https://doi.org/10.65166/bt13jr83


Journal of Enterprise Strategy & Management Innovation
Volume I, Issue 3, August 2026
ISSN: 3116-4277 (Online)
https://journal.ijhba.com/index.php/jesmi
https://slsipress.com

# Artificial Intelligence and the Strategic Reconfiguration of Work: A Conceptual Analysis of Substitution, Augmentation, and Organizational Redesign in Manufacturing and Marketing

Gilbert Tolentino[1], Cherry Ann Marie Espelita, Dr. Leah Quinto, Gay Marie Teodosio, Andrea Gwyneth Atento

## Abstract

Public discourse on artificial intelligence in business frequently frames AI's expansion across manufacturing and marketing functions as a uniform, inevitable displacement of human labor. This paper interrogates that framing through a structured conceptual literature review, synthesizing scholarship across labor economics, innovation management, and organizational behavior to examine how AI reconfigures work in these two functionally distinct domains. Drawing on task-based automation-augmentation theory, the analysis finds that manufacturing's comparatively codifiable task structure produces stronger displacement signals, while marketing's judgment-intensive, relational task structure produces stronger augmentation signals — a divergence explained by task composition rather than differences in AI capability. Across both sectors, evidence indicates that fully automated deployment architectures frequently underperform calibrated human-AI collaboration, not only in immediate productivity terms but in longer-run organizational resilience and workforce capability. A triangulating case from Philippine accounting practice indicates the model plausibly extends further, to functions where task outputs carry regulatory or fiduciary accountability, introducing accountability weight — operationalized through verification overhead and non-transferable liability — as an additional variable shaping deployment depth independent of technical capability. Strategic leadership and governance quality emerge as a further, sector-agnostic determinant of outcomes, mediating both implementation success and employee well-being. The paper concludes that whether AI "dominates" a given work system is not technologically predetermined but strategically chosen, contingent on how organizations design task allocation, human capital investment, and governance around AI's deployment. It offers a conceptual framework linking task-based labor economics to strategic management practice, and provides measured recommendations for enterprise leaders — including task-level portfolio mapping, parallel reskilling investment, calibrated leadership involvement, and explicit accountability-weight assessment — while identifying empirical validation of the proposed framework as a priority for future research.



**Keywords:** *artificial intelligence adoption; task-based automation; human-AI augmentation; strategic human capital management; organizational redesign; algorithmic governance; accountability weight*

Article History: Received May 15, 2026 | Revised June 16, 2026 | Accepted July 22, 2026

## 1. Introduction

Artificial intelligence has moved from a peripheral efficiency tool to a structural presence within core enterprise functions. On manufacturing floors, machine-vision quality control, predictive maintenance algorithms, and increasingly autonomous robotic systems now perform tasks once reserved for skilled human operators. Within marketing departments, algorithmic personalization engines, automated content generation, and AI-driven customer segmentation have reshaped how firms design, target, and deliver value propositions. These developments have generated a pervasive managerial and public narrative in which AI is understood to "dominate" work — a framing that implies an inevitable, wholesale substitution of human labor by machine capability across entire occupational categories.

This narrative, while rhetorically powerful, sits uneasily against a more differentiated body of scholarship on technology-driven labor change. The labor economics and innovation management literatures have long distinguished between the automation of discrete tasks and the elimination of entire jobs, recognizing that most occupations comprise bundles of tasks with varying degrees of susceptibility to machine performance. Parallel to this, strategic management scholarship has emphasized that technology adoption outcomes are not determined by technical capability alone but are mediated by organizational design choices — how firms choose to restructure workflows, redefine roles, and reallocate decision authority between human and machine agents. The gap between the popular "AI dominates, workers are replaced" narrative and this more contingent scholarly understanding constitutes the central problem this paper addresses.

The stakes of resolving this gap are strategic rather than merely technical. When enterprise leaders treat AI-driven displacement as an inevitability, they are prone to two related errors: first, underinvesting in the organizational redesign, human capital development, and process architecture that determine whether AI adoption yields sustainable competitive advantage or merely short-term cost reduction; and second, overestimating the uniformity of AI's impact across functions that differ substantially in task structure. Manufacturing and marketing represent a useful comparative pairing precisely because they diverge along these lines — the former historically associated with physical, procedural, and quality-control tasks amenable to codification, the latter with judgment-intensive, relational, and creative tasks that have proven comparatively resistant to full automation, even as AI tools increasingly augment marketing decision-making. Examining these two domains side by side allows the analysis to move beyond generalized claims about "AI and the future of work" toward a more precise account of where, how, and under what strategic conditions AI reconfigures — rather than simply eliminates — human contribution.

This paper undertakes a conceptual analysis of AI's role in reshaping work across manufacturing and marketing functions, with the aim of clarifying the strategic management implications of this reconfiguration. Specifically, the analysis seeks to synthesize existing theoretical and empirical literature on task-based automation, labor substitution, and human-AI augmentation as it applies to these two functional domains; to develop a conceptual distinction between AI's technical capability and its strategically chosen deployment, arguing that the latter — not the former — determines the extent of workforce displacement observed in practice; to examine how organizational design and human capital strategy mediate the transition from AI adoption to work-system outcomes; and to derive measured, non-deterministic recommendations for enterprise leaders navigating AI integration decisions. In pursuing these aims, the paper deliberately avoids treating AI's labor market effects as a matter of technological forecasting, focusing instead on the strategic and organizational logics that shape those effects.

The analysis proceeds from a position of academic caution regarding claims of AI "dominance." Rather than adjudicating whether AI will ultimately replace human labor in these functions — a question beyond the scope of a conceptual, non-empirical inquiry — this paper interrogates the conditions under which substitution, augmentation, or hybrid reconfiguration each become the more probable organizational outcome. This reframing carries direct relevance for two audiences central to the scholarly and practitioner readership this paper addresses. For scholars of innovation management and strategic leadership, it offers a conceptual framework linking task-level automation theory to firm-level strategic choice, addressing a connective gap between labor economics and management scholarship. For practitioners — executives, consultants, and policymakers responsible for workforce and technology strategy — it offers a corrective to deterministic narratives that can lead to either complacent underpreparation or reactive, poorly designed restructuring.

The remainder of the paper is organized to build this argument systematically: a review of related literature across five thematic areas spanning manufacturing automation, marketing AI applications, substitution-augmentation theory, organizational redesign, and strategic governance of AI-integrated work systems; a methodological account of the conceptual review design employed; an analytical synthesis comparing patterns across the two functional domains, extended by a triangulating case from accounting practice; and, finally, conclusions and recommendations for strategic management practice under conditions of ongoing AI-driven organizational change.

## 2. Review of Related Literature

### *2.1 AI and Automation in Manufacturing Operations*

Evidence from manufacturing settings converges on a broadly substitution-oriented pattern, in which AI-enabled automation displaces labor from routine physical and cognitive tasks while simultaneously generating measurable productivity gains. Welding, packaging, material handling, quality inspection, and repetitive data-entry functions have proven especially amenable to automation through computer-vision defect detection, robotic process automation, and intelligent sorting systems (Lodhi et al., 2024; Santhosh et al., 2023; Afrin et al., 2025). A structural vector autoregression analysis of South African manufacturing data found that AI-related shocks produced an immediate, statistically significant contraction in employment, accounting for close to 30 percent of forecast-error variance in manufacturing employment across a ten-quarter horizon (Giwa & Ho, 2026); this finding, however, derives from a single national context and should be read as illustrative of mechanism rather than as a generalizable displacement coefficient.

Not all manufacturing tasks are equally exposed. Work requiring physical dexterity, tacit knowledge, or situational flexibility has remained comparatively resistant to automation, and shop-floor roles specifically have been assessed as carrying limited additional displacement risk relative to routine cognitive back-office functions (Lei & Kim, 2024; Tyson & Zysman, 2022). This task-level heterogeneity is significant for the paper's thesis: it indicates that "automation" in manufacturing is not a uniform occupational event but a differentiated substitution process concentrated in codifiable task categories.

