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Project Management and the Adoption of Artificial Intelligence Tools: Opportunities and Challenges in Manufacturing Engineering

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Abstract: This study explores the opportunities, challenges, and enabling conditions for adopting Artificial Intelligence (AI) tools in manufacturing engineering project management. Positioned within the Industry 4.0 context, AI applications offer transformative potential for enhancing operational efficiency, risk forecasting, and decision-making. Yet, adoption remains uneven due to technical, organizational, and ethical constraints. Drawing upon the Technology Acceptance Model (TAM), Technology–Organization–Environment (TOE) framework, and Unified Theory of Acceptance and Use of Technology (UTAUT), this research adopts a qualitative, exploratory design using semi-structured interviews with project managers, engineers, and IT specialists. The findings reveal significant opportunities for process automation, real-time data analytics, and quality improvement, while highlighting challenges related to legacy system integration, workforce resistance, financial constraints, and cyber security concerns. Enablers such as leadership commitment, technological readiness, employee training, and regulatory frameworks emerge as critical for successful AI integration. The study contributes to theory by offering a holistic socio-technical perspective on AI adoption and to practice by providing actionable guidance for managers and policymakers aiming to leverage AI for competitive advantage. Future research directions include cross-sectoral comparisons and quantitative modeling to examine causal relationships between adoption enablers, barriers, and performance outcomes.

Keywords: Project Management, Artificial Intelligence, Manufacturing Engineering, Technology Adoption, Industry 4.0

1. Introduction

The rapid advancement of Industry 4.0 technologies—including automation, cyber-physical systems, and the Internet of Things (IoT)—has reshaped manufacturing processes and project management practices worldwide. Among these technologies, Artificial Intelligence (AI) has emerged as a transformative force capable of revolutionizing decision-making, resource allocation, and operational efficiency in manufacturing engineering. AI-driven applications such as predictive analytics, machine learning algorithms, and digital twin simulations now allow organizations to anticipate equipment failures, optimize production schedules, and monitor quality in real time (Sharabov & Tsochev, 2020).

In the context of project management, AI tools provide sophisticated capabilities for risk forecasting, scheduling optimization, and stakeholder communication, reducing human error while enabling data-driven strategies. These advances align with the broader goals of Industry 4.0, where interconnected systems, intelligent automation, and real-time analytics enhance organizational agility and competitiveness. Yet, despite the growing promise of AI integration in manufacturing project environments, adoption remains uneven and often limited to isolated pilot projects rather than organization-wide transformations. Understanding the opportunities, challenges, and enabling conditions for AI adoption in manufacturing project management is therefore important for both academic scholarship and industrial practice (Zahaib Nabeel, 2024).

While prior studies have explored AI's role in manufacturing and project management, the literature remains fragmented in several key areas. Most existing research focuses on either the technological capabilities of AI or its operational outcomes, often neglecting the organizational, managerial, and ethical dimensions that influence adoption success(Lawal et al., 2024; Masod & Zakaria, 2024). Moreover, studies typically examine opportunities and challenges in isolation, offering limited insight into how enabling factors such as leadership commitment, workforce readiness, or governance mechanisms, mediate the transition from potential to realization (Masod & Zakaria, 2024).

As a result, there is a lack of holistic frameworks that integrate the technical, organizational, and strategic aspects of AI adoption in manufacturing project contexts. This knowledge gap prevents both researchers and practitioners from fully understanding why AI adoption succeeds in some settings but fails in others, particularly in complex, multi-phase engineering projects.

Addressing these gaps, this study aims to explore the opportunities, challenges, and enablers of AI adoption in manufacturing project management through qualitative analysis of industry practitioners' experiences. By examining real-world cases across diverse organizational settings, the research seeks to identify factors shaping AI adoption and uncover the interplay between technological potential, organizational readiness, and strategic leadership.

Specifically, the study is guided by the following research questions (RQs):

- RQ1: What are the key opportunities and challenges associated with the adoption of AI tools in manufacturing project management?
- RQ2: What enabling factors support the successful integration of AI in manufacturing project environments, and how do they address adoption barriers?

These questions provide a structured lens for analyzing AI adoption not only as a technological decision but also as a socio-technical process influenced by organizational, managerial, and ethical considerations.

