Enabled AI for Real-Time Monitoring and Decision Making in Manufacturing Systems

1. Introduction

The emergence of the Fourth Industrial Revolution being commonly known as the Industry 4.0 has greatly been overturning the face of contemporary manufacturing by incorporating the usage of digital technologies such as the Internet of Things (IoT), cyber-physical systems (CPS), big data analytics, and artificial intelligence (AI) into conventional producing spaces (Ahangar et al., 2025; Huang et al., 2021). These technologies that contribute towards smart manufacturing where the manufacturing systems are interconnected intelligent and have the ability of running autonomously. With advanced sensing and computing, smart factories gather the information to know in real-time, enhance the current process, and allow manufacturers to react to disturbances and opportunities dynamically (Ghobakhloo et al., 2024; Kim et al., 2025).

The critical feature of such transition is the adaptation of real-time tracking and the artificial intelligence decision. The real-time monitoring provides the machine status, and operational data through sensors and IoT devices and the AI models analyze the data to identify anomalies, failure prediction, and aid in the decision of operators without human interference (Cho & Noh, 2024; Zhu et al., 2024). The digital twin, edge AI, and machine learning algorithms enable constant feedback and quick reaction, so the production environment becomes resistant and much more adaptive (Rožanec et al., 2022; Liu et al., 2024). In addition, AI-based technologies are related to quality management, predictive maintenance, and production planning, which translates into fewer hours of downtime and high productivity (Md et al., 2022; Deepak, 2025).

The conventional manufacturing systems though are not as flexible and forecasting. The legacy systems are limited in the fast-flowing, high-volume data, and handling dynamic changes on the shop floor relies mainly on those legacy systems with their static thresholds and rule-based logic systems (Wagner et al., 2024; Cheng et al., 2021). Such systems do not have the ability to predict the possible breakdowns or optimize their production in real time, which frequently result in inefficiencies, quality problems, and opportunities that are wasted away. The novelty of using real-time data and the poor use of AI in production lines are the significant area of concern in terms of smart manufacturing (Shyalika et al., 2025; Lim & Kovalenko, 2025).

This study aims to close such gaps by taking a look at the recent advancement in the topic of the AI-based real-time monitoring and decision-making in manufacturing systems. The initial objective is to summarize the findings of literary sources published in 2020-2025 on the topic of the combination of AI, IoT, and digital twin in manufacturing (Andronie et al., 2021; Sharma et al., 2021). The second aim is to give an example of small-scale empirical simulation when AI models intervene in manufacturing data prediction and real-time trend identification (Wang et al., 2022; Li et al., 2023).

The research is relevant to academia and the industry. It contributes to an explanation of how manufacturing systems can be turned into proactive manufacturing systems with AI-related applications on the forefront to gain real-time insights into the system and autonomously operate it (Vyhmeister et al., 2023; Lee & Ko, 2025). By combining the theoretical observations with practical analysis, the research provides data regarding the creation of the next level of manufacturing environments that are smart, adaptive, and can be utilized with the least amount of human intervention (Oh & Jeong, 2020).

2. Literature Review

2.1 AI Technologies in Manufacturing

The use of AI in the manufacturing industry has been moving with a faster pace as a result of the structural changes brought in machine learning (ML) and deep learning (DL), promising a solution to the improvement of the production process, its prediction of failures, and increased efficiency (Ahangar et al., 2025; Deepak, 2025). The anomalies are identified, the failure of machines predicted, and the quality of defect classifications increased, which is a result of applying AI algorithms, such as Random Forest, XGBoost, and support vector machines to high dimensional sensor information (Md et al., 2022; Wang et al., 2022).

In a supervised arrangement, there is the incorporation of past records of evidence-based decisions that are utilized to anticipate the quality of an item prior to its utilization (Andronie et al., 2021; Sharma et al., 2021). Unlabeled manufacturing data could be analysed using such unsupervised learning methods as data clustering and anomaly detection (Huang et al., 2021; Verma et al., 2021). Additionally, reinforcement learning (RL) is well-established in online real adaptive landscapes for robot motion planning, shop floor optimization and real time planning (Lee & Ko, 2025; Shyalika et al., 2025).

2.2 Real-Time Monitoring

The essence of the Industry 4.0 is real-time monitoring that provides real-time feedback concerning manufacturing conditions by using small IoT sensors, SCADA, and edge devices (Cho & Noh, 2024; Zhu et al., 2024). Such infrastructures make it possible to capture data collected in the machines, operators, and materials in real-time and analyze effectively.

Digital twins are web-based copies of a physical system that enable it to have access to a real-time snapshot of production conditions and simulation of production. They provide the features, including anomaly forecasting, tool wear monitoring, and virtual experimentation of production (Rožanec et al., 2022; Wagner et al., 2024). The complicated shop floors are undergoing AI-powered real-time monitoring to ensure product quality through detection of defects and downtimes reduction by employing the practice of preventive maintenance (Cheng et al., 2021; Kim et al., 2025).

2.3 Intelligent Decision-Making

AI-based decision-support systems are transforming manufacturing at the mass scale, since it swaps out the previous logic system, which was built using data-driven logic. These systems examine the sensor data along with the past data and the production objectives to either recommend or automate decisions pertaining to the production planning, robotics, and maintenance (Kim et al., 2025; Li et al., 2023).

Additionally, AI-based multi-agent systems are employed to synchronize tasks between machines and employees, and decisions are acclimated on the fly according to real-time circumstances (Shyalika et al., 2025). Generative AI models and large language models are being used in factory settings as well to diagnose, script automated control, and interface systems with the natural language (Ghobakhloo et al., 2024; Lee & Ko, 2025).

