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Distinctiveness of Subsidiary Knowledge

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Abstract

Multinational enterprises (MNEs) are increasingly providing the same generative AI tools to employees across their subsidiaries. Research on AI in international business has emphasized how AI transforms the way MNEs learn and decide, while research on AI and homogenization has shown that AI-assisted outputs tend to become more alike. Neither has examined how individual employees' use of AI in subsidiaries affects the knowledge that reaches headquarters. I argue that generative AI creates a paradox for MNEs: by lowering writing and language barriers, it increases the amount of knowledge subsidiaries send to headquarters, while potentially reducing how distinctive that knowledge is. I identify four points at which AI enters the production of subsidiary knowledge (gathering, interpreting, writing up, and receiving) and develop propositions on how AI use at these points affects distinctiveness, which employees are most affected, and how subsidiaries' role in the MNE may change over time. I also propose a competing outcome: AI can increase distinctiveness when it enables employees previously limited by the corporate language to share their own observations. The decisive question is whether AI replaces the first-hand work through which local knowledge is produced or carries knowledge employees already hold. The paper contributes to research on reverse knowledge transfer, AI in international business, and AI-driven homogenization.

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Keywords: generative AI; reverse knowledge transfer; MNE subsidiaries; homogenization; knowledge distinctiveness

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1. Introduction

In June 2026, Samsung Electronics began providing ChatGPT Enterprise to all of its employees in Korea and to all employees of its Device eXperience division worldwide (OpenAI, 2026). According to press coverage, the company intends to use generative artificial intelligence (AI) across knowledge work, from information search and analysis to document drafting, idea development, and data interpretation (Park, 2026). A few months earlier, BBVA had announced the rollout of the same tool to its roughly 120,000 employees across 25 countries (OpenAI, 2025). Decisions like these place a single AI tool in the hands of employees across many countries, for precisely the tasks through which local knowledge is gathered, interpreted, and written up.

For international business (IB) research, this development matters because of what multinational enterprises (MNEs) are thought to do well. A central argument in the field holds that MNEs exist because they create and transfer knowledge across borders more effectively than markets can (Kogut & Zander, 1993). Subsidiaries play a key part in this. They do not only apply what headquarters knows; some create new capabilities for the whole organization (Cantwell & Mudambi, 2005), and the knowledge they pass to other units depends on the value of what they know (Gupta & Govindarajan, 2000). Recent research confirms that subsidiaries' role as sources of knowledge remains central to understanding the MNE (Meyer et al., 2020), and shows that disruptive changes in context can rapidly reshape how subsidiaries create new capabilities (Godley et al., 2026). An MNE's ability to learn from the different places where it operates rests, in large part, on its subsidiaries producing knowledge that headquarters could not produce itself.

Current research offers two views of how AI affects this kind of learning, and both are incomplete. The first is optimistic. Recent IB scholarship argues that AI augments managerial cognition and transforms how MNEs learn and decide across borders (Buckley et al., 2026),

relaxing the limits of managers' rationality and reducing the behavioral biases that have long shaped MNE decisions (Lindner et al., 2025). From this view, AI should also ease the language and processing barriers that have made it hard for subsidiaries to pass knowledge to headquarters. The second view is concerned with sameness. Experimental studies show that outputs produced with generative AI tend to be better individually but more alike collectively (Doshi & Hauser, 2024), and Csaszar et al. (2024) argue that AI trained on common data may push firms toward similar strategies. Neither view, however, examines how individual employees inside subsidiaries actually use AI in their daily work, or how the effects of that use travel through the relationship between subsidiaries and headquarters. This omission reflects two broader tendencies. IB research on knowledge sharing has paid little attention to the individuals through whom knowledge is produced and shared (Foss & Pedersen, 2019). And research on knowledge flows from subsidiaries to headquarters has concentrated on getting knowledge to flow, largely taking for granted that what flows is distinctive.

This paper addresses that gap. I argue that generative AI creates a paradox for MNEs. By lowering writing and language barriers, it allows subsidiaries to send more knowledge to headquarters, faster and in more polished form. But when employees use the same tools to gather, interpret, and write up local knowledge, what they send may increasingly resemble what headquarters could have obtained from its own AI. The question I address is: *How does individual employees' use of generative AI in subsidiaries affect the distinctiveness of the knowledge that reaches headquarters, and under what conditions?*

In answering this question, the paper makes three contributions. First, it contributes to research on reverse knowledge transfer by separating the amount of knowledge that flows from subsidiaries to headquarters from its distinctiveness, and by proposing that distinctiveness should now be judged against what a widely used model would supply by default. Second, it contributes to research on AI in international business. Recent work

theorizes how AI transforms MNE learning and decision-making at the level of the firm (Buckley et al., 2026; Lindner et al., 2025). Responding to calls for more attention to individuals in IB research (Foss & Pedersen, 2019; Meyer et al., 2020), this paper shows where, in subsidiary employees' everyday knowledge work, AI can weaken rather than strengthen the MNE's ability to learn, and suggests that part of the limit on managers' rationality moves to employees' willingness and ability to adapt AI output to local reality. Third, it contributes to research on AI and homogenization by showing how organizational structure shapes convergence, and by taking seriously a competing possibility: that AI can increase distinctiveness when it gives voice to employees who were previously unable to communicate in the corporate language.

