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The Ubiquity Problem in Enterprise AI: Occupational Embedding as Management Innovation and the Relocation of Strategic Advantage

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Abstract

Artificial intelligence (AI) is diffusing through enterprises primarily by being incorporated into existing occupations rather than through the creation of dedicated AI roles. Labor-market indicators suggest that most AI-related demand now arises within established jobs, yet enterprise AI strategy continues to emphasize the acquisition of specialist talent and technology. This paper examines how the occupational embedding of AI reshapes the sources of enterprise capability and competitive advantage, and what organizational conditions allow firms to convert diffuse applied AI use into strategic value. The paper is an integrative conceptual review of literature on AI diffusion, the task content of work, organizational complements, contextual heterogeneity, and competitive advantage. It interprets this literature through resource-based, dynamic-capabilities, absorptive-capacity, and management-innovation perspectives. On that basis, it distinguishes the diffusion of AI use from its organizational integration. This distinction yields a typology of four deployment architectures: peripheral, specialist-centric, diffuse-unmanaged, and integratively embedded. The paper identifies work redesign, complementary skill formation, and integrative coordination as the conversion mechanisms through which distributed use becomes organizational capability, and it frames occupational embedding as a form of management innovation. It further articulates a "ubiquity problem": as access to general-purpose AI tools converges among competitors, the technology itself becomes an unlikely source of sustained advantage. Advantage instead relocates to the organizational architecture of AI use, which is harder to imitate because of its causal ambiguity, social complexity, and path dependence. Six propositions specify these relationships and their boundary conditions for future empirical testing. The paper concludes that AI strategy is substantially a problem of organizational design, and it offers implications for talent strategy, governance of employee-initiated AI use, and the measurement of AI capability.

Keywords: *artificial intelligence; occupational embedding; management innovation; competitive advantage; dynamic capabilities; resource-based view; organizational capability*

1. Introduction

Artificial intelligence has moved rapidly from a specialist technical domain into the ordinary fabric of work. Employer demand offers one visible indicator of this shift. In the United States, the share of job postings on Indeed containing AI-related terminology reached approximately 6.8 percent by the end of August 2026, nearly double the share recorded twelve months earlier (Indeed Hiring Lab, 2026).

More revealing than the scale of this demand, however, is where it occurs. Lightcast estimates that dedicated AI occupations made up only 0.3 percent of US job postings in the first quarter of 2026 and just 7 percent of total AI adoption; the remaining 93 percent came from existing occupations that had folded AI skills into everyday work (Lightcast, 2026). The pattern was already visible earlier: by 2024, roughly half of postings requiring AI skills were for roles outside information technology and computer science (Lightcast, 2025). AI, in other words, is diffusing less through the creation of new jobs than through the transformation of established ones.

Posting data must be interpreted with care. A posting that mentions AI signals employer intent and skill demand; it does not measure adoption, capability, or performance. Nonetheless, complementary evidence points in a consistent direction. An analysis of US posting data by Federal Reserve Bank of New York economists finds little indication of a distinct AI-driven decline in labor demand for exposed occupations, and the Bank's business surveys suggest that firms intend to incorporate AI mainly by retraining existing workers rather than by reducing hiring (Audoly et al., 2026).

Taken together, these signals suggest that AI is being absorbed into jobs rather than substituting for them at scale. This reframes the central question. If AI enters the enterprise mainly through the daily work of managers, analysts, marketers, operations staff, and service personnel, then realizing its value becomes less a matter of technology procurement or labor substitution than of organizational design and management practice.

Yet much enterprise AI strategy continues to rest on an acquisition logic. AI capability is commonly framed in terms of recruiting specialist talent, licensing models and platforms, and building data infrastructure. These investments matter, but the evidence on where AI is actually used suggests they address only part of the value-creation process. Field evidence on generative AI deployment indicates that productivity effects can materialize within ordinary roles: in one large customer-support setting, gains were concentrated among less-experienced workers (Brynjolfsson et al., 2025). If value is increasingly created at the point of use and distributed across many roles, the strategic question shifts from whether a firm possesses AI to how effectively it organizes the use of AI throughout its workforce.

This shift exposes a deeper tension, which this paper terms *the ubiquity problem*. Resource-based theory holds that sustained competitive advantage derives from resources that are valuable, rare, difficult to imitate, and lacking close substitutes (Barney, 1991). Technologies that become widely accessible tend to lose their differentiating power. Carr (2003) advanced this argument about information technology, contending that as it became shared infrastructure, it functioned increasingly as a cost of doing business rather than a source of distinction.

General-purpose AI tools, now available by subscription to firms of almost any size, may follow a similar trajectory. The more broadly AI diffuses across firms and occupations, the less its mere possession can explain performance differences among competitors. The ubiquity problem thus names the tension between the breadth of AI diffusion and the conditions under which AI can support sustained advantage.

Strategic-management theory offers resources for addressing this tension, but they have not been integrated around the phenomenon of embedded AI. The dynamic-capabilities perspective emphasizes a firm's capacity to sense and seize opportunities and to reconfigure its resource base (Teece, 2007; Teece et al., 1997). Absorptive-capacity theory explains how firms recognize, assimilate, and apply external knowledge (Cohen & Levinthal, 1990). Management-innovation research examines how new management practices, processes, and structures are generated and implemented as sources of advantage (Birkinshaw et al., 2008). Research on general-purpose technologies suggests that measurable returns depend on substantial complementary investment in intangible assets, including new processes, skills, and organizational arrangements (Brynjolfsson et al., 2021).

Labor-economics research, meanwhile, analyzes AI at the level of tasks and occupations but typically treats the firm as a black box. The result is a fragmented literature. One stream documents that AI is spreading through existing work; another theorizes competitive advantage; and little conceptual bridge connects the two.

This paper addresses that gap. It advances the concept of *occupational embedding*: the integration of AI into the tasks, routines, and decision processes of existing roles, as distinct from the acquisition of specialist AI capability. It argues that embedding is best understood as a form of management innovation.

The central argument is that as AI tools tend toward competitive parity, strategic advantage relocates from the technology itself to the organizational architecture through which it is used. That architecture comprises the redesign of work, the formation of complementary skills, and the coordination of AI use across functions. Accordingly, the paper asks how the occupational embedding of AI reshapes the sources of enterprise capability and competitive advantage, and what organizational conditions enable firms to convert diffuse, applied AI use into strategic value.

In pursuing this question, the paper distinguishes occupational embedding conceptually from specialist-led AI adoption; examines embedding through dynamic-capabilities, absorptive-capacity, management-innovation, and task-based perspectives; identifies the organizational complements that condition whether embedded AI generates value; analyzes the ubiquity problem and its implications for sustained advantage; and develops an integrative framework,

with propositions, to guide future empirical research. The paper is conceptual in design. It draws on published labor-market indicators to establish the phenomenon but does not claim to test its propositions empirically.

The argument proceeds as follows. Section 2 reviews the literature on organizational AI adoption, the task content of work, organizational complements, contextual heterogeneity, and the relationship between technology and competitive advantage. Section 3 describes the integrative conceptual approach. Section 4 develops the analytical synthesis, including a typology of enterprise AI deployment and a set of propositions. Section 5 discusses theoretical and managerial implications, and Section 6 concludes.

2. Review of Related Literature

2.1 Organizational AI Adoption and Diffusion: From Specialist Deployment to Embedded Use

A growing body of research describes organizational AI adoption as integration into existing work processes rather than as a capability confined to specialist teams (Chalmers et al., 2026; Uren & Edwards, 2023; Von Richthofen et al., 2022). In knowledge-work settings, adoption tends to shift the composition of tasks within established roles toward reviewing, editing, reasoning, and interpersonal judgment. It produces hybrid patterns of human–AI work rather than discrete AI positions added alongside existing ones (Von Richthofen et al., 2022).

