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COLLABORATIVE ROBOTICS AND ARTIFICIAL INTELLIGENCE IN THE AUTOMOTIVE INDUSTRY: SMART ASSEMBLY AND AUTOMATED QUALITY CONTROL

ABSTRACT: The modern automotive industry is undergoing an intensive technological transformation based on the principles of Industry 4.0 and Industry 5.0, where collaborative robots and artificial intelligence systems play a key role in improving manufacturing processes. This paper analyses the application of collaborative robots worldwide, with a particular focus on the automotive industry. An overview is given of the integration of collaborative robotics and artificial intelligence in assembly processes and automated quality control in the automotive industry. Special focus is placed on human–robot collaboration in flexible and intelligent manufacturing environments based on the principles of Industry 5.0, with the aim of optimizing assembly operations, increasing productivity, and reducing production errors. Modern methods based on machine learning, computer vision, and sensor data analysis for defect detection and real-time product quality monitoring are also discussed. The paper presents the possibilities of applying collaborative robotic systems in automotive component assembly, visual inspection, material handling, and adaptive process control. Technical, safety, and economic aspects of collaborative robot implementation are analysed, including increased manufacturing flexibility, reduced operational costs, and improved ergonomic working conditions. The research results indicate that the integration of collaborative robotics and artificial intelligence enables the development of intelligent manufacturing systems capable of autonomous decision-making, adaptive process management, and efficient quality control. Collaborative robotics and artificial intelligence, as fundamental technologies of Industry 4.0, represent a significant factor in the future development of smart factories and sustainable automotive manufacturing.

KEYWORDS: Collaborative Robots, Artificial Intelligence, Automotive Industry, Smart Assembly, Quality Control, Industry 5.0.

KOLABORATIVNA ROBOTIKA I UMJETNA INTELIGENCIJA U AUTOMOBILSKOJ INDUSTRIJI: PAMETNA MONTAŽA I AUTOMATIZIRANA KONTROLA KVALITETA

REZIME: Savremena automobilska industrija prolazi kroz intenzivnu tehnološku transformaciju zasnovanu na principima Industrije 4.0 i Industrije 5.0, pri čemu kolaborativni roboti i sistemi umjetne inteligencije imaju ključnu ulogu u unapređenju proizvodnih procesa. U radu se analizira primjena kolaborativnih robota u svijetu, s posebnim fokusom na automobilsku industriju. Dat je pregled integracije kolaborativne robotike i umjetne inteligencije u procesima montaže i automatizirane kontrole kvaliteta u automobilskoj industriji. Poseban naglasak stavljen je na

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saradnju čovjeka i robota u fleksibilnim i inteligentnim proizvodnim okruženjima zasnovanim na principima Industrije 5.0, s ciljem optimizacije montažnih operacija, povećanja produktivnosti i smanjenja proizvodnih grešaka. Također su razmatrane savremene metode zasnovane na mašinskom učenju, računarskom vidu i analizi senzorskih podataka za detekciju nedostataka i praćenje kvaliteta proizvoda u realnom vremenu. U radu su predstavljene mogućnosti primjene kolaborativnih robotskih sistema u montaži automobilskih komponenti, vizuelnoj inspekciji, rukovanju materijalom i adaptivnom upravljanju procesima. Analizirani su tehnički, sigurnosni i ekonomski aspekti implementacije kolaborativnih robota, uključujući povećanje fleksibilnosti proizvodnje, smanjenje operativnih troškova i poboljšanje ergonomske uslova rada. Rezultati istraživanja pokazuju da integracija kolaborativne robotike i umjetne inteligencije omogućava razvoj inteligentnih proizvodnih sistema sposobnih za autonomno donošenje odluka, adaptivno upravljanje procesima i efikasnu kontrolu kvaliteta. Kolaborativna robotika i umjetna inteligencija, kao temeljne tehnologije Industrije 4.0, predstavljaju značajan faktor budućeg razvoja pametnih fabrika i održive automobilske proizvodnje.

KLJUČNE REČI: kolaborativni roboti, umjetna inteligencija, automobilska industrija, pametna montaža, kontrola kvaliteta, Industrija 5.0.

INTRODUCTION

We are witnessing the fact that the automotive industry is undergoing an intensive digital transformation on a daily basis, fundamentally changing the way vehicles are designed, manufacturing processes are carried out, and the quality control of vehicles as products is performed. The continuous development of the core technologies of Industry 4.0, such as Cyber-Physical Systems (CPS), the Internet of Things (IoT), the Industrial Internet of Things (IIoT), Autonomous Robots (Industrial Robotics), Collaborative Robotics (Cobots), smart sensors, Artificial Intelligence (AI) and Machine Learning (ML), Big Data, simulation and digital twins, cloud computing, horizontal and vertical system integration, Additive Manufacturing (3D Printing), Augmented Reality (AR) and Virtual Reality (VR), Autonomous Mobile Robots (AMRs), Automated Guided Vehicles (AGVs), cybersecurity, and advanced automation systems, has enabled the creation of smart manufacturing environments in which information is collected and analysed in real time (Javaid, M. et al. 2022; Karabegović, I. et al. 2020). Automotive manufacturing companies are implementing the core technologies of Industry 4.0, thereby achieving a high level of connectivity among machines, sensors, robotic systems, and information platforms, which enables them to optimize manufacturing processes, reduce production costs, and improve product quality. Automotive companies, being exposed to the global market and increasingly demanding customer requirements, are compelled to implement flexible manufacturing systems capable of rapidly adapting to different vehicle models and individual customer requirements. The implementation of Industry 4.0 technologies not only involves the automation of manufacturing processes, but also the development of intelligent systems capable of making decisions based on data analysis and the prediction of future production states (Xu, X. et al. 2021). New-generation robotic systems play a particularly important role by enabling higher productivity, safety, and precision in manufacturing lines. Industry 4.0 represents the fourth industrial revolution based on the digitalization of manufacturing processes, the integration of cyber-physical systems, and machine-to-machine communication via the Internet. The primary objective of this concept is to create smart factories in which production processes operate autonomously, while continuously monitoring and optimizing system performance. The implementation of the core technologies of Industry 4.0 has made it possible to collect large volumes of data, analyse them, and support real-time decision-making. However, the evolution of industrial systems has demonstrated that complete automation cannot replace human creativity, experience, and the ability to make complex decisions. Consequently, the concept of Industry 5.0 has emerged in recent years, emphasizing a human-centric approach to manufacturing in which humans and intelligent technological systems jointly participate in value creation (Nahavandi, S. 2019). Industry 5.0 focuses on human-machine collaboration, sustainable manufacturing, and increasing the resilience of industrial systems to market and technological changes (Adel, A. 2022). Unlike Industry 4.0, which is primarily oriented toward automation and digitalization, Industry 5.0 integrates human capabilities with artificial intelligence, collaborative robotics, and advanced analytical systems. Such an approach enables the development of more flexible and intelligent manufacturing environments tailored to the needs of the modern automotive industry (Tóth, A. et al. 2023). Collaborative robots (cobots) represent one of the most important technologies of contemporary manufacturing systems. Unlike traditional industrial robots, which operate within physically separated work cells, cobots are designed to work safely in close proximity to human operators (Matheson, E. et al. 2019). Their design incorporates force sensors, vision systems, obstacle detection algorithms, and safety functions that enable direct collaboration with operators. In the automotive industry, collaborative robots are employed for component assembly, material handling, welding, adhesive application, product inspection, and final vehicle assembly operations. Their implementation contributes to increased productivity, reduced physical workload for workers, and improved ergonomic working conditions (Keshvarparast, A. et al. 2024). At the same time, collaborative systems provide greater manufacturing flexibility, which is particularly important in environments characterized by frequent vehicle model changes and increasing demands for product personalization. Modern concepts of human-robot collaboration are based on combining the precision, speed, and repeatability of robots with human judgment, creativity, and problem-solving capabilities. This form of interaction is becoming a key component of smart manufacturing systems and one of the fundamental pillars of Industry 5.0 development (Othman, U., & Yang, E. 2023). Artificial Intelligence

