



Artificial Intelligence's Transformative Impact on Management, Strategy, and Workplace Dynamics: A Systematic Literature Review

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Originality: 100% • Grammarly: 95% • Plagiarism: 0%

ABSTRACT

Article History

Received: 23 Jan 2026
Revised: 04 Aug 2026
Accepted: 18 Sept 2026
Published: 31 Oct 2026

Keywords— artificial intelligence; augmented leadership; business model innovation; workplace dynamics; systematic literature review; PRISMA 2020

The integration of artificial intelligence (AI) into organizations is reshaping management practice, competitive strategy, and the experience of work, yet scholarship remains fragmented across disciplines and is predominantly Western-centric. This systematic literature review synthesizes interdisciplinary evidence on how AI transforms leadership and management functions, drives business model innovation, and alters workplace dynamics, with particular attention to Southeast Asian and



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Philippine contexts. Peer-reviewed, English-language journal articles published between 2016 and 2025 addressing the organizational, strategic, or workforce implications of AI were included; purely technical studies and non-peer-reviewed materials were excluded from the corpus, with institutional reports used only for contextualization. Scopus, Web of Science, ABI/INFORM, Business Source Complete, and the ACM Digital Library were searched. Screening followed the PRISMA 2020 guidelines: 1,245 records were identified, and 128 studies met all inclusion criteria and were synthesized thematically. First, AI integration facilitates an augmented leadership model in which effective managers combine human judgment with algorithmic capability. Second, AI operates as a strategic capability that enables adaptive, data-centric business models. Third, workplace dynamics exhibit a bifurcation effect whereby AI augments some roles while displacing or deskilling others. The review contributes an integrative tripartite framework connecting leadership, strategy, and workforce transformation, and identifies priorities for research and policy in emerging economies. No protocol was registered.

INTRODUCTION

The integration of artificial intelligence (AI) into organizational settings represents one of the most consequential developments in contemporary management. From early rule-based expert systems to the current era of machine learning, generative models, and large language models, AI has evolved from a back-office automation tool into a core strategic capability that shapes how firms decide, compete, and organize work (Duan et al., 2019; Iansiti & Lakhani, 2020). This shift is recalibrating organizational life, prompting a transition from human-centric operational models toward what this paper terms the “augmented office”: a paradigm in which human intelligence and artificial intelligence operate as an integrated, synergistic system reshaping the foundations of management, corporate strategy, and workplace dynamics.

The impetus for this review lies in the pace and scope of AI’s diffusion into business processes. The initial wave of automation primarily affected routine manual tasks; the current wave encroaches upon cognitive, non-routine domains previously considered the exclusive province of human knowledge workers (Frey & Osborne, 2017; Acemoglu & Restrepo, 2019). AI-powered systems now analyze vast datasets to inform strategic decisions, optimize logistics networks, personalize marketing at the level of the individual customer, and screen job candidates at scale (Davenport & Ronanki, 2018; Tambe et al., 2019). Estimates of the economic stakes are substantial: generative AI alone is projected to add

trillions of dollars annually to global output, with disproportionate effects on knowledge-intensive functions such as marketing, software engineering, and customer operations (Chui et al., 2023). This is not merely a story of efficiency gains but a fundamental restructuring of how value is created and captured, and of how the managerial role itself is constituted (Raisch & Krakowski, 2021).

The stakes are particularly high for emerging economies. In Southeast Asia, digitalization is a central engine of growth, with the regional digital economy exceeding US\$260 billion in gross merchandise value (Google, Temasek, & Bain & Company, 2024). At the same time, the International Labour Organization estimates that approximately 56% of salaried employment in five major ASEAN economies is at high risk of automation in the coming decades, with the Philippine business process outsourcing (BPO) sector among the most exposed (Chang & Huynh, 2016; Errighi et al., 2016). How organizations in such contexts govern the transition from automation to augmentation is therefore a question of both managerial and societal significance (World Bank, 2020).

Problem Statement and Literature Gap

Despite a rapidly growing body of research, the literature on AI in organizations remains fragmented across management, information systems, economics, sociology, and ethics. Prior systematic reviews have made important but partial contributions: Loureiro et al. (2021) and Borges et al. (2021) mapped the strategic uses of AI in business; Vrontis et al. (2022) and Pereira et al. (2023) reviewed AI's implications for human resource management and workplace outcomes; and Bankins et al. (2024) provided a multilevel review of AI in organizational behavior. Each of these reviews, however, concentrates on a single domain—strategy, human resources, or behavior—without integrating the interconnected transformations of leadership, business models, and workforce dynamics into a single analytical frame. Conceptual agenda-setting work has likewise called for, but not yet delivered, such integration (Dwivedi et al., 2021; Benbya et al., 2020).

