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ПРОЦЕСИ НАКОПИЧЕННЯ ЗНАНЬ З ВИКОРИСТАННЯМ ШТУЧНОГО ІНТЕЛЕКТУ В МІЖНАРОДНИХ КОРПОРАЦІЯХ: НАВЧАННЯ, КООРДИНАЦІЯ ТА ІННОВАЦІЇ

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Анотація: *Мета: Метою дослідження є розробка концептуальної рамки для аналізу ролі штучного інтелекту (ШІ) як медіатора процесів знань у транснаціональних підприємствах (ТНП) з акцентом на навчанні, координації та інноваціях. Методи: Дослідження використовує систематичний огляд літератури, концептуальний аналіз теоретичних підходів (теорія знань, теорія динамічних здатностей, модель SECI) та компаративний аналіз емпіричних даних глобальних досліджень McKinsey, BCG та MIT Sloan Management Review, а також кейс-стаді транснаціональних корпорацій. Результати: Встановлено, що 78% підприємств впровадили ШІ принаймні в одній бізнес-функції станом на 2024 рік, проте лише 26% з них досягли здатності масштабувати ШІ-рішення та отримувати відчутну цінність. Визначено три ключові виміри впливу ШІ на процеси знань у ТНП: (1) прискорення організаційного навчання через автоматизацію екстерналізації та інтерналізації знань; (2) підвищення ефективності міжнародної координації через автоматизований переклад, аналіз даних у реальному часі та зниження транзакційних витрат; (3) стимулювання інновацій завдяки процесній та продуктовій амбідекстерності. Запропоновано оновлену модель HAC-SECI/GRAI, яка інтегрує генеративний ШІ у процес трансформації знань у мультинаціональному контексті. Висновки: Транснаціональні підприємства, які поєднують організаційне навчання з ШІ-специфічним навчанням (augmented learners), у 1,6 разу частіше ефективно управляють невизначеністю та вдвічі ефективніше справляються з порушеннями в управлінні талантами. Впровадження ефективних систем управління знаннями на основі ШІ потребує гібридних моделей управління, культурної адаптивності та розвитку відповідальних ШІ-практик.*

Ключові слова: *штучний інтелект, транснаціональні підприємства, управління знаннями, організаційне навчання, міжнародна координація, процесна інновація, динамічні здатності, модель SECI.*

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AI-MEDIATED KNOWLEDGE PROCESSES IN MULTINATIONAL ENTERPRISES: LEARNING, COORDINATION, AND INNOVATION

Abstract:*Purpose: The purpose of this study is to develop a conceptual framework for analyzing the role of artificial intelligence (AI) as a mediator of knowledge processes in multinational enterprises (MNEs), with a focus on learning, coordination, and innovation. Methods: The research employs a systematic literature review, conceptual analysis of theoretical frameworks (knowledge-based view, dynamic capabilities theory, SECI model), and comparative analysis of empirical data from global studies conducted by McKinsey, BCG, MIT Sloan Management Review, and the OECD, supplemented by case study evidence from leading MNEs. The study covers peer-reviewed sources published between 2021 and 2025. Results: The analysis establishes that 78% of enterprises had integrated AI into at least one business function by 2024, yet only 26% achieved the capability to scale AI solutions and generate tangible value. Three key dimensions of AI's influence on knowledge processes in MNEs are identified: (1) acceleration of organizational learning through automation of knowledge externalization and internalization; (2) enhanced international coordination through automated translation, real-time analytics, and reduced transaction costs; (3) stimulation of innovation through process and product ambidexterity. An updated HAC-SECI/GRAI model integrating generative AI into the knowledge transformation cycle is proposed for the multinational context. Conclusions: MNEs that combine organizational learning with AI-specific learning (augmented learners) are 1.6 times more likely to effectively manage uncertainty and twice as prepared for talent disruptions. Successful AI-mediated knowledge governance requires hybrid oversight models, cultural adaptability, and ethical AI frameworks aligned with emerging international standards.*

Keywords: *artificial intelligence, multinational enterprises, knowledge management, organizational learning, international coordination, process innovation, dynamic capabilities, SECI model.*

Problem statement. The accelerating diffusion of artificial intelligence (AI) technologies into the operational and strategic fabric of multinational enterprises (MNEs) constitutes one of the most profound transformations in the history of international business. Traditionally, the competitive advantage of MNEs has been explained through the lens of proprietary knowledge assets, the ability to generate, transfer, protect, and exploit superior knowledge across geographic and organizational boundaries [1]. However, the emergence of AI as a pervasive organizational mediator is challenging many of the foundational assumptions about how knowledge is created, stored, transferred, and leveraged within complex, globally dispersed organizational structures [7, 20].

The problem this research addresses is the insufficiently theorized and empirically examined role of AI as an active mediator, rather than a passive tool, in multinational knowledge processes. Whereas existing scholarship has extensively examined human-centric models of knowledge transfer between headquarters and subsidiaries, the literature has been slower to incorporate the transformative capacity of AI systems that now autonomously generate insights, facilitate real-time cross-border coordination, and accelerate learning loops across the MNE network [7, 20]. This gap is not merely academic: organizations that fail to understand how AI mediates knowledge dynamics risk misallocating resources, under-leveraging their multinational architectures, and falling behind AI-enabled competitors.

The connection to practical challenges is direct and significant. MNEs operating in 2024–2025 face a distinctive paradox: while AI adoption has accelerated dramatically, with AI use in at least one business function reaching 78% of companies by mid-2024 [11], approximately 74% of organizations still struggle to achieve and scale value from their AI investments [4]. This suggests

a fundamental problem in the management of AI-mediated knowledge processes, one rooted in misalignment between organizational learning capacities and AI deployment strategies. Resolving this tension has direct implications for MNE competitiveness, subsidiary management, innovation performance, and human resource strategy in an era of rapid technological disruption.

Analysis of recent research and publications. The academic literature at the intersection of AI and MNE management has grown considerably since 2021, yet remains fragmented across disciplinary boundaries. This section reviews key contributions organized around three clusters: (i) AI and knowledge management systems; (ii) AI in MNE-specific contexts; and (iii) AI, learning, and innovation.

The foundational theoretical architecture for understanding knowledge in organizations derives from the knowledge-based view (KBV) of the firm, which posits that knowledge is the primary source of sustainable competitive advantage [1]. Scholars such as Grant (1996) and Kogut & Zander (1993) established the framework through which MNEs are understood as vehicles for the cross-border transfer and exploitation of proprietary knowledge. A systematic review by Asmussen et al. (2024) of 124 KBV-aligned articles published between 1999 and 2021 in 40 academic journals confirms that the KBV remains the dominant lens for explaining MNE phenomena [1].

