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# AI-empowered intelligence in industrial robotics: technologies, challenges, and emerging trends

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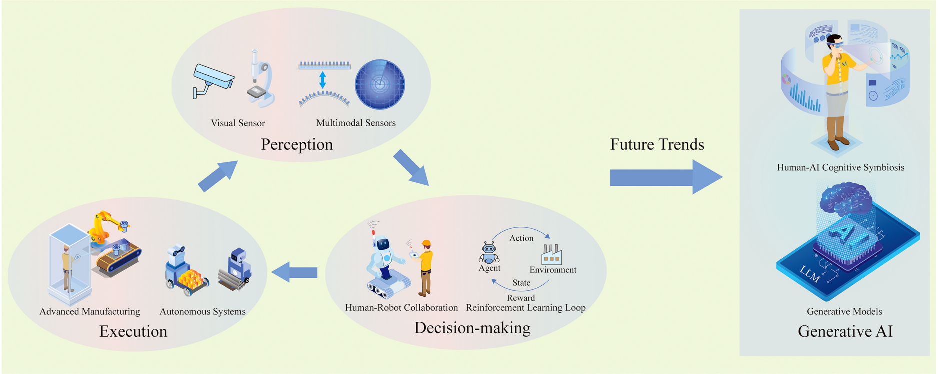

## Abstract

Artificial intelligence (AI) is profoundly reshaping the technological framework of industrial robotics, driving its transition from pre-programmed automation to autonomous, adaptive agents. This paper systematically reviews the key advancements of AI across three core dimensions of intelligence: perception, decision-making, and execution. Analysis indicates that AI is propelling industrial robots from tools executing predefined tasks towards intelligent partners capable of adapting to unstructured environments, autonomously planning amid dynamic changes, and engaging in nuanced interactions with the physical world. This evolution reveals a shift from optimizing specific skills towards developing rudimentary task-level cognitive reasoning capabilities. Nevertheless, fundamental challenges persist for industrial-scale deployment, including model generalization capabilities, long-term robustness, and human-machine trust. Collectively, these advancements are shaping a new generation of intelligent industrial robotic systems that are more adaptable and capable of deeper collaboration with humans.

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## 1. INTRODUCTION

Driven by Industry 4.0, global manufacturing is undergoing a profound transformation. This shift is from mass production to mass customization and high-mix, low-volume (HMLV) production models[1-3]. Industrial robots, as the core of traditional automation, were initially designed to execute repetitive tasks with high precision. This was intended for highly structured and predictable environments[4]. However, this inherent rigidity, optimized for scaled production, fundamentally contradicts the needs of modern manufacturing. These needs include operational flexibility, environmental adaptability, and rapid task switching. Bridging this gap, by evolving industrial robots from static tools into intelligent partners, is a core challenge in smart manufacturing[5,6].

Artificial intelligence (AI) provides the key technology to resolve this contradiction, fundamentally reshaping the core capabilities of industrial robots[7-9]. At the perception level, AI-driven vision systems are endowing robots with the ability to perform precise recognition and state understanding within unstructured environments[10-13]. At the decision-making level, AI-based adaptive strategies replace fixed algorithms, enabling robots to autonomously plan tasks and movements within dynamically changing environments[14-17]. At the execution level, AI employs learning-based control to endow robots with the dexterity to handle complex physical interactions, such as applying precise, adaptive forces during precision assembly[18-21].

Although multiple reviews have explored the intersection of AI and robotics, they provide a valuable foundation for understanding specific technologies. For example, Katona *et al.* systematically review the development of mobile robot obstacle avoidance and path planning[22]. This ranges from graph search algorithms to deep reinforcement learning (DRL). Ušinskis *et al.* focus on sensor fusion strategies for local perception and localization in complex environments[23]. Eren *et al.* highlight the value of AI in improving the precision of intelligent welding execution[24]. On the other hand, Fu *et al.* discuss intelligent coordination mechanisms for collaborative robots in human-robot interaction scenarios[25]. These studies review the application of AI in industrial robots from perspectives such as task type, robot category, or single AI technology. However, most of these studies primarily focus on specific tasks or isolated technologies. They often fail to closely link AI advancements with solving concrete, systemic industrial challenges. Therefore, a review systematically analyzing the synergistic evolution of AI in robot perception, decision-making, and execution, driven by industrial challenges, remains a critical research gap.

To address this, this paper systematically reviews key advancements in AI. These advancements are in shaping the core capabilities of industrial robots. Figure 1 illustrates the overall evolution of AI technologies across three levels: perception, decision-making, and execution in industrial robots. Section 2 delves into perception intelligence. It focuses on how AI addresses challenges such as unstructured object recognition and high-precision quality control (QC). Section 3 examines decision-making intelligence. It traces its evolution from rigid programming to AI-adaptive strategies. Section 4 investigates execution intelligence. It analyzes how AI enables delicate operations required for complex assembly. Section 5 systematically analyzes the fundamental challenges facing this field. Based on this, it then discusses future research directions. Section 6 concludes the entire paper.

## 2. PERCEPTUAL INTELLIGENCE

Perception intelligence is fundamental for industrial robots to interact with the physical world. It determines whether robots can operate effectively in complex and variable industrial environments[26]. Traditionally, robot perception capabilities were limited to highly structured scenarios. They struggled to cope with visual ambiguities caused by changes in lighting, object occlusion, and unstructured stacking[27,28]. To overcome these limitations, an important approach is to leverage AI technology. This transforms robots from passive

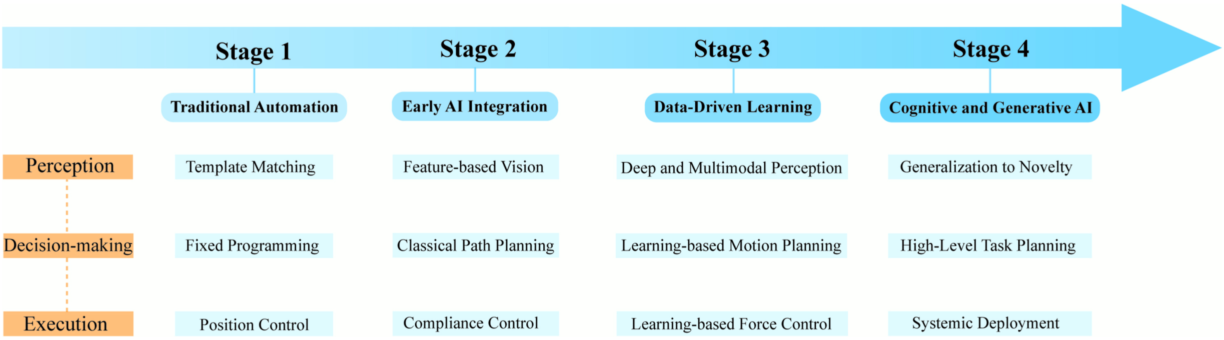

**Figure 1.** The technological evolution framework of AI in industrial robotics. AI: Artificial intelligence.

**Table 1. Research on AI-empowered perceptual intelligence for industrial robots**

| Ref. | Test platform | Baseline comparison | Key performance metric | Core capability |
|---|---|---|---|---|
| Wu *et al.*[29] | Aubo-i5 robot | Bidirectional RRT$^*$ | mAP: 99.5%; final success: 99.83% | High-precision construction tasks |
| Nguyen *et al.*[30] | Doosan robot | Low-cost 3D vision systems | Throughput: 220-250 items/hour; accuracy: 94% | High-speed adaptation |
| Wei *et al.*[31] | UR5 robot | GSNet (SOTA) | AP: 50.08% (+4.91%); success rate: 89.60% | Grasping visible objects |
| Huang *et al.*[32] | Hiwin robot | Grasp-only (VPG) | Success rate: 81.4%; training steps: -65% | Active scene manipulation before grasping |
| Wang *et al.*[33] | PAUT platform | ResNet152, GoogleNet | Accuracy: 99.3%; params: -75% | Volumetric non-destructive QC |
| Hassan *et al.*[34] | UR5 robot | Standard YOLO models | mAP: 97.49%; recall: 98.45% | Real-time multi-class identification |
| Zhou *et al.*[35] | UR3e robot | CNN-based methods | Recall: 94.95%; precision gain: 1.51 times | Annotation-free inspection |
| Rocha *et al.*[36] | ROSI robot | Human inspection | Accuracy: > 90% (thermal), 95% (acoustic) | Perception in degraded vision |
| Wong *et al.*[37] | ABB 6660 robot | Tool-based inspection | Classification accuracy: 100%; latency: 4 ms | In-process wear sensing |
| Chew *et al.*[38] | CSAM platform | RANSAC-based registration | RMS error: < 1 mm; frame rate: ~30 Hz | In-process geometric monitoring |
| Ni *et al.*[39] | Milling robot | No compensation | MAE and RMSE reduction: ~90% | Predictive QC |
| Chen and Lai[40] | Simulation | Baseline ZSL methods | MIoU improvement: > 5% | Adaptation to unseen objects |

AI: Artificial intelligence; RRT$^*$: rapidly-exploring random tree star; mAP: mean average precision; SOTA: state-of-the-art; AP: average precision; VPG: visual pushing for grasping; PAUT: phased array ultrasonic technology; QC: quality control; YOLO: You Only Look Once; CNN: convolutional neural network; ROSI: robot operating system inspection; CSAM: cold spray additive manufacturing; RANSAC: random sample consensus; RMS: root mean square; MAE: mean absolute error; RMSE: root mean square error; ZSL: zero-shot learning; MIoU: mean intersection over union.

sensor data collectors into active environment interpreters. Table 1 summarizes representative research in this domain.

