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СПІВПРАЦЯ МІЖ ЛЮДЬМИ ТА АГЕНТАМИ В ТРАНСНАЦІОНАЛЬНИХ КОРПОРАЦІЯХ: НАСЛІДКИ ДЛЯ ТРАНСКОРДОННОГО ОБМІНУ ЗНАННЯМИ

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Анотація. *Мета. Метою статті є розробка концептуального та емпірично обґрунтованого розуміння того, яким чином взаємодія людини й агента штучного інтелекту (ШІ) трансформує транскордонні потоки знань у транснаціональних корпораціях (ТНК), з особливою увагою до ролей агентів у процесах опрацювання знань, механізмів координації, абсорбційної здатності, довіри, прав на прийняття рішень та управлінської відповідальності.*

Методи. Стаття ґрунтується на якісному концептуальному дизайні у поєднанні з аналізом вторинних джерел. Методологічний підхід включає напівсистематичний огляд літератури з баз Scopus, Web of Science та Google Scholar за 2000–2026 рр. (з пріоритетом публікацій 2018–2026 рр.), тематичний синтез, розробку концептуальної рамки та аналітичне картування ролей агентів ШІ на етапах передачі знань. Теоретичне підґрунтя — знаннєва теорія фірми, теорія ТНК, організаційне навчання та концепція абсорбційної здатності.

Результати. Встановлено сім організаційних ролей агентів ШІ: посередники знань, перекладачі та контекстуалізатори, партнери з підтримки рішень, системи організаційної пам'яті, помічники координації, механізми моніторингу і фасилітатори навчання. Розроблена рамка пов'язує антецеденти (цифрова зрілість, культура довіри, якість даних), механізми взаємодії людини й агента, процеси передачі знань та модератори (культурна, інституційна і мовна дистанція, баланс сил штаб-квартира — дочірні підприємства) з результатами (швидкість передачі, якість знань, розвиток можливостей, управлінські ризики). Виявлено критичні ризики: перестандартизація, розмитість підзвітності, алгоритмічна упередженість, тіньове використання ШІ, послаблення реалізованої абсорбційної здатності.

Висновки. Агенти ШІ можуть підвищувати потенційну абсорбційну здатність, але ризикують послабити реалізовану за умов надмірної стандартизації та залежності від систем. Управлінські рекомендації охоплюють побудову гібридних механізмів управління, збереження людського судження на критичних етапах, розподіл прав на прийняття рішень, розвиток цифрової грамотності та впровадження відповідального використання ШІ. Обмеженням є опора на вторинні джерела.

Ключові слова: цифрова координація; організаційне навчання; абсорбційна здатність; управління ШІ; дочірні компанії; транснаціональні знаннєві потоки; відповідальне використання ШІ; управлінська відповідальність; взаємодія людини й агента; знаннєва робота..

Ключові слова: *цифрова координація; організаційне навчання; абсорбційна здатність; управління штучним інтелектом; дочірні компанії; транснаціональні знаннєві потоки; відповідальне використання ШІ; управлінська відповідальність; взаємодія людини й агента; знаннєва робота.*

HUMAN-AGENT COLLABORATION IN MULTINATIONAL ENTERPRISES: IMPLICATIONS FOR CROSS-BORDER KNOWLEDGE TRANSFER

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Abstract. *Purpose. This article develops a conceptual and evidence-informed understanding of how human-agent collaboration — the organizationally embedded interaction between human professionals and AI-enabled agents — reshapes cross-border knowledge transfer in multinational enterprises (MNEs). It addresses a substantive gap: while MNEs increasingly deploy AI agents in knowledge-intensive processes, international business frameworks have yet to integrate AI agent roles as organizationally meaningful participants rather than mere digital tools. The article focuses on knowledge-processing roles, coordination mechanisms, absorptive capacity, trust, decision rights, managerial accountability, and governance implications.*

Methods. The article employs a qualitative conceptual research design combined with evidence-informed secondary analysis. The methodology encompasses a semi-systematic literature review of peer-reviewed publications from 2000 to 2026 (emphasizing 2018–2026) drawn from Scopus, Web of Science, and leading journals in international business and knowledge management, thematic synthesis of research streams, conceptual framework development, and analytical mapping of AI-agent roles across knowledge-transfer stages.

Results. Seven primary organizational roles for AI agents are identified: knowledge intermediary, translator and contextualizer, decision-support partner, organizational memory system, coordination assistant, monitoring mechanism, and learning facilitator. A conceptual framework connects antecedents (AI readiness, data governance, digital maturity, trust climate, subsidiary capabilities), human-agent collaboration mechanisms (augmentation, mediation, codification, translation, recommendation, feedback), knowledge-transfer processes, moderators (cultural, institutional, and linguistic distance; knowledge tacitness; HQ-subsidiary power balance), and outcomes. AI agents can enhance potential absorptive capacity but may weaken realized absorptive capacity through over-standardization and dependency effects. Critical risks include knowledge distortion, accountability ambiguity, algorithmic bias, loss of tacit context, and shadow AI use.

Conclusions. Human-agent collaboration is a transformative organizational phenomenon requiring theoretical integration across MNE theory, knowledge-transfer research, and AI governance. The framework offers a foundation for future empirical research and actionable governance recommendations for MNE managers.

Keywords: digital coordination; organizational learning; absorptive capacity; AI governance; subsidiary capability; knowledge flows; responsible AI; managerial accountability; human-AI teaming; global knowledge work..

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Problem statement. The capacity to generate, transfer, and recombine knowledge across national, organizational, cultural, institutional, and technological boundaries has long been recognized as a defining competitive advantage of the multinational enterprise [1, p. 28]. Knowledge does not flow freely within organizations, and this friction is particularly pronounced in the multinational setting, where geographic dispersion amplifies the cognitive, cultural, and structural barriers that impede effective transfer. Despite decades of scholarship documenting the mechanisms and impediments of cross-border knowledge transfer, and despite substantial investments by MNEs in digital infrastructure, the fundamental challenge of moving valuable knowledge, particularly tacit, context-dependent, experientially grounded knowledge, across organizational and national boundaries remains unresolved [1, pp. 30–37].

The theoretical foundations of this challenge are well established. The knowledge-based view of the firm identifies knowledge as the most strategically significant resource, and the MNE can be understood as a superior vehicle for the cross-border transfer and deployment of knowledge compared with arms-length market transactions [2, p. 628]. Organizational knowledge is heterogeneous in character: it ranges from codified, explicit forms readily transmissible through formal channels, to deeply embedded tacit knowledge that resists codification and can be transferred only through sustained social interaction, joint practice, and shared context [3, pp. 112–113]. This heterogeneity creates a fundamental asymmetry: the most strategically valuable knowledge tends to be the most difficult to move [4, p. 17].

In the multinational context, knowledge transfer is complicated by at least four additional layers of friction. First, cultural distance between sending and receiving units affects the interpretive frames through which knowledge is understood [9]. Second, institutional distance, differences in regulatory environments, legal systems, cognitive frameworks, and normative contexts, creates barriers to the adoption and legitimation of knowledge originating from foreign units [9, p. 312]. Third, linguistic barriers impede not only literal translation but also the conveyance of conceptual and contextual nuances embedded in professional discourse. Fourth, the structural asymmetry between headquarters and subsidiaries, manifested in differences of power, resource dependency, and strategic mandate, shapes the motivation to share knowledge and the organizational channels through which knowledge is expected to flow [5, p. 477].

The concept of knowledge stickiness, introduced by Szulanski [1], captures the cumulative effect of these barriers. Stickiness refers to the difficulty of transferring knowledge from one organizational unit to another, arising from characteristics of the knowledge itself (causal ambiguity, tacitness, unproven applicability), the sender (low motivation, low codification ability), the recipient (insufficient absorptive capacity, organizational inertia), and the inter-unit relationship (lack of trust, absence of close communication ties). Within MNEs operating across multiple national contexts, these stickiness factors are systematically amplified by overlapping cultural, institutional, and organizational distance [5, p. 480].

Absorptive capacity, the ability of an organizational unit to recognize the value of new external information, assimilate it, and apply it to commercial ends, is widely regarded as the most significant determinant of effective knowledge absorption at the receiving unit [6, p. 128]. Absorptive capacity is shaped by prior related knowledge, organizational structures and processes that facilitate learning, and the quality of the firm's overall knowledge management practices. In the multinational context, subsidiaries vary substantially in their absorptive capacity, and this variation has direct implications for the effectiveness of both headquarters-to-subsidiary and reverse knowledge transfer [13].

Against this backdrop, the emergence of AI agents as organizationally embedded actors in knowledge-intensive work introduces a new dimension of theoretical and practical significance. AI agents, understood here as computational actors that can perform knowledge-related functions such as identification, retrieval, synthesis, translation, codification, recommendation, and monitoring within organizational workflows, have the potential to alter the mechanisms through which knowledge is identified, processed, and transmitted across organizational and national boundaries [7, p. 578]. The literature on human-AI collaboration has begun to articulate how AI systems and human professionals can complement one another in organizational decision-making, with AI addressing complexity through analytical processing while humans contribute contextual judgment, ethical reasoning, and interpretive sense-making [7, pp. 581–583].

The strategic implications for MNEs are substantial and largely uncharted. If AI agents can support the codification of experiential knowledge, facilitate cross-language and cross-cultural translation, accelerate knowledge retrieval from distributed repositories, and provide decision-relevant synthesis for managers in complex international environments, they may substantially reduce knowledge stickiness and enhance the speed and quality of cross-border knowledge flows. However, AI agents also introduce new risks: distortion of knowledge through training data biases, stripping of essential context from tacit knowledge during codification, reinforcement of existing headquarters-subsidiary power asymmetries through centralized system control, creation of accountability ambiguities when AI-generated recommendations prove erroneous, and encouragement of over-reliance that erodes the human expertise effective knowledge work requires [8, p. 25].

The unresolved research problem can be stated as follows: despite the growing deployment of AI agents in MNE knowledge processes, the organizational, managerial, and governance implications of human-agent collaboration for cross-border knowledge transfer have not been systematically theorized or empirically investigated. Existing research treats AI systems primarily as technical tools rather than as organizationally embedded participants in knowledge processes, and fails to integrate insights from human-AI collaboration research with the established theoretical frameworks of MNE theory, organizational learning, and absorptive capacity. The present article addresses this gap.

Analysis of recent research and publications. Research on cross-border knowledge transfer in MNEs has produced a rich and theoretically heterogeneous body of scholarship over the past three decades. Early studies established the foundational insight that MNEs derive competitive advantage from their superior ability to transfer knowledge across borders compared with market mechanisms [2, pp. 626–628]. Knowledge stickiness remains a recurring and empirically robust challenge: the causal ambiguity of complex organizational knowledge, the arduousness of inter-unit relationships, and insufficient absorptive capacity at the receiving unit have been consistently identified as the most powerful impediments to effective transfer [1, pp. 37–40].

The concept of transinstitutional transfer, introduced to capture the challenges of moving organizational practices across national institutional contexts, extends the stickiness framework by situating knowledge transfer within a multi-level contextual model [9, p. 309]. Kostova's model distinguishes among three layers of context: the country context (regulatory, cognitive, and normative dimensions of the institutional environment), the organizational context (organizational culture and history), and the relational context (the relationship between sending and receiving units). Transfer success depends on favorable conditions at all three levels. Methodologically, much of the early literature relied on single-country surveys or small-sample case studies, limiting generalizability across the full diversity of MNE structures and national contexts [10, pp. 384–385].

