

Embodied Intelligent Industrial Robotics: Concepts and Techniques

Chaoran Zhang^{a,†}, Chenhao Zhang^{a,†}, Zhaobo Xu^a, Qinghongbing Xie^a, Pingfa Feng^{a,b}, Long Zeng^{a,*}

^a Tsinghua Shenzhen International Graduate School, Tsinghua University, Shenzhen 518055, China

^b Department of Mechanical Engineering, Tsinghua University, Beijing 100084, China

* Corresponding author. E-mail address: zenglong@sz.tsinghua.edu.cn

† These authors equally contributed to this work.

Abstract:

In recent years, embodied intelligent robotics (EIR) has made significant progress in multi-modal perception, autonomous decision-making, and physical interaction. Some robots have already been tested in general-purpose scenarios such as homes and shopping malls. We aim to advance the research and application of embodied intelligence in industrial scenes. However, current EIR lacks a deep understanding of industrial environment semantics and the normative constraints between industrial operating objects. To address this gap, this paper first reviews the history of industrial robotics and the mainstream EIR frameworks. We then introduce the concept of the embodied intelligent industrial robotics (EIIR) and propose a knowledge-driven EIIR technology framework for industrial environments. The framework includes four main modules: world model, high-level task planner, low-level skill controller, and simulator. The world model provides industrial working environment knowledge (such as semantic map) and industrial operating object knowledge (such as knowledge graph) that large language model (LLM) lacks. The high-level task planner breaks down natural language tasks into a series of subtasks. The low-level skill controller translates these subtasks into specific, executable skill sequences to realize the physical execution. The simulator models kinematics, control logic, and environmental interactions to support algorithm development, virtual commissioning, and digital twins at both the single-robot and full-production-line scales. We also review the current development of technologies related to each module and highlight recent progress in adapting them to industrial applications. Finally, we summarize the key challenges EIIR faces in industrial scenarios and suggest future research directions. We believe that EIIR technology will shape the next generation of industrial robotics. Industrial systems based on embodied intelligent industrial robots offer strong potential for enabling intelligent manufacturing. We will continue to track and summarize new research in this area and hope this review will serve as a valuable reference for scholars and engineers interested in industrial embodied intelligence. Together, we can help drive the rapid advancement and application of this technology. The associated project can be found at https://github.com/jackyzengl/Embodied_Intelligent_Industrial_Robotics_Paper_List.

Key words: Embodied intelligence, Embodied intelligent industrial robotics, knowledge-driven, intelligent manufacturing.

1 Introduction

Embodied intelligent industrial robotics (EIIR¹) mainly studies an industrial agent that can independently perceive, make decisions, and execute tasks within industrial environments. It combines the strengths of embodied intelligence (EI) and traditional industrial robots. As the manufacturing industry shifts toward intelligence and digitalization, intelligent manufacturing is often seen as the crown of the industry, and embodied intelligence is the most valuable gem in that crown. With the rise of multi-modal large models (MLMs), embodied intelligent robotics (EIR) now has stronger closed-loop capabilities across perception, decision-making, and execution [1]. This advancement allows them to move beyond traditional teaching and programming methods, enabling autonomous task planning and execution guided by natural language. This makes task-level flexibility possible. However, most current research focuses on applying embodied intelligence in daily life scenarios such as home services and social interaction [2]. Few studies explore its potential in industrial applications like assembly, welding, and material handling [3]. This paper aims to systematically present the technical framework and application potential of embodied intelligence in the field of industrial robotics. We focus on the practical implementation path of EIIR and review the latest advances in its supporting technologies. Through this review, we hope to offer forward-looking insights and useful references for researchers and engineers interested in bringing embodied intelligence into industrial practice, helping bridge the gap from concept to real-world use.

According to a literature search on the Scopus database using the keywords "embodied intelligence" and "embodied intelligence AND (manufacturing OR industrial)", two clear trends have emerged over the past half-century. From Fig. 1(a), we can see that literature on industrial embodied intelligence remained limited from 1985 to 2018. However, it began to grow significantly after 2018 and peaked in 2024. From Fig. 1(b), general research on "embodied intelligence" has grown steadily since 2002 and has surged rapidly after 2020. Both topics showed slow growth at first, followed by a rapid increase. These trends are closely linked to recent breakthroughs in EIR, pre-trained models, and MLMs. These technologies have enhanced robots' perception and cognition abilities, making them more adaptable in industrial settings. Geographically, the main contributors to industrial embodied intelligence research are China, the United States, Italy, the United Kingdom, and Germany. Notably, nearly 60% of related publications are in the fields of computer science and engineering, reflecting a growing trend of interdisciplinary integration. Fig. 1(e) and (f) list all authors and affiliations with more than two publications in this field. These data suggest that a global research network around industrial embodied intelligence is beginning to take shape and is expanding rapidly.

¹ In this paper, EIIR may refer to either Embodied Intelligent Industrial Robotics (as a field of study) or an individual Embodied Intelligent Industrial Robot, depending on the context. When the meaning is unambiguous, the abbreviation is used without further distinction. EIR follows a similar usage.

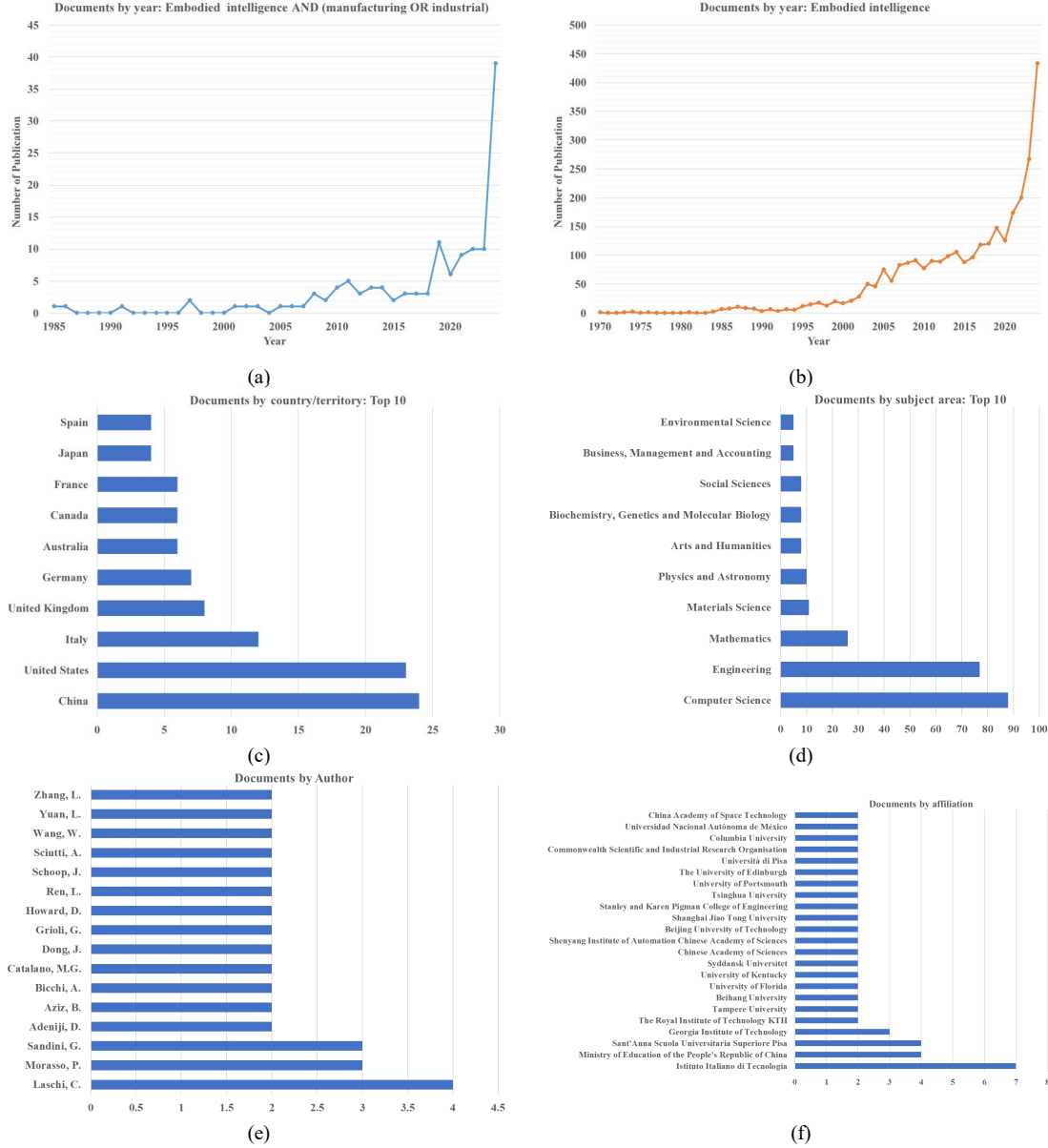


Fig. 1. Statistics from Scopus (search strategy: ‘*embodied intelligence AND (manufacturing OR industrial)*’). (a) Papers by year (‘*embodied intelligence AND (manufacturing OR industrial)*’, 1985~2024); (b) papers by year (‘*embodied intelligence*’, 1970~2024); (c) papers by country/territory: top 10; (d) papers by subject area: top 10; (e) papers by author; (f) papers by affiliation.

This review is different from existing work in the fields of embodied intelligence or embodied intelligent robotics. Table 1 lists six related review papers. Papers 1 to 3 are foundational reviews focused on embodied intelligence, while papers 4 to 6 explore the integration of large language model (LLM) with robotics. Specifically, Paper 1 highlights the interactions among morphology, action, perception, and learning in agent architecture. Paper 2 reviews recent technologies across four key areas: embodied perception, interaction, agent, and sim-to-real adaption. Paper 3 evaluates the features and performance of simulators used in embodied AI research, particularly in tasks like visual exploration, navigation, and embodied question answering. In contrast, our review makes three key contributions. First, it is the first to focus on embodied intelligence in industrial scenarios. We emphasize how

embodied intelligence can enhance adaptability and autonomous decision-making in industrial robots operating in complex production environments. Second, we propose a knowledge-driven EIIR technology framework. This framework serves as the foundation of our review, guiding the literature analysis. It also offers practical, end-to-end technical insights, from concept to real-world deployment. Finally, we identify the key challenges in applying embodied intelligence to industrial settings and outline future research directions.

Table 1 Published review papers on embodied intelligence.

No.	Title	Venue	Year
1	Embodied Intelligence: A Synergy of Morphology, Action, Perception and Learning [4]	ACM Computing Surveys	2025
2	Aligning cyber space with physical world: A comprehensive survey on embodied AI [1]	arXiv	2024
3	A Survey of Embodied AI: From Simulators to Research Tasks [2]	IEEE Transactions on Emerging Topics in Computational Intelligence	2022
4	Large language models for robotics: Opportunities, challenges, and perspectives [5]	Journal of Automation and Intelligence	2025
5	A Survey of Robot Intelligence with Large Language Models [6]	Applied Sciences	2024
6	A survey on integration of large language models with intelligent robots [7]	Intelligent Service Robotics	2024

The rest of the content is organized as follows. Section 2 introduces the definition and technical framework of EIIR. Section 3 elaborates on the world model, including semantic map for working environmental knowledge and knowledge graph for operating object knowledge. Section 4 focuses on techniques on how high-level task planner implements task decomposition, while Section 5 introduces techniques on how low-level skill controller drives physical body execution. Section 6 evaluates existing EIIR simulators. Last but not least, challenges and future research directions are delivered in Section 7.

2 EIIR definition and framework

This section first provides a systematic overview of the development, definition, and interdisciplinary background of EIIR. It then summarizes existing EIR technology frameworks and their main challenges. Finally, it introduces a knowledge-driven EIIR technology framework tailored for industrial scenarios.

2.1 Industrial robotics: From automation to embodied intelligence era

Since the advent of industrial robot (iRobot) in the 1960s, there have been many classification methods [8-10]. According to the development trend of its mainstream technology and flexibility, industrial robotics can be roughly divided into three eras, as shown in Fig. 2.

- *Automation era*: In the early stages, the main advantage of iRobot was their programmability. Research focused on developing robot bodies and core components. These robots executed fixed tasks and predefined actions using hard-coded instructions. While they offered high efficiency and accuracy, their flexibility was very limited.
- *Perception intelligence era*: With the advancement of sensors, machine vision, and deep learning, iRobot gained strong perception and visual servo capabilities. This enabled a higher degree of skill-level flexibility. For example, in loading and unloading tasks, robots could handle parts that were not precisely positioned, thanks to improved visual perception. However, they still lacked flexibility at the task level.
- *Embodied intelligence era*: The rapid development of technologies such as LLMs, MLMs, world models, and knowledge graphs is pushing iRobots into a new phase—the era of embodied intelligence. In this stage, a single iRobot evolves into an industrial agent capable of perception, autonomous decision-making, and execution within its environment, much like a human worker. These robots can now handle a variety of tasks, such as loading, unloading, handling, palletizing, and assembly. This demonstrates true task-level flexibility.

Each era of industrial robotics builds upon the technologies of the previous one. We believe that iRobot is now entering the early stage of the *Embodied intelligence era*. A key future trend is the integration of embodied intelligence with industrial robotics to form EIIR, which will be applied across diverse industrial systems.

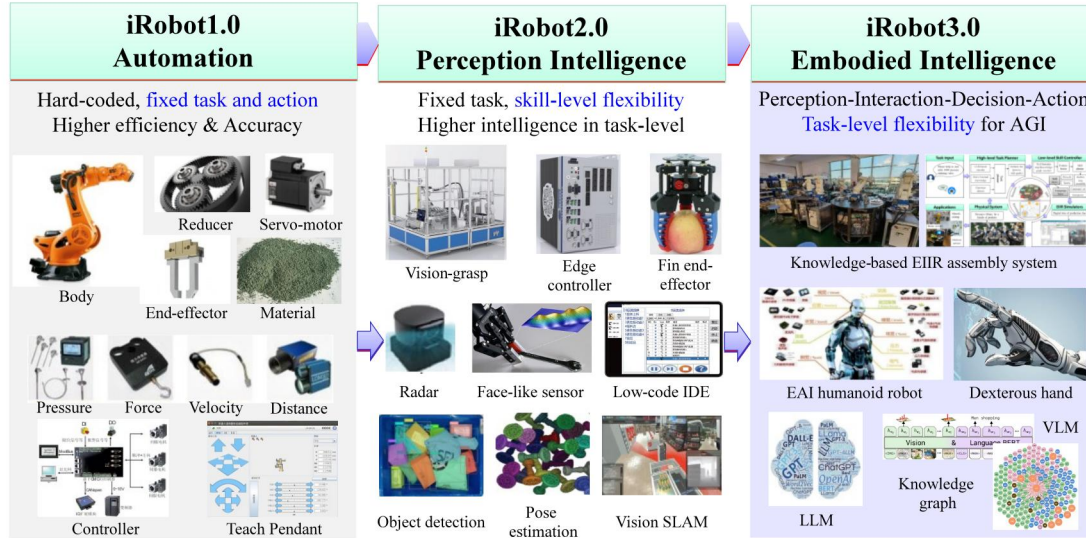


Fig. 2. Three eras of industrial robotics.

This paper attempts, for the first time, to systematically organize the related concepts of embodied intelligence and industrial robotics. Unlike previous work [11], we summarize the relationships among artificial intelligence (AI), embodied intelligence (EI), embodied intelligent robotics (EIR), and embodied intelligent industrial robotics (EIIR), as shown in Fig. 3. AI mainly consists of three technical schools: symbolism, connectionism, and behaviorism. EI represents the frontier of behaviorism. It focuses on agents that can perceive, make decisions, and interact with the environment. EI stresses that agent must be demonstrated through environment interaction, not just through symbolic computation, aligning with the

Embodied Turing Test proposed by Turing in 1950 [12]. EI can be divided into two categories: virtual agents and physical agents. Among physical agents, robots are considered the most suitable carriers, giving rise to EIR. The EIR uses multi-modal sensors to perceive its environment, applies cognitive models for dynamic decision-making, and controls physical actuators to interact with objects and complete complex tasks. The form of EIR depends heavily on its application domain and includes humanoid robots, quadruped robots, mobile robots, industrial robots, and service robots. Within this framework, industrial robots are a specific form of EIR designed for industrial applications, known as EIIR. Therefore, EIIR focuses on industrial robots equipped with independent perception, decision-making, and execution capabilities tailored to industrial environments, data, and tasks. Like embodied intelligence in general, industrial embodied intelligence also divides into two types: virtual and physical. Virtual industrial agent can exist in robot or production line simulators (discussed further in Section 6), while EIIR studies the typical physical industrial agent.

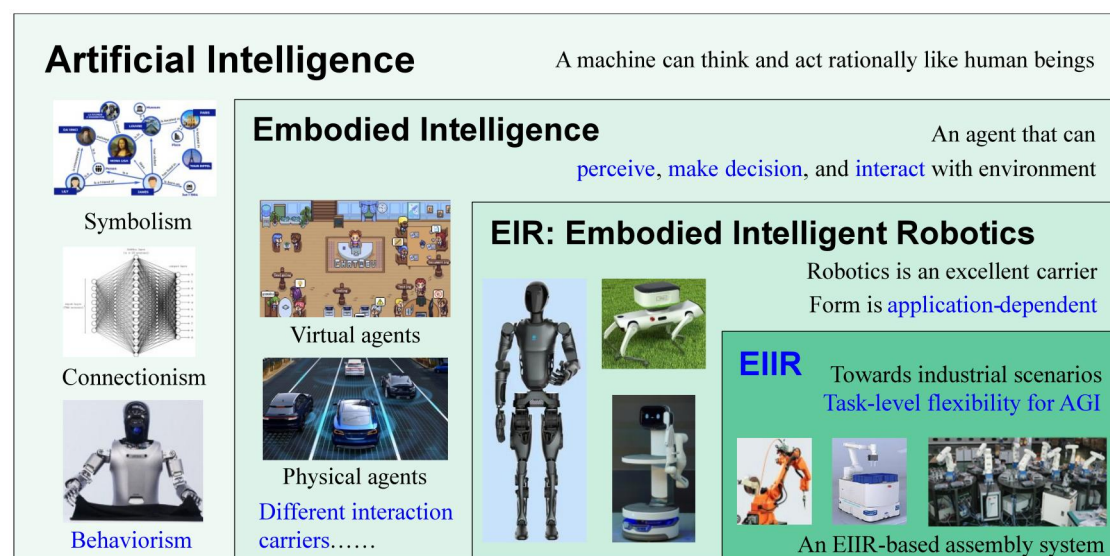


Fig. 3. The relationship between EIIR and other terms.

2.2 EIIR framework overview

Existing EIR frameworks can be broadly classified into two categories: hierarchical architecture and end-to-end architecture. Hierarchical architecture is the mainstream approach, as seen in examples like Figure AI's humanoid robot [13], which adopts a dual-system design inspired by the brain and cerebellum. This architecture typically consists of two main layers: a high-level planner and a low-level controller [1]. The high-level planner uses MLMs to process text (e.g., "take an apple to my room") and visual inputs (such as image captions or scene graphs). It then decomposes the abstract task into a sequence of executable subtasks through semantic reasoning (e.g., go to the kitchen → find the fridge → open the fridge...). The low-level controller handles execution. It uses embodied perception models (e.g., to estimate the apple's position and pose) and physical interaction models (e.g., to generate manipulator actions) to perform each subtask, guided by real-time sensor feedback. Simulators can also be integrated into this framework to train and test agents in diverse virtual environments. These simulators generate varied working conditions, such as lighting changes or object pose disturbances, to improve agent robustness and ensure safety. This virtual-real

fusion approach reduces the cost of physical trial-and-error and supports system self-improvement through continuous feedback from environmental interaction.

