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TECHNOLOGY MANAGEMENT AND STRATEGIC DECISION-MAKING IN U.S. MANUFACTURING FIRMS: INSIGHTS FROM ARTIFICIAL INTELLIGENCE AND DATA-DRIVEN SYSTEMS

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ABSTRACT

Artificial intelligence (AI) and data driven decision systems are transforming U.S. industry by delivering real time insights, assisting predictive maintenance and automating complicated decisions. Yet adoption remains unequal, and the managerial consequences of AI are poorly understood. This qualitative study analyses how technology management and strategic decision making evolve when AI and analytics are integrated into U.S. manufacturing organisations. The research relies only on secondary data—published case studies, academic literature, industry reports and policy documents—to minimise the biases inherent with primary interviews or surveys. The study targets one overarching objective: to understand how data driven technologies influence decision

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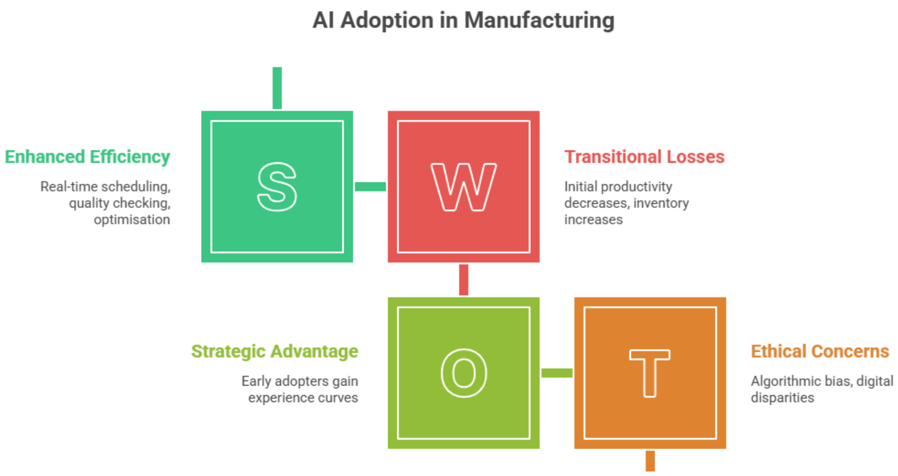
making practices and organizational capabilities. Two specific objectives are (i) to identify the socio technical and managerial factors that enable effective use of AI and data analytics in manufacturing, and (ii) to explore how firms cultivate strategic and dynamic capabilities to sustain competitive advantage in the face of rapid technological change. The findings reveal that AI adoption often follows a staged trajectory with short term inefficiencies before long term gains; that human–machine collaboration, data governance and ethical considerations are central to successful integration; and that capability building—through training, leadership and cross functional collaboration—is critical for realizing the benefits of data driven systems. The article proposes a conceptual model of technology management that emphasizes strategic alignment, collaborative design and continual learning. Implications for practitioners and policymakers are highlighted.

1 INTRODUCTION

Technological developments in machine learning, predictive analytics and industrial internet of things (IIoT) devices have brought artificial intelligence from science fiction into the heart of production (Rosin et al., 2022; Morgan & Choudhury, 2024). Industry 4.0 blends cyber physical systems, IoT and AI to develop adaptable, data driven industrial ecosystems (Rosin et al., 2022; Stojanovic & Doherty, 2021). These systems offer real time scheduling, computer vision quality checking and closed loop optimisation across factories and supply networks (Morgan & Choudhury, 2024; Krueger & Remy, 2024). However, converting technology potential into strategic advantage remains tough. Micro level studies of U.S. manufacturers suggest a J curve pattern of AI adoption in which initial productivity decreases and larger work in progress inventories precede ultimate performance increases (McElheran et al., 2025). These transitional losses occur from interruptions to established routines and investments in robots and digital infrastructure (McElheran et al., 2025; Wang & Chaudhry, 2021). Early adopters that spend before peers gain from experience curves and eventually beat laggards (McElheran et al., 2025; Brynjolfsson & Hitt, 2000). Adoption variation is strong across business size and sector. Real time surveys show that between 2020 and 2024 the share of U.S. firms using AI increased from roughly 4 % to about 14 %, yet adoption remains higher among large enterprises than small and medium sized enterprises (SMEs)(Census Bureau, 2024;Organisation for Economic Co operation and Development [OECD], 2025). Across the G7, the share of large firms using AI approaches 40 %, three times that of small firms

