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A review study on ai-driven robotics and automation in smart manufacturing: applications, challenges, and economic impacts

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HIGHLIGHTS

- AI-driven robotics transforms smart manufacturing by improving efficiency, flexibility, and productivity.
- Emerging tools like edge AI and digital twins enable real-time decisions through human-machine collaboration.
- AI-based automation reduces energy use, emissions, and waste, aligning with global sustainability objectives.
- The transition to Industry 5.0 shifts toward more human-focused and environmentally sustainable production.

Keywords:
Smart Manufacturing
AI-Driven Robotics
Machine Learning
Automation
Predictive Maintenance

ABSTRACT

Integrating AI-driven robotics and automation revolutionizes smart manufacturing by enhancing operational efficiency, productivity, and system flexibility across automotive, aerospace, and general equipment manufacturing industries. This review synthesizes findings from 84 peer-reviewed publications to evaluate the transformative potential of key AI technologies—including machine learning, digital twins, edge AI, and human-machine collaboration—in optimizing production lines and enabling predictive maintenance, real-time monitoring, and adaptive decision-making. While these innovations offer significant benefits in quality control, cost reduction, and sustainability, challenges remain in integrating AI with legacy systems, addressing workforce skill gaps, and ensuring cybersecurity and ethical compliance. Emerging trends such as 5G-enabled edge computing and collaborative robots (cobots) pave the way for low-latency communication and safer, more adaptable production environments aligned with Industry 5.0 principles. Real-world case studies demonstrate measurable economic impacts, including a 30% reduction in downtime at KONE's elevator manufacturing facility and scalable ROI for SMEs adopting AI-driven solutions. Furthermore, regulatory frameworks and ethical AI guidelines are increasingly essential for ensuring transparency, safety, and responsible deployment. Looking ahead, the convergence of immersive technologies (AR/VR/MR), digital twins, and ethical AI will further enhance virtual simulation, reduce material waste, and support sustainable industrial ecosystems. As manufacturers adopt these cutting-edge innovations, resilient, agile, and human-centric systems will become the new standard, balancing dynamic market demands with environmental and social responsibility. Ultimately, AI-driven automation promises to reshape global manufacturing ecosystems, driving economic growth and sustainable industrial transformation.

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1. Introduction

The Fourth Industrial Revolution, or Industry 4.0, also known as Smart Manufacturing (SM), is a paradigm shift that combines digital connectivity and automation to create intelligent, adaptive, and sustainable manufacturing systems [1, 2]. It has revolutionized production lines by integrating technologies like artificial intelligence (AI), the Internet of Things (IoT), big data analytics, and cyber-physical systems (CPS). These innovations introduced the concept of smart factories, enabling real-time communication and decision-making that optimizes energy use, labor management, and production efficiency [3, 4].

Building on the groundbreaking innovations of Industry 4.0, Industry 5.0 represents the next evolutionary step, emphasizing human–machine collaboration to achieve greater personalization, flexibility, and sustainability [5, 6]. As illustrated in Figure 1, which charts the technological advancement from Industry 4.0's automation-driven system (2011–2020) to Industry 5.0's human – centric frameworks (2020–present), this transition reflects a paradigm shift from optimizing productivity through IoT, AI and cyber – physical systems (CPS) to prioritizing shared autonomy, resilience and societal well-being [7]. For instance, collaborative robots (cobots) equipped with AI algorithms achieve 80% productivity gains in precision tasks like grinding castings by dramatically adapting to surface irregularities alongside human operators [8]. This aligns with Industry 5.0 emphasis on shared autonomy, where machines handle repetitive or hazardous tasks and humans focus on creativity and decision–making [9].

Furthermore, KONE's AI–driven predictive maintenance systems (see Section 6.1 [10]) reduce downtime by 30% and provide clients with real–time insights into equipment usage (e.g., energy consumption, load patterns), reflecting Industry 5.0's dual focus on transparency and stakeholder engagement. These advancements address both operational efficiency and global sustainability targets like the UN SDGs [7], moving beyond Industry 4.0's narrow focus on automation to embrace circular economy practices and social sustainability [11, 12]. By bridging technical innovation with human–centric design, Industry 5.0 redefines value creation, shifting from mass production (Industry 4.0) to hyper-personalization and agile manufacturing systems [9, 13], (see Table 1).

Table 1: Comparison of Industry 4.0 and Industry 5.0

Aspect	Industry 4.0	Industry 5.0	Ref.
Focus	Automation, efficiency-driven manufacturing, Emphasis on optimizing production processes and reducing costs.	Human-centric, collaborative, sustainable manufacturing, personalization, adaptability, and societal well-being.	[9, 11, 13]
Technologies	IoT, AI, robotics, big data analytics, and cyber-physical systems (CPS).	Collaborative robots (cobots), edge AI, digital twins, and immersive tech (AR/VR/MR)	[14, 15]
Workforce Role	Humans as operators and supervisors of automated systems, with limited human involvement in repetitive or hazardous tasks.	Humans are collaborators with machines, focusing on creativity and decision-making, and they enhance human-robot interaction for complex and value-added tasks.	[16, 17]
Sustainability	Focus on energy efficiency and waste reduction through automation, with limited integration of environmental and social goals.	Emphasis on circular economy practices, renewable energy, social sustainability, and alignment with global sustainability targets (e.g., UN SDGs).	[9, 18]
Outcomes	Increased productivity, reduced operational costs, improved quality, and highly efficient but less flexible production lines.	Resilient, adaptable, and sustainable production systems, customizable and agile manufacturing processes.	[18, 19]

