

**STRATEGIC INTEGRATION OF ARTIFICIAL INTELLIGENCE IN THE U.S.
INDUSTRIAL MANAGEMENT: A QUALITATIVE STUDY OF ORGANIZATIONAL
TRANSFORMATION**

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ABSTRACT

The fast expansion of artificial intelligence (AI) capabilities has spurred a fundamental discussion over how established industries in the United States might integrate this general purpose technology into basic management practices. Despite significant investments, U.S. manufacturers and service providers have struggled to transform AI pilots into scale deployments, and the larger management implications of AI remain opaque. This qualitative

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study analyses the strategic integration of AI within American industrial management, using exclusively secondary data sources taken from published case studies, industry reports, academic papers and government documents. The study sets forth one overall aim—to clarify how organizational transformation happens when AI goes from pilot projects to full production. Two specific objectives guide the inquiry: (i) to identify the managerial and socio technical aspects that influence effective AI adoption, and (ii) to characterise the organizational capabilities needed to maintain AI enabled transformation. Findings suggest that AI integration is less a plug and play activity than a holistic process needing cultural alignment, continual reskilling and smart governance. While the secondary sources highlight productivity improvements and new data driven insights, they also indicate transitional dips, higher work in progress inventory and the need to restructure workflows and reward systems. The study enriches the literature on digital transformation by presenting an empirically based model of AI integration that emphasizes strategic alignment, participatory change management and the balancing of efficiency and labour well being. Implications for practitioners and policymakers are highlighted.

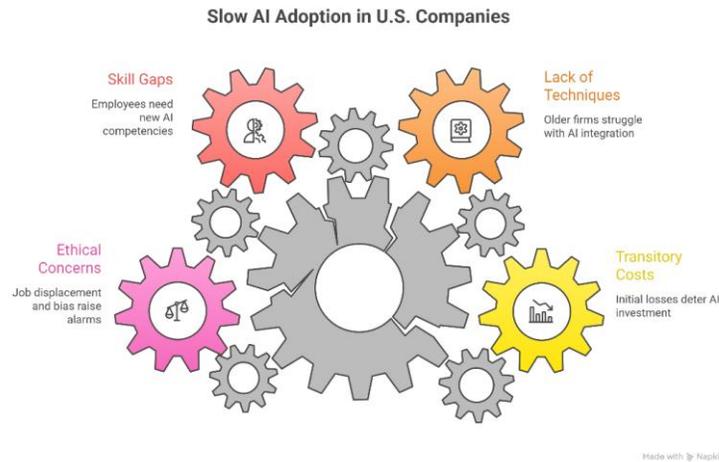
1 Introduction

Artificial intelligence has transitioned from a speculative possibility to a pervasive collection of technologies impacting industrial, logistics and service sectors around the globe. Advances in machine learning, neural networks and predictive analytics enable enterprises to automate complicated activities, personalize choices and generate insights at new speed. Yet despite the potential of AI, its integration into established U.S. companies remains inconsistent. Recent work by McElheran et al. (2025) reveals that AI adoption in American industry follows a “J-curve” trajectory—short-term productivity losses, greater work-in-progress inventory and labour shedding precede longer-term performance improvements. These transitory costs are worsened in older organisations and are partly due to the absence of established production-management techniques. In a complementary survey of U.S. enterprises, Bonney et al. (2024) find that just 3.7–5.4 percent of employer organisations employed AI between

September 2023 and February 2024, even though AI users demonstrated greater performance and higher employment growth. Adoption is stronger in large organisations but remains non-monotonic across firm size, while young firms look more likely to implement AI. These findings underline the heterogeneity of AI acceptance and the impact of organizational context.

