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Analysis of AI-Agent Implementation in Industry 5.0 Production Optimization: A Systematic Literature Review

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ABSTRACT

Industry 5.0 represents the next evolution of manufacturing, emphasizing the integration of advanced technologies with human-centered, sustainable, and resilient production systems. This study aims to analyze the implementation of AI agents in Industry 5.0 production optimization and evaluate their contributions to manufacturing performance. A Systematic Literature Review (SLR) approach was employed to examine relevant studies published between 2020 and 2026, sourced from Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. The selected literature was analyzed across three dimensions The findings indicate that various AI-agent technologies, including Intelligent Agents, Multi-Agent Systems (MAS), Reinforcement Learning Agents, and Generative AI Agents, are increasingly utilized in manufacturing environments. Their implementation has led to significant improvements in production scheduling through reduced scheduling conflicts and enhanced machine utilization, predictive maintenance through improved failure prediction and reduced downtime, quality control through intelligent defect detection and automated inspection, and resource allocation through optimized utilization of labor, machinery, materials, and energy. Furthermore, AI agents contribute substantially to the core pillars of Industry 5.0 by supporting human-centric manufacturing through decision assistance and workplace safety enhancement, promoting sustainability through waste reduction and energy optimization, and increasing operational resilience through adaptive responses to disruptions and demand fluctuations. Despite challenges related to data integration, implementation costs, workforce readiness, and ethical considerations, the overall findings demonstrate that AI agents are highly effective enablers of production optimization and intelligent manufacturing. Future research should focus on autonomous factory ecosystems, human–AI collaborative agents, Digital Twin–AI Agent integration, and Explainable AI frameworks to further advance Industry 5.0 adoption and manufacturing innovation.

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1. INTRODUCTION

The manufacturing sector is currently undergoing a significant transformation driven by rapid technological advancements and increasing demands for productivity, flexibility, and sustainability.

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The concept of Industry 4.0 introduced intelligent manufacturing through the integration of cyber-physical systems, the Internet of Things (IoT), big data analytics, cloud computing, and artificial intelligence(Tao et al., 2019). These technologies enabled factories to become more connected, automated, and data-driven. However, despite the substantial benefits achieved through Industry 4.0, many manufacturing organizations continue to face challenges related to system complexity, adaptability, human involvement, and resilience in responding to unexpected disruptions. As a result, the industrial landscape has begun transitioning toward Industry 5.0, a paradigm that emphasizes the collaboration between humans and intelligent technologies to create more sustainable, resilient, and human-centered production systems.

Unlike Industry 4.0, which primarily focuses on automation and efficiency, Industry 5.0 recognizes the importance of human creativity, expertise, and decision-making in manufacturing processes(Nahavandi, 2019). The integration of advanced artificial intelligence technologies enables organizations to move beyond simple automation toward intelligent collaboration between humans and machines. In this context, AI Agents have emerged as a promising technology capable of supporting autonomous decision-making and adaptive production management. AI agents are intelligent software entities that can perceive their environment, analyze information, learn from experiences, make decisions, and perform actions autonomously to achieve specific objectives. Their ability to continuously interact with dynamic manufacturing environments makes them particularly suitable for modern production systems that require real-time optimization and rapid adaptation.

The growing complexity of manufacturing operations further highlights the need for intelligent decision-support mechanisms. Modern production systems involve numerous interconnected machines, sensors, workers, and supply chain components that generate vast amounts of operational data. Managing these complex interactions using conventional automation systems or rule-based algorithms can be challenging because such approaches often lack adaptability and learning capabilities. Traditional systems typically rely on predefined rules and static decision frameworks, making them less effective in responding to changing production conditions, equipment failures, fluctuating customer demands, and resource constraints. Consequently, manufacturers are increasingly exploring AI-agent technologies to improve operational efficiency and support intelligent decision-making across various production activities(Leusin et al., 2018).

Production optimization remains one of the primary objectives of manufacturing organizations seeking to maintain competitiveness in global markets. Effective production optimization can improve productivity, reduce operational costs, enhance product quality, minimize downtime, increase resource utilization, and support sustainable manufacturing practices. AI agents offer significant potential to achieve these objectives by enabling dynamic scheduling, predictive maintenance, quality control, inventory management, resource allocation, and real-time process optimization. Through continuous learning and adaptation, AI agents can identify patterns, predict future events, and recommend optimal actions that enhance overall production performance.

Research on intelligent manufacturing has evolved significantly over the last decade, moving from the automation-oriented paradigm of Industry 4.0 toward the human-centric, sustainable, and resilient vision of Industry 5.0. One of the earliest contributions to the Industry 5.0 discourse was provided by Rožanec et al. (2022), who proposed a human-centric artificial intelligence architecture designed specifically for Industry 5.0 applications. Their study emphasized that future manufacturing systems should not solely focus on automation but should integrate explainable AI, predictive analytics, decision-support mechanisms, and human feedback into a unified framework. The authors argued that trustworthiness, transparency, and collaboration between human operators and intelligent systems are essential requirements for successful Industry 5.0 implementation. Their work established a conceptual foundation for AI-driven manufacturing environments where intelligent agents support rather than replace human workers.

In a related study, Leng et al. (2022) introduced a blockchain-enabled multi-agent autonomous process control framework for resilient and individualized manufacturing. The researchers proposed a smart-contract-based architecture in which multiple intelligent agents coordinate production activities autonomously while maintaining system resilience under dynamic manufacturing conditions. Their findings demonstrated that multi-agent systems could improve production flexibility, adaptive control, and responsiveness to disturbances, making them suitable for Industry 5.0 environments characterized by high customization demands and frequent operational changes.