## 2.1. Dexterous manipulation: grasping in clutter

A long-standing challenge in industrial automation is "Bin Picking". This involves robots grasping objects from containers filled with cluttered, randomly oriented items[41,42]. Traditional industrial robots typically perform highly structured tasks from fixed fixtures. This is due to a lack of sophisticated perception capabilities to handle occlusion and pose uncertainty. Therefore, empowering robots with visual autonomy in unstructured scenarios is a core problem[43]. Therefore, enabling robots to achieve visual autonomy in unstructured environments represents the core challenge in expanding their industrial applications.

Integrating AI-powered vision systems has become a primary driver for overcoming this limitation. It transforms industrial robots from pre-programmed automated equipment into adaptive executors. By equipping robots with Red-Green-Blue-Depth (RGB-D) sensors and deep learning (DL) models, they gain a fundamental ability. This ability is to identify objects and estimate their graspable positions in cluttered bins[44,45]. This method has proven effective in various industrial sectors. In construction automation, Wu *et al.* used the You Only Look Once version 5 (YOLOv5) model[29]. They addressed the high-precision localization and placement of embedded parts in precast concrete components. In high-throughput logistics sorting, Nguyen *et al.* employed You Only Look Once version 7 (YOLOv7) and combined it with generative adversarial networks (GANs) to synthesize training data, thereby enhancing the robot's adaptability to novel items[30].

To achieve more precise manipulation, AI models enable robots to evolve from simple object localization to full 3D spatial pose understanding. For scenarios with complex stacking or severe occlusion, Wei *et al.* constructed a multi-stage DL model that integrates a graspability estimation module, point feature aggregation, and six degrees of freedom (6-DoF) parameter prediction[31]. This model enables the stable and efficient generation of grasp strategies for robotic manipulation. Besides precision, operational efficiency is also a critical requirement in industrial environments. Song *et al.* developed a hierarchical fusion network that enables robots to complete the entire cycle from perception to prediction with real-time performance, a critical factor in maintaining production throughput[46]. This level of performance also extends to tasks requiring high-precision handling of minute components, such as the assembly of electronic components[47].

Beyond optimizing single grasping actions, AI is also enabling robots to learn multi-stage manipulation strategies. Huang *et al.* proposed a cooperative push-and-grasp method that combines image masking with DRL[32]. This method allows the robot to actively sort through disordered piles to isolate target objects, subsequently performing stable industrial grasping tasks.

## 2.2. Automated inspection: defect detection

Industrial robots are increasingly being employed as automated inspection platforms within QC processes[48,49]. However, significant challenges remain, including reliably identifying diverse and often microscopic surface defects[35], alongside addressing uncertainties arising from variations in products, lighting conditions, and background textures[50]. Such issues often lead to missed defects or elevated false-alarm rates, thereby limiting the reliability of automated inspection.

Under supervised learning (SL), robots can be trained for precise defect localization. For instance, Wang *et al.* developed a lightweight 3D-convolutional neural networks (3DCNN) architecture enabling robots to accurately classify multiple internal welding defects[33]. While achieving high classification accuracy, the model possesses significantly fewer parameters than traditional 3D models, rendering it suitable for deployment on edge devices. Similarly, in the surface inspection of composite materials, a hybrid model combining convolutional neural network (CNN) and support vector machine was used. This allowed robots to perform highly accurate online assessments of drilling quality[48].

The application of SL in QC has expanded to more diverse industries. In the traditionally labor-intensive textile industry, Hassan *et al.* employed an enhanced deep CNN [You Only Look Once version 8 nano (YOLOv8n)] to enable robots to identify up to 13 distinct fabric defects in real time[34]. This approach significantly enhanced detection performance while maintaining both real-time capability and operational safety. Similarly, within the automotive supply chain, Cheng *et al.* developed a system integrating 3D vision with DL, enabling robots to autonomously scan tire sidewalls[51]. This achieves exceptionally precise detection of minute embossed text anomalies on multi-specification tires without requiring computer aided design (CAD) models.

However, SL relies heavily on large volumes of labeled data. Consequently, model-driven and unsupervised learning approaches are addressing the issue of insufficient samples in industrial settings. Zhou *et al.* developed the robotic camera (RoboCam) system[35]. It integrates CAD model rendering, dual-domain pose error tuning, and visual comparison techniques, achieving the first high-precision robotic automatic detection of micro-mesh defects under unsupervised conditions. Moreover, lightweight and efficient AI models are crucial to meet real-time inspection demands on production lines. For dynamic quality sorting tasks, Lin *et al.* integrated a lightweight You Only Look Once version 4 (YOLOv4)-tiny model with a cascaded neural network onto a six-axis robot[52]. This system enables robots to perform multi-stage visual tasks in real time, demonstrating the potential of computationally efficient models within complex industrial inspection workflows.

### 2.3. Robust perception: multimodal fusion

In many industrial environments, factors such as smoke, dust, or strong light severely affect the performance of visual systems[36]. This makes single visual perception a critical point of failure. To address this challenge, researchers are employing multimodal fusion techniques. By intelligently combining data from diverse sensor types, these approaches enable robots to maintain reliable environmental awareness even under visually constrained conditions[53].

For equipment condition monitoring in extremely harsh environments such as mining sites, Rocha *et al.* developed the robot operating system inspection (ROSI) inspection robot system integrating multiple sensors, including vision, acoustics, and thermal imaging[36]. By employing algorithms such as CNN and random forests for multi-source data analysis, the system achieves reliable detection and assessment of various failure modes in critical equipment components[36].

Furthermore, researchers are exploring the integration of visual data with other physical signals for process monitoring and control. For instance, in robotic grinding operations, the condition of abrasive belts constitutes a critical quality-determining parameter. Research by Surindra *et al.* demonstrates that robots can precisely monitor belt wear by fusing data from accelerometers and force sensors[37]. Utilizing machine learning (ML) models such as decision trees and random forests, this approach achieves high-accuracy, low-latency multimodal wear recognition, providing valuable insights for intelligent industrial maintenance[37].

Multimodal perception is also extensively applied to enhance the naturalness and efficiency of human-robot collaboration in industrial settings. Effective collaboration demands that robots comprehend a range of human commands and physical cues, evolving from basic emergency stop functions to a more nuanced understanding of operator intent[54]. To this end, integrating multiple modalities such as speech and vision is considered a key technological pathway towards achieving this objective. For example, Mendez *et al.* developed a collaborative assembly system integrating three independent CNN models, each tasked with processing voice commands, tracking hand movements, or identifying components[55]. This multimodal approach enables operators to guide the robot through mechanical part assembly using natural language and gestures, achieving voice-controlled, contactless interaction within the collaborative assembly process.

In collaborative tasks involving substantial physical contact, a core challenge lies in managing inherent physical uncertainty, which has driven research into the fusion of vision with force/torque sensing. Bartyzel proposed a reinforcement learning (RL)-based multimodal variational deep Markov decision process (DeepMDP) approach for precision insertion tasks[56]. By learning dynamic representations through the fusion of visual and force/torque feedback, this method enables robots to perform precision assembly more robustly, enhancing the model’s generalization capabilities across varying background disturbances and object types.

## 2.4. In-process metrology: 3D modeling and measurement

The growing demand for *in-situ*, sub-millimeter precision measurement in precision manufacturing is driving the evolution of industrial robots from mere manipulator arms towards intelligent metrology platforms[57,58] As conventional offline inspection methods prove inefficient and unable to meet modern production rhythms, researchers are leveraging AI technologies to address this challenge by enhancing sensor accuracy, enabling dynamic process modeling, and optimizing measurement strategies[38].

To enhance the raw measurement accuracy of sensors, Yang *et al.* combined industrial 3D simulation, AI training, and multi-algorithm preprocessing to learn and correct sensor-specific error patterns[27]. This approach improved the positioning accuracy of time-of-flight cameras in industrial mobile robot vision inspection, facilitated robotic repositioning, and enhanced the stability and consistency of 3D visual inspection. This external vision-based measurement principle was also applied to the robot's own state assessment. Simoni *et al.* developed the double branch semi-perspective decoupled heatmaps (D-SPDH) system, which employs depth cameras and CNNs to perform high-frequency, high-precision 3D pose estimation of robotic arms without relying on internal encoders[59]. This provides a crucial capability for safe monitoring in industrial human-robot collaboration.

