

Artificial Intelligence in Manufacturing: A Systematic Literature Review of Applications, Adoption Challenges, and Performance Outcomes

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Abstract

Artificial intelligence (AI) is rapidly transforming manufacturing by enhancing process intelligence, operational efficiency, product quality, and supply chain responsiveness. Despite growing scholarly attention, the existing review literature remains fragmented, with most studies focusing either on AI applications or performance outcomes, while giving limited attention to the adoption challenges that shape implementation success. This gap is critical because manufacturing firms need a more integrated understanding of what AI can do, what barriers may arise during adoption, and how these factors influence actual performance outcomes. Addressing this need, the present study conducts a systematic literature review of 34 peer-reviewed articles published between 2019 and 2024 to examine AI applications, adoption challenges, and performance outcomes in manufacturing. Using a combined qualitative thematic synthesis and descriptive statistical analysis, the review identifies predictive maintenance, automated quality control, inventory optimization, process bottleneck detection, and predictive logistics as the most prominent AI applications. The findings show that AI generally improves efficiency, productivity, quality, and responsiveness; however, these benefits are uneven across sectors, firm sizes, and implementation contexts. Major adoption challenges include high investment costs, data quality issues, system integration difficulties, skills shortages, and organizational resistance, with SMEs facing particularly acute constraints. The review highlights that the value of AI in manufacturing depends not only on technological capability, but also on organizational readiness, governance, and strategic alignment. By integrating applications, adoption challenges, and performance outcomes within a single review, this study offers a more comprehensive evidence base for researchers and provides practical guidance for firms seeking to make informed AI adoption decisions.

Keywords: Artificial intelligence, Manufacturing industry, Industry 4.0, Organizational performance, Technological implementation, AI adoption, implementation challenges, performance outcomes.

1. Introduction

Artificial intelligence (AI) has quickly become one of the most influential technologies in today's industrial sector (Al-haimi et al., 2025), fundamentally changing how manufacturing companies plan, implement, and improve their processes. Powered by developments in machine learning (ML), deep learning, the Internet of Things (IoT), and large-scale data analysis, AI is increasingly integrated throughout the manufacturing supply chain, from sourcing raw materials and planning production to quality control and post-sales services. As global markets become more competitive and unpredictable, leveraging AI-based process intelligence has become essential for manufacturers aiming for operational excellence, flexibility, and long-term competitive advantage (Hassan et al., 2024; Moreira et al., 2023; Żywiołek 2024).

Within manufacturing environments, AI has demonstrated measurable impacts in key areas. Predictive maintenance leverages ML algorithms to forecast equipment failures before they occur, reducing unexpected downtime and extending asset lifespan (Sandu, 2023; Waqar et al., 2023). AI-powered quality control enables real-time defect detection and alerts for process deviations, improving yield and consistency on a large scale (Sandu, 2023). Process optimization tools utilize reinforcement learning and adaptive controls to enhance throughput, energy efficiency, and resource management across various production settings, from rubber manufacturing to semiconductor fabrication (Sandu, 2023). Outside the shop floor, AI plays a vital role in supply chain management, supporting demand forecasting, inventory control, logistics routing, and risk assessment, building resilience in complex global networks (Chukwu et al., 2024; Narayanan et al., 2024; Onu et al., 2023). As Industry 5.0 progresses, AI now also emphasizes human-centric co-production, generative AI for product design, and frameworks that promote automation while protecting workforce wellbeing and social responsibility (Ahmad et al., 2022; Hassan et al., 2024; Sande et al., 2024; Sira, 2023). Despite its broad and expanding potential, turning AI capabilities into practical implementation remains complex. Adopting AI in manufacturing involves more than just technical setup; it requires aligning organizational culture, workforce skills, data governance, infrastructure, and compliance, each presenting unique challenges. Financial barriers like high initial costs and uncertain ROI are significant, especially for SMEs and companies in developing countries with limited capital (Babu & Vasumathi, 2023; Folorunso et al., 2024; Moreira et al., 2023; Pinsky et al., 2024). Technical hurdles such as data quality, availability, and integration with legacy systems can slow or hinder AI projects (Babu & Vasumathi, 2023; Bolocan et al., 2025; Narayanan et al., 2024). Organizational resistance, low AI literacy, and job displacement fears also block adoption, even where AI benefits are clear (Hassan et al., 2024; Joshi et al., 2022; Moreira et al., 2023; Waqar et al., 2023). Governance issues, like the lack of transparency in AI decisions, accountability concerns, and changing regulations, add further complexity, especially in high-stakes or public manufacturing settings (Alhosani & Alhashmi, 2024; Pinsky et al., 2024; Sande et al., 2024; Sira, 2023).

Evidence on AI's performance in manufacturing is generally positive but depends on context. Research shows efficiency, productivity, and quality improvements due to AI, but the extent of these benefits varies based on data ecosystem quality, workforce involvement, and governance structures (Narayanan et al., 2024; Onu et al., 2023; Sandu, 2023). A common finding is the performance gap between AI systems tested in labs and those used in real-world manufacturing, where challenges like data drift, system integration issues, and workflow mismatch can significantly reduce potential gains (Bolocan et al., 2025; Sande et al., 2024; Sira, 2023). This highlights the importance of implementation science, the study of how to effectively integrate AI into manufacturing, to achieve and maintain AI's expected value (Bolocan et al., 2025; Pinsky et al., 2024; Sande et al., 2024).

An increasing number of systematic literature reviews (SLRs) have aimed to synthesize knowledge about AI in manufacturing. Nonetheless, most reviews have taken a limited perspective: some exclusively document AI application types and use cases, while others focus narrowly on performance metrics and efficiency results. Importantly, challenges to adoption—the barriers and enablers influencing whether AI moves from pilot projects to full production—are rarely analyzed as a core aspect alongside applications and performance within the same review. This segmentation creates a notable gap for practitioners and decision-makers. A manufacturing company considering AI investment needs not only to know what AI can do and potential outcomes but also, and more critically, what barriers might arise and how these could impact performance if not addressed. Without a comprehensive view that considers all three aspects together, the risk of making poorly informed decisions, encountering failed implementations, and wasting resources increases. This research addresses that gap by, for the first time in a single SLR, systematically analyzing AI applications, adoption challenges, and performance results, providing companies with the evidence needed to make well-informed decisions before deploying AI.

This paper presents a systematic literature review of AI in manufacturing that integrates all three dimensions within a single, cohesive analytical framework. Academic publications from 2019 to 2024 were systematically identified and screened across major databases, including Scopus, Web of Science, and IEEE Xplore, applying rigorous inclusion and exclusion criteria. The resulting synthesis spans diverse manufacturing sub-sectors and organizational contexts, with particular attention to SMEs and firms in emerging economies, given their distinct adoption profiles and underrepresentation in prior reviews. The review is structured to enable practitioners to prospectively assess the adoption landscape before committing to AI implementation, providing an evidence-based foundation for strategic investment decisions, change management planning, and governance design.

To structure this inquiry, the following three research questions guide the review:

RQ1: What are the primary AI applications being adopted in the manufacturing sector, and across which manufacturing domains and functions are they most prominently deployed?

