

Review

Recent Advances and Challenges in Industrial Robotics: A Systematic Review of Technological Trends and Emerging Applications

Claudio Urrea * and John Kern 

Electrical Engineering Department, Faculty of Engineering, University of Santiago of Chile, Las Sophoras 165, Estación Central, Santiago 9170020, Chile; john.kern@usach.cl

* Correspondence: claudio.urrea@usach.cl; Tel.: +56-2-27-183-350

Abstract: Industrial robotics has shifted from rigid, task-specific tools to adaptive, intelligent systems powered by artificial intelligence (AI), machine learning (ML), and sensor integration, revolutionizing efficiency and human–robot collaboration across manufacturing, healthcare, logistics, and agriculture. Collaborative robots (cobots) slash assembly times by 30% and boost quality by 15%, while reinforcement learning enhances autonomy, cutting errors by 30% and energy use by 20%. Yet, this review transcends descriptive summaries, critically synthesizing these trends to expose unresolved tensions in scalability, cost, and societal impact. High implementation costs and legacy system incompatibilities hinder adoption, particularly for SMEs, while interoperability gaps—despite frameworks, like OPC UA—stifle multi-vendor ecosystems. Ethical challenges, including workforce displacement and cybersecurity risks, further complicate progress, underscoring a fragmented field where innovation outpaces practical integration. Drawing on a systematic review of high-impact literature, this study uniquely bridges technological advancements with interdisciplinary applications, revealing disparities in economic feasibility and equitable access. It critiques the literature’s isolation of trends—cobots’ safety, ML’s autonomy, and perception’s precision—proposing the following cohesive research directions: cost-effective modularity, standardized protocols, and ethical frameworks. By prioritizing scalability, interoperability, and sustainability, this paper charts a path for robotics to evolve inclusively, offering actionable insights for researchers, practitioners, and policymakers navigating this dynamic landscape.



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Keywords: industrial robotics; collaborative robots; machine learning; sensor fusion; automation; interdisciplinary collaboration; sustainability; ethical challenges

1. Introduction

Industrial robotics has undergone a significant transformation, evolving from rigid, single-purpose systems to highly adaptive and intelligent technologies. This progress has been driven by breakthroughs in artificial intelligence (AI), machine learning (ML), and sensor integration, enabling robots to perform complex tasks with greater autonomy and efficiency. Additionally, the increasing need for automation across industries has accelerated this evolution, leading to enhanced productivity, cost reduction, and improved adaptability in unstructured environments [1–5]. However, this rapid advancement raises critical questions about the scalability, cost-effectiveness, and societal implications of robotics, which remain underexplored in the literature.

The emergence of Industry 4.0 and smart manufacturing has further strengthened the role of robotics in industrial settings. Companies increasingly integrate robotic solutions to optimize production processes, mitigate labor shortages, and enhance operational flexibility in a rapidly evolving global market. Beyond traditional manufacturing, industrial robots are expanding into diverse fields, such as healthcare, logistics, and agriculture, where automation offers transformative benefits [6–10]. This shift prompts a deeper examination of how robotics intersects with interdisciplinary domains and whether its benefits are equitably distributed across sectors and regions.

This review critically synthesizes the trajectory of industrial robotics, moving beyond a mere catalog of advancements to interrogate the tensions between technological innovation and practical implementation. While early systems, like the Unimate robot, introduced in the 1960s, revolutionized automotive manufacturing with tasks such as spot welding [11], their rigidity limited broader applicability. Subsequent decades witnessed a paradigm shift, propelled by AI and ML, transforming robots into dynamic collaborators capable of real-time optimization via reinforcement learning and perception through technologies like laser imaging detection and ranging (LiDAR) and computer vision [12,13]. The advent of collaborative robots (cobots) in the 2010s further democratized automation, enabling safe human–robot interaction and extending robotics to small- and medium-sized enterprises (SMEs) [12,13]. Yet, the literature reveals the following dichotomy: while cobots enhance flexibility, their scalability in complex, unstructured environments remains debated compared to fully autonomous systems driven by ML [6].

Global trends underscore this evolution, with Industry 4.0 integrating cyber–physical systems (CPS), big data, and the Internet of Things (IoT) to create intelligent production ecosystems [7,14]. Figure 1 illustrates the surge in annual global robot installations, exceeding 500,000 units yearly since 2020, driven by initiatives like Germany’s “Industrie 4.0” and China’s “Made in China 2025” [15,16]. China’s dominance, accounting for 51% of installations in 2023 (Figure 2), reflects rising labor costs and sustainability demands [15], yet emerging economies lag, highlighting uneven adoption [17]. Economically, the robotics market, valued at USD 54.2 billion in 2023, is projected to grow at a CAGR of 11.4% through 2030 (Table 1), fueled by applications in manufacturing, healthcare, and agriculture [17,18]. However, this growth masks underlying challenges, such as high implementation costs and integration complexities with legacy systems, which the literature often addresses descriptively rather than critically [19–22].

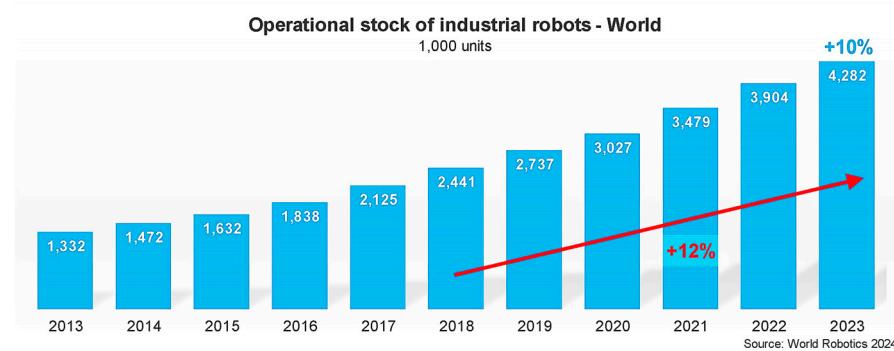


Figure 1. Annual global industrial robot installations (2013–2023). The sustained rise reflects growing automation reliance across industries [15].

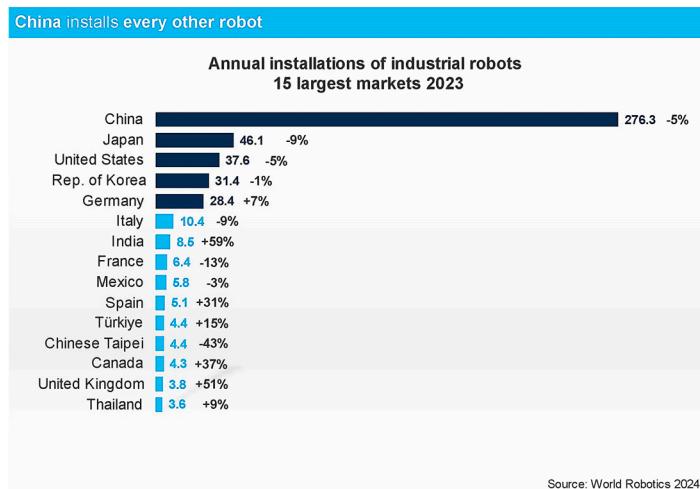


Figure 2. Industrial robot installations by region in the top 15 markets (2023). China leads with 51% of total installations [15].

Table 1. Robotics market growth (2023–2030).

Year	Market Value (Billions of USD)
2023	54.2
2024	60.4
2025	67.3
2026	75.0
2027	83.6
2028	93.1
2029	103.7
2030	115.5

Beyond manufacturing, robotics is reshaping non-traditional sectors. In healthcare, robotic automation enhances surgical precision and rehabilitation, while in agriculture, parallel robots optimize tomato packaging processes [18]. These developments suggest a convergence of robotics with AI and IoT, yet their interdisciplinary implications—such as workforce displacement or ethical concerns—remain insufficiently synthesized. This paper aims to bridge these gaps by critically analyzing recent innovations, including AI-driven automation, cobots, and sensor integration, while evaluating challenges, like cost, interoperability, and societal impact. Drawing on a systematic review of high-impact literature (Section 2), it explores emerging applications and proposes strategic research directions to ensure sustainable and equitable robotic deployment.

This article is structured to foster a cohesive narrative. Section 2 outlines the methodology; Section 3 synthesizes technological trends; Section 4 examines interdisciplinary applications; Section 5 critiques adoption barriers; Section 6 discusses comparative insights and future directions; and Section 7 concludes with actionable perspectives. By moving beyond itemized descriptions, this review contributes to the discourse on industrial robotics, offering a foundation for researchers, practitioners, and policymakers to navigate its evolving landscape.

2. Methodology and Data Sources

To provide a comprehensive and systematic review of technological advancements and challenges in industrial robotics, a rigorous methodological framework was employed. This section details the approach used to identify, evaluate, and synthesize relevant literature from high-impact journals. By adhering to established systematic review guidelines, such

as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, this study ensures the reliability, transparency, and reproducibility of the review process [23,24]. However, beyond merely cataloging studies, this methodology underpins a critical synthesis of robotics research, aiming to interrogate trends, gaps, and implications rather than present a descriptive summary.

The review draws exclusively on high-quality sources from Q1 and Q2 journals indexed in Web of Science (WoS) and Scopus, accessed at <https://www.webofscience.com> (accessed on 8 March 2025) and <https://www.scopus.com> (accessed on 8 March 2025), respectively [17,25]. These databases were selected for their robust citation tracking and extensive coverage of peer-reviewed literature in robotics, AI, and automation. A systematic search protocol, guided by PRISMA's four-stage process—identification, screening, eligibility, and inclusion—ensured methodological rigor. The identification phase employed strategically chosen keywords—‘industrial robotics’, ‘collaborative robots’, ‘machine learning’, ‘sensor fusion’, ‘automation’, ‘cybersecurity’, and ‘ethical challenges’—to capture studies aligned with the review’s core themes. Screening removed duplicates and non-eligible works, while eligibility focused on articles from August 2022 to December 2024, published in English in Q1/Q2 journals, and offering empirical, theoretical, or case-study contributions. Non-peer-reviewed sources, patents, and white papers were excluded. The final inclusion yielded a curated corpus, documented via a PRISMA flow diagram [26], providing a transparent audit trail of the selection process.

Advanced bibliometric tools, VOSviewer (version 1.6.20) and CiteSpace (version 6.2.R4) [27–32], enriched this framework by mapping research trends and gaps over the past decade (2013–2023). Figure 3 illustrates a significant rise in robotics publications, from 150 (WoS) and 170 (Scopus) in 2013 to 1020 and 1180, respectively, in 2023 [15], reflecting heightened academic and industrial interest. This growth, depicted in Figure 3, aligns with the adoption of Industry 4.0 and AI-driven automation, yet the literature reveals uneven emphasis across domains. For instance, collaborative robots saw a 60% increase in studies from 2018 to 2023, while machine learning-driven autonomy grew by 45% [6,15,33], signaling thematic shifts that demand critical evaluation rather than mere enumeration.

