ПЕРЕШКОДИ ДЛЯ ПЕРЕДАЧІ ЗНАНЬ ІЗ ВИКОРИСТАННЯМ ШТУЧНОГО ІНТЕЛЕКТУ В МІЖНАРОДНИХ ОРГАНІЗАЦІЯХ

Хмара Марина Петрівна[1], Домерат Юлія Євгеніївна[2]

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Анотація: Поширення агентного штучного інтелекту (ШІ) у глобальних організаціях кардинально змінило механізми організаційного навчання, перетворивши управління знаннями (УЗ) з пасивного зберігання на активну медіацію, у якій системи не лише зберігають дані, а й самостійно міркують, синтезують та проактивно поширюють знання відповідно до організаційних потреб. Однак впровадження в багатонаціональних підприємствах (МНП) стикається з комплексом багатовимірних перешкод, що знижують достовірність знань і породжують ризик «ерзац-навчання», коли працівники використовують згенеровані ШІ відповіді без глибинного засвоєння логіки та контексту, необхідних для самостійного розв'язання нестандартних задач. Стаття розмежовує чотири концептуально відмінні конструкти – доступність знань, ефективність передачі, засвоєння та достовірність знань – і доводить, що висока доступність є необхідною, але недостатньою умовою реального організаційного навчання. Спираючись на теорію соціотехнічних систем (STST), знання-орієнтований підхід (KBV), теорію епістемічної несправедливості та концепцію розподіленого пізнання, дослідження розробляє інтегровану концептуальну модель, у якій технологічні бар'єри (зокрема курикулярна компресія), організаційні силоси, тіньовий ШІ та епістемічне витіснення негативно впливають на ефективність передачі знань. Модель передбачає, що грамотність у сфері ШІ та зрілість управління ШІ діють як модератори, що захищають організації від деградації знань через метакогнітивну корекцію логіки та безперервний наскрізний нагляд за життєвим циклом систем. Інтегруючи літературу з міжнародного бізнесу та соціальної епістемології, стаття формалізує концепцію «генеративного герменевтичного стирання», висуває шість теоретичних пропозицій і пропонує методологічну програму змішаного дизайну для емпіричного дослідження циклу організаційної інтелектуальності (OIL) у транснаціональних підприємствах.
Ключові слова: *передача знань за допомогою ШІ, транснаціональні підприємства, соціотехнічні системи, епістемічна несправедливість, вірність знанням, зрілість управління ШІ, засвоєння знань, агентний ШІ, цикл організаційної інтелектуальності.*

BARRIERS TO AI-ENABLED KNOWLEDGE TRANSFER IN GLOBAL ORGANIZATIONS

Abstract: *The proliferation of agentic artificial intelligence (AI) within global organizations has fundamentally altered the mechanisms of organizational learning, moving knowledge management (KM) from passive storage toward active mediation in which systems no longer merely retrieve information but reason, synthesize, and proactively disseminate knowledge tailored to organizational needs. However, implementation in multinational enterprises (MNEs)*

[1] Кандидат економічних наук, доцент, доцент кафедри міжнародного бізнесу Навчально-наукового інституту міжнародних відносин Київського національного університету імені Тараса Шевченка, e-mail: marynahmara@gmail.com, ORCID: 0000-0002-9119-5223
[2] Магістр економічних наук та фінансів, факультет економіки та соціальних наук, Тюбінгенський університет імені Еберхарда-Карла, e-mail: ydomerat@gmail.com

faces a complex array of multidimensional barriers that degrade knowledge fidelity and generate the risk of "ersatz learning", in which employees consume AI-generated outputs without genuinely internalizing the underlying logic required for independent problem-solving under novel conditions. The article distinguishes four conceptually distinct constructs – knowledge accessibility, knowledge transfer effectiveness, knowledge absorption, and knowledge fidelity – and argues that high accessibility is a necessary but insufficient condition for substantive organizational learning. Drawing on Socio-Technical Systems Theory (STST), the Knowledge-Based View (KBV), Epistemic Injustice Theory, and Distributed Cognition, the study develops an integrated conceptual framework in which technological barriers (notably curricular compression), organizational silos, Shadow AI, and epistemic erasures negatively influence transfer effectiveness, while AI literacy and AI governance maturity function as moderators that buffer organizations against knowledge degradation through metacognitive repair and continuous lifecycle oversight. By integrating literature on international business and social epistemology, the article formalizes the concept of "Generative Hermeneutical Erasure", advances six theoretical propositions, and outlines a mixed-methods methodological agenda for empirical investigation of the Organizational Intelligence Loop (OIL) in cross-border knowledge processes.

Keywords: *AI-Enabled Knowledge Transfer, Multinational Enterprises, Socio-Technical Systems, Epistemic Injustice, Knowledge Fidelity, AI Governance Maturity, Knowledge Absorption, Agentic AI, Organizational Intelligence Loop.*

Problem statement. The competitive advantage of the multinational enterprise (MNE) is fundamentally rooted in its capacity to mobilize, integrate, and leverage idiosyncratic knowledge across diverse geographic and institutional boundaries [1]. In the contemporary global economy, the efficiency of knowledge transfer, defined as the successful movement of expertise, best practices, and organizational know-how from one unit to another, has become a primary determinant of long-term sustainability. Traditionally, the scholarship of Knowledge Management (KM) framed this challenge through the lens of codification and retrieval, focusing on the binary distinction between tacit and explicit knowledge and the technological systems required to store it [3]. However, as MNEs face increasingly volatile environments, the static models of the past are proving insufficient. The advent of agentic Artificial Intelligence (AI) has shifted the paradigm from a model of passive facilitation to one of active mediation, where systems do not merely store data but actively reason, synthesize, and proactively disseminate knowledge [20]. This shift theoretically enables a state of knowledge transcendence, allowing the enterprise to move beyond simple information retrieval toward continuous, self-optimizing organizational transformation.

Despite the transformative potential of AI-mediated systems, the promise of seamless global knowledge transfer remains elusive. The MNE represents a crucible of complexity, characterized by significant geographic dispersion, institutional heterogeneity, and deep-seated cultural asymmetries [32]. In these multifaceted environments, the implementation of AI does not automatically resolve the friction inherent in cross-border coordination; rather, it often introduces new layers of recursive complexity. Technological capability frequently outpaces the organizational structures required to sustain it, leading to a disconnect between the AI's generative outputs and the local realities of dispersed subsidiaries. When an AI system mediates knowledge, its linguistic and cultural training biases can create a technological asymmetry that mirrors existing organizational silos [17]. If a model lacks the necessary contextual sensitivity, the resulting transfer may fail to resonate within the specific socio-technical environment of a local unit, thereby eroding the firm's ability to leverage its location-specific advantages [24].

A central problem lies in the frequent conflation of several related but distinct constructs: knowledge accessibility, knowledge transfer effectiveness, knowledge absorption, and knowledge fidelity. Current organizational discourse often equates knowledge accessibility, namely the technical ease with which an agent can query and receive an answer from a system, with the deeper processes of organizational learning [3]. Yet high accessibility is only a necessary, not sufficient, condition for knowledge transfer effectiveness, which requires that transmitted information be accurate, timely, and relevant to the receiver's specific operational context [16]. Moreover, even an effective transfer process remains inert without knowledge absorption, understood as the firm's ability to recognize the value of new information, assimilate it, and apply it to organizational ends [10]. In AI-mediated environments, absorption is frequently hindered by insufficient AI literacy, as employees may retrieve AI-generated insights without possessing the critical framework necessary to internalize or adapt them.

Perhaps most critically, the strategic integrity of the MNE depends on knowledge fidelity, that is, the degree to which the nuanced, context-dependent essence of knowledge is preserved during the mediation process. Unlike human-to-human transfer, which allows iterative clarification, AI-mediated synthesis risks generative hermeneutical erasure [21]. This occurs when the AI, in its attempt to provide a coherent and generalized output, strips away the localized nuances that constitute a firm's unique competitive edge [5]. When the subtle complexities of a subsidiary's innovation are smoothed over by a centralized AI architecture, the firm suffers a loss of epistemic justice, as the valuable, non-standardized insights of peripheral units are marginalized in favor of dominant, model-friendly narratives [21]. Such failures in fidelity create a profound strategic risk: the gradual hollowing out of firm-specific advantages as the enterprise's collective intelligence becomes increasingly homogenized and detached from the ground-level expertise that drives innovation [19].

The practical and scientific significance of this problem is therefore substantial. From a practical standpoint, failures in AI-enabled knowledge transfer weaken the MNE's capacity to balance global integration with local responsiveness. If AI systems prioritize the speed of accessibility over the depth of fidelity, knowledge flows will be characterized by a veneer of competence that masks an underlying decay in actual organizational learning. From a scientific standpoint, this problem calls for a more rigorous conceptualization of AI-mediated knowledge processes that goes beyond efficiency-based interpretations and addresses the socio-technical, cognitive, and epistemic dimensions of knowledge transfer. In this context, the study of barriers to AI-enabled knowledge transfer becomes essential not only for understanding the limits of current organizational AI adoption, but also for identifying the conditions under which AI can be aligned with resilient, inclusive, and strategically valuable knowledge processes in global enterprises.