RQ2: What are the principal challenges that manufacturing firms encounter when adopting AI technologies, and how do these challenges vary across firm size, sector, and geographic context?

RQ3: How does AI adoption affect operational and strategic performance outcomes in manufacturing?

The rest of this paper is organized as follows. Section 2 provides the theoretical background and literature review. Section 3 explains the systematic review methodology, including the search strategy, screening criteria, and analytical approach used. Section 4 presents the findings related to each research question, focusing on AI applications, adoption challenges, and performance outcomes. Section 5 explores overarching themes, practical implications for managers and policymakers, and future research directions. Section 6 offers the conclusions, including an integrative framework that combines the review's main findings and provides strategic guidance for companies navigating AI adoption in manufacturing.

2. Literature Review

In recent years, the manufacturing industry has undergone a profound transformation resulting from the adoption of advanced digital technologies. The need to improve efficiency, respond to an increasingly dynamic market, and enhance product quality has led companies to incorporate smarter and more automated technological solutions (Kamble et al., 2018; Zhong et al., 2017). In this process, artificial intelligence (AI) has positioned itself as one of the fundamental pillars of the so-called Industry 4.0, enabling new forms of process optimization, quality control, and decision-making (Sony & Naik, 2019).

The specialized literature identifies a set of AI applications with a high impact on manufacturing: predictive maintenance, quality analysis using computer vision, logistics automation, supply chain optimization, and product customization through predictive models. These applications are based on technologies such as machine learning, deep learning, robotics, big data analytics, and cloud computing (Wang et al., 2018; Liao et al., 2017). For example, predictive maintenance allows anticipating equipment failures, reducing downtime, while AI-enabled quality control systems improve real-time defect detection and reduce waste (Breckle et al., 2021).

These capabilities are amplified when AI is combined with other enabling technologies such as the Internet of Things (IoT) and cyber-physical systems, resulting in connected, smart factories capable of making automated decisions based on continuous data streams (Tao et al., 2018; Wei et al., 2022). In this new model, data-driven decision-making becomes a strategic pillar of operations, contributing not only to operational efficiency but also to business agility and adaptability.

However, despite its potential, AI implementation is not without its barriers. Studies concur in pointing to significant technical challenges such as the low quality of available data, the lack of integration between systems, and cybersecurity concerns (Nam & So, 2022). At the organizational level, the changes required by digital transformation generate internal resistance, a shortage of specialized talent, and tensions with traditional management methods (Frank et al., 2019). Furthermore, the high initial investment cost and uncertainty about the economic return continue to be factors that influence decision-making in many companies, especially small and medium-sized ones (Moeuf et al., 2018; Carvalho et al., 2019).

Therefore, the reviewed studies agree that integrating AI into manufacturing requires a comprehensive strategic approach that considers technological alignment, organizational readiness, and resource availability. Incorporating advanced tools is not enough; it is essential to transform processes, structures, and competencies, and to foster an organizational culture that facilitates innovation (Egieya et al., 2022).

While the available theoretical framework has made it possible to identify trends, benefits, and barriers surrounding the use of AI in manufacturing, there is a fragmentation in the way these elements have been studied. Many studies focus on isolated cases or specific applications, without offering a systemic view that integrates uses, challenges, and impacts together. Furthermore, gaps persist regarding how these factors vary by sector, company size, or level of technological maturity.

Given this situation, it was deemed necessary to conduct a systematic review of the literature to rigorously and structurally synthesize the available knowledge, answering three key questions: What are the main applications of AI in manufacturing companies? What challenges do organizations face in its implementation? And what impact does AI have on their operational and strategic performance? To answer these questions in a coherent and methodologically sound manner, the following section describes the process followed to select, analyze, and categorize the most relevant studies published between 2019 and 2024.

3. Methodology

This research adopted a methodological approach based on a systematic literature review (SLR) with the aim of rigorously collecting, analyzing, and synthesizing existing knowledge on the role of artificial intelligence (AI) in the performance of manufacturing companies. This methodology was selected for its ability to offer a structured and comprehensive overview of the topic, allowing for the identification of both the most relevant advances and the theoretical and practical gaps in the field of study. To this end, detailed procedures were established at each stage of the process, from the initial search to the analysis of the results.

The bibliographic search was carried out in three high-impact scientific databases: Scopus, Web of Science, and IEEE Xplore. These sources were chosen for their coverage in key areas such as engineering, industrial management, and emerging technologies (Gusenbauer & Haddaway, 2020; Mongeon & Paul-Hus, 2016). In addition, Google Scholar was used as a complementary resource to identify potentially relevant studies that may have been left out of the main results.

Search strings included terms related to artificial intelligence (such as "machine learning," "deep learning," or "intelligent systems"), manufacturing context (e.g., "smart manufacturing" or "industry 4.0"), and effects on organizational performance (such as "efficiency," "performance," or "productivity"). Boolean operators were used to appropriately combine concepts, and filters were applied to narrow the results to peer-reviewed, English-language articles published between 2019 and 2024. The search string in Scopus was:

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TITLE ( "AI" OR "AI" ) AND ( "manufacturing firm" OR "manufacturing industry" ) AND ( "performance" OR "operational efficiency" ) AND PUBYEAR > 2019 AND PUBYEAR < 2025 AND ( LIMIT-TO ( SRCTYPE , "j" ) ) AND ( LIMIT-TO ( OA , "all" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( SUBJAREA , "BUSI" ) OR LIMIT-TO ( SUBJAREA , "DECI" ) OR LIMIT-TO ( SUBJAREA , "ECON" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) )
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And this search string was adapted for each database, based on the syntax used and the specific search features.

Once the initial sample was obtained, inclusion and exclusion criteria were established to ensure the relevance and quality of the selected studies. Only papers that explicitly addressed the use of AI in manufacturing companies, analyzed technical, organizational, or economic barriers to its implementation, and offered empirical evidence of its impact on performance metrics were included. Conversely, studies focused on other sectors (such as healthcare or education), theoretical articles without practical applications, and non-peer-reviewed literature were excluded. From an initial sample of 256 documents, and after a filtering and full-reading process, 34 studies that met all the established requirements were selected (Figure 1).

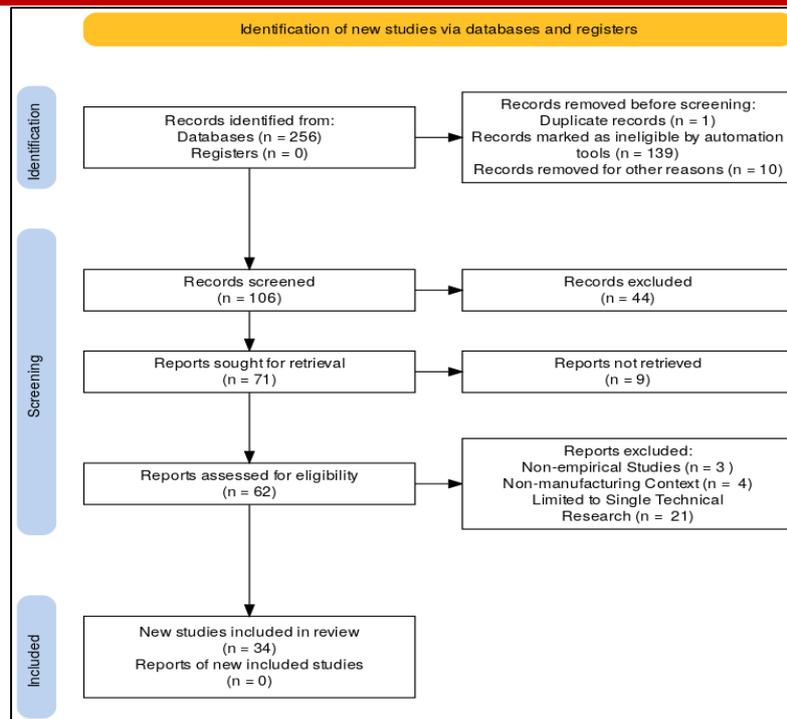


Figure 1. Sample selection process. Source: Own elaboration.