The end-to-end architecture integrates vision, language, and action into a single model, known as the Vision-Language-Action (VLA) model to directly model the full closed loop of perception, decision, and action. Representative work includes Google's RT series [14, 15] and OpenVLA [16]. This architecture typically consists of three core modules: multi-modal input processing, cross-modal fusion, and action decoding. First, the VLA model takes in three types of inputs: visual data (images or video), language text, and action data (such as past motion trajectories). Next, using a cross-attention mechanism, the model aligns visual features, language embeddings, and action representations within a shared semantic space. This enables the model to understand the relationships among different modalities and combine their information effectively. Finally, the fused multi-modal representation is passed to a action decoder, which generates either continuous control signals (e.g., joint angles for a robotic arm) or discrete action sequences (e.g., navigation paths or manipulation steps).

However, applying the above EIR frameworks to industrial scenarios presents several key challenges. First, although large models possess general knowledge, they lack deep semantic understanding of industrial contexts. For example, in valve assembly tasks, agents struggle to generate task decomposition plans that follow engineering constraints because they do not internalize critical industrial knowledge, such as part topology, assembly procedures, or torque parameters. Second, most action instructions generated by current frameworks are designed around the Robot Operating System (ROS) architecture. In contrast, industrial environments often involve a mix of heterogeneous control systems, including robots, PLC-driven conveyor belts, and servo presses. This discrepancy creates a gap in achieving coordinated control across multiple industrial devices. Finally, existing robot simulators typically focus on simulating individual robot. However, industrial production lines require system-level simulation that couples mechanical, electrical, hydraulic, and control domains. For instance, virtual commissioning of an automotive welding line must simulate the coordinated operation of robotic welding arms, PLC-controlled fixtures, and the logic of visual inspection systems. Current robot simulators lack the reconstruction capability of a cross-domain digital twin, making it difficult to support training data generation and virtual commissioning for industrial agents.

To address the above challenges, we propose a knowledge-driven EIIR technical framework, tailored to the needs of industrial scenarios, data, and tasks, as illustrated in Fig. 4. The framework consists of five components: world model, high-level task planner, low-level skill controller, simulators, and physical system. At the center of this framework is the world model, which serves as the main source of knowledge for the agent. It provides: (1) General knowledge, the semantic foundation of the LLM for interpreting natural language tasks. (2) Working environment knowledge, a semantic map of the production line that dynamically marks equipment poses, operable boundaries, and other environmental constraints. (3) Operating object knowledge, a domain-specific knowledge graph that structurally stores product processes and parameters, enabling the planner to generate subtask sequences that align with industrial specifications.

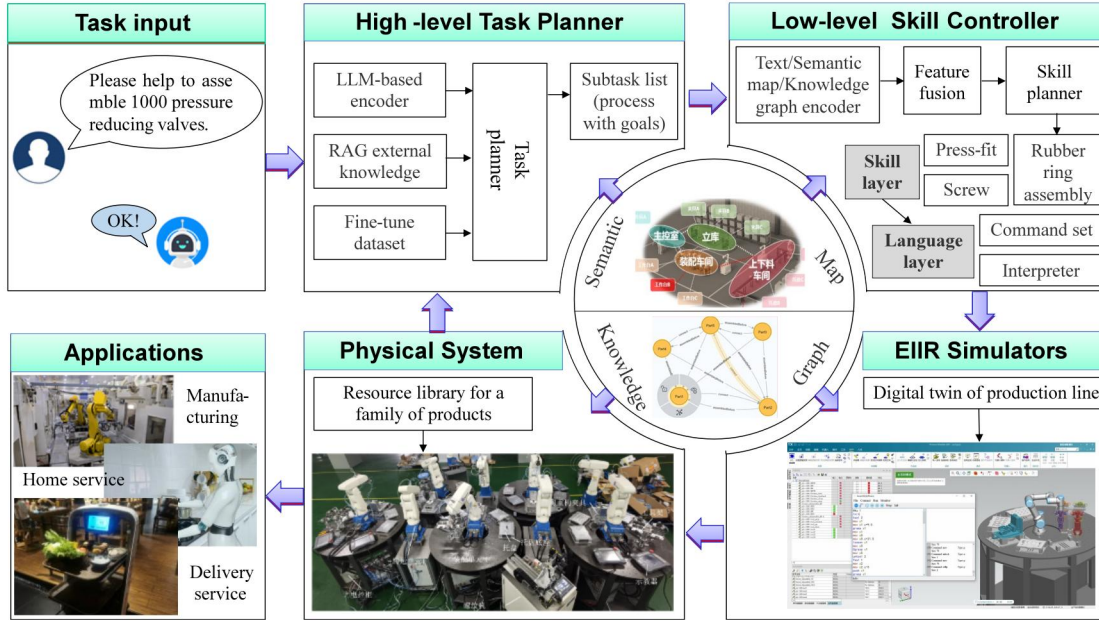


Fig. 4. The framework of EIIR based on LLM and knowledge.

When the user enters "Please help to assemble 1000 pressure reducing valves.", the high-level task planner parses the semantics through LLM-based encoder and integrates external knowledge to disassemble the task into a series of subtasks. Then the low-level skill controller maps the abstract subtasks to physical operations, where the skill layer can call the pre-defined skills in the library and convert them into device independent standardized instructions in the language layer. These instructions will be dynamically converted into protocol instructions of various target controllers through the interpreter, so as to drive the device to execute. EIIR simulator will build a production line level digital twin to generate the data set of manufacturing conditions in the virtual environment. At the same time, it will realize the cross platform collaborative simulation of robot and PLC through middleware such as ROS or OPC UA to verify the correctness of the generated instructions. Finally, the virtual-real linkage production line operation is completed in the physical system. Based on the above knowledge-driven EIIR framework, the following chapters will focus on world model, high-level task planner, low-level skill controller and EIIR simulator. These four core modules summarize the existing technologies, and explain how the components work together, which also provides a reference for scholars or engineers in this field to select EIIR technology.

3 World model of industrial scenarios

This paper believes that EIIR needs world model to provide three kinds of knowledge for agents in order to be successfully applied to industrial scenarios: general knowledge (LLM semantic understanding ability), working environment knowledge and operating object knowledge. Among them, the representation of work environment knowledge has evolved from a single Scene Graph that describes entities and relationships in the scene to a Semantic Map with richer semantic content. The semantic map not only contains the 3D spatial topology of the environment (such as device coordinates, accessibility of motion paths, etc.), but also gives interpretable semantics to the original geometric data through entity category

mapping, such as relationship semantics, functional semantics, etc., for further use in deeper reasoning [17]. The representation of operating object knowledge relies on the domain knowledge graph, and the ontology framework is used to structurally store the product assembly process, equipment operation parameters and quality specifications, forming a reasoning semantic network. These two ways of knowledge representation together with LLM will form the cognitive basis of EIIR. The following will summarize the construction technologies of semantic map and knowledge graph respectively.

3.1 Semantic map

Semantic map usually contains both geometric and semantic information. Firstly, researchers construct the geometric information of the scene through different methods, such as scene point cloud, object model and so on. Then, deep learning classification method and knowledge graph technology are used to extract semantic information related to objects, such as category, relationship semantics, functional semantics, etc. With the development of LLM and vision-language model (VLM), a lot of new work has emerged in the generation of high-dimensional scene semantic map. This section takes LLM as the distinguishing point to summarize the construction methods without LLM and with LLM. The characteristics of the two methods are shown in Table 2.

Table 2 Comparison of characteristics between two types of semantic map construction methods.

Dimension	Non-LLM methods	LLM-based methods
Semantic openness	Closed sets	Open vocabulary
Dynamic adaptation	Dependent on geometric updates	Real-time reasoning
Calculate load	Low, friendly deployment	High, collaborate with LLM
Generalization	Fine tune according to the scene	Zero-shot cross scene migration

The previous semantic map construction method usually uses the graph neural network (GNN) as the backbone to fuse the prior features in various 3D semantic scenes for feature extraction. Finally, the features are used to predict the semantic label of each object and the semantic relationship between the objects. Wald et al. [18] proposed a learning method of returning semantic map from the point cloud of the scene. This method was based on PointNet and graph convolution network (GCN) for the generation of semantic map. In addition, this paper also introduced a semi-automatic data set based on this task, which contains semantic maps with sufficient semantic information. This work and data set laid a good foundation for the development of semantic map generation. Aiming at the requirements of incrementalization and real-time in robot application scenes, Wu et al. [19] proposed a method of incrementally constructing semantic map through RGBD video sequences, called SceneGraphFusion. The method used GNN to aggregate PointNet features from the original scene components, and proposed a new attention mechanism, which had a good effect on incomplete data and missing graph data in the task of reconstructing scene frame by frame. Subsequently, in order to solve the problem of high computing power demand of dense point cloud in the process of semantic map construction, they optimized the above algorithm and

proposed MonoSSG [20]. Based on multi-modal features such as sparse point cloud and scene image, the algorithm used multi view and set features to aggregate GNNs and predict semantic map. This method greatly improved the construction speed of semantic map and maintained good accuracy. For indoor scenes with complex structures and dynamic scenes with pedestrians, Rosinol et al. [21] proposed a construction method of directed 3D dynamic semantic map. In the map, nodes represented entities in the scene (such as objects, walls, rooms, etc.), and edges represented the relationship between nodes (such as inclusion, proximity, etc.). At the same time, it also included mobile agents (such as humans, robots, etc.) and operable information to support planning and decision-making (such as space-time relationships, topological relationships at different levels of abstraction, etc.). For the problem of semantic map construction in the process of robot real-time perception, Hughes et al. [22] proposed Hydra, which is a real-time semantic map construction algorithm. Euclidean Signed Distance Field (ESDF) was used to reconstruct the scene perceived by the robot. At the same time, the semantic map constructed by ESDF was divided into rooms at a hierarchical level to build a multi-level semantic map. In addition, this method also constructed a loopback detection and global optimization algorithm for the map, which realized the real-time and efficient semantic map construction of the robot. In general, the semantic map construction algorithm without LLM usually uses point clouds and images as feature inputs. The model architecture uses GNN as the intermediate framework for feature aggregation, and the construction of semantic map is organized according to the spatial topology. This kind of algorithm has the characteristics of fast reasoning speed, suitable for end-to-end deployment and can meet the needs of dynamic scene construction, but its semantic feature dimension is limited, so it is difficult to obtain the complex semantic information in the scene.

The development of LLM has brought a new research perspective to the extraction and generation of semantics. The MLM integrated with vision can perceive and summarize all kinds of semantic information in the scene image. At the same time, the large model can further carry out retrieval, reasoning and planning according to the summarized semantic information, which has brought a leap forward in the semantic perception ability of embodied intelligence in the actual scene. Chang et al. [23] proposed an open vocabulary oriented semantic map construction framework, which was used to retrieve the connection between various entities in the form of natural language text output. Different from traditional semantic-based object localization methods, the framework proposed by this paper supported context aware entity localization, allowing queries such as "pick up a cup on the kitchen table" or "navigate to the sofa where someone is sitting". Compared with the existing research on semantic map, OVSG supported free text input and open vocabulary query.

In order to solve the problem of single modal label of semantic map, Jatavallabhula et al. [24] proposed a multi-modal semantic map construction method, Conceptfusion. This method can solve the closed set restriction of the existing semantic map concept reasoning, and expand the semantic retrieval to the open set of natural semantics. At the same time, the semantic map constructed by this method contained multi-modal semantic attributes. The method can retrieve objects from the map based on the input of language, image, audio and 3D geometry. Conceptfusion used the open set capability of the foundation model pre-trained on Internet scale data to infer concepts of different modes. Therefore, the method has the characteristics of zero-shot, does not need any additional training or fine-tuning, and can

better retain the concept of long tail, which is better than the supervised method.

Aiming at the complex and diverse difficulties of constructing semantic maps of large scenes from RGBD video sequences, Gu et al. [25] proposed a method using LLM. This method used 2D detection and segmentation model, and integrated the output of detection results into 3D through multi-view RGBD sequences. This method also has the characteristics of zero-shot, and can construct semantic map without collecting a large number of 3D data sets or fine-tuning models. Experiments showed that this method can support the downstream planning task of user input prompt assignment and complex reasoning combined with spatial and semantic concept understanding.

Facing the extremely complex spatial description problem of multi-storey building navigation, Werby et al. [26] proposed a semantic map construction method HOV-SG for multi-storey and multi-room navigation tasks. Firstly, the open vocabulary visual foundation model was used to construct a 3D open vocabulary semantic map. Then, the method divided the floors and rooms in the map, and determined the room name and type. Finally, the results were constructed into a 3D multi-level map. The main feature of the method is that it can represent multi-storey buildings and provide a semantic connection for robots in buildings. This method achieved very good experimental results in the long-distance multi-storey building navigation task.

The complexity and diversity of semantic information of outdoor scenes is one of the main reasons that restrict the application of semantic map construction technology. Strader et al. [27] proposed an ontology-based indoor and outdoor general semantic map construction technology to solve this problem. Firstly, the author proposed a method to establish spatial ontology, and defined the concepts and relationships related to the operation of indoor and outdoor robots. In particular, the author used LLM to build a basic semantic ontology, which greatly reduced the workload of manual annotation. Secondly, the author used logic tensor network (LTN) to construct semantic map based on spatial ontology. The logic rules or axioms added to the LLM provided additional monitoring signals during training, thus reducing the need for labeled data. The method can provide more accurate prediction and even predict concepts that have not been seen during training.

LLM plays the role of semantic related operators such as semantic extraction, reasoning and classification in the construction process of semantic map, while the existing work focuses more on semantic extraction and 3D reconstruction in visual perception. For robots, understanding the abstract semantics in space is one of the important prerequisites for perceiving the physical world. LLM builds an intuitive tool for robots to perceive the physical world, enabling robots to carry out in-depth semantic understanding and operation. Semantic map is the intermediate expression and element of this kind of operation.

3.2 Knowledge graph

Knowledge graph is a representation method introduced by Google in 2012 [28], which uses graph databases to organize and store information for efficient retrieval and reasoning. For EIIR, a key challenge is enabling agents to understand the operating object knowledge in industrial settings. This challenge becomes even more critical as manufacturing shifts toward greater flexibility and customization, requiring EIIR to handle mixed-line production involving multiple product types and small batch sizes. As the cognitive core of operating object knowledge, the knowledge graph plays a vital role. By structurally integrating product

parameters, manufacturing processes, and equipment resources, it enables interpretable process reasoning. This supports dynamic task planning that can adapt in real time based on sensor feedback and production changes.

In the industrial domain, researchers have developed industrial knowledge graphs of varying complexity, centered around the three fundamental elements of product, process, and resource [29]. Table 3 summarizes key characteristics of this body of work. For instance, Bharadwaj [30] structured product information hierarchically. They divided items into assemblies, sub-assemblies, and parts, and then stored this structure in a knowledge graph. Chen [31] proposed an assembly information model based on knowledge graph (KGAM) to integrate product data extracted from CAD models with process data from technical documents. This unified representation allowed engineers to query the manufacturing process and its attributes for specific products, enabling a semantic link between product and process. Shi [32, 33] extended this approach by building an industrial knowledge graph that incorporates resource alongside product and process (see Fig. 5). This resource-centric graph helped manage design assets and facilitated their reuse in future projects. In summary, industrial knowledge graphs offer a clear and structured representation of the entities and relationships in industrial scenarios. They effectively address data heterogeneity across design, planning, and production stages, and serve as a critical knowledge base for enabling autonomous decision-making in industrial embodied intelligence.

Table 3 Comparison of industrial knowledge graph of researched literature.

Literature	Elements			Applications		
	Product	Process	Resource	High-level		Low-level
				Sequence planning	Resource allocation	Action matching
Bharadwaj [30]	√					
Jia [34]	√					
Liu [35]	√			√		
Chen [31]	√	√				
Hu [36]	√	√				
Zhou [37]	√	√		√		
Xiao [38]	√	√		√		
Shi [32, 33]	√	√	√		√	
Järvenpää [39, 40]	√	√	√		√	
Mo [41, 42]	√	√	√		√	√
Zhong [43]		√	√			√

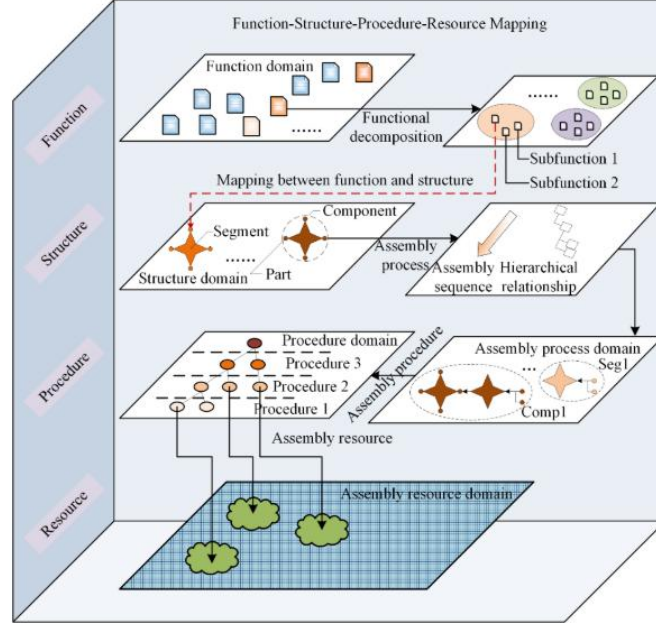


Fig. 5. Industrial knowledge graph that combines product, process, and resource [32].

Based on the industrial knowledge graph, an industrial system powered by embodied intelligence can support both high-level and low-level decision-making, including sequence planning, resource selection and allocation, and action matching. First, sequence planning is carried out using the knowledge, rules, and algorithms embedded in the product and process knowledge graph. For example, Liu [35] developed a three-layer assembly information model that represents product data and supported planning based on instantiated knowledge. Second, to improve resource reusability, Järvenpää [39, 40] defined a conceptual structure for resources. This structure integrated product, process, and resource information, enabling process-resource matching. Similarly, Mo [41, 42] built a knowledge graph using real data from OmniFactory to support both resource selection and system reconfiguration in response to changing requirements. Finally, the knowledge graph also supports action matching at the execution level. Zhong [43] stored robot skills in the knowledge graph, allowing the system to match suitable skills based on the input task. These skills were then decomposed into basic actions for execution.

4 High-level task planner

High-level task planner is located at the top level of the EIIR framework. It is used to receive tasks described by users in natural language and converts them into subtasks to guide the specific actions of robots [44]. This enables the robot to understand natural language, making it convenient for non-professional operators to control the robot to complete tasks. In this section, we first introduce the general task planning technology based on general knowledge. Next, we present the task planning technology for industrial scenarios with specifications and constraints.

