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Evolution and Impact of Digital Manufacturing Systems in the Age of Industry 4.0

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ABSTRACT

The rapid development of Digital Manufacturing Systems (DMS) has been a significant influence on industrial production, driving the evolution of Industry 4.0. These systems incorporate advanced technologies such as Artificial Intelligence (AI), Cyber-Physical Systems (CPS), the Internet of Things (IoT), and Digital Twin technologies to optimize manufacturing processes. The shift from Computer-Integrated Manufacturing (CIM) to Smart Manufacturing is aimed at enhancing flexibility, efficiency, and customization in production systems. These innovations are essential for adapting to the dynamic demands of global markets, despite challenges like workforce resistance and cybersecurity risks.

Keywords: *Digital Manufacturing Systems, Industry 4.0, Artificial Intelligence, Cyber-Physical Systems.*

I. INTRODUCTION

The rapid evolution of industrial production systems has been significantly shaped by the emergence of Digital Manufacturing Systems (DMS), which integrate advanced computational technologies, automation tools, and intelligent decision-making frameworks into traditional manufacturing environments. These systems represent a critical pillar of Industry 4.0, enabling real-time data exchange, predictive analytics, and seamless integration between physical and cyber environments. Over the past decade, manufacturing industries have progressively transitioned from Computer-Integrated Manufacturing (CIM) to Smart Manufacturing ecosystems characterized by Cyber-Physical Systems (CPS), Artificial Intelligence (AI), the Internet of Things (IoT), and Digital Twin technologies (Mourtzis et al., 2022; Cheung et al., 2023). One of the primary drivers of this transformation is the increasing demand for flexibility, efficiency, and customization in global production systems. Traditional manufacturing systems often face limitations in adaptability and scalability, particularly when responding to rapidly changing market demands. In contrast, digital manufacturing systems leverage automation and data-driven intelligence to optimize production processes in real time. According to Fenta et al. (2025), flexible manufacturing systems (FMS) have evolved to incorporate IoT, robotics, additive manufacturing, and AI-based optimization techniques, thereby improving responsiveness, reducing operational costs, and enhancing production agility. A central component of modern digital manufacturing is the Digital Twin (DT), which serves as a virtual representation of physical assets, processes, or systems. Digital twins enable continuous synchronization between physical and virtual environments, allowing manufacturers to simulate, monitor, and optimize operations before actual implementation. Reuther et al. (2026) proposed a digital twin framework for Programmable Logic Controllers (PLCs) that integrates standardized communication protocols such as OPC UA and IEC 61131-3. This framework enhances interoperability, reduces integration complexity, and enables real-time monitoring and control of industrial automation systems. Similarly, Leng et al. (2020) demonstrated that digital twin-driven manufacturing systems support rapid reconfiguration of production processes, thereby improving adaptability in dynamic industrial environments. Artificial Intelligence and Machine Learning (ML) have further strengthened the capabilities of digital manufacturing systems by enabling predictive maintenance, intelligent quality control, and autonomous decision-making. Rahman et al. (2025) highlighted that ML algorithms applied to sensor and operational data can significantly enhance process optimization, fault detection, and system reliability. Deep learning architectures such as convolutional and recurrent neural networks are increasingly being used for predictive analytics and real-time industrial decision support. Furthermore, Saranya et al. (2026) emphasized the integration of AI with Robotic Process Automation (RPA), which has enabled cognitive automation functions such as anomaly detection, semantic classification, and intelligent workflow optimization. The adoption of digital manufacturing technologies is also closely linked to advancements in Virtual Manufacturing and simulation-based systems. Soori et al. (2024) noted that virtual manufacturing platforms, combined with RFID systems and big data analytics, allow manufacturers to simulate production processes and optimize operational workflows in real time. This not only improves efficiency but also reduces production errors and material waste. In addition, Ponce et al. (2024) demonstrated that the integration of Virtual Reality (VR) and AI in manufacturing education enhances experiential learning and provides immersive environments for system design, evaluation, and training. Despite these technological advancements, several challenges continue to hinder the widespread adoption of digital manufacturing systems. Oostveen et al. (2025) found that workforce resistance, lack of digital literacy, and system complexity are significant barriers to implementation, particularly in traditional manufacturing sectors. Similarly, Sivasankaran (2024) emphasized that the successful deployment of Computer Integrated Manufacturing requires engineers to possess strong interdisciplinary knowledge in automation, control systems, and digital technologies. Cybersecurity risks, interoperability issues, and data governance concerns also remain critical challenges in fully realizing smart manufacturing ecosystems (Saranya et al., 2026; Rahman et al., 2025). From a broader perspective, the evolution of digital manufacturing reflects a shift toward fully integrated, intelligent, and autonomous production systems. Technologies such as Industrial IoT, AI-driven analytics, Digital Twins, and cloud-based manufacturing platforms are converging to form interconnected industrial ecosystems capable of self-optimization and adaptive decision-making (Cheung et al., 2023; Mourtzis et al., 2022). This transformation is not only technological but also organizational, requiring changes in workforce skills, industrial policies, and operational strategies.