To organize and analyze the data extracted from the selected articles, a coding system was designed to uniformly classify the information. This system considered aspects such as the specific AI applications described in the studies (including predictive maintenance, quality control, inventory optimization, bottleneck detection, and predictive logistics), the technologies used (e.g., machine learning, computer vision, IoT, or digital twins), organizational impact indicators (such as operational efficiency, productivity, cost reduction, and business value), and the main challenges identified in the literature. These challenges were grouped into three interrelated categories: technical (difficulties in systems integration, data quality, real-time processing requirements), organizational (resistance to change, lack of technical skills, need for cultural transformation), and financial (high initial costs, lengthy maintenance, uncertainty about return on investment). Data analysis was approached from two perspectives. On the one hand, a qualitative thematic analysis was conducted to identify recurring patterns, causal relationships, and research gaps around the three questions posed by the study: what AI applications are used in manufacturing, what barriers companies face in implementing them, and what impact these technologies have on organizational performance. On the other hand, a descriptive statistical analysis was applied to visualize the frequency of use of different technologies, the distribution of applications by industrial sectors and geographic regions, as well as the presence of specific challenges based on the size or level of technological maturity of organizations. This mixed approach allowed for the coherent integration of quantitative and qualitative evidence, ensuring a deep and contextualized understanding of the phenomenon studied. Throughout the process, quality controls were implemented to guarantee the validity and reliability of the results. The studies were evaluated following the methodological guidelines proposed by Kitchenham and Charters (2007), focusing on clarity of objectives, robustness of research design, transparency in analysis methods, and consistency in the presentation of results. In addition, an inter-researcher cross-validation strategy was applied to reduce bias in the selection and classification of articles. This rigorous approach consolidated a robust evidence base that supports the conclusions of this work, providing theoretical clarity and practical utility in a rapidly evolving field such as artificial intelligence applied to the manufacturing sector.

4. Results

The results from the analysis of the 34 selected studies enable a structured response to the three research questions posed in this paper. To this end, the findings were organized into three thematic sections that address, respectively, the main applications of artificial intelligence in the manufacturing industry (RQ1), the challenges and barriers organizations face in its implementation (RQ2), and the impact these technologies have on companies' operational, economic, and strategic performance (RQ3). The results corresponding to each of these dimensions are detailed below and integrated and fully presented in Figure 7.

4.1 RQ1: AI Applications in the Manufacturing Sector: The systematic review identified five major areas of artificial intelligence (AI) application in the manufacturing sector: predictive maintenance, quality management, inventory optimization, bottleneck detection, and predictive logistics (Figure 2). However, these applications are unevenly distributed across industry types, geographic regions, technological maturity, and the degree of digital integration within organizations.

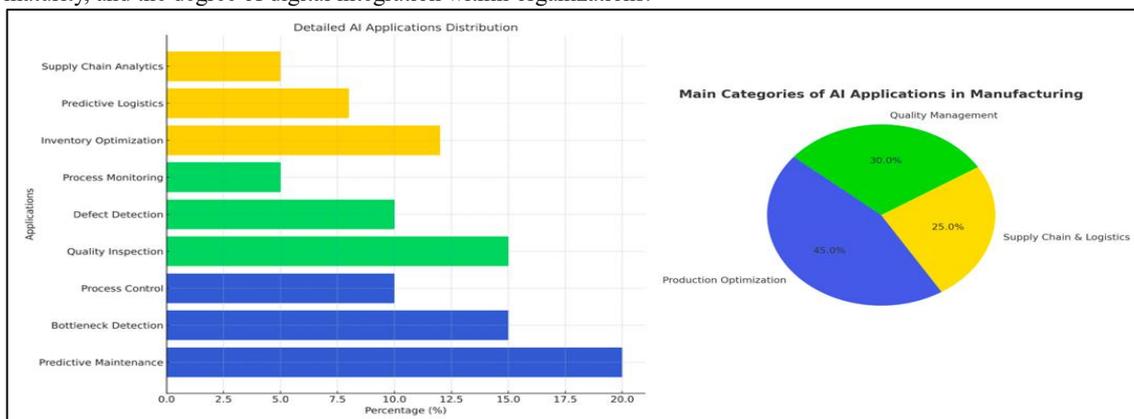


Figure 2. AI applications in manufacturing companies: detailed distribution and main categories by percentage of occurrence in the selected articles. Source: Own elaboration

“Predictive maintenance” is the most widespread application and stands out as the most mature, especially in Europe. This application combines deep learning and IoT to predict equipment failures before they occur, reduce downtime, increase machine availability, and optimize maintenance cycles (Yu et al., 2020; Bokrantz et al., 2024). High-value sectors, such as automotive and aerospace, have shown clear improvements in equipment reliability and reduced operating costs thanks to this technology (Tortorella et al., 2024; Gholami, 2024). Technologies such as 5G and generative AI are projected to expand their capabilities to remote maintenance (Monteiro et al., 2023; Zahoor et al., 2024). In “quality management,” AI, along with computer vision and digital twins, enables real-time monitoring, accurate defect detection, and proactive prevention in production processes, ensuring greater consistency in quality standards and reducing error and waste rates (Wang et al., 2024a; Valaskova et al., 2024). These solutions have improved product consistency even in small and medium-sized enterprises (SMEs), and their integration with generative AI and 5G connectivity is expected to accelerate the digital transformation of quality processes (Akhtar et al., 2024). “Inventory optimization” combines the use of machine learning algorithms and natural language processing (NLP) to dynamically manage the supply chain, improving replenishment, anticipating demand, minimizing outdated products, and reducing storage costs. Recent studies highlight benefits in operational efficiency and return on investment (ROI) from this application (Bokrantz et al., 2024; Peretz-Andersson et al., 2024). However, challenges persist in ERP integration, data governance, and information quality (Chen et al., 2024). Its adaptability to emerging markets has also been documented (Doanh et al., 2023).

“Bottleneck detection”, using techniques such as hierarchical clustering and time series analysis (Dynamic Time Warping), enables near-real-time monitoring of production processes, allowing companies to identify and correct constraints. Applications in the automotive industry have demonstrated tangible improvements in efficiency and cycle time reduction (Bokrantz et al., 2024; Chen et al., 2024). The trend points toward synergistic integration with predictive maintenance and quality control for more comprehensive solutions (Yu et al., 2020).