A second gap concerns geography. The majority of the empirical scholarship synthesized in prior reviews draws on North American and European organizational contexts. Comparatively little synthesis attends to emerging Southeast Asian economies, where adoption patterns, institutional conditions, labor market structures, and cultural norms differ substantially from those assumed in Western-centric accounts (Chang & Huynh, 2016; World Bank, 2020). A review that connects the global theoretical conversation with the realities of these economies is required now because the region is simultaneously among the fastest digitalizing markets in the world and among the most exposed

to automation-driven displacement.

RESEARCH QUESTIONS

This review addresses three research questions:

RQ1: How is AI transforming fundamental management functions, including leadership, decision-making, and performance management, and what new competencies are required of leaders in the augmented office?

RQ2: In what ways is AI reshaping corporate and business-level strategy, particularly through business model innovation and the dynamics of competition and industry structure?

RQ3: What is the impact of AI integration on workplace dynamics, including employment patterns, skills demand, employee well-being, and the evolving nature of human–AI collaboration?

Contributions of This Review

The review makes three contributions. First, it offers an integrative, tripartite synthesis that connects the typically siloed literatures on leadership, strategy, and workforce transformation under a unified socio-technical lens. Second, it contextualizes this synthesis for Southeast Asia and the Philippines, drawing on labor-market evidence and policy instruments specific to the region. Third, it derives a structured agenda for future research and articulates implications for practitioners and policymakers governing organizational AI adoption in emerging economies.

METHODOLOGY

Review Protocol and Guidelines

This study employed a systematic literature review methodology conducted and reported in accordance with the PRISMA 2020 statement (Page et al., 2021), with the search reported following the PRISMA-S extension for search documentation (Rethlefsen et al., 2021). The completed PRISMA 2020 checklist is provided as a supplementary file. No review protocol was registered in advance; the absence of prospective registration is acknowledged as a limitation in Section 5.3.

Search Strategy and Database Selection

Five electronic databases were searched: Scopus, Web of Science (Social Sciences Citation Index and Emerging Sources Citation Index), ABI/INFORM

Collection, Business Source Complete, and the ACM Digital Library. These databases were selected because they jointly provide the most comprehensive coverage of the management, business, information systems, and computing literatures in which organizational AI scholarship is published. The search covered publications from January 2016 through December 2025. The 2016 lower bound reflects the inflection point at which deep learning applications entered mainstream managerial discourse and at which the managerial AI literature began to accumulate at scale; it also aligns the corpus with contemporary journal expectations regarding source recency. All five databases were searched on October 2025 to January 2026, and no update search was conducted thereafter. The database-specific search strings, execution dates, and record yields required for replication are reported in Appendix A and Table A1.

The search strategy combined two concept blocks—AI-related terms and organizational terms—joined with the Boolean operator AND. The full Scopus string was:

TITLE-ABS-KEY ((“artificial intelligence” OR “machine learning” OR “deep learning” OR “generative AI” OR “large language model” OR “algorithmic management” OR “intelligent automation”) AND (*manag* OR leader* OR strateg* OR “business model” OR “competitive advantage” OR *workplace* OR *workforce* OR *employ* OR “future of work” OR “human resource*” OR “decision?making”)) AND PUBYEAR > 2015 AND PUBYEAR < 2026 AND (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (DOCTYPE , “ar”) OR LIMIT-TO (DOCTYPE , “re”)) AND (LIMIT-TO (SUBJAREA , “BUSI”) OR LIMIT-TO (SUBJAREA , “ECON”) OR LIMIT-TO (SUBJAREA , “SOCI”))

The Web of Science equivalent used the TS= field tag with the same concept blocks, refined by language (English), document type (Article or Review), and the SSCI and ESCI indexes. Database-specific translations for ABI/INFORM (noft fields with the Peer-Reviewed limiter), Business Source Complete (TI/AB/KW fields with the Peer-Reviewed limiter), and the ACM Digital Library (simplified two-block Title/Abstract query, reflecting that platform’s more limited Boolean support) are reported in Appendix A. The subject-area restriction in Scopus was applied to exclude purely technical computing and engineering literature and is disclosed here as a filter affecting recall.

Institutional and policy sources—including reports by the International Labour Organization, the Asian Development Bank, the World Bank, the World Economic Forum, the ASEAN Secretariat, and industry research consortia—

were identified through targeted searches of the issuing organizations' websites. Consistent with the peer-review requirement of the eligibility criteria, these sources were not entered into the systematic screening funnel; they are used in this review solely for contextualization, regional framing, and policy discussion, and are cited as such.

