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Review

Towards Industry 5.0: Emerging trends in dual-arm human–robot collaboration

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ABSTRACT

As industry transitions from the Industry 4.0 paradigm to the human-centered vision of Industry 5.0, robots are evolving from mere automation tools into intelligent partners capable of close collaboration with humans. Within this context, dual-arm human–robot collaboration (DA-HRC) has emerged as a key technology due to its human-like dexterity and ability to perform complex tasks. However, integrating dual-arm systems into collaborative environments is far more complex than merely doubling the number of manipulators; it also introduces a leap in system complexity, including challenges such as kinematic decoupling, dynamic coupling, and safe coordination. Despite growing research efforts, a comprehensive review of this inherently interdisciplinary field is still absent. This paper systematically surveys the literature on DA-HRC, with a particular focus on three core aspects: control, learning, and perception. It further discusses practical applications in industrial manufacturing and domestic service scenarios. The review highlights the ongoing paradigm shift from model-driven to data-driven approaches and identifies the integration of verifiable safety guarantees from traditional control theory with the adaptability of modern learning methods as a central technical challenge. Achieving safer, more efficient, and more natural interactions in dual-arm robots requires continuous iteration and deeper integration of these approaches.

1. Introduction

Modern industry is undergoing a critical transition from Industry 4.0 to Industry 5.0 [1]. While Industry 4.0 is centered on automation and digitalization, emphasizing efficiency and scalability, Industry 5.0 places the human at the core, prioritizing sustainability and resilience [2,3]. In this new paradigm, robots are no longer viewed merely as tools for replacing humans in hazardous or repetitive tasks. Instead, they are evolving into intelligent partners that extend human intelligence and amplify human capabilities, working side by side with humans. To fulfill this role, robots must not only be efficient but also safe, adaptable, and capable of naturally understanding and responding to human intentions [4,5].

Against this backdrop, dual-arm robots have attracted increasing attention. Although single-arm collaborative robots have achieved remarkable success in structured and semi-structured industrial environments, their limitations in dexterity, payload handling, and complex task execution are becoming increasingly evident [6,7]. Many real-world operations, such as manipulating large, irregular objects, performing precision assembly, or skillfully using tools, naturally require two-handed coordination. This is precisely where the humanoid-like configuration of dual-arm robots offers unique advantages [8–10]. However, introducing dual-arm robots into HRC scenarios represents more than simply adding an extra manipulator. It elevates system complexity to a new level by transforming the binary human–robot relationship into a triadic system involving human, left arm, and right arm. This introduces more intricate kinematic and dynamic couplings while also raising urgent challenges in safety, coordination, and natural interaction.

Although significant progress has been made in HRC, relevant studies remain fragmented across multiple disciplines, including robotics control, artificial intelligence, and computer vision, and a systematic consolidation of DA-HRC is still lacking. As summarized in Table 1, existing surveys exhibit three main limitations:

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Table 1
Comparison of representative surveys on HRC and foundation models.

Year	Reference	Topic focus	Scope (C/L/P)	HRC scope	Dual-Arm	Foundation models
2018	Villani et al. [11]	Safety, intuitive interfaces, and physical human–robot interaction in industrial HRC	C/P	✓	×	×
2022	McGirr et al. [12]	Taxonomy and framework of interaction levels in manufacturing collaboration	C/System-level	✓	×	×
2023	Tóth et al. [13]	Industry 5.0 human-centric collaboration architecture and system integration	System-level	✓	×	×
2024	Li et al. [14]	Safety assurance, perception fusion, and control strategies for industrial HRC	C/P	✓	×	×
2025	Kawaharazuka et al. [15]	Survey on vision–language–action models for embodied AI and robotic manipulation	L/P	×	×	✓
2025	Xiao et al. [16]	Comprehensive survey on robot learning in the era of foundation models	L	×	×	✓
2026	Ye et al. (**ours**)	Comprehensive dual-arm HRC review under the Industry 5.0 paradigm	C/L/P	✓	✓	✓

Note: C (Control), L (Learning), and P (Perception).

Table 2
Inclusion and exclusion criteria for literature selection.

Inclusion criteria	Exclusion criteria
• Research focusing on dual-arm robotic systems.	• Studies involving only single-arm robots or mobile platforms without manipulation capabilities.
• Studies addressing physical or cognitive HRC.	• Pure robot–robot interaction or teleoperation without collaborative intelligence.
• Articles published in peer-reviewed journals or conferences (2012–2025).	• Non-English publications, white papers, or technical reports.
• Works proposing specific control, learning, or perception algorithms with validation.	• Purely theoretical or simulation-based studies lacking physical validation potential.

(i) most surveys [11,14] focus on general HRC and treat the robot as an isolated agent, overlooking the distinctive "triadic" complexity of DA-HRC (i.e., a tightly coupled dynamic system involving the human, left arm, and right arm) and thus provide limited discussion of dual-arm specific challenges such as closed-chain kinematics, internal force regulation, and dual-arm coordination; (ii) control-theoretic surveys [12,13] often underemphasize the rapid advances in data-driven perception and learning, whereas learning-oriented surveys [16] may lack rigorous discussions on physical safety and stability guarantees, resulting in a disconnect between intelligence and compliance; and (iii) although [15] review the applications of vision–language–action (VLA) models in robotics, they do not systematically analyze how other generative foundation models (e.g., diffusion policies) can be adapted to address the low-level, high-dimensional continuous control problems inherent in dual-arm coordinated manipulation.

This paper aims to bridge these gaps. Through a systematic review of the literature, we construct a holistic picture of the field, spanning from classical approaches to the latest advances (see Fig. 1). We synthesize key advances in control strategies, perception technologies, and other core aspects of DA-HRC, while analyzing representative application scenarios. In particular, this work highlights the emerging trend of foundation model–driven robotics and explores how these approaches may enable deeper integration of physical control, environmental perception, and cognitive reasoning.

In summary, the main contributions of this paper are as follows:

- To unify the fragmented disciplines, this paper systematically integrates and analyzes key research directions in DA-HRC, including physical control strategies, learning-driven skill acquisition, multimodal perception, and emerging foundation models. We further contextualize these advances by examining their roles and impacts in representative application scenarios such as industrial assembly and domestic services. To the best of our knowledge, no prior survey has covered the core technical dimensions of this field with comparable breadth.
- Addressing the overlooked complexity, we discuss the unique challenges of DA-HRC as a triadic system, including dynamic coupling between the human and two robotic arms, the need for profound understanding of human intentions, verifiable safety and robustness guarantees, and the paradigm shifts brought by emerging foundation models. At the same time, we summarize current research trends, highlight limitations of existing approaches, and outline promising directions for future development.
- Unlike prior surveys, this work places particular emphasis on the latest progress in DA-HRC enabled by AI technologies, especially foundation models. In doing so, it offers readers a timely opportunity to develop a more profound understanding of the field and to anticipate its future trajectory.

The remainder of this paper is organized as follows (see Fig. 2): Section 2 introduces the research methodology and literature selection criteria. Section 3 focuses on physical interaction and control strategies. Section 4 explores learning-driven approaches for skill acquisition. Section 5 examines multimodal perception technologies. Section 6 highlights two major application domains: industrial manufacturing and domestic services. Section 7 discusses existing challenges and future research directions. Finally, Section 8 concludes the paper.

2. Research methodology and selection criteria

To ensure the comprehensiveness, systematicity, and scientific rigor of this review, we adopt a systematic literature review

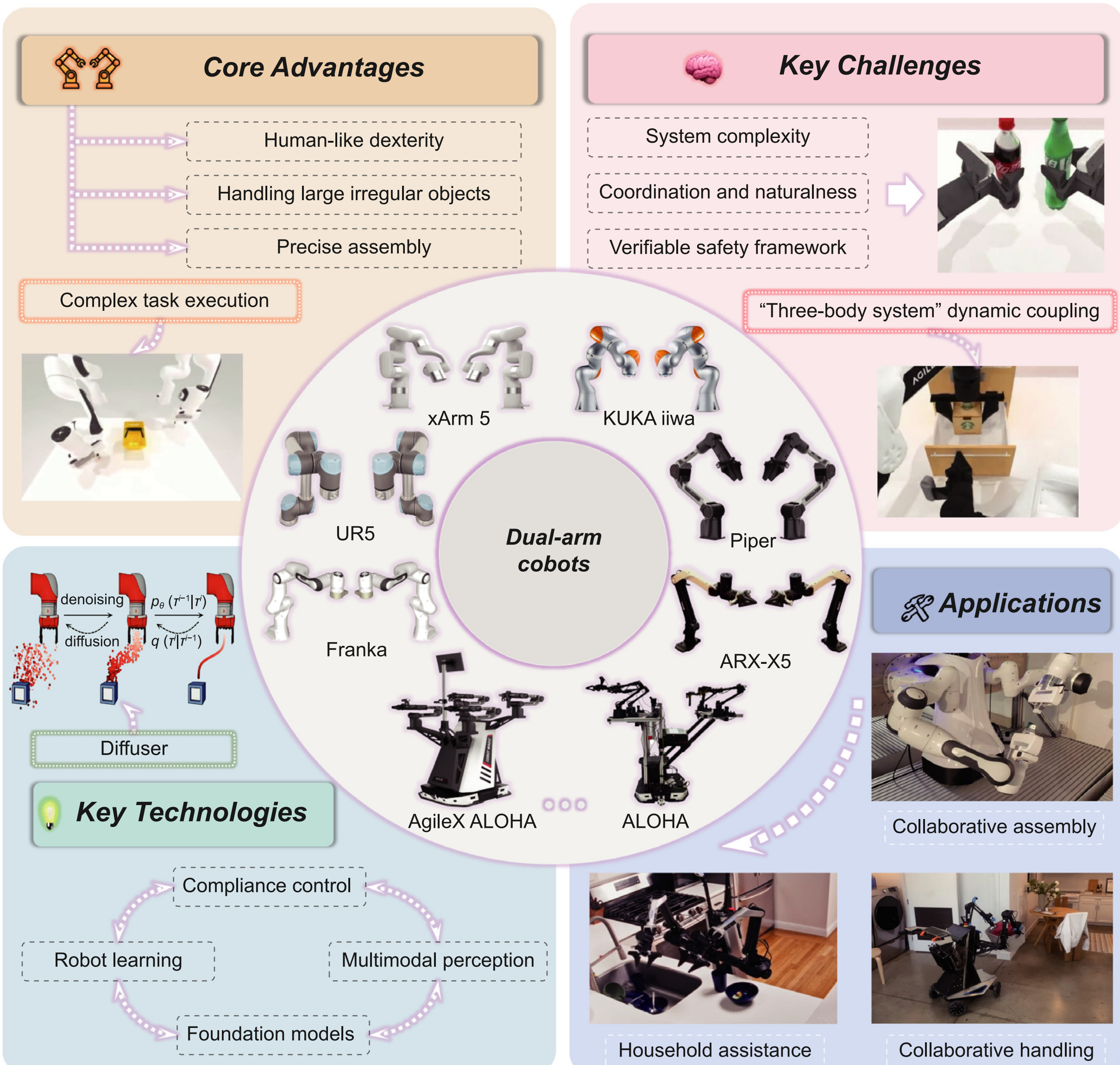

Fig. 1. Core technologies and application framework of DA-HRC.

(SLR) methodology. This approach is inspired by the workflows proposed by Semeraro et al. [17] and Dhanda et al. [1], which emphasize strictness and transparency throughout the processes of retrieval, screening, and analysis. This section details our search strategy, screening criteria, and final selection results.