Finally, “predictive logistics” combines AI with real-time data to optimize delivery routes, predict delays, and mitigate logistical risks. This application has gained relevance in global contexts, where supply chains are increasingly complex and vulnerable. While it offers clear benefits in operational resilience and sustainability (Sharabati et al., 2024; Chen et al., 2024), it faces challenges such as data quality, cross-system compatibility, and high initial costs, especially in emerging economies (Hatamlah et al., 2023). Future solutions are geared toward more scalable, sustainable, and collaborative platforms.

In summary, AI applications in manufacturing have diversified and specialized, covering everything from operational tasks to strategic processes. However, its effective adoption depends on factors such as technological infrastructure, data availability, and organizational preparedness. In terms of sectors, the aerospace, electronics, and automotive industries lead adoption (Bustanza et al., 2024), although AI penetration depends heavily on digital infrastructure, investment, and internal capabilities (Pillai et al., 2022). Geographically, developed countries adopt more advanced technologies, while emerging markets focus on basic automation (Horobet et al., 2024; Doanh et al., 2023).

Technological integration with big data, IoT, blockchain, and digital twins is key to scaling these solutions (Dey et al., 2024; Chen et al., 2024). Looking ahead, significant growth is expected in applications based on generative AI and 5G networks, with an emphasis on contextualized and adaptive solutions (Wong et al., 2024; Zahoor et al., 2024).

4.2 RQ2: Challenges in AI Implementation: The implementation of artificial intelligence (AI) in the manufacturing industry faces multiple challenges that vary depending on the size, location, and level of digital maturity of organizations. These challenges fall into three main categories: technical, organizational, and financial (Figure 3). These obstacles not only hinder initial adoption but can also compromise the long-term sustainability of AI projects if not properly addressed.

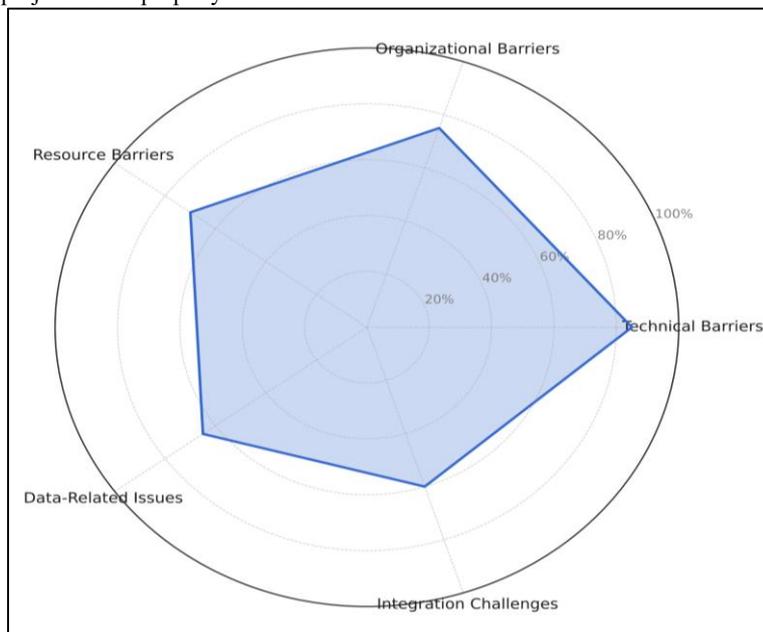


Figure 3. Distribution of implementation challenges. Source: Own elaboration.

From a “technical” perspective, one of the biggest challenges is data quality, availability, and standardization, which are essential for training reliable models (Figure 4). AI relies on large volumes of labeled and consistent data, but many companies face limitations in their information capture and management systems, and variability across plants makes it difficult to create generalizable systems (Doanh et al., 2023; Wang et al., 2024b). Furthermore, integrating AI solutions with existing enterprise systems (such as ERP or MES) poses complex challenges, especially when scaling tools such as digital twins or predictive maintenance (Bokrantz et al., 2024; Horobet et al., 2024; Wang et al., 2024b). Another major technical obstacle is real-time processing capacity, which is essential in applications such as quality control or human-robot collaboration (Asaad et al., 2024). Furthermore, it should be noted that SMEs also face structural infrastructure and cybersecurity constraints that hinder technology adoption (Binsaeed et al., 2023).

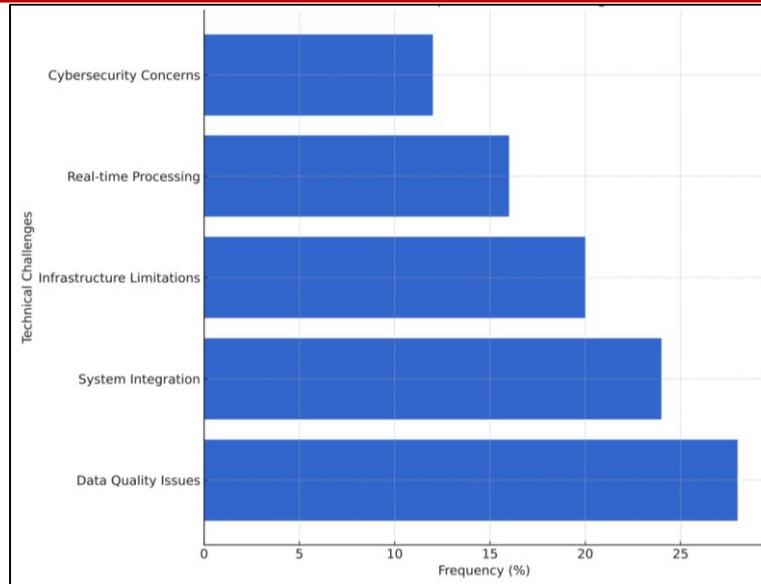


Figure 4. Technical implementation challenges based on the percentage of appearances in the selected articles. Source: Own elaboration.

Regarding "organizational challenges", the lack of specialized talent stands out. Many companies lack professionals with skills in data science, AI engineering, or advanced analytics (Chatterjee et al., 2021; Zahoor et al., 2024). This deficit is accentuated in SMEs and in regions with less technological development. There is also a strong resistance to cultural change, where the introduction of new technologies generates fears about job loss or the disruption of established routines, which requires effective change management (Horobet et al., 2024). The success of AI depends largely on employees' willingness to adopt new tools and on leadership alignment with the digital strategy (Dey et al., 2024). And on the "financial" side, high initial investment costs represent a critical barrier, especially for small and medium-sized businesses. These costs include not only the acquisition of technology but also process redesign, staff training, and ongoing maintenance. Added to this is the uncertainty surrounding return on investment (ROI), which leads many organizations to be reluctant to take risks without guarantees of tangible benefits (Horobet et al., 2024; Sharabati et al., 2024). Another cross-cutting factor is "regulatory fragmentation", particularly in international projects. The lack of uniform regulations hinders the integration of AI into global supply chains, affecting interoperability, data sharing, and standards compliance (Sharabati et al., 2024; Liang et al., 2022). These gaps hinder the creation of scalable and reliable solutions, especially in sectors with critical or data-intensive processes (Yu et al., 2020). Furthermore, concerns related to data privacy, cybersecurity, and ethics persist in the use of autonomous algorithms for decision-making. Faced with these challenges, some reviewed studies propose mitigation strategies such as developing internal capabilities through ongoing training, adopting interoperability standards, collaborating with technology partners, and using open-source platforms to reduce costs. They also highlight the importance of institutional support and public policies that promote AI adoption through tax incentives or industrial digitalization support programs. The literature identifies both technical and organizational solutions: from tools such as middleware, integration protocols, or fuzzy logic to internal mechanisms for strategic alignment, specialized training, and knowledge sharing (Wally et al., 2021; Binsaeed et al., 2023). In the case of SMEs in particular, the efficient use of resources depends on orchestration strategies and participation in collaborative ecosystems (Peretz-Andersson et al., 2024; Sjödin et al., 2021). Three factors emerge as key enablers of this process: a robust digital infrastructure, the ability to capture value from the ecosystem, and active leadership engagement (Valaskova et al., 2024; Bustinza et al., 2024). Finally, several studies advocate adopting a systemic perspective that considers aspects such as cybersecurity, human-machine integration, and organizational resilience as essential elements for achieving a sustainable and scalable implementation of artificial intelligence (Horobet et al., 2024; Asaad et al., 2024).

