

Review

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AI in Robot Manipulator Control: A Systematic Review

[Charles C. Nguyen](#)*, [Ha T.T. Ngo](#), [Tu T. C. Duong](#), Tri T. Nguyen, [Tuan M. Nguyen](#), [Lu Sun](#)

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Review

AI in Robot Manipulator Control: A Systematic Review

Charles C. Nguyen ^{1,*}, Ha T. T. Ngo ², Tu T.C. Duong ^{1,3}, Tri T. Nguyen ^{1,4}, Tuan M Nguyen ^{1,5}
and Lu Sun ⁶

¹ Department of Electrical Engineering and Computing Engineering, College of Engineering, Physics and Computing, The Catholic University of America, Washington, DC 20064, USA

² Department of Biomedical Engineering, College of Engineering, Physics and Computing, The Catholic University of America, Washington, DC 20064, USA

³ Faculty of Electrical and Electronics Engineering, Ho Chi Minh City University of Technology and Engineering, Ho Chi Minh City 700000, Vietnam

⁴ Department of Electrical and Electronics Engineering, Danang University of Science and Technology, Da Nang 550000, Vietnam

⁵ Amazon, Seattle, WA 98109, USA

⁶ Department of Civil Engineering Technology, Environmental Management and Safety, Rochester Institute of Technology, Rochester, NY 14623, USA

* Correspondence: nguyen@cua.edu

Abstract

This study presents a structured analysis of 343 publications on artificial intelligence-based methods for robot manipulator control published between 2015 and 2025. The review examines how AI has been incorporated into the control pipeline by organizing prior work according to functional roles, including perception and estimation, planning, learning based control, interaction and safety, and learning and adaptation. In addition to this functional taxonomy, the study analyzes publication growth, application domains, robot types, evaluation settings, and methodological patterns to characterize the evolution of the field over the past decade. The results show that research activity has been concentrated primarily in learning control, while other functional roles have received comparatively less attention. The literature also reveals an uneven distribution across application areas and robot platforms, with a strong reliance on simulation and limited evidence of integrated real-world deployment. These patterns indicate that, despite rapid growth and methodological diversity, the field remains imbalanced in both research focus and validation maturity. Rather than summarizing individual studies in isolation, this review provides a high-level perspective on where effort has been concentrated, where major gaps persist, and which directions are most critical for advancing AI-based robot manipulator control toward reliable and scalable real-world use.

Keywords: artificial intelligent; control; robot manipulator; robot control; planning; learning control

1. Introduction

Over six decades of development, robotic manipulators (RMs) have expanded far beyond structured manufacturing environments into military, aerospace, construction, agriculture, healthcare, and other industries with complex operations [1–7]. This progression represents not merely an expansion of application, but a substantial increase in control complexity, introducing control requirements that classical strategies were not designed to meet. Controllers such as PID relied heavily on linearized system models and predictable disturbances [8]. These conditions are rarely satisfied in modern applications, where manipulators must handle nonlinearities, high uncertainty, high speed, and direct human-robot interaction in unstructured environments [9]. As a result, the gap between what classical control can reliably guarantee and what modern robotic

applications require has become increasingly apparent. This has motivated substantial research into AI-based control strategies capable of handling model uncertainty, continuously adapting to changing conditions, learning autonomously from interaction with their surroundings, and updating toward optimal solutions without relying on predefined models or manual retuning.

Interest in AI-based approaches to manipulator control dates to the early 1990s, when data-driven adaptation and learning approaches began complementing classical control and gave rise to adaptive and intelligent control frameworks [10,11]. Subsequent developments in reinforcement learning (RL), deep learning (DL), and hybrid architectures have considerably expanded the scope of these applications. Hierarchical RL has been applied to learn joint-specific motor dynamics without manual tuning, achieving robust trajectory tracking under variable loads [12]. Neural network-based methods have been used to tune PID gains online in dual-arm systems, improving tracking accuracy under parametric uncertainty [13]. More recently, language-vision models have been applied to decompose manipulation demonstrations into executable action primitives and estimate latent task properties, such as contact forces and load distribution, that are not directly measurable from sensor data [14]. These developments have been accelerated by advanced literature research of AI and supporting infrastructure, including specialized accelerators, sensors, large-scale data centers, and expansive training data [15,16].

Many existing reviews addressed parts of this landscape, either by focusing on specific techniques [17,18] or by specific application areas [19,20]. A comparative summary of these reviews with ours is given in Table 1.

Table 1. Overview of existing reviews and the scope of this present review.

| Review ID | Summary | Contribution |
|-----------------------|---|--|
| Mareco et al. [21] | This review analyzes the use of AI enabled control-oriented techniques such as fuzzy logic, neuro fuzzy control, neural networks, and swarm or evolutionary optimization. The analysis is mainly qualitative and centered on methodological characteristics within specific application settings. | Provides a structured mapping of 188 studies across renewable energy, robotics, agriculture, and industrial processes, highlighting how AI has been adopted in application specific control problems. Its value lies in identifying major methodological trends, limitations, and research gaps in intelligent control design. |
| Nahavandi et al. [22] | This review evaluates machine learning for robotic manipulators, covering deep learning, RL, and imitation learning. It analyzes sim-to-real transfer and practical deployment across industrial, medical, and space sectors. | Provides a qualitative synthesis of machine learning strategies in robotic manipulation, utilizing algorithmic complexity estimates and tabulated comparisons instead of formal statistical analysis. It offers researchers a structured framework for evaluating the computational trade-offs and practical requirements of various control architectures across diverse operational domains. |
| Waseem et al. [17] | This qualitative review surveys the evolution of robotic manipulator control technologies from 2016 to 2024, spanning methods from classical PID and linear models to intelligent AI, hybrid, and quantum-inspired frameworks. No statistical analysis was performed; the study taxonomizes these strategies by their | Provides a foundational mapping of control theories against emerging paradigms such as digital twins, federated learning, and blockchain to address persistent challenges in non-linear dynamics and real-time performance. It informs future research directions by identifying critical gaps in multi-agent system integration and |

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|------------|---|--|
| | underlying architecture and optimization logic to highlight current operational trend | scalable control for unstructured environments. |
| Our review | This review analyzes 343 studies on AI-based robot manipulator control published between 2015 and 2025, focusing on research trends across functional roles, application domains, robot types, and evaluation approaches. It highlights major patterns in the distribution and development of AI methods within the manipulator control pipeline. | Provides the first structured quantitative mapping of AI based robot manipulator control over the past decade, together with a unified taxonomy of functional AI roles in the control pipeline. The review identifies major research concentrations and persistent gaps, providing a data driven reference for future development in underrepresented control functions. |

Although these reviews provide valuable depth, they do not provide cross-domain statistical analysis of the current literature. Without this high-level overview, it is difficult to identify which roles have received disproportionate research attention, which technique families are associated with which application contexts, and where the most persistent methodological gaps exist. This paper addresses that gap by presenting key statistics to highlight the trends about AI-based control techniques in robot manipulator control from 2015 to present.

This paper is organized into five sections. Section 1 introduces the topic and summarizes the existing review literature. Section 2 describes the data collection process and study selection methodology. Section 3 presents the included studies and their quantitative analysis. Sections 4 and 5 provide the discussion and conclusion, respectively.

2. Materials and Methods

This study provides a retrospective mapping of 343 studies on AI-based control for RMs published between 2015 and 2025. The selection process included identifying potentially relevant studies across major online databases, deduplication, title and abstract screening for eligibility assessments, and full-text screening for categorization and statistical analysis.

2.1. Search Strategy

The literature search for this review followed the modified PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) framework to ensure the transparency, reproducibility, and comprehensiveness in reporting search strategy and findings [23]. Explicated Boolean search strings were performed across multiple online databases, including IEEEXplore, PubMed, Scopus, and Google Scholar, to identify potentially relevant studies. Only for IEEEXplore that the search was conducted twice with the same query: first without content-type restrictions, then excluding conference proceedings. The search period was from 2015 to present, including early-access and online-first. The relevant Boolean strings applied are presented in Table 2.

Table 2. Databases and boolean search strings.

| Databases | Search Strings |
|----------------------------|---|
| IEEEXplore, PubMed, Scopus | ("robot manipulator" OR "robotic arm" OR "industrial robot" OR manipulator) AND (AI OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning") AND ("control" OR "adaptive control" OR "intelligent control" OR "learning-based control") |
| Google Scholar | ("robot manipulator" OR "robotic arm" OR "industrial robot" OR manipulator) AND (AI OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning") AND ("control" OR "adaptive control" OR "intelligent control" OR "learning-based control") |

"robot manipulator" AND ("reinforcement learning" OR DRL)
 AND ("trajectory optimization" OR "motion planning" OR
 control)
 "robot manipulator" OR "robotic arm" OR "robotic
 manipulation" AND ("reinforcement learning" OR DRL OR
 "deep reinforcement learning") AND (grasping OR "dexterous
 manipulation" OR "sim-to-real" OR sim2real)

2.2. Search Execution and Screening Process

The final search was completed on December 31, 2025, yielding a combined total of 800 records across all databases. Records were exported and de-duplicated in Zotero using its automatic duplicate-detection function, resulting in 672 unique records. Title and abstract screening were then conducted against the predefined inclusion and exclusion criteria. To maximize efficiency and consistency, Anara AI, an AI-powered research assistant, was used as a decision-support tool during this stage. All AI-assisted decisions were manually verified prior to inclusion or exclusion. After this screening stage, 343 studies were subjected for full-text assessment. Full texts were reviewed in detail to confirm eligibility, further analysis, and categorized according to the five functional modules in RM control: perception/estimation, planning, learning control, interaction/safety, and learning/adaptation.

2.2.1. Inclusion Criteria

- Published 2025 or later
- Written in English
- Proposed or applied AI-based techniques explicitly for control of RMs

2.2.2. Exclusion Criteria

- Soft robots, hydraulic robot, continuum systems, or quadrotor
- Simulation platforms evaluations using robot learning methods
- General/high-level control discussions without AI approaches
- Book chapters, reviews, editorials, patents, letters, abstracts, or other scientific journal formats

The selection process from 800 identified records to the final set of 343 selected studies was documented using the PRISMA-2020 flow diagram and presented in Figure 1.