In the field of robotic machining, Ni *et al.* developed a digital twin-based system where ML models predict final contour errors based on the numerical control (NC) code trajectory generated by robotic planning[39]. This enables pre-compensation of the path, significantly reducing machining errors. Such predictive analysis complements real-time feedback monitoring during the process. Chew *et al.* proposed a real-time 4D reconstruction system that employs multi-camera fusion technology to achieve object tracking and high-precision modelling in dynamic environments, providing robust support for online quality monitoring[38].

The role of industrial robots has expanded beyond passively executing measurement tasks to actively planning and optimizing measurement strategies themselves. Li *et al.* proposed the 3D scanning coverage prediction framework 3D scanning coverage prediction (3DSCP)-Net, which predicts the coverage of a structured light scanner on a workpiece prior to actual scanning, enabling efficient viewpoint planning[57]. Furthermore, Roos-Hoefgeest *et al.* proposed an end-to-end surface scanning trajectory optimization method incorporating the proximal policy optimization (PPO) algorithm[58]. This approach generates RL-driven transferable scanning paths based on CAD models for industrial contour measurement tasks, enabling high-quality surface acquisition.

## 2.5. Adaptive learning: generalization to novelty

Under the flexible manufacturing model of HMLV, traditional SL incurs high costs and time due to the frequent introduction of new products requiring extensive data collection, annotation, and model retraining[60]. Consequently, enabling industrial robots to rapidly generalize to new objects and tasks with minimal data represents a critical research challenge for achieving agile manufacturing.

To mitigate reliance on real-world data, researchers have turned to synthetic data generation techniques. Robots can be trained on large, automatically annotated virtual datasets rather than solely depending on real-world images. Mangat *et al.* successfully trained a You Only Look Once version 3 (YOLOv3) model for a pick-and-place task using only synthetic images generated from 3D models[60].

**Table 2. AI-powered decision-making intelligence techniques for industrial robots**

| Ref. | Test platform | Baseline comparison | Key performance metric | Core capability |
|---|---|---|---|---|
| Wu *et al.*[65] | Franka panda and actual robot | Traditional DRL | Success rate: 78.8% | Reactive motion |
| Lindner and Milecki[66] | Mitsubishi RV-12SDL-12S | PRM algorithm | Path: -3%~10%; error: < 3.84 mm | Efficient and precise paths |
| Liu *et al.*[67] | ABB IRB 1200 robot | Standard DRL (DDPG, TD3) | Risk reduction: -28.7% | Intrinsically safe behavior |
| Honelign *et al.*[68] | Franka panda robot | PPO | Success rate: 0%-100% | Mastering high-DoF control |
| Ji *et al.*[69] | KUKA KR3 robot | Spiral search | Time reduction: 4-6 times | Adaptive contact manipulation |
| Men *et al.*[70] | UR5e robot | PPO and direct transfer | Success: +26%; force: -30 N | Cross-task knowledge transfer |
| Zhou and Lin[71] | 7-DoF Diana robot | SOTA HRL | Success: 91% (dual-task), 62% (triple-task) | Solving sparse reward tasks |
| Ghafarian Tamizi *et al.*[41] | UR5 and Kinova Gen3 robot | Bi-RRT | Time: -70% | Data-efficient learning |
| Koubaa *et al.*[72] | Multiple robots | LLaMA models | Human rating: 4.28/5 | Intuitive HRC interface |
| Gupta *et al.*[73] | KUKA arm | Planning w/o feedback | Success rate: 81.25% | Autonomous task decomposition |
| Faroni *et al.*[63] | UR5 robot | Feasibility-oriented planner | Idle time: -95%; HRC time: +74% | Synergistic HRC coordination |
| Hou *et al.*[74] | UR5e robot | DDQN and dueling DDQN | Success: 25%-100%; time: -28.2% | Optimized human-robot teaming |

AI: Artificial intelligence; DRL: deep reinforcement learning; PRM: probabilistic roadmap; DDPG: deep deterministic policy gradient; TD3: twin delayed deep deterministic policy gradient; PPO: proximal policy optimization; SOTA: state-of-the-art; HRL: hierarchical reinforcement learning; UOF: universal option framework; Bi-RRT: bidirectional rapidly-exploring random tree; LLaMA: large language and action model; HRC: human-robot collaboration; DDQN: double deep Q-network.

Beyond generating additional data, another research direction focuses on endowing models with inherent generalization capabilities. Gao *et al.* employed few-shot learning methods to achieve high-precision translational manipulation of novelly shaped objects under unknown friction conditions[61]. In increasingly prevalent open and dynamic industrial settings, robots frequently need to recognize and handle novel objects or categories unseen during training. Within visual systems research for assembly tasks, Chen and Lai proposed a zero-shot learning (ZSL) framework for semantic segmentation[40]. This enhances preprocessing efficiency for industrial robot operations in human-robot interaction scenarios, enabling efficient perception of unseen object categories within industrial human-robot interaction contexts.

## 3. DECISION-MAKING INTELLIGENCE

Effective decision-making constitutes the cognitive core that translates perception into purposeful action. However, traditional industrial robots possess limited decision-making capabilities, typically only executing pre-programmed fixed trajectories[62]. Consequently, a central challenge lies in evolving robotic decision-making from a static, offline process into a dynamic, online capability that achieves genuine operational autonomy. The primary focus centers on employing methods such as DRL and imitation learning (IL) to equip robots with the means to learn and adapt their behavior when confronting real-world complexities[63,64]. Table 2 summarizes recent research progress in this domain.

### 3.1. Reactive motion planning

Deploying robots within human-centric collaborative environments presents primary safety and efficiency challenges in enabling secure navigation around dynamic and unpredictable obstacles[67]. Conventional path planning algorithms are typically computationally intensive and operate offline, struggling to respond to sudden changes[75]. DRL offers a viable solution by training an end-to-end policy that directly maps real-time sensor inputs to underlying control commands, thereby achieving responsive and fluid motion[65].

Multiple studies have demonstrated the efficacy of DRL in endowing industrial robots with robust dynamic obstacle avoidance capabilities. Wu *et al.* developed a hybrid DRL model integrating the strengths of deep deterministic policy gradient (DDPG) and soft actor-critic (SAC) algorithms, enabling a robot to achieve high success rates in real-world tests involving moving obstacles[65]. Beyond validating dynamic obstacle avoidance efficacy, the study further examined the quality and efficiency of DRL-generated paths. Lindner and Milecki proposed a DRL-based obstacle avoidance algorithm integrating DDPG and hindsight experience replay[66]. This approach not only achieved sub-millimeter positioning accuracy but also generated paths shorter than traditional path planning and manipulation algorithms. Furthermore, it ensured robotic behavior appeared safe and predictable to human collaborators. To this end, DRL is being employed to learn strategies that actively minimize risk, rather than relying solely on hard-coded safety rules. Liu *et al.* introduced an "intrinsic reward" function into the DDPG algorithm, enabling dynamic adjustment of motion trajectories based on human arm positions[67]. This allows industrial robots to simultaneously satisfy safety requirements and task efficiency, significantly enhancing the robustness and generalizability of the strategy.

### 3.2. Contact-rich task planning

The complexity of industrial robot decision-making is particularly evident in task and motion planning problems, especially within precision assembly tasks involving physical contact and multi-step sequences[63].

Traditional programming approaches lack the flexibility to handle such uncertainties, while standard DRL often proves inefficient due to sparse reward issues[76-79]. Consequently, recent research has focused on methods such as IL, hierarchical reinforcement learning (HRL), and policy transfer, aiming to enhance robotic autonomy and dexterity in assembly tasks[41,71,80].

The foundation of complex assembly tasks lies in robotic solutions for precise positioning under high degree of freedom (DoF). Honelign *et al.* employed DDPG to train a seven-DoF robotic arm policy network, enabling autonomous planning and execution of end-effector movements from arbitrary initial states to target positions under continuous control[68]. This demonstrated the capability of DRL to master complex high-dimensional control without explicit kinematic modelling. This learning-based approach has also extended to optimizing underlying inverse kinematics (IK) solvers. Yu and Tan combined PPO with Damping Least Squares to enhance the accuracy and efficiency of IK solving for multiple industrial robots[81].

The complexity of tasks significantly increases when robots transition from free-space positioning to contact-rich physical interaction. For the classic "plug-in" assembly task, Ji *et al.* proposed a DRL approach integrated with a non-diagonal compliant controller, enabling the robot to learn how to continuously adjust its stiffness and modify its trajectory during insertion without switching between different control modes[69]. To enhance the generalizability of these learned skills, Men *et al.* proposed the policy fusion transfer algorithm, which enables robots to transfer acquired assembly knowledge to novel tasks by fusing source and target task policies[70]. This approach effectively enhances both generalization capability and safety in unfamiliar insertion scenarios.