4.3 RQ3: Impact of AI Applications on Company Performance: The analysis of the selected studies reveals that the adoption of artificial intelligence has a significant and multifaceted impact on the performance of manufacturing companies (Figure 5). These effects manifest at different levels: operational, organizational, economic, and strategic.

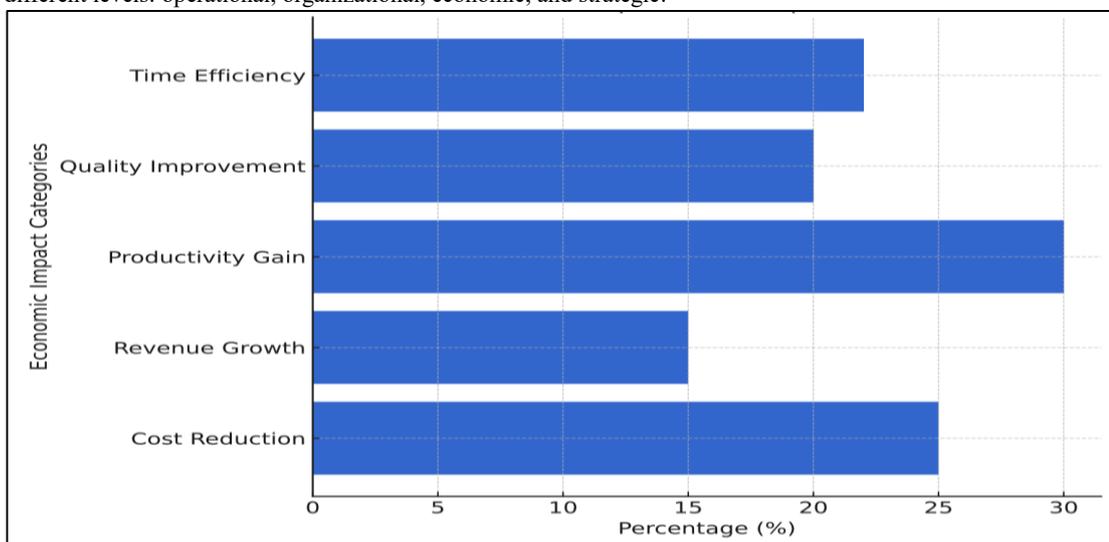


Figure 5. Economic impact of AI applications on company performance based on the percentage of appearances in the selected articles. Source: Own elaboration.

At the “operational” level, AI has been shown to substantially improve process efficiency, quality control accuracy, and the reliability of production systems. Manufacturing companies have reported significant increases in productivity and quality (Wang et al., 2024b; Valaskova et al., 2024), driven by the use of digital twins, predictive maintenance, and intelligent monitoring systems (Yu et al., 2020; Gholami, 2024). For example, predictive maintenance has increased equipment availability from 75% to 92%, while computer vision-based quality control has reduced defect rates by up to 10% (Wang et al., 2024b). These technologies facilitate proactive decisions and better knowledge management (Monteiro et al., 2023; Leoni et al., 2022), which translates into increased productivity, reduced cycle times, and fewer losses due to unplanned downtime. Likewise, AI enhances “organizational resilience” by improving the response capacity to supply chain disruptions or demand fluctuations. Predictive analytics tools and digital twin simulations allow for anticipating adverse scenarios and making more informed decisions (Dey et al., 2024; Leoni et al., 2022; Yu et al., 2020).

From an “economic” perspective, the implementation of AI contributes to cost optimization and increased profitability. Various studies report significant savings in companies of different sizes derived from improved inventory management, energy efficiency, and waste reduction (Binsaeced et al., 2023; Peretz-Andersson et al., 2024). Furthermore, there is a drive toward value innovation, product customization, agile design, and scalable production, which transforms business strategies toward a more digital, profitable, and sustainable economy (Bustinza et al., 2024; Akhtar et al., 2024; Doanh et al., 2023). Furthermore, it has been found that companies that systematically integrate AI improve their financial results and the quality of their accounting reports (Monteiro et al., 2023), thus strengthening their position with investors and other stakeholders. At the “strategic” level, AI enables new capabilities for innovation, organizational agility, and adaptability, strengthening competitive positioning. Technologies such as generative design, additive manufacturing, recommender systems, digital twins, and IoT enable the launch of personalized products, shorten development times, and respond more quickly to market changes. This translates into a sustainable competitive advantage, especially in highly demanding sectors such as automotive, electronics, and aerospace (Valaskova et al., 2024; Yu et al., 2020) (Figure 6). Furthermore, recent studies highlight how dynamic process reconfiguration, human-AI collaboration, and more effective knowledge management enable organizations to better adapt to changing scenarios and respond more effectively to environmental disruptions (Gholami, 2024; Bendoly et al., 2024; Kopka & Fornahl, 2024).

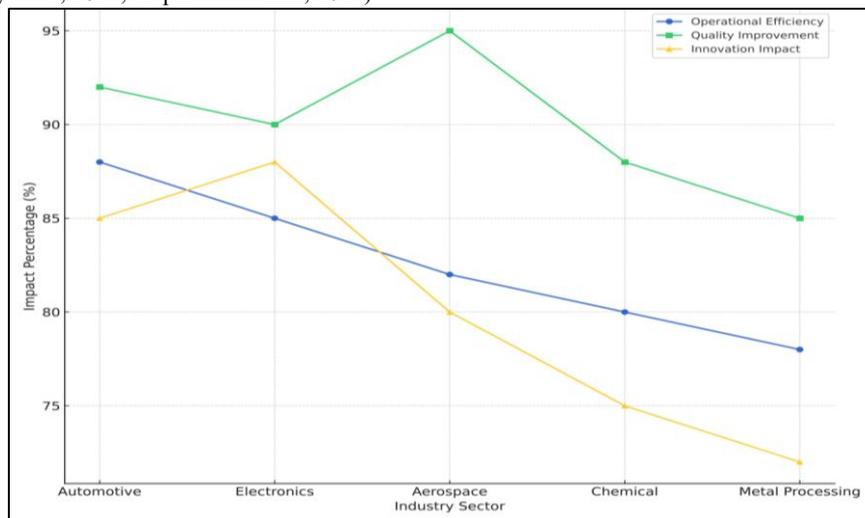


Figure 6. Analysis of the impact of AI on some industry sectors. Source: (Valaskova et al., 2024; Yu et al., 2020).