The SECI model (Socialization, Externalization, Combination, Internalization) introduced by Nonaka and Takeuchi (1995) has provided the most influential process-level framework for understanding how organizations create new knowledge through the recursive transformation between tacit and explicit forms. More recently, scholars have sought to reconfigure the SECI framework to incorporate AI as an active agent in the knowledge creation cycle. Böhm and Durst (2025) propose the GRAI (Generative, Receptive Artificial Intelligence) framework, which revises the SECI model by introducing bidirectional flows between AI-generated and human-generated knowledge, positioning generative AI as both a receptive input and a generative output actor in the knowledge creation spiral [3].

Complementing the GRAI framework, Watanabe et al. (2025) propose the Human-AI-Collaboration SECI (HAC-SECI) Model, which incorporates a dual-loop structure: an Inner Loop (Agent Growth Loop) in which humans provide knowledge to AI facilitating agent learning, and an Outer Loop (Target Development Loop) in which knowledge accumulated in AI helps humans develop their own cognitive growth [24]. Empirical evidence from a study of software development teams confirms that generative AI tools significantly improve knowledge externalization and combination processes within the SECI framework, while showing limitations in the socialization mode that depends on rich interpersonal interaction [22].

Omotosho et al. (2025) provide a comprehensive analysis of AI in knowledge management systems (KMS), identifying five major research themes and noting that the traditional SECI model and knowledge value chain models require extension to incorporate AI-enabled antecedents, consequences, and interventions [15]. Further empirical corroboration comes from a 2025 study in which AI-enabled KMS deployed with semantic search, vector similarity, and retrieval-augmented generation (RAG) frameworks produced double-digit gains in decision velocity, innovation output, and customer-response accuracy among early adopters [2]. Knowledge management platforms now serve as the governance core of the AI-enabled enterprise, with critical differentiators including automated content authoring, maintenance, and expiration processes [18].

Okechukwu and Bachmann (2025) present a systematic PRISMA-based review of AI integration within multinational corporations from 2021 to 2024, identifying 27 distinct functional applications of AI across supply chain optimization, market intelligence, human resource

management, and customer experience enhancement [14]. Their findings underscore AI's evolving role in fostering strategic agility and sustaining competitive advantage in global markets.

A pioneering empirical study by Gosen, Hewer, and Zanier (2025) at Linnaeus University uses abductive multiple-case design with 15 semi-structured interviews across financial services, technology, and energy/manufacturing sectors to examine how MNEs balance human-AI complementarity in culturally diverse markets [6]. Their findings reveal that cultural factors shape every stage of AI usage: power-distance norms affect authority splits in human-in-the-loop configurations, while local attitudes toward uncertainty determine trust thresholds for AI-generated outputs. Only 1% of companies surveyed described themselves as 'AI-mature,' pointing to a substantial capability gap [6].

A framework paper from the University of Vaasa (2024) constructs three characteristics of AI relevant to international expansion, autonomy, learning, and combinative capacity, and demonstrates how managers can utilize each in cross-border business management activities [20]. AI autonomy reduces monitoring, coordination, and transaction costs in international business operations, while AI learning capabilities enable dynamic updating of market knowledge that would otherwise require costly human networks [20].

Research specifically examining knowledge transfer between MNE headquarters and subsidiaries highlights the role of AI in reducing frictions in reverse knowledge transfer (RKT), the underexplored flow from subsidiaries back to headquarters [10]. Lee et al. (2024) identify motivational and cognitive barriers to RKT that AI-mediated communication platforms can systematically address, though organizational trust and relational embeddedness remain important human factors that AI cannot fully substitute [10].

The most comprehensive empirical analysis of the relationship between AI and organizational learning comes from the eighth annual global study conducted by MIT Sloan Management Review and BCG (2024), drawing on surveys of 3,467 respondents across 21 industries and 136 countries [8]. This research introduces the concept of 'Augmented Learners', the 15% of organizations that successfully integrate AI into their organizational learning capabilities, and demonstrates their systematic outperformance of peers. Augmented Learners are 1.6 times more likely than limited learning organizations to manage environmental and firm-specific uncertainties [8].

The relationship between AI and process innovation has been examined in a landmark study published in Technovation (2025), which draws on the concept of 'AI breadth', the number of AI technologies deployed and their pervasiveness across the organization, to demonstrate a positive causal relationship with process innovation likelihood [7]. Crucially, this relationship is strongest in organizations with high employee turnover, limited on-site training, and large headcount, suggesting that AI most powerfully compensates for constraints on interpersonal knowledge transfer [7].

For product and service innovation, a study of 260 Chinese companies published in Industrial Marketing Management (2025) employs dynamic capabilities theory to show that generative AI capabilities achieve competitive advantage primarily through three mediating innovation pathways: service concept innovation, process innovation, and customer experience innovation [23]. Firms with strong generative AI capabilities experienced a 7.8% boost in productivity and a 6.7% increase in customer engagement [23].

AI governance challenges specific to multinational firms are addressed by Nakajima (2025), who employs a mixed-methods approach combining qualitative interviews with corporate governance officers and quantitative surveys from global firms [12]. The findings reveal that while 65% of surveyed MNCs have implemented AI governance frameworks, only 30% fully comply with

international standards, with key challenges including the 'black box' nature of AI systems, regulatory fragmentation across jurisdictions, and ethical risks such as bias and labor displacement [12]. The dynamic capabilities framework has been applied to MNE global strategy by Pitelis, Teece, and Yang (2023) in a systematic literature review identifying sensing, seizing, and reconfiguration as the key DC constituents most relevant to cross-border strategy [16].

Despite the growing volume of relevant research, several critical aspects of AI-mediated knowledge processes in MNEs remain underexplored or unresolved, representing the primary gaps this study seeks to address.