(AI) and Machine Learning (ML) are currently at the centre of the transformation of manufacturing processes and are most commonly used for manufacturing process optimization, predictive maintenance of equipment, automated production planning, quality control, and decision support. Machine Learning (ML) algorithms enable systems to analyse large volumes of data and identify anomalies that are not easily detectable using conventional analytical methods (Lee, J. et al. 2018). AI is particularly important in automated quality control. Through the application of computer vision, deep neural networks, and pattern recognition algorithms, it is possible to detect surface defects, assembly irregularities, and dimensional deviations with significantly greater accuracy and speed than traditional inspection methods (Zonta, T. et al. 2020). The aforementioned systems enable continuous monitoring of product quality throughout the entire production system, thereby reducing the probability of defective products. Artificial intelligence plays a key role in the development of intelligent collaborative robots (cobots), because through the integration of deep learning methods, image processing, and sensor fusion, collaborative robots (cobots) can recognize human movements, predict operator intentions, and adapt their behaviour in real time (Cherubini, A., & Navarro-Alarcon, D. 2021). This level of adaptability provides the foundation for the development of advanced human–robot collaboration systems in future manufacturing environments. The objective of this paper is to analyse the application potential of collaborative robotics and artificial intelligence in the automotive industry, with particular emphasis on smart assembly and automated quality control. The study provides an overview of contemporary technologies that enable the integration of humans, robots, and intelligent information systems within the frameworks of Industry 4.0 and Industry 5.0. The scientific contribution of this paper lies in the systematization of existing knowledge on collaborative robotic systems and AI methods applied in automotive manufacturing, as well as in the analysis of their integration to enhance productivity, product quality, and workplace safety. Particular attention is devoted to the development of human-centric manufacturing systems in which humans and intelligent robotic systems operate as equal participants in the production process. The research findings may serve as a foundation for the further development of advanced automation models and the digital transformation of the automotive industry.

METHODOLOGY AND DATA SOURCES

Comparative Approach and Selection of Indicators

For the analysis of the robotization of manufacturing processes in the automotive industry, a comparative approach was used, enabling the comparison of different countries and regions based on key indicators, as this approach allows the identification of trends, patterns, and variations in the automation of vehicle manufacturing processes. The indicators selected in this study include annual vehicle production, the number of patents, the number of installed industrial robots, robot density (the number of robots per 10,000 employees), as well as the integration of core Industry 4.0 technologies and the implementation policy of Industry 4.0. These indicators provide a comprehensive insight into the level of automation and digitalization in the automotive industry.

Data Sources

The data used in this study were collected from internationally recognized databases, statistical reports, and scientific literature to ensure the reliability, comparability, and representativeness of the results. The data sources include:

- *International Organization of Motor Vehicle Manufacturers (OICA)* – the primary source of annual motor vehicle production data by country and region, enabling the analysis of the relationship between the development of the automotive industry and the level of manufacturing process robotization (OICA, 2025).
- *World Intellectual Property Organization (WIPO)* – the source of data on global patent application trends and innovation activities in the fields of robotics, automation, and advanced manufacturing technologies (World Intellectual Property Organization, 2024).
- *Organisation for Economic Co-operation and Development (OECD)* – the source of patent statistics and internationally comparable indicators of technological innovation, used to analyse the development of robotics and collaborative robotics at the global level (Organisation for Economic Co-operation and Development, 2025).
- *European Patent Office (EPO – PATSTAT)* – the source of detailed data on patent applications and technological trends in robotics, automation, and the digital transformation of industry (European Patent Office, 2024).
- *International Federation of Robotics (IFR)* – the principal source of data on global robotization trends, including the number of installed industrial robots, robot density, sectoral distribution of robots, and market trends in industrial and collaborative robotics (International Federation of Robotics (IFR), 2024).
- *National statistical and industrial databases* – used as supplementary sources to verify data on industrial production, employment, and the development of the automotive industry in individual countries.
- *Scientific and professional literature indexed in the Web of Science and Scopus databases* – used to establish the theoretical framework of the research, review existing knowledge, and interpret the results obtained through statistical analysis.

The combination of these data sources enabled a comprehensive analysis of the relationship between the development of the automotive industry, the implementation of industrial and collaborative robots, and the intensity of innovation activities measured through patent applications.

Evaluation Criteria

Annual Vehicle Production

Vehicle production data are collected from OICA and national statistical offices (OICA, 2025). This indicator measures the total vehicle production in a given year, providing insight into the size and capacity of the automotive industry in different countries. In the context of the highest vehicle production, the analysis includes the top five countries—China, the United States of America, and India, which produced the largest number of vehicles in 2025—and the number of vehicles produced is presented in Table 1. Table 1 presents the annual vehicle production in the five selected countries in 2025, as well as the total global vehicle production.

Table 1 Top Five Countries in the World by Motor Vehicle Production in 2025

Rank	Country	Number of Vehicles Produced
1	China	34,530,738
2	United States	10,243,844
3	Japan	8,410,232
4	India	6,490,810
5	Germany	4,148,836
Worldwide Total		96,400,000

Source: OICA – International Organization of Motor Vehicle Manufacturers, Production Statistics 2025.

The data presented in Table 1 are particularly useful for analysing the digital transformation of the automotive industry, as they demonstrate that the countries with the highest investments in robotics, artificial intelligence, and Industry 4.0 technologies (China, the United States, Japan, and Germany) dominate global vehicle production.

Trends in Patent Activity in Robotics and Collaborative Robotics

In the field of robotics, the most important indicators of development and innovation potential are the number of filed and granted patents. It has been established that the number of patent applications in the field of robotic technology has been continuously increasing, owing to intensive research and development of new robotic systems, sensor technologies, control algorithms, as well as solutions based on artificial intelligence. In the field of collaborative robotics, there has been a significant increase in patent applications, as it enables efficient and safe collaboration between humans and robots within the same workspace. By analysing the number of filed patents, it can be observed that collaborative robotics occupies an important position within the total number of innovations in robotic technology. The increase in the number of patent applications reflects the growing industrial application of collaborative robots in manufacturing, logistics, medicine, and other sectors. Table 2 presents the trend in the total number of robotics patents and patents related to collaborative robotics during the period 2015–2025 (World Intellectual Property Organization, 2024; Organisation for Economic Co-operation and Development, 2025; European Patent Office, 2024).

Table 2 Comparative Analysis of Patent Applications in Robotics and Collaborative Robotics Worldwide During the Period 2015–2025

Year	Total Number of Robotics Patent Applications	Collaborative Robotics Patent Applications	Share of Collaborative Robotics
2015	18,500	1,200	6.5%
2016	21,300	1,650	7.7%
2017	24,900	2,300	9.2%
2018	28,700	3,100	10.8%
2019	31,500	4,200	13.3%
2020	34,800	5,600	16.1%
2021	39,200	7,400	18.9%
2022	43,500	9,300	21.4%
2023	47,800	11,500	24.1%
2024	52,600	13,900	26.4%
2025*	56,000	15,500	27.7%

Source: Adapted and estimated based on data from the WIPO Patent Landscape Reports, OECD Patent Database, European Patent Office (EPO) PATSTAT Database, and reports published by the International Federation of Robotics (IFR).

Note: The data represent the number of patent applications filed with leading international patent organizations and do not refer to the number of granted or commercialized patents. The values for 2025 are estimates due to the time lag between patent filing and publication, which averages approximately 18 months.

Based on the analysis of the data presented in Table 2, it can be concluded that over the past ten years there has been a continuous and intensive increase in patent applications in the field of robotic technology. In 2015, the number of patent applications amounted to 18,500, while in 2025 it increased to approximately 56,000 patent applications, representing a growth of about 203%. It can also be concluded that the growth in patent applications related to collaborative robotics has been even more pronounced, increasing from 1,200 patent applications to approximately 15,500, which represents an increase of about 12.9 times over the past ten years. Particularly significant is the continuous increase in the share of collaborative robotics within the total patent activity, rising from 6.5% in 2015 to 27.7% in 2025. This trend confirms that collaborative robots represent one of the fastest-growing areas of contemporary robotics research and development. The key drivers of the growth in the implementation of collaborative robots are presented in Table 3.

Table 3 Key Drivers of the Growth in Collaborative Robotics Patent Applications

FACTOR	IMPACT
Industry 4.0	Significant growth in manufacturing automation
Labour shortages	Accelerated adoption of collaborative robots (cobots)
Workplace safety	Safe operation without protective safety fences
AI integration	Development of intelligent collaborative systems
CNC machine tending	Fastest-growing application area

There is an increasing demand for flexible, safe, and intelligent robotic systems that enable efficient human–robot collaboration within a shared workspace, thereby increasing interest in patent protection in this field. Robotic technology is a core technology of Industry 4.0, particularly collaborative robotics, and the presented results indicate that the future development of robotic technology is being directed toward human-centric and collaborative working concepts, as well as intelligent manufacturing systems. The growing trend in patent applications suggests that collaborative robotics will continue to play an important role in the transformation of industrial processes, logistics, healthcare, and other sectors over the next decade.