Analysis of recent research and publications. Recent scholarship on knowledge management and international business has consistently emphasized that the multinational enterprise derives its strategic advantage from its capacity to create, integrate, and transfer knowledge across geographically dispersed units [1]. Classical contributions in Knowledge Management framed this challenge largely through the distinction between tacit and explicit knowledge and through the design of systems for storage, codification, and retrieval [3]. Within this tradition, the firm was often conceptualized as a repository of organizational memory, while the main managerial challenge concerned how to reduce search costs and improve access to codified expertise. At the same time, the literature on knowledge transfer across multinational companies highlighted that the most valuable forms of knowledge remain context-dependent, localized, and difficult to standardize, which makes cross-border transfer structurally fragile [5], [16].

More recent studies have documented the transition from repository-based knowledge management toward AI-augmented and increasingly agentic systems. In contrast to traditional IT-enabled KM systems, which primarily store and retrieve information, agentic AI systems are described as capable of reasoning, synthesizing, monitoring, and proactively disseminating knowledge in alignment with changing organizational needs [15], [20]. This shift is significant because it alters the ontology of organizational learning: knowledge is no longer treated merely as an object to be accessed, but as something actively mediated and recursively restructured through human-machine interaction. Recent contributions have therefore begun to interpret AI-enabled knowledge transfer not simply as an issue of technical performance, but as a broader organizational and socio-technical process in which the value of outputs depends on context preservation, interpretive legitimacy, and organizational integration [19], [20].

A growing body of research has also problematized the assumption that improved access to AI-generated information automatically leads to effective learning. The literature increasingly distinguishes between knowledge accessibility, knowledge transfer effectiveness, knowledge absorption, and knowledge fidelity. Studies grounded in absorptive capacity theory emphasize that the mere availability of information does not guarantee that organizational actors can recognize its value, internalize it, and apply it to new problems [10]. In parallel, recent work on AI literacy suggests that users require more than technical familiarity with AI systems; they need the capacity to critically evaluate probabilistic outputs, recognize model limitations, and identify cases in which fluency masks distortion or simplification [11], [12], [19]. These contributions are especially relevant in global enterprises, where the practical usefulness of AI-generated knowledge depends on whether it remains sensitive to local operating conditions and whether it can be meaningfully absorbed by employees rather than mechanically repeated.

Another important strand of recent literature focuses on socio-technical and organizational barriers to AI-enabled knowledge transfer. Research informed by Socio-Technical Systems Theory argues that organizational performance depends not on technological sophistication alone, but on the joint optimization of social and technical subsystems [26], [27]. In this perspective, departmental silos, fragmented authority, managerial resistance, and the emergence of "Shadow AI" are not incidental implementation frictions, but structural obstacles that undermine the circulation, legitimacy, and integration of knowledge [14], [19], [20]. Recent discussions have shown that when employees rely on unauthorized external AI tools to bypass rigid internal systems, short-term productivity gains may coexist with fragmentation of organizational memory, intellectual property leakage, and declining trust in formal knowledge infrastructures [13], [14]. These findings are especially significant for multinational enterprises, where coordination already depends on balancing centralized control with local responsiveness.

Recent research has further extended the analysis of AI-mediated knowledge processes into the domains of epistemic validity and cross-border asymmetry. Building on Epistemic Injustice Theory, scholars have shown that AI systems can reproduce testimonial and hermeneutical injustice by assigning lower credibility to peripheral actors or by lacking the interpretive resources required to represent local realities adequately [21], [22]. In multinational settings, this problem is intensified when centralized models are trained on dominant epistemologies and then used to mediate knowledge from subsidiaries operating in institutionally distant or underrepresented environments [17], [24], [32]. In such cases, generative outputs may appear coherent while simultaneously erasing the local nuance necessary for practical application. This line of research is particularly relevant for studies of multinational knowledge transfer because it reframes AI failures not only as technical inaccuracies, but as forms of epistemic exclusion that can weaken location-specific advantages and reduce organizational diversity [21], [24], [32].

The literature on global AI governance has added another critical dimension to this debate. Recent studies and policy-oriented reports point to a growing global governance divide in which many countries remain excluded from meaningful participation in AI governance frameworks [24]. For multinational enterprises, this creates institutional heterogeneity in the regulation, oversight, and legitimacy of AI-enabled knowledge processes. Scholars have argued that in such fragmented environments, organizations require higher levels of AI governance maturity, understood not as a static compliance checklist, but as an organizational capability for continuous oversight, monitoring, and alignment of AI systems with strategic and ethical objectives [13], [14]. Related work has also stressed the importance of distributed cognition and human-AI collaboration in explaining whether AI-generated knowledge is truly internalized by organizational actors or merely used as a surface-level shortcut [20], [28]. Taken together, these streams of research indicate that AI-enabled knowledge transfer in global organizations must be examined as a multidimensional phenomenon shaped by technological constraints, organizational structure, governance quality, interpretive justice, and cognitive capability.

Identification of previously unresolved parts of the general problem. Despite the growing body of literature on knowledge management, multinational enterprises, and artificial intelligence, several important parts of the general problem remain insufficiently resolved. First, much of the existing research still treats AI-enabled knowledge processes primarily through the lens of efficiency, retrieval, or task augmentation. While this literature has significantly advanced understanding of how AI can improve access to information and support organizational productivity, it has not yet adequately clarified the distinction between knowledge accessibility and the deeper organizational outcomes of knowledge transfer effectiveness, knowledge absorption, and knowledge fidelity [3], [10], [19]. As a result, high system usage or rapid retrieval is too often interpreted as evidence of successful knowledge transfer, even when the transferred knowledge is not meaningfully internalized or contextually preserved.

Second, existing research does not yet sufficiently explain how agentic AI affects the preservation of tacit, localized, and institutionally embedded knowledge in global organizations. The literature acknowledges that multinational enterprises depend on the circulation of firm-specific and location-specific knowledge [1], [5], [16], yet the mechanisms through which AI-mediated synthesis may flatten or distort such knowledge remain underdeveloped. In particular, the problem of knowledge fidelity has not been adequately theorized as a distinct construct in studies of AI-enabled knowledge transfer. While prior work addresses inaccuracy, hallucination, and data quality failure, it pays less attention to cases in which an AI-generated output is factually plausible but stripped of the contextual depth, local texture, and interpretive nuance necessary for cross-border organizational learning. This unresolved issue is critical because it affects not only the formal correctness of transferred knowledge, but also its strategic usefulness within diverse subsidiary environments.

Third, the literature remains fragmented in its treatment of epistemic risks associated with AI-mediated knowledge transfer. Existing work on epistemic injustice provides a strong basis for understanding testimonial and hermeneutical exclusion [21], [22], yet these insights have not been sufficiently integrated into the study of multinational knowledge processes. In particular, the phenomenon described in this article as generative hermeneutical erasure remains underexplored in relation to organizational AI systems. Prior research has not fully examined how centralized or dominant AI architectures may systematically privilege model-friendly narratives while marginalizing the knowledge of peripheral units, especially those located in institutionally distant or underrepresented regions [17], [24], [32]. Consequently, an important unresolved part of the problem concerns how AI systems may reproduce not only technical error, but also epistemic asymmetry, thereby weakening the firm's ability to preserve internal diversity of expertise.

Fourth, although recent studies increasingly recognize the importance of governance and oversight, the literature still lacks an integrated explanation of how AI governance maturity influences the quality of knowledge transfer in multinational enterprises. Existing governance-oriented discussions often focus on compliance, standards, or policy instruments [13], [14], but they do not fully address how governance operates as an organizational capability that can buffer against knowledge degradation, institutional fragmentation, and epistemic exclusion.

Similarly, while the practical issue of Shadow AI has become more visible, it is still insufficiently connected to the broader problem of knowledge fragmentation, declining trust in formal systems, and erosion of organizational memory. What remains unresolved is how formal governance immaturity and informal tool adoption interact to shape the legitimacy, consistency, and absorptive value of AI-generated knowledge in the enterprise.

Fifth, the relationship between AI literacy and organizational learning remains conceptually incomplete. Prior research acknowledges the importance of user competence in working with AI outputs [11], [12], yet there is still limited understanding of how AI literacy functions not merely as a technical skill, but as a metacognitive and evaluative capacity that enables users to detect distortion, repair logic, and preserve nuance during AI-mediated transfer. In the absence of such an approach, the literature cannot fully explain why organizations with similar technical infrastructures may experience very different outcomes in terms of learning, adaptation, and resilience. This is especially important in multinational settings, where the quality of transferred knowledge depends not only on the system itself, but also on the ability of human actors to critically interpret, contextualize, and apply what the system produces.

