Baština Akademije nauka i umjetnosti Bosne i Hercegovine

SMART MANUFACTURING ON THE HORIZON: A Conceptual Shift from Industry 4.0 to Industry 5.0: Industrija

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2026

Academy of Sciences and Arts of Bosnia and Herzegovina

https://bastina.anubih.ba/handle/123456789/875

Preuzeto s Baštine Akademije nauka i umjetnosti Bosne i Hercegovine

https://bastina.anubih.ba/

DOI: 10.5644/PI2026.225.02

Architecture of Industry 4.0 Smart Manufacturing Systems Based on Mobile and Collaborative Robotics

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Abstract: *Research and development of advanced technologies underpinning the implementation of Industry 4.0 are driving the transformation of traditional manufacturing systems into flexible production systems whose high level of integration and intelligence is based on digital technologies. Mobile and collaborative robotics, supported by artificial intelligence, are becoming central elements of intelligent manufacturing processes through their implementation, complementing other Industry 4.0 technologies. This paper provides a clear and comprehensive overview of the architecture of Industry 4.0 smart manufacturing systems based on the integration of autonomous mobile robots and collaborative robots, with particular emphasis on system hierarchy, data flows, and interoperability with existing industrial information systems. Patent trends over the past decade in robotics and artificial intelligence are analyzed, along with trends in the implementation of mobile and collaborative robots in manufacturing processes. The role of robotic systems in process monitoring, decision-support, and adaptive production control is examined, including their integration with IoT platforms, manufacturing execution systems, and AI-based analytical modules. The paper also discusses the technical and organizational challenges associated with implementing such architectures, as well as their potential benefits in terms of flexibility, scalability, and resilience of manufacturing systems. The proposed architectural approach provides a foundation for the further development of smart manufacturing environments and offers guidelines for the industrial application of mobile and collaborative robotics in accordance with Industry 4.0 principles.*

Keywords: *smart manufacturing systems, Industry 4.0, mobile robotics, collaborative robotics, system architecture, artificial intelligence, systems integration*

1. Introduction

Organizational transformation in modern manufacturing increasingly begins with the adoption of Industry 4.0 technologies, which are characterized by the integration of digital, physical, and cognitive systems into unified smart

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production environments. The concept of Industry 4.0 emerged within the German industrial initiative “High-Tech Strategy 2020,” and the term itself was first introduced in 2011 at the Hannover Messe trade fair. It was subsequently formalized through reports produced by the Plattform Industrie 4.0 working group, which defined the core objectives of this paradigm, including cyber–physical systems, the Industrial Internet of Things, smart factories, and the horizontal and vertical integration of manufacturing processes [1-3]. The development and implementation of Industry 4.0 rely on the technological convergence of numerous advanced technologies, such as industrial robotics, the Industrial Internet of Things (IIoT), cloud computing, big data analytics, cyber–physical systems (CPS), artificial intelligence (AI), and intelligent sensing platforms. These technologies enable manufacturing systems to become increasingly automated, adaptive, and autonomous. In contrast, traditional production environments—still widely present today—are often characterized by rigid structures, centralized control, and limited flexibility, making it difficult for them to respond to modern market requirements such as short product life cycles, high product variability, and the growing demand for mass customization [4-6]. Through the adoption of Industry 4.0 principles, production systems are transformed into smart and flexible environments capable of autonomous adaptation, real-time resource optimization, and the integration of humans and machines within shared workspaces. Among the enabling technologies of Industry 4.0, mobile and collaborative robotics occupy a central position in the architecture of intelligent manufacturing systems. Autonomous mobile robots (AMRs) provide flexible transportation of materials, tools, and components without the need for fixed infrastructure, while collaborative robots (cobots) facilitate safe and efficient human–robot cooperation in industrial operations. Their integration contributes significantly to increased productivity, reduced downtime, improved workplace ergonomics, and enhanced operational continuity [7-9] .

A particularly important trend is that modern robotic systems increasingly rely on artificial intelligence algorithms, enabling advanced perception of the environment, learning from operational data, autonomous planning, and adaptive process control. The incorporation of AI into mobile and collaborative robotics represents a shift from deterministic pre-programmed automation toward intelligent systems capable of real-time decision-making and predictive performance optimization. Combined with smart sensors, vision systems, and analytical platforms, AI-driven robots actively support production process monitoring, decision-making assistance, and the implementation of predictive maintenance strategies [10-12] . In this way, AMRs and cobots become key carriers of manufacturing digitalization and fundamental components of smart factory ecosystems. The aim of this paper is to provide a systematic overview of the architecture of Industry 4.0 smart manufacturing systems based on the integration of autonomous mobile and collaborative robots, with particular

emphasis on system hierarchy, data flows, and interoperability with existing industrial information infrastructures. Special attention is devoted to patent trends in robotics and artificial intelligence over the past decade, as well as to the evolution of industrial implementation practices worldwide. Furthermore, the paper examines the role of mobile and collaborative robotics in monitoring, adaptive control, and predictive maintenance, while addressing the technical and organizational challenges associated with deploying such architectures in real manufacturing environments.

In accordance with these objectives, the study addresses the following research questions:

- How are global patent trends in robotics and artificial intelligence relevant to smart manufacturing evolving?
- What have been the dominant trends in the industrial implementation of mobile and collaborative robots over the past ten years?
- In what ways does the integration of these robotic systems contribute to monitoring, control, and predictive maintenance of manufacturing processes?
- What are the main barriers, opportunities, and long-term implications of such systems within the Industry 4.0 paradigm?

The remainder of this paper is organized as follows. Chapter 2 presents the theoretical framework of Industry 4.0 smart manufacturing systems. Chapter 3 discusses architectures based on mobile and collaborative robotics. Chapter 4 analyzes global patent activity in robotics and AI, while Chapter 5 reviews industrial implementation trends. Chapter 6 focuses on applications in monitoring, adaptive control, and predictive maintenance. Chapter 7 addresses technical and organizational challenges, followed by the final discussion and conclusions.

2. Theoretical Framework of Smart Manufacturing Systems of Industry 4.0

It is well known that the fourth industrial revolution, namely Industry 4.0, represents a modern approach to industrial development based on the application of advanced digital technologies, which aim to transform production processes in order to achieve high flexibility, efficiency, and autonomy. This concept implies the integration of physical production resources with digital technologies, enabling the transition from traditional, hierarchically rigid systems to smart, adaptive, and self-learning manufacturing structures [13-15]. The foundation of smart manufacturing consists of key digital technologies such as the Internet of Things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), and big data analytics, together with other Industry 4.0 technologies. IoT enables the networking of machines, sensors, and devices in real time, while CPS integrate computational and physical components for continuous monitoring and process optimization. AI and big data analytics further enable predictive decision-making,

adaptive planning, and autonomous optimization of production flows, which is essential for the realization of the smart factory concept [16-18]. Intelligent manufacturing systems are most often described through a multilayer hierarchy that includes sensor and actuator levels, control systems, manufacturing execution systems (MES), and enterprise resource planning (ERP) systems. Unlike classical hierarchies, Industry 4.0 introduces horizontal and vertical integration, enabling dynamic data exchange between different system levels and functions. Interconnection is one of the main challenges in intelligent manufacturing systems because it enables communication and data exchange between different systems. In order to achieve efficient integration, standardized communication protocols and common data models are required. Without interoperability, the application of digital technologies is limited, especially in complex manufacturing environments with many different devices and software solutions [19]. Industrial and mobile robotics has a central role in the architecture of the Industry 4.0 smart factory. Industrial, collaborative, and mobile robots act as execution elements of smart systems, directly connected to CPS and AI modules. Their ability to operate autonomously, collaborate with humans, and adapt to changes in the manufacturing environment makes them key enablers of flexible and intelligent production, as well as a bridge between the digital and physical worlds of smart manufacturing systems.