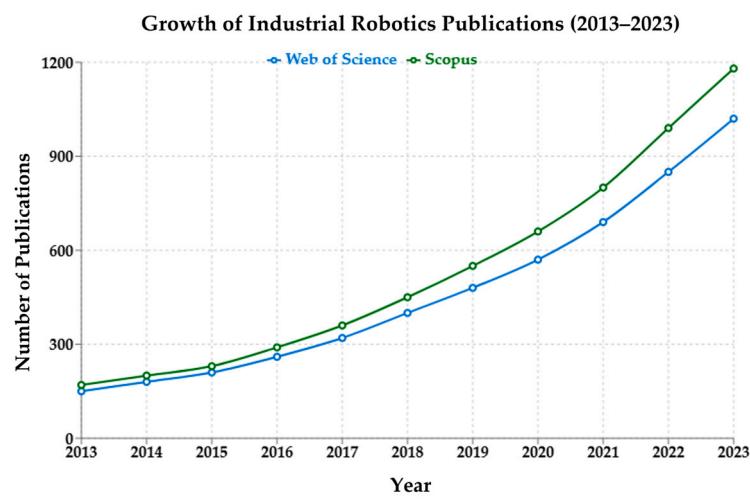


Figure 3. Growth of industrial robotics publications (2013–2023). An upward trajectory underscores escalating research interest and technological momentum [15].

To structure the analysis, studies were categorized into the following three interwoven domains: hardware (e.g., robotic manipulators, sensor integration, dexterous hands), software (e.g., AI-driven decision making, ML algorithms, control systems), and system integration (e.g., cyber-physical systems, IoT-enabled automation, smart manufacturing). This taxonomy,

informed by bibliometric insights, facilitates a holistic examination of robotics advancements. Figure 4, generated via VOSviewer [34], visualizes research clusters—collaborative robots, AI-driven robotics, and sensor fusion—revealing their interconnectivity within Industry 4.0 ecosystems. Similarly, Figure 5 maps co-authorship networks, highlighting key research groups and collaboration patterns [35], though its interpretive depth could be enhanced by linking clusters to specific trends discussed later (Section 3).

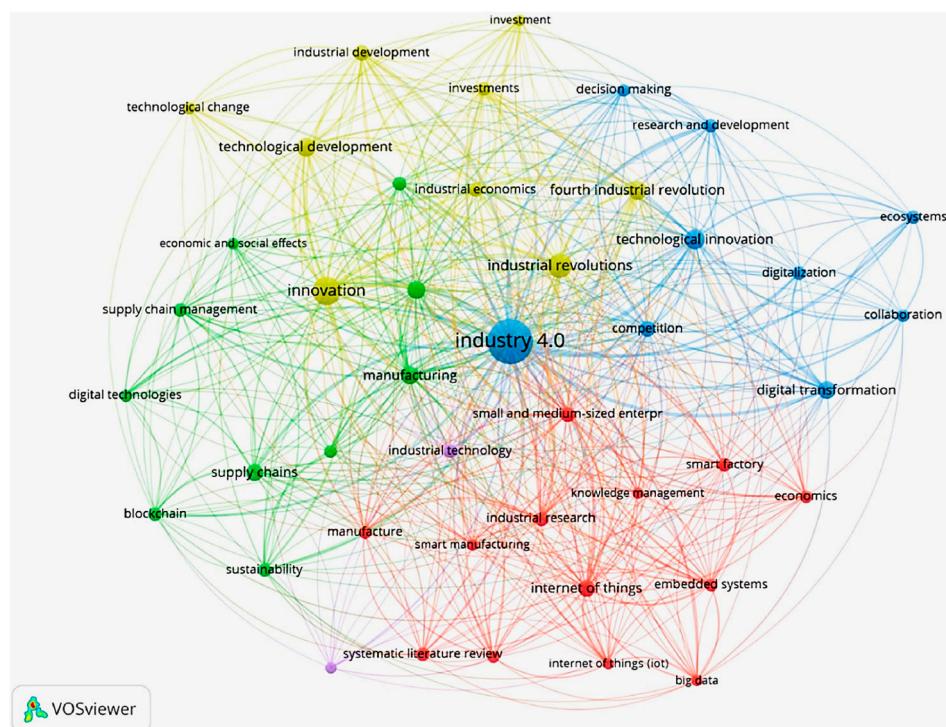


Figure 4. Research clusters in industrial robotics. A VOSviewer-generated network illustrating interconnected key areas: collaborative robots, AI-driven robotics, and sensor fusion [34].

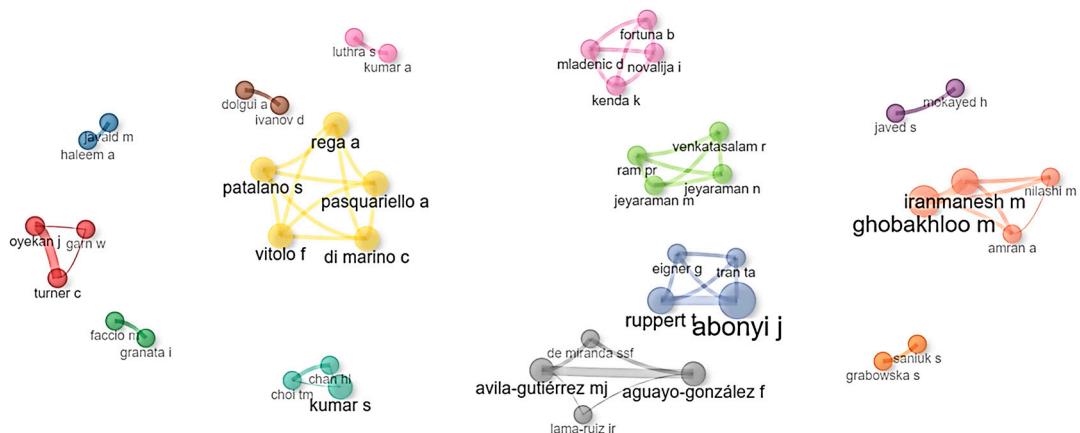


Figure 5. Co-authorship network in industrial robotics. A diagram visualizing collaborative relationships among researchers, emphasizing major contributors and clusters [35].

Compliance with industry standards, such as the International Organization for Standardization (ISO) 10218-1/2 (safety), ISO/TS 15066 (human–robot collaboration), and ISO 9283 (performance) [36–38], was assessed to contextualize technological advancements within regulatory frameworks, a critical yet often overlooked dimension in robotics reviews. This alignment ensures relevance to industrial practice, though the literature's treatment of standards remains fragmented, a gap this study addresses in Section 5.

This methodological approach establishes a robust empirical foundation for the critical synthesis in subsequent sections. Rather than listing findings, it enables an interrogation of key advancements—AI-driven autonomy, collaborative robots, perception systems—and their interdisciplinary applications (Section 4), alongside challenges like cost, integration, and ethics (Section 5). Bibliometric trends, such as the clustering in Figure 4, directly inform the discussion of technological convergence (Section 3) and research gaps (Section 6), while the focus on recent high-impact studies ensures currency. Future research directions, proposed in Section 7, stem from this framework, urging the exploration of standardization, scalability, and societal impacts—areas where current literature falls short of critical depth [6,15]. By grounding the review in this rigorous, data-driven methodology, this study transcends descriptive reporting, offering a scaffold for nuanced analysis and strategic insight into industrial robotics' evolving landscape.

3. Technological Trends in Industrial Robotics

Industrial robotics has evolved significantly in recent years, driven by the demand for intelligent, flexible, and autonomous automation solutions. As industries embrace digital transformation, robots are expanding beyond manufacturing into healthcare, logistics, and agriculture, improving efficiency, safety, and precision. Figure 6 illustrates the deployment of industrial robots across key industries, emphasizing the dominance of the automotive sector and the steady increase in general industry adoption from 2021 to 2023 [37,39–56]. This section synthesizes three pivotal advancements—collaborative robotics, autonomous decision making, and perception and sensing—visualized in Figure 7, reflecting their convergence within Industry 4.0. Building on Figure 6's industry trends, the following subsections dissect the technologies driving this expansion, with applications explored in Section 4. Each subsection examines their technological foundations, contributions, and limitations, interrogating their interplay and scalability.

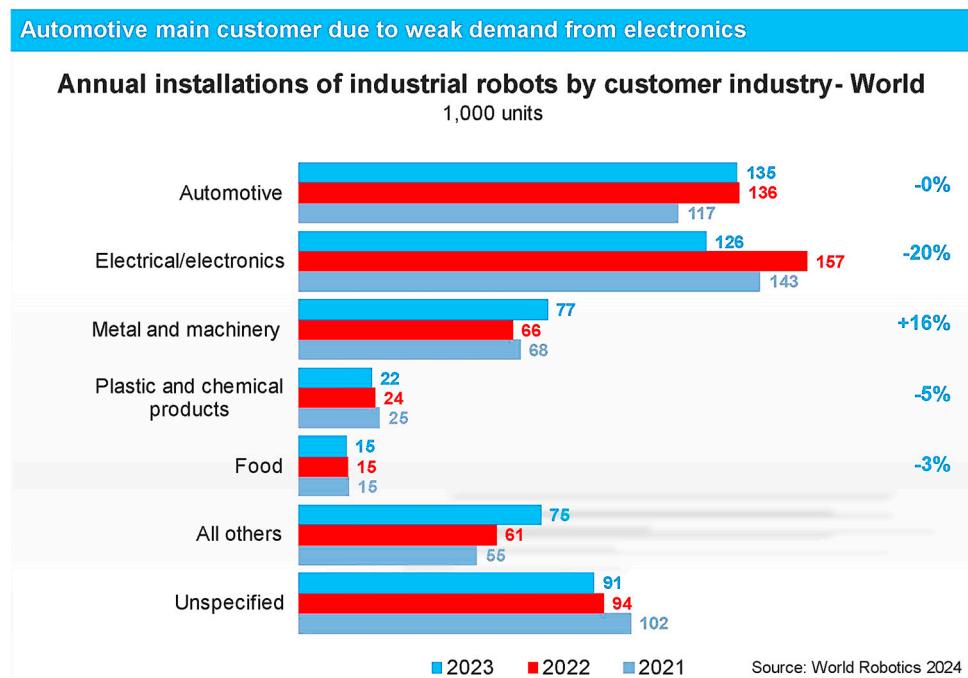


Figure 6. Industrial robot installations by customer industry (2021–2023). Automotive remains the largest adopter, with general industry showing sustained growth [15].