During the retrieval stage, we primarily relied on four major academic databases, Scopus, IEEE Xplore, Web of Science, and Google Scholar, to cover as broad a spectrum of research outcomes as possible. The search was limited to the period 2012–2025, with the aim of capturing technological progress over the past decade, particularly the breakthroughs emerging from the integration of artificial intelligence and machine learning with robotics.

The keyword design centered on two core concepts: dual-arm robots and human–robot collaboration. Boolean logic was applied to combine terms, for example: ("dual-arm robot" OR "bimanual robot" OR "dual-arm manipulator") AND ("human–robot interaction" OR "HRI" OR "human–robot collaboration"). In addition, extension keywords such as "control", "perception", "learning", "safety", and "cognition" were included to broaden the scope. To better capture specific subfields, we further incorporated terms related to imitation learning, reinforcement learning, shared control, intention recognition, and foundation models, as illustrated in Fig. 3.

In the screening process, we established clear inclusion and exclusion criteria (see Table 2). The inclusion criteria include (1) The research object must be dual-arm robotic systems; (2) The research must focus on actual human–robot interaction, such as physical contact, shared workspace, or close task collaboration; (3) The publication type must be peer-reviewed journal articles, conference papers, or high-quality surveys; and (4) The content must provide substantive contributions, such as theoretical analysis, algorithm design, system implementation, or experimental validation. The exclusion criteria include (1) Studies involving only single-arm robots or multi-robot collaboration (non-dual-arm); (2) Pure robot–robot interaction or purely theoretical/simulation studies without validation on physical systems; and (3) Publications with low relevance to control, perception, cognition, or other core technologies.

The entire screening process followed the PRISMA guidelines [18–20] and was divided into three core stages: identification, screening, and eligibility assessment (see Fig. 4). After retrieval from the four databases, about 1200 papers were initially obtained. After duplicate removal using a combination of

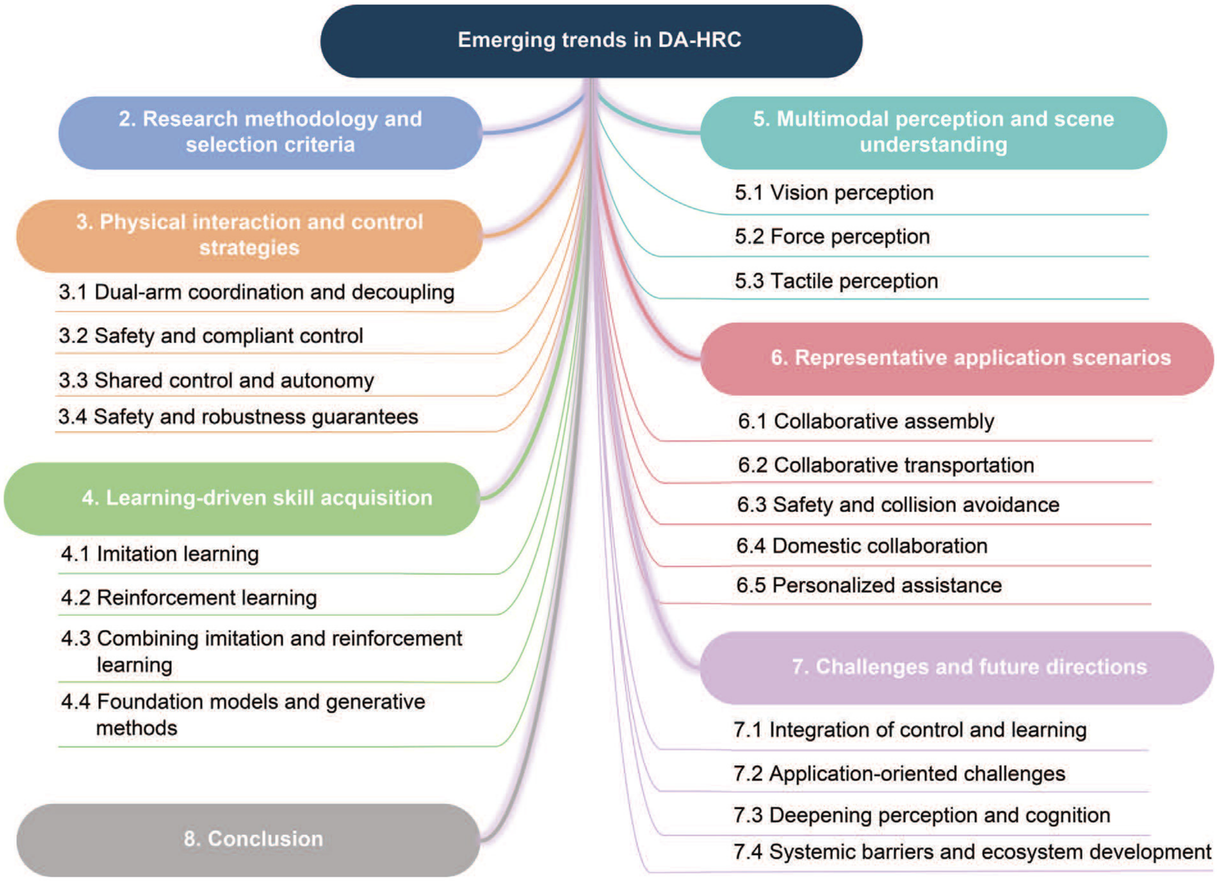

Fig. 2. Structure of this review.

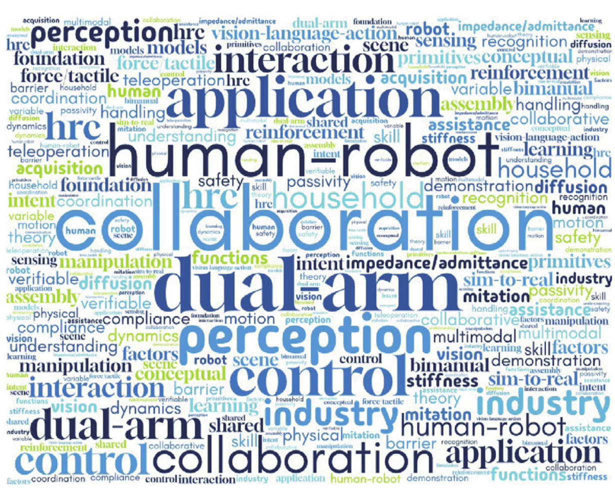

Fig. 3. Word cloud of keywords.

automated tools and manual checking, the number was reduced to about 500 papers; during the title-and-abstract screening stage, about 300 papers that did not meet the requirements were excluded. The remaining 200 papers were then reviewed in full text and evaluated according to research depth, novelty, and relevance. Finally, about 165 core papers were identified as the main body of literature for this survey.

To present the research landscape more intuitively, we conducted a statistical analysis of these papers [21], as shown in Fig. 5. From the perspective of disciplinary distribution (Fig. 5(a)), this research topic demonstrates high interdisciplinarity, with outcomes mainly concentrated in robotics, computer science, and automation/control systems. From the perspective of annual distribution (Fig. 5(b)), the number of related publications has steadily increased over the past decade, with an accelerated growth trend in the past five years, indicating that DA-HRC has become an increasingly active research hotspot. In terms of institutional distribution (Fig. 5(c)), the research landscape shows both globalization and concentration of expertise. On one hand, research forces represented by the Chinese Academy of Sciences and its affiliates stand out in terms of output, reflecting strong research capacity. On the other hand, internationally renowned institutions such as the Fraunhofer Institute in Germany and the Politecnico di Milano in Italy, along with many others across Europe and Asia, have contributed a large number of key achievements, forming a diverse global research network that jointly drives the development of this field.

To offer readers an intuitive overview of the technical landscape, representative studies are organized according to the core technical framework of this work, as summarized in Table 3, which serves as the basis for the subsequent in-depth analysis and discussion.

3. Physical interaction and control strategies

In DA-HRC, physical interaction lies at the core of collaboration, and its quality directly determines task efficiency and, most importantly, safety [119]. As robots gradually evolve from isolated automation tools into partners working alongside humans in shared spaces, the traditional rigid control paradigm, centered

Table 3
Overview of representative works in DA-HRC.

Category	Key technology	Method/Representative work
Physical interaction and control strategies	Coordination and decoupling	Classical control (Master-slave/Symmetric) [22–24]
		Optimization control (QP) [25–30]
	Safety and compliance control	Learning-enhanced/Robust control [31,32]
		Impedance/Admittance control [33–35]
		Variable impedance/Predictive control [36–38]
	Shared control and autonomy	Probabilistic/Mutual adaptation [39,40]
		Inverse optimal Control/Hindsight optimization [41]
		Visual affordance/Trust modeling [42,43]
	Safety and robustness guarantees	Passivity/Energy tanks [38,44–46]
		Control barrier functions (CBFs) [47–51]
		Sliding mode/Adaptive control [52–55]
Learning-driven skill acquisition	Imitation learning	Teleoperation [56–58]
		Skill transfer/Generalization (DMPs, ProMPs) [59–63]
	Reinforcement learning	Sim2Real [64,65]
		Offline RL/Model-based RL [66,67]
		Demonstration-aided RL [68,69]
	Imitation and reinforcement combined	One-shot learning and finetuning [68–72]
	Foundation models	Diffusion models [63,73–78]
		VLA models [79–85]
		LLM [86–88]
Multimodal perception and scene understanding	Visual perception	2D vision [89–91]
		3D vision [92,93]
		6D pose estimation/tracking [94–96]
	Force perception	Sensor-based [97–99]
		Sensorless estimation [100–103]
		Intent recognition [104–106]
	Tactile perception	Vision-based tactile (e.g., GelSight) [107–109]
		Distributed skin/Multi-contact [110,111]
		Vision-tactile fusion [112–116]
		Tactile transfer/learning [117,118]

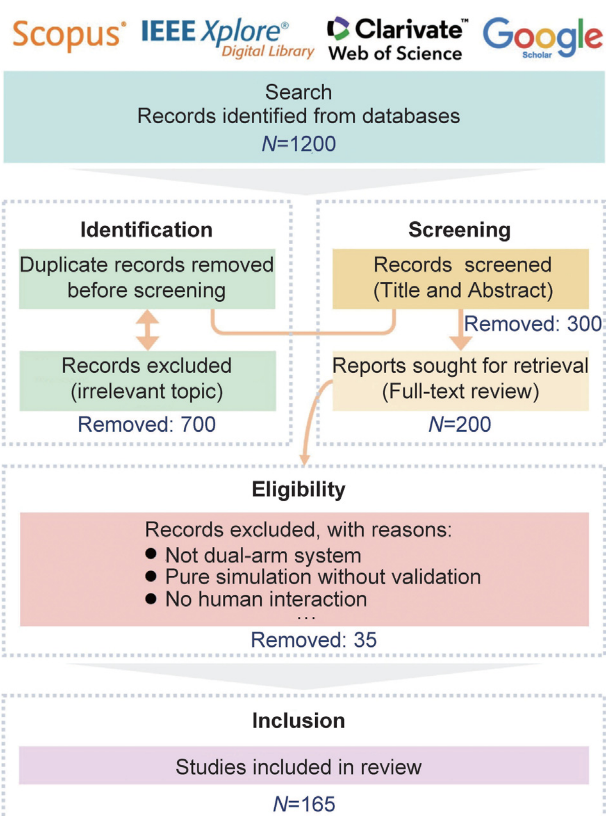

Fig. 4. PRISMA flow diagram of the literature selection process.

on high-precision position tracking, has become increasingly inadequate. The human-centric philosophy advocated by Industry 5.0 requires robots to possess compliance, adaptability, and predictability. This transition introduces new control challenges [13,120]:

- How can we manage the kinematic and dynamic couplings in the complex triadic system composed of a human and a dual-arm robot?
- How can we ensure absolute safety during close, or even zero-distance, contact?