More recent scholarship has deepened understanding of the micro-foundations of knowledge transfer, emphasizing the role of individual motivation, social ties, and interpersonal trust in facilitating or impeding knowledge flows [10, pp. 388–391]. Research has also examined how subsidiary initiative, strategic mandate, and local embeddedness shape the nature and direction of knowledge flows, moving beyond a unidirectional headquarters-to-subsidiary model toward recognition that knowledge can flow in multiple directions across the MNE network [5, pp. 482–484]. A key limitation of existing literature is its almost complete absence of attention to how AI agents embedded in organizational workflows alter the mechanisms and outcomes of cross-border knowledge transfer.

The knowledge-based view of the firm, synthesized by Grant [3], identifies knowledge as the primary source of competitive advantage and the principal rationale for the existence of firms as coordinators of specialized knowledge. Building on this foundation, organizational learning theory examines how firms create, retain, and transfer knowledge through cycles of experience, codification, and recombination [11, p. 151]. Knowledge embedded in the interactions of people, tools, and tasks is the most difficult to transfer to new organizational contexts, because the interactive dimension resists direct specification or replication [11, pp. 154–156]. When AI agents attempt to support or replicate interaction-based knowledge, they risk severing the relational and contextual bonds that give the knowledge its organizational meaning.

Knowledge management systems research has established a conceptual framework for understanding how organizations create, store, transfer, and apply knowledge through information technologies [12, p. 108]. Alavi and Leidner [12] distinguish between the representational and interpretive dimensions of knowledge, cautioning against the assumption that information systems can fully capture the socially embedded and contextually contingent dimensions of organizational knowledge [12, pp. 114–116]. A persistent limitation in the knowledge-based view literature is the tendency toward static conceptualizations of knowledge assets, which obscures the dynamic, relational, and politically contested nature of knowledge in distributed MNE networks.

The headquarters-subsidiary dimension of MNE knowledge flows has been extensively theorized. Gupta and Govindarajan [5] conceptualize individual subsidiaries as nodes in the MNE's knowledge network, characterized by their degree of outflow (sending knowledge to the rest of the network) and inflow (receiving knowledge from others). Subsidiaries vary substantially in their knowledge profiles: some serve primarily as implementers of headquarters knowledge; others develop distinctive local expertise that represents a potential source of competitive advantage for the entire MNE network [5, pp. 477–481].

Minbaeva and colleagues [13] have empirically established that subsidiary-level human resource management practices shape absorptive capacity through their effects on both employee ability and motivation, and that both dimensions are necessary for effective knowledge absorption [13, p. 591]. Reverse knowledge transfer, the flow of knowledge from subsidiaries to headquarters or across subsidiaries, has attracted growing research attention as scholars have recognized that subsidiaries in diverse national contexts can develop distinctive capabilities that represent sources of organizational learning for the broader MNE [14, pp. 295–297]. Structural and political barriers to reverse transfer remain significant, including headquarters inattention, subsidiary reluctance to share strategic competences, and formal knowledge systems designed for top-down rather than bottom-up flows [14, pp. 302–305].

The MNC as an interorganizational network, theorized by Ghoshal and Bartlett [15], emphasizes that headquarters-subsidiary relationships are complex webs of resource dependency, social capital, and reciprocal influence rather than simple hierarchical relationships. This network perspective implies that the introduction of AI-mediated knowledge systems into MNE networks is not politically neutral: depending on how such systems are governed, they may reinforce headquarters control, redistribute knowledge advantages across the network, or create new forms of institutional complexity [15, pp. 615–618].

Absorptive capacity, originally conceptualized by Cohen and Levinthal [6] as a firm's ability to recognize the value of new external information, assimilate it, and apply it to commercial ends, has been substantially reconceptualized and extended. Zahra and George [16] distinguished between potential absorptive capacity, comprising knowledge acquisition and assimilation, and realized absorptive capacity, comprising knowledge transformation and exploitation. This distinction has important practical implications: a unit may develop high potential absorptive capacity while underperforming on realized absorptive capacity [16, pp. 188–191].

Lane, Koka, and Pathak [17] conducted a critical review of absorptive capacity studies and identified significant reification risks: the construct has been operationalized in inconsistent ways, and the underlying processual logic of learning has often been treated as a black box. Their rejuvenation model emphasizes distinguishing among exploratory learning (recognizing and understanding new knowledge), transformative learning (assimilating and combining new knowledge with existing knowledge), and exploitative learning (using transformed knowledge to create value), each of which may be supported or impeded differently by AI agents [17, pp. 839–842].

Subsidiary capability development, the process through which foreign subsidiaries acquire, accumulate, and leverage distinctive organizational competencies, is closely linked to absorptive capacity but emphasizes the role of local embeddedness, learning from the host environment, and strategic initiative [18, pp. 775–778]. Birkinshaw and Hood [18] conceptualize subsidiary capability as the product of parent company assignment, host country environment, and subsidiary choice. The governance implication is significant: if AI agents are used primarily to transmit headquarters knowledge to subsidiaries, they may inadvertently suppress subsidiary initiative and local capability development by creating informational dependency rather than fostering autonomous learning.

The digital transformation of international business has introduced new mechanisms for cross-border coordination, knowledge sharing, and organizational learning. AI systems have shifted from narrow task-specific automation toward multi-functional knowledge platforms capable of synthesis, recommendation, translation, and contextual interpretation across diverse data types and organizational domains [19, pp. 7–10]. Haenlein and Kaplan [19] provide a conceptual history of AI that situates current AI capabilities within a trajectory from artificial narrow intelligence toward more integrated forms of machine-based cognition, while cautioning against exaggerating current AI capabilities in organizational settings.

The transition from AI as a technology toolkit to AI as an organizational actor embedded in workflows and decision processes is particularly significant for knowledge-intensive MNEs [20, pp. 64–65]. Fountaine, McCarthy, and Saleh [20] have documented how the successful deployment of AI in large organizations depends not primarily on technical factors but on organizational ones: the quality of data governance, alignment of AI initiatives with business strategy, redesign of workflows to enable human-AI collaboration, and cultivation of an organizational culture that supports AI-augmented decision-making [20, pp. 68–70]. The deployment of AI-based knowledge platforms centrally managed by headquarters raises questions about who controls the system, who determines relevance criteria for knowledge retrieval, and who benefits from AI-mediated knowledge flows.

The literature on human-AI collaboration has established a foundational argument for complementarity: AI systems excel at processing large volumes of structured data, identifying statistical patterns, reducing cognitive complexity, and maintaining consistency in routine judgment tasks, while humans contribute contextual intuition, ethical reasoning, relational intelligence, and interpretive flexibility in situations characterized by uncertainty and equivocality [7, pp. 579–582]. The concept of intelligence augmentation captures the design principle that AI systems should enhance rather than supplant human cognitive capabilities in organizational decision-making.

Effective human-agent teaming requires clear role allocation, mutual intelligibility of AI outputs for human collaborators, trust calibrated to the actual reliability of AI systems, and governance mechanisms that preserve human accountability while leveraging AI analytical power [7, p. 584]. In the knowledge management context, AI agents face distinctive challenges: knowledge work involves interpretive ambiguity, relational context, and situated judgment that resists reduction to pattern-matching processes on which current AI systems primarily rely [8, pp. 20–22]. The application of human-AI teaming concepts to cross-border knowledge transfer in MNEs has received very limited scholarly attention, representing one of the most consequential theoretical gaps addressed by the present article.

Trust in AI systems is multidimensional and context-dependent. Human trust in AI recommendations is shaped by prior experience, cognitive style, organizational culture, and the degree to which AI outputs are explainable and interpretable [8, pp. 20–22]. The explainability of AI outputs, the degree to which system reasoning can be communicated to and understood by human operators, is increasingly recognized as a governance prerequisite, particularly in high-stakes decision domains [21, p. 390]. Accountability in AI-mediated organizational processes raises novel governance challenges: assigning responsibility between human actors who used a recommendation and the organizational systems that produced it requires explicit governance arrangements [21, pp. 392–394]. Decision rights, the formal and informal authority to make knowledge-related judgments, must be clearly allocated between headquarters, subsidiaries, individual managers, and AI systems if accountability is to be maintained.

The governance of AI in organizational settings has moved from a primarily ethical and normative discourse toward a more operational and institutional focus [21, pp. 390–392]. The global landscape of AI ethics guidelines reveals broad convergence around core principles, transparency, justice and fairness, non-maleficence, responsibility, and privacy, while identifying significant variation in how these principles are operationalized and enforced across national and organizational contexts [21, p. 389]. For MNEs operating across multiple national regulatory environments, AI governance is complicated by the fragmentation of regulatory requirements. The organizational challenge of maintaining consistent responsible AI standards across heterogeneous institutional environments represents one of the most practically significant governance challenges facing globally operating organizations [22, pp. 997–1000].

Institutional theory applied to MNCs has established that the contextual embeddedness of organizational practices creates systematic barriers to their cross-border transfer [9, p. 312]. Kostova, Roth, and Dacin [22] argue that institutional theory in the MNC context must account for the institutional complexity faced by subsidiaries embedded simultaneously in multiple institutional fields, home country, host country, and the MNC organizational field, with potentially contradictory institutional demands [22, pp. 995–998]. Language diversity within MNEs shapes patterns of inclusion and exclusion in organizational knowledge processes, influences who has access to strategic information, and affects the perceived competence and status of non-native speakers of the corporate language [10, pp. 390–393].

The emergence of generative AI and large language model-based agents represents a qualitative shift in the organizational capabilities of AI systems for knowledge work. Unlike earlier AI applications that were primarily domain-specific and task-bounded, generative AI systems demonstrate capacity for natural language synthesis, cross-domain knowledge integration, multi-lingual translation, and contextual interpretation across diverse textual domains [23, pp. 3–6]. Alavi, Leidner, and Mousavi [23] examine these developments through a knowledge management lens, identifying transformative implications for each stage of the KM cycle while documenting significant risks including AI bias, marginalization of junior knowledge workers, and challenges in distinguishing AI-generated from human-originated knowledge [23, pp. 8–10].

AI agents with natural language capabilities can function as knowledge brokers that bridge language and cultural boundaries, synthesize knowledge from multilingual repositories, support the onboarding of employees in foreign subsidiaries, and assist in translating and adapting headquarters-developed frameworks for local contexts. However, the risk of AI hallucination, the generation of plausible but factually incorrect or contextually inappropriate content, is particularly consequential in cross-border knowledge work, where human validators in the receiving unit may lack the linguistic and contextual competence to identify AI errors in unfamiliar national and organizational contexts [23, pp. 8–10].

The foregoing analysis of ten research streams is synthesized in Table 1, which provides a structured comparison of theoretical contributions, research limitations, and implications for the conceptual framework.

Table 1.

