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A Theoretical Framework for AI-Mediated Distributed Cognition in Multicultural Firms

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Abstract

This paper develops a theoretical framework to address a critical gap in management theory at the intersection of artificial intelligence and global business. The literature on cognitive offloading—the delegation of cognitive tasks to technology—has largely ignored the influence of culture. Conversely, the literature on Cultural Intelligence (CQ) has not adequately addressed the increasing mediation of work by AI. We argue this disjuncture creates a strategic vulnerability for multinational organisations. This paper introduces the concept of ***Culturally Situated Cognitive Offloading (CSCO),*** *positing that the process of offloading is not universal but is culturally structured, interpreted, and enacted. We further propose Organisational Cultural Intelligence (OCQ), an organisation-level dynamic capability, as the key moderator that determines whether cognitive offloading results in beneficial cognitive augmentation or maladaptive cognitive dependence. The framework details how the dimensions of OCQ—metacognitive, motivational, and behavioural—moderate the offloading process at the levels of interpretation, motivation, and enactment. We derive a series of formal propositions and a conceptual model, and explore potential pathologies such as cultural algorithmic myopia, blind algorithmic authority, and cognitive deskilling. The paper concludes by discussing implications for theory and practice, offering a new agenda for research and leadership in an era of global, AI-enabled work.*

Keywords: Cognitive Offloading, Cultural Intelligence, Artificial Intelligence, Distributed Cognition, Sociomateriality, Dynamic Capabilities, Organisational Learning, AI Governance, Sensemaking, Knowledge Creation

1. Introduction

The contemporary organization operates at the confluence of two powerful currents: the exponential growth of artificial intelligence (AI) and the deepening complexity of multiculturalism in the global workforce. The integration of AI-driven algorithmic decision-systems into the daily operations of global firms is no longer a futuristic projection but a present-day reality, reshaping the nature of knowledge work and strategic decision-making [1]. These systems, ranging from automated data analysis to sophisticated predictive modelling, offer the promise of enhanced efficiency, optimised performance, and unprecedented scale in information processing. A direct consequence of this technological integration is the pervasive rise of 'cognitive offloading', the process by which individuals and, by extension, organisations, delegate cognitive tasks to external technological aids [2]. This delegation—whether it is using a digital calendar to remember appointments or a complex AI to analyse market trends—allows for the conservation of finite cognitive resources, theoretically freeing human agents to focus on higher-order tasks such as innovation, strategy, and interpersonal engagement.

Simultaneously, the landscape of modern business is characterised by an ever-increasing cultural diversity. As multinational enterprises (MNEs) expand their global footprint and teams become more geographically dispersed and culturally heterogeneous, the ability to navigate and leverage this diversity has become a critical determinant of organisational success [3]. This multicultural complexity introduces a rich tapestry of perspectives, problem-solving approaches, and interpretive frameworks, but it also presents significant challenges related to communication, coordination, and the establishment of shared understanding. The dominant paradigm for addressing these challenges has been the development of Cultural Intelligence (CQ), defined as an individual's capability to function effectively in culturally diverse settings) [4]. CQ has emerged as a robust predictor of performance in cross-cultural contexts, with research demonstrating its positive association with intercultural adjustment, task performance, and creative problem-solving [5].

However, a critical disjuncture exists between the discourses surrounding these two transformative trends.

The burgeoning literature on cognitive offloading and its organisational implications has, to a large extent, proceeded with a form of cultural blindness. It has implicitly assumed that the mechanisms, motivations, and consequences of offloading cognitive tasks to technology are universal, operating uniformly across different cultural contexts. Theories of the extended mind and distributed cognition, which provide the foundational pillars for understanding cognitive offloading, have rarely been interrogated through a cultural lens [6,7]. This oversight neglects the profound influence of cultural values, norms, and schemas on how individuals and groups perceive, trust, and interact with technology. The decision to offload a cognitive task is not a culturally neutral act of pure efficiency; it is a behaviour embedded in and shaped by cultural predispositions concerning authority, uncertainty, and the very nature of knowledge [8,9]. Hofstede's foundational work on cultural dimensions provides compelling evidence that societies differ systematically in their orientations towards uncertainty avoidance and power distance dimensions that are directly relevant to how individuals and organisations relate to algorithmic authority.

Conversely, the extensive body of research on Cultural Intelligence has remained largely technologically blind. While CQ theory has provided invaluable insights into managing cross-cultural interactions, it has not adequately contended with the reality that these interactions are increasingly mediated by AI and other advanced technologies. The four key facets of CQ metacognitive, cognitive, motivational, and behavioural have been conceptualised primarily in the context of human-to-human interaction [3]. The theory has yet to systematically explore how these capabilities translate to the human-technology interface, particularly when the technology itself is an active participant in cognitive processes [10]. We lack a theoretical understanding of how an organisation's collective cultural competence shapes its engagement with AI-driven cognitive tools, impacting core processes like organisational sensemaking and knowledge creation [11,12]. This paper addresses this significant theoretical gap. We argue that the intersection of cognitive offloading and cultural intelligence is not an empty space but a critical nexus for understanding the future of work in global organisations. The central problem is that without a framework integrating these two domains, organisations risk adopting AI-driven cognitive offloading strategies that are at best suboptimal and at worst maladaptive. A failure to account for cultural dynamics can lead to a host of pathologies, including the miscalibration of trust in AI, the amplification of algorithmic biases across cultural contexts, the erosion of strategic capabilities in low-CQ environments, and the phenomenon of automation complacency [13-15]. The assumption of cultural neutrality in cognitive offloading is a strategic vulnerability that demands theoretical attention.