Figure 1: AI Adoption in Manufacturing



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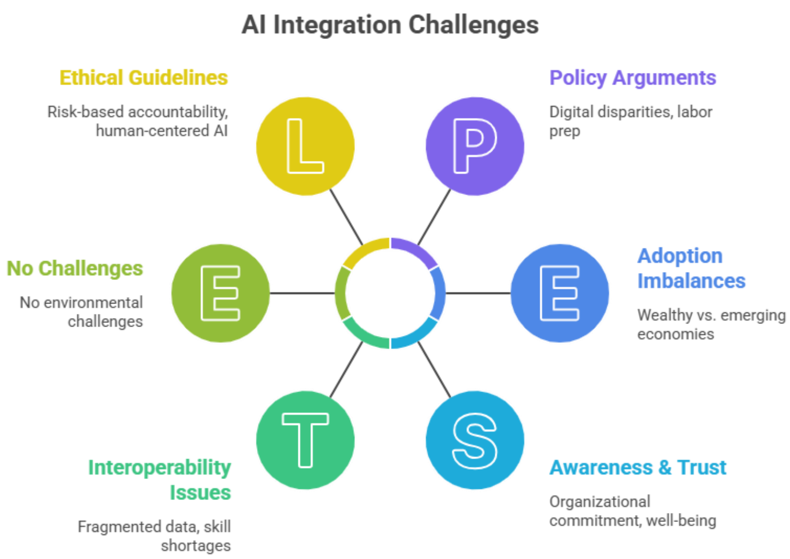
(OECD, 2025). Sectorally, information and professional services lead, while manufacturing trails (Census Bureau, 2024; Murthy et al., 2021). The National Association of Manufacturers (NAM) reports that manufacturers are both developers and deployers of AI technolog ies—machine learning, machine vision, digital twins and robotics—and that these innovations enhance efficiency, product development and safety (National Association of Manufacturers [NAM], 2024; Krueger & Remy, 2024). Yet the same research cautions that AI functions best when humans remain the key decision makers, necessitating major upskilling and ethical governance frameworks (NAM, 2024; Papagiannidis et al., 2024; Jentzsch & Preibusch, 2024).

Data-driven decision-making (DDDM) alters managerial processes by methodically evaluating digital data to enhance accuracy (Dhar, 2020; Gupta & George, 2016; Morgan & Choudhury, 2024). Digital capabilities—including big data, cloud computing and advanced analytics—improve performance, although assessing their impact is complex and context dependant (Gupta & George, 2016; Kavak & Rusu, 2025; Abrokwah-Larbi & Awuku-Larbi, 2024). Plant-level study suggests that implementing DDDM increases value added and that returns are higher when analytics are combined with skilled people and decentralised decision rights (Johnson & Winters, 2023). Adoption is earlier and more widespread among larger, older facilities, while smaller single-establishment enterprises adopt later (OECD, 2025).

Technological integration also interacts with socio-technical variables. Awareness of automation can impair organisational commitment and career happiness, but trust in AI and positive impressions of its prospects can boost productivity and well-being (Papagiannidis et al., 2024; Robey & Sahay, 1996). Scholars highlight that AI is best viewed as a socio-technical system needing collaborative design and transparency (Papagiannidis et al., 2024; Batool et al., 2025; Robey & Sahay, 1996). Algorithmic bias emerges through history, selection and optimisation processes, prompting calls for fairness diagnostics and governance methods (Jentzsch & Preibusch, 2024; Batool et al., 2025). Ethical guidelines from the White House and international authorities promote risk-based accountability and human-centred AI (White House, 2025; United Nations Environment Programme [UNEP], 2025; Krueger & Remy, 2024). Cases from healthcare and manufacturing demonstrate the significance of keeping human judgment and managing data fragmentation, skills variability and ethical considerations when using AI for decision assistance (Papagiannidis et al., 2024; Krueger & Remy, 2024).

As AI diffuses, bigger policy arguments emerge concerning digital disparities and labour preparation.

Figure 2: AI Integration Challenges



Generative AI adoption is developing quicker in wealthy economies than in emerging nations, aggravating global imbalances (Abrokwah Larbi & Awuku Larbi, 2024; Murthy et al., 2021). OECD analyses note that enablers for SME adoption include connectivity, access to high quality datasets and compute resources, skilled talent and financing, and warn that without complementary investments in training, data infrastructure and management practices AI's potential remains unrealised (OECD, 2025; Abrokwah Larbi & Awuku Larbi, 2024). In manufacturing, dynamic scheduling, predictive maintenance and self aware digital twins are expanding possibilities, yet interoperability challenges, fragmented data infrastructures and skill shortages impede adoption (Stojanovic & Doherty, 2021; Krueger & Remy, 2024; Morgan & Choudhury, 2024; Wang & Chaudhry, 2021). These insights underline the need to consider not just technological readiness but also how companies manage technology, make strategic decisions and foster capabilities (Barney, 1991; Teece et al., 1997; Eisenhardt & Martin, 2000).