Productivity evidence reinforces the strategic rather than purely operational significance of these changes. Predictive maintenance, adaptive cobotic systems, and AI-driven workflow optimization have been associated with reduced cycle times, lower operational costs, and improved quality outcomes across automotive, food-processing, and logistics contexts (Shah et al., 2025; Kumar et al., 2021; Kotte, 2024). Notably, firm-level analysis of AI patenting activity found that productivity gains concentrate disproportionately in SMEs and service-oriented firms rather than the largest manufacturing enterprises, complicating any assumption that AI's productivity dividend accrues uniformly across the sector (Damioli et al., 2021). Countervailing this, the same literature cautions that anticipated productivity benefits are unlikely to be evenly distributed and may instead intensify labor-market inequality, while displacement of existing tasks is partially — though not fully — offset by rising demand for workers able to operate and maintain increasingly capable systems (Tyson & Zysman, 2022).

### *2.2 AI in Marketing and Customer-Facing Functions*

The marketing literature presents a markedly different pattern from manufacturing: strong, consistent evidence of performance improvement coupled with comparatively weak evidence of direct personnel substitution. AI-driven personalization has been linked to measurable gains in conversion, retention, and engagement across e-commerce, financial services, and advertising contexts, including a reported 30 percent increase in retention and 5.3 percent increase in conversion in e-commerce applications, a 15 percent conversion lift for generative-AI-produced advertising copy, and a 177 percent increase in leads from AI-personalized financial offers (Ammupriya et al., 2025; Grewal et al., 2024). A positive relationship between personalization effectiveness and purchase likelihood recurs across multiple studies, though at least one analysis found this relationship to be mediated by consumer trust and perceived usefulness rather than operating directly (Logalakshmi & Poornima, 2025; Teepapal, 2025).

Regarding effects on marketing personnel, the evidence base leans toward augmentation rather than wholesale substitution. Generative AI tools have reduced workload and response time substantially — Unilever's use of generative AI for initial customer-response drafting cut agent response time by approximately 90 percent — while allowing staff to reallocate effort toward strategic and creative work (Grewal et al., 2024; Vongpanich et al., 2025). Importantly, the literature explicitly identifies limits to this substitution: AI's inability to replicate emotional depth and nuanced creativity is cited as a structural constraint necessitating continued human involvement, and comparative work on AI versus human influencers concludes that a complete replacement of human creative and relational labor is unlikely, with a hybrid model instead emerging in which AI handles data-driven recommendation while humans sustain emotional engagement and brand trust (Vongpanich et al., 2025; Gerlich, 2025). This finding is directly relevant to the paper's comparative framing: it suggests that marketing's task composition — weighted toward judgment, creativity, and relational nuance — produces a fundamentally different AI-labor relationship than manufacturing's more codifiable task structure. Caveats in this literature include risks of intrusive personalization, "filter bubble" effects narrowing consumer exposure, persistent data-privacy and algorithmic-bias concerns, and resource barriers that may limit smaller firms' ability to adopt these tools at comparable scale (Amin, 2024; Babadoğan, 2024; Khan, 2025). Comparable Philippine evidence shows that consumer-centered strategy can be strengthened by translating stakeholder and community insight into credible value propositions, while digital engagement and brand trust can shape behavioral intention in market-facing contexts (Atento & Espelita, 2025; Espelita et al., 2026). Strategic analysis of a legacy Philippine retailer further suggests that digital disruption is addressed most effectively through integrated omnichannel capability rather than digital presence alone (Atento & Atento, 2026).

### *2.3 Labor Substitution vs. Augmentation Theory*

The task-based framework associated with Acemoglu and Restrepo provides the theoretical mechanism connecting the sector-specific patterns observed in manufacturing and marketing. This framework decomposes AI's labor impact into two opposing channels: a displacement effect, in which capital-performed tasks expand at labor's expense, and a reinstatement effect, in which new task creation expands labor's comparative advantage; the net employment outcome is treated as endogenous to the relative pace of these two channels rather than as a fixed technological property (Gupta & Kumar, 2026; Tyson & Zysman, 2022). Formal modeling indicates that task automation tends to erode employment within the automating sector because substitution effects dominate countervailing productivity-driven demand effects, whereas augmentation innovations raise occupational labor demand unambiguously through both channels simultaneously (Autor et al., 2022). Corroborating this asymmetry, empirical work distinguishing automation-type from augmentation-type AI found that automation AI depressed new-work creation, employment, and wages in lower-skilled occupations, while augmentation AI raised wages and generated new work in higher-skilled occupations (Marguerit, 2025).

Reinstatement evidence, while real, is neither immediate nor guaranteed to fully offset displacement. New task creation accounted for roughly half of United States employment growth between 1980 and 2010, and the majority of current employment resides in job specialties introduced since 1940 (Autor et al., 2022; Marguerit, 2025); AI-era analogues include newly identified categories such as prompt engineering, AI model training, and AI governance roles (Marguerit, 2025; Gupta & Kumar, 2026). Critically, displacement operates on a faster timescale than reinstatement, with productivity and new-task benefits typically materializing over years or decades (Tyson & Zysman, 2022), and outcomes are further moderated by workers' digital-skill levels and by substantial cross-country variation in automation exposure and digital infrastructure (Georgieff & Hyee, 2022; Gmyrek et al., 2026). Survey evidence broadly supports an augmentation-leaning interpretation at the individual worker level, with more workers reporting task augmentation than job-loss concern, and analysis suggesting that most economic value from AI arises from task redesign rather than outright role elimination (Chhibber et al., 2025; Ledingham et al., 2025). Read against Sections 2.1 and 2.2, this theoretical apparatus explains why manufacturing's more codifiable task structure exhibits stronger displacement signals while marketing's judgment-intensive structure exhibits stronger augmentation and reinstatement signals — the sectoral divergence is not anomalous but predicted by task-based theory. A parallel pattern appears in education, where stakeholders largely viewed AI as a supplementary and collaborative tool rather than a complete replacement for traditional instruction, despite recognizing benefits in personalization, engagement, and analytics (Rao et al., 2025).

### *2.4 Organizational Redesign and Human Capital Strategy Under AI*

A distinct strand of literature shifts attention from AI's technical capability to the organizational choices governing its deployment, offering direct support for the paper's central contention that strategic design — not technology alone — determines labor outcomes. Structured reskilling investment is associated with reduced workforce resistance and lower job insecurity during AI-driven transformation, though evidence on the direct productivity returns of upskilling programs is mixed, suggesting such interventions require careful tailoring rather than uniform application (Lahuerta et al., 2026; Joseph, 2024). Effective reskilling design accounts for both technical competencies and soft skills — problem-solving, creativity, emotional intelligence — that remain comparatively resistant to automation, alongside demographic and cultural factors shaping program uptake (Jadhav & Banubakode, 2024; Morandini et al., 2023). Adjacent Philippine evidence similarly links employee productivity to role-relevant self-efficacy and supportive work environments, reinforcing the importance of organizational support alongside technological change (Espelita & Atento, 2026). Evidence from vocational institutions preparing motor-vehicle safety and technical inspectors likewise underscores the continuing need for effective and continuously improved training when specialized technical work evolves (Yu & Atento, 2026).

Task-allocation research offers a more granular account of how complementarity should be structured: an empirically validated framework proposes that AI should automate relatively easy tasks, augment human performance on tasks where human and AI competence are comparable, and leave humans to work unassisted on the most difficult tasks, with the optimal balance depending on whether a task exhibits between-task or within-task complementarity (Fügener et al., 2025). Empirical support for collaborative over fully automated designs is substantial: explainable, human-overseen AI systems improved task performance by 7.7 percentage points in manufacturing and 4.7 percentage points in medical settings relative to opaque automation, and hybrid human-AI teams have been associated with productivity increases of up to 40 percent in iterative design work (Senoner et al., 2024; Rabbani et al., 2025). Perhaps most consequential for the paper's argument, evidence indicates that full automation can actively degrade organizational capability over time: training conditions removing human decision involvement reduced perceived autonomy, motivation, and skill acquisition, leaving personnel less able to intervene when automated systems failed, whereas partially automated designs preserved engagement and built adaptive resilience (Passalacqua et al., 2024). Parallel findings in creative work show that excluding humans from AI-assisted tasks reduces output quality, satisfaction, and creative diversity relative to designs retaining meaningful human input (Hosanagar & Ahn, 2024). Collectively, this literature reframes "AI dominance" of a work system less as a capability ceiling and more as a design choice — one that available evidence suggests is frequently suboptimal relative to deliberately structured collaboration. Research on accounting-software adoption among Philippine SMEs likewise indicates that technology value depends on the fit among technological, organizational, and environmental conditions rather than on software capability in isolation (Carandang et al., 2026). A related conceptual framework for integrated analytics treats data integration, analytics capability, decision quality, and organizational alignment as a linked socio-technical pathway for realizing organizational outcomes (Atento et al., 2025).

