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Cultural Intelligence and Generative AI in Cross-Cultural Knowledge Management: A Conceptual Framework for Organizational Learning

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ABSTRACT

This conceptual article develops the Cultural Intelligence–Generative AI Knowledge Integration (CQ–GKI) framework to explain how managers preserve culturally situated meaning when transferring organizational knowledge using generative artificial intelligence (GenAI). Integrating cultural intelligence, organizational knowledge transfer, absorptive capacity, and organizational learning, it distinguishes information accessibility, source fidelity, and receiving-context applicability. Cultural knowledge recontextualization is proposed as an observable managerial mechanism involving assumption elicitation, cross-context comparison, human verification, and documented adaptation. Eight propositions specify accessibility, managerial recontextualization, complementary knowledge-quality outcomes, moderators, and the institutionalization of validated lessons. The article distinguishes individual interpretation from unit-level reuse and organizational learning, develops falsifiable alternatives, and proposes experimental and multilevel tests. Its contribution is a conditional explanation of when culturally intelligent oversight adds value beyond technical expertise and routine AI verification. The framework treats source and receiving-context verification as complementary practices and differentiates the accessibility of candidate information from validated knowledge reuse. It also outlines research designs capable of testing these distinctions across managerial episodes and organizational settings.

1. INTRODUCTION

Organizations increasingly use generative artificial intelligence (GenAI) to turn scattered policies, meeting records, project reports, and experiential accounts into accessible summaries and reusable guidance. In globally distributed firms, the attraction is immediate: an employee in

one business unit may seek an explanation of a practice developed in another, without waiting for an expert to prepare a bespoke account. Yet the ease of producing fluent text should not be mistaken for the successful transfer of organizational knowledge. Terms such as escalation, commitment, consensus, or exception may refer to different practical expectations in different settings. An answer can be grammatically accurate while being operationally misleading.

This article examines a managerial problem that arises between the production of a GenAI output and its organizational use. When knowledge travels across cultural boundaries, source practices often embody unwritten assumptions about hierarchy, relationship management, risk, professional responsibility, and the meaning of agreement. Removing those assumptions may make an output concise, but also less usable. Moreover, an apparently complete answer may conceal uncertainty, contradictory local practices, or the difference between an organization-wide rule and a context-specific convention. Such limitations matter because managers must decide whether employees can act on an AI-generated representation of another unit's experience.

Generative AI has demonstrated important capabilities in professional tasks, including gains in the speed and assessed quality of writing under experimental conditions (Noy & Zhang, 2023). Research in knowledge management also recognizes the potential for GenAI to change how firms create, organize, and access knowledge (Kaczorowska-Spychalska et al., 2024). At the same time, assessments of language models document variation in cultural alignment and demonstrate that context-sensitive prompting changes some model responses (Tao et al., 2024). The management question is therefore not only whether a system can generate a useful representation of information but also who verifies that the representation retains what local actors consider essential.

Cultural intelligence (CQ) provides a way to theorize that verification. CQ is a multidimensional capability for effective functioning in culturally diverse situations; its metacognitive, cognitive, motivational, and behavioral components have distinct associations with cultural judgment and adaptation (Ang et al., 2007). In the present argument, CQ does not simply increase willingness to use technology. It enables managers to notice that a seemingly portable explanation rests on contingent cultural premises, seek accounts from knowledgeable participants, and specify the conditions under which the knowledge can be applied.

The article develops the Cultural Intelligence–Generative AI Knowledge Integration (CQ–GKI) framework. Its central claim is that GenAI increases the accessibility of organizational information, whereas culturally intelligent managerial recontextualization helps determine

whether the transferred material becomes faithful and applicable knowledge. The framework separates knowledge fidelity—retaining the meaning and limits of a source practice—from contextual applicability—making that practice actionable in a receiving setting. It then explains how feedback from use can update organizational memory. This mechanism-oriented account is distinct from studies whose primary outcomes are generalized trust, collaboration, or strategic performance.

The article makes three contributions. First, it identifies cultural knowledge recontextualization as a managerial mechanism connecting AI-generated representations to cross-cultural knowledge reuse. Second, it proposes fidelity and applicability as analytically separate, jointly necessary knowledge-quality dimensions. Third, it presents boundary conditions and an empirical agenda that distinguish beneficial GenAI augmentation from merely faster dissemination of decontextualized information. The paper is a theory-development article: its propositions are not presented as empirically established findings.

The relevance of this question is now sharpened by the emergence of research that directly examines GenAI-enabled knowledge management. Storey (2025) argues that GenAI may reconfigure how novice and expert knowledge workers locate, generate, and evaluate organizational knowledge, while warning that tacit expertise can be lost through overreliance. Böhm and Durst (2026) conceptually revise assumptions of the SECI knowledge-creation model in light of generative and receptive AI, while Cerchione et al. (2026) use bibliometric mapping to survey the emerging literature on artificial knowledge generation. These contributions underscore the importance of AI in knowledge processes but leave room for a more precise explanation of cross-cultural interpretive judgment at the point of organizational transfer.