The emergence of Industry 5.0 as a human-centered manufacturing paradigm was further examined by Alves, Lima, and Gaspar (2023). Through a systematic literature review, the authors highlighted that Industry 5.0 prioritizes worker well-being, sustainability, and resilience alongside technological advancement. Their findings suggested that future intelligent manufacturing systems should leverage AI technologies to enhance human capabilities rather than pursue complete automation. This perspective provides an important theoretical basis for AI-agent implementation because intelligent agents are increasingly viewed as collaborative partners in manufacturing decision-making processes.

Similarly, Longo et al. (2023) conducted a comprehensive review of human-centric smart manufacturing in Industry 5.0. Their study identified key enabling technologies, including artificial intelligence, digital twins, cyber-physical systems, and intelligent decision-support platforms. The authors concluded that future manufacturing systems require adaptive AI mechanisms capable of balancing productivity, sustainability, and human-centered objectives. They also emphasized the importance of integrating autonomous decision-making capabilities into production systems while maintaining human oversight.

Further investigation into the technological foundations of Industry 5.0 was carried out by researchers in 2023 through a systematic review of Industry 5.0 technologies. Their findings indicated that the transition from Industry 4.0 to Industry 5.0 requires moving beyond purely technology-driven optimization toward socio-technical systems that integrate human expertise with intelligent automation. The study identified artificial intelligence, cyber-physical systems, and IoT-based decision-support mechanisms as critical technologies for enabling future autonomous manufacturing environments.

Gladysz et al. (2023) examined the evolution from Operator 4.0 to Operator 5.0 and emphasized the growing role of intelligent technologies in supporting human workers. Their systematic review demonstrated that AI-enabled assistance systems, collaborative robots, and intelligent decision-support tools can significantly improve operational performance while preserving human control over critical manufacturing decisions. The authors argued that future manufacturing environments will increasingly rely on collaborative relationships between human operators and autonomous agents.

As Industry 5.0 research matured, increasing attention was directed toward optimization techniques. Akundi et al. (2024) analyzed major research themes within Industry 5.0 and identified smart and sustainable manufacturing, supply chain optimization, enterprise digitization, and human–machine connectivity as dominant topics. Their findings highlighted the growing significance of AI-based optimization methods for improving production efficiency while supporting sustainability and human-centric objectives. The study also revealed that intelligent decision-making systems remain one of the most promising research directions for future manufacturing development.

Despite the growing interest in artificial intelligence applications within manufacturing, several research gaps remain. Existing studies predominantly focus on AI technologies within the context of Industry 4.0, including machine learning, predictive analytics, and industrial automation. While these studies demonstrate the benefits of intelligent technologies, relatively few investigations specifically examine the role of AI-agent systems within the Industry 5.0 framework. Furthermore, there is limited comprehensive analysis regarding how AI agents contribute to production optimization while simultaneously supporting the human-centric, sustainable, and resilient principles of Industry 5.0. The lack of integrated research in this area creates a need for a systematic evaluation of AI-agent implementation and its implications for modern manufacturing systems.

Based on these considerations, this study aims to analyze the implementation of AI agents in Industry 5.0 manufacturing environments and evaluate their contribution to production optimization(Massaro, 2021). Specifically, the research seeks to identify the major applications of AI agents in manufacturing processes, assess their impact on key production performance indicators, and examine the challenges and opportunities associated with their implementation. By investigating current developments and emerging trends, this study provides a comprehensive understanding of the role of AI-agent technologies in supporting next-generation manufacturing systems.

The significance of this research can be viewed from both theoretical and practical perspectives. Theoretically, the study contributes to the growing body of knowledge on Industry 5.0 by providing insights into the integration of AI-agent technologies within intelligent manufacturing environments. It also expands existing literature on autonomous decision-making systems and their role in production optimization. Practically, the findings can assist manufacturing organizations, technology developers, and policymakers in understanding the benefits, limitations, and implementation requirements of AI-agent systems. The insights generated from this research may support strategic decision-making and facilitate the adoption of AI-driven solutions that enhance productivity, sustainability, and resilience in future manufacturing operations.

2. RESEARCH METHOD

This study employs a Systematic Literature Review (SLR) methodology to investigate the implementation of AI agents in Industry 5.0 production optimization(Varela et al., 2018). The SLR approach was selected because it provides a rigorous and transparent process for identifying, evaluating, and synthesizing existing scientific evidence related to a specific research topic. As AI-agent technologies and Industry 5.0 concepts are rapidly evolving fields, a systematic review enables the comprehensive examination of current knowledge, technological developments, implementation strategies, benefits, and challenges reported in the literature. Furthermore, the SLR method facilitates the identification of research trends, knowledge gaps, and future research opportunities within the context of intelligent manufacturing systems.

The research process began with the formulation of research questions focusing on the role of AI agents in optimizing production systems within Industry 5.0 environments. Subsequently, relevant academic publications were collected from several internationally recognized scientific databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. These databases were selected due to their extensive coverage of high-quality peer-reviewed publications in the fields of artificial intelligence, manufacturing engineering, industrial automation, and smart production systems. Utilizing multiple databases ensured broader coverage of relevant studies and minimized the risk of excluding significant contributions from the scientific community.