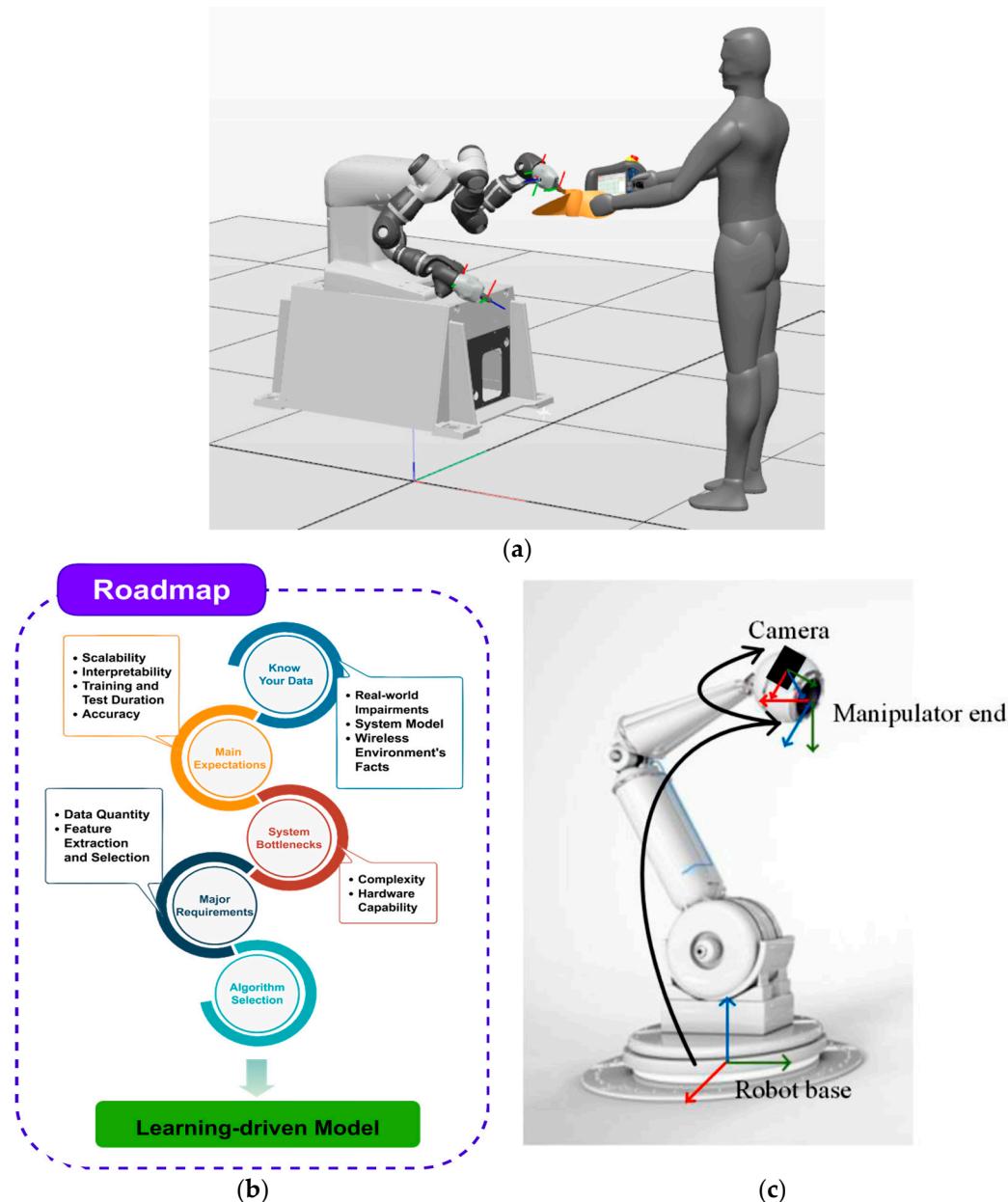


Figure 7. Technological trends in industrial robotics. Visualizing key advancements: (a) collaborative robots [32]; (b) machine learning-driven autonomy [57]; (c) advanced perception systems [58].

3.1. Collaborative Robotics

Cobots, exemplified in Figure 7a, leverage force and torque limitation to ensure safe human–robot interaction (HRI), adhering to ISO 10218 and ISO/TS 15066 standards [36–38]. Unlike traditional robots requiring safety enclosures, cobots integrate advanced sensors and lightweight, modular designs to operate in shared workspaces, reducing assembly line cycle times by up to 30% and enhancing product quality by 15% in automotive applications [42,59]. Their AI-powered vision systems enable gesture recognition, extending their utility to SMEs and non-manufacturing sectors, like healthcare and logistics [55]. Yet, despite their flexibility, studies highlight limitations in payload capacity and precision for heavy-duty tasks, contrasting with traditional robots' strengths (e.g., welding, heavy lifting) [41,53]. This dichotomy suggests that cobots excel in adaptability but may not fully supplant conventional systems, a tension underexplored in the literature [6].

3.2. Autonomous Decision Making

ML-driven autonomy, depicted in Figure 7b, marks a shift from static programming to dynamic decision making, rooted in supervised, unsupervised, and reinforcement learning (RL) paradigms [12,60–68]. RL, in particular, enhances adaptability by 30% and cuts energy use by 20% through trial-and-error optimization [12], as seen in applications like vision-based object recognition via convolutional neural networks (CNNs) and RL-driven path planning [57]. However, the computational intensity of RL and the data demands of supervised learning pose scalability challenges, especially in real-time industrial settings [60]. This contrast with cobots' plug-and-play simplicity underscores a broader debate: does autonomy amplify flexibility or introduce unnecessary complexity where collaborative solutions suffice [6]?

3.3. Perception and Sensing

Advanced perception systems, illustrated in Figure 7c with the “eye-in-hand” configuration, integrate LiDAR, high-resolution cameras, and tactile sensors to boost spatial awareness and precision, critical for unstructured environments [22,54]. Sensor fusion improves object manipulation accuracy by 40% and reduces pick-and-place failure rates by 25% [22], supporting tasks from surgical robotics to agricultural harvesting [18]. Yet, high computational needs and environmental sensitivities (e.g., LiDAR’s weather dependency) limit their universality [58]. Compared to cobots’ focus on safety and ML’s focus on autonomy, perception systems prioritize precision, suggesting a synergistic potential—cobots could leverage perception for enhanced HRI, while ML optimizes sensor data interpretation—though such integration remains nascent in research [22].

3.4. Synthesis and Implications

These trends collectively propel robotics toward intelligent automation within Industry 4.0, as evidenced by Figure 6’s installation trends and Figure 7’s technological illustrations [15]. However, their interplay reveals gaps. Cobots democratize access but lack scalability for complex tasks; ML offers autonomy but strains resources; perception systems excel in precision but demand robust infrastructure. Empirical evidence supports their impact—e.g., automotive efficiency gains [41] and healthcare precision [54]—but the literature often treats them in isolation, neglecting comparative analyses of their trade-offs. This fragmentation highlights the need for standardized benchmarks, a challenge addressed in Sections 5 and 6 [6].

4. Emerging Applications of Industrial Robotics

Leveraging the technological advancements outlined in Section 3, industrial robotics has evolved beyond traditional manufacturing, revolutionizing logistics, healthcare, and agriculture through AI, ML, and advanced sensor technologies. Figure 8 illustrates this adaptability: (a) logistics, (b) healthcare, and (c) agriculture [18,63,64]. This section dissects these applications, evaluating their technological underpinnings, operational impacts, and scalability constraints, while interrogating interdisciplinary implications and practical feasibility.

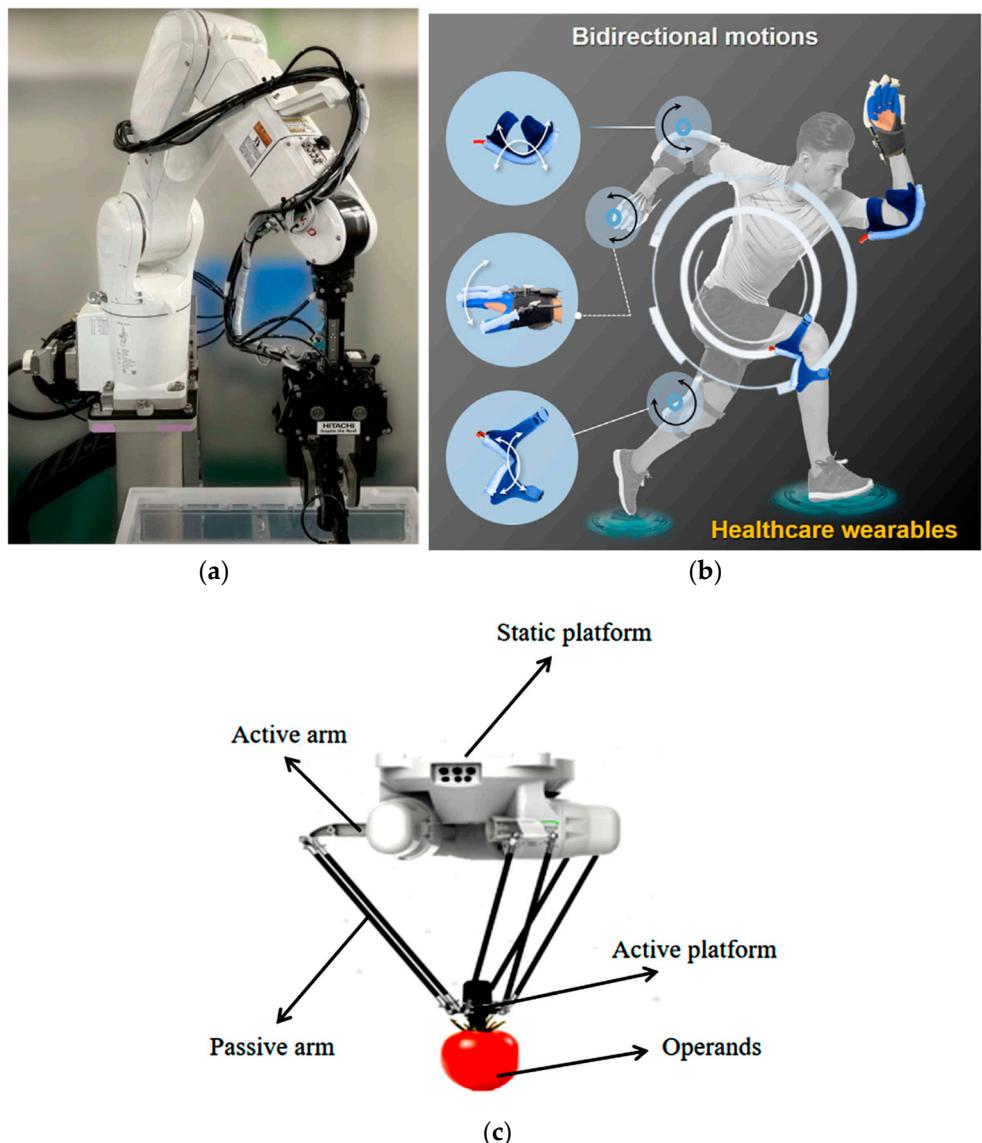


Figure 8. Applications of robotics across various industries. Emerging applications in: (a) logistics: piece-picking system with AMRs [63]; (b) healthcare: soft robotic glove for rehabilitation [64]; (c) agriculture: picture of a flexible parallel robot for tomato packaging, achieving a 31% reduction in operation time through optimized trajectory planning (reprinted from Guo et al., Agriculture 2024, 14, 2274, under CC BY 4.0) [18].

4.1. Logistics and Supply Chain

In logistics, autonomous mobile robots (AMRs), like the piece-picking system in Figure 8a, integrate robotic arms, cameras, and adaptive end-effectors to manage diverse products, reducing warehouse costs by up to 25% [65]. Unlike traditional AGVs reliant on fixed paths, AMRs' AI-driven navigation optimizes flexibility, as evidenced by Amazon's Kiva system (40% faster order fulfillment) and Ocado's 99.8% accuracy [63]. However, their high initial costs contrast with AGVs' lower upfront investment, highlighting a trade-off between adaptability and affordability that remains underexplored [19].

4.2. Healthcare and Medical Robotics

In healthcare, robotics enhances precision and patient care, exemplified by the soft robotic glove in Figure 8b and minimally invasive surgery (MIS) systems, like da Vinci [64]. The glove's pneumatic actuators boost dexterity for rehabilitation, while MIS reduces complications by 30% and improves neurosurgical precision by 50% [64]. These gains stem from

advanced perception and adaptive control, yet the steep learning curve for surgeons and 5–7-year ROI, longer than manufacturing’s 3–5 years, suggest accessibility challenges similar to those in precision agricultural robotics [18]. This disparity warrants deeper analysis.