Accounting offers an instructive case. Core occupations persist, but tasks are redistributed between human professionals and AI systems, and some activities migrate entirely to the latter (Leitner-Hanetseder et al., 2021). Interview evidence from Philippine accounting practitioners similarly indicates that AI enters the profession first through low-risk assistive uses, such as summarization and preliminary document review, while deeper integration into core accounting processes remains conditional on top-management sponsorship, data readiness, and governance (Bendal et al., 2026). In software engineering, adoption depends less on the technology's capabilities than on its compatibility with existing development routines (Russo, 2023). Evidence from European workplaces similarly indicates that generative AI adoption concentrates in jobs with abstract cognitive content and greater worker influence over how tasks are performed, with substantial variation across countries and occupations (Henseke, 2026).

Posting-based research adds a within-firm dimension to this picture. Evidence that generative AI mentions spread across occupations inside firms, not only through firm-level hiring of specialists, suggests that adoption propagates through existing role structures once organizational conditions permit (Schubert, 2026). The same research notes an important measurement limitation. Job postings capture formalized hiring intent and therefore miss decentralized use by incumbent employees. Posting data are thus likely to understate the extent of embedded adoption rather than overstate it.

That decentralized use forms a second, closely related strand of literature. Employees frequently use generative AI tools independently of, and often ahead of, formal organizational strategy. In public administration, civil servants draft reports, refine policy proposals, and generate content with generative AI without explicit approval, governing frameworks, training, or oversight (Tangi et al., 2025). Comparable patterns appear in research institutions, where regular use is common and some staff pay personally for premium tools when institutional access is lacking (Cabras et al., 2026). A comparable gap appears in Philippine educational settings, where students report high use of generative AI for schoolwork but comparatively low exposure to structured, classroom-based AI-assisted gamified learning (R. G. Atento et al., 2026).

The drivers of such use are partly organizational. Employees turn to external tools when approved alternatives are absent, unclear, or inadequate. They conceal use when disclosure norms are ambiguous or when they fear competence penalties and sanctions (Mızrak et al., 2026; Waters-Lynch et al., 2025).

The literature diverges, however, in how it interprets this phenomenon. One stream frames "shadow AI" principally as a governance and risk problem, emphasizing data disclosure, privacy exposure, and loss of organizational control (Sebastian, 2026; Silic & Silic, 2025). Another treats covert employee use as a form of user innovation: a distributed source of experimentation that, if surfaced and governed rather than suppressed, can contribute to the renewal of organizational capabilities (Waters-Lynch et al., 2025). These positions are not necessarily incompatible, but they imply very different managerial responses, and the literature has not reconciled them.

Methodologically, the evidence base relies heavily on cross-sectional surveys, single-sector case settings, and studies of early-stage adoption. Adoption is typically measured as individual or organizational use rather than as an

organizational capability. Longitudinal, firm-level evidence on how distributed use evolves into, or fails to become, coordinated organizational practice remains scarce.

Taken together, this literature establishes the phenomenon at the center of the present paper. AI is diffusing through existing roles and routines, frequently in advance of managerial intent. It also suggests that occupational embedding is not automatically a managed or strategic process. Whether diffuse use becomes an organizational asset or remains fragmented individual practice appears to depend on how organizations respond to it, a question the adoption literature raises but does not resolve.

2.2 AI and the Task Content of Work: Augmentation, Substitution, and Skill Complementarity

Research on the task content of work converges on a consistent near-term pattern: generative AI more often augments tasks within existing occupations than it replaces occupations outright. Experimental evidence is the most precise. In professional writing tasks, access to a generative AI assistant reduced completion time by roughly 40 percent and raised output quality by about 18 percent (Noy & Zhang, 2023). This is an augmentation effect within an established task rather than a substitution of the role performing it.

Field evidence from customer support points in the same direction. Productivity gains were concentrated among less-experienced workers, which suggests that AI can diffuse tacit know-how across a workforce and narrow performance gaps (Brynjolfsson et al., 2025).

Firm-level and economy-wide studies reinforce the distinction between tasks and jobs. Survey evidence from US firms indicates that AI-using businesses report replacing worker tasks considerably more often than they report changes in employment (Bonney et al., 2024). Global exposure analysis likewise finds that most occupations are only partially exposed to generative AI, so the dominant effect is the automation of some tasks alongside the reallocation of time toward others (Gmyrek et al., 2023). Analysis of real-world usage data adds heterogeneity: in some occupations AI is used chiefly to improve existing workflows, whereas in others bounded tasks are delegated to the system and human effort shifts toward work requiring interpersonal engagement (Tomlinson et al., 2025).

Substitution is nonetheless real, and its location is fairly consistent across studies. It clusters in routine, standardized, and codifiable cognitive tasks, such as templated drafting, summarization, classification, and basic data processing. Tasks involving judgment, verification, accountability, and interpersonal interaction remain comparatively dependent on human performance (Gmyrek et al., 2023; Makela et al., 2024; Tomlinson et al., 2025). A conceptual synthesis of manufacturing and marketing work attributes the stronger displacement signals in manufacturing and the stronger augmentation signals in marketing to differences in task composition rather than to differences in AI capability (Tolentino et al., 2026).

A parallel literature examines the skills that rise in value as AI diffuses. Large-scale analysis of job postings across the United States, the United Kingdom, and Australia finds that AI diffusion increases demand for complementary capabilities, including analytical thinking, resilience, ethics, and digital literacy, even in roles that are not themselves AI-related. Demand for substitutable skills such as summarization and translation declines (Makela et al., 2024).

Cross-national evidence identifies rising emphasis on communication, teamwork, creativity, and problem solving in AI-related jobs (OECD, 2023; Squicciarini & Nachtigall, 2021), and on management and communication capabilities in non-specialist occupations (OECD, 2024). Studies of business professionals and systematic reviews of skill transformation similarly foreground character, communication, and human–AI collaboration capabilities (Babashahi et al., 2024; Cardon et al., 2023). Firm–worker evidence further suggests that the returns to social skills are strongest in the early stages of technology adoption (Pustovalova & Vahter, 2025).

The complementarity thesis is not uncontested, however. Analysis of roles adopting generative AI finds that emphasis on social skills declined after the release of ChatGPT, particularly in non-managerial positions. The authors interpret this as AI-enabled self-service displacing some coordination work rather than intensifying it (Gulati et al., 2025). OECD evidence also cautions that communication requirements are common across vacancies generally, which complicates attributing their prevalence specifically to AI (OECD, 2023).

Read together, these findings suggest that complementarity may be differentiated by hierarchical level. Coordination and integrative demands may concentrate in managerial roles even as they diminish in some operational ones. If so, the distribution of complementary skills becomes a matter of how work is designed, not merely of which technologies are adopted.

The methodological profile of this literature tempers its conclusions. Experimental studies achieve strong internal validity but examine narrow, well-defined tasks. Posting-based studies measure stated employer demand rather than actual use or performance. A substantial share of the most recent evidence circulates as working papers. For the present argument, the principal implication is nonetheless clear: AI's value is realized largely at the level of tasks within existing roles, and the human complements that condition that value are themselves shaped by organizational choices about work design.

2.3 Organizational Complements: Absorptive Capacity, Dynamic Capabilities, and Management Innovation in AI Integration

If AI's value is realized within roles, a central question is what enables organizations to capture that value. The literature on absorptive capacity, the firm's ability to recognize, assimilate, and apply external knowledge (Cohen & Levinthal, 1990), offers one consistent answer.