4.1 General task planning

General task planning uses general knowledge to handle tasks in unstructured settings

like shopping malls and restaurants. It aims to break tasks into subtask sequences via natural language input. By combining visual perception and multi-modal information processing, robots can adapt to environmental changes and finish tasks in real time. For instance, given the command “Please help me get an apple”, the robot splits the task into subtasks: “Find the apple”, “Go to the apple's location”, “Grab the apple”, “Navigate to the dining table”, and “Place the apple on the table without touching other objects”. Meanwhile, the robot can collect relevant scene information through vision. If the scene changes, it can automatically update and adapt via visual signals or sensor data, addressing the generalization problem of traditional planning methods. In this section, based on planning methods and input modes, general task planning methods are categorized into **LLM-based** and **Vision Language Action (VLA) -based methods**.

4.1.1 LLM-based methods

The general task planning method based on LLM uses natural language described tasks as input. It harnesses the reasoning ability of LLM to decompose complex tasks. The core of this technology is the powerful language understanding, generation, and reasoning capabilities of LLM. With specific modular designs, it can further improve the planning ability of LLM in complex environments. Researchers have introduced various auxiliary modules, such as the prompt, visual module, and security module in Table 4. They are added to improve LLM's adaptability and enable more efficient task planning.

1) **LLM + prompt:** Inputting specific prompts to LLM can greatly boost its ability to break down input tasks. PROG PROMPT [45] used a programmed prompt structure. It combined with operable objects in the environment and provided LLM with sample programs to guide task planning. LLM-GROP [46] and G-PlanET [47] symbolized environmental information and stored it in data or symbol form. This allowed LLM to use environmental information for planning. LLM-State [48] treated LLM as an attention mechanism, state estimator, and strategy generator. It tackled long sight distance issues in open worlds and allowed LLM to adjust task planning in real time based on scene information. GRID [49] was a graph-based robot task resolver. It used scene graphs instead of images to perceive global scene information and iteratively planned subtasks for a given task.

2) **LLM + visual module:** Adding a visual module to LLM helps perceive environmental information for task planning. When using LLM alone, the agent can't sense the surroundings in real time. For task planning in complex environments, LLM-Planner [50] used a visual module to collect physical environmental information. It dynamically replanned if a task failed or timed out. TaPA [51] didn't directly use existing large models. Instead, it built a planning dataset to fine-tune LLaMA-7B. This boosted the success rate of task planning. ViLaIn [52] integrated the Grounding-DINO scene detection module. It converted scene information into Planning Domain Definition Language (PDDL) format. The initial PDDL state was generated by combining BLIP-2 and GPT-4 models. Also, it introduced Corrective Re-Prompting error feedback and Chain-of-Thought (CoT) mechanisms. These improved the granularity and accuracy of the generated tasks. Liu et al. [53] added high-quality teaching cases to visual information. This enhanced the robot's reasoning ability for complex problems.

3) **LLM + security module:** Adding a security module to LLM ensures the safety and reliability of the generated plan. LLM may be unaware of real-scene details, causing

dangerous robot actions. CLSS [54] presented a Cross-Layer Sequence Supervision Mechanism. Using linear temporal logic (LTL) syntax, it expressed safety constraints and detected violations in task and motion planning and corrected them. To assess existing planning methods' safety, SafeAgentBench [55] offered a dataset. It evaluated if methods are safe and reliable. The dataset includes 750 tasks, covering ten hazards and three task types. This paper tested eight LLM-based agents and evaluated via rejection rate, success rate, and execution rate. Results showed current agents' security and stability were still weak. Safe Planner [56] incorporated a safety module, which gave LLM safety awareness. It used a multi-head neural network to predict execution skill safety. ROBOGUARD [57] combined high-level safety rules with robot environmental context. It used the CoT reasoning mechanism to create strict and adaptable safety rules. ROBOGUARD's contextual grounding module used a root-of-trust LLM, to transform abstract safety rules into concrete LTL formulas for inference.

Table 4 Classification of existing LLM-based planning methods.

Category	Methods	Base model	Evaluation	Core idea
LLM + prompt	PROGPROMPT [45]	GPT-3	SR, Exec, GCR	Improve LLM's understanding of human commands and robot tasks.
	LLM-GROP [46]	GPT-3	UR	
	G-PlanET [47]	BART	CIDEr, SPICE, KAS	
	LLM-State [48]	GPT-4	ACC	
	GRID [49]	INSTRUCTOR	SR	
LLM + visual module	LLM-Planner [50]	BERT	ACC	Improve robot's environmental perception ability during task execution through visual information.
	TaPA [51]	LLaMA-7B	SR	
	ViLaIn [52]	GPT-4	Rsyntax, Rplan, Rpart, Rall	
	H. Liu et al. [53]	GPT-4	SR, Exec	
	CLEAR [58]	GPT-4, GPT-3.5, LLaMA2	SR	
LLM + security module	CLSS [54]	GPT-4	SFR, SR, Exec	Improve the safety of plan generation and task execution.
	SafeAgentBench [55]	GPT-4	Rej, SR, ER	
	Z. Yang et al. [59]	GPT-4	SFR, SR	
	ROBOGUARD [57]	GPT-4o	ASR	
	Safe Planner [56]	GPT-4	Collisions, SR	

Table 4 also lists the evaluation metrics used in the studies mentioned above. SR (Success Rate) is the ratio of the number of tasks the robot successfully completes to the total number of tasks executed. Exec (Executability) is the ratio of tasks the robot can perform to the total number of tasks generated. ACC (Accuracy) refers to the robot's accuracy in performing tasks and is used to measure the quality of task completion. Rej (Reject Rate) is the ratio of the number of times the robot refuses dangerous tasks to the total number of tasks generated. ER (Execution Rate) is the ratio of tasks actually executed by the robot to the total number of tasks generated. SFR (Safety Rate) is the ratio of the number of times the robot performs tasks without dangerous behavior to the total number of task executions. UR (User

Rating) reflects the user's subjective evaluation of the robot's task performance, expressed in scores or grades. KAS (Key Action Score) evaluates the robot's performance in key actions. CIDEr and SPICE are indicators for evaluating text and image generation tasks. They measure the quality of generated text by comparing it with reference descriptions and are used in robotics to assess the accuracy of natural language descriptions or instructions generated by robots. Collisions indicate the number of collisions during task execution. Rsyntax measures the syntax correctness of the generated planning description (PD) by calculating the proportion of grammatically correct PDs. Rplan calculates the proportion of PDs with effective plans. Rpart and Rall evaluate the similarity between the generated PD and the ground truth.

In recent years, more research has focused on robot high-level task planning. However, this is just the first step in robot task execution. An embodied agent needs not only high-level task planning ability but also a corresponding low-level action controller. The emergence of VLA technology has combined high-level planners with low-level controllers to directly generate specific robot actions. Next, the differences and connections between VLA technology and LLM-based task planning methods will be further described.

4.1.2 VLA-based methods

The general task planning method based on VLA considers both visual information and natural language input during task planning. Typical VLA architectures are shown in [Fig. 6 \[60\]](#). The VLA model can directly convert natural language input into specific actions that robots can execute. Generally, LLM is only a part of VLA. The main differences between VLA-based and LLM-based task planning methods include:

- **Input mode difference:** LLM only accepts language as input. Thus, when robots perform task planning using LLM, they need to combine it with other modules to perceive environmental information. In contrast, VLA integrates vision, language and action. It can directly utilize visual information to enhance the robot's ability to understand the environment.
- **Architecture difference:** The LLM consists primarily of a language encoder and a decoder. In contrast, the VLA architecture is more complex. It includes a visual encoder, a language encoder, and an action decoder. This allows the VLA to directly integrate visual and textual information and generate specific actions.
- **Specific differences in task planning:** LLM-based task planning can only generate subtask sequences. It must work with low-level controllers to interact with the physical world. The VLA model, however, directly translates texts and visual information into specific actions. This enables better environmental interaction.

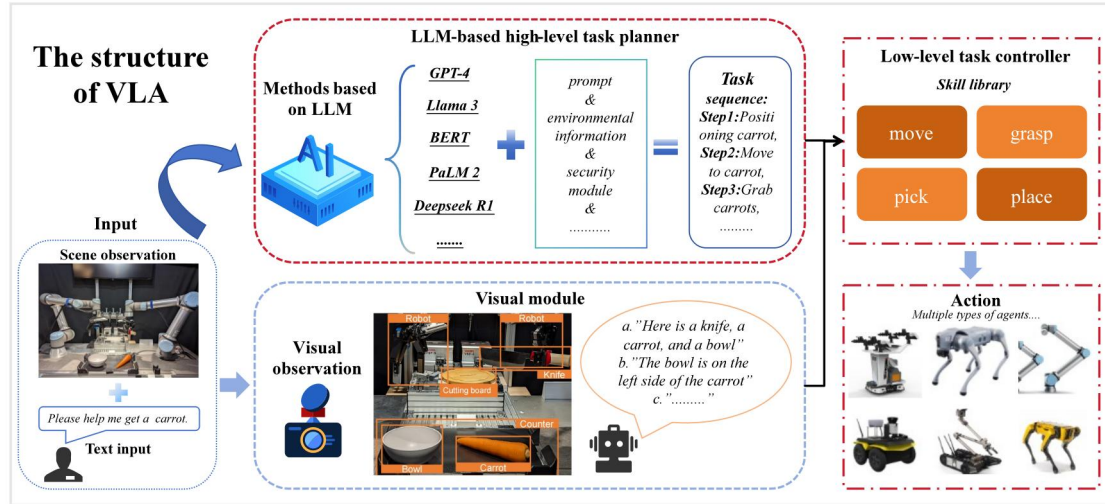


Fig. 6. Structure of VLA.

In recent years, researchers have proposed various general VLA architectures, such as RT-1 [14], RT-2 [15], OpenVLA [16], and have continued to improve upon these architectures. To enhance the performance of the VLA model, 3D-VLA [61] integrated 3D perception and reasoning into the VLA architecture. This improved the VLA model's operation ability in complex environments. Dual Process VLA [62] proposed a dual-process VLA framework that separated the complex reasoning process from the real-time motion control. The separation improved the robot's operational efficiency and accuracy. SpatialVLA [63] enhanced the VLA model's understanding of 3D space by introducing a self-centered 3D position encoding module and an adaptive action network. The VLA model has been applied to various types of robots. Bi-VLA [64] proposed a flexible operating system for dual-arm robots based on VLA. This system can interpret complex human commands and perform dual-arm operations. RoboNurse-VLA [65] applied VLA technology to surgical nurse robot systems. It can process surgeons' commands in real time and accurately grasp and transfer surgical instruments. For the testing of VLA, VLABench [66] proposed a large-scale dataset and evaluation benchmark. It included 100 task categories and 2000 3D objects. This benchmark assessed the VLA model's capabilities across various tasks, particularly in long-term reasoning and multi-step planning.

LLM and VLA have demonstrated strong general task planning capabilities, but their main application areas are still household and open-world daily life scenarios. Due to insufficient industrial knowledge and weak industrial data perception, directly transferring them to industrial settings would fail to yield solutions satisfying industrial specifications and process constraints.

4.2 Industrial task planning

Unlike general task planning, industrial task planning addresses production tasks in industrial settings with strict requirements and constraints. It demands higher planning accuracy, allows little room for errors, and has more serious consequences of planning mistakes. For example, placing a fork on either side of a bowl works for a household task, but in an industrial scene, parts A and B on a production line must stay fixed, and processing steps must follow a strict sequence. Meeting industrial norms and constraints in subtask sequences

is the main challenge for applying general task planning methods in industry. This section will cover **knowledge and skill-based**, **learning-based**, and **LLM-based methods**.

4.2.1 Knowledge and skill-based methods

Most knowledge and skill-based methods involve a world model and a skill library (details in Section 5). These methods utilize the knowledge in the world model for reasoning, selecting and combining skills from the skill library to generate the required planning scheme. Based on different reasoning approaches, these methods are categorized into knowledge graph-based task planning and Domain Specific Language (DSL)-based task planning, as shown in Fig. 7.

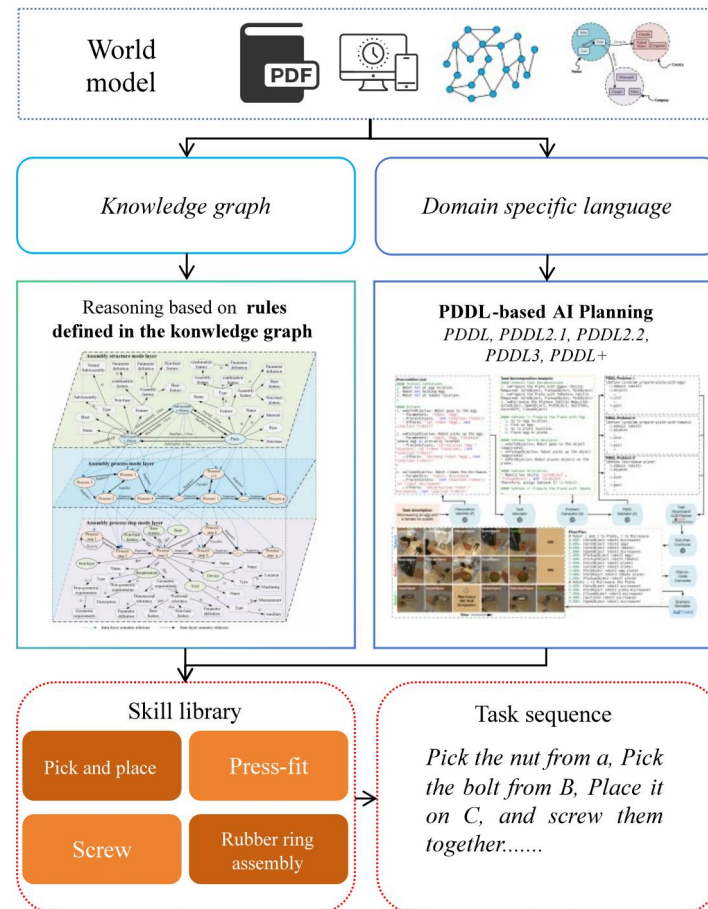


Fig. 7. Task planning based on knowledge and skill.

1) **Based on knowledge graph:** Knowledge graph-based task planning calls on knowledge from the knowledge graph and predefined rules. Knowledge graph [67] is a graph structure for knowledge representation and storage. It has nodes (entities) and edges (relationships), and can show complex entity relationships and semantic information. Before the knowledge graph had been proposed, the expert system was used in industrial task planning [68-70]. But this method had some problems. It had fixed reasoning rules, so its generalization ability was weak and knowledge updates required manual operation. These issues limited its application scope and led to its gradual elimination. Knowledge graph has strong knowledge storage. It allows convenient knowledge updates and has good reasoning ability. Due to these advantages, it is increasingly used in the manufacturing field. Table 5 lists some research on industrial task planning based on knowledge and skill.

Table 5 Surveyed literature on industrial task planning based on knowledge and skill.

Method	Publication	Application scenario	Core idea	Common ground
Based on knowledge graph	M. Merdan et al. [71]	Industrial robot	Reasoning based on rules defined by the knowledge graph	Based on a world model, knowledge is obtained from a knowledge base for inference.
	Y. Jiang et al. [72]	Automatic assembly		
	T.Hoebert et al. [73]	Industrial robot		
	B. Zhou et al. [74]	Automatic assembly		
	Z. Qin, Y.Lu [75]	Adaptive manufacturing control		
Based on DSL	Z. Kootbally et al. [76]	Automatic assembly	AI planning based on PDDL	Skills are obtained from a skill base and combined.
	M. Cashmore et al. [77]	ROS		
	F.Rovida et al. [78]	Industrial robot		
	L. Heuss et al. [79]	Industrial robot		
	A. Rogalla [80]	Process planning		

To enhance industrial robot flexibility and applicability, M. Merdan et al. and T. Hoebrechts et al. [71, 73] applied an ontology-based knowledge driven framework. They proposed a new scheme to solve the complex programming and high configuration costs of traditional industrial robots. For assembly process planning, Y. Jiang et al. [72] explored combining digital twins with knowledge graph technology. This approach effectively managed complex assembly process knowledge. B. Zhou et al. [74] proposed a knowledge graph driven method for generating and evaluating assembly processes. They constructed an assembly process knowledge graph (APKG) to generate assembly plans. Using interference detection and quality assessment methods, they identified feasible assembly sequences. This method was validated in an aeroengine compressor rotor assembly case. Z. Qin et al. [75] tackled adaptive control in large scale personalized manufacturing and proposed a semantic representation method for dynamic manufacturing environments based on knowledge graphs. By integrating factual data and machine preference information, they presented a new adaptive manufacturing control scheme.

2) **Based on DSL:** DSL-based task planning uses specific languages like PDDL [81] to express and solve planning problems. PDDL, a standardized language for robotics planning problems, can handle complex planning issues flexibly and has gained popularity in industrial task planning in recent years. Z. Kootbally et al. [76] proposed a knowledge-driven method that combines knowledge with PDDL to directly convert Web Ontology Language (OWL) to PDDL. This method's value in assembly applications was discussed. The ROSPLAN [77] framework integrated task planning into the ROS system. Through modular design of the knowledge base and planning system, it can automatically process planning and schedule low-level controller activities. SkiROS [78] platform addressed knowledge representation and autonomous task planning in robot development using modular design and knowledge integration. The REpac [79] framework offered an extensible, skill-based software architecture, which supported flexible configuration and autonomous task planning for industrial robots. By reusing skills and modular components, it gradually expanded robot reasoning ability to support multi-task planning. A. Rogalla et al. [80] proposed a domain

modeling method for discrete manufacturing, which includes modeling manufacturing systems and orders in PDDL, helping planners understand and solve problems.

Despite excellent performance in industrial fields, knowledge and skill-based task planning faces challenges. These include difficulties in knowledge updating, the need for predefined rules and reasoning methods, and limited scalability in new tasks and scenarios. These issues lead to a high dependence on human.

4.2.2 Learning-based methods

Learning-based methods involve harnessing technologies like deep learning and reinforcement learning to extract task planning information from vast datasets. With the evolution of deep learning, these methods have applied the intelligent manufacturing sphere [82]. They showcase extensive applications in areas such as robotic grasping, assembly and disassembly, process control, and industrial human machine collaboration [83]. Contrasted with knowledge and skill-based methods, learning-based methods eliminate much manual definition. Different learning strategies have distinct pros and cons, leading to varied application contexts and methodologies. This section will summarize three primary learning strategies rooted in deep learning, reinforcement learning, and imitation learning, as shown in Table 6.

Table 6 Surveyed literature on industrial task planning based on learning methods.

Method	Application scenario	Publications	Algorithm	Advantage	Disadvantage
Deep learning	Human-robot collaboration	H. Zhang et al. [84]	CNN	Processing complex data to enhance reliability	Need a large amount of data
		H. Liu et al. [85]	CNN		
	Object recognition	X. Chen, J. Guhl [86]	RCNN		
		E. Solowjow et al. [87]	Dex-Net		
	Subassembly recognition	C. Zhang et al. [88]	GCN		
Reinforcement learning	Robot assembly	Y. Liu et al. [89]	DQN	Learning can be achieved through autonomous interaction with the environment and policy functions	Unstable training may lead to unstable model performance
		J. Li et al. [90]	DDPG		
	Robot additive manufacturing	Y. Xiong et al. [91]	DQN		
	Logistics robot	F. Fan et al. [92]	DODPG		
	Automatic assembly	M. Jiang et al. [93]	DRL		
Imitation learning	Robot assembly	Y. Wang et al. [94]	GMM+GMR	No need for extensive mathematical modeling and optimization	Need a large amount of high-quality sample data to train
		S. Scherzinger [95]	LSTM		
		T. Zhang [96]	p-LSTM		
		S. Ji et al. [97]	DDPG		

1) **Deep learning:** Deep learning-based methods can process complex production data and easily uncover hidden data patterns. But they rely heavily on data, limiting their use in data-scarce scenarios. H. Zhang et al. [84], using CNN and LSTM, predicted human assembly actions. H. Liu et al. [85] developed a CNN-based multi-modal user interface for easy robot

control by non-professionals. For industrial robot grasping, X. Chen et al. [86] applied the RCNN algorithm for object recognition in work areas. E. Solowjow et al. [87] created a DEX-Net-based grasping robot with a high success rate. C. Zhang et al. [88] integrated geometric and engineering information via Model-based Design (MBD) constructed heterogeneous knowledge graphs and used the GCN algorithm to identify subassemblies.