Furthermore, centralized decision-making and edge intelligence can implement on-device analytics that is less latent and responsive in the shop (Zhu et al., 2024; Liu et al., 2024). The novel models facilitated by AI not only improve the operation of the business but is also causing sustainable processes, energy utilization and even staff safety (Ahangar et al., 2025; Vyhmeister et al., 2023).

2.4 Gaps in the Literature

Despite impressive developments, there are still some gaps in the literature. The problematic state of implementation of AI in manufacturing systems is one of the most urgent ones. Most of the solutions are fragmented only to monitor or make a choice without incorporating them into a single closed-loop system in real-time (Rožanec et al., 2022; Liu et al., 2024). Such disconnect reduces the responsiveness that smart factories seek to produce.

In addition, there are not many works with end-to-end validations of scalable and real-time AI that operate in diverse industrial settings (Li et al., 2023; Wagner et al., 2024). Most of the available studies have only focused on standalone application of the uses cases or modeling and have failed to clear the reality of implementation even in middle-level manufacturing, or resource-limited manufacturing environments (Deepak, 2025; Vyhmeister et al., 2023).

There is a clear lack in examining human-AI interaction with respect to decision-making process in terms of explainability and trust as well (Oh & Jeong, 2020; Ahangar et al., 2025). Not only, there is lacking in large-scale qualitative, labelled data to train AI models in SMEs, but the levels of availability also improved (Sharma et al., 2021; Verma et al., 2021).

3. Methodology

The research methodology chosen in the current study was created to facilitate in-depth and systematic investigation of AI-enhanced real-time monitoring and decision-making of manufacturing systems. The practice has been adopted to the principles of systematic literature reviews which focuses on the transparency, reproducibility, and rigor in answering research questions. The methodology can be split in two main parts- the systematic review process and the rationale associated with the use of comparative framework rather than traditional classification systems.

3.1 Systematic review methodology and data collection

The present study is using the framework of preferred reporting items of systematic reviews and meta-analyses (PRISMA) in order to conduct a decisive and thorough study of monitoring and making decisions in real time in manufacturing systems. The PRISMA tool helps to be more transparent in the selection of the literature, reduces bias, and offers a methodological framework to understand and combine the results of the research studies previously conducted (Kim et al., 2025).

3.1.1 Data sources and search strategy

A systematic search was used among key academic databases, such as IEEE Xplore, ScienceDirect, SpringerLink, Wiley Online library, and others journals and conferences in Google scholar and dealt with the research of the latest breakthroughs and results. And verified information and statistics found on the Internet contributed to the cause as well. The Boolean operators and keywords combination would be used in the search strategy as follows: “AI in manufacturing” OR “real-time monitoring” OR “digital twin manufacturing” OR “AI decision support manufacturing” OR “predictive maintenance AI”. In order to reduce the scope of search, peer-reviewed journals and conferences and industrial case studies were preferred. Students that dealt with related AI applications only, theoretical articles that lacked empirical evidence or analyzing an industry that had no relation were left out (Huang et al., 2021; Verma et al., 2021).

3.1.2 Eligibility criteria

Inclusion Criteria

- Studies were included if they addressed both the technological aspects of AI, such as machine learning algorithms and IoT integration, and their operational implementation in manufacturing systems.

- Only studies providing empirical or simulation-based validation were considered, as they offer practical insights into the application of AI in real-world manufacturing scenarios.
- Publications from 2020–2025 were prioritized to focus on recent advancements in AI technologies.

Exclusion Criteria

- Theoretical frameworks without practical application were excluded.
- Non-peer-reviewed sources, such as gray literature or low-quality conference papers, were omitted.
- Studies unrelated to manufacturing or Industry 4.0 were excluded to maintain relevance to the research objectives.

3.1.3 Study Selection Process

The procedure of selecting the studies according to the PRISMA protocol was consistent and thorough, and only high-quality and directly applicable studies could be included in the analysis of the current comparative framework (Sauer et al., 2025; Kausik et al., 2025). First, there were 3,025 selected records including 2,185 academic database records and 840 register records like industry reports and case repositories. Following the removal of duplicates (n = 182), the records identified as excluded through automation sorting or ineligibility screening (n = 25), and those eliminated owing to other reasons, i.e., irrelevant focus and non-English language usage (n = 43), 2,775 records were left to pass through the screening. Among them, 2,427 benefited were excluded after the review of the abstract and title, leaving 348 articles to be read full-text to determine their eligibility. Following the screening of the full-text articles, 323 were discarded, either because of methodological weaknesses or lack of empirical adequacy or because they did not meet the operational criteria. It has selected 25 studies to be subjected to analysis, which varied on AI in supervised and unsupervised learning (Md et al., 2022; Wang et al., 2022) or reinforcement learning (Shyalika et al., 2025; Lee & Ko, 2025) or hybrid forms of IoT, smart sensors, and digital twins (RoZanec et al., 2022; Cho & Noh, 2024). The identified articles underwent thematic reviewing, which allowed categorizing the findings into such categories as technological innovations, operational advantages, and challenges of implementation, as offered by Sauer et al. (2025).