Key Research Streams on Human-Agent Collaboration and Cross-Border Knowledge Flows

Research Stream	**Representative Sources**	**Main Theoretical Contribution**	**Relevance for the Article**	**Limitations**	**Implication for Framework**
Cross-border KT in MNEs	Szulanski [1]; Gupta & Govindarajan [5]; Michailova & Mustaffa [10]	Knowledge stickiness, causal ambiguity, relational barriers as transfer impediments	Establishes foundational barriers AI agents may reduce or exacerbate	Survey-based; limited digital infrastructure focus	AI as stickiness-reducing mechanism
Knowledge-based view and OL	Grant [3]; Nonaka [4]; Argote & Ingram [11]; Alavi & Leidner [12]	Knowledge as primary strategic resource; tacit-explicit spectrum; contextual embeddedness	Provides lens for assessing AI codification and translation functions	Static conceptualizations; underemphasizes relational dimensions	Codification capability and limits of AI agents
HQ-subsidiary flows and reverse KT	Gupta & Govindarajan [5]; Minbaeva et al. [13]; Ambos et al. [14]; Ghoshal & Bartlett [15]	Power dynamics, motivation, structural channels in intra-MNE flows	Situates AI deployment within HQ-subsidiary power context	HRM focus; limited AI context; survey limitations	AI as potential equalizer or reinforcer of HQ control
Absorptive capacity and subsidiary learning	Cohen & Levinthal [6]; Zahra & George [16]; Lane et al. [17]; Birkinshaw & Hood [18]	Potential vs. realized ACAP; exploratory, transformative, exploitative learning	AI may support potential ACAP while risking realized ACAP	Reification risk; inconsistent operationalization	Differential AI impact on ACAP dimensions

Digital transformation and AI in MNEs	Haenlein & Kaplan [19]; Fountaine et al. [20]; Dwivedi et al. [8]	AI organizational deployment; human-AI complementarity; organizational prerequisites	Documents organizational and cultural requirements for effective AI integration	Technology focus; limited IB context	Organizational readiness antecedents
Human-AI collaboration and teaming	Jarrahi [7]; Dwivedi et al. [8]	Intelligence augmentation; analytical vs. intuitive complementarity; trust calibration	Core conceptual building block for human-agent teaming in MNEs	Limited organizational context; single-country focus	AI augmentation of managerial judgment in cross-border processes
Trust, explainability, decision rights	Jobin et al. [21]; Dwivedi et al. [8]	Trust calibration; explainability requirements; accountability structures	Informs governance layer of the conceptual framework	Primarily normative; limited empirical MNE evidence	Trust and accountability governance mechanisms
AI governance and responsible AI	Jobin et al. [21]; Kostova et al. [22]	Ethics principles convergence; regulatory diversity; responsible AI operationalization	Contextualizes MNE AI governance challenges	Limited MNE-specific governance frameworks	Governance antecedents and outcome moderators
Cultural, institutional, linguistic barriers	Kostova [9]; Kostova et al. [22]; Michailova & Mustaffa [10]	Institutional distance; multilevel embeddedness; language as political resource	Identifies moderators of AI-agent effectiveness across national contexts	Limited AI context; normative emphasis	Cultural and institutional distance as moderators
Generative AI and knowledge work	Alavi et al. [23]; Dwivedi et al. [8]	Generative AI implications for KM cycle; risks of hallucination and marginalization	Most proximate literature to the article's focus	Very recent; limited empirical validation	Generative AI as cross-border knowledge agent

Source: developed by the author based on literature synthesis [1; 3–23].

The table reveals both the breadth and the fragmentation of the relevant literature. The streams addressing AI (streams 5, 6, 7, 8, and 10) are largely disconnected from the streams addressing MNE knowledge processes (streams 1, 2, 3, and 4). This disconnection reflects genuinely separate scholarly communities with different theoretical vocabularies, methodological traditions, and publication venues. The result is a body of literature in which AI in organizations is theorized without reference to the cross-border complexity of MNEs, and cross-border knowledge transfer is theorized without reference to the AI agents increasingly embedded in the relevant organizational processes.

The absorptive capacity stream is notable for its internal conceptual richness but its methodological limitations regarding the influence of digital intermediaries on learning processes. Lane, Koka, and Pathak [17] have identified that the processual logic of absorptive capacity, the sequence from exploratory to transformative to exploitative learning, is rarely examined in sufficient granularity in empirical studies. AI agents could theoretically intervene at each of these three sub-processes in distinct ways, yet the absorptive capacity literature has not yet engaged with this possibility.

The trust and governance streams provide normative and conceptual foundations for AI governance but lack integration with the organizational politics of MNE headquarters-subsidiary relationships. The table collectively reveals a set of critically understudied interactions: the effect of AI agent involvement on knowledge stickiness at different stages of the transfer process; the differential impact of AI intermediation on potential versus realized absorptive capacity; the governance of AI-mediated reverse knowledge transfer; and the implications of generative AI for the tacit-explicit knowledge spectrum in cross-border organizational contexts.

Synthesizing the research streams examined several interconnected and consequential gaps can be identified. The most fundamental gap is conceptual: AI agents are consistently framed in the existing literature as digital tools or technological artefacts rather than as organizationally embedded actors in knowledge processes. This framing forecloses theoretically important questions about the organizational roles, relational effects, and governance implications of AI agents in knowledge work. When an AI agent synthesizes dispersed knowledge from a multinational repository and presents a recommendation to a subsidiary manager in a different national context, the agent is performing an organizational function, knowledge mediation, with structural, political, and epistemic dimensions well beyond those captured by a purely technical framing.

The human-AI collaboration literature, while conceptually rich, is almost entirely disconnected from the theoretical frameworks of MNE theory and cross-border knowledge transfer research. The distinctive challenges of knowledge transfer in multinational contexts, institutional and cultural distance, headquarters-subsidiary power asymmetry, reverse transfer dynamics, subsidiary autonomy, and multilevel embeddedness of knowledge in nationally specific contexts, do not appear in the human-AI teaming literature. Conversely, the MNE literature's sophisticated understanding of knowledge barriers and organizational learning dynamics is rarely applied to the human-AI collaboration question.

The effect of AI agents on tacit knowledge transfer remains deeply unclear. Tacit knowledge, embedded in individual and collective practice, difficult to articulate, and transmitted primarily through experiential interaction and social learning [4, p. 16], represents both the most strategically valuable and the most transfer-resistant form of organizational knowledge. Whether AI codification of tacit knowledge increases or decreases its transferability across organizational and national boundaries is an unresolved empirical question with significant managerial implications.

The relationship between AI agent deployment and the two dimensions of absorptive capacity, potential and realized, is theoretically underdeveloped. It is plausible that AI agents enhance potential absorptive capacity by increasing the volume and diversity of new knowledge that subsidiary units can access and process. However, it is equally plausible that over-reliance on AI-mediated knowledge retrieval weakens realized absorptive capacity by substituting algorithmic synthesis for the genuine organizational learning processes through which knowledge is actually transformed and exploited [16, pp. 193–196].

The governance of decision rights in human-agent multinational teams is almost entirely undeveloped in the existing literature. Without explicit decision-right frameworks, organizations risk either accountability voids (where AI errors result in harm without assignable human responsibility) or excessive centralization (where headquarters control over AI systems translates into de facto control over subsidiary knowledge processes). Trust calibration across countries and subsidiaries is insufficiently studied in the context of AI-mediated knowledge work, and shadow AI use, the deployment of AI tools in ways that circumvent organizational governance structures, represents a growing risk that has received virtually no attention in the MNE literature. The present article contributes to the resolution of these gaps by developing a conceptual framework that integrates AI-agent roles, knowledge-transfer stages, absorptive capacity dynamics, trust and governance mechanisms, and MNE organizational context into a coherent analytical structure.

Purpose of the article. The aim of this article is to develop a conceptual and evidence-informed understanding of how human-agent collaboration reshapes cross-border knowledge transfer in multinational enterprises, with particular attention to knowledge-processing roles, coordination mechanisms, absorptive capacity, trust, decision rights, managerial accountability, and governance implications.

In pursuit of this aim, the following research tasks are addressed:

1. To systematize recent research on knowledge transfer, MNE coordination, and human-agent collaboration across ten identified research streams.
2. To clarify the organizational meaning of AI agents in multinational knowledge work, situating them as embedded organizational actors rather than neutral technical tools.
3. To identify how AI agents influence each of nine stages of cross-border knowledge transfer, from initial knowledge identification through to feedback and recombination.
4. To assess the differential implications of human-agent collaboration for tacit knowledge, for the potential versus realized dimensions of absorptive capacity, and for subsidiary learning.
5. To examine the effects of AI-mediated knowledge systems on headquarters-subsidiary power relations, including the risks of excessive centralization and the potential for supporting reverse knowledge transfer.
6. To analyze risks related to trust miscalibration, accountability ambiguity, algorithmic bias, over-standardization, and shadow AI use in cross-border knowledge work.
7. To develop a conceptual framework linking antecedents, human-agent collaboration mechanisms, knowledge-transfer processes, moderators, and organizational outcomes.
8. To provide an evidence-informed analysis of AI-enabled knowledge practices in MNE contexts based on secondary academic, corporate, and consulting sources.
9. To formulate managerial and governance recommendations for MNEs seeking to deploy AI agents responsibly in cross-border knowledge processes.

Presentation of the main research material. This article employs a qualitative conceptual research design combined with an evidence-informed secondary analysis. The choice of methodology reflects the early theoretical state of the research field: the integration of human-agent collaboration with MNE knowledge transfer theory is nascent, and the development of a conceptual framework represents an appropriate and necessary scholarly contribution before empirical testing is meaningful or feasible. Conceptual articles that develop theoretically grounded frameworks have a well-established tradition in international business and organizational scholarship, particularly at junctures where emerging phenomena challenge the adequacy of existing theoretical models.

The semi-systematic literature review was conducted across multiple databases including Scopus, Web of Science, and Google Scholar, using search terms combining knowledge transfer, multinational enterprise, absorptive capacity, AI governance, human-AI collaboration, knowledge management, organizational learning, and related variants. Source selection prioritized peer-reviewed articles in journals with high impact and theoretical relevance: the Journal of International Business Studies, Journal of World Business, International Business Review, Academy of Management Review, Organization Science, MIS Quarterly, Journal of the Association for Information Systems, Business Horizons, California Management Review, and Administrative Science Quarterly. Priority was assigned to publications from 2018 onward. Foundational theoretical sources published before 2018 were included where their theoretical contribution is essential and not superseded by more recent scholarship.

Inclusion criteria for scholarly sources required: publication in a peer-reviewed academic journal; clear relevance to at least one of the ten research streams; theoretical or empirical contribution beyond purely technical descriptions of AI systems; and availability in the English language. Secondary evidence from corporate reports, consulting studies, and institutional documents was treated as illustrative and contextualizing material rather than as primary empirical evidence. Such sources are distinguished from scholarly sources in the reference list and are presented with appropriate epistemic caution. Thematic synthesis followed an approach of initial descriptive coding of key themes, analytical grouping of thematically related findings, and development of higher-order theoretical constructs that cut across individual research streams. The primary limitation is the absence of primary empirical data and the consequent inability to test causal propositions.

Human-agent collaboration in MNEs is defined in this article as the organizationally embedded, knowledge-intensive interaction between human professionals and AI-enabled agents, software systems capable of processing, generating, and communicating knowledge-relevant outputs, in pursuit of organizational objectives related to knowledge creation, transfer, absorption, application, and recombination. This definition situates AI agents as organizational actors whose roles, responsibilities, and governance requirements derive from their organizational functions rather than from their technical architecture. The organizational embeddedness of AI agents means that their effects on knowledge processes cannot be understood in isolation from the organizational structures, power relations, cultural contexts, and governance arrangements within which they operate.