To identify relevant literature, a comprehensive search strategy was developed using a combination of keywords associated with AI agents and Industry 5.0 manufacturing systems. The primary search terms included “AI Agent,” “Intelligent Agent,” “Autonomous Agent,” “Industry 5.0,” “Smart Manufacturing,” “Production Optimization,” “Human-AI Collaboration,” and “Intelligent Production Systems.” Boolean operators such as AND and OR were used to combine keywords and refine the search process. Examples of search strings included “AI Agent AND Industry 5.0,” “Autonomous Agent AND Smart Manufacturing,” and “Production Optimization AND Intelligent Production Systems.” This strategy ensured that the search captured studies addressing both technological and operational aspects of AI-agent implementation in manufacturing environments.

To maintain the quality and relevance of the reviewed literature, specific inclusion criteria were established. First, only articles published between 2020 and 2026 were considered to ensure that the analysis reflected the most recent developments in AI-agent technologies and Industry 5.0 research. Second, only peer-reviewed journal articles and high-quality conference proceedings were included to ensure scientific rigor and reliability. Third, publications were required to be written in English to facilitate consistent analysis and comparison. Finally, the selected studies had to explicitly discuss the implementation, application, evaluation, or conceptual development of AI agents within manufacturing, production optimization, or Industry 5.0 contexts. Publications that focused solely on general artificial intelligence applications without a manufacturing perspective, duplicate records, editorials, book reviews, and non-scientific articles were excluded from the review.

After the selection process, the retrieved studies underwent systematic screening and evaluation(Waffenschmidt et al., 2019). Titles, abstracts, and full-text articles were examined to determine their relevance to the research objectives. Relevant data were extracted and organized into a structured review framework to facilitate comparative analysis across studies. The extracted information included publication details, research objectives, AI-agent technologies employed, manufacturing applications, optimization approaches, reported benefits, implementation challenges, and performance outcomes.

The analysis was conducted across three primary dimensions: technology, manufacturing application, and performance impact. The technology dimension focused on identifying the types of AI agents utilized in manufacturing systems(Peres et al., 2020). Particular attention was given to Reinforcement Learning Agents, which are capable of learning optimal actions through continuous interaction with production environments; Multi-Agent Systems (MAS), which enable decentralized coordination among multiple intelligent entities; Generative AI Agents, which support decision-making, knowledge generation, and process recommendations; and Digital Twin Agents, which integrate virtual representations of physical manufacturing systems with autonomous decision-making capabilities. Examining these technologies allowed the study to evaluate the technological maturity and applicability of different AI-agent approaches in Industry 5.0 environments.

The manufacturing application dimension analyzed how AI agents contribute to specific production optimization activities. Key application areas included production scheduling, resource allocation, quality control, predictive maintenance, and supply chain optimization. Production scheduling studies were examined to determine how AI agents improve machine utilization, reduce bottlenecks, and enhance production flexibility. Resource allocation research was evaluated to assess the effectiveness of AI agents in optimizing labor, equipment, material, and energy usage. Quality control applications focused on defect detection, process monitoring, and intelligent inspection systems, while predictive maintenance studies investigated the role of AI agents in equipment health monitoring and failure prediction. Supply chain optimization research explored how autonomous agents support inventory management, logistics coordination, and demand forecasting within interconnected manufacturing ecosystems.

The final analytical dimension focused on performance indicators used to evaluate the effectiveness of AI-agent implementation(Peres et al., 2020). These indicators included productivity, throughput, downtime, production cost, product quality, and energy efficiency. Productivity and throughput metrics were analyzed to determine improvements in manufacturing output and operational efficiency. Downtime reduction was examined as an indicator of system reliability and maintenance effectiveness. Production cost analysis assessed the economic benefits associated with AI-agent adoption, while product quality metrics evaluated improvements in defect reduction and process consistency. Energy efficiency was included as a critical indicator because sustainability represents a core principle of Industry 5.0. By examining these performance measures, the study provides a comprehensive assessment of how AI agents influence production optimization outcomes across diverse manufacturing environments.

Through this systematic methodology, the study aims to generate a comprehensive understanding of AI-agent implementation in Industry 5.0 production systems and provide evidence-based insights regarding their contributions, limitations, and future potential. The findings derived from this review are expected to support researchers, practitioners, and policymakers in developing more intelligent, sustainable, and human-centric manufacturing strategies.

3. RESULT AND DISCUSSIONS

3.1 Overview of AI-Agent Technologies

The systematic review of recent literature reveals that AI-agent technologies have become fundamental enablers of intelligent manufacturing within the Industry 5.0 paradigm(SHARKAWY, 2020). Unlike traditional automation systems that rely on predefined rules and static operational procedures, AI agents possess advanced cognitive capabilities that enable them to perceive environmental conditions, analyze complex datasets, learn from experience, and make autonomous decisions in real time. These characteristics make AI agents particularly valuable in modern production environments where manufacturing systems are increasingly dynamic, interconnected, and data-intensive. The reviewed studies indicate that the implementation of AI agents contributes significantly to production optimization by enhancing operational flexibility, improving decision quality, reducing response times, and supporting human-machine collaboration.

One of the most widely discussed categories in the literature is the intelligent agent. Intelligent agents are autonomous computational entities designed to interact with their environment

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and perform tasks without continuous human intervention. Several studies emphasize four fundamental characteristics that distinguish intelligent agents from conventional software systems: autonomy, learning capability, adaptability, and decision-making ability. Autonomy allows intelligent agents to perform assigned tasks independently while continuously monitoring production conditions. Learning capability enables agents to improve their performance over time by analyzing historical data and operational experiences. Adaptability refers to the capacity of intelligent agents to respond effectively to changing production requirements, machine conditions, and market demands. Decision-making ability allows agents to evaluate multiple alternatives and select optimal actions based on predefined objectives and real-time information.