Number of Installed Industrial and Collaborative Robots Worldwide

The third indicator evaluates the number of newly installed industrial robots in manufacturing processes and the estimated number of newly installed collaborative robots (cobots). The data presented in Table 4 are based on IFR reports, which provide detailed statistics on robot installations by industry (International Federation of Robotics (IFR), 2024 & 2025).

Table 4 Annual Global Number of Newly Installed Industrial Robots and Collaborative Robots Worldwide (2015–2025)

Year	Total Number of Newly Installed Industrial Robots	Newly Installed Collaborative Robots	Share of Collaborative Robots
2015	254,000	8,500	3.3%
2016	294,000	11,000	3.7%
2017	381,000	16,500	4.3%
2018	423,000	23,000	5.4%
2019	387,000	28,500	7.4%
2020	390,000	34,000	8.7%
2021	526,000	49,500	9.4%
2022	553,000	58,000	10.5%
2023	541,000	60,000	11.1%
2024	542,000	67,000	12.4%
2025*	555,000	75,000	13.5%

Note: The data for 2025 represent estimates based on International Federation of Robotics (IFR) growth trends and the projected development of the collaborative robotics market.

Analysis of the data in Table 4 leads to the conclusion that the total number of implemented industrial robots continuously increased from 2015 to 2025, rising from 254,000 robot units in 2015 to approximately 555,000 robot units, representing a 2.18-fold increase. Likewise, the trend in the implementation of collaborative robots over the same period increased from 8,500 robot units to approximately 75,000 robot units, which is 8.82 times higher. This growing trend in robot implementation indicates that an intensive global transformation of manufacturing processes toward a higher level of automation is taking place. By analysing the last column of Table 4, we conclude that the share of collaborative robots in total installations increased from 3.3% to 13.5% in only ten years. We conclude that the implementation of collaborative robots has a significantly higher growth rate compared to first-generation traditional industrial robots, primarily due to the increasing demand for flexibility and human-centric manufacturing solutions. This growing trend in the adoption of industrial robots, and particularly collaborative robots, confirms the implementation of the core technologies of Industry 4.0 and Industry 5.0, where robotics is one of the fundamental

technologies of these industrial paradigms because it enables more efficient human–robot collaboration in modern manufacturing environments. Compared with other industrial sectors, the automotive industry is the largest user of robotic technologies at the global level. The high degree of automation in manufacturing processes, the need for precision and quality, and the requirements for increased productivity have led to the intensive application of industrial and collaborative robots in the production of vehicles and their components. An analysis of the estimated newly installed industrial and collaborative robots in the world's leading automobile-producing countries is presented in Table 5, with particular emphasis on their application in the automotive industry (International Federation of Robotics (IFR), 2024 & 2025).

Table 5 Trend in the application of industrial and collaborative robots in the five leading countries in the world and in the automotive industry in 2025.

Country	Industrial Robots (Newly Installed Units)	Collaborative Robots	Industrial Robots in the Automotive Industry	Collaborative Robots in the Automotive Industry
China	310,000	37,200	108,500	16,740
United States	36,000	4,320	14,400	2,160
Japan	46,000	5,290	18,400	2,650
Germany	28,000	3,360	12,600	1,680
India	11,500	1,380	3,450	620
Total	431,500	51,550	157,350	23,850

Note: The values represent estimated figures for 2025 based on trends reported by the International Federation of Robotics (IFR). The number of industrial robots deployed in the automotive industry was estimated according to the share of the automotive sector in total annual robot installations (30–45%, depending on the country). The number of collaborative robots in the automotive industry was estimated based on their increasing adoption in assembly operations, material handling, quality inspection, welding, and final assembly processes

The trend in the implementation of industrial and collaborative robots in the world's five leading countries—China, the United States, Japan, Germany, and India—in 2025, as presented in Table 5, shows that the automotive industry continues to be the leading sector compared with other industries. China is the world's leading country in robot implementation, having deployed approximately 108,000 robot units in the automotive industry alone in 2025. The implementation trend in Japan and Germany is also at a remarkably high level, both across all industries and within the automotive industry, while the United States continues to increase the adoption of collaborative robots in final assembly and logistics processes. At the same time, India is recording the fastest relative growth due to the expansion of manufacturing capacities by both domestic and international vehicle manufacturers. This trend in robot adoption in the automotive industry confirms that the automotive sector remains the key driver of the research, development, and implementation of advanced robotic technologies in the global market.

Robot Density per 10,000 Employees in Industry

One of the main indicators showing the level of automation of manufacturing processes in a particular industrial sector is the robot density per 10,000 employees in that industrial sector or in the entire industry of a country. The robot density indicator enables an objective comparison of the level of implementation of robotic technologies among different countries and industrial sectors, regardless of their size or number of employees. By analysing this indicator, we can observe a significant difference between the overall manufacturing industry and the automotive industry, which is considered the most highly automated manufacturing sector in the world. For the analysis of this indicator, the data presented in Table 6 are based on the data on industrial robot density in the manufacturing and automotive industries presented in Table 6 are based on IFR reports, which provide detailed statistics on robot installations in the manufacturing and automotive industries for the world's top five countries: China, Germany, Japan, the United States, and India, as well as the corresponding world average industry (International Federation of Robotics (IFR), 2025; Karabegović, I. 2025; Karabegović, I. et al. 2020).

Table 6 Industrial Robot Density Indicator per 10,000 Employees in the Manufacturing and Automotive Industries in the World's Top Five Countries in 2024

Country	Industrial Robot Density in the Manufacturing Industry	Industrial Robot Density in the Automotive Industry
China	470	1,250
Germany	429	1,500
Japan	419	1,470
United States	295	1,320
India	30	280
Global Average	162	1,020

Note: Robot density represents the number of operational industrial robots per 10,000 employees. The values for the manufacturing industry are based on data published by the International Federation of Robotics (IFR), whereas the values for the automotive industry are estimated on the basis of sector-specific IFR analyses, which indicate that the automotive sector achieves a substantially higher robot density than the average manufacturing industry.

Based on the data presented in Table 6, we conclude that the automotive industry in the five selected leading countries is the most highly automated sector compared to other industrial sectors. Among these five leading countries, the robot density indicator in the manufacturing industry ranges from 30 robots per 10,000 employees in India to 470 robots in China. However, in the automotive industry, the robot density indicator in almost all of the observed countries exceeds 1,000 robots per 10,000 employees. The highest robot density indicator is recorded in Germany, amounting to approximately 1,500 robots, which allows us to conclude that Germany maintains a very high level of automation in vehicle and automotive component manufacturing. China has been investing intensively in robotization and the modernization of its manufacturing capacities year after year, which has enabled it to become the world's leading economy. Despite its significantly lower level of automation, India demonstrates continuous growth as a result of the expansion of its domestic automotive industry. These indicators confirm that the automotive sector remains the key driver of research, development, and implementation of advanced robotic technologies at the global level.

Integration of Smart Technologies and Digitalization Policies

The indicator of smart technology integration and digitalization policies assesses the extent to which the core Industry 4.0 technologies, such as the Internet of Things (IoT), Industrial Internet of Things (IIoT), Autonomous Robots (Industrial Robotics), Collaborative Robotics (Cobots), smart sensors, Artificial Intelligence (AI) and Machine Learning (ML), Big Data, simulation and digital twins, cloud computing, horizontal and vertical system integration, Additive Manufacturing (3D Printing), Augmented Reality (AR) and Virtual Reality (VR), Autonomous Mobile Robots (AMR), Automated Guided Vehicles (AGV), cybersecurity, and advanced systems, are integrated into industrial manufacturing systems. Their integration into manufacturing systems is one of the key indicators of the digital transformation of advanced industry. By implementing these technologies, manufacturing processes are optimized, operating costs are reduced, productivity is increased, predictive maintenance is introduced, product quality is improved, and greater flexibility and adaptability of manufacturing systems to market requirements are achieved. In addition to the technological component, the level of industrial digitalization also depends on national policies, investments in research and development (R&D), the development of digital infrastructure, the education of a skilled workforce, and cooperation between industry, academia, and government institutions. Therefore, the assessment of smart technology integration is based on a combination of quantitative and qualitative indicators that enable a comprehensive evaluation of the digital maturity of industrial systems. Table 7 presents the key indicators for assessing the integration of smart technologies in the world's five leading economies during the 2024–2025 period (PwC, 2025; McKinsey & Company, 2025; World Economic Forum, 2025; Statista, 2025; Organisation for Economic Co-operation and Development, 2025; Deloitte, 2025; United Nations Industrial Development Organization; 2025).