2) **Reinforcement learning:** Reinforcement learning methods excel in scenarios with limited data and requiring independent decision making, as they can learn autonomously through interaction with the environment. But the training process's randomness can cause unstable results. Regarding human-machine interaction in manufacturing, Y. Liu et al. [89] presented a vision-combined reinforcement learning scheme. It allows robots to observe human collaborator information and adjust decisions and actions. For multi-variety and small-batch assembly issues, J. Li et al. [90] combined digital twin and deep reinforcement learning. They established digital twin models and trained reinforcement learning models to plan assembly and predict production line faults. In additive manufacturing, Y. Xiong et al. [91] applied the Kriging dynamic function. It enabled learning through multiple agents and workspaces, reducing material consumption in additive manufacturing. Focusing on aviation product assembly sequence planning, M. Jiang et al. [93] proposed a novel fine-grained assembly sequence planning method by integrating knowledge graph and deep reinforcement learning. For internal logistics in the manufacturing industry, especially in complex workshop environments, F. Fan et al. [92] proposed a navigation method based on deep reinforcement learning and wheeled mobile robots. By introducing dynamic observing Markov decision process and distributed scene training, it achieved efficient scene modeling and path tracking control in complex industrial settings.

3) **Imitation learning:** Imitation learning methods offer faster learning than reinforcement learning and require less mathematical modeling and optimization. They are ideal for scenarios with clear tasks and abundant human expert demonstration data. The results from these methods are more deterministic but they need a large number of high quality demonstration cases. In recent years, imitation learning has been widely used in robot assembly scenarios [94-97]. These methods use demonstrations as learning data for robots to enhance the robots' ability in assembly task planning.

Compared to knowledge and skill-based methods, learning-based methods eliminate the need for manual rule definition. But they require substantial data support and demand significant computational power and training time. Models are typically trained for specific scenarios or tasks, so their generalization ability is average, making it difficult to transfer them to other tasks.

4.2.3 LLM-based methods

In industrial task planning, LLM-based methods leverage the powerful text generation and understanding abilities of LLMs. They process complex industrial documents, operation manuals, and user feedback, enhancing information processing efficiency and accuracy. These methods utilize externally acquired knowledge and the reasoning ability of LLMs for task planning. As AI technology advances rapidly, LLMs are significantly impacting the industrial field due to their natural language understanding and multi-modal information processing capabilities [11, 98]. In the high-level task planning of industrial robots, LLMs can effectively interpret fuzzy input tasks and break them down into a series of subtasks. Unlike other

methods, they don't require a large number of human defined rules or extensive training data. Although extensively studied in general task planning, research on LLMs in the industrial field is still in its early stage. Most existing work relies on the reasoning ability of LLMs, with some studies achieving positive results through fine-tuning LLMs with new data.

LLM-based industrial task planning methods have been applied in various manufacturing tasks. Y. Tanaka et al. [99] developed a voice-controlled polishing robot's control system using LLMs. They analyzed natural language via GPT-3 and converted it into numerical commands, enabling users to control robot actions through voice input. This approach allowed workers to use robots for specific functions without complex programming. T. Wang et al. [100] proposed an LLM-based visual language navigation method for intelligent manufacturing systems. Their method involved three steps: reconstructing real world manufacturing scenes using 3D point cloud, triggering navigation actions with LLM's code generation capability and planning paths with the Pathfinder algorithm, and finally obtaining executable robot actions. M. Fakhri et al. [101] used LLMs to achieve verifiable PLC programming in industrial control systems and introduced the LLM4PLC framework. By using engineering prompts and low-rank adaptation (LoRA) to fine-tune the model, and incorporating user feedback and external tools to guide the LLM's generation process, they verified the system on the Fischertechnik Manufacturing Test Platform (MFTB). This significantly reduced PLC code writing time and improved the quality of LLM-generated PLC code. H. Fan et al. [102] explored applying LLMs to industrial robots and proposed a framework for the independent design, decision-making, and task execution of industrial robots. The framework used LLMs to extract manufacturing tasks and process parameters from natural language, select end effectors, generate motion paths based on predefined conditions, and evaluate path effectiveness. It then completed manufacturing tasks with the help of skills in the code base and task base. Y. Gan et al. [103] proposed a bionic robot controller to meet the manufacturing industry's needs for autonomous task planning. The controller integrated motion control, visual perception, and autonomous planning modules to achieve multi-object rearrangement functions. C. Gkourmelos et al. [104] applied LLMs to manufacturing systems to enhance human-machine interaction in factories. Their system was based on extensible components which can be divided into Agents and Modules. Agents included formatting, interactive, and manufacturing agents with natural language processing capabilities. Modules included robot behavior planning and human-machine interaction modules. Tested in two cases of inverter and industrial air compressor assembly, the system achieved positive results. J. Xu et al. [105] discussed applying embodied intelligence technology to additive manufacturing. They studied how to make 3D printers interact with the environment like organisms by learning from biological growth processes. For fixed 3D printers, their approach automatically generated tool paths and machine code via basic models, reducing expert knowledge demand.

There are also application cases in electric vehicle automatic disassembly, industrial drones, construction robots, and other fields. Y. Peng et al. [106] proposed an autonomous mobile robot system for battery disassembly based on neural symbol AI (BEAM-1) to solve electric vehicle battery disassembly problems. The system achieved environmental perception and autonomous planning through neural predicates and action primitives, and introduced LLM heuristic search in planning to improve efficiency and address search space explosion

issues. H. Zhao et al. [107] proposed an AeroAgent architecture for industrial drones. It treats agents as the brain and controllers as the cerebellum for industrial tasks. Based on MLMs, agents can analyze multi-modal data, customize plans based on environmental information, and quickly adapt to new tasks using small sample learning. The ROSchain framework integrated MLMs with the ROS, enabling direct control of drone actions and ensuring input matches actuator capabilities. H. You et al. [108] applied embodied intelligence technology to construction robots and proposed the Dexbot framework. It outlined six key steps to achieve robot flexibility and adaptability for three main construction tasks: structural assembly, material processing, and quality inspection.

Although LLM has found some application scenarios in the industrial field, most of these applications only use LLM as an auxiliary component in the task planning process. The core method of industrial robot task planning is still based on traditional technology. The role of LLM is mainly reflected in the optimization and improvement of traditional methods, rather than completely replacing or redefining these methods.

In summary of Section 4.2, the existing industrial task planning methods are mainly divided into three categories: knowledge and skill-based methods, learning-based methods, and LLM-based methods. Knowledge and skill-based methods rely too much on artificially set rules. When facing new scenarios or tasks, professionals are often required to redefine relevant rules, which is less flexible. Learning-based methods require a lot of data and computing resources for training, and usually need to be retrained in the face of new scenes or tasks, with limited generalization ability. These two methods are difficult to effectively meet the needs of small batch and customized manufacturing. However, due to the limitations of training resources, the emerging LLM-based methods in recent years often fail to fully understand the professional knowledge in the industrial field, and their application effect in industrial task planning is still mediocre.

To solve the above problems, we propose a potential solution: combining the LLM with the retrieval-augmented generation (RAG) technology. By establishing a specific external knowledge base as the world model, the LLM can master the unique knowledge of the industrial field, and then improve its ability to answer the industrial questions. At present, a few studies in this area have achieved some results, but this method has not been directly applied to industrial task planning. Yijun Bei et al. [109] proposed a question and answer system, which was based on the integrated term enhancement method. By accurately extracting and interpreting key terms from knowledge documents and building a term dictionary, it enhanced the query ability. The question and answer system AMGPT [110] was based on the pre-trained LLaMa 2-7B model in cooperation with RAG to enhance the ability to answer questions in the field of additive manufacturing by dynamically integrating information. There were also studies based on the LLM + RAG method to process a large number of data in the process of industrial production [111-113], so as to make better use of these data for prediction and decision-making. Some research combined LLM with the knowledge graph in the industrial field [114, 115], using the generalization ability of the large model in each task and the accurate reasoning rules in the knowledge graph to improve the performance of the LLM on specific industrial tasks.

This scheme aims to give full play to the powerful representation learning ability of the LLM and the advantages of RAG technology in knowledge integration and retrieval. It aims

to enhance the generalization ability and adaptability while improving the accuracy of industrial task planning. The application of the scheme in the task planning of industrial robots can well solve the shortcomings of existing methods, so as to better meet the needs of flexible production and customized manufacturing in the manufacturing industry.

5 Low-level skill controller

As the core hub connecting high-level task abstraction and robot physical execution, the low-level skill controller is used to convert decomposed subtasks into a series of skills and further output executable programs. Different from the skills in the existing review of EIR [1, 116] (such as perception, navigation, manipulation and other skills for unstructured environments), this section focuses on the unique skill paradigm in the industrial scenes, especially for assembly tasks. EIIR's low-level skill controller adopts a two-layer architecture of "skill-language": skill layer converts action/primitive into reusable skills through modular encapsulation. Language layer is based on domain specific language (DSL) and constraint rules to realize the physical execution of skill. The transformation from subtask to skill sequences mainly relies on two approaches: knowledge and skill-based methods, and LLM-based methods, both of which have been discussed in Section 4. The following will analyze the related work of the two layers respectively to provide reference for readers to select the appropriate skill library and control language to form the low-level skill controller.

5.1 Skills in industry

Skills in industry refers to the standardized, reusable and programmable unit provided by robot or other equipment combination in order to achieve specific manufacturing goals (such as assembly, welding, inspection, etc.) in a structured or semi-structured industrial environment. Through hardware-software encapsulation, these skills abstract the underlying sensor data, control algorithms, and actuator actions into process semantics oriented functional interfaces, thus transforming complex physical interactions into programmable industrial behavior modules. Combined with the rigid constraints and task requirements of industrial scenarios, the concept levels of "*Task-Subtask-Skill-Action*" is proposed here, and the standardized mapping of complex processes is realized through level by level decoupling. Fig. 8 taking the shuttle valve assembly task as an example, the relationship between the four concepts is introduced.

1) *Task*: A high-level production activity with a complete functional objective, such as "assemble shuttle valve" or "weld PCB board", that encapsulates process semantics. As described in Section 4, EIIR can decompose tasks into subtasks using a high-level planner combining LLM and RAG, guided by process knowledge from the industrial knowledge graph.

2) *Subtask*: A fundamental process unit analogous to an "procedure" in manufacturing execution system (MES). For example, the task "assemble shuttle valve" may be split into four subtasks: "assemble large rubber ring – place steel balls – assemble small rubber ring – press piston." Subtasks are semantically linked to skills via the knowledge graph, which also transforms their process requirements into parameters for execution.

3) *Skill*: An abstracted capability provided by one or more devices, responsible for transforming subtasks into executable physical actions. Skills have two key attributes:

Cross-device collaboration, e.g., a “Press-fit” skill may coordinate the actions of multiple devices, such as robot arm motion, force sensor feedback contact state, and vision system correction posture; Logical container, defining action sequences using finite state machines (FSMs) or temporal logic.

4) *Action*: The atomic physical operation performed by a device, often tied directly to hardware via DSLs or protocols (e.g., EtherCAT, PROFINET). Actions lack context awareness. For instance, a “grasp” action triggers on a Boolean signal but cannot detect object presence. Actions standardize device interfaces, decoupling vendor-specific APIs from skills. For example, differing joint controls of different brands of manipulators are abstracted behind a “move” action exposing only generic parameters like target pose, speed, and acceleration.

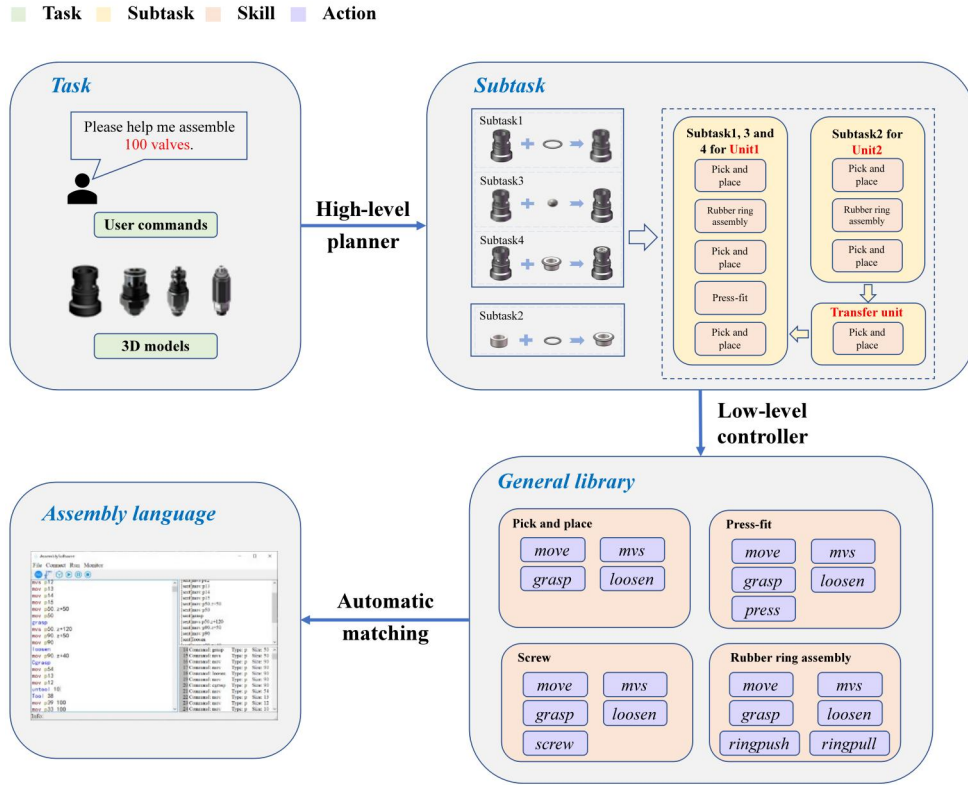





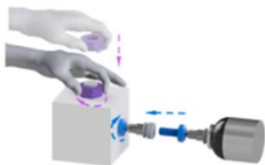

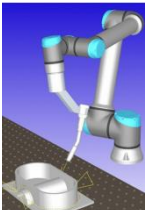

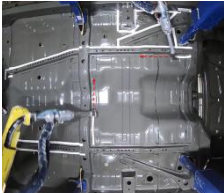
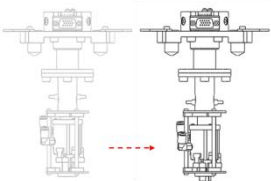
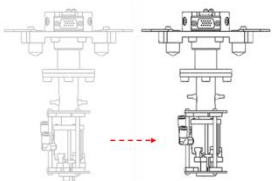


Fig. 8. Example of “Task-Subtask-Skill-Action” architecture. The task is usually a description based on user commands input combined with 3D models. After being decomposed by the high-level task planner, the shuttle valve assembly task was split into a series of subtasks and assigned to different units for execution. Each subtask can be automatically matched with skills from the general library by the low-level controller, and transformed into a program by combining the lowest level actions.

In the above architecture, the construction of standardized skill libraries and action libraries is fundamental for executing industrial tasks. These libraries provide reusable and extensible foundational capabilities, enabling rapid composition of complex processes through modular encapsulation. Reinhart et al. [117, 118] reviewed a range of publications, standards, and studies in the field of skill taxonomy and ontology, and proposed a skill classification method specifically for assembly. Lee et al. [119] identified nine atomic actions commonly used in assembly processes. Building on these classification schemes, we conducted a literature survey to analyze and categorize recent developments. Fig. 9 defines 15 commonly used robotic actions, the taxonomy following two principles:

- **General vs. Specific Actions:** General actions ranging from **Move** to **Sense** cover the majority of common industrial operations and can typically be executed using only a robotic arm and simple tools. In contrast, specific actions require special tools or additional material support. For instance, **Ringpush** involves inserting an elastic seal ring into a groove via precise axial pressing using a dedicated end-effector; **Print** requires an integrated material feeding system and a dispensing nozzle. Beyond the eight specific actions listed, users may extend the library based on application needs (e.g., drill, mill for subtractive manufacturing).
- **Semantic Merging:** The taxonomy consolidates actions with similar semantics found across literature. Translational actions such as push, retract, and slide are abstracted into a parameterized variant of **Move**. Similarly, assembly actions like insert, snap_in, and mount are unified under the **Press** category, which encapsulates force-controlled pressing behaviors. This merging streamlines the action library for more efficient reuse and system integration.

<p>Move <i>Move robot to specific position.</i></p> 	<p>Approach <i>Move slowly in a fixed direction when approaching the target.</i></p> 	<p>Grasp <i>Use robot hand to grab things.</i></p> 
<p>Loosen <i>Let go what's being held.</i></p> 	<p>Press <i>Force application through linear motion.</i></p> 	<p>Screw <i>Rotational fastening/disassembling.</i></p> 
<p>Sense <i>Check surrounding with sensors.</i></p> 	<p>Weld <i>Material fusion using energy source.</i></p> 	<p>Rivet <i>Fix parts with metal pins.</i></p> 
<p>Glue <i>Controlled adhesive deposition.</i></p> 	<p>RingPush <i>Precision ring component installation.</i></p> 	<p>RingPull <i>Reverse tool action of Ringpush.</i></p> 

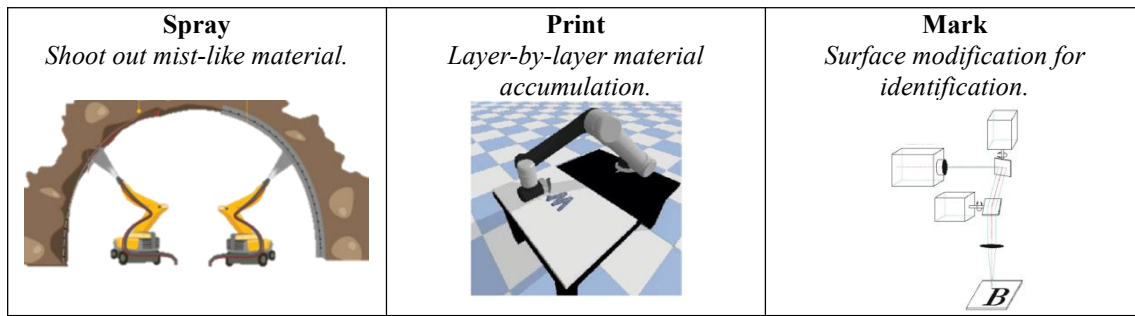


Fig. 9. Taxonomy of robotic actions in literature review. Illustrations are adapted from [102, 119-123].