A second stream documents cultural variation in AI-generated representations. Tao et al. (2024), using survey-based measures of cultural values, report systematic cultural biases in language-model responses and evaluate culturally targeted prompts as one approach to improving measured alignment. Their findings should not be interpreted as proving that prompts alone capture the situated meaning of a firm's routines: aggregate measures of cultural alignment are different from the validity of a particular organizational instruction. The present article therefore treats a fluent output as a candidate representation requiring domain- and context-specific evaluation.

The research question becomes especially relevant to multinational firms whose knowledge travels among headquarters, subsidiaries, vendors, and cross-border teams. A process standard

developed in one unit may presuppose a distinctive hierarchy, communication convention, legal constraint, or occupational norm. The recipient may benefit from the standard without replicating these premises. What managers require is a repeatable procedure that distinguishes what should remain invariant from what may appropriately change.

2. Conceptual Foundations

2.1. Cultural intelligence as interpretive managerial capability

Cultural intelligence concerns effective action when culturally relevant expectations and behavioral cues differ. The four-dimensional account distinguishes metacognitive CQ, which involves awareness and regulation of assumptions; cognitive CQ, which concerns knowledge about cultural systems and practices; motivational CQ, which concerns interest and energy directed toward intercultural situations; and behavioral CQ, which concerns flexible verbal and nonverbal action (Ang et al., 2007). These dimensions should not be reduced to national stereotypes. Individuals within a national or regional setting vary, and organizational, occupational, and team cultures may matter as much as country of origin.

For knowledge transfer, metacognitive CQ is especially important when a manager recognizes that a supposedly universal account may encode the perspective of the source unit. Cognitive CQ can help identify potentially relevant institutions and conventions, but it cannot substitute for direct local evidence. Motivational CQ supports the effort required to reconcile discordant interpretations; behavioral CQ assists managers in discussing sensitive differences without framing one convention as deficient. Taken together, the dimensions are expected to improve the quality of inquiry around AI-generated information, not to guarantee accurate cultural judgments.

We therefore conceptualize managerial CQ as an enabling capability rather than a universal cure for model error. A culturally intelligent manager might still make an inaccurate decision when information is inaccessible, incentives discourage dissent, or a generated output contains invented facts. Conversely, a manager with lower measured CQ might achieve good results if organizational review routines and knowledgeable collaborators compensate for individual limitations. Such qualifications help make the framework testable and prevent CQ from becoming an unexplained label for managerial effectiveness.

Recent empirical research provides a relevant but bounded link between CQ and knowledge behavior. Li (2024), analyzing host-country employees in foreign subsidiaries, finds that cultural intelligence predicts knowledge sharing. This finding supports the plausibility of CQ as a capability influencing knowledge-related interactions; it does not establish that CQ corrects

GenAI outputs, which is the novel proposition advanced here. A single-site study at a Chinese electronics plant identified the combined importance of people-, process-, and knowledge-related factors for workplace knowledge sharing (Muniz et al., 2024); it did not test GenAI-mediated transfer.

The four CQ dimensions may support different stages of recontextualization. Metacognitive CQ motivates explicit questioning of taken-for-granted premises; cognitive CQ supplies provisional knowledge of institutional and social norms; motivational CQ helps sustain engagement when clarifications reveal disagreement; and behavioral CQ facilitates communication and adaptation of resulting instructions. These functions are analytically separable. A manager could correctly diagnose a cultural assumption while failing to solicit relevant local testimony, or successfully negotiate local adaptation without preserving a crucial source constraint. Ma (2026, p. 4) similarly emphasizes the managerial importance of interpreting and adapting to diverse communication styles, expectations, values, and norms; the present framework extends that general management insight specifically to the verification of GenAI-mediated knowledge transfer.

2.1.1. Knowledge processes and retrieval

Alavi and Leidner (2001) distinguish knowledge creation, storage and retrieval, transfer, and application. This process distinction is essential to the present framework because an AI-generated answer may improve retrieval while leaving transfer and application unchanged. A multinational organization could make policies searchable in several languages, yet employees might still lack the experience needed to interpret exceptions, identify appropriate decision authorities, or recognize when a local practice cannot be generalized. Thus, the proposed framework treats search convenience as an enabling condition, and not as evidence that organizational learning has occurred.

2.1.2. The portability problem

Organizational knowledge is often partly situated in relationships among people, tools, and tasks. Argote and Ingram (2000) argue that knowledge embedded in interactions among these elements can be particularly difficult to transfer when the receiving context differs. GenAI can describe procedures and reorganize text, but it cannot independently demonstrate that the work system in the receiving unit supports equivalent action. The relevant question is whether the generated representation contains sufficient information about the conditions under which the source

practice worked. This yields a stronger conceptual boundary between documenting a practice and reproducing its effectiveness.

2.2. GenAI-supported organizational knowledge processing

Knowledge management distinguishes obtaining information from integrating it into practice. Nonaka (1994) showed how organizational knowledge creation depends on interactions between tacit and explicit knowledge; tacit knowledge includes experiential understanding that is difficult to fully describe in documents. GenAI can support selected activities in this process, such as drafting explanations, retrieving relevant passages, comparing documents, translating, and proposing syntheses. It does not establish that every nuance present in the original interaction survives the conversion to generated text.

