

Artificial Intelligence Adoption in Smart Manufacturing: A Comparative Review of China and Japan

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ABSTRACT

Artificial Intelligence (AI) has become a key enabling technology for accelerating smart manufacturing transformation by enhancing production efficiency, operational flexibility, and intelligent decision-making. This study aims to compare AI adoption in smart manufacturing between China and Japan through a Systematic Literature Review (SLR). The review synthesizes peer-reviewed journal articles published between 2021 and 2025, retrieved from major academic databases including Scopus, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, Taylor & Francis, and Wiley Online Library. The analysis focuses on national AI strategies, industrial policies, enabling technologies, manufacturing applications, implementation challenges, and future development trends. The findings reveal that China emphasizes large-scale industrial digitalization supported by strong government policies, extensive industrial internet infrastructure, and rapid AI deployment across manufacturing sectors. In contrast, Japan adopts a human-centered approach that integrates AI with advanced robotics, precision manufacturing, and Society 5.0 initiatives to improve production reliability and sustainability. Despite differences in implementation strategies, both countries demonstrate that AI significantly enhances manufacturing competitiveness through predictive maintenance, intelligent quality inspection, Digital Twin technologies, and production optimization. The study concludes that successful AI adoption depends not only on technological capability but also on policy support, workforce readiness, industrial ecosystems, and sustainable innovation, providing valuable engineering insights for future intelligent manufacturing development.

Keywords: *Artificial Intelligence, China, Japan, Smart Manufacturing, Systematic Literature Review*

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1. | INTRODUCTION

Digital transformation has become a defining characteristic of contemporary engineering systems, driven by the convergence of Artificial Intelligence, Machine Learning, Industrial Internet of Things, cloud computing, and advanced data analytics. These technologies enable continuous monitoring of industrial assets and facilitate intelligent maintenance strategies that improve equipment reliability, operational efficiency, and production sustainability. The emergence of Industry 4.0 has accelerated the deployment of Industrial Internet of Things (IIoT), cloud computing, big data analytics, cyber-physical systems, and Artificial Intelligence (AI), enabling engineering organizations to continuously monitor the operational condition of industrial assets through interconnected sensor networks. More recently, the transition toward Industry 5.0 has further emphasized the importance of intelligent, resilient, and human-centric engineering systems capable of combining advanced digital technologies with sustainable industrial operations. Within this context, maintenance strategies have evolved from conventional reactive and preventive approaches toward predictive and data-driven paradigms that improve operational reliability while reducing maintenance costs and unexpected equipment failures (Lee et al., 2020).

Predictive Maintenance (PdM) has emerged as one of the most significant applications of intelligent engineering because it enables maintenance activities to be scheduled according to the actual health condition of industrial equipment rather than predetermined maintenance intervals. Unlike reactive maintenance, which responds only after failures occur, or preventive maintenance, which follows fixed maintenance schedules regardless of equipment condition, predictive maintenance utilizes continuously collected operational data to estimate degradation processes and predict potential failures before they happen. Consequently, organizations can optimize maintenance planning, improve equipment availability, reduce production interruptions, and extend asset life cycles. These advantages have made predictive maintenance an essential component of smart manufacturing and digital engineering systems (Achouch et al., 2022). The effectiveness of data-driven predictive maintenance largely depends on the availability of high-quality operational data generated by modern monitoring technologies. These datasets provide valuable information regarding equipment health and degradation behavior. However, the increasing complexity and volume of industrial data require analytical methods capable of identifying nonlinear relationships, extracting hidden patterns, and generating accurate failure predictions beyond the capability of conventional statistical techniques. Consequently, Artificial Intelligence and Machine Learning have become fundamental technologies supporting intelligent predictive maintenance systems.