In the research and application of robotic skills, skills can be functionally categorized into four main types: Handle, Join, Inspect, and Special Operations, as summarized in Table 7. Each skill consists of multiple underlying actions, and various skills can be composed into subtasks that enable robots to execute complex industrial tasks. Among them, Handle skills such as pick and place and transport, form the foundation of robotic manipulation and are extensively applied in automated production, warehousing, logistics, and service robotics. Notably, pick and place was featured in 82.19% of the surveyed literature, underscoring its essential role in any skill library. Transport skill involve robot navigation and material transfer and are often combined with environmental perception enabled by sense action to perform effectively.

Join skills primarily involve the connection of components and typically require high-precision pose alignment, force control strategies, and sensor feedback. These skills are fundamental to industrial robots, particularly in electronic assembly, mechanical manufacturing, and related domains. Press-fit and screw skills are the most frequently referenced in the literature, reflecting their broad applicability. In contrast, weld, rivet, and glue are more specialized and commonly employed in sectors such as automotive manufacturing and metal processing. Notably, while ring assembly is rarely discussed in existing publications, it is a prevalent task in real-world production settings and has therefore been considered in the construction of the skill base.

Inspection skills involve measure and check. Although both involve detection, they have different focuses. Measure focuses on acquiring quantitative data, such as size, position, or force. It uses tools like force/torque (F/T) sensors and visual sensors to achieve this. These measurements provide critical input or output parameters for Handling and Joining skills. In contrast, check is oriented toward anomaly detection, assessing whether an action has been successfully completed or if a system state deviates from predefined thresholds. It is typically implemented through tactile sensing, collision detection, or force feedback-based anomaly analysis. These inspection skills play a vital role in quality assurance, automated testing, and predictive maintenance in industrial applications.

Special operations skills cover some other specific tasks performed by robots, such as spray, 3D-print and mark. These skills are usually specific to some manufacturing or processing requirements. Spray and 3D-print involve coating spraying and additive manufacturing, while mark is very common in real production lines, such as laser marking, ink-jet marking and other applications, and is still worth preserving in the skill library.

Based on the frequency of references, certain skills are indispensable in constructing an industrial robot skill library. These skills include pick and place, transport, press-fit, screw,

measure, and check. These cover the essential capabilities of grasping, motion, assembly, and inspection, forming the foundational skill set for virtually all industrial and service robot systems. Notably, several works, such as [120, 124-126], presented frameworks that incorporate more than four skills and propose comprehensive robot control architectures built around skill modularization. These references offer valuable insights and are particularly recommended for readers aiming to design a robust and extensible skill library.

Table 7 Taxonomy of robotic skills and 73 related articles. Some literature come from the survey by Pantano et al.[127], while the rest of the publications were identified through a systematic search on WOS. The search strategy employed the Boolean query: ‘*robot AND skill AND (industry OR manufacturing)*’. All retrieved studies were rigorously reclassified under the proposed skill taxonomy.

Skill category	Skill	Actions included	Refs.	Parameters
Handle	Pick and place	move, approach, grasp, loosen	[43, 78, 79, 97, 122, 124-126, 128-179]	End_pose, Vel, Acc, Move_type (PTP/LIN/CIRC)
	Transport	move, sense	[78, 118, 120, 125, 126, 128, 133, 145, 150, 151, 154-156, 158, 160, 162, 164, 167, 174, 180-183]	Path_plan (RRT/PRM), Vel, Payload_mass, Env_map, Obst_avoid
Join	Press-fit	move, approach, press	[43, 97, 124-126, 128, 129, 134, 135, 138, 139, 141, 144, 146, 148, 149, 157, 159, 161, 164-166, 171, 184-187]	Force_set, Insert_depth, Align_tolerance
	Screw	move, approach, screw	[118, 124, 125, 131, 142, 143, 149, 167-169, 186, 188, 189]	Torque_set, RPM, Screw_type (M3/M4), Ang_alignment
	Weld	move, approach, weld	[118, 121, 149, 185]	Voltage, Current, Feed_speed, Weld_path, Gas_flow
	Rivet	move, approach, rivet	[122, 128]	Impact_force, Align_offset
	Glue	move, approach, glue	[128]	Dispense_vol, Glue_path
	Ring assembly	move, approach, grasp, loosen, ringpush, ringpull	-	Spread_force, Ring_dim (ID/OD), Align_guide
Inspect	Measure	move, sense	[78, 97, 124, 128, 132, 133, 137, 139-141, 145-148, 150, 151, 153-156, 158, 159, 175-183, 185, 188, 190, 191]	Sensor_type (Laser/Force), Accuracy, Data_output
	Check	move, sense	[79, 118, 124, 136-138, 141, 153-156, 159, 164, 172, 174, 184]	Sensor_type (Laser/Force), Check_value, Tolerance

Special operations	Spray	move, approach, spray	[120, 181]	Paint, Flow_rate, Nozzle_vel
	3D-Print	move, approach, print	[120]	Layer_height, Print_speed, Nozzle_temp
	Mark	move, approach, mark	-	Depth_set, Mark_speed

On top of a skill library, parameter settings shape both task success and overall efficiency. Table 7 lists the most common parameters commonly used in the literature. From the perspective of motion control, velocity (Vel) and acceleration (Acc) are the core parameters of all skills related to motion, which determine the stability and response speed of the action, but also need to weigh the inertia and safety of the mechanical system. Path planning parameters, such as RRT or PRM, mainly affect the autonomy and environmental adaptability of robots from the algorithm, especially the obstacle avoidance ability in complex or dynamic environments. For skills involving physical interaction, such as press fit or screw, Force_set and Torque_set are very important, too large will damage the workpiece, and too small may lead to assembly failure. In addition, parameters such as Align_tolerance and Check_value reflect the tolerance of users to skill errors, and are also closely related to sensor accuracy. In some special material processing skills, such as weld, spray and 3D-print, temperature, flow rate and feed rate directly determine the uniformity and final quality of material deposition. It is worth noting that some parameters affect not only a single skill, but also the stability of the whole task. For example, the Payload_mass of the robot will affect the planning of the motion trajectory, while the Env_map will affect the long-term path optimization. Therefore, in the construction of skill library, the selection of skill parameters not only needs to be optimized for a single execution, but also needs to consider their interaction at the global level to ensure that the robot can effectively perform skills in different application scenarios.

In the research of embodied intelligence, skill library plays a central role in low-level as a structured interface between LLM and physical environment. PRC3S [192] generated parameterized skill codes through LLM (such as grasp/place actions with coordinate parameters), and combined with Continuous Constraint Satisfaction Problem (CCSP) solver to process kinematic, geometric and physical constraints. This setup enabled natural-language-driven drawing and stacking tasks. PromptBook [193] proposed a instruction-example prompt method. It described skill parameters (such as pose coordinate system) and physical constraints (such as robot arm accessibility) through API documents. This allowed the LLM to generate new skill codes such as drawer switches with zero samples. Wiemann et al. [194] encapsulated skills as the service of ROS2, and used LLM to analyze the implied semantics in natural language (such as "moving camera 10mm" mapped to the moving relative coordinate service and automatically filled in parameters). This approach lowered the barrier to user programming. LiP-LLM [195] proposed to build a skill dependency graph and extracts temporal logic from language text, such as "Clear A before placing B." It then used linear programming to optimize task allocation among multiple robots.

The above LLMs combined with skill reveals a feature that the code generation paradigm based on structured skill base has become the mainstream implementation path of

LLM-driven embodied intelligence. These works generally use strong encapsulation interface in the design of skill library, so that the skill code generated by LLM can be directly mapped to the physical execution. This design paradigm mainly relies on two types of structured languages: the first is the robot middleware interface language (such as the ROS2 adopted in [194]), which realizes the matching between skill and device through predefined service types and message structures. The second is the domain specific programming interface (such as the robot API description proposed in [193]), which ensures the physical enforceability of the generated code by strictly restricting the function signature and coordinate system. However, in the field of industrial control, in addition to robots, such interfaces also need to be connected with PLC ladder diagram or structured text (IEC 61131-3). How to establish a unified Domain Specific Language (DSL) to be compatible with different types of controllers will become the key to realize LLM-driven EIIR.

5.2 Low-level control language

In the low-level skill controller of the EIIR framework, a language is often needed as the expression of skill to facilitate the understanding of the actuator. This kind of language needs to have dual attributes: it should not only retain the abstraction of skill semantics to support low-level reasoning, but also embed hardware interface specifications to ensure physical enforceability. Domain Specific Language (DSL) effectively fills the gap between abstract skills and hardware instructions through semantic layered architecture. Van deursen et al. [196] defined DSL as a programming language or executable specification language that offers, through appropriate notations and abstractions, expressive power focused on, and usually restricted to, a particular problem domain. Its core feature is that it not only provides natural abstraction friendly to domain experts, but also maintains strict machine processability. This feature is particularly important in industrial control scenarios. Facing the problem of interface fragmentation of heterogeneous devices such as robot controllers and PLCs, DSL can not only encapsulate the underlying languages of different control protocols, but also inject reasoning rules through coordinate system constraints, kinematics rules and other fields by building a standardized semantic model. For example, an industrial DSL can define a unified skill "pick and place", and its parametric interface can automatically map to the RAPID command of ABB robot and the ST of Siemens PLC. At the same time, the compatibility between the tool path and the workpiece coordinate system is verified through the geometric reasoning engine. This semantic design paradigm makes DSL the preferred technology carrier for cross controller code generation and runtime verification.

Nordmann et al. [197] systematically sorted out the robotic DSLs in 2015, and divided the DSLs into nine categories based on Part A of the Springer Handbook of Robotics [198]. However, its taxonomy focuses more on the category of general robotics, which is difficult to adapt to the special requirements of heterogeneous equipment and executability in industrial control scenarios. By retrieving DSL literature in the field of industrial robot from 2016 to 2025, we evaluated their engineering value through seven dimensions, as shown in Table 8.

1) *Kinematics*: checks whether DSL has the basic ability to drive robot motion. You can call robot API (such as MoveIt! of ROS) or directly generate joint control instructions to verify the completeness of DSL kinematic modeling.

2) *Path planning*: evaluates the flexibility and configurability of trajectory planning. The minimum standard is to support basic navigation path generation, and the high-order

requirements include speed/acceleration curve parameterization, dynamic obstacle avoidance, etc.

3) *Real time*: emphasizes the online schedulability of control instructions. Different from the mode of code import after offline programming, it needs to support hard real-time features such as runtime task interruption (such as emergency stop), priority preemption, etc.

4) *Perception-Action*: verifies the dynamic correction ability of perception data to execution logic. Typical implementations include sensor event triggering state migration, such as visual positioning error triggering relocation. Conditional branching and asynchronous event processing mechanisms need to be provided at the DSL syntax level.

5) *PLC*: checks the interoperability with industrial controllers. It is required to support the generation of IEC 61131-3 code (such as structured text), or the data exchange with PLC through OPC UA protocol.

6) *Tool chain*: mainly focuses on GUI development environment and simulation verification capability. The former requires integrated graphical interfaces (such as debugging tools), while the latter requires seamless docking with the simulation platform to achieve control logic verification.

7) *Industrial application*: although it is not a necessary technical indicator, the actual scenario verification can help the author optimize the robustness of DSL in the design process, especially providing empirical feedback on exception handling and long-term operation stability.

Table 8 Overview of the 20 surveyed DSLs from 2016 to 2025 and their evaluation. The search strategy employed the Boolean query: ‘(domain specific language OR domain specific modeling language OR dsl) AND (robot OR robotic) AND (industry OR manufacturing)’. ✓ indicates that the DSL meets this standard. ○ indicates that it partially satisfies this.

DSLs	Kinem atics	Path planning	Real- time	Perception -Action	PLC	Tool chain	Industrial application
Reversible Execution [199]				✓			Product assembly
Web-Application [200]					✓	○	Modular production plants
Block-based language [201]					✓	○	Automotive manufacturing
RoboticSpec [202]	✓		✓				Failure detection
BDD [203]	✓			✓			-
DSL in wood [204]	✓			✓			Wood manufacturing
GeometrySL [205]	✓					✓	Medical robots
LoTLan [206]		✓	✓	✓			Warehouse logistics

RoboLang [207]		✓		✓	○	Healthcare robot	
Salty [208]		✓		✓	○	UAV	
PyDSLRep[209]		✓		✓	✓	Mobile robot	
CAPIRCI [210]	✓			✓	○	Collaborative robots	
EzSkiROS [211]	✓	✓		✓		-	
SMACHA [212]	✓		✓		✓	-	
Assembly [213]	✓		✓		✓	Product assembly	
RoboSC [214]		✓	✓	✓	○	Supervisor of ROS	
PDDL [162, 215]	✓	✓		✓	○	Kitting	
RoboArch [216]	✓	✓	✓	✓	✓	Nuclear robotic systems	
UMRF [217]	✓	✓	✓	✓	○	Remote inspection	
A-code [218, 219]	✓		✓	✓	✓	○	Product assembly

In the LLM-driven skill library, DSL realizes another direct mapping from natural language to physical execution by binding structured skills. Different DSLs have different emphases on PLC, navigation path planning, robot motion and so on. For example, Block-based language [201] deeply integrated blockly programming with industrial automation. It realized the seamless connection between graphical modules and Rockwell/Siemens hardware, and constructed a PLC verification system based on semantic mapping. Lotlan [206] based on natural language processing (NLP) and DSL, realized the cooperation framework between human and mobile robot. Its core innovation was to transform voice into standardized task description (SVO structure), and support the dynamic task scheduling of AGV through a lightweight syntax that separates logic and control. SMACHA [212] was a DSL based on meta script, templating and code generation. It simplified robot skills arrangement through declarative YAML script, supported modular skill encapsulation (such as grabbing, placing, etc.), and realized efficient reuse and combination of skills in complex tasks. Heuss et al. [162] proposed an automatic planning domain adaptation method based on PDDL. By dynamically associating the abstract planning model with parameterized robot skills, the planning domain description oriented to specific assembly scenes was automatically generated, so that non-professional users can realize industrial robot autonomous task planning only by configuring skill parameters. Wanna et al. [217] proposed

Unified Meaning Representation Format (UMRF) and the task planning framework for industrial scenarios. LLM converted natural language into UMRF graphs in JSON format. Each node corresponded to executable robot skills (such as navigation, grabbing, and scanning), and supported sequential, concurrent, and circular structures. A-code [218, 219] was the only DSL supporting cooperative control between robot and PLC in the survey. Its syntax and four-level architecture enabled modular assembly programming. An IDE and cross-device synchronization made it work on the reconfigurable flexible assembly line [220, 221]. In general, these DSLs provide a flexible and scalable technical basis for industrial automation and robot control systems, and serve as an intermediate medium to help agents seamlessly connect with hardware. So far, the agent has transformed the natural language into the executable program of the device.

6 EIIR simulator

EIIR simulator is a high fidelity virtual platform based on digital technology. It simulates the movement and operation process of the robot in the real industrial environment by accurately modeling the hardware, dynamics, sensors and control logic of the robot. It can not only reproduce the physical behavior of the robot, but also simulate the environmental interference and action feedback, so as to provide data for algorithm development. With the help of the simulator, we can generate a large number of training data in the virtual space to accelerate the iteration of the high-level planning algorithm in Section 4; The program generated by the low-level controller in Section 5 is tested and optimized in the off-line debugging stage, which significantly reduces the real debugging cost and security risk; At the same time, through the construction of digital twins, the real-time monitoring, system optimization and predictive maintenance of the running state of the robot and the whole production line are realized.

In this section, the commonly used EIIR simulators are divided into two parts: robot simulator and production line simulator.

6.1 Robot simulator

Robot simulator focuses on simulating the motion, control and perception of robot, and its core is to finely restore the internal motion mechanism and sensor feedback of robot. It is based on the integration of high fidelity physical engine and robot middleware such as ROS, integrates a variety of sensor models, and provides high-quality training data for deep learning, reinforcement learning and other algorithms. At present, some reviews [1, 2] have discussed robot simulators in the field of embodied intelligence, but these works mainly focus on service scenarios (such as living room, kitchen and restaurant), and the evaluation criteria are uneven, while the industrial field has different requirements. In view of this situation, we propose the EIIR simulator evaluation criteria for industrial scenarios in this section, mainly including the following dimensions:

- 1) *High-Fidelity Motion Simulation (HFMS)*: this indicator evaluates whether the simulator can obtain a simulation effect that is highly consistent with the motion of a real robot. Specifically, it examines whether the simulator is integrated with ROS, so that it can use the control algorithm and motion planning tool tested by industrial practice in the ROS framework to support the fine and accurate motion simulation of different brands of robots.

For software without an official direct ROS interface, this indicator also recognizes that the communication between ROS and simulator realized through a python custom interface, so as to make up for the lack of native support. HFMS not only includes the restoration of static posture, but also emphasizes whether the motion response and mechanical properties under dynamic motion and load changes are consistent with the actual robot behavior.

2) *Rich Robot Library (RRL)*: this indicator mainly focuses on whether there are a large number of robot models preset in the simulator. A rich robot library means that users can directly use preset models for simulation without building robot models from scratch or defining complex kinematic and dynamic parameters. For industrial applications, there are many brands and models of robots. The preset model library can significantly reduce the workload of model construction, ensure that all kinds of robots can be quickly verified and applied on the simulation platform, improve the development efficiency and ensure the credibility of the simulation results.

3) **Python API**: this indicator determines whether the simulator provides a seamless interface with Python. Because Python is widely used in the fields of deep learning, reinforcement learning and data processing. A good Python API allows developers to easily call the functions of the simulator, and seamlessly integrate the simulation environment with the processes of deep learning training and algorithm debugging.

4) *Multiple Sensor Simulation (MSS)*: the indicator evaluates whether the simulator has the feedback function of a variety of simulated sensors common in industrial scenes. Industrial robots often rely on sensors to obtain environmental and state information, such as in place feedback, proximity sensors, photoelectric sensors and force sensors. The high-level MSS not only requires the sensor model to have sufficient accuracy, but also needs to simulate the response delay, noise characteristics and interference effects of the sensor. Only in this way can we ensure that the sensor data in the simulation environment is consistent with the actual application, and provide a real and reliable basis for robot decision-making and action control.

5) **RGB-D**: this indicator checks whether the simulator has built-in simulation function of RGB-D camera. RGB-D sensor can collect color image and depth information at the same time, providing rich perceptual data for robot vision. Vision system plays a key role in robot perception, navigation and manipulation. RGB-D data can be used for object recognition, 3D reconstruction, path planning and environment modeling.

Based on the above indicators, we can more comprehensively evaluate the performance of robot simulators in industrial applications, so as to select the most suitable simulation platform for specific industrial scenarios, as shown in [Table 9](#).

Table 9 Robot Simulator. ✓ indicates that the simulator meets this standard. ○ indicates that it can be implemented through custom interfaces.