From a theoretical perspective, the study advances the understanding of AI adoption by integrating insights from the Technology Acceptance Model (TAM)(Davis, 1989), the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). By combining these frameworks with empirical evidence from manufacturing project settings, the research highlights the multi-dimensional nature of AI adoption, where technological feasibility, organizational readiness, and managerial leadership interact to shape implementation outcomes.

Practically, the findings offer actionable guidance for manufacturing firms, project managers, and policymakers seeking to leverage AI for competitive advantage. For practitioners, the study identifies specific opportunities such as predictive analytics, process automation, and data-driven decision-making, that can enhance project performance. At the same time, it sheds light on barriers, including technical integration issues, workforce resistance, and ethical concerns, offering strategies to overcome them through leadership commitment, training programs, and governance mechanisms.

For policymakers, the research underscores the need for standardized ethical frameworks, data security regulations, and innovation incentives to foster responsible and sustainable AI adoption. Ultimately, the study bridges the gap between technological innovation and managerial practice, providing a roadmap for organizations aiming to navigate the complexities of AI integration in the era of Industry 4.0.

2. Literature Review

2.1 AI in Manufacturing

Artificial Intelligence (AI) has emerged as a transformative force in the manufacturing sector, reshaping production processes, decision-making systems, and organizational competitiveness. Early research emphasized automation and robotics as initial AI applications, particularly in assembly lines and quality control. However, recent studies highlight AI's broader role in predictive maintenance, supply chain optimization, and production planning, enabling firms to achieve higher operational efficiency and cost reduction (Rakholia et al., 2024).

One of AI's most significant contributions lies in predictive analytics, where machine learning algorithms analyze sensor data to anticipate equipment failures before they occur, minimizing downtime and maintenance costs. Additionally, computer vision technologies integrated into production systems enhance defect detection accuracy beyond human capabilities, ensuring consistent product quality (Elmouhib & Idrissi, 2025). This shift toward real-time data processing supports smart manufacturing initiatives aligned with Industry 4.0 paradigms, where interconnected systems enable autonomous decision-making and continuous process optimization.

Moreover, AI adoption facilitates mass customization, allowing manufacturers to efficiently tailor products to individual customer requirements without compromising production speed or cost-effectiveness. Reinforcement learning techniques have also demonstrated potential in dynamic scheduling, where production sequences adapt autonomously to fluctuating demand or resource constraints (Qin et al., 2023).

Despite these advances, challenges persist regarding data integration, cyber security, workforce readiness, and ethical concerns about algorithmic transparency. Scholars argue that successful AI deployment requires not only technological infrastructure but also organizational change management, skills development, and clear governance frameworks (Nidhi.V, 2025).

2.2 AI in Project Management

The integration of Artificial Intelligence (AI) into project management has attracted significant scholarly attention, reflecting its potential to enhance planning, execution, and decision-making across diverse industries. Traditional project management relies heavily on human expertise for scheduling, risk assessment, and resource allocation. However, recent literature demonstrates that AI can automate and optimize these tasks, thereby reducing human error and improving project outcomes (Sravanthi et al., 2023).

One of the primary applications of AI in project management is predictive analytics, where machine learning algorithms analyze historical project data to forecast potential delays, budget overruns, or resource bottlenecks. Such capabilities enable project managers to implement proactive strategies, enhancing both time and cost efficiency. Similarly, natural language processing (NLP) tools facilitate automated report generation, stakeholder communication analysis, and sentiment monitoring, streamlining administrative workloads (Zahaib Nabeel, 2024).

Moreover, AI-powered decision support systems provide real-time recommendations for risk mitigation and scheduling optimization, particularly in complex, multi-phase projects. Chatbots and virtual assistants further assist in routine project coordination tasks, improving collaboration among distributed teams. In large-scale engineering projects, AI-driven simulation and digital twin technologies allow project managers to model alternative scenarios, evaluate their implications, and select the most efficient strategies (Almalki, 2025).

Despite these advantages, literature highlights several challenges, including data quality concerns, resistance to technological change, and the ethical implications of delegating critical decisions to AI systems. Successful AI adoption in project management therefore requires integrating technical innovation with organizational readiness, stakeholder engagement, and appropriate governance mechanisms (Siddiqui et al., 2025).