Therefore, the unresolved parts of the general problem concern not only whether AI can accelerate knowledge transfer, but whether it can do so without degrading knowledge fidelity, weakening local interpretive legitimacy, fragmenting organizational memory, and producing only superficial forms of learning. These unresolved aspects justify the need for a more integrated conceptual framework that connects technological barriers, organizational structures, epistemic risks, governance maturity, and AI literacy within a single model of AI-enabled knowledge transfer in global organizations.

Purpose of the article. The purpose of this article is to systematize and conceptually explain the principal barriers to AI-enabled knowledge transfer in global organizations, with particular attention to multinational enterprises operating across geographically dispersed and institutionally heterogeneous environments. The article seeks to clarify how technological constraints, organizational fragmentation, epistemic risks, and governance asymmetries affect the quality of knowledge transfer when knowledge is mediated by agentic AI systems rather than by traditional repository-based knowledge management mechanisms.

To achieve this purpose, the article addresses several interrelated tasks. First, it distinguishes between the core constructs that are frequently conflated in contemporary discussions of AI-enabled organizational learning, namely knowledge accessibility, knowledge transfer effectiveness, knowledge absorption, and knowledge fidelity. Second, it identifies and categorizes the main groups of barriers that reduce the effectiveness of AI-mediated knowledge transfer, including technological and data infrastructure constraints, organizational structure and Shadow AI, epistemic risks and hermeneutical erasure, and the global governance divide. Third, it integrates the insights of Socio-Technical Systems Theory, the Knowledge-Based View, Epistemic Injustice Theory, and Distributed Cognition into a unified analytical framework for examining AI-mediated knowledge processes in multinational enterprises. Fourth, it formulates a set of theoretical propositions that explain the relationships between identified barriers and the key outcomes of AI-enabled knowledge transfer. Finally, it outlines a methodological agenda for future empirical inquiry into the Organizational Intelligence Loop as a socio-technical and cross-border knowledge process.

In this way, the article aims to contribute to the development of a more rigorous conceptual foundation for studying AI-enabled knowledge transfer and to provide a framework for understanding how global organizations can deploy AI systems without undermining the contextual integrity, absorptive value, and strategic relevance of organizational knowledge.

Presentation of the main research material. The main material of this study develops a conceptual explanation of why AI-enabled knowledge transfer in global organizations frequently fails to deliver the learning and coordination outcomes it promises. Building on the problem statement, literature review, and identified research gaps, this section systematizes the core constructs of the inquiry, examines the transformation of knowledge management in the era of agentic AI, and then categorizes the principal barriers that undermine knowledge fidelity, absorption, and transfer effectiveness in multinational enterprises. The section further grounds the analysis in a multi-lens theoretical framework, formulates the core propositions of the study, and outlines a methodological agenda for future empirical inquiry.

At the center of the analysis lies the argument that AI-enabled knowledge transfer should not be understood as a neutral technical process of information delivery. Rather, it is a socio-technical, organizational, and epistemic process in which the quality of transfer depends on how knowledge is synthesized, interpreted, legitimized, and absorbed across diverse local contexts. For this reason, the main research material is structured around the interdependence of technological capability, organizational design, interpretive justice, governance maturity, and human evaluative competence.

To move beyond descriptive observations about AI tools and toward a rigorous analytical framework for multinational enterprises, it is necessary to define the core constructs that govern AI-mediated knowledge flows. In the context of global operations, where knowledge is both the main source of competitive advantage and one of the most complex coordination challenges, conceptual ambiguity often leads to analytical weakness. In particular, the distinction between technological availability and cognitive internalization is frequently blurred in current management discussions [3]. To address this, the following conceptual distinctions establish the boundaries of the inquiry and clarify the mechanisms through which AI-enabled knowledge transfer should be analyzed.

The transition from traditional Knowledge Management to AI-mediated systems represents a fundamental shift in how the firm stores, reasons with, and mobilizes knowledge. While traditional IT-enabled knowledge management focused primarily on the storage and retrieval of explicit information [3], AI-enabled knowledge transfer involves agentic mediation, in which systems engage in reasoning, synthesis, and the proactive dissemination of insights tailored to organizational needs [20]. This shift requires more precise conceptual vocabulary in order to distinguish between the technical movement of information and the substantive transfer of knowledge that can support strategic action.

Within this framework, AI-enabled knowledge transfer can be understood as the process by which agentic AI captures, synthesizes, and disseminates organizational knowledge to a recipient unit. This construct differs from retrieval because it includes automated reasoning and context-sensitive synthesis rather than mere access to stored material. Knowledge transfer effectiveness refers to the measurable degree to which the recipient understands, internalizes, and applies the transferred knowledge to operational tasks. It therefore concerns substantive cognitive and operational outcomes rather than usage frequency alone [3], [11]. Knowledge fidelity refers to the degree to which the nuanced, idiosyncratic, and context-dependent essence of knowledge is preserved during mediation. Unlike factual accuracy, which concerns whether an output is correct, fidelity concerns whether meaning, tacit nuance, and interpretive relevance survive the transfer process [5], [21]. Knowledge absorption, in turn, refers to the cognitive process by which AI-generated insights are internalized so that the human actor can use them for independent problem-solving. It must therefore be distinguished from simple access or exposure, because absorption implies a transition from tool dependence to autonomous competence [10].

Two additional constructs are central to the model. AI literacy is treated as a multidimensional competence involving the ability to use, critically evaluate, and ethically apply AI-generated outputs. It extends beyond technical familiarity and includes awareness of the probabilistic nature, possible bias, and interpretive limits of agentic systems [19]. AI governance maturity is defined as the organizational capability to monitor, manage, and align AI lifecycles with strategic, operational, and ethical objectives. Rather than being treated as a narrow compliance checklist, it is understood here as an integrated operating capability concerned with model drift, interpretive integrity, and accountability [14].

These distinctions are necessary because the causal logic of global organizational learning depends on them. Knowledge transfer effectiveness must be separated from tool adoption rates: a subsidiary may use an AI interface frequently without achieving the cognitive shifts required for meaningful organizational learning [11]. In the same way, the intersection between knowledge fidelity and knowledge absorption is critical. An output may appear accurate and coherent while still lacking the localized texture necessary for deep understanding. High-accuracy AI outputs can therefore still suffer from low fidelity if they engage in generative hermeneutical erasure, that is, when the system strips away peripheral yet essential context in order to generate a generalized answer [21]. When fidelity is low, the recipient receives information that can be repeated but not adapted to novel local challenges.

Similarly, knowledge absorption must be rigorously distinguished from access. Following the classical absorptive-capacity perspective, absorption involves the assimilation and exploitation of knowledge rather than simple exposure to it [10]. In AI-mediated environments, the risk of ersatz learning becomes especially acute: users may derive correct answers from a system without understanding the logic behind them, which creates dependency and gradually weakens collective intelligence [19]. AI literacy functions as a crucial moderator in this process because it allows users to evaluate when a system is hallucinating, simplifying, or sacrificing fidelity in favor of coherence.

At the organizational level, AI governance maturity serves as the overarching capability that keeps these constructs aligned. Unlike a static compliance mechanism, governance maturity concerns the firm's ability to manage the Organizational Intelligence Loop as a continuous process of monitoring, correction, and inclusion. This includes recognizing model drift, preventing epistemic injustice, and ensuring that AI systems do not systematically marginalize the knowledge of smaller, distant, or non-dominant units [14], [21]. Without such capability, the multinational enterprise risks producing a fragmented knowledge landscape in which AI-mediated transfer becomes a source of noise rather than a driver of strategic integration.

These foundational constructs provide the analytical scaffold for the rest of the section. They clarify that AI-enabled knowledge transfer is not reducible to the successful functioning of an interface, but must instead be evaluated in terms of whether knowledge remains intelligible, contextually valid, cognitively absorbable, and strategically useful across the diverse environments in which the multinational enterprise operates.

The historical trajectory of Knowledge Management reflects a persistent tension between the fluid, idiosyncratic nature of human expertise and the rigid requirements of technological storage and retrieval. Traditionally, the scholarship of knowledge management was anchored in the logic of codification, namely the transformation of tacit insights into explicit, structured data capable of being stored in centralized repositories [3]. This repository paradigm viewed the firm essentially as a static library in which the main challenge was to optimize indexing and minimize search costs. Under the Knowledge-Based View of the firm, competitive advantage was linked to the efficiency with which these repositories could be accessed to solve recurring operational problems [1]. However, this model relied on a passive architecture. It required the human actor to initiate the search, interpret the retrieved data, and contextualize it for a specific task. In the multinational enterprise, this often led to knowledge stickiness, where the most valuable insights remained trapped within local units because centralized repositories lacked the semantic depth necessary to convey the nuances of location-specific expertise [5].

The transition to AI-augmented and, subsequently, agentic AI systems represents a fundamental shift in the management of organizational intelligence. Early AI-augmented systems improved search capabilities through natural language processing, but they remained largely reactive, operating within fixed parameters and predetermined goals. By contrast, agentic AI systems are characterized by their ability to maintain recursive loops of perception and action, allowing them to represent, monitor, and revise their own goals in alignment with shifting organizational objectives [15]. This evolution marks the movement from passive storage to active reasoning. Unlike a repository that merely contains a best practice, an agentic system can synthesize disparate streams of data, ranging from real-time market signals to historical project reviews, and proactively suggest interventions before a human actor even identifies a knowledge gap [20]. In this sense, AI is no longer simply a retrieval tool, but becomes an active participant in the mediation of organizational expertise.