II. RESEARCH BACKGROUND

Reuther et al. (2026) reported that the integration of industrial automation systems, especially programmable logic controllers (PLCs), had remained complex due to heterogeneous hardware, proprietary programming environments, and interoperability constraints. Their study presented a digital twin framework for PLCs that enabled live monitoring, control, programming, and simulation. It was stated that the framework had been developed in compliance with the IEC 61131-3 standard and had employed standardized communication protocols such as OPC UA to improve interoperability and reduce integration costs. The authors further indicated that Virtual Reality interfaces had been incorporated to support interaction with automation environments, thereby allowing engineers to visualize, configure, and validate PLC control logic before deployment. A structured Asset Administration Shell model had also been utilized to ensure standardized PLC data representation and real-time synchronization between digital and physical systems. The framework had supported bidirectional communication, and experimental validation had demonstrated its successful implementation within a Motion Device System.

Saranya et al. (2026) examined recent advancements in intelligent systems and industrial automation that had accelerated the development of digital manufacturing ecosystems within the framework of Industry 4.0. The chapter had emphasized the transformative role of AI-driven intelligent automation through the convergence of Robotic Process Automation (RPA) and artificial intelligence technologies in optimizing complex industrial and enterprise operations. It had been reported that while RPA handled repetitive and rule-based tasks efficiently, its integration with machine learning, natural language processing, and neural network-based modelling had enabled cognitive capabilities such as anomaly detection, predictive analytics, semantic classification, and data inference. The review had highlighted important applications in manufacturing, agriculture, healthcare, finance, and retail. The authors had further observed that AI-RPA integration had improved efficiency, reduced costs, enhanced scalability, and supported real-time decision-making. However, challenges related to interoperability, data governance, algorithmic bias, and cybersecurity had also been identified.

Fenta et al. (2025) had examined the growing importance of flexible manufacturing systems (FMSs) in response to increasing global competition and the rising emphasis on efficiency and quality in modern industries. The study had described FMS as an advanced automated production system operating under computerized control, capable of adapting rapidly to changes in product design, batch size, and production sequence. It had reviewed the evolution of FMS and had highlighted the potential advantages of integrating emerging technologies such as the Internet of Things (IoT), artificial intelligence (AI), advanced robotics, enterprise wearables, 3D/4D printing, and virtual manufacturing. The authors had further assessed enabling technologies, flexible machining systems, and reconfigurable manufacturing systems to forecast the future of next-generation manufacturing. The review had suggested that FMS would play a significant role in enhancing agility, reducing overall costs, minimizing waste, and improving operational efficiency. It had concluded that future manufacturing would increasingly require more adaptive, responsive, and technology-driven systems.

Rahman et al. (2025) reviewed how machine learning (ML) had been increasingly integrated into industrial automation and had significantly transformed the monitoring, inspection, and optimization of manufacturing systems. The authors reported that ML models, when applied to real-time sensor data and historical operational records, had enabled proactive fault prediction, intelligent inspection, and dynamic process control, thereby improving system reliability, product quality, and operational efficiency. The review focused on three major domains, namely Predictive Maintenance (PdM), Quality Control (QC), and Process Optimization (PO). It was further observed that Digital Twin (DT) and Edge AI technologies had expanded the practical applications of ML in industrial settings. The study highlighted the growing adoption of deep learning approaches, particularly convolutional and recurrent neural networks, alongside a shift toward real-time edge deployment. It also identified emerging directions such as self-learning systems, federated architectures, explainable AI, collaborative intelligence, and autonomous defect diagnosis in future industrial operations.