2.3. Data Extraction

An additional systematic extraction was conducted on 343 selected studies to capture the following data:

- Authors and year of publication
- The functional role of implemented strategy within the robot manipulator control system, categorized as one of the following:
 - Perception and Estimation: outputs state estimates such as pose, velocity, maps, or object identity for downstream use
 - Planning: outputs a plan/trajectory/waypoints/goals or select actions at a symbolic/task level that are then tracked by a controller.
 - Learning Control: outputs low-level commands or a control policy that directly drives the robot's motion (joint velocities/torques/actions each timestep).
 - Interaction and Safety: outputs safety constraints or regulates contact/force/compliance, including human-aware limits and safe-set filtering
 - Learning and Adaptation: updates models or policies online/continually across conditions, improving with new deployment data

- Robot type
- Application area
- Control techniques
- AI/ML methods
- Learning paradigm (supervised, unsupervised, reinforcement learning, hybrid)
- Evaluation method (simulation, experiments, both)

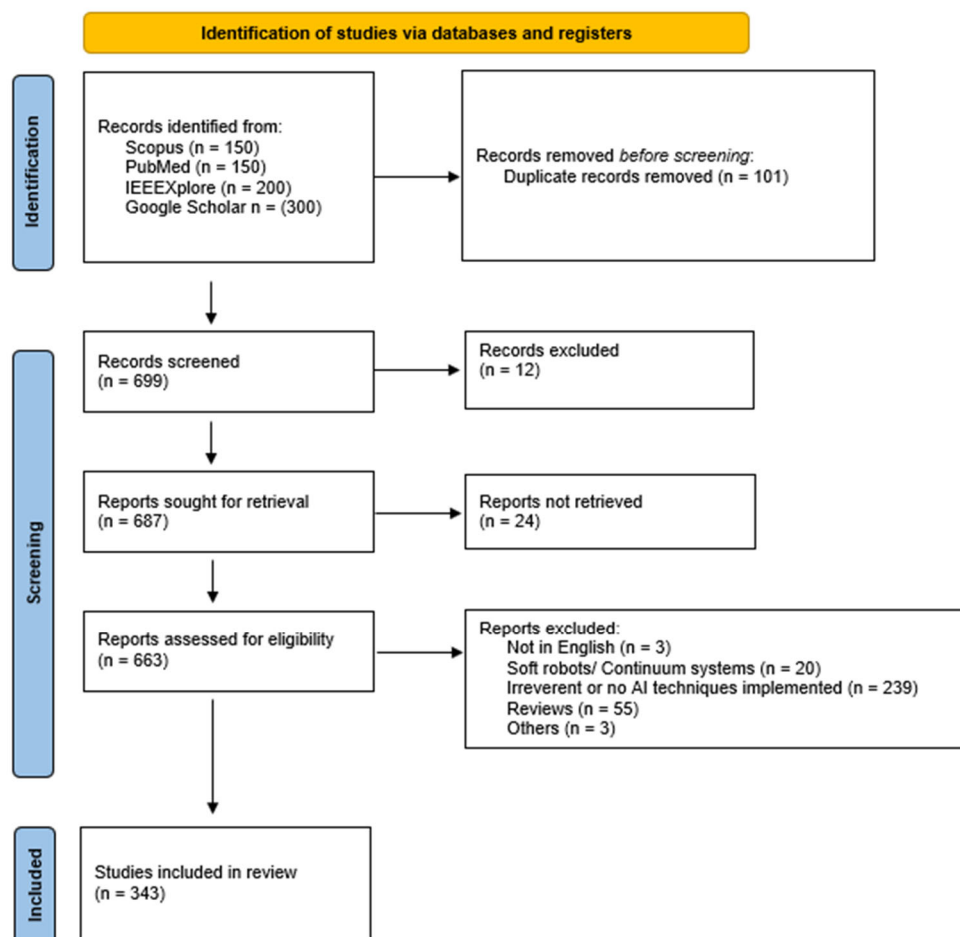


Figure 1. PRISMA flow diagram of the search and selection process.

2.4. Research Question

This review is guided by the following four research questions:

RQ1: How has the volume and distribution of AI/ML-based robot manipulator control research evolved over the last decade in terms of publication trends and temporal shifts in method adoption?

RQ2: Which functional control roles, spanning perception and estimation, planning, learning-based control, interaction and safety, and online adaptation, have attracted the greatest research concentration, and are those concentrations proportionate to the demands of the application domains they serve?

RQ3: Across which application domains has AI/ML-based robot manipulator control been most actively studied, measured by publication volume and methodological diversity, and which domains remain comparatively underserved relative to their real-world significance?

RQ4: Based on observed publication trends, shifts in method adoption, and gaps between research concentration and application demand, what emerging directions are most likely to define the next stage of AI/ML-enabled robot manipulator control?

3. Review of Publications

Tables 3–7 list the selected studies on AI-based control techniques in robot manipulator control from 2015 to 2025, organized by functional category and summarizing their key aspects

Table 3. AI-based control techniques in robot manipulator control from 2015–2025.

| Functional Role | Authors | Year | Robot Type | Application Area | Control Technique | Methods | Evaluation Paradigm | Method |
|---------------------------|-------------------------|------|-------------|------------------|--|---|---------------------|------------|
| Perception and Estimation | Bertono et al. [24] | 2019 | Serial | NS | Learning-based pose estimation | CNN | Supervised | Experiment |
| | Catalán et al. [25] | 2023 | Exoskeleton | Rehabilitation | Vision-guided learning-based | EEG/EOG classification, RGB-D object pose estimation, DMP | Supervised | Experiment |
| | Chen et al. [26] | 2023 | Serial | Manufacturing | Learning-based grasp planning | Min-Pnet, 1D CNN | Supervised | Robot |
| | Chen et al. [27] | 2018 | Serial | Manufacturing | Vision-guided learning-based | Faster R-CNN | Supervised | Experiment |
| | Ghiasvand et al. [28] | 2024 | Serial | Aerospace | DNN-based visual servoing | DNN | Supervised | Robot |
| | Gul et al. [29] | 2023 | Serial | Rehabilitation | Learning-based | KNN, LSTM, SVM, DT | Supervised | Experiment |
| | Heris et al. [30] | 2022 | Magnetic | Healthcare | Learning-based magnetic field estimation | ANN, Simulated Annealing | Supervised | Robot |
| | Kirda et al. [31] | 2025 | Serial | Manufacturing | Vision-guided | YOLOv5 | Supervised | Experiment |
| | Kondratenko et al. [32] | 2022 | Mobile | NS | ML-based sensor processing | Fuzzy logic, neuro-fuzzy, YOLOv2, ResNet34 | Supervised | Experiment |

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|------------------------|------|-------------|--------------------|---|-------------------------|------------------------------|------------|
| Kružić et al. [33] | 2020 | Serial | NS | Sensorless force estimation for interaction control | MLP, 1D CNN, LSTM | Supervised | Experiment |
| Liu et al. [34] | 2021 | Mobile | Garbage Management | Learning-based | YOLACT, GPD | Supervised | Experiment |
| Liu et al. [35] | 2022 | Serial | Manufacturing | Vision-guided DRL-based | DQN, FCN (DenseNet-121) | RL | Both |
| Luo et al. [36] | 2020 | Industrial | Manufacturing | Vision-guided learning-based | YOLO-v2-ROI | Supervised | Experiment |
| Marchionna et al. [37] | 2023 | Serial | Dexterity Game | Vision-guided visual servoing | YOLACT++ | Supervised | Experiment |
| Martin et al. [38] | 2018 | Serial | Manufacturing | Pose estimation-based | OpenPose, HMR | Supervised | Experiment |
| Panasiuk [39] | 2025 | NS | Manufacturing | Vision-guided positioning | YOLOv8 | Supervised | Experiment |
| Piltan [40] | 2020 | Serial | Multiple | Neuro-fuzzy-based fault-tolerant | SVM, NN, Fuzzy logic | Supervised | Experiment |
| Pitan et al. [41] | 2020 | Serial | Multiple | Adaptive fuzzy fault-tolerant | DT, TSK fuzzy | Supervised | Experiment |
| Sacchi et al. [42] | 2023 | Serial | NS | DRL-based fault estimation | TD3 | RL | Simulation |
| Shukla et al. [43] | 2021 | Serial | Multiple | Learning-based grasp pose estimation | GA, DQN | RL, Supervised, Evolutionary | Experiment |
| Wang et al. [44] | 2024 | Myoelectric | Rehabilitation | sEMG gesture recognition | MS-CLSTM, CNN-LSTM | Supervised | Experiment |

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|-----------------------|-------------------------|------------------|----------|--------------------------|-----------------------------|---|-----------------|------------|
| Planning | Ahn et al. [45] | 2025 | Serial | Logistics | Learning-based planning | PPO, CMPNet | RL, IL | Both |
| | Ak et al. [46] | 2022 | Serial | Rehabilitation | Learning-based | GoogLeNet | Supervised | Experiment |
| | Andersen et al. [47] | 2015 | Serial | Manufacturing | Learning-based predictive | NN, RT, GP | Supervised | Experiment |
| | Andriyanov [48] | 2023 | Serial | Agriculture | RL-based planning | Q-learning, YOLOv5 | RL, Supervised | Both |
| | Azizi [49] | 2020 | Serial | Manufacturing | Learning-based optimization | ANN, GA | Supervised | Simulation |
| | Batzianouis et al. [50] | 2021 | Serial | Rehabilitation | IRL-based planning | GP IRL, LDA | RL, Supervised | Experiment |
| | Bucinskas et al. [51] | 2022 | Serial | Manufacturing | DRL-based | DQN | RL | Experiment |
| | Chen et al. [52] | 2023 | Serial | Healthcare | DRL-based planning | PPO, DNN | RL, Supervised | Both |
| | Cheng et al. [53] | 2024 | Humanoid | NS | Learning-based planning | CNN | Supervised | Both |
| | Chi et al. [54] | 2018 | Platform | Healthcare | RL-based | PI2, DMP | RL, IL | Both |
| | Ebert et al. [55] | 2018 | Serial | NS | Learning-based | Video prediction model, Registration network, Meta-learned classifier | Self-supervised | Both |
| Emamzadeh et al. [56] | 2015 | Serial | NS | Fuzzy-based hierarchical | TSK fuzzy predictor | Supervised | Simulation | |
| Jaquier et al. [57] | 2021 | Humanoid | NS | Learning-based | Tensor-based GMM, GMR | IL, Unsupervised | Both | |
| Karimi et al. [58] | 2022 | Redundant Serial | NS | DRL-based | DQN | RL | Simulation | |

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|---------------------|------|--------------------------|----------------|--------------------------------|-----------------------------------|----------------------------|------------|
| Kim et al. [59] | 2020 | Serializing Human | Manufacturing | DRL-based planning | TD3, HER | RL | Both |
| Kwon et al. [60] | 2020 | Robotic Hand | Rehabilitation | Learning- based | CNN | Supervised | Experiment |
| Lee et al. [61] | 2025 | Serializing | Rehabilitation | Copilot- assisted | EEGNet, PPO, Grounding DINO | RL | Experiment |
| Liu et al. [62] | 2022 | Serializing | Manufacturing | Learning- based | TAC-CA, ANN | RL, Hybrid | Both |
| Liu et al. [63] | 2021 | Serializing | Manufacturing | RL-based | AC, Double Q- Learning | RL | Both |
| Liu et al. [64] | 2021 | Serializing | NS | RL-based | RL, Q-learning | RL, Hybrid | Both |
| Li et al. [65] | 2024 | Redundant Serializing | Manufacturing | DRL-based planning | AC DRL, ANN | RL, Hybrid | Both |
| Li et al. [66] | 2023 | Serializing | Manufacturing | DRL-based | DQN, Consensus- based training | RL | Both |
| Li et al. [67] | 2023 | Serializing | NS | DRL-based | DRL, ResNet-50 | RL, Self- supervised | Both |
| Parag et al. [68] | 2025 | Serializing | NS | Learning- based | Sobolev regression, NN | Hybrid | Simulation |
| Parák et al. [69] | 2024 | Serializing | Manufacturing | DRL-based | DDPG, TD3, Soft AC | RL | Simulation |
| Prianto et al. [70] | 2021 | Serializing | Manufacturing | Learning- based planning | Soft AC, HER | RL, Hybrid | Both |
| Sacchi et al. [71] | 2021 | Serializing | Manufacturing | DRL-based | DQN, Q-learning | RL | Simulation |