Environment	Simulator	Year	HFMS	RRL	Python API	MSS	RGB-D	Industrial applications
Game-based	Gazebo [222]	2004	✓	✓	✓	✓	✓	[223-226]
	MuJoCo [227]	2012	✓		✓	✓	✓	[228, 229]
	CoppeliaSim [230]	2013	○	✓	✓	✓	✓	[231-233]
	PyBullet [234]	2017	○		✓	✓	✓	[102, 235-237]
	Isaac Gym [238]	2019	○		✓	✓	✓	-
	Isaac Sim [239]	2023	✓	✓	✓	✓	✓	[240]
Real-world-based	AI2-THOR [241]	2017	○		✓		✓	-
	VirtualHome [242]	2018	✓		✓		✓	-
	VRKitchen [243]	2019			✓		✓	-
	Habitat [244]	2019	○		✓	✓	✓	[100]
	iGibson [245, 246]	2021	○		✓		✓	-
	TDW [247]	2021	○		✓		✓	-

The game-based simulator is mainly based on 3D virtual resources to build the environment, in which the scene and objects are composed of 3D models created in advance. The advantages of such simulators are low resource requirements and fast scene construction, which are suitable for use in scenes that do not require a high sense of reality. Especially in the manufacturing industry, 3D models of various equipment and products are usually obtained in the design stage, which can be directly used for the construction of simulation environment. **Gazebo** [222] is a powerful open source simulation platform, which is closely integrated with ROS to support high fidelity motion simulation, and provides official robot library and multi-sensor support, especially suitable for the simulation of multi robot cooperation in industrial scenes. **Mujoco** [227] is famous for its high-precision physical engine, which is suitable for robot control and reinforcement learning tasks. Its accurate dynamic simulation makes it widely used in academia. **Pybullet** [234] is a lightweight physical engine suitable for rapid simulation and algorithm testing, especially for RL tasks. Its simple API and Python support reduce the user's threshold. **Isaac Sim** [239] provides high fidelity motion simulation and multi-sensor system based on NVIDIA Omniverse platform, with comprehensive performance. In general, these simulators can provide necessary functions and support for the simulation of robot motion, perception and task execution in industrial applications. The difference is mainly reflected in HFMS and RRL. If the application scenario focuses on close integration with ROS and needs to deal with multi robot

cooperative tasks, Gazebo is an ideal choice. While Isaac Sim has stronger physical simulation and complex environment modeling capabilities. Table 9 describes the main functions of six game-based simulators. Fig. 10 shows some industrial application cases of the game-based simulator.

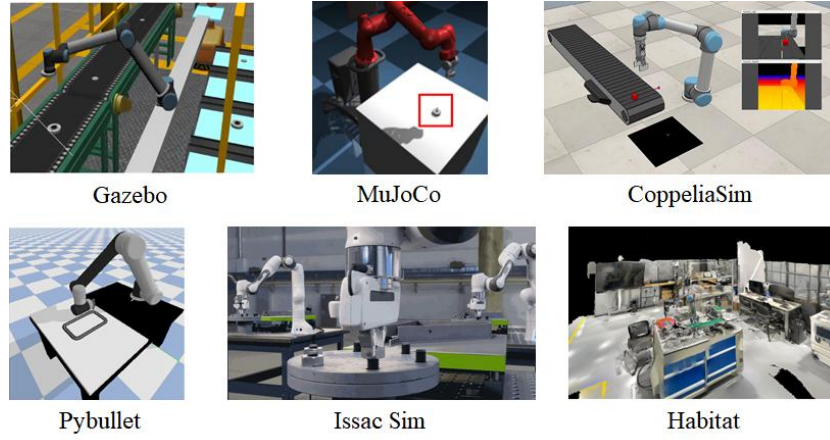


Fig. 10. Industrial examples of robot simulator. The figures are from literature or cases.

Real-world-based simulator usually builds simulation environments based on real-world scanning data. Unlike game-based simulator, it relies on 3D scanning technology to transform real-world environments into digital models, thus providing a higher sense of reality and object details. Due to its high fidelity, real-world-based-simulator is often used in application scenarios that require higher simulation accuracy and Sim2real migration, such as navigation and interaction in an indoor environment. Table 9 introduces six real-world-based simulators. From the evaluation, it can be seen that such simulators generally use humans as agents when running, and generally do not contain robot library. But they have a large number of real-world 3D resources, such as furniture, home appliances and indoor layout, to support the simulation interaction of multi-agent. In addition, real-world-based simulators generally lack the support of commonly used sensors in industrial manufacturing scenarios, which is difficult to meet the needs of industrial automation. Therefore, only **Habitat** [244] provides a certain degree of EIIR simulation capability, making it the most potential choice in the field of industrial robot.

In real industrial applications, the above simulators are widely used in different types of robot task simulation, especially in automated production environment. For example, **Gazebo** is used to simulate the robot grasping and classification tasks on the conveyor belt, including the object recognition and processing based on the RGB-D camera. This is to verify the performance and task execution efficiency of the robot in the dynamic environment [223, 226]. **Isaac Sim** can be used as the basis of generative simulation system to provide core support for large-scale manufacturing robot training data [240]. With its powerful physical simulation ability, the system can simulate different types of robots, manipulation tasks and manufacturing environments, and can also simulate the abnormal behavior of robots and abnormal conditions that may occur in the manufacturing process. This can provide high-quality data support for abnormal detection in the manufacturing process. In **Habitat**, human-machine collaborative manufacturing scenes can be reconstructed and annotated based on 3D point cloud, and further path planning and navigation tasks can be supported [100].

Specifically, as an AI simulation environment, Habitat supports the integration of LLM to understand natural language and generate robot actions. The Pathfinder module is also stored in Habitat, which can help AGV realize path planning from the current point to the target position.

Although the above simulators play an important role in the task simulation of industrial robots, they still face some important challenges in the production line level tasks. Robot simulator is more concerned with simulating the behavior of the robot itself. However, the industrial production line not only involves the motion control of the robot, but also needs to integrate and coordinate the relationship among multiple devices. For example, in addition to the robot controller, industrial automation usually relies on PLC to manage other equipment besides the robot. Therefore, in order to apply embodied intelligence to the actual production line, the functions of the existing simulation platform need to be further expanded, and the close integration with the industrial automation system needs to be considered.

6.2 Production line simulator

Production line simulator is mainly used to simulate the operation of the entire production line, not just the robot. Unlike the robot simulator, the production line simulator focuses on the coordination of multiple devices, robots, sensors, actuators and control systems, and is more suitable for industrial scenarios. The software usually integrates the controllers of a variety of industrial equipment and robots, and can simulate the workflow of the whole production line, such as material handling and assembly process. Since the production line simulator already has its own robot controller and device interface, they do not rely on the integration with ROS, but focus more on the simulation of device collaboration in industrial automation scenarios.

Due to these characteristics, the evaluation criteria of the production line simulator are also different from those of the robot simulator. First of all, HFMS no longer focuses on whether to integrate ROS, but instead investigates the number of robot controllers supported by the simulator to evaluate the applicable robot brand range. RRL examines the number of robot models provided in the simulator or on the official website, reflecting its ability to support different robot models. In addition, the production line simulator adds two evaluation dimensions, PLC and Multi-devices, to measure whether the simulator can effectively simulate PLC for production line control and realize the interaction among multiple devices. As shown in [Table 10](#), we will evaluate 10 production line simulators from the above dimensions. Relevant information comes from the official website, instructions, relevant research and case blog. Relevant values and standards may change due to iteration of software version update.

Table 10 Production line simulator. ✓ indicates that the simulator meets this standard. ○ in Python API indicates that it can be implemented through custom interfaces. ○ in RGB-D indicates that it only supports RGB image acquisition.

Simulator	HFMS	RRL	Python API	MSS	RGB-D	PLC	Multi-devices
KUKA.Sim [248]	for KUKA robots		✓	✓	○	✓	✓
RobotStudio [249]	for ABB robots		✓	✓	✓	✓	✓
ROBOGUIDE [250]	for FANUC robots		○	✓	✓	✓	✓
MotoSim [251]	for Yaskawa robots		✓	✓			✓
Robotmaster [252]	22	534					✓
RoboDK [253]	40+	1295	✓		○	✓	✓
ArtiMinds RPS [254]	6	50+		✓	✓	✓	✓
DELMIA [255]	20	2000+	○	✓	○	✓	✓
Visual Components [256]	17	1900+	✓	✓	○	✓	✓
Tecnomatix [257]	18+	940	○	✓	✓	✓	✓

Most of the world's major industrial robot manufacturers have developed adaptive industrial simulators for their own brands of robots. For example, **KUKA.Sim** is a simulation software specially used for offline programming of KUKA robot [248]. This software can display the motion of the robot in virtual environment before the equipment is put into operation, and optimize it from the aspect of beat time. It can also ensure the feasibility of the robot program and layout through the accessibility check and collision recognition functions of the software. Further, based on the software's support for MSS, PLC and Multi-devices interaction, KUKA.Sim can create a digital twin, that is, an image exactly like the real production line. 3D simulation covers the whole planning process: from process design, to material flow and visualization of bottleneck, and then to PLC code. Therefore, the virtual and real control systems use exactly the same data to work. KUKA.Sim has become the basis of virtual commissioning in this way, testing and optimizing the new production line in the virtual environment. **RobotStudio** [249] developed for ABB robot and **ROBOGUIDE** [250] developed for FANUC robot can realize similar functions. However, **MotoSim** [251] does not support the connection with external PLC and cannot completely simulate the operation of the entire production line. At the same time, EIIR also needs the simulator to support the robot's deep learning. The above four software can directly or indirectly support Python API, which is convenient for integration with external systems or deep learning modules. However, KUKA.Sim and MotoSim do not support the setting of RGB-D camera in the simulation environment, lacking the visual ability to perceive the environmental for robots. In terms of production line simulation and support for deep learning, RobotStudio has more comprehensive performance.

In addition to the simulators dedicated to a single robot brand, there are a series of

production line simulators that integrate a wealth of robot controllers and post processors after being authorized by various robot manufacturers, so that offline programming can also be realized. For example, **Visual Components** integrates 17 post processors and more than 40 robot controllers, including ABB, KUKA, FANUC, UR and other robot brands, so there is no need to use multiple software or understand multiple robot programming languages [256]. At the same time, the online model library eCatalog of Visual Components also provides more than 1900 robots for simulation. Visual Components also supports the integration of sensors and PLC, and can accurately reflect the real control system used by the physical machine in the model, so as to realize the virtual commissioning of the production line. Visual Components and Python are also closely integrated. Python script editor can be directly called in the software, and robot control, trigger setting and signal events can be carried out in combination with API. A similar integrated simulator is **Tecnomatix**, which is the core industrial software of Siemens Xcelerator digital ecosystem. It is deeply compatible with Siemens PLC, SCADA system and MES/MOM platform [257]. It can accurately analyze the robot motion trajectory, beat time and production line bottlenecks, and is especially good at handling complex process flows such as multi robot cooperative welding and flexible body assembly. In addition to the production line simulation, Tecnomatix also includes RGB-D simulation camera, which simulates the imaging characteristics of real industrial vision system through ray tracing algorithm, and supports the training and verification of defect detection algorithm. The Virtual Reality (VR) system inside the software not only provides an immersive factory roaming experience, but also integrates motion capture and ergonomic analysis tools. A series of innovative functions of Tecnomatix are suitable for researchers to further explore and apply in the industrial scene. Fig. 11 shows some industrial application cases of the production line simulator.

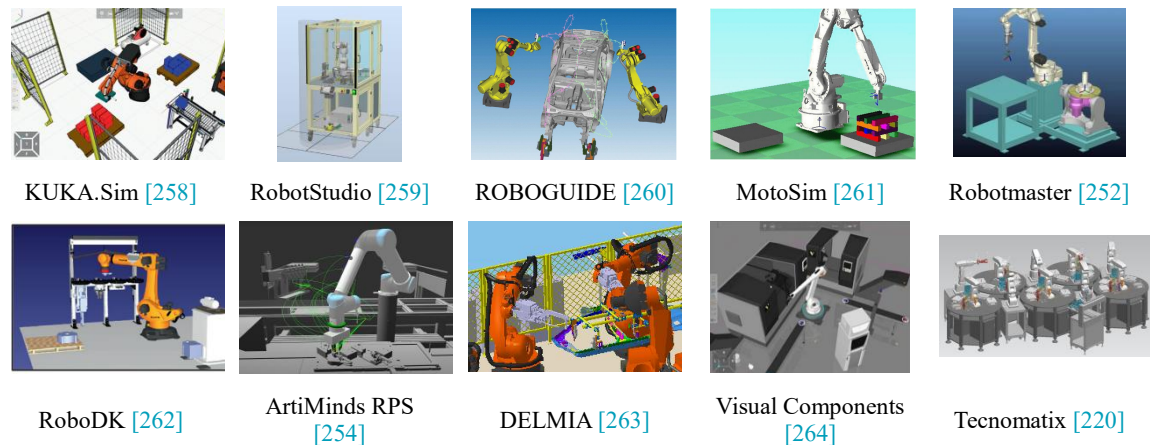


Fig. 11. Industrial examples of production line simulator. The figures are from literature or cases.

In conclusion, although the current mainstream production line simulators tend to be mature in the field of industrial equipment integration and production line level virtual commissioning, there is still a significant gap between their integration with embodied intelligence. On the one hand, such platforms generally lack open Python API and extensible deep learning frameworks, which are difficult to support the training and testing of decision algorithms. On the other hand, the key modules such as deep camera simulation and tactile feedback simulation for real physical interaction are not yet perfect, which makes it difficult

for agents to obtain near real sensor input in the virtual environment. Although robot simulators described in Section 5.1 perform well in single machine deep learning training, high fidelity data acquisition and other aspects, they are limited by the lack of compatibility of PLC communication protocol, weak linkage ability of MES system and other problems. So they cannot build a complete industrial scenario including transmission lines, sensor networks and other elements. Therefore, when building EIIR simulator, developers need to fully weigh the differences between the two types of simulators: the production line simulator can be used first to build a production line digital twin base with accurate equipment model, and then access the special robot simulation node supporting deep learning through ROS/OPC UA middleware, and finally form a composite simulation architecture that takes into account the fidelity of industrial equipment and the flexibility of agent training.

7 Challenges and future work

Based on the development status and trends of the technologies related to the four modules in the EIIR framework summarized in Section 3-6, this section summarizes the possible challenges and potential future research directions to apply EIIR technologies to industrial scenes or systems.

7.1 Industrial world model

This paper believes that the EIIR that can be successfully deployed in the real industrial scene should have the most basic three kinds of knowledge: general knowledge, working environment knowledge and operating object knowledge. The existing LLM is prone to "industrial illusion" in industrial tasks, that is, it looks correct semantically, but can not be used in industrial scenarios. Therefore, it is urgent to establish an industrial foundation model, which can quickly and accurately solve the tasks related to the whole life cycle of product design, manufacturing, testing and maintenance in the industrial scene [265], such as process generation, defect detection, etc.

In terms of potential solutions, due to the complexity of industrial scenarios and processes, we believe that the industrial foundation model can first be decomposed into a series of domain foundation models, such as the foundation model of assembly, processing, and product design. Then, a mechanism such as Mixture of Experts (MOE) is designed to integrate various domain foundation models to form the final output. It is expected that with the development of industrial foundation model, the level of LLM to complete various tasks should reach or even exceed the level of experts in various fields of industry. In the training process, the industrial foundation model will also have a large number of working environment knowledge and operating object knowledge in the industrial scene, which can also be used to assist the construction of semantic map and knowledge graph.

7.2 Industrial high-level task planner

In the industrial scene, the lack of working environment knowledge and operating object knowledge of agents has become the core bottleneck restricting the embodied intelligent task planning. The traditional framework relies on the general knowledge of large model (LLM or VLA), which can interpret natural language tasks and perceive the position of objects. But due to the lack of in-depth knowledge in the industrial field (such as ISO standards and

process manuals), the task decomposition results deviate from engineering constraints (such as wrong sequencing of assembly steps or ignoring process requirements). In the existing industrial methods, the rule-based system is limited by the rigid logic defined manually, which is difficult to adapt to the requirements of flexible manufacturing. The learning-based methods rely on massive annotation data and cannot be quickly migrated to new production lines.

Therefore, it is urgent to study RAG-like high-level task planning technology based on semantic map and domain knowledge graph. Semantic map and knowledge graph can structurally store environment information, part parameters, assembly process and other knowledge, and constrain the reasoning path of the large model. RAG dynamically enhances the domain cognition of the large model through real-time retrieval of process documents, quality inspection standards and other external knowledge bases. This integration path is expected to break through the "knowledge blind spot" of the existing framework and realize the leap from general semantic understanding to industrial deterministic planning.

7.3 Industrial low-level skill controller

Firstly, we need to study EIIR skills with the ability to generalize industrial data, such as industrial object detection for open vocabulary. In order to reduce the threshold for industrial customers to use EIIR, industrial data sensing technology with stronger generalization ability is urgently needed in the industrial field. Taking 6D pose estimation in measure skill as an example, most industrial parts are series of parametric parts, that is, the same series of parts are basically instantiated from the same parametric template by using different parameter values, while the primitives of a parametric template and the constraint relationship between primitives are the same. However, the existing point cloud deep learning methods have not found this data feature. If this kind of method is directly applied to industrial data, its performance will decline significantly. Therefore, it is very necessary to deeply study the perception technology for two-dimensional [266] and three-dimensional industrial data [267, 268]. Similar requirements for industrial scenarios also exist in other skills, such as pick and place, transport, etc.

Secondly, it is also necessary to study the general low-level control language for industrial heterogeneous devices. In the industrial scene, the embodied intelligent "body" not only has a single robot, but also needs to cooperate with other devices driven by PLC. However, the existing low-level controller in EIR framework is limited to the robot operating system (such as ROS), and the generated standardized action instructions cannot be directly adapted to the industrial controller, resulting in a "protocol wall" in the cooperation among multiple devices. For example, the grasp command of the robot needs to trigger the cylinder clamping action controlled by PLC synchronously, but the timing mismatch between ROS and industrial fieldbus is easy to cause the action out of step and even other safety risks. To eliminate this gap, it is necessary to build an industrial DSL as an intermediate link between agents and physical devices. The core design objectives of DSL include: Protocol independence, dynamic compilation of instructions into the native control language of the target device (such as URScript of the robot and ST of the PLC), so as to realize the seamless connection of cross brand and cross type devices; Scalability, support protocol plug-in based on modular architecture, and adapt to the rapid reconfiguration requirements of flexible production lines.

7.4 Industrial production line simulator

Existing robot simulators (such as Gazebo and Isaac Sim) focus on the dynamic modeling and motion simulation of single robot, while the industrial production line needs to realize the system level simulation of "mechanical, electrical, hydraulic and control" multi domain coupling. It is difficult for current simulators to model such cross domain interaction processes, resulting in significant deviation between virtual commissioning result and real production line condition. In addition, although traditional industrial production line simulators (such as Tecnomatix and DELMIA) can build high fidelity production line digital twins, they cannot support the online training and strategy optimization of embodied agents due to the lack of open deep learning interfaces.

To meet the dual needs of multi domain coupling and training data of agents, it is necessary to build EIIR simulator with virtual and real fusion, which mainly includes two directions. First, an open source simulator should be proposed to support the operation of virtual industrial agents. The next generation simulator needs to break through the limitations of single robot modeling, build an open platform to support single robot and production line agent in industrial scenes, and support the rapid deployment of agents. Through open source community collaboration, the simulator can integrate a variety of industrial control protocols, and is compatible with ROS and deep learning framework, providing a plug and play training environment for industrial agents. Second, establish the simulation data engine for industrial foundation model adaptation. According to the training requirements of large model, the simulator needs to strengthen the ability of data generation, and generate millions of diversified working condition data in batches through parametric scene configuration. For example, robot trajectory, sensor, visual, tactile and force sensing data. Based on the above high fidelity multi-modal training data, a closed-loop path of "Equipment level physical fidelity \rightarrow Production line level logic verification \rightarrow Agent strategy optimization" is formed.