This section will systematically review the control strategies developed to address these challenges, following the logical path of dual-arm coordination, compliant interaction, and safety mechanisms.

3.1. Dual-arm coordination and decoupling

Before involving HRC, the primary task is to enable two independent robotic arms to function as a unified whole, much like human hands [22]. Essentially, this involves controlling a high-DOF redundant system under closed-chain kinematic constraints. The core challenge lies in effectively decoupling global object manipulation from the internal forces exerted on the object [6,24].

Early master–slave control strategies, though structurally simple, imposed rigid role assignments that severely limited system flexibility in complex tasks. To overcome this limitation, the symmetric control paradigm emerged. Zhang et al. [23] proposed a relative dynamics modeling method for dual-arm coordinated robots, establishing the relationship between end-effector relative forces and joint parameters, thus providing a theoretical foundation for internal force distribution in dual-arm collaboration. Xia et al. [121] proposed a dual-arm grasping control method that explicitly considers internal forces; by implementing coordinated stable control, they effectively reduced squeezing and pulling forces during contact, thereby improving system stability. Wang et al. [122] introduced a holistic dynamic modeling and coordinated control approach for dual-arm robots, treating the

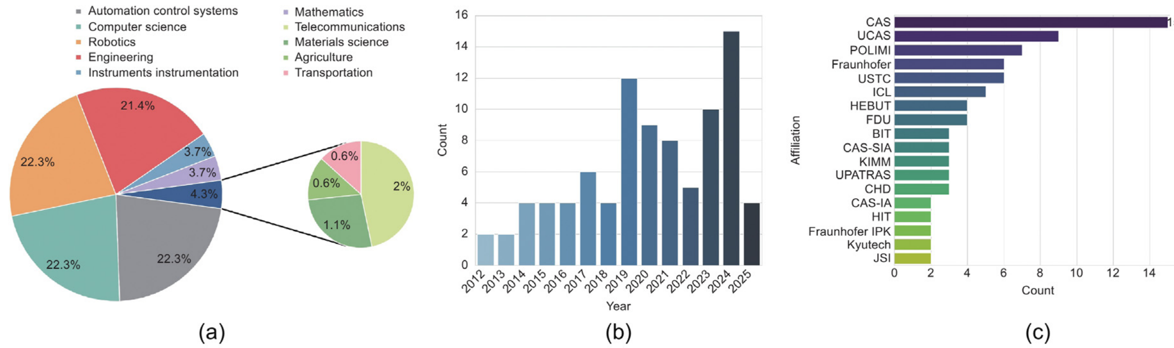

Fig. 5. Statistical distribution of the screened literature. (a) Distribution by discipline. (b) Distribution by year. (c) Distribution by major research institutions.

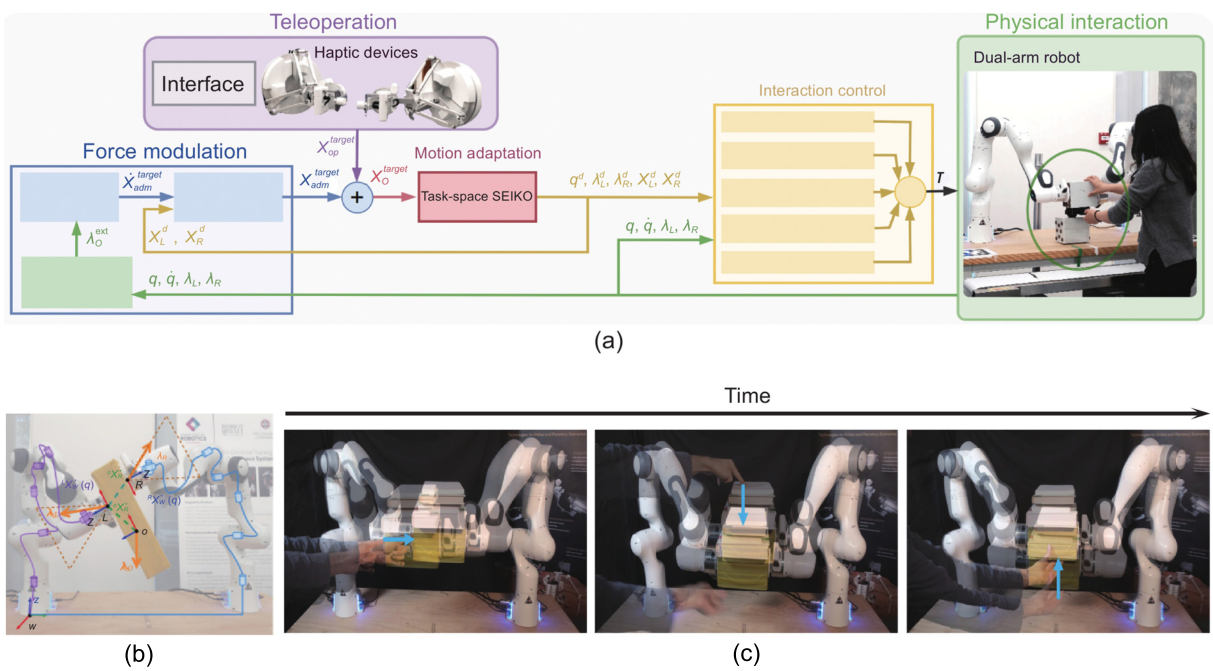

Fig. 6. Optimal motion adaptation and interactive control. (a) Overall framework of optimal motion adaptation and interaction control for cooperative dual-arm manipulation. (b) Reference coordinate systems and generalized force definitions for task-space SEIKO modeling in dual-arm operations. (c) Human–robot physical interaction experiment of dual-arm manipulation in a book-stacking task. Reproduced with permission from [124]. © 2024 IEEE.

system as a unified whole for analysis and control, thus enabling stable cooperation in complex manipulation tasks.

With increasing task complexity, research has shifted toward achieving more efficient collaboration under redundant degrees of freedom. Task-priority control was extended to dual-arm scenarios, allowing optimization of internal forces while preserving the primary task [123]. Tarbouriech et al. [25] exploited null-space optimization within an admittance control framework to minimize stress on manipulated objects. Meanwhile, optimization-based methods have gradually become mainstream. For example, Völz and Graichen [26] formulated dual-arm motion constraints as a quadratic programming (QP) problem solved in real time, ensuring closed-chain consistency while avoiding collisions.

Recent studies have further emphasized learning-enhanced robust control. Pham et al. [31] combined neural networks with dynamic surface control to handle modeling uncertainties. Nguyen et al. [32] proposed an approach that integrates adaptive fuzzy neural networks with sliding mode control, effectively compensating for performance degradation under external disturbances and thereby improving trajectory-tracking accuracy and system stability.

Building on this foundation, research has advanced toward integrating optimization with redundancy management. Zhang et al. [27] proposed a coordinated planning and control framework for mobile dual-arm robots, combining manipulation capability optimization with internal force tracking, while handling joint limits, singularities, and velocity/acceleration constraints simultaneously through QP to improve motion feasibility and safety. Fried and Paternain [28] adopted a bi-level optimization strategy to solve the minimum-time problem for redundant systems: the lower layer maximizes velocity along a fixed trajectory, while the upper layer updates the trajectory to further shorten execution time, achieving time-optimal dual-arm collaboration. At the same time, Zhang et al. [29] proposed a real-time inverse kinematics optimization method considering inequality constraints, ensuring strict compliance with both joint-space and Cartesian-space inequality constraints under redundancy, thereby enhancing safety for real-world deployment. Niu et al. [30] focused on highly redundant humanoid dual-arm mobile systems, introducing an optimization method based on arm potential energy, which reduced energy consumption and improved posture during global coordination, further demonstrating the value of optimization strategies in whole-body collaboration.

In summary, current research has shifted toward how to fully exploit redundant DOFs under dynamic environments and complex constraints to achieve efficient, safe, and stable dual-arm cooperative control. Wen et al. [124] proposed a typical dual-arm collaborative manipulation framework, as illustrated in Fig. 6. The framework integrates multi-source commands from remote operators and local interactors, ensuring task safety and efficiency through an optimized control process. Fig. 6(a) presents the core architecture, in which a module for motion adaptation converts unsafe or infeasible raw commands into valid trajectories that satisfy torque, velocity, and task constraints in real time. Fig. 6(b) shows the physical modeling basis of the optimization process, including definitions of objects, end-effectors, the world coordinate system, and contact force modeling. Fig. 6(c) validates the effectiveness and robustness of the framework through an experiment in which a human and a dual-arm robot collaboratively transport a book.

3.2. Safety and compliant control

Although safety and compliant control form the universal cornerstone of all physical HRC, their application to dual-arm systems introduces unique challenges. It is not only necessary to ensure compliance for each arm independently but also to coordinate the dynamic responses of both arms to guarantee overall interaction safety. When humans enter the robot's workspace and physical contact occurs, the control objectives must shift from position accuracy to safety and naturalness.

Compliant control lies at the heart of this transition, as it regulates the dynamic response of the robot's end-effectors to external forces, thereby ensuring safe and smooth interaction. Impedance control and admittance control are the mainstream techniques for achieving compliance. Hogan's pioneering work [33] laid the theoretical foundation of impedance control by modeling the interaction between a robot's end-effector and its environment as a virtual mass–spring–damper system. However, fixed impedance parameters are difficult to adapt to dynamically changing interaction demands. To address this issue, variable impedance/admittance control has gradually become a research focus. Duan et al. [34] further introduced adaptive damping to compensate for trajectory deviations caused by human operation. Keemink et al. [35] reviewed the application of admittance control in HRC and proposed strategies to adapt to dynamically changing interaction dynamics.

In recent years, research has shifted toward ensuring compliance while simultaneously meeting safety standards and dynamic adaptability. Xue et al. [36] integrated model predictive control into variable impedance design, enabling robots to proactively adjust parameters in anticipation of external disturbances, thereby significantly reducing impact during collaboration. In parallel, recent works have attempted to align control frameworks with international safety standards. For example, a variable impedance method based on ISO/TS 15066 [37] enables real-time adjustment of stiffness and damping to ensure that contact forces always remain within safe thresholds.

At the same time, studies on admittance control have advanced toward higher levels of adaptivity. Going even further, the principles of compliant control have been extended to highly flexible morphologies such as continuum robots. Wang et al. [38] proposed a virtual integration approach for admittance control, which combines virtual forces with actual contact forces to proactively adjust motion trajectories before contact occurs, thereby balancing safety and task performance throughout the interaction. In summary, the evolution of compliant control has progressed from fixed-parameter models to adaptive mechanisms to intelligent approaches integrating predictive capabilities and safety standards and finally to extensions toward more complex robotic morphologies.

3.3. Shared control and autonomy

Building on physical coordination and safety, a higher-level challenge lies in achieving cognitive collaboration between humans and robots. Although the concept of shared control is broadly applicable, in the context of dual-arm collaboration, the dimensionality and complexity of human intentions increase significantly, placing greater demands on how robots dynamically adjust the autonomy levels of their two arms to provide effective assistance. During interactions, shared control reduces the cognitive and physical load on humans by distributing control authority between the human and the robot. However, traditional approaches often adopt fixed authority allocation [125], which fails to adapt to dynamic task requirements. To overcome this limitation, more advanced forms of shared autonomy have emerged, with the core idea being that the robot can dynamically adjust its autonomy level based on human intentions and the interaction context.