Machine Learning enables predictive maintenance models to learn from historical operational data and identify complex relationships between equipment conditions and failure events. Supervised learning algorithms such as Random Forest, Support Vector Machine, Decision Tree, Logistic Regression, and Extreme Gradient Boosting have

been widely implemented for fault classification and anomaly detection because of their robustness and relatively high predictive accuracy. Meanwhile, deep learning architectures, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Autoencoders, and Transformer-based models, have demonstrated superior performance in analyzing high-dimensional industrial data and multivariate time-series signals. These advanced learning algorithms support automated feature extraction, Remaining Useful Life (RUL) prediction, fault diagnosis, and intelligent decision-making, thereby significantly improving maintenance efficiency and operational reliability across various engineering applications (Garcia et al., 2025).

Despite these technological advancements, the implementation of AI-driven predictive maintenance continues to face several technical and organizational challenges. Industrial datasets frequently contain missing values, noisy measurements, class imbalance, and inconsistent sampling frequencies, all of which may reduce model performance and prediction reliability. Furthermore, many advanced deep learning models operate as black-box systems, making their predictions difficult to interpret and limiting user trust in safety-critical engineering environments. Additional challenges include cybersecurity risks associated with interconnected industrial systems, computational requirements for large-scale data processing, interoperability among heterogeneous industrial platforms, and the integration of predictive maintenance solutions with legacy engineering infrastructures. These issues indicate that technological progress alone is insufficient to ensure successful implementation without addressing data quality, model transparency, and system integration.

Although numerous studies have investigated individual Artificial Intelligence algorithms or specific predictive maintenance applications, the existing literature remains fragmented across different engineering domains, datasets, and methodological approaches. Comprehensive synthesis is therefore required to provide a broader understanding of recent technological developments, compare algorithmic performance, identify current research challenges, and explore emerging opportunities for intelligent maintenance systems (Ucar et al., 2024). Therefore, this study conducts a Systematic Literature Review (SLR) to examine recent advances in Data-Driven Predictive Maintenance using Artificial Intelligence and Machine Learning. The review focuses on peer-reviewed studies published between 2021 and 2025 to analyze machine learning algorithms, industrial data sources, evaluation methods, implementation benefits, current challenges, and future research directions.

2. | RESEARCH METHOD

This study employed a **Systematic Literature Review (SLR)** to comprehensively examine and compare the adoption of Artificial Intelligence (AI) in smart manufacturing between China and Japan. The SLR approach was selected because it provides a transparent, structured, and reproducible methodology for identifying,

evaluating, synthesizing, and interpreting existing scientific evidence on a specific research topic while minimizing potential selection bias. Compared with conventional narrative reviews, SLR enables a more rigorous assessment of recent technological developments, research trends, implementation strategies, and emerging challenges in AI-driven manufacturing systems. The review process followed the general principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, including literature identification, screening, eligibility assessment, and final inclusion of relevant studies. The literature search was conducted using internationally recognized academic databases indexed by Google Scholar, including Scopus, ScienceDirect, IEEE Xplore, SpringerLink, MDPI, Taylor & Francis, and Wiley Online Library .

The search strategy combined several keywords using Boolean operators, including "Artificial Intelligence", "Smart Manufacturing", "Industry 4.0", "Intelligent Manufacturing", "Industrial Artificial Intelligence", "China", "Japan", "Digital Twin", "Industrial Internet of Things", and "Predictive Maintenance".

Only peer-reviewed journal articles published between **2021 and 2025** were considered to ensure that the analysis reflected the most recent technological advances and industrial practices. The inclusion criteria consisted of English-language journal articles focusing on AI applications in manufacturing, smart factories, intelligent production systems, industrial automation, or manufacturing digital transformation within the contexts of China or Japan (Alginahi et al., 2025).