Absorptive capacity has been found to strengthen the relationship between AI-enabled knowledge sharing and innovation performance in manufacturing (Lin & Wu, 2025), and between AI capabilities and servitization outcomes (Abou-Foul et al., 2023). In financial settings, it emerges as the most influential of several dynamic capabilities moderating AI's effect on asset allocation efficiency (Li et al., 2024).

The literature disagrees, however, on the theoretical role absorptive capacity plays. A number of studies model it as a mediating pathway through which AI affects performance, open innovation, ESG outcomes, or green innovation, rather than as a moderating condition (Qu & Kim, 2025; Wahab & Radmehr, 2024; Zhang & Yang, 2024; Zhang et al., 2025). Others find that its dimensions behave differently: potential absorptive capacity improves sustainability performance while realized absorptive capacity shows no direct effect (Nguyen et al., 2026). Whether absorptive capacity is a precondition for AI value or a capability that AI use itself develops therefore remains unresolved. That distinction matters for how embedding should be theorized.

A broader stream examines complementary organizational investments. Large-scale European evidence indicates that AI improves organizational performance through decision-making and business-process performance, with process automation, organizational learning, and process innovation acting as significant mediators. Radical process redesign is associated with larger gains than incremental improvement (Zebec & Stemberger, 2024).

AI combined with knowledge-sharing practices outperforms standalone adoption (Olan et al., 2022). Studies of organizational readiness indicate that people, processes, data, and technology must mature together for AI to deliver operational value (Uren & Edwards, 2023). A systematic review of AI–productivity research concludes that complementary investments are frequently necessary for productivity gains, while siloed structures and weak management attenuate returns (Cebulla et al., 2026; see also Hölzle et al., 2024). These findings align with the broader argument that general-purpose technologies yield measurable returns only after substantial investment in intangible complements (Brynjolfsson et al., 2021).

The relationship is also non-linear. Evidence of an inverted-U relationship between AI and corporate innovation performance (Fan & Wang, 2026) suggests that complements are necessary but not sufficient, as does evidence that AI–performance links depend on dynamic capabilities and on the balance between exploration and exploitation (Gong et al., 2025). Beyond a certain point, or without adequate organizational absorption, additional AI investment may yield diminishing or negative returns.

Two features of this literature are significant for the present paper. First, although many of the complements it identifies, including process redesign, new coordination arrangements, and novel learning routines, correspond closely to what management-innovation research defines as new management practices, processes, and structures (Birkinshaw et al., 2008), they are rarely theorized in those terms. The dominant frameworks are drawn from information systems and technology acceptance, such as the technology–organization–environment model and the technology acceptance model (e.g., Carandang et al., 2026; Qu & Kim, 2025), rather than from strategic management.

Second, the evidence base is methodologically narrow. It relies predominantly on cross-sectional surveys analyzed with structural equation modeling, often in single-country samples, using perceptual measures of both AI capability and performance. This raises concerns about common-method variance and limits causal inference. Most of these studies also treat AI adoption as a firm-level decision rather than as a pattern of distributed use across roles. The literature thus establishes that AI value is fundamentally a conversion problem. It has not yet examined how conversion operates when AI enters the firm through many hands rather than through a single implementation.

2.4 Contextual Heterogeneity: Sector, Firm Size, and Institutional Conditions in AI Adoption

The relationship between AI and organizational performance is not uniform across contexts. At the sectoral level, meta-analytic evidence identifies industry sector and sectoral technology intensity as significant sources of variance in the relationship between digital technologies and firm performance (Oduro et al., 2023). Systematic reviews of SME adoption similarly conclude that AI outcomes vary across sectors, with more digitalized sectors exhibiting broader adoption and more favorable implementation conditions (Landini & Machado, 2026). In education, for example, digital learning platforms have been reported as widely integrated while AI-powered adaptive systems remain comparatively limited, with inequitable access and high implementation costs cited as systemic constraints (Rao et al., 2025).

Recent comparative studies suggest that this heterogeneity operates primarily through sector-specific complements rather than through differences in the technology itself. Some drivers of AI adoption hold across manufacturing and services, but high-technology industries depend more on software infrastructure, whereas lower-technology industries depend more on hardware and equipment conditions (Song et al., 2026). Even where firms across sectors report similar levels of AI integration and similar expected strategic benefits, the barriers they face differ substantially, particularly with respect to data quality, system integration, and implementation complexity (Motyckova & Urbánek, 2026).

Outcome heterogeneity compounds the picture. Innovation and process gains have been observed mainly where AI was already diffusing and where the breadth of its application across functions mattered (Rammer et al., 2022). Survey evidence from Chinese commercial banks likewise associates AI application with operational efficiency, particularly where AI is deployed across strategic, risk-control, and process-improvement functions rather than only in customer-facing roles (Ying & Encio, 2026). Sustainability gains have been stronger in non-polluting industries and in more mature firms (Zhang & Yang, 2024). AI's competitive effects also appear to interact with market concentration (Akhtar et al., 2026).

Firm size is the second major boundary condition, and here the evidence is less uniform. Meta-analytic findings identify firm size as a moderator of technology–performance relationships (Oduro et al., 2023). Larger firms adopt AI more frequently and benefit from infrastructure and resource advantages (Forgione & Migliardo, 2026; Licht & Wohlrabe, 2026; Rammer et al., 2022). They also appear better able to convert AI into upskilling and efficiency gains (Boros et al., 2026).

Yet the direction of size effects is not consistent. Productivity gains have been found to be stronger in small frontier firms, while innovation gains are stronger in larger firms catching up to the frontier (Kopka & Fornahl, 2023). Micro and small hospitality enterprises have realized revenue gains from simple AI tools, which the authors attribute to flexibility and lower organizational inertia, while more complex tools produced no significant effect (Kukanja & Planinc, 2025). Among SMEs, medium-sized firms strengthen some adoption–performance pathways relative to smaller ones (Badghish & Soomro, 2024). At least one study finds that firm size, despite a direct effect on performance, does not moderate the relationship between AI usage and performance at all. Its authors characterize the pattern as adoption without impact in the absence of complementary capabilities (Rahmani et al., 2025).

Institutional conditions run through both dimensions. In emerging and resource-constrained economies, skill shortages, limited financing, infrastructure gaps, regulatory conditions, and the availability of government support shape whether AI adoption translates into measurable gains (Furqan et al., 2026; Haq et al., 2025). Among hospital-based medical technologists in Metro Manila, for instance, willingness to learn AI-based diagnostic tools was high while perceived laboratory readiness was low, and financial constraints, inadequate infrastructure, and limited training opportunities were rated as major challenges (Fernandez et al., 2026). Regulation, trust, privacy concerns, and external coordination often prove more decisive than the technology itself (Landini & Machado, 2026).

A common thread across these findings bears directly on the present argument. Contextual differences appear to operate mainly through complements, constraints, and institutional support, not through differential access to AI. The finding that small firms can benefit from simple, accessible tools is particularly relevant. Widely available AI may lower the threshold for value creation, which strengthens the case that differentiating outcomes depend on organizational rather than technological factors.

Comparability across this literature is limited, however. Performance is operationalized inconsistently, as revenue, innovation, productivity, ESG outcomes, or perceived performance. Samples are largely national. Evidence

from emerging economies consists mostly of SME surveys. These limitations constrain generalization and indicate that any conceptual framework must specify its boundary conditions explicitly.

2.5 AI and Sustainable Competitive Advantage: Ubiquity, Imitability, and the Parity Problem

Research on AI and firm performance has increasingly shifted its explanatory focus from AI investment to AI capability. AI capability, conceptualized as a firm's ability to select, orchestrate, and leverage AI-specific resources, has been positively associated with organizational creativity and firm performance (Mikalef & Gupta, 2021). This association extends to performance in public organizations (Mikalef, Lemmer, et al., 2023) and to sustainability-oriented performance, the latter mediated by a data-driven culture (Wamba et al., 2024).