Kaczorowska-Spychalska et al. (2024) explicitly examine GenAI as a source of change in knowledge management and identify oversight and information-quality questions. Noy and Zhang (2023) show gains in professional writing performance but do not test cross-cultural knowledge fidelity. These contributions motivate a distinction between processing efficiency and representational adequacy. Processing efficiency concerns the time and effort required to find, summarize, or distribute information. Representational adequacy concerns whether the output retains relevant conditions, meanings, exceptions, and uncertainties.

In the CQ–GKI framework, GenAI-supported knowledge processing comprises four functions: capture of documented organizational experience, synthesis of material from multiple sources, retrieval or reformulation for a user's question, and multilingual or cross-context representation. The functions describe possible uses, not necessarily equally effective capabilities. Their value depends on access to reliable source material, the suitability of the model and retrieval system, appropriate confidentiality controls, and the human capacity to evaluate the resulting output.

The established distinction between explicit and tacit knowledge is particularly useful here. Explicit knowledge can be written into a template, whereas tacit knowledge may reside in practiced judgment, relationships, or exceptions understood by experienced employees. GenAI can help generate a document from an interview, but that output remains an imperfect proxy for the competence that produced the practice. The GRAI conceptual revision developed by Böhm and Durst (2026) reinforces the need to revisit conventional knowledge-cycle assumptions when generative systems participate in representation and processing.

The presence of AI also changes the economics of attention. Cheap generation can make a draft available to many units, but managerial verification remains costly. Consequently, organizations

may face an output-abundance problem in which more knowledge artifacts compete for fewer units of expert review. Storey (2025) distinguishes opportunities for novices from the continuing importance of expert quality assessment; this article develops that insight in explicitly intercultural terms.

Organizations should therefore separate three performance outcomes: representational availability (whether a candidate account is accessible), semantic fidelity (whether it preserves source meaning), and contextual applicability (whether the receiving unit can use it responsibly). A GenAI deployment can improve the first while leaving the second and third unchanged, or even weakening them where culturally important exceptions disappear in a summary.

2.2.1. Social impediments to transfer

Szulanski (1996) found that internal transfers of best practices encounter substantial barriers associated with causal ambiguity, inadequate recipient absorptive capacity, and difficult source–recipient relationships. These barriers challenge any assumption that lower communication costs automatically produce effective transfer. A fluent GenAI summary may reduce the time needed to locate a procedure while concealing unresolved causal ambiguity. In the CQ–GKI model, managers must therefore inquire not only what a source unit did but why the practice succeeded and which contextual conditions enabled it.

2.2.2. Networks and contextual verification

Informal networks influence the communication of complex knowledge. Reagans and McEvily (2003) distinguish the effects of network cohesion and network range, showing why the relational structure surrounding a transfer matters to conveying and understanding complex ideas. For AI-assisted transfer, the implication is that managerial verification must access the relevant knowledge holders, including individuals who know exceptions and localized meanings. CQ may help a manager recognize why different participants interpret the same text differently, while network access determines whether the manager can obtain credible correction. The two capabilities should be modeled as complementary rather than interchangeable.

2.2.3. Learning climate and dissent

A further organizational condition is the willingness to challenge apparently authoritative outputs. Edmondson (1999) identifies psychological safety as associated with learning behavior in work teams. Applied cautiously to GenAI-mediated transfers, that finding suggests a plausible enabling condition: members of the receiving unit must be able to question an AI-generated directive or a headquarters-endorsed summary without interpersonal penalty. This extension is a

new theoretical inference; Edmondson's study did not test GenAI. It explains why even managers with high CQ may fail to recontextualize knowledge when employees do not disclose errors or conflicting local experience.

2.3. Organizational learning and absorptive capacity

Organizational learning occurs when experience informs subsequent interpretation, routines, and action. The knowledge-creation account emphasizes conversion and amplification of knowledge across levels (Nonaka, 1994). Absorptive-capacity theory likewise argues that organizations must recognize the value of information, assimilate it, and apply it, with prior related knowledge affecting these processes (Cohen & Levinthal, 1990). These perspectives provide a basis for expecting that an accessible answer is only one input to learning. In discussing the contemporary intersection of management and leadership, Ma (2026, pp. 3–4) identifies human judgment, organizational culture, adaptability, and emerging technologies as concurrent managerial concerns. These observations contextualize, without empirically testing, the proposed knowledge-recontextualization mechanism.

A receiving unit may possess technical capacity to access AI-generated instructions but lack the prior knowledge needed to identify their contextual boundaries. An AI summary of a customer-resolution protocol, for example, may correctly list sequence and timing while omitting a locally accepted process for obtaining authority. The receiving unit therefore has to reconcile the information with its own requirements before implementation. Successful reuse involves both faithful understanding of source knowledge and adaptation to receiving-context constraints.

Organizational memory is also dynamic. If managers record why generated instructions were rejected, qualified, or adapted, the resulting annotations can improve subsequent retrieval and training materials. If corrections remain in private conversations, the organization may repeat the same interpretive error. The proposed learning process thus contains a feedback loop: application reveals contextual mismatches; managers investigate them; verified lessons enter maintained knowledge repositories; and later outputs can incorporate updated context.