The literature demonstrates that intelligent agents are increasingly deployed in manufacturing systems to support production monitoring, predictive maintenance, quality assurance, and operational planning. Their ability to process large volumes of sensor-generated data enables them to identify inefficiencies, detect anomalies, and recommend corrective actions more effectively than traditional rule-based systems. Furthermore, intelligent agents contribute to Industry 5.0 objectives by serving as collaborative decision-support tools that augment human expertise rather than replacing human workers. This human-centric approach aligns with the fundamental principles of Industry 5.0, which emphasize cooperation between humans and intelligent technologies.

Another prominent technology identified in the reviewed studies is the Multi-Agent System (MAS). A Multi-Agent System consists of multiple autonomous agents that communicate, cooperate, and coordinate with one another to achieve common organizational goals. Unlike centralized manufacturing control systems, MAS architectures distribute decision-making responsibilities among multiple intelligent entities, enabling greater scalability, flexibility, and resilience. The decentralized nature of MAS is particularly advantageous in modern manufacturing environments where production processes involve numerous interconnected machines, workstations, and supply chain components.

The reviewed literature indicates that Multi-Agent Systems are extensively applied in production planning, scheduling, resource coordination, and distributed manufacturing. In production planning, autonomous agents collaborate to allocate resources, balance workloads, and optimize production sequences based on current operational requirements. In scheduling applications, agents dynamically adjust production schedules in response to machine breakdowns, material shortages, or changing customer demands. Resource coordination is another major application area, where agents negotiate and allocate machinery, labor, materials, and energy resources to maximize efficiency. Furthermore, MAS architectures are increasingly utilized in distributed manufacturing environments, where geographically dispersed production facilities must coordinate activities in real time. The findings suggest that Multi-Agent Systems significantly improve operational responsiveness and manufacturing agility while reducing bottlenecks and coordination delays.

Reinforcement Learning (RL) Agents represent another important category of AI-agent technology identified in the literature. Reinforcement learning is a machine learning approach in which agents learn optimal behavior through continuous interaction with their environment. Instead of relying on predefined instructions, RL agents improve their decision-making capabilities by receiving rewards or penalties based on the outcomes of their actions. Through repeated learning cycles, these agents develop strategies that maximize long-term performance objectives.

The review findings indicate that Reinforcement Learning Agents are particularly effective in dynamic scheduling, adaptive control, and process optimization applications. In dynamic scheduling environments, RL agents continuously evaluate production conditions and adjust schedules to optimize machine utilization, minimize waiting times, and improve throughput. In adaptive control systems, reinforcement learning enables manufacturing equipment to automatically adjust operating parameters in response to changing environmental conditions and process variations. This capability enhances process stability and reduces performance degradation. Furthermore, RL agents have demonstrated significant potential in process optimization by identifying operational strategies that improve productivity, reduce waste, and minimize energy consumption. Compared with traditional optimization methods, reinforcement learning offers superior adaptability and can effectively manage the uncertainty and complexity characteristic of Industry 5.0 manufacturing systems.

Recent literature also highlights the growing importance of Generative AI Agents in intelligent manufacturing environments. Unlike conventional AI systems that primarily focus on prediction and classification tasks, Generative AI Agents possess the capability to generate new knowledge, recommendations, solutions, and insights based on contextual information. Advances in large language models, foundation models, and generative artificial intelligence have accelerated the adoption of these agents in industrial applications, particularly in areas requiring complex reasoning and decision support.

The reviewed studies reveal that Generative AI Agents are increasingly utilized for production recommendations, operational decision support, and knowledge management. In production optimization, these agents analyze operational data, historical records, and production constraints to generate recommendations that improve efficiency and resource utilization. For operational decision support, Generative AI Agents assist managers and production planners by providing explanations, scenario analyses, and strategic recommendations for addressing manufacturing challenges. Additionally, these agents play an important role in knowledge management by capturing organizational expertise, facilitating information sharing, and supporting workforce training. Their ability to transform large volumes of structured and unstructured data into actionable knowledge makes them valuable tools for enhancing human decision-making capabilities within Industry 5.0 environments.

3.2 AI-Agent Applications in Production Optimization

The systematic review findings indicate that AI-agent technologies have been extensively applied across multiple areas of production optimization in Industry 5.0 manufacturing environments(SHARKAWY, 2020). As production systems become increasingly complex and interconnected, manufacturers require intelligent solutions capable of making autonomous decisions, adapting to changing operational conditions, and supporting human decision-makers. AI agents address these requirements by continuously monitoring production activities, analyzing large volumes of operational data, and recommending or executing optimal actions in real time. The reviewed literature demonstrates that AI agents contribute significantly to production scheduling, predictive maintenance, quality control, and resource allocation, resulting in measurable improvements in productivity, efficiency, flexibility, and sustainability.

One of the most prominent application areas of AI agents is production scheduling. Scheduling is a critical manufacturing activity that determines the allocation of jobs, machines, and resources within a production system. Traditional scheduling methods often struggle to cope with dynamic production environments characterized by fluctuating customer demands, machine breakdowns, material shortages, and unexpected disruptions(Ouelhadj & Petrovic, 2009). AI agents overcome these limitations by continuously analyzing production conditions and dynamically adjusting schedules based on real-time information. The reviewed studies consistently report that AI-agent-based scheduling systems reduce scheduling conflicts by improving coordination among production resources and minimizing competition for shared equipment. Furthermore, intelligent scheduling agents enhance machine utilization by allocating workloads more efficiently and reducing idle time across manufacturing operations. Another significant benefit identified in the literature is the ability of AI agents to respond rapidly to demand fluctuations. When customer requirements change unexpectedly, AI agents can recalculate production schedules and recommend alternative plans with minimal disruption to ongoing operations. Consequently, AI-agent-driven scheduling systems contribute to greater operational flexibility and improved responsiveness in Industry 5.0 manufacturing environments.