The mechanisms proposed are consistently organizational: improved speed and quality of decision-making (Kwon et al., 2026; Neiroukh et al., 2024); strengthened marketing capabilities (Mikalef, Islam, et al., 2023); and the combined effects of AI-enabled dynamic capability, data-driven culture, and organizational learning (Ayoub & Sopuru, 2026). Evidence that AI investment generates innovation chiefly through accompanying organizational capabilities reinforces this view (Qiao et al., 2026). A thematic review of big data capability in Chinese enterprises reaches a parallel conclusion: data capability generates competitive value through organizational mediators, including dynamic capabilities, learning, governance, and culture, rather than through technology investment alone (Chen & Atento, 2026). Perhaps the sharpest finding comes from emerging-market SMEs. There, high AI usage intensity was not a core condition for strong performance outcomes, whereas governance, ethical practice, skills, and top-management involvement were (Lambert et al., 2026).

A conceptual caution is warranted, however. Prominent measures of AI capability explicitly bundle tangible, human, and intangible resources, including skills, inter-departmental coordination, and organizational change capacity (Mikalef & Gupta, 2021). The finding that capability outperforms investment is therefore partly built into how capability is defined: the construct already contains the organizational complements to which its effects are attributed. The literature thus confirms that bundles matter. It does less to specify which elements of the bundle carry the explanatory weight, or how those elements arise when AI use is distributed across roles rather than centrally orchestrated.

The second strand of this theme revisits a long-standing debate in strategy and information systems research. From a resource-based perspective, sustained advantage requires resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). The argument that information technology, once widely available, functions as shared infrastructure rather than a source of distinction (Carr, 2003) has been met with a now-familiar response. IT contributes to advantage when bundled with firm-specific complements such as human expertise, governance, culture, knowledge management, and strategic alignment (Adama et al., 2024; Muazu & Abdulmalik, 2021; Vafaei-Zadeh et al., 2024). Case evidence from Philippine retail pharmacy applies a comparable resource-based and dynamic-capabilities reading to an incumbent's efforts to sustain competitiveness amid digital disruption (A. G. Atento & Atento, 2025).

Recent theorizing extends this logic directly to AI. Cloud-delivered AI may initially narrow performance gaps by making advanced tools broadly accessible, after which differences re-widen as firms accumulate proprietary data, learning loops, routines, and managerial capability (Musau et al., 2026). The implication is that AI-based advantage, where it exists, must be continuously maintained through alignment, adaptation, and reinvestment rather than secured through a one-time acquisition (Adama et al., 2024; Gopal et al., 2025; Musau et al., 2026).

The literature therefore converges on two propositions: capability matters more than investment, and widely available technology tends toward competitive parity unless embedded in firm-specific complements. Its evidentiary basis for the second proposition, however, is considerably thinner than for the first. Most empirical studies are cross-sectional and rely on self-reported performance. As a result, they cannot observe whether advantages are sustained over time or whether they persist relative to competitors, which is precisely what the parity problem concerns. Moreover, whether generative AI, accessed by subscription and used directly by employees across functions, differs in its competitive dynamics from earlier forms of enterprise IT remains largely theorized rather than examined. This is the point at which the present paper's argument begins: the conditions under which diffuse, occupation-level AI use can become a source of advantage that competitors cannot readily replicate.

2.6 Synthesis of Literature

Read together, the five bodies of literature reviewed above converge on a single pattern: at every level of analysis, the locus of AI value shifts away from the technology itself and toward the organization that uses it.

At the level of diffusion, AI is spreading primarily through existing roles and routines, frequently ahead of formal managerial intent (Henseke, 2026; Tangi et al., 2025; Von Richthofen et al., 2022). At the level of tasks, its dominant near-term effect is augmentation within occupations rather than substitution of them, and its value is conditioned by complementary human capabilities (Gmyrek et al., 2023; Makela et al., 2024; Noy & Zhang, 2023). At the level of the firm, returns depend on absorptive capacity, process redesign, learning, and coordination, so complements are necessary though not always sufficient (Cebulla et al., 2026; Fan & Wang, 2026; Zebec & Stemberger, 2024). Across contexts, heterogeneity in outcomes appears to operate through complements, constraints, and institutional support rather than through differential access to AI (Landini & Machado, 2026; Oduro et al., 2023; Song et al., 2026). Finally, at the level of competition, AI capability predicts performance more consistently than AI investment, and widely available technologies tend toward parity unless they are embedded in firm-specific complements (Lambert et al., 2026; Mikalef & Gupta, 2021; Musau et al., 2026).

The literature is also marked by unresolved tensions. Bottom-up employee use is framed both as a governance risk and as a source of distributed innovation (Silic & Silic, 2025; Waters-Lynch et al., 2025). Evidence on complementary skills suggests that demand for coordination may intensify in managerial roles while declining in some operational ones (Gulati et al., 2025). Absorptive capacity is modeled alternately as a moderating precondition and as a mediating pathway (Lin & Wu, 2025; Wahab & Radmehr, 2024). The direction of firm-size effects is inconsistent (Kopka & Fornahl, 2023; Rahmani et al., 2025). And the dominant measure of AI capability partly contains the organizational complements to which its effects are attributed (Mikalef & Gupta, 2021). These tensions do not undermine the convergent pattern. They do indicate that the mechanisms through which organizational factors convert AI use into value remain incompletely specified.

2.7 Gaps in the Literature

Five gaps follow from this synthesis. The first is a *level-of-analysis gap*. Research on diffusion and task change operates at the level of occupations and tasks, whereas research on capability and performance operates at the level of the firm. Neither literature explains how distributed, occupation-level AI use aggregates into, or fails to aggregate into, firm-level capability. The phenomenon the labor-market evidence documents, AI entering the enterprise through many roles at once, therefore falls between the two.

The second is a *theoretical gap*. The organizational complements identified as decisive for AI value, including process redesign, new coordination arrangements, and novel learning routines, correspond closely to the substance of management innovation. Yet they are seldom theorized in those terms. Frameworks from information systems and technology acceptance dominate, and the strategic-management significance of these complements remains underdeveloped.

The third is the *ubiquity gap*. The proposition that widely available technology tends toward competitive parity was developed for earlier forms of enterprise IT. Whether it applies to generative AI, which is accessed by subscription, used directly by employees, and often adopted bottom-up, has been theorized only preliminarily. Moreover, the predominantly cross-sectional, self-reported evidence base cannot observe whether AI-related advantages are sustained over time or persist relative to competitors.

The fourth is a *construct gap*. Because prominent measures of AI capability bundle technological, human, and organizational resources, the literature cannot say which elements of the bundle carry explanatory weight. Nor can it say how those elements emerge when AI use is distributed rather than centrally orchestrated. The fifth is a *governance gap*. The literature offers no integrated account of how organizations should respond to employee-initiated AI use, whether by suppressing it, formalizing it, or channeling it into organizational learning, nor of how that response affects the value AI ultimately generates.

These gaps are compounded by methodological and contextual limitations: reliance on cross-sectional designs and perceptual measures, inconsistent operationalization of performance, a substantial share of non-peer-reviewed working papers, and posting-based indicators drawn from a small number of advanced economies.

2.8 Contribution of the Present Paper

The present paper addresses these gaps through conceptual integration rather than empirical testing. Its contribution is fourfold. First, it introduces the concept of occupational embedding, the integration of AI into the tasks, routines, and decision processes of existing roles, and distinguishes it analytically from specialist-led AI adoption, which provides a conceptual bridge between occupation-level and firm-level research. Second, it reframes embedding

as a form of management innovation, connecting the complements identified in the AI–performance literature to strategic-management theory, specifically the dynamic-capabilities, absorptive-capacity, and management-innovation perspectives, rather than leaving them within technology-adoption frameworks.