Oostveen et al. (2025) examined the adoption of digital manufacturing technologies (DMTs) in the UK manufacturing sector, noting that although the UK ranked as the twelfth-largest manufacturing nation globally, its progress in digital transformation remained slower than that of several other European countries. The study investigated the perceptions of 313 manufacturing employees regarding the usefulness, ease of use, and workplace implications of DMTs. It was reported that employees generally acknowledged the benefits of DMTs, including improved productivity, better product quality, and enhanced industrial competitiveness. However, concerns were also observed regarding the complexity of use, the need for workforce upskilling, and physical interaction with advanced technologies. The findings further suggested that employees with lower educational qualifications demonstrated greater scepticism toward the relevance and applicability of DMTs. Moreover, workers employed in organisations already using such technologies were found to hold more favourable views, indicating that prior experience positively influenced acceptance. The study emphasised the importance of targeted training and effective change management strategies.

Ponce et al. (2024) examined the rapid expansion of the manufacturing sector in Mexico and observed that, despite increasing nearshoring opportunities, there remained a notable lack of effective educational tools for engineers, students, and decision-makers. The authors proposed a state-of-the-art framework that integrated virtual reality (VR) and artificial intelligence (AI) to transform the teaching and learning of advanced manufacturing systems. Through a case study centered on the design, production, and evaluation of a robotic platform, it was reported that the framework provided a comprehensive and immersive educational experience. The study highlighted three major components: robotic platform design and modeling, a virtual manufacturing company environment, and VR-based product evaluation. It was indicated that this framework successfully combined theoretical understanding with practical application. The findings suggested that the proposed approach enhanced comprehension of modern manufacturing challenges and could support skill development, sectoral growth, and the effective utilization of nearshoring opportunities in Mexico’s competitive manufacturing landscape.

Soori et al. (2024) had examined virtual manufacturing as a crucial component of Industry 4.0 for improving manufacturing processes and enhancing productivity in part production. The study had indicated that virtual manufacturing enabled manufacturers to optimize production activities through real-time data collected from sensors and interconnected devices. It had been reported that web-based virtual manufacturing platforms supported collaborative design, testing, and process optimization. The authors had further observed that RFID technology provided real-time visibility, supply chain control, and automation within manufacturing systems. Big data analytics had been identified as an important tool for generating valuable insights and improving operational efficiency. Moreover, the integration of artificial intelligence with virtual manufacturing had been found to enhance process effectiveness, consistency, and adaptability, leading to faster production cycles, improved product quality, and reduced costs. The review had also discussed recent developments, advantages, limitations, and future research directions related to virtual manufacturing applications in Industry 4.0.

Sivasankaran (2024) had described Computer Integrated Manufacturing (CIM) automation as a manufacturing process fully managed through automated systems, incorporating robotics, automated integration, corporate management systems, computer-aided engineering, and other advanced automation technologies. The study had emphasized that modern engineers interested in manufacturing needed to understand computer architecture and the interfacing of electromechanical processes with digital controllers for data acquisition and machinery operation. It had further highlighted that the primary objective of *Computer Automation in Factory: An Introduction* was to provide readers with a broad understanding of digital control technology and its application in factory automation. The review had noted that such technology was applied across multiple levels, including machine, manufacturing cell, and shop floor operations. Covering topics from computer and controller architecture to practical shop floor applications, the paper had presented a comprehensive review of the significance of computer applications in manufacturing systems by synthesizing insights from several national and international refereed journals.

Cheung et al. (2023) had examined how advances in internet connectivity, communication technologies, and computational power had significantly accelerated new product development cycles and improved supply chain efficiency in manufacturing. The study had indicated that digital technology had served as a crucial tool for optimizing production efficiency through simulation before actual operations and for enabling manufacturing automation through effective tracking of production data, materials, finished goods, personnel, and equipment across the value chain. It had identified two major applications of digital technology in manufacturing: first, the modeling, simulation, and visualization of manufacturing systems;

and second, the automatic acquisition, retrieval, and processing of manufacturing data for supply chain operations. The chapter had summarized the state-of-the-art in digital manufacturing, focusing on virtual manufacturing, smart manufacturing, and Industrial Internet of Things systems. It had also highlighted associated technologies, current research trends, practical applications, and key social and technological barriers affecting implementation**.**