2.3 Technology Adoption Frameworks

Technology adoption frameworks provide theoretical foundations for understanding how organizations embrace innovations such as Artificial Intelligence (AI). Among the most cited models is the Technology Acceptance Model (TAM), developed by Davis (1989), which emphasizes two primary determinants: perceived usefulness and perceived ease of use. Numerous studies have applied TAM to explain managerial and employee intentions toward adopting emerging digital technologies, including AI in manufacturing and project management (Ibrahim et al., 2025).

Another widely used framework is the Technology–Organization–Environment (TOE) model, introduced by Tornatzky and Fleischer (1990). TOE considers technological characteristics (e.g., complexity, compatibility), organizational factors (e.g., size, resources, managerial support), and environmental conditions (e.g., competitive pressure, regulatory context) as critical dimensions influencing adoption. Recent research shows that TOE effectively captures the interplay between internal readiness and external drivers in AI implementation (Masod & Zakaria, 2024).

Additionally, the Unified Theory of Acceptance and Use of Technology (UTAUT) consolidates elements from multiple models, incorporating factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT has been extended to address organizational-level considerations, including cultural and structural readiness, making it particularly relevant for large-scale AI projects.

Comparative studies indicate that no single framework fully explains AI adoption, especially in complex settings like manufacturing engineering where technological, organizational, and environmental uncertainties intersect. Hence, integrating multiple frameworks offers a more comprehensive lens for analyzing adoption determinants, challenges, and enablers (Chatterjee et al., 2021).

2.4 Opportunities & Challenges from Prior Studies

Prior studies highlight both significant opportunities and pressing challenges associated with the adoption of Artificial Intelligence (AI) in manufacturing engineering and project management. On the opportunity side, AI enables process automation, predictive maintenance, and real-time decision-making, leading to substantial gains in efficiency, cost reduction, and product quality (Rakholia et al., 2024). Its capacity for data-driven forecasting improves risk assessment, resource allocation, and scheduling accuracy, ultimately enhancing project delivery performance. Moreover, AI-powered simulation models and digital twins offer unprecedented capabilities for scenario analysis and proactive problem-solving in complex engineering environments (Md Sohanur Rahman Sourav et al., 2025).

However, scholars also underscore several challenges. Data integration issues, particularly in legacy manufacturing systems, hinder seamless AI deployment. Organizational resistance to change, lack of technical expertise, and concerns over ethical transparency further complicate adoption efforts. Financial constraints and uncertainties regarding return on investment (ROI) often limit firms' willingness to commit to large-scale AI initiatives. Additionally, cyber security risks associated with interconnected AI-driven systems raise concerns about data privacy and operational security (Rana et al., 2024).

3. Methodology

3.1 Design & Justification: Qualitative, exploratory

This study adopts a qualitative, exploratory research design to investigate the opportunities and challenges associated with adopting Artificial Intelligence (AI) tools in manufacturing engineering project management. Given the emerging nature of AI applications in this field, limited empirical evidence exists to guide managerial and technological decisions. As Creswell and Poth (2018) emphasize, exploratory qualitative designs are particularly suitable when research seeks to develop an in-depth understanding of complex phenomena in real-world contexts rather than to test pre-established hypotheses (Creswell & Poth, 2025).

Through semi-structured interviews with project managers, engineers, and technology specialists, this approach enables the collection of rich, nuanced data on organizational experiences, perceptions, and adoption practices. It also facilitates the identification of unforeseen variables influencing AI integration, such as cultural readiness, technical constraints, or ethical concerns, which may not emerge in quantitative surveys.

Furthermore, an exploratory design allows for flexibility in data interpretation, supporting the development of conceptual insights and theoretical propositions for future studies. By prioritizing depth over breadth, this method aligns with the study's objective to uncover underlying mechanisms shaping AI adoption in manufacturing project management, thereby contributing to both academic literature and practical decision-making.