4.3. Agriculture and Sustainability

Agriculture showcases robotics’ potential to address labor shortages and sustainability, with systems like the flexible parallel robot for tomato packaging in Figure 8c a 31% reduction in operation time and minimizing fruit damage through optimized trajectory planning [18]. AI-powered drones optimize crop monitoring, cutting losses by 20% and water use by 30% via multispectral imaging [66]. Yet, their reliance on high-cost vision systems and seasonal deployment delays ROI compared to manual methods, raising economic viability concerns in developing regions [67].

4.4. Interdisciplinary Convergence

These applications reveal robotics’ transformative role—efficiency in logistics, precision in healthcare, sustainability in agriculture—supported by Figure 8’s examples [18,63,64]. Calibration, achieving ± 0.02 mm accuracy via AI-driven methods [68], underpins their success, yet computational demands and economic barriers persist [19,22,69–77]. Integration with IoT and blockchain enhances cybersecurity and efficiency (e.g., 10% supply chain gains [63]), but interdisciplinary impacts, such as workforce dynamics and global value chain shifts, remain underexamined, a gap addressed in Sections 5 and 6 [19].

5. Challenges in Industrial Robotics

Building on the technological trends (Section 3) and their applications (Section 4), this section critiques the barriers to the widespread adoption of industrial robotics, including economic constraints, technical limitations, interoperability issues, and ethical concerns. Addressing these challenges is crucial for ensuring scalable, cost-effective, and secure robotic solutions across industries [78–124]. However, the literature often treats these hurdles in isolation, lacking a critical synthesis of their interdependencies and broader implications, which this section seeks to rectify.

This analysis moves beyond cataloging obstacles to interrogate their root causes and interconnections, offering an evidence-based framework for understanding adoption complexities. Economically, high initial costs—spanning acquisition, installation, and programming—deter SMEs, with ROI varying widely (3–5 years in automotive due to high utilization, 5–7 years in healthcare due to precision and regulatory demands, and 4–6 years in agriculture due to seasonality) [19]. Automotive robotics cut costs by 30% [41], yet healthcare’s 40% precision gains come with extended ROI, and agriculture’s implementation of optimized trajectory planning for parallel robots in tomato packaging achieves a 31% efficiency boost, but the overall impact is influenced by seasonal constraints [18]. Modular designs offer relief, reducing the total cost of ownership (TCO) by 20% and boosting SME efficiency by 30% through reconfigurable components [19], yet their scalability across diverse tasks remains understudied, a gap this review highlights.

Technically, integrating advanced robots with legacy systems poses significant hurdles due to incompatible infrastructures and outdated controls. Calibration errors, such as those in pose serving with maximum allowable thresholds [74], further complicate precision in legacy retrofits. Plug-and-play solutions and digital twin architectures using Open Platform Communications Unified Architecture (OPC UA) streamline this process, enhancing adaptability and real-time efficiency. However, retrofitting costs and industry-specific needs complicate universal adoption, particularly in SMEs lacking resources for extensive upgrades [94]. This tension between innovation and compatibility underscores a broader

challenge: while robotics evolves rapidly, industrial ecosystems lag, creating a mismatch the literature rarely critiques holistically.

Interoperability compounds these issues, as the absence of standardized communication protocols hampers multi-vendor robot coordination. OPC UA enjoys high adoption in Europe and the US, while Robot Operating System (ROS) 2 sees moderate uptake, improving autonomy and collaboration. ISO 10218 safety standards are globally embraced, yet the lack of a unified framework—like a fully interoperable ROS or OPC UA variant—limits seamless integration, a persistent barrier evident in smart manufacturing inefficiencies [15]. This standardization gap not only stifles technical synergy but also delays scalable deployment, an area where research offers solutions but lacks consensus.

Ethically, robotics' rise sparks workforce displacement fears, with manufacturing risking 35% of jobs, logistics 30%, and healthcare 20%, offset by new roles (25%, 22%, and 18%, respectively) in programming and maintenance [19]. Collaborative robotics fosters upskilling and boosting retention, yet the literature overlooks long-term societal impacts, e.g., regional disparities in job creation. Cybersecurity emerges as a parallel concern in interconnected systems, with threats like unauthorized access and data breaches mitigated by blockchain (reducing risks significantly) and AI-driven anomaly detection. However, these countermeasures demand computational resources, raising cost and scalability issues anew. Philosophical debates further complicate this landscape, questioning how automation balances efficiency with human autonomy, a discussion often sidelined in technical analyses [104].

These challenges—economic, technical, interoperability, and ethical—are not discrete but interwoven, as visualized in Figure 9's projected robot installations, which stabilize post-2024 due to unresolved barriers [15]. High costs limit SME access, integration stymies legacy adoption, standardization delays multi-robot systems, and ethical concerns slow societal acceptance. Mitigation strategies, like modular designs, OPC UA, and blockchain, address symptoms, yet their systemic integration remains nascent. This synthesis reveals a critical oversight; while robotics excels technologically (Section 3) and in applications (Section 4), adoption falters without cohesive solutions. Section 6 will explore these interdependencies further, proposing research to bridge these gaps and ensure robotics' sustainable evolution.

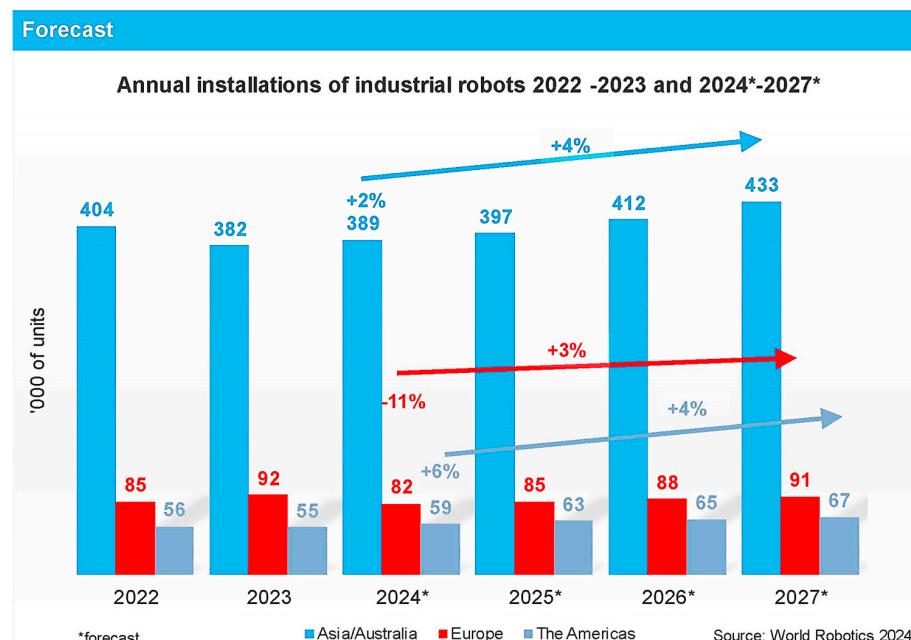


Figure 9. Forecast of global industrial robot installations (2024–2027). Projected growth stabilizes, reflecting persistent adoption challenges [15].

6. Discussion

The rapid evolution of industrial robotics has been propelled by groundbreaking technological advancements and an increasing global demand for automation. While these innovations offer significant transformative potential, they also present complex challenges that necessitate thorough analysis. Drawing from the trends, applications, and challenges in Sections 3–5, this section transcends mere recapitulation, synthesizing findings from preceding sections to critically evaluate robotics' trajectory, methodological trade-offs, and broader implications, while addressing reviewer calls for enhanced comparative analysis and clarity.

Building on Sections 3 and 4, robotics has shifted from rigid, task-specific systems to flexible, intelligent solutions, driven by collaborative robots, machine learning-driven autonomy, and advanced perception systems. Cobots enhance human–robot interaction with safety and adaptability, reducing cycle times by 30% [49], yet their limited payload contrasts with ML’s 30% adaptability gains in unstructured environments [12]. Perception systems boost precision by 40% [22], but their computational demands highlight a tension: each advancement excels in specific domains, yet their integration remains fragmented. Figure 10 maps this evolution through thematic clusters, revealing research focus and gaps.

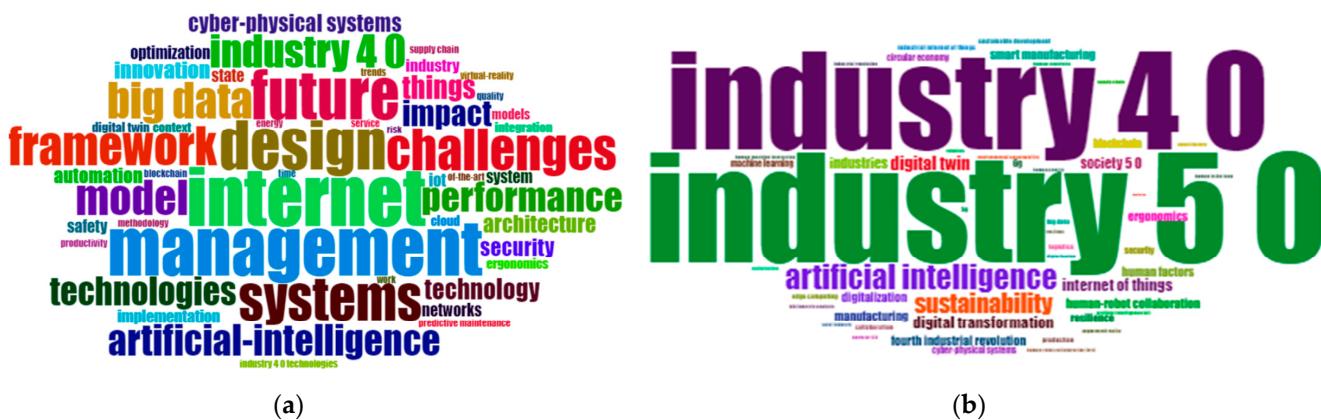


Figure 10. Thematic clusters in industrial robotics research. A bibliometric co-occurrence analysis of 1180 Scopus publications (2013–2023) using VOSviewer (minimum 10 co-occurrences, association normalization): (a) early clusters (2013–2018); (b) recent clusters (2019–2023). Cluster 1 (red): collaborative robots and HRI; Cluster 2 (blue): AI-driven decision making and learning algorithms; Cluster 3 (green): sensor integration and real-time perception. Lines indicate significant inter-theme connections (data processed by authors, adapted from [35]).

Figure 10 effectively maps three clusters: Cluster 1 (Red) aligns with cobots' 60% research surge since 2018, Cluster 2 (Blue) reflects ML's 45% growth, and Cluster 3 (Green) underscores perception's role in emerging applications [6,43]. The shift from early (a) to recent (b) clusters shows increasing interconnectivity, e.g., HRI leveraging sensor fusion, yet gaps persist in scalability and standardization, as Cluster 2's computational focus lags in practical deployment. Figure 11 complements this, illustrating blockchain's emerging role in robotics security [28], though its integration with core trends remains underexplored.