Third, it articulates the ubiquity problem and develops the argument that, as AI tools tend toward parity, strategic advantage relocates to the organizational architecture through which AI is used: work design, complementary skill formation, and cross-functional coordination. Fourth, it proposes a typology of enterprise AI deployment architectures and a set of propositions that specify the organizational conditions and boundary conditions under which embedded AI may generate distinctive value, offering a foundation for future firm-level empirical research. These contributions are offered as theoretical propositions grounded in the literature, not as empirically validated findings.

3. Methodology

3.1 Research Design

This paper adopts a conceptual research design, using integrative literature synthesis and theoretical framework development. It does not collect or analyze primary data, and it does not test hypotheses. Its purpose is to integrate two bodies of knowledge that have developed largely in parallel, namely research on the occupational and task-level diffusion of AI and research on organizational capability and competitive advantage, and from that integration to develop a theoretically grounded account of how embedded AI use relates to enterprise strategy.

The design is appropriate because the central research problem is theoretical. The question is not whether a particular relationship holds in a given sample. It is how an observed phenomenon, the diffusion of AI through existing roles, should be conceptualized from a strategic-management perspective, and what that conceptualization implies for the sources of competitive advantage.

The review is integrative rather than systematic. It does not follow a formal, reproducible protocol for identifying, screening, and selecting studies, and it makes no claim to exhaustive coverage. Its rigor rests instead on the explicit structuring of the literature around theoretically motivated themes, the deliberate inclusion of disconfirming and contradictory evidence, and the transparent application of defined theoretical lenses.

3.2 Source Orientation and Retrieval Strategy

The literature base was assembled through structured searches of a large-scale academic search index covering peer-reviewed literature. Retrieval was organized around five themes derived from the paper's central research question: organizational AI adoption and diffusion; AI and the task content of work; organizational complements to AI; contextual heterogeneity in AI adoption and outcomes; and AI and sustainable competitive advantage.

For each theme, two closed-form guide questions were formulated, each answerable in principle as yes or no; for example, whether generative AI use augments rather than substitutes for workers' tasks within existing occupations, and whether AI capability, rather than AI investment alone, is associated with superior firm performance. This question-driven strategy served two purposes. It anchored retrieval to empirically addressable relationships rather than to broad topical keywords, which improved the relevance of the evidence returned. And because the questions were framed neutrally, they were capable of retrieving both supporting and contrary evidence, which reduced the risk of confirmatory selection. Ten guide questions structured the retrieval in total.

Two further categories of sources supplemented the academic literature. Seminal contributions to the resource-based view, dynamic capabilities, absorptive capacity, management innovation, and the economics of general-purpose technologies were included purposively to provide the theoretical lenses described in Section 3.4. In addition, publicly available labor-market indicators were consulted directly from their publishing organizations to establish the empirical phenomenon motivating the paper: the Indeed Hiring Lab AI tracker (accessed on 21 October 2026), labor-market analyses published by Lightcast, and analysis published by economists at the Federal Reserve Bank of New York. These indicators are cited descriptively and are not analyzed as a dataset.

3.3 Source Selection Logic

Sources were selected according to four principles. The first was *relevance*: sources had to address one or more of the five themes, with priority given to studies examining AI in organizational or occupational settings rather than AI as a purely technical artifact. The second was *quality*: peer-reviewed journal articles were prioritized. Working

papers and conference proceedings were retained where they addressed questions central to the argument and where comparable peer-reviewed evidence was not yet available, a common situation given how rapidly research on generative AI is developing; such sources are identified as preliminary where they are interpreted.

The third principle was the deliberate retention of *contrary evidence*. Findings that complicated or contradicted the dominant pattern in a theme, such as evidence of declining social-skill emphasis in roles adopting generative AI and evidence that firm size did not moderate the AI–performance relationship, were retained because contradictory findings are central to identifying the tensions from which the conceptual analysis proceeds. The fourth was *exclusion*: sources were excluded where authorship could not be identified, or where the publication venue offered no evident quality assurance and the substantive point was supported by stronger evidence. The literature reviewed is concentrated in the period 2021–2026, reflecting the recency of generative AI, with earlier foundational works included for theoretical grounding.

3.4 Theoretical Lenses

The analysis applies one primary and several supporting theoretical lenses. The primary lens is drawn from strategic management. It combines the resource-based view, which specifies the conditions under which resources support sustained competitive advantage, with the dynamic-capabilities perspective, which addresses how firms sense, seize, and reconfigure resources under conditions of change.

Three supporting lenses are used. Absorptive-capacity theory is used to examine how firms assimilate and apply AI-related knowledge. Management-innovation theory is used to conceptualize the new practices, processes, and structures through which AI is embedded in work. Task-based perspectives from labor economics are used selectively to ground the analysis in the task-level effects of AI; this perspective informs the mechanism but remains subordinate to the strategic-management problem the paper addresses.

3.5 Analytical and Synthesis Procedure

The analysis proceeded in four stages. In the first stage, thematic synthesis, the literature within each theme was examined for convergent findings, points of disagreement, methodological tendencies, and contextual variation; the results are reported in Sections 2.1 to 2.5. In the second stage, cross-thematic integration, patterns recurring across themes were identified, most notably the shift of AI's value from the technology to its organizational complements, together with unresolved tensions (Section 2.6).

In the third stage, theoretical interpretation, the integrated findings were interpreted through the lenses described above, with particular attention to whether the conditions for sustained advantage specified by resource-based theory can be met by widely available AI. In the fourth stage, framework development, the paper developed a typology of enterprise AI deployment architectures and a set of propositions specifying relationships and boundary conditions suitable for future empirical testing (Section 4). Throughout, the analysis distinguishes between findings established in the literature, interpretations drawn from them, and propositions advanced by the present paper.

3.6 Limitations of the Approach

Several limitations follow from this design. Literature was retrieved primarily from a single academic search index, so relevant studies not indexed there, or not surfaced by the guide questions, may have been omitted. Because the review is integrative rather than systematic, its coverage is purposive rather than exhaustive, and its selection decisions, though guided by explicit principles, involve interpretive judgment.

The evidence base on which the synthesis draws is itself predominantly cross-sectional and reliant on self-reported measures, and a meaningful share of recent work has not yet completed peer review. The labor-market indicators used to establish the phenomenon measure employer demand expressed in job postings rather than actual AI use or organizational capability, and they are drawn from a limited set of advanced economies. Finally, the framework and propositions developed in this paper are conceptual. They are offered as a foundation for empirical inquiry, not as empirically confirmed relationships.

4. Analytical Synthesis and Conceptual Analysis

4.1 Reconceptualizing Enterprise AI: From Acquisition to Embedding

The literature reviewed in Section 2 supports a reconceptualization of how AI enters and creates value within the enterprise. The prevailing strategic logic treats AI as something a firm acquires: specialist talent, models, platforms, and data infrastructure. Acquisition remains necessary, but the evidence suggests it is an incomplete description of where value originates.

The diffusion of AI through existing roles, often ahead of managerial intent (Section 2.1), means that a large share of AI use takes place outside any deliberate acquisition decision. The predominance of task-level augmentation (Section 2.2) means that the value of that use is realized at the point where AI meets ordinary work. The centrality of organizational complements (Sections 2.3 and 2.5) means that whether this value accrues to the firm, rather than remaining with individual employees, depends on organizational arrangements that acquisition alone does not supply.