Beyond acceptance rates, experts note that AI integration necessitates new skills and competencies. A thorough evaluation of AI in the workplace underlines that AI applications streamline operations across industries and demand adaptable methods and constant skill development. The analysis underlines the requirement for technological expertise and adaptation and urges attention to ethical and societal consequences such as job displacement, privacy risks and algorithmic bias. At the plant level, the National Association of Manufacturers observes that manufacturers have been both innovators and

Figure 1: Slow AI Adoption in US Companies

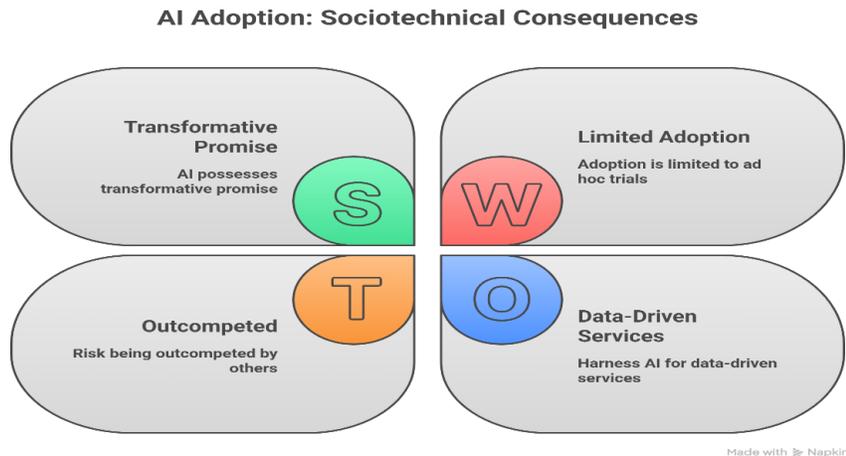


deployers of AI technologies—including machine learning, machine vision, digital twins and robotics—and that these breakthroughs can boost efficiency, product creation and safety. However, the same paper cautions that AI functions best when people remain the fundamental decision-makers, needing upskilling and ethical frameworks to guide implementation. AI-driven cybersecurity analytics indicate that artificial intelligence can discern intricate threat patterns from extensive and evolving datasets, supporting the notion that effective AI integration relies on technical proficiency as well as strategic alignment, governance, and human supervision (Adnan, et al., 2024). Cross-sector evidence from healthcare indicates that successful AI integration relies on technical capability, usability, trust, and user acceptance. Tanji et al. (2025) discovered that AI-driven automation markedly enhanced clinical efficiency, diagnostic accuracy, and patient satisfaction in tertiary hospitals. Their findings suggest that user-friendly and precise AI systems are more likely to yield significant performance improvements, underscoring the necessity for AI adoption to be underpinned by human-centered design, governance, and confidence-enhancing strategies (Tanji et al., 2025). The sociotechnical consequences of AI

adoption are not restricted to productivity indicators. Employee well-being studies demonstrate that awareness of smart technologies and automation can lower organizational engagement and career happiness while boosting turnover intentions. Trust in AI and good impressions of AI potential, on the other hand, can boost well-being and supervisor-rated productivity. In manufacturing, CEOs are confronted with a paradox: AI possesses transformative promise, yet its adoption is limited to ad hoc trials and single-process applications. Scholars suggest that organisations that only partially commit to AI risk being outcompeted by those who harness AI for data-driven services. National policy discussions further complicate the picture. The White House's 2025 AI Action Plan advocates for accelerating innovation, reducing regulatory impediments and empowering American workers while promoting next-generation manufacturing. Simultaneously, the Microsoft AI Economy Institute says that around one in six persons worldwide utilised generative AI tools in the second half of 2025, though usage in the Global North expanded almost twice as fast as in the Global South. These macro-level results indicate both

momentum and splits in AI dissemination and stress the necessity for context-specific research.