Beyond task-level generalization, addressing complexity within individual tasks is equally crucial. Zhou and Lin employed the multiple goal-conditioned hierarchical learning framework to decompose complex operations into multiple subtasks[71]. Each subtask is learned by a unified policy network, with exploration guided by intermediate objectives to enhance convergence speed and robustness. This approach effectively resolves the training instability inherent in standard RL under sparse rewards. Complementing RL, IL circumvents RL's inefficient exploration by directly learning expert policies, offering a more data-efficient pathway for complex motion planning. The path planning and collision checking network framework proposed by Ghafarian Tamizi generates paths for disordered grasping by imitating expert planners, utilizing neural networks for rapid collision detection on each path segment[41]. This approach significantly reduces the planning time required by traditional sampling algorithms.

### 3.3. High-level strategic planning

The decision-making capabilities of industrial robots are evolving from fundamental motion control towards higher-level task planning and strategic coordination, particularly within the framework of human-robot collaboration[82,83]. A central challenge in this evolution is enabling robots to comprehend abstract, natural language instructions from human operators[68,73]. Another is empowering robots to engage in dynamic, efficient task allocation within human-robot teams[63,74].

The advent of large language models (LLMs) has opened new avenues for robots to directly interpret high-level human commands. The robot operating system generative pre-trained transformer (ROSGPT) framework developed by Koubaa *et al.* integrates generative pre-trained transformer (GPT)-4 with robot operating system 2 (ROS2), enabling efficient conversion from natural language to robotic control commands[72]. Moving beyond simple instruction translation, Gupta *et al.* proposed a novel robotic action contextualization framework combining LLMs with dynamical system (DS) controllers[73]. This allows robots to fine-tune action parameters and correct execution errors based on task contexts, thereby enhancing autonomy and adaptability. This capability has also extended to mobile platforms. Wang *et al.* employed GPT-3.5-turbo to generate Python code from natural language instructions, controlling automated guided vehicles to execute navigation tasks within an intelligent workshop[84]. By integrating semantic annotation with the Pathfinder algorithm for path planning and execution, they achieved natural human-machine interaction and multimodal intelligence fusion.

However, effectively applying these general LLMs in industrial environments requires addressing their lack of domain knowledge. To this end, Li *et al.* constructed the inaugural industrial robot Wizard-of-Oz dialoguing dataset (IRWoZ) dialogue dataset, specifically tailored for industrial tasks such as assembly and material handling[85,86]. This provides an indispensable foundation for fine-tuning and evaluating LLM capabilities within manufacturing-specific scenarios.

Beyond interpreting instructions, higher-level decision-making involves optimizing task allocation between robots and humans to maximize team efficiency and fluidity. Faroni *et al.* proposed the task and motion planning framework[63]. This framework dynamically plans and assigns assembly subtasks to humans and robots by integrating timeline task modelling with multi-objective action search, effectively enhancing the execution efficiency and robustness of multi-agent systems. Furthermore, RL has been applied to this challenge. For instance, Hou *et al.* developed a DRL-based model for mobile collaborative robots in automotive assembly scenarios[74]. This model decomposes tasks through a hierarchical task network and utilizes the revival double deep Q-network algorithm to optimize task allocation, achieving exceptionally high success rates and efficiency in complex final assembly tasks.

## 4. EXECUTION INTELLIGENCE

Although perception and decision-making constitute the cognitive core of intelligent robots, executive intelligence represents their capacity to translate digital instructions into precise, robust physical actions. Even with flawless planning, successful execution in the real world remains challenged by the complexity of physical interactions, such as friction, material compliance, and unexpected contact forces[87]. Furthermore, the inherent imprecision of robotic hardware[88] and stringent safety requirements for human-robot collaboration[89] necessitate dexterity and adaptability beyond classical control. Consequently, recent research focuses on enabling robots to learn complex control strategies through data-driven approaches, thereby bridging the gap between instructions and physical reality[90,91]. Relevant studies are summarized in Table 3.

**Table 3. AI-powered execution intelligence techniques for industrial robots**

| Ref. | Test platform | Baseline comparison | Key performance metric | Core capability contribution |
|---|---|---|---|---|
| Ma *et al.*[93] | UR robot | PPO, TD3, BC-SAC | Success: 93%; force: -91.7% | Low-force dexterous manipulation |
| Zhang *et al.*[94] | AUBO-i5 robot | Fixed admittance | Time: -9.6%; force: -26%~-45% | Adaptive compliance |
| Hu *et al.*[95] | UR10e robot | Manual tuning | Convergence: +33%; response: +44% | Rapid parameter tuning |
| Deng *et al.*[91] | KUKA iiwa | Data-driven NN | Torque accuracy: 97.1%; MSE: -72% | Interpretable dynamics learning |
| Shan and Pham[90] | Denso VS060 (industrial arm) | GMO (model-based) | Error reduction: -52% (H-guiding) | Low-cost force sensing and control |
| Zheyuan *et al.*[96] | HRC experiment | GTM, HAZOP | Team perf.: +8.2% | Predictive risk avoidance |
| Xin *et al.*[97] | UR10e and Franka Emika | 100% trust model | Fail. predict: 1.3%-79% | Confidence-aware safe action |
| Hickman *et al.*[98] | Grid World Sim | Gaussian process SRL | Reward: +41.7%; cost: -39.9% | Safety under data shift and outliers |
| Kana *et al.*[99] | KUKA iiwa | Gravity comp. mode | Chamfering error: < 0.1 mm | Virtual guidance for human operator |
| Amaya and Von Arnim[100] | KUKA iiwa | Policies w/o randomization | Success: 100% (on Loihi); latency: 1.8 ms | Zero-shot transfer via robustness |
| Mahdi *et al.*[101] | FANUC robot | Traditional monitoring | Defect detection AUC: 0.92 | System-level integration for QC |
| Li *et al.*[102] | UR5 and KUKA robot | On-site operation | Target hit rate: 98.7% | Human-in-the-loop cyber-physical system |
| Zhang *et al.*[103] | Fetch robot | SAC-NUR | Success rate: +20%-30% | Robust policy transfer |
| Zhang *et al.*[104] | UR10 robot | Direct transfer | Prediction accuracy: 94.1% | Zero-shot sim-to-real transfer |
| Liu *et al.*[105] | UR5 robot | Direct sim-to-real | Grasp success: 65.5%-79.5% | Fine-tuning bridge for policies |

AI: Artificial intelligence; PPO: proximal policy optimization; TD3: twin delayed deep deterministic policy gradient; BC-SAC: behavior cloning Soft Actor-Critic; NN: neural network; MSE: mean square error; GMO: generalized momentum observer; HRC: human-robot collaboration; GTM: Go-to-Market; HAZOP: hazard and operability study; SRL: safe reinforcement learning; AUC: area under curve; QC: quality control; NUR: no unified representation.

### 4.1. Dexterous manipulation: precision force control

A primary operational challenge for industrial robots lies in maintaining precise force control during contact-intensive tasks such as grinding, polishing, and precision component assembly[92]. Conventional position-controlled robots cannot respond compliantly to surface variations or contact forces, posing risks of damaging both workpieces and themselves. Meanwhile, classical force control methods often struggle to model complex contact dynamics accurately. To address this challenge, researchers have begun employing DRL to directly learn end-to-end force control strategies. Ma *et al.* proposed a robot flexible assembly strategy system based on SAC, achieving high-precision, low-contact-force autonomous assembly of flexible components such as flexible printed circuits under simulated real-world physical constraints[93].

In industrial practice, DRL is also employed to optimize mature classical controllers, enhancing their adaptive capabilities. For instance, addressing challenging assembly tasks such as inclined holes, Zhang *et al.* utilized the twin delayed DDPG algorithm to optimize the virtual damping parameters of a robotic admittance controller online[94]. This approach improved mating assembly precision while reducing contact forces. To further enhance controller responsiveness in unknown or rapidly changing environments, Hu *et al.* combined Gaussian processes with DDPG for optimizing admittance control parameters[95]. By introducing an initial strategy to accelerate the training process, they achieved rapid convergence and high robustness in force control for industrial robots operating within uncertain environments.

The foundation of force control applications relies upon an accurate understanding of the robot's dynamic model. By substituting analytical models with learned neural networks, robots can achieve more precise torque prediction. Deng *et al.* introduced an energy-to-neural network, embedding the structural form of the dynamic equations within the network itself[91]. This approach combines the interpretability of physical models with the flexibility of ML, enhancing the precision and robustness of robots in parameter identification and trajectory fitting.

Furthermore, research by Shan and Pham demonstrated that neural networks can learn to estimate external forces and torques directly from motor currents and joint states within the robot[90]. This breakthrough enables high-precision force control and sensitive manual guidance without any external force/torque sensors, significantly enhancing the autonomy and cost-effectiveness of industrial robots in precision manipulation scenarios.