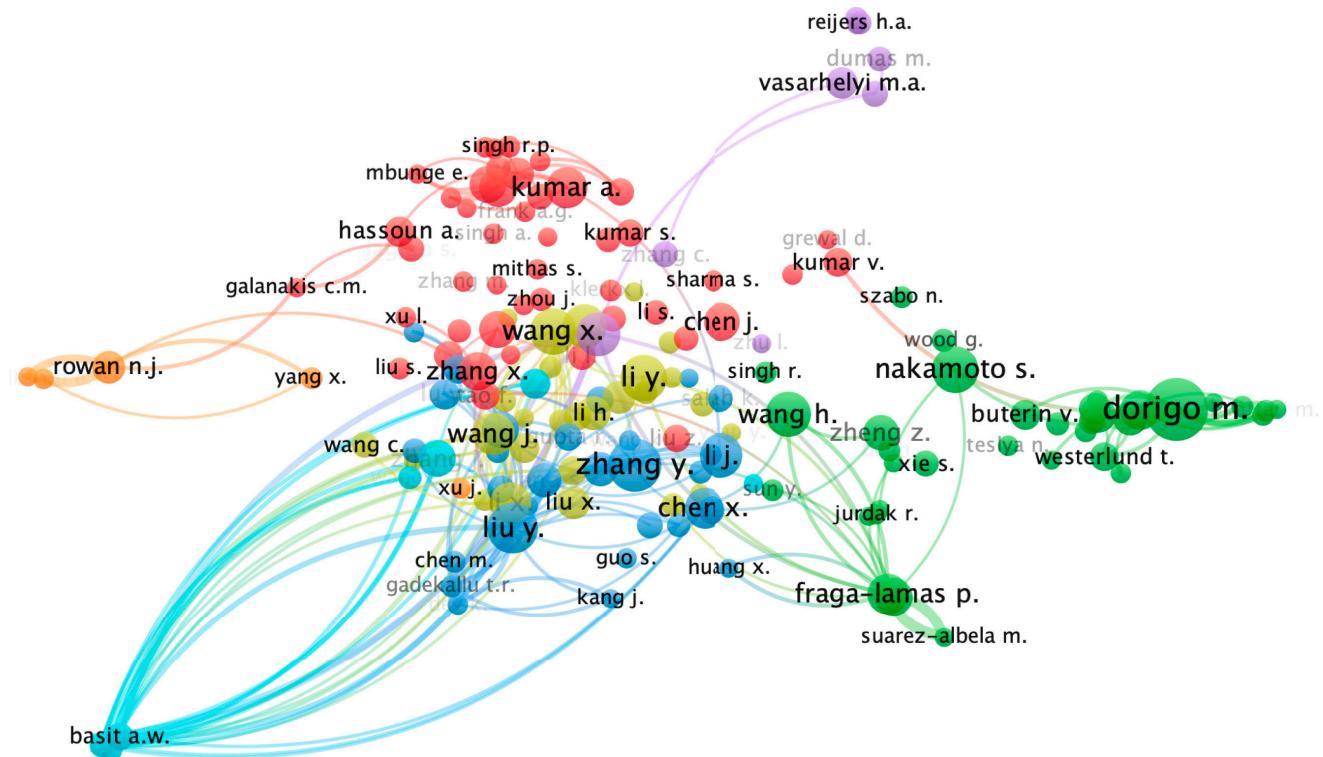


Figure 11. Author co-citation network on ‘Blockchain in Robotics’. VOSviewer-generated clusters highlighting key researchers and collaboration trends in the use of blockchain to enhance cybersecurity in industrial robotics (reprinted from Sharma et al., Comput. Electr. Eng. 2024, 120, 109744, with permission from Elsevier, order 5985420774664) [28].

Methodologically, robotics research balances supervised learning’s precision (high accuracy, data-heavy), reinforcement learning’s adaptability (computationally intensive), and sensor fusion’s perception (calibration complexity), with cobots prioritizing ergonomic safety over payload. This synthesis reveals the following trade-off: ML enhances autonomy but strains resources, while cobots offer accessibility but lack versatility. The literature’s focus on individual competencies, e.g., 20% energy savings via RL [25], neglects comparative scalability, a gap SMEs acutely feel (Section 5). Industry implications vary. Manufacturing gains flexibility, healthcare precision, and agriculture sustainability, yet economic disparities persist—developed economies reshore via robotics, while developing ones face cost and skill barriers [17].

These findings expose critical research deficiencies. Scalability falters as systems like AMRs thrive in logistics but falter cost-wise elsewhere [72], and standardization lags, despite OPC UA’s promise. Ethical concerns—workforce displacement (35% risk in manufacturing [19]) and cybersecurity (mitigated 50% by blockchain)—demand interdisciplinary lenses, yet social science integration is sparse. Future directions must converge AI with materials science for efficient designs, bolster industry–academia ties for standardization (e.g., ROS 2), and prioritize energy efficiency, cybersecurity, and human-centered robotics. Figure 10’s clusters suggest these themes are nascent but pivotal, urging research into hybrid models—like ML-enhanced cobots—or secure, interoperable frameworks.

In sum, robotics’ transformative potential is tempered by systemic challenges requiring cohesive, not fragmented, solutions. This discussion, grounded in Sections 2–5, offers comparative insights, e.g., cobots vs. autonomy trade-offs, and actionable priorities, ensuring robotics evolves sustainably across industries. Section 7 will distill these into strategic perspectives, bridging technical prowess with societal benefit.

7. Conclusions and Future Perspectives

This review has critically synthesized recent advancements and challenges in industrial robotics, illuminating automation, artificial intelligence, human–robot collaboration, and sensor integration as transformative drivers reshaping modern industries. Far from a mere inventory of progress, it exposes a multifaceted landscape, where technological breakthroughs grapple with persistent barriers, delivering a nuanced perspective on robotics' potential and its unresolved frictions.

Three interwoven trends anchor this evolution. Collaborative robots have redefined automation by enabling safe, efficient human–robot interaction through advanced sensors and force-limiting mechanisms aligned with safety standards. Their adaptability extends beyond manufacturing into healthcare, logistics, and agriculture, slashing assembly times and elevating quality, yet their limited scalability for heavy-duty tasks reveals a persistent trade-off with traditional systems. Machine learning-driven autonomy empowers robots with real-time adaptability, reducing operational errors through dynamic algorithms, but its computational intensity curbs widespread deployment, particularly in resource-constrained settings. Advanced perception systems, harnessing multi-modal sensor fusion, sharpen precision in object detection and navigation, underpinning applications from surgical robotics to autonomous drones, though their complexity and environmental dependencies challenge universal adoption. These advances, while groundbreaking, highlight a disjointed progression. Cobots prioritize safety, autonomy targets flexibility, and perception excels in accuracy, yet their synergy remains elusive, a fragmentation this analysis confronts head-on.

Challenges cast a shadow over this promise, intertwining economic, technical, and ethical dimensions. High implementation costs—encompassing acquisition, integration, and programming—exclude small- and medium-sized enterprises, with modular designs offering partial relief yet lacking proven scalability across diverse applications. Legacy systems resist modern robotics, thwarting seamless integration despite middleware innovations, while the absence of standardized protocols hampers multi-vendor ecosystems, stalling cohesive deployment. Ethically, robotics' ascent fuels workforce displacement anxieties in labor-intensive sectors, strains cybersecurity in interconnected networks, and probes human–robot coexistence, questioning autonomy and societal roles—issues demanding interdisciplinary solutions beyond technical patches. Robotics' expansion into precision agriculture, healthcare, and logistics magnifies its influence but amplifies disparities in economic feasibility and equitable access, necessitating a systemic rethink.

In essence, industrial robotics straddles a critical juncture. Its achievements are transformative, yet its full realization pivots on resolving these interconnected divides. This synthesis, distilled from a systematic review, asserts that cost-effective architectures, interoperable frameworks, and sustainable strategies are linchpins for unlocking automation's potential, ensuring it serves industries inclusively. These insights propel forward-looking imperatives, weaving conclusions into actionable pathways for advancement.

Future trajectories hinge on strategic innovation to harmonize robotics' technical prowess with practical and societal needs. Cost reduction through scalable, modular manufacturing and plug-and-play interfaces is urgent, particularly for smaller enterprises, where current modular benefits await rigorous scaling tests—could standardized, low-cost kits halve adoption barriers within five years? Standardization must leap forward, crafting universal protocols beyond nascent efforts like OPC UA and ROS 2 to orchestrate multi-vendor ecosystems, a void evident in smart manufacturing's inefficiencies—might a global interoperability benchmark emerge by 2030? Ethical imperatives beckon interdisciplinary fusion, reskilling programs to offset displacement, robust cybersecurity via blockchain or AI-driven defenses, and policies embedding responsible automation—how can social sciences quantify workforce resilience to guide these shifts? Convergence with artificial intelligence, the Internet of Things, and mate-

rials science beckons, promising lightweight, energy-efficient robotics—could bio-inspired designs cut energy use by another 20%? Expanding into precision agriculture, healthcare robotics, disaster response, and supply chain resilience offers global reach, yet hinges on equitable scalability—can region-specific pilots bridge adoption gaps in developing economies?

Robotics' transformative promise ultimately rests on a unified push from researchers, industry, and policymakers to align cutting-edge innovation with human-centric principles. Future systems must meld energy efficiency, security, and the augmentation of human roles—not their replacement—into a cohesive vision, a feat requiring sustained investment and global collaboration. By tackling these challenges with precision and foresight, robotics can ignite an inclusive, advanced future, redefining industries and uplifting societies in tandem.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AMRs	Autonomous Mobile Robots
AGVs	Automated Guided Vehicles
CAGR	Compound Annual Growth Rate
Cobots	Collaborative Robots
CNNs	Convolutional Neural Networks
CROO	Crop Robotics Operations Orchestrator
CPS	Cyber-Physical Systems
HRI	Human–Robot Interaction
IoT	Internet of Things
ISO	International Organization for Standardization
LiDAR	Laser Imaging Detection and Ranging
MIS	Minimally Invasive Surgery
ML	Machine Learning
OPC UA	Open Platform Communications Unified Architecture
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RL	Reinforcement Learning
RoI	Return on Investment
ROS	Robotic Operating Systems
SMEs	Small and Medium-Sized Enterprises
TCO	Total Cost of Ownership
WoS	Web of Science