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|------------------|----------------------|------|-------------------------------|----------------------------------|---|------------------------|------------|
| Learning Control | Solowjow et al. [72] | 2020 | Serial Multiple | Learning-based grasping planning | MobileNet-SSD, FC-GQ-CNN | Supervised | Both |
| | Sunwoo et al. [73] | 2021 | Serial Manufacturing | DRL-based | D3QN, PER | RL | Simulation |
| | Wang et al. [74] | 2022 | Serial Manufacturing | Hybrid imitation-RL | HGCIL, DMP, Soft AC | RL, IL, Hybrid | Both |
| | Wang et al. [75] | 2025 | Serial Manufacturing | DRL-based trajectory planning | DDPG, Autoencoder | RL, Unsupervised | Both |
| | Wang et al. [76] | 2023 | Serial Manufacturing | DRL-based planning | DDQN, Q-learning | RL | Simulation |
| | Wilson et al. [77] | 2025 | NS Rehabilitation | DRL-based | DRL-ANN, Improved ResNet, MSBO | RL, Supervised | Both |
| | Wong et al. [78] | 2019 | Serial Manufacturing | ACO-based planning | ACO, k-means clustering | Unsupervised | Both |
| | Yang et al. [79] | 2019 | Serial NS | Learning-based | DMP, GMM, GMR, RBFNN | IL, Supervised, Hybrid | Experiment |
| | Zeng et al. [79] | 2018 | Serial NS | DRL-based with MP | Q-learning, FCN, DenseNet | RL, Self-supervised | Both |
| | Zhang [80] | 2025 | Serial NS | Hierarchical DRL-based | TCN-attention, dDRL, RL parameter adaptatio | RL | Both |
| | Zhao et al. [81] | 2025 | serial Multiple Manufacturing | DRL-based planning | M2ACD | Supervised | Both |
| | Zhong et al. [82] | 2022 | serial Manufacturing | DRL-based | DDPG | RL, Hybrid | Simulation |
| | Ahmed et al. [83] | 2022 | Serial NS | Adaptive sliding mode | Adaptive Law | - | Simulation |
| | Aiello [84] | 2020 | Serial Service | DRL-based | DDPG, HER | RL | Simulation |

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|------------------------|------|--------|------------------------------|------------------------|--|---------------------|------------|
| Al-Shanoon et al. [85] | 2021 | Serial | NS | DRL-based | DRL, Q-learning, Fully convolutional network | RL, Self-supervised | Both |
| Alhousani et al. [86] | 2023 | Serial | NS | Geometric RL-based | Geometric RL, Soft AC, PPO, PoWER, CMA-ES | RL | Both |
| Aljalbout et al. [87] | 2024 | Serial | NS | RL-based | PPO, RL | RL | Both |
| Alles et al. [88] | 2022 | Serial | Manufacturing | DRL-based | Soft AC, HER | RL | Both |
| Amaya et al. [89] | 2023 | Serial | Manufacturing | Neuromorphic RL-based | Soft AC, SNN | RL | Simulation |
| An et al. [90] | 2024 | Serial | Rehabilitation | ADP-based optimization | ADP, Critic NN, RBFNN | RL | Experiment |
| Avhad et al. [91] | 2024 | Serial | NS | Adaptive DRL-based | DRL, Model ensembles, Q-networks | RL | Both |
| Azimirad et al. [92] | 2024 | Serial | Mobile | Learning-based | SNN, RL, STDP | RL | Simulation |
| Añazco et al. [93] | 2021 | Serial | Anthropomorphic Service Hand | DRL-based | DRL, 3D CNN | RL, Supervised | Simulation |
| Baek et al. [94] | 2022 | Serial | NS | DRL-based | Soft AC | RL | Simulation |
| Barnoy et al. [95] | 2022 | Serial | Mobile Healthcare need | Learning-based | TD3, NN dynamics model | RL, Supervised | Both |
| Bashabsheh [96] | 2025 | Serial | NS | RL-based | Policy-gradient RL | RL | Simulation |
| Bejar et al. [97] | 2021 | Serial | NS | DRL-based | DDPG | RL | Simulation |
| Blaise et al. [98] | 2023 | Serial | Aerospace | DRL-based | DDPG | RL | Simulation |

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|--|------|--------------------------------|----------|---------------------------------|--|-------------------------|------------|
| Brito et al. [99]3/31/2026 10:47:00 AM | 2020 | Serial Manufacturing | Manuf | RL-based | AC, LSTM | RL, Supervised | Experiment |
| Calderón-Cordova et al. [100] | 2024 | Serial Industrial | Indu | DRL-based | DDPG, DRL | RL | Simulation |
| Cao et al. [101] | 2023 | Serial NS | NS | Learning-based | RL, AC, RBFNN | RL | Both |
| Carron et al. [102] | 2019 | Compliant Serial | NS | Learning-based model predictive | GP | Supervised | Experiment |
| Castelli et al. [103] | 2017 | Serial Manufacturing | Manuf | Learning-based visual servoing | GMM, GMR | Supervised | Experiment |
| Chen et al. [104] | 2018 | Parallel | NS | Neural-dynamics-based | Zeroing neural-dynamics, ZND model | - | Simulation |
| Chen [105] | 2021 | Dexterous Hand | Multiple | Learning-based | DQN, PPO, Soft AC, DAPG | RL, IL, Self-supervised | Simulation |
| Chen et al. [106] | 2022 | Redundant Serial | NS | DRL-based | Soft AC, DDPG | RL | Simulation |
| Chen et al. [107] | 2016 | Serial | NS | Robust adaptive compensation | Adaptive fuzzy | Hybrid | Both |
| Chen et al. [108] | 2022 | Redundant Serial | NS | DRL-based | Soft AC, Prioritized Experience Replay | RL | Simulation |
| Chen et al. [109] | 2021 | Redundant Serial Manufacturing | Manuf | DRL-based | Soft AC | RL | Both |
| Chen et al. [110] | 2021 | Serial Manufacturing | Manuf | Learning-based | multi-layer NN | Supervised | Both |
| Chen [111] | 2025 | Serial | NS | DRL-based | DDPG | RL | Simulation |

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|-----------------------|------|---------------------------------|----|-------------------------|---|--------|------------|
| Chen et al. [112] | 2023 | Serial | NS | Vision-guided DRL-based | YOLOv3, Soft AC | RL | Both |
| Chen et al. [113] | 2021 | Dexterous Hand | NS | RL-based | PPO, TRPO, Soft AC, MAPPO, HAPPO | RL | Simulation |
| Chen et al. [114] | 2024 | Dexterous Hand | NS | Learning-based | PPO, Soft AC, TRPO, DAPG, HAPPO, HATRPO, MAPPO, BCQ, TD3+BC, IQL, ProMP | RL, IL | Simulation |
| Chen et al. [115] | 2023 | Serial | NS | DRL-based | Soft AC, MLP | RL, IL | Both |
| Chen et al. [116] | 2024 | Redundant Serial Dexterous Hand | NS | DRL-based | DDPG, TD3, Soft AC | RL | Both |
| Christen et al. [117] | 2019 | Serial Dexterous Hand | NS | DRL-based | DDPG, DRL | RL, IL | Simulation |
| Chu et al. [118] | 2020 | Redundant Serial Dexterous Hand | NS | DRL-based | DDPG, D4PG | RL | Simulation |
| Cotrim et al. [119] | 2021 | Serial Manufacturing | NS | RL-based | REINFORCE, DQN | RL | Simulation |
| Cui et al. [120] | 2025 | Serial Multiple | NS | DRL-based | Soft AC | RL | Both |
| Cutler et al. [121] | 2024 | Serial | NS | DRL-based | TD3, Soft AC, DDPG | RL | Experiment |
| Ding et al. [122] | 2021 | Serial | NS | DRL-based | TD3 | RL | Both |
| Dong [123] | 2024 | NS | NS | RL-based adaptive | RL, PG | RL | Both |
| Dong et al. [124] | 2023 | Redundant Serial | NS | DRL-based | DDPG | RL | Simulation |

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|------------------------------|------|------------------|-------------------------|-----------------------------|-----------------------------------|--------------------|------------|
| Ducaju et al. [125] | 2024 | Serial | Redundant Manufacturing | Iterative learning-based | Iterative Learning Control | - | Experiment |
| Du et al. [126] | 2017 | Serial with RCM | Healthcare | Fuzzy RL-based admittance | Fuzzy Sarsa(λ), RL | RL | Experiment |
| Ehrlich et al. [127] | 2022 | Serial | Rehabilitation | Neuromorphic learning-based | NEF, SNN, PES | Supervised | Both |
| Enayati et al. [128] | 2024 | Serial | NS | Learning-based | PPO, RL | RL | Both |
| Fareh et al. [129] | 2025 | Serial | NS | DRL-based | DDPG, PINNs | RL | Both |
| Filho et al. [130] | 2025 | Serial | NS | Multi-agent DRL-based | Multi DQN, DQN | RL | Both |
| Franceschetti et al. [131] | 2020 | Serial | NS | DRL-based | TRPO, DQN-NAF | RL | Both |
| Fu et al. [132] | 2022 | Quadruped | NS | RL-based whole-body | PPO, RL | RL | Both |
| Ganie et al. [133] | 2023 | Serial | NS | Learning-based | DNN, Elastic weight consolidation | Hybrid | Simulation |
| Gao [134] | 2022 | Serial | NS | DRL-based | DDPG | RL | Both |
| Garcia-Hernando et al. [135] | 2020 | Dexterous Hand | NS | Residual RL-based | PPO, Adversarial IL | RL, IL, Simulation | Hybrid |
| Gawali et al. [136] | 2023 | NS | NS | Learning-based | TERL, RNN, RL | RL | Simulation |
| Ghediri et al. [137] | 2022 | Serial | NS | DRL-based | DDPG, DRL | RL | Simulation |
| Grandesso [138] | 2023 | Redundant Serial | NS | RL-based | AC RL, DDPG variant | RL | Simulation |
| Gupta et al. [139] | 2015 | Serial | Manufacturing | Neuro-fuzzy-based | ANFIS | Hybrid | Simulation |
| Gu et al. [140] | 2017 | Serial | NS | DRL-based | NAF, DDPG | RL | Both |