Mourtzis et al. (2022) examined the evolution of manufacturing systems over the past seven decades, highlighting changes in their structure, organization, and operation. They outlined the progression from Computer-Aided Manufacturing to Computer-Integrated Manufacturing systems, emphasizing the technical developments that shaped these paradigms. The study described the contemporary Smart Manufacturing model central to Industry 4.0, identifying key components of the Smart Factory and discussing associated technical challenges through various frameworks and architectures. It was noted that the autonomous optimization of interconnected processes required disparate computer and communication systems to function cohesively across machines, devices, and manufacturing infrastructures, necessitating advanced protocols and standards. Interoperability was recognized as a significant challenge, demanding ongoing research to integrate diverse devices in industrial environments and establish global standards. Furthermore, the authors highlighted the potential of Digital Twins for predictive maintenance and emphasized that Product Lifecycle Management systems now allowed comprehensive digital capture of design, production, and usage, illustrating the gradual realization of interoperable smart manufacturing ecosystems.

Novák and Vyskočil (2022) investigated smart production systems aligned with the Industry 4.0 vision, emphasizing that these systems were composed of integrated subsystems enabling high flexibility and reconfigurability. They highlighted that components such as industrial and mobile robots or transport systems had evolved into fully functional subsystems, collectively forming a system-of-systems within Industry 4.0 production. The authors noted that tasks like testing, fine-tuning, and production planning were critical across the production system life cycle and could be substantially enhanced by digital twins, which acted as digital replicas synchronized with physical systems in real time. They observed, however, that designing and implementing digital twins for integrated yet partly standalone industrial subsystems posed complex and time-consuming engineering challenges. Novák and Vyskočil proposed utilizing formal descriptions of production resources and their operations, from which executable digital twins could be automatically derived. These digital twins were further improved using operation durations obtained via process mining, and the approach was successfully validated in the Industry 4.0 Testbed with four robots and a transport system.

Guerra-Zubiaga et al. (2021) highlighted that the emergence of digital manufacturing and the Industry 4.0 paradigm had facilitated the integration of recent manufacturing advancements with contemporary information and communication technologies. They argued that incorporating digital simulation tools into production systems could enhance time and cost efficiency, while enabling faster, more flexible, and higher-quality production processes. The study emphasized that the use of digital simulations, combined with sensory data, could strengthen the reliability of production systems and improve the effectiveness of production planning and execution. The authors proposed an approach for developing a Digital Twin of production systems aimed at optimizing planning and commissioning processes. They noted that the virtual cell interacted with the physical system through various Digital Manufacturing Tools (DMT), permitting the testing of different programs under alternative scenarios to identify potential shortcomings prior to implementation. The feasibility of this approach was demonstrated through multiple case studies across different production systems.

Chandra Sekaran et al. (2021) highlighted that the global manufacturing trend had shifted from a manufacturing-centric to a user-centric approach, which had led to shorter product lifespans and increased replacement rates. They reported that Germany had introduced Industry Revolution 4.0 (IR 4.0) to transform manufacturing processes into cyber-physical systems (CPS). The study indicated that digital factories represented the first step toward CPS and IR 4.0 and were considered a crucial evolution in the manufacturing sector. The authors explained the distinctions between digital factories and related domains such as smart factories, CPS, and virtual factories, while outlining the requirements and objectives necessary for developing digital factory tools. They further identified challenges in implementing digital factories and proposed that these could be addressed through interoperable virtual reality (VR) technologies. The study emphasized that VR could simulate digital factory operations, thereby supporting decision-making and operational efficiency, and reviewed recommendations from prior research for developing VR-based digital factory solutions.

Leng et al. (2020) investigated the challenges posed by increasing individualization demands in products, which required high flexibility in manufacturing systems to accommodate frequent changes. They proposed a digital twin-driven approach for rapid reconfiguration of automated manufacturing systems, in which the digital twin consisted of a semi-physical simulation that captured system data and provided input to an optimization module. The optimization results were then fed back into the simulation for verification. They introduced the concept of open-architecture machine tools (OAMTs), comprising a fixed standard platform with interchangeable individualized modules, allowing engineers to flexibly reconfigure systems for process planning. The study detailed key techniques for integrating cyber and physical systems and for quickly programming production capacity and functionality at a bi-level to adapt to rapid product changes. A physical implementation was conducted, which demonstrated the approach’s effectiveness in enhancing system performance while minimizing reconfiguration overheads through automated, rapid optimization.