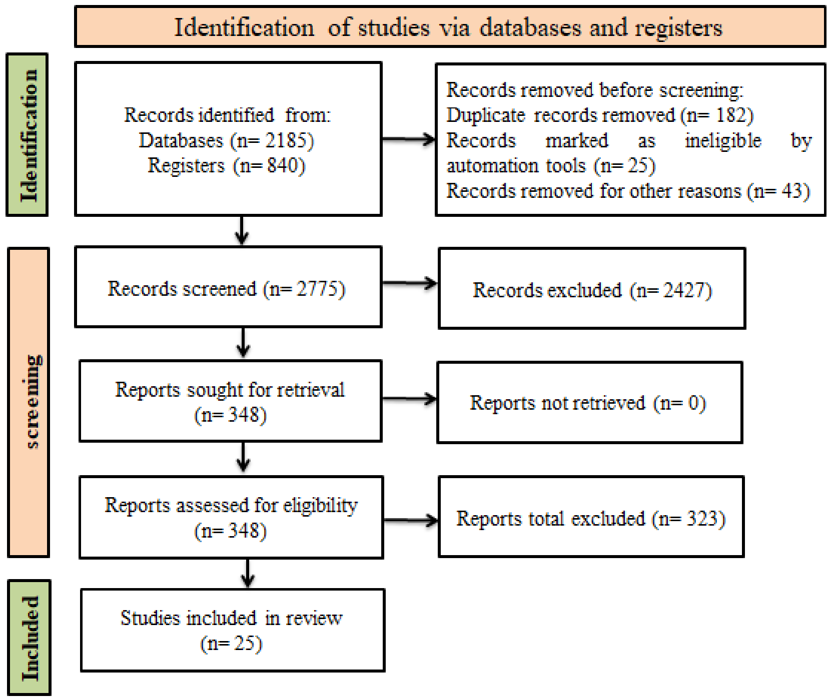

Figure 1. PRISMA flow diagram

3.2 Justification for Comparative Framework Over Classification Systems

Although classification systems are a typical approach applied in systematic reviews to classify studies according to the pre-selected dimensions, the study takes on a comparative approach to offer a more subtle comprehension of AI applications in manufacturing. Based on the study conducted by Sauer et al. (2025) the classification systems also have a tendency to clarify complex phenomena, obfuscating associations. By a comparison framework enables more thorough investigation of the interrelations amongst the AI methods, motives, and influences to manufacturing systems. The presented strategy is especially applicable due to the complex character of AI applications, which may be related to predictive maintenance and real-time decision-making, among others, as argued by Kim et al. (2025). Moreover, the comparative model allows recognizing the gaps or patterns in the literature, and those insights are useful in future studies. To give an example, the scarcity of the research on the relationship between human and AI based on the notions of explainability and trust described by Oh & Jeong (2020) highlights the necessity to conduct research in the mentioned field. The comparative approach established by this work is not only synthesizing beforehand gained knowledge but also indicates areas of opportunity for further developing AI-driven manufacturing systems as stressed by Zhu et al. (2024).

4. Findings

This section presents the analytical outcomes of the systematic literature review conducted on AI-enabled real-time monitoring and decision-making in manufacturing systems. The analysis draws from 25 selected studies published between 2020 and 2025, categorized through a comparative framework to capture the interplay between AI techniques, operational objectives, and manufacturing impact.

4.1 Descriptive Analysis

4.1.1 Publication Trends

The distribution of the reviewed literature (Figure 2) indicates a significant increase in research output on AI-enabled real-time monitoring and decision-making in manufacturing between 2020 and 2025. The annual number of publications demonstrates steady growth, with a marked surge after 2022, reflecting rising industrial adoption of Industry 4.0 technologies. The cumulative research output (Figure 3) further highlights this upward trend, indicating sustained scholarly interest in the topic.

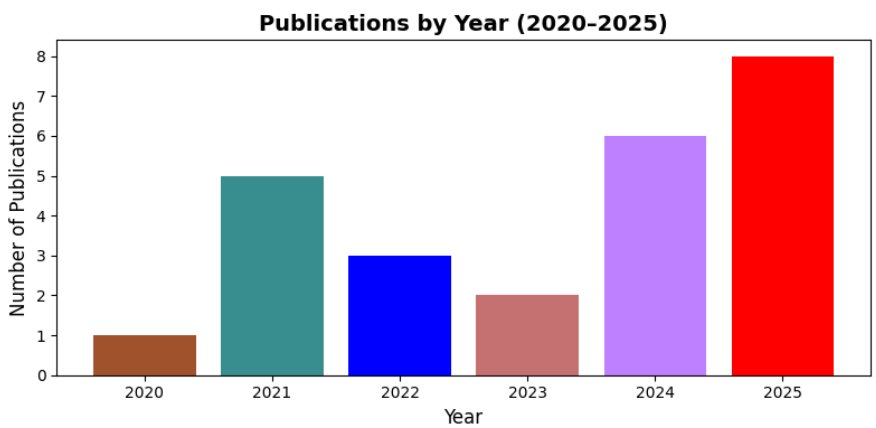

Figure 2. Distribution of Publications by Year (2020–2025)