Another major application of AI agents is predictive maintenance. Maintenance activities play a crucial role in ensuring the reliability and availability of manufacturing equipment. Conventional maintenance strategies, such as corrective maintenance and preventive maintenance, often result in either unexpected failures or unnecessary maintenance interventions(Zhu et al., 2019). AI-agent technologies offer a more intelligent approach by continuously monitoring machine conditions through sensor data and operational indicators. By applying machine learning, pattern recognition, and predictive analytics techniques, AI agents can identify early signs of equipment degradation and forecast potential failures before they occur. The reviewed literature demonstrates that AI-agent-based predictive maintenance systems significantly improve failure prediction accuracy, enabling maintenance teams to take corrective actions proactively. As a result, manufacturers experience substantial reductions in unplanned downtime, which directly improves production continuity and operational efficiency. Additionally, predictive maintenance supported by AI agents increases equipment availability by ensuring that machines remain operational for longer periods and maintenance activities are performed only when necessary. These benefits not only reduce maintenance costs but also enhance overall manufacturing productivity and system reliability.

Quality control represents another important domain where AI agents have demonstrated considerable value. Maintaining consistent product quality is essential for customer satisfaction, regulatory compliance, and competitive advantage. Traditional quality inspection methods often rely heavily on human inspectors, making them susceptible to inconsistencies, fatigue, and limited scalability(Kang et al., 2018). AI-agent technologies address these challenges through intelligent defect detection, process monitoring, and automated inspection systems. The literature indicates that AI agents can analyze images, sensor signals, and production parameters to identify defects with greater speed and accuracy than conventional inspection approaches. Through continuous process monitoring, AI agents can detect deviations from established quality standards and initiate corrective actions before defects propagate throughout the production line. Furthermore, automated inspection systems powered by AI agents enable real-time quality assessment without interrupting manufacturing operations. These capabilities contribute to reduced defect rates, improved product consistency, lower rework costs, and enhanced customer satisfaction. In Industry 5.0 environments, AI agents also support quality engineers by providing actionable insights and recommendations that facilitate more informed decision-making.

Resource allocation is another critical area where AI agents contribute to production optimization(Shen et al., 2006). Manufacturing organizations must efficiently manage various resources, including labor, machinery, raw materials, and energy, to achieve optimal operational performance. The reviewed studies reveal that AI agents are increasingly utilized to optimize resource allocation by analyzing production requirements, resource availability, and operational constraints in real time. In labor management, intelligent agents assist in assigning workers to tasks based on skill levels, workload distribution, and production priorities, thereby improving workforce productivity and reducing inefficiencies. In machine allocation, AI agents identify optimal equipment utilization strategies that maximize production output while minimizing idle time and operational bottlenecks. The literature also highlights the role of AI agents in optimizing raw material usage through improved inventory management, demand forecasting, and material planning. Such capabilities help reduce waste and ensure the timely availability of production inputs. Additionally, energy management has emerged as a significant application area due to increasing sustainability requirements. AI agents can monitor energy consumption patterns, identify inefficiencies, and recommend operational adjustments that reduce energy usage without compromising production performance. These capabilities align closely with the sustainability objectives of Industry 5.0 and support the development of environmentally responsible manufacturing systems.

3.3 Impact on Production Performance

The findings from the systematic literature review indicate that the implementation of AI-agent technologies has a substantial positive impact on production performance across various manufacturing environments. By integrating autonomous decision-making, adaptive learning capabilities, predictive analytics, and real-time optimization mechanisms, AI agents contribute significantly to the achievement of key operational objectives within Industry 5.0. The reviewed studies consistently report improvements in productivity, reductions in downtime and operational costs, enhanced product quality, increased manufacturing flexibility, and strengthened sustainability performance. These outcomes demonstrate the growing importance of AI agents as strategic enablers of intelligent and human-centric manufacturing systems.

One of the most frequently reported benefits of AI-agent implementation is the improvement of productivity. AI agents continuously analyze production data, monitor machine performance, and optimize workflow coordination, enabling manufacturing systems to operate more efficiently(Trakadas et al., 2020). Through intelligent scheduling, automated decision-making, and real-time process adjustments, production bottlenecks can be minimized and resource utilization can be enhanced. The reviewed studies reveal that organizations adopting AI-agent technologies often experience increased production output, improved throughput rates, and more effective utilization of manufacturing assets. These productivity gains are particularly evident in highly dynamic production environments where rapid decision-making and adaptive control are essential for maintaining operational efficiency.

A significant reduction in downtime is another major impact identified in the literature. Unplanned downtime represents one of the most costly challenges in manufacturing operations because it disrupts production schedules, delays deliveries, and increases maintenance expenses(J. Lee et al., 2020). AI agents contribute to downtime reduction primarily through predictive maintenance and real-time monitoring capabilities. By continuously analyzing sensor data and equipment performance indicators, AI agents can identify early warning signs of potential failures and recommend preventive actions before breakdowns occur. As a result, maintenance activities can be scheduled proactively, reducing unexpected interruptions and increasing equipment reliability. The reviewed studies consistently demonstrate that AI-agent-based maintenance systems contribute to higher machine availability and more stable production operations.