AI agents in MNE knowledge work perform multiple distinct organizational roles simultaneously. Seven primary roles can be identified. As knowledge intermediaries, AI agents connect knowledge sources with knowledge seekers across the MNE network, reducing search costs and increasing the discoverability of knowledge that would otherwise remain invisible to units in distant contexts. As translators and contextualizers, AI agents bridge linguistic and cultural gaps in cross-border knowledge communication, adapting tone, framing, and conceptual categories for different national and organizational audiences. As decision-support partners, AI agents present synthesized evidence, comparative analysis, and ranked recommendations to human decision-makers [7, p. 582]. As organizational memory systems, AI agents maintain and provide access to accumulated organizational knowledge in structured repositories, reducing the organizational cost of knowledge loss through employee turnover. As coordination assistants, AI agents support the synchronization of knowledge-intensive work across time zones, functional boundaries, and national contexts. As monitoring and governance mechanisms, AI agents track knowledge flows, identify deviations from governance protocols, and generate audit trails. As learning facilitators, AI agents identify knowledge gaps and support the development of absorptive capacity.

These roles are bounded by important organizational limitations. AI agents lack lived experience and cannot contribute the embodied, situationally grounded knowledge that emerges from direct engagement with organizational contexts and interpersonal relationships. Their contextual judgment is limited by the quality and scope of their training data and organizational data quality [23, pp. 5–7]. The risk of hallucination or contextual distortion is organizationally significant, particularly in cross-border settings where human validators may lack the local knowledge to identify AI errors. Most fundamentally, AI agents cannot assume moral or legal responsibility for the knowledge processes they mediate: responsibility remains with the human individuals and organizational structures that authorize, deploy, and use AI agents. Table 2 provides a structured analytical overview of AI-agent organizational roles.

Table 2.

Organizational Roles of AI Agents in Cross-Border Knowledge Work

AI-Agent Role	Knowledge-Transfer Function	Human Responsibility	Expected Benefit	Main Risk	Governance Requirement
Knowledge intermediary	Connects source and recipient units; reduces search friction	Validate relevance and contextual fit; authorize dissemination	Faster discovery of relevant knowledge across MNE network	Biased retrieval; surfacing irrelevant or low-quality knowledge	Quality standards for repositories; relevance oversight
Translator and contextualizer	Bridges linguistic and cultural gaps in knowledge communication	Verify accuracy; adapt culturally sensitive content	Broader accessibility across language communities	Mistranslation; cultural distortion; loss of nuance	Human expert review of AI-translated knowledge before dissemination
Decision-support partner	Synthesizes evidence; ranks knowledge options for decision-makers	Critical evaluation; judgment on context-specific fit	Improved decision quality; reduced cognitive overload	Over-trust; suppression of human judgment	Explainability requirements; audit of recommendations
Organizational memory system	Archives, retrieves, and presents accumulated knowledge	Curate; update; validate currency and accuracy	Reduced knowledge loss; scalable institutional memory	Perpetuation of outdated or biased knowledge	Version control; expiration protocols; access governance
Coordination assistant	Synchronizes knowledge-intensive work across units and time zones	Resolve conflicts; manage escalations; exercise relational judgment	Reduced coordination costs; more intensive knowledge exchange	Dependency on AI; erosion of interpersonal coordination	Human escalation protocols; override authority
Monitoring mechanism	Tracks knowledge flows; flags governance deviations; generates audit trails	Investigate anomalies; take corrective action	Enhanced governance visibility; compliance assurance	Surveillance excess; chilling effect on knowledge sharing	Proportionality rules; privacy protection; employee consent
Learning facilitator	Identifies knowledge	Validate learning	Accelerated capability	Reduced initiative;	Learning design

	gaps; recommends learning interventions	objectives; mentor; provide experiential context	development; targeted ACAP building	passive learning dependence	oversight; human mentorship complementarity

Source: developed by the author.

The table reveals that each AI-agent role carries both organizational benefits and governance risks, and that human responsibility remains central to the effective and ethical deployment of each role. Governance requirements vary by role: while knowledge intermediation requires primarily quality and relevance oversight, monitoring roles require careful attention to proportionality and privacy. Decision-support roles require explainability mechanisms to prevent the displacement of human judgment by algorithmic authority. Across all roles, the common governance imperative is the maintenance of clear human accountability structures that prevent the diffusion of responsibility into the AI system itself.

Cross-border knowledge transfer in MNEs is a multi-stage process, and the nature and significance of AI-agent involvement varies substantially across stages. Nine analytically distinct stages can be identified, each presenting characteristic challenges in the MNE context and each offering specific opportunities for AI support.

Knowledge identification involves recognizing that relevant knowledge exists and locating it within the MNE network. In large MNEs with hundreds of subsidiaries and thousands of organizational units, the identification problem is acute: valuable knowledge generated in one unit frequently remains invisible to units in other countries that could benefit from it. AI agents can perform continuous monitoring of organizational knowledge repositories, flag potentially relevant expertise, and recommend knowledge connections based on semantic similarity, substantially reducing the search costs associated with knowledge identification [12, pp. 112–114]. Human validation remains necessary to assess contextual fit. Governance risk: retrieval bias may systematically favor knowledge from high-profile or data-rich units, further marginalizing knowledge produced in smaller or less digitally mature subsidiaries.

Knowledge selection involves evaluating which identified knowledge is worth investing in for transfer. This stage requires substantive organizational judgment about strategic fit, resource requirements, and potential for local adaptation. AI agents can support selection by providing comparative analysis, surfacing analogous transfer cases, and estimating transfer difficulty based on characteristics of the knowledge and the receiving context. Human decision authority over selection must be maintained to prevent the algorithmic ossification of strategic priorities.

Knowledge codification transforms tacit or semi-tacit knowledge into forms communicable across organizational boundaries. AI agents with natural language capabilities can assist in drafting, structuring, and formatting organizational knowledge documents, procedural guides, and best-practice summaries. However, codification necessarily entails selection and simplification: the process of transforming experiential knowledge into explicit documentation strips it of contextual, relational, and affective dimensions that constitute much of its organizational value [4, pp. 18–20]. Human oversight of codification is essential to prevent the generation of codified knowledge that misrepresents its source, omits critical contextual caveats, or creates a false impression of completeness.

Knowledge translation and contextualization adapts codified knowledge for the linguistic, cultural, and organizational context of the receiving unit. This is where the capabilities of current AI systems, particularly large language model-based agents, have the most direct organizational applicability. AI agents can perform high-quality linguistic translation and adapt conceptual frameworks for different national cultural contexts, but they require human verification of cultural appropriateness, particularly for knowledge with significant normative or relational content [23, pp. 6–8].

Knowledge transmission delivers the adapted knowledge to the receiving unit. AI agents can manage the logistics of knowledge delivery, timing, format, channel selection, notification, but the effectiveness of transmission depends on the quality of the relationship between sender and receiver units, which AI cannot substitute [1, pp. 35–37]. Knowledge absorption at the receiving unit is the most fundamentally human stage: it requires active engagement, experimentation, social sense-making, and the integration of new knowledge with existing organizational routines and practices. AI agents can support potential absorptive capacity by ensuring that relevant knowledge is accessible and well-presented, but they cannot substitute for the organizational learning processes through which knowledge becomes genuinely integrated into practice [6, pp. 131–133].

Knowledge application involves deploying absorbed knowledge in local organizational processes and decision-making. AI agents can support application by providing decision-relevant synthesis and monitoring implementation, but local managers retain full accountability for application decisions and their consequences. Feedback and reverse knowledge transfer involves communicating experience-based learning from the applying unit back to the source. AI agents can facilitate feedback loops by monitoring performance indicators, documenting implementation experiences, and surfacing patterns across multiple subsidiary applications that would be invisible to headquarters analysts reviewing individual cases [14, pp. 298–300]. Finally, knowledge recombination and innovation involves combining transferred knowledge with local knowledge to generate novel organizational solutions, the most creative and context-dependent stage, requiring human cognitive synthesis, relational trust, and organizational creativity that AI agents can support but not replicate. Table 3 summarizes human-agent collaboration across all nine knowledge-transfer stages.

Table 3.

Human-Agent Collaboration Across Knowledge-Transfer Stages

KT Stage	**Traditional MNE Challenge**	**AI-Agent Contribution**	**Required Human Role**	**Risk of Misalignment**	**Possible Governance Control**
Knowledge identification	High search costs; invisible expertise; silo effects	Semantic search; expertise mapping; cross-unit connection recommendations	Validate contextual relevance; authorize sharing	Retrieval bias against smaller units	Repository quality standards; bias audits
Knowledge selection	Strategic complexity; uncertain transfer feasibility	Comparative case analysis; difficulty estimation; strategic alignment checking	Exercise final judgment; assess local strategic fit	Algorithmic perpetuation of historical biases	Human approval gating; escalation protocols
Knowledge codification	Tacit knowledge resistance; context loss; quality variation	Drafting support; structuring and formatting assistance	Verify completeness; preserve contextual nuance	Oversimplification; false impression of comprehensiveness	Human review of all codified outputs

Translation and contextualization	Language barriers; cultural misalignment; conceptual mismatch	High-quality linguistic translation; cultural adaptation	Verify cultural appropriateness; adjust for normative content	Culturally inappropriate framing	Native expert review; iterative validation
Knowledge transmission	Channel limitations; relationship quality variation	Logistics management; format optimization; targeted delivery	Manage sender-receiver relationship; motivate acceptance	Technology substituting for relationship	Communication governance protocols
Knowledge absorption	Insufficient ACAP; organizational inertia; motivation deficits	Accessible presentation; structured learning pathways	Active organizational engagement; sense-making; practice integration	Over-reliance reducing genuine learning	Human mentorship requirement; peer learning design
Knowledge application	Adaptation challenges; accountability ambiguity	Decision-support synthesis; implementation monitoring	Retain application accountability; contextual adaptation	AI dependency in adaptation decisions	Clear decision-right allocation
Feedback and reverse KT	HQ inattention; subsidiary reluctance; political barriers	Performance monitoring; experience documentation; pattern synthesis	Assess feedback quality; communicate reverse insights	HQ ignoring AI-surfaced subsidiary knowledge	Feedback governance structures; reverse transfer incentives
Recombination and innovation	Combinative integration; creative synthesis; capability limitations	Cross-unit pattern recognition; solution templates	Creative synthesis; relational knowledge integration	Algorithmic replication replacing innovation	Innovation governance; human-led recombination

Source: developed by the author based on literature synthesis [1; 4; 5; 6; 11; 14; 23].

Figure 1 illustrates the overall architecture of human-agent collaboration across the cross-border knowledge-transfer process.

Figure 1.