The paper proceeds as follows. Section 2 reviews research on subsidiary knowledge, the barriers to its flow, and individual use of generative AI. Section 3 develops a framework identifying four points at which AI enters the production of subsidiary knowledge. Section 4 presents propositions, and Section 5 discusses implications, directions for future research, and the boundaries of the argument.

2. Background

This section reviews the research on which the argument builds. I first explain why subsidiaries matter as sources of knowledge for the MNE (2.1) and where the distinctive part of that knowledge comes from (2.2). I then show that research on getting subsidiary knowledge to headquarters has concentrated on barriers to its flow (2.3). Finally, I examine what is known about how employees actually use generative AI, and why that evidence does not yet answer the question this paper asks (2.4).

2.1 Subsidiaries as sources of knowledge

Research on the MNE has long viewed it as an organization that creates and transfers knowledge across borders more effectively than markets can (Kogut & Zander, 1993). Within this view, subsidiaries are not merely units that carry out headquarters' plans: they can take initiative (Birkinshaw, 1997), and some hold competence-creating mandates that generate new capabilities for the MNE, rather than only applying capabilities developed elsewhere (Cantwell & Mudambi, 2005). Recent work confirms that this view remains central. Reviewing more than 600 articles, Meyer et al. (2020) identify knowledge management as one of six main lines of subsidiary research, and Andrews et al. (2023) argue that the subsidiary remains an essential concept even as MNEs adopt more decentralized and fluid organizational designs.

For the MNE to benefit from what its subsidiaries know, that knowledge must flow to other units, and above all to headquarters. Knowledge outflows from a subsidiary are associated with the value of its knowledge stock and the richness of its transmission channels (Gupta & Govindarajan, 2000), and research on reverse knowledge transfer, the flow of knowledge from subsidiaries to headquarters, has grown into a substantial field (see Kogut & de Mello, 2017, for a review). This literature has also begun to question its own simple assumptions. Mudambi et al. (2014) note that theory has often taken for granted that more innovative subsidiaries transfer more knowledge to headquarters, and find instead an inverted U-shaped relationship.

Two recent developments make these questions pressing. First, Godley et al. (2026) show that a disruptive change in context can rapidly reshape how subsidiaries create competences, in ways established theory did not predict. Second, IB scholars have begun to treat AI as such a change. Buckley et al. (2026) conceptualize AI as a “cognitive substrate” that transforms how MNEs learn, innovate, and make decisions across borders, and argue that established IB theories may need new perspectives to account for it. Their analysis, however,

does not examine what happens to the knowledge subsidiaries produce. The value of that knowledge depends on its being different from what headquarters already knows, which raises a prior question: where does that difference come from?

2.2 Where distinctiveness comes from

Much of what makes subsidiary knowledge valuable is difficult to state. Polanyi (1966, p. 4) observed that “we can know more than we can tell,” and Nonaka (1994) argued that while organizations articulate and amplify knowledge, new knowledge is developed by individuals. Moving such knowledge is costly: transfers within firms are often “sticky” and require considerable effort (Szulanski, 1996), and knowledge rooted in local experience is especially hard to express in a form others can use.

The implication is that the distinctive part of subsidiary knowledge is produced by individuals in their everyday work: talking to customers and partners, interpreting local developments, and writing up what they have learned. IB research has been slow to take this individual level seriously. Foss and Pedersen (2019) document that, compared with other management fields, international management research on knowledge sharing has paid little attention to microfoundations, partly because of the weight IB scholars place on context and structure. Studies that do examine individuals show that their knowledge sharing depends on motivation, perceived organizational values, and work practices, and that these drivers work differently within and across units of the same MNE (Dasí et al., 2017). Meyer et al. (2020) likewise call for more microfoundational research on subsidiaries.

Generative AI makes this gap more consequential, because it intervenes directly in the individual work through which knowledge is produced. From a knowledge management perspective, Alavi et al. (2024) argue that generative AI can support knowledge creation, but also risks reducing the social interaction through which knowledge is formed, encourages overreliance, and raises the question of how human tacit knowledge should be balanced

against AI-generated explicit knowledge. If distinctiveness is produced in employees' daily work of gathering, interpreting, and expressing local knowledge, any change in how that work is done may affect what subsidiaries can offer. Research on reverse knowledge transfer has, however, focused less on this production of knowledge than on the obstacles to moving it.

2.3 Getting knowledge to headquarters: barriers to flow

Two barriers have received particular attention. The first is language. Language-sensitive research has become an established stream of IB scholarship (Karhunen et al., 2018; Tenzer et al., 2017). Language barriers strain relations between headquarters and subsidiaries (Harzing & Feely, 2008) and affect trust in multinational teams (Tenzer et al., 2014). Language skills shape knowledge transfer through their effects on communication competence, networks, identity, and power (Peltokorpi & Vaara, 2014), and studies of foreign subsidiaries in Japan show that host-country employees' proficiency in the corporate language is positively associated with reverse knowledge transfer (Peltokorpi, 2015; Peltokorpi & Yamao, 2017).

The second barrier is headquarters' attention, which has become a major theme in IB research (see Andrews et al., 2022, for a review). Headquarters' attention depends partly on a subsidiary's structural position, its "weight," and partly on its own efforts to be heard, its "voice" (Bouquet & Birkinshaw, 2008), and subsidiary initiatives raise a subsidiary's influence only when they gain that attention (Ambos et al., 2010). Attention is also selective in a way that bears directly on distinctiveness. In a study of knowledge-sourcing opportunities in a large MNE, Monteiro (2015) found that headquarters' decision-makers tended to favor opportunities that were market-proven and confirmed what the MNE already knew, even though subsidiaries had been established far from headquarters precisely to find novel knowledge.