This shift fundamentally transforms the nature of organizational learning. In traditional systems, learning was largely an individual act of consumption. In agentic systems, learning becomes a co-constitutive process of synthesis. This is where the concept of the metacognitive mirror becomes theoretically significant. The metacognitive mirror refers to a system's ability to reflect a learner's internal cognitive state, such as assumptions, gaps in logic, or linguistic biases, back to that learner through iterative dialogue [20]. By generating a response that exposes possible misunderstandings or by posing clarifying questions that probe the limits of a user's expertise, the agentic system can facilitate what may be termed comprehension repair. This process can deepen knowledge absorption by forcing the human actor to confront cognitive limits and refine understanding. However, the effectiveness of this mirror is not a simple function of computational power or benchmark performance. High scores on standardized AI benchmarks do not necessarily translate into effective human-AI knowledge transfer in corporate settings [8]. What matters is whether the system can preserve knowledge fidelity, namely the subtle, context-heavy nuance that benchmarks often ignore [5].

In the multinational enterprise, the introduction of agentic AI intensifies pre-existing organizational complexity. The MNE is rarely a homogeneous epistemic space; rather, it is a fragmented landscape shaped by different power distances, institutional conditions, and local routines [32]. In subsidiaries characterized by high power distance, employees may treat the outputs of a centralized AI system as infallible directives rather than as starting points for dialogue [17]. When the metacognitive mirror produces a synthesis, subordinate actors may hesitate to question the model's reasoning even when it conflicts with local expertise. This increases the risk of generative hermeneutical erasure, in which generalized model logic systematically overwrites the sticky, localized knowledge of the subsidiary [21]. The problem is further intensified by institutional voids, that is, gaps in formal regulatory or organizational structures in certain markets, which force AI systems to operate within fragmented compliance and legitimacy environments [16]. Technical refinement alone cannot resolve such conditions; what is required is a high level of AI governance maturity capable of aligning centralized reasoning with both global standards and local legitimacy.

The strategic risk for the multinational enterprise therefore lies in the possibility of ersatz learning. This occurs when the firm achieves high knowledge accessibility through agentic systems but fails to sustain knowledge transfer effectiveness because the human workforce lacks the AI literacy necessary to critically engage with the system's syntheses [19]. If employees become overly dependent on the AI's reasoning without internalizing the logic behind it, the firm's collective intelligence begins to weaken. The knowledge becomes technically transferable, but not genuinely absorbed in a way that supports independent problem-solving. This produces a condition of fragile competence, in which the firm can execute known procedures but lacks the resilience to innovate under novel conditions.

To mitigate these risks, the evolution of knowledge management must be understood as a socio-technical transition toward the Organizational Intelligence Loop. Within this perspective, agentic AI should be integrated into a recursive cycle in which human judgment and machine synthesis continuously refine one another. This requires a shift from managing knowledge objects, as in the codification era, toward managing knowledge flows and knowledge fidelity. By prioritizing the preservation of nuance and the empowerment of local actors through AI literacy and governance maturity, the multinational enterprise can move beyond the limitations of centralized repositories toward a more adaptive and globally responsive intelligence architecture. This conceptual evolution provides the foundation for the following analysis of the specific barriers that disrupt AI-enabled knowledge transfer in global organizations.

In the context of the Knowledge-Based View of the firm, technological infrastructure is not merely a passive utility but the primary substrate through which firm-specific advantages are codified and mobilized. Within AI-enabled knowledge transfer, technological barriers should therefore be understood as structural inhibitors that degrade the epistemic quality of information before it reaches the human learner. These barriers are often misinterpreted as temporary computational imperfections; however, a more rigorous analysis reveals them as systemic defects that transform high-value organizational expertise into low-fidelity knowledge, thereby weakening the Organizational Intelligence Loop [1], [20]. To understand this degradation, it is necessary to distinguish between visible failures such as hallucination and deeper structural failures such as simplification, decontextualization, and infrastructural fragmentation.

While hallucination, namely the generation of factually incorrect but syntactically plausible outputs, represents an obvious risk to accuracy, it is often easier to detect through standard verification than the more insidious process of simplification. In agentic systems, simplification is an architectural byproduct of the model's attempt to generate coherent, generalized syntheses. This leads to what may be described as curricular compression, whereby the system prioritizes high-probability patterns present in its training data over the low-probability, idiosyncratic tail knowledge that often defines an MNE's competitive advantage [8], [15]. Curricular compression systematically strips away the sticky nuances of localized expertise in order to fit the probabilistic logic of the model. When a system compresses a complex, multivariable organizational protocol into a streamlined summary, it may increase knowledge accessibility while simultaneously reducing knowledge fidelity. The resulting output may remain technically plausible in its basic factual structure, yet become functionally defective because it lacks the contextual depth required for high-stakes, cross-border decision-making [5], [9].

Decontextualization intensifies this loss of fidelity by severing the connection between an insight and its socio-technical meta-knowledge, that is, the specific conditions, cultural caveats, operational exceptions, and institutional contingencies that make knowledge genuinely actionable. In traditional knowledge management systems, decontextualization was often a human failure of insufficient documentation. In AI-mediated systems, it becomes an architectural feature of automated synthesis [3]. This produces a crucial shift: technical defects become knowledge defects. A technical defect might involve a failed integration, query timeout, or incomplete retrieval, whereas a knowledge defect involves the delivery of a fluent and confident output that is epistemically hollow. Such defects are particularly dangerous in global enterprises, where the source of truth is often already fragmented across legacy systems, regional practices, and inconsistent reporting architectures [16].

The existence of knowledge islands, namely dispersed organizational units operating on non-interoperable data architectures, creates a foundational interoperability failure. In such settings, AI does not necessarily function as a unifying force; instead, it can become a confusion multiplier [19]. When an agentic system attempts to synthesize knowledge from conflicting databases, for example where one subsidiary's compliance records contradict another unit's operational logs, it often produces a veneer of coherence that masks the contradiction rather than resolving it. In doing so, the system may present a singular synthesized truth while obscuring the legitimate institutional heterogeneity of the organization. Because the AI frequently lacks the capacity to signal provenance, uncertainty, or contradiction with sufficient transparency, the recipient is confronted with an authoritative-seeming output that remains only weakly verifiable in practice [20], [31].

The downstream cognitive and organizational consequences of these technological constraints are substantial. When AI-enabled knowledge transfer systems repeatedly produce compressed and decontextualized outputs, they facilitate a condition of ersatz learning. In such cases, workers achieve surface-level familiarity with a task through high accessibility, yet do not internalize the underlying logic necessary for independent adaptation and problem-solving [19]. Over time, this creates a condition of intellectual atrophy in which the workforce becomes dependent on simplified AI syntheses and gradually loses the critical capacity for comprehension repair. This deskilling is not a byproduct of AI success, but a consequence of infrastructures that privilege speed of retrieval over depth of transfer. As a result, the multinational enterprise may become more efficient in routine execution while simultaneously becoming less resilient and less innovative in the face of non-routine disruptions. Under such conditions, the metacognitive mirror provided by agentic AI becomes distorted, reflecting only a shallow version of organizational intelligence and thereby weakening the deeper absorption of expertise across the enterprise [19], [20].

In the context of the Knowledge-Based View of the firm, the strategic advantage of a multinational enterprise depends on its ability to integrate idiosyncratic knowledge across diverse organizational units [1]. However, the introduction of agentic AI into this environment reveals that organizational barriers are not merely secondary implementation frictions, but constitutive constraints that shape the validity, circulation, and absorptive value of expertise. From a Socio-Technical Systems perspective, the effectiveness of AI-enabled knowledge transfer depends on the joint optimization of social structures and technical tools [20]. When the social substrate of the organization, including hierarchies, departmental boundaries, routines of coordination, and managerial authority, is misaligned with the logic of AI-mediated knowledge transfer, the resulting transfer effectiveness is substantially weakened. This misalignment manifests most clearly through departmental silos, managerial resistance, and the proliferation of Shadow AI.

Departmental silos represent a foundational structural barrier because they interrupt the visibility of expertise necessary for the Organizational Intelligence Loop to function effectively. In traditional knowledge management, silos made retrieval more difficult. In the AI era, they act as epistemic filters that prevent agentic systems from accessing the full range of cross-functional data necessary for high-fidelity synthesis [3]. When knowledge ownership is fragmented across departments, systems, or subsidiaries, the AI is forced to generate outputs on the basis of incomplete or skewed information, which degrades knowledge fidelity. Silos also break coordination signals between units. If, for example, a technical subsidiary develops locally valuable expertise that remains invisible to the centralized AI environment used elsewhere in the enterprise, then the resulting AI-generated synthesis may appear coherent while lacking operational validity in practice. In this way, organizational fragmentation ensures that even technically advanced AI systems remain structurally blind, reinforcing local optimization at the expense of enterprise-wide learning [20].