Following this idea, researchers have proposed multiple approaches. Jain et al. [39] designed a probabilistic intent recognition model, enabling robots to predict human goals and provide corresponding assistance. Nikolaidis et al. [40] developed a human–robot mutual adaptation model, allowing the robot not only to learn human behaviors but also to guide humans toward more efficient collaboration through its actions. Javdani et al. [41] proposed an inverse optimal control framework that allows robots to infer the user's true intention from imperfect teleoperation demonstrations and then autonomously optimize execution.

Recently, research has continued to advance shared autonomy. For example, Belsare et al. [42] introduced the VOSA framework, which can infer user intent visually in previously unseen tasks, enabling zero-shot HRC. Li et al. [43] incorporated trust modeling, dynamically adjusting the level of autonomy according to the human's trust in the robot, thereby improving efficiency while enhancing user acceptance.

3.4. Safety and robustness guarantees

While compliance control provides "soft" safety for interaction, formal theoretical frameworks aim for "hard" guarantees, ensuring that the system remains controllable and stable under all circumstances. Passivity theory is one such important tool. By designing passive controllers, it is possible to guarantee that the coupled human–robot–environment system is always dissipative at the energy level. The seminal work of Colgate and Hogan [44] laid the theoretical foundation for passivity in physical interaction. Guo et al. [45] further develop passivity-based control frameworks for physical human–robot interaction, enabling robotic systems to achieve stable and high-performance haptic interaction.

In HRC, this theory guarantees that uncertain physical contacts will not cause energy accumulation leading to oscillation or instability. For example, Zanella et al. [46] proposed learning passive strategies through virtual energy tanks, enabling robots to maintain passivity even in complex dynamic environments, thereby ensuring stability during interaction. Wang et al. [38], in their method for virtual integration and admittance control, reduced contact impact by proactively adjusting trajectories before contact occurred, thereby suppressing energy injection during the contact process.

Control Barrier Functions (CBFs) provide another form of formalized safety guarantee [47]. CBFs mathematically encode safety constraints as a safe set, reformulating the control problem as a real-time QP problem [48]. In recent studies, Busellato et al. [49] proposed predictive CBFs, combining human motion prediction with probabilistic boundary estimation to allow robots to dynamically adjust safety boundaries in uncertain environments, ensuring safety without being overly conservative. Sharma et al. [50] introduced a risk-tunable CBF framework, allowing users to balance efficiency and safety. Meanwhile, Lee et al. [51] proposed a hierarchical relaxation strategy for safety-critical controllers, introducing prioritized CBF constraints within a quadratic programming framework to resolve conflicts among multiple safety conditions while maintaining feasible and stable control. Although most of these studies targeted single-arm or multi-robot systems, the methods are equally applicable to dual-arm collaboration. Since dual-arm systems often involve closed-chain constraints and complex redundancy management, integrating CBFs into dual-arm tasks could enable stricter mathematical safety guarantees and provide robust theoretical tools for HRC in dynamic environments.

In the face of inevitable model uncertainties and external disturbances in real-world applications, robust control and adaptive control play complementary roles. Robust control methods, such as sliding mode control [52], ensure system stability in the presence of bounded uncertainties. Liu et al. [53] combined sliding mode with impedance control and proposed an adaptive sliding-mode impedance control strategy for dual-arm object manipulation, effectively improving robustness under contact constraints.

Meanwhile, adaptive control dynamically adjusts the control law by online estimation of unknown parameters. Pham et al. [31] proposed an adaptive strategy based on dynamic surface control and RBF neural networks, which demonstrated both stability and robustness in trajectory tracking tasks. Jiao et al. [55] introduced an adaptive hybrid impedance control method for dual-arm cooperative manipulation of unknown objects, which achieved a good balance between motion tracking accuracy and internal force regulation when the object dynamics were uncertain.

4. Learning-driven skill acquisition

Traditional model-based control methods, while theoretically understandable and capable of providing safety guarantees, are increasingly revealing their limitations in complex, dynamic, and uncertain HRC scenarios. For high-dimensional systems such as dual-arm collaboration, constructing an accurate physical model is extremely challenging, while the stochastic and unpredictable nature of human behavior makes it difficult for predefined control laws to cope effectively. Against this backdrop, data-driven paradigms that learn from experience have demonstrated tremendous potential. This section systematically reviews the development of this direction: from imitation learning and reinforcement learning to hybrid paradigms that combine the two and finally focusing on the new generation of foundation model-based generative approaches, exploring how they may reshape the future of robotic skill learning.

4.1. Imitation learning

Imitation Learning (IL), also known as learning from demonstration, provides an efficient and intuitive pathway for robotic skill acquisition [126]. Its core idea is to enable robots to master complex dual-arm collaborative skills by observing and imitating human experts. Human demonstrations can take various forms, including kinesthetic teaching, where a human physically guides the robot through the motions. For example, Rozo et al. [127] taught a robot to perform tasks involving HRC in transportation via kinesthetic teaching and employed probabilistic learning methods to encode the demonstration data while simultaneously

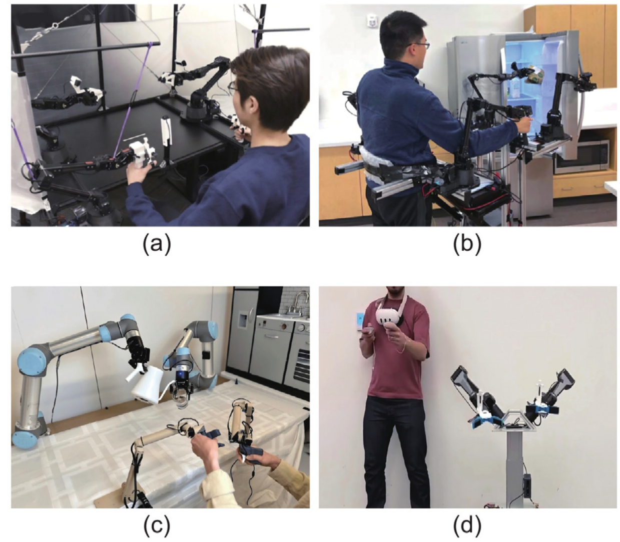

Fig. 7. Representative dual-arm teleoperation systems for imitation learning. (a) A low-cost dual-arm teleoperation system, ALOHA. (b) The mobile platform version of the ALOHA system, Mobile-ALOHA. (c) The general GELLO framework, adaptable to various robotic arms. (d) Traditional VR controllers for comparison.

estimating stiffness, thereby achieving collaborative control that integrates trajectory with force-impedance behavior.

Another approach leverages teleoperation devices for remote demonstrations. A typical example is the ALOHA system developed by Zhao et al. [56], which is based on a low-cost master–slave teleoperation setup and allows researchers to efficiently collect large-scale, high-quality dual-arm manipulation data, as shown in Fig. 7(a). The subsequent Mobile-ALOHA [57] extended this paradigm to mobile dual-arm platforms, enabling more complex whole-body teleoperation and data collection, as illustrated in Fig. 7(b). By contrast, the recently proposed GELLO framework by Wu et al. [58] emphasizes generality, as shown in Fig. 7(c). By constructing a kinematically isomorphic low-cost controller to the target manipulator, GELLO enables intuitive teleoperation across different robotic arms, significantly outperforming traditional VR/AR controllers and 3D mice in terms of demonstration efficiency and stability for contact-rich tasks, as shown in Fig. 7(d).

Once demonstration data is collected, the key challenge becomes encoding them into skill models capable of generalizing and adapting to new scenarios. Motion primitives are the mainstream approach to this problem. Among them, Dynamic Movement Primitives (DMPs) represent trajectories using a set of nonlinear differential equations. Ijspeert et al. [59] elaborated on the mathematical framework of DMPs, showing how starting points, goals, and duration of actions can be flexibly adjusted.

For dual-arm systems, the real difficulty lies in capturing the subtle spatiotemporal couplings between the two arms. To address this, probabilistic movement primitives (ProMPs) were introduced, modeling the joint trajectories of both arms as a unified probabilistic distribution. This framework learns the mean of trajectories and captures their variance. Paraschos et al. [60] demonstrated that such a probabilistic framework enables robots to generate coordinated and consistent actions in new tasks while maintaining natural variability closer to human behavior. Maeda et al. [61] combined ProMPs with phase estimation, enabling dual-arm robots to adapt their collaborative rhythm in real time according to human actions.

Recent research has further advanced generalization and adaptive control in dual-arm manipulation. For instance, Zhang et al.

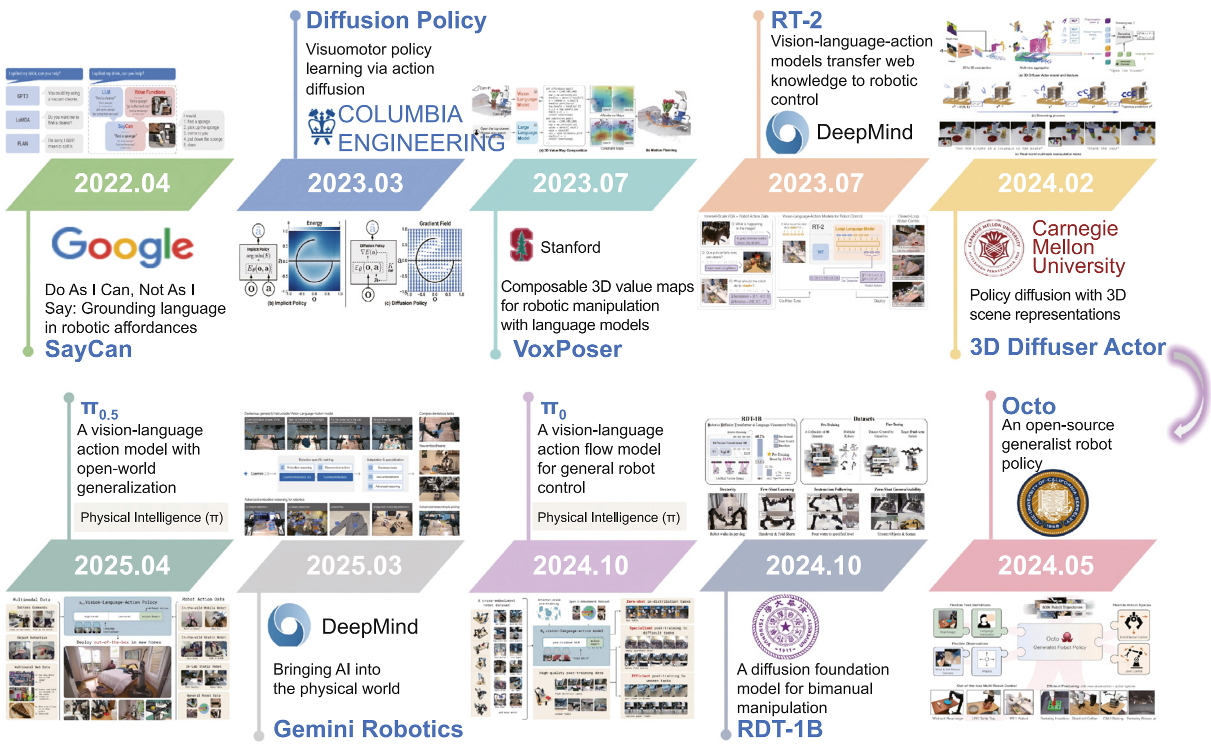

Fig. 8. Evolution timeline of key foundational models for dual-arm robots.

[62], in their study on human–robot variable impedance skill transfer, utilized visual feedback and electromyography (EMG) signals for stiffness estimation and combined these techniques with the DMP framework to achieve skill transfer, significantly enhancing system stability in dynamic and uncertain environments. Chen et al. [63] proposed the VLM-SFD framework, which employs a vision–language model-assisted diffusion network to generate target motion flows from a small number of demonstrations, achieving rapid generalization across multiple tasks and scenarios.