Across this research, the central problem has been getting knowledge to flow: overcoming language barriers, earning attention, and building channels. Whether the knowledge that flows is distinctive has largely been taken for granted. A subsidiary report written in the corporate language and noticed by headquarters is implicitly assumed to carry local knowledge that headquarters lacked. Generative AI calls this assumption into question: a subsidiary report can now be fluent, written in the corporate language, and noticed by headquarters, yet contain little that headquarters could not have obtained from its own AI tools.

2.4 How employees actually use generative AI

Research on AI in management has emphasized its potential to improve decisions. Raisch and Krakowski (2021) distinguish between AI that automates tasks and AI that augments human work. Lindner et al. (2025) argue that AI-augmented decision-making relaxes the limits of managers' rationality, giving them access to more information and greater processing capacity and thereby reducing behavioral biases in MNEs. They also caution that AI introduces biases of its own, including biases in how humans interact with it. This view implicitly assumes that employees engage critically with what AI produces.

Individual-level evidence suggests that such engagement varies. In a survey of 319 knowledge workers reporting 936 real examples of generative AI use, Lee et al. (2025) find that higher confidence in AI is associated with less critical thinking. They also find that the effort of critical thinking shifts from gathering information to verifying it, from solving problems to integrating AI output, and from doing tasks to overseeing them. Field and experimental studies show that generative AI raises productivity and quality on many tasks, with the largest gains for less experienced or lower-performing workers (Brynjolfsson et al., 2025; Noy & Zhang, 2023). But the benefits are uneven. In a field experiment with 758 consultants, AI improved performance on tasks within its capabilities but made consultants

less likely to reach the correct answer on a task outside them (Dell'Acqua et al., 2026). These studies differ in design, ranging from a self-report survey to field and laboratory experiments, but together they show that the effect of AI depends on how individuals use it.

This evidence has a limitation for the present question. It concerns individuals performing single tasks, and it does not ask what happens when many employees across an organization use the same tools. Balasubramanian et al. (2022) take a step in this direction. They argue that replacing human decision-making with machine learning risks reducing diversity in organizational routines and the contextual knowledge associated with them, worsening the myopia of learning. Their argument concerns machine learning that substitutes for human decisions within an organization. The question here is different: what happens to the distinctiveness of knowledge flowing to headquarters when employees across an MNE's subsidiaries *use* generative AI in their own knowledge work. Answering it requires looking at the specific points at which AI enters the production of subsidiary knowledge, which the next section sets out.

3. Framework: Where Distinctiveness Is Made and Lost

Section 2 showed that research on subsidiary knowledge has treated getting knowledge to flow as the central problem, while largely taking the distinctiveness of what flows for granted. This section develops a framework for examining that assumption once generative AI enters subsidiary work. I first define three concepts on which the argument rests. I then explain why outputs from widely shared models tend to converge and why this matters for organizational learning. Finally, I identify four points at which AI enters the production of subsidiary knowledge, and one countervailing force.

3.1 Three key concepts

Distinctive local knowledge. As Section 2.1 showed, the value of subsidiary knowledge lies largely in what headquarters does not already possess. I define distinctive local knowledge as knowledge that headquarters could not easily obtain from other sources, *including from its own AI tools*. The final clause is what changes when generative AI becomes widely available. Previously, a subsidiary report about its local market was likely to be distinctive simply because headquarters had no comparable source. Now headquarters can ask a model about almost any market and receive a fluent, plausible answer within seconds. Knowledge is no longer distinctive merely because it concerns a local context; it must also add something the model does not already supply.

Shared model baseline. I use this term for what a widely used model would say about a question by default, without input from a particular subsidiary. The baseline is the benchmark against which distinctiveness should now be judged. Knowledge is distinctive to the extent that it departs from this baseline *and* the departure is grounded in local evidence, such as a conversation with a customer, an observation of a competitor, or a signal from a regulator. Both conditions matter. Departure without grounding may simply be error; grounding without departure adds nothing headquarters could not have obtained itself. The baseline is not fixed, as it changes with each model and version, but at any given time it can be approximated by putting the same question to the model without local input (see Section 5.3).

Adaptation work. Generative AI output rarely fits a task as delivered. Lee et al. (2025) find that knowledge workers integrate AI output by selecting the parts relevant to their situation and by modifying its style and content to suit their purpose, and that this oversight of AI, which the authors describe as stewardship, has become a central part of AI-assisted work. Tankelevitch et al. (2024) similarly emphasize the effort users must invest in setting goals for AI, steering it, and evaluating its output. I use the term adaptation work for the individual

effort of selecting, questioning, and changing AI output to fit local reality. Adaptation work is where an employee's first-hand knowledge can enter, or fail to enter, an AI-assisted product. It is therefore the point at which the individual level of analysis, which Section 2.2 showed IB research has largely neglected, connects to the distinctiveness of subsidiary knowledge.