### 4.2. Safe collaboration: risk management and fluent interaction

In human-robot collaboration, the challenges facing a robot's executive intelligence extend beyond physical collision avoidance in dynamic path planning[89]. A safe and effective collaborative system not only requires robots to avoid physical contact but must also ensure their behavior appears fluid and predictable to human collaborators, as hesitant or unstable movements undermine human-robot trust and diminish team efficiency[54]. Consequently, recent research focuses on developing robotic execution systems capable of actively assessing risks and autonomously learning safe interaction strategies from data[96-98].

In safe human-robot physical interactions, industrial robots must simultaneously address external interaction risks stemming from human behavior and internal errors within their own perception systems. To mitigate external risks, Zheyuan *et al.* proposed the advanced human-robot collaborative model for industrial collaborative settings[94]. This model predicts interaction risks based on human behavior and semantic scene graphs, adjusting action strategies to optimize team task completion. Furthermore, ensuring safe execution necessitates accounting for uncertainties within the robot's own perception systems. Xin *et al.* proposed a runtime compositional model verification framework[97]. This framework calculates trust metrics based on sensor data, updates state transition probabilities to predict system failure risks, thereby enabling runtime model verification and dynamic safety assurance.

To enable robots to autonomously learn safety policies from data, researchers are turning to safety-oriented RL (SRL). However, a core challenge for SRL in industrial applications lies in handling the common presence of outliers in data and the distribution shift between deployment environments and training data. Addressing this issue, Hickman *et al.* developed a SRL designed to learn policies that maximize task rewards while satisfying safety constraints[98]. By employing a student-t process instead of the standard Gaussian process, this framework better accommodates data anomalies during safety policy learning, thereby achieving a superior balance between task performance and safety constraints.

### 4.3. Robust deployment: sim-to-real transfer

Numerous studies have actively introduced uncertainty during the training phase to compel AI strategies to learn generalization capabilities insensitive to differences between virtual and real environments. A representative technique is domain randomization, which deliberately alters the physical and visual parameters of simulations throughout training. For instance, Amaya and Von Arnim randomized dynamic parameters such as friction within the simulation environment when training a spiking neural network controller for precision hole-punching tasks[100]. Strategies trained in this manner could be directly deployed onto physical robots controlled by Loihi neuromorphic chips without any real-world fine-tuning, while maintaining high success rates.

Beyond randomizing environments, unifying simulation and reality through "scene representation" proves equally effective. Zhang *et al.* proposed an end-to-end approach that avoids direct use of raw images, instead converting them into a unified 3D bounding box representation insensitive to object shape and appearance[103]. This significantly enhanced the transfer success rate of obstacle avoidance strategies. Furthermore, robustness can be bolstered by refining the learning algorithms themselves. Considering sensor noise as a primary cause of transfer failure, Wang *et al.* proposed the Density estimation-SAC algorithm[106]. This technique integrates density estimation into the DRL framework, enabling explicit modelling and adaptation to noisy measurements during training.

Complementary domain adaptation techniques explicitly aim to minimize feature-level discrepancies between simulated and real-world data. For instance, when investigating multimodal grasping stability assessment, Zhang *et al.* encountered the challenge of stark stylistic differences between simulated and real tactile images[104]. They employed a conditional GAN specifically trained to convert real tactile images into the simulated style. Following this processing, an evaluation network trained entirely on simulated data could directly process real tactile data from the physical world, achieving successful zero-shot transfer.

At the system level, high-fidelity digital twins are emerging as powerful system-level tools to bridge this gap. Rather than directly transferring strategies from general-purpose simulators to reality, an alternative approach involves utilizing digital twins as an intermediary layer. Liu *et al.* developed a transfer learning framework wherein grasping strategies pre-trained in simulation are first fine-tuned within a digital twin highly synchronized with the physical robot[105]. This enables final optimization of the strategy within an environment closer to reality, significantly enhancing its ultimate grasping success rate on the actual robot.

## 5. FUTURE DIRECTIONS

### 5.1. Learning and generalization

The generalization capability and data efficiency of existing AI models constitute the primary constraints limiting their adaptation to HMLV production patterns. Whilst paradigms such as meta-learning offer avenues for rapid task adaptation[107], strategy formulation under conditions of extremely sparse interactive data remains a core challenge in industrial settings. Future research must develop more robust self-SL frameworks to leverage vast amounts of unlabeled data in industrial environments for pre-training general-purpose world models. Moreover, as models grow increasingly large, efficient knowledge transfer from cloud-based large models to resource-constrained edge controllers emerges as a critical issue. Strategy distillation stands as one of the promising techniques in this field; however, establishing a mature theoretical framework remains necessary to address the issue of insufficient behavioral diversity and generalization in teacher models when strategy optimization is inadequate[108].

### 5.2. Robustness and reliability

The long-term robustness and self-maintenance capabilities of systems are pivotal for transitioning technology from laboratory to factory settings. Current research predominantly focuses on immediate success at the task level, with less attention given to performance degradation in robots during prolonged continuous operation due to mechanical wear or gradual environmental changes[109,110]. A significant future direction lies in developing robotic systems capable of proactive fault prediction, diagnosis, and autonomous recovery. Whilst initial explorations exist in online fault diagnosis, translating concepts such as reversible execution into robust, generalizable error recovery strategies feasible within the physical world holds substantial value for minimizing unplanned downtime on industrial production lines[111].

### 5.3. Cognition and interaction

Generative AI is providing novel technical pathways for long-standing challenges in robotics, such as high-level task planning and sparse perception data. At the perception level, researchers are employing models such as conditional GANs to address the simulation-to-reality domain gap. Examples include enhancing the transfer performance of perception models by learning style transfer between simulated and real tactile images[104], or directly generating kinematic solutions for robotic motions[112]. At the decision-making level, research centered on LLMs has begun exploring the autonomous decomposition of natural language instructions into robot-executable task sequences[72,73]. However, applying these technologies to industrial manufacturing, where safety and reliability demands are exceptionally high, still presents fundamental challenges. For LLMs, core issues requiring resolution in task planning include inference latency, lack of logical consistency, and insufficient understanding of physical world constraints. Regarding data generation, ensuring the fidelity and diversity of synthetic data to cover extreme conditions and long-tail problems in real industrial environments remains a key research topic requiring in-depth investigation. Consequently, future research will focus on establishing effective mechanisms to validate and constrain the outputs of generative models. It will also explore how generative models can be leveraged at scale to synthesize high-quality, diverse multimodal training data, thereby reducing the dependence of industrial AI applications on costly manual data collection and annotation.

## 6. CONCLUSION

This paper, driven by industrial challenges, provides a systematic review of how AI empowers industrial robots in perception, decision-making, and execution capabilities. The analysis focuses on how AI transforms robots from rigid tools on traditional automated production lines into intelligent partners capable of adapting to the dynamism and complexity of modern manufacturing. It examines the evolution and applied value of relevant AI technologies from the perspective of solving specific industrial problems.

Analysis indicates that AI applications are expanding the capabilities of industrial robots beyond optimizing predefined specific skills to handling more complex tasks that require rudimentary cognition and reasoning. At the perception level, robots no longer merely recognize known objects but are developing the capacity to generalize to unseen entities. At the decision-making level, robots are progressing from executing explicit commands to comprehending abstract natural language, decomposing complex tasks, and engaging in strategic coordination within human-robot teams. At the execution level, robots are learning to autonomously recover from errors and adapt online to dynamic changes in the physical world. This evolution from skill execution to task-level reasoning represents a core trend in the current AI-empowered industrial robotics domain.

These advances across perception, decision-making, and execution collectively form integrated robotic systems capable of navigating physical world uncertainties. Research focus is shifting from solving well-defined single tasks towards building system-level solutions that address process-level complexity, laying the groundwork for the next generation of more autonomous, adaptive industrial robots.

## DECLARATIONS

### Authors' contributions

Conceived the overall structure of the review: Chen, Y. (Yifan Chen); Ren, T.
Conducted the literature investigation and wrote the initial draft: Chen, Y. (Yifan Chen)
Contributed to data curation, analysis, and figure design: Li, Y.; Jiang, G.; Liu, Q.

Provided technical supervision and critical revisions throughout the writing process: Chen, Y. (Yonghua Chen); Yang, S. X.
Supervised the project, finalized the manuscript, and ensured overall coherence: Ren, T.
All authors reviewed and approved the final version of the manuscript.

## Availability of data and materials

Not applicable.

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## Conflicts of interest

Ren, T. is an Editorial Board Member of *Intelligence & Robotics*, and Yang, S. X. serves as the Editor-in-Chief. Neither was involved in any aspect of the editorial process for this manuscript, including reviewer selection, handling, or decision-making. The other authors declare no conflicts of interest.

## Ethical approval and consent to participate

Not applicable.

## Consent for publication

Not applicable.