8 Conclusion

By integrating multi-modal perception, autonomous decision-making, and physical interaction capabilities, embodied intelligent industrial robotics are reshaping the technical paradigm of traditional industrial automation. Instead of relying on rigid manual-teaching controls and predefined programs, they now enable flexible, autonomous production. In this new model, natural language serves as the primary interaction medium and knowledge lies at its core. This paper systematically proposes and analyzes the knowledge-driven EIIR technology framework, and summarizes the four modules: world model, high-level task planner, low-level skill controller and simulator. The comparison and summary of the existing semantic map and knowledge graph construction methods, general task and industrial task planning methods, skills, control languages and simulators provide a clear picture of the latest development of EIIR. The ultimate vision of industrial embodied intelligence is to become the "cognitive center" of the intelligent factory, with natural language as the interactive entry, world model as the decision-making core, and virtual-real interaction as the verification cornerstone, to promote the transition of manufacturing industry from "program solidification" to "independent evolution". This process requires not only the collaborative

breakthrough of algorithm and hardware, but also the reconstruction of industrial software ecology, and ultimately the creation of a new industrial paradigm with embodied intelligence.

Acknowledgements

This work was supported by National Natural Science Foundation of China (61972220, 92467204), Natural Science Foundation of Guangdong (2022A1515011234), and Shenzhen Major Undertaking Plan (CJGJZD20240729141702003).

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.

CRediT authorship contribution statement

Conceptualization and framework, Chaoran Zhang and Long Zeng; investigation, Chaoran Zhang, Chenhao Zhang, Zhaobo Xu, Qinghongbing Xie; writing-original draft, Chaoran Zhang, Chenhao Zhang; writing-review & editing Zhaobo Xu, Long Zeng; project administration, Pingfa Feng. All authors have read and agreed to the published version of the manuscript.

References

- [1] Y. Liu, W. Chen, Y. Bai, J.-H. Luo, X. Song, K. Jiang, Z. Li, G. Zhao, J. Lin, G. Li, W. Gao, L. Lin, Aligning Cyber Space with Physical World: A Comprehensive Survey on Embodied AI, *ArXiv*, abs/2407.06886 (2024).
- [2] J. Duan, S. Yu, H.L. Tan, H. Zhu, C. Tan, A Survey of Embodied AI: From Simulators to Research Tasks, *Ieee Transactions on Emerging Topics in Computational Intelligence*, 6 (2022) 230-244.
- [3] Z. Li, S. Li, X. Luo, An overview of calibration technology of industrial robots, *IEEE/CAA Journal of Automatica Sinica*, 8 (2021) 23-36.
- [4] H. Liu, D. Guo, A. Cangelosi, Embodied Intelligence: A Synergy of Morphology, Action, Perception and Learning, *ACM Comput. Surv.*, 57 (2025) Article 186.
- [5] J. Wang, E. Shi, H. Hu, C. Ma, Y. Liu, X. Wang, Y. Yao, X. Liu, B. Ge, S. Zhang, Large language models for robotics: Opportunities, challenges, and perspectives, *Journal of Automation and Intelligence*, (2025).
- [6] H. Jeong, H. Lee, C. Kim, S. Shin, A Survey of Robot Intelligence with Large Language Models, *Applied Sciences (Switzerland)*, 14 (2024).
- [7] Y. Kim, D. Kim, J. Choi, J. Park, N. Oh, D. Park, A survey on integration of large language models with intelligent robots, *Intelligent Service Robotics*, 17 (2024) 1091-1107.
- [8] W. Ji, L. Wang, Industrial robotic machining: a review, *The International Journal of Advanced Manufacturing Technology*, 103 (2019) 1239-1255.
- [9] S. Robla-Gómez, V.M. Becerra, J.R. Llata, E. González-Sarabia, C. Torre-Ferrero, J. Pérez-Oria, Working Together: A Review on Safe Human-Robot Collaboration in Industrial Environments, *Ieee Access*, 5 (2017) 26754-26773.
- [10] Q. Meng, Y. Qi, S. Zhang, C. Du, B. Yin, Y. Gao, Intelligent Robots and Development, *Journal of Ocean University of China*, 34 (2004) 831-838.

- [11] L. Ren, J. Dong, S. Liu, L. Zhang, L. Wang, Embodied Intelligence Toward Future Smart Manufacturing in the Era of AI Foundation Model, *Ieee-Asme Transactions on Mechatronics*, (2024).
- [12] C. Machinery, Computing machinery and intelligence-AM Turing, *Mind*, 59 (1950) 433.
- [13] Figure, Figure is the first-of-its-kind AI robotics company bringing a general purpose humanoid to life., in, <https://www.figure.ai>.
- [14] A. Brohan, N. Brown, J. Carbajal, Y. Chebotar, J. Dabis, C. Finn, K. Gopalakrishnan, K. Hausman, A. Herzog, J. Hsu, J. Ibarz, B. Ichter, A. Irpan, T. Jackson, S. Jesmonth, N.J. Joshi, R. Julian, D. Kalashnikov, Y. Kuang, I. Leal, K.-H. Lee, S. Levine, Y. Lu, U. Malla, D. Manjunath, I. Mordatch, O. Nachum, C. Parada, J. Peralta, E. Perez, K. Pertsch, J. Quiambao, K. Rao, M. Ryoo, G. Salazar, P. Sanketi, K. Sayed, J. Singh, S. Sontakke, A. Stone, C. Tan, H. Tran, V. Vanhoucke, S. Vega, Q. Vuong, F. Xia, T. Xiao, P. Xu, S. Xu, T. Yu, B. Zitkovich, RT-1: Robotics Transformer for Real-World Control at Scale, in, 2022, pp. arXiv:2212.06817.
- [15] A. Brohan, N. Brown, J. Carbajal, Y. Chebotar, X. Chen, K. Choromanski, T. Ding, D. Driess, A. Dubey, C. Finn, P. Florence, C. Fu, M. Gonzalez Arenas, K. Gopalakrishnan, K. Han, K. Hausman, A. Herzog, J. Hsu, B. Ichter, A. Irpan, N. Joshi, R. Julian, D. Kalashnikov, Y. Kuang, I. Leal, L. Lee, T.-W.E. Lee, S. Levine, Y. Lu, H. Michalewski, I. Mordatch, K. Pertsch, K. Rao, K. Reymann, M. Ryoo, G. Salazar, P. Sanketi, P. Sermanet, J. Singh, A. Singh, R. Soricut, H. Tran, V. Vanhoucke, Q. Vuong, A. Wahid, S. Welker, P. Wohlhart, J. Wu, F. Xia, T. Xiao, P. Xu, S. Xu, T. Yu, B. Zitkovich, RT-2: Vision-Language-Action Models Transfer Web Knowledge to Robotic Control, in, 2023, pp. arXiv:2307.15818.
- [16] M.J. Kim, K. Pertsch, S. Karamcheti, T. Xiao, A. Balakrishna, S. Nair, R. Rafailov, E. Foster, G. Lam, P. Sanketi, Q. Vuong, T. Kollar, B. Burchfiel, R. Tedrake, D. Sadigh, S. Levine, P. Liang, C. Finn, OpenVLA: An Open-Source Vision-Language-Action Model, in, 2024, pp. arXiv:2406.09246.
- [17] A. Nüchter, J. Hertzberg, Towards semantic maps for mobile robots, *Robotics and Autonomous Systems*, 56 (2008) 915-926.
- [18] J. Wald, H. Dhano, N. Navab, F. Tombari, Learning 3d semantic scene graphs from 3d indoor reconstructions, in: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 3961-3970.
- [19] S.-C. Wu, J. Wald, K. Tateno, N. Navab, F. Tombari, Scenegraphfusion: Incremental 3d scene graph prediction from rgb-d sequences, in: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021, pp. 7515-7525.
- [20] S.-C. Wu, K. Tateno, N. Navab, F. Tombari, Incremental 3d semantic scene graph prediction from rgb sequences, in: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2023, pp. 5064-5074.
- [21] A. Rosinol, A. Gupta, M. Abate, J. Shi, L. Carlone, 3D dynamic scene graphs: Actionable spatial perception with places, objects, and humans, *arXiv preprint arXiv:2002.06289*, (2020).
- [22] N. Hughes, Y. Chang, L. Carlone, Hydra: A real-time spatial perception system for 3D scene graph construction and optimization, *arXiv preprint arXiv:2201.13360*, (2022).
- [23] H. Chang, K. Boyalakuntla, S. Lu, S. Cai, E.P. Jing, S. Keskar, S. Geng, A. Abbas, L. Zhou, K. Bekris, Context-Aware Entity Grounding with Open-Vocabulary 3D Scene Graphs, in: *Conference on Robot Learning*, PMLR, 2023, pp. 1950-1974.
- [24] K.M. Jatavallabhula, A. Kuwajerwala, Q. Gu, M. Omama, T. Chen, A. Maalouf, S. Li, G.S. Iyer, S. Saryazdi, N.V. Keetha, ConceptFusion: Open-set Multimodal 3D Mapping, in: *ICRA2023 Workshop on Pretraining for Robotics (PT4R)*, 2023.

- [25] Q. Gu, A. Kuwajerwala, S. Morin, K.M. Jatavallabhula, B. Sen, A. Agarwal, C. Rivera, W. Paul, K. Ellis, R. Chellappa, Conceptgraphs: Open-vocabulary 3d scene graphs for perception and planning, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2024, pp. 5021-5028.
- [26] A. Werby, C. Huang, M. Büchner, A. Valada, W. Burgard, Hierarchical open-vocabulary 3d scene graphs for language-grounded robot navigation, in: First Workshop on Vision-Language Models for Navigation and Manipulation at ICRA 2024, 2024.
- [27] J. Strader, N. Hughes, W. Chen, A. Speranzon, L. Carlone, Indoor and outdoor 3d scene graph generation via language-enabled spatial ontologies, IEEE Robotics and Automation Letters, (2024).
- [28] X. Chen, S. Jia, Y. Xiang, A review: Knowledge reasoning over knowledge graph, Expert Syst. Appl., 141 (2020) 112948.
- [29] H.K. Rampersad, Integrated and assembly oriented product design, Integrated Manufacturing Systems, 7 (1996) 5-15.
- [30] A.G. Bharadwaj, B. Starly, Knowledge graph construction for product designs from large CAD model repositories, Adv. Eng. Inf., 53 (2022) 101680.
- [31] Z. Chen, J. Bao, X. Zheng, T. Liu, Assembly Information Model Based on Knowledge Graph, J. Shanghai Jiaotong Univ., Sci. (Germany), 25 (2020) 578-588.
- [32] X. Shi, X. Tian, J. Gu, F. Yang, L. Ma, Y. Chen, T. Su, Knowledge Graph-Based Assembly Resource Knowledge Reuse towards Complex Product Assembly Process, in: Sustainability, MDPI AG, 2022, pp. 15541.
- [33] X. Shi, X. Tian, L. Ma, X. Wu, J. Gu, A knowledge graph-based structured representation of assembly process planning combined with deep learning, The International Journal of Advanced Manufacturing Technology, 133 (2024) 1807-1821.
- [34] J. Jia, Y. Zhang, M. Saad, An approach to capturing and reusing tacit design knowledge using relational learning for knowledge graphs, Adv. Eng. Inf., 51 (2022) 101505.
- [35] M. Liu, B. Zhou, J. Li, X. Li, J. Bao, A Knowledge Graph-Based Approach for Assembly Sequence Recommendations for Wind Turbines, Machines, 11 (2023).
- [36] Z. Hu, X. Li, X. Pan, S. Wen, J. Bao, A question answering system for assembly process of wind turbines based on multi-modal knowledge graph and large language model, J. Eng. Des., 1-25.
- [37] B. Zhou, J. Bao, Z. Chen, Y. Liu, KGAssembly: Knowledge graph-driven assembly process generation and evaluation for complex components, Int. J. Computer Integr. Manuf., 35 (2022) 1151-1171.
- [38] Y. Xiao, S. Zheng, J. Leng, R. Gao, Z. Fu, J. Hong, An assembly process planning pipeline for industrial electronic equipment based on knowledge graph with bidirectional extracted knowledge from historical process documents, Journal of Intelligent Manufacturing, (2024).
- [39] E. Järvenpää, N. Siltala, O. Hylli, M. Lanz, The development of an ontology for describing the capabilities of manufacturing resources, Journal of Intelligent Manufacturing, 30 (2019) 959-978.
- [40] E. Järvenpää, N. Siltala, O. Hylli, M. Lanz, Implementation of capability matchmaking software facilitating faster production system design and reconfiguration planning, J. Manuf. Syst., 53 (2019) 261-270.
- [41] F. Mo, J.C. Chaplin, D. Sanderson, G. Martinez-Arellano, S. Ratchev, Semantic models and knowledge graphs as manufacturing system reconfiguration enablers, Rob. Comput. Integr. Manuf., 86 (2024).

- [42] F. Mo, H.U. Rehman, F.M. Monetti, J.C. Chaplin, D. Sanderson, A. Popov, A. Maffei, S. Ratchev, A framework for manufacturing system reconfiguration and optimisation utilising digital twins and modular artificial intelligence, *Rob. Comput. Integr. Manuf.*, 82 (2023).
- [43] D. Zhong, S. Miao, R. Miao, F. Sun, Z. Wen, H. Huang, N. Wang, Skill Manipulation Method of Industrial Robot Based on Knowledge Graph for Assembly Scene, in: F. Sun, J. Li, H. Liu, Z. Chu (Eds.) *Cognit. Comput. Syst.*, Springer Nature Singapore, Singapore, 2023, pp. 280-290.
- [44] Y. Liu, W. Chen, Y. Bai, X. Liang, G. Li, W. Gao, L. Lin, Aligning Cyber Space with Physical World: A Comprehensive Survey on Embodied AI, in, 2024, pp. arXiv:2407.06886.
- [45] I. Singh, V. Blukis, A. Mousavian, A. Goyal, D. Xu, J. Tremblay, D. Fox, J. Thomason, A. Garg, ProgPrompt: Generating Situated Robot Task Plans using Large Language Models, in, 2022, pp. arXiv:2209.11302.
- [46] Y. Ding, X. Zhang, C. Paxton, S. Zhang, Task and Motion Planning with Large Language Models for Object Rearrangement, in: 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2023, pp. 2086-2092.
- [47] B. Yuchen Lin, C. Huang, Q. Liu, W. Gu, S. Sommerer, X. Ren, On Grounded Planning for Embodied Tasks with Language Models, in, 2022, pp. arXiv:2209.00465.
- [48] S. Chen, A. Xiao, D. Hsu, LLM-State: Open World State Representation for Long-horizon Task Planning with Large Language Model, in, 2023, pp. arXiv:2311.17406.
- [49] Z. Ni, X. Deng, C. Tai, X. Zhu, Q. Xie, W. Huang, X. Wu, L. Zeng, GRID: Scene-Graph-based Instruction-driven Robotic Task Planning, in: 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024, pp. 13765-13772.
- [50] C.H. Song, J. Wu, C. Washington, B.M. Sadler, W.-L. Chao, Y. Su, LLM-Planner: Few-Shot Grounded Planning for Embodied Agents with Large Language Models, in, 2022, pp. arXiv:2212.04088.
- [51] Z. Wu, Z. Wang, X. Xu, J. Lu, H. Yan, Embodied Task Planning with Large Language Models, in, 2023, pp. arXiv:2307.01848.
- [52] K. Shirai, C.C. Beltran-Hernandez, M. Hamaya, A. Hashimoto, S. Tanaka, K. Kawaharazuka, K. Tanaka, Y. Ushiku, S. Mori, Vision-Language Interpreter for Robot Task Planning, in, 2023, pp. arXiv:2311.00967.
- [53] H. Liu, Y. Zhu, K. Kato, A. Tsukahara, I. Kondo, T. Aoyama, Y. Hasegawa, Enhancing the LLM-Based Robot Manipulation Through Human-Robot Collaboration, *IEEE Robotics and Automation Letters*, 9 (2024) 6904-6911.
- [54] Z. Wang, Q. Liu, J. Qin, M. Li, Ensuring Safety in LLM-Driven Robotics: A Cross-Layer Sequence Supervision Mechanism, in: 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024, pp. 9620-9627.
- [55] S. Yin, X. Pang, Y. Ding, M. Chen, Y. Bi, Y. Xiong, W. Huang, Z. Xiang, J. Shao, S. Chen, SafeAgentBench: A Benchmark for Safe Task Planning of Embodied LLM Agents, in, 2024, pp. arXiv:2412.13178.
- [56] S. Li, Z. Ma, F. Liu, J. Lu, Q. Xiao, K. Sun, L. Cui, X. Yang, P. Liu, X. Wang, Safe Planner: Empowering Safety Awareness in Large Pre-Trained Models for Robot Task Planning, in, 2024, pp. arXiv:2411.06920.
- [57] Z. Ravichandran, A. Robey, V. Kumar, G.J. Pappas, H. Hassani, Safety Guardrails for LLM-Enabled Robots, in, 2025, pp. arXiv:2503.07885.

- [58] J.P. Macdonald, R. Mallick, A.B. Wollaber, J.D. Peña, N. McNeese, H.C. Siu, Language, Camera, Autonomy! Prompt-engineered Robot Control for Rapidly Evolving Deployment, in: Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction, Association for Computing Machinery, Boulder, CO, USA, 2024, pp. 717–721.
- [59] Z. Yang, S.S. Raman, A. Shah, S. Tellex, Plug in the Safety Chip: Enforcing Constraints for LLM-driven Robot Agents, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), 2024, pp. 14435-14442.
- [60] Y. Ma, Z. Song, Y. Zhuang, J. Hao, I. King, A Survey on Vision-Language-Action Models for Embodied AI, in, 2024, pp. arXiv:2405.14093.
- [61] H. Zhen, X. Qiu, P. Chen, J. Yang, X. Yan, Y. Du, Y. Hong, C. Gan, 3D-VLA: A 3D Vision-Language-Action Generative World Model, in, 2024, pp. arXiv:2403.09631.
- [62] B. Han, J. Kim, J. Jang, A Dual Process VLA: Efficient Robotic Manipulation Leveraging VLM, in, 2024, pp. arXiv:2410.15549.
- [63] D. Qu, H. Song, Q. Chen, Y. Yao, X. Ye, Y. Ding, Z. Wang, J. Gu, B. Zhao, D. Wang, X. Li, SpatialVLA: Exploring Spatial Representations for Visual-Language-Action Model, in, 2025, pp. arXiv:2501.15830.
- [64] K. Fidèle Gbagbe, M. Altamirano Cabrera, A. Alabbas, O. Alyunes, A. Lykov, D. Tsetserukou, Bi-VLA: Vision-Language-Action Model-Based System for Bimanual Robotic Dexterous Manipulations, in, 2024, pp. arXiv:2405.06039.
- [65] S. Li, J. Wang, R. Dai, W. Ma, W.Y. Ng, Y. Hu, Z. Li, RoboNurse-VLA: Robotic Scrub Nurse System based on Vision-Language-Action Model, in, 2024, pp. arXiv:2409.19590.
- [66] S. Zhang, Z. Xu, P. Liu, X. Yu, Y. Li, Q. Gao, Z. Fei, Z. Yin, Z. Wu, Y.-G. Jiang, X. Qiu, VLABench: A Large-Scale Benchmark for Language-Conditioned Robotics Manipulation with Long-Horizon Reasoning Tasks, in, 2024, pp. arXiv:2412.18194.
- [67] G. Buchgeher, D. Gabauer, J. Martinez-Gil, L. Ehrlinger, Knowledge Graphs in Manufacturing and Production: A Systematic Literature Review, IEEE Access, 9 (2021) 55537-55554.
- [68] A. Iqbal, N.U. Dar, N. He, M.M.I. Hammouda, L. Li, Self-developing fuzzy expert system: a novel learning approach, fitting for manufacturing domain, Journal of Intelligent Manufacturing, 21 (2009) 761-776.
- [69] J. Gámez García, J. Gómez Ortega, S. Satorres Martínez, A. Sánchez García, Expert system based controller for the high-accuracy automatic assembly of vehicle headlamps, Expert Systems with Applications, 38 (2011) 12818-12825.
- [70] A. Manoria, S.K. Mishra, S.U. Maheshwar, Expert System based on RPW Technique to Evaluating Multi Product Assembly Line Balancing Solution, International Journal of Computer Applications, 40 (2012) 27-32.
- [71] M. Merdan, E. List, W. Lepuschitz, Knowledge-driven industrial robotics for flexible production, in: 2017 IEEE 21st International Conference on Intelligent Engineering Systems (INES), 2017, pp. 000225-000230.
- [72] Y. Jiang, C. Chen, X. Liu, Assembly Process Knowledge Graph for Digital Twin, in: 2021 IEEE 17th International Conference on Automation Science and Engineering (CASE), 2021, pp. 758-763.
- [73] T. Hoebert, W. Lepuschitz, M. Vincze, M. Merdan, Knowledge-driven framework for industrial robotic systems, Journal of Intelligent Manufacturing, 34 (2021) 771-788.