1.1 Objective of the Study

The overarching aim of this research is to understand how U.S. manufacturing firms integrate AI and data-driven systems into technology management and strategic decision-making. Two specific objectives guide the study:

i. To identify the socio-technical and managerial factors enabling effective AI and data-driven decision-making in U.S. manufacturing firms. [Evidence demonstrates that successful adoption requires on organisational culture, leadership, workforce skills and governance—not just technological capabilities (NAM, 2024; Papagiannidis et al., 2024; Batool et al., 2025).]

ii. To explore how firms develop strategic and dynamic capabilities to sustain competitive advantage in the face of rapid technological change. Studies show that dynamic capabilities—sensing, seizing and reconfiguring resources—mediate the relationship between AI adoption and innovation performance (Pérez-Campdesuñer et al., 2025; Teece et al., 1997; Feliciano-Cestero et al., 2023). [Understanding how businesses nurture these competencies will explain avenues to long-term competitiveness.]

2 LITERATURE REVIEW

2.1 AI and Data-Driven Decision-Making as General-Purpose Technologies

Artificial intelligence is frequently defined as a general-purpose technology with the ability to alter productivity, creativity and decision-making across industries (Brynjolfsson & Hitt, 2000; Davenport & Ronanki, 2018). Micro-level study on U.S. manufacturing reveals that AI adoption causes a J-curve: businesses initially endure productivity reductions, increased work-in-progress inventory and manpower shedding before achieving improvements (McElheran et al., 2025). These losses result from learning expenses and interruption to established habits and are greatest among older establishments (McElheran et al., 2025). Early adopters that invest in AI ahead of competition eventually outperform, demonstrating the value of experimenting and learning (McElheran et al., 2025; Brynjolfsson & Hitt, 2000). Such trends parallel past evaluations of computing and other general-purpose technologies, which require complementary advances in work practices and human capital to achieve profits (Brynjolfsson & Hitt, 2000; Gupta & George, 2016).

Adoption statistics suggest modest diffusion: U.S. surveys report that AI use climbed from roughly 4 % in 2023 to 14 % by 2024, with adoption higher among major enterprises and particular industries such as information services (Census Bureau, 2024). OECD assessments similarly reveal that across the G7 roughly 40 % of large enterprises utilise AI, compared with 11–14 % of small firms (OECD, 2025). Common uses include marketing automation, virtual agents, predictive maintenance and data analytics (Census Bureau, 2024; Morgan & Choudhury, 2024; Krueger & Remy, 2024). Despite these applications, adoption remains inconsistent across geographies and firm sizes, mainly due to disparities in digital infrastructure and managerial capacities (Murthy et al., 2021; Lythreatis et al., 2022).

Beyond adoption numbers, DDDM impacts managerial cognition and decision processes. Pioneering research reveals that systematic analysis of high-volume digital data increases decision accuracy, enabling managers to detect patterns that would otherwise remain concealed (Dhar, 2020; Gupta & George, 2016). Digital technologies such as IoT, cloud computing and AI revolutionise operations by offering real-time data streams and predictive insights (Gupta & George, 2016; Rosin et al., 2022; Morgan & Choudhury, 2024). Documented benefits include improved forecasting, better inventory control and greater product quality (Rosin et al., 2022; Krueger & Remy, 2024). Nevertheless, assessing the impact of DDDM is problematic because outcomes depend on complementing resources, data quality and the ability to act on insights (Gupta & George, 2016; Kavak & Rusu, 2025). Plant-level evidence demonstrates that adopting data-driven systems increases value added and that returns are higher when decision rights are delegated to frontline workers and paired with skilled personnel (Johnson & Winters, 2023). This underlines the necessity of matching decision hierarchies with analytic capabilities (Morgan & Choudhury, 2024; Wang & Chaudhry, 2021). Research indicates that AI-driven cybersecurity analytics enhance real-time threat detection and anomaly recognition, reinforcing the notion that proficient technology management increasingly depends on integrated analytics, swift decision support, and human-machine collaboration (Adnan, et al., 2024).

2.2 Technology Management and Organizational Transformation

AI adoption demands rethinking technology management and organisational frameworks. Manufacturers utilise AI technologies such as machine vision, digital twins and robots to boost efficiency, product development and safety (NAM, 2024; Krueger & Remy, 2024). Self-aware digital twins incorporate big data analysis and simulation to continually monitor system activity, uncover improvement possibilities and support "what if" studies (Stojanovic & Doherty, 2021; Krueger & Remy, 2024). Big data analytics and AI increase sensory capacities, enabling detection of images, voice and odd situations (Rosin et al., 2022; Krueger & Remy, 2024). IoT and cloud computing facilitate the capture and storage of vast datasets, allowing finding of hidden patterns and correlations (Gupta & George, 2016; Rosin et al., 2022). Despite these gains, research on decision-making processes frequently focused on separate tasks rather than holistic integration (Rosin et al., 2022; Krueger & Remy, 2024). Many models enhance only some parts of the decision process and remain context specific (Rosin et al., 2022). Manufacturing organisations must consequently invest in systems that integrate data flows across functions and support end-to-end decision cycles (Morgan & Choudhury, 2024; Wang & Chaudhry, 2021).