3. Architecture of Smart Manufacturing Systems Based on Mobile and Collaborative Robotics

The architecture of smart manufacturing systems based on mobile and collaborative robotics represents a key element in the implementation of Industry 4.0 in modern factories. Such an architecture is designed as a modular, distributed, and scalable structure that enables flexible integration of various hardware and software components, with support for real-time operation, autonomous decision-making, and adaptive control of manufacturing processes. Fundamentally, it is based on the close integration of physical production resources and digital control layers, thereby creating the foundation for smart and responsive manufacturing. The conceptual system architecture is most often organized through a multilayer model that includes the physical layer, communication layer, control layer, and application layer. The physical layer includes autonomous mobile robots, collaborative robots, sensors, and production equipment, while the communication layer enables data exchange through industrial networks and wireless technologies. The control layer integrates algorithms for coordination, planning, and supervision, while the application layer includes analytical and visualization tools for higher-level decision-making [20]. The integration of autonomous mobile robots (AMRs) and collaborative robots (cobots) enables the realization of highly flexible manufacturing and logistics processes. AMR

systems take over tasks such as internal transport, workstation supply, and dynamic material rerouting, while collaborative robots directly cooperate with humans in assembly, processing, and inspection. Their mutual coordination is based on distributed control mechanisms and shared databases, enabling synchronized operation and adaptation to changes in the manufacturing environment [21]. Data flows and communication structures form the backbone of the architecture of smart manufacturing systems. Data are generated at the level of sensors and robots, processed at the network edge (edge computing) or in cloud environments, and used for real-time process optimization. Standardized communication protocols enable reliable and secure information exchange between AMRs, cobots, control systems, and information platforms, thereby achieving high transparency and traceability of manufacturing processes. Integration with manufacturing execution systems (MES), enterprise resource planning (ERP) systems, and IoT platforms enables vertical connectivity between the operational and business levels. In this way, a continuous flow of information from the shop floor to strategic management is achieved, allowing more efficient planning, performance monitoring, and data-driven decision-making. In this context, AMRs and collaborative robots act as active nodes of the IoT ecosystem, continuously exchanging data with higher-level systems [22]. Security, organizational, and interoperability aspects of the architecture represent particular challenges in smart manufacturing systems. Security involves the protection of people, equipment, and data, especially in environments where humans and robots share the same workspace. Organizational aspects relate to the adaptation of work processes, employee training, and the redefinition of roles in the digitalized factory. Interoperability, as a prerequisite for efficient integration, requires the alignment of technical standards and software solutions to ensure the smooth operation of complex and heterogeneous systems [23,24].

4. Trends in Robotics and Artificial Intelligence Patents

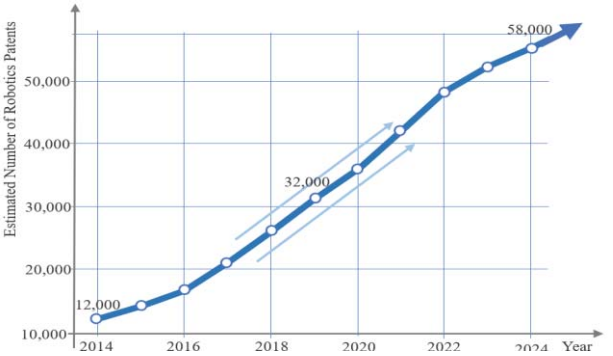
The analysis of patent trends in the fields of robotics and artificial intelligence represents a reliable indicator of technological progress, innovation dynamics, and strategic directions of industrial development within the framework of Industry 4.0. Patents reflect not only the intensity of research and development activities, but also the ability of industries and countries to commercialize knowledge and secure long-term competitive advantage. This chapter examines the methodological aspects of patent analysis, global trends in robotics and artificial intelligence, their geographical and sectoral distribution, as well as the implications of these trends for the development of industrial robotics and smart manufacturing systems.

4.1. Patent Analysis Methodology

The methodology of patent analysis is based on the use of internationally recognized patent and scientific databases that are widely applied in technology and innovation research. In this study, secondary data and search results from databases such as Lens.org and WIPO PATENTSCOPE were used, relying on methodological frameworks from previously published studies indexed in the Scopus and Web of Science databases. The analysis includes a combination of searches based on the Cooperative Patent Classification (CPC) and relevant keywords, ensuring coverage of both hardware and software innovations in robotics and artificial intelligence. As the main search criteria, CPC classes related to industrial robots, manipulators, control systems, machine learning, and intelligent algorithms were used, with a time frame covering the last ten years. The number of patent applications and patent families per year was used as an indicator of innovation activity. This approach enables the identification of long-term trends and reduces the impact of methodological differences between individual databases [25-27].

4.2. Global Trends in Robotics Patents over the Last Decade

Global trends in robotics patents over the last decade indicate a continuous and accelerated growth of innovation activity. Particularly after 2016, a significant increase in the number of patents has been observed, which is associated with the intensive implementation of Industry 4.0 concepts, the development of collaborative robots, and the expansion of autonomous mobile robotic systems.



Note: *The presented data represent estimates of the number of patent families, derived from observed growth patterns and publicly available patent analyses (Lens, PatStat, WIPO, CSET, and industry sources). Variations may arise due to differences in the applied keywords, CPC classifications, and filtering criteria.*

Figure 1. Global trends in robotics patents worldwide for the period 2014–2024 [28-31]

Robotics is increasingly positioned as a key technology for flexible and reconfigurable manufacturing, moving beyond the boundaries of traditional automation. Over the past ten years, global patent activity in the field of robotics has exhibited a strong and continuous growth, reflecting an increased level of innovation and strategic investment in automation technologies. Between 2005 and 2019, more than 72,000 robotics-related patents were granted worldwide, with a significant acceleration in the number of applications as countries and companies intensified research and development activities in robotics and autonomous systems.