Therefore, the primary theoretical contribution of this paper is to develop an integrative framework that theorises the cultural moderation of cognitive offloading in AI-enabled organisations. We introduce the concept of **Culturally Situated Cognitive Offloading (CSCO)** to capture the phenomenon that offloading is not a uniform process but is culturally structured, interpreted, and enacted. We argue that an organisation's collective Cultural Intelligence (which we term **Organisational Cultural Intelligence, or OCQ**) acts as a dynamic capability that moderates the relationship between cognitive offloading and organisational outcomes [16]. A high level of OCQ enables an organisation to achieve 'balanced cognitive augmentation', where AI tools enhance and extend human cognitive capabilities. In contrast, a low level of OCQ can lead to 'maladaptive cognitive dependence', where the uncritical delegation of cognition to technology results in strategic homogeneity, cognitive deskilling, and an increased risk of culturally-inflected algorithmic errors.

This paper makes four contributions to theory. First, we extend the literature on cognitive offloading and distributed cognition by introducing culture as a critical moderating variable, moving the discourse beyond its culturally blind origins. Second, we advance Cultural Intelligence theory by applying it to the increasingly vital domain of human-AI interaction, demonstrating how CQ is essential for navigating the sociotechnical challenges of the 21st-century organisation. Third, by conceptualising OCQ as a dynamic capability, we contribute to the strategic management literature by offering a new perspective on how firms can build adaptive capacity in the face of technological and cultural change [17]. Finally, we provide a novel framework for the emerging field of AI governance, highlighting the need to move beyond purely technical or ethical considerations to include a deep understanding of the cultural context of AI implementation. This article is structured as follows. We first review the foundational literature on cognitive offloading and the extended organisation, introducing the concept of the Organisational Cognitive Architecture (OCA). We then develop the construct of Organisational Cultural Intelligence (OCQ) as a firm-level dynamic capability. The core of the paper presents our integrative framework, detailing how OCQ moderates cognitive offloading at the levels of interpretation, motivation, and enactment. From this framework, we derive a series of formal propositions. We then explore the potential risks and pathologies of unmanaged cognitive offloading, before concluding with a discussion of the implications for theory, leadership, and future research.

2. Cognitive Offloading and the Extended Organisation

The concept of cognitive offloading, while contemporary in its application to digital technology, is rooted in a long history of human interaction with the material world. From the earliest forms of writing to the use of complex scientific instruments, humans have consistently sought to augment their innate cognitive abilities by externalising mental processes. This section provides a theoretical foundation for understanding cognitive offloading, tracing its intellectual lineage from the individual-level phenomenon of the 'extended mind' to its manifestation at the collective, organisational level. We argue that the proliferation of AI and algorithmic systems necessitates a conceptual shift from viewing offloading as a series of discrete individual acts to understanding it as a systemic property of the organisation's cognitive architecture.

2.1. The Foundations of Cognitive Offloading

The modern discourse on cognitive offloading is significantly shaped by the work of Risko and Gilbert (2016), who define it as "the use of external resources to reduce internal cognitive demands." Their framework synthesises research from multiple domains to understand the triggers and consequences of offloading behaviour. A key insight is that the decision to offload is not arbitrary but is governed by a metacognitive assessment of costs and benefits. Individuals implicitly weigh the internal effort required to complete a cognitive task against the perceived effort of using an external tool. This cost-benefit analysis is influenced by factors such as the perceived reliability of the external resource, the accessibility of the tool, and the individual's confidence in their own cognitive abilities. The choice to use a calculator for a complex multiplication, for instance, is a rapid metacognitive judgment that the external tool offers a more efficient and reliable pathway to the correct answer than mental arithmetic.

This perspective builds upon the seminal philosophical argument for the 'extended mind', proposed by Clark and Chalmers [6]. They provocatively argued that the boundaries of the mind are not confined to the skull but can extend into the external world. In their famous thought experiment, they describe a man named Otto who suffers from Alzheimer's disease and relies on a notebook to store information. Clark and Chalmers contend that the notebook is not merely an aid but an integral part of Otto's cognitive process, functionally equivalent to biological memory. For a tool to be considered part of the extended mind, it must be consistently available, readily accessible, and the information it contains must be automatically endorsed. This principle of 'active externalism' challenges the traditional demarcation between the internal cognitive agent and the external environment, suggesting that cognitive processes are often constituted by a coupled system of brain, body, and world. Cognitive offloading, from this perspective, is the mechanism through which the mind extends itself. It is crucial, however, to distinguish between two forms of offloading: **delegation** and **augmentation**. Delegation implies a complete hand-off of a cognitive task to an external agent, with the human user becoming a passive recipient of the output. Augmentation, in contrast, implies a collaborative partnership where the technology enhances and complements human cognitive capabilities. For example, delegating navigation entirely to a GPS system without maintaining situational awareness represents pure delegation, whereas using a GPS to supplement one's own navigational reasoning represents augmentation. The distinction lies in the nature of the human-tool interaction; augmentation preserves user engagement and agency, whereas delegation can lead to cognitive passivity and skill atrophy. This distinction is central to our framework, as the type of offloading—delegation versus augmentation—is itself a culturally moderated outcome.

The risks associated with excessive delegation have been well-documented in the human factor's literature. Parasuraman and Manzey describe **automation complacency**, a reduction in vigilance and monitoring that occurs when individuals over-rely on automated systems [15]. When humans delegate cognitive tasks to automation, they may fail to detect errors or anomalies in the system's output, particularly when the system is generally reliable. This risk is compounded in organisational settings, where the diffusion of responsibility across a team can further reduce individual vigilance. The organisational manifestation of automation complacency is a systemic failure of oversight, where no individual feels responsible for critically evaluating the outputs of an AI system, and errors propagate unchecked through the organisation's decision-making processes. Understanding the conditions under which delegation shades into complacency is therefore a critical concern for the management of AI-enabled organisations, and one that, as we argue, is deeply shaped by the cultural context of the organisation.