3.2 Sampling & Participants

The study employs a purposive sampling strategy to ensure the inclusion of participants with direct experience in both project management and the adoption of AI tools within manufacturing engineering contexts. As Patton (2015) suggests, purposive sampling is appropriate when the objective is to gain deep insights from individuals possessing specialized knowledge rather than to generalize findings statistically (Patton, 2015).

Participants are drawn from project managers, engineers, IT specialists, and technology consultants engaged in AI-related initiatives across manufacturing firms. This heterogeneous profile enables the exploration of multiple perspectives, ranging from strategic decision-making to technical implementation challenges. Criteria for inclusion include at least three years of professional experience, direct involvement in AI-enabled projects, and familiarity with project planning, execution, or evaluation processes.

The sample size follows the principle of thematic saturation. Recruitment is facilitated through professional networks, industry associations, and LinkedIn outreach, ensuring access to qualified participants across different organizational levels and firm sizes.

This selection method supports the study's exploratory objectives, allowing for rich, context-specific data on how project management practices intersect with AI adoption opportunities and challenges in manufacturing engineering.

3.3 Data Collection and analysis

Data collection relies on semi-structured interviews designed to capture participants' experiences and perceptions regarding the adoption of AI tools in manufacturing project management. An interview guide was developed based on prior literature and the study's research objectives, covering themes such as technological readiness, organizational barriers, managerial practices, and ethical considerations. This approach ensures consistency across interviews while allowing flexibility to explore emerging topics in depth.

A total of 15 interviews will be conducted, as this number is commonly recommended to achieve thematic saturation while remaining manageable for detailed qualitative analysis. Interviews are conducted online via Zoom or Microsoft Teams to facilitate participation from geographically dispersed professionals. Each interview lasts approximately 45–60 minutes, balancing the need for rich insights with participants' time constraints. All sessions are audio-recorded with consent and transcribed verbatim for subsequent analysis.

Data analysis follows a thematic coding process, combining both manual coding for interpretive sensitivity and NVivo software for systematic data management. Initial open coding identifies recurring concepts, followed by axial coding to organize these into broader themes such as opportunities, challenges, and strategic enablers. Finally, selective coding integrates themes into a coherent analytical framework aligned with the research objectives.

The analysis proceeds through five key steps: familiarization with the data, initial coding, theme development, theme review and refinement, and final interpretation. This iterative process ensures analytic rigor, enabling the study to generate nuanced insights into the interplay between project management practices and AI adoption in manufacturing engineering.

4. Results

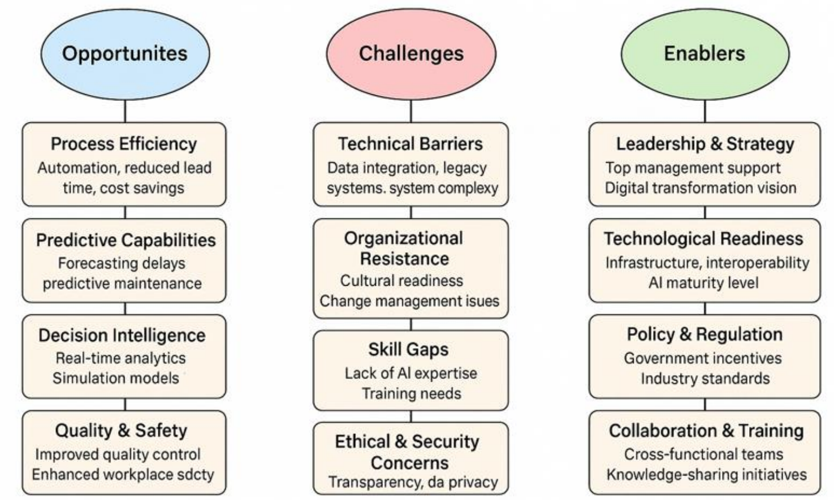
4.1 Thematic analysis of AI adoption opportunities, challenges, and enablers

Figure 1 illustrates the thematic coding map derived from the qualitative interviews, organizing participants' insights into three overarching dimensions: Opportunities, Challenges, and Enablers.