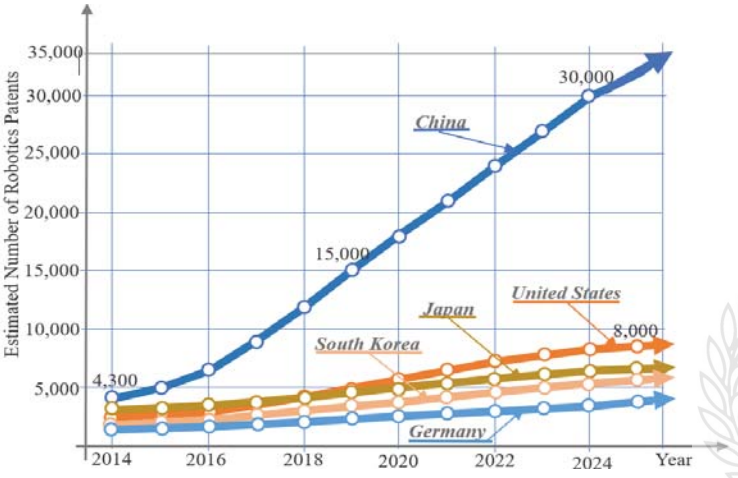


Figure 2. Global trends in robotics patents in the five leading countries: China, the United States, Japan, South Korea, and Germany over the period (2014–2025)

Figure 2 presents the estimated trends in robotics-related patent activity for the five leading countries China, the United States, Japan, South Korea, and Germany over the period 2014–2025 [28-31]. The results indicate a pronounced dominance of China, characterized by accelerated growth, particularly after 2017, followed by steady growth in the United States and Japan, largely driven by industrial and AI-enabled robotics. South Korea demonstrates strong technological continuity and sustained innovation capacity. Germany, ranked fifth globally in terms of the number of robotics patents, exhibits moderate but stable growth, consistent with its strong industrial automation base and the principles of Industry 4.0. Patent filings indicate broader technological advancement in robotics, with high activity in industrial automation, service robots, and systems integrating artificial intelligence. The increasing number of robotics patents further confirms the strategic importance of intellectual property in securing technological leadership and commercial advantage in global markets. Moreover, recent analyses suggest

a continued increase in patent activity, particularly in areas that combine robotics with artificial intelligence and Internet of Things (IoT) technologies. An analysis of patent structures reveals a growing share of solutions related to safety, adaptive control, and human–robot interaction. These trends indicate a shift toward production systems in which robots operate in shared workspaces with humans and other intelligent systems. Robotics patents thus directly reflect industry demands for greater flexibility, cost reduction, and increased productivity [32-33].

4.3. Trends in Artificial Intelligence Patents Relevant to Manufacturing

Compared to robotics, the field of artificial intelligence exhibits an even more intensive growth in patent filings. AI technologies, including machine learning, deep neural networks, and data analytics algorithms, have become key drivers of smart manufacturing. Patents in this domain increasingly address predictive maintenance, optimization of production processes, and intelligent quality control. It is particularly notable that a large share of AI-related patents is directly linked to manufacturing systems, robotics, and industrial IoT platforms. This trend indicates a strong convergence of AI and industrial automation, where algorithms learn from data collected on the shop floor and enable autonomous decisionmaking. The sharp increase in AI patent activity after 2017 confirms that artificial intelligence represents a foundational technology for the realization of smart manufacturing systems [34-35]. Figure 3 illustrates the global trend in artificial intelligence patents relevant to manufacturing processes, that is, global manufacturing, for the period 2014–2024.

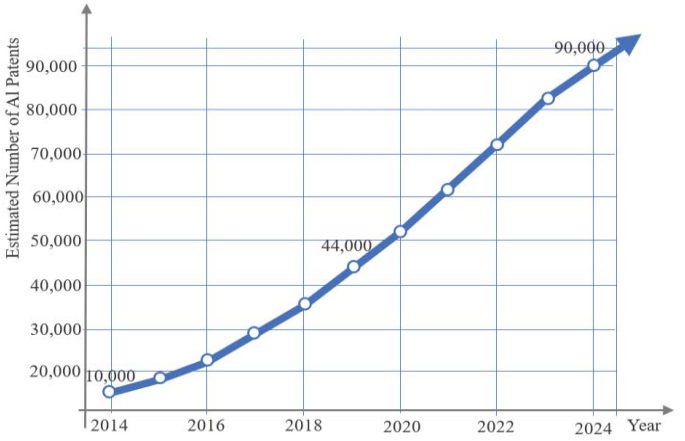


Figure 3. Global trend of AI patents relevant to manufacturing (2014–2024) [28-31]

Over the past decade, a strong and continuous growth in patent activity in the field of artificial intelligence (AI) has been observed, particularly in segments relevant to smart manufacturing and Industry 4.0, as illustrated in Figure 3. The global trend indicates that the number of AI-related patents increased almost multiple times over the period 2014–2024, reflecting the growing role of machine learning algorithms, deep neural networks, computer vision, and autonomous systems in the optimization of manufacturing processes. This growth has been especially pronounced after 2017, when AI technologies became a key factor of competitiveness in industrial automation, predictive maintenance, and intelligent production management.

An analysis of trends in artificial intelligence patents relevant to manufacturing processes, that is, global manufacturing, was conducted for the period 2014–2024 across the five leading countries worldwide: China, the United States, Japan, South Korea, and Germany, and is presented in Figure 4 [28-31].

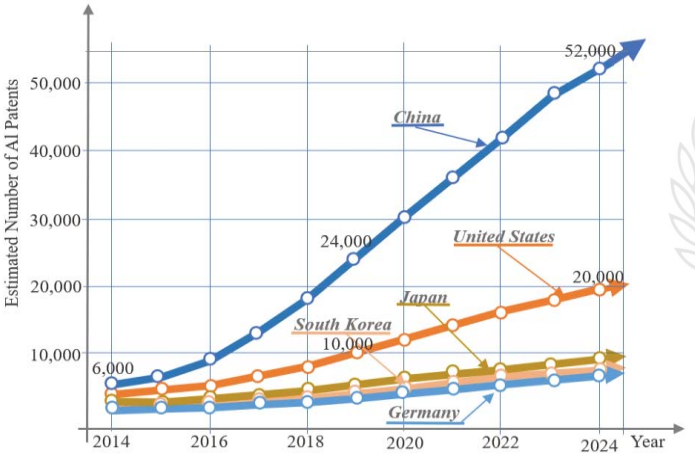


Figure 4. AI patent trends in the top five countries relevant to manufacturing: China, the United States, Japan, South Korea, and Germany (2014–2024)

An analysis of the five leading countries by the number of AI patents reveals a clear dominance of China, which exhibits exponential growth and significantly outperforms the other countries throughout the observed period. This trend is the result of strong state-driven strategies, intensive investments, and the close integration of AI technologies with industrial production. The United States and Japan rank second and third, respectively, showing stable and gradual growth, particularly in the areas of industrial analytics, autonomous systems, and the integration of AI into robotic applications. South Korea and Germany demonstrate moderate but consistent growth, in line with their focus on high-quality industrial automation and smart factories.

Overall, AI patent trends confirm that artificial intelligence represents one of the key technologies of future manufacturing, enabling higher levels of autonomy, flexibility, and efficiency in smart manufacturing systems.
The geographical analysis of patent activity indicates a pronounced concentration of patents in a limited number of technologically leading regions. Asian countries, primarily China, Japan, and South Korea, exhibit a high intensity of patenting in robotics and artificial intelligence, driven by strong government policies and long-term investments in automation. China stands out in particular due to the rapid growth in the number of patents, while Japan and South Korea maintain stable and technologically sophisticated development. The United States plays a dominant role in the development of software- and AI-oriented patents, whereas European countries, especially Germany, retain a strong focus on industrial application, quality, and standardization. From a sectoral perspective, the largest share of patents relates to industrial manufacturing, the automotive industry, and logistics, with a noticeable increase in patents in service robotics and smart energy systems [36-37].