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|-------------------------|------|-----------------------|---------------|------------------------------|-----------------------------------|--------|------------|
| Haiderbhai et al. [141] | 2025 | Serial | Healthcare | Vision-guided learning-based | PPO, RL | RL | Both |
| Hardman et al. [142] | 2022 | Serial | NS | DRL-based | DDPG | RL | Experiment |
| Hazem et al. [143] | 2025 | Serial | NS | DRL-based | DDPG, LC-DDPG, TD3-ADX | RL | Simulation |
| Heaton et al. [144] | 2023 | Redundant Serial | NS | DRL-based | Soft AC | RL | Simulation |
| He et al. [145] | 2017 | Serial | NS | Learning-based | RBFNN | - | Simulation |
| He et al. [146] | 2021 | Serial | NS | RL-based | AC, RBFNN | RL | Both |
| He et al. [147] | 2018 | Flexible-joint Serial | Manufacturing | Learning-based | NN | Hybrid | Both |
| Homsy et al. [148] | 2025 | Serial | Logistics | DRL-based | DQN, DQN variants, Self-attention | RL | Simulation |
| Hosny et al. [149] | 2023 | Serial | Manufacturing | Learning-based | RL, AC, Value iteration | RL | Simulation |
| Huang et al. [150] | 2024 | Serial | Manufacturing | DRL-based | Multi-agent TD3, H-memory | RL | Both |
| Hu et al. [150] | 2024 | Serial | NS | DRL-based | Soft AC, GAIL, LSTM | RL, IL | Simulation |
| Hu et al. [151] | 2024 | Serial | NS | DRL-based | Soft AC, ERND | RL | Simulation |
| Hu et al. [152] | 2024 | Serial | NS | DRL-based | Soft AC, HER | RL | Simulation |
| Hu et al. [153] | 2018 | Serial | NS | RL NN | RL, AC NN | RL | Simulation |
| Hu et al. [154] | 2020 | Serial | NS | MBRL-based | RL, kernel methods | RL | Simulation |

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|-------------------------|------|-----------------------|----|-------------------------|---|------------------------|------------|
| Hu et al. [155] | 2023 | Dexterous Hand | NS | Learning-based | IRL, RL, Graph convolutional network | RL | Both |
| Hwang et al. [156] | 2017 | Serial | NS | Neuro-fuzzy-based | Interval type-2 fuzzy logic | - | Simulation |
| Incremona et al. [157] | 2021 | Manufacturing | | DRL-based | DQN, NAF | RL | Both |
| Iqdymat et al. [158] | 2025 | Serial Logistics | | DRL-based | DDPG, AC | RL | Both |
| Iriondo et al. [159] | 2019 | Mobile Logistics | | DRL-based | DDPG, PPO | RL | Simulation |
| Iwasaki et al. [160] | 2021 | Inverted Pendulum | NS | DRL-based | DDPG | RL | Simulation |
| James et al. [161] | 2016 | Serial | NS | DRL-based | DQN | RL | Both |
| Jeong et al. [162] | 2020 | Serial Rehabilitation | | Learning-based | MDCBN, CNN-BiLSTM | Supervised | Experiment |
| Jiang et al. [163] | 2023 | Manufacturing | | DRL-based | PPO, GAIL, Transformer | RL, IL | Both |
| Jiang et al. [164] | 2024 | Serial | NS | Fuzzy RL-based optimal | fuzzy logic system, Integral RL, Value iteration | RL | Experiment |
| Jiang et al. [165] | 2022 | Serial Service | | Vision-guided DRL-based | Asym-DDPG, Position-CycleGAN, Supervised learning | RL, Supervised, Hybrid | Both |
| Jin et al. [166] | 2024 | Redundant Serial | NS | Learning-based | Echo State Network, Kalman Filter | Supervised | Both |
| Joshi et al. [167] | 2020 | Hybrid | NS | DRL-based | DDQN, Grasp-Q-Network | RL, Off-policy | Both |
| Josifovski et al. [168] | 2022 | Serial | NS | Learning-based | PPO | RL | Both |

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|--------------------------|------|--------------------------------|----|-------------------------|---|----------------------|-----------------|
| Kalashnikov et al. [169] | 2018 | Serial | NS | Vision-guided DRL-based | QT-Opt, DQN, CEM | RL, Self-supervised | Both |
| Kamali et al. [170] | 2020 | Serial Industrial | | DRL-based | PPO, DRL | RL | Both |
| Kang et al. [171] | 2021 | Serial | NS | NN-based MPC | RBFNN, AC NN | RL, Hybrid | Simulation |
| Kankashvar et al. [172] | 2015 | Parallel | NS | BBO-based PID | modified BBO | - | Simulation |
| Kataoka et al. [173] | 2022 | Serial | NS | Learning-based | PPO, MLP | RL | Both Simulation |
| Katyal et al. [174] | 2017 | Serial | NS | DRL-based | DRL, DQN | RL | Simulation |
| Kaur et al. [175] | 2025 | Serial Industrial | | DRL-based | DRL, DQN | RL | Simulation |
| Khan et al. [176] | 2020 | Redundant Serial | NS | Metaheuristic-based | BAORNN, RNN, Beetle antennae olfactory | - | Simulation |
| Khodamipour et al. [177] | 2021 | Serial | NS | RL-based adaptive | RL, Fourier series expansion | RL | Simulation |
| Kilinc et al. [178] | 2022 | Dexterous Hand Anthropomorphic | NS | RL-based | DDPG, HER | RL | Simulation |
| Kim et al. [179] | 2024 | Gripper Anthropomorphic | NS | Learning-based | PPO | RL | Both |
| Kuang [180] | 2023 | Anthropomorphic Gripper | NS | Learning-based | DDPG+HER, GAIL, GDP, PL-CGS, Goal-SGAIL | RL, IL | Simulation |
| Kumar et al. [181] | 2017 | Serial Multiple | | GA-optimized fuzzy | GA, Fuzzy logic, Neuro-fuzzy | Unsupervised, Hybrid | Simulation |

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| Kumar et al. [182] | 2021 | Serial | Redundant NS | DRL-based | PPO, Deep neural policy | RL | Both |
| Kunal et al. [183] | 2025 | Serial | Manufacturing Man | DRL-based | PPO, DNN | RL | Both |
| Kurrek et al. [184] | 2020 | Serial | Manufacturing Man | DRL-based | Q-learning, DQN, PPO | RL | Simulation |
| Lahmann et al. [185] | 2025 | Serial | NS | DRL-based | PPO | RL | Simulation |
| Lee et al. [186] | 2022 | Serial | Redundant NS | Learning-based | RL, ANN | RL, Supervised | Simulation |
| Lee et al. [187] | 2020 | Serial | NS | DRL-based | HER, DDPG | RL | Simulation |
| Lee et al. [188] | 2024 | Serial | Rehabilitation | Learning-based | CNN-KF, PPO, Grounding DINO | RL, Supervised | Experiment |
| Liang et al. [189] | 2024 | Serial | NS | RL-based adaptive | AC, NN | RL | Both |
| Lin et al. [190] | 2025 | Humanoid | Service | Vision-guided learning-based | RL, PPO, Diffusion policy, Policy distillation | RL, IL | Both |
| Lin et al. [191] | 2017 | Serial | NS | Cerebellar-inspired learning-based | Distributed cerebellar model, Spike-timing-dependent plasticity | RL | Both |
| Lin et al. [192] | 2023 | Serial | NS | DRL-based | PPO, DRL, Pix2Pix GAN | RL | Both |
| Lin et al. [193] | 2022 | Serial | NS | DRL-based | PPO, GAN | RL | Both |
| Liu et al. [194] | 2021 | Serial | Multiple | Learning-based | RBFNN | Supervised, Hybrid | Simulation |
| Liu et al. [195] | 2020 | Serial | NS | RL-based | MAPPO | RL | Both |
| Liu et al. [196] | 2024 | Serial | NS | DRL-based | TD3 | RL | Simulation |

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| Liu et al. [197] | 2020 | Serial | NS | DRL-based | DQN | RL | Both |
| Liu et al. [198] | 2019 | Redundant Serial | Multiple | Learning-based | LSTM | Supervised | Simulation |
| Liu et al. [199] | 2021 | Serial | NS | DRL-based | Off-policy AC, DRL | RL | Simulation |
| Liu et al. [200] | 2024 | Serial | NS | HRL-based | Hierarchical RL, PGPE | RL | Both |
| Li et al. [201] | 2025 | Serial | Manufacturing | DRL-based | PPO, Simulated Annealing | RL | Both |
| Li et al. [202] | 2023 | Redundant Serial | NS | Biomimetic learning-based | SNN, DDPG, STDP | RL, Unsupervised | Both |
| Li [203] | 2021 | Serial | Manufacturing | DRL-based | DQN | RL | Simulation |
| Li et al. [204] | 2019 | Serial | NS | Automaton-guided RL | RL, PPO | RL | Both Experiment |
| Li et al. [205] | 2021 | Serial | Service | DRL-based | DRL, CNN, Policy search | RL | Simulation |
| Li et al. [206] | 2024 | Serial | NS | RL-based sliding mode | RL, AC NN, RBFNN | RL | Simulation |
| Li et al. [207] | 2015 | Serial | NS | Learning-based | AC, RBFNN | RL | Simulation |
| Li et al. [208] | 2021 | Serial | Aerospace | DRL-based | DDPG | RL | Simulation |
| Li et al. [209] | 2023 | Redundant Serial | NS | Autoencoder-based kinematic | sparse autoencoder, RNN | - | Simulation |
| Li et al. [210] | 2018 | Humanoid | NS | RL-based | RL, DMP | RL | Experiment |
| Lobbezoo et al. [211] | 2023 | Serial | Manufacturing | Learning-based | PPO, Soft AC | RL | Both |

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| Luo et al. [212] | 2018 | Serial Manufacturing | Man | DRL-based | MDGPS, DNN | RL | Experiment |
| Luo et al. [213] | 2025 | Serial Manufacturing | Man | Vision-guided learning-based | Off-policy RL, RLPD, Soft AC | RL, IL, Hybrid | Experiment |
| Luo et al. [214] | 2025 | Serial | NS | RL-based | PPO | RL | Simulation |
| Lu et al. [14] | 2023 | Parallel | NS | DRL-based | DRL, Soft AC | RL | Both |
| Majumder et al. [215] | 2024 | Serial | NS | DRL-based | DDPG, AC | RL | Simulation |
| Majumder et al. [216] | 2023 | Serial | NS | DRL-based | Improved DDPG | RL | Simulation |
| Maldonado-Ramirez et al. [217] | 2021 | Serial Manufacturing | Man | Vision-guided DRL-based | PPO, A2C, TRPO | RL | Both |
| Malik et al. [218] | 2022 | Redundant Serial | NS | DRL-based | DQN | RL | Both |
| Mannaa et al. [219] | 2023 | Serial Manufacturing | Man | DRL-based | DDPG, HER | RL | Both |
| Mao et al. [220] | 2025 | Serial | NS | Vision-guided learning-based | Soft AC | RL | Both |
| Matas et al. [221] | 2018 | Serial Service | Service | DRL-based | DDPG | RL, IL | Both |
| Mazzaglia et al. [222] | 2024 | Redundant Serial | NS | Learning-based | RL, IL | RL, IL | Both |
| Ma et al. [223] | 2025 | Serial Multiple | Multiple | Learning-based | Multimodal contrastive learning, Diffusion models | RL, Self-supervised | Simulation |
| Mellatshahi et al. [224] | 2021 | Serial | NS | DRL-based | DQN | RL | Simulation |