Organizational learning research provides a further reason to avoid equating information production with learning. Wiesenfeld and Kellogg (2026), drawing on a case study in a healthcare organization, theorize generative organizational learning as emerging from the interaction of LLM affordances, actors' goals, and organizational institutions. This perspective locates technology inside a social system rather than granting causal agency exclusively to a model. Similarly, recent knowledge-management research investigates the integration of GenAI

into innovation-related creation, retrieval, storage, transfer, and application processes (Storey, 2025; Cerchione et al., 2026). The present framework narrows the analytic lens to the transfer episode, where a receiving unit must decide whether a generated representation retains the source practice's conditions of validity.

Absorptive capacity is relevant because a receiving unit needs sufficient expertise to recognize, assimilate, and exploit external knowledge (Cohen & Levinthal, 1990). Yet absorptive capacity does not itself specify how managers identify conflicting cultural assumptions in AI-mediated descriptions. The CQ–GKI framework proposes culturally informed recontextualization as that intermediate activity. CQ and absorptive capacity may be complementary rather than substitutable; contextual cultural judgment without technical comprehension is inadequate, and technical expertise without contextual reflection can be equally limited.

2.3.1. Automation and augmentation

Raisch and Krakowski (2021) frame artificial intelligence in management through an automation–augmentation paradox: organizations seek labor-saving substitution while also seeking enhanced human judgment, and these goals are often interdependent. The CQ–GKI framework specifies one domain in which this tension is unusually consequential. Automated synthesis can increase the volume of transferable documents, but determining whether those documents retain culturally embedded meaning requires human interpretation. The framework does not assume augmentation is always superior; it predicts that the required degree of interpretive intervention depends on knowledge tacitness, consequences of error, and verifiability.

2.3.2. Heterogeneous GenAI outcomes

Brynjolfsson et al. (2025), studying a real-world customer-support setting, report productivity gains associated with access to a generative AI assistant, with substantial variation across workers. Their evidence supports the proposition that AI assistance can help diffuse useful practices under some conditions. It does not establish successful knowledge transfer across national cultures, nor does it establish that AI preserves tacit meaning. Accordingly, we treat such productivity findings as evidence about the enabling role of AI-mediated information access, while positioning fidelity and local applicability as separate empirical questions.

3. The Research Gap and Framework Architecture

Existing contributions support three separate insights: CQ is related to effective cultural judgment (Ang et al., 2007); GenAI changes the speed and manner of producing knowledge

artifacts (Noy & Zhang, 2023; Kaczorowska-Spychalska et al., 2024); and language models may reflect cultural patterns that vary by population and prompting context (Tao et al., 2024). The proposed gap lies in specifying the managerial process through which such artifacts are evaluated and transformed into context-appropriate organizational knowledge. This is a conceptual positioning claim, not a claim that no prior scholar has connected these broad topics.

The unit of the main mechanism is the managerial knowledge-transfer episode: a bounded occasion in which an organization uses GenAI to represent a practice originating in one cultural or organizational context for potential use in another. The focal actor is the manager responsible for approving, amending, or withholding the output. The source may be a team, subsidiary, functional unit, or professional community; the receiver may be an analogous unit operating under different assumptions. This episode-level specification permits observations of the original source, generated output, review decisions, and downstream use.

We define cultural knowledge recontextualization as the deliberate managerial process of (a) eliciting source-specific assumptions, (b) comparing those assumptions with a receiving context, (c) verifying ambiguities with relevant human knowledge holders, and (d) documenting how the output should be interpreted or adapted. This construct differs from editing for style or fluency. It refers to substantive examination of the meaning, boundary conditions, and practical consequences of a piece of knowledge.

Knowledge fidelity is the degree to which a transferred representation preserves the original knowledge's intended meaning, causal rationale, critical exceptions, and uncertainty. Contextual applicability is the degree to which that knowledge, whether preserved intact or deliberately adapted, can guide appropriate action under receiving-unit conditions. High fidelity need not imply high applicability: an accurate description of one unit's practice may be unsuitable elsewhere. Conversely, an output might appear applicable because it matches local expectations while misrepresenting the source. Treating these outcomes separately exposes both failure modes.

The incremental role of CQ is conditional, rather than universal. Domain expertise can identify a technically incorrect procedure; absorptive capacity explains a receiving unit's ability to recognize, assimilate, and apply knowledge (Cohen & Levinthal, 1990); and conscientiousness may promote careful review. CQ predicts additional explanatory power when the source and recipient attribute different socially embedded meanings to the same instruction. Such differences require a manager to question culturally taken-for-granted premises, seek

perspectives across contexts, and negotiate adaptations without stereotyping (Ang et al., 2007). The distinctive prediction is therefore not that high-CQ managers always outperform experts, but that CQ has greater incremental value where culturally consequential implicit assumptions survive neither literal translation nor ordinary technical checks.

Cross-level transmission must be specified. The managerial knowledge-transfer episode is the primary observation unit; the reviewing manager supplies individual CQ; source and recipient experts provide collective verification; the receiving unit enacts or rejects the revised guidance; and organizational learning occurs only when validated interpretations are retained in shared routines or repositories and shape later decisions. A favorable output rating is not equivalent to downstream learning. Repeated uptake, subsequent correction rates, institutionalized review rules, and repository changes provide observable evidence of this transition. This logic is consistent with distinguishing knowledge storage from application (Alavi & Leidner, 2001) and with accounts of GenAI learning as jointly shaped by actors and organizational institutions (Wiesenfeld & Kellogg, 2026).

