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Artificial Intelligence into Manufacturing Execution Systems and Supply Chain Systems

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ABSTRACT

Artificial Intelligence (AI) is transforming the manufacturing industry by revolutionizing Manufacturing Execution Systems (MES) and supply chain management. AI-driven MES enhances real-time monitoring, predictive maintenance, and quality control, leading to reduced downtime, cost savings, and improved efficiency. Advanced computer vision and machine learning algorithms enable defect detection, optimizing production processes while minimizing waste. Additionally, AI facilitates seamless human-machine collaboration through cobots, enhancing workplace safety and productivity. In supply chain management, AI plays a crucial role in demand forecasting, inventory optimization, and supplier relationship management. AI-powered predictive analytics help manufacturers make data-driven decisions, reducing overproduction and minimizing stock shortages. Automated inventory management ensures efficient resource allocation, while AI-driven supplier evaluation enhances reliability and mitigates risks in procurement. Despite these advancements, AI implementation in manufacturing faces challenges such as high costs, data security concerns, and workforce resistance. The need for skilled AI professionals and robust cybersecurity measures is essential to safeguard sensitive data and maintain operational integrity. Addressing employee apprehensions through strategic training and change management is crucial for successful AI adoption. The future of AI in manufacturing is promising, with emerging technologies like the Internet of Things (IoT), 5G, and edge computing further enhancing real-time decision-making. AI's integration into agriculture machinery manufacturing and explainable AI (XAI) will increase transparency and trust in automated processes. As AI continues to evolve, it will drive smarter, more sustainable manufacturing solutions, optimizing efficiency and reducing environmental impact. In conclusion, AI's role in MES and supply chain management is reshaping the manufacturing landscape. While challenges remain, proactive strategies can unlock AI's full potential, ensuring cost-effective, secure, and future-ready manufacturing operations.

Keywords: *Artificial Intelligence, Supply Chain, Manufacturing Industry*

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INTRODUCTION

Artificial intelligence (AI) is poised to revolutionize the manufacturing industry, fundamentally transforming traditional processes, decision-making, and supply chain operations. With rapid advancements in machine learning, big data analytics, and automation, AI has emerged as a critical enabler of efficiency, cost reduction, and innovation in modern manufacturing systems. The integration of AI in manufacturing execution systems (MES) and supply chain management (SCM) is driving the industry's transition toward smart manufacturing, where real-time data, predictive analytics, and autonomous decision-making enhance operational performance (Sivakumar *et al*., 2024).

Manufacturing Execution Systems (MES) have traditionally served as intermediaries between enterprise resource planning (ERP) and the shop floor, ensuring seamless operations. AI augments MES capabilities by enabling predictive maintenance, quality control, and adaptive process optimization. AI-powered computer vision systems improve defect detection, while deep learning models analyze production data to optimize efficiency and minimize waste (Islam *et al*., 2024). Furthermore, the integration of AI-driven collaborative robots (cobots) enhances worker productivity and safety by automating repetitive tasks while allowing human oversight (Borboni *et al*., 2023).

Similarly, AI in supply chain management has introduced advanced forecasting models, dynamic inventory control, and intelligent supplier relationship management. AI-driven demand forecasting enables manufacturers to anticipate market trends with greater accuracy, reducing excess inventory and ensuring efficient resource allocation (Okeleke *et al*., 2024). Automated procurement systems utilize AI algorithms to assess supplier performance, mitigate risks, and streamline logistics, ensuring timely deliveries and cost-effective sourcing (Grant, 2024). Additionally, AI facilitates sustainability initiatives by optimizing energy consumption, minimizing material waste, and reducing carbon footprints across the supply chain (Alijoyo, 2024).

Despite these advancements, AI implementation in manufacturing is not without challenges. High adoption costs, workforce resistance, data privacy concerns, and cybersecurity threats pose significant hurdles (Boza and Evgeniou, 2024). Overcoming these challenges requires strategic management, investment in upskilling employees, and the development of robust cybersecurity frameworks (Li, 2024). As AI continues to evolve, its potential to reshape manufacturing operations will become increasingly evident, paving the way for a more efficient, flexible, and sustainable industrial landscape.

AI in Manufacturing Execution Systems (MES)

Manufacturing execution systems (MES) are operational systems that capture the happenings occurring on the production floor in real-time. AI in MES has turned these systems into intelligent systems to enable predictive and prescriptive analysis. However, when comparing all the uses of AI in MES, then it is evident that predictive maintenance is one of the most beneficial. The reliability of equipment can be predicted through AI, through the collected data from activity sensors and maintenance logs. This is a precaution that should be taken because it may preserve time, extend equipment life, and lower maintenance costs (Sivakumar *et al*., 2024.