2.2. From Individual to Organisational Cognitive Offloading

These individual-level concepts have profoundly organisational implications. To understand collective offloading, we turn to **distributed cognition**, pioneered by Hutchins [7]. His study of navigation aboard a naval vessel demonstrated that the cognitive system is not the individual navigator but the entire team and its environment. Knowledge is embedded not only in individual minds but also in the design of tools, the structure of routines, and the organisation of the workspace. Distributed cognition posits that cognitive processes are distributed across a system of people and artifacts, and that the system as a whole performs cognitive work that no individual could perform alone. This perspective has been foundational for understanding human-computer interaction as a distributed process, and it provides a powerful lens for analysing how organisations collectively offload cognitive tasks to AI systems [10].

This resonates deeply with the lens of **sociomateriality**, which rejects the analytical separation of the social and the material in organisational life [18]. A sociomaterial perspective argues that technology and social structures are mutually constitutive; they are 'entangled' in practice. The introduction of a new AI system does not simply add a new tool to an existing social order; it reconfigures that order, reshaping roles, routines, and power relations. Orlikowski and Scott argue that this entanglement means we cannot understand the effects of technology without understanding the social context in which it is embedded, and vice versa. For our purposes, this means that the consequences of cognitive offloading are inseparable from the social and cultural context of the organisation [19]. Decision-making in an AI-enabled firm is an emergent property of this entangled sociomaterial assemblage. **Algorithmic management** and **AI decision-support systems** represent the institutionalisation of cognitive offloading at an organisational scale. Algorithmic management refers to the use of software to monitor, evaluate, and direct the work of employees, while AI decision-support systems augment or automate complex decisions previously made by human managers [20]. These systems function as powerful external cognitive resources, processing vast amounts of data and generating recommendations that guide organisational behaviour. When an organisation adopts such a system, it offloads a significant portion of its collective cognitive labour to the algorithm. The organisation's cognitive architecture is fundamentally reconfigured.

To capture this systemic reconfiguration, we introduce the concept of the **Organisational Cognitive Architecture (OCA)**, defined as: *The structured distribution of cognitive labour between humans, technologies, and routines within an organisation, encompassing the formal allocation of tasks, the informal practices that shape information processing, and the relational dynamics between human and artificial agents*. The OCA is a dynamic configuration, not a static blueprint. It evolves as new technologies are adopted, as routines are modified, and as the organisation learns. The OCA determines which tasks are retained by humans, which are delegated to technology, and how the outputs of each are integrated into organisational action. It is the substrate upon which organisational intelligence is built and the primary arena in which the consequences of cognitive offloading play out. Crucially, as we argue in the sections that follow, the effectiveness of any given OCA is not a purely technical matter; it is deeply contingent upon the cultural context in which it is embedded.

The concept of the OCA has important implications for how we understand organisational knowledge and learning. Classical models of organisational learning, such as that proposed by Levitt and March, focused on the encoding of experience into routines [21]. In an AI-enabled organisation, this process is complicated by the fact that a significant portion of the organisation's cognitive work is performed by non-human agents. The routines that govern the OCA—the rules for when to delegate to AI, how to interpret its outputs, and when to override its recommendations—become the primary locus of organisational learning. Rerup and Feldman have shown how routines can be a source of both stability and change in organisations, and this insight is directly applicable to the routines that govern the OCA [22]. The design and governance of these routines is therefore a critical strategic challenge for the AI-enabled organisation, and one that, as we argue, cannot be addressed without a deep understanding of the cultural context in which the OCA is embedded.

3. Organisational Cultural Intelligence as a Dynamic Capability

As organisations globalize, the ability to navigate cultural differences has become a core strategic imperative. The dominant framework for understanding this ability, Cultural Intelligence (CQ), has focused primarily on the individual level. However, just as cognitive offloading has scaled from an individual phenomenon to an organisational one, so too must our understanding of cultural intelligence. This section builds the theoretical case for an organisational-level construct of CQ and argues for its conceptualisation as a dynamic capability.

3.1. The Foundations of Cultural Intelligence Theory

Cultural Intelligence (CQ), conceptualised by Earley and Ang, is a multi-faceted construct defined as "an individual's capability to function and manage effectively in culturally diverse settings [4]." Drawing on Sternberg's triarchic theory of intelligence, Earley and Ang argued that cultural intelligence is a distinct form of intelligence, separate from general cognitive ability and emotional intelligence [23]. The most widely accepted model delineates four key factors [3]. **Metacognitive CQ** refers to an individual's cultural consciousness and awareness during intercultural encounters. It involves the capacity to plan, monitor, and revise mental models of cultural norms and expectations.

- **Cognitive CQ** encompasses knowledge of norms, practices, and conventions in different cultures, including knowledge of cultural systems, values, and institutions.
- **Motivational CQ** is the drive and energy to direct attention and effort toward learning about and functioning in culturally diverse situations, reflecting intrinsic interest and confidence in cross-cultural interactions.
- **Behavioural CQ** is the capability to exhibit appropriate verbal and nonverbal actions when interacting with people from different cultures, including the ability to adapt one's communication style.

These dimensions work in concert, and the four-factor model has been validated across numerous cultural contexts. Research has demonstrated that CQ is a robust predictor of positive outcomes in culturally diverse settings, including intercultural adjustment, task performance, and creative problem-solving [5]. Livermore, Van Dyne, and Ang have further articulated how CQ can be developed and applied in organisational settings [24].