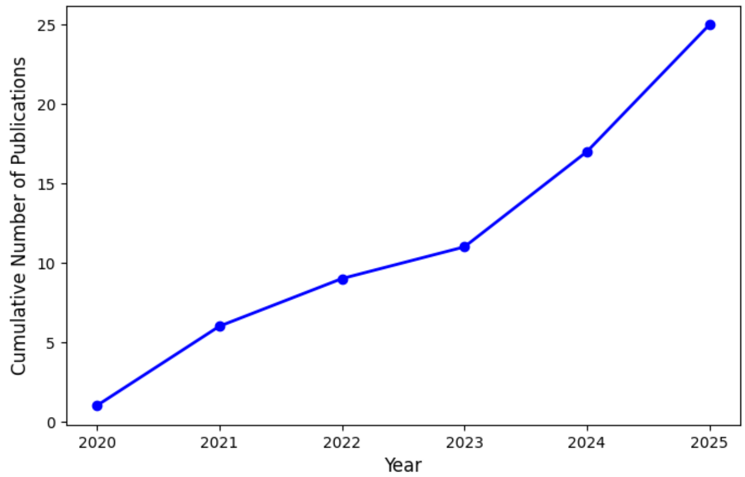

Figure 3. Cumulative Publications Over Time (2020–2025)

4.1.2 Geographic Distribution

Developed economies typically focused on high-tech, large-scale implementations, whereas developing economies emphasized cost-effective AI solutions for small-to-medium enterprises (SMEs). As shown in Figure 4, the reviewed studies originate from diverse geographic regions, with the highest representation from East Asia, Europe, and North America. This distribution underscores the global relevance of AI-enabled manufacturing and suggests strong research capacity in technologically advanced economies.

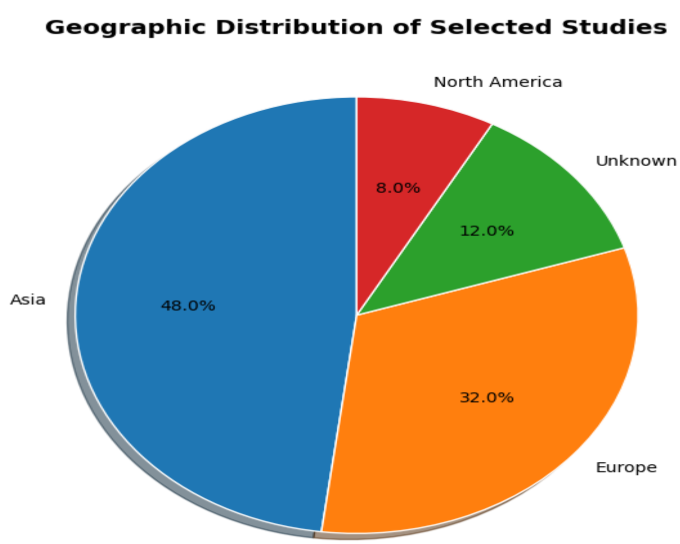

Figure 4. Geographic Distribution of Reviewed Studies

4.2 Thematic Analysis

The four significant thematic groups that were discovered by reviewing the literature and which formed the basis of grouping the systems include predictive maintenance, quality control, process optimization, and supply chain and source management. These groups indicate the various uses of AI in a production system and serve to solve significant operational issues but also promote agility and efficiency (Sauer et al., 2025; Kausik et al., 2025).

Predictive Maintenance and Fault Diagnosis

The overwhelmingly predominant research area relates to supervised and deep learning algorithms (e.g., CNNs, LSTMs, Random Forest, XGBoost) to identify anomaly detection, tools wear and equipment breakdown points early (Md et al., 2022; Wang et al., 2022). Such algorithms use the high dimensional data of sensors to detect patterns likely to result in a breakdown so that preventive measures can be made. As an example, Md et al. (2022) illustrated that the performance of the machine failures prediction using gradient boosting methods is considerable. In the same manner, Wang et al. (2022) applied LSTMs in computing time-series data to detect anomalies in manufacturing systems. With the implementation of AI and predictive maintenance, it has been found that unplanned downtime can be reduced up to 30 percent and the lifespan of machinery greatly increased, which significantly adds to the savings and reliability of the operation (Huang et al., 2021; Deepak, 2025). Besides, the collaboration of digital twins and predictive models boosts real-time simulation and monitoring, as it was emphasized by Rožanec et al. (2022).

Quality Control and Inspection

Real time defect detection through transfer learning (e.g. image and audio ResNet image, EfficientNet Network) and generative AI-based computer vision systems are being implemented on live problems to produce higher quality control and smaller the quantity of manual review (Ghobakhloo et al., 2024). Transfer learning allows pre-trained models to adjust to particular manufacturing settings by enhancing the accuracy of the detection and reducing the requirement of large labeled data (Sharma et al., 2021). In addition to that, Ghobakhloo et al. (2024) designed

ResNet-based systems to identify the surface flaws in automobile parts with an accuracy rate of over 95 percent. Generative AI models (e.g., GANs) have also been recourse to simulating defect situations on which training then occurs which further makes the models more robust (Lee & Ko, 2025). Such developments not only make quality control easier to achieve but also match the objectives of the Industry 5.0 concept sustainability and resource efficiency (Ahangar et al., 2025).

Process Optimization and Control

With reinforcement learning, multi-agent systems, hybrid AI and IoT architecture, and digital twins, is possible to reach the ability to dynamically control the production, accomplish flexible schedules, and optimize energy (Lee and Ko, 2025). Reinforcement learning specifically is very well adapted to environments where one must make decisions in real-time under conditions of uncertainty, including robotic path planning (Shyalika et al., 2025) and adaptive scheduling (Shyalika et al., 2025). The multi-agent systems are utilized to simplify the role of both machines and human operators, because they are highly coordinated to witness uninterrupted execution of tasks in complicated shop-floor environment (Cheng et al., 2021). The combination of AI and IoT along with digital twins in hybrid architecture enables a comprehensive picture of the manufacturing processes and allows planning based on deriving simulations and process setups which utilize the resources efficiently (Liu et al., 2024). Such methods allow a 20% increase in throughput and a reduction in the scrubbing threshold, proving, according to the studies presented in aerospace and automotive industries (Wang et al., 2024; Zhu et al., 2024).