In addition, AI also makes quality control better: real-time production line data can be analyzed. Computer vision systems can easily detect complexities, like defects, in products compared to human inspectors by operating in a machine learning approach. For instance, in the automobile industry AI systems are used to check whether the paint applied is perfect and if there are any defects that are not noticeable (Islam *et al*., 2024). This leads to high-quality products with little or no scrap since the company can get back its investment in equipment within a short time due to increased efficiency. In addition, it is used to analyze large amounts of production information and to determine what changes should be made. For instance, it is possible to use AI to control the settings of a particular machine and optimize the use of energy or material, thus, making a company save money and the environment (Alijoyo, 2024).

Another area of AI's importance in MES is enabling the integration of humans and machines. Cobots are integrated with artificial intelligence to accompany human operators in shared work activities, with robots performing repetitive tasks that are adjusted with input from a human operator. Efficiency is implied, and this also helps reduce employee accidents (Borboni *et al*., 2023).

AI in Supply Chain Management

The role of artificial intelligence in the supply chain is extensive in the manufacturing industry. One of the most significant uses of AI in this context is demand forecasting. AI demands make forecasts more precise because of sales progression and such conditions as preparation, prevention, weather, or the state of the economy. This enables the manufacturers to arrange their production schedule in a way that is more advantageous to them and not have to produce stock that they never sell or sell stocks that were produced way ahead of time (Okeleke *et al*., 2024).

In the same way, it assists in inventory management tasks such as ensuring that the appropriate and adequate stock levels are obtained from the current inventory data. Some of these systems are designed to reorder materials when a defined stock level is reached so as not to disrupt production. Moreover, it is used to filter slow-moving stocking since it will meet the requirement of stocking at the bare minimum while reducing stock pile-up (Nweje, and Taiwo, 2025), along with measuring buffer and safety stock calculations incorporated into the AI model.

The concept of supply chain management (SCM) has evolved significantly, encompassing production, distribution, and integration of stakeholders (Seyedghorban *et al*., 2020). Traditional IT systems such as Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES) support SCM processes (Haas, 2020). However, these systems lack adaptability to dynamic supply chain environments. AI, through technologies like machine learning and neural networks, enhances decision-making and optimizes SCM processes.

Theoretical Background

AI in SCM

AI includes machine learning, expert systems, and neural networks, facilitating intelligent decision-making (Russell & Norvig, 2016). AI systems can learn, adapt, and optimize logistics and operations management. AI applications in SCM include predictive analytics, real-time decision-making, and automation (Duan *et al*., 2019).

AI Implementation in SCM Key AI applications in SCM involve:

1. Learning systems adapting to real-time data (Baryannis *et al*., 2019).
2. Situation-aware systems that adjust operations dynamically (Min, 2010).
3. Autonomous decision-making, replacing traditional decision support systems (Zijm & Klumpp, 2016).

Moreover, another facet of supply chain management is supplier relationship management in which the efficiency of suppliers and also the level of risk associated with them can be evaluated with the help of AI. Forecasting aids in identifying possible negative factors that may cause delays or compromise quality; manufacturers can minimize or even halt these negative issues (Grant, 2024). This, in a way, helps to ensure a more total, reliable source of the materials needed for production. The use of Artificial intelligence in supply chain activities to improve the degree of effectiveness, cost, and flexibility in manufacturing.

Challenges of AI Implementation in Manufacturing

However, it must also be said that this development of AI manufacturing, as well as the supply chain, is not without its challenges. A problem is the high cost associated with the deployment of AI technologies. In addition, acquiring the right talent and supporting infrastructure and software is an even bigger challenge to emerging SMEs (Boza and Evgeniou, 2024). Data privacy and protection are a limitation since much of the information processed and analysed for operations and strategies is deemed sensitive along with unknown threat from data hackers or data malfunction. Concerns such as hacking and unauthorized access of the data since the AI systems work with a large volume of data can be raised. In the process of formulating the policy of the industry, the manufacturers have to ensure that adequate measures have been put in place to protect data (Paul, 2024) taking initiative of having self-data protection policies put in place. The integration of Artificial Intelligence (AI) within Manufacturing Execution Systems (MES) is revolutionizing modern manufacturing by enhancing automation, computational assistance, and system complexity (Kusiak, 2018). MES serves as the backbone for real-time production data collection, integrating inputs from robots, machine monitors, and operators to streamline manufacturing operations (Kletti, 2019). However, conventional MES solutions primarily function as data visualization tools rather than direct enhancers of Overall Equipment Effectiveness (OEE).To counteract this limitation, AI-driven MES platforms incorporate automated analytical tools that provide deeper insights into operational data, ultimately boosting profitability (Turner, 2019).AI methodologies, particularly machine learning (ML), enable MES to evolve from mere data collection systems into intelligent decision-making platforms (Goodfellow *et al*., 2017). AI applications in MES enhance product scheduling (Novák, Vyskočil, and Kadera, 2019), improve product quality and optimize human resource allocation (Stadnicka, Litwin, and Antonelli, 2019). A key advantage of AI-supported MES is its ability to analyze vast datasets, identifying patterns and anomalies that facilitate predictive maintenance and production optimization. The integration of AI is projected to increase manufacturing industry profits by up to 39% by 2035 (Purdy and Daughert, 2018).