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| Meyes et al. [225] | 2017 | Serial Manufacturing | Human | RL-based | Q-learning | RL | Both |
| Molina [226] | 2018 | Serial Service | | RL-based | Relational RL, Q-Learning | RL, IL | Both |
| Moon et al. [227] | 2021 | Redundant Structure | Underwater | Meta-RL-based control | meta-RL, Model-based RL | RL | Simulation |
| Mueangprasert et al. [228] | 2023 | Serial NS | | MBRL-based | GPR, ANN, SVR, PSO | RL | Simulation |
| Naranjo-Campos et al. [229] | 2024 | Mobile | Rehabilitation | DRL-based | PPO, DRL | RL | Both |
| Nguyen et al. [230] | 2023 | Serial NS | | DRL-based | DDPG, HER | RL | Both |
| Nohooji et al. [231] | 2024 | Serial Multiple | | RL-based PID | AC, RBFNN | RL | Simulation |
| Ouyang et al. [232] | 2017 | Serial NS | | RL-based | RBFNN, AC | RL | Both |
| Pane et al. [233] | 2016 | Serial Manufacturing | Human | RL-based | AC | RL | Experiment |
| Pane et al. [234] | 2019 | Serial Manufacturing | | RL-based compensation | AC, RBFNN | RL | Experiment |
| Pantoja-Garcia et al. [235] | 2022 | Serial NS | | AC-based | AC, NN | RL | Simulation |
| Pan et al. [236] | 2025 | Serial Multiple | | DRL-based | TD3 | RL | Simulation |
| Pan et al. [237] | 2023 | Serial NS | | DRL-based | DRL | RL | Simulation |
| Park et al. [238] | 2024 | Serial NS | | DRL-based | PPO | RL | Both |
| Pavlichenko et al. [239] | 2022 | Redundant Structure | | DRL-based | Soft AC, Beta policy | RL | Both |
| Pedersen et al. [240] | 2020 | Serial NS | | DRL-based | PPO, CycleGAN | RL, Unsupervised | Experiment |

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| Perrusquia et al. [241] | 2021 | Serial | NS | RL-based optimal tracking | NN, RL, Experience replay | RL | Simulation |
| Perrusquía et al. [242] | 2019 | Pan and tilt | NS | RL-based impedance | RL, Q-learning, TD-learning, NRBF, K-means | RL | Experiment |
| Pham et al. [243] | 2025 | Parallel | NS | RL-based adaptive | AC RL, NN | RL | Experiment |
| Polydoros et al. [244] | 2015 | Manufacturing | NS | Learning-based | PC-ESN, Echo State Network, Generalized Hebbian Learning, Bayesian linear regression | Supervised | Experiment |
| Popov et al. [245] | 2017 | Serial | NS | DRL-based | DDPG | RL | Both Simulation |
| Qiao et al. [246] | 2021 | Serial | NS | MPC-guided DRL-based | DQN | RL | Simulation |
| Qin et al. [247] | 2022 | Dexterous Hand | NS | DRL-based | PPO, PointNet | RL | Both |
| Qi et al. [248] | 2021 | Serial | NS | DRL-based | improved DDPG | RL | Simulation |
| Quillen et al. [249] | 2018 | Hybrid | NS | Vision-guided DRL-based | DQN, DDPG, Path consistency learning, Monte Carlo policy evaluation, Corrected Monte Carlo | RL, Supervised | Simulation |
| Rajeswaran et al. [250] | 2018 | Anthropomorphic Gripper Redundant | NS | DRL-based | DRL, DAPG, Behavior cloning, NPG | RL, IL, Hybrid | Simulation |
| Ramirez et al. [251] | 2022 | Serial | NS | DRL-based | TD3, Supervised learning | RL, IL, Supervised | Simulation |

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| Ramirez et al. [252] | 2023 | Serial | Redundant NS | RLED-based | TD3, Supervised learning | RL, IL, Simulation |
| Ren et al. [253] | 2020 | Serial | NS | Learning-based | RBFNN | Simulation |
| Ren et al. [254] | 2020 | Serial | NS | GAN-based inverse modeling | CGAN, LSGAN, BiGAN, DualGAN | Simulation |
| Rizzardo et al. [255] | 2023 | Serial | NS | DRL-based | Soft AC, Variational Autoencoder | Simulation |
| Rubagotti et al. [256] | 2023 | Serial | NS | DRL-based | DRL, Q-learning, NAF | Simulation |
| Saeed et al. [257] | 2021 | Serial | NS | DRL-based | DDPG, DDPG+HER, PPO | Simulation |
| Sahu et al. [258] | 2021 | Serial | NS | DRL-based | DDPG, AC | Simulation |
| Saidi et al. [259] | 2023 | Serial | NS | GA-optimized backstepping | GA | Simulation |
| Said et al. [260] | 2019 | Serial | NS | ABC-optimized PID | ABC, PSO | Simulation |
| Sajadi et al. [261] | 2022 | Serial | Healthcare | DRL-based | DDPG | Simulation |
| Sangiovanni et al. [262] | 2021 | Serial | Redundant Manufacturing | DRL-based | DRL, NAF | Simulation |
| Sangiovanni et al. [263] | 2018 | Serial | Anthropomorphic Manufacturing | DRL-based | DRL, NAF | Simulation |
| Sangiovanni et al. [264] | 2018 | Serial | Manufacturing | DRL-based | DRL, NAF | Simulation |
| Scheikl et al. [265] | 2023 | Serial | Healthcare | Vision-guided learning-based | PPO, Contrastive GAN, DCL | Simulation |

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| Sekkat et al. [266] | 2021 | Serial | NS | DRL-based | DDPG, YOLOv5 | RL | Simulation |
| Shahid et al. [267] | 2022 | Redundan t Serial | Manu factur ing | RL-based | PPO, Soft AC | RL | Both |
| Shahna et al. [268] | 2024 | Serial | NS | DRL-based | Soft AC | RL | Simulation |
| Shao et al. [269] | 2025 | Serial | NS | DRL-based impedance | DDPG, Behavior cloning | RL, IL, Sim Hybrid | Simulation |
| Shetty et al. [270] | 2021 | Serial | NS | DRL-based | DDPG | RL | Simulation |
| Shiferaw et al. [271] | 2024 | Serial | Multiple | DRL-based | DQN, DenseNet- 121 | RL, Self- supervised | Simulation |
| Shin et al. [272] | 2019 | Cable- drive n | Health care | Learning- based predictiv e | RL, Learning from demonstration, NN | RL, IL | Both |
| Siddique et al. [273] | 2024 | Serial | Reha bilita tion | DRL-based | DDPG | RL | Simulation |
| Simon et al. [274] | 2024 | Serial | Multiple | DRL-based | DQN, DMP | RL, IL | Both |
| Sivertsvik et al. [275] | 2024 | Hybrid | Multiple Man | DRL-based | PPO, PPG | RL | Both |
| Song et al. [276] | 2024 | Serial | Manufactur ing | RL-based | Q-learning | RL | Both |
| Song et al. [277] | 2024 | Serial | NS | RL-based consensus | RL, AC, NN | RL | Simulation Simulation |
| Staley et al. [278] | 2018 | Serial | NS | DRL-based | DQN, DRL | RL | Simulation |
| Sun et al. [279] | 2021 | Redundan t Serial | Manu factur ing | Learning- based | Fully connected NN | Super vised | Simulation |
| Sun et al. [280] | 2023 | Redundan t Serial | NS | Hybrid LfD- RL | DMP, RL, Policy network, Q- network | RL, IL, Hybri d | Expe ri me nt |

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| Sun et al. [281] | 2020 | Serial | NS | DRL-based | DRL, Soft AC | RL | Both |
| Su et al. [282] | 2024 | Serial | NS | RL-based | PPO | RL | Both |
| Su et al. [283] | 2025 | Serial | NS | RL-based backstepping | AC NN, RL | RL | Simulation |
| Su et al. [284] | 2020 | Anthropomorphic | Healthcare | Learning-based | DCNN | Supervised | Both |
| Tajdari et al. [285] | 2017 | Serial | Manufacturing | Adaptive sliding-mode | Model reference adaptive control, Adaptive sliding mode | - | Experiment |
| Takeda et al. [286] | 2025 | Serial | NS | Hierarchical RL-based | Soft AC, Goal-conditioned RL | RL | Simulation |
| Tang et al. [287] | 2022 | Serial | Rehabilitation | DRL-based | PPO, DRL | RL | Simulation |
| Uchibe et al. [288] | 2021 | Humanoid | NS | IL-based | ERIL, Soft AC, IRL | RL, IL | Both |
| Valencia et al. [289] | 2023 | Serial | NS | RL-based | TD3, Probabilistic NN, Gaussian mixture | RL | Simulation |
| Vijay et al. [290] | 2018 | Serial | Power Transmission | Learning-based | RBFNN | Supervised, Hybrid | Simulation |
| Vu et al. [291] | 2021 | Serial | NS | ARL-based | AC NN, ADP | RL | Simulation |
| V et al. [292] | 2025 | Flexible Joint | NS | DRL-based | CPPO, PPO, CNN | RL | Experiment |
| Wang et al. [293] | 2020 | Mobile | NS | DRL-based | PPO, DRL | RL | Both |
| Wang et al. [294] | 2025 | Serial | NS | DRL-based | Soft AC, LSTM, Random Network Distillation, attention mechanism | RL | Simulation |
| Wang, et al. [295] | 2024 | Serial | NS | DRL-based | DDPG | RL | Both |
| Wang et al. [296] | 2025 | Serial | Multiple | DRL-based | HTSK Fuzzy system, GABC, Rainbow-DDPG, CPL | RL, IL, Hybrid | Both |

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| Wang et al. [297] | 2024 | Serial | NS | RL-based | RL, NN | RL | Simulation |
| Wang, et al. [298] | 2017 | Serial | NS | Learning-based | RBFNN | - | Simulation |
| Wang et al. [299] | 2023 | Dexterous | NS | DRL-based | DDPG, HER, Knowledge Transfer | RL | Both |
| Wang et al. [300] | 2020 | Serial | NS | Learning-based | LSTM, Attention mechanism | Supervised | Experiment |
| Wang et al. [301] | 2024 | Serial | NS | MBRL-based | Model-based RL, Curiosity-driven RL, Soft AC | RL, Self-supervised | Simulation |
| Wang et al. [302] | 2025 | Redundant Serial | NS | Neuro-fuzzy-based | Fuzzy Logic System, AC-Identify, ADP | RL, Hybrid | Experiment |
| Wang et al. [303] | 2025 | Serial Multiple | | Learning-based optimal | Multilayer FNN, RL | RL | Simulation |
| Wang et al. [304] | 2023 | Redundant Serial | NS | Hierarchical multi-agent RL-based | Multi-agent PPO, hierarchical RL, PPO | RL | Simulation |
| Weber et al. [305] | 2021 | Serial | NS | DRL-based | DDPG | RL | Both |
| Wu et al. [306] | 2025 | Serial Manufacturing | | RL-based | Soft AC, DDPG, gated feature extractor | RL | Both |
| Wu et al. [307] | 2022 | Serial | NS | Adversarial RL-based | Adversarial RL | RL | Both |
| Wu et al. [308] | 2023 | Serial | NS | Learning-based | RBFNN | - | Both |
| Wu et al. [309] | 2024 | Serial | NS | RL-based output feedback | RL, RBFNN | RL | Simulation |
| Wu et al. [310] | 2025 | Serial | NS | DRL-based | Soft AC, Soft ACwB | RL | Both |
| Xhin et al. [311] | 2024 | Serial | NS | DRL-based | DDPG | RL | Both |
| Xiao et al. [312] | 2024 | Serial Manufacturing | | Learning-based | PPO, IL | RL, IL | Both |