Strategic management experts suggest that AI adoption includes building dynamic capabilities—the abilities to recognise opportunities, grab them through innovation and reconfigure resources (Teece et al., 1997; Eisenhardt & Martin, 2000; Teece, 2007). Dynamic capacities theory extends the resource-based paradigm by emphasising adaptation and learning in turbulent contexts (Teece et al., 1997; Feliciano-Cestero et al., 2023). Firms with high dynamic capacities can integrate AI into existing routines, experiment with new business models and pivot when technologies advance (Pérez-Campdesuñer et al., 2025; Kavak & Rusu, 2025). Empirical studies on SMEs in emerging economies show that AI adoption enhances innovation and competitiveness both directly and indirectly through dynamic capabilities such as sensing opportunities, seizing them through innovation and reconfiguring resources (Sánchez-Rodríguez et al., 2025; Pérez-Campdesuñer et al., 2025). These findings fit with theoretical claims that AI functions as a catalyst for creating new knowledge and capacities (Teece et al., 1997; Teece, 2007). The resource-based view (RBV) asserts that organisations derive advantage from distinctive bundles of resources—physical, human and organisational capital (Barney, 1991). Dynamic capacities supplement this by explaining how businesses adapt resource bases in response to change (Teece et al., 1997; Eisenhardt & Martin, 2000). Together, RBV and dynamic capabilities provide a theoretical lens for understanding how data-driven systems contribute to long-term competitiveness.

2.3 Socio-Technical and Human Factors

Technology integration does not occur in a vacuum; it is profoundly interwoven with organisational culture, employee attitudes and power dynamics. Studies demonstrate that understanding of automation and smart technology can lower organisational commitment and raise turnover intentions (Papagiannidis et al., 2024). Conversely, trust in AI and good evaluations of its utility can boost job satisfaction and supervisor-rated productivity (Saleem et al., 2024). Qualitative study in healthcare management suggests that managers regard AI as a tool to support, not replace, human judgment; they underline the necessity for solid data infrastructure, training and ethical safeguards (Papagiannidis et al., 2024; Krueger & Remy, 2024). These managers also identify issues such as poor communication, solitary decision-making, data fragmentation and unwillingness to change (Krueger & Remy, 2024; Robey & Sahay, 1996). Manufacturing leaders confront comparable difficulties when integrating AI: worker anxiety over job security, talent gaps and the need for participatory design (NAM, 2024). A thorough assessment of AI bias identifies four forms of bias—historical, selection, algorithmic optimisation and feedback—and advocates for fairness-aware modelling, dataset diversity and post-deployment auditing (Jentzsch & Preibusch, 2024; Batool et al., 2025). Governance systems and regulatory frameworks, such as the U.S. Blueprint for an AI Bill of Rights and the OECD AI Principles, promote openness, accountability and human-centred design (White House, 2025; OECD, 2025; Papagiannidis et al., 2024). These considerations underline that technology management must balance efficiency with ethical and social dimensions (Jentzsch & Preibusch, 2024; Batool et al., 2025).

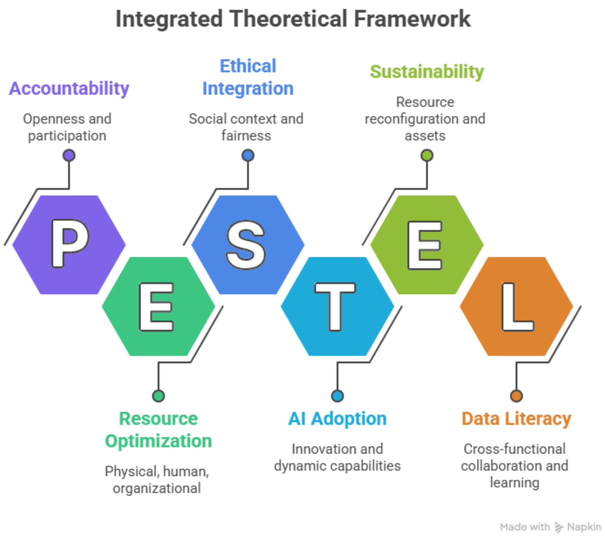
2.4 Policy Environment and Digital Divides