Beyond fragmentation, the redistribution of authority associated with AI mediation often triggers managerial resistance. This resistance should not be understood simply as personal reluctance, but as a rational organizational response to perceived shifts in status, expertise, and control. As agentic systems assume functions traditionally performed by mid-level managers, such as synthesizing knowledge, validating interpretations, or proactively distributing guidance, the gatekeeping position of these actors becomes less secure [20]. This may generate managerial anxiety about deskilling, loss of professional autonomy, or erosion of expert capital. In such situations, managers may hesitate to endorse or legitimize AI-generated knowledge, or they may engage in forms of knowledge hoarding in order to preserve their relevance. These political dynamics directly undermine knowledge absorption, because when managerial endorsement is absent, subordinates are less likely to trust, internalize, or critically engage with the system's outputs [19].

The failure of formal organizational structures to respond adequately to AI-mediated knowledge needs often results in the spread of Shadow AI, that is, the unauthorized use of external or consumer-grade AI tools by employees seeking to bypass rigid internal systems or slow governance processes. While Shadow AI is often framed purely as a compliance failure, it is more accurately understood as an adaptive response to insufficient AI governance maturity [14]. Employees turn to such tools because formal systems do not adequately address immediate, localized knowledge gaps. However, this creates inconsistent interpretive regimes inside the enterprise. Since Shadow AI operates outside the firm's integrated data backbone, validation routines, and ethical safeguards, it generates fragmented knowledge practices in which standards for accuracy, confidentiality, and intellectual property protection remain uncertain [13]. The result is a paradoxical situation in which individual productivity may rise in the short term while the firm's collective intelligence is weakened, because critical expertise is processed through external tools that do not feed back into organizational memory. This increases the risk of intellectual property leakage and erodes the long-term integrity of the firm's knowledge base [1], [14].

Ultimately, these organizational barriers converge around the problem of trust in AI-generated knowledge. Trust is the crucial mediator between the availability of knowledge and its actual absorption within the organization [13]. In fragmented organizational settings where authority is contested and Shadow AI is widespread, employees receive conflicting knowledge signals. If the formal AI-enabled knowledge transfer system is perceived as an instrument of centralized control, or if it is built on siloed and low-fidelity information, its outputs will be met with skepticism rather than engagement. Under such conditions, employees may still use AI tools as surface-level crutches, but without undergoing the deeper cognitive internalization required for independent problem-solving. This produces a form of ersatz learning in which the technology is present, but the underlying organizational learning process remains weak [19].

For this reason, AI governance maturity must be understood as extending beyond procedural oversight. It must also include the active restructuring of authority, coordination routines, and knowledge visibility across the enterprise [14]. Only when organizational structures are aligned with the requirements of AI-mediated knowledge transfer can the multinational enterprise ensure that AI functions as a catalyst for genuine knowledge integration rather than as a source of epistemic fragmentation.

The transition to agentic AI-mediated knowledge transfer introduces risks that extend beyond technical reliability into the domain of epistemic validity. While technological barriers concern the accuracy and structure of outputs, epistemic barriers concern the integrity of the knowledge being produced and the status of the actors whose knowledge is being mediated. In organizational research, these risks can be most effectively understood through the lens of epistemic injustice, a framework that identifies harms done to individuals and groups specifically in their capacity as knowers [21]. In the context of the multinational enterprise, where competitive advantage depends on the synthesis of diverse and geographically dispersed expertise, epistemic injustice is not only a social or ethical concern but a direct threat to collective intelligence and strategic coherence [32]. When AI systems become primary mediators of expertise, they risk institutionalizing biases that marginalize the contributions of peripheral units and weaken the location-specific advantages on which the MNE relies.

A central distinction in this discussion is the difference between testimonial injustice and hermeneutical injustice, both of which can be amplified by generative and agentic AI systems. Testimonial injustice occurs when a speaker receives a credibility deficit because of prejudice on the part of the hearer [21]. In AI-enabled knowledge transfer, this deficit can become algorithmic. An AI system may assign lower interpretive weight or lower predictive significance to insights generated by subsidiaries in the Global South or by units using non-standardized reporting formats [22], [24]. If a model's training environment is disproportionately shaped by headquarters-centric or Western-centric epistemologies, then the contributions of local experts may be treated as outliers or peripheral noise rather than as legitimate organizational knowledge. This creates an institutionalized credibility deficit that distorts the Organizational Intelligence Loop by preventing the system from recognizing the value of knowledge that does not conform to dominant patterns [17], [21].

Hermeneutical injustice represents an even more structural form of epistemic barrier. It occurs when a gap in collective interpretive resources places a group at an unfair disadvantage in making sense of its own experience [21]. Within the multinational enterprise, this problem appears when the conceptual categories and interpretive assumptions embedded in centralized AI systems are not capable of adequately representing the operational realities of local subsidiaries [32]. It is in this context that the article identifies the phenomenon of generative hermeneutical erasure. This refers to the systemic process by which generative AI, in its drive toward coherence and synthesis, replaces localized interpretive frameworks with generalized model logic. Unlike a simple technical error, erasure involves the removal of the conceptual tools necessary for local units to articulate their own circumstances, innovations, and constraints. When an agentic system constructs a global best practice by averaging out local variation, it may erase the very nuances that constitute the sticky knowledge essential to innovation and adaptation [16].

This process has direct consequences for both knowledge fidelity and knowledge absorption. Knowledge fidelity depends on the preservation of the idiosyncratic texture of expertise. When this texture is smoothed over by a centralized AI architecture, the resulting output becomes decontextualized. For the local recipient, such knowledge lacks local legitimacy: it appears detached from the socio-institutional conditions within which the recipient actually operates [32]. As a result, the recipient's ability to absorb the knowledge is weakened. Absorption requires that new information be recognized as valuable and assimilated into existing cognitive structures [10]. When the knowledge arrives stripped of the interpretive context required for local sense-making, the recipient cannot meaningfully internalize it for independent problem-solving. The result is a condition of epistemic alienation in which local actors are asked to operate through a global logic that does not adequately reflect their ground-level reality [21], [22].

The global governance divide intensifies these epistemic risks by creating institutional voids in the oversight of AI-mediated systems [24]. In many regions, particularly those excluded from international AI governance processes, organizations lack the regulatory and interpretive resources needed to question the computational authority of centralized models. This lack of oversight allows generative hermeneutical erasure to proceed unchecked and contributes to a broader process of epistemicide, in which diverse cognitive resources inside the enterprise are gradually replaced by a homogenized, model-friendly narrative [24], [32]. Such a condition is strategically unsustainable because it reduces the internal diversity of the firm and makes the organization less responsive to heterogeneous market demands and locally emergent knowledge.

To mitigate these risks, multinational enterprises must cultivate both AI literacy and AI governance maturity. In this context, AI literacy involves the ability of human actors to recognize and resist hermeneutical erasure by acting as logic-repair mechanisms within the transfer process [20]. This requires not only technical familiarity with AI tools but also epistemic awareness, namely the ability to detect when a fluent synthesis has sacrificed local fidelity for global coherence. At the same time, AI governance maturity requires preventive oversight frameworks that prioritize the protection of local interpretive regimes and the representation of marginalized knowers [14]. Only through the integration of these capacities can AI-enabled knowledge transfer be transformed from a source of erasure into a mechanism of epistemic justice in which the expertise of different organizational units is preserved, legitimized, and successfully absorbed across the global enterprise.

The implementation of agentic AI systems within multinational enterprises does not occur in a regulatory vacuum. However, the present international environment is marked by a profound and systemic global governance divide. While technological narratives often advocate globally centralized AI architectures in the name of efficiency and knowledge accessibility, such models frequently collide with the reality of institutional heterogeneity across countries and regions [32]. This divide is not merely a matter of differing legal standards. It reflects a deeper structural asymmetry in the global epistemic and regulatory landscape. As recent discussions have emphasized, large numbers of countries, particularly in the Global South, remain excluded from substantive participation in international AI governance initiatives, creating significant institutional voids [24]. In the context of AI-enabled knowledge transfer, these voids are not simply absences of regulation; they become active inhibitors of knowledge fidelity and knowledge transfer effectiveness.

Within the multinational enterprise, the governance divide appears as a fragmented regulatory environment in which data sovereignty rules, intellectual property protections, compliance expectations, and ethical mandates vary sharply across jurisdictions. When a centralized agentic system attempts to synthesize knowledge from subsidiaries operating within these heterogeneous environments, it may lack the localized oversight and contextual validation mechanisms required to assess the ground truth of the data and practices it processes [17], [24]. In the absence of robust local governance frameworks, the AI system tends to default to the dominant normative logic embedded in its training environment, which is often shaped by headquarters-based assumptions or Global North standards [21], [32]. This default logic increases the likelihood of generative hermeneutical erasure, because the institutional and cultural specificities of peripheral units are overwritten by a centralized mode of reasoning. As a result, knowledge transferred from these environments suffers a loss of fidelity and may appear to the broader enterprise as noise, anomaly, or low-value deviation instead of as strategically significant local expertise.