Table 7 Indicators for Assessing the Level of Integration of Core Industry 4.0 Technologies into the Manufacturing Processes of the World's Top Five Countries: China, the United States, Japan, Germany, and India (2024/2025)

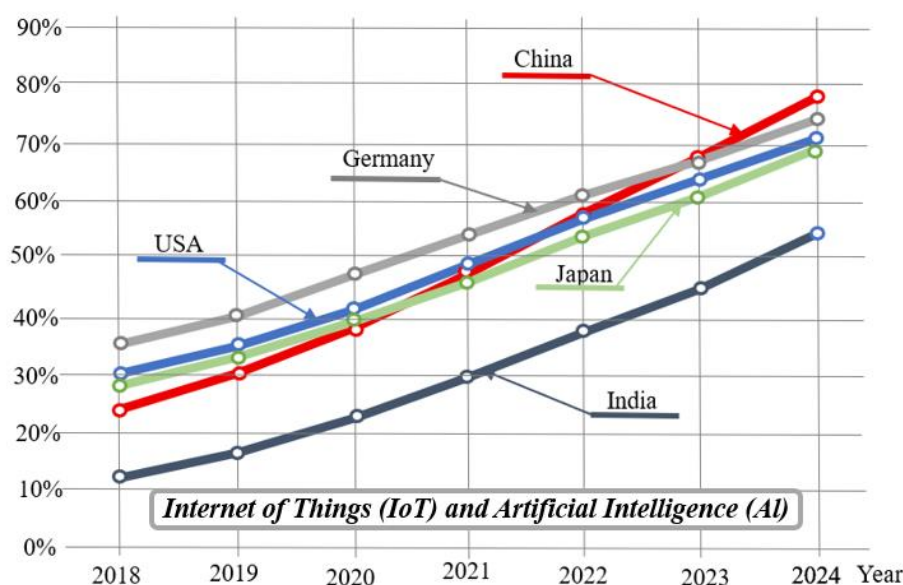
INDICATOR	China	United States	Japan	Germany	India	Source / Remarks
Share of smart factories in total manufacturing (%)	42	38	36	40	17	PwC; OECD
Adoption of IoT systems in manufacturing lines (%)	71	68	65	69	29	McKinsey; IFR
Adoption of AI and predictive analytics in manufacturing (%)	61	54	57	59	21	WEF; Statista
Adoption of Digital Twin technology in manufacturing (%)	39	34	36	41	12	Deloitte; WEF
Investment in digital infrastructure (USD billion)	210	125	58	47	27	OECD; IMF
Number of smart industrial zones / clusters	62	48	31	36	22	UNIDO
R&D expenditure (% of GDP)	2.6	3.5	3.4	3.1	0.9	OECD
Number of industrial IoT devices (million)	1,460	1,150	620	510	310	Statista
Industrial digital maturity level (scale 1–5)	4.4	4.6	4.5	4.7	3.1	Deloitte Industry 4.0 Index

Note: The data represent the latest available values for the 2024–2025 period and were collected from internationally recognized reports and databases. For certain indicators, estimated values based on current industrial digital transformation trends were used to facilitate international comparisons among the world's leading industrial economies.

Source: Authors' compilation based on data from OECD (2025), World Economic Forum (2025), International Federation of Robotics (2025), UNIDO (2025), Statista (2025), Deloitte (2025), PwC (2025), McKinsey & Company (2025), and the IMF Digital Economy Report (2025).

Based on the data on the magnitude of the indicators assessing the degree of integration of the core Industry 4.0 technologies into the manufacturing processes of the world's top five countries, we conclude that China is the country with the leading position in the implementation of IoT systems, artificial intelligence, the number of smart industrial zones, and investments in digital infrastructure, confirming its strategy of accelerated development of smart

manufacturing processes. China achieves a high level of digitalization in manufacturing processes because it maintains a leading position in research and development of Industry 4.0 technologies. Germany and Japan are characterized by a high degree of implementation of digital twins, automation, and advanced manufacturing technologies, which is the result of their long-standing industrial tradition and strong technological base. India records lower values for most of the analysed indicators but demonstrates significant growth potential owing to accelerated investments in digital infrastructure, industrial automation, and digital manufacturing transformation programs. All five countries—China, the United States, Japan, Germany, and India—are developing artificial intelligence technologies, the Industrial Internet of Things, and digital twins, which are becoming key elements of the smart factories of the future. The successful integration of smart technologies represents one of the fundamental prerequisites for increasing industrial competitiveness and the effective implementation of the Industry 4.0 concept. At the same time, the growing application of these technologies creates the technological foundation for the further development of collaborative robotics, autonomous manufacturing systems, and digitally connected value chains, which will play a key role in the future transformation of the automotive and other high-technology industries. To obtain a more comprehensive picture of the dynamics of industrial digital transformation, Figure 1 presents the estimated trend of IoT and AI technology integration into the manufacturing processes of the world's leading economies during the period 2018–2025 (PwC, 2025; McKinsey & Company, 2025; World Economic Forum, 2025; Statista, 2025; Organisation for Economic Co-operation and Development, 2025; Deloitte, 2025; United Nations Industrial Development Organization; 2025).



Note: This represents an estimated trend of IoT and AI technology integration.

Figure 1 Trend of IoT and AI technology integration in industrial manufacturing in the world's top five countries: China, the United States, Japan, Germany, and India during the period 2018–2025 (prepared by the authors based on (PwC, 2025; McKinsey & Company, 2025; World Economic Forum, 2025; Statista, 2025; Organisation for Economic Co-operation and Development, 2025; Deloitte, 2025; United Nations Industrial Development Organization; 2025)).

Based on Figure 1, we conclude that the five top countries analysed—China, the United States, Japan, Germany, and India—have recorded continuous growth in the implementation of IoT and AI technologies in manufacturing processes, with China standing out as the country achieving the most pronounced growth trend. We conclude that the United States, Germany, and Japan maintain a high level of digital integration owing to strong investments in innovation, research and development, and advanced manufacturing technologies. These trends confirm that digitalization is becoming one of the key factors of competitiveness in modern industry. Although all the observed countries pursue the same goal—increasing the efficiency, flexibility, and resilience of industrial manufacturing—their approaches to digital transformation differ significantly. The United States relies on market-driven innovation, a strong private sector, and advanced technology companies that lead the development of artificial intelligence, cloud infrastructure, and industrial digital platforms. China applies a coordinated government approach through national digitalization strategies and industrial modernization programs, together with the intensive implementation of 5G networks, the Internet of Things, and artificial intelligence-based technologies. Germany and Japan represent examples of highly developed industrial economies that successfully combine traditional manufacturing excellence with modern digital technologies. Germany bases its digital transformation on the Industry 4.0 concept, while Japan is intensively developing the Society 5.0 concept, which emphasizes the integration of digital technologies into industry and society. Both countries achieve a high level of digital maturity, particularly in the areas of automation, digital twins, robotics, and smart manufacturing systems. India is in a phase of accelerated digital transformation and records significant progress owing to national initiatives aimed at developing digital infrastructure, smart manufacturing, and the digitalization of small and medium-sized enterprises. Although it lags behind the leading

industrial economies according to most of the analysed indicators, its high growth rate and strong development of the IT sector indicate considerable potential for further improving digital competitiveness. The cumulative results presented in Table 7 and Figure 1 indicate the transition of industry from the phase of basic digitalization to the phase of intelligent industrial optimization, in which artificial intelligence, the Internet of Things, digital twins, and advanced data analytics become integral parts of manufacturing processes and business decision-making. These technologies no longer represent only support for manufacturing but are key drivers of productivity, innovation, and sustainable competitive advantage. Based on the conducted analyses, it can be concluded that digital policies, investments in research and development, the development of digital infrastructure, and the application of smart technologies play a decisive role in strengthening industrial competitiveness and the technological resilience of national economies. At the same time, the results confirm that China and the United States are currently leading the global digital transformation of industry, while Germany and Japan maintain a leading position in advanced industrial automation. These trends create a solid foundation for the further development of collaborative robotics, autonomous manufacturing systems, and artificial intelligence-based industrial solutions, which will mark the next phase of the evolution of global manufacturing.