3.2. From Individual CQ to Organisational CQ

While the individual-level focus of the four-factor model has been enormously productive, it is insufficient for capturing the full scope of an organisation's cultural competence. An organisation is not merely the sum of its members' individual CQ scores. The collective capability is an emergent property of the organisation's culture, routines, and structures. To make the conceptual leap from individual to organisational CQ, we draw on several streams of literature. First, the concept of **collective intelligence** suggests that groups can exhibit an intelligence that is distinct from, and not reducible to, the abilities of their individual members [25]. This collective intelligence emerges from the interaction dynamics of the group, including communication patterns and the distribution of cognitive labour. By analogy, an organisation's cultural intelligence is an emergent property of its collective interactions and structures. Second, **organisational learning** theories provide a mechanism for translating individual knowledge into collective capability. Levitt and March argued that organisations learn by encoding inferences from history into routines, rules, and procedures [21]. A culturally intelligent organisation is one that has embedded CQ principles into its routines and structures, creating a form of institutional memory that guides culturally sensitive behaviour even when individual members lack high personal CQ scores. Rerup and Feldman further developed this idea, showing how routines can be a source of organisational learning and change [22]. Third, recent work has begun to formalise this organisational-level construct. Moon conceptualised Organisational Cultural Intelligence from a dynamic capability perspective, arguing that it represents a firm-level capability to manage cultural diversity effectively [26]. Livermore, Van Dyne, and Ang have articulated OCQ as a critical capability for 21st-century organisations, identifying its key components and implications for leadership [24].

Drawing these threads together, we conceptualise OCQ as a **dynamic capability**: "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" [16]. In a world of increasing cultural complexity and technological disruption, the ability to manage the intersection of culture and technology is a quintessential dynamic capability [17]. OCQ allows an organisation to sense cultural nuances in its environment, seize opportunities to leverage cultural diversity, and transform its cognitive architecture to ensure that both human and artificial intelligence are deployed in a culturally sensitive and strategically effective manner. Conceptualising OCQ as a dynamic capability has several important implications. First, it suggests that OCQ is not a fixed organisational trait but a capability that can be developed, invested in, and deliberately cultivated over time. Just as firms can invest in research and development to build technological capabilities, they can invest in training, hiring, and organisational design to build OCQ. Second, it suggests that OCQ is a source of competitive advantage. In a world where many firms are deploying similar AI technologies, the ability to use those technologies more effectively in a culturally diverse context is a source of differentiation that is difficult for competitors to imitate. Third, it suggests that OCQ is subject to the same risks of rigidity and path dependence as other dynamic capabilities (Helfat et al., 2007). An organisation that has developed OCQ in one cultural context may find that its routines and practices are not easily transferable to a new context, requiring a process of deliberate unlearning and relearning. This dynamic quality of OCQ is central to our framework, as it suggests that the management of cognitive offloading in a global organisation is not a one-time design challenge but an ongoing process of cultural adaptation and learning.

4. Theoretical Integration: The Cultural Moderation of Cognitive Offloading

This section constitutes the theoretical core of the paper. We bridge the gap between the culturally blind literature on cognitive offloading and the technologically blind literature on CQ, presenting an integrative framework for understanding how culture moderates cognitive offloading in AI-enabled firms. We argue that the human-AI interaction is a deeply social and cultural process, where the effectiveness of offloading is contingent upon the organisation's collective cultural intelligence. Our central thesis is that OCQ acts as a moderating dynamic capability that shapes the consequences of an organisation's reliance on its OCA. In high-OCQ organisations, cognitive offloading is more likely to manifest as balanced augmentation, where AI tools enhance human capabilities and contribute to organisational learning. In low-OCQ organisations, the same practices are more likely to result in maladaptive dependence, where the uncritical delegation of cognition to technology leads to strategic homogeneity and cognitive deskilling. This moderation operates at three distinct but interrelated levels: interpretation, motivation, and enactment.

Level 1: Interpretation and Sensemaking

The first level at which OCQ moderates cognitive offloading is the interpretive level. The output of an AI system—a recommendation, a prediction, a classification—does not speak for itself. It must be interpreted, and this interpretive process is profoundly shaped by culture. As Weick argued in his seminal work on organisational sensemaking, individuals and organisations actively construct their understanding of the world through an ongoing process of interpretation and action [11]. Data is never raw; it is always interpreted through the lens of pre-existing assumptions, mental models, and cultural schemas. The same AI-generated recommendation can be understood very differently by managers from different cultural backgrounds, depending on their cultural assumptions about the nature of knowledge, the reliability of quantitative data, and the appropriate relationship between human judgment and algorithmic output.

This is where **Metacognitive CQ** becomes critical at an organisational level. A high-OCQ organisation has developed routines and practices for questioning the cultural assumptions embedded in its data and algorithms. It fosters a climate of critical inquiry, where managers are encouraged to ask: 'What cultural assumptions are embedded in this model? What perspectives might it be missing? How might different cultural groups interpret this output?' This capacity for critical reflection enables effective **trust calibration** [13]. Instead of blindly accepting or reflexively rejecting AI outputs, a high-OCQ organisation dynamically adjusts its trust based on a sophisticated understanding of the AI's capabilities and limitations in a specific cultural context. In low-OCQ organisations, this calibration is poor, leading either to 'blind algorithmic authority' uncritical acceptance or to the rejection of valuable insights due to cultural misunderstanding.