On this basis, the paper distinguishes two analytically separate dimensions of enterprise AI. *Diffusion* is the extent to which AI is used across the roles, functions, and routines of the organization. *Integration* is the extent to which that use is connected to the organization's work design, skill development, coordination mechanisms, and learning processes. The acquisition logic implicitly assumes that these dimensions move together: once AI is acquired and deployed, it is both used and integrated. The evidence suggests they can diverge sharply. Employees may use AI extensively without the organization learning from, coordinating, or building on that use. Conversely, an organization may integrate AI tightly into a small number of specialist processes while leaving most roles untouched.

Occupational embedding, as defined in this paper, denotes the condition in which high diffusion is matched by high integration. It is a property of organizational design rather than of technology, and in this sense it is best understood as a management innovation: the introduction of new management practices, processes, and structures intended to further organizational goals (Birkinshaw et al., 2008).

4.2 A Typology of Enterprise AI Deployment Architectures

Crossing the two dimensions yields four deployment architectures (Table 1). The typology is offered as an analytical device for distinguishing organizational configurations and their implications. It is not an empirically derived classification.

Table 1. *A Typology of Enterprise AI Deployment Architectures*

Diffusion \ Integration	Low integration	High integration
High diffusion	**Diffuse-unmanaged** AI is widely used across roles, often informally or covertly; gains accrue mainly to individuals; organizational learning is limited and governance risk is elevated.	**Integratively embedded** AI use is widespread and connected to redesigned work, complementary skill formation, and cross-functional coordination; individual gains are captured as organizational capability.
Low diffusion	**Peripheral** AI is confined to isolated pilots or individual experimentation; limited value and limited risk.	**Specialist-centric** AI is concentrated in expert units and tightly governed processes; strong control, but limited reach into ordinary work.

Note. Rows indicate the extent of AI diffusion across roles; columns indicate the extent to which that use is integrated with work design, skill formation, coordination, and organizational learning. The typology is an analytical device developed from the literature synthesis in Section 2, not an empirically derived classification.

Each architecture implies a distinct logic of value creation and a distinct exposure to the ubiquity problem. The *specialist-centric* architecture corresponds most closely to the acquisition logic. It offers control and technical depth, but it engages only a small share of the work in which, according to the labor-market and task-level evidence, AI is

increasingly being used. Its advantages rest substantially on specialist talent and proprietary systems, which remain contestable as competitors acquire similar resources.

The *diffuse-unmanaged* architecture is the one most consistent with the evidence on bottom-up and shadow use (Tangi et al., 2025; Waters-Lynch et al., 2025). Its defining feature is a gap between use and capture. Individual employees may become more productive, as experimental evidence on task-level augmentation suggests (Noy & Zhang, 2023), but the organization neither observes nor builds on these gains. This is a plausible organizational expression of the adoption-without-impact pattern reported in the contextual literature (Rahmani et al., 2025). The *peripheral* architecture represents early or tentative engagement and is of limited strategic interest except as a starting position. The *integratively embedded* architecture is the configuration in which, the paper argues, AI is most likely to become a source of distinctive organizational capability. It combines the reach of diffuse use with the organizational capture associated with integration.

The typology clarifies one of the tensions identified in Section 2.6. The divergent framings of employee-initiated AI use, as risk or as innovation, can be understood as descriptions of different trajectories out of the diffuse-unmanaged configuration. Suppression moves the organization toward the peripheral or specialist-centric architectures, sacrificing reach. Neglect leaves it diffuse-unmanaged, sacrificing capture. Integration converts distributed experimentation into organizational capability. On this reading, the governance question is less whether bottom-up use should be permitted than whether the organization possesses the mechanisms to integrate it.

4.3 Organizational Complements as Conversion Mechanisms

The movement toward integrative embedding depends on what this paper terms *conversion mechanisms*: organizational processes that translate distributed AI use into firm-level capability. Synthesizing the literature, three mechanisms appear central.

The first is *work redesign*. Because AI alters the task composition of roles rather than replacing them wholesale (Bonney et al., 2024; Gmyrek et al., 2023), its value depends on whether tasks, responsibilities, and workflows are deliberately reconfigured around it. Adding AI tools to otherwise unchanged roles captures only part of the potential gain. Evidence that radical process redesign yields larger performance improvements than incremental adjustment (Zebec & Stemberger, 2024) is consistent with this interpretation.

The second is *complementary skill formation*. The task-level literature indicates that AI raises the relative value of judgment, verification, analytical thinking, and coordination (Makela et al., 2024; OECD, 2023). Machine learning has also been characterized as moving from data to emergent pattern through procedures that are non-intentional and substantially opaque (R. G. Atento & Quinto, 2026), a feature that plausibly heightens the importance of human verification and interpretive judgment in AI-integrated work. These complements are not supplied automatically. They must be developed, and their distribution across roles is itself a design choice. The finding that social-skill emphasis declined in non-managerial roles adopting generative AI (Gulati et al., 2025) suggests that embedding may concentrate integrative demands at particular organizational levels, so skill formation must be aligned with the redesigned distribution of work rather than applied uniformly.

The third is *integrative coordination*. Distributed use generates distributed learning: individual employees discover effective applications, workarounds, and limitations. Absent mechanisms to surface, evaluate, codify, and diffuse these discoveries, such learning remains local. Integrative coordination comprises the practices through which individual AI use becomes shared organizational routine, including structured disclosure, cross-functional communities of practice, the codification of effective workflows, and governance that channels rather than suppresses experimentation. This mechanism corresponds most directly to the conversion of diffuse-unmanaged use into embedded capability.

The analysis also suggests a resolution of the disagreement over whether absorptive capacity moderates or mediates AI's effects (Section 2.3). If absorptive capacity is understood dynamically, both findings can hold: potential absorptive capacity may condition a firm's ability to embed AI, while the practice of embedding develops realized absorptive capacity over time (cf. Nguyen et al., 2026). The relationship would then be recursive rather than unidirectional. Cross-sectional designs observing it at a single point could plausibly detect either a moderating or a mediating pattern, depending on the stage of development captured.

4.4 Resolving the Ubiquity Problem: Where Advantage Relocates

The ubiquity problem asks how AI can support sustained competitive advantage when access to it is broadly available. The resource-based view provides the analytical criteria. A resource supports sustained advantage when it is valuable, rare, imperfectly imitable, and non-substitutable, and imperfect imitability arises from unique historical conditions, causal ambiguity, and social complexity (Barney, 1991).

Assessed against these criteria, general-purpose AI tools are increasingly valuable but neither rare nor difficult to imitate. Their acquisition is therefore unlikely, by itself, to sustain advantage. This is consistent with the long-standing argument concerning widely available information technology (Carr, 2003) and with the evidence that capability, rather than investment, is the more reliable predictor of performance (Lambert et al., 2026; Mikalef & Gupta, 2021).

The organizational architecture of AI use, however, plausibly satisfies the criteria for imperfect imitability to a far greater degree, on each of the three grounds. With respect to *causal ambiguity*, an integratively embedded architecture is distributed across many roles, routines, and decisions; its contribution to performance is difficult to observe from outside, and partly from inside, the firm, so competitors cannot readily identify what to copy. With respect to *social complexity*, the architecture depends on coordination relationships, shared practices, and norms of disclosure and experimentation, resources that are embedded in social relations and cannot be purchased. With respect to *unique historical conditions*, the architecture is accumulated through iterative learning, in which each cycle of use, evaluation, and codification builds on the last; the result is a path-dependent capability that a later entrant cannot reproduce by acquiring the same tools.