APPLICATION OF COLLABORATIVE ROBOTICS AND ARTIFICIAL INTELLIGENCE IN ASSEMBLY AND QUALITY CONTROL PROCESSES IN THE AUTOMOTIVE INDUSTRY

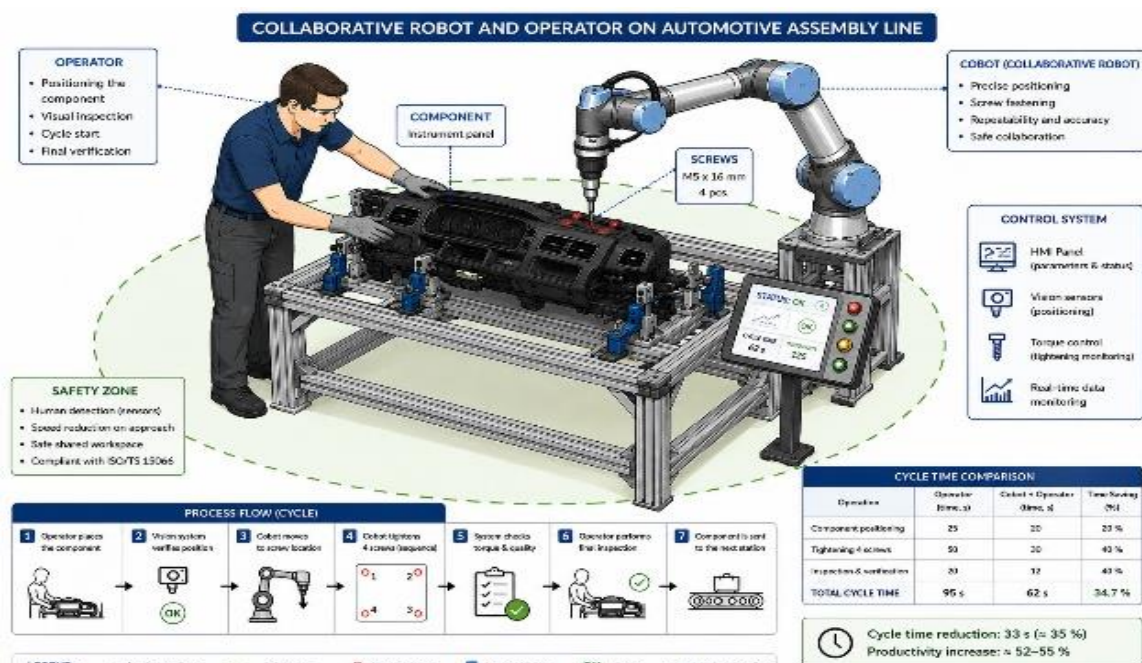
The modern automotive industry represents one of the most technologically advanced application areas of collaborative robotics and artificial intelligence. Intense global competition, increasing product quality requirements, shorter vehicle life cycles, and the growing demand for flexible manufacturing have encouraged automotive manufacturers to develop intelligent manufacturing systems based on human–robot collaboration. Within such systems, collaborative robots perform repetitive, physically demanding, and highly precise operations, while human operators carry out tasks requiring experience, judgment, and decision-making capabilities (Villani, V. et al. 2018). One of the most significant application areas of collaborative robots is the assembly of automotive components. Unlike conventional industrial robots that operate within isolated work cells, collaborative robots enable direct interaction with operators in a shared workspace. This approach is particularly suitable for the assembly of electronic components, vehicle interior modules, air-conditioning systems, and electric vehicle components, where a combination of human flexibility and robotic precision is required. Research has shown that the implementation of collaborative robots can increase assembly process productivity by more than 20%, while simultaneously reducing workers' physical workload and improving ergonomic working conditions (Leng, J. et al. 2022). The development of artificial intelligence has further enhanced the capabilities of collaborative robotic systems. Through the integration of machine learning algorithms and deep neural networks, robots become capable of object recognition, motion planning, and adaptation to changes in the manufacturing environment. Such systems can analyse sensor data in real time and make decisions without requiring continuous operator intervention. Deep learning algorithms play a particularly important role by enabling adaptive control of robotic systems operating in complex manufacturing processes (Piccarozzi, M. et al. 2024). In the automotive industry, quality control represents one of the most critical stages of the manufacturing process. Traditional inspection methods often depend on human factors, which may result in subjective assessments and variations in product quality. The application of artificial intelligence and computer vision enables the automation of quality inspection processes while significantly improving defect detection accuracy. High-resolution cameras combined with deep learning algorithms enable the identification of surface defects, assembly irregularities, missing components, and dimensional deviations with a level of accuracy and speed substantially exceeding that of conventional inspection methods (Zafar, M. H. et al. 2024). Convolutional Neural Networks (CNNs) play a particularly important role by enabling the automatic detection and classification of product defects. These methods achieve considerably higher accuracy than conventional machine vision systems and provide continuous quality monitoring throughout the entire manufacturing process. Research has demonstrated that deep learning-based systems can achieve defect detection accuracies exceeding 95%, significantly reducing the number of defective products reaching end users (Ghahramani, M. et al. 2020). In addition to quality control, artificial intelligence plays an important role in predictive maintenance of manufacturing equipment. Modern manufacturing systems generate vast amounts of operational data related to machines, robots, tools, and production lines. By analysing these data, it is possible to identify patterns that precede equipment failures and schedule maintenance interventions in a timely manner. This approach reduces unplanned downtime, increases equipment availability, and lowers maintenance costs. According to recent studies, AI-based predictive maintenance systems can reduce maintenance costs by 20–30% while increasing equipment availability by more than 15% (Carvalho, T. P. et al. 2019). Digital Twins are also becoming increasingly important, representing virtual models of manufacturing systems synchronized with real production processes. By integrating collaborative robots, sensors, and AI algorithms, different production scenarios can be simulated before implementation in the actual manufacturing environment. Digital Twins enable the optimization of robot trajectories, the identification of production bottlenecks, and the improvement of quality control processes. Such systems are becoming an essential tool for the development of smart factories and next-generation industrial systems (Feng, X., & Wan, J. 2024). The application of collaborative robotics is particularly prominent in electric vehicle manufacturing. The complex assembly processes of battery systems, electronic components, and control systems require a high level of precision and flexibility. Collaborative robots enable safe cooperation with operators during battery module assembly and the handling of sensitive components. At the same

time, AI systems optimize manufacturing parameters and continuously monitor process quality, thereby improving the reliability and safety of the final product (Valette, E. et al. 20203). Despite their numerous advantages, the implementation of collaborative robotics and artificial intelligence faces several challenges. Among the most important are ensuring the safety of human–robot collaboration, data security, interoperability among heterogeneous systems, and the need for continuous workforce education and training. In addition to technical aspects, successful implementation also requires organizational changes involving the development of new employee competencies and the adaptation of business processes to the digital manufacturing environment (Dhanda, M. et al. 2025). Based on the available research, it can be concluded that the integration of collaborative robotics and artificial intelligence represents one of the principal directions for the future development of the automotive industry. The combination of human capabilities and intelligent robotic systems enables improvements in productivity, product quality, and manufacturing flexibility, while simultaneously enhancing workplace safety and ergonomics. It is expected that further advances in artificial intelligence, advanced sensing technologies, and Digital Twin systems will further accelerate the transformation of the automotive industry toward the concepts of Industry 5.0 and fully interconnected smart factories.

IMPLEMENTATION COLLABORATIVE ROBOTS IN THE AUTOMOTIVE INDUSTRY AND CASE STUDIES

Implementation of Collaborative Robots on Assembly Lines

In addition to the two primary applications of collaborative robots in the processes of automobile body welding and painting, the assembly of automotive components also represents one of the most significant application areas. In recent years, advanced manufacturing systems in the automotive industry have required a high degree of flexibility, reduced production time, as well as the ability to adapt to different vehicle models. Unlike first-generation industrial robots that operate in enclosed spaces, collaborative robots enable direct collaboration with workers in a shared workspace, and this approach makes it possible to combine human decision-making capabilities with robotic precision, resulting in increased productivity and reduced errors in assembly processes. A very common and significant application of collaborative robots in the assembly process includes: the assembly of electronic components, vehicle interior trim, doors, instrument panels, and battery modules of electric vehicles. In these assembly processes, collaborative robots perform repetitive tasks that require high precision, while the operator carries out final inspections and more complex manipulations, as shown in Figure 2 (Villani, V. et al. 2018; Bdiwi, M. et al. 2018).