3.2 Why shared baselines matter

A growing body of evidence shows that when many people use the same generative AI tools, their outputs become more alike, even when each individual output improves. In an online experiment, writers who obtained story ideas from a large language model (LLM) wrote short stories that evaluators rated as more creative, especially among less creative writers, yet these stories were more similar to each other than stories written without AI ideas (Doshi & Hauser, 2024). Writing with a model tuned on human feedback made essays by different authors more similar (Padmakumar & He, 2024), and ideas developed with ChatGPT were less distinct across users than ideas developed without it (Anderson et al., 2024). Comparing human and AI-written essays, Moon et al. (2025) find that human writing adds more new ideas than AI writing, and that the gap grows as more texts are pooled. Most of this evidence comes from controlled studies of writing and idea generation rather than from organizations, but the pattern is consistent across designs.

Csaszar et al. (2024) extend this concern to strategy. They argue that, because models learn from past data, they tend to propose ideas in areas well represented in that data, and that AI trained on common data may push firms toward similar strategies, weakening the distinctiveness on which competitive advantage depends. The authors present this argument as a set of conjectures rather than established findings, but it shows that the concern is not limited to individual writing tasks.

Why should such convergence matter for an organization's ability to learn? March's (1991) model of organizational learning offers an explanation. In the model, an organization's

shared knowledge, its “code,” improves by learning from individuals whose beliefs depart from it in ways that prove more accurate. When individuals adopt the code too quickly, the organization gains in the short run but loses the variety it needs to improve the code over time. A widely used model can play the role of such a code across an entire MNE: employees in every subsidiary consult it, and their outputs move toward it. If this happens quickly and widely, the MNE gains efficiency but may lose the differences from which it learns.

3.3 Four points at which AI enters subsidiary knowledge work

Subsidiary knowledge passes through several stages before it can inform headquarters’ decisions. At each, generative AI can be used in ways that preserve distinctiveness or reduce it. I distinguish four stages, each associated with a mechanism developed in Section 4.

Gathering. Knowledge begins with information collected from the local environment: customers, partners, competitors, officials. Employees can now ask a model instead. When they do, AI-provided information *substitutes* for first-hand sources (developed in P1).

Interpreting. Information must be made sense of: classified, compared, and explained. When employees use AI for this, the model supplies the categories and explanations, and local observations may be *framed* in the model’s terms, even when employees check the output carefully (P2).

Writing up. Knowledge must be expressed in a form others in the MNE can use, often in the corporate language. When AI drafts or polishes this text, unusual points may be *smoothed* toward conventional wording or dropped (P3).

Receiving. At headquarters, knowledge from many subsidiaries competes for limited attention (Bouquet & Birkinshaw, 2008). When incoming reports become more numerous and more alike, distinctive contributions are *diluted* and become harder to recognize. Because dilution concerns how headquarters responds over time rather than how subsidiary employees work, I develop it as part of the long-term consequences in P6.

The first three stages take place within the subsidiary and depend on individual employees' choices about how to use AI. Whether those choices preserve distinctiveness depends largely on adaptation work, which varies with employees' experience, time pressure, and confidence in AI (P4). The fourth stage is where the effects of these individual choices accumulate at the level of the MNE.

3.4 The countervailing force: a wider channel

The four stages describe how AI can reduce the distinctiveness of subsidiary knowledge. A countervailing force must be considered alongside them. As Section 2.3 showed, language has long been one of the main barriers to the flow of knowledge from subsidiaries to headquarters, and proficiency in the corporate language is associated with more reverse knowledge transfer.

Generative AI lowers these barriers. Employees who could not write well in the corporate language can now produce fluent reports; those who could write can do so faster. The channel through which subsidiary knowledge travels to headquarters therefore widens in two ways: more knowledge can be sent, and more people can send it.

A wider channel does not by itself determine whether the knowledge reaching headquarters becomes more or less distinctive. That depends on what travels through it. If AI widens the channel while also substituting for, framing, and smoothing local knowledge, more knowledge arrives but less of it is distinctive (P5a). If AI widens the channel by allowing previously excluded employees to contribute their own first-hand observations, distinctiveness may increase (P5b). The framework thus leads to a central question that Section 4 addresses: whether AI *replaces* the first-hand work through which local knowledge is produced, or *carries* the knowledge employees already hold. Figure 1 brings these elements together: the four stages and their mechanisms, the individual conditions that act on the first three stages, and the wider channel that works against them.