Policy initiatives shape the diffusion of AI and data analytics. The White House's AI Action Plan aims for boosting innovation and empowering American workers while guaranteeing responsible AI development (White House, 2025). OECD evaluations demonstrate persistent adoption gaps between large enterprises and SMEs and stress enablers such as high-quality connectivity, access to AI-enabling inputs, skills and funding (OECD, 2025). AI adoption is higher in sectors with robust digital infrastructure and access to talent (OECD, 2025; Census Bureau, 2024). Case studies classify AI adopters into categories ranging from novices to champions and indicate that even skilled organisations struggle with challenges including accuracy, damaging content and legal uncertainties (OECD, 2025; NAM, 2024). As generative AI spreads, national and global agencies offer codes of behaviour and risk-based frameworks (UNEP, 2025; Papagiannidis et al., 2024). Nonetheless, digital differences persist: adoption grows approximately twice as fast in industrialised nations as in the Global South (Abrokwah-Larbi & Awuku-Larbi, 2024). Within the United States, discrepancies occur between areas and company sizes; rural manufacturers often lack adequate broadband and cloud infrastructure (Murthy et al., 2021; Lythreatis et al., 2022). Policy solutions include infrastructure expenditures, worker training programmes and tax incentives to boost AI deployment (OECD, 2025; NAM, 2024). Researchers caution that regulation must combine innovative incentives with protection of privacy, labour rights and competitiveness (Batool et al., 2025; Jentzsch & Preibusch, 2024).

2.5 Organisational Capabilities and Dynamic Learning

The last theme covers the competences required to maintain data-driven transformation. Successful organisations establish dynamic capacities by continuously recognising new AI prospects, experimenting with prototype projects and rearranging resources (Teece et al., 1997; Feliciano-Cestero et al., 2023). Evidence suggests that early adopters often learn from failures—abandoning inefficient AI tools, changing workflows and then redeploying AI more effectively (McElheran et al., 2025; Pérez-Campdesuñer et al., 2025). Manufacturers invest in training and cross-functional collaboration to promote data literacy and link AI initiatives with business strategy (NAM, 2024; Feliciano-Cestero et al., 2023; Pérez-Campdesuñer et al., 2025). Census surveys reveal that AI adopters often retrain workers, establish new workflows and invest in cloud services and data protection (Census Bureau, 2024; Johnson & Winters, 2023). Research on Industry 4.0 emphasises that big data, AI and digital twins might increase problem recognition and solution diagnosis but that present models generally focus on specialised activities and disregard holistic integration (Rosin et al., 2022; Saleem et al., 2024). There is a growing realisation that dynamic capabilities must incorporate both technical competencies and soft skills—communication, creativity and learning—to harness AI for supply chain resilience and strategy renewal (Saleem et al., 2024; Wang & Chaudhry, 2021; Feliciano-Cestero et al., 2023). Building such capacities is particularly critical for SMEs, which confront resource limits and digital divides (OECD, 2025; Sánchez-Rodríguez et al., 2025).

Figure 3: Integrated Theoretical Framework



2.6 Theoretical Framework

This study utilises an integrated theoretical framework that incorporates the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT) and socio-technical systems (STS) perspective. RBV conceptualises enterprises as bundles of physical, human and organisational resources whose heterogeneity and immobility underlying competitive advantage (Barney, 1991). Physical resources comprise plant and equipment; human resources encompass skills and expertise; organisational resources involve routines, culture and governance (Barney, 1991). However, RBV has been critiqued for its static orientation in dynamic situations. DCT tackles this by emphasising on the firm's ability to integrate, build and rearrange resources to response to changing situations (Teece et al., 1997; Eisenhardt & Martin, 2000). Dynamic capacities encompass three processes: recognising opportunities and threats, capturing opportunities through investments and innovation, and altering or reconfiguring assets and structures (Teece, 2007; Eisenhardt & Martin, 2000). These qualities help organisations to react to technology shocks and leverage general-purpose technologies such as AI. Empirical research shows that AI adoption enhances innovation performance via dynamic capabilities and that firms must build data literacy, cross-functional collaboration and continuous learning to realise benefits (Feliciano-Cestero et al., 2023; Pérez-Campdesuñer et al., 2025; Sánchez-Rodríguez et al., 2025). The socio-technical systems perspective complements RBV and DCT by highlighting that technology integration is rooted in social contexts (Robey & Sahay, 1996; Papagiannidis et al., 2024). STS theory states that successful adoption needs combined optimisation of social and technical subsystems and that disregarding social variables can lead to failure (Robey & Sahay, 1996; Jentzsch & Preibusch, 2024). Bias and ethical challenges develop when AI systems are isolated from their social surroundings, leading to fairness concerns and mistrust (Jentzsch & Preibusch, 2024; Batool et al., 2025). STS consequently stresses the significance of participatory design, openness and accountability. Integrating RBV, DCT and STS allows this study to evaluate how data-driven technologies affect both resources and routines and how organisations grow capacities while addressing human and ethical elements.