The literature also highlights significant cost reductions associated with AI-agent implementation. Manufacturing costs are influenced by multiple factors, including labor utilization, machine efficiency, energy consumption, maintenance expenses, and material waste. AI agents support cost optimization by improving operational efficiency across these areas. Intelligent scheduling reduces idle machine time, predictive maintenance lowers repair costs, and optimized resource allocation minimizes unnecessary consumption of materials and energy. Furthermore, AI-driven process optimization helps manufacturers identify inefficiencies and implement corrective actions that improve overall cost effectiveness. Consequently, organizations utilizing AI-agent technologies can achieve substantial economic benefits while maintaining or improving production performance.

Product quality improvement represents another important outcome observed across the reviewed studies. Maintaining consistent product quality is essential for customer satisfaction, regulatory compliance, and long-term competitiveness(Gotzamani & Tsiotras, 2001). AI agents contribute to quality enhancement through continuous process monitoring, automated inspection systems, and intelligent defect detection mechanisms. By analyzing production data in real time, AI agents can identify deviations from quality standards and initiate corrective actions before defects become widespread. Advanced machine learning algorithms further enable the detection of complex quality issues that may be difficult to identify through conventional inspection methods. As a result, manufacturers experience lower defect rates, reduced rework requirements, improved product consistency, and enhanced customer confidence in product quality.

In addition to productivity and quality improvements, AI agents significantly increase manufacturing flexibility. Modern production environments must respond rapidly to changing customer demands, product customization requirements, supply chain disruptions, and fluctuating market conditions. Traditional manufacturing systems often struggle to adapt efficiently to such changes because they rely on fixed operational procedures and centralized decision-making structures. AI agents address this limitation by continuously learning from operational data and dynamically adjusting production activities based on current conditions. The reviewed literature demonstrates that AI-agent-enabled systems can rapidly modify production schedules, reallocate resources, and optimize workflows in response to unexpected events. This adaptability enhances organizational agility and enables manufacturers to remain competitive in increasingly volatile business environments.

Sustainability improvement is another critical impact associated with AI-agent implementation, particularly within the context of Industry 5.0(Shahbakhsh et al., 2021). Sustainability has emerged as a strategic priority for manufacturers seeking to reduce environmental impacts while maintaining economic performance. AI agents contribute to sustainable manufacturing through optimized resource utilization, reduced waste generation, improved energy management, and enhanced process efficiency. Intelligent resource allocation systems help minimize material consumption, while energy optimization algorithms reduce unnecessary energy usage across production facilities. Additionally, predictive maintenance extends equipment life cycles and reduces the environmental impact associated with premature equipment replacement. The reviewed studies indicate that AI-agent technologies play a significant role in supporting environmentally responsible manufacturing practices and advancing the sustainability objectives of Industry 5.0.

3.4 Industry 5.0 Perspective

The findings of this systematic literature review indicate that the implementation of AI-agent technologies aligns closely with the core principles of Industry 5.0. Unlike Industry 4.0, which primarily emphasizes automation, connectivity, and operational efficiency, Industry 5.0 seeks to establish a more balanced relationship between technological advancement and human well-being. The Industry 5.0 paradigm is built upon three fundamental pillars: human-centricity, sustainability, and resilience.

Human-centricity represents one of the defining characteristics of Industry 5.0(Müller, 2020). Rather than replacing human workers with fully autonomous systems, Industry 5.0 emphasizes the integration of advanced technologies that enhance human capabilities, improve working conditions, and support collaborative decision-making. The reviewed literature consistently highlights the role of AI agents as intelligent assistants that augment human expertise and facilitate more informed operational decisions.

One of the primary ways AI agents support workers is through real-time information processing and decision support. Modern manufacturing environments generate vast quantities of operational data that can be difficult for human operators to analyze effectively within limited timeframes. AI agents continuously monitor production activities, identify relevant patterns, and provide actionable recommendations that help workers perform their tasks more efficiently. This capability reduces cognitive workload and allows employees to focus on higher-value activities that require creativity, critical thinking, and problem-solving skills.

AI agents also play a significant role in assisting decision-making across multiple levels of manufacturing operations(Marik & McFarlane, 2005). Production managers, maintenance engineers, and quality control personnel can utilize insights generated by AI agents to evaluate alternative actions and select optimal strategies. By combining human expertise with data-driven intelligence, organizations can achieve more accurate and consistent decision outcomes. This collaborative approach reflects the fundamental Industry 5.0 objective of fostering effective partnerships between humans and intelligent technologies.

Furthermore, workplace safety is substantially enhanced through AI-agent implementation. Intelligent monitoring systems can continuously assess operational conditions, identify potential hazards, and provide early warnings before accidents occur. AI agents can detect abnormal machine behavior, unsafe operating conditions, and human errors that may compromise worker safety. As a result, organizations can proactively implement corrective measures, reduce occupational risks, and create safer working environments. The literature suggests that such human-centered applications of AI contribute not only to productivity improvements but also to employee well-being and job satisfaction.

Sustainability is another central pillar of Industry 5.0, reflecting the growing need for manufacturing systems to minimize environmental impacts while maintaining economic competitiveness(Yerram, 2021). The reviewed studies reveal that AI agents contribute significantly to sustainable manufacturing by improving resource utilization, reducing waste generation, and optimizing energy consumption throughout production processes.

One of the most widely reported sustainability benefits of AI agents is waste reduction. Through continuous monitoring and process optimization, AI agents can identify inefficiencies that lead to excessive material consumption, defective products, and unnecessary production losses. By detecting quality deviations at early stages and recommending corrective actions, AI agents help manufacturers reduce scrap rates and improve overall production efficiency. This not only lowers operational costs but also minimizes the environmental burden associated with wasted raw materials and resources.