### *2.5 Strategic Governance of AI-Dominated Work Systems*

The final theme addresses how leadership and governance practices condition both implementation success and workforce well-being under AI integration. Strategic leadership is repeatedly identified as a critical determinant of AI adoption outcomes, encompassing digital-transformation guidance, cross-functional alignment, and the cultivation of trust between human and automated decision-making processes (Zamir, 2025; Abonamah & Abdelhamid, 2024).

Leadership commitment has been associated with measurable implementation gains — AI-enabled matrix organizations reporting 23 percent higher decision-making efficiency where leadership commitment was strong — though the relationship is not simply linear: case evidence indicates that overly active leadership intervention early in an AI rollout can be detrimental, implying that governance effectiveness depends on calibrated timing rather than sustained maximal involvement (Joshi, 2025; Canciglieri et al., 2026). Executive-level qualitative evidence further suggests that leaders predominantly conceive of generative AI as a decision-support and innovation-amplifying tool rather than an autonomous decision-maker, framing strategic oversight as an ongoing process of ethical stewardship rather than a one-time implementation decision (Varouchas, 2026).

Algorithmic management's effect on employee well-being emerges as genuinely contested rather than uniformly negative or positive, contingent on design features including autonomy preservation, transparency, surveillance intensity, and perceived fairness (Ahmad et al., 2025). Where algorithmic systems reduce worker autonomy and obscure decision logic, they are associated with diminished job satisfaction and well-being; conversely, transparent algorithmic design has been linked to stronger fairness perceptions and improved well-being, and algorithm-supported autonomy has been shown, in at least one study, to mediate positively into job satisfaction (Deng et al., 2024; Sharifah et al., 2024). This bidirectional evidence indicates that algorithmic management's welfare consequences are themselves a governance outcome rather than an inherent property of the technology. Consistent with this, the governance literature calls for proactive bias auditing, human-in-the-loop oversight, and dismantling of organizational silos between technical, compliance, and operational functions, positioning strategic leadership — rather than AI capability itself — as the pivotal differentiator of sustained competitive advantage under AI-driven transformation (Haque, 2025; Suljic, 2025). In adjacent enterprise research, big-data capability is likewise framed as strategically valuable when embedded in managerial intelligence and business-model transformation rather than treated as a stand-alone technical resource (Chen & Atento, 2026). Manufacturing evidence from the Philippines further links stronger IT infrastructure with stronger data-privacy practices, supporting privacy-by-design and formal governance as integral components of digital capability (Somono & Generoso, 2026).

### *2.6 Synthesis of Literature*

Read together, the five thematic areas reviewed above converge on a central pattern: AI's labor effects are not a uniform property of the technology but a function of task structure, interacting with organizational and leadership choices that mediate whether substitution, augmentation, or hybrid reconfiguration predominates. The manufacturing and marketing evidence bases, considered comparatively, illustrate this directly. Manufacturing exhibits stronger displacement signals concentrated in codifiable, routine physical and cognitive tasks — welding, packaging, inspection, data entry — while tasks requiring dexterity, tacit knowledge, or situational judgment remain comparatively resistant (Santhosh et al., 2023; Lei & Kim, 2024). Marketing exhibits the inverse tendency: strong, consistently reported performance gains from AI personalization coexist with comparatively weak evidence of personnel substitution, constrained by AI's documented inability to replicate emotional depth and relational nuance (Vongpanich et al., 2025; Gerlich, 2025). This divergence is not incidental but is predicted by task-based automation theory, in which displacement dominates where substitution effects outweigh productivity-driven demand effects, and augmentation dominates where the reverse holds (Autor et al., 2022; Marguerit, 2025).

A second cross-cutting pattern concerns the mediating role of organizational choice. Evidence on reskilling, task-allocation design, and human-AI collaboration converges on the finding that fully automated designs frequently underperform — in productivity, quality, and workforce capability terms — relative to deliberately structured collaborative arrangements (Senoner et al., 2024; Passalacqua et al., 2024). This holds across both codifiable and judgment-intensive task types, suggesting the substitution/augmentation split observed between manufacturing and marketing is not solely a technical constraint but is compounded by whether firms choose collaborative or fully automated implementation architectures.

A third pattern concerns governance and well-being. Strategic leadership involvement is consistently associated with better implementation outcomes, though its effectiveness is time- and calibration-dependent rather than simply additive (Canciglieri et al., 2026; Joshi, 2025). Algorithmic management's welfare effects are similarly contingent — neither uniformly harmful nor beneficial — but shaped by design features such as transparency and preserved autonomy (Ahmad et al., 2025; Deng et al., 2024). Taken together, the literature supports the paper's central thesis: AI's reconfiguration of manufacturing and marketing work is jointly determined by task structure and strategic design choice, with reinstatement and augmentation effects materializing on a slower timescale than displacement, and with net outcomes remaining genuinely open rather than technologically predetermined (Tyson & Zysman, 2022).

### *2.7 Gaps in the Literature*

Several limitations constrain the current evidence base's ability to fully resolve the paper's central problem. First, the reviewed literature treats manufacturing and marketing as largely separate research streams; no study identified here directly juxtaposes the two sectors within a single comparative analytical frame, leaving the sectoral divergence documented in Section 2.6 as an inference drawn across studies rather than a finding established within any single investigation. Second, several of the most quantitatively specific findings rest on narrow empirical bases — a single-country structural vector autoregression for manufacturing employment effects (Giwa & Ho, 2026) and a single case study of leadership calibration (Canciglieri et al., 2026) — limiting generalizability beyond their originating contexts. Third, evidence on reinstatement and new-task creation, while directionally consistent, is temporally thin: because reinstatement is acknowledged to operate on a multi-year or multi-decade horizon (Tyson & Zysman, 2022), current studies capture only early-stage indicators rather than mature outcomes of the present AI adoption wave. Fourth, the task-allocation framework linking automation, augmentation, and human-AI complementarity (Fügener et al., 2025) has not yet been applied specifically to differentiate manufacturing from marketing task portfolios, leaving a conceptual bridge between Sections 2.1–2.3 underdeveloped. Finally, measurement across the reviewed studies is inconsistent — productivity, well-being, and implementation-success outcomes are operationalized differently across contexts — constraining direct comparison and synthesis.

### *2.8 Contribution of the Present Paper*

This paper addresses these gaps by constructing an integrative conceptual framework that explicitly compares manufacturing and marketing as structurally distinct cases of AI-driven work reconfiguration, using task-based automation-augmentation theory as the connective mechanism. Rather than treating organizational redesign, human capital strategy, and governance as separate literatures, the paper synthesizes them as interacting strategic levers that jointly determine whether AI adoption in a given function tends toward substitution or augmentation. In doing so, it offers scholars a conceptual bridge between labor economics' task-based models and strategic management's organizational-design literature, and offers practitioners a framework for interpreting AI's impact on their own functions as a matter of strategic choice rather than technological inevitability.

## 3. Methodology

This paper adopts a structured conceptual literature review design, oriented toward comparative sectoral analysis rather than primary empirical investigation. The choice of this design reflects the nature of the research problem: assessing whether artificial intelligence "dominates" work in manufacturing and marketing functions is not a question resolvable through original data collection within the scope of a single paper, but one that requires the systematic synthesis, comparison, and theoretical integration of existing scholarship across labor economics, innovation management, and organizational behavior. Accordingly, no primary data — survey, interview, experimental, or observational — was collected for this study, and no statistical procedures were applied to original datasets. All empirical claims presented in the Review of Related Literature and Analytical Synthesis sections are drawn from, and attributed to, previously published peer-reviewed research.