- First, while existing research has examined AI's role in either knowledge management systems or MNE contexts, very few studies integrate both perspectives into a coherent theory of AI-mediated knowledge processes sensitive to the distinctive features of multinational organizational architectures, specifically the headquarters-subsidiary-network structure, institutional diversity, and multi-cultural complexity [6, 20]. The overwhelming majority of empirical work treats AI as a uniform technology, failing to differentiate between the effects of narrow AI applications, general AI platforms (LLMs, foundation models), and agentic AI systems on knowledge dynamics within MNEs.
- Second, the existing literature on the SECI model and its AI-enhanced variants (HAC-SECI, GRAI) focuses primarily on single-organization or single-country contexts [22, 24]. The implications of AI for knowledge conversion processes in cross-border, multicultural, and legally diverse environments, where the socialization dimension of SECI is profoundly complicated by geographic distance, institutional differences, and language barriers, have not been adequately theorized or empirically validated.
- Third, the governance dimension of AI-mediated knowledge processes in MNEs is treated largely in isolation from knowledge strategy considerations [12]. The dynamic interaction between AI governance architecture (global vs. local, principled vs. rules-based) and the effectiveness of knowledge transfer, innovation, and learning processes has not been mapped at the firm level. The finding that only 30% of MNEs achieve full compliance with international AI governance standards [12] raises urgent questions about the reliability of AI-mediated knowledge flows.
- Fourth, the cultural dimension of AI trust and AI-human complementarity in knowledge work remains insufficiently understood [6]. The systematic relationship between national cultural dimensions (e.g., uncertainty avoidance, power distance, collectivism) and AI-mediated knowledge process effectiveness in MNEs has not been captured in large-scale empirical studies.
- Fifth, the feedback loops between AI-mediated knowledge processes and MNE competitive advantage, and how they differ from traditional knowledge-based competitive dynamics, have not been formally modeled. Whether AI-mediated knowledge processes constitute a replicable or inimitable source of competitive advantage for MNEs, given the rapid commoditization of AI infrastructure, remains an open question.

Purpose of the article. Building on the identified gaps in existing research, this article pursues the following clearly defined research objectives:

Objective 1: To develop a comprehensive conceptual framework that integrates AI as a mediator of knowledge processes in MNEs across learning, coordination, and innovation dimensions, drawing on the knowledge-based view, dynamic capabilities theory, and the AI-extended SECI frameworks (HAC-SECI and GRAI) [3, 24].

Objective 2: To analyze and systematize the mechanisms through which different categories of AI technology (predictive AI, generative AI, agentic AI) differentially affect the four knowledge conversion modes of the SECI model in the multinational context.

Objective 3: To examine empirical evidence on the outcomes of AI-mediated knowledge processes in MNEs, specifically with respect to: (a) organizational learning efficiency and uncertainty management; (b) cross-border coordination costs and effectiveness; and (c) process and product innovation performance.

Objective 4: To identify governance, cultural, and institutional contingencies that moderate the relationship between AI adoption and knowledge process effectiveness in MNEs, and to derive actionable implications for multinational managers and policymakers.

Presentation of the main research material. The conceptual framework developed in this study positions AI not as a standalone technology but as an active mediator that fundamentally reconfigures the relationships between knowledge actors, knowledge assets, and knowledge processes within and across the organizational boundaries of MNEs. This framing draws on three interlocking theoretical pillars.

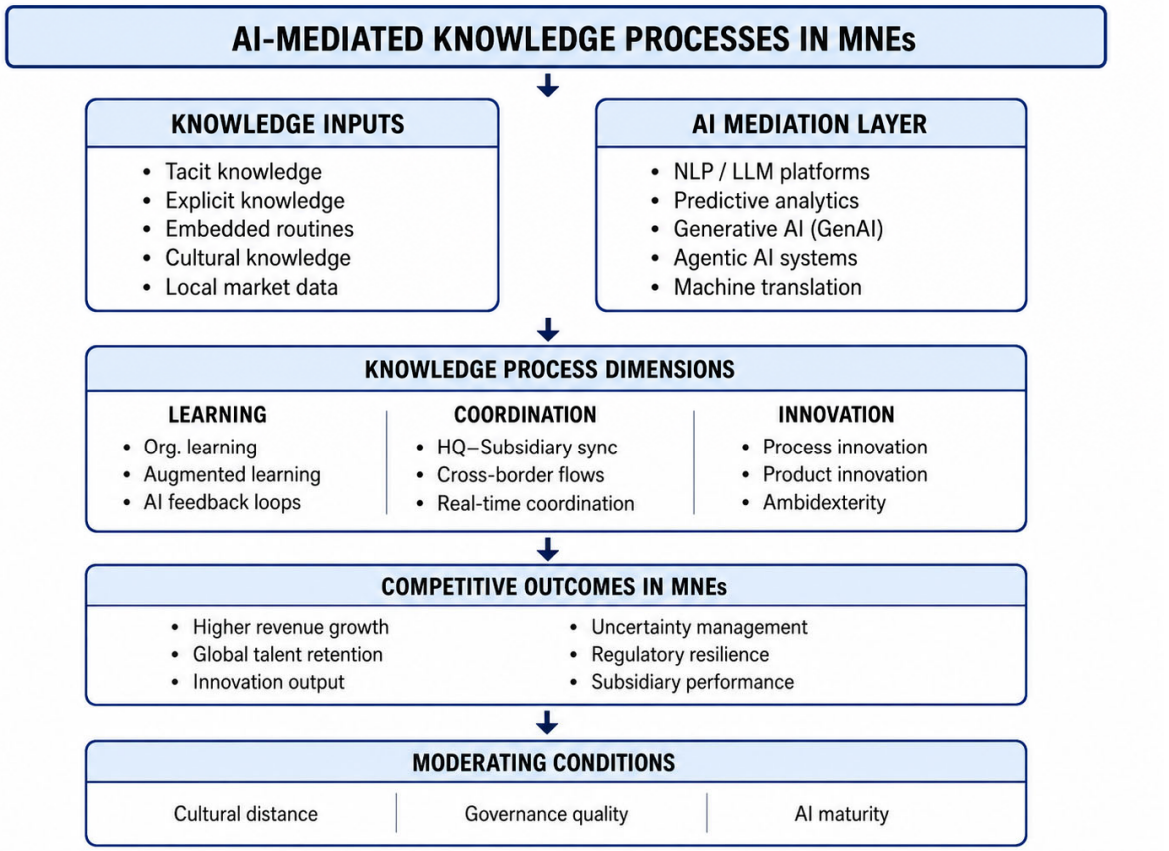
Pillar 1: Knowledge-Based View (KBV) of the MNE. The KBV holds that the MNE exists primarily as a vehicle for the cross-border exploitation and creation of knowledge assets that are imperfectly tradeable in factor markets [1]. AI mediates these processes by reducing the stickiness of tacit knowledge through pattern recognition, natural language processing, and multimodal learning systems [21]. Generative AI tools make tacit knowledge explicit by transforming apprenticeship-based expertise into codified, transferable documentation, a function particularly valuable in MNEs where expert knowledge is distributed across geographically dispersed subsidiaries [21].

Pillar 2: Dynamic Capabilities Theory. The dynamic capabilities (DC) framework conceives of competitive advantage in terms of the firm's ability to sense opportunities, seize them through resource reconfiguration, and transform its organizational base in response to environmental change [16]. AI augments all three DC dimensions: it expands sensing capabilities through real-time market intelligence; it accelerates seizing through algorithmic decision support; and it facilitates transformation through process automation [5]. In MNEs, these DC-AI interactions occur simultaneously across multiple institutional environments, creating both synergies and tensions requiring explicit governance.