Eligibility and Inclusion/Exclusion Criteria

Studies were included if they satisfied all of the following criteria: (a) peer-reviewed journal article (empirical or conceptual); (b) written in English; (c) published between January 2016 and December 2025; and (d) substantively focused on the organizational, managerial, strategic, or workforce implications of AI, machine learning, or algorithmic systems. The rationale for criterion (a) is quality assurance through peer review; for (b), the review team's language competence, acknowledged as a limitation; for (c), the alignment of the corpus with the modern managerial AI era; and for (d), the review's organizational rather than technical focus.

Studies were excluded, applying criteria hierarchically so that each record received a single, mutually exclusive exclusion reason, if they: (E1) had no organizational, managerial, or workforce focus; (E2) were purely technical or computational contributions without organizational analysis; (E3) were not peer-reviewed journal articles (e.g., editorials, news items, book reviews, conference abstracts, preprints); (E4) addressed AI only incidentally, without substantive analysis; or (E5) fell outside the publication window or were otherwise ineligible.

Screening and Selection Process

The initial database search yielded 1,245 records. Duplicates ($n = 312$) were removed using reference-management software followed by manual verification, leaving 933 unique records. Titles and abstracts of all 933 records were screened against the eligibility criteria, resulting in the exclusion of 587 records. The remaining 346 articles were retrieved and assessed in full text, of which 218 were excluded for the following reasons: no organizational, managerial, or workforce focus (E1, $n = 84$); purely technical or computational contribution (E2, $n = 57$); ineligible publication type (E3, $n = 41$); AI addressed only incidentally (E4, $n = 22$); and outside the publication window or otherwise ineligible (E5, $n = 14$). This yielded a final corpus of 128 studies. Figure 1 presents the PRISMA 2020 flow diagram.

All screening was performed by the sole author. Records judged borderline at title-and-abstract stage were retained for full-text assessment, and all full-text exclusion decisions were re-examined in a second pass conducted after an interval

of two weeks to reduce intra-rater inconsistency. The absence of an independent second screener is acknowledged as a limitation.

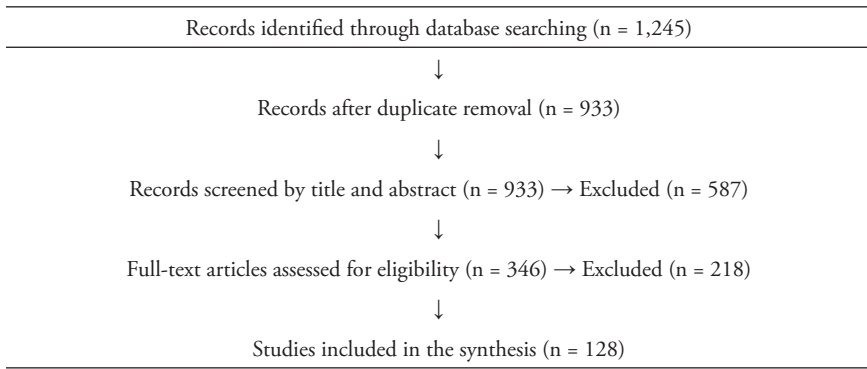


Figure 1. PRISMA 2020 flow diagram of study selection. (*Identification: records identified from databases, $n = 1,245$; records removed before screening: duplicates, $n = 312$. Screening: records screened, $n = 933$; records excluded, $n = 587$. Retrieval and eligibility: reports assessed for eligibility, $n = 346$; reports excluded: E1 $n = 84$, E2 $n = 57$, E3 $n = 41$, E4 $n = 22$, E5 $n = 14$. Included: studies included in the synthesis, $n = 128$.)*

Quality Assessment

No formal, instrument-based appraisal of methodological quality was undertaken for the included studies. Given the heterogeneity of the corpus—which comprises qualitative, quantitative, mixed-methods, and conceptual contributions—and the review’s aim of thematic rather than effect-size synthesis, studies were not scored against a standardized appraisal instrument. Quality was instead safeguarded at the eligibility stage: inclusion was restricted to peer-reviewed journal articles, thereby excluding non-refereed material from the corpus, and institutional and policy sources were kept outside the systematic corpus and used only for contextualization. During synthesis, interpretive weight was accorded to patterns that converged across multiple independent studies rather than to isolated findings, and the design of each study was recorded during extraction and taken into account when interpreting its contribution. The absence of a formal quality appraisal nonetheless limits the strength of the inferences that may be drawn from the corpus and is acknowledged as a limitation in Section 5.3.