Source Orientation and Retrieval Process. Literature was retrieved using Consensus, an AI-assisted academic search platform indexing peer-reviewed publications, in response to ten guide questions developed across five thematic areas established during the paper's framing stage. Each guide question was formulated as a binary (yes/no) proposition suitable for evidence-based retrieval, following the logic that binary framing forces retrieved literature to take an identifiable evidentiary position rather than surfacing tangentially related material. This retrieval approach was selected for its capacity to surface recent, directly relevant peer-reviewed sources efficiently, though it is acknowledged as narrower in scope than a systematic review conducted across multiple databases with formal PRISMA-style screening protocols; this paper does not claim systematic-review status and is more accurately characterized as a structured, theory-guided narrative synthesis.

Inclusion Logic. Sources were retained for synthesis on the basis of three criteria: (1) direct relevance to one of the five thematic areas — manufacturing automation, marketing AI applications, substitution-augmentation theory, organizational redesign and human capital strategy, or strategic governance of AI-integrated work systems; (2) peer-reviewed or rigorously conducted working-paper status, with DOI identification where available; and (3) substantive engagement with labor, productivity, or organizational outcomes rather than purely technical description of AI system architecture. Sources returned by the retrieval process that addressed AI capability in the abstract, without connecting to labor, task, or organizational outcomes, were treated as background context rather than incorporated as evidentiary citations. A single additional source — a qualitative study of AI adoption in Philippine accounting practice — was subsequently incorporated as a triangulating case during the analytical synthesis stage on the basis of direct thematic relevance to the paper's substitution-augmentation and governance arguments, following the same relevance and evidentiary standards applied to the initial retrieval set.

Thematic Grouping and Analytical Framework. The five themes were sequenced deliberately, moving from sector-specific empirical patterns (manufacturing, then marketing) to the theoretical mechanism explaining sectoral divergence (substitution-augmentation theory), and finally to the organizational and governance levers through which firms shape outcomes within that mechanism (human capital strategy, strategic leadership). This sequencing reflects the paper's central analytical move: using task-based automation-augmentation theory, most closely associated with the Acemoglu-Restrepo displacement-reinstatement framework, as the connective mechanism linking the two sectoral literatures. Findings from each theme were cross-referenced against this framework to assess consistency, divergence, and the conditions under which each sector's evidence pattern holds.

Evaluative Criteria. Throughout the synthesis, claims are classified according to their evidentiary status: findings drawn from empirical studies (surveys, econometric models, case analyses) are treated as established evidence within the bounds of their originating context; theoretical propositions are identified as such; and any extrapolation beyond what a given study directly supports is explicitly flagged as inference. Where studies rely on narrow samples — a single country, firm, or case — this limitation is noted rather than generalized. Causal language is avoided in favor of associative framing ("associated with," "linked to") except where the cited source itself employs a design capable of supporting causal inference, such as the structural vector autoregression analysis discussed in Section 2.1.

Sectoral and Analytical Scope. The paper's sectoral scope is deliberately bounded to manufacturing and marketing, selected for their contrasting task compositions — the former weighted toward codifiable physical and procedural tasks, the latter toward judgment-intensive and relational tasks — rather than for claims of comprehensive coverage across all business functions. A single triangulating case from accounting practice is used in Section 4 strictly as a boundary test of the paper's conceptual model, not as an expansion of formal comparative scope. No geographic scope restriction was applied to source retrieval; the review draws on studies spanning multiple national and organizational contexts, with country-specific findings explicitly identified as such rather than generalized globally.

Limitations. This design carries several acknowledged limitations. Reliance on a single retrieval platform, however comprehensive, is narrower than multi-database systematic review protocols and may omit relevant literature outside that platform's indexing coverage. The binary-question retrieval method, while efficient, privileges studies that report clear directional findings and may underrepresent null or inconclusive results. The absence of primary data collection means the paper cannot adjudicate empirically between competing findings in the literature; its contribution is integrative and theoretical rather than evidentiary. Finally, because several underlying studies are themselves limited to single-country or single-firm contexts, the comparative synthesis offered in this paper should be read as a conceptual framework for interpreting AI's sector-differentiated labor effects, not as a generalizable empirical estimate of displacement or augmentation magnitudes.

## 4. Analytical Synthesis

### *4.1 Task Structure as the Primary Determinant of Sectoral Divergence*

The comparative evidence assembled in the literature review permits a more precise analytical claim than the general proposition that "AI affects work." Read as a single dataset, the manufacturing and marketing literatures describe two structurally distinct distributions of task types, and it is this distributional difference — not a difference in AI's underlying technical capability — that best explains the divergent labor patterns observed in each domain. Manufacturing's task portfolio is weighted toward activities that are procedurally codifiable: physical assembly operations, visual quality inspection, and repetitive data-handling functions, each of which has demonstrated substantial automation susceptibility (Santhosh et al., 2023; Lodhi et al., 2024). Marketing's task portfolio, by contrast, is weighted toward activities requiring interpretive judgment, emotional calibration, and relational trust-building — functions in which AI has demonstrated strong analytical and generative performance but has not been shown to substitute fully for human contribution (Vongpanich et al., 2025; Gerlich, 2025).

This reframing has direct analytical consequence for the paper's central question. Asking whether "AI dominates" manufacturing or marketing work treats each sector as a monolithic unit subject to a single verdict. The evidence instead supports treating each sector as a portfolio of tasks distributed along a codifiability spectrum, with the aggregate labor outcome of AI adoption determined by where the bulk of that portfolio sits. Manufacturing's portfolio sits closer to the high-codifiability end, producing the stronger displacement signal documented in econometric analysis (Giwa & Ho, 2026); marketing's portfolio sits closer to the low-codifiability end, producing the augmentation-dominant pattern documented across personalization and content-generation studies (Ammupriya et al., 2025; Grewal et al., 2024). Critically, this is a difference of degree along a shared spectrum rather than a categorical difference between an "automatable" sector and an "unautomatable" one — even manufacturing retains dexterity- and tacit-knowledge-dependent tasks resistant to automation, and even marketing contains codifiable sub-tasks, such as data-driven segmentation, that have been substantially automated (Lei & Kim, 2024; Amin, 2024).

### *4.2 Reframing Replaceability: From Occupations to Task Bundles*

The question "are workers replaceable?" as commonly posed presupposes that replaceability is a fixed, binary property of an occupation. The task-based automation-augmentation framework central to Section 2.3 supports a different formulation: replaceability is a property of discrete tasks within an occupation, and occupational-level outcomes are the aggregate — not the average — of task-level substitution and complementarity effects (Autor et al., 2022; Fügener et al., 2025). Under this formulation, most manufacturing and marketing occupations are neither wholly replaceable nor wholly insulated; they are bundles in which some constituent tasks are displaced, others are augmented, and the occupation's net trajectory depends on the relative weight and complementarity structure of each.

This reframing also clarifies why displacement and reinstatement evidence can appear contradictory when read at the occupational level but is in fact consistent at the task level. Displacement effects materialize quickly because they operate on existing, already-codified tasks; reinstatement effects materialize slowly because they require the emergence of genuinely new task categories — prompt engineering, AI governance, human-AI collaboration oversight — that do not yet exist in mature form (Tyson & Zysman, 2022; Gupta & Kumar, 2026). It follows that at any given point in an AI adoption cycle, an occupation may appear to be undergoing net displacement even where its longer-run trajectory is toward reconfiguration rather than elimination — a temporal asymmetry the evidence supports as inference rather than as an established quantified timeline, since no study reviewed here tracks a single occupational cohort through a complete displacement-to-reinstatement cycle.