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| Xie et al. [313] | 2019 | Serial | NS | DRL-based | DDPG, A3C, DPPO | RL | Simulation |
| Xu et al. [314] | 2023 | Serial | NS | Learning-based | CURL, Soft AC, U-Net | RL, Self-supervised, Unsupervised | Both |
| Xu et al. [315] | 2024 | Serial | NS | Learning-based | Hybrid NN, RBFNN, DiffNEA | Supervised | Experiment |
| Yagi et al. [12] | 2025 | Serial | NS | Hierarchical RL-based | Hierarchical RL, PPO | RL | Experiment |
| Yang et al. [316] | 2025 | Serial | Mini | DRL-based | IM-DQN, Prioritized experience replay, ICM | RL | Both |
| Yang et al. [317] | 2023 | Serial | NS | Hybrid model-free RL, broader industrial applications | Soft AC, PETS, CEM | RL | Both |
| Yang et al. [318] | 2025 | Serial | NS | Learning-based fault-tolerant | AC RL, RBFNN | RL | Both |
| Yang et al. [319] | 2025 | Serial | NS | Learning-based | Deterministic learning, RBFNN, Knowledge fusion | - | Simulation |
| Yang et al. [320] | 2022 | Serial | NS | RL-based impedance | Off-policy reinforcement | RL | Both |
| Yuan et al. [321] | 2025 | Serial | NS | Dexterous Hand Vision-guided learning-based | PPO, DrM, DAgger | RL, IL | Both |
| Zhang et al. [322] | 2015 | Serial | NS | DRL-based | DQN | RL | Both |
| Zhang et al. [323] | 2023 | Serial | NS | DRL-based | Soft AC, GAN | RL | Both |

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| Zhang [324] | 2025 | Serial | Manufacturing | Learning-based | MLP, CNN, LSTM, Q-learning, AC | RL, Supervised, Hybrid | Both |
| Zhang et al. [325] | 2023 | Redundant Serial | NS | DRL-based | DQN, Soft AC | RL | Simulation |
| Zhang et al. [326] | 2023 | Serial | NS | DRL-based trajectory | PPO, DRL | RL | Both |
| Zhang et al. [327] | 2022 | Serial | NS | DRL-based | Mask R-CNN, Soft AC | RL | Both |
| Zhang et al. [328] | 2023 | Serial | NS | symbolic regression-based | Symbolic regression, Genetic programming | Supervised | Simulation |
| Zhang et al. [329] | 2022 | Serial | NS | DRL-based | PPO, CNN | RL | Simulation |
| Zhan et al. [330] | 2022 | Serial | NS | Vision-guided learning-based | Soft AC, Contrastive learning, Data augmentation | RL, IL, Self-supervised | Both |
| Zhao et al. [331] | 2024 | Serial | Manufacturing | DRL-based | MAPPO, PPO | RL | Both |
| Zhao et al. [332] | 2020 | Serial | NS | DRL-based | PPO, DRL | RL | Simulation |
| Zheng et al. [333] | 2023 | Serial | NS | DRL-based trajectory | DDPG, TD3, Soft AC | RL | Simulation |
| Zhou et al. [334] | 2021 | Serial | NS | DRL-based | DDPG | RL | Simulation |
| Zhu et al. [335] | 2022 | Serial | Aerospace | Fuzzy RL-based | Fuzzy wavelet network, RL | RL | Simulation |
| Zhu et al. [336] | 2019 | Desktop Hand | NS | DRL-based | DRL, DAPG, natural policy gradient | RL, IL, Hybrid | Both |
| Zhu et al. [337] | 2025 | Serial | Multiple | RL-based optimal tracking | AC-identifier NN, RL | RL | Simulation |

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| Interaction and Safety | Zong et al. [338] | 2025 | Dexterous Hand | Manufacturing | DRL-based | TD3, D2SR, pruning | RL | Simulation |
| | Modares et al. [339] | 2016 | Serial | NS | Learning-based | Integral RL, NN | RL | Both |
| | Perrusquía et al. [340] | 2019 | Serial | NS | Learning-based position/force | Q-learning, Sarsa | RL | Both |
| | Sasaki et al. [341] | 2022 | Serial | NS | DRL-based | DDQN, CNN | RL, Supervised | Both |
| | Wang et al. [342] | 2024 | Serial | Multiple | Learning-based teleoperation | 1D CNN, Multiview multitask | Supervised | Experiment |
| | AlAttar et al. [343] | 2022 | Serial | NS | Learning-based predictive | Local linear models, Least squares regression | Self-supervised | Both |
| | Baselizadeh, et al. [344] | 2022 | Serial | NS | Learning-based | Q-Learning, RL | RL | Simulation |
| | Ding et al. [345] | 2021 | Serial | NS | NS | Model-based off-policy RL | RL | Simulation |
| | Elsisi et al. [13] | 2021 | Serial | NS | NS | Modified NN Algorithm, polynomial mutation | - | Simulation |
| | Haddad et al. [346] | 2021 | Serial | NS | Swarm-optimized | PSO, SSO | - | Simulation |
| Learning and Adaptation | Jeong et al. [347] | 2020 | Serial | NS | Vision-guided learning-based | MPO, behavioral cloning, Contrastive Forward Dynamics | RL, IL, Self-supervised | Both |
| | Jhan et al. [348] | 2015 | Serial | NS | Fuzzy neural-based adaptive impedance force | fuzzy NN, FNS | Hybrid | Simulation |
| | Kallel et al. [349] | 2025 | Serial | NS | Learning-based | MLP Regressor, Random Forest Regressor, PINNs | Hybrid, Supervised | Simulation |
| | Kuang et al. [350] | 2025 | Serial | NS | DRL-based | DRL, Soft AC | RL | Both |

| | | | | | | | |
|--------------------------|------|-------------|----------------|------------------------------|--|-----------------------|------------|
| Li et al. [351] | 2022 | Serial | NS | Learning-based adaptive | Concurrent learning | - | Both |
| Li et al. [352] | 2023 | Serial | NS | RL-tuned MPC visual servoing | DDPG | RL | Simulation |
| Li et al. [353] | 2017 | Exoskeleton | Rehabilitation | RL-based adaptive impedance | Integral RL | RL | Experiment |
| Lu et al. [354] | 2024 | Serial | NS | Learning-based | SARSA, RL | RL | Simulation |
| Pradhan et al. [355] | 2020 | Serial | NS | Nonlinear self-tuning PID | NARMAX, RLS | - | Both |
| Sacchi et al. [356] | 2023 | Serial | NS | DRL-assisted ISM | DNN, TD3, DRL | RL | Simulation |
| Shcherbakov et al. [357] | 2020 | Serial | Manufacturing | Digital-twin based adaptive | Kalman filtering, System identification, Predictive modeling | - | Simulation |
| Wu et al. [358] | 2025 | Serial | Multiple | DRL-based admittance | DRL, NAF | RL | Both |
| Xie et al. [359] | 2020 | Serial | Aerospace | RL-based fuzzy sliding mode | Fuzzy logic, RL, Q-learning | RL | Simulation |
| Yousef et al. [360] | 2024 | Serial | NS | DRL-based | DDPG | RL | Simulation |
| Zhang et al. [361] | 2024 | Serial | NS | Deep MPC-based | Deep MPC, NN | RL, Adaptive Learning | Simulation |

* ACO: Ant Colony Optimization; ADP: Adaptive Dynamic Programming; ANN: Artificial Neural Network; ARL: Adoption Readiness Levels; BBO: Biogeography-based Optimization; BCI: Brain-Computer Interface; Both: Simulation and Experiment; CNN: Convolutional Neural Network; CNN-LSTM: Convolutional Neural Network-Long Short-Term Memory; DDPG: Deep Deterministic Policy Gradient; DDQN: Double Deep Q-Network; DMP: Dynamic movement primitives; DNN: Deep Neural Network; DQN: Deep Q-Network; DRL: Deep Reinforcement Learning; dDRL: Distributed Deep Reinforcement Learning; DT: Decision Tree; FL: Fuzzy Logic; GA: Genetic Algorithm; GAN: Generative Adversarial Networks; GP: Gaussian Process; GPR: Gaussian Process Regression; HER: Hindsight Experience Replay; HGCIL: Hierarchical goal-conditioned imitation learning.; ID: Inverse Dynamics; IK: Inverse Kinematics; IL: Imitation Learning; IRL: Inverse Reinforcement Learning; ISM: Interpretive Structural Modeling; KNN: k-Nearest Neighbor; LSTM: Long Short-Term Memory network; MBRL: Model-based Reinforcement Learning; MDGPS: Mirror-descent Guided Policy Search; MLP: Multilayer Perceptron; MP: Movement primitives; MPC: Model Predictive Control; MS-CLSTM: Multi-Scale CNN-LSTM (MS Block-ResCBAM-Bi-LSTM hybrid); MSBO: Modified Smell Bee Optimization (for EMG); NAF: Normalized Advantage Function; NN: Neural Network; NS: Not Specified; PG: Policy Gradient; PPG: Phasic Policy Gradient; PPO: Proximal Policy Optimization;

PSO: Particle Swarm Optimization; R-CNN: Region-based CNN; RBFNN: Radial Basis Function Neural Network; RL: Reinforcement Learning; RLED: Reinforcement Learning from Expert Demonstration; RNN: Recurrent Neural Network; RT: Regression tree; SNN: Spiking Neural Network; SVM: Support Vector Machine; SVR: Support Vector Regression; sEMG: Surface Electromyography; TAC-CA: Tsallis Actor-Critic with Clipped Automatic; TD3: Twin Delayed Deep Deterministic Policy Gradient; TSK: Takagi-Sugeno-Kang.

Table 4. Frequency and percentage of use in robot types.

| Robot Type | Frequency of Use | Percentage |
|-----------------|------------------|------------|
| Serial | 255 | 74.3% |
| Robotic Hand | 32 | 9.3% |
| Others | 18 | 5.2% |
| Flexible Joint | 15 | 4.4% |
| Anthropomorphic | 6 | 1.7% |
| Parallel | 5 | 1.5% |
| Magnetic | 5 | 1.5% |
| Mobile | 3 | 0.9% |
| Hybrid | 3 | 0.9% |
| Not Specified | 1 | 0.3% |

Table 5. Frequency and percentage of use in applications.

| Application | Frequency of Use | Percentage |
|----------------|------------------|------------|
| Not Specified | 207 | 60.3% |
| Manufacturing | 64 | 18.7% |
| Multiple | 21 | 6.1% |
| Rehabilitation | 16 | 4.7% |
| Healthcare | 10 | 2.9% |
| Service | 7 | 2.0% |
| Aerospace | 5 | 1.5% |
| Logistics | 4 | 1.2% |
| Industrial | 3 | 0.9% |
| Others | 6 | 1.7% |

Table 6. Frequency and percentage of use in control technique.

| Control Technical Family | Frequency of Use | Percentage |
|-------------------------------------|------------------|------------|
| Learning-based | 311 | 90.7% |
| Fuzzy-based | 8 | 2.3% |
| Optimization-based | 6 | 1.7% |
| Adaptive / Robust classical control | 6 | 1.7% |
| MPC-based / Hybrid MPC | 3 | 0.9% |
| Perception / Estimation-guided | 6 | 1.7% |
| Assistive / Copilot-based | 1 | 0.3% |
| Not Specified | 2 | 0.6% |

*MPC: Model Predictive Control.