4.4. Impact of Patent Trends on Industrial Robotics and Smart Manufacturing Systems

Patent trends in robotics and artificial intelligence have a strong impact on the development of industrial robotics and smart manufacturing systems. Increased patent activity indicates accelerated innovation and intensified global competition, resulting in a faster transfer of new technologies into industrial practice. The integration of AI into robotic systems enables the development of autonomous and self-learning systems capable of adapting to and optimizing production processes in real time. These trends contribute to the development of more flexible, energy-efficient, and reliable manufacturing systems, while simultaneously imposing the need for standardization and interoperability. Patent analysis thus confirms that robotics and artificial intelligence are key technologies of future industry and form the foundation of the architecture of Industry 4.0 smart manufacturing systems [38-39].

5. Trends in the Implementation of Mobile and Collaborative Robots over the Last Decade

Over the past decade, industrial manufacturing has undergone a profound transformation marked by a shift from rigid, hierarchically organized systems toward flexible, adaptive, and highly digitalized production environments. In this context, mobile robots and collaborative robots (cobots) have become key technological pillars of modern smart manufacturing systems. Their implementation enables efficient integration of physical processes, information

systems, and human labor, significantly increasing the agility and resilience of production systems to market and operational changes. Unlike traditional industrial robots, which are designed to perform predefined tasks in strictly controlled environments, mobile and collaborative robots enable dynamic reorganization of production, rapid reconfiguration of workstations, and safe interaction with human operators. Over the past decade, industrial manufacturing has undergone a profound transformation marked by a shift toward flexible, adaptive, and highly digitalized production environments. Mobile robots and collaborative robots (cobots) have become key technological pillars of smart manufacturing systems, significantly enhancing agility and resilience in line with Industry 4.0 principles [40].

5.1. Evolution of Mobile Robotics in Industry

Industrial mobile robotics has undergone significant evolution, transitioning from conventional automated guided vehicles (AGVs) to autonomous mobile robots (AMRs) that employ advanced sensor systems, real-time computing, and artificial intelligence. While AGV systems relied on fixed infrastructure such as magnetic tapes or reflective markers, modern AMR systems use a combination of lidar sensors, cameras, and simultaneous localization and mapping (SLAM) algorithms to navigate independently in complex and dynamic industrial environments. In contemporary manufacturing systems, mobile robots are primarily used for the autonomous execution of transport and process-support tasks, with their functionality depending on the level of environmental perception, navigation algorithms, and integration with higher-level information systems. Key enabling technologies include localization and mapping techniques, sensor data fusion, and real-time communication, which ensure reliable operation under dynamic industrial conditions. This technological approach makes mobile robots suitable for flexible production concepts and rapid process reconfiguration, regardless of the specific industrial sector, as illustrated in Figure 5.

Figure 5. Autonomous mobile robots perform various tasks in manufacturing processes [43-45]

Numerous studies have shown that the implementation of AMR systems contributes to reduced production downtime, optimized material flows, and increased utilization of manufacturing capacities .In addition, mobile robots are increasingly integrated with manufacturing information systems such as MES and ERP, thereby becoming an integral part of digital twins of production systems Advances in mobile robotics have also enabled the development of hybrid systems in which mobile robots are combined with robotic manipulators, expanding their functional scope to machine tending, assembly, and inspection. Such systems are particularly suitable for flexible production lines and small-batch manufacturing with frequent product changes [42,46].

5.2. Development and Expansion of Collaborative Robots in Manufacturing Environments

Collaborative robots represent one of the fastest-growing categories of industrial robotics. Their development is based on the integration of force and torque sensors, advanced collision detection algorithms, and functional safety standards, enabling safe operation in shared workspaces with humans . This characteristic makes cobots particularly suitable for applications requiring close human–robot collaboration. In manufacturing environments, cobots are increasingly used for tasks that require precision, repeatability, and ergonomic support for workers. Empirical studies indicate that the use of collaborative robots reduces physical workload, increases productivity, and contributes to improved product quality They are particularly prevalent in assembly, packaging, palletizing, CNC machine tending, and quality inspection, as shown in Figure 6 [47-51].

Figure 6. Collaborative robots performing CNC machine tending in manufacturing processes

An important factor driving the adoption of cobots is their relatively simple integration and programming. Unlike traditional industrial robots, which require specialized expertise and lengthy setup procedures, collaborative robots often employ intuitive programming methods such as hand-guiding or graphical user interfaces. This enables faster deployment and easier adaptation of production processes.

5.3. Statistical Indicators and Industrial Implementation Examples

Trends in the implementation of professional service robots, logistics service robots, and collaborative robots worldwide were analyzed based on statistical data obtained from the International Federation of Robotics (IFR), the United Nations Economic Commission for Europe (UNECE), and the Organisation for Economic Co-operation and Development (OECD). These data are presented in Figures 7, 8, 9, and 10 [52-60]. Research and development in robotics technology have contributed to the advancement of professional service robots used in manufacturing processes. Currently, service robots for transport and logistics represent the most widespread applications, supporting finished product inspection, monitoring, and tracking of production processes The global trend in the deployment of professional service robots over the period 2014–2024 is illustrated in Figure 7.

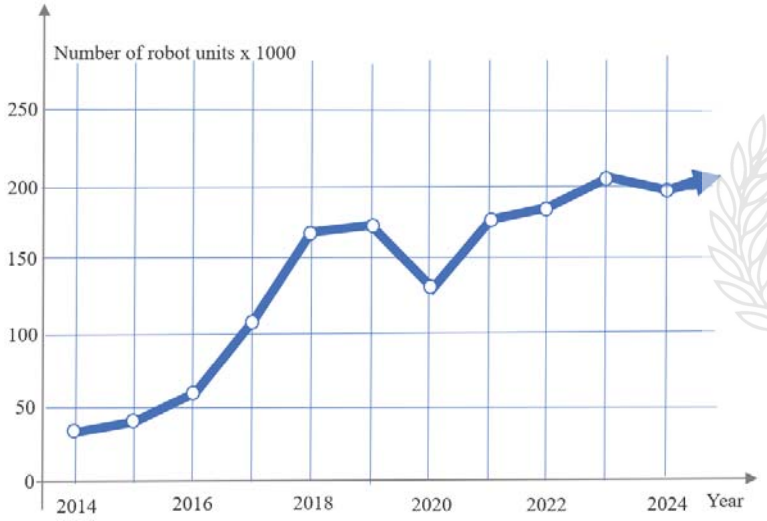


Figure 7. Global trend in the implementation of professional service robots (2014–2024).