### *4.3 The Design Variable: How Organizational Choice Converts Capability into Outcome*

The most analytically consequential finding across the reviewed literature is that AI's technical capability to perform a task does not determine whether that task is, in practice, fully automated. This capability-deployment gap is where strategic management — rather than technology — becomes the operative variable. Task-allocation evidence demonstrates that optimal performance is frequently achieved not through maximal automation but through calibrated allocation: AI handling tasks where its performance clearly exceeds human capability, humans and AI jointly handling tasks of comparable performance, and humans retaining tasks that remain genuinely difficult for AI systems (Fügener et al., 2025). Firms deploying AI according to this logic report measurable performance advantages over firms pursuing full automation — explainable, human-overseen systems outperformed opaque full-automation designs by 4.7 to 7.7 percentage points depending on domain (Senoner et al., 2024) — indicating that the "AI dominates" framing is not merely descriptively imprecise but may describe a strategically suboptimal deployment choice.

This point is reinforced by evidence on organizational capability erosion under full automation. Where AI is deployed to fully remove human decision involvement, the evidence indicates degraded operator motivation, reduced skill acquisition, and diminished capacity to intervene when automated systems fail (Passalacqua et al., 2024). Partially automated designs, by contrast, preserved engagement and built adaptive resilience among personnel. Parallel findings from creative and marketing-adjacent contexts show that excluding human input from AI-assisted work reduces output quality and diversity relative to designs retaining meaningful human contribution (Hosanagar & Ahn, 2024).

### *4.4 Toward a Reconfiguration Model of AI-Integrated Work Systems*

Synthesizing Sections 4.1 through 4.3 supports a conceptual model in which AI-integrated work systems settle into one of several trajectories, determined jointly by task-portfolio composition and organizational design choice, rather than by AI capability alone. Where a function's task portfolio is heavily weighted toward codifiable, high-substitutability tasks and firms pursue full-automation deployment, the evidence indicates a genuine displacement-dominant trajectory, consistent with observed manufacturing employment contractions (Giwa & Ho, 2026). Where a function's task portfolio is weighted toward judgment-intensive, relationally complex tasks — as in much of marketing — even aggressive AI deployment tends toward augmentation, since the technology's demonstrated limitations in emotional and creative domains constrain full substitution regardless of organizational intent (Gerlich, 2025; Vongpanich et al., 2025). Between these poles lies a substantial middle range, characteristic of mixed-task functions in both sectors, in which organizational design choice becomes the decisive variable: collaborative task-allocation and sustained reskilling investment are associated with augmentation-dominant, capability-preserving outcomes, while full-automation deployment in mixed contexts is associated with the fragility and quality costs documented in Section 4.3 (Lahuerta et al., 2026; Passalacqua et al., 2024).

### *4.5 A Triangulating Case: Verification Overhead and Recomposition in Accounting*

Although this paper's declared scope is bounded to manufacturing and marketing, a recent qualitative study of AI adoption among Philippine accounting practitioners offers a useful boundary test of the reconfiguration model developed above, examined here as a corroborating touchpoint rather than a formal extension of scope. Bendal et al. (2026) found that, across practitioners spanning manufacturing, services, retail, logistics, and banking contexts, AI is currently adopted most comfortably in low-risk assistive roles — summarization and document clarification — while deeper integration into core accounting judgment remains conditional and uneven, constrained less by individual resistance than by an institutionalization gap in top-management sponsorship, policy direction, and data readiness.

This pattern is directly consistent with the task-portfolio logic of Sections 4.1 and 4.2: accounting's codifiable, high-volume documentation tasks show adoption patterns resembling manufacturing's routine functions, while its judgment-dependent tasks — forecasting, exception handling, sign-off accountability — resist substitution in a manner resembling marketing's relational and creative tasks, producing a hybrid profile within a single occupation rather than a sector-wide verdict.

The study's central contribution to this paper's model is the concept of verification overhead: in high-accountability settings, AI outputs that lack traceability or auditability can add an additional validation step rather than removing work, meaning automation's net efficiency gain is conditional on whether outputs can be defended and governed, not merely on whether they can be generated (Bendal et al., 2026). This constitutes a friction cost absent from the manufacturing and marketing literatures reviewed above, both of which emphasize productivity gains and creative limitations but do not foreground accountability-driven re-checking as a distinct cost category. Its presence here suggests that task codifiability, while a strong predictor of displacement risk in manufacturing and marketing, may interact with a further variable — the accountability weight attached to a task's output — that becomes salient specifically in functions where errors carry regulatory, financial, or fiduciary consequence. Bendal et al. (2026) further report that practitioners anticipate workforce recomposition rather than displacement, with routine work shrinking while effort shifts toward interpretation, exception handling, and governance competence — a trajectory consistent with the task-reallocation pattern already established for marketing (Section 2.2) and with the collaborative-design advantage documented in Section 4.3, rather than a divergent finding requiring separate theoretical treatment.

### *4.6 Governance as a Convergent Strategic Lever Across Sectors*

A final analytical point cuts across the manufacturing-marketing distinction developed above and is reinforced by the accounting evidence introduced in Section 4.5: irrespective of a function's task-portfolio composition, strategic leadership and governance quality operate as a convergent lever shaping implementation outcomes and workforce well-being alike. Leadership commitment is associated with measurably better implementation outcomes, though the relationship is calibration-sensitive rather than linear — overly aggressive early leadership intervention has been associated with worse, not better, outcomes (Canciglieri et al., 2026; Joshi, 2025). Similarly, algorithmic management's effect on employee well-being is neither uniformly harmful nor uniformly beneficial but is instead contingent on design features — transparency, preserved autonomy, perceived fairness — that organizations choose to implement or omit (Ahmad et al., 2025; Deng et al., 2024). The accounting evidence sharpens this governance theme with a specific mechanism: practitioners identified confidentiality exposure, cybersecurity risk, error opacity, and — most distinctively — non-transferable accountability, in which regulatory and professional liability attaches to the human signer rather than to the algorithm, as decisive constraints on deeper AI integration regardless of the technology's demonstrated capability (Bendal et al., 2026). This finding generalizes a principle only implicit in the manufacturing and marketing literatures: that governance quality does not merely moderate well-being outcomes, as documented in Sections 2.5 and 4.6 above, but can independently cap the depth of AI deployment in any function where human accountability cannot be technically or legally delegated to an automated system.

### *4.7 Discussion of Findings*

The analytical synthesis developed in Sections 4.1–4.6 carries implications that extend beyond the specific comparison of manufacturing and marketing functions, speaking to broader theoretical and practical questions about how enterprises should conceptualize AI-driven organizational change.

At the theoretical level, the findings support a reframing of the substitution-augmentation debate in innovation management scholarship. Rather than treating substitution and augmentation as competing predictions about AI's eventual labor effect, the evidence assembled here indicates they are better understood as coexisting outcomes distributed across a task-composition spectrum, with their relative weight in any given function determined jointly by task codifiability and organizational design choice. The accounting evidence introduced in Section 4.5 sharpens this framework by identifying a variable not fully visible in the manufacturing and marketing literatures alone: accountability weight. Where a task's output carries regulatory, fiduciary, or professional liability, verification overhead can offset apparent efficiency gains even when the underlying task is otherwise codifiable, and — more distinctively — non-transferable accountability can cap deployment depth independent of what the technology is capable of performing (Bendal et al., 2026). This suggests that task-based automation theory, as applied to strategic management, should be extended to treat accountability weight as a variable alongside codifiability and organizational design choice, rather than assuming codifiability alone predicts substitution risk. This is a meaningful theoretical departure from techno-deterministic framings that dominate popular discourse and, to a lesser extent, portions of the practitioner literature.