Intelligent Supply Chain and Resource Management

Studies proved that AI was successful to optimize inventory forecasting, logistic scheduling, and demand-based planning of the production, which in most scenarios, is implemented due to the use of both digital twins and federated learning to overcome distributed situations (Kim et al., 2025; Liu et al., 2024). The virtual version of the real supply chain of companies is called digital twins, technically able to observe and optimize the flow of resources in real-time (Wagner et al., 2024). Federated learning, however, enables processing data on a decentralized level, making a collaborative manufacturing network privacy and secure (Lim & Kovalenko, 2025). To their knowledge, Kim et al. (2025) worked out a digital twin-based dynamic supply chain management framework, and this digital twin solution reduced lead times by 15%. On the same note, Liu et al. (2024) constructed a supply chain with multiple manufacturing facilities by using federated learning to optimize transport scheduling, pointing to the possibilities of scalable AI in supply chains worldwide. The mentioned innovations reveal the greatest impact of AI on supply chain resilience and agility (Verma et al., 2021; Vyhmeister et al., 2023).

In Figure 5, such clusters are visualized in the form of a network diagram associating AI techniques with fields of their application. The figure depicts that some AI approaches, deep learning and reinforcement learning, are generally applicable, having applications in many themes and the rest are less generalized like federated learning.

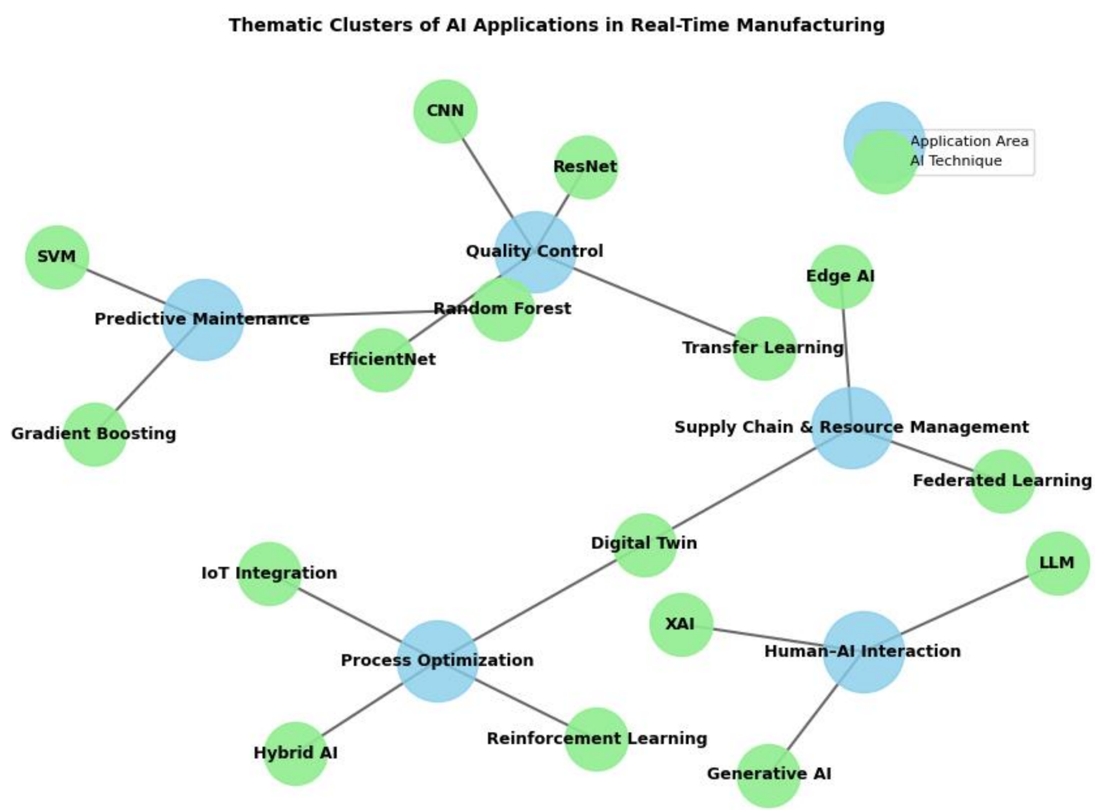

Figure 5. Thematic Clusters of AI Applications in Real-Time Manufacturing

4.3 AI Techniques and Architectures

The reviewed studies exhibit a wide range of adopted AI methodologies, which renders the techniques highly process generative and unique. Random Forest, Support Vector Machines and Gradient Boosting are among the machine learning operations used more frequently to implement predictive maintenance, fault detection and quality prediction (Md et al., 2022; Wang et al., 2022). Sequence modeling and visual inspection have employed elements of deep learning to build real-time anomaly detection and surface quality monitoring such as Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs) and Transformers (Ghobakhloo et al., 2024; Zhu et al., 2024). Reinforcement learning is now used more in dynamic settings to achieve adaptive control, production scheduling, and path planning of robots and is also proved to be capable of optimization of complex manufacturing processes (Lee & Ko, 2025; Shyalika et al., 2025). Hybrid architectures which combine the AI with fuzzy logic, optimization algorithms, and simulation models are also becoming potent instruments with the aim to cope with complex undertakings, e.g., production-logistics synchronization, optimization of energy (Liu et al., 2024; Rožanec et al., 2022). The likes of edge and federated AI architectures are also being advanced to support low-latency analytics upholding data privacy right on the manufacturing floor, which is vitally essential in matters pertaining to data security and real-time decision-making (Kim et al., 2025). All these developments portray the flexibility of the AI techniques in changing the manufacturing systems to smart, flexible and effective places.