Table 7. Frequency and percentage of use in control technique.

| Learning Paradigm | Frequency of Use | Percentage |
|------------------------|------------------|------------|
| Reinforcement Learning | 202 | 58.9% |
| Supervised | 42 | 12.2% |
| Self-supervised | 2 | 0.6% |
| Unsupervised | 1 | 0.3% |

| | | |
|----------------|----|-------|
| Hybrid | 48 | 14.0% |
| Multi-paradigm | 29 | 8.5% |
| Not Specified | 19 | 5.5% |

3.1. Publications

Figure 2 demonstrates a clear increase in publication output on AI-based robot manipulator control from 2015 to 2025. This indicates a progressive expansion of the field over the review period. The annual number of publications remained relatively low and variable during 2015–2019, suggesting that research activity was still limited and not yet consolidated. Beginning in 2020, publication output increased sharply, marking a clear inflection point in the development of the literature. This growth continued through 2023, where the annual count reached its maximum, followed by a slight decline in 2024–2025. Despite this modest reduction, the number of publications in the final years remained substantially higher than that observed in the earlier period. Overall, the trend indicates that AI-based robot manipulator control has emerged as a rapidly expanding research area over the past decade.

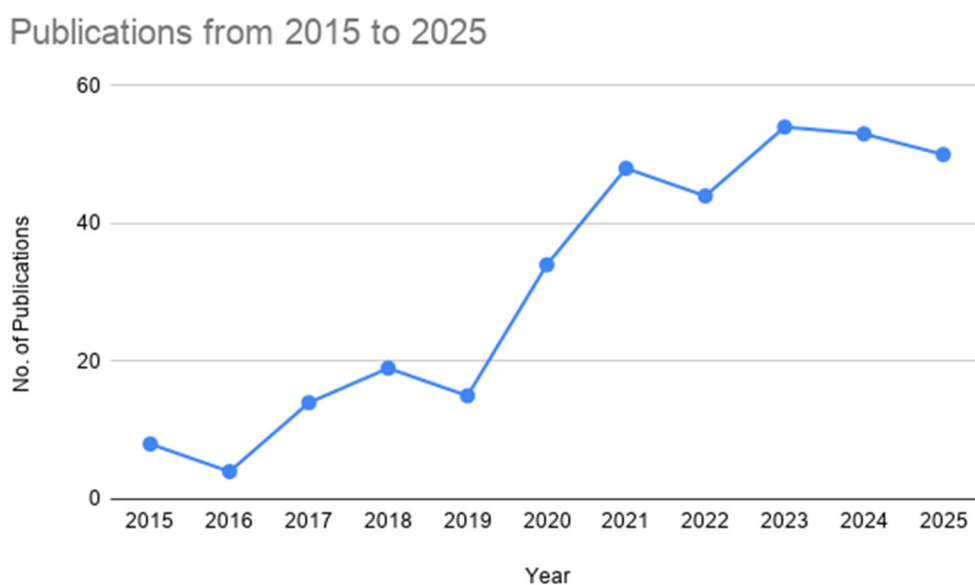


Figure 2. The distribution of publications in AI-based robot manipulator control from 2015 to 2015.

3.2. Research Interest

Figure 3 shows that the included studies were unevenly distributed across functional roles. learning control accounted for 75.5% of the literature, far exceeding planning (11.4%), perception and estimation (6.1%), learning and adaptation (5.8%), and interaction and safety (1.2%). These results indicate that AI-based robot manipulator control research was concentrated predominantly in learning control, whereas the other functional roles were represented at much lower levels. The year-by-year distribution of publications across these roles is presented in Figure 4.

Figure 4 shows that the five functional-role categories followed different patterns over the review period. Learning control remained the dominant category in nearly every year and accounted for the largest share of publications throughout the dataset. Planning, perception and estimation, and learning and adaptation were represented at lower but recurring levels, although their annual counts remained comparatively small. Interaction and safety was the least represented category across the full period. Overall, the increase in annual publication output was associated primarily with continued growth in learning control, whereas the other functional roles remained limited in frequency.

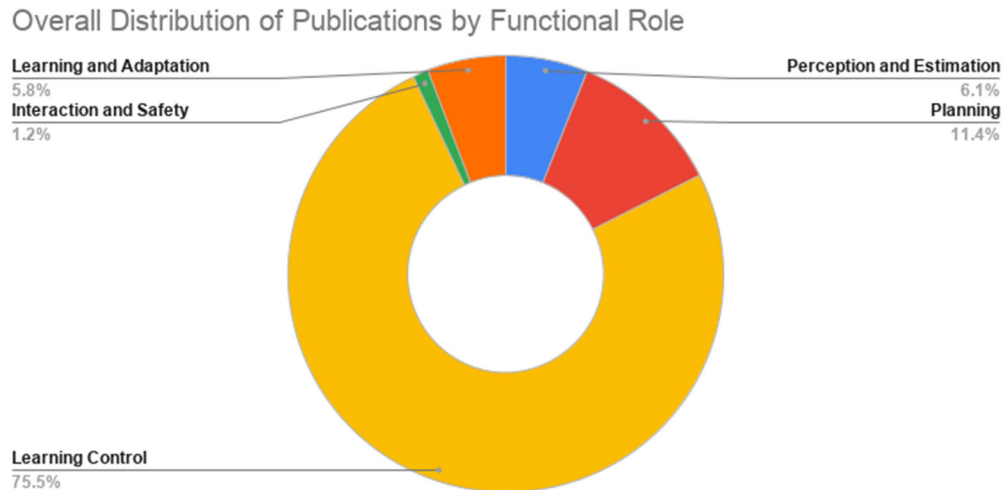


Figure 3. The distribution of publications in AI-based robot manipulator control by functional roles.

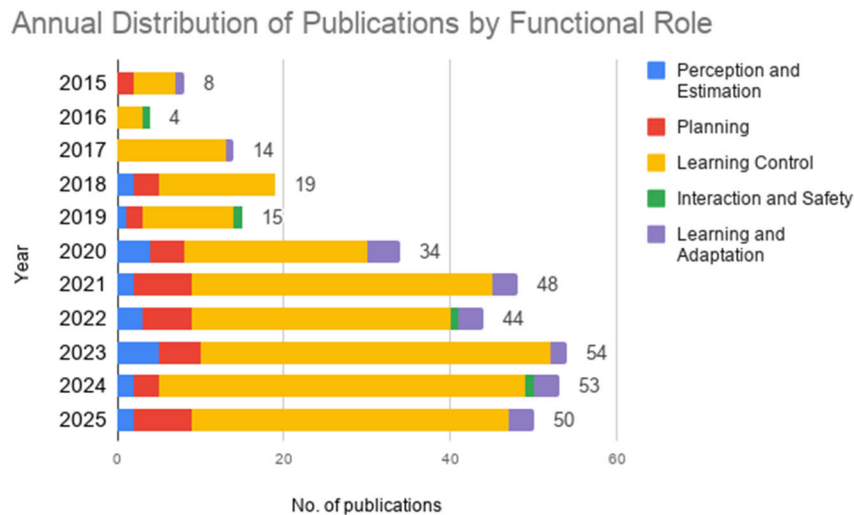


Figure 4. The distribution of publications across five categories from 2015 to 2015.

3.3. Robot Types

Table 4 summarizes the distribution of studies by robot type. The literature was strongly dominated by serial manipulators, which accounted for 74% of the included studies. Robotic hands (9.3%) and flexible-joint robots (4.4%) formed the next largest categories, while all remaining robot types each represented only a small share of the dataset. This distribution indicates that the field has been centered primarily on conventional serial robotic platforms, with comparatively limited representation of more specialized configurations such as parallel manipulators, exoskeletons, humanoids, magnetic systems, and mobile manipulators.

3.4. Applications

Table 5 summarizes the distribution of studies by application domain. The largest share of the literature fell under Not Specified, indicating that more than half of the included studies were not linked to a clearly defined end-use setting. Among the explicitly reported domains, Manufacturing accounted for the largest proportion with 18.7% of the total studies, while all other application areas were represented less frequently. This distribution indicates that AI-based robot manipulator control

has been investigated across multiple sectors, but that explicit domain-specific application has been concentrated primarily in Manufacturing.

3.5. Control Techniques

Table 6 presents the grouping of 44 distinct control techniques into higher-order control families. The resulting distribution was strongly concentrated in learning-based control, which accounted for 90.7% of all publications, while the remaining families each represented only a small proportion of the dataset. Within this dominant family, deep reinforcement learning (DRL) based control comprised 150 studies, corresponding to approximately 48% of learning-based studies and 43.7% of the full dataset. Other learning-based subgroups, including hybrid RL–neural networks (NN), adaptive dynamic programming (ADP) based, and deep NN-based visual servoing, were represented at lower frequencies. This pattern indicates that the methodological concentration of the literature occurred not only at the family level, but also within the learning-based family itself, where reinforcement-learning-oriented approaches formed the principal subgroup.

3.4. AI-based Methods

A total of 278 distinct AI methods were identified across the dataset. The complete list is provided in supplementary material, while the present figure reports only the 20 most frequently used methods for clarity in Figure 5. The distribution shows that the literature has been dominated by reinforcement-learning-based approaches, particularly soft actor-critic (SAC), proximal policy optimization (PPO), deep deterministic policy gradient (DDPG), and related variants, whereas other methods occurred less frequently. Because individual studies could employ multiple methods, these frequencies do not correspond directly to the number of studies. Overall, the results indicate both methodological diversity across the dataset and concentration around a small core of recurrent RL-based techniques.

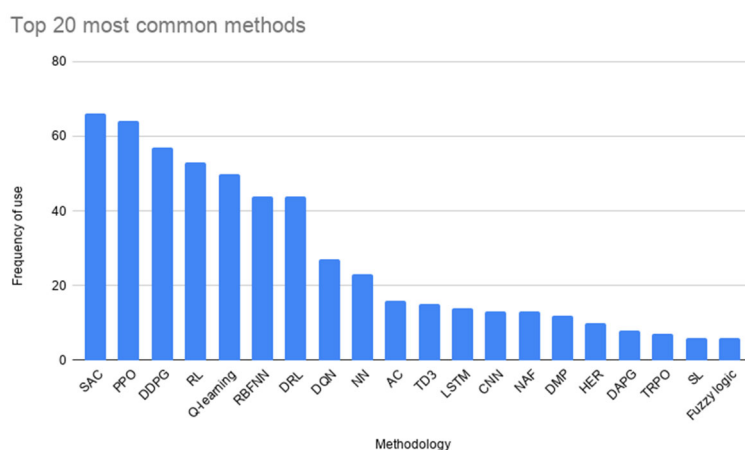


Figure 5. Distribution of the top 20 most employed AI methods. (SAC: Soft Actor-Critic; PPO: Proximal Policy Optimization; DDPG: Deep Deterministic Policy Gradient; RL: Reinforcement Learning; DQN: Deep Q-Network; NN: Neural Networks).