Umeda et al. (2019) investigated the transformation of manufacturing system engineers’ activities within the Industry 4.0 framework, highlighting the shift toward cyber-physical systems (CPS) in Japanese factories. They noted that engineers were traditionally stationed on the shop floor, collaborating directly with workers to continuously improve manufacturing processes. To support these evolving engineering activities, they proposed the concept of the ‘Digital Triplet’ as an extension of the Digital Twin, incorporating an intelligent activity world alongside the cyber and physical worlds. The study emphasized that this framework facilitated the development of engineering processes by enabling engineers to integrate insights from both cyber and physical domains. Furthermore, Umeda et al. described the implementation of an educational program based on the Digital Triplet, which included a course where novice engineers conducted ‘Kaizen’ exercises using a prototype CPS system in a learning factory environment. The authors suggested that this approach enhanced practical learning and the effective application of CPS concepts in real-world manufacturing contexts.

III. KEY FINDINGS FROM STUDY

S. No.	Author(s) & Year	Focus of Study	Methodology / Approach	Key Findings	Research Contribution
1	Reuther et al. (2026)	Digital Twin framework for PLC-based industrial automation	Development of DT framework using IEC 61131-3 and OPC UA standards with VR integration	Improved interoperability, real-time monitoring, and reduced integration complexity	Proposed standardized DT-based PLC architecture for industrial automation

2	Saranya et al. (2026)	AI and RPA integration in industrial automation	Conceptual and application-based review of AI-RPA systems	Enhanced predictive analytics, anomaly detection, and automation efficiency	Demonstrated convergence of AI and RPA in smart manufacturing ecosystems
3	Fenta et al. (2025)	Flexible Manufacturing Systems (FMS) evolution	Literature-based review of FMS technologies	FMS improves adaptability, reduces cost, and enhances productivity	Highlighted role of IoT, AI, robotics in next-gen FMS
4	Rahman et al. (2025)	Machine learning in industrial automation	Systematic review of ML applications in PdM, QC, PO	ML improves fault prediction, quality control, and process optimization	Identified role of deep learning, edge AI, and digital twins
5	Oostveen et al. (2025)	Workforce perception of DMT adoption	Survey of 313 manufacturing employees	Employees recognize benefits but face training and usability challenges	Highlighted human factors influencing digital manufacturing adoption
6	Ponce et al. (2024)	VR and AI in manufacturing education	Case study-based framework development	Improved immersive learning and skill development	Integrated VR-AI for advanced manufacturing training systems
7	Soori et al. (2024)	Virtual manufacturing in Industry 4.0	Review of digital manufacturing platforms	Improved real-time optimization and production efficiency	Identified role of RFID, AI, and big data in virtual manufacturing
8	Sivasankaran (2024)	Computer Integrated Manufacturing systems	Theoretical review of CIM and automation systems	CIM enhances automation across machine and shop-floor levels	Provided comprehensive overview of digital control systems
9	Cheung et al. (2023)	Digital manufacturing systems and IoT	Literature review and conceptual analysis	Digital tech improves simulation, tracking, and automation	Classified digital manufacturing applications in supply chains
10	Mourtzis et al. (2022)	Evolution of smart manufacturing	System architecture and framework analysis	Interoperability is key challenge in smart manufacturing	Defined transition from CIM to Smart Manufacturing ecosystem
11	Novák & Vyskočil (2022)	Digital twins in production systems	Experimental implementation in Industry 4.0 testbed	DT improves system synchronization and engineering efficiency	Proposed automated DT generation using process mining

12	Guerra-Zubiaga et al. (2021)	Digital twin for production systems	Case study-based simulation approach	DT improves planning, commissioning, and system reliability	Demonstrated simulation-based optimization of production systems
13	Chandra Sekaran et al. (2021)	VR in digital factories	Comprehensive literature review	VR improves simulation, training, and decision-making	Defined role of VR in CPS and smart factory development
14	Leng et al. (2020)	Digital twin-driven reconfiguration	Open-architecture machine tool model	Enables rapid system reconfiguration and optimization	Introduced bi-level optimization in manufacturing systems
15	Umeda et al. (2019)	Digital Triplet concept in manufacturing education	Educational system development in CPS environment	Enhances engineering learning and shop-floor integration	Extended digital twin with human cognitive layer