Pillar 3: AI-Extended SECI Model. The original SECI framework models knowledge creation through four conversion modes. The GRAI framework (Böhm & Durst, 2025) introduces bidirectional interactions between generative AI and organizational knowledge, positioning AI as both a receptive receiver of organizational knowledge and a generative producer of new knowledge forms [3]. The HAC-SECI model (Watanabe et al., 2025) adds a dual-loop structure: AI agents grow through human knowledge input (Inner Loop), while human targets develop cognitive capacity from AI-accumulated knowledge (Outer Loop) [24]. This study extends these frameworks to the MNE context, arguing that AI also mediates a fifth conversion mode: Transborderization, the cross-institutional adaptation of knowledge as it moves between subsidiary environments with different cognitive, cultural, and regulatory frameworks (see Figure 1).

Figure 1.

Conceptual Framework: AI-Mediated Knowledge Processes in MNEs



Source: Developed by the author based on analysis of [3, 6, 8, 20, 24]

Building upon the GRAI framework [3], the HAC-SECI model [24], and empirical work on GenAI in knowledge-intensive teams [22], Table 1 presents an updated mapping of AI mediation onto each knowledge conversion mode within the multinational enterprise context, including the newly proposed Transborderization mode specific to cross-border knowledge adaptation.

Table 1

AI Mediation of SECI Knowledge Conversion Modes in the MNE Context

SECI Mode	Knowledge Conversion	AI Technologies	MNE-Specific Mechanism	AI Mediation Intensity
Socialization	Tacit → Tacit	Virtual collab. platforms, AI meeting assistants, avatar-based mentors	Cross-cultural knowledge sharing between subsidiary employees; international team socialization	Low–Medium (human interaction remains dominant)
Externalization	Tacit → Explicit	LLMs, NLP, automatic documentation, GenAI-assisted expert interviews [21]	Capturing local market knowledge from subsidiary managers; converting contextual expertise into transferable docs	High (AI strongly accelerates this mode)
Combination	Explicit → Explicit	RAG frameworks, semantic search, knowledge graphs, vector databases [2]	Integrating regulatory knowledge, market reports, and R&D outputs across international subsidiaries	Very High (AI core competency domain)
Internalization	Explicit → Tacit	Personalized AI learning systems, adaptive training platforms,	Enabling global employees to absorb HQ-generated knowledge in	Medium (AI-enhanced personalization)

		simulation-based learning	culturally relevant formats; HAC-SECI Outer Loop [24]	
Transborderization (proposed)	Contextualized → Re-contextualized	Machine translation, cultural AI adapters, regulatory compliance bots, GRAI receptive agents [3]	Adapting knowledge for institutional and cultural re-embedding across different subsidiary environments	Medium-High (emerging AI capability)

Source: Developed by the author based on [3, 22, 24, 21]

Organizational learning, defined as an organization's capability to change its knowledge through experience [8], represents the first critical dimension through which AI mediates knowledge processes in MNEs. The 2024 MIT SMR/BCG global study reveals a structural bifurcation in the MNE landscape: organizations that combine robust organizational learning with AI-specific learning (Augmented Learners, approximately 15% of firms) systematically outperform those relying on either capability alone [8].

The mechanism through which AI accelerates organizational learning in MNEs can be understood through three distinct feedback loops. First, the Data-to-Insight Loop: AI systems continuously process operational and market data across multiple subsidiary environments and surface insights to decision-makers, compressing the time between experience and learning that in traditional organizations can take months as information travels through hierarchical reporting structures [8]. Second, the Knowledge Loss Prevention Loop: MNEs are particularly vulnerable to knowledge depreciation through employee turnover. AI mitigates this risk by systematically capturing and codifying expert knowledge before it exits the organization, among Augmented Learners, 83% are prepared to manage knowledge disruption from talent mobility, compared to only 39% of organizations with limited learning capabilities [8]. Third, the Cross-Subsidiary Learning Loop: AI systems identify patterns across geographically dispersed operations that are invisible to individual subsidiary managers, enabling 'distributed learning arbitrage', the systematic identification and transfer of locally discovered best practices [7].

Table 2

Learning and Uncertainty Management Outcomes: Augmented Learners vs. Limited Learners

Performance Dimension	**Limited Learners**	**Strong Org. Learners (No AI)**	**Augmented Learners (AI + Org. Learning)**	**Source**
Prepared for technology disruptions	49%	~55%	86%	[8]
Prepared for regulatory disruptions	48%	~52%	79%	[8]
Prepared for talent mobility disruption	39%	64%	83%	[8]
Overall uncertainty management	Baseline	1.0× (reference)	1.6× more likely	[8]
Revenue growth (3-year CAGR)	Baseline	+0.8×	+1.5×	[4]
Shareholder returns	Baseline	+0.9×	+1.6×	[4]
Return on invested capital	Baseline	+0.85×	+1.4×	[4]
Scale of AI solutions deployed	Baseline	N/A	2.0× more than peers	[4]

Source: Compiled by the author based on [4, 8]

Cross-border coordination within MNEs has historically been one of the most resource-intensive management activities, requiring extensive formal and informal mechanisms to align headquarters and subsidiary managers across time zones, languages, cultures, and institutional environments. AI introduces a new category of coordination mechanism that operates autonomously, continuously, and at negligible marginal cost compared to traditional human-mediated coordination [20].

Language and Cultural Barrier Reduction. Natural language processing (NLP) and machine translation represent perhaps the most immediately impactful AI applications for MNE

coordination. The global NLP market is projected to reach USD 791.16 billion by 2034 at a CAGR of 38.4%, reflecting the massive organizational demand for language-intelligent systems. AI-powered multilingual tools enable real-time knowledge sharing across language boundaries that have historically segmented MNE knowledge networks [9].

Transaction Cost Reduction in Knowledge Transfer. The knowledge-based theory of MNEs emphasizes that internalization of cross-border knowledge transfer is efficient because of high transaction costs in knowledge markets. AI reduces these internalization costs further by automating knowledge capture, codification, and retrieval, enabling MNEs to achieve higher coordination intensity at lower administrative overhead [20]. Knowledge management platforms have evolved from passive repositories into dynamic, AI-powered systems that deliver real-time intelligence across customer experience, employee experience, and enterprise resource planning functions simultaneously [18].

Real-Time Headquarters–Subsidiary Synchronization. BCG research on AI-enabled organizations documents that leaders in AI deployment pursue fewer strategic opportunities but achieve more than twice the ROI, suggesting that AI improves the quality of coordination by filtering signal from noise across the global information environment [4].