This fragmentation of governance also weakens trust and accountability across the organization. The perceived legitimacy of AI systems depends heavily on the clarity of oversight and the auditability of outputs [13]. In a multinational setting, the absence of unified governance standards means that a subsidiary operating in a tightly regulated environment may view AI-mediated knowledge originating from a governance-void context with suspicion, doubting its compliance, ethical legitimacy, or verifiability. This trust deficit directly undermines knowledge absorption. If employees do not trust the provenance, governance quality, or institutional legitimacy of AI-generated insights, they are unlikely to internalize them for independent problem-solving. Instead, the knowledge may be used superficially, reinforcing a state of ersatz learning rather than producing substantive organizational learning [16], [19].

The governance divide also intensifies the risk of epistemicide, that is, the systematic marginalization and eventual disappearance of localized knowledge systems within the enterprise [32]. When an MNE's AI architecture is optimized for global efficiency without adequate regard for local institutional legitimacy, only model-compliant knowledge is allowed to circulate effectively. Insights that are deeply embedded in specific social, legal, or institutional conditions are filtered out because they cannot easily be reconciled with the centralized governance logic [24]. This not only harms local units in their capacity as knowers, but also creates a strategic vulnerability for the firm as a whole. By hollowing out internal diversity, the governance divide reduces the enterprise's ability to sense and respond to heterogeneous market conditions, thereby weakening the very location-specific and firm-specific advantages on which multinational competitiveness depends [14], [21].

For this reason, the global governance divide must be understood as a core barrier to AI-enabled knowledge transfer rather than as an external background condition. It shapes which knowledge is considered legitimate, which outputs are trusted, and which organizational actors are represented within AI-mediated reasoning processes. In global organizations, resilient AI-enabled knowledge transfer therefore requires not only technical capability, but also governance architectures capable of bridging institutional heterogeneity, protecting contextual legitimacy, and preventing the systematic exclusion of peripheral expertise.

The complexity of agentic AI-mediated knowledge transfer within multinational enterprises cannot be adequately explained through a single theoretical perspective. Because AI-enabled knowledge transfer involves the recursive interaction of algorithmic reasoning, organizational power relations, cross-border institutional heterogeneity, and human cognitive internalization, this study adopts a multi-lens theoretical architecture. This approach is not a loose combination of disparate ideas, but a structured synthesis designed to capture the strategic, structural, interpretive, and cognitive dimensions of the phenomenon. By integrating Socio-Technical Systems Theory as the primary lens with the Knowledge-Based View, Epistemic Injustice Theory, and Distributed Cognition, the article establishes a conceptual foundation for analyzing how global firms can manage the Organizational Intelligence Loop without sacrificing the localized expertise that underpins competitive advantage.

Socio-Technical Systems Theory serves as the primary structural lens of the study. This perspective holds that organizational performance does not arise from technological sophistication alone, but from the joint optimization of social and technical subsystems [26], [27]. In the era of agentic AI, this insight remains fundamental because AI is no longer a passive tool but an active participant in organizational processes [17], [20]. The technical subsystem now possesses capabilities of reasoning, synthesis, and goal adjustment, while the social subsystem consists of trust, authority, legitimacy, routines of coordination, and human expertise. From this perspective, failures in AI-enabled knowledge transfer are rarely purely technical or purely human. Rather, they emerge when advanced systems are introduced into social structures that are not prepared to absorb, govern, or critically engage with them. Socio-Technical Systems Theory therefore provides the structural explanation for why AI governance maturity must be treated as an organizational capability rather than as a narrow compliance instrument [14], [26].

The Knowledge-Based View provides the strategic logic of the framework. According to this perspective, the most important strategic resources of the firm are the forms of knowledge that are difficult to imitate, transfer, or standardize [1]. In the multinational enterprise, the firm exists in part to integrate and mobilize such knowledge across dispersed units. Yet the same perspective also highlights a paradox: the most valuable knowledge is often tacit, sticky, localized, and deeply embedded in context [5]. This makes it vulnerable to degradation during AI-mediated synthesis. The Knowledge-Based View is therefore essential for grounding the construct of knowledge fidelity. While accuracy is a technical criterion, fidelity is a strategic one. It concerns whether the nuance, context, and practical essence of knowledge survive mediation in a way that preserves the firm's specific and location-specific advantages. From this perspective, failures in AI-enabled knowledge transfer are not merely inefficiencies, but risks to the strategic integrity of the enterprise itself.

Epistemic Injustice Theory provides the interpretive and ethical dimension of the model. This perspective is especially important for analyzing the cross-border asymmetries inherent in multinational organizations. Epistemic injustice occurs when specific actors are marginalized in their capacity as knowers or when dominant interpretive frameworks prevent certain experiences from being understood or represented adequately [21]. In AI-enabled knowledge transfer, this becomes highly relevant when centralized AI systems privilege some knowledge sources over others or when local realities cannot be translated into the categories embedded in dominant models [21], [22]. This lens helps explain why local knowledge inclusion and generative hermeneutical erasure are central to the analysis. What appears as a neutral AI synthesis may in fact be a view from nowhere that suppresses peripheral expertise, especially in institutionally distant or underrepresented environments [24], [32]. Epistemic Injustice Theory therefore allows the study to move beyond the language of data quality and toward questions of epistemic legitimacy, interpretive inclusion, and the preservation of plural knowledge systems inside the enterprise.

Distributed Cognition adds the cognitive dimension of the framework by explaining how knowledge is processed across the human-AI assemblage rather than within either actor alone [28]. In this perspective, cognition is not located exclusively in the human or in the machine, but distributed across people, tools, interfaces, and representations. This is essential for understanding knowledge absorption and AI literacy. Absorption is not a passive receipt of output, but the internalization of knowledge in a form that enables independent problem-solving. Distributed Cognition helps explain why this depends on the compatibility between AI-generated representations and the human cognitive structures through which they are interpreted. It also clarifies why AI literacy should not be seen merely as operational skill, but as an evaluative and metacognitive capacity. A literate user does not simply consume AI output but participates in logic repair, interrogates the system's reasoning, and helps preserve knowledge fidelity through critical interaction [19], [20], [28].

Taken together, these four theoretical lenses form a coherent analytical hierarchy. Socio-Technical Systems Theory explains the structural conditions under which AI-enabled knowledge transfer can succeed or fail. The Knowledge-Based View explains why the preservation of high-fidelity knowledge matters strategically. Epistemic Injustice Theory explains how power, inclusion, and interpretive asymmetry shape the legitimacy and representativeness of AI-mediated knowledge. Distributed Cognition explains how such knowledge is, or is not, internalized by the human actors who must use it in practice. Their combination allows the article to address the full recursive complexity of the Organizational Intelligence Loop. A firm may possess advanced AI systems and formal governance structures, yet still fail if its knowledge becomes homogenized, its local actors become marginalized, or its employees become dependent on outputs they cannot independently interpret. The multi-lens approach is therefore necessary to understand AI-enabled knowledge transfer as a socio-technical, strategic, epistemic, and cognitive process rather than as a purely technological one.

The theoretical architecture established in the preceding subsections suggests that AI-enabled knowledge transfer is a recursive process that remains vulnerable to identifiable socio-technical, organizational, and epistemic frictions. In order to move from descriptive categorization toward an analytically predictive model, it is necessary to formalize the relationships between the identified barriers and the main outcomes of the Organizational Intelligence Loop. The following propositions articulate how technological, organizational, and epistemic constraints impair the strategic mobilization of expertise, while also identifying the moderating capabilities, namely AI literacy and AI governance maturity, that can buffer these negative effects. In this way, the article moves from a taxonomy of obstacles toward a causal framework of organizational learning in the age of agentic AI.

Proposition 1. Technological constraints and knowledge fidelity

Proposition 1: Technological barriers, specifically curricular compression in probabilistic agentic systems, are negatively associated with knowledge fidelity in global organizations.

The Knowledge-Based View suggests that the most valuable organizational resources are tacit, context-bound, and difficult to imitate [1]. However, the architectural logic of agentic AI frequently runs counter to this stickiness. Curricular compression, understood as the mechanism by which a model privileges high-probability linguistic and logical patterns over specialized tail knowledge, functions as a reductive filter during synthesis [8]. When an AI system mediates the transfer of complex operational expertise, it tends to smooth data in accordance with its probabilistic structure, thereby stripping away local nuance and meta-knowledge. This process reduces the depth and contextual precision of the resulting output.

Accordingly, as technological compression increases, knowledge fidelity declines, and recipient units receive a more homogenized and strategically thinner version of expertise.

Proposition 2. Organizational barriers and trust in AI-generated knowledge

Proposition 2: Organizational barriers, manifested through departmental silos and the proliferation of Shadow AI, are negatively associated with trust in AI-generated knowledge.