IV. CONCLUSION

Digital Manufacturing Systems (DMS) have emerged as a transformative force in modern industrial automation, fundamentally reshaping traditional production paradigms into intelligent, interconnected, and data-driven ecosystems. The reviewed literature consistently highlights that the integration of advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), Digital Twins (DT), Internet of Things (IoT), Virtual Reality (VR), and Flexible Manufacturing Systems (FMS) has significantly enhanced productivity, operational efficiency, and system adaptability in manufacturing environments (Mourtzis et al., 2022; Rahman et al., 2025). A key finding across studies is the central role of Digital Twin technology in bridging the gap between physical and virtual manufacturing systems. As demonstrated by Reuther et al. (2026), DT frameworks enable real-time monitoring, simulation, and control of Programmable Logic Controllers (PLCs), improving interoperability and reducing system integration complexity. Similarly, Leng et al. (2020) and Novák and Vyskočil (2022) emphasized that digital twins facilitate rapid system reconfiguration and intelligent synchronization between cyber and physical environments, which is essential for adaptive and flexible manufacturing operations. Furthermore, AI and ML technologies have become critical enablers of intelligent decision-making in industrial automation. Rahman et al. (2025) found that predictive maintenance, fault detection, and process optimization can be significantly improved using deep learning models applied to real-time and historical data. Saranya et al. (2026) further highlighted that the integration of AI with Robotic Process Automation (RPA) enhances cognitive automation capabilities, enabling anomaly detection, semantic reasoning, and autonomous industrial operations. The literature also underscores the importance of Flexible Manufacturing Systems (FMS) and virtual manufacturing platforms in achieving agility and responsiveness in production systems. Fenta et al. (2025) and Soori et al. (2024) demonstrated that the integration of IoT, robotics, and big data analytics supports dynamic production optimization, cost reduction, and improved quality control. Additionally, VR-based manufacturing education systems, as discussed by Ponce et al. (2024), play a crucial role in bridging the gap between theoretical knowledge and practical industrial applications. Despite these advancements, challenges such as interoperability issues, cybersecurity risks, high implementation costs, and workforce skill gaps remain significant barriers to full-scale adoption of digital manufacturing systems (Oostveen et al., 2025; Sivasankaran, 2024). Therefore, while digital manufacturing has achieved substantial progress, its full potential is yet to be realized in many industrial sectors.

V. FUTURE SCOPE

The future of Digital Manufacturing Systems is expected to be shaped by deeper integration of intelligent technologies, autonomous systems, and human-centered design approaches. One of the most promising directions is the advancement of **fully autonomous smart factories**, where AI-driven systems will independently manage production planning, execution, quality control, and maintenance with minimal human intervention. Another important future development lies in the enhancement of **Digital Twin ecosystems**, particularly through real-time synchronization, multi-scale modeling, and integration with edge and cloud computing platforms. Future research is likely to focus on developing **self-evolving digital twins** that can continuously learn from operational data and improve system performance dynamically. The expansion of **Edge AI and federated learning** in industrial environments will also play a critical role in improving real-time decision-making while maintaining data privacy and reducing latency. These technologies will enable distributed intelligence across manufacturing networks, making systems more scalable and secure (Rahman et al., 2025). In addition, the integration of **Blockchain technology** is expected to enhance data security, traceability, and transparency in supply chains and industrial operations. This will address existing concerns related to cybersecurity and data integrity in interconnected manufacturing systems. From a human resource perspective, future manufacturing systems will require significant investment in **skill development and digital literacy programs**. As highlighted by Oostveen et al. (2025), workforce readiness is a critical factor in successful technology adoption. Therefore, future industrial ecosystems will likely emphasize human–machine collaboration, supported by immersive training environments using Virtual and Augmented Reality technologies. Finally, future research should focus on developing **standardized interoperability frameworks and global communication protocols** to ensure seamless integration across heterogeneous manufacturing systems. The convergence of AI, IoT, Digital Twins, and advanced robotics is expected to lead toward a fully **self-optimizing, adaptive, and sustainable manufacturing ecosystem** that defines the next generation of industrial automation.

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