Level 2: Motivation to Delegate Cognition

The second level at which OCQ moderates cognitive offloading is the motivational level. The decision to delegate a cognitive task to an AI system is not purely a rational, efficiency-driven calculation; it is also a motivational and cultural one. Cultural values related to uncertainty avoidance and power distance are directly relevant to the propensity to offload [9]. Cultures with **high uncertainty avoidance** may be more resistant to the perceived opacity of complex algorithms, preferring the certainty of human judgment even when it is demonstrably less accurate. The cultural dimension of **power distance** can also influence the governance of cognitive offloading. In high power distance cultures, the recommendations of an AI system may be seen as an extension of senior leadership's authority, accepted without question by subordinates. Recent research suggests these cultural patterns hold in AI adoption contexts. Yam, Tan, and Jackson found that cultural background significantly moderates individuals' reactions to AI and robots, with systematic differences in acceptance and trust [27]. Furthermore, the phenomenon of **algorithm aversion** the tendency to reject algorithmic recommendations after observing a single error may be more pronounced in cultures with high uncertainty avoidance, where the failure of a technological system is particularly threatening to the established order. **Motivational CQ** at the organisational level moderates these cultural tendencies [28]. A high-OCQ organisation creates a psychologically safe environment for engaging with AI, fostering a culture of curiosity and openness that overcomes culturally-rooted resistance to technology. It also guards against the opposite failure: the uncritical adoption of AI driven by cultural deference to authority rather than a genuine assessment of its value. In this way, high motivational CQ ensures that the organisation's engagement with AI is driven by a genuine desire for augmentation and improvement, rather than by cultural inertia or blind obedience.

Level 3: Behavioural Enactment

The third level at which OCQ moderates cognitive offloading is the behavioural level. Even if an AI-generated insight is correctly interpreted and the organisation is motivated to act on it, the value of that insight depends on its effective implementation. The process of translating a strategic recommendation into coordinated action is a complex social process, and one that is deeply shaped by culture. Different cultural groups have different norms regarding planning, coordination, communication, and the resolution of conflict [8]. Markus demonstrated that even the choice of communication medium is culturally influenced, with different cultural groups preferring different channels for different types of messages [29]. In a multicultural team, the implementation of an AI-driven recommendation requires navigating these cultural differences in work style and communication. A team member from a culture that values explicit, low-context communication may interpret the recommendation very differently from a colleague from a high-context culture, leading to misaligned implementation strategies. An organisation with high **Behavioural CQ** has developed routines for facilitating effective cross-cultural action. Its project management methodologies are flexible and culturally sensitive, and its communication protocols are designed to ensure clarity across cultural boundaries. This ensures that the implementation of AI-driven insights is not distorted by cultural misunderstandings or communication failures.

Culturally Situated Cognitive Offloading (CSCO): A Formal Definition

Our framework demonstrates that cognitive offloading is not a monolithic, culture-free process. The selection of AI tools, the interpretation of their outputs, the motivation to use them, and the enactment of their recommendations are all moderated by the cultural context of the organisation. To capture this insight, we introduce the concept of **Culturally Situated Cognitive Offloading (CSCO)**, formally defined as: *The process by which an organisation delegates or augments its cognitive processes using technological aids, where the selection, interpretation, and enactment of this offloading are moderated by the organisation's collective cultural intelligence (OCQ) and the cultural values of its members*. CSCO recognises that the OCA is not a purely technical system but a sociomaterial system embedded in a cultural matrix. It provides a lens for analysing why the same AI technology can lead to vastly different outcomes in different organisational and cultural settings. The concept of CSCO is the central theoretical contribution of this paper, and it provides the foundation for the propositions and implications that follow. The CSCO framework can be represented as a conceptual model with three key components. The *input* is the organisation's OCA—the structured distribution of cognitive labour between humans and AI systems. The *moderator* is the organisation's OCQ—its collective cultural intelligence, encompassing metacognitive, motivational, and behavioural dimensions. The *output* is the nature of the cognitive offloading that results: either 'balanced cognitive augmentation', characterised by a collaborative human-AI partnership that enhances organisational capabilities, or 'maladaptive cognitive dependence', characterised by uncritical delegation that erodes organisational capabilities. The relationship between the OCA and the output is not direct but is mediated by the three levels of moderation—interpretation, motivation, and enactment—that we have described above. This model provides a parsimonious but powerful framework for understanding the cultural dynamics of AI adoption in global organisations, and it generates a rich set of empirically testable propositions that we develop in the following section. It is worth noting that the CSCO framework is not merely descriptive but also normative. It implies that organisations should aspire to a state of balanced cognitive augmentation, and that achieving this state requires deliberate investment in OCQ. The framework also implies that the risks of maladaptive cognitive dependence are not inevitable but can be mitigated through the development of cultural intelligence at the organisational level. In this sense, the CSCO framework is a call to action for leaders and managers in global organisations, urging them to take seriously the cultural dimensions of AI adoption and to invest in the organisational capabilities needed to navigate them effectively.

5. Propositional Development

Building on the theoretical framework developed above, we now formalise our arguments into a set of testable propositions. These propositions are intended to guide future empirical research and to make the theoretical contributions of the paper more precise and falsifiable.

• **Proposition 1:** *The metacognitive dimension of OCQ positively moderates the relationship between AI-based cognitive offloading and the quality of organisational decision-making, such that the positive effect of offloading on decision quality is stronger in organisations with higher metacognitive CQ*. This proposition captures the idea that the value of AI-generated insights is contingent upon the organisation's capacity for critical reflection. In high-OCQ organisations, the metacognitive routines for questioning algorithmic outputs and calibrating trust ensure that AI is used as a tool for augmentation rather than a source of unquestioned authority. In low-OCQ organisations, the absence of these routines means that AI outputs are either accepted uncritically or rejected reflexively, both of which undermine decision quality.

• **Proposition 2:** *The motivational dimension of OCQ negatively moderates the relationship between AI-based cognitive offloading and the risk of maladaptive cognitive dependence, such that the risk of dependence is lower in organisations with higher motivational CQ*. This proposition captures the idea that the motivational climate of the organisation shapes the nature of its engagement with AI. In high-OCQ organisations, a culture of curiosity and psychological safety fosters an engagement with AI that is driven by a genuine desire for learning and improvement. This intrinsic motivation guards against both algorithm aversion and blind algorithmic authority, reducing the risk of maladaptive dependence.