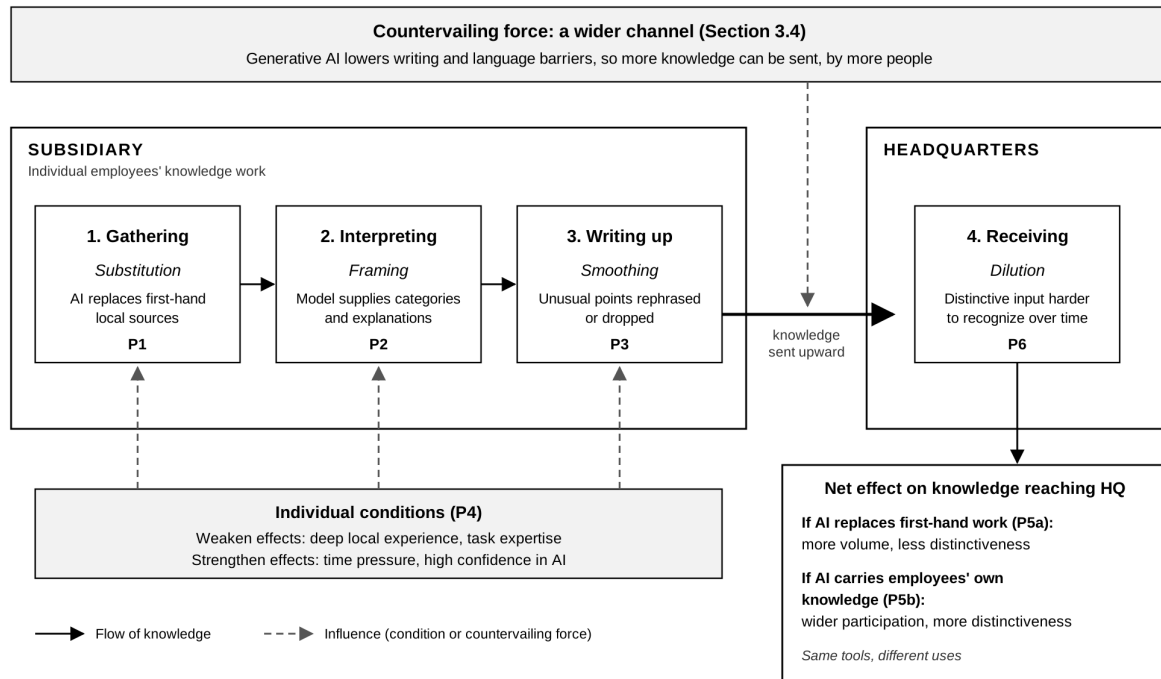


Figure 1. How generative AI enters the production of subsidiary knowledge. Generative AI can enter at four stages: gathering, interpreting, and writing up within the subsidiary, and receiving at headquarters. Each stage is associated with a mechanism that can reduce distinctiveness (P1–P3, P6). Individual conditions shape the first three stages (P4). A wider channel acts as a countervailing force. The net effect depends on whether AI replaces first-hand work (P5a) or carries knowledge employees already hold (P5b).

4. Propositions

The framework in Section 3 identified four points at which generative AI enters the production of subsidiary knowledge: gathering, interpreting, writing up, and receiving. I now develop propositions in four steps. I first examine how AI enters individual knowledge work in subsidiaries (P1–P3). I then consider which employees are most affected (P4), what net effect results for the knowledge that reaches headquarters (P5a and P5b), and what may follow over time (P6). Where I draw on current corporate practice, I present it as illustration: it shows that the mechanisms are recognizable in practice, not that they have been demonstrated.

4.1 How generative AI enters local knowledge work

Substitution

Subsidiary knowledge begins with gathering: talking to customers and distributors, reading signals from regulators, observing local competitors. Generative AI offers a faster alternative, which is to ask the model. Lee et al. (2025) find that knowledge workers perceive less effort in gathering task-relevant information when using generative AI, and more effort in verifying it. Effort shifts from gathering to verification.

For subsidiary knowledge, this shift is not neutral. Verification can catch errors in what a model says, but it cannot recover information the model never had. Models learn from data that already exist and are widely available (Csaszar et al., 2024). The private, first-hand knowledge that gives a subsidiary its value, such as a distributor's complaint or a regulator's informal signal, is precisely what such data lack. Csaszar et al. also note that LLMs can now simulate "virtual crowds" of customers for testing product ideas, which makes this substitution increasingly easy.

The market research industry illustrates the mechanism. Providers such as Qualtrics now offer synthetic panels that generate survey responses from AI "respondents" (Stokel-Walker, 2026). Industry voices caution that these should accelerate rather than replace research with real people (Shedlock, 2026), partly because synthetic panels are often trained on internet or public model data and may miss current local sentiment (Warfel, 2026). A subsidiary team that tests a campaign on synthetic local consumers produces knowledge that looks local but originates in the model.

Proposition 1: The more subsidiary employees use generative AI to gather information about their local environment, the smaller the share of subsidiary knowledge that is drawn from private, first-hand local sources.

Framing

Even when employees gather first-hand information, they may use AI to interpret it. Interpretation involves choosing categories: what kind of problem this is, what it should be

compared with, and what explains it. When a model proposes these categories, local observations are fitted into them.

As noted in Section 3.2, Csaszar et al. (2024) argue that models tend to propose ideas in areas well represented in their training data. In their experiment, business plans generated by an LLM were rated higher overall and on execution, but not on innovation. Similarly, Anderson et al. (2024) find that ideas produced with ChatGPT's help were more alike across participants than ideas produced without it.

Importantly, this mechanism operates even when employees think critically. In Lee et al.'s (2025) data, critical thinking with AI mostly takes the form of quality assurance: checking accuracy, fit with requirements, and tone. An employee can carefully verify that an AI-supported interpretation is accurate and still adopt the model's view of what matters. Accuracy and distinctiveness are different properties, and checking secures the first but not the second. Because framing is largely invisible to the person being framed, this proposition is the hardest to observe; Section 5.3 suggests one way to test it.

Proposition 2: Even when subsidiary employees critically check AI output, using generative AI to interpret local information moves their conclusions toward the categories and explanations the model supplies.

Smoothing

The last stage within the subsidiary is writing knowledge up for others in the MNE, often in the corporate language. Transferring knowledge within firms is often “sticky” and takes considerable effort (Szulanski, 1996), and knowledge rooted in local experience is especially challenging to express. Generative AI removes much of that effort. But the ease may come at a cost. The parts of local knowledge that are hardest to express, such as unusual observations or insights that contradict received views, are the parts most likely to be

rephrased toward conventional wording, or dropped as noise, when a model drafts or polishes the text.