## Copyright

## REFERENCES

1. Mo, F.; Rehman, H. U.; Monetti, F. M.; et al. A framework for manufacturing system reconfiguration and optimisation utilising digital twins and modular artificial intelligence. *Robot. Comput. Integr. Manuf.* **2023**, *82*, 102524. DOI
2. De Winter, J.; Ei Makrini, I.; Van de Perre, G.; Nowé, A.; Verstraten, T.; Vanderborght, B. Autonomous assembly planning of demonstrated skills with reinforcement learning in simulation. *Auton. Robot.* **2021**, *45*, 1097-110. DOI
3. Ibrahim, A.; Kumar, G. Selection of Industry 4.0 technologies for Lean Six Sigma integration using fuzzy DEMATEL approach. *Int. J. Lean. Six. Sigma.* **2024**, *15*, 1025-42. DOI
4. Zafar, M. H.; Langås, E. F.; Sanfilippo, F. Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: a state-of-the-art review. *Robot. Comput. Integr. Manuf.* **2024**, *89*, 102769. DOI
5. Soori, M.; Arezoo, B.; Dastres, R. Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cogn. Robot.* **2023**, *3*, 54-70. DOI
6. Hao, M.; Li, H.; Luo, X.; Xu, G.; Yang, H.; Liu, S. Efficient and privacy-enhanced federated learning for industrial artificial intelligence. *IEEE. Trans. Ind. Inf.* **2020**, *16*, 6532-42. DOI
7. Velazquez, L.; Palardy, G.; Barbalata, C. A robotic 3D printer for UV-curable thermosets: dimensionality prediction using a data-driven approach. *Int. J. Comput. Integr. Manuf.* **2024**, *37*, 772-89. DOI
8. Canas-Moreno, S.; Piñero-Fuentes, E.; Rios-Navarro, A.; Cascado-Caballero, D.; Perez-Peña, F.; Linares-Barranco, A. Towards neuromorphic FPGA-based infrastructures for a robotic arm. *Auton. Robot.* **2023**, *47*, 947-61. DOI
9. Intisar, M.; Monirujjaman Khan, M.; Rezaul Islam, M.; Masud, M. Computer vision based robotic arm controlled using interactive GUI. *Intell. Autom. Soft. Comput.* **2021**, *27*, 533-50. DOI
10. Cazacu, C.; Iorga, I.; Parpală, R. C.; Popa, C. L.; Coteț, C. E. Optimizing assembly in wiring boxes using API technology for digital twin. *Appl. Sci.* **2024**, *14*, 9483. DOI
11. Ardanza, A.; Moreno, A.; Segura, Á.; de la Cruz, M.; Aguinaga, D. Sustainable and flexible industrial human machine interfaces to support adaptable applications in the Industry 4.0 paradigm. *Int. J. Prod. Res.* **2019**, *57*, 4045-59. DOI
12. Tsai, Y.; Lee, C.; Liu, T.; et al. Utilization of a reinforcement learning algorithm for the accurate alignment of a robotic arm in a complete soft fabric shoe tongues automation process. *J. Manuf. Syst.* **2020**, *56*, 501-13. DOI

13. Jeong, J. H.; Shim, K. H.; Kim, D. J.; Lee, S. W. Brain-controlled robotic arm system based on multi-directional CNN-BiLSTM network using EEG signals. *IEEE. Trans. Neural. Syst. Rehabil. Eng.* **2020**, *28*, 1226-38. DOI PubMed
14. Liu, J.; Chen, X.; Yu, S. From junk to genius: robotic arms and AI crafting creative designs from scraps. *Buildings* **2024**, *14*, 4076. DOI
15. Liu, Q.; Ji, Z.; Xu, W.; Liu, Z.; Yao, B.; Zhou, Z. Knowledge-guided robot learning on compliance control for robotic assembly task with predictive model. *Expert. Syst. Appl.* **2023**, *234*, 121037. DOI
16. Cao, G.; Bai, J. Multi-agent deep reinforcement learning-based robotic arm assembly research. *PLoS. One.* **2025**, *20*, e0311550. DOI PubMed
17. Gao, T. Optimizing robotic arm control using deep Q-learning and artificial neural networks through demonstration-based methodologies: a case study of dynamic and static conditions. *Robot. Auton. Syst.* **2024**, *181*, 104771. DOI
18. Li, T.; Zeng, Q.; Li, J.; et al. An adaptive control method and learning strategy for ultrasound-guided puncture robot. *Electronics* **2024**, *13*, 580. DOI
19. Kumar, A.; Sharma, R. Linguistic Lyapunov reinforcement learning control for robotic manipulators. *Neurocomputing* **2018**, *272*, 84-95. DOI
20. Juarez-Lora, A.; Ponce-Ponce, V. H.; Sossa, H.; Rubio-Espino, E. R-STDP spiking neural network architecture for motion control on a changing friction joint robotic arm. *Front. Neurorobot.* **2022**, *16*, 904017. DOI PubMed PMC
21. Guo, C.; Luk, W. FPGA-accelerated sim-to-real control policy learning for robotic arms. *IEEE. Trans. Circuits. Syst. II.* **2024**, *71*, 1690-4. DOI
22. Katona, K.; Neamah, H. A.; Korondi, P. Obstacle avoidance and path planning methods for autonomous navigation of mobile robot. *Sensors* **2024**, *24*, 3573. DOI PubMed PMC
23. Ušinskis, V.; Nowicki, M.; Dzedzickis, A.; Bučinskas, V. Sensor-fusion based navigation for autonomous mobile robot. *Sensors* **2025**, *25*, 1248. DOI PubMed PMC
24. Eren, B.; Demir, M. H.; Mistikoglu, S. Recent developments in computer vision and artificial intelligence aided intelligent robotic welding applications. *Int. J. Adv. Manuf. Technol.* **2023**, *126*, 4763-809. DOI
25. Fu, J.; Rota, A.; Li, S.; et al. Recent advancements in augmented reality for robotic applications: a survey. *Actuators* **2023**, *12*, 323. DOI
26. Rho, E.; Kim, W.; Mun, J.; Yu, S. Y.; Cho, K.; Jo, S. Impact of physical parameters and vision data on deep learning-based grip force estimation for fluidic origami soft grippers. *IEEE. Robot. Autom. Lett.* **2024**, *9*, 2487-94. DOI
27. Yang, C.; Kang, J.; Eom, D. Enhancing ToF sensor precision using 3D models and simulation for vision inspection in industrial mobile robots. *Appl. Sci.* **2024**, *14*, 4595. DOI
28. Mena-Almonte, R. A.; Zulueta, E.; Etxeberria-Agiriano, I.; Fernandez-Gamiz, U. Efficient robot localization through deep learning-based natural fiduciary pattern recognition. *Mathematics* **2025**, *13*, 467. DOI
29. Wu, H.; Zhang, W.; Lu, W.; Chen, J.; Bao, J.; Liu, Y. Automated part placement for precast concrete component manufacturing: an intelligent robotic system using target detection and path planning. *J. Comput. Civ. Eng.* **2025**, *39*, 04024044. DOI
30. Nguyen, V.; Nguyen, P.; Su, S.; Tan, P. X.; Bui, T. Vision-based pick and place control system for industrial robots using an eye-in-hand camera. *IEEE. Access.* **2025**, *13*, 25127-40. DOI
31. Wei, D.; Cao, J.; Gu, Y. Robot grasp in cluttered scene using a multi-stage deep learning model. *IEEE. Robot. Autom. Lett.* **2024**, *9*, 6512-9. DOI
32. Huang, C.; Su, G.; Shao, Y.; Wang, Y.; Yang, S. Rapid-learning collaborative pushing and grasping via deep reinforcement learning and image masking. *Appl. Sci.* **2024**, *14*, 9018. DOI
33. Wang, S.; Zhang, E.; Zhou, L.; Han, Y.; Liu, W.; Hong, J. 3DWDC-Net: an improved 3DCNN with separable structure and global attention for weld internal defect classification based on phased array ultrasonic tomography images. *Mech. Syst. Signal. Process.* **2025**, *229*, 112564. DOI
34. Hassan, S. A.; Beliatis, M. J.; Radziwon, A.; Menciassi, A.; Oddo, C. M. Textile fabric defect detection using enhanced deep convolutional neural network with safe human–robot collaborative interaction. *Electronics* **2024**, *13*, 4314. DOI
35. Zhou, S.; Le, D. V.; Jiang, L.; et al. RoboCam: model-based robotic visual sensing for precise inspection of mesh screens. *ACM. Trans. Sens. Netw.* **2025**, *21*, 1-23. DOI
36. Rocha, F.; Garcia, G.; Pereira, R. F. S.; et al. ROSI: a robotic system for harsh outdoor industrial inspection - system design and applications. *J. Intell. Robot. Syst.* **2021**, *103*, 1459. DOI
37. Surindra, M. D.; Alfarisy, G. A. F.; Caesarendra, W.; et al. Use of machine learning models in condition monitoring of abrasive belt in robotic arm grinding process. *J. Intell. Manuf.* **2025**, *36*, 3345-58. DOI
38. Chew, S. Y.; Asadi, E.; Vargas-Uscategui, A.; et al. In-process 4D reconstruction in robotic additive manufacturing. *Robot. Comput. Integr. Manuf.* **2024**, *89*, 102784. DOI
39. Ni, H.; Hu, T.; Deng, J.; Chen, B.; Luo, S.; Ji, S. Digital twin-driven virtual commissioning for robotic machining enhanced by machine learning. *Robot. Comput. Integr. Manuf.* **2025**, *93*, 102908. DOI