• **Proposition 3:** *The behavioural dimension of OCQ positively moderates the fidelity of implementation of AI-generated insights in multicultural teams, such that the relationship between AI recommendation quality and implementation effectiveness is stronger in organisations with higher behavioural CQ*. This proposition captures the idea that the value of AI-generated insights can be lost in implementation if the organisation lacks the cultural competence to translate recommendations into coordinated action across cultural boundaries. High behavioural CQ provides the routines and communication protocols necessary to ensure that implementation is not distorted by cultural misunderstandings.

• **Proposition 4:** *The overall level of OCQ moderates the relationship between the extent of cognitive offloading and the organisation's capacity for adaptive learning, such that extensive cognitive offloading leads to strategic homogeneity in low-OCQ organisations but enhances adaptive learning in high-OCQ organisations*. This proposition captures the idea that the relationship between cognitive offloading and organisational learning is not linear but is moderated by OCQ. Drawing on March's (1991) framework of exploration and exploitation, we argue that high-OCQ organisations are better able to manage the tension between exploiting the efficiency gains of AI and exploring new possibilities, whereas low-OCQ organisations are more likely to become trapped in a cycle of algorithmic exploitation that crowds out exploration.

• **Proposition 5:** *The interplay of the three dimensions of OCQ determines whether an organisation achieves 'balanced cognitive augmentation' or suffers from 'maladaptive cognitive displacement', such that organisations high on all three dimensions are more likely to achieve augmentation, while organisations deficient in one or more dimensions are more likely to experience displacement*. This final proposition captures the holistic nature of our framework. The three dimensions of OCQ are not independent; they interact to shape the overall quality of the organisation's engagement with AI. An organisation may have high metacognitive CQ but low motivational CQ, leading to a situation where critical reflection is possible but not acted upon. The full benefits of CSCO are only realised when all three dimensions are developed in concert.

6. Risks and Pathologies of Unmanaged Cognitive Offloading

The uncritical or culturally blind implementation of AI-driven cognitive offloading is fraught with peril. When the cultural situatedness of cognitive offloading is ignored, and when OCQ is low, a number of predictable pathologies can emerge. These pathologies represent not merely technical failures but systemic organisational dysfunctions rooted in the misalignment between an organisation's cognitive architecture and its cultural context.

6.1. Cultural Algorithmic Myopia

Organisations that heavily offload cognitive processes to a homogenous set of AI tools risk developing **cultural algorithmic myopia**: a state of strategic shortsightedness caused by an over-reliance on a narrow range of algorithmically generated perspectives. AI models are trained on vast datasets that are never truly universal; they are inevitably skewed towards the cultures, languages, and contexts that produced the majority of the training data [14]. An organisation that uncritically adopts the outputs of these models is, in effect, viewing the world through a culturally biased lens. In a low-OCQ organisation, there is little metacognitive capacity to question this lens, and the organisation gradually loses the ability to perceive strategic opportunities and threats that fall outside the algorithm's cultural purview. This can lead to a dangerous form of strategic homogeneity, where the diversity of perspectives that is the hallmark of a truly global organisation is eroded by the homogenising influence of a culturally biased AI.

6.2. Blind Algorithmic Authority

In organisations with low motivational CQ, particularly those operating in high power distance cultures, cognitive offloading can lead to **blind algorithmic authority**. This pathology occurs when the recommendations of an AI system are accepted without question, not because of a rational assessment of their quality, but because of a deferential attitude towards the technology itself. The algorithm becomes an oracle, and its outputs are treated as authoritative pronouncements rather than probabilistic recommendations to be evaluated and challenged. This pathology is particularly risky in high-stakes decision-making contexts, such as financial risk management or medical diagnosis, where the consequences of an erroneous recommendation can be severe. The human is effectively removed from the decision loop, not by design, but by a culture of uncritical deference, creating a significant risk of automated, large-scale errors. This is closely related to the phenomenon of automation complacency, where over-reliance on automated systems leads to a reduction in vigilance and monitoring [15].

6.3. Cross-Cultural Miscalibration of AI Trust

Effective use of AI requires careful **trust calibration**, where the user's trust in the system is appropriate to its actual capabilities and limitations in a given context [13]. This calibration is highly sensitive to cultural factors. In low-OCQ organisations, there is a high risk of **cross-cultural miscalibration**, where the level of trust placed in an AI system is systematically inappropriate for the cultural context in which it is being used. This can manifest in two directions. Over-trust, or automation bias, occurs when individuals place inappropriately high confidence in an AI system, accepting its outputs even when they conflict with other available evidence. Under-trust, or algorithm aversion, is the opposite problem, where individuals refuse to use a perfectly good algorithmic tool because of a culturally-rooted preference for human judgment or a disproportionate reaction to observed algorithmic errors [28]. A low-OCQ organisation lacks the cultural awareness and metacognitive routines to manage these dynamics of trust, leaving it vulnerable to both forms of miscalibration.

6.4. Cognitive Deskilling in Low-OCQ Firms

A final, insidious risk is cognitive deskilling. When an organisation consistently delegates core cognitive tasks to technology without a corresponding strategy for human skill development and maintenance, it risks the gradual atrophy of its internal cognitive capabilities. For example, if junior analysts no longer perform their own data analysis because an AI system does it for them, they may never develop the deep, intuitive understanding of data patterns that is essential for strategic insight. If managers no longer engage in the difficult cognitive work of cross-cultural negotiation because an AI system provides them with scripts and recommendations, they may never develop the nuanced cultural empathy that is the foundation of genuine intercultural competence. This risk is particularly acute in low-OCQ organisations because they lack the routines and incentives to ensure that cognitive offloading is a form of augmentation rather than displacement. Over time, this can lead to a hollowing out of the organisation's cognitive core, leaving it entirely dependent on its external technological aids and dangerously vulnerable to their failures.