Socio-Technical Systems Theory suggests that the performance of the Organizational Intelligence Loop depends on the alignment of social and technical subsystems [26]. Organizational barriers disrupt this alignment by fragmenting expertise, weakening visibility of knowledge sources, and undermining the perceived legitimacy of AI outputs. Departmental silos produce epistemic enclaves in which knowledge remains isolated, while Shadow AI creates competing and ungoverned interpretive regimes inside the firm [14], [20]. When users cannot trace the provenance of AI-generated insights or verify their consistency with organizational routines, they are more likely to perceive the system as lacking credibility. This credibility deficit reduces trust and diminishes willingness to rely on AI-mediated knowledge in substantive ways.

Proposition 3. Epistemic barriers and knowledge absorption

Proposition 3: Epistemic barriers, specifically generative hermeneutical erasure, are negatively associated with knowledge absorption in multinational enterprises.

Epistemic barriers concern the interpretive validity of transferred knowledge. When AI systems project a generalized and decontextualized synthesis that suppresses the contributions of peripheral or underrepresented units, they produce a form of hermeneutical injustice [21], [22]. Generative hermeneutical erasure deprives recipients of the interpretive context needed to make sense of AI-generated knowledge in their own local conditions. Because knowledge absorption requires that individuals recognize the value of new information and assimilate it into their cognitive structures [10], such erasure creates cognitive incompatibility. Under these conditions, employees may repeat AI-generated outputs without being able to internalize or adapt them, producing a state of ersatz learning rather than genuine absorption.

Proposition 4. The amplifying role of institutional voids

Proposition 4: The global governance divide positively moderates the negative relationship between technological barriers and knowledge transfer effectiveness, such that the detrimental effect of technological barriers is stronger in environments characterized by institutional voids.

In global organizations, the consequences of technological defects are not uniform. Where local governance systems are weak, fragmented, or absent, the technical limitations of AI systems are less likely to be detected, challenged, or corrected [16], [24]. Institutional voids create what may be termed a verification gap, in which local actors lack the oversight structures necessary to question centralized AI outputs. In such contexts, hallucinations, simplifications, and distortions are more likely to become institutionalized within organizational practice rather than repaired. As a result, the negative effect of technological barriers on knowledge transfer effectiveness becomes more severe in jurisdictions distant from the governance core of the enterprise.

Proposition 5. Governance maturity as an epistemic buffer

Proposition 5: AI governance maturity moderates the relationship between epistemic barriers and knowledge transfer effectiveness, such that higher governance maturity reduces the negative effect of generative hermeneutical erasure through continuous oversight and validation.

AI governance maturity is conceptualized here as a preventive organizational capability concerned with the full lifecycle of AI systems [14]. In contrast to static compliance routines, mature governance introduces recursive oversight mechanisms that allow organizations to monitor model drift, assess interpretive validity, and audit whether local nuance is being preserved in synthesized outputs. Through such runtime validation, the enterprise can create a buffer that reduces the impact of epistemic erasure before distorted outputs reach end users. Consequently, even under conditions of high epistemic risk, organizations with stronger governance maturity can sustain higher levels of knowledge transfer effectiveness because they are better equipped to maintain legitimacy, contextual adequacy, and interpretive inclusion within the Organizational Intelligence Loop.

Proposition 6. AI literacy and the metacognitive repair mechanism

Proposition 6: AI literacy moderates the relationship between technological barriers and knowledge fidelity by enabling users to act as metacognitive repair agents who identify and correct distortions in AI-mediated synthesis.

Distributed Cognition emphasizes that knowledge in human-AI systems is not located solely in the machine or solely in the human user, but distributed across the interaction between them [28]. Within this framework, AI literacy functions as a crucial cognitive moderator. It is not limited to technical fluency, but includes the capacity to critically assess probabilistic outputs, identify simplification or distortion, and restore lost context through logic repair [19], [20]. Highly literate users can recognize when AI-generated syntheses have compressed, decontextualized, or flattened complex knowledge, and they can intervene to reintroduce nuance. In this sense, the user becomes a metacognitive mirror who helps preserve fidelity despite the reductive tendencies of the system. Higher AI literacy therefore weakens the negative relationship between technological barriers and knowledge fidelity.

Taken together, these propositions formalize the article's central claim that AI-enabled knowledge transfer in global organizations is shaped by a dynamic interaction between technological architecture, organizational structure, epistemic legitimacy, governance capability, and human evaluative competence. They also provide the analytical basis for the methodological agenda proposed in the following subsection.

The conceptual framework developed in this article establishes a recursive model of AI-enabled knowledge transfer that requires a correspondingly robust empirical validation strategy. Because the Organizational Intelligence Loop involves latent cognitive processes, structural organizational barriers, and cross-border institutional pressures, a single-method design would be unlikely to capture the multilevel nature of the phenomenon. For this reason, the article proposes a future empirical research agenda grounded in the tradition of critical realism. This perspective is particularly appropriate for the study of socio-technical systems because it distinguishes between underlying generative mechanisms, actual organizational events, and empirical observations. In the present context, this allows researchers to move beyond surface-level correlations and investigate the deeper causal structures that enable or inhibit knowledge fidelity, knowledge absorption, and transfer effectiveness in multinational enterprises.

To operationalize this agenda, the study proposes a mixed-methods sequential explanatory design. Such an approach begins with a large-scale quantitative phase to test the formal propositions developed in the previous subsection and is followed by a qualitative phase aimed at explaining the organizational and interpretive mechanisms behind the observed patterns. The main unit of analysis should be the human-AI dyad within specific knowledge transfer events, while the level of analysis should remain multilevel, taking into account individual-level AI literacy, department-level structural barriers, and firm-level governance maturity. This design is particularly suitable because AI-enabled knowledge transfer is simultaneously cognitive, organizational, and cross-border in nature.

The first phase of the empirical agenda involves quantitative validation through a two-wave longitudinal survey design. This design is intended to reduce common method bias by introducing temporal separation between the measurement of predictor variables and outcome variables. In the first wave, researchers should measure the principal independent variables, including technological barriers, organizational barriers, epistemic barriers, and the global governance divide, as well as the moderating variables of AI literacy and AI governance maturity. AI literacy should be treated as a multidimensional capability encompassing not only operational skill, but also critical evaluation, metacognitive reflection, and ethical judgment in working with AI outputs. AI governance maturity should be measured at the organizational level through indicators of lifecycle oversight, auditability, internal standards, and alignment with governance frameworks such as ISO/IEC 42001 [14].

In the second wave, conducted after an appropriate time interval, researchers should measure the main outcome variables: knowledge transfer effectiveness, knowledge fidelity, and knowledge absorption. Knowledge fidelity should be operationalized through the extent to which transferred knowledge preserves contextual nuance, local relevance, and tacit detail. Knowledge absorption should be operationalized through the recipient's ability to internalize and apply AI-mediated knowledge independently to new problems, rather than simply reproducing an output [10]. Knowledge transfer effectiveness should be assessed not only in terms of perceived usefulness, but also in terms of practical applicability and task-related integration into organizational routines. Given the international and multilevel nature of the phenomenon, the use of multilevel modeling is especially appropriate, as it makes it possible to account for institutional distance, subsidiary context, and governance heterogeneity across countries and organizational units [16], [32].

To move beyond the limitations of self-reported perceptions, the methodological agenda also proposes the inclusion of objective performance measures. In this regard, the article points to the potential value of an Elo-calibrated task design. Under this approach, a series of specialized organizational tasks, such as technical troubleshooting, knowledge interpretation, or complex compliance reasoning, would be assigned difficulty levels derived from prior human performance. The purpose would be to determine whether a human-AI dyad can perform tasks above the baseline capability of the unaided human actor. However, to distinguish between knowledge transfer effectiveness and actual knowledge absorption, a two-stage protocol is needed. In the first stage, the human-AI dyad completes the task together, thereby demonstrating mediated performance. In the second stage, after a washout period, the human actor completes a structurally similar but contextually different task without AI support. If the performance gain is sustained, this would provide evidence of absorption. If performance reverts to the initial baseline, the result would indicate tool dependency rather than internalized learning. In this way, the design offers a possible empirical route for distinguishing substantive learning from ersatz learning.

The second phase of the agenda involves qualitative exploration of the epistemic and organizational dynamics that quantitative methods may fail to capture fully. The article therefore proposes semi-structured interviews with actors directly involved in enterprise AI deployment and knowledge coordination, such as Chief AI Officers, knowledge management leaders, and subsidiary heads. The purpose of these interviews would be to identify how AI-mediated synthesis affects the visibility, credibility, and interpretive legitimacy of local knowledge within the multinational enterprise. A critical incident technique would be especially useful here, as it would allow participants to describe concrete situations in which AI-generated summaries failed to capture local nuance, distorted operational meaning, or weakened the perceived credibility of particular actors or units. Such evidence would be crucial for tracing the mechanisms of generative hermeneutical erasure and for understanding how governance maturity operates in practice rather than only in formal policy documents.