Source: Authors' own illustration based on the literature synthesis; visualization assisted by generative AI (2026).

Figure 2 Assembly process of an automotive instrument panel in an intelligent manufacturing cell, illustrating collaboration between a worker and a collaborative robot during assembly (prepared by the authors).

Figure 2 illustrates a modern assembly cell in the automotive industry based on the concept of collaboration between a human and a collaborative robot. The worker performs the positioning and inspection of the vehicle instrument panel component, while the collaborative robot simultaneously carries out the precise fastening operation using an

electric screwdriver. The assembly cell is equipped with a component positioning system, a digital control panel, and a display for monitoring production parameters in real time. The presented configuration illustrates the Industry 5.0 concept, in which human flexibility, experience, and decision-making capabilities are combined with the precision, repeatability, and reliability of a collaborative robot. This form of collaboration enables increased productivity, reduced assembly time, and improved quality of assembly operations (Kakade, S. et al. 2023).

Table 8 Comparison of Assembly Time Between a Worker and a Collaborative Robot

Parameter	Worker	Collaborative Robot (Cobot)
Assembly time per component (s)	95	62
Components assembled per hour	38	58
Average error rate (%)	2.8	0.7
Rework rate (%)	3.2	0.9
Productivity (%)	100	153

The data presented in Table 8 show that the collaborative robot achieves a reduction in assembly time of approximately 35% in this example, while productivity increases by more than 50%. At the same time, the number of errors and the need for additional product corrections are significantly reduced.

Table 9 Estimated Daily Production of the Assembly Cell

Parameter	Worker	Collaborative Robot (Cobot)
Components per shift	304	464
Components per day (3 shifts)	912	1,392
Annual production	228,000	348,000

The values presented in Tables 8 and 9 indicate the significant potential of collaborative robotics for optimizing assembly processes in the automotive industry. The observed reduction in cycle time of approximately 35% and the increase in productivity of more than 50% confirm that the integration of cobots contributes to more efficient utilization of production resources and increased production capacity. At the same time, the reduction in the error rate from 2.8% to 0.7% and the need for rework from 3.2% to 0.9% indicate a significant improvement in the quality of assembly operations. From an annual perspective, the increase in production capacity by approximately 120,000 components confirms the economic justification for implementing collaborative robotic systems in modern manufacturing environments based on the principles of Industry 5.0.

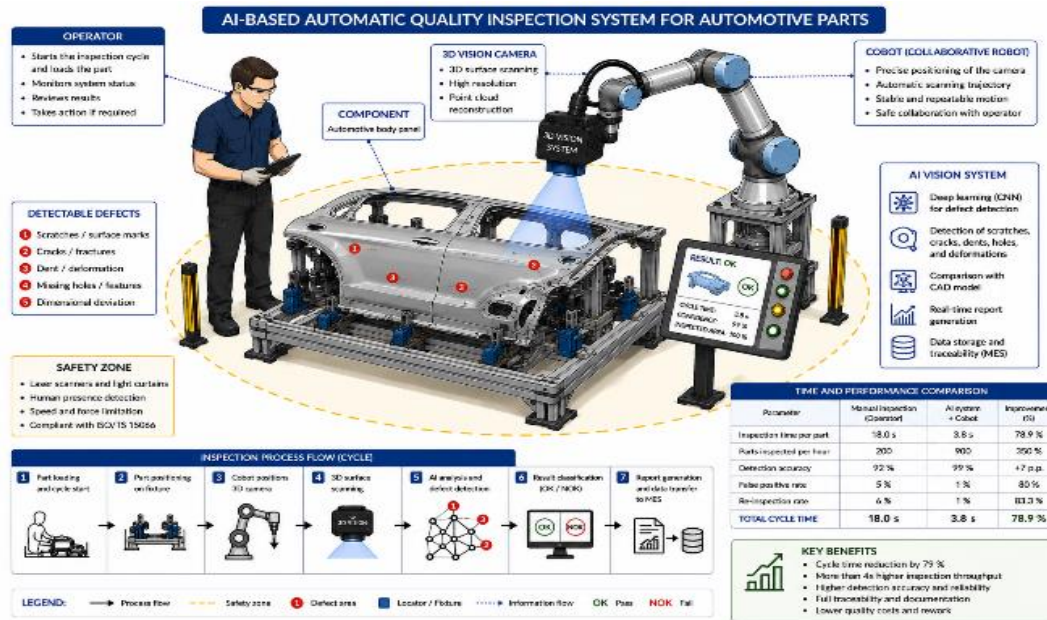
Implementation of Artificial Intelligence Systems in the Quality Control of Automotive Parts

In the manufacturing process of the automotive industry, quality control represents a critical stage of the production process. Traditional visual quality control has so far been based on human work and is often limited by subjective assessments, fatigue, and variations in inspection quality. The development of advanced Industry 4.0 technologies such as artificial intelligence, computer vision, and deep neural networks has enabled the automation of inspection processes in manufacturing, resulting in a significant increase in the reliability of defect detection. Advanced artificial intelligence systems use high-resolution cameras, laser sensors, and deep learning algorithms to identify surface defects, cracks, irregular gaps, missing components, and dimensional deviations, as shown in Figure 3 (Zhou, C. et al. 2022; Sun, Y. et al. 2023).

Figure 3 illustrates an intelligent automated quality control system for automotive components based on the integration of a collaborative robot, a 3D machine vision system, and artificial intelligence (AI) algorithms. The collaborative robot manipulates a 3D camera that performs detailed surface scanning of an automotive body component to identify manufacturing deviations and potential defects. The AI system employs deep learning and computer vision techniques to automatically detect surface scratches, cracks, dents, deformations, missing holes, and dimensional deviations from the product's CAD model.

The illustrated workstation incorporates a safety zone equipped with laser scanners and safety barriers in accordance with the ISO/TS 15066 standard, thereby enabling safe human–robot collaboration within a shared workspace. The inspection workflow includes component positioning, automated 3D scanning, AI-based analysis of the acquired data, classification of inspection results as acceptable (OK) or defective (NOK), followed by the automatic generation of inspection reports and transmission of data to the manufacturing information system.

The comparative analysis presented in the figure demonstrates that the implementation of the AI system and the collaborative robot reduces inspection time by approximately 79%, increases the number of inspected components per hour by more than fourfold, and improves defect detection accuracy from 92% to 99%. Such systems represent an essential element of the digital transformation of the automotive industry and the development of smart factories based on the principles of Industry 4.0 and Industry 5.0 (Yan, J. et al. 2024).



Source: Authors' own illustration based on the literature synthesis; visualization assisted by generative AI (2026).

Figure 3 Implementation of an Advanced Quality Control System for Automotive Parts Based on a Collaborative Robot and Artificial Intelligence (prepared by the authors).

Table 10 Comparison of the Performance of Quality Control Systems

Parameter	Worker	AI + Collaborative Robot (Cobot)
Inspection time (s)	18	4
Components inspected per hour	200	900
Detection accuracy (%)	92	99
False-positive rate (%)	5	1
Repeated inspections (%)	6	1

The data presented in Table 10 show that the AI system enables a reduction in inspection time of approximately 78%, while increasing the detection accuracy from 92% to 99%.