Figure 2: AI Adoption: Socio-technical Consequences



1.1 Objective of the Study

The overarching aim of this research is to understand how U.S. industrial firms strategically integrate artificial intelligence into their management practices. Two specific objectives guide the study:

- i. To identify the managerial and socio-technical factors influencing successful AI adoption in U.S. industrial firms. (Prior evidence demonstrates that technology readiness alone is insufficient and that corporate culture, personnel capabilities and leadership play significant roles.)
- ii. To delineate the capabilities and governance mechanisms needed to sustain AI-enabled organizational transformation. (Early adoption may bring negative productivity shocks, but organisations that invest in organised management techniques, continual learning and ethical monitoring might enjoy long-term rewards.)

By focusing on these aims, this study seeks to contribute to the burgeoning literature on digital transformation and to provide meaningful assistance for industrial managers navigating the complexity of AI integration.

2 Literature Review

2.1 AI as a General-Purpose Technology

Artificial intelligence is typically described as a general-purpose technology (GPT) with far-reaching consequences on productivity, creativity and organizational structures. McElheran et al. (2025) show micro-level evidence that AI adoption in American manufacturing exhibits a J-curve pattern: short-term performance losses due to costly alterations in core production processes are followed by longer-term gains. These losses stem from increases in work-in-progress inventory, investment in industrial robots and manpower shedding, particularly among older enterprises. Early adopters who invested in AI prior to 2017 enjoyed better growth over time, demonstrating that learning curves and complementing

organizational changes matter. The productivity paradox reported in the MIT Sloan Management Review article echoes this finding: AI introduction initially reduces productivity, but organisations that endure eventually surpass their counterparts. Such trends underline the necessity to see AI as a GPT whose benefits accrue only after extensive organizational transformation. Historical comparisons with earlier GPTs, such as electricity and information technology, show the intricacy of AI dissemination. Brynjolfsson and Hitt (2000) suggested that computing technologies provide productivity benefits only when accompanied by complementary changes in work practices and human capital. The same rationale applies to AI, which needs revamping decision processes, data infrastructures and governance structures. The Census Bureau's real-time survey of businesses indicated that AI use remained modest but expanding; bi-weekly estimates climbed from 3.7 percent to 5.4 percent between September 2023 and February 2024, with forecasts of 6.6 percent by early fall 2024. Adoption is stronger in large organisations however non-monotonic across firm size, while young firms exhibit increased tendency to embrace AI. Common uses include marketing automation, virtual agents and data/text analytics. Notably, AI adoption rarely leads to immediate employment losses; instead, enterprises generally retrain people, rethink procedures and invest in cloud services. The biggest hurdle to adoption is the inapplicability of AI to certain business scenarios.

2.2 AI in Manufacturing and Industrial Management

Manufacturing has historically been at the forefront of technical progress. The National Association of Manufacturers discusses how U.S. corporations develop and utilise AI technologies, including machine learning, machine vision,

natural language processing, digital twins and robotics. These instruments offer predictive maintenance, quality control, and safer workplaces, but their successful application rests on human operators who are well-trained and empowered to make judgements. The same paper underlines AI's function as a force multiplier that increases human talents while demanding ethical frameworks and data science expertise.

Academic research corroborates these conclusions. Eklöf (2024) adds that although AI provides transformative potential for manufacturing, only a small percentage of enterprises across industries engage in widespread adoption, and most perform ad hoc pilots or apply AI to a specific process. Researchers believe that organisations who partially commit to AI risk being outcompeted by those that offer new data-driven services. Leadership plays a significant role: willingness to learn about AI and to promote multidisciplinary collaboration emerges as a fundamental capability for enabling wider adoption. However, the democratization of AI through easy-to-use tools poses obstacles such as quality assurance concerns, inefficient solutions and skill scarcity.

2.3 Human Factors and Organizational Culture

The integration of AI changes employees' responsibilities, attitudes and well-being. A bibliometric analysis of AI use in the workplace reveals that AI applications improve processes and automate operations across sectors, and that firms must adapt through constant skill development and ethical technological policies. The same review highlights sector-specific applications: healthcare uses AI for diagnostics and personalized medicine; finance automates fraud detection and risk analysis; retail optimizes supply chains and personalizes customer

experiences; education employs intelligent tutoring systems; and manufacturing improves efficiency through predictive analytics. However, the increasing deployment of AI also introduces ethical and social challenges, including employment displacement, privacy threats and algorithmic biases.