Reverse Knowledge Transfer Facilitation. AI systems address cognitive and communication barriers to reverse knowledge transfer directly: NLP-based knowledge extraction identifies valuable local market insights in subsidiary communications, while recommendation systems automatically surface these insights to relevant headquarters functions [6, 10]. AI-mediated RKT is particularly significant in emerging market subsidiaries, where local knowledge is often tacit and embedded in relationships that are difficult to formalize through traditional reporting mechanisms [10].

Table 3

Traditional vs. AI-Mediated Cross-Border Coordination in MNEs

Coordination Dimension	Traditional Mechanism	AI-Mediated Mechanism	Performance Impact
Language barriers	Professional translators, bilingual managers	Real-time NLP machine translation, multilingual AI assistants	Near-elimination of language delays [9]
Knowledge capture	Manual documentation, expatriate knowledge transfer	Automated externalization via LLMs, GenAI-assisted expert interviews [21]	10–30% reduction in documentation time [2]
HQ–Subsidiary reporting	Periodic batch reporting, quarterly reviews	Continuous AI-generated dashboards, exception alerts	Real-time situational awareness [8]
Knowledge search & retrieval	Manual databases, keyword search	Semantic vector search, RAG-enabled knowledge discovery [2]	Significant improvement in cross-departmental knowledge flows
Reverse knowledge transfer	Expatriate networks, liaison roles	AI-assisted knowledge extraction, recommendation systems [10]	Reduced cognitive and communication barriers [10]
Regulatory compliance	Local legal teams, periodic audits	AI regulatory monitoring, compliance automation [12]	Simultaneous multi-jurisdiction compliance tracking
Cultural adaptation	Cross-cultural training programs, local HR	AI cultural sentiment analysis, adaptive communication tools [6]	Improved cultural alignment in global teams
Innovation diffusion	Best-practice sharing programs	Automated pattern identification and internal benchmarking [7]	Accelerated best practice transfer across subsidiaries

Source: Developed by the author based on [2, 4, 6, 7, 8, 9, 10, 12, 18, 20, 21]

Innovation, the creation of new products, processes, business models, or organizational capabilities, represents the ultimate expression of knowledge process excellence in MNEs. AI

mediates innovation in MNEs through multiple pathways, and its effects are most strongly observed at the intersection of process, product, and organizational innovation.

Process Innovation. Process innovation has historically been undervalued relative to product innovation, yet drives much of the competitive differentiation between leading and lagging MNEs [7]. AI enables process innovation through two primary mechanisms: (1) by reducing barriers to interpersonal knowledge transfer within organizations, AI allows best practices developed in one part of the MNE network to be rapidly identified and diffused to other units; and (2) AI systems themselves continuously analyze operational data to identify inefficiencies and propose improvements. Empirical research confirms that AI breadth has a significant positive effect on process innovation likelihood, with this effect amplified in large MNEs and those with high employee turnover [7]. Knowledge managers should increasingly structure content and data with AI in mind to capitalize on this dynamic [25].

Product and Service Innovation. Research on 260 Chinese companies operating globally identifies three primary innovation pathways through which generative AI capabilities translate into competitive advantage: service concept innovation, process innovation, and customer experience innovation [23]. Firms with strong generative AI capabilities experienced average productivity improvements of 7.8% and customer engagement increases of 6.7% [23]. The five-element management agenda for generative AI transformation identified by Ritala et al. (2025) includes fostering a human-centered approach, developing customer value integration, and creating future-proofing mechanisms against imitation [19].

Innovation Ambidexterity. Innovation ambidexterity, the simultaneous pursuit of exploitation and exploration, represents a particularly demanding organizational challenge for MNEs, which must balance local adaptation with global integration [5]. AI creates new possibilities for ambidextrous innovation by enabling MNEs to automate exploitation activities while simultaneously using AI-generated data insights to identify new market opportunities. A European study of 102 firms demonstrates that AI ambidexterity mediates the relationship between ecosystem participation and dynamic capabilities, with sensing, seizing, and transforming capabilities all significantly enhanced by balanced AI exploitation and exploration [5].

Open Innovation and External Knowledge Sourcing. AI also reconfigures the boundary between internal and external knowledge processes in MNEs, facilitating open innovation by enabling the systematic monitoring of external knowledge sources at a scale impossible for human research teams. Predictive analytics allow organizations to anticipate future knowledge needs, tying knowledge management directly to organizational performance outcomes [25]. For MNEs, AI-powered competitive intelligence systems transform environmental scanning from an episodic activity into a continuous capability spanning all subsidiary environments simultaneously.

A critical dimension of AI-mediated knowledge processes in MNEs is governance, the policies, structures, and processes that ensure AI systems operate with integrity and accountability across the MNE's diverse institutional environments. Research by Nakajima (2025) reveals that 65% of MNCs have implemented some form of AI governance framework, yet only 30% achieve full compliance with international standards [12]. The governance gap is most severe in three areas: (i) the 'black box' opacity of AI decision-making systems; (ii) regulatory fragmentation across jurisdictions; and (iii) ethical risks including algorithmic bias and labor displacement [12].

The EU AI Act, which became effective in August 2024, has emerged as a de facto global governance reference standard for MNEs with European operations, establishing risk-based compliance requirements across high-impact domains, HR screening, performance monitoring, and strategic decision support, that are central to MNE knowledge processes. By 2025, 77% of

organizations were actively developing AI governance programs, with 47% ranking it among their top five strategic priorities [17].

For MNEs, the governance challenge is compounded by the need to balance global coherence with local legitimacy. The most effective AI governance approaches in MNEs adopt 'universal baselines' that establish non-negotiable ethical and technical standards globally, while allowing local adaptation that respects cultural and regulatory specificities [6]. Guardrails and governance mechanisms should be embedded within KM platforms themselves, ensuring compliance and curating trusted knowledge sources across the multinational network [18].

Table 4

AI Governance Frameworks and Their Relevance to MNE Knowledge Process Management

Governance Framework	Origin	Core Mechanism	Risk Classification	MNE Relevance for Knowledge Processes
EU AI Act (2024)	European Union	Risk-based regulatory compliance	Prohibited / High / Limited / Minimal	High – applies to all AI in HR, decision support, and knowledge curation within EU operations
NIST AI RMF	United States	Govern-Map-Measure-Manage cycle	Context-dependent	High – widely adopted globally; aligns with KM auditing needs [17]
ISO/IEC 42001	International	AI management system standard	Organization-level	Medium-High – enables cross-subsidiary governance harmonization [12]
OECD AI Principles	OECD Nations	Human-centered, trustworthy AI	Voluntary	Medium – informs policy and enterprise standard-setting [13]
Databricks DAGF	Private sector	5-pillar: risk, legal, ethical, data, operational	Enterprise-specific	High – directly applicable to AI-based KMS in MNEs [17]
Hybrid Governance Model (Nakajima, 2025)	Academic	Universal baseline + local adaptation	Contextual	Very High – designed for MNE multi-jurisdiction environments [12]

Source: Developed by the author based on [6, 12, 13, 17, 18]

The effectiveness of AI-mediated knowledge processes in MNEs is substantially moderated by cultural and institutional contextual factors that previous research has only begun to map systematically.