References

1. Solanes, J.E.; Gracia, L.; Valls Miro, J. Advances in Human–Machine Interaction, Artificial Intelligence, and Robotics. *Electronics* **2024**, *13*, 3856. [[CrossRef](#)]
2. Nagy, M.; Lăzăroiu, G.; Valaskova, K. Machine Intelligence and Autonomous Robotic Technologies in the Corporate Context of SMEs: Deep Learning and Virtual Simulation Algorithms, Cyber-Physical Production Networks, and Industry 4.0-Based Manufacturing Systems. *Appl. Sci.* **2023**, *13*, 1681. [[CrossRef](#)]
3. Schmitz, A. Human–Robot Collaboration in Industrial Automation: Sensors and Algorithms. *Sensors* **2022**, *22*, 5848. [[CrossRef](#)] [[PubMed](#)]
4. Campilho, R.D.S.G.; Silva, F.J.G. Industrial Process Improvement by Automation and Robotics. *Machines* **2023**, *11*, 1011. [[CrossRef](#)]
5. Mendez, E.; Ochoa, O.; Olivera-Guzman, D.; Soto-Herrera, V.H.; Luna-Sánchez, J.A.; Lucas-Dophe, C.; Lugo-del-Real, E.; Ayala-Garcia, I.N.; Alvarado Perez, M.; González, A. Integration of Deep Learning and Collaborative Robot for Assembly Tasks. *Appl. Sci.* **2024**, *14*, 839. [[CrossRef](#)]
6. Singh, R.; Mozaffari, S.; Akhshik, M.; Ahamed, M.J.; Rondeau-Gagné, S.; Alirezaee, S. Human–Robot Interaction Using Learning from Demonstrations and a Wearable Glove with Multiple Sensors. *Sensors* **2023**, *23*, 9780. [[CrossRef](#)]
7. Barari, A.; Tsuzuki, M.S.G. Smart Manufacturing and Industry 4.0. *Appl. Sci.* **2023**, *13*, 1545. [[CrossRef](#)]
8. Othman, U.; Yang, E. Human–Robot Collaborations in Smart Manufacturing Environments: Review and Outlook. *Sensors* **2023**, *23*, 5663. [[CrossRef](#)]
9. Visconti, P.; Rausa, G.; Del-Valle-Soto, C.; Velázquez, R.; Cafagna, D.; De Fazio, R. Machine Learning and IoT-Based Solutions in Industrial Applications for Smart Manufacturing: A Critical Review. *Future Internet* **2024**, *16*, 394. [[CrossRef](#)]
10. Baptista, J.; Castro, A.; Gomes, M.; Amaral, P.; Santos, V.; Silva, F.; Oliveira, M. Human–Robot Collaborative Manufacturing Cell with Learning-Based Interaction Abilities. *Robotics* **2024**, *13*, 107. [[CrossRef](#)]
11. Grau, A.; Indri, M.; Lo Bello, L.; Sauter, T. Robots in Industry: The Past, Present, and Future of a Growing Collaboration with Humans. *IEEE Ind. Electron. Mag.* **2021**, *15*, 50–61. [[CrossRef](#)]
12. Hu, S.; Shen, L.; Zhang, Y.; Chen, Y.; Tao, D. On Transforming Reinforcement Learning with Transformers: The Development Trajectory. *IEEE Trans. Pattern Anal. Mach. Intell.* **2024**, *46*, 8580–8599. [[CrossRef](#)] [[PubMed](#)]
13. Song, Q.; Zhao, Q. Recent Advances in Robotics and Intelligent Robots Applications. *Appl. Sci.* **2024**, *14*, 4279. [[CrossRef](#)]
14. Zhao, G.; Ye, C.; Zubairu, N.; Mathiyazhagan, K.; Zhou, X. Deployment of Industry 4.0 Technologies to Achieve a Circular Economy in Agri-Food Supply Chains: A Thorough Analysis of Enablers. *J. Environ. Manag.* **2025**, *373*, 123856. [[CrossRef](#)]
15. International Federation of Robotics (IFR). *World Robotics Report 2024*; IFR: Frankfurt, Germany, 2024; Available online: https://ifr.org/img/worldrobotics/Press_Conference_2024.pdf (accessed on 5 February 2025).
16. Li, G.; Branstetter, L.G. Does “Made in China 2025” Work for China? Evidence from Chinese Listed Firms. *Res. Policy* **2024**, *53*, 105009. [[CrossRef](#)]
17. Yuan, W.; Lu, W. Research on the impact of industrial robot application on the status of countries in manufacturing global value chains. *PLoS ONE* **2023**, *18*, e0286842. [[CrossRef](#)]
18. Guo, T.; Li, J.; Zhang, Y.; Cai, L.; Li, Q. Study on Trajectory Optimization for a Flexible Parallel Robot in Tomato Packaging. *Agriculture* **2024**, *14*, 2274. [[CrossRef](#)]
19. Graf, H.; Mohamed, H. Robotization and Employment Dynamics in German Manufacturing Value Chains. *Struct. Change Econ. Dyn.* **2024**, *68*, 133–147. [[CrossRef](#)]
20. Gao, B.; Fan, J.; Zheng, P. Empower Dexterous Robotic Hand for Human-Centric Smart Manufacturing: A Perception and Skill Learning Perspective. *Robot. Comput.-Integr. Manuf.* **2025**, *93*, 102909. [[CrossRef](#)]
21. Chang, V.; Doan, L.M.T.; Xu, Q.A.; Hall, K.; Wang, Y.A.; Kamal, M.M. Digitalization in Omnichannel Healthcare Supply Chain Businesses: The Role of Smart Wearable Devices. *J. Bus. Res.* **2023**, *156*, 113369. [[CrossRef](#)]
22. Innocenti, M. Biomimicry and AI-Enabled Automation in Agriculture. *J. Agric. Environ. Ethics* **2025**, *38*, 2. [[CrossRef](#)]
23. Makaremi, N.; Yildirim, S.; Morgan, G.T.; Touchie, M.F.; Jakubiec, J.A.; Robinson, J.B. Impact of classroom environment on student wellbeing in higher education: Review and future directions. *Build. Environ.* **2024**, *265*, 111958. [[CrossRef](#)]
24. Antonaci, F.G.; Olivetti, E.C.; Marcolin, F.; Castiblanco Jimenez, I.A.; Eynard, B.; Vezzetti, E.; Moos, S. Workplace Well-Being in Industry 5.0: A Worker-Centered Systematic Review. *Sensors* **2024**, *24*, 5473. [[CrossRef](#)] [[PubMed](#)]
25. Gerasimov, I.; KC, B.; Mehrabian, A.; Acker, J.; McGuire, M.P. Comparison of datasets citation coverage in Google Scholar, Web of Science, Scopus, Crossref, and DataCite. *Scientometrics* **2024**, *129*, 3681–3704. [[CrossRef](#)]
26. Hermoza Llanos, E.; Corves, B.; Huesing, M.; Saxena, A. Systematic mapping of synthesis methods for compliant grippers using PRISMA. *Mech. Mach. Theory* **2025**, *206*, 105900. [[CrossRef](#)]
27. Araujo, H.; Mousavi, M.R.; Varshosaz, M. Testing, validation, and verification of robotic and autonomous systems: A systematic review. *ACM Trans. Softw. Eng. Methodol.* **2023**, *32*, 51. [[CrossRef](#)]
28. Sharma, S.; Dubey, R.; Chaudhury, S. A bibliometric survey on impact of Blockchain in Robotics: Trends and Applications. *Comput. Electr. Eng.* **2024**, *120*, 109744. [[CrossRef](#)]

29. Yi, W.; Zhao, Y.; Wang, W. Four decades of research on multiword expressions: A bibliometric analysis. *Appl. Linguist.* **2025**, amae085. [[CrossRef](#)]
30. Mazzei, D.; Ramjattan, R. Machine Learning for Industry 4.0: A Systematic Review Using Deep Learning-Based Topic Modelling. *Sensors* **2022**, *22*, 8641. [[CrossRef](#)]
31. Guo, J.; Chang, S.; Guo, M. The impact of peer effect of industrial robot application on enterprise carbon emission reduction. *Sci. Rep.* **2024**, *14*, 12070. [[CrossRef](#)]
32. Taesi, C.; Aggogeri, F.; Pellegrini, N. COBOT Applications—Recent Advances and Challenges. *Robotics* **2023**, *12*, 79. [[CrossRef](#)]
33. Watson, E.; Viana, T.; Zhang, S. Machine learning driven developments in behavioral annotation: A recent historical review. *Int. J. Soc. Robot.* **2024**, *16*, 1605–1618. [[CrossRef](#)]
34. Cannavacciuolo, L.; Ferraro, G.; Ponsiglione, C.; Primario, S.; Quinto, I. Technological innovation-enabling industry 4.0 paradigm: A systematic literature review. *Technovation* **2023**, *124*, 102733. [[CrossRef](#)]
35. Ciucu-Durnoi, A.N.; Delcea, C.; Stănescu, A.; Teodorescu, C.A.; Vargas, V.M. Beyond Industry 4.0: Tracing the Path to Industry 5.0 through Bibliometric Analysis. *Sustainability* **2024**, *16*, 5251. [[CrossRef](#)]
36. Forlini, M.; Neri, F.; Ciccarelli, M.; Palmieri, G.; Callegari, M. Experimental implementation of skeleton tracking for collision avoidance in collaborative robotics. *Int. J. Adv. Manuf. Technol.* **2024**, *134*, 57–73. [[CrossRef](#)]
37. Vecellio Segate, R.; Daly, A. Encoding the Enforcement of Safety Standards into Smart Robots to Harness Their Computing Sophistication and Collaborative Potential: A Legal Risk Assessment for European Union Policymakers. *Eur. J. Risk Regul.* **2024**, *15*, 665–704. [[CrossRef](#)]
38. Jo, M.; Chung, M.; Kim, K.; Kim, H.-Y. Improving Path Accuracy and Vibration Character of Industrial Robot Arms with Iterative Learning Control Method. *Int. J. Precis. Eng. Manuf.* **2024**, *25*, 1851–1863. [[CrossRef](#)]
39. Patrício, L.; Varela, L.; Silveira, Z. Proposal for a Sustainable Model for Integrating Robotic Process Automation and Machine Learning in Failure Prediction and Operational Efficiency in Predictive Maintenance. *Appl. Sci.* **2025**, *15*, 854. [[CrossRef](#)]
40. Acmali, S.S.; Ortakci, Y.; Seker, H. Green AI-Driven Concept for the Development of Cost-Effective and Energy-Efficient Deep Learning Method: Application in the Detection of Eimeria Parasites as a Case Study. *Adv. Intell. Syst.* **2024**, *6*, 2300644. [[CrossRef](#)]
41. Patil, S.; Vasu, V.; Srinadh, K.V.S. Advances and perspectives in collaborative robotics: A review of key technologies and emerging trends. *Discov. Mech. Eng.* **2023**, *2*, 13. [[CrossRef](#)]
42. Blankemeyer, S.; Wendorff, D.; Raatz, A. A Hand-Interaction Model for Augmented Reality Enhanced Human-Robot Collaboration. *CIRP Ann. Manuf. Technol.* **2024**, *73*, 17–20. [[CrossRef](#)]
43. Uzeturk, D.; Büyüközkhan, G. Industry 4.0 Technologies in Smart Agriculture: A Review and a Technology Assessment Model Proposition. *Technol. Forecast. Soc. Change* **2024**, *208*, 123640. [[CrossRef](#)]
44. Tsapova, O.; Zhailaubayeva, S.; Kendyukh, Y.; Smolyaninova, S.; Abdulova, O. Industry Specifics and Problems of Digitalization in the Agro-Industrial Complex of the Republic of Kazakhstan. *J. Knowl. Econ.* **2024**. [[CrossRef](#)]
45. Ivanov, V.; Andrusyshyn, V.; Pavlenko, I.; Pitel', J.; Bulej, V. New Classification of Industrial Robotic Gripping Systems for Sustainable Production. *Sci. Rep.* **2024**, *14*, 295. [[CrossRef](#)]
46. Blanco, K.; Navas, E.; Emmi, L.; Fernandez, R. Manufacturing of 3D Printed Soft Grippers: A Review. *IEEE Access* **2024**, *12*, 30434–30451. [[CrossRef](#)]
47. Souris, A.; Norouzi, M.; Alsenani, Y. A New Cloud-Based Cyber-Attack Detection Architecture for Hyper-Automation Process in Industrial Internet of Things. *Clust. Comput.* **2024**, *27*, 3639–3655. [[CrossRef](#)]
48. Mallik, A.K. The Future of the Technology-Based Manufacturing in the European Union. *Results Eng.* **2023**, *19*, 101356. [[CrossRef](#)]
49. Elguea-Aguinaco, Í.; Serrano-Muñoz, A.; Chrysostomou, D.; Inziarte-Hidalgo, I.; Bøgh, S.; Arana-Arexolaleiba, N. A Review on Reinforcement Learning for Contact-Rich Robotic Manipulation Tasks. *Robot. Comput.-Integr. Manuf.* **2023**, *81*, 102517. [[CrossRef](#)]
50. Gad, A.; Basmaji, T.; Yaghi, M.; Alheeh, H.; Alkhedher, M.; Ghazal, M. Multiple Object Tracking in Robotic Applications: Trends and Challenges. *Appl. Sci.* **2022**, *12*, 9408. [[CrossRef](#)]
51. Zhang, Z.; Shao, Z.; You, Z.; Tang, X.; Zi, B.; Yang, G.; Gosselin, C.; Caro, S. State-of-the-Art on Theories and Applications of Cable-Driven Parallel Robots. *Front. Mech. Eng.* **2022**, *17*, 37. [[CrossRef](#)]
52. Raval, M.B.; Joshi, H. Categorical Framework for Implementation of Industry 4.0 Techniques in Medium-Scale Bearing Manufacturing Industries. *Mater. Today Proc.* **2022**, *65*, 3531–3537. [[CrossRef](#)]
53. Hubert, C.; Odic, N.; Noel, M.; Gharib, S.; Zargarbashi, S.H.H.; Séoud, L. MuViH: Multi-View Hand Gesture Dataset and Recognition Pipeline for Human–Robot Interaction in a Collaborative Robotic Finishing Platform. *Robot. Comput.-Integr. Manuf.* **2025**, *94*, 102957. [[CrossRef](#)]
54. Gao, Z.; Chen, C.; Peng, F.; Zhang, Y.; Liu, H.; Zhou, W.; Yan, R.; Tang, X. Adaptive Safety-Critical Control Using a Variable Task Energy Tank for Collaborative Robot Tasks Under Dynamic Environments. *Robot. Comput.-Integr. Manuf.* **2025**, *94*, 102964. [[CrossRef](#)]
55. Silano, G.; Caballero, A.; Liuzza, D.; Iannelli, L.; Bogdan, S.; Saska, M. A Signal Temporal Logic Approach for Task-Based Coordination of Multi-Aerial Systems: A Wind Turbine Inspection Case Study. *Robot. Auton. Syst.* **2025**, *186*, 104905. [[CrossRef](#)]