Evidence on writing supports this concern. Writing with a language model tuned on human feedback reduced the diversity of content across writers (Padmakumar & He, 2024). In three preregistered studies of 2,200 essays, Moon et al. (2025) find that each additional human-written essay added more new ideas than each additional GPT-4 essay; the gap widened as more essays were included and persisted despite changes to prompts and model settings. Prompting alone is therefore unlikely to be a full remedy.

Practice offers a parallel. In a survey of 1,150 US full-time workers, 40% reported receiving AI-generated work that looked polished but was incomplete or missing crucial business context (Niederhoffer et al., 2025). Missing context is what smoothing would produce. The effect should be strongest for insights that depart most from conventional views, which are also the most valuable.

Proposition 3: Writing up local insight with generative AI reduces its distinctiveness, and this effect is stronger the more the insight departs from conventional views.

4.2 Who is most affected

The effects in P1–P3 are unlikely to be uniform across employees. As noted in Section 2.4, higher confidence in AI is associated with less critical thinking (Lee et al., 2025).¹ Participants also reported skipping critical thinking under time pressure, for tasks they saw as trivial, and when they lacked the domain knowledge to evaluate output. These conditions bear directly on adaptation work. Employees with deep local experience have both the knowledge

¹Lee et al. (2025) also report a positive association between confidence in one's own ability and critical thinking ($p = .026$). I do not rely on this result because the paper is ambiguous about whether reported p-values were adjusted for multiple comparisons (corrected threshold $p = .007$).

to notice what a model has missed and the grounds to override it. Employees under deadline pressure, a familiar condition in subsidiaries reporting to headquarters, are more likely to accept output as it is.

The role of confidence may also grow over time. If, as seems likely, users' confidence in AI rises as models become more capable and reliable, the felt need to check and adapt AI output may decline further. Part of this decline would be a sensible response to better tools, since more reliable models produce more accurate output. But greater reliability does not make output more distinctive. As confidence rises, employees may do less of the adaptation work through which local knowledge enters AI-assisted products, so that their outputs become more correct and more alike at the same time.

A further tension follows. Brynjolfsson et al. (2025) find that AI assistance raises productivity most for less experienced workers. Yet these are the employees least equipped to recognize what a model leaves out. The gains and the risks of AI thus concentrate on the same people. Practitioners recognize a similar divide: the researchers behind the workslop survey distinguish “pilots,” who use AI actively and creatively, from “passengers,” who use it mainly to avoid workload (Niederhoffer et al., 2025).

Proposition 4: Deep local experience and task expertise among subsidiary employees weaken the effects described in P1–P3, whereas time pressure and high confidence in AI strengthen them.

4.3 The net effect: two competing outcomes

The paradox

Combining the wider channel (Section 3.4) with P1–P3 yields the paper's central paradox. Generative AI lowers writing and language barriers, so subsidiaries can send more reports, faster and in more polished form. But to the extent these reports are produced through substitution, framing, and smoothing, more of what arrives resembles the shared model

baseline. This is most pronounced when headquarters and subsidiaries use the same company-wide model: what a subsidiary sends then comes close to what headquarters could have obtained by asking its own tool.

Experimental evidence shows the same pattern of individual gain and collective convergence: AI raised the creativity of individual writers while reducing the diversity of their work as a group (Doshi & Hauser, 2024), and, as noted in Section 3.2, the diversity gap grows as more outputs are pooled (Moon et al., 2025). The second finding matters for MNEs, whose learning advantage rests on pooling knowledge from many subsidiaries. Current practice makes the shared-model condition realistic. BBVA is rolling out the same enterprise AI tool to all of its roughly 120,000 employees across 25 countries (OpenAI, 2025), and Samsung Electronics is doing so for all its employees in Korea and all employees of its Device eXperience division worldwide (OpenAI, 2026; Park, 2026).

Proposition 5a: Where subsidiaries and headquarters use the same generative AI models, AI use increases the volume and speed of knowledge sent to headquarters while reducing its distinctiveness. As a result, the value of this knowledge to headquarters may stagnate or decline despite its greater volume.

Voice expansion

A competing outcome deserves equal weight. As Section 2.3 showed, language skills shape who takes part in knowledge transfer within MNEs (Peltokorpi & Vaara, 2014), and host-country employees' proficiency in the corporate language is positively associated with reverse knowledge transfer (Peltokorpi, 2015; Peltokorpi & Yamao, 2017). Employees without strong skills in the corporate language have therefore been at a disadvantage in passing their observations upward. If generative AI allows these employees to contribute directly, first-hand knowledge that was previously unheard can enter the MNE.

Corporate case material, published by an AI translation vendor and therefore likely to emphasize benefits, illustrates the mechanism. At JERA, a manager reports that since real-time AI translation was introduced, participants from overseas group companies speak up more often in regular meetings, and that discussions once led mainly by headquarters staff now include local perspectives that better reflect on-the-ground realities (DeepL, n.d.-c). Pioneer reports that employees can now take part in English-language meetings regardless of their English proficiency (DeepL, n.d.-b), and at Hitachi Industrial Equipment Systems, an employee who does not speak English uses AI translation to work with an English-speaking manager (DeepL, n.d.-a). These cases show that AI translation lets more employees take part. However, whether they then share their own first-hand observations is a question the cases do not answer.