The implementation trend of professional service robots shows long-term and structurally stable growth, with occasional short-term fluctuations caused by global economic and societal disruptions. As shown in Figure 7, the number of deployed professional service robots increased significantly from 33,000 units in 2014 to 199,000 units in 2024, representing approximately a sixfold increase and an average annual growth rate (CAGR) of about 19.7% . A notable decline occurred during the pandemic year 2020, followed by a strong recovery in 2021. The data also indicate a peak in 2023, with a slight decline in 2024, suggesting short-term market correction or saturation in certain segments. After a phase of

rapid expansion, the market is entering a more mature stage characterized by gradual stabilization and selective sectoral growth.
The distribution of professional service robot applications across six major application areas in 2024 is shown in Figure 8.

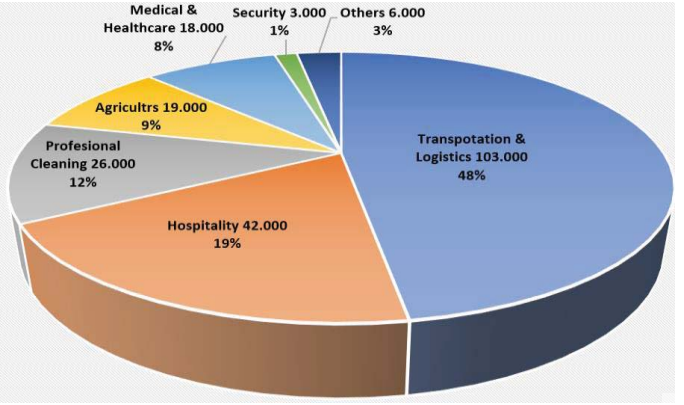


Figure 8. Implementation of professional service robots across six major application areas in 2024.

Based on the data presented in Figure 9, the distribution of service robot applications across sectors can be observed. The largest number of installations is recorded in the transport and logistics sector, with 103,000 units, accounting for 48% of total usage [21]. This is followed by hospitality, with 42,000 units used for food preparation, serving, and delivery in hotels and restaurants. In agriculture, 19,000 units are deployed for harvesting, irrigation, mowing, milking, and crop maintenance. Medical robots account for 8% of total usage, with 18,000 units supporting surgical assistance, rehabilitation, and patient care. Professional cleaning includes 26,000 units, while security, search, and rescue applications represent the smallest share, with 3,000 units, mainly due to high implementation costs and specific operational requirements.
The global trend in the deployment of service robots in logistics and transport over the period 2014–2024 is presented in Figure 9.

The data shown in Figure 9 indicate continuous growth in the number of deployed professional service robots in logistics and transport. After moderate growth until 2018, a period of relative stability followed, with a pronounced increase in installations observed from 2021 onward.

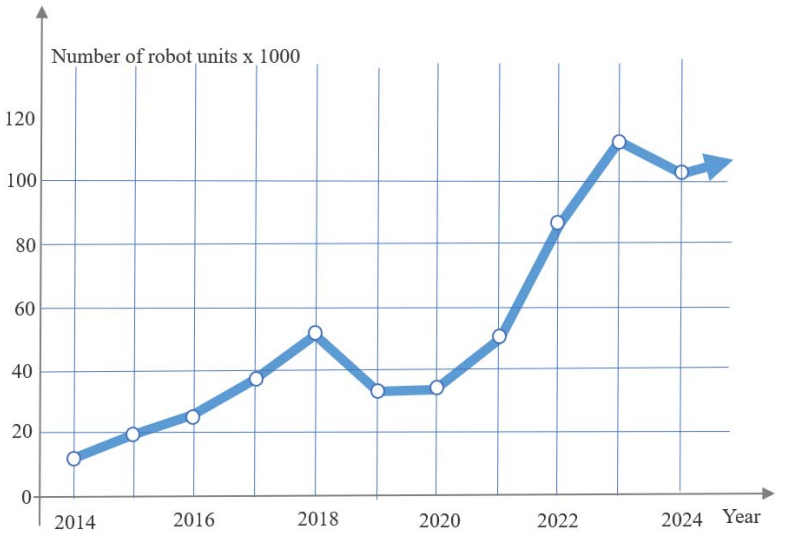


Figure 9. Global trend in the implementation of service robots in logistics and transport (2014–2024).

In 2024, a total of 103,000 units were deployed, representing the highest recorded value during the observed period.
Collaborative robots have become an important component of modern industrial automation between 2017 and 2023. The global trend in their implementation, together with the percentage distribution in 2023, is shown in Figure 10.

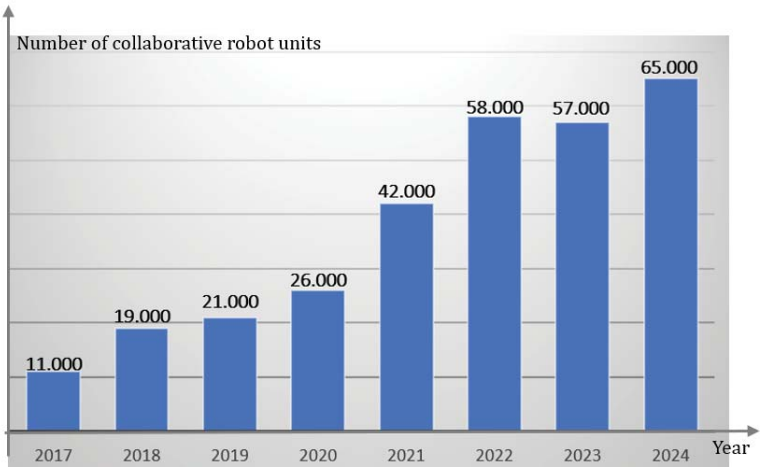


Figure 10. Global implementation of collaborative robots (2017–2023) and percentage distribution in 2023.

According to available data, the global deployment of collaborative robots shows steady growth throughout the observed period. This growth is driven by their flexibility, safety features, and ability to adapt rapidly to diverse production processes Despite increasing adoption, collaborative robots still account for a relatively small share of the total industrial robot population, while traditional industrial robots continue to dominate automated production facilities.

5.4. Key Factors Influencing Implementation Growth and Sectoral Comparison

The growth in the implementation of mobile and collaborative robots results from the interaction of technological, economic, and organizational factors. Technological advances in sensors, artificial intelligence, edge computing, and wireless communication have enabled reliable robot operation under real industrial conditions. At the same time, declining hardware costs and the development of modular robotic platforms have made these technologies accessible to a broader range of enterprises. Economic factors include rising labor costs, shortages of skilled workers, and the need to enhance competitiveness. In many industrial sectors, robots are not viewed as replacements for human workers but as supportive tools that allow employees to focus on more complex and creative tasks . Organizational factors, such as the adoption of lean and agile production concepts, further stimulate the implementation of flexible robotic systems [42,47]. The application of mobile and collaborative robots varies considerably across industrial sectors, confirming that these technologies represent universal yet adaptable solutions implemented in accordance with the specific requirements of industrial processes.