Energy optimization represents another important contribution of AI agents to sustainability objectives(Chui et al., 2018). Manufacturing facilities are among the largest consumers of industrial energy, making energy management a critical factor in sustainable production. AI agents can analyze real-time energy consumption patterns, identify inefficient operating conditions, and recommend adjustments that reduce energy usage without compromising productivity. Intelligent scheduling systems can further optimize energy-intensive processes by aligning production activities with periods of lower energy demand or greater energy availability. As a result, organizations can decrease operational costs while simultaneously reducing greenhouse gas emissions and environmental impacts.

In addition to waste and energy management, AI agents improve overall resource efficiency by optimizing the allocation and utilization of labor, machinery, materials, and production capacity. Intelligent resource management systems ensure that manufacturing resources are utilized effectively, minimizing idle time and maximizing productivity(Wan et al., 2018). These capabilities support the broader sustainability goals of Industry 5.0 by promoting responsible resource consumption and enhancing the long-term viability of manufacturing operations.

The third pillar of Industry 5.0 is resilience, which refers to the ability of manufacturing systems to withstand, adapt to, and recover from disruptions(Romero & Stahre, 2021). Recent global events, including supply chain disruptions, economic uncertainty, and rapidly changing market conditions, have highlighted the importance of resilient manufacturing systems. The literature reviewed in this study indicates that AI agents play a crucial role in strengthening organizational resilience through adaptive decision-making and real-time operational intelligence.

One of the most significant contributions of AI agents to resilience is their ability to adapt to disruptions. Manufacturing environments frequently encounter unexpected events such as machine failures, material shortages, transportation delays, and workforce fluctuations. AI agents continuously monitor operational conditions and can rapidly identify disruptions as they occur. Through autonomous decision-making and adaptive learning capabilities, these agents can recommend alternative production plans, resource allocations, and scheduling strategies that minimize operational impacts. This adaptability enables organizations to maintain continuity and reduce the negative consequences of unexpected events.

AI agents also improve the ability of manufacturers to respond effectively to demand fluctuations. Modern markets are characterized by increasing volatility and customer demand uncertainty. Traditional production systems often struggle to adjust rapidly to changing market conditions, resulting in inefficiencies and lost opportunities. AI agents address this challenge by analyzing market trends, forecasting demand patterns, and dynamically adjusting production activities to align with current requirements. Such responsiveness enables manufacturers to improve customer satisfaction while maintaining operational efficiency.

Another important resilience-related benefit is the enhancement of supply chain robustness. Contemporary manufacturing systems depend on highly interconnected supply networks that are vulnerable to disruptions at multiple points. AI agents support supply chain resilience by monitoring inventory levels, tracking supplier performance, predicting potential disruptions, and recommending proactive mitigation strategies. Through intelligent coordination and real-time information sharing, AI agents facilitate more effective collaboration among supply chain partners and improve overall system stability. Consequently, organizations can better manage uncertainty and maintain production continuity in increasingly complex and unpredictable business environments.

3.5 Challenges of AI-Agent Implementation

Despite the significant benefits associated with AI-agent technologies in Industry 5.0 production optimization, the findings of this systematic literature review reveal several challenges that may hinder successful implementation. While AI agents have demonstrated their ability to improve productivity, flexibility, sustainability, and decision-making, organizations must address a range of technical, organizational, and ethical issues before realizing their full potential. The reviewed studies consistently indicate that the effectiveness of AI-agent systems depends not only on technological capabilities but also on the readiness of organizational structures, workforce competencies, and governance frameworks. Consequently, understanding these implementation challenges is essential for achieving sustainable and successful adoption of AI-agent technologies in manufacturing environments.

Technical barriers remain among the most significant obstacles to AI-agent implementation in Industry 5.0. One of the most frequently reported issues in the literature is data quality. AI agents rely heavily on large volumes of accurate, consistent, and real-time data to perform learning, prediction, and decision-making functions. However, manufacturing environments often generate incomplete, inconsistent, or noisy datasets due to sensor failures, communication interruptions, data-entry errors, and heterogeneous information sources. Poor-quality data can negatively affect the

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learning performance of AI agents, resulting in inaccurate predictions, suboptimal decisions, and reduced system reliability. Therefore, ensuring data integrity and establishing robust data management practices are critical prerequisites for successful AI-agent deployment.

Another major technical challenge involves system interoperability. Modern manufacturing systems typically consist of diverse hardware platforms, software applications, communication protocols, and industrial control systems developed by different vendors. Integrating AI agents into such heterogeneous environments can be difficult because many systems lack standardized interfaces and communication mechanisms. The reviewed studies indicate that interoperability issues frequently limit the ability of AI agents to exchange information effectively across different manufacturing subsystems. As a result, organizations may experience difficulties in achieving seamless coordination among machines, sensors, enterprise systems, and intelligent decision-support platforms.

Integration with legacy equipment represents an additional technical challenge(Zambetti et al., 2020). Many manufacturing facilities continue to operate machinery and production systems that were not originally designed for digital connectivity or intelligent automation. These legacy systems often lack the sensors, communication capabilities, and computational infrastructure required to support AI-agent technologies. Consequently, manufacturers may need to invest in retrofitting, system upgrades, or middleware solutions to enable integration between existing equipment and modern AI-based platforms. Such integration efforts can be technically complex and time-consuming, particularly in large-scale manufacturing environments where multiple generations of equipment coexist.

Beyond technological concerns, organizational factors play a crucial role in determining the success of AI-agent implementation. One of the most commonly reported challenges is employee resistance to technological change. The introduction of AI agents may create uncertainty among workers regarding job security, changing responsibilities, and the future role of human labor in manufacturing operations. Some employees may perceive intelligent systems as threats rather than supportive tools, leading to reluctance in adopting new technologies. The literature suggests that organizations must actively promote awareness, communication, and employee involvement throughout the implementation process to foster trust and acceptance of AI-agent systems.