The overall goal of Industry 4.0 is to create highly efficient, adaptive, and sustainable production systems. By leveraging advanced optimized techniques, digital tools, and AI–driven robotics, manufacturers can reduce energy consumption, carbon emissions, and production costs, which align with the global sustainability targets and the UN Sustainability 2030 agenda [20, 21]. According to Jamwal et al., and Abir [21, 12], industry 4.0 supports sustainability by lowering material and energy waste and facilitating circular economic flow, which is in line with the UN Sustainability 2030 agenda. Moreover, these technologies not only reduce production costs but also facilitate more agile responses to supply chain distributions and market fluctuations, making companies more resilient in an increasingly complex global economy with minimal human intervention [22]. Adoption of smart manufacturing is essential to achieving sustainability goals while going beyond traditional economic benefits. Simulation and artificial intelligence will help producers increase resource management efficiency, not only from a financial point of view but also from an environmental and social point of view [23]. Advanced multi-objective optimization techniques enable simultaneous reduction in energy consumption, carbon emissions, and production costs, integrating environmental and social considerations into decision-making processes [24, 25]. Besides, digital optimization, fueled by advances in Information and Communication Technology (ICT), significantly enhances the implementation of clean technologies while promoting circular economy practices such as recycling and sharing [26]. These practices serve as essential pillars for developing sustainable production systems. By integrating renewable energy sources, particularly solar power, manufacturers can further reduce their carbon footprint, ensuring greater alignment with international sustainability goals. Collectively, these strategies work together to minimize material waste, decrease carbon emissions, and lower energy consumption, ultimately supporting the economic viability of production operations [25].

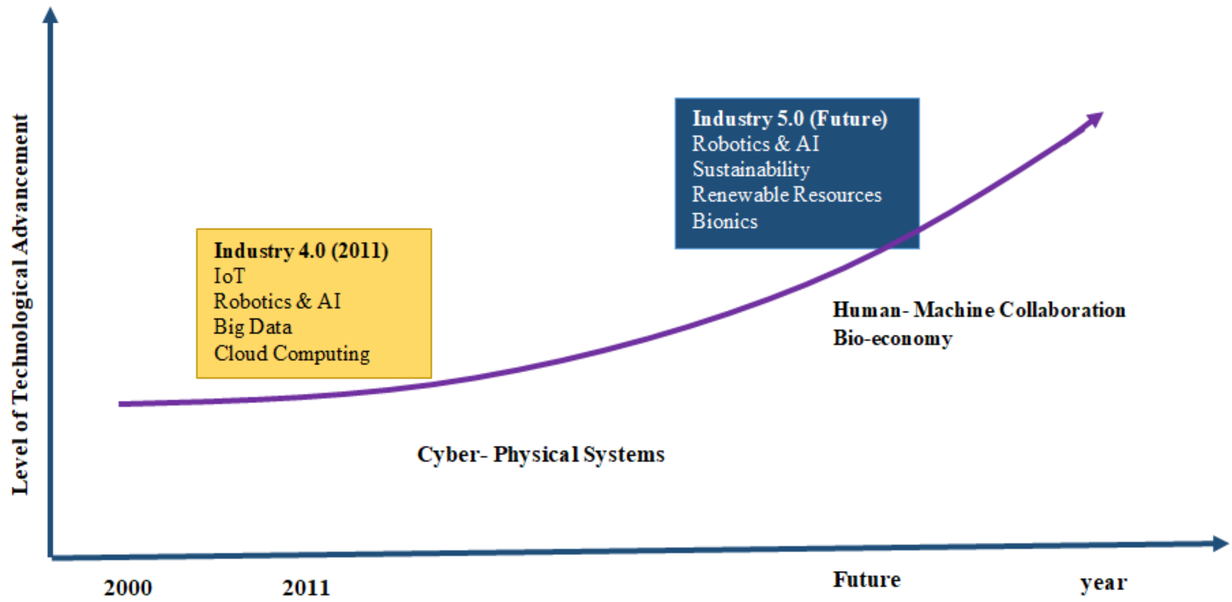

Figure 1: The Evolution from Industry 4.0 to Industry 5.0 [27]

In this review article, we closely examine how AI-driven automation and robotics are reshaping smart manufacturing. We address core issues in operational efficiency, sustainability, and workforce adjustment by bringing together the latest technologies in domains from multi-objective optimization to digital twins and man-machine interaction. Utilizing real-world practices (Section 6.0), leading technology paradigms (Section 4.0), and budding trends in regulation (Section 8.0), we identify pragmatic means for aligning Industry 4.0's tech advancement with Industry 5.0's people-centered objectives.

Despite advancements, critical gaps persist in integrating AI-driven robotics into production lines to achieve optimal performance, particularly in balancing energy efficiency, cost-effectiveness, and sustainability. This study bridges these gaps by evaluating AI-driven optimization through advanced modelling techniques such as multi-objective algorithms and digital twins, harmonizing operational efficiency with environmental goals, as demonstrated in predictive maintenance and fault diagnosis case studies. By exploring adaptive automation, human-machine collaboration frameworks, and agile decision-making, the work identifies pathways to overcome technical, economic, and workforce barriers, proposing resilient manufacturing systems that align global sustainability targets with next-generation industrial innovations. The synthesis positions AI-driven robotics as pivotal for future-ready smart manufacturing, where emerging technologies such as edge computing and ethical AI frameworks ensure adaptability and scalability in dynamic industrial ecosystems.