3 METHODOLOGY

3.1 Research Design

This study adopts a qualitative research design based exclusively on secondary data to analyse AI-enabled technology management and strategic decision-making in U.S. manufacturing organisations. Qualitative research is ideal for examining complicated phenomena in real-world contexts and for yielding rich, contextualised insights (Patton, 2015). The analysis employs document analysis and interpretive content analysis to extract themes from a wide range of published sources: peer-reviewed journal articles, government reports, industry white papers, case studies and policy documents (Rowe & Wright, 1999; Robey & Sahay, 1996). This approach avoids the biases of primary interviews and surveys while allowing triangulation across multiple data types. Consistent with qualitative research guidelines, documents were selected based on credibility, relevance and diversity of perspectives (e.g., academic, practitioner, policy), and were evaluated iteratively to detect recurring themes, contradictions and gaps (Patton, 2015).

3.2 Data Collection

Data were acquired from scholarly databases, official repositories (e.g., U.S. Census Bureau, OECD), business groups and think tanks. Key sources include working papers on AI adoption in U.S. manufacturing (McElheran et al., 2025), studies on data-driven decision-making (Johnson & Winters, 2023; Dhar, 2020), reports from the National Association of Manufacturers (NAM, 2024), policy documents such as the OECD SME AI adoption paper (OECD, 2025) and literature on dynamic capabilities (Teece et al., 1997; Feliciano-Cestero et al., 2023). Additional sources address socio-technical systems, algorithmic bias, ethical principles and digital infrastructure (Papagiannidis et al., 2024; Jentzsch & Preibusch, 2024). Articles published between 2020 and 2026 were chosen to capture recent changes. Only secondary data were used; no interviews, surveys or observations were done.

3.3 Data Analysis

The analysis used an inductive approach. First, all acquired documents were read and annotated. Key concepts, arguments, evidence and suggestions were coded using thematic analysis (Patton, 2015). Codes were organised into higher-level groups related to issues such as adoption trends, technology management, human aspects, governance and capabilities. The themes were iteratively improved by comparing findings across sources and using theoretical ideas from RBV, DCT and STS. Contradictions and exceptions were indicated to avoid oversimplification. The resulting synthesis informs the findings reported below.

4 FINDINGS & DISCUSSION

4.1 Adoption Patterns and Performance Trajectories

Secondary research confirms that AI adoption in U.S. manufacturing is inconsistent and frequently follows a phased trajectory. Early adoption is concentrated in large enterprises with considerable digital infrastructure and financial resources (Census Bureau, 2024). SMEs have adoption gaps due to poor connection, lack of access to high-quality data and computational resources, skills shortages and budgetary restrictions (OECD, 2025; Sánchez-Rodríguez et al., 2025). Researchers find that early adopters endure short-term productivity decreases and greater inventories while they invest in robots and change processes (McElheran et al., 2025). Over time, however, these organisations earn efficiency improvements and innovation benefits, whereas laggards risk falling behind (McElheran et al., 2025; Teece et al., 1997). Plant-level assessments demonstrate that data-driven decision systems generate an approximately three percent improvement in value added and that integrating analytics with skilled people and decentralised decision rights amplifies returns (Johnson & Winters, 2023; Gupta & George, 2016). Yet adoption remains low overall; by 2024 only roughly 14 % of enterprises in the OECD use AI (OECD, 2025; Census Bureau, 2024).

4.2 Technology Management and Strategic Decision-Making

Data-driven systems transform managerial cognition and decision processes. High-volume digital data allow managers to uncover patterns and correlations that are imperceptible to intuition (Dhar, 2020; Gupta & George, 2016). IoT and cloud platforms gather and store huge datasets, enabling AI to detect images, voice and abnormalities (Rosin et al., 2022; Morgan & Choudhury, 2024). Self-aware digital twins integrate large data and simulation to monitor systems continuously and assist hypothetical “what if” studies (Stojanovic & Doherty, 2021; Krueger & Remy, 2024). AI thus enables predictive maintenance, dynamic scheduling and quality control, giving real-time decision assistance (Morgan & Choudhury, 2024; Krueger & Remy, 2024). However, digital readiness varies greatly across organisations; many manufacturers still rely on old technologies and spreadsheets and