- Opportunities: Participants consistently highlighted AI's potential to improve process efficiency through automation, reduced lead times, and cost savings. Predictive capabilities, particularly for forecasting delays and enabling predictive maintenance, were also emphasized. AI was perceived to enhance decision intelligence by supporting real-time analytics and simulation models, while quality and safety improvements were linked to better defect detection and workplace safety monitoring.
- Challenges: Despite these benefits, participants pointed to critical technical barriers such as data integration complexities and legacy system constraints. Organizational resistance, including cultural readiness and change management difficulties, also emerged as major obstacles. Further, skill and ethical and security concerns regarding data privacy and transparency were recurrent themes.
- Enablers: To address these challenges, interviewees stressed the importance of leadership and strategy, particularly top management support and a clear digital transformation vision. Technological readiness, covering infrastructure and interoperability, was also viewed as essential. Moreover, participants emphasized the need for policy and regulation to provide industry standards and incentives, as well as collaboration and training initiatives to build cross-functional skills and knowledge-sharing cultures.

Overall, the thematic coding map provides a holistic view of the complex interplay between AI's potential benefits, its implementation challenges, and the enabling conditions required for successful adoption.

Figure 1: Thematic coding map of AI adoption opportunities and challenges



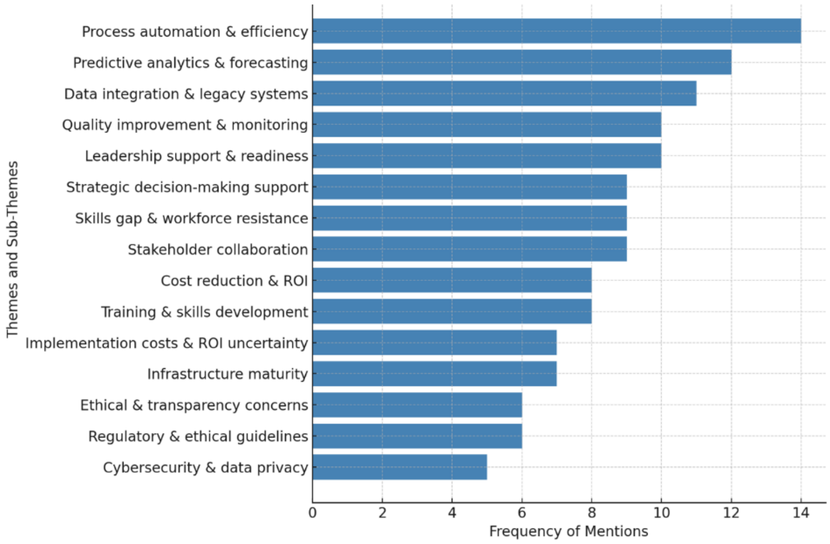
Source: Authors

Figure 2 presents the frequency distribution of the identified themes across interview participants, offering a quantitative perspective on the qualitative findings.

- The most frequently cited opportunities included process automation & efficiency (14 mentions) and predictive analytics & forecasting (12 mentions), underscoring participants' focus on operational optimization and proactive risk management. Data integration & legacy systems (11 mentions) and quality improvement & monitoring (10 mentions) also ranked highly, reflecting concerns about both technological and performance aspects.
- On the enabler side, leadership support & readiness (10 mentions) and strategic decision-making support (9 mentions) were frequently highlighted, reinforcing the role of managerial commitment and informed decision-making in driving AI adoption.
- In terms of challenges, skills gap & workforce resistance (9 mentions) and implementation costs & ROI uncertainty (7 mentions) were frequently raised, pointing to human capital and financial barriers. Ethical and security concerns, including cyber security & data privacy (5 mentions), although less frequent, were still considered significant by participants.

The frequency analysis thus complements the thematic coding map by indicating not only the diversity of issues discussed but also their relative salience across the sample, providing a robust foundation for subsequent discussion and interpretation.

Figure 2: Frequency of identified themes across interview participants



Source: Authors

4.2 Opportunities of AI Adoption in manufacturing project management

The analysis revealed that the adoption of Artificial Intelligence (AI) tools in manufacturing project management creates significant opportunities for improving efficiency, decision-making, and overall project performance. Across the interviews, participants consistently emphasized AI's capacity to transform project practices by reducing manual workloads, enhancing predictive capabilities, and fostering innovation throughout the manufacturing process.