Cultural Distance and AI Trust. Research by Gosen et al. (2025) identifies power-distance norms and uncertainty avoidance as the two cultural dimensions most consequential for AI-mediated knowledge processes in MNEs [6]. In high power-distance cultures, employees may be less likely to challenge AI recommendations, creating risks of systematic error propagation in knowledge systems. In high uncertainty-avoidance cultures, the probabilistic and opaque nature of AI outputs may generate resistance regardless of technical quality. MNEs must therefore calibrate AI deployment strategies culturally, investing in trust-building, interpretability, and cultural adaptation of AI interfaces.

Institutional Quality and AI Infrastructure. The OECD's 2025 analysis of AI adoption in enterprises confirms that the intensity and quality of AI adoption varies substantially by institutional environment, with skilled talent availability, digital infrastructure, and public-private R&D ecosystems being the primary determinants of enterprise AI capability [13]. For MNEs, this translates into asymmetric AI capabilities across subsidiaries, creating both knowledge gaps and opportunities for capability diffusion from advanced to developing subsidiaries.

Industry and Competitive Context. AI adoption rates vary considerably by industry. Technology and telecom sectors lead with 72% of organizations integrating AI, followed by financial services (67%) and healthcare (61%) [11]. Raisch and Fomina (2024) emphasize that hybrid human-AI configurations are most effective when the cognitive architecture of the AI

system is matched to the type of problem-solving required, structured and well-defined problems benefit most from algorithmic AI autonomy, while ambiguous and complex problems require sustained human oversight and co-creation [17].

The empirical evidence base for AI-mediated knowledge processes in MNEs, while growing, remains dominated by surveys, case studies, and cross-sectional analyses rather than longitudinal causal studies. Nevertheless, convergence of evidence across multiple methodologies provides sufficient basis for robust theoretical conclusions.

McKinsey Global AI Survey (2024). Based on responses from thousands of executives across industries and geographies, the survey reports a jump in AI adoption from approximately 50% to 72% of organizations between 2023 and 2024 [11]. Half of respondents now report AI adoption in two or more business functions, up from less than one-third in 2023 [11]. This diffusion across functions corresponds to the 'AI breadth' variable that research associates with process innovation and cross-unit knowledge transfer enhancement [7].

BCG AI Maturity Study (2024). This comprehensive study of 1,000 CxO and senior executives across 59 countries documents the emergence of a distinct 'AI leader' cohort, the 26% of companies that have developed capabilities to generate tangible, scalable AI value [4]. These leaders achieved 1.5× higher revenue growth, 1.6× greater shareholder returns, and 1.4× higher return on invested capital over the prior three years, while investing twice as much in AI and digital capabilities [4]. Their approach is strategically focused: they pursue fewer but higher-impact AI initiatives and achieve more than twice the ROI [4].

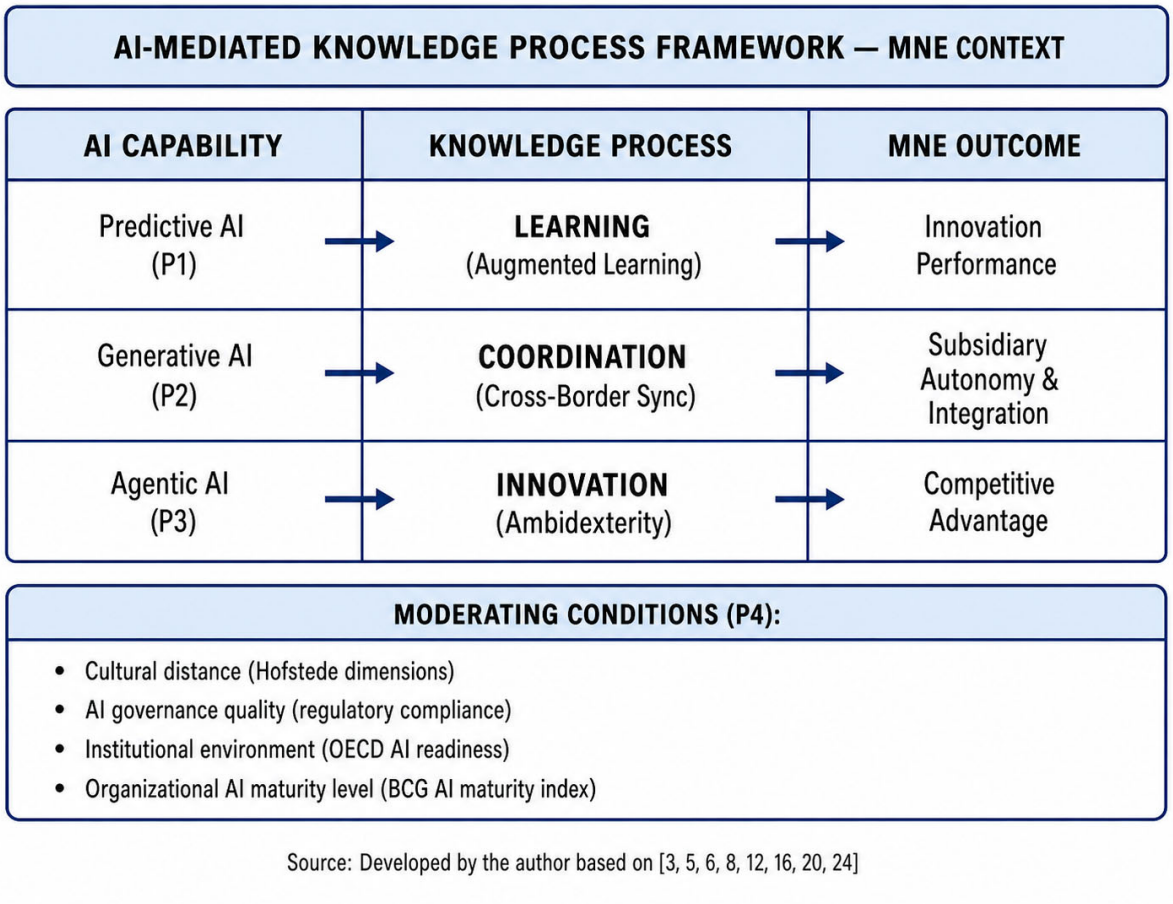
Case Evidence: Multinational Knowledge Coordination. Qualitative research from the University of Vaasa (2024) analyzing AI applications in multinational expansion activities provides case-based evidence that AI autonomy reduces monitoring and coordination costs, AI learning enables dynamic updating of market knowledge, and AI combinative capability enhances integration of complementary knowledge assets across subsidiaries [20]. Gosen et al.'s (2025) multi-case study of 15 interviews across three MNE sectors finds that modular data architectures, digital upskilling programs, and AI 'enthusiast' networks are the organizational-level enablers of effective human-AI complementarity in globally diverse markets [6].