40. Chen, Y.; Lai, C. An intuitive pre-processing method based on human–robot interactions: zero-shot learning semantic segmentation based on synthetic semantic template. *J. Supercomput.* **2023**, *79*, 11743-66. DOI

41. Ghafarian Tamizi, M.; Honari, H.; Nozdryn-Plotnicki, A.; Najjaran, H. End-to-end deep learning-based framework for path planning and collision checking: bin-picking application. *Robotica* **2024**, *42*, 1094-112. DOI

42. Arents, J.; Greitans, M. Smart industrial robot control trends, challenges and opportunities within manufacturing. *Appl. Sci.* **2022**, *12*, 937. DOI

43. De Roovere, P.; Moonen, S.; Michiels, N.; wyffels, F. Sim-to-real dataset of industrial metal objects. *Machines* **2024**, *12*, 99. DOI

44. Lee, J.; Chang, C.; Cheng, E.; Kuo, C.; Hsieh, C. Intelligent robotic palletizer system. *Appl. Sci.* **2021**, *11*, 12159. DOI

45. Hou, R.; Yin, J.; Liu, Y.; Lu, H. Research on multi-hole localization tracking based on a combination of machine vision and deep learning. *Sensors* **2024**, *24*, 984. DOI PubMed PMC

46. Song, Y.; Wen, J.; Fei, Y.; Yu, C. Deep robotic prediction with hierarchical RGB-D fusion. *arXiv* **2019**, arXiv:1909.06585. Available online: https://doi.org/10.48550/arXiv.1909.06585. (accessed 3 December 2025).

47. Lin, C.; Lin, P.; Shih, C. Vision-based robotic arm control for screwdriver bit placement tasks. *Sens. Mater.* **2024**, *36*, 1003. DOI

48. Lee, S. K. H.; Simeth, A.; Hinchy, E. P.; Plapper, P.; O'dowd, N. P.; Mccarthy, C. T. A vision-based hole quality assessment technique for robotic drilling of composite materials using a hybrid classification model. *Int. J. Adv. Manuf. Technol.* **2023**, *129*, 1249-58. DOI

49. Comari, S.; Carricato, M. Autonomous scanning and cleanliness classification of pharmaceutical bins through artificial intelligence and robotics. *IEEE. Access.* **2024**, *12*, 117256-70. DOI

50. Kohut, P.; Skop, K. Vision systems for a UR5 cobot on a quality control robotic station. *Appl. Sci.* **2024**, *14*, 9469. DOI

51. Cheng, A.; Lu, S.; Gao, F. Anomaly detection of tire tiny text: mechanism and method. *IEEE. Trans. Autom. Sci. Eng.* **2024**, *21*, 1911-28. DOI

52. Lin, C.; Jhang, J.; Gao, Y.; Huang, H. Vision-based robotic arm in defect detection and object classification applications. *Sens. Mater.* **2024**, *36*, 655. DOI

53. Pereira, F. R.; Rodrigues, C. D.; Souza, H. D. S. E.; et al. Force and vision-based system for robotic sealing monitoring. *Int. J. Adv. Manuf. Technol.* **2023**, *126*, 391-403. DOI

54. Mukherjee, D.; Gupta, K.; Chang, L. H.; Najjaran, H. A survey of robot learning strategies for human-robot collaboration in industrial settings. *Robot. Comput. Integr. Manuf.* **2022**, *73*, 102231. DOI

55. Mendez, E.; Ochoa, O.; Olivera-Guzman, D.; et al. Integration of deep learning and collaborative robot for assembly tasks. *Appl. Sci.* **2024**, *14*, 839. DOI

56. Bartyzel, G. Multimodal variational DeepMDP: an efficient approach for industrial assembly in high-mix, low-volume production. *IEEE. Robot. Autom. Lett.* **2024**, *9*, 11297-304. DOI

57. Li, T.; Polette, A.; Lou, R.; Jubert, M.; Nozais, D.; Pernot, J. Machine learning-based 3D scan coverage prediction for smart-control applications. *Comput. Aided. Des.* **2024**, *176*, 103775. DOI

58. Roos-Hoefgeest, S.; Roos-Hoefgeest, M.; Alvarez, I.; González, R. C. Reinforcement learning approach to optimizing profilometric sensor trajectories for surface inspection. *arXiv* **2024**, arXiv:2409.03429. Available online: https://doi.org/10.48550/arXiv.2409.03429. (accessed 3 December 2025).

59. Simoni, A.; Borghi, G.; Garattoni, L.; Francesca, G.; Vezzani, R. D-SPDH: improving 3D robot pose estimation in Sim2Real scenario via depth data. *IEEE. Access.* **2024**, *12*, 166660-73. DOI

60. Mangat, A. S.; Mangler, J.; Rinderle-Ma, S. Interactive process automation based on lightweight object detection in manufacturing processes. *Comput. Ind.* **2021**, *130*, 103482. DOI

61. Gao, Z.; Elibol, A.; Chong, N. Y. Zero moment two edge pushing of novel objects with center of mass estimation. *IEEE. Trans. Autom. Sci. Eng.* **2023**, *20*, 1487-99. DOI

62. Celikel, R.; Aydogmus, O. NARMA-L2 controller for single link manipulator. In *2018 International Conference on Artificial Intelligence and Data Processing (IDAP)*, Malatya, Turkey, September 28-30, 2018. IEEE; 2018. p. 1-6. DOI

63. Faroni, M.; Umbrico, A.; Beschi, M.; Orlandini, A.; Cesta, A.; Pedrocchi, N. Optimal task and motion planning and execution for multiagent systems in dynamic environments. *IEEE. Trans. Cybern.* **2024**, *54*, 3366-77. DOI PubMed

64. Calderón-Cordova, C.; Sarango, R.; Castillo, D.; Lakshminarayanan, V. A deep reinforcement learning framework for control of robotic manipulators in simulated environments. *IEEE. Access.* **2024**, *12*, 103133-61. DOI

65. Wu, P.; Su, H.; Dong, H.; Liu, T.; Li, M.; Chen, Z. An obstacle avoidance method for robotic arm based on reinforcement learning. *Ind. Robot.* **2025**, *52*, 9-17. DOI

66. Lindner, T.; Milecki, A. Reinforcement learning-based algorithm to avoid obstacles by the anthropomorphic robotic arm. *Appl. Sci.* **2022**, *12*, 6629. DOI

67. Liu, Q.; Liu, Z.; Xiong, B.; Xu, W.; Liu, Y. Deep reinforcement learning-based safe interaction for industrial human-robot collaboration using intrinsic reward function. *Adv. Eng. Inform.* **2021**, *49*, 101360. DOI