This review integrates results from 84 peer-reviewed papers, including a targeted review of 52 papers focused on AI-based robotics in smart manufacturing. These include industrial case studies, technical overviews, and empirical verifications of technologies such as predictive maintenance and human-robot collaboration. The remaining papers are used to establish background on Industry 4.0/5.0, sustainability principles, and people's dynamics to provide complete knowledge of how the field is developing. All the included studies were published between 2018 and 2024, which are the recent developments and trends in smart manufacturing.

2. Scope and methodology: focus areas and manufacturing sectors

This review study focuses on AI-driven robotics and automation technologies that enhance smart manufacturing through predictive analytics, human-machine collaboration, and adaptive decision-making. The scope includes:

2.1 Core technologies

- Predictive maintenance systems (e.g., Health Index/RUL estimation [28], IoT-enabled sensor networks)
- Collaborative robots (cobots) equipped with machine learning (ML), edge AI, and computer vision
- Digital twins for virtual simulation and real-time optimization

2.2 Manufacturing sectors

- Automotive (e.g., KONE's predictive maintenance [29])
- Aerospace (e.g., AI-driven gearbox diagnostics [30])

The analysis prioritizes technologies with demonstrated economic feasibility and scalability in SMEs, excluding niche applications like nanorobotics or AI in non-industrial contexts.

2.3 Methodology overview

This study adopts a systematic literature review (SLR) approach to synthesize findings from peer-reviewed publications between 2010 and 2024, with some early-access works from 2025 included where available. A total of 84 papers were initially identified using a structured search strategy across major databases (IEEE Xplore, ScienceDirect, Scopus, Google Scholar, SpringerLink) with keywords such as:

- AI-driven robotics AND smart manufacturing
- Machine learning AND automation
- Industry 5.0 AND human-robot collaboration

Boolean logic was applied to refine results and ensure relevance.

From these, 52 core studies were selected based on inclusion/exclusion criteria and a Quality Assessment Rule (QAR) evaluating organizational clarity, research objectives, dataset identification, and methodological appropriateness. Papers scoring below 6 out of 10 were excluded. These 52 papers formed the basis for analyzing AI-based robotics and automation trends, challenges, benefits, and future directions in smart manufacturing.

3. Challenges in traditional production lines

3.1 Inefficiencies in manual labor and legacy systems

The conventional production lines, which have long relied on manual labour and legacy systems, have several challenges that impede their functionality in meeting modern manufacturing demands and overall efficiency. According to Adrita et al., manual manufacturing processes are liable to human error, inefficiency, and inconsistent quality [31]. Furthermore, repetitive tasks in industrial settings often lead to inefficiency and challenges. Manufacturing workers performing tasks may experience mental fatigue and a decrement in vigilance, which potentially results in operational errors and safety issues [32].

Moreover, physical fatigue and postural loads can result in work-related musculoskeletal disorders [32]. Bennett et al. [33], reported that while the implementation of the division of labour tends to improve efficiency, it may also lead to monotony and potential physical injuries from repetition. Additionally, legacy systems in manufacturing industries often face inefficiencies in manual labour and outdated technologies. Although these systems are vital, they are challenging to modernize because of their complexity and lack of flexibility to integrate new technologies or embedded knowledge required to meet the modern manufacturing demands [34]. Cost overruns and delays are also part of the challenges in the manual approach to modernization.

3.2 Limited flexibility and adaptability to changing demand

One of the major limitations of traditional production systems is limited flexibility and adaptability to changing market demand. It has been reported that high manufacturing flexibility is an essential tool for improving market responsiveness while facing uncertain product demand [35]. Process flexibility allows manufacturing multiple product types in the same plant or production facility. Research suggested some fundamental principles illustrating the benefits of process flexibility [36]. First, it was determined that a little flexibility, where each plant manufactures only a limited number of products, can capture most of the benefits of complete flexibility, where all plants can produce all products as long as it is appropriately designed. Second, limited flexibility is most potent when it links products and plants extensively to form a powerful production network. This power provides analytical support for these findings. The author develops a planning model for allocating production across plants and shows that under realistic demand uncertainty, limited flexibility, and configurations, defining which products are made and which plants produce sales results is equivalent to total flexibility.

3.3 Quality control issues and defect rates

Maintaining consistent product quality is crucial for manufacturing excellence. Traditional production lines, despite having stringent protocols, often encounter quality control issues. These issues stem from human error, equipment malfunction, and process variability [20]. As a result, defective products are introduced into the market, affecting customer satisfaction and company reputation. These challenges contribute to high defect rates, resulting in significant financial losses and reputational damage. For instance, manufacturing defects account for substantial waste and rework costs annually, particularly in welding processes and electronic component assembly [37]. The impact of defective products extends beyond financial losses, affecting customer trust and loyalty. Integrating AI-driven robotics and automation in industrial settings can effectively mitigate these challenges. Manufacturers can significantly enhance product quality by leveraging predictive maintenance, real-time monitoring, and data-driven decision-making [38, 39]. This integrated approach minimizes defects, reduces waste, and improves customer satisfaction, ultimately driving manufacturing excellence.