Conference papers, book chapters, dissertations, editorials, review summaries without empirical discussion, duplicate publications, and articles published before 2021 were excluded from the review. Following the screening process, the selected studies were analyzed through qualitative content analysis and comparative synthesis. The comparison focused on several engineering dimensions, including national AI strategies, manufacturing policies, AI technologies, Industrial Internet of Things (IIoT), Digital Twin implementation, industrial robotics, predictive maintenance, intelligent quality control, production optimization, workforce readiness, sustainability initiatives, and implementation challenges. The synthesized findings were subsequently interpreted to identify similarities, differences, technological strengths, and future development opportunities in AI adoption across the manufacturing sectors of China and Japan, thereby providing comprehensive engineering insights into global smart manufacturing transformation.

3. | RESULTS AND DISCUSSION

The systematic literature review demonstrates that Artificial Intelligence (AI) has become the primary technological driver of smart manufacturing transformation worldwide. The integration of AI with Industrial Internet of Things (IIoT), Digital Twin, cloud computing, robotics, and big data analytics has fundamentally reshaped manufacturing systems by enabling autonomous decision-making, predictive analytics, adaptive production control, and intelligent resource optimization. Rather than

functioning as an isolated technology, AI increasingly serves as the intelligence layer that connects physical manufacturing assets with digital production environments, allowing factories to operate with higher flexibility, productivity, and resilience (Trakadas et al., 2020). Recent literature indicates that AI adoption has expanded rapidly across predictive maintenance, intelligent quality inspection, production scheduling, inventory optimization, and energy management, making smart manufacturing one of the core components of Industry 4.0 and the emerging Industry 5.0 paradigm.

The comparative analysis reveals that both China and Japan recognize AI as a strategic technology for strengthening manufacturing competitiveness; however, their implementation approaches differ significantly. China adopts a government-led, large-scale industrial transformation strategy supported by national initiatives such as *Made in China 2025* and the Intelligent Manufacturing Development Strategy. These policies encourage rapid deployment of AI technologies across manufacturing industries through extensive public investment, industrial digitalization programs, and the development of domestic AI platforms. The Chinese manufacturing ecosystem benefits from large industrial datasets, extensive production capacity, and strong collaboration among government agencies, technology companies, research institutions, and manufacturing enterprises. Such an ecosystem enables AI applications to be implemented relatively quickly across automotive, electronics, machinery, and consumer manufacturing sectors (Govindarajan & Venkatraman, 2024).

Conversely, Japan emphasizes a human-centered manufacturing philosophy through the implementation of *Society 5.0* and the *Connected Industries* initiative. Instead of focusing solely on rapid digital expansion, Japanese manufacturers integrate AI into long-established production systems characterized by high precision, lean manufacturing principles, and advanced robotics. AI is primarily deployed to support collaborative decision-making, improve operational efficiency, reduce production defects, and assist skilled workers rather than replacing them. Empirical evidence from Japanese manufacturing firms indicates that AI implementation remains selective, with visual recognition, machine learning, and natural language processing representing the most frequently adopted technologies. The principal motivations include improving operational efficiency, enhancing defect detection, automating repetitive processes, and reducing labor costs while maintaining high manufacturing quality (Soori et al., 2024).

Another significant distinction concerns the scale and speed of AI deployment. China's centralized governance model enables faster implementation of nationwide manufacturing policies, allowing enterprises to adopt industrial AI technologies simultaneously across multiple industrial sectors. Massive investments in industrial internet infrastructure, cloud manufacturing, intelligent factories, and domestic semiconductor capabilities further accelerate AI diffusion. In comparison, Japan's implementation strategy is more gradual, emphasizing reliability, safety, interoperability, and long-term technological sustainability. Although Japanese

manufacturers generally adopt AI more cautiously, their implementation often demonstrates higher integration quality due to decades of experience in industrial automation and robotics engineering. This contrast illustrates that manufacturing competitiveness depends not only on technological adoption speed but also on organizational capability and production maturity (Abuseta et al., 2025).