Generative AI and MNE Innovation. Research on managing generative AI for strategic advantage (Ritala et al., 2025), based on interviews with 18 managing directors in Finland, identifies a five-element management agenda for leading generative AI transformation, including fostering a human-centered approach and creating future-proofing mechanisms against imitation [19]. The challenge of achieving lasting competitive advantage through generative AI, given its rapid commoditization, emerges as a central strategic puzzle for MNE knowledge managers, and is most effectively addressed through combinations of AI capabilities with hard-to-imitate organizational factors: cultural alignment, deep domain expertise, and proprietary data assets [19].

Synthesizing the theoretical and empirical evidence reviewed in this study, this section proposes an integrated model that captures the key relationships between AI mediation, knowledge processes, and MNE performance outcomes. The model (Figure 2) identifies four primary propositions suitable for future empirical testing.

Figure 2.

The AI-Mediated Knowledge Process Framework: Key Propositions



Source: Developed by the author based on [3, 5, 6, 8, 12, 16, 20, 24]

Proposition 1 (P1): The broader and deeper the deployment of AI technologies across MNE operations (AI breadth and depth), the stronger the enhancement of organizational learning capabilities, as measured by uncertainty management effectiveness and knowledge loss prevention [7, 8].

Proposition 2 (P2): AI-mediated cross-border coordination mechanisms significantly reduce knowledge transfer frictions (language barriers, cognitive distance, temporal delays) in MNEs, enhancing both forward and reverse knowledge flows [10, 20].

Proposition 3 (P3): MNEs with higher AI capability levels achieve greater innovation ambidexterity, the simultaneous pursuit of process exploitation and product/service exploration, through AI-enabled automation of routine knowledge work and AI-facilitated market sensing [5, 23].

Proposition 4 (P4): The relationship between AI capability and knowledge process effectiveness in MNEs is moderated by cultural distance between subsidiaries, the quality of AI governance frameworks, the institutional environment of host countries, and the overall AI maturity of the organization [6, 12, 13].

Pathway 1: Build AI-Ready Knowledge Infrastructure. Semantic layers, knowledge graphs, and enterprise data architectures must precede advanced AI deployment. Organizations should begin creating content with AI in mind, ensuring teams can access relevant, up-to-date, and secure

results requires knowledge assets to be AI-optimized from the ground up [25]. MNEs should treat data as a dynamic entity, developing frameworks to evaluate how data impacts revenue, efficiency, and cost reduction.

Pathway 2: Develop Augmented Learning Capabilities**.** BCG and MIT SMR research identifies five strategies: fostering growth in both organizational and AI-driven learning simultaneously; leveraging AI to drive exploration; accelerating learning cadence with AI analytical tools; selecting AI initiatives that support continuous learning feedback loops; and ensuring responsible and ethical AI usage [8].

Pathway 3: Establish Hybrid AI Governance. MNEs should adopt governance models that combine universal ethical baselines with locally adaptive implementation [6, 12]. Guardrails and governance mechanisms should be embedded within KM platforms themselves, ensuring compliance and curating trusted knowledge sources across the multinational network [18].

Pathway 4: Invest in AI-Cultural Competency. The effectiveness of AI-mediated knowledge processes depends critically on the capacity of multinational employees to interact productively with AI systems, requiring digital upskilling that develops AI judgment, the ability to critically evaluate AI-generated knowledge, identify its limitations, and calibrate appropriate reliance [6]. Organizations that identify and empower AI enthusiasts within subsidiaries as internal champions significantly accelerate adoption and knowledge quality [6].

Pathway 5: Develop AI-Mediated Reverse Knowledge Transfer Systems. Given the documented barriers to reverse knowledge transfer in MNEs [10], AI systems specifically designed to identify, extract, and surface subsidiary-generated knowledge to headquarters and peer subsidiaries represent a high-leverage investment. NLP-based knowledge mining tools that analyze subsidiary communications and customer interaction data for transferable insights address both motivational and cognitive barriers to RKT.

Conclusion. This research has developed a comprehensive conceptual framework for understanding the role of artificial intelligence as an active mediator of knowledge processes in multinational enterprises, with specific attention to the learning, coordination, and innovation dimensions of multinational knowledge dynamics. The principal conclusions are as follows.

First, AI fundamentally reconfigures the knowledge-based competitive advantage of MNEs by transforming the economics of tacit-to-explicit knowledge conversion, reducing cross-border knowledge transfer frictions, and enabling new forms of coordination that operate continuously at near-zero marginal cost. The extended SECI model proposed here, synthesizing the GRAI framework [3], the HAC-SECI model [24], and the newly proposed Transborderization mode, provides a more adequate theoretical architecture for understanding these transformations than existing single-organization models.

Second, the evidence clearly demonstrates that AI-mediated knowledge processes generate the greatest organizational learning benefits when AI deployment is combined with intentional organizational learning architecture. Augmented Learners, organizations that integrate AI into their learning capabilities, are 1.6 times more likely to manage uncertainty effectively and achieve systematically superior financial and operational performance [8]. The learning-AI synergy, rather than AI technology per se, is the true source of competitive advantage.

Third, cross-border coordination in MNEs is being fundamentally restructured by AI's capacity to automate language translation, knowledge extraction, regulatory monitoring, and real-time performance synchronization [20]. These capabilities are particularly valuable for facilitating reverse knowledge transfer from subsidiaries to headquarters [10], a historically underdeveloped direction in MNE knowledge strategy.

Fourth, AI drives MNE innovation through multiple pathways: process innovation through knowledge transfer automation [7]; product and service innovation through generative AI capabilities and enhanced market sensing [23]; and innovation ambidexterity through simultaneous automation of exploitation and acceleration of exploration [5]. The sustainability of AI-generated innovation advantage depends on combining AI capabilities with organizational capabilities that are hard to imitate, cultural alignment, deep domain expertise, and high-quality proprietary data assets.