However, the impact of AI is not uniform. It varies by company size, industry sector, geographic region, and level of technological maturity. Large companies tend to achieve greater benefits due to their investment capacity and scalability, while SMEs face greater barriers to capitalizing on these technologies (Peretz-Andersson et al., 2024). In turn, geographic factors such as digital infrastructure and the local regulatory environment directly impact the effectiveness of AI-based solutions (Dey et al., 2024; Binsaeced et al., 2023). Sectoral differences are also reflected in the levels of technological adoption and the results achieved (Monteiro et al., 2023).

Overall, the results of the review show that AI not only improves short-term performance indicators, but also profoundly transforms the way manufacturing companies operate, compete, and innovate. Despite existing barriers, organizations that adopt comprehensive implementation strategies aligned with their internal capabilities and strategic objectives are able to maximize the value of artificial intelligence on their path to operational excellence.

5. Discussion

After analyzing the findings from the systematic review, this section interprets the results and addresses their theoretical and practical implications. The discussion is structured around three main axes: the essential elements that determine the success of AI implementation in manufacturing, the phases and processes that organizations follow to effectively adopt it, and the theoretical contributions that emerge from the study, along with proposals for future lines of research. This analysis allows us to understand the complexity of the phenomenon beyond the data and offers a solid basis for strategic decision-making and the development of conceptual frameworks in the field of industrial digital transformation.

5.1 Key Elements and Paths to AI Implementation in Manufacturing: The effective integration of artificial intelligence (AI) in the manufacturing industry cannot be approached solely from a technological perspective. Evidence gathered through a mixed-methods approach, qualitative thematic analysis to identify patterns and causal relationships, along with descriptive statistical analysis on usage frequencies and sectoral and geographic distribution, suggests that the successful adoption of these technologies depends on the interaction of three fundamental elements: available technological resources, organizational capabilities, and the institutional environment or industrial ecosystem (Bokrantz et al., 2024; Horobet et al., 2024). From a “technological” perspective, the data show that the combination of AI with other technologies such as the Internet of Things (IoT), digital twins, and real-time data analytics has been key for applications such as predictive maintenance, quality management, and bottleneck detection. These integrations have enabled improvements in efficiency, defect reduction, and process optimization in sectors such as automotive, aerospace, and electronics (Tortorella et al., 2024; Valaskova et al., 2024). For example, the combination of AI with digital twin technologies has made it possible to reduce defects and reconfigure production lines in real time, while deep learning-based systems have been able to detect anomalies with significantly greater accuracy (Wang et al., 2024b).

These technological breakthroughs are framed within a sociotechnical perspective, where AI not only improves operational efficiency but also amplifies human capabilities. This is evidenced by studies showing how AI, when integrated with organizational expert knowledge, enables more accurate and faster decision-making (Tortorella et al., 2024). This approach aligns with sociotechnical systems theory, which posits the need for coevolution between the technical and social aspects to achieve sustained organizational performance (Baxter & Sommerville, 2011). From an "organizational perspective", the reviewed studies agree that AI implementation requires an internal structural transformation. It is not just about introducing technological tools, but also about redesigning processes, adapting structures, and fostering a culture oriented toward continuous change (Monteiro et al., 2023). According to dynamic capabilities theory (Helfat, 2007), companies must acquire new competencies, such as digital leadership, data governance, and analytical skills, that allow them to absorb and exploit emerging technologies. Qualitative analysis revealed that organizations with greater digital maturity and agile organizational structures showed better adoption results, especially in scenarios where AI was integrated as part of a cross-cutting digital transformation strategy (Sharabati et al., 2024).

Furthermore, statistical analysis indicated significant differences depending on the size and maturity level of organizations. Large companies exhibit a greater capacity to coordinate technical and human resources, while SMEs face limitations in talent, financing, and organizational culture, making them more vulnerable to implementation failures (Pillai et al., 2022; Peretz-Andersson et al., 2024).

Finally, the "institutional environment" emerges as a key factor that can facilitate or inhibit AI adoption. Factors such as the level of regional digital infrastructure, the availability of specialized talent, public incentive policies, and the existence of industrial collaboration networks directly impact the level of technological maturity achieved by companies (Dey et al., 2024; Chen et al., 2024). In contexts such as Western Europe and North America, quantitative analysis revealed a higher density of advanced AI initiatives, while in emerging regions, adoption is limited to basic automation solutions due to structural constraints (Doanh et al., 2023; Horobet et al., 2024).

In sum, the findings show that AI adoption in manufacturing should not be approached as an isolated technological intervention, but rather as a "systemic" process that requires strategic alignment, cultural transformation, and coordination with the institutional environment. Effective implementation occurs when a flexible technological infrastructure, dynamic organizational capabilities, and a political-institutional environment that facilitates experimentation and scaling come together. As recent literature points out, concepts such as "digital integration maturity" and "predictive organizational capability" offer new theoretical perspectives for understanding AI adoption processes in complex industrial contexts (Dogru & Keskin, 2020; Teichert, 2019).

5.2 Phases and Processes for the Effective Adoption of AI: The empirical evidence analyzed indicates that the implementation of artificial intelligence (AI) in the manufacturing sector follows an evolutionary process, comprised of distinct phases that, while not necessarily linear, share common patterns in terms of organizational learning, technological maturity, and strategic alignment. This analysis is based on a mixed methodology that allowed combining qualitative patterns derived from thematic analysis with quantitative information on sector distribution and adoption levels in different regions and organizational sizes.

In an initial phase, organizations typically focus on executing pilot projects or proofs of concept. These early applications often concentrate on narrow areas such as predictive maintenance, failure analysis, or automated visual inspection (Tortorella et al., 2024; Valaskova et al., 2024). These initiatives allow for familiarization with the technologies and assess their viability in real-world environments. However, the data analyzed show that many of these efforts fail to scale due to technical barriers, such as integration with legacy systems, or the lack of a long-term strategic vision (Bokrantz et al., 2024; Wang et al., 2024b).

As they move into a second phase, organizations begin to accumulate practical experience and develop more robust capabilities. This stage is marked by the formation of multidisciplinary teams, the definition of scalable technological architectures, and investment in human capital, especially in analytical skills and data management (Monteiro et al., 2023; Chatterjee et al., 2021). AI then begins to be integrated transversally into different business units, no longer as an isolated experiment, but as a fundamental part of the operating model and organizational strategy. During this process, organizational learning becomes a pillar for capability consolidation. As Argote and Miron-Spektor (2011) point out, knowledge systematization, reflection on errors, and the ability to adapt are key to evolving toward more sophisticated models of technological integration. This review found that companies with the best AI performance are those that have developed internal mechanisms to iteratively evaluate their implementations and adjust their practices based on the data obtained (Zahoor et al., 2024; Horobet et al., 2024).