6. Implementation of Mobile and Collaborative Robots in Manufacturing Processes

The implementation of mobile autonomous robots (AMRs) and collaborative robots (cobots) represents a crucial operational stage in the transition toward smart manufacturing systems aligned with the principles of Industry 4.0. Unlike conventional automation solutions—typically characterized by rigid structures and centralized control—mobile and collaborative robotic systems operate as integral components of cyber–physical production environments. Their functionality extends beyond task execution to encompass continuous process monitoring, adaptive production control, and support for predictive maintenance strategies. This chapter provides an interpretative and integrative discussion of how mobile and collaborative robots are implemented within manufacturing processes, explicitly building on the empirical findings presented in Chapters 4 and 5. Rather than reiterating quantitative results, the focus is placed on explaining

the underlying mechanisms, operational implications, and industrial relevance of the observed performance improvements. The discussion is structured around three interconnected domains: (i) monitoring and real-time supervision of manufacturing processes, (ii) adaptive and data-driven control of production operations, and (iii) robot-supported predictive maintenance aimed at reducing downtime and enhancing system reliability.

6.1. Monitoring and Supervision of Manufacturing Processes

❖ **Robotic Systems for Data Acquisition and Visual Inspection**

Mobile and collaborative robots increasingly function as distributed sensing and inspection platforms within modern manufacturing environments. Equipped with advanced vision systems—such as 2D and 3D cameras—as well as vibration, temperature, and acoustic sensors, these robots enable continuous acquisition of operational and condition-related data. Compared with fixed inspection solutions, AMRs offer superior spatial flexibility, allowing inspection tasks to be performed across multiple production lines without additional infrastructure investments. The integrated sensing configuration of the AMR–cobot system employed in this study is illustrated in Figure 11.

Figure 11. Autonomous mobile robot and collaborative robot equipped with multiple sensors.

This setup enables continuous visual inspection of components and equipment while simultaneously collecting data relevant to quality assurance and maintenance planning. Such capabilities support early detection of defects, misalignments, and abnormal operating conditions, thereby reducing reliance on manual inspections and mitigating the risk of human error. From an operational perspective, robotic inspection systems enhance consistency and repeatability—two critical factors in high-throughput manufacturing environments. Previous studies have demonstrated that robotic visual inspection systems, particularly

when combined with machine vision and learning-based techniques, outperform manual inspection in terms of accuracy, objectivity, and scalability [61].

❖ **Integration of Sensors and AI Algorithms for Real-Time Monitoring**

The effectiveness of robotic monitoring systems is substantially enhanced through the integration of sensor networks with artificial intelligence (AI) and machine learning (ML) algorithms. Data acquired by mobile and collaborative robots are processed in real time to identify anomalies, degradation trends, and early indicators of potential failures. This capability enables a shift from passive condition monitoring to active, intelligence-driven process supervision.The real-time data processing and decision-making workflow adopted in this research is illustrated in Figure 12. The figure demonstrates how sensor data collected by the AMR and cobot are analyzed using convolutional neural network (CNN) models and subsequently integrated with Computerized Maintenance Management Systems (CMMS) and Enterprise Resource Planning (ERP) platforms. This architecture ensures that inspection outcomes are directly translated into actionable maintenance and operational decisions.

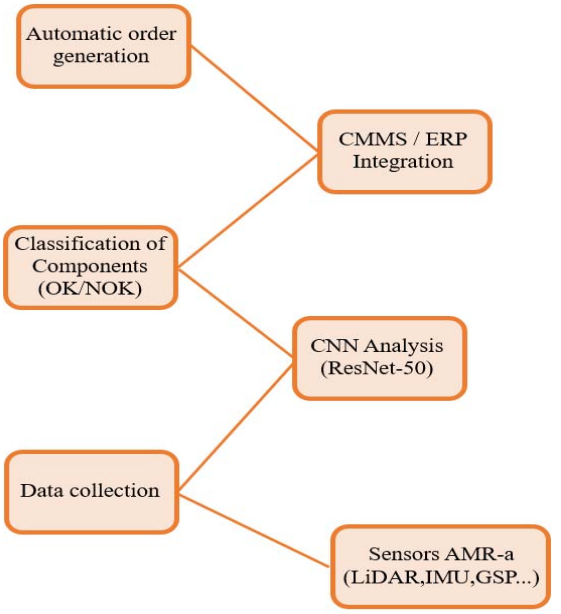


Figure 12. Workflow diagram of the integrated AMR–cobot inspection process.

Such cyber–physical integration is widely recognized as a cornerstone of intelligent manufacturing systems, as it enables continuous learning, rapid response to process deviations, and improved operational transparency [10, 62].

6.2. Control and Adaptive Management of Manufacturing Operations

❖ Role of Robots in Decentralized Process Control

The deployment of mobile and collaborative robots facilitates a transition from centralized control architectures toward decentralized and distributed manufacturing control. In this paradigm, robots operate as autonomous agents capable of local decision-making while remaining interconnected with higher-level manufacturing execution systems. Such decentralization enhances system resilience and flexibility, particularly in production environments subject to frequent changes in demand, product variants, or operating conditions.Through continuous monitoring and bidirectional data exchange, robotic systems dynamically adjust task allocation, inspection frequency, and maintenance priorities. This capability supports adaptive control strategies that respond to real-time system states rather than relying exclusively on predefined schedules. The methodological role of robots in decentralized control frameworks has been extensively discussed in the literature, highlighting improvements in fault tolerance, responsiveness, and overall system robustness [8, 63].

❖ Data-Driven Decision-Making and AI-Supported Control

Data-driven decision-making constitutes a central element of adaptive manufacturing control enabled by mobile and collaborative robots. By continuously collecting, aggregating, and analyzing operational data, robotic systems generate actionable insights that support the optimization of production parameters and predictive maintenance strategies.

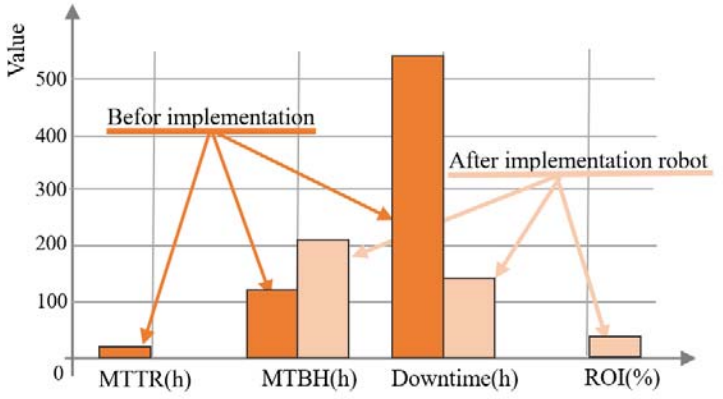


Figure 13. Comparative bar chart of key performance indicators (MTTR, MTBF, downtime, ROI) before and after robotic system implementation.