Employee well-being study provides a nuanced picture. Studies suggest that understanding of Smart Technology, Artificial Intelligence, Robotics and Automation (STARA) corresponds with reduced organizational commitment and increased turnover intentions. AI learning fear can diminish psychological well-being, but positive perceptions of AI opportunities and faith in AI boost well-being and supervisor-rated productivity. Adoption of AI may boost job stress but can also promote flexibility, autonomy and employee confidence. Algorithmic management approaches, while enhancing efficiency, may decrease professional autonomy and consequently damage well-being. These varied outcomes underline the significance of matching technical integration with supporting leadership and clear communication.

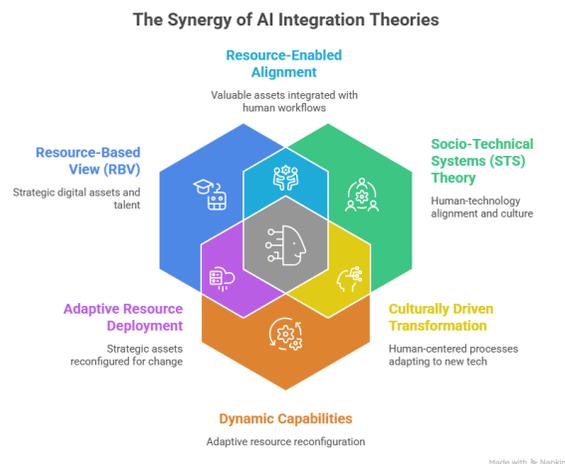
2.4 Policy and Global Diffusion

At the macro level, policy initiatives shape AI adoption. The White House’s 2025 AI Action Plan stresses driving innovation, reducing regulatory impediments, allowing adoption and empowering American workers while boosting next-generation manufacturing. By outlining pillars focused on innovation, infrastructure and international diplomacy, the plan presents AI as a national goal. Meanwhile, Microsoft’s AI diffusion report adds that global generative AI utilisation climbed by 1.2 percentage points in the second half of 2025 and that nearly one in six persons globally employed generative AI tools. The research also reveals a rising digital divide: adoption in the Global North is nearly twice that of the Global South. These discrepancies show that infrastructure, digital skills and regulatory contexts are major determinants of AI proliferation.

2.5 Theoretical Framework

This study draws on three distinct theoretical lenses to evaluate AI integration in U.S. industrial management: the Resource-Based View (RBV), Socio-Technical Systems (STS) theory and the Dynamic Capabilities framework. The RBV

Figure 3: The Synergy of AI Integration Theories



asserts that firms acquire persistent competitive advantage by producing resources that are valuable, unique, inimitable and non-substitutable. Classic formulations of RBV stress that enterprises are heterogeneous bundles of physical, human and organisational resources, and that these resources must be difficult to mimic and immobile across firms. In the context of AI, data assets, machine-learning models and digital talent form strategic resources. Evidence from U.S. manufacturing reveals that organisations with solid digital infrastructure and in-house AI human capital are better positioned to capture long-term profits. Conversely, organisations that abandon organised management methods during AI deployment face significant short-term losses. These patterns correlate with the RBV's emphasis on the alignment of technological assets with managerial procedures and the difficulties of transmitting tacit knowledge.

Socio-technological Systems theory highlights the combined optimisation of social and technological subsystems. AI integration includes not only implementing algorithms but also revamping workflows, training personnel and managing cultural change. The National Association of Manufacturers reports that AI runs best when people remain fundamental decision-makers and that upskilling and ethical frameworks are vital. Employee well-being research suggests that trust in AI and favourable impressions of its prospects promote productivity and contentment, whereas algorithmic management might diminish autonomy and raise stress. These findings reinforce the STS perspective that technology must be integrated with organisational structures and human needs.