Human-Agent Collaboration Across the Cross-Border Knowledge-Transfer Process

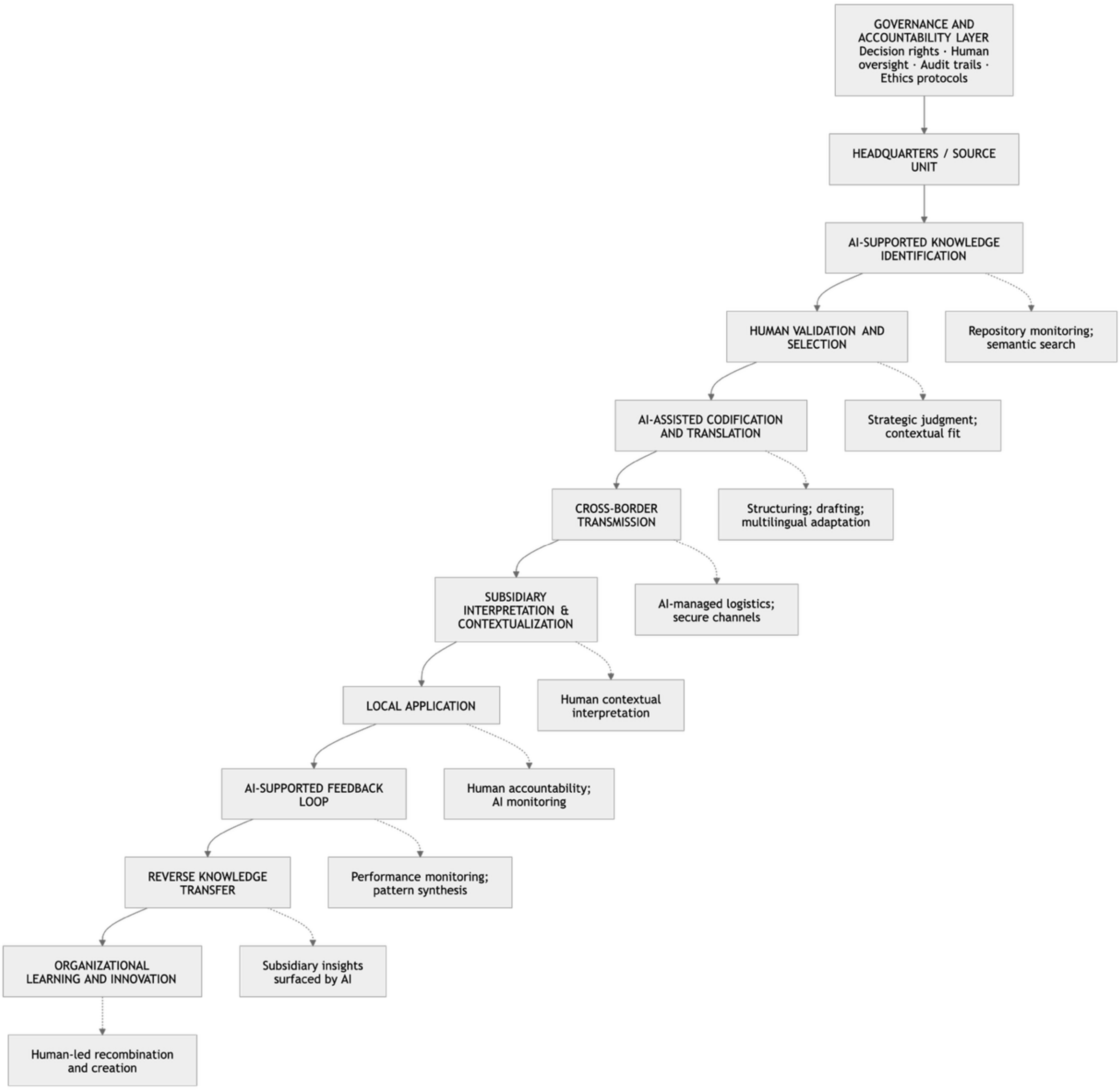

Figure 1. Human-Agent Collaboration Across the Cross-Border Knowledge-Transfer Process. Source: developed by the author.

Figure 1 illustrates the sequential logic of cross-border knowledge transfer as a human-agent collaborative process. Three structural features merit emphasis. First, human validation and decision authority appear at multiple points in the process, following AI-supported identification, at the codification and translation stage, at the point of local application, and in the interpretation of feedback, reflecting the principle that AI augments but does not supplant human judgment. Second, the governance and accountability layer extends across all stages, indicating that governance is not a terminal or post-hoc mechanism but a continuous structural requirement embedded in the architecture of the process itself. Third, the diagram visualizes the bidirectionality of knowledge flow: the process does not terminate at local application but continues through feedback and reverse transfer to organizational learning and innovation.

The governance layer encompasses decision rights, the formal allocation of authority to approve, validate, or override at each stage, as well as audit mechanisms, ethics protocols, and human oversight arrangements. Without this layer, the process risks becoming self-reinforcing in ways that perpetuate AI errors, organizational biases, or headquarters-centric power arrangements. The diagram also highlights that reverse knowledge transfer receives AI support through performance monitoring and pattern synthesis at the feedback stage, theoretically important because, if AI agents can make subsidiary-generated knowledge more visible to headquarters, they may partially offset the structural political barriers to reverse transfer documented in the MNE literature [14, pp. 300–304].

The absence of AI involvement at certain stages, particularly knowledge application and final organizational recombination, is deliberate and theoretically meaningful. It reflects the argument that the most creative and accountable stages of the knowledge-transfer process must remain fundamentally human-driven, with AI serving as a support mechanism rather than a principal decision-making actor.

The relationship between AI-agent involvement and tacit knowledge transfer is among the most consequential and theoretically complex dimensions of the present research question. Tacit knowledge, defined by Nonaka [4, pp. 16–18] as knowledge embedded in individual skill, intuition, and embodied practice that resists articulation and formal codification, represents both the most organizationally valuable and the most transfer-resistant knowledge in the MNE context. The knowledge-based view treats tacit knowledge as the principal source of durable competitive advantage precisely because its resistance to transfer prevents imitation [3, pp. 111–113].

AI agents can support the codification of tacit knowledge by identifying behavioral patterns in organizational data, documenting observable expert practices, and generating structured descriptions of complex processes. However, this support is bounded by a fundamental epistemological constraint: what can be captured in AI-processable data represents, at best, the explicable surface of expert practice, not the embodied, situationally sensitive, and relationally grounded dimensions of expertise that define genuine tacit knowledge [4, p. 19]. Codification through AI may produce detailed procedural documentation that captures the form of expert practice without capturing its substance, creating an illusion of knowledge transfer that may be more dangerous than acknowledged knowledge stickiness.

The implications for absorptive capacity are both enabling and constraining. AI agents can enhance potential absorptive capacity by increasing the volume, diversity, and accessibility of new knowledge that subsidiary units can encounter and process. Regular exposure to AI-curated knowledge feeds, structured learning recommendations, and synthesized knowledge summaries from across the MNE network can broaden the knowledge base from which subsidiaries can draw in assimilation and recombination processes [6, pp. 132–134]. However, if subsidiaries come to rely on AI-mediated knowledge synthesis as the primary mechanism for learning, their realized absorptive capacity may weaken over time as the muscles of independent knowledge seeking and organizational sense-making atrophy from disuse [16, pp. 193–196].

Subsidiary learning faces a distinctive tension in the AI-mediated knowledge context. On the one hand, AI agents can support local capability development by connecting subsidiary employees with relevant global knowledge and surfacing best practices from analogous organizational contexts. On the other hand, centrally managed AI knowledge systems may impose headquarters-centric relevance criteria on knowledge retrieval and presentation, effectively filtering out knowledge that challenges headquarters assumptions or reflects distinctively local insights [5, p. 484]. Reverse knowledge transfer, the flow of subsidiary-generated knowledge to headquarters, represents an area where AI support has particular promise, as AI agents with monitoring and pattern-synthesis capabilities could make subsidiary-generated knowledge more visible to headquarters [14, pp. 298–300]. However, the risk of surveillance, where AI monitoring of subsidiary practices creates an environment of heightened headquarters control, must be carefully managed to preserve the subsidiary autonomy and initiative that are preconditions for the generation of the distinctive local knowledge that makes reverse transfer valuable [18, pp. 776–779]. Human sensemaking remains irreplaceable: determining whether a particular practice from a distant subsidiary is genuinely transferable, potentially transformable, or fundamentally context-specific requires precisely the kind of embodied, contextually situated judgment that AI agents lack.

Trust in AI systems deployed in cross-border knowledge work is a multidimensional governance challenge that operates simultaneously at individual, organizational, and institutional levels. Trust calibration, the alignment of an individual's trust in AI outputs with the actual reliability of those outputs, is complicated by the opacity of current AI systems, variation in AI performance across different knowledge domains, and the cognitive mechanisms that lead humans to either overtrust consistent AI outputs or undertrust AI outputs that diverge from established expectations [8, pp. 22–24]. Overtrust is particularly dangerous in cross-border knowledge work, where AI systems may systematically underperform in national contexts underrepresented in their training data.

National-cultural dimensions of trust further complicate AI calibration in multinational settings. Cultural differences in attitudes toward uncertainty, authority, and institutional reliability shape the degree to which employees and managers are willing to trust AI recommendations in knowledge-relevant decisions. In cultural contexts characterized by high uncertainty avoidance, employees and managers may resist AI knowledge recommendations because their outputs are probabilistic and explainability-limited; in high-power-distance contexts, AI recommendations endorsed by senior management may receive uncritical acceptance regardless of their actual reliability [9, pp. 314–316].

Accountability in human-agent knowledge processes requires explicit governance architecture. The accountability gap that emerges when AI agents mediate knowledge transfer decisions, the ambiguity about whether responsibility for incorrect or harmful AI-mediated knowledge rests with human operators, system developers, or organizational deployers, represents one of the most consequential governance challenges in the responsible AI literature [21, pp. 392–394]. Decision rights must be distributed across at least five dimensions: the right to authorize AI deployment; the right to validate and override AI outputs at each stage; the right to determine governance parameters; the right to audit AI performance; and the right to suspend AI involvement in processes that raise governance concerns. Human veto rights, the formal authority of human actors to override AI recommendations at any stage, must be institutionalized through organizational policies that make clear the circumstances under which human override is expected, the process through which override decisions are documented, and the accountability structure governing post-override review. Table 4 summarizes risks and governance responses in human-agent knowledge transfer.

Table 4.

Risks and Governance Responses in Human-Agent Knowledge Transfer

Risk Category	**Description in MNE Context**	**Effect on Knowledge Transfer**	**Governance Response**	**Responsible Actor**	**Suggested Performance Indicator**
Knowledge distortion	AI misrepresents or reframes knowledge during codification or translation	Transmission of inaccurate knowledge; harmful operational decisions in receiving unit	Multi-stage human review; explainability requirements; validation protocols	Knowledge governance officer; subsidiary manager	Rate of validated knowledge revisions per transfer cycle
Loss of tacit context	Codification removes contextual and relational dimensions	Diminished knowledge value at receiving unit; inability	Human expert involvement in codification; contextual	Subject-matter expert; HR and learning function	Receiving unit application success rate; absorption quality surveys

	of expert knowledge	to apply effectively	annotation requirements		
Algorithmic bias	AI retrieval systematically favors certain units, languages, or perspectives	Marginalization of peripheral subsidiary knowledge; reinforcement of HQ-centric flows	Bias auditing; diverse training data; equity review processes	AI governance board; headquarters IT; D&I function	Representation of subsidiary-origin knowledge in AI-surfaced outputs
Over-standardization	AI imposes uniform knowledge formats ignoring local institutional requirements	Reduced relevance of transferred knowledge; subsidiary resistance; compliance risk	Local adaptation protocols; flexibility parameters in AI systems	Regional knowledge managers; subsidiary teams	Adaptation requests per transfer; local compliance audit outcomes
Excessive HQ control	HQ uses AI systems to centralize knowledge governance and monitor subsidiaries	Erosion of subsidiary autonomy; reduced innovation; reverse transfer suppression	Distributed decision-right frameworks; subsidiary AI governance participation	Board of directors; regional management	Subsidiary autonomy index; reverse transfer volume
Subsidiary resistance	Subsidiaries reject AI-mediated knowledge or circumvent governance structures	Incomplete absorption; shadow AI use; governance gaps	Co-design of AI governance with subsidiaries; local adaptation rights	Regional directors; change management function	Uptake rates; reported governance deviations
Accountability ambiguity	Unclear responsibility when AI-mediated knowledge causes harm	Organizational inertia in corrective response; legal exposure; trust erosion	Explicit decision-right documentation; human veto protocols; audit trails	Legal and compliance; AI governance board	Mean time to assign accountability for AI errors; audit completeness
Data confidentiality risk	AI processing of sensitive knowledge creates regulatory	Reputational damage; regulatory fines; knowledge security compromise	Data classification systems; access controls; jurisdictional compliance	CISO; data protection officer	Number of unauthorized access incidents; data breach response time