One of the most frequently cited benefits was process automation, where AI tools streamline routine tasks such as scheduling, resource allocation, and production monitoring. This automation not only minimizes human error but also allows project managers to focus on strategic activities rather than administrative coordination. As one participant noted, *"Integrating AI into our scheduling processes cut project delays by nearly 20%, mainly because the system adapts to real-time changes far faster than humans can"* (Participant 3).

Another recurring theme was predictive analytics and risk forecasting. Through real-time data analysis, AI enables early detection of equipment failures, production bottlenecks, and potential project delays. This proactive approach significantly enhances project resilience and operational reliability. One engineering specialist explained, *"Before AI, we relied on past experience to predict risks. Now, real-time analytics show us patterns we couldn't see before, allowing us to act before problems escalate"* (Participant 7).

Participants also highlighted AI's role in data-driven decision-making, particularly through the use of simulation models and digital twins that allow project managers to test multiple scenarios before committing resources. A senior engineer remarked, *"AI-powered simulations allow us to test different project strategies virtually, so we can choose the one with the least cost and risk before execution"* (Participant 11).

Finally, several participants emphasized improvements in product quality and customization. Computer vision systems enable advanced defect detection, ensuring consistent product standards, while AI-powered planning tools support mass customization without sacrificing production efficiency. As one project manager stated, *"AI systems flag even microscopic defects we could never catch manually, which boosts both quality and customer trust"* (Participant 5).

4.3 Challenges in AI Adoption

The findings reveal that while Artificial Intelligence (AI) offers significant potential for improving project management in manufacturing engineering, its adoption is constrained by several interconnected challenges. Across interviews, participants consistently emphasized the technical, organizational, financial, and ethical barriers shaping implementation decisions.

One major concern related to technical barriers, particularly the difficulty of integrating AI systems with existing legacy infrastructures. Many firms rely on fragmented production technologies, where data are dispersed across different platforms and equipment generations, limiting the smooth deployment of AI tools that require real-time, high-quality data. As one participant noted, *"Our production lines generate massive amounts of data, but integrating these into a single AI system is a nightmare because our machines come from different decades and vendors."* This technical complexity often slows down initial pilot projects and inflates implementation costs.

In addition to technical hurdles, organizational resistance was widely reported. Some employees, particularly experienced engineers, expressed skepticism toward AI-driven recommendations, fearing that algorithmic decision-making might undermine their professional expertise or even threaten job security. One project manager explained, *"Introducing AI meant asking our senior engineers to rely on algorithms rather than their own judgment. Some felt threatened, as if we were undermining their expertise."* Compounding this issue is the lack of workforce readiness, as many staff lack the training needed to interpret AI outputs and integrate them effectively into project workflows.

Financial considerations also play a central role. The high initial cost of AI solutions—covering software acquisition, infrastructure upgrades, and training programs—creates hesitation among top management, particularly when return on investment (ROI) remains uncertain in the short term. As one participant put it, *"Top management hesitated because they wanted clear numbers on cost savings before committing, but AI doesn't give immediate results."* This concern reflects the broader organizational risk perception surrounding emerging technologies in manufacturing settings.

Finally, ethical and security concerns were frequently raised, especially regarding algorithmic transparency and data privacy. Some managers were reluctant to delegate critical scheduling or resource allocation decisions to AI systems whose internal reasoning remained opaque, while others worried about cybersecurity vulnerabilities when AI platforms connected with external suppliers or cloud-based systems. As one participant noted, *"If the AI recommends delaying a shipment or changing production priorities, we need to understand why. Blind trust is not acceptable."*

Taken together, these findings highlight that AI adoption in manufacturing project management is not purely a technological decision. It requires organizational change management, strategic financial planning, and robust governance mechanisms to address resistance, skill gaps, investment hesitations, and ethical risks. Without confronting these barriers holistically, the transformative potential of AI remains difficult to realize in practice.

4.4 Enablers for Successful AI Integration

Despite the multiple challenges surrounding the adoption of Artificial Intelligence (AI) in manufacturing project management, participants highlighted several key enablers that can significantly improve the likelihood of successful integration. These factors span managerial, technological, organizational, and institutional dimensions, illustrating that AI adoption depends as much on human and strategic readiness as on technological capacity.