3.4 Safety concerns and workplace accidents

Safety at work is of utmost importance in manufacturing, as the manual handling of heavy machinery and repetitive tasks is very hazardous. Workers are exposed to hazards, including musculoskeletal disorders (MSDs), leading to accidents and death [40]. Manufacturing has consistently been one of the top industries in occupational injury rates due to manual handling of hazardous machinery and repetitive tasks. According to records, about 24% of the manufacturing sector's hazards are caused by heavy machinery [40]. Furthermore, MSDs are prevalent among workers performing repetitive tasks, with low back discomfort being widespread–occurring in 37.3% of machinery operators and 63.8% of manual material handlers [41]. A study by Mohd Nur et al. [42], further highlights this severity by examining MSD prevalence among workers in automobile manufacturing firms. Their findings, illustrated in Figure 2, reveal that a significant percentage of workers experience symptoms or pain in various parts of their bodies, with the neck (49.3%), hand/wrist (48.0%), and shoulder (46.7%) being the most affected areas. Overall, 76.97% of workers reported experiencing MSD-related symptoms in at least one part of their body. These statistics underscore the urgent need for automation and AI-driven robotics interventions to reduce human exposure to repetitive and physically strenuous tasks, thereby promoting safer and healthier work environments.

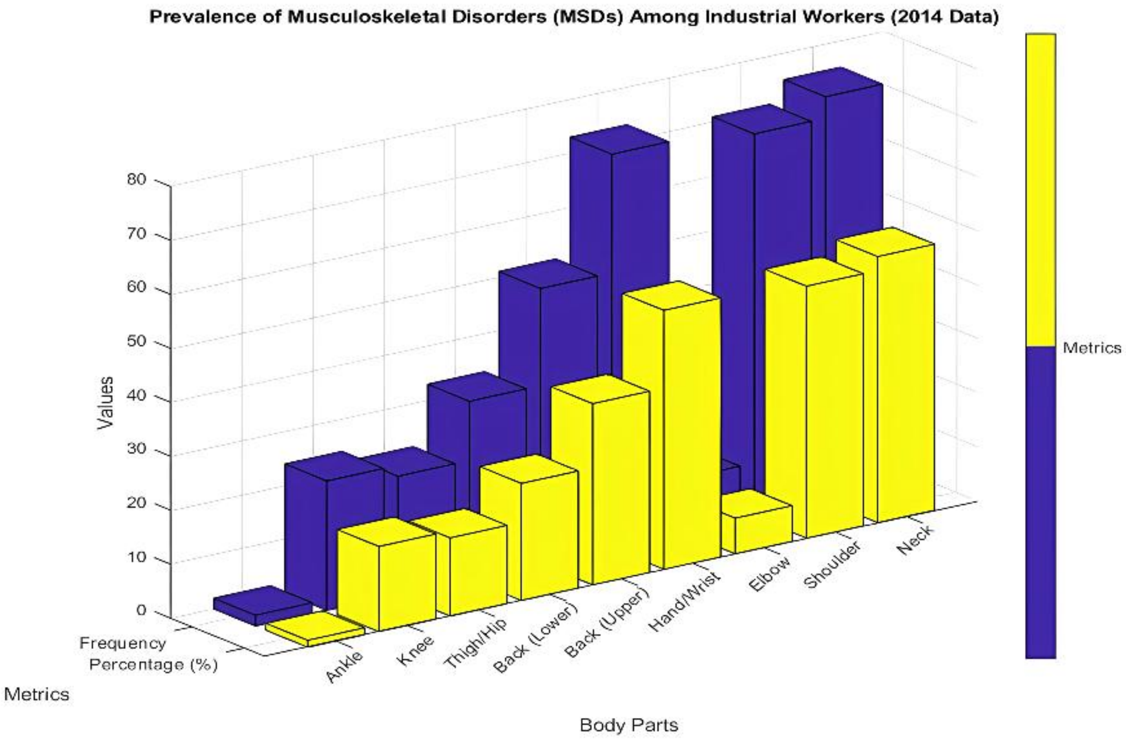

Figure 2: Prevalence of Musculoskeletal Disorders (MSDs) among industrial workers

These occupational hazards can be considerably reduced by automation and intelligent systems. AI robotics and automation reduce human exposure to high-risk environments, promoting a much safer and healthier work environment. Advanced sensors and preventive analytics improve incident detection and prevention. With such innovative solutions, manufacturers can reduce these hazards, mitigate risks, and build a resilient workforce that will assure them of operational excellence and employees' well–being.

3.5 Inventory strategies and data analysis

The production process, traditionally controlled by humans, usually leads to inefficiencies and inaccuracy in data analysis. Data collection previously obtained manually is being transformed through data digitalization, which helps to detect faults in the production process, predict failure, and minimize waste [31]. Real-time data collection can be enabled from the production process with the use of sensors, IoT devices, and advanced data analysis tools on machines or robots, thereby providing visibility into stock levels, helping to optimize scheduled production, predictive analysis to anticipate demand fluctuations, predictive and planned maintenance, etc. [38]. Real-time data includes material usage, machine status, production rate, etc.