68. Honelign, L.; Abebe, Y.; Tullu, A.; Jung, S. Deep reinforcement learning-based enhancement of robotic arm target-reaching performance. *Actuators* **2025**, *14*, 165. DOI
69. Ji, Z.; Liu, G.; Xu, W.; Yao, B.; Liu, X.; Zhou, Z. Deep reinforcement learning on variable stiffness compliant control for programming-free robotic assembly in smart manufacturing. *Int. J. Prod. Res.* **2024**, *62*, 7073-95. DOI
70. Men, Y.; Jin, L.; Cui, T.; Bai, Y.; Li, F.; Song, R. Policy fusion transfer: the knowledge transfer for different robot peg-in-hole insertion assemblies. *IEEE. Trans. Instrum. Meas.* **2023**, *72*, 1-10. DOI
71. Zhou, H.; Lin, X. Intelligent redundant manipulation for long-horizon operations with multiple goal-conditioned hierarchical learning. *Adv. Robot.* **2025**, *39*, 291-304. DOI
72. Koubaa, A.; Ammar, A.; Boulila, W. Next-generation human-robot interaction with ChatGPT and robot operating system. *Softw. Pract. Exp.* **2025**, *55*, 355-82. DOI
73. Gupta, S.; Yao, K.; Niederhauser, L.; Billard, A. Action contextualization: adaptive task planning and action tuning using large language models. *IEEE. Robot. Autom. Lett.* **2024**, *9*, 9407-14. DOI
74. Hou, W.; Xiong, Z.; Yue, M.; Chen, H. Human-robot collaborative assembly task planning for mobile cobots based on deep reinforcement learning. *Proc. Inst. Mech. Eng. C.* **2024**, *238*, 11097-114. DOI
75. Angelidis, A.; Plevritakis, E.; Vosniakos, G.; Matsas, E. An open extended reality platform supporting dynamic robot paths for studying human–robot collaboration in manufacturing. *Int. J. Adv. Manuf. Technol.* **2025**, *138*, 3-15. DOI
76. Zhao, D.; Ding, Z.; Li, W.; Zhao, S.; Du, Y. Cascaded fuzzy reward mechanisms in deep reinforcement learning for comprehensive path planning in textile robotic systems. *Appl. Sci.* **2024**, *14*, 851. DOI
77. Lin, J.; Wei, X.; Xian, W.; et al. Continuous reinforcement learning via advantage value difference reward shaping: a proximal policy optimization perspective. *Eng. Appl. Artif. Intell.* **2025**, *151*, 110676. DOI
78. Bing, Z.; Zhou, H.; Li, R.; et al. Solving robotic manipulation with sparse reward reinforcement learning via graph-based diversity and proximity. *IEEE. Trans. Ind. Electron.* **2023**, *70*, 2759-69. DOI
79. Yu, C.; Yang, Y.; Cheng, Y.; Wang, Z.; Shi, M. Trajectory tracking control of an unmanned aerial vehicle with deep reinforcement learning for tasks inside the EAST. *Fusion. Eng. Des.* **2023**, *194*, 113894. DOI
80. Bartyzel, G.; Półchłopek, W.; Rzepka, D. Reinforcement learning with stereo-view observation for robust electronic component robotic insertion. *J. Intell. Robot. Syst.* **2023**, *109*, 1970. DOI
81. Yu, S.; Tan, G. Inverse kinematics of a 7-degree-of-freedom robotic arm based on deep reinforcement learning and damped least squares. *IEEE. Access.* **2025**, *13*, 4857-68. DOI
82. Amirnia, A.; Keivanpour, S. Real-time sustainable cobotic disassembly planning using fuzzy reinforcement learning. *Int. J. Prod. Res.* **2025**, *63*, 3798-821. DOI
83. Tian, B.; Kaul, H.; Janardhanan, M. Balancing heterogeneous assembly line with multi-skilled human-robot collaboration via adaptive cooperative co-evolutionary algorithm. *Swarm. Evol. Comput.* **2024**, *91*, 101762. DOI
84. Wang, T.; Fan, J.; Zheng, P. An LLM-based vision and language cobot navigation approach for human-centric smart manufacturing. *J. Manuf. Syst.* **2024**, *75*, 299-305. DOI
85. Li, C.; Chrysostomou, D.; Zhang, X.; Yang, H. IRWoZ: constructing an industrial robot Wizard-of-OZ dialoguing dataset. *IEEE. Access.* **2023**, *11*, 28236-51. DOI
86. Li, C.; Zhang, X.; Chrysostomou, D.; Yang, H. ToD4IR: a humanised task-oriented dialogue system for industrial robots. *IEEE. Access.* **2022**, *10*, 91631-49. DOI
87. Čakurda, T.; Trojanová, M.; Pomin, P.; Hošovský, A. Deep learning methods in soft robotics: architectures and applications. *Adv. Intell. Syst.* **2025**, *7*, 2400576. DOI
88. Bilancia, P.; Locatelli, A.; Tutarini, A.; Mucciarini, M.; Iori, M.; Pellicciari, M. Online motion accuracy compensation of industrial servomechanisms using machine learning approaches. *Robot. Comput. Integr. Manuf.* **2025**, *91*, 102838. DOI
89. Bi, Z.; Luo, C.; Miao, Z.; Zhang, B.; Zhang, W.; Wang, L. Safety assurance mechanisms of collaborative robotic systems in manufacturing. *Robot. Comput. Integr. Manuf.* **2021**, *67*, 102022. DOI
90. Shan, S.; Pham, Q. Fine robotic manipulation without force/torque sensor. *IEEE. Robot. Autom. Lett.* **2024**, *9*, 1206-13. DOI
91. Deng, W.; Ardiani, F.; Nguyen, K. T.; Benoussaad, M.; Medjaher, K. Physics informed machine learning model for inverse dynamics in robotic manipulators. *Appl. Soft. Comput.* **2024**, *163*, 111877. DOI
92. Zhou, H.; Ma, S.; Wang, G.; Deng, Y.; Liu, Z. A hybrid control strategy for grinding and polishing robot based on adaptive impedance control. *Adv. Mech. Eng.* **2021**, *13*, 168781402110040. DOI
93. Ma, H.; Zhang, Y.; Li, Z.; Zhang, J.; Wu, X.; Chen, W. Research on 3C compliant assembly strategy method of manipulator based on deep reinforcement learning. *Comput. Electr. Eng.* **2024**, *119*, 109605. DOI
94. Zhang, S.; Wang, Y.; Liang, S.; Han, H.; Jiang, Z.; Zhang, M. Research on robotic peg-in-hole assembly method based on variable admittance. *Appl. Sci.* **2025**, *15*, 2143. DOI

95. Hu, X.; Liu, G.; Ren, P.; et al. An admittance parameter optimization method based on reinforcement learning for robot force control. *Actuators* **2024**, *13*, 354. DOI
96. Zheyuan, C.; Rahman, M. A.; Tao, H.; Liu, Y.; Pengxuan, D.; Yaseen, Z. M. Need for developing a security robot-based risk management for emerging practices in the workplace using the advanced human-robot collaboration model. *Work* **2021**, *68*, 825-34. DOI PubMed
97. Xin, X.; Keoh, S. L.; Sevegnani, M.; Saerbeck, M.; Khoo, T. P. Adaptive model verification for modularized industry 4.0 applications. *IEEE. Access.* **2022**, *10*, 125353-64. DOI
98. Hickman, X.; Lu, Y.; Prince, D. Hybrid safe reinforcement learning: tackling distribution shift and outliers with the Student-t's process. *Neurocomputing* **2025**, *634*, 129912. DOI
99. Kana, S.; Lakshminarayanan, S.; Mohan, D. M.; Campolo, D. Impedance controlled human–robot collaborative tooling for edge chamfering and polishing applications. *Robot. Comput. Integr. Manuf.* **2021**, *72*, 102199. DOI
100. Amaya, C.; von Arnim, A. Neurorobotic reinforcement learning for domains with parametrical uncertainty. *Front. Neurorobot.* **2023**, *17*, 1239581. DOI PubMed PMC
101. 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. DOI
102. Li, C.; Zheng, P.; Li, S.; Pang, Y.; Lee, C. K. AR-assisted digital twin-enabled robot collaborative manufacturing system with human-in-the-loop. *Robot. Comput. Integr. Manuf.* **2022**, *76*, 102321. DOI
103. Zhang, T.; Zhang, K.; Lin, J.; Louie, W. G.; Huang, H. Sim2real learning of obstacle avoidance for robotic manipulators in uncertain environments. *IEEE. Robot. Autom. Lett.* **2022**, *7*, 65-72. DOI
104. Zhang, Z.; Zhang, Z.; Wang, L.; Zhu, X.; Huang, H.; Cao, Q. Digital twin-enabled grasp outcomes assessment for unknown objects using visual-tactile fusion perception. *Robot. Comput. Integr. Manuf.* **2023**, *84*, 102601. DOI
105. Liu, Y.; Xu, H.; Liu, D.; Wang, L. A digital twin-based sim-to-real transfer for deep reinforcement learning-enabled industrial robot grasping. *Robot. Comput. Integr. Manuf.* **2022**, *78*, 102365. DOI
106. Wang, R.; Tian, Y.; Kashima, K. Density estimation based soft actor-critic: deep reinforcement learning for static output feedback control with measurement noise. *Adv. Robot.* **2024**, *38*, 398-409. DOI
107. Salehi, A.; Rühl, S.; Doncieux, S. Adaptive asynchronous control using meta-learned neural ordinary differential equations. *IEEE. Trans. Robot.* **2024**, *40*, 403-20. DOI
108. Shin, G.; Yun, S.; Kim, W. A novel policy distillation with WPA-based knowledge filtering algorithm for efficient industrial robot control. *IEEE. Access.* **2024**, *12*, 154514-25. DOI
109. Wang, S.; Tao, J.; Jiang, Q.; Chen, W.; Liu, C. Manipulator joint fault localization for intelligent flexible manufacturing based on reinforcement learning and robot dynamics. *Robot. Comput. Integr. Manuf.* **2024**, *86*, 102684. DOI
110. Kim, H. Robot dynamics-based cable fault diagnosis using stacked transformer encoder layers. *Electr. Eng.* **2025**, *107*, 3697-708. DOI
111. Lanese, I.; Schultz, U. P.; Ulidowski, I. Reversible execution for robustness in embodied AI and industrial robots. *IT. Prof.* **2021**, *23*, 12-7. DOI
112. Hsieh, Y.; Xu, F.; Lin, S. Deep convolutional generative adversarial network for inverse kinematics of self-assembly robotic arm based on the depth sensor. *IEEE. Sens. J.* **2023**, *23*, 758-65. DOI