The Dynamic Capabilities paradigm proposes that organisations must identify opportunities, grasp them and restructure resources to stay

competitive. Developed to solve constraints of the RBV in dynamic situations, dynamic capabilities emphasise higher-order competencies that enable businesses to integrate, build and rearrange resources in response to rapid change. Micro-foundational processes such as perceiving, seizing and changing are key to this theory. Rapid advances in AI technology demand ongoing learning and adaptation; leaders' desire to learn about AI and to create multidisciplinary collaboration is vital for wider adoption. The Census poll states that many organisations participate in training, design new procedures and purchase cloud services to enable AI deployment. These acts represent dynamic capacities that enable organisations to absorb new technologies and alter operations. Moreover, early adopters that invested in AI before 2017 exhibit better growth, demonstrating the necessity of timely sensing and seizing.

Integrating these ideas gives a holistic lens: the RBV highlights strategic resources, STS theory stresses human-technology alignment, and dynamic capabilities emphasize ongoing renewal. Together, they explain why AI adoption creates diverse outcomes across organisations and underline the necessity for complementary assets, supportive culture and proactive leadership.

3 Methodology

3.1 Research Design

This study utilises a qualitative multiple-case design to analyse how AI integration unfolds in U.S. industrial organisations. Qualitative techniques are particularly well-suited to examining complex socio-technical phenomena where context matters and where quantifiable measures alone cannot represent organizational dynamics. Previous study emphasises the

relevance of qualitative insights for understanding digital transformation, as AI adoption is typically unequal and requires contextualisation. A multiple-case design allows for cross-case comparisons and identification of patterns while keeping the richness of each organizational narrative.

3.2 Data Sources

Consistent with the intention to rely entirely on secondary data, this study drew upon a varied corpus of publicly available resources rather than interviewing organizational members. Sources included peer-reviewed academic articles, industry white papers, government reports, company disclosures, and documented case studies of AI application in U.S. manufacturing enterprises and allied industrial sectors. To be included, sources have to describe AI initiatives beyond the pilot level and originate from or pertain to firms operating in the United States. By pooling ideas across numerous sectors—such as automotive, aircraft, food processing, chemicals and industrial equipment—the study created a comprehensive secondary dataset covering varied experiences with AI integration.

3.3 Data Collection

Consistent with a qualitative secondary-data methodology, the study compiled a large collection of papers that addressed motives for AI adoption, implementation methods, perceived benefits and obstacles, workforce impacts and governance systems. Sources included published research articles, industry white papers, policy documents, corporate sustainability reports, conference proceedings, and media coverage of AI efforts. The materials covered from 2018 to early 2026 and were retrieved from academic databases, government websites, industry groups and corporate archives.

All selected documents were read attentively and relevant passages relating to AI integration were extracted into a qualitative analysis software. No human participants were involved, and hence no ethical consent was required. This documentary approach allowed for triangulation across many categories of secondary evidence and encouraged comparison between reported behaviours and strategic narratives.

3.4 Data Analysis

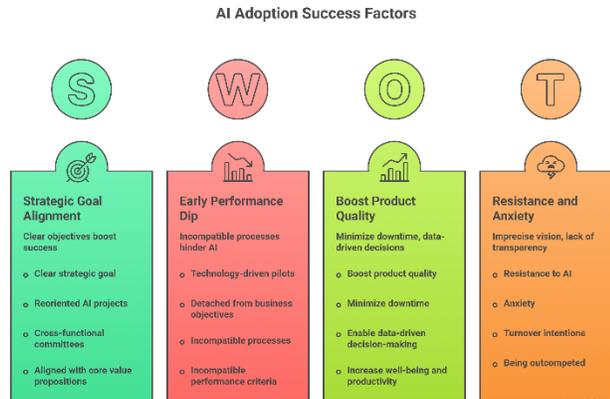
Data were examined using theme analysis. Documents were coded inductively and deductively: initial coding caught emergent themes, while further coding was driven by the theoretical framework (RBV, STS and dynamic capacities). Codes were compared across cases to detect trends, contrasts and contextual factors. Memo writing and iterative talks among the authors ensured reflexivity. Because the study depended on secondary data, credibility was strengthened by triangulation across different sources and peer debriefing among the authors.