Despite these advancements, pure Imitation Learning remains fundamentally limited by the quality and coverage of the demonstration data. It struggles to recover from perturbations or adapt to dynamic environments that were not represented in the training set. This limitation necessitates a shift toward paradigms that allow robots to actively explore and optimize their policies through interaction with the environment, leading to the domain of Reinforcement Learning discussed in the next section.

4.2. Reinforcement learning

Reinforcement Learning (RL) provides another pathway for robots to acquire skills. It enables robots to gradually optimize their behaviors through continuous interaction and trial-and-error with the environment, with the goal of maximizing predefined cumulative rewards. In dual-arm interaction scenarios, RL has been widely applied to optimize compliant behaviors. Karim et al. [70] combined RL with variable impedance control, allowing dual-arm robots to actively adjust impedance parameters according to the mass and geometry of objects during grasping and placement tasks, thereby achieving greater stability and interaction comfort in collaboration.

However, applying RL directly to physical robots faces challenges such as low sample efficiency and insufficient exploration safety. To address these issues, researchers have proposed several solutions. Sim-to-real transfer methods allow robots to first undergo large-scale training in virtual environments. Peng et al. [64] introduced randomization of system dynamics parameters — including friction coefficients, object mass, and damping — during simulation training, which significantly improved the robustness of policy transfer to real robots. Mu et al. [65] leveraged generative digital twin technology in the RoboTwin benchmark to expand task and environment diversity, and by combining dual-arm simulation with real-world evaluation, they achieved policy transfer and generalization across multiple tasks and scenarios.

Another direction is offline reinforcement learning, which trains policies using existing interaction datasets. The work of Kumar et al. [66] demonstrated how conservative policy updates can prevent policy degradation caused by overestimation of Q-values for out-of-distribution actions. On the other hand, model-based RL improves efficiency by learning a dynamic model of the environment and performing policy optimization within the model. A successful example is the probabilistic ensemble dynamics model developed by Chua et al. [67], which uses planning over model predictions to significantly enhance learning efficiency in complex manipulation tasks.

However, the intrinsic 'trial-and-error' nature of RL introduces significant hurdles in physical DA-HRC, particularly regarding low sample efficiency and potential safety risks during exploration. Learning complex dual-arm coordination from scratch is often prohibitively time-consuming and dangerous. To mitigate these issues, a natural evolution is to combine the efficiency of human demonstrations with the self-improvement capability of RL. This hybrid paradigm, which leverages the strengths of both approaches, is examined in the following section.

4.3. Combining imitation and reinforcement learning

IL and RL are not mutually exclusive but rather complementary. Recently, the hybrid paradigm of "first imitate, then optimize" has gradually become mainstream. Within this framework, the robot first leverages IL to quickly acquire a reasonable and safe initial policy from a small number of human demonstrations,

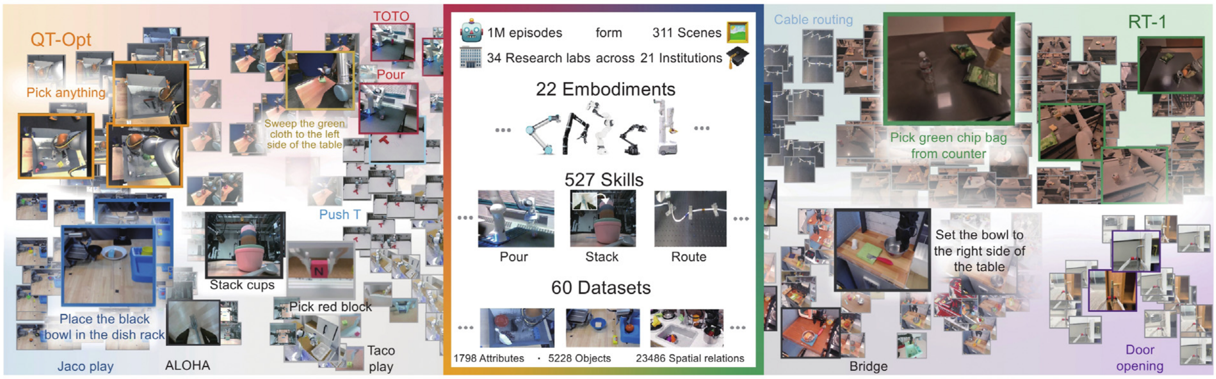

Fig. 9. Overview of the Open X-Embodiment dataset. Reproduced with permission from [80]. © 2024 IEEE.

thereby avoiding the inefficiency and risks of RL when starting from scratch. A classic algorithm in this field is Deep Q-learning from Demonstrations (DQfD) proposed by Hester et al. [68], which employs a prioritized experience replay mechanism to combine demonstration data with data from the robot's autonomous exploration, significantly accelerating the learning process.

Subsequently, RL takes over in the fine-tuning phase, gradually optimizing the policy through continuous interaction. Nair et al. [69] combined this idea with continuous control algorithms (e.g., DDPG), achieving success in complex robotic manipulation tasks. Karim et al. [70] integrated RL with variable impedance control, where IL first provided an initial policy for dual-arm trajectory tasks, and RL was then used to fine-tune the policy to adapt to different object properties, thereby achieving higher stability and accuracy. Wang et al. [71] initialized dual-arm collaboration strategies with only a single demonstration and incorporated RL during the fine-tuning phase, enabling the robot to maintain high success rates even under occlusions or partial disturbances. Meanwhile, Zhan et al. [72] proposed leveraging large-scale offline imitation data for pretraining and combining it with online RL for fine-tuning, which significantly enhanced policy robustness and generalization across multiple tasks and complex scenarios.

4.4. Foundation models and generative methods

Recently, foundation models, represented by large language models (LLMs) and multimodal models, have profoundly reshaped the development trajectory of robotics, as illustrated in Fig. 8. These general-purpose models, pretrained on massive datasets, demonstrate powerful generalization and multimodal reasoning capabilities. Among generative approaches, diffusion models are particularly noteworthy. Chi et al. [74] proposed a diffusion policy that formulates action generation as a stepwise denoising process, naturally capturing high-dimensional, complex, and even multimodal action distributions. RDT-1B [75] marked the first successful application of diffusion models to complex dual-arm manipulation tasks, showcasing strong capabilities in generating coordinated and smooth dual-arm trajectories. Reuss et al. [76] developed the Multimodal Diffusion Transformer (MDT), capable of generating actions from diverse goal modalities.

Recent studies have extensively expanded the application of diffusion models to dual-arm manipulation. For example, KStar Diffuser [77] improved the physical feasibility of trajectories through spatiotemporal graph structures and kinematic constraints. Diffuser [73] formulated control as a conditional diffusion-based trajectory generation problem, enabling robots to synthesize feasible action sequences under task constraints. VLM-SFD [63] used vision–language models to guide diffusion-generated motion flows, achieving cross-scene and multi-task generalization. Furthermore, AdaptDiffuser [78] proposes an adaptive diffusion-based planning framework that refines the model through high-quality synthetic data, improving generalization and performance in robotic control tasks.

Meanwhile, VLA models, such as Google's RT-2 [79], tightly couple language, vision, and action into a unified representation space. Trained on large-scale multimodal datasets such as Open X-Embodiment [80], VLA models demonstrate unprecedented zero-shot and few-shot generalization capabilities (see Fig. 9). Recently, researchers have begun extending VLA frameworks to dual-arm systems. The π_0 model [81], trained across morphologies, included dual-arm manipulation scenarios and exhibited stable coordination in tasks such as "cloth folding" and "table cleaning". Its upgraded version, $\pi_{0.5}$ [82], further enhanced zero-shot adaptability for complex dual-arm tasks in real household environments. GF-VLA [83], through graph-structured and language-integrated reasoning, achieved over 90% grasp-and-place accuracy across four dual-arm assembly benchmarks, demonstrating deep fusion of visual semantic understanding with dual-arm action generation. HybridVLA [84] combined autoregressive and diffusion-based policies, achieving strong generalization in both single-arm and dual-arm robots, with significant improvements in motion stability and coordination for dual-arm manipulation. Similarly, Octo [85] introduced an open-source vision–language–action policy trained on the large-scale Open X-Embodiment dataset, enabling a single model to generalize across diverse robotic manipulation tasks and embodiments. Its strong cross-task and cross-environment generalization further highlights the potential of VLA-style policies for scalable robot manipulation.

Although LLMs themselves lack physical execution capabilities, their commonsense reasoning and logical planning abilities make them a natural "brain" for human–robot interaction systems. The SayCan framework proposed by Ahn et al. [86] combined the planning capacity of LLMs with pre-learned robotic skills, enabling robots to understand and execute high-level, ambiguous natural language instructions. Reuss et al. [87] integrated vision–language conditioning with streaming policies, enabling models to generate actions from natural language instructions with both logical consistency and execution coherence across simulated and real scenarios, thereby achieving closed-loop control. Driess et al. [88] proposed PaLM-E, an embodied multimodal language model that integrates language reasoning with visual perception and robot state inputs. By embedding continuous sensor observations into the language model token space, PaLM-E enables robots to perform multimodal reasoning and generate grounded robotic actions from natural language instructions. In dual-arm systems, this paradigm is being actively explored, with researchers attempting to delegate high-level task decomposition and action allocation to LLMs, while diffusion or VLA models handle the generation of smooth and coordinated dual-arm trajectories at the low level.

5. Multimodal perception and scene understanding

To achieve truly safe, natural, and efficient HRC, robots must go beyond mere geometric and physical perception and evolve toward a cognitive level that enables them to understand the environment, objects, and even the internal states of their human partners. This requires them, much like humans, to integrate multiple sensory modalities — such as vision, force, and touch — to construct a dynamic and holistic world model.

In the complex scenarios of DA-HRC, perception systems face unprecedented challenges. The motions of humans and dual robot arms often cause severe occlusions, the working environment is inherently dynamic, and human behavior and intentions carry intrinsic uncertainty. Therefore, a robust perception system is not only a prerequisite for task execution but also a cognitive cornerstone for building trust, ensuring safety, and enabling smooth interaction. This section will discuss the topic from three perspectives: vision, force perception, and tactile sensing.

5.1. Vision perception

Accurate perception of the manipulated objects and the surrounding environment is the prerequisite for any robotic physical operation. Among all sensing modalities, vision remains the primary source of information. Traditional 2D vision relies on RGB cameras to provide color and texture information, combined with either classical image processing techniques [89] or modern convolutional neural networks (CNNs) [90], forming the basis for object recognition, segmentation, and classification. For example, in a collaborative assembly task, Huang et al. [91] employed a monocular eye-in-hand camera to capture 2D images, estimate component positions and relative pose errors, and apply PID compensation to achieve high-precision insertion. Using a Baxter dual-arm robot, they completed the entire process of grasping, alignment, and insertion under a 1 mm clearance condition.

However, 2D vision lacks depth information, making it insufficient for precise manipulation. To overcome this limitation, 3D vision technologies have been developed, utilizing depth cameras (e.g., Intel RealSense) or LiDAR to generate 3D point clouds. Sa et al. [92], for instance, applied 3D point cloud and color data in an agricultural harvesting robot to segment and localize sweet peppers, providing critical spatial information for accurate robotic grasping.

In more complex industrial scenarios, Medjram et al. [93] used an RGB-D camera to provide dual-arm systems with a 3D representation of the scene, enabling markerless box grasping. Nonetheless, 3D vision continues to face challenges when dealing with transparent or reflective objects. Moreover, frequent arm and human motion in DA-HRC settings often leads to severe occlusions, requiring algorithms to remain robust even when point cloud data is incomplete.