	or security exposure				
Regulatory non-compliance	AI deployment breaches national AI regulations in subsidiary jurisdictions	Regulatory sanctions; operational interruption; reputation damage	Jurisdictional compliance mapping; legal review of AI deployments	Chief compliance officer; legal function	Regulatory violation rate; compliance certification coverage
Shadow AI use	Employees use unauthorized AI tools outside governance structures	Loss of organizational knowledge visibility; confidentiality breaches; governance gaps	Employee AI literacy programs; clear acceptable-use policies; channel provision	CHRO; line managers; IT governance	Reported unauthorized AI tool use; policy acknowledgment rates
Trust miscalibration	Employees over-trust or under-trust AI knowledge outputs across cultural contexts	Inconsistent knowledge absorption; biased decision-making; cultural adoption gaps	Calibration training; cultural trust adaptation programs; explainability enhancement	HR and learning function; AI ethics function	Trust calibration survey scores; cross-unit absorption variation
Weakening of human expertise	Over-reliance on AI reduces human knowledge-seeking and judgment capabilities	Long-term absorptive capacity decline; organizational fragility	Skill preservation requirements; AI-free zones in learning; mentorship mandates	CHRO; HR business partners; knowledge managers	Proportion of AI-unassisted knowledge tasks; employee capability assessments

Source: developed by the author based on literature synthesis [1; 5; 6; 7; 21; 22].

The governance responses detailed in Table 4 reflect a consistent architectural principle: for each risk category, the primary governance response involves human oversight, organizational policy design, and accountability assignment rather than purely technical AI fixes. This principle, that AI governance is fundamentally an organizational and managerial challenge rather than a technical one, is a central contribution of the present article. The suggested performance indicators provide operational anchors for governance assessment, enabling organizations to track governance effectiveness over time without relying exclusively on post-hoc incident analysis. The twelve risk categories documented in the table represent a comprehensive risk taxonomy for AI-mediated cross-border knowledge work, extending existing responsible AI frameworks [21] to the specific organizational and institutional context of the MNE.

The deployment of AI agents in cross-border knowledge processes within large MNEs is sufficiently documented in secondary sources to permit evidence-informed, cautiously interpreted analysis. The following discussion draws on consulting reports, corporate documentation, and academic case evidence to illustrate the organizational patterns identified in the preceding conceptual sections. All quantitative claims are appropriately qualified as reported or estimated rather than empirically established. Do not interpret the examples below as systematic empirical evidence; rather, they are illustrative of organizational patterns consistent with the theoretical analysis.

McKinsey's annual survey of AI adoption in enterprises [24] suggests that a substantial and growing proportion of large organizations globally are deploying AI in at least one business function, with knowledge management, HR and talent management, and product development among the most commonly cited domains. The survey data indicates that organizations in sectors characterized by high knowledge intensity, professional services, pharmaceutical, technology, and financial services, report the highest rates of AI deployment in knowledge-intensive functions. The survey also notes that realizing value from AI investment is consistently reported as more challenging than the initial deployment, with organizational change management, data governance, and talent capability identified as the primary limiting factors [24]. These findings align with the theoretical argument developed in this article: effective human-agent collaboration requires organizational preparation, not merely technological deployment.

OECD guidance on responsible AI [25] establishes five core principles, inclusive growth and sustainability; human-centered values and fairness; transparency and explainability; robustness, security, and safety; and accountability, that provide a normative foundation for MNE AI governance across national regulatory contexts. These principles have direct organizational implementation implications for MNEs: they require governance architectures that maintain human oversight, provide for audit and review, and ensure that AI systems serve broad human interests. The OECD principles are particularly relevant to cross-border knowledge work because they emphasize that accountability and transparency requirements must extend across jurisdictional boundaries [25].

The EU AI Act [26] introduces a risk-based classification of AI applications with specific implications for MNEs operating in European markets. Systems used in employment-related processes, including HR management, training, learning, and capability assessment, are classified as high-risk applications subject to mandatory transparency, human oversight, and documentation requirements. For MNEs with significant European operations, this regulatory framework creates concrete governance obligations for AI agents deployed in cross-border knowledge and learning systems, including the requirement to maintain detailed technical documentation, conduct conformity assessments, and ensure that high-risk AI systems are subject to effective human oversight mechanisms [26]. The regulatory fragmentation between the EU's prescriptive approach and more permissive frameworks in other major jurisdictions creates a compliance challenge for globally operating MNEs.

In the technology sector, multinational firms have documented the deployment of AI-based internal knowledge management platforms that serve global developer communities across dozens of national offices [20, pp. 67–69]. These platforms illustrate patterns consistent with the theoretical analysis: they support knowledge identification and retrieval at scale, reduce the effort required for subsidiary teams to access global best practices, and enable more consistent onboarding of new employees in geographically dispersed offices. However, reported challenges include the difficulty of capturing tacit knowledge from senior practitioners, the tendency for AI retrieval systems to surface well-documented but potentially outdated explicit knowledge in preference to more current but less formally documented expertise, and the risk that standardized knowledge platforms marginalize context-specific adaptations developed by national teams.

In the pharmaceutical sector, cross-border clinical knowledge flows represent a domain where AI-supported knowledge management has particular organizational relevance [23, pp. 9–10]. Pharmaceutical MNEs managing regulatory submissions, clinical trial knowledge, and pharmacovigilance data across multiple national jurisdictions face intense knowledge transfer challenges related to the tacit-explicit spectrum, regulatory diversity, and the high stakes of knowledge errors. AI agents in this context can support the codification of regulatory knowledge and facilitate cross-country comparison of compliance requirements. However, these functions operate under stringent human oversight requirements embedded in pharmaceutical regulatory frameworks, which provide an instructive governance model: the regulatory mandate for human expert validation of all knowledge submitted to national authorities creates a natural governance structure that prevents the over-displacement of human expertise by AI systems. Table 5 provides a structured overview of illustrative AI-enabled knowledge practices in MNE contexts, drawing on secondary evidence sources.

Table 5.

Illustrative Evidence of AI-Enabled Knowledge Practices in Multinational Enterprises

Organization / Sector / Context	**AI-Supported Knowledge Activity**	**Cross-Border KT Function**	**Human-Agent Collaboration Pattern**	**Reported or Expected Benefit**	**Limitation or Risk**	**Source**
Technology sector MNEs (global)	AI-based internal developer knowledge platforms	Knowledge identification and retrieval across global R&D and engineering teams	AI surfaces relevant documentation; human engineers validate and apply	Suggests reduced onboarding time; faster access to global best practice	Tendency to surface explicit over tacit knowledge; context loss risk	[20; 24]
Pharmaceutical MNEs (EU, US, Asia-Pacific)	AI-assisted regulatory knowledge management across national jurisdictions	Translation and adaptation of clinical and regulatory knowledge for national submissions	AI drafts and adapts; regulatory affairs professionals validate against national requirements	May support compliance consistency; reduces manual translation effort	High hallucination risk in high-stakes regulatory content; mandatory human review required	[23; 26]
Professional services MNEs (global)	AI-enabled expertise matching and knowledge repository search	Knowledge intermediation across global office networks	AI recommends relevant expertise and precedents; human professionals select and apply	Appears to improve cross-office knowledge utilization; faster expertise location	Risk of over-standardization; bias toward well-documented large-office knowledge	[20; 24]
Multinational HR and talent management	AI learning platforms for employee development across global	Knowledge transfer in capability building and onboarding	AI recommends learning pathways; HR professionals oversee	Suggests improved learning efficiency; broader access to global	Risk of weakening mentorship; cultural inappropriateness of	[8; 24]

	subsidiaries		and personalize	learning resources	standardized content	
Manufacturing sector MNEs	AI-supported quality management and process knowledge sharing across plants	Cross-plant transfer of quality standards and operational procedures	AI documents and transmits process knowledge; plant managers adapt and validate locally	May improve quality consistency across geographically dispersed plants	Loss of plant-specific tacit knowledge; resistance from experienced operators	[23; 24]
Global compliance and risk management	AI-assisted monitoring and documentation of compliance knowledge flows	Cross-border regulatory knowledge transfer; multi-jurisdictional compliance coordination	AI monitors and synthesizes regulatory changes; compliance officers review and implement	Appears to reduce compliance risk exposure; supports regulatory intelligence	Regulatory diversity requires extensive human customization of AI outputs	[25; 26]
Cross-border digital service firms	Generative AI for multilingual knowledge translation and customer knowledge bases	Linguistic and cultural knowledge transfer across national market operations	AI translates and contextualizes; human subject-matter experts verify and adapt	Suggests improved accessibility of knowledge in multilingual contexts	Hallucination in technical or culturally sensitive content; quality variance by language	[23; 27]

Source: developed by the author based on secondary evidence analysis [8; 20; 23; 24; 25; 26; 27].

The evidence reviewed in this section consistently indicates that AI agents contribute most reliably to the logistical and structural dimensions of cross-border knowledge work, search, retrieval, formatting, delivery management, and monitoring, while requiring the most intensive human oversight at the interpretive and contextual dimensions, validation, adaptation, application, and sense-making. This pattern aligns closely with the theoretical framework developed in this article and with the argument advanced by Jarrahi [7] regarding the complementarity of human and AI capabilities in organizational decision-making. It also underscores the imperative of maintaining robust human expertise and governance structures as AI deployment in knowledge processes deepens: the organizational value of AI agents is contingent on the quality of the human judgment that operates alongside them.

Drawing on the theoretical analysis and evidence-informed discussion presented in the preceding subsections, a comprehensive conceptual framework is developed to explain how human-agent collaboration affects cross-border knowledge-transfer outcomes in multinational enterprises. The framework integrates five categories of constructs: antecedents, human-agent collaboration mechanisms, knowledge-transfer processes, moderators, and outcomes. It is designed to be theoretically testable, empirically operationalizable, and practically actionable.

Antecedents are the organizational and contextual conditions that determine the effectiveness with which human-agent collaboration can be deployed in cross-border knowledge work. Eight antecedent constructs are identified: AI readiness (the organization's technical infrastructure, data quality, and deployment capability); data governance quality (the clarity, completeness, and consistency of organizational data available for AI processing); digital maturity (the broader digital transformation trajectory of the organization); organizational culture (the degree to which the organizational culture supports experimentation, trust, and learning); trust climate (the prevailing level of inter-unit trust within the MNE network); subsidiary capabilities (the absorptive capacity and learning infrastructure of individual subsidiaries); headquarters-subsidiary relationship quality (the degree of reciprocal respect, open communication, and strategic alignment between corporate center and national units); and responsible AI maturity (the organization's experience and institutional capacity for governance, accountability, and ethical AI deployment).