4. AI-Driven robotics and automation in smart manufacturing

Integrating AI–driven robotics and automation is a game changer that has greatly transformed the manufacturing landscape. Table 2 summarizes the key characteristics, benefits, and limitations of prominent AI–driven robotics and automation technologies to comprehensively understand the various technologies involved.

AI-driven robotics and automation have transformed SM by synergizing machine learning, computer vision, and sensor fusion. Such a synergy enables intelligent decision-making, autonomously operated systems, and real-time adaptability by analyzing large datasets, thereby identifying patterns and responding to changing conditions without human intervention [57, 39]. These systems optimize production workflows, enhance product quality, and reduce operational costs. Integrating collaborative robots (cobots) with AI algorithms has become increasingly prevalent, particularly for tasks demanding precision, adaptability, and flexibility, redefining the manufacturing landscape.

Table 2: Comparison of AI-Driven Robotics and Automation Technologies

Technology	Benefits	Limitations	Key Applications	Ref.
Industrial Robots	- High precision and repeatability - Fast operation - Handles heavy-duty tasks	- High initial cost - Limited adaptability to dynamic environments	Assembly lines, welding, and painting	[43, 44]
Collaborative Robots (Cobots)	- Safe human-robot interaction - Easy to program and deploy - Flexible task allocation	- Limited payload capacity - Slower than industrial robots	Small assembly tasks, pick-and-place operations	[8]
Autonomous Mobile Robots (AMRs)	- Dynamic navigation - Real-time path planning - Flexible in changing layouts	- Challenges in navigating highly cluttered environments - Limited battery life	Logistics, material handling, warehousing	[45]
AI-Enabled Machine Vision	- Real-time defect detection - Enhanced quality control - Non-contact measurements	- Susceptible to environmental factors like lighting - High computational requirements	Inspection, sorting, process monitoring	[46]
Digital Twins	- Real-time simulation - Predictive insights - Optimization of operations	- Requires high-quality data - Integration complexity	Process optimization, predictive maintenance	[47, 48]
Predictive Maintenance Systems	- Reduces downtime - Prevents unexpected failures - Cost-effective in the long term	- High implementation cost - Dependent on sensor reliability	Equipment monitoring, maintenance scheduling	[49, 50]
Edge AI Robotics	- Low latency - Real-time decision-making - Reduced dependency on cloud connectivity	- Limited processing power - Challenges in scaling for complex tasks	On-site monitoring, immediate responses in production lines	[51]
Natural Language Processing (NLP)	- Simplifies robot communication - Enables voice-based control - Improves usability	- Context understanding challenges - Limited by language diversity and dialects	Human-robot interfaces, customer service	[52]
Generative AI for Robotics	- Automated task optimization - Dynamic learning from simulations - Reduces programming effort	- Computationally intensive - Risk of overfitting to specific tasks	Task planning, robotic process optimization	[53]
Hyper-Automation Systems	- End-to-end process automation - Integrated AI, IoT, and robotics - Maximizes efficiency	- Complex to implement - High initial investment	Fully automated factories, supply chain integration	[54]
AI-Powered Nanorobots	- Precision at the nanoscale - Advanced material manipulation - Potential for breakthrough innovation	- Technology is still in development - Requires significant research funding	Nanomanufacturing, advanced materials development	[55, 56]

4.1 Applications of AI in smart manufacturing (SM)

Building on the AI-driven robotics and automation technologies outlined in Table 2, this section explores their applications in smart manufacturing, driving efficiency, productivity, and quality.

4.1.1 Predictive maintenance and quality control:

Predictive maintenance systems leverage AI algorithms to analyze equipment performance data, predicting potential failures before they occur [58]. As summarized in Table 1, this reduces downtime and enhances overall efficiency [51, 50]. By integrating AI-driven quality control systems, manufacturers can detect defects quickly, minimize waste, and ensure consistent product quality.

4.1.2 Adaptive production scheduling and planning

AI-driven systems optimize production schedules by dynamically adjusting to real-time demand and resource availability, minimizing delays and bottlenecks. This adaptive approach enables manufacturers to respond swiftly to changes in market conditions, reducing the risk of inventory obsolescence and overproduction [59].

4.1.3 Real-Time monitoring and optimization

Continuous monitoring of production processes allows for immediate identification and correction of inefficiencies, ensuring consistent output quality. AI-driven analytics provide actionable insights, enabling manufacturers to fine-tune processes, reduce variability, and improve overall performance [59, 60].

4.1.4 Autonomous material handling and logistics

AI-powered robots streamline material movement within factories, improving workflow and reducing human error in logistics. Autonomous systems optimize inventory management, reduce transportation costs, and enhance supply chain resilience [61].

5. Benefits of optimizing production lines with AI-Driven robotics and automation

5.1 Improved efficiency and productivity

AI-driven automation has been the main driver for operational efficiency in smart manufacturing. AI–driven systems optimize the production workflows and reduce cycle times by employing advanced algorithms and real-time data analytics. This eventually leads to substantial productivity, which helps manufacturers produce more products at lower costs and of better quality. Studies have repeatedly indicated that factories that use smart technologies, such as AI-driven automation, are found to achieve significant productivity gains compared to traditional settings, reporting increases of up to 20% [62].