Data Extraction and Synthesis Strategy

A structured extraction form captured, for each included study: author(s) and year; geographic context; research design; sample or data characteristics; core findings; and theoretical contributions. Extracted data were organized in a thematic matrix aligned with the three research questions. Synthesis followed the reflexive thematic analysis approach (Braun & Clarke, 2019): initial codes were generated inductively from the extracted findings, iteratively clustered into sub-themes, and consolidated into three overarching domains corresponding to RQ1–RQ3. Throughout, the synthesis prioritized patterns of convergence and divergence across studies and attended to contextual moderators—organizational size, sector, and institutional setting—rather than aggregating findings as though they were context-free.

RESULTS AND DISCUSSION

Descriptive Analysis of the Corpus

The 128 included studies display three descriptive patterns. First, publication activity accelerates sharply from 2018 onward, with more than two-thirds of the corpus published in 2019 or later, mirroring the diffusion of machine learning into mainstream managerial practice and, after 2022, the arrival of generative AI on the management research agenda. Second, the corpus is concentrated in management and information systems outlets—including journals in the business research, information management, human resource management, and management annals traditions—with a smaller computing-oriented contingent from the ACM Digital Library. Third, the geography of evidence is uneven: the majority of empirical studies draw on North American, European, or East Asian organizational settings, while Southeast Asian evidence, though growing, remains thin relative to the region's exposure to AI-driven labor market change. This asymmetry itself constitutes a finding, and it motivates the review's use of institutional and policy sources for regional contextualization. Table 1 summarizes the distribution of included studies across the three thematic domains.

Table 1
Distribution of included studies by thematic domain (N = 128)

Thematic domain	n	Qualitative	Quantitative	Conceptual
Management and leadership	47	22	12	13
Business model innovation and strategy	39	15	14	10
Workplace dynamics	42	19	15	8
Total	128	56	41	31

Note. Studies addressing multiple themes were classified under their dominant theme.

AI and the Transformation of Management and Leadership (RQ1)

From Command-and-Control to Augmented Leadership

The reviewed literature converges on the conclusion that AI integration into management functions facilitates a shift from traditional, hierarchical leadership models toward a hybrid “augmented leadership” configuration, in which effective managers combine human competencies—contextual judgment, ethical reasoning, emotional intelligence, and strategic vision—with AI-driven capabilities such as prediction, pattern recognition, and large-scale data processing (Jarrahi, 2018; Wilson & Daugherty, 2018). Jarrahi (2018) articulates the foundational logic: human and machine intelligence possess complementary strengths, with AI superior in analytical breadth and humans superior in intuition under uncertainty, equivocality, and ambiguity. The managerial implication is that decision authority is reorganized rather than transferred: Shrestha et al. (2019) delineate distinct configurations—full delegation to algorithms, hybrid sequential structures, and aggregated human–machine judgment—whose appropriateness depends on decision specificity, interpretability requirements, and accountability demands.

This reorganization reframes leadership work as orchestration and sensemaking rather than command-and-control. Leaders in AI-intensive organizations curate data pipelines, interrogate model outputs, and translate analytics into strategically actionable narratives (Davenport & Kirby, 2016; Fountaine et al., 2019). Working effectively “in the age of the learning algorithm” also requires managers to grasp the recursive character of algorithmic systems: algorithms learn from organizational behavior even as they reshape it, making management a continuous exercise in supervising systems that are themselves changing (Faraj et al., 2018; von Krogh, 2018).

Competencies and Trust in the Augmented Office

The emerging model demands a dual competency portfolio. On one side sit data literacy, algorithmic fluency, and sufficient technical understanding to

interrogate—rather than merely accept—machine recommendations (Davenport & Ronanki, 2018; Berente et al., 2021). On the other side sit distinctly human capacities: ethical discernment, empathy, and the ability to sustain trust in human–machine partnerships. Trust emerges from the corpus as a pivotal variable: Glikson and Woolley (2020) synthesize empirical evidence showing that cognitive and emotional trust in AI develop through different mechanisms—tangibility, transparency, reliability, and anthropomorphism—implying that leaders must actively manage the conditions of trust rather than assume it. Benbya et al. (2020) similarly identify managing the human–AI boundary, rather than the technology itself, as the central leadership challenge of current AI deployments.

Governance Obligations and Contingencies

Augmented leadership carries governance obligations. As algorithmic management diffuses, leaders become responsible for procedural safeguards—model interpretability, bias auditing, role redesign, and the preservation of meaningful human oversight over consequential decisions (Kellogg et al., 2020; Zerilli et al., 2019; Mittelstadt et al., 2016). The realization of the augmented model is, moreover, contingent. It presumes organizational data maturity and absorptive capacity that many firms—particularly small and medium enterprises in emerging economies—do not yet possess, with the result that AI adoption in such firms frequently takes the form of ad hoc task automation rather than a purposeful reconfiguration of managerial work (Ghobakhloo, 2020; World Bank, 2020). In Southeast Asia specifically, the policy literature underscores that leadership capability, not technology access, is increasingly the binding constraint on productive AI adoption (Asian Development Bank, 2018).