For practitioners, the practical implications are now fourfold. First, enterprise leaders evaluating AI adoption in manufacturing or marketing functions should resist treating "AI dominance" as a unified organizational objective or threat, and should instead conduct task-level audits of the specific functions under consideration, distinguishing codifiable, high-substitutability tasks from judgment-intensive, relationally embedded ones. Second, the evidence on organizational capability erosion under full automation — reduced motivation, degraded skill acquisition, diminished capacity to recover from system failure — constitutes a strategic risk that conventional short-run productivity metrics are likely to understate. Third, the convergent importance of governance quality — leadership calibration, transparency, preserved worker autonomy — indicates that human capital strategy and AI deployment strategy must be designed jointly from the outset of adoption planning, not sequentially. Fourth, and newly informed by the accounting evidence, firms operating in any function where task outputs carry accountability consequences should budget explicitly for verification overhead in their productivity projections, and should treat governance design — particularly the clear allocation of sign-off responsibility where liability cannot be delegated to an algorithm — as a precondition for AI deployment rather than a downstream compliance concern.

It is equally important to state clearly what this analysis does not establish. The paper does not, and cannot, quantify the net employment effect of AI adoption across manufacturing and marketing sectors in aggregate; the underlying literature itself acknowledges that reinstatement effects operate on multi-year to multi-decade timescales not yet fully observable within the current AI adoption wave. Nor does the analysis support firm-specific predictions: several of the most quantitatively precise findings incorporated into this synthesis derive from single-country or single-case studies, and their magnitudes should not be extrapolated to other organizational or national contexts without independent verification. The accounting evidence carries its own explicit boundary: it derives from a qualitative, purposively sampled study of 45 practitioners in a single Philippine region, and its authors caution against treating it as evidence of causal effects, as generalizable beyond that sample, or as a longitudinal trend rather than a late-2025 snapshot (Bendal et al., 2026). It is presented here strictly as a triangulating illustration that the task-and-design model developed for manufacturing and marketing plausibly extends to accountability-bound functions — not as a validated third case within the paper's formal comparative scope. The paper's task-composition model more broadly, while consistent with the reviewed evidence, has not itself been empirically tested against manufacturing and marketing data within a single unified study, and should accordingly be read as a conceptual synthesis offered for further empirical scrutiny rather than a validated predictive framework. Finally, the equity implications flagged in Section 4.4 — the risk that AI-driven productivity gains concentrate unevenly across firm sizes, digital-skill levels, and national contexts — are identified here as a documented concern within the literature rather than a phenomenon this paper independently measures or resolves.

Within these bounds, the discussion supports a central practical conclusion: the question of whether AI "dominates" work in a given enterprise function is less a matter of what AI can technically do than of what organizations choose to have it do, how deliberately that choice is designed and governed, and — as the accounting evidence indicates — who remains accountable when it fails.

## 5. Conclusions and Recommendations

This paper set out to examine whether artificial intelligence's expanding presence in manufacturing and marketing functions constitutes a uniform displacement of human labor, or a more differentiated process of strategic and organizational reconfiguration. The synthesis of existing scholarship supports the latter interpretation. AI's labor effects are best understood as a function of task-portfolio composition — with manufacturing's more codifiable task structure producing stronger displacement signals and marketing's more judgment-intensive structure producing stronger augmentation signals — compounded by organizational design choices that determine whether a given firm's deployment of AI tends toward full automation or calibrated human-AI collaboration. A triangulating case from Philippine accounting practice indicates this model plausibly extends further: to functions where task outputs carry regulatory or fiduciary accountability, where a further variable — accountability weight — introduces verification overhead and non-transferable liability as additional constraints on deployment depth, independent of technical capability (Bendal et al., 2026). Across all examined domains, the evidence indicates that full-automation strategies frequently underperform collaborative alternatives, not only in immediate performance terms but in longer-run organizational resilience, while strategic leadership and governance quality operate as a convergent factor shaping outcomes irrespective of sector.

The central conclusion follows directly from this synthesis: whether AI "dominates" a work system in the sense implied by popular discourse is not a technologically predetermined outcome but a strategically chosen one. Enterprises retain meaningful latitude in how they configure the relationship between AI capability and human contribution, and the available evidence suggests that the exercise of this latitude — rather than AI capability alone — is what differentiates organizations that achieve sustainable competitive advantage from those that incur unrecognized resilience, quality, and accountability costs.

Several measured recommendations follow for enterprise practice. Organizations planning AI adoption in manufacturing or marketing functions should begin with task-level portfolio mapping rather than function-level automation targets, identifying which specific tasks within a role are genuinely amenable to substitution and which are more appropriately positioned for augmentation or human retention. Reskilling and human capital investment should be treated as a parallel strategic workstream from the outset of AI adoption planning, not a downstream mitigation measure introduced after deployment decisions are finalized. Governance structures should incorporate explicit mechanisms for algorithmic transparency and preserved worker autonomy, given the evidence linking these design features to both implementation success and employee well-being. Leadership involvement in AI rollout should be calibrated rather than maximal, with attention to the evidence suggesting that overly aggressive early intervention can undermine outcomes that more adaptive, phased leadership approaches achieve more effectively. Where task outputs carry regulatory, fiduciary, or professional accountability — a condition present to varying degrees in both manufacturing (safety and quality compliance) and marketing (data-privacy and consumer-protection obligations) — organizations should map accountability weight alongside task codifiability, budget for verification overhead in productivity projections, and formally assign human sign-off responsibility before AI deployment rather than after an incident exposes the gap.

For institutional and policy audiences, the findings suggest that workforce transition support should be differentiated by sector and task-exposure profile rather than designed around generic "AI and jobs" assumptions, and that digital-skill development initiatives warrant particular attention given their documented role in mediating which workers are able to shift into complementary, augmentation-oriented task categories as displacement occurs.

Future research would benefit from several extensions this conceptual synthesis cannot itself provide: empirical studies directly comparing task-level automation and augmentation patterns within a single unified manufacturing-marketing sample; longitudinal tracking of occupational cohorts through complete displacement-to-reinstatement cycles; formal empirical testing of accountability weight as a predictor of AI deployment depth, extending beyond the qualitative accounting case introduced here; and comparative analysis of governance and reskilling program design across firms of varying size and national context. Pending such research, the framework developed in this paper offers scholars and practitioners a conceptual basis for treating AI's organizational impact as a matter of deliberate strategic design — and deliberate accountability design — rather than technological inevitability.

## References

A, P., Arunprakash, A., Kulothungan, V., & Radha, P. (2025). The role of artificial intelligence in revolutionizing customer-centric marketing strategies: A data-driven approach. NPRC Journal of Multidisciplinary Research. https://doi.org/10.3126/nprcjmr.v2i1.74691

Abonamah, A., & Abdelhamid, N. (2024). Managerial insights for AI/ML implementation: A playbook for successful organizational integration. Discover Artificial Intelligence, 4. https://doi.org/10.1007/s44163-023-00100-5

Afrin, S., Roksana, S., & Akram, R. (2025). AI-enhanced robotic process automation: A review of intelligent automation innovations. IEEE Access, 13, 173–197. https://doi.org/10.1109/access.2024.3513279

Ahmad, A. R., Sapry, H. R. M., Seman, N. A., & Jameel, A. S. (2025). Reimagining job happiness: The role of algorithmic design in human-centered organizational well-being. Quantum Journal of Social Sciences and Humanities. https://doi.org/10.55197/qjssh.v6i4.756

Amin, M. (2024). AI-powered personalized marketing: A deep dive into customer segmentation and targeting. International Journal of Science, Engineering and Management. https://doi.org/10.36647/ijsem/11.12.a001

Ammupriya, A., J, A., P, B., M, K., A, K., & Kumaran, S. (2025). AI-driven personalization in digital marketing applications in e-commerce and customer engagement. 2025 IEEE International Conference on Emerging Trends in Computing and Communication (ETCOM), 1–6. https://doi.org/10.1109/etcom66606.2025.11437269

Atento, R. G., Quinto, L., Espelita, C. A. M., & Castaneda, C. (2025). Integrating business and health analytics: A conceptual framework for dual outcomes in healthcare. International Journal of Health & Business Analytics, 1(1). https://doi.org/10.65166/04pdc866

Atento, R. G., & Espelita, C. A. M. H. (2025). From community voice to marketing strategy: The feeder-school ecosystem as basis for a consumer-centered marketing framework. International Journal of Health and Business Analytics, 1(2). https://doi.org/10.65166/mt4em434