This reasoning yields the paper's central conceptual claim. Ubiquity does not eliminate AI-based advantage; it relocates it. As access to AI tools converges across competitors, the share of performance variation attributable to having AI should diminish, while the share attributable to how AI is organized should grow. This interpretation is consistent with theoretical arguments that broadly accessible AI may initially narrow performance gaps before differences re-widen as firms accumulate data, learning loops, routines, and managerial capability (Musau et al., 2026). It is also consistent with evidence that smaller firms can realize gains from simple, accessible tools (Kukanja & Planinc, 2025). Lower access barriers flatten the technological starting line, which increases the relative importance of organizational factors in determining who benefits.

Two qualifications are necessary. First, organizational architectures are not permanently inimitable. Management practices diffuse through consulting, labor mobility, and imitation, so advantage derived from embedding is likely to be durable rather than permanent, and its maintenance requires ongoing reconfiguration. This places dynamic capabilities, the capacity to sense, seize, and reconfigure (Teece, 2007), at the center of sustaining AI-related advantage. Second, the argument concerns the relative contribution of technology and organization. Specialist capability retains strategic importance, particularly in technology-intensive sectors where proprietary systems may themselves be difficult to imitate.

4.5 Integrative Framework and Propositions

The preceding analysis is integrated in a conceptual framework (Figure 1). The framework links antecedent conditions, namely the diffusion of AI through existing roles and the convergence of tool access across firms, to conversion mechanisms, namely work redesign, complementary skill formation, and integrative coordination, with absorptive capacity operating recursively. These mechanisms shape the resulting embedding architecture, as classified in Table 1, which in turn determines the strategic outcome: the relocation of advantage from technology to organizational architecture. The relationships between architecture and outcome are conditioned by sectoral technology intensity, firm size, and institutional context.

The framework gives rise to the following propositions, which are offered for empirical examination rather than as established relationships.

> ***Proposition 1.*** *Occupational embedding of AI is more strongly associated with firm-level performance gains when accompanied by deliberate work redesign than when AI tools are added to otherwise unchanged roles.*

> ***Proposition 2.*** *Firms with high AI diffusion but low integration (diffuse-unmanaged architectures) will convert individual-level productivity gains into firm-level capability less effectively than firms with integratively embedded architectures.*

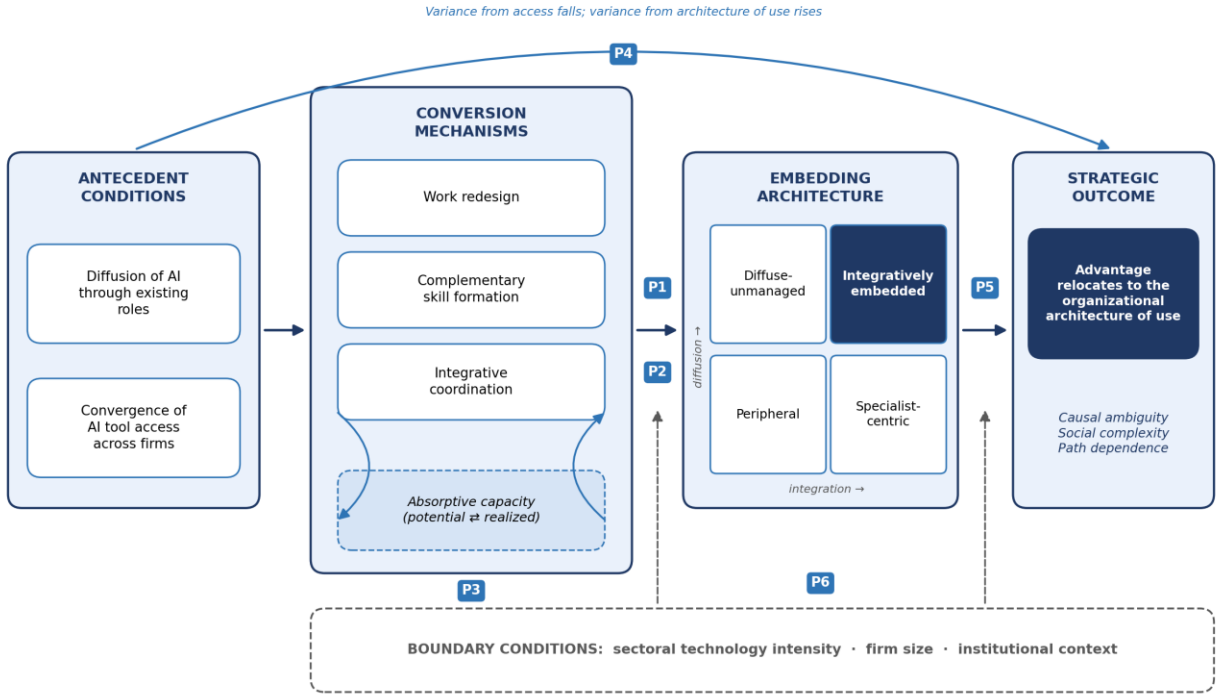
Proposition 3. *Absorptive capacity and occupational embedding are reciprocally related: potential absorptive capacity facilitates embedding, and sustained embedding develops realized absorptive capacity over time.*

Proposition 4. *As access to general-purpose AI tools converges among competitors, the variance in firm performance attributable to AI access will decline, while the variance attributable to the organizational architecture of AI use will increase.*

Proposition 5. *AI-related advantages grounded in the organizational architecture of use will be more durable than those grounded in AI acquisition, because the former exhibit greater causal ambiguity, social complexity, and path dependence.*

Proposition 6. *The relationships specified in Propositions 1–5 are moderated by sectoral technology intensity, firm size, and institutional context. In particular, they will be weaker where institutional constraints limit firms' capacity to invest in conversion mechanisms.*

Figure 1 *Integrative Framework: Occupational Embedding and the Relocation of Strategic Advantage*



Note. P1–P6 denote Propositions 1–6 (Section 4.5). Dashed elements indicate the recursive role of absorptive capacity and the moderating boundary conditions. The framework is conceptual and has not been empirically validated.

Taken together, the framework and propositions translate the paper's central argument into relationships that can be examined empirically. They move the analysis from the observation that AI is diffusing through existing work toward an explanation of when, and through what organizational means, that diffusion becomes a source of strategic advantage.

5. Discussion and Implications

5.1 Theoretical Implications

The analysis carries four implications for strategic-management theory. First, the ubiquity problem relocates advantage rather than eliminating it. The debate over whether widely available information technology can sustain advantage has often been framed as a binary: either the technology differentiates or it becomes infrastructure (Carr, 2003). The present analysis suggests a different formulation. Ubiquity removes the technology itself as a plausible

source of sustained advantage, but it simultaneously raises the strategic significance of the organizational arrangements through which the technology is used. The resource-based view remains the appropriate framework (Barney, 1991). What changes is the unit to which its criteria are applied: the architecture of use rather than the tool.

Second, management-innovation theory belongs in the study of enterprise AI. Much of the literature theorizes AI through frameworks of technology adoption and information-systems capability. Reframing occupational embedding as management innovation (Birkinshaw et al., 2008) shifts analytical attention from the adoption decision to the organizational practices, processes, and structures that determine what adoption yields. This reframing helps explain why firms with similar access to AI can achieve divergent outcomes. It also positions the study of AI within an established tradition concerned with how firms generate distinctive ways of organizing.

Third, occupational embedding is a candidate micro-foundation of AI capability. Prevailing measures of AI capability bundle technological, human, and organizational resources (Mikalef & Gupta, 2021), which makes it difficult to identify which elements drive performance. By decomposing capability into diffusion, integration, and specific conversion mechanisms, the framework suggests how firm-level capability may be built up from distributed, occupation-level use. It thereby connects research conducted at the level of tasks and occupations with research conducted at the level of the firm.