AI as a Driver of Business Model Innovation and Competitive Advantage (RQ2)

AI as a Dynamic Capability

The corpus supports the proposition that AI functions as a driver of business model innovation and a force redefining competitive advantage. Theoretically, this claim is anchored in the dynamic capabilities framework: the firm's capacity to sense opportunities, seize them, and reconfigure resources underpins durable advantage in volatile environments, and business models are the concrete architecture through which those capabilities are expressed (Teece, 2018). Empirical and conceptual work extends this framework to AI, showing that AI-enabled firms sense market change through predictive analytics, seize opportunities through personalization and rapid experimentation, and reconfigure

operations through automated adaptation (Warner & Wäger, 2019; Verhoef et al., 2021). Evidence on AI capability—the firm-level bundle of tangible, human, and intangible resources surrounding the technology—indicates that it is this organizational capability, rather than tool adoption per se, that predicts creativity and performance gains (Mikalef & Gupta, 2021; Enholm et al., 2022; Wamba-Taguimdje et al., 2020).

From Static Assets to Learning Strategic Processes

Across the strategy-oriented studies, sustainable advantage migrates from static proprietary assets toward proprietary data flows and the models built upon them. Iansiti and Lakhani (2020) describe the resulting competitive logic: when the critical path of value delivery runs through data pipelines and algorithms, scale, scope, and learning effects compound, producing self-reinforcing advantage for firms whose business models are architected around continuous environmental feedback. Reviews of the strategic AI literature corroborate this shift, finding that the dominant emerging theme is the integration of AI with organizational strategy and learning processes rather than isolated efficiency applications (Borges et al., 2021; Loureiro et al., 2021; Duan et al., 2019).

Regional Dynamics and the Readiness Gap

In Southeast Asia, the strategic stakes of this transition are visible at macro scale: the regional digital economy continues double-digit growth, with AI-related investment increasingly concentrated in e-commerce, logistics, and financial services (Google, Temasek, & Bain & Company, 2024). Yet the corpus and the policy literature jointly identify a pronounced readiness gap. Many firms—especially the micro, small, and medium enterprises that dominate regional employment—confront limitations in data infrastructure, digital skills, and capital that confine AI use to back-office automation rather than business model innovation (Ghobakhloo, 2020; World Bank, 2020; Asian Development Bank, 2018). The strategic implication drawn across studies is consistent: realizing AI-driven advantage requires top-management commitment to operating as a learning organization—championing a data-first culture, investing in analytical capability, and re-architecting processes around feedback—rather than treating AI as an IT procurement decision (Fountain et al., 2019; Enholm et al., 2022). At the frontier, analyses of generative AI suggest that these dynamics will intensify as the technology moves from prediction into content generation and autonomous task execution across the value chain (Chui et al., 2023).

AI and Workplace Dynamics: The Bifurcation Effect (RQ3)

The Augmentation Pathway

The reviewed literature consistently characterizes AI's workforce impact as a bifurcation: an augmentation pathway along which AI enriches roles, and a displacement pathway along which it eliminates or degrades them. On the augmentation side, studies document how the automation of routine cognitive tasks can free workers for higher-value activity, with task reinstatement—the creation of new tasks in which labor holds comparative advantage—operating alongside displacement (Acemoglu & Restrepo, 2019; Tschang & Almirall, 2021). Raisch and Krakowski (2021) caution, however, against treating automation and augmentation as freely chosen alternatives: the two are interdependent across time and organizational levels, and firms that pursue augmentation without governing its automation consequences encounter the paradox that today's augmentation prepares tomorrow's automation. In human resource management specifically, AI supports recruitment, development, and retention decisions, but the field's evidence base emphasizes that data-quality, fairness, and accountability constraints must be engineered into such systems for augmentation benefits to materialize (Tambe et al., 2019; Vrontis et al., 2022; Budhwar et al., 2023).

The Displacement Pathway

On the displacement side, occupation-level estimates indicate that a substantial share of employment is technically susceptible to computerization (Frey & Osborne, 2017), and the exposure is regionally concentrated: an estimated 56% of salaried employment in five ASEAN economies—Cambodia, Indonesia, the Philippines, Thailand, and Vietnam—faces high automation risk over the coming decades (Chang & Huynh, 2016). The Philippine BPO industry illustrates the stakes with particular clarity: the sector is a pillar of national employment and export earnings, yet the routine voice and data-processing services on which much of it was built are precisely the tasks most amenable to AI substitution, making workforce upgrading toward complex, judgment-intensive services an existential imperative (Errighi et al., 2016; World Bank, 2020).