Table 11 Detection Efficiency for Different Types of Defects

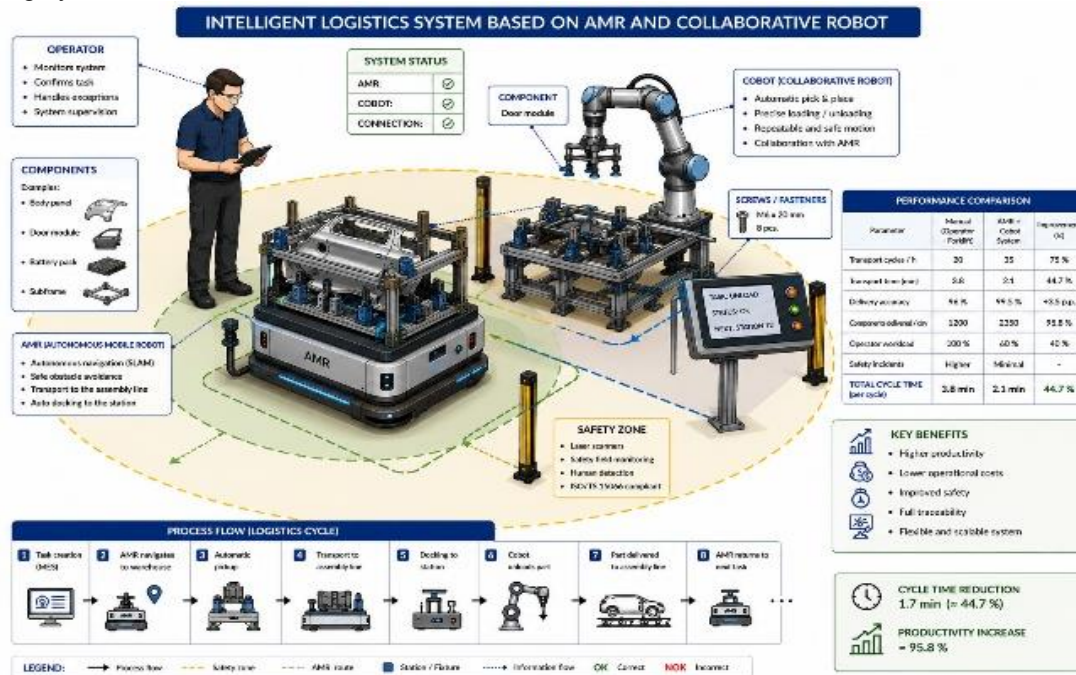
Defect Type	Worker (%)	AI System (%)
Scratches	89	98
Cracks	87	99
Missing components	94	100
Dimensional deviations	85	98

The results presented in Tables 10 and 11 clearly demonstrate the effectiveness of integrating collaborative robots, 3D machine vision systems, and artificial intelligence algorithms into automotive quality control processes. The reduction in inspection time by approximately 79% and the more than fourfold increase in inspection throughput represent a significant contribution to improving the productivity of manufacturing systems. Furthermore, the achieved 99% detection accuracy confirms the high reliability of AI-based systems in identifying various types of manufacturing defects, including scratches, cracks, missing components, and dimensional deviations. The reduction in the number of false-positive detections and the need for repeat inspections further contributes to lowering quality-related costs, improving manufacturing traceability, and enhancing the overall efficiency of quality management systems in the automotive industry.

Intelligent Material Handling and Logistics

It is well known that material handling in the automotive manufacturing process was carried out using forklifts and manual transport systems, which represents an important part of the overall process where time is consumed and production delays occur. The development of advanced technologies has led to the development of autonomous mobile robots (AMRs) and collaborative robots, enabling the creation of intelligent logistics systems that autonomously deliver components from the warehouse to the production process and transport finished products back to the warehouse (Boysen, N. et al. 2021). By integrating AI algorithms, it is possible to optimize movement trajectories, reduce delays, and increase the efficiency of material transportation (Fragapane, G. et al. 2022).

The figure illustrates an intelligent logistics system in the automotive industry based on the integration of an autonomous mobile robot (AMR), a collaborative robot (cobot), and a digital production management system. The autonomous mobile robot (AMR) autonomously transports automotive components between the warehouse, intermediate zones, and assembly stations using Simultaneous Localization and Mapping (SLAM) technology, obstacle avoidance sensors, and route optimization algorithms. The collaborative robot performs the automatic loading and unloading of components from the AMR platform and precisely positions the parts at the assembly stations. The system enables safe human–robot collaboration within a shared workspace through the implementation of laser scanners, operator presence detection systems, and safety functions in accordance with the requirements of the ISO/TS 15066 standard. The presented process flow includes the creation of a logistics task in the MES system, autonomous route planning, component pickup, transportation to the assembly line, automatic unloading using the collaborative robot, and the return of the AMR system to the next logistics task. The integration of AMR and cobot technologies enables continuous material flow, reduced transportation time, and increased flexibility of manufacturing systems.



Source: Authors' own illustration based on the literature synthesis; visualization assisted by generative AI (2026).

Figure 4 Intelligent Logistics System for Material Handling and Transportation of Automotive Components in the Automotive Industry Based on an Autonomous Mobile Robot (AMR) and a Collaborative Robot

The comparative analysis presented in the Figure 4 shows that the implementation of the intelligent logistics system increases the number of transport cycles from 20 to 35 cycles per hour (as shown in Table 12), reduces transportation time by approximately 45%, and increases the daily component delivery capacity by nearly 96% compared to traditional transportation based on operators and forklifts. At the same time, operator workload is significantly reduced, workplace safety is improved, and the traceability of logistics processes is enhanced. Such systems represent an important element of Industry 4.0 and Industry 5.0 smart factories, where autonomous logistics, artificial intelligence, and collaborative robotics enable the development of flexible, digitally connected, and highly productive manufacturing environments (Matt, O. et al. 2026).

Table 12 Comparison of Logistics Performance

Parameter	Worker + Forklift	AMR + Collaborative Robot (Cobot)
Transportation cycles per hour	20	35
Transportation time (min)	3.8	2.1
Delivery error rate (%)	3.5	0.5
Safety incidents	Higher risk	Minimal

Table 13 Material Handling Performance

Performance Indicator	Worker	Intelligent System
Components transported per day	1,200	2,350
Productivity (%)	100	196
Operating costs (%)	100	72
System availability (%)	90	98

The data presented in Tables 12 and 13 clearly show that the integration of AMR systems and collaborative robots represents a significant step toward the development of autonomous intralogistics within smart factories. The

increase in the number of transported components from 1,200 to 2,350 per day, together with the increase in productivity from 100% to 196%, confirms the high potential of these technologies for optimizing logistics processes. At the same time, the reduction in operating costs from 100% to 72% and the increase in system availability from 90% to 98% indicate significant economic and organizational benefits of implementing intelligent logistics solutions. Particularly significant is the reduction in delivery errors and safety risks, confirming that AMRs and collaborative robots enable more reliable, flexible, and safer material handling in modern automotive manufacturing systems based on the principles of Industry 4.0 and Industry 5.0.

Case Studies of Leading Global Automotive Companies

Over the past decade, the world's leading automotive manufacturers have invested extensively in the development and implementation of collaborative robotics, artificial intelligence (AI), and the digital technologies of Industry 4.0 and Industry 5.0. These investments are driven by the need to increase productivity, improve product quality, reduce manufacturing costs, and enhance the flexibility of production systems. Collaborative robots enable safe cooperation with human operators within a shared workspace, while artificial intelligence systems facilitate the analysis of large volumes of data, process optimization, and real-time decision-making. As a result, leading automotive manufacturers are developing smart factories based on the integration of humans, robots, and intelligent information systems (Peruzzini, M., & Pellicciari, M. 2017).

Table 14 Application of Collaborative Robotics and Artificial Intelligence in Leading Automotive Companies

Company	Application of Collaborative Robots	Application of Artificial Intelligence
Toyota	Door and electronic component assembly	Predictive maintenance
BMW	Final vehicle assembly	Visual inspection
Mercedes-Benz	Human–robot collaborative assembly stations	Digital Twins
Volkswagen	Electric vehicle battery assembly	AI-based production optimization
Tesla	Battery module assembly	AI-based quality control

Toyota is regarded as one of the pioneers of manufacturing automation and robotization in the automotive industry. In its production facilities, the company employs collaborative robots for the assembly of vehicle doors, electronic components, and interior finishing elements. At the same time, artificial intelligence systems analyse production-line data to predict equipment failures and optimize maintenance activities. This approach reduces unplanned downtime, while increasing the availability of manufacturing systems. BMW utilizes collaborative robots during the final stages of vehicle assembly, particularly in the installation of interior components, control modules, and instrument panel assemblies. Through the integration of machine vision and artificial intelligence, BMW has developed advanced automated visual inspection systems capable of detecting defects and manufacturing deviations in real time. Consequently, the quality of the final product is improved, while costs associated with customer claims and product rework are reduced. Mercedes-Benz develops manufacturing systems based on the Industry 5.0 concept, in which humans and robots operate as equal partners throughout the production process. Collaborative robots are employed for the assembly of complex components, while Digital Twin technology enables the simulation and optimization of manufacturing processes before their implementation in the real production environment. This approach contributes to greater manufacturing flexibility and faster adaptation to new vehicle models (Guo, Y. et al. 2024).

Volkswagen extensively utilizes collaborative robots in the production of electric vehicles and battery assembly systems. The application of artificial intelligence enables production planning optimization, material flow management, and performance analysis of manufacturing lines. Particular emphasis is placed on the development of smart factories that integrate all manufacturing resources into a unified digital ecosystem. Tesla represents one of the most advanced examples of artificial intelligence implementation in the automotive industry. The company employs AI systems for manufacturing process optimization, automated quality control, and battery module production management. Through the integration of machine vision, deep learning, and robotic systems, Tesla achieves a high level of automation, precision, and productivity in electric vehicle manufacturing (Mourtzis, D. et al. 2023).