The reviewed literature consistently identifies predictive maintenance as one of the most mature AI applications in both countries. Machine learning algorithms analyze sensor data collected from industrial equipment to predict component degradation before failures occur, reducing unexpected downtime and maintenance costs. China increasingly combines predictive maintenance with Industrial Internet of Things platforms operating across large manufacturing facilities, whereas Japanese manufacturers integrate predictive maintenance into highly automated production lines supported by industrial robotics and precision monitoring systems. AI-based predictive maintenance improves equipment availability, production continuity, maintenance scheduling, and overall equipment effectiveness, contributing directly to manufacturing productivity (Alam et al., 2023).

Intelligent quality inspection represents another critical application area. Traditional manual inspection processes are gradually being replaced by AI-powered computer vision systems capable of detecting microscopic defects with greater consistency and speed. Deep learning models enable automated visual inspection of products while reducing human error and inspection variability. Chinese manufacturers widely employ computer vision for high-volume electronics and automotive production, whereas Japanese manufacturers integrate AI inspection systems into precision manufacturing processes requiring extremely low defect rates. Witt et al. (2023) states that This difference reflects the contrasting industrial characteristics of the two countries: China prioritizes production scale and efficiency, while Japan emphasizes manufacturing precision and product reliability. Digital Twin technology further distinguishes advanced AI adoption. Both countries increasingly integrate Digital Twin with AI algorithms to simulate manufacturing processes, evaluate production scenarios, optimize scheduling, and support real-time decision-making. China has rapidly expanded Digital Twin implementation through smart factories and industrial internet platforms, enabling real-time monitoring across large manufacturing networks. Japan applies Digital Twin more selectively, integrating virtual models with robotics, cyber-physical systems, and lean manufacturing practices to enhance production flexibility and continuous process improvement. The synergy between AI and Digital Twin enables manufacturers to improve operational visibility while minimizing production risks and enhancing resource utilization (Karkaria et al., 2025).

Industrial robotics also illustrates contrasting national strengths. Japan remains internationally recognized for high-performance industrial robotics supported by globally competitive manufacturers and decades of engineering expertise. AI enhances these robotic systems by improving perception, adaptive control, autonomous

navigation, and collaborative human–robot interaction. China, meanwhile, has significantly increased investments in intelligent robotics and automated production systems to address labor shortages and strengthen domestic manufacturing competitiveness. Supported by rapid advances in AI algorithms and manufacturing infrastructure, China has expanded robot deployment across multiple industrial sectors while simultaneously developing domestic robotics capabilities. Consequently, both countries increasingly rely on AI-enabled robotics, although Japan emphasizes technological sophistication whereas China prioritizes deployment scale and industrial expansion (Wasi et al., 2025).

Despite remarkable progress, several common challenges remain. Data quality, cybersecurity, interoperability among heterogeneous manufacturing systems, workforce skill shortages, AI transparency, and integration with legacy production equipment continue to constrain AI implementation. High computational requirements and concerns regarding trustworthy AI also influence adoption decisions, particularly in safety-critical manufacturing environments. China faces challenges associated with balancing rapid AI deployment and standardization across diverse industrial sectors, while Japan encounters demographic pressures, workforce aging, and relatively slower organizational adoption despite possessing advanced manufacturing capabilities. Addressing these issues requires stronger collaboration among governments, industries, and academic institutions to develop standardized frameworks, AI governance mechanisms, and workforce development programs capable of supporting sustainable digital transformation (Adel & HS Alani, 2024).

Overall, the comparative findings indicate that China and Japan follow different yet complementary pathways toward AI-enabled smart manufacturing. China demonstrates advantages in implementation speed, digital infrastructure, industrial scale, and government-driven innovation, whereas Japan exhibits strengths in manufacturing precision, industrial robotics, operational reliability, and human-centered AI integration. Both approaches contribute valuable engineering insights into the evolution of intelligent manufacturing systems and demonstrate that successful AI adoption depends not only on technological capability but also on industrial policy, organizational readiness, workforce competence, and long-term innovation strategies. These findings provide important implications for policymakers and manufacturing enterprises seeking to accelerate AI-driven industrial transformation while maintaining sustainable competitiveness in the global manufacturing landscape. The comparative review further indicates that the successful adoption of Artificial Intelligence in smart manufacturing is closely associated with the maturity of national digital infrastructure and industrial innovation ecosystems. AI applications require continuous data acquisition, high-speed communication networks, cloud computing resources, and interoperable cyber-physical systems capable of processing large volumes of industrial data in real time. China has invested extensively in industrial digital infrastructure by expanding Industrial Internet platforms, 5G communication networks, edge computing