To address these challenges, recent studies have proposed various improvements. FuseGrasp [94] enhances depth completeness for transparent object grasping by fusing RGB-D with millimeter-wave radar. MASt3R [95], as a geometry foundation model, improves scene understanding in complex environments through robust image matching and 3D reconstruction. Meanwhile, FoundationPose [96] provides unified 6D pose estimation and tracking, offering reliable object pose priors for dual-arm manipulation.

5.2. Force perception

When interaction transitions from observation to physical contact, force and tactile perception become indispensable. For dual-arm systems, the core challenge of force perception lies not only in measuring contact forces but also in decoupling the force signals from both arms, distinguishing external forces for collaboration from internal forces for grasp stabilization. Six-axis force/torque sensors installed at the wrist or joints can accurately measure 3D forces and torques, providing critical input for impedance and admittance control. For example, Abbas and Dwivedy [97] designed an event-triggered admittance controller using force feedback, enabling dual-arm robots to compliantly respond to human pushes during physical interaction. Duan et al. [98] proposed a hybrid position–impedance–force control method for manipulators in unknown environments, where force feedback is integrated with position and impedance regulation to enable compliant interaction during contact tasks. More recently, with the miniaturization and high-precision development of sensors, Tan et al. [99] proposed MEMS-based six-axis force/torque sensors that can be integrated into dual-arm wrists and joints, providing high-resolution force inputs to enhance sensitivity and stability in complex interaction tasks.

Beyond direct measurement, sensorless force estimation offers a cost-effective alternative for force perception. For instance, Kallu et al. [100] estimated end-effector reaction forces in dual-arm robots using sliding mode control combined with a disturbance observer. Le and Kang [101] introduced an adaptive third-order sliding mode observer for contact force estimation in collaborative robots. In general, these approaches do not rely on expensive external sensors but instead exploit accurate robot dynamic models, using joint motor currents and encoder data to infer external forces on the end-effector. Their core techniques are often based on disturbance observers [102,103]. Although their precision and bandwidth are usually lower than those of dedicated force sensors, such methods show enormous potential in scenarios requiring compliant interaction rather than high-precision force control.

Going further, force information is not only a low-level input for controllers but also a key cue for robots to understand collaboration intentions and task states [104]. Studies have shown that by analyzing temporal patterns of force/torque signals, robots can recognize whether a human intends to guide, hand over, or resist. For example, Peternel et al. [105] proposed a method for human–robot cooperative manipulation based on human sensorimotor information, enabling differentiation of various interaction intentions. Haddadin et al. [106] investigated collision detection and reaction strategies in physical human–robot interaction, showing that monitoring interaction forces can effectively identify collisions and improve safety.

In recent years, integrating force perception with learning methods has become a research hotspot. Rozo et al. [128] proposed a learning-from-demonstration framework that enables robots not only to imitate human motion trajectories but also to learn and reproduce the force profiles exerted by experts, thereby achieving near-human performance in skill-dependent tasks such as polishing and massage. Cutting-edge research has further focused on force–vision fusion. For example, Jin et al. [129] introduced a curriculum learning method combining visual and force information, enabling robots to make more context-aware decisions in contact-rich assembly tasks. When the vision system identifies the manipulated object as fragile, the force control system automatically switches to a lower force threshold. Such multimodal fusion is pushing robots from merely “sensing force” toward actually “understanding force”, marking a key step toward advanced physical intelligence.

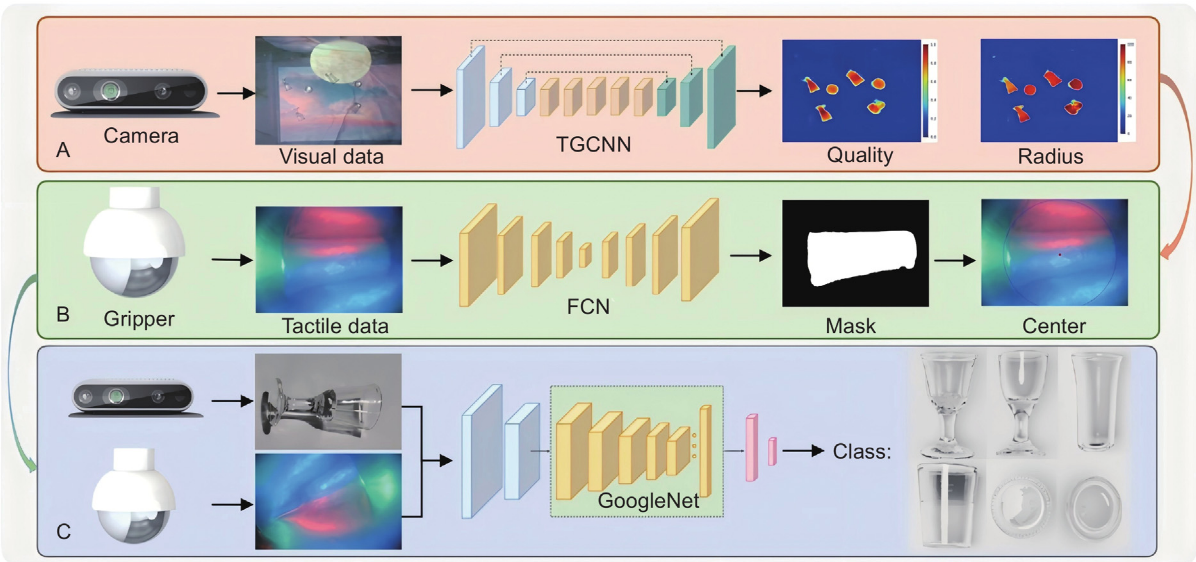

Fig. 10. Vision–tactile fusion framework for transparent object grasping. Reproduced with permission from [116]. © 2023 IEEE.

5.3. Tactile perception

Complementary to force perception is tactile sensing, which provides high-resolution information about contact surfaces. In dual-arm collaboration, the challenges of this technology extend from fine manipulation with a single hand to integrating tactile information across both hands for coordinated dexterity, as well as expanding the sensing range from fingertips to the whole body to ensure safety in close-proximity interaction. Tactile sensors embedded in fingertips or palms cannot only detect pressure distribution but also identify texture, temperature, and slip. Modern tactile sensing technologies are evolving toward high-resolution and multimodal sensing, with vision-based sensors (e.g., GelSight) being particularly prominent [107]. Such sensors capture subtle deformations of a gel surface via cameras, reconstructing the 3D geometry, texture, and shear force distribution of the contacted object [108]. Dong et al. [109] employed a vision-based tactile sensor to detect incipient slip and provide feedback for timely grip adjustment, preventing object slippage and improving grasp stability. Such mechanisms are especially critical in dual-arm cooperative tasks involving objects of unknown weight or fragile materials.

Recent studies are pushing tactile sensing from passive perception to active control. Tac-Man [130] leverages tactile feedback to maintain stable contact and manipulate articulated objects without relying on prior knowledge of their kinematic structures, enabling robots to robustly interact with mechanisms such as doors, drawers, and other jointed objects even under uncertainty. At the same time, distributed robotic skin has begun to be applied to multi-contact and dual-arm collaboration scenarios [110]. These technologies integrate large-scale tactile sensor arrays across robot arms, torsos, and other non-manipulative body parts, not only enabling multi-point contact perception but, more importantly, enhancing safety in whole-body physical interaction. For instance, Sun et al. [111] designed a highly sensitive flexible tactile sensing array based on carbon nanotube–polydimethylsiloxane composites, capable of precisely detecting the location and intensity of touch. When a human inadvertently touches the robot's arms during collaboration, the skin system can instantly provide feedback, triggering the robot to decelerate, stop, or enter compliant mode, thereby offering crucial safety assurance for close-range human–robot interaction.

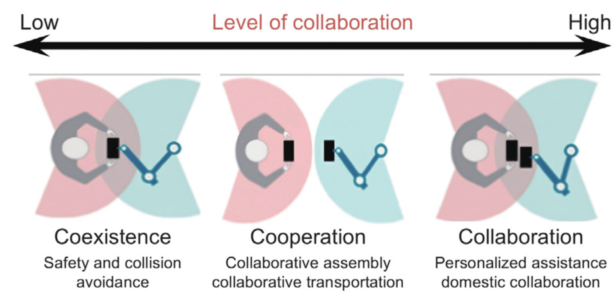

Fig. 11. Classification of DA-HRC under different applications and collaboration levels.

Driven by high-resolution tactile data, robots are able to achieve more advanced dexterous manipulation, such as adjusting an object's pose solely through coordinated finger movements without setting it down. Andrychowicz et al. [131] demonstrated via deep reinforcement learning that robots equipped with tactile sensing can perform in-hand manipulation similar to humans, adjusting object poses effectively. Dong et al. [132] improved the GelSight tactile sensor, enhancing resolution and stability in geometry and slip detection, thus providing reliable tactile input for fine motion adjustment.

In addition, visuo-tactile fusion has become an important research direction [112,113]. Vision provides global information about objects, while tactile sensing offers precise local contact information. Combining the two can overcome the limitations of either modality, for example, tactile sensing can be used to improve contact perception and enhance manipulation stability during in-hand object interaction [114], or leveraging visual priors to guide tactile exploration, thereby achieving more robust perception and manipulation in complex tasks [115]. Li et al. [116] proposed a visuo-tactile grasping framework, illustrated in Fig. 10. In this framework, the visual pathway predicts the initial grasp pose, while the tactile pathway extracts the contact region and centroid upon object contact. The two modalities are then fused to achieve robust classification of visually challenging objects, such as transparent items, ultimately enhancing overall grasp robustness.

Furthermore, the transfer of tactile information across different sensors and morphologies is becoming a significant trend.

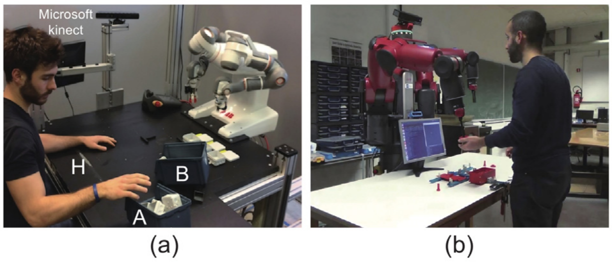

Fig. 12. Applications of collaborative assembly. (a) YuMi robot collaborating with a human in assembly. (b) Baxter robot collaborating with a human in gearbox assembly.

Zhao et al. [117] proposed transferable tactile representations across diverse sensors and tasks, enabling contact knowledge to generalize across heterogeneous sensing setups. Furthermore, tactile learning from human demonstrations is also rapidly advancing. Yu et al. [118] introduced MimicTouch, a framework that leverages multimodal human tactile demonstrations and imitation learning to transfer tactile control strategies to robots for contact-rich manipulation.

6. Representative application scenarios

Advances in DA-HRC are steadily extending application boundaries from structured industrial sites toward semi-structured and even fully unstructured complex environments. Fig. 11 illustrates the classification of five application scenarios across different levels of collaboration. This section will discuss in detail collaborative assembly, collaborative transportation, safety and collision avoidance, domestic collaboration, and personalized assistance.

6.1. Collaborative assembly

In the field of precision assembly, dual-arm robots, owing to their human-like structure and coordination capabilities, have become an ideal platform for HRC. Traditional collaborative assembly modes are not only limited to rigid component assembly, such as constant velocity joint assembly in the automotive industry or plastic pipette assembly in the electronics industry, but also lack sufficient flexibility to meet dynamically changing demands. Zanchettin et al. [133] proposed a dynamic collaboration control framework based on the YuMi robot, capable of optimizing task allocation and collaboration efficiency, as shown in Fig. 12(a). This study demonstrated YuMi's potential in collaborative assembly. Makrini et al. [134] introduced a novel ergonomics-driven collaboration strategy using the Baxter robot, which significantly improved assembly efficiency and robotic accuracy, as shown in Fig. 12(b).