Finally, any empirical investigation of AI-enabled knowledge transfer in global organizations must explicitly account for cross-border validity problems. Institutional distance means that constructs such as trust, authority, legitimacy, and even AI literacy may not carry identical meanings across different national and organizational contexts [32]. For this reason, cross-cultural pretesting of research instruments is essential in order to ensure conceptual equivalence across settings. In addition, the phenomenon of Shadow AI may be underreported in conventional surveys because of compliance concerns, which suggests the need for indirect or anonymized measurement strategies. By integrating such controls, future research can move from the conceptual propositions developed in this article toward a more rigorous and empirically grounded understanding of how AI-enabled knowledge transfer operates in multinational enterprises.

The theoretical synthesis developed in this article challenges the prevailing managerial tendency to frame artificial intelligence primarily as a discrete productivity tool. By integrating Socio-Technical Systems Theory, the Knowledge-Based View, Epistemic Injustice Theory, and Distributed Cognition, the present study instead reframes agentic AI as a socio-technical substrate, that is, as an underlying medium through which an enterprise's collective intelligence is codified, synthesized, circulated, and transformed across organizational and geographic boundaries. This shift in perspective is theoretically important because a tool is an external instrument applied to a task, whereas a substrate is a foundational layer that alters the nature of the resource it carries. When knowledge is mediated by agentic systems, it ceases to be a static object stored in a repository and becomes a dynamic, probabilistic output whose value depends on the structural, interpretive, and cognitive integrity of the mediation process itself [20].

Within this perspective, the Organizational Intelligence Loop emerges as the central conceptual contribution of the article. The loop should not be understood merely as a procedural flow of information, but as a governed runtime context in which human expertise visibility and machine reasoning continuously interact. In traditional knowledge management, the context surrounding a piece of expertise was often lost during codification [3]. In contrast, the Organizational Intelligence Loop assumes that trust, local operational nuance, decision rights, and interpretive legitimacy must remain active variables within the synthesis process. Its significance lies in its ability to preserve knowledge fidelity in environments that are otherwise prone to curricular compression and generalized abstraction. By ensuring that AI-mediated reasoning remains open to local correction, human judgment, and iterative refinement, the multinational enterprise can move beyond simple information retrieval toward a model of active mediation that supports the preservation of firm-specific and location-specific advantages [1], [5].

This perspective also helps explain the emerging productivity paradox in AI-enabled organizations. That paradox may be understood as a condition in which high system usage, often interpreted as a sign of success, coexists with declining knowledge fidelity and only superficial forms of learning. When organizations optimize for knowledge accessibility without equal attention to knowledge absorption, they risk hollowing out human expertise. Employees may become increasingly reliant on AI-generated syntheses while losing the critical capacity for comprehension repair and context-sensitive reasoning [19], [20]. Under such conditions, the organization appears efficient in executing known tasks, but becomes less capable of innovation, adaptation, and resilient problem-solving under novel circumstances. What seems to be productivity at the level of process speed may therefore conceal a deeper degradation of organizational intelligence.

The discussion also underscores that the global governance divide is not merely an institutional backdrop, but a structural constraint on the adaptive capacity of multinational enterprises. The exclusion of many regions and knowledge communities from meaningful participation in AI governance processes means that the normative assumptions embedded in enterprise AI systems are often unevenly distributed and weakly representative [24]. In the framework developed here, this contributes to the marginalization of peripheral expertise and to the erosion of internal knowledge diversity. When an enterprise's AI substrate is optimized primarily for dominant headquarters-centered epistemologies, it risks systematically erasing the sticky, context-rich knowledge of subsidiaries and replacing it with generalized model logic [21], [32]. This weakens the firm's ability to sense and respond to heterogeneous market environments and thereby introduces a strategic vulnerability that extends beyond ethics into competitiveness itself.

For this reason, epistemic inclusion must be treated as a strategic necessity rather than a normative add-on. The ability of the multinational enterprise to respond to location-specific risks and opportunities depends directly on whether its AI-mediated knowledge processes can represent, preserve, and legitimize diverse forms of expertise. In this sense, the concept of generative hermeneutical erasure has particular value because it identifies a failure mode that conventional discussions of AI accuracy do not adequately capture. A system may generate an output that is fluent and seemingly coherent while still erasing the interpretive structure that gives local knowledge its practical relevance. The strategic problem, therefore, is not only whether AI outputs are correct in a formal sense, but whether they remain faithful to the situated knowledge conditions from which competitive advantage is derived.

The discussion further suggests that multinational enterprises must move toward a preventive and deeply integrated governance model. Alignment with international standards may provide part of the formal architecture for such governance, but the substance of governance maturity lies in whether the organization can protect the Organizational Intelligence Loop from drift, exclusion, and distortion [14]. In this context, governance cannot remain a static compliance layer. It must become a design condition of AI deployment, ensuring that systems remain auditable, context-sensitive, and compatible with local legitimacy. Similarly, AI literacy should be understood not merely as upskilling, but as a core cognitive competence of the human-AI dyad. It is through AI literacy that organizational actors retain the ability to evaluate outputs critically, repair model logic, and prevent superficial fluency from displacing substantive understanding [19], [20], [28].

Taken together, these arguments position the contribution of the article at the intersection of knowledge management, international business, and AI governance. For knowledge management, the article proposes the Organizational Intelligence Loop as a conceptual model that accounts for agentic mediation rather than passive storage. For international business, it explains how institutional voids, governance asymmetries, and cross-border epistemic exclusion amplify failures in knowledge transfer [16], [24], [32]. For AI governance, it provides a socio-technical rationale for why knowledge fidelity, epistemic justice, and human absorptive capacity are necessary conditions for sustainable organizational performance. At the same time, the article remains conceptually grounded rather than empirically final. The relationships it identifies are theoretically derived propositions that call for empirical testing through the methodological agenda outlined above.

Ultimately, the strategic imperative for the contemporary multinational enterprise is to recognize that AI is never neutral. It is a socially embedded and politically conditioned infrastructure that shapes which knowledge is visible, credible, transferable, and absorbable. Only by prioritizing governance maturity, AI literacy, and epistemic inclusion as core design conditions can global organizations ensure that AI-enabled knowledge transfer becomes a driver of genuine organizational transformation rather than a mechanism for the gradual erosion of their unique intellectual assets.

Conclusions. The article has shown that the strategic viability of the multinational enterprise in the era of agentic artificial intelligence depends on its ability to organize knowledge flows without eroding the contextual and idiosyncratic expertise that underpins competitive advantage. AI-enabled knowledge transfer should not be understood as a purely technical act of information delivery, but as a recursive socio-technical process in which the quality of transfer depends on how knowledge is synthesized, interpreted, legitimized, and absorbed across diverse organizational and institutional environments.

A central conclusion of the study is that knowledge accessibility must be clearly distinguished from knowledge fidelity and knowledge absorption. Although agentic systems can significantly improve access to information, they may simultaneously reduce the contextual integrity of knowledge through simplification, decontextualization, and generalized synthesis. Under such conditions, organizations risk producing only superficial forms of learning in which employees can retrieve answers but cannot independently internalize, adapt, or apply the underlying logic. This creates a condition of fragile competence that may increase short-term efficiency while weakening long-term organizational resilience and innovation capacity.

The study also demonstrates that barriers to AI-enabled knowledge transfer are multidimensional. Technological and data infrastructure constraints reduce the fidelity of transferred knowledge. Organizational fragmentation, managerial resistance, and Shadow AI undermine trust in formal knowledge systems and weaken coordinated learning. Epistemic risks, especially generative hermeneutical erasure, threaten the inclusion and legitimacy of localized knowledge within the multinational enterprise. At the same time, the global governance divide intensifies these problems by creating institutional asymmetries that make knowledge validation, oversight, and cross-border transfer more difficult.

Another important conclusion is that AI governance maturity and AI literacy should be treated as central enabling conditions for resilient organizational intelligence. Governance maturity is important not only as a compliance function, but as an organizational capability for preserving contextual validity, interpretive inclusion, and accountability throughout the lifecycle of AI systems. AI literacy, in turn, is not limited to technical skill, but includes the evaluative and metacognitive ability to identify distortion, question model logic, and restore lost nuance in AI-mediated outputs. Together, these capabilities can reduce the negative effects of technological, organizational, and epistemic barriers.

The article contributes to the study of knowledge management, international business, and AI governance by proposing an integrated conceptual framework for understanding AI-enabled knowledge transfer in global organizations. It clarifies the main constructs involved in the process, categorizes the principal barriers, develops a set of theoretical propositions, and outlines a methodological agenda for future empirical research. In this way, the study establishes a foundation for further investigation of how multinational enterprises can deploy AI systems in ways that strengthen rather than weaken their collective intelligence.

At the same time, the article indicates that additional research is needed to validate the proposed relationships empirically and to examine how these dynamics unfold across different institutional and organizational contexts. Future studies may build on the proposed framework by testing the interaction between governance maturity, AI literacy, and localized knowledge inclusion, as well as by exploring how multinational enterprises can design AI-mediated knowledge processes that preserve both global coordination and local responsiveness.

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