Displacement risk is compounded by qualitative degradation of work under algorithmic management. Evidence from platform labor—including studies of remote gig workers in Southeast Asia—shows that algorithmic allocation and rating systems deliver flexibility while simultaneously producing overwork, insecurity, opaque evaluation, and constrained autonomy (Wood et al., 2019; Graham et al., 2017). Within conventional organizations, algorithmic systems extend employer control across hiring, direction, evaluation, and discipline, generating what Kellogg et al. (2020) term a new contested terrain between

employers and workers. Pervasive workplace datafication raises surveillance and privacy concerns that existing legal frameworks only partially address (Ajunwa et al., 2017), and the opacity of algorithmic decision systems creates documented risks of encoded bias in consequential employment decisions (Mittelstadt et al., 2016).

Reskilling and Governance as the Dividing Line

Across the corpus, the balance between the two pathways is treated as a function of strategic and institutional choice rather than technological destiny. Employer surveys indicate that skills disruption is accelerating—with analytical thinking, AI literacy, and socio-emotional capabilities atop demand projections—while a large share of the workforce will require reskilling within the decade (World Economic Forum, 2025). Reviews of workplace AI outcomes converge on the conclusion that organizational implementation choices, rather than the technology itself, determine whether AI improves or degrades employee outcomes (Pereira et al., 2023; Bankins et al., 2024). At the institutional level, the ASEAN Guide on AI Governance and Ethics operationalizes principles of transparency, fairness, human-centricity, and accountability for member-state organizations, providing a regional scaffold for the ethical governance that the scholarly literature identifies as the precondition of a socially sustainable augmentation pathway (ASEAN, 2024).

Critical Synthesis Across Domains

Two patterns cut across the three thematic domains. The first is the primacy of strategic choice over technological determinism. Whether in leadership transformation (RQ1), business model innovation (RQ2), or workforce dynamics (RQ3), outcomes are shaped less by the technology itself than by the organizational, cultural, and policy decisions surrounding implementation. Augmented leadership, learning strategic processes, and the balance between augmentation and displacement are all contingent achievements, produced by deliberate managerial and institutional action. This convergence is consistent with the socio-technical tradition, which holds that jointly optimizing social and technical subsystems—rather than optimizing the technical subsystem alone—is the condition of effective organizational change (Pasmore et al., 2019; Makarius et al., 2020).

The second cross-cutting pattern is the moderating role of organizational maturity and resources. Across all three domains, large, digitally mature firms are consistently better positioned to convert AI into strategic advantage, while smaller firms face structural constraints—capital, skills, data infrastructure—that

confine adoption to basic automation (Ghobakhloo, 2020; Mikalef & Gupta, 2021). The corpus thus suggests a paradox with distributional consequences: a technology often promoted as democratizing may, absent targeted intervention, widen competitive inequality between firms and, through the bifurcation effect, economic inequality between workers.

Figure 2 consolidates these cross-cutting observations into the integrative tripartite framework that this review proposes. The framework locates the three thematic domains—augmented leadership, AI as a dynamic capability, and the workplace bifurcation effect—within a single socio-technical system, specifies the reciprocal pathways through which each domain conditions the others, and positions organizational maturity, cultural–institutional context, and governance regimes as moderators operating on every pathway rather than as background conditions. Its analytical claim is that the three domains cannot be theorized independently: leadership capability supplies the absorptive capacity through which AI becomes a strategic capability; business model architecture determines how tasks are allocated between labour and algorithm; and the governance choices exercised through leadership determine which arm of the bifurcation prevails. Read in this way, the framework specifies where the strategic choices identified above are actually made, and it is the locus of those choices, rather than the technology, that the review identifies as the object of managerial and policy intervention.