Interfunctional coordination also plays a decisive role. The thematic approach identified that successful implementation requires alignment between technical, operational, and management areas, avoiding friction and promoting synergies (Sharabati et al., 2024). Added to this is the need for structured change management processes, including ongoing training, effective internal communication, and active staff engagement, especially in contexts where cultural resistance can hinder adoption (Chatterjee et al., 2021; Dey et al., 2024).

Furthermore, statistical analysis showed that the degree of technological maturity significantly influences organizations' ability to move toward more integrated adoption phases. Larger companies, with greater resources and more complex structures, tend to move more quickly to advanced implementation phases. In contrast, SMEs often face greater challenges scaling their initial solutions due to limitations in infrastructure, financing, and specialized talent (Peretz-Andersson et al., 2024; Pillai et al., 2022).

In short, AI adoption in manufacturing should be understood as a progressive and adaptive process, with each phase requiring a specific combination of technical, organizational, and strategic capabilities. Organizations that manage to align their human and technological resources around a shared vision of digital transformation, and that develop iterative learning processes, are the ones that reap the greatest benefits from these technologies. This finding reaffirms the need to design flexible roadmaps, accompanied by technological governance structures and knowledge management models that enable digital evolution to be sustained over time.

5.3 Theoretical Considerations and Future Research Directions: From a theoretical perspective, this study promotes a more comprehensive understanding of AI adoption in manufacturing by demonstrating that its value cannot be explained solely through a technological lens. The findings suggest that AI adoption in manufacturing is best viewed as a multilevel sociotechnical process where technical applications, implementation challenges, and performance outcomes are deeply interconnected. As shown in Figure 7, AI applications such as predictive maintenance, quality management, inventory optimization, bottleneck detection, and predictive logistics are connected to a range of technical, organizational, financial, and governance-related factors that ultimately influence operational, organizational, economic, and strategic results. This view builds on prior research that has often looked at AI applications or performance outcomes separately, without adequately considering the implementation conditions that determine whether AI can generate value in practice (Bokrantz et al., 2024; Dey et al., 2024). A key theoretical contribution of this review is the recognition that successful AI adoption requires the development of new organizational capabilities beyond technology acquisition alone. The evidence suggests that capabilities such as digital operational flexibility, technological integration maturity, predictive decision capacity, and cross-functional coordination play a crucial role in translating AI investments into measurable performance benefits (Dogru & Keskin, 2020; Teichert, 2019). In this sense, AI should be viewed not merely as a tool for process automation, but as an organizational capability that depends on the firm's ability to combine data infrastructure, human skills, leadership commitment, and adaptive routines. Organizations with stronger digital leadership, agile structures, and iterative learning processes appear better positioned to scale AI solutions and convert experimentation into sustained performance gains (Monteiro et al., 2023; Valaskova et al., 2024).

The review also supports the idea that AI adoption in manufacturing is more of a transformative change than just operational. The findings show that implementing AI often requires structural changes, new workflows, stronger human-machine collaboration, and a move toward evidence-based and data-driven cultures. These changes are closely connected to issues of trust, transparency, explainability, and responsible governance, showing that AI cannot be separated from the social and institutional settings where it is used (Gholami, 2024; Bendoly et al., 2024). This is especially clear in the broad challenges shown in Figure 7, including regulatory fragmentation, data privacy, ethics, and governance, all of which impact both how successfully AI is adopted and the results it delivers.

These findings suggest the need to revisit and expand existing frameworks of technology adoption and industrial transformation. Traditional views that focus only on technological readiness or economic efficiency seem not enough to explain the different outcomes of AI adoption across various firms and sectors. Instead, the results point to a more relational and capability-focused approach, where AI success depends on the interaction between technological resources, organizational readiness, workforce skills, governance, and context factors such as firm size, location, and digital maturity. Concepts like digital resilience, dynamic capabilities, organizational learning, and smart industrial ecosystem maturity become increasingly important for understanding why some firms see greater performance improvements from AI than others (Leoni et al., 2022; Kusiak, 2018).

Figure 7 further highlights an important theoretical insight: the link between AI applications and firm performance is not straightforward. Instead, challenges in implementation act as an intermediate factor that can facilitate, delay, or reduce performance improvements. This indicates that outcomes like efficiency, quality, resilience, profitability, innovation, and competitive advantage depend on factors such as data ecosystem quality, governance structures, workforce preparedness, and strategic alignment. This perspective adds to theory by demonstrating that AI-driven value creation in manufacturing is dependent on context, influenced by feedback effects over time, and not guaranteed simply by adoption.

Several future research directions emerge from these findings. First, there is a strong need for longitudinal studies that trace AI adoption over time and examine how implementation challenges evolve at different stages, from experimentation and pilot deployment to scaling and institutionalization. Such studies would offer deeper insights into whether short-term operational gains lead to lasting organizational and strategic advantages, and how firms respond to issues such as model drift, integration complexity, and workforce adaptation over time (Akhtar et al., 2024).

Second, future research should more explicitly examine contextual variation. As shown in Figure 7, both challenges and performance outcomes differ by company size, industrial sector, geographic region, and level of technological maturity. More comparative studies are needed to understand how these contextual factors influence AI adoption pathways, especially in SMEs, emerging economies, and under-digitized industrial environments, which are still underrepresented in the literature despite facing some of the most extreme constraints (Peretz-Andersson et al., 2024; Bendoly et al., 2024).