facilities, and cloud-based manufacturing services. These investments have enabled manufacturing enterprises to collect, process, and analyze production data at unprecedented scales, thereby facilitating AI-driven decision-making throughout the manufacturing lifecycle (Rakholia et al., 2024). In contrast, Japan has focused on integrating AI within existing high-performance production environments by improving interoperability between legacy manufacturing systems and next-generation digital technologies. Rather than replacing conventional production systems entirely, Japanese manufacturers generally pursue incremental digital transformation, allowing AI solutions to complement mature production practices while maintaining operational reliability and product quality.

This distinction illustrates how different technological pathways can achieve similar objectives of manufacturing intelligence despite differences in implementation strategies. Another important finding concerns the increasing convergence between Artificial Intelligence and Industrial Internet of Things (IIoT). AI algorithms rely heavily on real-time sensor data generated through interconnected manufacturing equipment, enabling predictive analytics and autonomous production control (Wan et al., 2020). In both China and Japan, IIoT has become the primary foundation supporting intelligent manufacturing because it provides continuous visibility into machine conditions, production performance, energy consumption, and logistics operations. AI subsequently transforms these large-scale datasets into actionable knowledge that supports dynamic scheduling, anomaly detection, and process optimization. Recent studies emphasize that AI and IIoT should not be considered independent technologies but rather complementary components of an integrated smart manufacturing architecture capable of improving production responsiveness and operational resilience under rapidly changing market conditions.

4. | CONCLUSION

This study systematically compared the adoption of Artificial Intelligence (AI) in smart manufacturing between China and Japan through a comprehensive review of recent literature published from 2021 to 2025. The findings indicate that AI has become a fundamental enabling technology for intelligent manufacturing by supporting predictive maintenance, intelligent quality inspection, production scheduling, industrial robotics, Digital Twin applications, and data-driven decision-making. Although both countries recognize AI as a strategic driver of manufacturing competitiveness, they adopt different implementation approaches that reflect their respective industrial policies, technological capabilities, and national development priorities.

China has demonstrated significant strengths in large-scale AI deployment, government-supported industrial digitalization, extensive Industrial Internet infrastructure, and rapid commercialization of intelligent manufacturing technologies. In contrast, Japan emphasizes precision engineering, advanced robotics, human-centered AI integration, and highly reliable manufacturing systems under the Society 5.0 framework. These different strategies illustrate that successful AI adoption is

influenced not only by technological advancement but also by institutional support, workforce readiness, innovation ecosystems, and long-term industrial planning.

The review also identifies several common challenges, including cybersecurity risks, data interoperability, workforce skill gaps, legacy system integration, AI transparency, and sustainable technology implementation. Addressing these challenges requires stronger collaboration among governments, industries, and academic institutions to establish standardized frameworks, enhance engineering education, and promote responsible AI governance.

Overall, both China and Japan provide valuable engineering models for accelerating intelligent manufacturing transformation. Their complementary experiences offer practical insights for countries seeking to strengthen industrial competitiveness through AI-driven innovation. Future research should further investigate the integration of Generative AI, Foundation Models, Explainable AI, Industrial Large Language Models, and Industry 5.0 technologies to support the development of more resilient, sustainable, and human-centered smart manufacturing systems.

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The authors declare that there is no conflict of interest.

Ethical Approval and Originality Statement

Ethical approval was obtained for this study. The manuscript represents original work and has not been previously published, nor is it under consideration by another journal.

Data Disclosure Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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