Fourth, absorptive capacity may be better understood as recursive in AI contexts. The proposition that absorptive capacity both enables and is developed by embedding offers a possible reconciliation of findings that treat it as moderator in some studies and mediator in others. If supported empirically, this would argue for longitudinal designs capable of distinguishing its potential and realized dimensions over time.

5.2 Implications for Management Practice

For managers, the analysis implies that AI strategy is substantially an organizational-design problem rather than a technology-procurement problem. With respect to talent strategy, specialist hiring remains important, but the evidence that AI adoption occurs predominantly within existing occupations suggests that investment in specialist talent should be balanced by investment in the AI-related capabilities of the broader workforce, which is where most AI use is already taking place. This emphasis is consistent with the broader labor-market shift from degree-based toward skills-based signaling (Espelita & Atento, 2026). With respect to resource allocation, licensing platforms while leaving roles and workflows unchanged is likely to capture only part of AI's potential value. Budgeting for process redesign, role reconfiguration, and complementary training should be treated as integral to AI investment rather than as an afterthought.

With respect to governance, bottom-up AI use is better treated as a signal than as a violation. Organizations that respond solely through restriction risk sacrificing reach. Those that neglect such use risk forgoing capture and incurring data and compliance exposure. The more productive response is to establish mechanisms that make use visible, evaluate what works, and diffuse effective practices across the organization, while managing genuine risks to data and privacy. With respect to measurement, indicators such as license counts, usage rates, or the number of AI-related hires measure diffusion and acquisition, not integration. Managers seeking to assess AI capability would benefit from measures that capture whether AI use is connected to redesigned processes, shared routines, and organizational learning.

5.3 Implications for Competitive Positioning

At the level of competitive strategy, the analysis implies that access to AI tools is unlikely to constitute a durable competitive moat. Positioning based on early or extensive tool adoption is vulnerable to rapid imitation. Positioning based on the speed and quality of organizational learning around AI is likely to be more defensible.

This has particular relevance for smaller firms. Broadly accessible tools lower the technological barrier to participation, which may allow small and flexible firms to capture gains that were previously available mainly to large organizations. Sustaining those gains, however, depends on developing integration capacity, which is often constrained by limited managerial, financial, and skill resources, especially in resource-constrained institutional environments.

Sectoral differences also matter. In technology-intensive sectors, specialist depth and proprietary systems may themselves be difficult to imitate, so specialist-centric architectures may retain greater strategic value. In sectors where AI use is predominantly applied rather than developmental, the organizational architecture of use is likely to be the

more significant differentiator. Finally, because advantages grounded in organizational architecture are durable rather than permanent, they place a premium on dynamic capabilities: the capacity to keep reconfiguring work and coordination as AI tools and competitors' practices evolve (Teece, 2007). Case analysis of a Philippine legacy retailer's omnichannel transition under digital disruption similarly draws on dynamic capabilities to explain incumbent adaptation (A. G. Atento & Atento, 2026).

5.4 Theoretical Boundaries and Limitations

Several boundaries qualify these implications. The argument is conceptual, and its propositions have not been tested. The literature on which it draws is predominantly cross-sectional and reliant on self-reported measures, and a meaningful share of recent evidence has not completed peer review. The motivating labor-market indicators describe employer demand expressed in job postings rather than actual use or capability, and they are drawn from a small number of advanced economies, which limits generalization to other institutional settings.

The typology describes ideal types; actual organizations are likely to combine architectures across units and functions, and to move between them over time. Integration also has costs. Coordination, redesign, and governance consume managerial attention and resources, and the evidence of non-linear returns to AI (Fan & Wang, 2026) suggests that the benefits of integration may diminish, or reverse, beyond some point. Finally, the technology is changing rapidly. Developments such as increasingly autonomous AI agents could alter the balance between specialist-centric and embedded architectures, for example by shifting value back toward the technical capability needed to build and orchestrate such systems. This possibility is speculative, but it underscores that the framework describes the current phase of AI diffusion and may require revision as the technology develops.

6. Conclusions and Recommendations

This paper set out to explain how the occupational embedding of AI reshapes the sources of enterprise capability and competitive advantage, and what organizational conditions enable firms to convert diffuse applied AI use into strategic value. The answer it develops is that AI's strategic significance is shifting from the technology to the organization. The available evidence indicates that AI is diffusing predominantly through existing roles rather than through new specialist occupations. Its near-term effects consist mainly of augmenting tasks within those roles, and its returns depend heavily on organizational complements. Under these conditions, access to AI tools becomes progressively less capable of distinguishing one firm from another. What remains capable of doing so is the organizational architecture through which AI is used.

Three conceptual insights are, in the paper's assessment, the most strongly grounded in the literature reviewed. First, diffusion and integration are distinct dimensions of enterprise AI. Widespread use does not imply organizational capability, and the gap between the two, evident in the prevalence of informal and unmanaged use, helps explain why AI adoption does not consistently translate into firm-level performance. This distinction underlies the paper's typology of four deployment architectures: peripheral, specialist-centric, diffuse-unmanaged, and integratively embedded.

Second, specific conversion mechanisms move a firm from use to capability. Work redesign, complementary skill formation, and integrative coordination together constitute occupational embedding as a form of management innovation rather than a technology implementation, and absorptive capacity appears to operate recursively within this process, both enabling embedding and being developed through it. Third, the ubiquity problem relocates advantage rather than eliminating it. Widely available AI tools fail the resource-based criteria for sustained advantage, whereas integratively embedded architectures, being causally ambiguous, socially complex, and path-dependent, plausibly satisfy them to a greater degree. Advantage grounded in such architectures is likely to be durable but not permanent, and it requires continual reconfiguration.

These conclusions must be read within the paper's limitations. The argument is conceptual, and its framework and propositions have not been empirically validated. The literature on which it draws is largely cross-sectional and reliant on self-reported measures, and much of the most recent evidence has not yet completed peer review. The labor-market indicators that motivate the analysis measure employer demand rather than actual use, and they come from a limited set of advanced economies. The rapid evolution of AI technologies means the framework describes the current phase of diffusion and may require revision as the technology develops.

Four recommendations for practice follow, offered in proportion to the conceptual and preliminary nature of the evidence. First, organizations should treat AI strategy as organizational design, planning AI investment together with

investment in process redesign, role reconfiguration, and complementary training rather than as a technology purchase alone. Second, they should channel rather than merely restrict employee-initiated AI use, establishing mechanisms that make such use visible, evaluate effective practices, and diffuse them across functions, while managing genuine data and privacy risks. Third, they should balance specialist and distributed capability, complementing specialist hiring with sustained development of the broader workforce's capacity to work with AI, consistent with where AI use is actually occurring. Fourth, they should measure integration, not only adoption, extending the assessment of AI capability beyond license counts, usage rates, and AI-related hiring to examine whether AI use is connected to redesigned processes, shared routines, and organizational learning.

The propositions developed in Section 4.5 define an agenda for future research. Longitudinal, firm-level studies are needed to examine whether integratively embedded architectures yield more durable performance advantages than specialist-centric or diffuse-unmanaged ones, and to test the proposed recursive relationship between absorptive capacity and embedding. The development of instruments that measure integration separately from diffusion would allow the typology to be operationalized and would address the construct overlap in current measures of AI capability. Competitor-relative analyses comparing performance across firms with converging access to AI tools would allow direct examination of whether variance attributable to the architecture of use rises as variance attributable to access falls.

Comparative research across sectors, firm sizes, and institutional settings, including emerging economies where evidence remains limited, is needed to establish the boundary conditions of the framework. Finally, qualitative and case-based research on how organizations surface, govern, and codify bottom-up AI use would illuminate the conversion mechanisms that the framework treats as central but that current evidence describes only in general terms.

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