56. Li, Z.; Wei, H.; Zhang, H.; Liu, C. A Variable Admittance Control Strategy for Stable and Compliant Human-Robot Physical Interaction. *IEEE Robot. Autom. Lett.* **2025**, *10*, 1138–1145. [[CrossRef](#)]
57. Cetin, S.G.; Goztepe, C.; Karabulut Kurt, G.; Yanikomeroglu, H. A Glimpse of Physical Layer Decision Mechanisms: Facts, Challenges, and Remedies. *IEEE Open J. Commun. Soc.* **2022**, *3*, 1280–1294. [[CrossRef](#)]
58. Li, C.; Nan, R.; Wei, Y.; Li, L.; Liang, J.; Li, N. Application Research of Vision-Guided Grinding Robot for Wheel Hub Castings. *Processes* **2025**, *13*, 238. [[CrossRef](#)]
59. Fan, J.; Yin, Y.; Wang, T.; Dong, W.; Zheng, P.; Wang, L. Vision-Language Model-Based Human-Robot Collaboration for Smart Manufacturing: A State-of-the-Art Survey. *Front. Eng. Manag.* **2025**. [[CrossRef](#)]
60. Belyakov, B.; Sizykh, D. Adaptive algorithm for selecting the optimal trading strategy based on reinforcement learning for managing a hedge fund. *IEEE Access* **2024**, *12*, 189047–189063. [[CrossRef](#)]
61. Shi, Y.; Xiao, X.; Han, Q.-L.; Jin, J.; Wen, S.; Xiang, Y. InforTest: Informer-Based Testing for Applications in the Internet of Robotic Things. *IEEE Trans. Ind. Inform.* **2025**, *21*, 1499–1507. [[CrossRef](#)]
62. Lăzăroiu, G.; Gedeon, T.; Valaskova, K.; Vrbka, J.; Šuleř, P.; Zvarikova, K.; Kramarova, K.; Rowland, Z.; Stehel, V.; Gajanova, L.; et al. Cognitive Digital Twin-Based Internet of Robotic Things, Multi-Sensory Extended Reality and Simulation Modeling Technologies, and Generative Artificial Intelligence and Cyber–Physical Manufacturing Systems in the Immersive Industrial Metaverse. *Equilib. Q. J. Econ. Econ. Policy* **2024**, *19*, 719–748. [[CrossRef](#)]
63. Yoshimura, K.; Yamauchi, Y.; Takahashi, H. Managing the Variability of a Logistics Robotic System. *J. Syst. Softw.* **2025**, *222*, 112328. [[CrossRef](#)]
64. Li, H.; Zhao, Z.; Yang, M.; Peng, Y.; Du, Z.; Sun, F. Yarn-Grouping Weaving Soft Robotics with Directional Inflation, Bilateral Bending, and Self-Sensing for Healthcare. *Cell Rep. Phys. Sci.* **2024**, *5*, 102137. [[CrossRef](#)]
65. Velastegui, R.; Poler, R.; Díaz-Madroñero, M. Revolutionising Industrial Operations: The Synergy of Multiagent Robotic Systems and Blockchain Technology in Operations Planning and Control. *Expert Syst. Appl.* **2025**, *269*, 126460. [[CrossRef](#)]
66. Rebelo, P.M.; Lima, J.; Soares, S.P.; Moura Oliveira, P.; Sobreira, H.; Costa, P. A Performance Comparison between Different Industrial Real-Time Indoor Localization Systems for Mobile Platforms. *Sensors* **2024**, *24*, 2095. [[CrossRef](#)]
67. Rana, A.; Petitti, A.; Ugenti, A.; Galati, R.; Reina, G.; Milella, A. Toward Digital Twin of Off-Road Vehicles Using Robot Simulation Frameworks. *IEEE Access* **2024**, *12*, 178047–178061. [[CrossRef](#)]
68. Urrea, C.; Agramonte, R. Improving Exoskeleton Functionality: Design and Comparative Evaluation of Control Techniques for Pneumatic Artificial Muscle Actuators in Lower Limb Rehabilitation and Work Tasks. *Processes* **2023**, *11*, 3278. [[CrossRef](#)]
69. Khanesar, M.A.; Yan, M.; Isa, M.; Piano, S.; Branson, D.T. Precision Denavit–Hartenberg Parameter Calibration for Industrial Robots Using a Laser Tracker System and Intelligent Optimization Approaches. *Sensors* **2023**, *23*, 5368. [[CrossRef](#)]
70. Ye, F.; Jia, G.; Wang, Y.; Chen, X.; Xi, J. Kinematic and Joint Compliance Modeling Method to Improve Position Accuracy of a Robotic Vision System. *Sensors* **2024**, *24*, 2559. [[CrossRef](#)]
71. Zheng, Y.; Liu, W.; Zhang, Y.; Han, L.; Li, J.; Lu, Y. Integration and Calibration of an In Situ Robotic Manufacturing System for High-Precision Machining of Large-Span Spacecraft Brackets with Associated Datum. *Robot. Comput.-Integr. Manuf.* **2025**, *94*, 102928. [[CrossRef](#)]
72. Huang, Q.; Zhang, X.; Pan, H.; Lu, K.; Cheng, Y. POE-Based Kinematic Calibration for Serial Robots Using Left-Invariant Error Representation and Decomposed Iterative Method. *Robot. Auton. Syst.* **2025**, *186*, 104896. [[CrossRef](#)]
73. Wei, H.; Jiao, J.; Hu, X.; Yu, J.; Xie, X.; Wu, J.; Zhu, Y.; Liu, Y.; Wang, L.; Liu, M. FusionPortableV2: A Unified Multi-Sensor Dataset for Generalized SLAM Across Diverse Platforms and Scalable Environments. *Int. J. Robot. Res.* **2024**. [[CrossRef](#)]
74. Hou, J.; Xing, S.; Ma, Y.; Jing, F.; Tan, M. Maximum Allowable TCF Calibration Error for Robotic Pose Servoing. *IEEE Robot. Autom. Lett.* **2025**, *10*, 1744–1751. [[CrossRef](#)]
75. Meng, F.; Wei, J.; Feng, Q.; Dong, Z.; Kang, R.; Guo, D.; Yang, J. A Robot Error Prediction and Compensation Method Using Joint Weights Optimization Within Configuration Space. *Appl. Sci.* **2024**, *14*, 11682. [[CrossRef](#)]
76. Li, B.; Wang, P.; Li, Y.; Tian, W.; Liao, W. Neural-Network-Based Trajectory Error Compensation for Industrial Robots with Milling Force Disturbance. *Int. J. Comput. Integr. Manuf.* **2024**. [[CrossRef](#)]
77. Cui, S.; Wang, Y.; Li, J.; Zhang, X.; Liu, Z.; Chen, H.; Zhou, F. GelStereo BioTip: Self-Calibrating Bionic Fingertip Visuotactile Sensor for Robotic Manipulation. *IEEE/ASME Trans. Mechatron.* **2024**, *29*, 2451–2462. [[CrossRef](#)]
78. Nahrendra, I.M.A.; Oh, M.; Yu, B.; Myung, H. TRG-Planner: Traversal Risk Graph-Based Path Planning in Unstructured Environments for Safe and Efficient Navigation. *IEEE Robot. Autom. Lett.* **2025**, *10*, 1736–1743. [[CrossRef](#)]
79. Wu, L.; Wang, C.; Liu, J.; Zou, B.; Chakrabarty, S.; Bao, T.; Xie, S.Q. Novel Design on Knee Exoskeleton with Compliant Actuator for Post-Stroke Rehabilitation. *Sensors* **2025**, *25*, 153. [[CrossRef](#)]
80. Ramadan, M.; Youssef, A.; Ayyad, A.; AbuAssi, L.; Hay, O.A.; Salah, M.; Moyo, B.; Zweiri, Y.; Abdulrahman, Y. Vision-Guided Robotic System for Aero-Engine Inspection and Dynamic Balancing. *Sci. Rep.* **2024**, *14*, 30742. [[CrossRef](#)]
81. Kim, Y.; Shin, J.; Won, J.; Lee, W.; Seo, T. LBH Gripper: Linkage-Belt Based Hybrid Adaptive Gripper Design for Dish Collecting Robots. *Robot. Auton. Syst.* **2025**, *185*, 104886. [[CrossRef](#)]