The synergy between AI and MES allows manufacturing firms to leverage advanced analytics for optimizing production layouts and workflows (Gentsch, 2018). AI systems, unlike traditional algorithms, adapt dynamically to operational constraints and continuously refine decision-making strategies (Schmitt, 2020). AI methodologies applied in MES encompass anomaly detection in production lines (Palensky and Dietrich, 2011), energy efficiency optimization (Vieira, Herrmann, and Lin, 2003), and predictive modeling for equipment maintenance (Ko *et al*., 2017]. Additionally, AI-enhanced MES supports real-time tracking of materials and workflow management, thereby reducing production downtime.

Despite the advantages, the deployment of AI in MES is accompanied by challenges such as data consistency, integration complexities, and the need for substantial computational resources. The lack of standardized frameworks for assessing MES functions with respect to AI suitability further complicates widespread adoption (Zhou *et al*., 2020). Researchers emphasize the necessity of developing assessment methodologies that establish decisive criteria and indicators for evaluating MES-AI integration potential (Berres *et al*., 2018). Such frameworks can facilitate MES providers in systematically embedding AI capabilities into their systems, ensuring optimal functionality and efficiency gains (Kletti, 2015).
There is also the workforce's resistance to incorporating AI. Some potential challenges that may be expected in implementing the solutions include loss of jobs or inherent poor adaptability to the technologies to be implemented.

Moreover, the complexity of AI systems' implementation can hinder manufacturers from getting the most out of their capabilities (Sjödin *et al*., 2021). To overcome these challenges, there is a need for strategic management with an emphasis on stakeholder involvement and learning (Li, 2024).

Future Potential of AI in Manufacturing

The further development of AI in the manufacturing industry is expected with different technologies in its activity, such as IoT, 5G, and edge computing. These will facilitate fast real-time processing and decision-making in relation to the AI-MES and AI-SC systems (Chang *et al*., 2021).

Also, in Agriculture machinery manufacturing and its usage without human involvement will be achievable in near future using AI technology (Kilari, 2025). Further, the introduction of explainable artificial intelligence (XAI) will also mitigate problems of opaqueness, making artificial intelligence more relatable and believable (Thalpage, 2023). The future of artificial intelligence (AI) in manufacturing is poised for transformative advancements, driven by the increasing complexity, interconnectivity, and dynamic nature of modern industrial operations. AI's integration with cutting-edge technologies like the Internet of Things (IoT), 5G, and edge computing will further enhance real-time data processing, predictive analytics, and autonomous decision-making, making manufacturing systems more efficient, flexible, and resilient (Dummy.docx).

One significant area of development is AI-powered manufacturing system optimization. AI-driven models will enable manufacturers to enhance throughput, improve product quality, and reduce operational costs by analyzing vast datasets from sensors, production lines, and supply chains. Advanced machine learning algorithms will refine predictive maintenance techniques, minimizing downtime and extending equipment life. Additionally, AI will play a key role in human-robot collaboration, improving workplace safety and efficiency through intelligent automation and cobots that can learn and adapt to dynamic environments (Dummy.docx).

AI's capabilities in process monitoring, diagnostics, and prognosis are expected to expand, allowing manufacturers to detect inefficiencies and anomalies in real time. Advanced AI models will not only predict failures but also suggest corrective actions, ensuring optimal production performance. Furthermore, AI will be instrumental in material engineering, optimizing manufacturing processes to enhance product durability, sustainability, and performance (Dummy.docx).

Despite these promising advancements, challenges remain, including data security concerns, workforce resistance, and the high costs associated with AI implementation. However, continuous research in explainable AI (XAI), transfer learning, and intelligent automation is expected to mitigate these challenges, paving the way for a more adaptive and intelligent manufacturing landscape.

Conclusion

The use of Artificial Intelligence in the Manufacturing Execution Systems and supply chain is becoming revolutionary in the production line. With the help of AI, trends may be easily predicted, top quality may be maintained, production processes may be optimized, and supply chains may be made smarter, less costly, and environmentally sustainable. Nevertheless, different issues, including high costs, information security, and resistance by the workers, are some of the issues that need to be resolved to unlock the potential of AI. Thus, establishing AI as a key element for defining new trends in manufacturing as smart, efficient, and sustainable. Help reduce its costs in manufacturing is very significant in near future.

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