Fifth, the governance of AI-mediated knowledge processes represents a critical challenge for MNEs. With only 30% of multinational firms achieving full compliance with international AI governance standards [12], the integrity of AI-generated knowledge flows across subsidiary networks is at risk. Hybrid governance models combining universal ethical baselines with locally adaptive implementation represent the most promising approach. Several important questions remain for future research: longitudinal studies establishing causal relationships between AI-mediated knowledge capabilities and MNE performance; theoretical development of AI's role in reshaping headquarters-subsidiary relationships; and systematic empirical examination of the interaction between national AI governance frameworks and MNE knowledge management strategy.

References

1. Asmussen C. G., Foss N. J., Pedersen T. The knowledge-based view in international business: A systematic literature review. International Business Review. 2024. Vol. 33, No. 2. URL: https://doi.org/10.1016/j.ibusrev.2023.102189

2. Bhardwaj A., Singh R. K. AI-enhanced knowledge management systems in enterprises. World Journal of Advanced Research and Reviews. 2025. Vol. 26, No. 02. P. 2020–2030. URL: https://wjarr.com/sites/default/files/fulltext_pdf/WJARR-2025-1913.pdf

3. Böhm S., Durst S. The GRAI framework, extending the SECI model to reflect generative AI. RealKM Magazine. 2025. URL: https://realkm.com/2025/05/21/the-grai-framework-extending-the-seci-model-to-reflect-generative-ai/

4. Boston Consulting Group. AI adoption in 2024: 74% of companies struggle to achieve and scale value. BCG Press Release. 2024. URL: https://www.bcg.com/press/24october2024-ai-adoption-in-2024-74-of-companies-struggle-to-achieve-and-scale-value

5. Farzaneh M., Wilden R., Afshari L., Mehralian G. Dynamic capabilities and innovation ambidexterity: The roles of intellectual capital and innovation orientation. Journal of Business Research. 2022. Vol. 148. P. 47–59.

6. Gosen R., Hewer K., Zanier J. The synergy between humans & AI in multinational enterprises: A cross-cultural investigation. Master Thesis, Linnaeus University. 2025. URL: https://www.diva-portal.org/smash/get/diva2:1965729/FULLTEXT02

7. Hecker A., Ganter A. Overcoming difficulties in knowledge transfer: Harnessing the power of AI to drive process innovation. Technovation. 2025. URL: https://doi.org/10.1016/j.technovation.2025.103211

8. Kiron D., Khodabandeh S., Zhukov L. Learning to manage uncertainty, with AI. MIT Sloan Management Review / BCG. 2024. URL: https://www.bcg.com/press/12november2024-organizational-learning-and-ai-specific-learning-managing-uncertainty

9. Kuzior A., Mytrofanova M. et al. The impact of artificial intelligence on the transformation of organizations. Proceedings in Business and Economics. 2025. Vol. 25, No. 343. URL: https://reference-global.com/download/article/10.2478/picbe-2025-0343.pdf

10. Lee S. K., Ghauri P. N., Oh K.-S., Xiao S., Park B. I., Romero-Martínez A. M. Reverse knowledge transfer from subsidiaries to headquarters. Journal of International Management. 2024. URL: https://doi.org/10.1016/j.intman.2023.101114
11. McKinsey & Company. The state of AI in early 2024. McKinsey Global Survey. 2024. URL: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-2024
12. Nakajima R. The generative artificial intelligence governance paradox: Driving innovation while challenging global corporate oversight in multinational firms. Corporate Governance and Organizational Behavior Review. 2025. URL: https://virtusinterpress.org/The-generative-artificial-intelligence-governance-paradox
13. OECD. The adoption of artificial intelligence in firms. OECD Publishing, Paris. 2025. URL: https://www.oecd.org/en/publications/the-adoption-of-artificial-intelligence-in-firms_f9ef33c3-en.html
14. Okechukwu C., Bachmann P. Artificial intelligence in multinational corporations: A systematic review of strategic integration and applications. Forum Scientiae Oeconomia. 2025. Vol. 17, No. 2. P. 191–201. URL: https://digilib.uhk.cz/bitstream/handle/20.500.12603/901/17_2025-01-17_191_201.pdf
15. Omotosho A. et al. Understanding the role of artificial intelligence in knowledge management systems. Journal of Work-Applied Management. 2025. URL: https://doi.org/10.1108/JWAM-05-2025-0082
16. Pitelis C. N., Teece D. J., Yang H. Dynamic capabilities and MNE global strategy: A systematic literature review-based novel conceptual framework. Journal of Management Studies. 2023. URL: https://doi.org/10.1111/joms.13021
17. Raisch S., Fomina K. Combining human and artificial intelligence: Hybrid problem-solving in organizations. University of Geneva Working Paper. 2024. URL: https://emba-unige.ch/wp-content/uploads/2024/02/Raisch-Fomina-2024-Combining-Human-and-Artificial-Intelligence.pdf
18. Research and Markets. Knowledge management for the AI-enabled enterprise 2024–2025. 2025. URL: https://www.globenewswire.com/news-release/2025/01/20/3012141/28124/en/knowledge-management-for-the-ai-enabled-enterprise
19. Ritala P. et al. Managing generative AI for strategic advantage. Research-Technology Management. 2025. URL: https://doi.org/10.1080/08956308.2025.2497687
20. Sainio L., Ojanperä J., Myllymäki M. Managing artificial intelligence in international business. University of Vaasa Working Paper. 2024. URL: https://osuva.uwasa.fi/bitstreams/1613009c-c4eb-47f6-8c43-bef76caf0693/download
21. Salvatore M. et al. Making tacit knowledge explicit: Generative AI's role in enhancing apprenticeship systems. SAGE Journals. 2024. URL: https://doi.org/10.1177/18724981251397523
22. Mühlböck A. et al. How the usage of generative AI tools enhances knowledge management processes and team performance. Journal of Management and Leadership. 2025. URL: https://pubs.wi-kassel.de/wp-content/uploads/2025/09/JML_1040.pdf
23. Wang X. et al. Leveraging generative AI capabilities for competitive advantage. Industrial Marketing Management. 2025. URL: https://doi.org/10.1016/j.indmarman.2025.103847
24. Watanabe T. et al. Human-AI-Collaboration SECI Model: The knowledge management model for human-AI collaboration. In: Agents and Multi-agent Systems: Technologies and Applications 2024 – Proceedings of KES-AMSTA 2024. Springer. 2025. P. 135–145.

25. Altuent. 5 knowledge management trends in 2025 that could impact your organization. 2025. URL: https://altuent.com/insights/knowledge-management-trends-2025/