2025)

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5.5.Governance, Transparency, and Accountability

The distributed nature of knowledge agency introduces challenges related to transparency and responsibility. Algorithmic systems may operate as opaque "black boxes," complicating the attribution of decision accountability (Shrestha, Ben-Menahem, & von Krogh, 2019).

Edmondson (2008) emphasizes that effective learning requires psychological safety—an environment where individuals can question assumptions and surface errors. In AI-mediated contexts, maintaining psychological safety involves encouraging employees to critically evaluate algorithmic outputs rather than accept them uncritically.

Consequently, governance mechanisms must evolve alongside technological integration. Transparency in algorithmic processes, clear oversight structures, and ethical review mechanisms are integral to sustaining responsible distributed learning systems.

5.6. Integrative Perspective

Overall, the discussion underscores that organizational learning is transitioning from a human-centered paradigm to a distributed socio-technical model. Knowledge agents—composed of human cognition, algorithmic intelligence, and digital infrastructure—function as the operative units of learning.

This transformation does not eliminate foundational learning principles; rather, it reconfigures them. Reflection, exploration, institutionalization, and knowledge conversion remain essential processes, but they are increasingly mediated through AI-enabled systems. Organizational learning thus becomes a hybrid phenomenon—simultaneously cognitive, computational, and infrastructural.

6.Theoretical Implications

The transition from knowledge workers to knowledge agents extends and integrates several foundational theoretical perspectives in organizational studies.

First, the study advances **organizational learning theory** by reconceptualizing agency. Classical frameworks such as Argyris and Schön's (1978) model of single- and double-loop learning and Crossan, Lane, and White's (1999) 4I framework assume that learning originates in individual cognition and becomes embedded in organizational systems. By introducing algorithmic systems as active participants in knowledge processes, this study extends these models to incorporate distributed socio-technical agency. Learning is no longer solely an outcome of human interpretation but emerges from recursive interactions between human cognition and computational intelligence.

Second, the framework enriches the **knowledge-based view of the firm** (Grant, 1996; Barney, 1991) by broadening the locus of knowledge resources. Traditionally, knowledge was conceptualized as residing in individuals, routines, or organizational culture. The knowledge agent model proposes that strategic knowledge is increasingly embedded within digital infrastructures and machine-learning architectures. This extension reframes intellectual capital to include algorithmic assets and data ecosystems as integral components of competitive advantage.

Third, the study contributes to the literature on **AI and organizational design**. Raisch and Krakowski (2021) describe the automation–augmentation paradox, highlighting the tension between substitution and complementarity in human–AI collaboration. The knowledge agent framework theoretically clarifies this paradox by positioning complementarity as the central mechanism of effective learning. AI does not replace human agency; instead, it reshapes learning structures through shared cognitive and computational processes.

Fourth, the framework bridges **sociomaterial theory** and organizational learning. Orlikowski and Scott (2008) argue that technologies are constitutive elements of organizational practice rather than neutral tools. By embedding algorithmic

ISSN Online: 3007-3154
ISSN Print: 3007-3146
DIALOGUE SOCIAL SCIENCE REVIEW
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intelligence within the core of learning dynamics, this study offers a concrete application of sociomateriality in knowledge creation and institutionalization processes.

Finally, the framework contributes to dynamic capability theory (Teece, 2018) by conceptualizing sensing and transformation as hybrid human–AI processes. Adaptive capacity is reframed as an emergent property of distributed knowledge agents rather than isolated managerial cognition.

7. Practical Implications

The shift toward knowledge agents has significant implications for organizational structure, leadership, capability development, and governance.

First, organizations must redesign workflows to support **human–AI complementarity**. Effective learning systems require clear delineation of roles in which AI handles data-intensive analysis while humans provide contextual judgment and ethical oversight (Jarrahi, 2018; Raisch & Krakowski, 2021). Poor integration may result in either over-automation or underutilization of AI capabilities.

Second, leadership roles evolve from supervising individual expertise to **orchestrating socio-technical systems**. Managers must cultivate digital literacy and AI fluency to effectively interpret algorithmic outputs and integrate them into strategic decision-making processes (Faraj, Pachidi, & Sayegh, 2018).

Third, governance structures must adapt to ensure **transparency and accountability**. As Shrestha, Ben-Menahem, and von Krogh (2019) note, algorithmic opacity complicates responsibility attribution. Organizations must implement oversight mechanisms, audit processes, and ethical review structures to sustain trust in AI-enabled decision systems.

Fourth, maintaining **psychological safety** remains critical. Edmondson (2008) emphasizes that open dialogue and error reporting are central to learning. In AI-mediated contexts, employees must feel empowered to question algorithmic recommendations without fear of repercussion.

Finally, organizations should treat digital infrastructure as a strategic asset. Continuous investment in data quality, interoperability, and machine-learning capability enhances sensing and adaptation functions central to dynamic capabilities (Teece, 2018).

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