3.5. Learning Paradigm

The distribution of the learning paradigm across studies is presented in Table 7 by frequency and percentage. The learning-paradigm distribution shows that RL was the dominant paradigm, accounting for 58.9% of the included studies. Supervised learning represented 12.2%, whereas self-supervised and unsupervised learning were only rarely reported. Combined learning formulations were also common with hybrid approaches (14.0%) using two paradigms and multi-paradigm

approaches (8.5%). The most common hybrid combinations involved RL and imitation learning (IL), followed by RL with supervised learning and RL with self-supervised learning. These results indicate that the literature was centered primarily on RL, either as a standalone paradigm or as the core element of integrated learning frameworks.

3.6. Trends in Evaluation Method

Figure 6 shows that the evaluation-method distribution is tied between both simulation and experiment (42.3%) and simulation-only (42.0%), whereas experiment-only studies represented 15.7% of the dataset. This indicates that the current literature still relies heavily on simulation for development and validation, while experimental testing is growing as an important step toward practical deployment. The fact that simulation-only studies greatly outnumber experiment-only studies also suggests that much of the literature remains closer to the proof-of-concept or pre-deployment stage than to full real-world implementation.

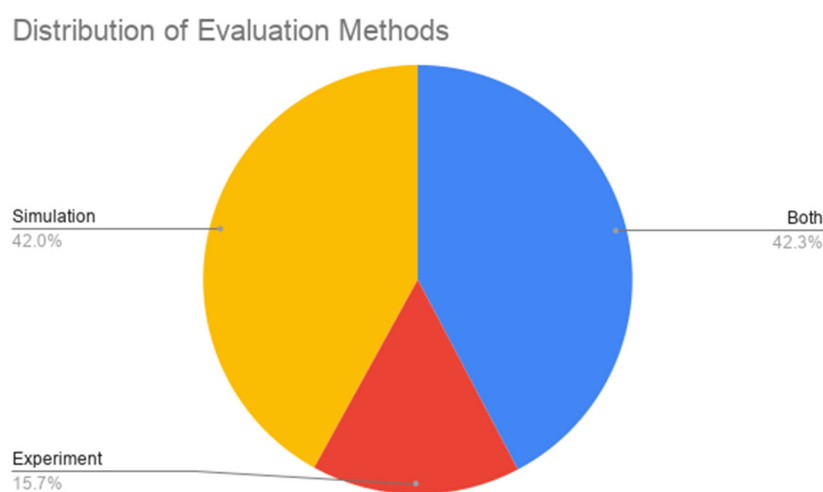


Figure 7. The distribution of evaluation methods among publications.

4. Discussion

4.1. Limitations in AI-Based Robot Manipulator Control

A recurring pattern across the analyzed literature is that the reported limitations were not confined to individual studies, but reflected broader weaknesses in how AI-based control strategies are currently developed and validated for robot manipulators. Although many studies reported favorable control performance, the supporting evidence was often constrained by simplified validation settings, narrowly defined tasks, and limited demonstration of deployment readiness. These limitations were observed across reinforcement learning, supervised learning, imitation learning, adaptive learning, and hybrid AI-control approaches.

The most common limitations can be grouped into several recurring categories. First, validation maturity remained limited, as many studies relied on simulation-only evaluation, while experimental studies were often restricted to controlled laboratory settings, simplified workspaces, small datasets, or narrowly scoped tasks. Second, sim-to-real transfer remained a persistent challenge, with many studies reporting degraded performance during hardware deployment or not evaluating transfer at all. Third, low sample efficiency and high training burden were especially common in DRL-based studies, where training often required extensive exploration, large numbers of episodes, and repeated retraining under modified conditions. Fourth, generalizability remained limited, as many controllers were validated on a single robot, task, object set, or workspace and were not assessed under broader

environmental or task variation. Fifth, performance was often sensitive to reward design, hyperparameter tuning, dataset quality, and other task-specific configuration choices, which reduced reproducibility and complicated cross-study comparison. Finally, in perception-dependent pipelines, control performance was frequently constrained by upstream sensing limitations, including occlusion, clutter, calibration drift, noisy signals, and limited data diversity.

Additional limitations were reported less consistently but remained important, including the lack of formal stability or safety guarantees, simplified physical assumptions, computational and real-time constraints, and system-integration issues such as communication delay, hardware limitations, and execution jitter. Collectively, these limitations restrict confidence in whether reported performance can be reproduced outside the original test conditions or maintained under more realistic manipulator operating environments. Overall, the literature demonstrates substantial algorithmic potential, but the evidence for robust, transferable, and deployment-ready manipulator control remains limited.

4.2. General Challenges in AI-Based Robot Manipulator Control

A recurrent pattern across the analyzed literature is that the main challenges of AI-based robot manipulator control are not confined to individual methods, but reflect broader barriers to achieving robust, generalizable, and practically deployable systems. Across reinforcement learning, supervised learning, imitation learning, adaptive learning, and hybrid approaches, authors repeatedly identified difficulties that extend beyond algorithmic performance under bounded test conditions.

The reported challenges can be grouped into several recurring categories. First, generalization beyond narrow training conditions remained a major challenge, as many studies reported difficulty extending learned controllers across new tasks, objects, robot platforms, workspaces, or environmental conditions. Second, data efficiency and scalable learning remained problematic, particularly in DRL-based methods, where sparse rewards, large exploration spaces, expensive demonstration collection, long training times, and unstable optimization limited scalability. Third, sim-to-real transfer and domain mismatch continued to constrain deployment, with visual domain gaps, physics mismatch, calibration error, sensing differences, and hardware variability repeatedly identified as barriers to reliable transfer from simulation to physical systems. Fourth, robustness under uncertainty and nonlinear dynamics remained a central challenge, especially in the presence of external disturbances, friction, payload variation, delays, partial observability, and time-varying operating conditions. Fifth, perception reliability in unstructured environments was frequently identified as a limiting factor, particularly under occlusion, clutter, illumination variation, noisy sensing, or dynamic scenes. Finally, many studies highlighted the joint challenge of safety, stability, and real-time deployment, emphasizing the need for safe exploration, collision-aware operation, computational efficiency, and compatibility with control-theoretic requirements.

Additional field-level challenges were reported less consistently but remained important, including scalability to high- degree of freedom (DOF), redundant, bimanual, or closed-chain systems, integration of perception, planning, and control within unified architectures, reduced dependence on structured environments and handcrafted assumptions, interpretability and verification of learned policies, and adaptation to contact-rich, long-horizon, and multi-stage manipulation tasks. Collectively, these challenges indicate that the field has advanced beyond demonstrating isolated algorithmic success, but continues to face substantial barriers to building manipulator controllers that are simultaneously generalizable, data-efficient, robust, safe, and deployment-ready.

4.3. Future Directions

A notable pattern identified across the analyzed literature is that proposed future work did not diverge into isolated directions, but instead converged around a relatively consistent set of developmental priorities. Across different AI methodologies, authors repeatedly pointed to similar next-step needs, indicating a shared maturation trajectory for AI-based robot manipulator control.

The reported future directions can be grouped into several recurring categories. First, many studies proposed expansion from constrained evaluation toward real-world and real-robot validation, including testing on physical platforms, broader industrial settings, and more realistic manipulation scenarios. Second, improving sim-to-real transfer and deployment readiness remained a frequent priority, with recommendations including domain randomization, real-world fine-tuning, calibration improvement, synthetic data generation, and more rigorous transfer protocols. Third, many studies emphasized extension to more complex tasks, richer environments, and broader generalization, including cluttered scenes, deformable objects, dynamic settings, long-horizon tasks, dexterous manipulation, and broader cross-robot evaluation. Fourth, authors frequently identified the need to improve data efficiency, training stability, and learning scalability, particularly through better reward design, curriculum learning, hierarchical learning, imitation learning integration, and more efficient training strategies. Fifth, many future-work statements emphasized stronger perception and multimodal sensing integration, including improved visual backbones, larger datasets, tactile and force sensing, RGB-D systems, and multimodal sensor fusion. Finally, a consistent direction was the development of safer, more adaptive, and more unified control architectures that integrate perception, planning, adaptation, and control more tightly while incorporating online adaptation, uncertainty handling, and safety-aware behavior.

Additional future directions were reported less consistently but remained important, including extension to high-DOF, redundant, flexible, soft, underactuated, or multi-robot systems, greater use of advanced computational infrastructure, increased methodological hybridization, and stronger attention to interpretability, verification, and practical usability. Collectively, these trends indicate that the field is moving beyond isolated algorithmic improvement toward broader goals of real-world validation, transferability, efficiency, robustness, multimodal integration, and deployment-oriented system design. Overall, the future-work statements suggest that the next stage of progress in AI-based robot manipulator control will depend less on achieving higher benchmark performance alone and more on building systems that are generalizable, efficient, safety-aware, and practically deployable.

5. Conclusions

This systematic review, conducted in accordance with the PRISMA framework, identified 343 studies published between 2015 and 2025 on AI based control for RMs. By synthesizing evidence across functional roles, control techniques, robot types, application settings, learning paradigms, and evaluation methods, the review provided a high-level view of how this research area has developed in the literature. Overall, AI based RM control has expanded rapidly over the past decade, particularly since 2020, confirming its emergence as a rapid growing area of research. However, this growth has been markedly uneven, with research activity concentrated in a limited set of functional and methodological directions.

The main trends identified are as follows:

- Uneven functional development: The literature was concentrated predominantly in learning control, with substantially lower representation of planning, perception and estimation, learning and adaptation, and especially interaction and safety.
- Methodological concentration: Learning-based control overwhelmingly dominates the field, particularly RL and DRL. Although many distinct AI methods were identified overall, recurrent use remained centered on a relatively small core of RL oriented techniques.
- Narrow robot and application coverage: The reviewed studies focused primarily on serial manipulators, while many specialized robotic configurations remained sparsely represented. A large proportion of studies also lacked a clearly specified application setting. Among the explicitly reported domains, manufacturing was the most represented.
- Strong reliance on simulation-based evaluation: Most studies relied simulation only or combined simulation and experiment for validation, whereas fully experimental evaluation remained comparatively limited.

Taken together, these findings indicated that AI based control for RMs has achieved substantial methodological growth, but its development remained uneven in scope, validation maturity, and deployment readiness. Building on this descriptive trend analysis, future work can perform more advanced relational analyses to further assess the impact of AI on RM control. Key potential areas for investigation include method evolution and co-occurrence, cross-variable patterns, limitation clustering, hybrid versus single-paradigm performance, technique-outcome alignment, and future direction mapping.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org. The complete list of all AI methods was identified across the dataset can be found here.

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