Moreover, the design of an efficient collaborative assembly unit goes beyond the mere physical coexistence of robots and humans; it demands systematic optimization of task modeling, safety strategies, human ergonomics, and cognitive load, as well as intuitive human–robot interaction interface design. Zhang et al. [135] proposed a deep learning-based task modeling approach for adaptive task allocation in collaborative assembly. Wang et al. [136] presented a task allocation method based on assembly stability and complexity, combined with human–robot interface design, which effectively improved the efficiency and safety of collaborative assembly systems.

When it comes to complex material handling, the irreplaceable value of dual-arm collaboration becomes even more evident. For example, when a human and a robot jointly manipulate a large flexible sheet (e.g., aerospace composites or automotive interiors), the robot must use vision and force feedback to perceive and adapt to human actions in real time, collaboratively maintaining proper tension to prevent wrinkling or damage—something single-arm systems struggle to accomplish efficiently. Wang et al. [137] proposed a DA-HRC method for handling flexible materials, combining vision and force feedback to maintain tension, thereby effectively avoiding wrinkles and improving collaborative precision. Zhou et al. [138] developed a dual-arm collaboration system for deformable bags, which identified key structural regions of interest, built their dynamic models, and used model predictive control (MPC) to achieve high-precision and stable manipulation of deformations.

The latest research efforts aim to comprehensively enhance the intelligence and autonomy of dual-arm assembly. By incorporating imitation learning and reinforcement learning, robots can autonomously learn complex assembly strategies from human demonstrations instead of relying on tedious manual programming. This is especially crucial for tasks with complex geometric constraints and contact dynamics. For instance, the classic peg-in-hole task is a core challenge in precision assembly. Alles et al. [139] proposed a reinforcement learning framework for dual-arm peg-in-hole assembly, enabling policies trained in simulation to be directly transferred to real robots, achieving high-precision insertion under contact constraints. Wu et al. [140], focusing on dual-hole micro-device assembly, combined deep reinforcement learning with simulation pretraining and online training to achieve compliant insertion with accurate force control.

Learning-based dual-arm collaboration frameworks enable high-precision alignment and compliant insertion of micro-components by deeply integrating visual servoing with high-resolution force/torque sensing. Such sensor fusion allows robots to cope with target pose uncertainties and adjust their actions in real time according to physical feedback during contact. Aranda et al. [141] combined deep neural networks with dual force/torque sensors, significantly improving alignment accuracy and success rates in dual-arm peg-in-hole assembly. Shen et al. [142] proposed a learning-based visual servoing framework, achieving greater precision and compliance in micro-component insertion.

More cutting-edge work has begun to leverage large multimodal models to address cognitive and planning challenges in assembly. For example, Shridhar et al. [143] proposed CLIPort, a vision–language-based manipulation framework that combines semantic understanding from language models with spatial reasoning for action generation. By aligning visual features with language instructions, their approach enables robots to interpret task goals and execute corresponding manipulation policies across a range of tabletop tasks. Kim et al. [144] introduced OpenVLA, a vision–language–action model that converts visual observations and language instructions into robot control actions, enabling robots to interpret complex tasks and generalize manipulation policies across diverse environments. Ge et al. [145] presented a dual-arm collaborative framework for multi-peg-in-hole assembly, demonstrating high precision in alignment and insertion across multiple assembly tasks.

6.2. Collaborative transportation

In the field of collaborative material handling, dual-arm robots act as "strength-augmenting assistants" for humans, effectively reducing workers' physical load and significantly lowering the risk of workplace injuries caused by handling heavy or large, irregular objects. The core challenge in this scenario lies in achieving high synchronization between humans and robots at both the physical and cognitive levels, which can be decomposed into two key problems: accurate human intention prediction and dynamic force/motion coordination control.

Early studies primarily relied on non-contact or contact-based sensors. For example, Wen et al. [124] proposed a dual-arm collaborative manipulation framework that combined visual observations and contact force sensing to infer human intentions in insertion and co-transport tasks, while coordinating dual-arm actions and regulating internal forces to maintain stable object posture. Zhang et al. [146] developed a vision-servoing dual-arm system that used non-contact marker tracking and image feature alignment to reduce pose errors, thereby minimizing interaction force fluctuations and improving coordination and safety.

More recent advances increasingly leverage wearable sensors and advanced learning algorithms, enabling a shift from behavior-level to state-level perception. For instance, Yang et al. [147], targeting dual-arm nursing transfer scenarios, proposed a human–robot biomechanical modeling method based on wearable sensing and MLP networks to identify hip joint torque, thereby dynamically distributing loads during co-carrying and ensuring both safety and comfort. Wen [148] introduced distributed MPC combined with YOLOv8 visual detection in dual-humanoid collaborative lifting tasks, achieving real-time trajectory and force coordination in dual-arm systems and effectively reducing trajectory deviation and velocity errors during transportation.

At the control strategy level, coordinated impedance/admittance control has become the mainstream technique for ensuring stable and safe transportation. The key lies in decoupling internal and external forces: on one hand, precisely controlling the net external force applied to the object to achieve smooth transportation trajectories; on the other, minimizing or regulating the internal forces exerted by the dual arms to prevent object damage or unstable grasping. Zhang et al. [149] proposed an adaptive coordinated impedance control scheme, which, in symmetric dual-arm tasks, simultaneously regulated internal and external forces within a unified framework, achieving precise decoupling and control. Similarly, Dimeas and Aspragathos [150] introduced an online adaptive admittance control method capable of real-time parameter adjustment to accommodate changes in human stiffness and dynamic uncertainties during interaction, thereby enhancing system robustness and stability.

In more complex scenarios such as smart logistics, foundation models represented by VLA architectures have demonstrated tremendous potential. Fei et al. [151] proposed the BTLA framework, in which, during dual-arm teleoperation tasks, one arm was controlled via voice commands to assist, while the primary arm was teleoperated to perform fine object manipulation, achieving higher task coverage and success rates compared to traditional methods. Li et al. [83], within the GF-VLA model, generated hierarchical behavior trees and interpretable action commands using scene graphs and language-conditioned Transformers, achieving a grasp success rate of 94% and task success rate of about 90% across four dual-arm assembly tasks, showcasing strong generalization and robustness.

6.3. Safety and collision avoidance

Safety is the most fundamental and critical requirement in HRC, serving as the cornerstone for all collaborative tasks. Traditional approaches mainly rely on active and predictive strategies. By using external sensors (e.g., laser scanners or depth cameras) to construct safety zones, robots immediately decelerate or trigger safety-rated monitored stops once a human or obstacle enters the predefined protective area [152,153]. For example, Karagiannis et al. [153] proposed an adaptive SSM framework that monitors the relative position and velocity between humans and dual-arm robots in real time through laser scanners and depth cameras. Based on predefined safety zones, the system dynamically switches control strategies — automatically slowing down or stopping when a person enters the protective area — thereby balancing safety and efficiency. Although highly reliable, this strategy's frequent halting behaviors significantly reduce fluency and efficiency, making human–robot interaction stiff and inefficient.

At the implementation level, different technical paths provide safeguards for collision avoidance. Optimization-based approaches model collision avoidance as a severe constraint within the control system and integrate it into a real-time quadratic programming (QP) problem. As discussed earlier, control barrier functions (CBFs) are a typical example [47,48]. CBFs mathematically define a "safe set" (the minimum safety distance between humans and robots) and generate control inputs that ensure the robot's state always remains within this set, offering strong theoretical guarantees for safety in dynamic environments. For instance, Kaypak et al. [154] employed 3D convex shapes as geometric safe sets in dual-arm robot interaction and used higher-order CBFs to model collision avoidance as a significant constraint. By integrating this method into real-time QP control, they ensured that the arms always maintained a safe distance while executing task motions.

Beyond collision avoidance, more advanced concepts emphasize collision mitigation, ensuring that even when contact occurs, it remains safe. This relies on power and force limiting (PFL) techniques. By integrating high-precision force/torque sensors at robot joints or end-effectors and combining them with compliant control algorithms (e.g., impedance/admittance control), the maximum force exerted upon contact can be strictly limited. This method effectively makes the robot physically "soft", with any unintended contact forces constrained within safe thresholds, thereby achieving inherent safety. For example, Zhang et al. [149] combined force/torque sensing with coordinated impedance control in symmetric dual-arm tasks, ensuring contact forces stayed within safe limits and significantly mitigating impact effects. Ren et al. [155] fused admittance control with force sensors and inertia observers in stable dual-arm grasping tasks, enabling compliant responses and safety protection under external disturbances or object interactions.

Recently, deep reinforcement learning (DRL) has opened new pathways for solving complex collision-avoidance problems. By undergoing massive training in simulation environments, robots can learn more sophisticated and human-like avoidance strategies compared to traditional optimization methods. For instance, DA-VIL [70] combined variable impedance control with RL, allowing dual-arm robots to reduce stiffness or adjust trajectories near obstacles or potential collisions—exhibiting natural avoidance behaviors akin to raising an arm or leaning slightly sideways. Similarly, Wang and Kasaei [156] trained a dual-arm DRL framework for large panel-grasping tasks, enabling the robot to learn coordinated motions in confined spaces. This allowed the robot to approach the target more directly without wide detours, thereby improving efficiency and naturalness in collaboration.

6.4. Domestic collaboration

Bringing robots into households and offices — highly unstructured environments — represents one of the long-term goals and ultimate frontiers of robotics. Such environments are full of dynamic changes, object diversity, and unpredictability, posing extreme requirements on robots' adaptability, robustness, and safety.

Early studies laid the foundation for this field, demonstrating the potential of dual-arm robots in specific challenging tasks. For example, Maitin-Shepard et al. [157] enabled the PR2 robot to successfully fold towels, a seemingly mundane household chore but a milestone in robotics for handling highly deformable objects, showcasing the early capabilities of dual arms in perceiving and manipulating soft materials. In more complex multi-step cooking tasks, Beetz et al. [158] demonstrated how dual-arm robots could parse online recipes and coordinate the full process — from preparing batter to flipping pancakes — validating the feasibility of robots executing long-horizon, logically connected task chains.

However, these early systems often relied on meticulously crafted algorithms tailored for specific tasks. Recent breakthroughs, driven largely by large-scale datasets and foundation models, are shifting household robotics from specialized to general-purpose paradigms. For instance, Liu et al. [159] extracted manipulation patterns from a large corpus of human demonstration data and incorporated them into a Transformer-based architecture, enabling dual-arm robots to achieve coordinated actions and visual feedback regulation in the dynamic and non-rigid task of stir-frying. Seita et al. [160] proposed a learning-based approach for robotic fabric manipulation, where sequential smoothing policies were trained through deep imitation learning using data generated in a fabric simulation environment. Guided by visual observations, the robot iteratively executed grasp-and-pull actions to progressively transform highly wrinkled fabrics into flattened configurations. The learned policies were successfully transferred from simulation to physical experiments, demonstrating the effectiveness of data-driven methods for improving robustness in deformable object manipulation.

Building upon large-scale teleoperation data, the Mobile-ALOHA system [57] elevated household collaboration to a new level. Using a low-cost data collection pipeline, this system enabled a mobile dual-arm platform to learn and execute various complex whole-body coordination tasks, including kitchen cleaning, object transportation, and even cooking. This marks a transition of general-purpose household robots from laboratory proof-of-concept toward real-world deployment. On this basis, the aforementioned $\pi_{0.5}$ framework [82] further introduced a cross-environment, cross-task paradigm for general physical intelligence. By jointly modeling vision, language, and action, it enabled robots not only to execute complex tasks in familiar settings but also to generalize and adapt to unfamiliar household environments. This progress lays a critical foundation for personalized assistance and long-term autonomous operation.