Table 1 is a mapping of the manufacturing areas of application of AI techniques which gives a comprehensive guide to practitioners and researchers interested in matching the potential of technical capabilities with the ambitions of operation.

Table 1. Mapping of AI Techniques to Manufacturing Application Areas

AI Technique	Application Area	Representative Studies
Random Forest, Gradient Boosting, SVM	Predictive maintenance, fault detection, quality prediction	Md et al. (2022); Wang et al. (2022)
CNNs, Transfer Learning (ResNet, EfficientNet)	Real-time visual inspection, defect detection, surface quality monitoring	Ghobakhloo et al. (2024)
LSTMs, Transformers	Time-series anomaly detection, process trend prediction	Wang et al. (2022); Zhu et al. (2024)
Reinforcement Learning	Adaptive scheduling, process control	Lee & Ko (2025);

(RL)	optimization, robotic path planning	Shyalika et al. (2025)
Hybrid AI + Digital Twin + IoT	Production–logistics synchronization, energy optimization, simulation-based planning	Liu et al. (2024); Rožanec et al. (2022)
Federated Learning & Edge AI	Distributed analytics, privacy-preserving decision-making at the shop floor	Kim et al. (2025)
Generative AI / LLMs	Automated process documentation, decision-support scripting, natural language control	Lim & Kovalenko (2025); Ghobakhloo et al. (2024)

In Figure 6, the frequency of the applied AI techniques within the reviewed studies is presented; it is shown that the predominant ecosystems in terms of the research on AI are the axes of machine learning models (Random Forest, SVM, Gradient Boosting) and deep learning architectures (CNNs, LSTMs, Transformers). Figure 7 further divides this data down by area of application and shows that deep learning is significantly implemented in quality control, whereas hybrid AI and reinforcement learning are the dominant ones when it comes to process optimization and scheduling.