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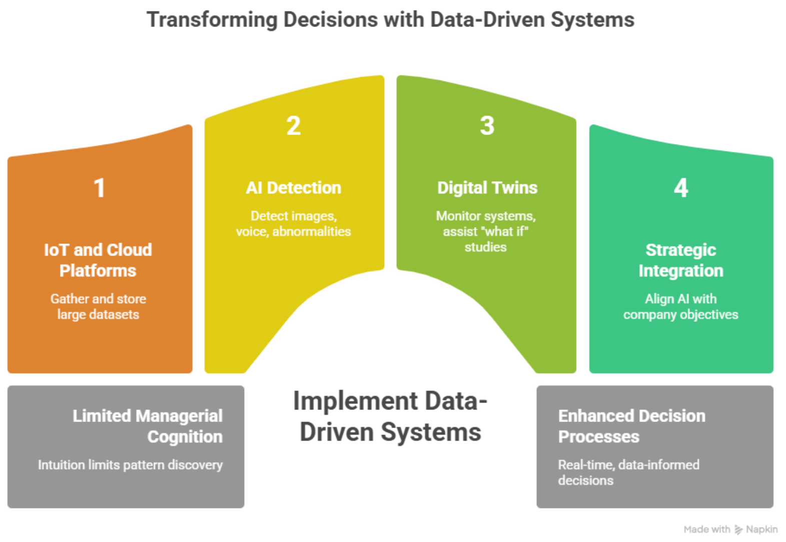
Figure 4: Transforming Decisions with Data-Driven Systems



struggle to integrate data across functions (Krueger & Remy, 2024; Robey & Sahay, 1996). Decision processes often remain segregated, limiting the benefits of analytics. Strategic management entails integrating AI activities with company objectives and ensuring cross-functional collaboration (NAM, 2024; Feliciano-Cestero et al., 2023). Without a clear strategic vision and governance, AI pilots stagnate and fail to scale (Papagiannidis et al., 2024; Batool et al., 2025).

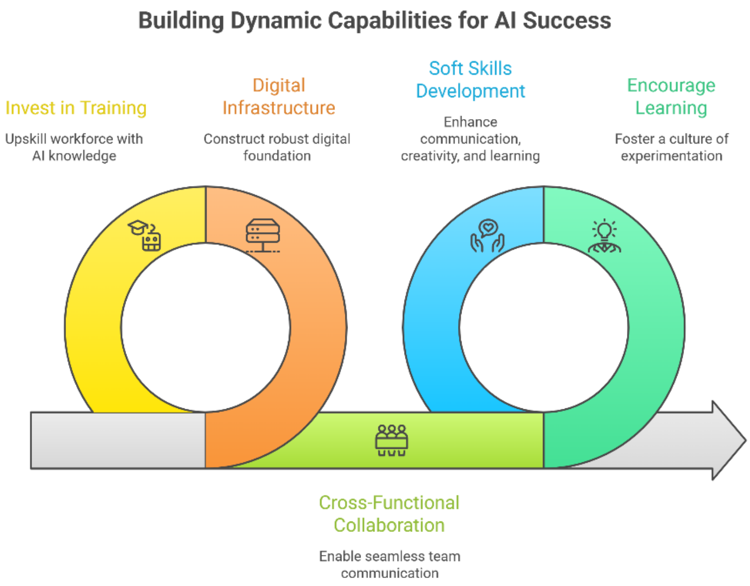
4.3 Socio-Technical Integration and Ethical Considerations

Healthcare evidence indicates that the efficacy of AI-enabled decision systems is significantly influenced by usability and human acceptance, rather than only by algorithmic proficiency. Tanji et al. (2025) indicated that system usability and diagnostic accuracy were significant predictors of patient satisfaction and clinical efficiency, reinforcing the notion that data-driven systems yield superior outcomes when technical functionality is harmonised with human-centered workflows and trust (Tanji et al., 2025). Successful AI adoption hinges on human aspects and socio-technical integration. Workers' views of AI dramatically influence adoption: fear of job loss and limited autonomy might hinder uptake, but trust and perceived usefulness improve productivity and commitment (Papagiannidis et al., 2024). Managers underline that AI should supplement rather than replace human judgment, highlighting the need for training, participatory design and ethical protections (NAM, 2024; Papagiannidis et al., 2024; Krueger & Remy, 2024). Bias studies show that AI systems can perpetuate past disparities and urge dataset diversity, fairness-aware modelling and constant auditing (Jentzsch & Preibusch, 2024; Batool et al., 2025). Regulatory frameworks such as the OECD AI Principles and the U.S. Blueprint for an AI Bill of Rights promote openness, accountability and human-centred design (White House, 2025; OECD, 2025). Manufacturing organisations must consequently integrate ethical norms into technology management, preserve data privacy and address any bias in predictive models (Papagiannidis et al., 2024; Jentzsch & Preibusch, 2024).