6.5. Personalized assistance

The goal of personalized assistance is to transform robots from generic, task-driven tools into proactive, user-centered partners. This requires robots to go beyond fixed, universal instructions and deeply adapt to the user's physical characteristics, behavioral habits, cognitive preferences, and even capability limitations, thereby providing assistance that is truly efficient, comfortable, and dignified.

Early research mainly focused on physical-level adaptability. In the field of dual-arm robotics, Yang et al. [161] proposed a human–robot object handover framework based on model predictive control. By integrating perception-driven grasp reachability estimation with motion planning constraints, their approach enabled robots to generate smooth and responsive handover motions while maintaining manipulability and interaction stability. User studies demonstrated that the generated motions significantly improved the fluidity and comfort of human–robot object exchange. Such approaches lay the foundation for personalized ergonomic optimization, which is particularly meaningful for elderly users or individuals with physical limitations.

Recent research trends have further advanced toward cognitive-level personalization, emphasizing real-time adaptation to natural human movements and implicit intentions. Göksu et al. [162] proposed a humanoid dual-arm handover generation framework under kinematic constraints. Using hidden semi-Markov models, they inferred human hand trajectories and temporal features, allowing robots to generate handover postures aligned with human habits. This was especially effective when handling bulky or deformable objects, demonstrating greater naturalness and stability. These results indicate that the dynamic nature of physical interaction is an equally critical challenge in personalization.

In fast-paced or continuous task scenarios, dual-arm robots exhibit unique advantages. For instance, Bombile and Billard [163] proposed a control framework for bimanual robots to dynamically grab and manipulate objects under moving target conditions. By combining analytical modeling with optimization-based motion planning, the system predicts feasible interception states and generates coordinated dual-arm motions in real time, demonstrating robust performance under target motion perturbations. Similarly, Zhang et al. [164] demonstrated that robots could generate real-time grasping trajectories even while objects were moving or rotating in the user's hand, maintaining high success rates and robustness in continuous dynamic handovers.

When addressing the uncertainty of physical interactions, multimodal perception plays a pivotal role. Costanzo et al. [165] proposed a dual-arm collaborative object transportation method based on tactile feedback. By leveraging embedded tactile sensors, their system enabled internal force control and contact point adjustment during dual-arm carrying and rotating tasks, thereby ensuring object stability and operational safety. This work highlights how tactile and force feedback can significantly enhance the robustness and reliability of dual-arm handovers, particularly in complex or visually constrained environments.

7. Challenges and future directions

DA-HRC is currently at a critical stage of transformation, with the research paradigm rapidly shifting from model-driven to data-driven approaches. As discussed in Section 6, large-scale deployment is still constrained by common bottlenecks: in industrial settings, stringent safety requirements conflict with the demand for flexible collaboration, whereas in domestic environments, limited generalization to unseen objects and difficulties in interpreting ambiguous human intentions remain major obstacles. Building on these observations, this section analyzes the core contradictions and key challenges in the field, and summarizes future research directions in Table 4.

7.1. Integration of control and learning

The core technological challenge in the field of DA-HRC lies in how to combine the safety of traditional control theory with the adaptability of modern learning methods. Traditional control approaches, as detailed in Section 3, (such as strategies based on passivity theory or CBFs), provide verifiable "hard" safety guarantees for physical interaction and remain the cornerstone of ensuring human safety. However, these methods rely heavily on precise system models, and their adaptability and generalization are limited when faced with unstructured environments and diverse tasks.

In contrast, data-driven methods reviewed in Section 4, represented by imitation learning and reinforcement learning, demonstrate remarkable adaptability, being able to directly learn complex nonlinear policies from experience without requiring precise modeling. Yet, the "black-box" nature of these methods makes their decision-making processes lack transparency, and they usually lack formal safety verification. When exploring

Table 4
Key challenges and future directions of DA-HRC.

Research area	Key challenges	Future directions
Integration of Control and Learning	• Tension between interpretable control ("white-box") and data-driven learning ("black-box") paradigms. • Safety risks of real-world exploratory learning (e.g., RL).	• Develop hierarchical safe-learning architectures. • Design verifiable learning algorithms. • Embed physical constraints into generative models.
Gap in Application Domains	• Industrial tasks emphasize precision and determinism, while household tasks are diverse and open-ended. • Inconsistent datasets and evaluation criteria across domains.	• Research bidirectional skill transfer. • Develop scene understanding for industrial applications. • Enable large-scale customized collaboration.
Deepening of Perception and Cognition	• Difficulty in modeling internal human states (e.g., trust, fatigue, intent, cognitive load). • Challenge of fusing low-dimensional physical signals (force, pose) with high-dimensional semantic information (language, context).	• Develop multimodal human-state models. • Construct dynamic human–robot trust models. • Achieve predictable and fluent collaboration.
Systemic Challenges and Ecosystem Building	• Simulators fail to accurately capture complex contact dynamics and soft-body interactions. • Lack of standardized benchmarks and datasets hinders fair cross-study comparisons.	• Develop high-fidelity physics simulation engines. • Establish open benchmarks and competitions. • Promote interdisciplinary standards and collaboration.

unknown behaviors, they may generate unforeseen risks—an outcome that is unacceptable in physical human–robot interaction.

Future research should not treat these as binary choices but instead focus on their deep integration, building a unified intelligent framework that combines deterministic safety with high adaptability. One feasible pathway is to develop a hierarchical safety-intelligence architecture: the top layer employs LLMs for high-level task planning and commonsense reasoning; the middle layer uses VLA models to generate semantically grounded action sequences; and the bottom layer leverages robust controllers based on CBFs to guarantee the physical safety of each action execution. Such a "cognition–perception–action" full-stack safety intelligence represents the most valuable direction of exploration for this field.

7.2. Application-oriented challenges

Industrial manufacturing and household services are the two primary application domains of DA-HRC, yet their technical demands differ greatly, creating a pronounced application gap. In industrial scenarios (see Sections 6.1 and 6.2), the core requirements are efficiency, precision, and reliability. The environment is relatively structured, and tasks are defined. Technical challenges are concentrated at the physical execution level, such as high-precision force/position hybrid control, stable manipulation of large deformable objects, and ensuring absolute safety under high-speed operation.

In contrast, the core requirements of household services (exemplified in Sections 6.4 and 6.5) are generalization, robustness, and natural interaction. Household environments are fully unstructured and highly dynamic, and task instructions are often ambiguous natural language commands. Thus, the technical challenges are primarily concentrated at the cognitive and perceptual levels: how to robustly recognize and localize objects in cluttered scenes, how to interpret and decompose vague instructions, and how to achieve personalized adaptation.

With the advancement of mass customization and the commercialization of household robots, the boundaries between these two domains will gradually blur. Future research should focus on bidirectional technology transfer: on the one hand, transferring industrial-grade fine manipulation skills (e.g., precision assembly) into household scenarios (e.g., toy repair); and on the other, leveraging the powerful scene understanding and generalization capabilities developed in household environments to enhance industrial applications, thereby improving flexibility and adaptability in rapidly changing production lines.

7.3. Deepening perception and cognition

To achieve truly fluent and natural collaboration, robots must go beyond simple physical perception and develop a profound understanding of their human partners' internal states and intentions. While current multimodal perception (systematically surveyed in Section 5) integrates vision, force, and tactile information, the challenge lies in elevating these low-level signals into high-level semantic understanding. Robots should sense a force and interpret whether it indicates guidance, handover, or accidental collision—and respond accordingly in ways that align with social norms.

More importantly, current research on human modeling remains insufficient. In most cases, humans are still treated as external command or disturbance sources. Critical human factors such as cognitive load, fatigue, trust, and even emotions are still at a preliminary stage of modeling and understanding. Without incorporating these factors into closed-loop control, robots will remain passive tools rather than proactive and empathetic collaborators.

Therefore, future research should focus on developing more advanced human state sensing and modeling techniques and integrating these models into dynamic interaction frameworks. Robots should be able to adjust their levels of autonomy and assistance strategies in real time based on predictions of user intent and assessments of trust, thereby enabling truly personalized, predictable, and seamless collaboration.

7.4. Systemic barriers and ecosystem development

Several systemic foundational obstacles still constrain the overall development of the DA-HRC field, in addition to the specific technical challenges discussed above. Among them, the Sim-to-Real gap (previously identified as a major bottleneck for RL in Section 4.2) is particularly critical. Advanced learning algorithms heavily rely on simulation-based training, yet phenomena such as complex contact dynamics in dual-arm collaboration and the deformation of flexible objects remain extremely difficult to simulate with high fidelity. This difficulty has become a major bottleneck preventing algorithms from reaching real-world applications.

Another key obstacle is the lack of standardization and benchmarking. Without widely accepted testing platforms, tasks, and evaluation metrics, cross-comparison between different studies is extremely difficult, which in turn slows down the iterative progress of the entire field.

To promote the healthy development of the domain, future efforts should prioritize ecosystem building. This includes investing resources into the development of high-fidelity physical simulation engines, with particular focus on multi-body contact and soft-body dynamics. At the same time, academia and industry should jointly promote the establishment of open benchmarks, analogous to ImageNet in computer vision, that include standardized tasks, datasets, and evaluation tools. Finally, genuine interdisciplinary collaboration must be strengthened, integrating insights from cognitive science and human factors engineering into the design and control of robotic systems, thereby enabling the creation of truly human-centered collaborative intelligence.

8. Conclusion

As industry transitions from the automation-centered paradigm of Industry 4.0 to the human-centric vision of Industry 5.0, robots are evolving from isolated automation tools into intelligent partners capable of working closely with humans. In this context, DA-HRC has emerged as a key driver of progress, enabling robots to perform complex tasks with human-like dexterity. Through a systematic literature review, this paper has synthesized the recent advances in this vibrant interdisciplinary field, highlighting its profound paradigm shift—from traditional model-based control toward data-driven approaches for intelligent skill acquisition.

At the level of physical interaction and perception, control strategies have advanced toward optimization-based dynamic decoupling and variable impedance/admittance compliance control, complemented by formal methods that ensure safety. Multi-modal perception, achieved by integrating vision with force/tactile sensing and enhanced by foundation models and learning-based
techniques, is enabling robots to move beyond raw physical perception toward deeper intent understanding. In terms of skill acquisition, imitation learning and reinforcement learning have become the dominant paradigms. Particularly, foundation models such as diffusion models and VLA models — with their strong generative capacity and generalization ability — are opening new pathways for solving complex dual-arm coordination problems, making them one of the most dynamic frontiers of current research.

Looking ahead, the core challenge of the field lies in reconciling the determinism and verifiable safety of traditional control with the adaptability of modern learning. Future breakthroughs will depend on their deep integration, yielding a unified intelligent framework that is both formally safe and highly adaptive to real-world environments. To achieve this, researchers must also overcome systemic obstacles, including insufficient modeling of human internal states, the Sim-to-Real gap, and the lack of standardized benchmarks.

In summary, DA-HRC stands at the intersection of robotics and artificial intelligence. As these challenges are gradually addressed, DA-HRC is poised to play an increasingly vital role in both intelligent manufacturing and quality-of-life enhancement in the era of Industry 5.0.

CRediT authorship contribution statement

Jinhua Ye: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Yechen Fan:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Gengfeng Zheng:** Validation, Supervision, Methodology, Conceptualization. **Houde Dai:** Resources, Project administration, Investigation. **Chenyang Song:** Software, Formal analysis, Data curation. **Haibin Wu:** Supervision, Funding acquisition. **Yu Zhang:** Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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