Human-agent collaboration mechanisms, the core mediating constructs of the framework, are the specific ways in which AI agents and human professionals interact in cross-border knowledge work. Nine mechanisms are identified: augmentation (AI enhancing human analytical capacity without replacing judgment); mediation (AI serving as an intermediary between knowledge sources and recipients); translation (AI enabling cross-linguistic and cross-cultural knowledge communication); codification (AI supporting the transformation of tacit and experiential knowledge into transferable explicit form); recommendation (AI proposing knowledge transfer options for human selection); monitoring (AI tracking knowledge flows and governance compliance); feedback support (AI enabling structured reverse knowledge communication from recipient to source); learning support (AI facilitating capability development at receiving units); and contextualization (AI adapting knowledge for specific receiving unit contexts).

Knowledge-transfer processes are the sequential organizational activities through which knowledge moves from source to recipient within the MNE. These correspond to the nine stages constitute the core operative processes of the framework. Moderators are the contextual variables that amplify or attenuate the relationship between human-agent collaboration mechanisms and knowledge-transfer outcomes. Eight moderators are identified: cultural distance (the degree of cultural difference between source and receiving units); institutional distance (the degree of regulatory, cognitive, and normative difference between operating environments); linguistic distance (the degree of linguistic difference affecting translation and interpretation quality); knowledge tacitness (the degree to which the knowledge being transferred is context-bound and resistant to codification); regulatory environment (the national and supranational regulatory framework governing AI use in the receiving context); headquarters-subsidiary power balance (the degree of structural power parity versus asymmetry between the two units); subsidiary autonomy (the degree of strategic independence available to the subsidiary); and data quality (the accuracy, completeness, and currency of the organizational data on which AI systems operate).

Outcomes are the results of the knowledge-transfer process, shaped by the interaction between collaboration mechanisms and moderating conditions. Nine outcome constructs are identified: transfer speed (the time required to complete the knowledge-transfer cycle); knowledge quality (the accuracy, relevance, and applicability of transferred knowledge); learning effectiveness (the degree to which transferred knowledge is genuinely absorbed and applied); coordination efficiency (the reduction in coordination costs achieved through AI support); innovation (the generation of novel organizational solutions through knowledge recombination); subsidiary capability development (the enhancement of local absorptive capacity and strategic competence); reverse knowledge transfer (the flow of subsidiary-generated insights back to the MNE network); governance risk (the exposure to accountability, bias, and compliance failures); and accountability clarity (the degree to which responsibility for knowledge decisions is clearly assigned). Figure 2 presents the conceptual framework in diagrammatic form.

The framework advances the argument that the relationship between human-agent collaboration and knowledge-transfer outcomes is not direct but mediated by specific collaboration mechanisms and moderated by organizational, cultural, institutional, and epistemic contextual factors. This design reflects the theoretical insight that AI agents are not uniformly effective across all knowledge types, organizational contexts, and national environments: their contribution to knowledge-transfer outcomes depends critically on the conditions under which they are deployed, the mechanisms through which they interact with human collaborators, and the governance structures that shape their operation.

The antecedents block reflects the argument, consistent with Fountaine, McCarthy, and Saleh [20], that AI effectiveness in organizational settings is primarily determined by organizational prerequisites rather than technical factors. AI readiness and data governance quality are particularly significant for cross-border knowledge work, as the performance of AI agents in multilingual, multi-institutional environments depends fundamentally on the completeness and quality of the underlying data. Responsible AI maturity is included as a distinct antecedent because organizations that have invested in governance capacity for ethical AI deployment are better positioned to realize the benefits of human-agent collaboration while managing its risks.

The moderators block captures the boundary conditions of the framework, the conditions under which the hypothesized relationships are expected to hold, weaken, or reverse. Cultural and institutional distance are theorized as amplifying governance risks while constraining translation and contextualization effectiveness; high knowledge tacitness is expected to reduce the effectiveness of AI codification mechanisms while increasing the importance of human judgment at transfer stages; high subsidiary autonomy is expected to moderate the risk of over-standardization and HQ control concentration; and data quality directly moderates the reliability of all AI-mediated mechanisms. The feedback loops indicated at the base of the diagram reflect the theoretical assumption that knowledge-transfer outcomes feed back into antecedent conditions over time: successful transfers build trust climate, enhance subsidiary capabilities, and improve the HQ-subsidiary relationship quality that constitutes the organizational foundation for subsequent rounds of AI-mediated knowledge work.

The framework is designed to generate theoretically derived propositions suitable for empirical testing in future research. For example: propositions relating AI readiness and data governance quality to collaboration mechanism effectiveness; propositions relating cultural and institutional distance to the moderation of translation mechanism outcomes; propositions relating subsidiary autonomy to the mitigation of over-standardization risks; and propositions relating responsible AI maturity to governance risk outcomes. Future empirical work using survey instruments, multi-case comparative designs, or longitudinal organizational studies could operationalize these constructs and test the proposed relationships.

Figure 2.

Conceptual Framework of Human-Agent Collaboration and Cross-Border Knowledge Transfer in MNEs

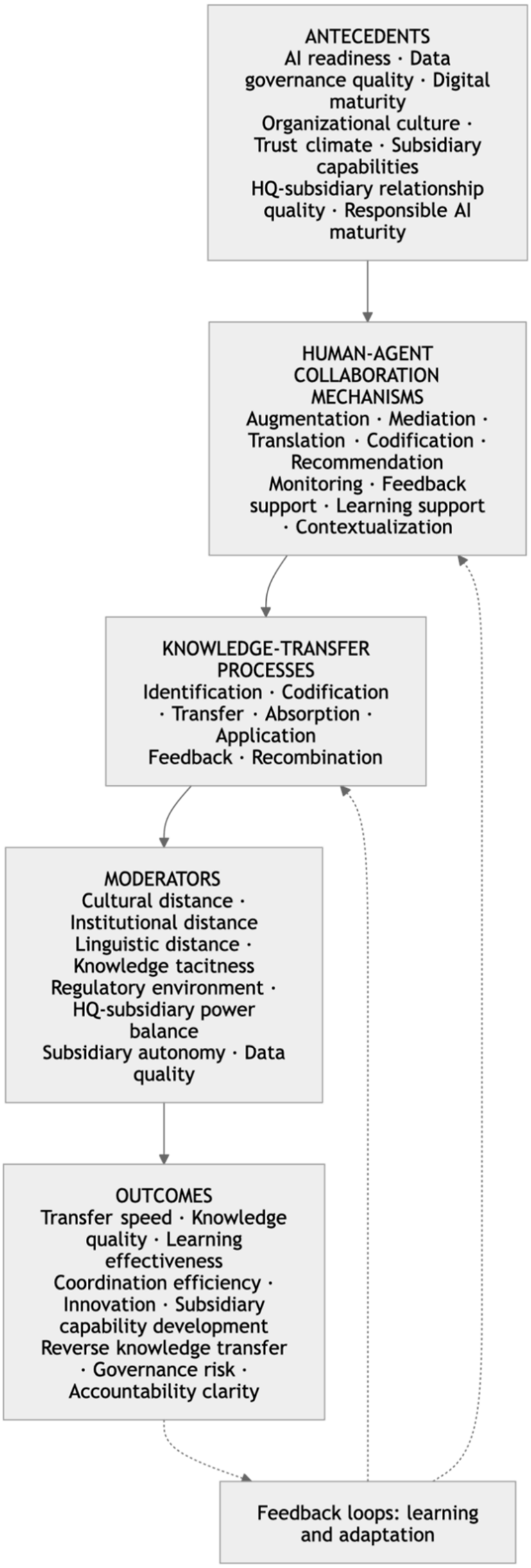

Figure 2. Conceptual Framework of Human-Agent Collaboration and Cross-Border Knowledge Transfer in MNEs.
Source: developed by the author based on literature synthesis [1; 3; 4; 5; 6; 7; 9; 16; 21].

The conceptual framework and analysis presented in this article make theoretical contributions to six scholarly domains, each of which is examined in this section.

First, the article extends the knowledge-based view of the firm [3] by introducing AI agents as a new class of organizational actor in the knowledge-coordination processes that define the MNE's existence and competitive advantage. The KBV explains why firms exist as coordinators of specialized knowledge and why MNEs are superior coordinators across national boundaries

[2, pp. 627–630]. This article extends this logic by showing that AI agents alter the micro-mechanisms of knowledge coordination, reducing search costs, enabling cross-language synthesis, and providing new forms of organizational memory, while introducing new coordination risks that require explicitly designed governance mechanisms. The extension is significant because it challenges the implicit assumption in the KBV that knowledge coordination is a human activity, and proposes instead that it is an increasingly hybridized human-agent process with distinctive governance requirements.

Second, the article contributes to multinational enterprise theory by providing the first systematic theoretical framework connecting AI-agent organizational roles to the structural dynamics of headquarters-subsidiary relationships. The analysis shows that AI agents are not organizational-power-neutral: their governance architecture has direct implications for the balance of knowledge control between headquarters and subsidiaries, the direction and intensity of knowledge flows in the MNE network, and the organizational conditions under which reverse knowledge transfer can thrive [5; 14; 15]. This contribution addresses the gap in MNE theory identified by Ghoshal and Bartlett [15] regarding the need for more nuanced theorization of the mechanisms through which MNE network coordination operates.

Third, the article advances organizational learning theory by distinguishing the differential impacts of AI agents on potential and realized absorptive capacity. Building on Zahra and George's [16] distinction, the analysis demonstrates that AI agents may simultaneously enhance potential absorptive capacity (by improving access and assimilation of new knowledge) while creating risks for realized absorptive capacity (through dependency and over-standardization effects). This contribution has particular significance for the micro-foundations of organizational learning: it suggests that the organizational benefits of AI-augmented knowledge access depend critically on the preservation of the human learning processes, exploration, transformation, and exploitation, through which knowledge becomes genuinely integrated into organizational practice.

Fourth, the article extends absorptive capacity theory by identifying AI readiness and responsible AI maturity as antecedent conditions that shape the organization's capacity to leverage AI agents in knowledge absorption processes. This extension moves beyond the HRM-centric operationalizations of absorptive capacity in the MNE literature [13] toward a broader conception that incorporates digital infrastructure and governance capacity as determinants of learning effectiveness in the AI-augmented organizational context.

Fifth, the article contributes to human-AI collaboration research by providing an MNE-specific theoretical context that has been absent from this literature. The analysis of how cultural, institutional, and organizational dimensions of the multinational context moderate the effectiveness of human-agent teaming mechanisms significantly extends the relatively context-neutral human-AI collaboration models in the existing literature [7; 8]. The framework's moderator constructs, cultural distance, institutional distance, HQ-subsidiary power balance, subsidiary autonomy, are specifically designed to capture the distinctive complexity of the multinational context.

Sixth, the article advances AI governance research by developing a governance framework that is simultaneously grounded in responsible AI principles [21] and in the specific organizational realities of MNEs, including regulatory fragmentation, cross-cultural trust variation, headquarters-subsidiary power dynamics, and the political economy of knowledge sharing. This contribution addresses the observation by Kostova, Roth, and Dacin [22] that institutional theory in the MNC context must engage with the multilevel institutional complexity experienced by globally operating organizations. The twelve risk categories and governance responses in Table 4, together with the governance performance indicators, provide operationalizable governance guidance extending well beyond the normative-principled approach characteristic of current responsible AI guidelines.

The conceptual framework and analysis developed in this article generate a set of substantive managerial recommendations for MNE leaders concerned with governing human-agent collaboration in cross-border knowledge processes. These recommendations address the governance architecture required for responsible and effective AI deployment, the preservation of human expertise and organizational learning capabilities, and the management of the distinctive risks identified in the preceding sections.