7. Implications for Theory

Our framework of CSCO and OCQ builds bridges between several major streams of organisational and management theory, extending each in a novel direction. This section articulates these theoretical contributions in detail.

7.1. Extending Cognitive Science in Organisations

Our primary contribution is to the application of cognitive science in organisational studies. The existing literature on distributed cognition and sociomateriality has provided powerful tools for understanding how cognitive work is distributed across human-technology systems [7,18]. However, these frameworks have largely bracketed the question of culture. By introducing OCQ as a key moderating variable, we theorise that the 'coupling' between an internal cognitive agent and an external resource—the very foundation of the extended mind thesis is culturally contingent [6]. We extend the concept of the OCA by arguing that its effectiveness is not merely a function of its technical design but of its cultural embeddedness, bringing a much-needed social and cultural dimension to this field [10].

7.2. Extending International Business Theory

We contribute to International Business (IB) theory by introducing AI as a critical variable in the management of cultural diversity. The traditional challenges of IB—managing cross-cultural teams, adapting strategies to local contexts, building global coordination—are being fundamentally reshaped by AI-mediated work. Our concept of OCQ provides a new lens for understanding why some MNEs are more successful than others at leveraging technology in a global context. We extend the dominant focus on human-to-human cultural interaction to include the critical domain of human-AI interaction, a significant extension given the changing nature of global work [27].

7.3. Extending the Dynamic Capabilities Perspective

We contribute to the dynamic capability's perspective by proposing OCQ as a novel and critical dynamic capability for the AI era [16]. In an environment characterized by rapid technological disruption and deepening global integration, the ability to manage the interplay between AI and culture is a key source of competitive advantage [17]. Our framework specifies the microfoundations of this capability, rooting it in the three dimensions of CQ—metacognitive, motivational, and behavioural—and linking it to concrete organisational routines and practices.

7.4. Extending AI Governance Research

We contribute to the emerging field of AI governance by highlighting the critical but often overlooked dimension of culture. The dominant discourse in AI governance has focused on technical issues of bias and fairness and on legal and regulatory frameworks [14]. While these are essential, they are insufficient. Our framework argues that a purely technical or legalistic approach to AI governance is blind to the sociomaterial realities of AI implementation [19]. The risks of AI are not just technical problems; they are sociomaterial ones, rooted in the cultural contexts in which AI systems are deployed. Our concept of OCQ provides a framework for what 'culturally intelligent AI governance' might look like.

7.5. Extending Organisational Learning Theory

Our framework has significant implications for organisational learning theory. The rise of AI presents a fundamental challenge to classical models of organisational learning (Levitt & March, 1988). When cognitive tasks are offloaded to AI, where does the learning happen? We propose that the relationship between cognitive offloading and organisational learning is moderated by OCQ. In low-OCQ firms, extensive offloading can lead to cognitive deskilling and a reduction in the organisation's capacity for adaptive learning. However, in high-OCQ firms, AI can become a powerful engine for organisational learning, accelerating the processes of knowledge creation and enabling a more effective balance between exploration and exploitation [12,30]. This insight has important implications for how we think about the relationship between AI and human expertise. The classical view of organisational learning emphasises the importance of experience and tacit knowledge [12]. When organisations offload cognitive tasks to AI, they risk losing the experiential learning that comes from performing those tasks manually. This is the cognitive deskilling problem we identified in Section 6. However, our framework suggests that this risk is not inherent in cognitive offloading per se, but is a consequence of low OCQ. In high-OCQ organisations, the routines that govern the OCA are designed to ensure that offloading is a form of augmentation, not displacement. These organisations invest in creating opportunities for human learning alongside AI deployment, ensuring that the tacit knowledge and experiential expertise of their members is preserved and developed even as AI takes on an increasing share of the cognitive workload. This suggests a new model of organisational learning for the AI era, one that is grounded in the principles of CSCO and that places OCQ at the centre of the organisation's learning strategy.

8. Implications for Leadership and Strategy

Our theoretical framework has profound practical implications for leaders and strategists in global organisations. The shift from viewing cognitive offloading as a technical efficiency to understanding it as a culturally situated practice requires a fundamental rethinking of digital transformation, talent management, and strategic decision-making.

- **Strategising AI Adoption as Culturally Adapted Deployment**. Leaders must abandon the assumption that a single, globally uniform AI strategy is optimal. A one-size-fits-all approach to cognitive offloading is destined to fail in a culturally diverse MNE. Instead, leaders should adopt a strategy of **culturally adapted AI deployment**, designing a flexible OCA that can be tailored to the specific cultural needs and capabilities of each subsidiary or business unit. This requires a deep understanding of the cultural dimensions that shape AI adoption in different contexts, drawing on frameworks such as Hofstede's cultural dimensions theory and Trompenaars and Hampden-Turner's model of cultural values [8,9].
- **Embedding OCQ in Digital Transformation Initiatives**. The development of OCQ must become a central pillar of any digital transformation initiative. This requires investing in metacognitive CQ by developing critical thinking skills and routines for questioning algorithmic outputs; fostering motivational CQ by creating a climate of psychological safety and curiosity around AI; and cultivating behavioural CQ by equipping multicultural teams with the skills and protocols needed for effective virtual collaboration and cross-cultural communication. Digital transformation cannot be treated as a purely technical project; it is, at its core, a cultural change initiative.
- **Designing Culturally Intelligent AI Governance**. Leaders must design governance structures that ensure algorithmic authority is exercised responsibly in a culturally diverse context. This means moving beyond technical audits to a holistic assessment of how algorithms are used, interpreted, and enacted in different cultural contexts. It means establishing diverse governance bodies that include representatives from different cultural backgrounds, ensuring that the cultural assumptions embedded in AI systems are regularly scrutinised and challenged. Governance must be a distributed cultural capability, not the sole responsibility of a technically-focused IT department.
- **Investing in the Development of Culturally Intelligent AI Tools**. Finally, the development of the next generation of AI systems must be informed by a deep understanding of cultural diversity. The goal should be to create AI tools that are not only technically accurate but also culturally sensitive and adaptable. This requires involving a more diverse group of stakeholders in the design and development process, including representatives from the cultural communities that will be most affected by the technology. The development of culturally intelligent AI is not merely an ethical imperative; it is a strategic one.