The analysis of these industrial examples confirms that leading automotive manufacturers are increasingly transitioning from conventional automated systems toward intelligent manufacturing systems based on the collaboration of humans, collaborative robots, and artificial intelligence. This approach enables the development of more flexible, productive, and sustainable manufacturing environments that form the foundation of future smart factories.

Analysis of System Productivity and Performance

Based on the previously analysed case studies, an overall assessment of the impact of collaborative robotics and artificial intelligence on manufacturing system performance in the automotive industry can be conducted. The integration of collaborative robots into assembly operations, AI-based systems into quality control, and autonomous

logistics systems into material handling results in significant improvements in productivity, product quality, and workplace safety. It is particularly important that these improvements affect not only individual operations but also the overall manufacturing system (Ribeiro, J. et al. 2021). The results presented in Table 15 demonstrate that the combination of collaborative robots and artificial intelligence increases productivity by approximately 60%, while reducing the overall production cycle time by approximately 35%. At the same time, the number of quality defects is reduced by more than 70%, directly contributing to improved product reliability and lower costs associated with warranty claims and product rework.

Table 15 Overall Comparison of Manufacturing System Performance

Performance Indicator	Worker	Collaborative Robot + AI
Productivity	100%	160%
Cycle time	100%	65%
Quality defects	100%	25%
Quality-related costs	100%	60%
Workplace safety	Moderate	High
System availability	90%	98%

The reduction of quality-related costs to approximately 60% of their initial value confirms the economic viability of investing in intelligent manufacturing systems. A particularly significant benefit is the improvement of workplace safety, as collaborative robots perform physically demanding, repetitive, and potentially hazardous tasks, thereby reducing operator workload and minimizing the risk of occupational injuries. Furthermore, the increase in system availability from 90% to 98% indicates greater manufacturing reliability achieved through the implementation of predictive maintenance, continuous process monitoring, and intelligent management of manufacturing resources.

From the perspective of Industry 5.0, the obtained results confirm that the greatest benefits arise from the synergy between human capabilities and intelligent technological systems. While humans retain the primary role in decision-making, solving complex problems, and supervising manufacturing processes, collaborative robots and AI systems ensure high precision, speed, and repeatability of operations. This collaborative model enables the development of human-centric manufacturing systems that simultaneously improve productivity, product quality, and manufacturing sustainability. Based on the overall analysis, it can be concluded that collaborative robotics and artificial intelligence represent the key technological pillars of future smart factories in the automotive industry. Their integration enables the development of flexible, digitally connected, and autonomous manufacturing systems capable of meeting the demands of modern markets, mass product customization, and sustainable industrial development (Renard, D. et al. 2024; Kusiak, A. 2018).

CHALLENGES AND FUTURE TRENDS

Despite the significant advantages offered by collaborative robotics and artificial intelligence, their widespread implementation in the automotive industry faces numerous technical, organizational, economic, and safety-related challenges. Although modern collaborative robots enable direct cooperation with human operators, ensuring human–robot safety remains one of the key factors for successful implementation. The development of reliable systems for operator presence detection, motion tracking, and automatic robot speed adaptation continues to represent an important research challenge. Particular attention is being devoted to the advancement of safety standards such as ISO 10218 and ISO/TS 15066, which define the requirements for safe collaboration between humans and collaborative robotic systems. Another major challenge concerns the integration of diverse digital technologies within a unified manufacturing environment. Modern factories employ a wide variety of heterogeneous systems, including robots, sensors, AI algorithms, Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) platforms, Digital Twins, and industrial Internet of Things (IIoT) networks. Interoperability among these systems represents a fundamental prerequisite for the development of fully connected smart factories. At the same time, the growing volume of data generated during manufacturing processes requires the development of efficient methods for data processing, analysis, and protection against cyber threats. Data security, manufacturing system resilience, and effective management of digital resources are becoming increasingly important elements in the successful transformation of modern industry toward the Industry 5.0 paradigm (Ivanov, D. 2023). The implementation of collaborative robots and artificial intelligence also requires substantial financial investment. The costs associated with equipment acquisition, system integration, workforce training, and the adaptation of manufacturing processes may represent limiting factors, particularly for small and medium-sized enterprises (SMEs). Nevertheless, the long-term benefits achieved through increased productivity, reduced errors, improved product quality, and lower operating costs generally justify the initial investment. In addition to technical and economic challenges, the development of new workforce competencies represents another critical factor. The industry of the future requires professionals capable of working in environments where humans, robots, and artificial intelligence operate as an integrated system. Consequently, educational institutions and industry must develop new training programs encompassing robotics, artificial intelligence, data analytics, Digital Twin technologies, and the management of smart manufacturing systems. Future trends in the automotive industry are directed toward increasing levels of manufacturing autonomy. More extensive adoption of generative artificial intelligence, Digital Twins, Autonomous Mobile Robots (AMRs), advanced

machine vision systems, and intelligent collaborative robots capable of autonomous real-time decision-making is expected. Furthermore, the development of 5G and future 6G communication networks will further enhance manufacturing system connectivity and enable more efficient data exchange among machines, robots, and digital information platforms. A particularly significant trend is the evolution of Industry 5.0, which places humans at the centre of the manufacturing process. Unlike approaches based solely on automation, Industry 5.0 promotes collaboration between humans and intelligent technologies with the objective of creating more flexible, sustainable, and resilient manufacturing systems. Within such an environment, collaborative robots will not replace human workers but will function as intelligent partners that complement human capabilities and enable higher levels of productivity, product quality, and manufacturing innovation (Ivanov, D. 2023).

At the same time, future developments in collaborative robotics are expected to focus on improving the quality of human–robot interaction, where safety, ergonomics, intuitive operation, and technology acceptance by operators will play essential roles. Advanced AI-based systems will enable robots to better understand human intentions, exhibit adaptive behaviour, and collaborate more effectively in dynamic manufacturing environments. Such an approach represents one of the fundamental prerequisites for the development of next-generation human-centric manufacturing systems, which are expected to characterize Industry 5.0 and the smart factories of the future (Coronado, E. et al. 2022).

CONCLUSIONS

The modern automotive industry is undergoing an intensive transformation driven by the technologies of Industry 4.0 and Industry 5.0, in which collaborative robotics and artificial intelligence represent the principal drivers of smart manufacturing systems. The analysis of global trends has demonstrated a continuous increase in the deployment of industrial and collaborative robots, growing patent activity in the field of robotics, and the extensive integration of digital technologies such as artificial intelligence, the Internet of Things, Digital Twins, and advanced automation systems. The research findings confirm that collaborative robots provide significant advantages in automotive component assembly processes. The analysis presented in the industrial application section demonstrated a cycle time reduction of approximately 35%, a productivity increase exceeding 50%, and a substantial reduction in both assembly errors and rework requirements. At the same time, the integration of artificial intelligence into quality control systems increases defect detection accuracy from 92% to 99%, while significantly expanding inspection capacity and reducing quality-related costs. Particularly important results have been achieved in the field of intelligent material handling and logistics, where the integration of Autonomous Mobile Robots (AMRs) and collaborative robotic systems enables productivity improvements approaching 100%, reduces transportation time, and increases the availability of logistics systems. These findings confirm that the combination of collaborative robotics and artificial intelligence contributes to the development of flexible, efficient, and highly automated manufacturing environments. The analysis of leading global automotive manufacturers, including Toyota, BMW, Mercedes-Benz, Volkswagen, and Tesla, demonstrated that the future of manufacturing is based on the integration of humans, robots, and intelligent information systems. These companies already employ collaborative robots, machine vision systems, Digital Twins, and artificial intelligence algorithms to optimize manufacturing processes, improve quality control, and manage logistics operations.

Based on the conducted analyses, it can be concluded that collaborative robotics and artificial intelligence constitute the fundamental technologies of future smart factories. Their integration enables increased productivity, improved product quality, reduced operating costs, enhanced workplace safety, and the development of human-centric manufacturing systems based on the principles of Industry 5.0. It is expected that further advances in artificial intelligence, Autonomous Mobile Robots (AMRs), Digital Twin technologies, and next-generation communication networks will further accelerate the transformation of the automotive industry toward fully connected, intelligent, and sustainable manufacturing systems of the future.

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