Headquarters leaders should resist the organizational temptation to use AI-mediated knowledge systems as instruments of centralized control. The governance architecture of AI knowledge platforms, the parameters that determine what knowledge is retrieved, how it is ranked, and what filters are applied, constitutes, in effect, a knowledge policy for the MNE. If this architecture is designed and controlled exclusively from the center without meaningful subsidiary participation, it will reproduce and amplify the structural biases in knowledge flow direction that existing MNE research has documented [5, pp. 482–484]. Effective governance requires the co-design of AI system parameters with subsidiary teams, the inclusion of subsidiary-perspective validity criteria in knowledge quality standards, and the active use of AI feedback mechanisms to surface subsidiary-generated knowledge for headquarters attention.

Decision right allocation in human-agent knowledge systems requires explicit organizational policy rather than emergent informal practice. Organizations that allow decision rights to evolve without formal design risk creating accountability voids and trust deficits that undermine both the effectiveness and the governance integrity of AI-mediated knowledge processes [21, pp. 392–394]. Recommended practice involves creating tiered decision-right frameworks that specify, for each knowledge-transfer stage: which decisions are delegated to AI agents; which require human validation; which require managerial approval; and which are subject to formal escalation protocols.

The protection of tacit knowledge and human expertise is a governance imperative, not merely a cultural preference. Over time, organizations that over-rely on AI knowledge intermediation risk eroding the human expertise, professional judgment, and interpersonal knowledge-sharing networks that constitute their most durable competitive advantages. Governance mechanisms should mandate preserved human expertise zones in critical knowledge domains, areas where AI support is permitted but human capability development is actively required and assessed, alongside AI-free learning experiences and mentorship structures that maintain the social transmission of tacit knowledge. Table 6 provides a structured set of managerial recommendations for governing human-agent collaboration in cross-border knowledge work.

Table 6.

Managerial Recommendations for Governing Human-Agent Collaboration in Cross-Border Knowledge Work

Governance Area	**Recommended Action**	**Expected Contribution to KT**	**Implementation Challenge**	**Responsible Actor**	**Performance Indicator**
Decision-right allocation	Develop tiered decision-right frameworks specifying AI authority, human validation requirements, and escalation	Prevents accountability voids; ensures human oversight at critical decision points	Requires organizational policy design and multi-level buy-in	Knowledge governance board; legal and compliance	Proportion of KT stages with documented decision-right policies; accountability resolution time

	protocols for each KT stage				
HQ-subsidiary AI governance co-design	Include subsidiary representatives in design of AI knowledge system parameters, relevance criteria, and governance protocols	Reduces HQ control bias; improves relevance for local contexts; supports reverse KT	Coordination costs; HQ resistance to sharing governance authority	Regional management; AI governance board	Subsidiary representation in governance bodies; volume of subsidiary-surfaced knowledge
Tacit knowledge and human expertise protection	Mandate preserved human expertise zones; require AI-free mentorship activities; build expert networks alongside AI platforms	Maintains realized absorptive capacity; preserves long-term KT effectiveness	Requires management commitment; may conflict with efficiency pressures	CHRO; knowledge managers; organizational development	Mentorship participation rates; human expert competency assessments
Trust calibration and AI literacy	Develop cross-cultural AI literacy programs; adapt trust calibration training to national cultural contexts	Reduces over-trust and under-trust risks; improves quality of human-AI teaming	Cultural adaptation of training materials; multilingual delivery	HR and learning function; regional HR business partners	AI literacy scores; trust calibration survey results by subsidiary
Shadow AI governance	Develop clear and proportionate AI acceptable-use policies; provide official AI tools that meet employee needs; create safe reporting channels	Reduces unmonitored AI use; maintains governance visibility; prevents data confidentiality breaches	Risk of overly restrictive policies creating additional shadow AI; requires ongoing policy review	IT governance; CHRO; compliance	Reported unauthorized AI tool use; policy awareness rates; incident rates
Regulatory compliance mapping	Conduct jurisdictional AI regulatory	Prevents regulatory exposure;	Regulatory fragmentation; rapidly	Chief compliance officer;	Compliance audit scores; regulatory

	compliance mapping; integrate EU AI Act requirements for high-risk applications; maintain compliance documentation	supports responsible AI governance globally	evolving legal landscape	legal; regional regulatory affairs	violation incidents; coverage of jurisdictional requirements
Reverse knowledge transfer incentives	Design AI systems to actively surface and present subsidiary knowledge to headquarters; establish incentive structures rewarding reverse KT	Balances knowledge flow direction; improves MNE-wide learning; supports subsidiary autonomy	HQ inattention; subsidiary reluctance; political barriers	Regional management; knowledge governance board	Volume and quality of reverse KT flows; headquarters utilization of subsidiary knowledge
Auditability and traceability	Require complete audit trails for AI-mediated knowledge transfer decisions; establish periodic governance reviews	Supports accountability; enables learning from AI errors; demonstrates regulatory compliance	Technical infrastructure requirements; data management complexity	AI governance board; internal audit; legal	Audit trail completeness; governance review frequency; corrective action rates
Data governance for AI	Invest in cross-border data quality, completeness, and interoperability; establish data governance standards for all knowledge repositories used by AI agents	Improves reliability of AI-mediated knowledge; reduces hallucination and distortion risk	High investment requirements; organizational coordination across units	Chief data officer; IT; regional operations	Data quality scores; AI output accuracy rates; correction frequencies
Cross-cultural	Adapt AI governance	Improves governance	Requires deep cross-cultural	Regional HR;	Governance acceptance

governance adaptation	frameworks and communication approaches to national cultural and institutional contexts of individual subsidiaries	effectiveness and legitimacy across diverse contexts	competence; may increase complexity	organizational development; diversity and inclusion	surveys by subsidiary; cultural appropriateness assessments

Source: developed by the author based on literature synthesis and secondary evidence analysis [1; 5; 7; 14; 20; 21; 24; 25; 26].

The ten governance domains in Table 6 reflect a common organizing principle: effective governance of human-agent collaboration in cross-border knowledge work requires organizational investment in people, process design, and governance structures at least as significant as investment in the AI technologies themselves. This principle is consistent with the evidence-informed analysis, which indicates that the gap between AI deployment and AI value realization is predominantly organizational rather than technological in character [20; 24]. The performance indicators proposed for each governance domain provide MNE leaders with operational measurement frameworks that can be adapted to specific organizational contexts and monitoring requirements.

Conclusion. This article has developed a conceptual and evidence-informed understanding of how human-agent collaboration reshapes cross-border knowledge transfer in multinational enterprises. The analysis demonstrates that AI agents should not be understood merely as technical instruments or neutral digital tools. In multinational knowledge work, they increasingly perform organizational functions: they identify relevant knowledge, support codification and translation, mediate access to distributed repositories, assist in coordination, monitor feedback, and contribute to the visibility of subsidiary-generated knowledge. However, these functions remain dependent on human judgment, contextual interpretation, and governance mechanisms that ensure accountability.

The central conclusion of the article is that human-agent collaboration can strengthen cross-border knowledge transfer, but only under conditions of carefully designed organizational governance. AI agents are particularly useful in activities involving knowledge search, retrieval, classification, synthesis, documentation, translation, and monitoring. These capabilities may reduce search costs, accelerate knowledge circulation, improve access to distributed expertise, and support more systematic feedback between headquarters and subsidiaries. At the same time, AI agents are less reliable in activities requiring tacit understanding, cultural sensitivity, ethical judgment, local adaptation, and strategic interpretation. For this reason, the value of AI-supported knowledge transfer depends not on automation alone, but on the quality of the human-agent arrangement within which AI systems are embedded.

The article also shows that the influence of AI agents on absorptive capacity is ambivalent. On the one hand, AI agents may enhance potential absorptive capacity by increasing the availability, accessibility, and clarity of knowledge that subsidiaries can receive from headquarters or from other units of the multinational network. On the other hand, excessive reliance on AI-mediated knowledge may weaken realized absorptive capacity if employees and managers become passive recipients of synthesized outputs rather than active participants in learning, interpretation, experimentation, and contextual adaptation. Thus, AI can support learning, but it cannot replace the human and organizational processes through which knowledge becomes meaningful and useful in practice.

A further conclusion is that AI-mediated knowledge systems are not power-neutral. The design and governance of such systems influence whose knowledge becomes visible, which units are treated as authoritative sources, how subsidiary knowledge is evaluated, and whether reverse knowledge transfer is encouraged or suppressed. If AI systems are designed exclusively from the headquarters perspective, they may reinforce centralized control and marginalize local insights. If they are designed with subsidiary participation, transparent governance, and mechanisms for surfacing peripheral knowledge, they may support more balanced knowledge flows and strengthen organizational learning across the multinational enterprise.

The article contributes theoretically by integrating human-agent collaboration with multinational enterprise theory, knowledge-transfer research, organizational learning, absorptive capacity, and AI governance. It advances the argument that cross-border knowledge transfer should increasingly be understood as a hybrid human-agent process rather than a purely human, technological, or organizational process. This perspective helps explain why AI adoption in multinational enterprises cannot be assessed only through efficiency gains or technological capability. It must also be evaluated through its effects on trust, interpretation, autonomy, accountability, learning quality, and the distribution of knowledge authority between headquarters and subsidiaries.

The practical contribution of the article lies in identifying the governance conditions under which AI agents can support rather than distort cross-border knowledge work. Multinational enterprises should establish clear decision rights, preserve human validation at critical stages, protect tacit knowledge and professional expertise, create transparent audit mechanisms, involve subsidiaries in the design of AI knowledge systems, and develop responsible AI practices adapted to different cultural and regulatory contexts. These measures are necessary because the main risks of human-agent collaboration are not only technical. They are organizational, managerial, relational, and institutional.

The study has several limitations. Its conclusions are based on conceptual synthesis and secondary evidence rather than primary empirical research. Therefore, the proposed framework should be treated as a theoretically grounded foundation for further investigation rather than as a fully validated empirical model. The analysis is also developed at a general level and may not fully capture sector-specific differences, regional institutional variation, or the diversity of multinational enterprise structures. Knowledge-intensive sectors, highly regulated industries, platform-based firms, and manufacturing networks may each display different patterns of human-agent collaboration and knowledge-transfer governance.

Future research should empirically examine how human-agent collaboration operates inside multinational enterprises over time. Longitudinal case studies could show how AI-supported knowledge practices evolve from experimentation to institutionalization. Comparative studies across countries could clarify how cultural, institutional, and linguistic distance shape trust in AI-mediated knowledge systems. Surveys of headquarters and subsidiary managers could test how decision rights, AI governance maturity, and trust calibration influence knowledge-transfer outcomes. Sector-specific research could also identify how different forms of knowledge, technical, managerial, regulatory, market-based, or tacit operational knowledge, require different human-agent governance arrangements.

Overall, human-agent collaboration represents a significant transformation in the organization of knowledge work within multinational enterprises. Its promise lies in improving the speed, reach, and visibility of cross-border knowledge flows. Its risk lies in the possible loss of context, weakening of human expertise, reinforcement of power asymmetries, and diffusion of accountability. The most effective multinational enterprises will therefore not be those that simply automate knowledge transfer, but those that design responsible, human-centered, and context-sensitive systems in which AI agents extend human capabilities while remaining subject to human interpretation, oversight, and accountability.

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