82. Mehak, S.; Ramos, I.F.; Sagar, K.; Ramasubramanian, A.; Kelleher, J.D.; Guilfoyle, M.; Gianini, G.; Damiani, E.; Leva, M.C. A Roadmap for Improving Data Quality through Standards for Collaborative Intelligence in Human-Robot Applications. *Front. Robot. AI* **2024**, *11*, 1434351. [CrossRef]
83. Salvato, E.; Blanchini, F.; Fenu, G.; Giordano, G.; Pellegrino, F.A. Model-Free Kinematic Control for Robotic Systems. *Automatica* **2025**, *173*, 112030. [CrossRef]
84. Turcato, C.R.P.; Pedroso, B.; Arnold, M.; Picinin, C.T. Adapting to Industry 4.0 in France: Essential Competencies for a Future-Ready Workforce. *Adm. Sci.* **2024**, *14*, 322. [CrossRef]
85. Wu, F.; Zhu, R.; Meng, F.; Qiu, J.; Yang, X.; Li, J.; Zou, X. An Enhanced Cycle Generative Adversarial Network Approach for Nighttime Pineapple Detection of Automated Harvesting Robots. *Agronomy* **2024**, *14*, 3002. [CrossRef]
86. Li, D.; Zhang, H.; Liu, N.; Wang, G. Multiscale Residual and Attention Guidance for Low-Light Image Enhancement in Visual SLAM. *IEEE Internet Things J.* **2024**, *11*, 38370–38379. [CrossRef]
87. Arroyabe, M.F.; Arranz, C.F.A.; Fernandez de Arroyabe, I.; Fernandez de Arroyabe, J.C. The Effect of IT Security Issues on the Implementation of Industry 4.0 in SMEs: Barriers and Challenges. *Technol. Forecast. Soc. Change* **2024**, *199*, 123051. [CrossRef]
88. Khan, M.I.; Yasmeen, T.; Khan, M.; Ul Hadi, N.; Asif, M.; Farooq, M.; Al-Ghamdi, S.G. Integrating Industry 4.0 for Enhanced Sustainability: Pathways and Prospects. *Sustain. Prod. Consum.* **2025**, *54*, 149–189. [CrossRef]
89. Vorndamme, J.; Melone, A.; Kirschner, R.; Figueredo, L.; Haddadin, S. Safe Robot Reflexes: A Taxonomy-Based Decision and Modulation Framework. *IEEE Trans. Robot.* **2025**, *41*, 982–1001. [CrossRef]
90. Ali, S.; Deiab, I.; Pervaiz, S. State-of-the-Art Review on Fused Deposition Modeling (FDM) for 3D Printing of Polymer Blends and Composites: Innovations, Challenges, and Applications. *Int. J. Adv. Manuf. Technol.* **2024**, *135*, 5085–5113. [CrossRef]
91. Nuccio, M.; Guerzoni, M.; Cappelli, R.; Geuna, A. The diffusion of industrial robots in Europe: Regional or country effect? *Sci. Public Policy* **2025**, *52*, 65–80. [CrossRef]
92. Sun, M.; Ding, J.; Zhao, Z.; Chen, J.; Huang, G.Q.; Wang, L. Out-of-order execution enabled deep reinforcement learning for dynamic additive manufacturing scheduling. *Robot. Comput. -Integr. Manuf.* **2025**, *91*, 102841. [CrossRef]
93. Dai, Y.; Kim, D.; Lee, K. An advanced approach to object detection and tracking in robotics and autonomous vehicles using YOLOv8 and LiDAR data fusion. *Electronics* **2024**, *13*, 2250. [CrossRef]
94. Ciccarelli, M.; Forlini, M.; Papetti, A.; Palmieri, G.; Germani, M. Advancing human–robot collaboration in handcrafted manufacturing: Cobot-assisted polishing design boosted by virtual reality and human-in-the-loop. *Int. J. Adv. Manuf. Technol.* **2024**, *132*, 4489–4504. [CrossRef]
95. Halwani, M.; Ayyad, A.; AbuAssi, L.; Abdulrahman, Y.; Almaskari, F.; Hassanin, H.; Abusafieh, A.; Zweiri, Y. A novel vision-based multi-functional sensor for normality and position measurements in precise robotic manufacturing. *Precis. Eng.* **2024**, *88*, 367–381. [CrossRef]
96. Rakholia, R.; Suárez-Cetrulo, A.L.; Singh, M.; Simón Carbajo, R. Advancing manufacturing through artificial intelligence: Current landscape, perspectives, best practices, challenges, and future direction. *IEEE Access* **2024**, *12*, 131621–131637. [CrossRef]
97. Fresnillo, P.M.; Vasudevan, S.; Perez Garcia, J.A.; Martinez Lastra, J.L. An open and reconfigurable user interface to manage complex ROS-based robotic systems. *IEEE Access* **2024**, *12*, 114601–114617. [CrossRef]
98. Makulavičius, M.; Petkevičius, S.; Rožénė, J.; Dzedzickis, A.; Bučinskas, V. Industrial Robots in Mechanical Machining: Perspectives and Limitations. *Robotics* **2023**, *12*, 160. [CrossRef]
99. Cotta, W.A.A.; Lopes, S.I.; Vassallo, R.F. Towards the Cognitive Factory in Industry 5.0: From Concept to Implementation. *Smart Cities* **2023**, *6*, 1901–1921. [CrossRef]
100. Amadio, F.; Delgado-Guerrero, J.A.; Colomé, A.; Torras, C. Controlled Gaussian process dynamical models with application to robotic cloth manipulation. *Int. J. Dyn. Control* **2023**, *11*, 3209–3219. [CrossRef]
101. Yadav, A.; Yadav, N.; Wu, Y.; Ramakrishna, S.; Hongyu, Z. Wearable strain sensors: State-of-the-art and future applications. *Mater. Adv.* **2023**, *4*, 1444–1459. [CrossRef]
102. Lorenzini, M.; Lagomarsino, M.; Fortini, L.; Gholami, S.; Ajoudani, A. Ergonomic human–robot collaboration in industry: A review. *Front. Robot. AI* **2023**, *9*, 813907. [CrossRef]
103. Tourani, A.; Bavle, H.; Sanchez-Lopez, J.L.; Voos, H. Visual SLAM: What Are the Current Trends and What to Expect? *Sensors* **2022**, *22*, 9297. [CrossRef] [PubMed]
104. Coelho, D.A. Sustainable Design and Management of Industrial Systems—A Human Factors Perspective. *Appl. Syst. Innov.* **2022**, *5*, 95. [CrossRef]
105. Arnarson, H.; Mahdi, H.; Solvang, B.; Bremsdal, B.A. Towards automatic configuration and programming of a manufacturing cell. *J. Manuf. Syst.* **2022**, *64*, 225–235. [CrossRef]
106. Xue, B.; Xu, H.; Huang, X.; Zhu, K.; Xu, Z.; Pei, H. Similarity-based prediction method for machinery remaining useful life: A review. *Int. J. Adv. Manuf. Technol.* **2022**, *121*, 1501–1531. [CrossRef]
107. Yu, Y.-H.; Zhang, Y.-T. Collision avoidance and path planning for industrial manipulator using slice-based heuristic fast marching tree. *Robot. Comput.-Integr. Manuf.* **2022**, *75*, 102289. [CrossRef]

108. Ha, S.; Park, J.-S.; Jeong, S.W. Let me shop alone: Consumers' psychological reactance toward retail robotics. *Technol. Forecast. Soc. Change* **2025**, *212*, 123962. [[CrossRef](#)]
109. Cao, G.; Zhang, B.; Li, Y.; Wang, Z.; Diao, Z.; Zhu, Q.; Liang, Z. Environmental mapping and path planning for robots in orchard based on traversability analysis, improved LeGO-LOAM and RRT* algorithms. *Comput. Electron. Agric.* **2025**, *230*, 109889. [[CrossRef](#)]
110. Zhang, M.; Zhang, Z.; Ren, X. A constrained workspace entrance crossing motion generation scheme synthesized by recurrent neural networks for redundant robot manipulators. *IEEE/ASME Trans. Mechatron.* **2024**. [[CrossRef](#)]
111. Urrea, C.; Kern, J.; Torres, V. Design, Simulation, and Comparison of Advanced Control Strategies for a 3-Degree-of-Freedom Robot. *Appl. Sci.* **2024**, *14*, 11010. [[CrossRef](#)]
112. D'Angelo, S.; Selvaggio, M.; Lippiello, V.; Ruggiero, F. Semi-autonomous unmanned aerial manipulator teleoperation for push-and-slide inspection using parallel force/vision control. *Robot. Auton. Syst.* **2025**, *186*, 104912. [[CrossRef](#)]
113. Ma, W.; Duan, A.; Lee, H.-Y.; Zheng, P.; Navarro-Alarcon, D. Human-aware reactive task planning of sequential robotic manipulation tasks. *IEEE Trans. Ind. Inform.* **2024**. [[CrossRef](#)]
114. Schorr, L.; Cobilean, V.; Mavikumbure, H.S.; Manic, M.; Hadimani, R.L. Industrial workspace detection of a robotic arm using combined 2D and 3D vision processing. *Int. J. Adv. Manuf. Technol.* **2025**, *136*, 1317–1326. [[CrossRef](#)]
115. Berx, N.; Decré, W.; De Schutter, J.; Pintelon, L. A harmonious synergy between robotic performance and well-being in human-robot collaboration: A vision and key recommendations. *Annu. Rev. Control* **2025**, *59*, 100984. [[CrossRef](#)]
116. Bilal, H.; Obaidat, M.S.; Aslam, M.S.; Zhang, J.; Yin, B.; Mahmood, K. Online fault diagnosis of industrial robot using IoT and hybrid deep learning techniques: An experimental approach. *IEEE Internet Things J.* **2024**, *11*, 31422–31437. [[CrossRef](#)]
117. Li, S.; Xie, H.-L.; Zheng, P.; Wang, L. Industrial Metaverse: A proactive human-robot collaboration perspective. *J. Manuf. Syst.* **2024**, *76*, 314–319. [[CrossRef](#)]
118. Slavković, N.; Živanović, S.; Dimić, Z.; Kokotović, B. An advanced machining robot flexible programming methodology supported by verification in a virtual environment. *Int. J. Comput. Integr. Manuf.* **2024**. [[CrossRef](#)]
119. Villani, V.; Picone, M.; Mamei, M.; Sabattini, L. A digital twin driven human-centric ecosystem for Industry 5.0. *IEEE Trans. Autom. Sci. Eng.* **2024**. [[CrossRef](#)]
120. Bonci, A.; Gaudeni, F.; Giannini, M.C.; Longhi, S. Robot Operating System 2 (ROS2)-Based Frameworks for Increasing Robot Autonomy: A Survey. *Appl. Sci.* **2023**, *13*, 12796. [[CrossRef](#)]
121. Mahdi, M.M.; Bajestani, M.S.; Noh, S.D.; Kim, D.B. Digital twin-based architecture for wire arc additive manufacturing using OPC UA. *Robot. Comput.-Integr. Manuf.* **2025**, *94*, 102944. [[CrossRef](#)]
122. Dornelles, J.A.; Ayala, N.F.; Frank, A.G. Collaborative or substitutive robots? Effects on workers' skills in manufacturing activities. *Int. J. Prod. Res.* **2023**, *61*, 7922–7955. [[CrossRef](#)]
123. Li, L.; Li, J.; Liu, R.; Li, Z. Overview of blockchain-based terminal-edge-cloud collaborative computing paradigm. *Comput. Electron. Eng.* **2024**, *120*, 109737. [[CrossRef](#)]
124. Xia, C.; Wang, R.; Jin, X.; Xu, C.; Li, D.; Zeng, P. Deterministic network–computation–manufacturing interaction mechanism for AI-driven cyber–physical production systems. *IEEE Internet Things J.* **2024**, *11*, 18852–18868. [[CrossRef](#)]

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