A second organizational challenge is the shortage of AI-related expertise(Bérubé et al., 2021). Successful implementation and maintenance of AI-agent technologies require specialized knowledge in artificial intelligence, machine learning, data analytics, industrial automation, and system integration. However, many manufacturing organizations face difficulties in recruiting and retaining personnel with these advanced technical skills. The lack of qualified professionals can delay implementation projects, increase dependency on external consultants, and limit the organization’s ability to fully utilize AI-agent capabilities. To address this challenge, organizations must invest in workforce development, continuous training programs, and interdisciplinary collaboration between manufacturing experts and AI specialists.

High implementation costs also represent a significant organizational barrier. Although AI-agent technologies can generate substantial long-term benefits, their initial deployment often requires considerable financial investment. Costs may include infrastructure upgrades, sensor installation, software acquisition, cloud computing resources, employee training, system integration, and ongoing maintenance. Small and medium-sized enterprises (SMEs) may face particular difficulties in allocating sufficient resources for AI-agent adoption. Consequently, organizations must carefully evaluate the economic feasibility of implementation projects and develop strategic investment plans that balance short-term expenditures with long-term performance gains.

In addition to technical and organizational concerns, ethical considerations have become increasingly important in the context of AI-agent deployment within Industry 5.0. One of the primary ethical challenges identified in the literature is transparency. Many AI-agent systems, particularly those based on advanced machine learning and deep learning algorithms, operate through highly complex computational processes that are not easily understood by users. Limited transparency can reduce trust in AI-generated recommendations and make it difficult for decision-makers to verify the rationale behind autonomous actions.

Closely related to transparency is the issue of explainability. Industry 5.0 emphasizes human-centered decision-making, which requires that intelligent systems provide understandable explanations for their recommendations and actions. When AI agents function as "black-box" systems, managers and operators may be reluctant to rely on their outputs, particularly in critical manufacturing situations involving safety, quality, or operational risks. The reviewed studies emphasize the growing importance of Explainable Artificial Intelligence (XAI) techniques that enable users to understand how decisions are generated and evaluate their validity.

Data privacy represents another significant ethical concern(W. W. Lee et al., 2016). AI agents frequently process large volumes of operational, organizational, and sometimes employee-related data. The collection, storage, and analysis of such information raise concerns regarding unauthorized access, misuse, and potential violations of privacy regulations. Manufacturing organizations must therefore establish comprehensive data governance frameworks that ensure secure data handling, compliance with regulatory requirements, and protection of sensitive information throughout the AI lifecycle.

Finally, the literature highlights the continuing need for human oversight in AI-agent-enabled manufacturing systems. Although AI agents are capable of autonomous decision-making, complete reliance on automated systems may introduce risks related to accountability, safety, and ethical responsibility. Industry 5.0 advocates a collaborative relationship between humans and intelligent technologies, where AI agents support rather than replace human judgment. Maintaining appropriate levels of human supervision ensures that critical decisions remain aligned with organizational objectives, ethical principles, and societal expectations. Human oversight also provides a safeguard against unexpected system behavior, algorithmic bias, and decision-making errors that may arise in complex manufacturing environments.

Overall, the findings indicate that the successful implementation of AI agents in Industry 5.0 requires a balanced approach that addresses technical, organizational, and ethical challenges simultaneously. While data quality, interoperability, and legacy system integration remain key technological concerns, organizations must also overcome workforce-related barriers and ensure responsible AI governance. Addressing these challenges effectively will be essential for maximizing the benefits of AI-agent technologies and supporting the development of intelligent, sustainable, and human-centric manufacturing ecosystems.

4. CONCLUSION

i This study analyzed the implementation of AI agents in Industry 5.0 production optimization through a systematic review of recent literature. The findings indicate that AI agents play a significant role in enhancing manufacturing performance by enabling autonomous decision-making, adaptive learning, and real-time optimization across various production activities. Among the identified technologies, Multi-Agent Systems (MAS) and Reinforcement Learning (RL) agents emerged as the most widely applied approaches due to their ability to coordinate distributed manufacturing resources, optimize production schedules, and adapt to dynamic operational conditions. The review further revealed that the most substantial improvements resulting from AI-agent implementation occur in production scheduling, predictive maintenance, quality control, and resource allocation, leading to higher productivity, reduced downtime, lower operational costs, improved product quality, and greater manufacturing flexibility. From an Industry 5.0 perspective, AI agents contribute significantly to the realization of human-centric manufacturing by supporting workers and enhancing decision-making processes, while simultaneously promoting sustainability through waste reduction, energy optimization, and efficient resource utilization. Furthermore, AI agents strengthen operational resilience by enabling manufacturing systems to adapt to disruptions, respond to changing market demands, and improve supply chain robustness. Despite these benefits, several challenges remain, including issues related to data integration and quality, interoperability with existing systems, high implementation costs, and the need for workforce readiness and AI-related competencies. Ethical concerns such as transparency, explainability, data privacy, and human oversight also require careful consideration to ensure responsible deployment. Therefore, while AI agents represent a critical technological foundation for Industry 5.0, their successful implementation requires a balanced approach that integrates technological innovation with organizational preparedness and ethical governance. Future research should focus on the development of autonomous factory ecosystems, advanced human–AI collaborative agents, the integration of Digital Twin and AI-agent technologies, and Explainable AI (XAI) frameworks that enhance transparency and trust in intelligent manufacturing environments.

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