Table 1 Maps the eight propositions explicitly. Managerial CQ predicts cultural knowledge recontextualization (P1), while GenAI processing predicts accessibility of candidate knowledge representations (P2). Recontextualization predicts fidelity and applicability separately (P3–P4); their positive interaction predicts effective reuse (P5). Tacitness and cultural contextual complexity moderate the recontextualization–fidelity relationship (P6), and access to knowledgeable reviewers moderates the CQ–recontextualization relationship (P7). Institutionalized capture and reuse of validated lessons links successful transfer to organizational learning (P8). The feedback relationship represents future learning cycles, not a tested causal estimate.

Table 1. CQ–GKI conceptual framework and eight hypothesized relationships

Antecedent / affordance	P1 Managerial CQ → quality of cultural recontextualization
	P2 GenAI-supported processing → candidate information accessibility
Managerial mechanism	Cultural recontextualization: elicit source premises → compare receiving context → consult experts → annotate / approve / reject
Quality of transfer	P3 Recontextualization → source knowledge fidelity
	P4 Recontextualization → receiving-context applicability
Reuse and learning	P5 Fidelity × applicability → effective cross-cultural reuse
	P8 Effective reuse × institutionalized capture →

	subsequent organizational learning
Moderating conditions	P6 Tacitness and contextual complexity strengthen P3
	P7 Knowledgeable-reviewer availability strengthens P1
Feedback across episodes	Validated annotations, exceptions, and corrections → knowledge repositories and future reuse (proposed longitudinal learning cycle)

Note. Arrows indicate proposed relationships, not established causal effects. The product sign (×) represents a hypothesized positive interaction. Episode-level measures and organizational learning outcomes occur at different levels and should be evaluated separately. The table summarizes the proposed conceptual relationships.

The scope of the proposed contribution should be distinguished from three closely related literatures. First, the CQ–knowledge-sharing relationship concerns a person's willingness or capacity to exchange knowledge, as exemplified by Li (2024). Second, the GenAI–knowledge-management literature explains opportunities and risks associated with producing and organizing AI-enabled knowledge resources (Böhm & Durst, 2026; Cerchione et al., 2026; Storey, 2025). Third, research on large-language-model cultural alignment documents model-level representational patterns (Tao et al., 2024). CQ–GKI examines an organizational process not fully resolved by any one of these streams: a manager's intervention to preserve provenance and meaning while making an AI-generated representation usable in another unit.

A transfer episode begins with a source practice and an intended recipient. The source practice contains articulated rules and, potentially, unstated assumptions. GenAI generates a candidate account from materials available to it, with the quality of that account conditional on the source material and system configuration. The manager then compares the account with source testimony and receiving-unit constraints, records necessary qualifications, and authorizes, revises, or rejects the account. Subsequent use generates feedback that may update the organization's repository and verification procedures. Because this is a process model, propositions refer to associations expected under specified conditions rather than previously established causal effects.

4. Proposition Development

4.1. Cultural intelligence and recontextualization

The first mechanism is the recognition of a possible mismatch between an apparently satisfactory output and the meanings embedded in its source. Metacognitive CQ makes it more likely that a manager questions taken-for-granted interpretations; cognitive CQ provides hypotheses about what contextual features might matter. Motivational CQ supports the time-consuming task of

resolving uncertainty, while behavioral CQ facilitates discussion with people who may interpret organizational practice differently (Ang et al., 2007). These capabilities should increase the frequency and quality of meaningful recontextualization, conditional on access to relevant evidence.

Proposition 1. Higher managerial cultural intelligence is positively associated with the quality of cultural knowledge recontextualization during GenAI-assisted cross-cultural knowledge-transfer episodes.

4.2. GenAI processing and information accessibility

GenAI may reduce the effort needed to locate, restate, and combine documented practices. Its capacity to generate useful prose from a prompt may lower the cost of creating candidate knowledge artifacts, a proposition consistent with observed improvements in writing-related tasks (Noy & Zhang, 2023). Accessibility refers here to the ease with which a recipient can locate and comprehend a candidate explanation, not whether that explanation is accurate enough to implement. This restriction avoids attributing contextual understanding to the technology by definition.

Proposition 2. Greater use of GenAI-supported processing for sufficiently documented organizational knowledge is positively associated with the accessibility of candidate knowledge representations, holding source quality and access permissions constant.

4.3. Recontextualization, fidelity, and applicability

An explicit check of local assumptions can reveal that the same term has different operational implications across settings. For instance, a generated guide may recommend consultation before a staffing change without identifying who must be consulted, whether consent is expected, or what constitutes a formal decision. Recontextualization requires a manager to compare the generated guide with source evidence and consult appropriate stakeholders. Where checks identify omissions or misinterpretations, the manager can qualify the output or withhold it rather than allow an ambiguous summary to be treated as authoritative.

This process supports fidelity because it encourages preservation of the source practice's rationale and limits. It can also support applicability because the manager makes any required local adaptation explicit instead of presenting adaptation as an unacknowledged replacement of original knowledge. The two outcomes remain distinguishable even when the same review process benefits both.

Proposition 3. The quality of cultural knowledge recontextualization is positively associated with the fidelity of GenAI-assisted knowledge transfer.