4 Findings and Discussion

4.1 Strategic Alignment and Vision

Across the case studies studied, AI adoption was based in a clear strategic goal. Reports stated that many first pilot programs were technology-driven but detached from broader business objectives. Over time, successful cases reoriented AI projects toward boosting product quality, minimising downtime and enabling data-driven decision-making. Sources recognised that early performance dipped—mirroring the J-curve—because traditional processes and performance criteria were incompatible with AI capabilities. Firms that reassessed their objectives, established cross-functional steering

Figure 4: AI Adoption Success Factors



committees and aligned AI projects with core value propositions reported more lasting success.

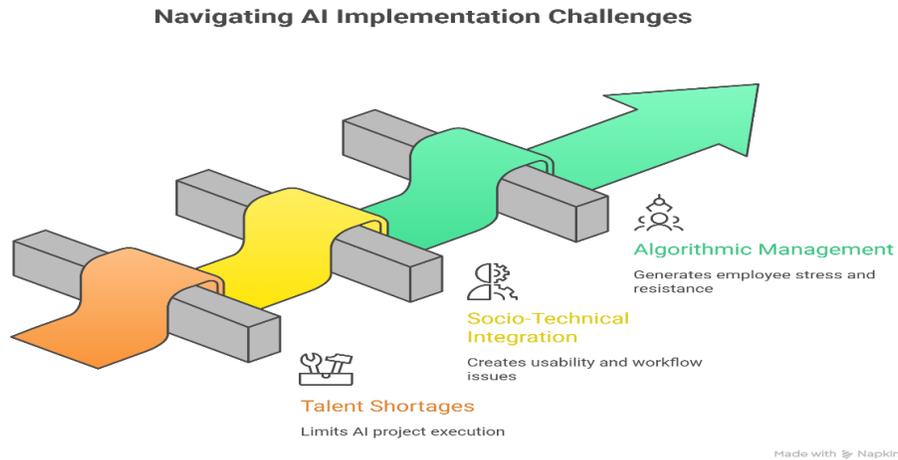
The importance of alignment mirrors research suggesting that organisations that only partially commit to AI risk being outcompeted. Secondary sources underlined that senior management sponsorship and clear communication were crucial; without these, people regarded AI as a threat rather than an opportunity, resulting to resistance. This coincides with studies demonstrating that positive perceptions of AI potential increase well-being and productivity. Conversely, imprecise vision and lack of transparency promote anxiety and turnover intentions.

4.2 Workforce Reskilling and Socio-Technical Integration

The secondary literature frequently stressed the centrality of human capital. AI projects required new technical competencies—data engineering, machine-learning model maintenance—and related soft abilities like as cooperation and problem-solving. Firms invested in training programs and cooperation with colleges. Several

stories detailed developing internal “AI academies” to build data literacy across jobs, echoing needs for constant skill adaptation and ethical technological practices. Despite these attempts, talent shortages remained; the democratization of AI tools posed quality-assurance difficulties and emphasised the scarcity of qualified practitioners. Socio-technical integration was a persistent difficulty. Sources indicated that early projects were led by technical teams with insufficient engagement from operations or human resources, resulting in solutions that lacked usability or disagreed with established workflows. Successful organisations embedded cross-functional teams, co-designed AI systems with end-users and preserved people as decision-makers. Employees who trusted AI systems and regarded them as supporting tools enjoyed increased job satisfaction and productivity, whereas algorithmic management approaches that decreased autonomy generated stress and resistance. These observations reinforce the STS perspective and underscore the need for participatory design.