5.2 Enhanced quality control and reduced defect rates

Integrating advanced AI algorithms in quality inspection processes enables manufacturers to detect defects early, significantly minimizing waste and rework. AI-powered vision systems, for example, utilize deep learning techniques such as convolutional neural networks (CNNs) approaches to achieve higher accuracy in defect detection compared to human inspectors [63]. By automating quality control, manufacturers can ensure consistent product quality, reduce the risk of defective products reaching customers, and lower the associated rework and scrap costs, ultimately enhancing overall manufacturing efficiency.

5.3 Increased flexibility and adaptability to changing demand

Smart manufacturing systems provide unparalleled flexibility, empowering manufacturers to rapidly respond to shifting market demands. Automated systems can swiftly reconfigure production lines to accommodate new products, variations, or design changes with minimal downtime. This agility ensures competitiveness in dynamic markets, where speed and adaptability are crucial. By leveraging smart manufacturing technologies, businesses can quickly capitalize on emerging trends, expand product offerings, and improve customer satisfaction, ultimately driving growth and profitability in an increasingly competitive landscape [64].

5.4 Improved workplace safety and reduced accidents

Automation plays a key role in minimizing the need for human involvement in hazardous tasks, thereby creating safer work environments. Manufacturers significantly reduce the risk of workplace accidents and injuries by relegating perilous duties to machines. Furthermore, AI-enhanced safety systems such as real-time hazard detection and predictive analytics proactively identify potential threats, enabling prompt intervention. This harmonious blend of automation and AI fosters a culture of safety, safeguarding employees' well–being and promoting a healthier and more productive work environment [65].

5.5 Cost savings and reduced waste

Incorporation of AI–driven technologies in production lines yields significant cost savings and drives business profitability. By optimizing processes, manufacturers can reduce material waste, lower energy consumption, and minimize labour costs. Predictive maintenance also plays a key role in decreasing repair expenses by identifying potential equipment failures before they occur. This proactive approach extends equipment lifespan, reduces downtime, and lowers the overall maintenance costs [66]. By leveraging AI–driven optimization, businesses can achieve substantial cost savings, enhancing their competitive edge in the market.

6. Case studies and success stories

6.1 Predictive maintenance in elevator manufacturing (KONE)

KONE, the world's leading manufacturer of elevators and escalators, has maintained prosperity through process innovation, strategic management, and a revolutionary transformation towards service-led offerings, with services accounting for a major proportion of revenues [67, 68]. Its research and development efforts have been focused on elevator planning and control system innovations, especially in high-rise buildings. Other notable innovations include the Traffic Master System 9000 (TMS9000), which lowers waiting times for commuters and enhances the extent of service efficiency [29, 69], and the Advanced Lift Traffic Simulator (ALTS). This elevator simulator predicts and optimizes the performance of lifts in new and existing buildings.

Building on this legacy, KONE applies IoT sensors and AI analysis for real-time equipment condition monitoring. KONE puts sensors on escalators and elevators, detecting vibration, temperature, and patterns of loads, which it feeds into cloud-based AI software for processing. This method decreases unplanned downtime by 30%, and proactive intervention maintenance, for example, swapping out components before they fail, is facilitated. The KONE 24/7 Connected Services platform also supplies customers with energy consumption and usage information, rendering the system even more transparent and cost-effective [70].

6.2 AI-Driven prognostic modeling for industrial equipment

Integrating AI with robotics and automation has revolutionized production lines, enabling unprecedented optimization in smart manufacturing environments. This section highlights key case studies and success stories that illustrate the transformative impact of AI-driven solutions in machine health monitoring and diagnostics.

One prominent example is the use of AI-based machine prognosis through Health Index (HI) and Remaining Useful Life (RUL) estimation [28]. In scenarios where direct measurement of machine performance is challenging, HIs derived from multi-sensor data act as proxies to represent the machine's health state. These indices consolidate complex inputs—such as vibration, temperature, pressure, and sound—into single, interpretable values that serve as the foundation for predictive maintenance, as illustrated in Figure 3 [71]. Methods like wavelet packet decomposition and dimensionality reduction techniques, such as isometric feature mapping, are employed to extract features from sensor data and construct the HI [72].

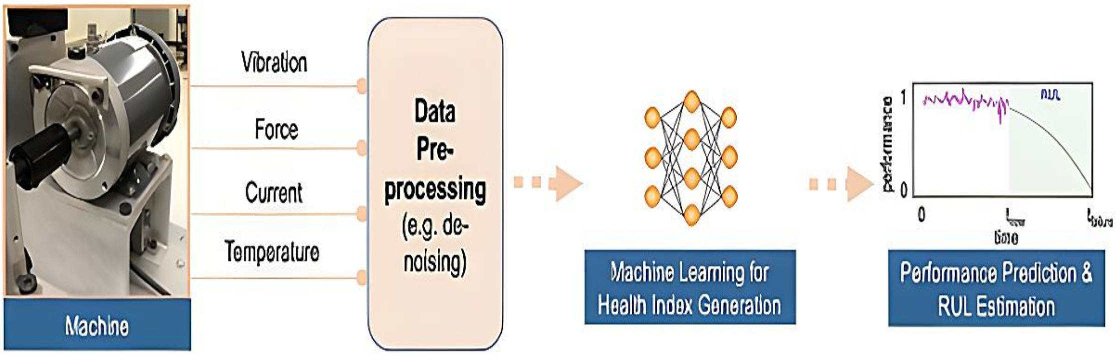

Figure 3: 3 HI – Based on machine prognosis and RUL estimation [30]

Once an HI is established, advanced models like Support Vector Machines (SVM) and Recurrent Neural Networks (RNN) are used to analyze its temporal sequence to recognize degradation patterns and estimate RUL. For instance, SVM has been employed in bearing prognosis to analyze HIs constructed from vibration and temperature data, enabling accurate predictions of degradation trends and the RUL. Similarly, compressor systems and aircraft engines have benefited from HI-based approaches, with sensing signals such as vibration and temperature feeding SVM and Long Short-Term Memory (LSTM) networks to forecast performance degradation. Notably, LSTMs have also been used in lithium-ion battery prognosis, offering robust RUL predictions displayed as probability distributions, even in noisy environments.