Proposition 4. The quality of cultural knowledge recontextualization is positively associated with the contextual applicability of the transferred knowledge, provided that local adaptation is explicitly documented and validated.

4.4. Joint knowledge quality and subsequent reuse

Organizational knowledge reuse depends on whether employees understand the source logic and whether the practice is suitable for implementation in the receiving context. Fidelity and applicability should be assessed by different judges: source experts can judge missing rationale or exceptions, and receiving-unit experts can judge local feasibility and legitimacy. An accurate but locally unsuitable procedure can properly be rejected; an apparently useful procedure founded on a misrepresentation can produce false learning. P5 therefore predicts complementarity for effective, appropriate reuse—not simply higher intention to reuse. The positive interaction is an empirical hypothesis whose alternatives include additive or threshold effects.

Proposition 5. Knowledge fidelity and contextual applicability interact positively in predicting effective cross-cultural knowledge reuse, such that reuse is greatest when both dimensions are high.

4.5. Boundary conditions: tacitness and verification

The advantage of managerial recontextualization should be greatest when source knowledge contains implicit social or procedural rules. Such rules may be omitted from written records precisely because source-team members treat them as obvious. In a transfer of standardized inventory codes, ambiguity may be low; in a transfer of negotiation practices, managerial escalation conventions, or post-merger integration lessons, it may be high. Because tacit knowledge is difficult to make fully explicit (Nonaka, 1994), a technically fluent output can mask important gaps.

Proposition 6. Knowledge tacitness and cultural contextual complexity strengthen the positive association between cultural knowledge recontextualization and transfer fidelity.

Human verification provides a distinct organizational condition. It concerns access to source and receiving-context experts who can corroborate or challenge the output. An empirical comparison of language-model responses with population-level cultural indicators identifies patterned cultural alignment and bias (Tao et al., 2024), although this does not directly measure

organizational procedural knowledge. Local experts can identify problems that standardized review prompts overlook, although disagreement among experts may itself require resolution. The added value of CQ is therefore expected to be contingent in part on whether managers can obtain reliable local testimony.

Proposition 7. Availability of knowledgeable source- and receiving-context reviewers strengthens the positive relationship between managerial cultural intelligence and the quality of cultural knowledge recontextualization.

Two distinctions prevent the proposition set from collapsing into a generic technology-adoption model. First, P2 predicts increased access to candidate representations, not an unconditional improvement in their accuracy. Second, P3 and P4 identify separate products of human review: fidelity to the originating meaning and applicability in the target context. An organization may responsibly conclude that a faithful source practice should not be adopted by the receiving unit. In such a case, high fidelity and low applicability represent a valid diagnosis rather than a failure of the conceptual model.

The moderating conditions in P6 and P7 similarly address different limitations. Tacitness and contextual complexity determine how much potentially consequential information is missing from the explicit record. Reviewer availability determines whether the manager can test interpretations against knowledgeable people. Although high CQ should facilitate recognition of uncertainty, it cannot compensate completely for inaccessible expertise, poor record quality, or organizational incentives that suppress inconvenient corrections.

The danger of surface alignment. Tao et al. (2024) document cultural bias in outputs of several large language models and show that some culturally targeted prompting can improve alignment with population-level survey responses. Such findings caution against equating grammatical accuracy or locally familiar language with cultural fidelity. Prompting alone cannot verify whether an organization's specialized terms reflect the actual decision rights and informal routines of a particular unit. The CQ–GKI framework therefore treats prompts as possible inputs to a review process, not substitutes for source-owner and recipient-owner validation.

Homogenization and organizational memory. Doshi and Hauser (2024) report an experimental trade-off in which GenAI assistance improved individual creative output under their study conditions while reducing diversity across outputs. Their study concerns creative writing, not organizational knowledge transfer; nevertheless, it motivates a specific, testable risk: repeated AI standardization may make distinct local practices appear similar, reducing the variety of practices

preserved in organizational memory. This concern should be evaluated as a boundary condition, especially where culturally distinctive routines are an important source of organizational resilience.

4.6. Institutionalization of validated knowledge and organizational learning

Cross-cultural reuse is an episode-level outcome; organizational learning requires the verified lesson to become available for future action and to alter an organizational knowledge stock, routine, or decision process. A transfer can succeed once without changing organizational memory if corrections remain with individual reviewers. Conversely, capturing and validating boundary conditions, reviewer dissent, reasons for rejection, and adaptation decisions may help the organization avoid repeating errors across later episodes. The mechanism requires codified provenance, authority to update shared repositories, access by subsequent users, and periodic reassessment. It is distinct from mere archival accumulation because future actors must retrieve and use the verified qualification. The separation of creation, transfer, storage, and application in Alavi and Leidner (2001), together with the institutionally situated account of GenAI-assisted learning in Wiesenfeld and Kellogg (2026), supports this proposed distinction, although neither study directly tests the CQ–GKI pathway.

Proposition 8. Effective cross-cultural knowledge reuse is positively associated with subsequent organizational learning when validated interpretations and contextual qualifications are systematically incorporated into shared repositories or routines and demonstrably inform later decisions.