Atento, A. G. B., & Atento, R. G. O. (2026). Legacy retail under digital disruption: Strategic insights from National Book Store's omnichannel transition in the Philippines. Journal of Enterprise Strategy & Management Innovation, 1(1). https://doi.org/10.65166/nny9z718

Autor, D., Chin, C., Salomons, A., & Seegmiller, B. (2022). New frontiers: The origins and content of new work, 1940–2018. SSRN Electronic Journal. https://doi.org/10.3386/w30389

Babadoğan, B. (2024). Unveiling the power of AI-driven personalization: Transforming consumer behavior in the age of digital marketing. Next Frontier for Life Sciences and AI. https://doi.org/10.62802/fj43xy18

Babatunde, S. O., Odejide, O. A., Edunjobi, T. E., & Ogundipe, D. O. (2024). The role of AI in marketing personalization: A theoretical exploration of consumer engagement strategies. International Journal of Management & Entrepreneurship Research. https://doi.org/10.51594/ijmer.v6i3.964

Badet, J. (2021). AI, automation and new jobs. Open Journal of Business and Management. https://doi.org/10.4236/ojbm.2021.95132

Bendal, A., Sabasa, S. A., Espelita, C. A. M. H., & Atento, R. G. O. (2026). Artificial intelligence as disruptive technology in accounting: A qualitative study of practitioner perceptions on automation, judgment, and decision support. Journal of Enterprise Strategy & Management Innovation, 1(1). https://doi.org/10.65166/0sdayg70

Bevilacqua, S., Masárová, J., Perotti, F. A., & Ferraris, A. (2025). Enhancing top managers' leadership with artificial intelligence: Insights from a systematic literature review. Review of Managerial Science, 19, 2899–2935. https://doi.org/10.1007/s11846-025-00836-7

Canciglieri, A., Seelent, J. F. C., Kai, D. A., Franco, C., & Benitez, G. B. (2026). Adaptive leadership in artificial intelligence solutions in operations and supply chain management projects: The Robert Bosch GmbH case. International Journal of Physical Distribution & Logistics Management. https://doi.org/10.1108/ijpdlm-12-2024-0497

Chen, S., & Atento, R. G. (2026). Big data as a strategic asset: Competitive advantage, business model transformation, and managerial intelligence in Chinese enterprises. Journal of Enterprise Strategy and Management Innovation, 1(2).

Carandang, D., Baran, B., Espelita, C. A. M. H., Atento, A. G. B., & Atento, R. G. O. (2026). Perceptions of accounting software among SMEs in Calamba City, Philippines: A Technology-Organization-Environment (TOE) framework. Journal of Enterprise Strategy & Management Innovation, 1(1). https://doi.org/10.65166/dxqbny15

Chhibber, S., Rajkumar, S., & Dassanayake, S. (2025). Will artificial intelligence reshape the global workforce by 2030? A cross-sectoral analysis of job displacement and transformation. Blockchain, Artificial Intelligence, and Future Research. https://doi.org/10.70211/bafr.v1i1.178

Damioli, G., Van Roy, V., & Vértesy, D. (2021). The impact of artificial intelligence on labor productivity. Eurasian Business Review, 11, 1–25. https://doi.org/10.1007/s40821-020-00172-8

Deng, H., Lu, Y., Fan, D., Liu, W., & Xia, Y. (2024). The power of precision: How algorithmic monitoring and performance management enhances employee workplace well-being. New Technology, Work and Employment, 40. https://doi.org/10.1111/ntwe.12328

Espelita, C. A. M. H., Atento, A. G. B., & Atento, R. G. O. (2026). Social media marketing and enrollment intent among college-bound learners: Evidence from a private higher education institution in Region IV-A, Philippines. Journal of Enterprise Strategy & Management Innovation, 1(1). https://doi.org/10.65166/bcn4pt87

Espelita, C. A. M. H., & Atento, R. G. O. (2026). Self-efficacy, work environment support, and employee productivity in Philippine trading companies. Journal of Enterprise Strategy & Management Innovation, 1(1). https://doi.org/10.65166/nwv9wg88

Fügener, A., Walzner, D. D., & Gupta, A. (2025). Roles of artificial intelligence in collaboration with humans: Automation, augmentation, and the future of work. Management Science, 72, 538–557. https://doi.org/10.1287/mnsc.2024.05684

Georgieff, A., & Hyee, R. (2022). Artificial intelligence and employment: New cross-country evidence. Frontiers in Artificial Intelligence, 5. https://doi.org/10.3389/frai.2022.832736

Gerlich, M. (2025). The shifting influence: Comparing AI tools and human influencers in consumer decision-making. AI, 6(1). https://doi.org/10.3390/ai6010011

Giwa, F., & Ho, S.-Y. (2026). Artificial intelligence shock in manufacturing: A threat or an opportunity for South Africa's labour market? Journal of Open Innovation: Technology, Market, and Complexity. https://doi.org/10.1016/j.joitmc.2025.100696

Gmyrek, P., Viollaz, M., & Winkler, H. (2026). Disruption without dividend? How the digital divide and task differences split GenAI's global impact. https://doi.org/10.1596/1813-9450-11328

Gong, L. (2025). Enhancing operational efficiency in manufacturing firms using AI-driven robotic process automation. Creativity and Innovation. https://doi.org/10.47297/wspciwsp2516-252729.20250904

Grewal, D., Satornino, C. B., Davenport, T. H., & Guha, A. (2024). How generative AI is shaping the future of marketing. Journal of the Academy of Marketing Science, 53, 702–722. https://doi.org/10.1007/s11747-024-01064-3

Gupta, R., & Kumar, S. (2026). Agentic AI and occupational displacement: A multi-regional task exposure analysis of emerging labor market disruption. ArXiv, abs/2604.00186. https://doi.org/10.48550/arxiv.2604.00186

Haque, A. (2025). Responsible artificial intelligence (AI) in healthcare: A paradigm shift in leadership and strategic management. Leadership in Health Services, 38, 644–656. https://doi.org/10.1108/lhs-01-2025-0018

Hosanagar, K., & Ahn, D. (2024). Designing human and generative AI collaboration. ArXiv, abs/2412.14199. https://doi.org/10.48550/arxiv.2412.14199

Ibrahim, I., Thomas, P., & Adhikari, P. (2025). The integration of artificial intelligence in engineering design, manufacturing, and CAD: A triangular revolution of innovation, efficiency, and automation. Global Journal of Engineering and Technology Advances. https://doi.org/10.30574/gjeta.2025.24.2.0256

Jadhav, R. D., & Banubakode, A. (2024). The implications of artificial intelligence on the employment sector. International Journal for Multidisciplinary Research. https://doi.org/10.36948/ijfmr.2024.v06i03.22716

Joseph, S. (2024). Organizational workforce management in the digital age: The role of technocultural interventions in mitigating the negative impacts of AI-driven technological change. Archives of Current Research International. https://doi.org/10.9734/acri/2024/v24i10917

Joshi, S. (2025). Review of artificial intelligence in management, leadership, decision-making and collaboration. International Journal of Science and Social Science Research. https://doi.org/10.63671/ijsssr.v3i1.388

Khan, S. (2025). Role of generative AI in digital campaigns. International Journal of Scientific Research in Engineering and Management. https://doi.org/10.55041/ijsrem50580

Kotte, K. R. (2024). Smart factories, smarter finances: AI's role in cost efficiency & profitability. International Journal on Science and Technology. https://doi.org/10.71097/ijsat.v15.i4.6119

Kumar, I., Rawat, J., Mohd, N., & Husain, S. (2021). Opportunities of artificial intelligence and machine learning in the food industry. Journal of Food Quality. https://doi.org/10.1155/2021/4535567

Lahuerta, L. A., López Ramajo, M. R., & Gandía, A. (2026). Artificial intelligence and organisational transformation: Technical skills, job insecurity and adoption. Management Decision. https://doi.org/10.1108/md-05-2025-1462