To synthesise these imperatives, Figure 1 visually integrates the core components of our argument into a coherent leadership architecture for AI-enabled multinational enterprises. The framework positions **Organizational Cultural Intelligence (OCQ)** as the moderating capability that shapes how **Organizational Cognitive Architecture (OCA)** is designed, governed, and enacted across diverse cultural environments. Rather than treating AI deployment as a linear technical rollout, the model depicts a dynamic system in which culturally adapted strategy, embedded OCQ development, distributed governance, and culturally intelligent tool design interact recursively. Leadership, in this schema, functions as the integrative force aligning technological infrastructure with cultural interpretation, motivation, and behavioural enactment. The figure therefore operationalises the concept of Culturally Situated Cognitive Offloading (CSCO) by illustrating how culturally intelligent leadership transforms AI from a generic efficiency mechanism into a context-sensitive strategic capability.

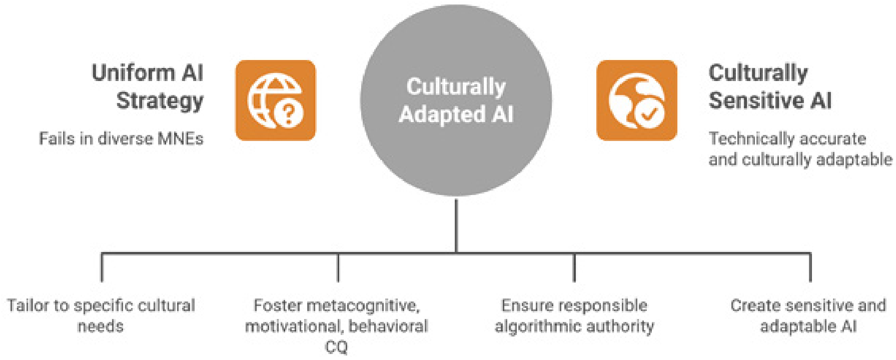

Figure 1: Culturally Intelligent AI Deployment Framework

Taken together, these four imperatives constitute a new agenda for leadership in the AI era. They represent a fundamental shift in how leaders think about the relationship between technology and culture, moving from a view of culture as a constraint to be managed to a view of culture as a resource to be leveraged. The most successful organisations of the coming decades will be those that learn to harness the power of AI while remaining deeply attuned to the cultural contexts in which they operate. This requires a new kind of leader: one who is not only technologically literate but also culturally intelligent, and who understands that the two forms of intelligence are not separate but deeply intertwined. The framework of CSCO and OCQ provides a theoretical foundation for developing this new form of leadership, and we hope that it will inspire both further research and practical action in the years ahead.

9. Future Research Agenda

The framework of CSCO and OCQ opens up a rich and largely unexplored territory for empirical and theoretical research. We propose four key avenues for future inquiry.

• **Multi-Level Empirical Tests of the Framework**. The most immediate need is for rigorous empirical tests of our propositions. This could involve developing and validating a survey instrument to measure OCQ at individual, team, and organisational levels, and then conducting large-scale, multi-level studies in MNEs to test the moderating effects we have theorised. Longitudinal designs would be particularly valuable for understanding how OCQ develops over time and how it shapes the long-term consequences of cognitive offloading.

• **Cross-National Comparative Studies**. The cultural dimension of our framework demands cross-national comparative research. Future studies should be conducted in different national contexts to explore how the dynamics of algorithmic authority, trust calibration, and cognitive deskilling differ across cultural clusters. For example, comparative studies contrasting high and low power distance cultures, or high and low uncertainty avoidance cultures, would provide valuable insights into the cultural contingencies of our framework.

• **Experimental Simulations of Human-AI Interaction in Multicultural Teams**. The micro-foundations of our framework are well-suited to investigation through controlled laboratory experiments. Researchers could design experimental simulations in which multicultural teams are asked to complete tasks with the assistance of AI decision-support systems, manipulating the cultural composition of the team, the cultural context of the task, and the quality of the AI recommendations. Such studies would allow researchers to isolate the causal mechanisms that link CQ, AI, and performance.

• **Research on AI-Culture Trust Calibration**. Finally, we propose a dedicated stream of research on the cultural dynamics of trust calibration in human-AI interaction. Future research should explore how the process of trust calibration unfolds in different cultural contexts, using a combination of qualitative methods (to understand the subjective experience of trusting or distrusting AI) and quantitative methods (to measure the accuracy of trust calibration across cultural groups). A deeper understanding of the cultural dynamics of trust is of immense practical importance for the design of responsible and effective AI systems.

In conclusion, this paper has argued that the future of work in global organisations cannot be understood without attending to the intersection of cognitive offloading and cultural intelligence. The framework of CSCO and OCQ provides a new theoretical vocabulary for this intersection, and the propositions we have derived provide a roadmap for empirical research. We believe that this framework has the potential to make a significant contribution to the management of AI-enabled organisations, and we invite scholars and practitioners alike to engage with it critically, to test its propositions, and to extend it in new directions. The stakes are high: as AI becomes an ever more pervasive presence in organisational life, the ability to manage its cultural dimensions will become an increasingly critical determinant of organisational success and human well-being.

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