5. Illustrative Management Applications

The first application is cross-border onboarding. Headquarters may use GenAI to turn human-resource manuals and experienced employees' notes into orientation guides for new subsidiary managers. A guide could accurately describe performance-feedback procedures while failing to explain whether critical feedback is normally delivered in writing, privately, or through a line manager. A culturally intelligent reviewer would identify the operational ambiguity, compare established policies with local practice, and document an approved explanation. The benefit is neither the suppression of local difference nor the uncritical elevation of headquarters convention, but a more faithful explanation of how to perform the process.

The second application is post-project learning. A multinational project team may use GenAI to synthesize lessons learned across sites after a service failure. One site might label a quick unilateral decision as decisive leadership, while another views the same action as bypassing

legitimate consultation. A machine-produced list of best practices could combine these accounts into general prescriptions that fit neither site. Recontextualization would separate shared technical lessons from culturally conditioned governance expectations and indicate which conditions must hold before reuse.

The third application is knowledge retention when personnel leave or transfer. Organizations may convert interviews and documents into searchable archives. Doing so is valuable, but employees often communicate critical expertise through examples, exceptions, and tacit workarounds. GenAI summaries can omit these qualifications because they seem repetitive or peripheral. Managers who request counterexamples, preserve source provenance, and obtain local review make retained knowledge more useful to successors. These cases are analytical illustrations, not observations from field research.

A fourth application involves multinational compliance and policy communication. An enterprise may ask GenAI to summarize a headquarters policy for a subsidiary whose reporting obligations and employment practices differ. A literal translation may convey the official wording but fail to explain which elements are binding, which procedures are local, and how exceptions are escalated. Under CQ–GKI, designated source and receiving experts must jointly classify these elements. This is a conceptual illustration, not a claim that GenAI output can replace legal or regulatory review.

A fifth application concerns integration following mergers or acquisitions. A newly acquired unit may use familiar words such as “approval,” “escalation,” or “ownership” with meanings conditioned by its informal hierarchy and decision rights. The AI-produced consolidation manual may create false equivalence across these terms. A culturally intelligent integration manager can use dual-context interviews to uncover these differences, record translation decisions, and determine where harmonization would destroy useful local expertise.

A risk-tiered verification architecture. A practical implementation can divide knowledge transfers into low-, medium-, and high-consequence cases. Low-consequence transfers involving explicit, easily checked facts may rely primarily on automated retrieval and periodic sampling. Medium-consequence transfers involving local exceptions should receive recipient-side contextual review. High-consequence transfers involving legal duties, customer safety, employment relations, or sensitive negotiations should require both source- and recipient-context validation, documented accountability, and clear escalation criteria. This is a proposed

governance design, not a validated universal standard. Its value lies in matching costly human attention to the consequences and interpretive ambiguity of each transfer.

Evidence trails and contestability. An effective knowledge record should include the originating source and version, its intended audience, the AI-processing steps used, explicit boundary conditions, local reviewers, and an account of rejected or revised interpretations. Alavi and Leidner (2001) provide a process-oriented rationale for treating storage, transfer, and application as distinguishable functions; Raisch and Krakowski (2021) clarify the governance tension between automation and augmentation. In practice, organizations should preserve both the AI-generated candidate text and the validated text so that employees can identify what changed, assess why it changed, and challenge a downstream instruction when local conditions change.

6. Implications for Management Practice

The CQ–GKI framework implies that organizations should govern AI-assisted knowledge transfer as a managed interpretation process, not simply a content-production service. A first control is provenance: generated guidance should identify the source documents, originating unit, and date of underlying practices wherever feasible. Without provenance, a recipient cannot distinguish an approved policy from an anecdotal convention or determine whether a practice remains current.

A second control is contextual annotation. For high-impact transfers, managers should attach short notes identifying the purpose of the practice, assumptions about decision authority, known exceptions, and circumstances under which the practice should not be copied. These annotations reduce the risk that repeated summarization removes the very qualifications that make knowledge safe and useful. They also support later reviewers who were not present during the original transfer.

A third control is dual-context review. The source unit should validate fidelity, whereas receiving-unit personnel should evaluate applicability. A single reviewer may be highly knowledgeable about one context but unable to judge both accurately. Review procedures should provide room for disagreement and escalation, particularly in regulated, safety-sensitive, or personnel-related decisions. GenAI outputs should not be represented as authoritative merely because they are fluent and internally consistent.

A fourth control is structured correction. Organizations should record what an output originally said, why it was amended, who authorized the change, and whether subsequent use revealed

additional problems. This correction log is an input to organizational learning, and it helps distinguish a model defect from stale source data or a legitimate difference in local requirements. Managers can then prioritize recurring areas of misunderstanding for targeted training.

Finally, CQ development should be integrated with AI governance rather than treated as unrelated diversity training. Development activities may include comparing alternative interpretations of the same procedural account, identifying missing local assumptions, and interviewing stakeholders before approving a generated synthesis. Such training should emphasize evidence-based inquiry, because a claim to be culturally sensitive can itself become a source of stereotyping when managers rely on broad cultural categories instead of actual local practice.

The choice between automation and augmentation is important. Fügener et al. (2025) emphasize the complementarity of different human–AI work arrangements. The CQ–GKI model implies an augmentation-oriented arrangement for culturally ambiguous and high-consequence transfers, while allowing automation in well-specified, easily checked processing tasks. This assignment of roles is a managerial recommendation to be tested, not evidence that all human oversight improves performance.