Another compelling case study involves advanced gearbox diagnostics using Deep Convolutional Neural Networks (DCNN). In a pioneering effort, 1D vibration signals were transformed into time-frequency images, which a DCNN then analyzed to classify the severity levels of gearbox faults [30]. The flowchart of this methodology, as shown in Figure 4, highlights how AI enhances fault detection, reduces maintenance downtime, and increases operational precision in industrial systems.

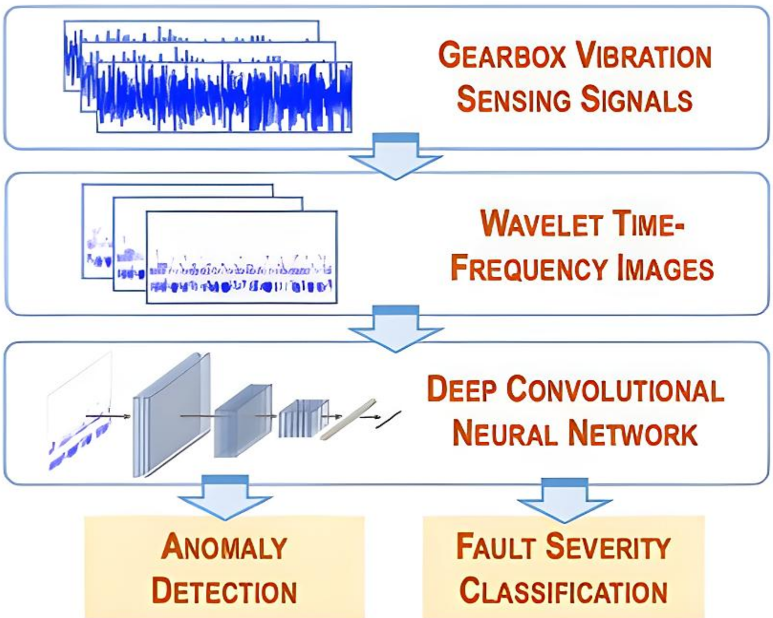

Figure 4: DCNN–based gearbox fault severity level diagnosis [71]

6.3 Supervised machine learning for multisector failure prediction

Supervised machine learning algorithms trained on historic failure data effectively predict failure across diverse domains. ARMA and GARCH statistical models have been used in the field of medicine to predict the failure rates of medical devices

[73], whereas in laser systems, a deep learning-based LSTM model achieved a 95.52% accuracy in degradation mode identification, superior to traditional threshold-based as well as conventional ML approaches [74]. According to Moraes et al, [75], materials science has witnessed improvement by phase-field ML models that are already able to predict material brittle failures even from noisy data, and water distribution networks are supported by multi-source data-aggregation models with socioeconomic information, and LightGBM has been proven to be the top-performing algorithm for predicting pipe failure [76]. When trained, historical failure record-based supervised ML models (e.g., vibration signature, tool wear) provide accurate failure prediction for machining operations. In manufacturing electronics, defective components are sifted out of surface roughness measurements by ML algorithms, and 25% of unplanned downtime is reduced. Tool life is optimized additionally through regression models predicting times to failure based on continuous sensor readings [77].

7. Challenges and limitations of implementing ai-driven robotics and automation in smart manufacturing

Integrating AI-driven robotics and automation into production lines in smart manufacturing environments has transformative potential. However, its adoption is not without challenges. These limitations span technical, workforce, financial, and cybersecurity dimensions, each presenting significant barriers that manufacturers must address to realize the full benefits of these advanced technologies.

7.1 Technical challenges

One of the primary obstacles in implementing AI-driven robotics and automation is the difficulty of integrating these cutting-edge systems with legacy infrastructure. Many manufacturing facilities operate with outdated equipment and processes, making seamless integration a complex and resource-intensive endeavor. Furthermore, data management poses a substantial challenge [78]. The deployment of AI systems requires collecting, storing, and analyzing vast amounts of data from sensors, devices, and machines. Ensuring that data is clean, well-structured, and compatible with AI algorithms is a formidable task, often necessitating significant upgrades to existing IT infrastructure.

7.2 Skills gap and workforce development challenges

Implementing AI in manufacturing demands a workforce proficient in emerging technologies such as machine learning, robotics programming, and data analytics. However, the industry has a growing skills gap, with many employees lacking the expertise needed to operate and maintain these advanced systems. Workforce development programs are critical, but they require time and investment to upskill employees and prepare them for the AI-driven manufacturing environment [79]. Additionally, resistance to change from employees accustomed to traditional manufacturing processes can further hinder the adoption of these technologies.