Foremost among these enablers is strong leadership commitment and strategic vision. Several participants emphasized that top management support is essential not only for financial investment but also for building organizational confidence in AI systems. As one project manager noted, *"When senior leaders clearly articulate why AI matters for our competitiveness, employees are more willing to experiment with new tools."* Leadership involvement also ensures that AI initiatives align with broader organizational goals rather than being perceived as isolated technological experiments.

Equally critical is technological readiness, particularly the development of robust digital infrastructures and interoperable systems capable of supporting real-time data analytics. Participants explained that initial investments in data integration platforms and cloud-based architectures created a solid foundation for AI tools to function effectively. One engineer observed, *"Once we had a unified data platform, integrating AI for predictive maintenance became much smoother because the systems could finally talk to each other."*

Another frequently cited enabler was employee training and capacity building. Participants underscored the need for structured programs that equip staff with both the technical knowledge to interpret AI outputs and the managerial skills to integrate algorithmic insights into decision-making. As one participant explained, *"AI adoption is not just about technology; it's about people learning to trust and use it effectively."* This emphasis on human capital development reflects findings in prior studies linking digital transformation success to workforce readiness and learning culture (Papadopoulos et al., 2021).

Additionally, cross-functional collaboration and stakeholder engagement emerged as important enablers. Many participants described how collaboration among IT teams, project managers, engineers, and external technology providers accelerated problem-solving and reduced resistance to change. Policy frameworks and clear governance mechanisms were also highlighted, particularly in relation to ethical concerns and data security. By establishing transparent rules for algorithmic decision-making, firms were able to build trust among employees and external partners.

5. Discussion

5.1 Interpretation of findings in light of prior literature

The findings confirm and extend earlier studies emphasizing AI's transformative potential in manufacturing and project management. Consistent with prior research, opportunities centered on process automation, predictive analytics, data-driven decision-making, and product quality improvements highlight AI's role as a strategic asset enabling operational efficiency and competitive differentiation (Zahaib Nabeel, 2024).

However, this study advances the literature by demonstrating that these opportunities remain contingent on organizational readiness and leadership vision, aligning with the TOE framework's emphasis on technological, organizational, and environmental factors (Tornatzky & Fleischer, 1990).

Furthermore, the results resonate with TAM's constructs of perceived usefulness and perceived ease of use (Davis, 1989), as participants linked successful adoption not only to technical feasibility but also to user trust, training, and clear communication from management. Similarly, UTAUT's dimensions, particularly performance expectancy, social influence, and facilitating conditions were evident, as employee willingness to engage with AI tools increased when peers, supervisors, and organizational culture collectively supported the transition.

5.2 Managerial and Policy Implications

From a practical standpoint, the results offer actionable insights for manufacturing firms and policymakers.

- For managers, the study underscores the need to prioritize change management strategies alongside technological investments. Leadership commitment should translate into clear communication of AI's strategic value, employee training programs, and incentive structures that encourage adoption rather than resistance.
- For technology teams, ensuring data integration and system interoperability emerges as a prerequisite for AI effectiveness. Investments in unified data platforms and cybersecurity infrastructures should accompany AI deployments to mitigate technical and ethical risks.
- For policymakers and industry regulators, the findings point to the importance of standardized governance frameworks, ethical guidelines, and financial incentives (e.g., tax credits, innovation grants) that can accelerate AI adoption while safeguarding data privacy and workforce interests.

Collectively, these implications highlight that AI adoption requires multi-level coordination among organizational leaders, technical experts, employees, and regulatory bodies.

5.3 Limitations and Directions for Future Research

While offering rich insights, this study has certain limitations that open avenues for future research. First, the qualitative design captures in-depth perspectives but limits the generalizability of findings across broader manufacturing contexts. Future studies could employ mixed-method or longitudinal designs to examine how adoption dynamics evolve over time.

Second, this research focuses on the manufacturing sector; comparative studies across industries such as healthcare, logistics, or construction could reveal sector-specific barriers and enablers.

Finally, quantitative modeling using structural equation modeling (SEM) could test relationships among opportunities, challenges, enablers, and performance outcomes, providing causal insights beyond the exploratory scope of the current study.

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