4.4 Dynamic Capabilities and Capability Building

Data-driven transformation demands creating dynamic skills. Firms must continuously perceive technological opportunities, grab them through trial and investment, and reorganise resources and procedures (Teece et al., 1997; Feliciano-Cestero et al., 2023). Evidence from SMEs demonstrates that AI adoption promotes innovation and competitiveness indirectly through dynamic capabilities (Pérez-Campdesuñer et al., 2025; Sánchez-Rodríguez et al., 2025). Capability building requires constructing digital infrastructure, investing in training, enabling cross-functional collaboration and encouraging learning from failures (NAM, 2024; Feliciano-Cestero et al., 2023). Manufacturers that educate people, rethink workflows and exploit cloud

Figure 5: Building Dynamic Capabilities for AI Success



services and digital twins are better positioned to reap AI's benefits (Census Bureau, 2024; Morgan & Choudhury, 2024).

Conversely, enterprises who consider AI as a plug-and-play technology without investing in complementary assets often experience the J-curve's bad side without future recovery (McElheran et al., 2025). Dynamic capabilities also encompass soft skills—communication, creativity and learning—that enable supply chain resilience and innovation (Saleem et al., 2024; Wang & Chaudhry, 2021). Building such capacities is particularly critical for SMEs, which confront resource limits and digital divides (OECD, 2025; Sánchez-Rodríguez et al., 2025).

5 RECOMMENDATIONS

Based on the findings, several recommendations are offered for managers, policymakers and researchers:

i. **Integrate AI Initiatives into Strategic Planning and Anticipate J-Curve Effects:** Firms should include AI projects within long-term strategies and invest resources for testing and change management. Recognising that initial production declines are common helps moderate expectations and retain commitment (McElheran et al., 2025).

ii. **Invest in Data Infrastructure and Interoperability:** Organisations must establish robust data pipelines, integrate IoT devices and embrace cloud architectures that enable the capture, storage and analysis of enormous datasets (Gupta & George, 2016; Morgan & Choudhury, 2024). Interoperability across IT and operational systems minimises silos and supports end-to-end decision-making (Wang & Chaudhry, 2021; Krueger & Remy, 2024).

iii. **Develop Human Capital Through Continuous Training and Participatory Design:** Upskilling programmes should focus on data literacy, AI ethics and cross-functional collaboration (NAM, 2024; Papagiannidis et al., 2024). Engaging employees in the design and deployment of AI develops trust and minimises resistance (Saleem et al., 2024).

iv. **Establish Ethical and Governance Frameworks:** Companies require AI-specific rules that address bias, transparency, accountability and data privacy (Jentzsch & Preibusch, 2024; Batool et al., 2025). These frameworks should accord with national and international criteria and be integrated into corporate governance (White House, 2025; Papagiannidis et al., 2024).

v. **Cultivate Dynamic Capabilities and a Learning Orientation:** Successful adoption entails sensing opportunities, grabbing them through pilot projects and restructuring resources and routines (Teece et al., 1997; Feliciano-Cestero et al., 2023). Firms should foster experimentation, assess outcomes and scale successful ideas while abandoning ineffective ones (McElheran et al., 2025; Pérez-Campdesuñer et al., 2025).

vi. **Address Digital Divides and Support SMEs:** Policymakers should invest in connectivity, data infrastructure, skills development and financing to enable SMEs to embrace AI (OECD, 2025; Sánchez-Rodríguez et al., 2025). Programmes should be adapted to diverse adoption profiles—from novices to champions—and incorporate instruction on ethical deployment (NAM, 2024).

vii. **Promote Interdisciplinary Research and Knowledge Sharing:** Researchers should mix knowledge from engineering, business and social sciences to understand socio-technical dynamics. Industry groups and public bodies should support knowledge exchange through case repositories and benchmarking (Robey & Sahay, 1996; Papagiannidis et al., 2024).

6 CONCLUSION

This qualitative study studied how technology management and strategic decision-making in U.S. manufacturing organisations are impacted by the integration of artificial intelligence and data-driven systems. By synthesising findings from a wide array of secondary sources, the research indicated that AI adoption is not merely a technical upgrade but a comprehensive organisational transformation. Adoption trends follow a J-curve, with initial productivity declines giving way to long-term gains for organisations that invest in complementary assets and dynamic capabilities. Data-driven decision-making boosts managerial cognition and operational efficiency, although its benefits depend on robust data infrastructure, cross-functional collaboration and strategic alignment. Socio-technical integration—addressing workforce perspectives, ethical considerations and governance—is indispensable. The study underscores the relevance of dynamic capabilities in enabling organisations to recognise, grasp and restructure resources in response to technological change. Ultimately, the findings underline that sustainable competitive advantage in the age of AI demands a comprehensive approach that balances technology innovation with human development, ethical governance and continual learning.

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