7.3 Cost and ROI considerations

While AI-driven robotics and automation promise significant long-term gains in efficiency and productivity, their initial implementation often involves substantial costs [80]. These include expenses for acquiring advanced robotics, integrating AI systems, upgrading legacy equipment, and training personnel. Manufacturers, particularly small and medium-sized enterprises (SMEs), may struggle to justify these upfront investments without clear projections of return on investment (ROI). Moreover, the variable nature of manufacturing needs makes it challenging to estimate the payback period, which can deter stakeholders from committing to large-scale adoption.

7.4 Cybersecurity concerns

As production lines become increasingly connected through IoT devices and AI systems, they become more vulnerable to cybersecurity threats. Cyberattacks targeting manufacturing facilities can lead to production halts, intellectual property theft, and compromised safety. AI systems, while powerful, can also introduce new vulnerabilities, such as the risk of adversarial attacks that manipulate machine learning algorithms [81]. To mitigate these risks, robust cybersecurity measures must be implemented, including real-time monitoring, threat detection, and secure data encryption. However, developing and maintaining these protections adds another layer of complexity and cost to AI adoption.

8. Future directions and trends

AI-driven automation and robots in smart manufacturing have a bright future ahead of them, as new technologies stand to improve overall operational excellence, productivity, and efficiency. Several significant developments and trends are influencing the future of various industries as they continue to change.

It is anticipated that 5G networks and edge AI will be essential to the transformation of smart manufacturing systems [82]. By lowering latency, edge AI, which processes data at the point of data generation instead of depending only on cloud computing, will enable quicker decision-making. This technology will improve production line productivity by enabling real-time communication between machines, sensors, and AI algorithms when combined with the fast speeds of 5G networks. With this combination, manufacturers can implement intelligent systems that can forecast maintenance requirements, evaluate data in real-time, and optimize manufacturing processes without the delays of cloud-based processing. As a result, automation systems will become more flexible and responsive to shifting production needs.

Another significant trend for the future is the growing emphasis on human-machine collaboration. The development of augmented workforces—where humans and machines collaborate side by side—will become more and more important as AI and robots develop [83]. AI-driven robots will enhance human capabilities by helping with physically taxing or precise jobs, rather than taking the place of workers. Through this partnership, human employees can concentrate on more complex decision-making and problem-solving while robots handle dangerous or repetitive activities. AI-driven systems will therefore help create more scalable and adaptable manufacturing lines that can meet various demands without compromising worker safety or quality.

Moreover, the management of manufacturing lines is about to undergo a revolution due to the increasing significance of digital twins and data analytics. Thanks to data analytics, manufacturers can continuously monitor and adjust manufacturing processes, guaranteeing increased efficiency and lower operating costs. Artificial intelligence (AI) systems can evaluate trends, spot bottlenecks, and anticipate maintenance requirements with previously unheard-of accuracy by gathering enormous data from sensors built into equipment. Manufacturers can model different production situations and test possible solutions in a virtual setting before deployment thanks to digital twins, which are virtual copies of physical systems. This technology will speed up the design and implementation of efficient systems, enhance decision-making, and offer a greater understanding of industrial processes.

Finally, the future of smart manufacturing is anticipated to be shaped by the changing regulatory environment and robots and artificial intelligence standards. Regulatory agencies must provide precise guidelines when AI technologies are incorporated more into manufacturing procedures to guarantee AI applications' safety, equity, and openness [84]. Manufacturers must manage this changing environment while maintaining regulatory compliance, innovating, and implementing cutting-edge AI-driven systems. These rules will probably cover data protection, moral AI use, and integrating self-governing systems into human-centered settings. Certain standards must be developed to promote confidence in AI technology and guarantee its long-term application across industries.

9. Conclusion

Integrating AI-driven robotics and automation in smart manufacturing is a leap into an industrial future. As we move into an era driven by interconnected systems, AI, and human-machine collaboration, manufacturers are poised to witness a revolution promising high productivity, efficiency, and flexibility. Yet, many of these advancements have not reached their fullest potential due to challenges such as legacy infrastructure, workforce skill gaps, and cybersecurity concerns. As we look to the future, emerging technologies such as edge AI, digital twins, and dynamically changing regulatory environments will continue to facilitate smart manufacturing, which creates intelligent, scalable systems that are efficient, reactive, and agile enough to adjust to infinite changes in the market. As a result, the integration of AI-driven robotics and automation approaches towards immersive technologies, like Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), will enable a path forward for production shops and factories to create a higher-level and more sustainable human-centered environment. We encourage further studies that investigate human-machine collaborative potentials and their role in sustainability and resilience, as well as the research gaps to achieve the goal of Industry 5.0. By advancing these initiatives at scale, manufacturers can realize new opportunities for economic growth, competitiveness, and social responsibility, propelling industries toward a more intelligent, safer, and sustainable future.

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Author contributions

Conceptualization, **T. Adeyi, J. Adebayo, O. Oresegun, S. Ademokoya, S. Jegede,** and **A. Cheok**; supervision, **A. Cheok**; writing—original draft preparation, **T. Adeyi,** and **J. Adebayo**; writing—review and editing, **O. Oresegun, S. Ademokoya,** and **S. Jegede**. All authors have read and agreed to the published version of the manuscript.

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

Conflicts of interest

The authors declare no conflict of interest.

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