The quantitative impact of AI-supported decision-making observed in the analyzed case study is summarized in Figure 13, providing a comparative

overview of key performance indicators before and after robotic system implementation. The substantial improvements in mean time to repair (MTTR), mean time between failures (MTBF), and return on investment (ROI) demonstrate the effectiveness of integrating robotic monitoring with AI-driven analytics. Figure 14 presents a comparative analysis of key manufacturing performance indicators before and after the deployment of mobile and collaborative robotic systems supported by AI-driven analytics. The results indicate significant reductions in mean time to repair (MTTR) and overall downtime, reflecting faster recovery from failures and improved operational continuity. At the same time, an increase in mean time between failures (MTBF) highlights enhanced system reliability achieved through predictive monitoring and adaptive maintenance interventions. Furthermore, the observed improvement in return on investment (ROI) demonstrates the economic benefits of combining robotic automation with data-driven decision-making processes. Overall, the figure confirms the positive contribution of decentralized robotic control and intelligent analytics to manufacturing efficiency, resilience, and long-term sustainability, consistent with prior research findings [62].

6.3. Predictive Maintenance Supported by Mobile and Collaborative Robots

❖ **Robotic Contribution to Predictive Maintenance Systems**

Predictive maintenance (PdM) represents one of the most significant advantages of implementing mobile and collaborative robots in modern manufacturing systems. Acting as mobile inspection and intelligent sensing units, these robots enable continuous condition monitoring of critical equipment while minimizing interruptions to ongoing production activities.

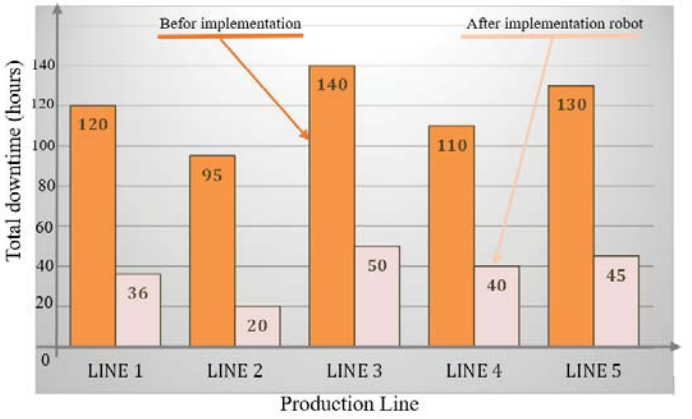


Figure 14. Comparative analysis of total downtime across production lines before and after robotic system implementation

The operational benefits of this approach are reflected in the comparative downtime performance presented in Figure 14, which highlights the measurable impact of robotic support on maintenance efficiency and overall manufacturing stability. Figure 14 presents a comparative analysis of total unplanned downtime across production lines before and after the implementation of mobile and collaborative robotic systems for predictive maintenance [64]. The results indicate a substantial reduction in downtime following the introduction of robotic inspection, autonomous monitoring, and data-driven maintenance interventions. This improvement demonstrates the effectiveness of robot-supported predictive maintenance strategies in identifying early-stage failures, preventing unexpected breakdowns, and enabling timely corrective actions. By providing real-time equipment assessment without disrupting production processes, robotic systems contribute to enhanced operational continuity, increased equipment availability, and improved manufacturing reliability. Overall, the figure emphasizes the critical role of autonomous robotics in minimizing production disruptions and supporting resilient and sustainable smart manufacturing environments.

- **Integration with Analytical and AI Modules**

Robotic data acquisition systems are closely integrated with advanced analytical platforms employing machine learning and deep learning models to forecast equipment failures and degradation trends. This integration allows maintenance activities to be scheduled based on actual equipment condition rather than fixed time intervals, resulting in optimized resource utilization and reduced maintenance costs.The literature consistently reports that AI-enhanced predictive maintenance frameworks outperform traditional preventive maintenance approaches in terms of accuracy and cost efficiency [65,66]. The results discussed in this study further corroborate these findings by demonstrating improved system reliability and sustained reductions in downtime.

- **Reduction of Downtime and Improvement of System Reliability**

The cumulative effect of implementing mobile and collaborative robots is reflected in long-term improvements in production stability and system reliability. The temporal evolution of downtime reduction is presented in Figure 15, which provides a detailed monthly perspective on system performance and operational continuity over the evaluation period. Figure 15 presents the monthly trend of total downtime before and after the implementation of mobile and collaborative robotic systems [64]. The results demonstrate a sustained and progressive decline in downtime throughout the observed timeframe, indicating continuous improvements in production stability and enhanced system reliability. This temporal pattern confirms that robot-supported predictive maintenance offers not only immediate operational advantages but also supports long-term performance optimization through adaptive monitoring strategies.

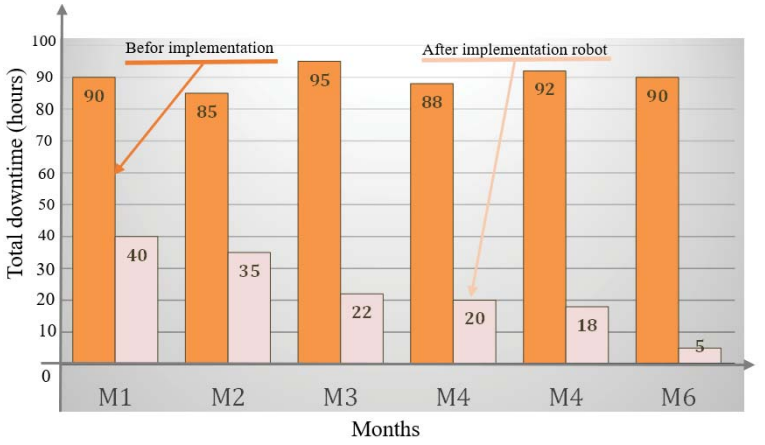


Figure 15. Monthly trend of total downtime before and after robotic system implementation

By enabling proactive interventions, continuous condition assessment, and early-stage fault detection, robotic systems significantly increase equipment availability while reducing unexpected disruptions. Overall, the figure emphasizes the essential role of autonomous robotics in achieving sustainable, resilient, and reliable smart manufacturing operations.

6.4. Critical Discussion and Implementation Implications

While the results demonstrate clear benefits of integrating mobile and collaborative robots into smart manufacturing environments, several practical implementation constraints must be carefully considered. Key challenges include ensuring seamless interaction between robotic platforms and existing industrial infrastructures, addressing cybersecurity vulnerabilities arising from increased digital connectivity, and developing comprehensive workforce reskilling programs to support the operation and maintenance of advanced robotic technologies [67]. In addition, the question of how effectively the proposed architecture can be expanded into less digitally mature manufacturing contexts remains an important area for further investigation. Nevertheless, when appropriately deployed, mobile and collaborative robots should not be viewed merely as automation tools, but rather as strategic enablers of data-driven, cyber–physical production ecosystems. Their combined contribution to real-time monitoring, adaptive process control, and predictive maintenance highlights their role as a technological foundation for resilient, efficient, and sustainable smart manufacturing systems.

7. Technical and Organizational Challenges of Implementing Mobile and Collaborative Robots

Despite the well-documented benefits of mobile and collaborative robots in modern manufacturing systems, their implementation is accompanied by a range of technical, organizational, and economic challenges. The successful integration of these technologies depends not only on the technological maturity of robotic solutions but also on the readiness of organizations to adapt existing processes, structures, and management strategies. This section analyzes the key challenges associated with implementation, with particular emphasis on system interoperability, safety and scalability, organizational and workforce-related issues, economic viability, and standardization and regulatory frameworks.