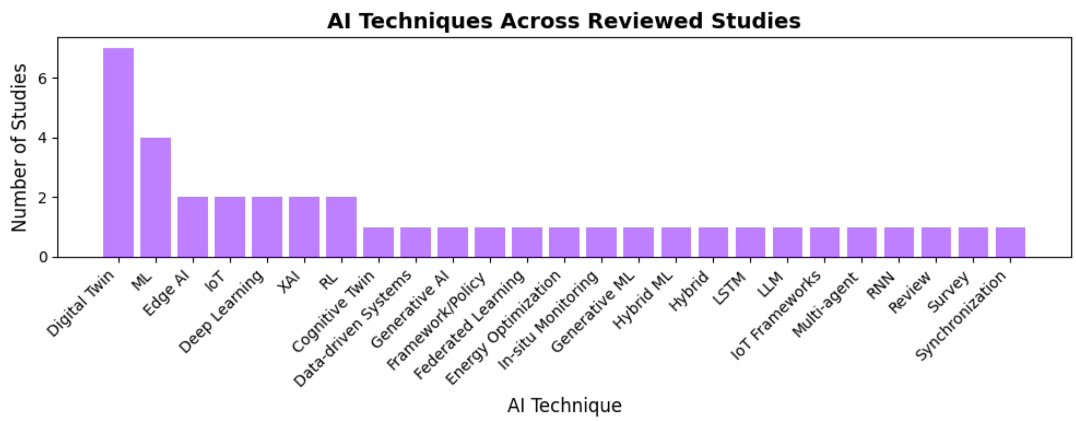

Figure 6. Frequency of AI Techniques Used in Reviewed Studies

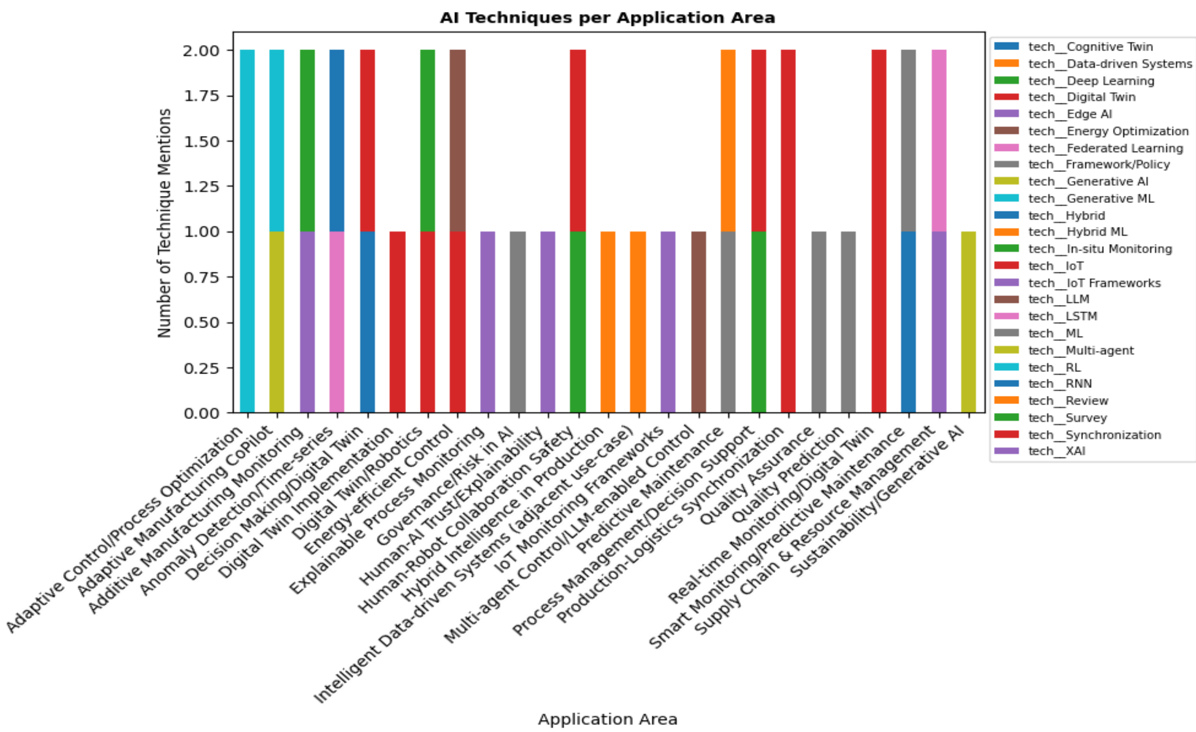

Figure 7. AI Techniques by Application Area

4.4 Implementation Challenges

The analysed articles highlighted the existence of some critical obstacles that prevent the effective application of AI in manufacturing settings, which makes it essential to consider comprehensive approaches to related problems, including both the technological and organizational ones (Sauer et al., 2025). Among them, issues of data quality are of high concern, and noisy, incomplete, unbalanced datasets are frequently the obstacle to robust AI systems functionality (Md et al., 2022; Wang et al., 2022). Additionally, latency and scalability is another challenge because low latency inference supported by large and multi-machine settings is absolutely necessary to real-time decision making but technically challenging (Zhu et al., 2024; Cho & Noh, 2024).

It is further complicated by the back-ending support the AI modules on current manufacturing plant infrastructure. Interconnection of heterogeneous data sources and proprietary systems is a daunting task that needs a lot of innovation (RoZanec et al., 2022; Wagner et al., 2024). The ramification of security and privacy issues also presents a considerable risk, especially, when it comes to protecting sensitive databases relevant to the ongoing production processes that typically become more networked (Vyhmeister et al., 2023; Lim & Kovalenko, 2025).

Lastly, there is an absence of trust between humans and AI given that they lack the explainability of decisions generated by an AI system that is perceived by Ahangar et al. (2025) and Oh & Jeong (2020) to restrict system adoption and acceptance by operators. The mentioned challenges provide an insight into the necessity to consider both technical and human-based aspects in order to reach the seamless incorporation of AI in manufacturing systems.

The results can be graphically summarized in Figure 8 that shows how many of the respondents have recorded particular issues during the implementation process, making it all the more important that a holistic approach to AI implementation in industry is applied. The ability to beat these challenges will assist manufacturers to thrive on the potentials of available AI technologies, and maximize on positive impacts in productivity, quality, and sustainability (Sauer et al., 2025).