Lăzăroiu, G., Gedeon, T., Rogalska, E., Valášková, K., Nagy, M., Musa, H., Zvaríková, K., Poliak, M., Horák, J., Crețoiu, R., Krulický, T., Ionescu, L., Popa, C., Hurloiu, L., Nistor, F., Avram, L., & Braga, V. (2024). Digital twin-based cyber-physical manufacturing systems, extended reality metaverse enterprise and production management algorithms, and Internet of Things financial and labor market technologies in generative artificial intelligence economics. Oeconomia Copernicana. https://doi.org/10.24136/oc.3183

Ledingham, A., Hollins, M., Lyon, M., Gillespie, D., Yunis-Guerra, U., Siviter, J., Duncan, D., & Hauser, O. P. (2025). Beyond automation: Redesigning jobs with LLMs to enhance productivity. https://doi.org/10.48550/arxiv.2512.05659

Lei, Y.-W., & Kim, R. Y. (2024). Automation and augmentation: Artificial intelligence, robots, and work. Annual Review of Sociology. https://doi.org/10.1146/annurev-soc-090523-050708

Lodhi, S. K., Gill, A. Y., & Hussain, I. (2024). AI-powered innovations in contemporary manufacturing procedures: An extensive analysis. International Journal of Multidisciplinary Sciences and Arts. https://doi.org/10.47709/ijmdsa.v3i4.4616

Logalakshmi, S., & Poornima, S. (2025). AI-powered personalization algorithms for digital marketing. International Journal of Trendy Research in Engineering and Technology. https://doi.org/10.54473/ijtret.2025.9306

Mahabub, S., Hossain, R., & Snigdha, E. Z. (2025). Data-driven decision-making and strategic leadership: AI-powered business operations for competitive advantage and sustainable growth. Journal of Computer Science and Technology Studies. https://doi.org/10.32996/jcsts.2025.7.1.24

Marguerit, D. (2025). Augmenting or automating labor? The effect of AI development on new work, employment, and wages. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5169611

Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. Informing Science: The International Journal of an Emerging Transdiscipline, 26, 39–68. https://doi.org/10.28945/5078

Nagubathula, V. (2025). AI and human-AI collaboration in enterprise integration and document automation. International Journal on Science and Technology. https://doi.org/10.71097/ijsat.v16.i1.2317

Passalacqua, M., Pellerin, R., Yahia, E., Magnani, F., Rosin, F., Joblot, L., & Léger, P.-M. (2024). Practice with less AI makes perfect: Partially automated AI during training leads to better worker motivation, engagement, and skill acquisition. International Journal of Human–Computer Interaction, 41, 2268–2288. https://doi.org/10.1080/10447318.2024.2319914

Przegalinska, A. K., Triantoro, T., Kovbasiuk, A., Ciechanowski, L., Freeman, R. B., & Sowa, K. (2025). Collaborative AI in the workplace: Enhancing organizational performance through resource-based and task-technology fit perspectives. International Journal of Information Management, 81. https://doi.org/10.1016/j.ijinfomgt.2024.102853

Rabbani, M. M., Khan, M. N., Desai, K., Islam, M. M., Ahmad, S., & Snigdha, E. Z. (2025). Human-AI collaboration in IT systems design: A comprehensive framework for intelligent co-creation. The American Journal of Engineering and Technology. https://doi.org/10.37547/tajet/volume07issue03-05

Rao, L., Tian, Y., & Atento, R. G. O. (2025). Adoption and perceived effectiveness of AI in education: Personalization, outcomes, and equity. International Journal of Health & Business Analytics, 1(1). https://doi.org/10.65166/qgq89291

Romeo, G., & Conti, D. (2025). Exploring automation bias in human–AI collaboration: A review and implications for explainable AI. AI & Society, 41, 259–278. https://doi.org/10.1007/s00146-025-02422-7

Santhosh, A., Unnikrishnan, R., Shibu, S., Meenakshi, K. M., & Joseph, G. (2023). AI impact on job automation. International Journal of Engineering Technology and Management Sciences. https://doi.org/10.46647/ijetms.2023.v07i04.055

Saputra, R., & Silaban, Y. (2026). Artificial intelligence-based automation systems for improving efficiency in industrial manufacturing. Journal of Scientia Technologiae. https://doi.org/10.67171/aheqm297

Satpal, M. (2026). AI-driven marketing personalization and customer loyalty. Scriptora International Journal of Research and Innovation, 2(SI1). https://doi.org/10.65579/sijri.2026.v2si1.09

Senoner, J., Schallmoser, S., Kratzwald, B., Feuerriegel, S., & Netland, T. (2024). Explainable AI improves task performance in human–AI collaboration. Scientific Reports, 14. https://doi.org/10.1038/s41598-024-82501-9

Shah, R., Doss, A., & Lakshmaiya, N. (2025). Advancements in AI-enhanced collaborative robotics: Towards safer, smarter, and human-centric industrial automation. Results in Engineering. https://doi.org/10.1016/j.rineng.2025.105704

Shao, Y., Zope, H., Jiang, Y., Pei, J., Nguyen, D., Brynjolfsson, E., & Yang, D. (2025). Future of work with AI agents: Auditing automation and augmentation potential across the U.S. workforce. ArXiv, abs/2506.06576. https://doi.org/10.48550/arxiv.2506.06576

Sharifah, N., Wajdi, F., Susila, I., & Achmed, N. (2024). The impact of algorithm management on employee job satisfaction: Exploring the mediating role of job autonomy and the moderating effect of employee attitude. Journal of Business and Management Studies. https://doi.org/10.32996/jbms.2024.6.3.20

Somono, L., & Generoso, M. J. I. A., II. (2026). IT infrastructure and data privacy practices in manufacturing companies. Journal of Enterprise Strategy & Management Innovation, 1(1). https://doi.org/10.65166/dyzqhe81

Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics: A review. Cognitive Robotics. https://doi.org/10.1016/j.cogr.2023.04.001

Suljic, V. (2025). Strategic leadership in AI-driven digital transformation: Ethical governance, innovation management, and sustainable practices for global enterprises and SMEs. SBS Journal of Applied Business Research. https://doi.org/10.70301/jour/sbs-jabr/2025/13/1/2

Tarafdar, R. (2025). Human-AI collaboration in workflow optimization: A framework for hybrid decision systems in automation-heavy industries. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. https://doi.org/10.32628/cseit251112384

Teepapal, T. (2025). AI-driven personalization: Unraveling consumer perceptions in social media engagement. Computers in Human Behavior, 165. https://doi.org/10.1016/j.chb.2024.108549

Tyson, L., & Zysman, J. (2022). Automation, AI & work. Daedalus, 151, 256–271. https://doi.org/10.1162/daed_a_01914

Ugbaja, U. S., Nwabekee, U. S., Owobu, W. O., & Abieba, O. (2023). Revolutionizing sales strategies through AI-driven customer insights, market intelligence, and automated engagement tools. International Journal of Social Science Exceptional Research. https://doi.org/10.54660/ijsser.2023.2.1.193-210

Varouchas, E. (2026). Executives' perspectives on the impact of generative AI in business: A qualitative study of strategic, ethical and organizational transformations. Journal of Science and Technology Policy Management. https://doi.org/10.1108/jstpm-10-2025-0493

Vongpanich, K., Boonyapitaktumrong, K., Veerathanusvet, C., & Kerdvibulvech, C. (2025). The impact of AI on enhancing productivity in digital marketing production. Proceedings of the 2025 7th Asia Pacific Information Technology Conference. https://doi.org/10.1145/3726101.3726112

Vössing, M., Kühl, N., Lind, M., & Satzger, G. (2022). Designing transparency for effective human-AI collaboration. Information Systems Frontiers, 24, 877–895. https://doi.org/10.1007/s10796-022-10284-3

Yu, X., & Atento, R. G. (2026). Training effectiveness and improvement strategies for motor vehicle safety and technical inspectors: Evidence from two vocational institutions in Fujian, China. Journal of Enterprise Strategy and Management Innovation (JESMI), 1(2). https://doi.org/10.65166/msxhtj07

Zamir, N. A. (2025). The role of leadership in supporting artificial intelligence (AI) integration in organizations. International Journal of Entrepreneurship and Management Practices. https://doi.org/10.35631/ijemp.831054