7.1. Technical Challenges: Interoperability, Safety, and Scalability

From a technical perspective, one of the most demanding aspects of implementing mobile and collaborative robots lies in achieving interoperability with established industrial systems. Manufacturing environments are frequently characterized by heterogeneous machinery, diverse software solutions, and multiple communication protocols, which complicates the integration of robotic technologies into legacy production frameworks. The absence of universally adopted interfaces, together with inconsistent implementation of industrial standards, often results in fragmented system architectures and increased engineering complexity. Safety constitutes another fundamental challenge, particularly in collaborative workspaces where humans and robots operate in close physical proximity. Although modern collaborative robots incorporate advanced safety functionalities—such as force and speed limitation, human presence detection, and emergency stop mechanisms—their effective configuration, validation, and certification in real industrial conditions remains a complex and highly context-dependent task. Moreover, the growing dependence of robotic systems on networked industrial environments and cloud-based infrastructures introduces additional cybersecurity risks, including unauthorized access, data manipulation, and operational disruption [68]. Scalability further intensifies implementation difficulties, as solutions proven in pilot deployments often require major adjustments when extended across multiple production lines or facilities. Without modular system architectures and carefully planned infrastructure upgrades, scaling robotic solutions may lead to disproportionate increases in costs, network demands, and overall technical complexity.

7.2. Organizational and Workforce-Related Challenges

In addition to technical barriers, organizational and workforce-related challenges often play a decisive role in the success or failure of implementing mobile and collaborative robots. The introduction of advanced robotic systems necessitates changes in work organization, task allocation, and the redefinition of employee roles. Resistance to change—particularly among operators and technical staff—can significantly slow down the implementation process. A shortage of appropriate skills represents one of the key challenges. Operating, programming, and maintaining mobile and collaborative robots requires multidisciplinary expertise encompassing robotics, information technologies, and data analytics. Organizations that fail to invest systematically in training and workforce development frequently experience reduced system performance and increased dependence on external vendors and service providers. Moreover, the transformation of human–robot interaction dynamics requires adjustments to safety procedures and organizational culture. Successful implementation relies on building employee trust in robotic systems, which can be achieved through transparent communication, participatory implementation approaches, and continuous education programs.

7.3. Economic Viability and Return on Investment

The economic viability of implementing mobile and collaborative robots is a frequent topic of discussion in industrial practice. Although initial investments in robotic equipment, infrastructure, and training can be substantial, long-term benefits are typically reflected in reduced operating costs, increased productivity, and improved product quality. Return on investment (ROI) depends on multiple factors, including process complexity, robot utilization rates, and the level of integration with other manufacturing systems. Studies indicate that organizations implementing robotics as part of a well-defined digital transformation strategy achieve faster and more stable ROI compared to ad hoc automation initiatives [63]. Nevertheless, economic risks remain, particularly for small and medium-sized enterprises, where limited financial resources and market uncertainty can hinder the justification of initial investments. In such cases, phased implementation strategies and pilot projects represent effective approaches for mitigating financial risk.

7.4. Standardization and Regulatory Frameworks

Standardization and regulatory frameworks play a crucial role in the safe and efficient implementation of mobile and collaborative robots. International standards such as ISO 10218 and ISO/TS 15066 have significantly improved the

safety of collaborative robotic systems; however, their practical application often requires additional interpretation and adaptation to specific industrial contexts. The rapid pace of technological development frequently outstrips the evolution of regulatory frameworks, creating legal and operational uncertainty for organizations deploying advanced robotic solutions. Particular challenges arise with respect to liability in the event of accidents, system certification, and compliance with national and international occupational safety regulations [69]. Further development of harmonized standards and clearer regulatory guidelines is therefore a prerequisite for the broader and safer adoption of mobile and collaborative robots, especially in industries with stringent safety and reliability requirements.

8. Discussion

The results presented in the previous chapters enable a comprehensive discussion of ongoing developments in the industrial deployment of mobile and collaborative robots. By combining patent-based insights with evidence from real implementation cases, the study reveals a clear movement toward robotic systems that are increasingly autonomous, adaptive, and tightly connected with digital manufacturing infrastructures. Patent trends demonstrate an intensified emphasis on artificial intelligence, sensor integration, and autonomous decision support, reflecting the same priorities observed in contemporary industrial applications. This alignment indicates that innovation in robotics is progressively shaped by concrete production requirements and operational challenges rather than purely experimental laboratory advancement. A central outcome of the analysis is the strong linkage between system-level architecture and successful implementation practice. The adoption of modular cyber–physical frameworks provides the structural foundation for integrating mobile and collaborative robots into heterogeneous manufacturing environments. Such architectures enable coordinated data exchange, distributed control functionalities, and improved responsiveness of production systems. The performance improvements discussed in Chapters 6 and 7 suggest that architectural design decisions influence not only technical feasibility but also operational stability and manufacturing continuity. Nevertheless, several limitations must be acknowledged. The study relies on a restricted selection of patent datasets and industrial case implementations, which may limit the broader applicability of the conclusions across all manufacturing sectors. Furthermore, most evaluated examples originate from digitally advanced environments, meaning that the transferability of these findings to less automated or resource-limited contexts remains uncertain. Additionally, longer-term organizational dimensions—including workforce adaptation processes, institutional change, and sustained investment impacts—extend beyond the available observation period. Despite these constraints, the study offers

meaningful implications for industrial stakeholders and future academic inquiry. For industry, the results underline the importance of adopting robotics within an integrated socio-technical framework rather than through isolated automation upgrades. For researchers, the findings emphasize the need to deepen investigations into scalable deployment strategies, harmonized industrial standards, and next-generation intelligent control approaches that support broader adoption across diverse manufacturing settings.

9. Conclusion

This study provides an integrated examination of how mobile and collaborative robots contribute to the evolution of smart manufacturing, drawing together theoretical perspectives, patent development patterns, and practical implementation evidence. The work advances a holistic understanding of robotics adoption by addressing not only technological progress but also the organizational and economic considerations that shape industrial feasibility. The findings indicate that mobile and collaborative robots play a transformative role in enabling new production paradigms characterized by adaptive coordination, predictive capabilities, and increased responsiveness to operational disturbances. Rather than functioning solely as automated machinery, these robotic systems emerge as interconnected elements within intelligent cyber–physical production networks that support more robust manufacturing performance. From an applied perspective, the study suggests that robotics integration should be approached through structured digital transformation planning, with careful consideration of interoperability, safety validation, and workforce qualification. Incremental deployment through pilot-based implementation and continuous evaluation is particularly relevant for manufacturers aiming to balance innovation benefits with investment and operational risks. Future research should focus on expanding empirical validation across broader industrial sectors, advancing AI-enabled autonomy, and developing standardized architectures capable of supporting long-term sustainability objectives. In particular, greater attention is required to understand the socio-economic consequences of robotics-driven transformation as manufacturing systems continue to evolve within dynamic global competitive environments.

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