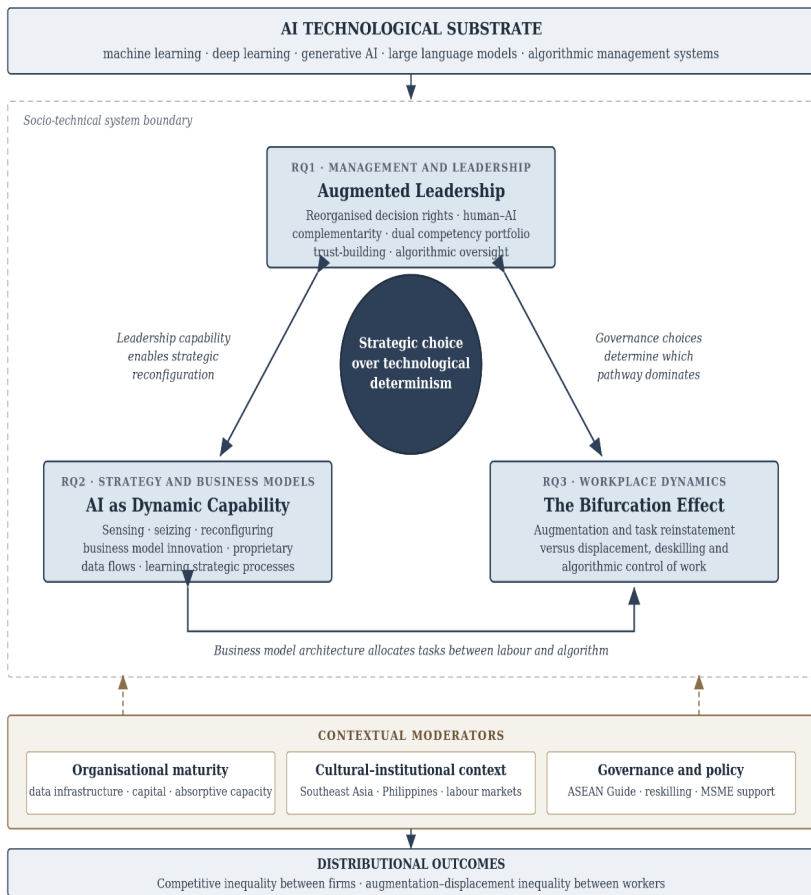


Figure 2. An integrative tripartite framework of AI-driven organizational transformation. *Reciprocal arrows denote the mutual conditioning of the three domains addressed by RQ1–RQ3. The central node denotes the cross-cutting finding that outcomes are determined by strategic and institutional choice rather than by properties of the technology. The lower panels denote, respectively, the contextual moderators identified in the synthesis and the distributional outcomes that follow when those moderators are left ungoverned.*

Alignment with Existing Theoretical Frameworks

The synthesis aligns with, and extends, three theoretical traditions. It extends dynamic capabilities theory (Teece, 2018) by positioning AI as a meta-

capability that strengthens sensing, seizing, and reconfiguring simultaneously—an interpretation supported by the empirical AI-capability literature (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). It refines the labor economics of automation (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017) by embedding task-level displacement and reinstatement within organizational governance: the same task profile can eventuate in augmentation or displacement depending on implementation choices, which macro-level models treat as exogenous. And it corroborates the automation–augmentation paradox (Raisch & Krakowski, 2021) with regionally grounded evidence that the two logics are managed jointly or not at all.

The regional lens adds a theoretical qualification largely absent from Western-centric accounts: cultural and institutional context moderates every mechanism the review identifies. Hierarchical and relational value systems documented in Southeast Asian organizational cultures (Komin, 1991) interact with the egalitarian, data-driven ethos presumed by augmented decision-making; labor-market institutions and the size of the informal sector condition how the bifurcation effect propagates (Chang & Huynh, 2016). Multilevel treatments of organizational AI are beginning to accommodate such moderators (Bankins et al., 2024), but the theory-building task remains substantially open.

Alternative Explanations

The patterns identified here may not be attributable solely to AI. Observed workforce bifurcation partly reflects broader processes of economic restructuring, globalization, and labor-market deregulation that predate and operate independently of AI adoption. Likewise, the shift toward adaptive business models is driven as much by general digital transformation and platform dynamics as by AI specifically (Verhoef et al., 2021). Future research should employ designs capable of isolating AI's distinctive contribution from these concurrent forces.

Gaps in Current Research

Four gaps emerge. First, longitudinal evidence is scarce: the corpus is dominated by cross-sectional and conceptual work, leaving the temporal dynamics of augmentation, displacement, and capability-building underexplored. Second, Southeast Asian empirical scholarship in indexed journals remains thin relative to the region's exposure, forcing reviews to rely on institutional sources for regional evidence—a gap that is itself a research opportunity. Third, the governance literature is stronger on diagnosis than on remedy: validated, implementable audit procedures and oversight mechanisms feasible for resource-constrained firms are largely missing. Fourth, the micro-foundations of augmented leadership—how

specific competencies are acquired, exercised, and rewarded—await systematic empirical treatment.

IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

Theoretical and Methodological Implications

Theoretically, the review contributes an integrative tripartite framework (Figure 2) that connects leadership, strategy, and workforce transformation under a single socio-technical lens, correcting the domain-siloed character of prior reviews. It positions AI as a dynamic meta-capability, embeds task-level automation economics within organizational governance, and identifies cultural-institutional context as a first-order moderator rather than background noise. Methodologically, the review demonstrates the value—and documents the difficulty—of regionally contextualized synthesis: where indexed empirical scholarship is thin, reviews must either transparently incorporate institutional grey literature outside the systematic corpus, as done here, or overstate the generality of Western evidence. Future SLRs in emerging-economy management research may adopt this two-track design, provided the boundary between systematic corpus and contextual sources is kept explicit.

Practical and Managerial Implications

For organizational leaders, the findings imply that AI adoption should be governed as a socio-technical change program, not a technology procurement. Priorities include building hybrid competency profiles that pair data literacy with ethical and interpersonal capability; redesigning decision rights to specify where human oversight is mandatory; and instituting bias audits and interpretability requirements for consequential algorithmic decisions. For strategy, advantage accrues to firms that architect business models around proprietary data flows and continuous learning, which requires board-level commitment to data-first operating cultures. For human capital, corporate-led reskilling—transitioning employees from routine tasks toward analytics, oversight, and complex customer-facing work—is the single most decisive lever over which pathway of the bifurcation dominates. For policymakers in Southeast Asia and the Philippines, the review underscores the urgency of MSME-targeted AI readiness programs, workforce transition support for exposed sectors such as BPO, and the operationalization of the ASEAN Guide on AI Governance and Ethics into enforceable organizational practice.

Study Limitations

This review has limitations. First, restriction to English-language sources may introduce language bias, particularly against regional-language scholarship from Southeast Asia. Second, all screening and coding were performed by a single reviewer; despite the two-pass re-examination procedure, the absence of an independent second screener and of an inter-rater agreement statistic is a methodological weakness. Third, no formal methodological quality appraisal instrument was applied to the included studies; the corpus was therefore not assessed against standardized, design-specific quality criteria, and the synthesis reflects the findings as reported by the primary studies rather than findings weighted by assessed methodological rigor. Fourth, no protocol was prospectively registered. Fifth, the heterogeneity of included designs limits direct comparability, and thematic synthesis necessarily involves interpretive judgment. Sixth, institutional and policy sources used for regional contextualization, while transparently separated from the systematic corpus, are not peer-reviewed. Finally, the pace of AI development—particularly in generative and agentic systems—means that findings will require periodic updating.

Agenda for Future Research

Five concrete directions follow. (1) Longitudinal, sector-specific studies tracking organizations that adopt augmented leadership and adaptive business models, measuring performance, well-being, and ethical outcomes against matched non-adopters. (2) Comparative sectoral research within Southeast Asia—for example, BPO versus agriculture versus manufacturing—identifying context-specific barriers and success factors in the AI transition. (3) Design-science research developing and field-testing governance instruments (bias audits, oversight protocols, explainability standards) that are feasible for MSMEs, not only for large corporations. (4) Empirical study of reskilling program efficacy, including public–private partnership models, with displaced and at-risk workers as the focal population. (5) Cross-cultural research systematically testing how national and organizational cultural dimensions moderate the acceptance and effectiveness of AI-driven management practices across ASEAN economies.

CONCLUSION

This systematic literature review synthesized 128 peer-reviewed studies, following PRISMA 2020, to examine artificial intelligence’s transformative impact on management, strategy, and workplace dynamics, with contextual attention to Southeast Asia and the Philippines. Three conclusions stand out.

First, AI is reconstituting managerial work into an augmented leadership model whose effectiveness depends on combining algorithmic capability with human judgment, trust-building, and ethical governance. Second, AI is redefining competitive advantage: durable advantage now accrues to firms that convert AI into a dynamic capability embedded in adaptive, data-centric business models, rather than to those that deploy it for isolated efficiency gains. Third, AI's workforce impact is bifurcated—augmenting some roles while displacing or deskilling others—and the balance between these pathways is decided by organizational reskilling investment and governance choices, not by the technology itself. The overarching message for scholars, managers, and policymakers is the same: in the augmented office, outcomes are chosen. The future of work in AI-intensive organizations—and in the emerging economies most exposed to its disruptions—will be determined by the quality of human decisions about how intelligent systems are deployed, governed, and shared.

DECLARATIONS

Funding: This research received no external funding.

Conflicts of interest: The author declares no conflict of interest.

Data availability: The data extraction matrix and the list of the 128 included studies are available from the author upon reasonable request and are provided as supplementary material at submission.

Ethical approval: Ethical approval was not required for this study. The review synthesized previously published, publicly available scholarly literature and institutional documents; it involved no human participants, no animal subjects, and no collection, generation, or processing of personal or identifiable data. Institutional review board approval and informed consent were therefore not applicable.

Consent for publication: Not applicable. No individual person's data, images, or identifiable details are reported.

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