Figure 5: Navigating AI Implementation Challenges



4.3 Governance, Ethics and Regulatory Environment

Secondary sources cited issues about data privacy, bias and compliance. Although most organisations have implemented general data-governance rules, few had AI-specific ethical principles. The White House AI Action Plan provided high-level direction on innovation and worker empowerment, but commentators underlined the need for stricter norms for algorithmic openness and liability. Commentaries urged that AI legislation should be targeted to sectoral risks, mirroring recommendations in industry reports for right-sized compliance and global coherence. Reports also examined the global diffusion of generative AI and highlighted the widening digital gap. Some concerned that more regulation could hamper innovation, while others supported stronger standards to promote public trust.

4.4 Organizational Capabilities and Dynamic Learning

The last theme covers the competences required to maintain AI-enabled transformation.

Successful organisations created dynamic capabilities by continuously sensing new AI opportunities, capturing them through pilot projects and restructuring resources. Case studies indicated that early adopters typically learned from failures: one firm abandoned an AI-driven scheduling tool after it caused bottlenecks, reflecting findings that abandoning of organised processes correlates to short-term losses. Over time, however, the same corporation redeployed AI for predictive maintenance and achieved significant downtime savings. Commentaries underlined the necessity of willingness to learn, multidisciplinary teamwork and investment in data infrastructure. These capabilities correlate with the dynamic capabilities framework and are mirrored by the Census poll, which revealed that AI users often retrain workers, establish new workflows and invest in cloud services.

5 Recommendations

Based on the findings and literature, numerous recommendations are provided to industry managers, legislators and researchers:

- i. **Strategic Alignment and Holistic Planning:** AI projects should be entrenched in strategic planning and tied to explicit commercial objectives. Firms need to expect transitional productivity decreases and allocate resources for change management, matching with findings that AI adoption follows a J-curve.
- ii. **Invest in Workforce Development:** Continuous reskilling and upskilling are needed. Companies should develop AI academies and work with educational institutions to build data literacy and technical competencies. Training should also address ethical considerations and algorithmic transparency.
- iii. **Foster Participatory Socio-Technical Design:** AI solutions must be co-developed with end-users to ensure usability and confidence. Maintaining humans as main decision-makers improves adoption and mitigates stress. Leadership should speak openly about AI ambitions to prevent fear and churn.
- iv. **Establish Robust Governance Frameworks:** Organizations need AI-specific governance systems that handle data privacy, bias mitigation and accountability. Policymakers should give sector-specific recommendations that balance innovation with worker protection.
- v. **Develop Dynamic Capabilities:** Firms should embrace an experimental approach, learning from pilots and growing successful use cases. Investing in digital infrastructure and human resources, and building a culture of continuous development, prepares organisations to seize opportunities and adapt to new AI technology.

- vi. **Address Digital Divides:** National and regional initiatives should invest in infrastructure and digital skills to ensure equitable AI deployment. Reports reveal considerable variations in AI dispersion across the Global North and Global South; similar divisions may exist across U.S. regions and sectors.

6 Conclusion

This qualitative study explores how U.S. industrial organisations strategically integrate artificial intelligence into their management processes based on secondary data. By synthesising findings from published case studies, industry analysis and policy documents, the research indicates that AI adoption is not a straightforward technology implementation but a comprehensive organizational transformation. Early productivity declines and increased work-in-progress inventory give way to long-term gains only when firms align AI projects with strategic objectives, invest in workforce development, design socio-technical systems that maintain human agency and establish governance structures that address ethics and compliance. The findings underline the importance of dynamic capabilities and learning orientation, mirroring larger evidence that AI acts as a general-purpose technology whose benefits are achieved through complementary organizational reforms. As AI diffusion speeds and legislative initiatives expand, managers must negotiate both possibilities and threats to exploit AI's revolutionary potential for sustainable industrial competitiveness.

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