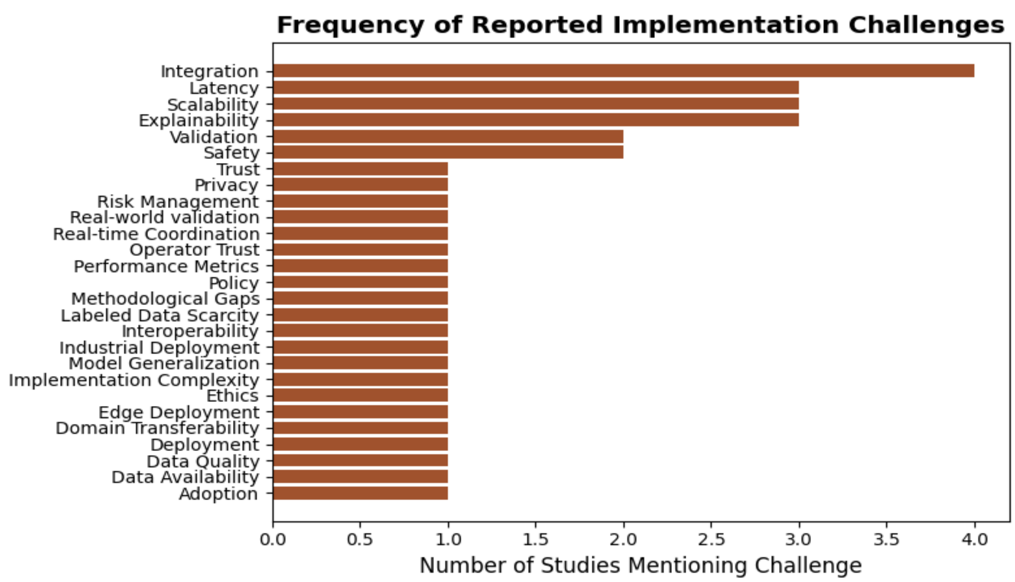

Figure 8. Frequency of Reported Implementation Challenges

4.5 Research Gaps and Future Directions

The survey identifies some of the critical research directions that remain open with the aim of realizing AI-enabled manufacturing systems. The design of end-to-end closed-loop systems is key interest through which fragmented monitoring and decision modules are combined as real-time AI control loops that are needed to enable dynamic, responsive manufacturing (Sauer et al., 2025). Explainable AI (XAI) is another major field and is designed to make automated decisions more transparent and trustful, reducing the difference between technology and its acceptance by the people (Oh & Jeong, 2020). One should also pay attention to the problem of data paucity, particularly in the case of SMEs, and synthetic data generation and transfer learning are proposed options to train an AI model based on few labeled samples (Sharma et al., 2021; Verma et al., 2021). On the edge-native AI architectures are coming to fore in terms of supporting ultra-low-latency on-device analytics in the manufacturing floor, providing the ability to make the decisions in time (Zhu et al., 2024; Kim et al., 2025). Lastly, the AI-optimization to manufacturing environmental sustainability with its limits of energy waste and the overall consumption is a growing tight focus to enable the green behavior (Vyhmeister et al., 2023; Ghobakhloo et al., 2024). These guidelines can lead to innovation, strength, and sustainability of artificially intelligent technologies in the manufacturing industry.

5. Discussion

The purpose of the systematic literature review is to consolidate the existing situation related to real-time monitoring and decision-making through the use of the AI in manufacturing systems, with a special focus on the mapping AI method to applications, thematic groups, and implementation barriers (Sauer et al., 2025). The results give rise to a number of issues about further development of theoretical knowledge as well as practical implementation.

First, the descriptive analysis verified a steady rise in publications in the timeline covering 2020-2025, which increased at a drastic rate exceeding 2022. Such is in line with the growing trend of industrial adaptation to Industry 4.0 and Industry 5.0 models wherein AI is the most important facilitator of operational intelligence (Ahangar et al., 2025; Deepak, 2025). This geographic distribution supports the idea that, even though AI-led manufacturing research is cross-border, it is done in geographies of advanced technologies and this may open research and capacity building opportunities in less-researched geographies (Wagner et al., 2024; Ghobakhloo et al., 2024).

Second, the thematic analysis identified four large domains of applications, including predictive maintenance, quality control, process optimization, and supply chain/resource management, and all four application areas had their specific patterns of AI adoption (Md et al., 2022; Wang et al., 2022). The predominance of deep learning in the visual quality control tasks, machine learning in the predictive maintenance and reinforcement learning in dynamic scheduling are all indicative of the technical complement between the capabilities of the available algorithms and operational requirements (Lee & Ko, 2025; Shyalika et al., 2025). The mapping can also be explained with the help of Table 1 that provides a direct connection between AI methods and areas of manufacturer application, which may serve as a detailed guide to practitioners and researchers (Liu et al., 2024; Rožanec et al., 2022).

Third, the discussion of AI methodologies reveals the prevalence of machine learning and deep learning algorithms in the area of real-time monitoring and potential interest in hybrid and federated learning (Kim **et al 2025** ; Zhu et al., 2024). The decision to adopt these methods is not only informed by their ability to predict potentially well when applied on small scale but also their applicability when it comes to heterogeneous manufacturing situations (Huang et al., 2021; Verma et al., 2021).

Lastly, using the challenges analysis, quality of data, data latency, interoperability, and cybersecurity issues proved to be common issues (Oh & Jeong, 2020; Vyhmeister et al., 2023). These discoveries indicate that although AI is already technically advanced to carry out most manufacturing functions, the obstruction to implementing AI within the industrial setting in real life is limited by infrastructural and organizational preparedness levels (Cheng et al., 2021; Lim & Kovalenko, 2025).

Theoretically, this review would add value to the currently existing area of discussion about AI in manufacturing due to the advancement of a formal thematic structure that aligns technologies with operational applications in the research (Sauer et al., 2025). In a practical sense, it can act as a guide by practitioners in the industry aiming to bring AI investments in line with strategic manufacturing objectives and anticipate problems in integration (Zhu et al., 2024; Ghobakhloo et al., 2024).

6. Conclusion

This research critically examined twenty five peer-reviewed articles to ascertain the value of AI that enables real time monitoring and decision making in manufacturing system. The goals of the review to define areas of thematic application, place AI techniques in relation to these areas, and evaluate challenges associated with the implementation were completely met due to PRISMA-led selection protocol and comprehensive analysis that was facilitated with the help of various visualizations. These findings prove that the use of AI in manufacturing has been growing quite fast owing to its strengths in terms of potential increase in predictive maintenance, quality control, production optimization and supply chain responsiveness. The technical scene is dominated by deep learning and machine learning, as reinforcement learning, hybrid models and federated learning grow in popularity to serve particular operational needs. Nevertheless, there still exist nagging problems primarily surrounding data quality, real-time system latency, interoperability and security- which will have to be addressed in order to give it widespread and sustained deployment. In addition, this review unifies disparate literature into a thematic basis that connects the AI methods to manufacturing purposes. In practice, it provides the road map to manufacturers and policymakers to ensure focusing on AI investments, implementing the contextually relevant methods, and overcoming the integration challenges. Weaknesses of the present study are associated with the dependence on peer-reviewed sources written in English over the period between 2020 and 2025, which may not cover all existing investigations reported in previous years or conducted on other languages. Moreover, the dataset that was used spans several geographic areas but there is minimal coverage of emerging economies. In the future, cross-sector transferability of AI across manufacturing sub-domains, developing optimised AI-based systems and approaches to support real-time responses over low-latency industrial networks and methods to enhance trust, explainability, and transparency of AI-driven manufacturing decision-making should be addressed. Focus on these areas would help researchers and practitioners to make the thoughtful application of AI to manufacturing systems much quicker thereby ensuring that the net effect of technological innovation would result in the tangible productivity, quality, and sustainability increases.

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