Proposition 5b: Generative AI increases the distinctiveness of subsidiary knowledge when it enables local employees who previously could not communicate in the corporate language to contribute their own first-hand observations.

Replacing versus carrying

P5a and P5b are not contradictory. They describe different uses of the same technology. The decisive question is whether AI *replaces* first-hand gathering and interpretation (P1 and P2) or *carries* first-hand knowledge that employees already hold, for example by translating or drafting their own observations. When AI carries knowledge, it widens the channel without thinning the content, although some risk of smoothing (P3) remains. When it replaces gathering and interpretation, it does both. For managers, the relevant question is therefore not how much AI subsidiaries use, but at which stage of knowledge work they use it.

4.4 Long-term consequence

Headquarters' attention is limited, and subsidiaries gain influence partly by standing out (Bouquet & Birkinshaw, 2008); subsidiary initiatives raise a subsidiary's influence only when they gain headquarters' attention (Ambos et al., 2010). The paradox in P5a affects both. A larger volume of similar reports makes distinctive contributions harder to recognize. Headquarters' attention is also selective in a way that compounds the problem. Monteiro (2015) found that headquarters' decision-makers tended to favor opportunities that confirmed what the MNE already knew, even though subsidiaries had been established far from headquarters to find novel knowledge. Reports that resemble the shared model baseline fit this preference for the familiar. Truly distinctive input therefore becomes both rarer and more likely to be overlooked when it does arrive. Practice offers a parallel on the sender's side: in the workslop survey, about half of the workers viewed colleagues who sent polished but generic work as less creative, capable, or reliable, and 42% trusted them less (Niederhoffer et al., 2025), although that evidence concerns colleagues rather than headquarters–subsidiary relations.

Over time, subsidiaries whose reports add little beyond what headquarters' own AI provides may lose voice, and their roles may shift from creating new competences toward exploiting competences developed elsewhere in the MNE (Cantwell & Mudambi, 2005). Organizational learning theory explains why this matters. When individuals adapt quickly to a shared organizational code, the organization loses the variety it needs to keep improving that code (March, 1991), and organizational learning tends to overlook distant times, distant places, and failures (Levinthal & March, 1993). A widely used model can act as such a code across the entire MNE. Notably, no one needs to decide on this outcome. It can emerge from many individual choices about how to use AI in everyday work.

Proposition 6: As AI-assisted subsidiary input becomes more voluminous but more alike, headquarters may find distinctive subsidiary knowledge harder to recognize, and subsidiaries may lose influence over headquarters' decisions. Over time, subsidiaries that created new knowledge for the MNE may drift toward implementing headquarters' plans, weakening the MNE's ability to learn from geographic diversity.

Table 1 summarizes the propositions, the stage and mechanism each addresses, the research on which each draws, and, where available, practice examples that illustrate it.

Table 1. Summary of propositions and their basis of support

Proposition	Stage and mechanism	Supporting research (type of evidence)	Main basis	Practice illustration
P1 AI use for gathering reduces the share of knowledge drawn from private, first-hand local sources	Gathering: substitution	Lee et al. (2025), survey of knowledge workers; Csaszar et al. (2024), conceptual argument with experiments	Indirect evidence and reasoning	Synthetic survey panels
P2 AI use for interpreting moves conclusions toward the model's categories, even when output is checked	Interpreting: framing	Csaszar et al. (2024), experiments; Anderson et al. (2024), experiment with 36 participants; Lee et al. (2025), survey	Mainly reasoning	None
P3 AI-assisted writing up reduces distinctiveness, especially for unconventional insights	Writing up: smoothing	Szulanski (1996), empirical study; Padmakumar & He (2024), controlled writing study; Moon et al. (2025), three preregistered studies	Indirect evidence from writing studies	Survey on AI-generated "workslop"
P4 Local experience and expertise weaken P1–P3; time pressure and confidence in AI strengthen them	Conditions on gathering, interpreting, and writing up	Lee et al. (2025), survey; Brynjolfsson et al. (2025), field study of customer support agents	Indirect evidence and reasoning	"Pilots" versus "passengers"
P5a With shared models, more knowledge reaches headquarters but less of it is distinctive	Net effect: wider channel combined with P1–P3	Doshi & Hauser (2024), online experiment; Moon et al. (2025), preregistered studies	Reasoning building on experimental evidence	BBVA and Samsung enterprise AI rollouts
P5b AI increases distinctiveness when it enables employees previously limited by the corporate language to contribute their own observations	Net effect: wider channel carrying first-hand knowledge	Peltokorpi & Vaara (2014), interviews and survey; Peltokorpi (2015), survey of 661 departments; Peltokorpi & Yamao (2017), survey of 574 managers	Direct evidence on language and knowledge transfer; link to AI by reasoning	AI translation at JERA, Pioneer, Hitachi IES

Proposition	Stage and mechanism	Supporting research (type of evidence)	Main basis	Practice illustration
P6 Subsidiaries may lose influence and drift from creating to applying knowledge	Receiving: dilution, and long-term consequences	Bouquet & Birkinshaw (2008), study of 283 subsidiaries; Monteiro (2015), field study in one MNE; Ambos et al. (2010), empirical study; Cantwell & Mudambi (2005); March (1991), simulation model; Levinthal & March (1993), conceptual	Theory-based reasoning	Survey on AI-generated “workslop”

Note. Practice illustrations show that mechanisms are recognizable in current practice; they are not evidence for the propositions.