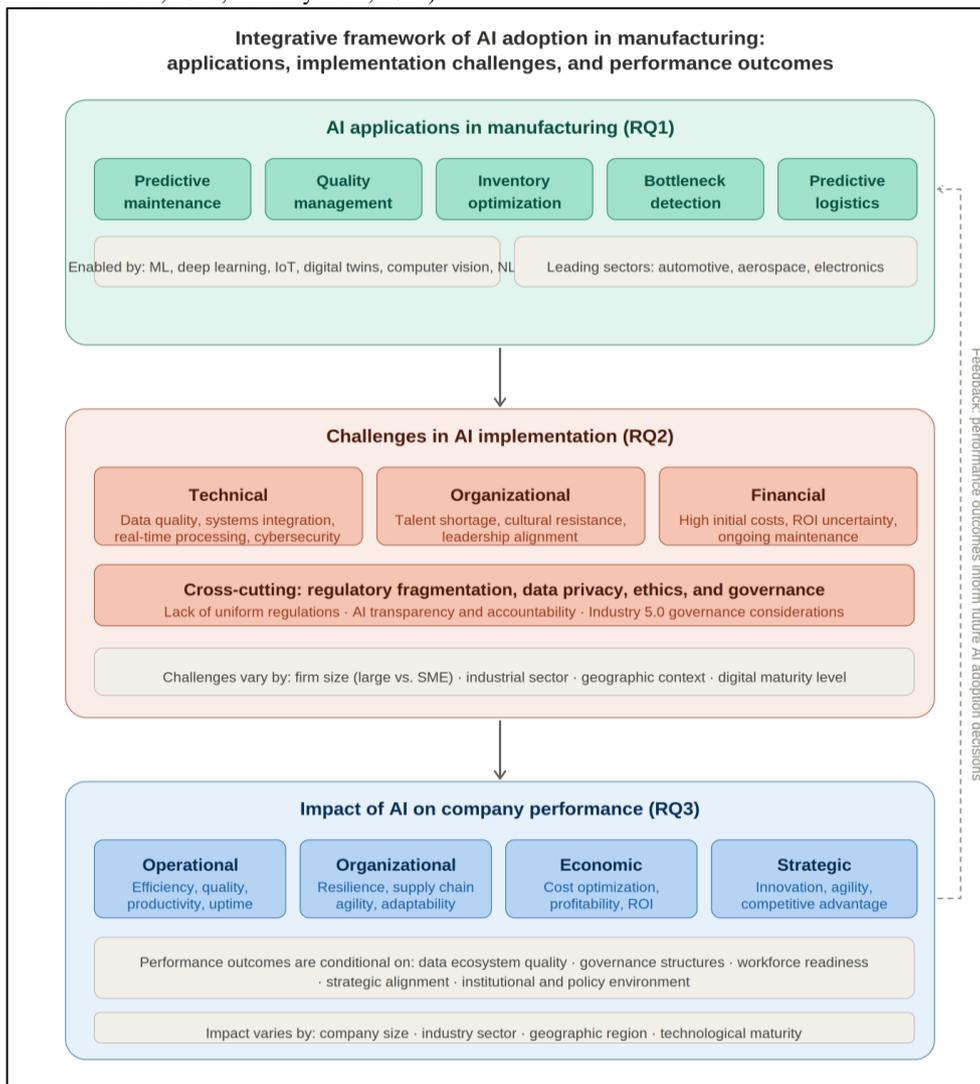


Figure 7 : Integrative Framework of AI adoption in Manufacturing: Applications, Challenges, and Performance Outcomes

Third, the findings suggest that the institutional and governance dimension deserves much greater attention in future theory building. Public policy, standards, training ecosystems, tax incentives, and regulatory clarity may significantly influence firms' willingness and ability to adopt AI at scale. Future studies should therefore incorporate institutional variables more explicitly into AI adoption models, moving beyond firm-level analysis to include the role of governments, industry bodies, and innovation ecosystems in shaping industrial AI trajectories (Chen et al., 2024; Horobet et al., 2024).

Finally, the review highlights the need to connect AI adoption more closely with industrial sustainability and responsible transformation. Although several studies indicate that AI can enhance energy efficiency, traceability, waste reduction, and more sustainable resource use, the integration of AI, sustainability, and manufacturing strategy is still underdeveloped (Dey et al., 2024; Gholami, 2024). Future research should therefore explore how AI can support not only operational and financial performance but also broader sustainability objectives and responsible industrial growth. This includes examining how AI-driven manufacturing can align with environmental goals, social responsibility, and long-term resilience within Industry 4.0 and Industry 5.0 contexts. Overall, this review advances the theory by moving beyond fragmented views of AI in manufacturing and offering a more integrated perspective where applications, implementation challenges, and performance outcomes are analyzed together. In doing so, it establishes a stronger conceptual foundation for understanding AI not just as an emerging technology, but as a strategic, organizational, and institutional phenomenon that transforms the logic of manufacturing change.

6. Conclusions

This systematic literature review aims to provide a thorough understanding of artificial intelligence in manufacturing by exploring three interconnected dimensions: AI applications, adoption challenges, and performance outcomes. Analyzing 34 peer-reviewed studies published between 2019 and 2024, the review confirms that AI has become a key driver of manufacturing transformation, but also indicates that its value depends heavily on the conditions of its implementation. Instead of offering automatic benefits, AI generates value through a complex interaction of technological capabilities, organizational readiness, financial investment, and governance quality.

The findings show that AI is most frequently used in predictive maintenance, quality management, inventory optimization, bottleneck detection, and predictive logistics. These uses demonstrate that AI already helps create smarter and more responsive manufacturing systems by enhancing monitoring, forecasting, defect detection, production flow, and supply chain coordination. However, the use of AI varies across industries and organizational settings. As shown in Figure 7, sectors like automotive, aerospace, and electronics tend to lead in AI adoption, while smaller companies and those in less digitally advanced environments have fewer opportunities for implementation.

The review indicates that AI implementation in manufacturing faces a wide range of interconnected challenges. Technical obstacles include poor data quality, integration issues, cybersecurity risks, and the need for real-time processing. Organizational barriers involve talent shortages, cultural resistance, low AI literacy, and weak leadership alignment. Financial challenges, especially high initial investments, ongoing maintenance costs, and uncertainty about return on investment, are particularly significant for SMEs. Additionally, broader issues like regulatory complexity, data privacy, ethics, transparency, and governance make adoption more difficult. These results highlight that AI implementation is more than just a technical task; it is a complex change process influenced by internal capabilities and external institutional factors. In relation to performance, the evidence reviewed is broadly positive but clearly conditional. AI adoption is associated with improvements in operational performance, including efficiency, quality, productivity, and uptime; organizational performance, including resilience, agility, and adaptability; economic outcomes, including cost optimization and profitability; and strategic outcomes, including innovation and competitive advantage. Yet these gains do not occur uniformly. As Figure 7 shows, performance outcomes depend on enabling conditions such as data ecosystem quality, governance structures, workforce readiness, strategic alignment, and the broader institutional and policy environment. This explains why some firms achieve substantial returns from AI while others struggle to move beyond pilot initiatives or fail to realize expected benefits at scale.

An important conclusion emerging from this review is that AI adoption in manufacturing should be approached from a systemic and integrative perspective. The overall findings, summarized in Figure 7, demonstrate that applications, implementation challenges, and performance outcomes are not separate domains, but part of an interconnected adoption logic. AI applications generate potential value, implementation challenges mediate whether and how that value can be realized, and performance outcomes provide feedback that can influence subsequent adoption decisions. This integrative interpretation offers a more realistic and practically useful view of manufacturing AI than approaches that focus only on use cases or isolated performance metrics.

From a theoretical perspective, the review contributes by strengthening the case for a sociotechnical and capability-based understanding of AI in manufacturing. It highlights the importance of concepts such as digital maturity, organizational learning, dynamic capabilities, technological resilience, and governance readiness in explaining differential adoption outcomes. In this sense, the study moves beyond reductionist explanations centered only on technical functionality or financial returns and instead positions AI as part of a broader transformation involving strategy, culture, institutions, and organizational design.

From a practical perspective, the findings suggest that managers and policymakers should treat AI as a strategic transformation agenda rather than a standalone technological investment. Firms need to build strong data foundations, improve interoperability, invest in workforce development, and create governance mechanisms that support transparency, accountability, and trust. Policymakers can also play a key enabling role by strengthening digital infrastructure, clarifying regulations, supporting training ecosystems, and designing incentives that lower the barriers to adoption, especially for SMEs and firms in emerging economies.

Finally, this review identifies several priorities for future research, including longitudinal studies of AI implementation, comparative studies across sectors and regions, deeper investigation into governance and regulatory issues, and stronger integration of AI with sustainability and responsible manufacturing agendas. Overall, AI represents a significant strategic opportunity for manufacturing firms, but its success depends on contextualized, well-governed, and organizationally supported implementation. By synthesizing AI applications, adoption challenges, and performance outcomes in a single review, this study provides a more complete foundation for both scholarship and practice in the emerging field of AI-enabled manufacturing transformation.

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