7. Research Agenda and Testable Operationalization

The framework permits a staged empirical program. A first study could employ a randomized vignette or laboratory design in which managers evaluate GenAI-generated transfer memos. The source memos would vary in the degree to which important contextual conditions are omitted. Participants would be asked to approve, revise, or reject outputs while researchers measure CQ with an established multidimensional instrument and code specific verification actions. Fidelity could be scored by independent raters who have access to the complete source scenario; applicability could be scored against receiving-context constraints.

A second study could examine actual cross-unit knowledge-transfer episodes in multinational firms. A nested dataset would capture the originating unit, receiving unit, manager, system configuration, source document set, generated artifact, reviewer comments, and post-transfer implementation. Researchers could estimate associations among CQ, recontextualization behavior, review availability, and knowledge outcomes using multilevel models. Such a design would need to address selection effects: complex transfers may receive more oversight precisely because they are considered risky.

Third, an experimental comparison could manipulate review architecture while holding the source material and GenAI system constant. For example, one condition might permit no reviewer, a second source-context verification only, and a third dual-context verification. The outcome would not simply be perceived answer quality; it would include the proportion of critical source qualifications retained, the number of unacknowledged local adaptations, and performance on realistic implementation decisions. This approach can test whether dual-context verification contributes beyond individual CQ.

Construct validity requires particular care. Cultural knowledge recontextualization should be observed as behavior—requests for source verification, detection of boundary conditions, negotiation of interpretations, and explicit annotations—rather than inferred from an overall positive attitude toward cultural difference. Knowledge fidelity should be evaluated against source-validated meaning, not by asking respondents whether an output sounds credible. Contextual applicability should be assessed by receiving-context experts or through task outcomes. Organizational learning should be measured over time through documented corrections, updating of repositories, and improved accuracy in later transfer episodes.

Potential confounds include domain expertise, language proficiency, prior collaboration between the units, organizational power asymmetries, underlying data quality, model choice, retrieval design, and managerial incentives. The same manager may perform well because of experience in a particular subsidiary rather than general CQ. Researchers should therefore measure or experimentally vary local expertise where possible. Cross-cultural settings should be sampled at more than the country level, allowing comparisons across professional, functional, and organizational cultures.

A longitudinal design could examine whether repeated use of annotated corrections reduces recurring interpretive errors. It could also assess unintended consequences: review delays, overstandardization, increased reliance on centrally approved interpretations, or exclusion of local voices from knowledge repositories. Such findings would qualify the framework and clarify conditions under which AI-assisted knowledge transfer genuinely improves learning.

A complementary qualitative program could follow disputes over AI-generated documents from initial draft through approval and downstream use. Process tracing would reveal when managers discover assumptions, whose perspectives count as authoritative, how modifications are negotiated, and whether corrections feed back into organizational memory. Mixed-method

evidence is especially valuable because self-report surveys may overstate the extent of genuine verification.

Several competing mechanisms deserve attention. General conscientiousness might predict careful verification independently of CQ. Domain experience may enable expert judgment without intercultural capability. Language competence may help a manager notice mistranslation. Organizational incentives can reward speed and compliance rather than faithful transfer. These explanations should be represented explicitly as controls or competing hypotheses in future tests.

An important potential negative consequence is procedural friction: high CQ could prompt repeated consultation and delay the use of otherwise sound knowledge. A nonlinear relationship is therefore possible, in which recontextualization is most valuable for ambiguous or high-stakes episodes. Another unintended consequence is excessive localization, where managers adapt so aggressively that the core source logic is lost. The dual outcomes of fidelity and applicability allow such failures to be detected.

8. Limitations and Conclusion

The framework has several limitations. It is conceptual and offers no direct evidence that CQ causes superior GenAI-assisted knowledge outcomes. The CQ construct was developed for intercultural effectiveness generally, whereas the present model extends its explanatory role to an AI-mediated knowledge-transfer episode. The proposed relationships therefore require empirical validation. Moreover, model performance, retrieval accuracy, confidentiality controls, and source completeness may vary substantially by firm and task.

The proposed process also presumes that organizations can identify knowledgeable reviewers, preserve source provenance, and maintain correction records. These conditions may not hold in small firms, rapidly changing operations, or situations in which participants disagree about whose account is authoritative. Finally, the distinction between source fidelity and receiving-context applicability can involve normative conflict: knowledge that is locally actionable is not automatically legitimate or ethical. Managers remain responsible for legal compliance, worker protection, and professional judgment.

GenAI can reduce the cost of producing and distributing candidate organizational information. Such accessibility alone neither preserves the meaning of a source practice nor establishes its suitability for another unit. The CQ–GKI framework identifies cultural knowledge recontextualization as an observable, conditional managerial mechanism connecting CQ to the fidelity and contextual applicability of AI-assisted transfers. By distinguishing these transfer-

quality dimensions, their complementary effects on reuse, and the separate institutionalization required for organizational learning, the eight-proposition model offers sharper conceptual boundaries and disconfirmable predictions. Its key claim is conditional: CQ should add explanatory value beyond technical expertise where culturally embedded premises matter and managers can consult reliable source and recipient experts. Comparative experiments, longitudinal transfer records, and multilevel field studies can establish when that value outweighs verification costs.

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