5. Discussion and Conclusion

This paper has argued that generative AI can increase the amount of knowledge subsidiaries send to headquarters while reducing how distinctive that knowledge is, and that the outcome depends on whether AI replaces or carries the first-hand work through which local knowledge is produced. In this section, I discuss the implications for theory and practice, outline directions for research, and note the boundaries of the argument.

5.1 Theoretical implications

Reverse knowledge transfer. Research on reverse knowledge transfer has focused on how to get knowledge to flow from subsidiaries to headquarters. This paper suggests that the amount of knowledge that flows and its distinctiveness need to be treated as separate outcomes, because generative AI can increase the first while reducing the second. It also suggests that distinctiveness can no longer be judged only against what headquarters already knows; it must also be judged against what a widely used model would supply by default. In this respect, the paper continues the work of scholars who have questioned simple assumptions in this literature, such as the assumption that more innovative subsidiaries necessarily transfer more knowledge (Mudambi et al., 2014).

AI in international business. Recent IB scholarship treats AI as a force that transforms how MNEs learn, innovate, and decide across borders (Buckley et al., 2026). This paper specifies one place where that transformation can cut the other way: in the everyday

work through which subsidiary employees produce knowledge, AI can make the MNE's learning more efficient while narrowing what it learns. In doing so, it responds to calls for more attention to individuals in IB research on knowledge sharing and subsidiaries (Foss & Pedersen, 2019; Meyer et al., 2020). The argument also qualifies the view that AI relaxes the limits of managers' rationality by expanding the information they can access and process (Lindner et al., 2025). It does not dispute this, but suggests that part of the limit moves rather than disappears. With generative AI, the binding constraint becomes employees' willingness and ability to do adaptation work: to notice what a model has missed and add what only they know. This offers an individual-level account of what they describe as biased interaction between humans and AI, and it locates that interaction in specific stages of knowledge work.

Homogenization. Research on AI and homogenization has mostly studied individuals or firms in isolation. This paper shows that organizational structure matters. Because an MNE learns by pooling knowledge from many subsidiaries, it is exposed to the finding that convergence grows as outputs are pooled (Moon et al., 2025). At the same time, the competing proposition (P5b) shows that convergence is not inevitable: when AI carries knowledge employees already hold, it can widen participation without thinning content. The argument also differs from work on machine learning replacing human decisions (Balasubramanian et al., 2022), because the risk arises here not from replacing employees but from how they use AI in their own work.

5.2 Managerial implications

For managers, the main implication is that the important question is not how much AI subsidiaries use, but at which stage of knowledge work they use it. AI that translates and drafts employees' own observations is likely to add value; AI that substitutes for talking to customers or for interpreting local developments is more likely to erode it.

Headquarters can influence this through its reporting practices. Practices that reward fast, polished reports are likely to strengthen the paradox described in P5a. Practices that ask subsidiaries for first-hand evidence, such as customer quotes, field observations, and local data, are likely to weaken it, because they require employees to gather and present what a model cannot supply. Subsidiary managers, for their part, can protect time for adaptation work rather than treating it as a cost to be eliminated.

Language deserves particular attention. AI can supply much of the language ability that research has linked to reverse knowledge transfer. But research on foreign subsidiaries in Japan suggests that ability is not enough: employees' commitment to headquarters (Peltokorpi, 2015) and shared vision (Peltokorpi & Yamao, 2017) also shape whether knowledge is transferred. AI translation is therefore unlikely to replace efforts to build these relationships.

5.3 Directions for future research

The propositions invite several kinds of research. First, distinctiveness can be measured against the shared model baseline. Researchers could put the questions subsidiaries were asked to address to the same model, without local input, and compare the model's answers with the subsidiaries' actual reports. The degree of overlap would offer a direct test of framing (P2) and smoothing (P3), which are otherwise difficult to observe.

Second, qualitative studies of subsidiary employees could examine how AI is used at each of the four stages, and when employees choose to replace or carry their own knowledge. Third, longitudinal studies are needed to test the long-term drift in P6, and to examine whether employees' confidence in AI, and with it their adaptation work, changes as models become more capable, as argued in Section 4.2.

Finally, the argument can be extended from subsidiaries to countries. Institutional theory explains why organizations become alike, including through imitation under

uncertainty (DiMaggio & Powell, 1983). Widely shared AI models may become a new source of such similarity, operating not only within MNEs but across firms from different countries. Whether this narrows differences between national business systems is a question for future work.

5.4 Boundaries of the argument

The argument has clear limits. Routine, technical, and well-codified knowledge is likely to transfer more efficiently with AI, with little loss of value. Convergence is not always harmful: spreading good practices or reducing the behavioral biases discussed in Section 2.4 are genuine benefits. The concern of this paper is specifically the knowledge that makes an MNE's geographic diversity valuable. In addition, generative AI is changing rapidly, and some mechanisms may weaken or strengthen as tools develop.

5.5 Conclusion

Generative AI promises to remove one of the oldest obstacles to learning within MNEs: the difficulty of getting knowledge from subsidiaries to headquarters. This paper has argued that removing that obstacle may come at a cost that existing research has not anticipated. When employees across subsidiaries use the same tools, more knowledge may reach headquarters while less of it is distinctive. Whether this happens depends on a choice made every day by individual employees: whether AI replaces the work through which local knowledge is produced, or carries the knowledge they already hold.

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