- [74] B. Zhou, J. Bao, Z. Chen, Y. Liu, KGAssembly: Knowledge graph-driven assembly process generation and evaluation for complex components, *International Journal of Computer Integrated Manufacturing*, 35 (2021) 1151-1171.
- [75] Z. Qin, Y. Lu, A Knowledge Graph-based knowledge representation for adaptive manufacturing control under mass personalization, *Manufacturing Letters*, 35 (2023) 96-104.
- [76] Z. Kootbally, C. Schlenoff, C. Lawler, T. Kramer, S.K. Gupta, Towards robust assembly with knowledge representation for the planning domain definition language (PDDL), *Robotics and Computer-Integrated Manufacturing*, 33 (2015) 42-55.
- [77] M. Cashmore, M. Fox, D. Long, D. Magazzeni, B. Ridder, A. Carrera, N. Palomeras, N. Hurtós, M. Carreras, ROSPlan: Planning in the Robot Operating System, in: *International Conference on Automated Planning and Scheduling*, 2015.
- [78] F. Rovida, M. Crosby, D. Holz, A.S. Polydoros, B. Großmann, R.P.A. Petrick, V. Krüger, SkiROS—A Skill-Based Robot Control Platform on Top of ROS, in: A. Koubaa (Ed.) *Robot Operating System (ROS): The Complete Reference (Volume 2)*, Springer International Publishing, Cham, 2017, pp. 121-160.
- [79] L. Heuss, C. Gonnermann, G. Reinhart, An extendable framework for intelligent and easily configurable skills-based industrial robot applications, *The International Journal of Advanced Manufacturing Technology*, 120 (2022) 6269-6285.
- [80] A. Rogalla, A. Fay, O. Niggemann, Improved Domain Modeling for Realistic Automated Planning and Scheduling in Discrete Manufacturing, in: *2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*, 2018, pp. 464-471.
- [81] P. Smirnov, F. Joubin, A. Ceravola, M. Gienger, Generating consistent PDDL domains with Large Language Models, in, 2024, pp. arXiv:2404.07751.
- [82] C. Li, P. Zheng, Y. Yin, B. Wang, L. Wang, Deep reinforcement learning in smart manufacturing: A review and prospects, *CIRP Journal of Manufacturing Science and Technology*, 40 (2023) 75-101.
- [83] Z. Liu, Q. Liu, W. Xu, L. Wang, Z. Zhou, Robot learning towards smart robotic manufacturing: A review, *Robotics and Computer-Integrated Manufacturing*, 77 (2022).
- [84] H. Zhang, L.Z. Liu, H. Xie, Y. Jiang, J. Zhou, Y. Wang, Deep Learning-Based Robot Vision: High-End Tools for Smart Manufacturing, *IEEE Instrumentation & Measurement Magazine*, 25 (2022) 27-35.
- [85] H. Liu, T. Fang, T. Zhou, Y. Wang, L. Wang, Deep Learning-based Multimodal Control Interface for Human-Robot Collaboration, *Procedia CIRP*, 72 (2018) 3-8.
- [86] X. Chen, J. Guhl, Industrial Robot Control with Object Recognition based on Deep Learning, *Procedia CIRP*, 76 (2018) 149-154.
- [87] E. Solowjow, I. Ugalde, Y. Shahapurkar, J. Aparicio, J. Mahler, V. Satish, K. Goldberg, H. Claussen, Industrial Robot Grasping with Deep Learning using a Programmable Logic Controller (PLC), in: *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*, 2020, pp. 97-103.
- [88] C. Zhang, Y. Jing, G. Zhou, H. Yan, F. Chang, Heterogeneous knowledge graph-driven subassembly identification with ensemble deep learning in Industry 4.0, *International Journal of Production Research*, (2024) 1-17.
- [89] H. Oliff, Y. Liu, M. Kumar, M. Williams, M. Ryan, Reinforcement learning for facilitating human-robot-interaction in manufacturing, *Journal of Manufacturing Systems*, 56 (2020) 326-340.

- [90] J. Li, D. Pang, Y. Zheng, X. Guan, X. Le, A flexible manufacturing assembly system with deep reinforcement learning, *Control Engineering Practice*, 118 (2022).
- [91] A.G. Dharmawan, Y. Xiong, S. Foong, G.S. Soh, A Model-Based Reinforcement Learning and Correction Framework for Process Control of Robotic Wire Arc Additive Manufacturing, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 4030-4036.
- [92] F. Fan, G. Xu, N. Feng, L. Li, W. Jiang, L. Yu, X. Xiong, Spatiotemporal path tracking via deep reinforcement learning of robot for manufacturing internal logistics, *Journal of Manufacturing Systems*, 69 (2023) 150-169.
- [93] M. Jiang, Y. Guo, S. Huang, J. Pu, L. Zhang, S. Wang, A novel fine-grained assembly sequence planning method based on knowledge graph and deep reinforcement learning, *Journal of Manufacturing Systems*, 76 (2024) 371-384.
- [94] Y.Q. Wang, Y.D. Hu, S.E. Zaatari, W.D. Li, Y. Zhou, Optimised Learning from Demonstrations for Collaborative Robots, *Robotics and Computer-Integrated Manufacturing*, 71 (2021).
- [95] S. Scherzinger, A. Roennau, R. Dillmann, Contact Skill Imitation Learning for Robot-Independent Assembly Programming, in: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019, pp. 4309-4316.
- [96] T. Zhang, H. Sun, Y. Zou, H. Chu, An electromyography signals-based human-robot collaboration method for human skill learning and imitation, *Journal of Manufacturing Systems*, 64 (2022) 330-343.
- [97] S. Ji, S. Lee, S. Yoo, I. Suh, I. Kwon, F.C. Park, S. Lee, H. Kim, Learning-Based Automation of Robotic Assembly for Smart Manufacturing, *Proceedings of the IEEE*, 109 (2021) 423-440.
- [98] L. Ren, H. Wang, J. Dong, Z. Jia, S. Li, Y. Wang, Y. Laili, D. Huang, L. Zhang, W. Wu, B. Li, Industrial foundation model: architecture, key technologies, and typical applications, *Scientia Sinica Informationis*, 54 (2024) 2606-2622.
- [99] Y. Tanaka, S. Katsura, A Voice-Controlled Motion Reproduction Using Large Language Models for Polishing Robots, in: 2023 IEEE International Conference on Mechatronics (ICM), 2023, pp. 1-6.
- [100] T. Wang, J. Fan, P. Zheng, An LLM-based vision and language cobot navigation approach for Human-centric Smart Manufacturing, *Journal of Manufacturing Systems*, 75 (2024) 299-305.
- [101] M. Fakihi, R. Dharmaji, Y. Moghaddas, G.Q. Araya, O. Ogundare, M.A.A. Faruque, LLM4PIC: Harnessing large Language Models for Verifiable Programming of PICs in Industrial Control Systems, in: 2024 IEEE/ACM 46th International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP), 2024, pp. 192-203.
- [102] H. Fan, X. Liu, J.Y.H. Fuh, W.F. Lu, B. Li, Embodied intelligence in manufacturing: leveraging large language models for autonomous industrial robotics, *Journal of Intelligent Manufacturing*, (2024).
- [103] Y. Gan, B. Zhang, J. Shao, Z. Han, A. Li, X. Dai, Embodied Intelligence: Bionic Robot Controller Integrating Environment Perception, Autonomous Planning, and Motion Control, *Ieee Robotics and Automation Letters*, 9 (2024) 4559-4566.
- [104] C. Gkournelos, C. Konstantinou, S. Makris, An LLM-based approach for enabling seamless Human-Robot collaboration in assembly, *CIRP Annals*, 73 (2024) 9-12.
- [105] J. Xu, Y. Xie, F. Iida, Embodied Intelligence in Additive Manufacturing, *IOP Conference Series: Materials Science and Engineering*, 1321 (2024) 012005.
- [106] Y. Peng, Z. Wang, Y. Zhang, S. Zhang, N. Cai, F. Wu, M. Chen, Revolutionizing Battery Disassembly: The Design and Implementation of a Battery Disassembly Autonomous Mobile Manipulator Robot(BEAM-1), in: 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024, pp. 6367-6374.

- [107] H. Zhao, F. Pan, H. Ping, Y. Zhou, Agent as Cerebrum, Controller as Cerebellum: Implementing an Embodied LMM-based Agent on Drones arXiv, Agent as Cerebrum, Controller as Cerebellum: Implementing an Embodied LMM-based Agent on Drones [arXiv], (2024).
- [108] H. You, T. Zhou, Q. Zhu, Y. Ye, E.J. Du, Embodied AI for dexterity-capable construction Robots: DEXBOT framework, *Advanced Engineering Informatics*, 62 (2024) 102572.
- [109] Y. Bei, Z. Fang, S. Mao, S. Yu, Y. Jiang, Y. Tong, W. Cai, Manufacturing Domain QA with Integrated Term Enhanced RAG, in: 2024 International Joint Conference on Neural Networks (IJCNN), 2024, pp. 1-8.
- [110] A. Chandrasekhar, J. Chan, F. Ogoke, O. Ajenifujah, A. Barati Farimani, AMGPT: A large language model for contextual querying in additive manufacturing, *Additive Manufacturing Letters*, 11 (2024) 100232.
- [111] H. Choi, J. Jeong, A Conceptual Framework for a Latest Information-Maintaining Method Using Retrieval-Augmented Generation and a Large Language Model in Smart Manufacturing: Theoretical Approach and Performance Analysis, *Machines*, 13 (2025).
- [112] H. Choi, J. Jeong, Domain-Specific Manufacturing Analytics Framework: An Integrated Architecture with Retrieval-Augmented Generation and Ollama-Based Models for Manufacturing Execution Systems Environments, in: *Processes*, 2025.
- [113] J.A. Heredia Álvaro, J.G. Barreda, An advanced retrieval-augmented generation system for manufacturing quality control, *Advanced Engineering Informatics*, 64 (2025).
- [114] P. Liu, L. Qian, X. Zhao, B. Tao, Joint Knowledge Graph and Large Language Model for Fault Diagnosis and Its Application in Aviation Assembly, *IEEE Transactions on Industrial Informatics*, 20 (2024) 8160-8169.
- [115] Y. Song, P. Sun, H. Liu, Z. Li, W. Song, Y. Xiao, X. Zhou, Scene-Driven Multimodal Knowledge Graph Construction for Embodied AI, *IEEE Transactions on Knowledge and Data Engineering*, 36 (2024) 6962-6976.
- [116] A. O'Neill, A. Rehman, A. Maddukuri, A. Gupta, A. Padalkar, A. Lee, A. Pooley, A. Gupta, A. Mandlekar, A. Jain et al., Open X-Embodiment: Robotic Learning Datasets and RT-X Models : Open X-Embodiment Collaboration0, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), 2024, pp. 6892-6903.
- [117] V. Hammerstingl, G. Reinhart, Skills in Assembly, in, *Institut für Werkzeugmaschinen und Betriebswissenschaften (iwb)*, 2018.
- [118] J. Backhaus, G. Reinhart, Digital description of products, processes and resources for task-oriented programming of assembly systems, *Journal of Intelligent Manufacturing*, 28 (2017) 1787-1800.
- [119] R.K.-J. Lee, H. Zheng, Y. Lu, Human-Robot Shared Assembly Taxonomy: A step toward seamless human-robot knowledge transfer, *Robotics and Computer-Integrated Manufacturing*, 86 (2024) 102686.
- [120] I. Kostavelis, L. Nalpantidis, R. Detry, H. Bruyninckx, A. Billard, S. Christian, M. Bosch, K. Andronikidis, H. Lund-Nielsen, P. Yosefipor, U. Wajid, R. Tomar, F.L. Martinez, F. Fugaroli, D. Papargyriou, N. Mehandjiev, G. Bhullar, E. Goncalves, J. Bentzen, M. Essenbak, C. Cremona, M. Wong, M. Sanchez, D. Giakoumis, D. Tzovaras, RoBetArme Project: Human-robot collaborative construction system for shotcrete digitization and automation through advanced perception, cognition, mobility and additive manufacturing skills, *Open research Europe*, 4 (2024) 4.

- [121] I.-M. Sarivan, O. Madsen, B.V. Wæhrens, Automatic welding-robot programming based on product-process-resource models, *The International Journal of Advanced Manufacturing Technology*, 132 (2024) 1931-1950.
- [122] L. Wang, S. Jia, G. Wang, A. Turner, S. Ratchev, Enhancing Learning Capabilities of Movement Primitives under Distributed Probabilistic Framework for Assembly Tasks, in: 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2020, pp. 3832-3838.
- [123] FANUC, Cobot and Robot Automation Solutions for Dispensing and Sealing, in, <https://www.fanucamerica.com/solutions/applications/dispensing-robot-adhesive-dispensing-systems>.
- [124] F. Nägele, L. Halt, P. Tenbrock, A. Pott, A Prototype-Based Skill Model for Specifying Robotic Assembly Tasks, in: 2018 IEEE International Conference on Robotics and Automation (ICRA), 2018, pp. 558-565.
- [125] J. Zhao, B. Vogel-Heuser, J. Ao, Y. Wu, L. Zhang, F. Hartl, D. Hujo, Z. Bing, F. Wu, A. Knoll, S. Haddadin, B. Vojanec, T. Markert, A. Kraft, Ontology Based AI Planning and Scheduling for Robotic Assembly, in: 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024, pp. 9855-9862.
- [126] M. Mayr, F. Rovida, V. Krueger, Ieee, SkiROS2: A skill-based Robot Control Platform for ROS, in: IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Detroit, MI, 2023, pp. 6273-6280.
- [127] M. Pantano, T. Eiband, D. Lee, Capability-based Frameworks for Industrial Robot Skills: a Survey, in: 2022 IEEE 18th International Conference on Automation Science and Engineering (CASE), 2022, pp. 2355-2362.
- [128] J. Huckaby, H.I. Christensen, A Taxonomic Framework for Task Modeling and Knowledge Transfer in Manufacturing Robotics, in: CogRob@AAAI, 2012.
- [129] U. Thomas, G. Hirzinger, B. Rumpe, C. Schulze, A. Wortmann, A new skill based robot programming language using UML/P Statecharts, in: 2013 IEEE International Conference on Robotics and Automation, 2013, pp. 461-466.
- [130] M. Stenmark, J. Malec, Knowledge-based instruction of manipulation tasks for industrial robotics, *Robotics and Computer-Integrated Manufacturing*, 33 (2015) 56-67.
- [131] P. Schäfer, F. Steinmetz, S. Schneyer, T. Bachmann, T. Eiband, F. Lay, A. Padalkar, C. Sürig, F. Stulp, K. Nottensteiner, Flexible Robotic Assembly Based on Ontological Representation of Tasks, Skills, and Resources, 2021.
- [132] R.H. Andersen, T. Solund, J. Hallam, Definition and Initial Case-Based Evaluation of Hardware-Independent Robot Skills for Industrial Robotic Co-Workers, in: ISR/Robotik 2014; 41st International Symposium on Robotics, 2014, pp. 1-7.
- [133] C. Schou, R.S. Andersen, D. Chrysostomou, S. Bøgh, O. Madsen, Skill-based instruction of collaborative robots in industrial settings, *Robotics and Computer-Integrated Manufacturing*, 53 (2018) 72-80.
- [134] F. Steinmetz, A. Wollschläger, R. Weitschat, RAZER—A HRI for Visual Task-Level Programming and Intuitive Skill Parameterization, *IEEE Robotics and Automation Letters*, 3 (2018) 1362-1369.
- [135] F. Steinmetz, V. Nitsch, F. Stulp, Intuitive Task-Level Programming by Demonstration Through Semantic Skill Recognition, *IEEE Robotics and Automation Letters*, 4 (2019) 3742-3749.

- [136] C. Willibald, T. Eiband, D. Lee, Collaborative Programming of Conditional Robot Tasks, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020, pp. 5402-5409.
- [137] M.J. Aein, E.E. Aksoy, M. Tamosiunaite, J. Papon, A. Ude, F. Wörgötter, Toward a library of manipulation actions based on semantic object-action relations, in: 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2013, pp. 4555-4562.
- [138] M. Stenmark, E.A. Topp, M. Haage, J. Malec, Knowledge for Synchronized Dual-Arm Robot Programming, in: AAAI Fall Symposia, 2017.
- [139] P. Zimmermann, E. Axmann, B. Brandenbourger, K. Dorofeev, A. Mankowski, P. Zanini, Skill-based Engineering and Control on Field-Device-Level with OPC UA, in: 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2019, pp. 1101-1108.
- [140] C.A.A. Calderon, R.E. Mohan, Z. Changjiu, Teaching new tricks to a robot learning to solve a task by imitation, in: 2010 IEEE Conference on Robotics, Automation and Mechatronics, 2010, pp. 256-262.
- [141] Y. Pane, E. Aertbeliën, J.D. Schutter, W. Decré, Skill-based Programming Framework for Composable Reactive Robot Behaviors, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020, pp. 7087-7094.
- [142] L.C. Sørensen, S. Mathiesen, R. Waspe, C. Schlette, Towards Digital Twins for Industrial Assembly - Improving Robot Solutions by Intuitive User Guidance and Robot Programming, in: 2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2020, pp. 1480-1484.
- [143] Y. Wang, Y. Jiao, R. Xiong, H. Yu, J. Zhang, Y. Liu, MASD: A Multimodal Assembly Skill Decoding System for Robot Programming by Demonstration, IEEE Transactions on Automation Science and Engineering, 15 (2018) 1722-1734.
- [144] F. Dai, A. Wahrburg, B. Matthias, H. Ding, Robot Assembly Skills Based on Compliant Motion, in: Proceedings of ISR 2016: 47th International Symposium on Robotics, 2016, pp. 1-6.
- [145] M. weser, J. Zhang, Autonomous planning for mobile manipulation services based on multi-level robot skills, in: 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2009, pp. 1999-2004.
- [146] M. Stenmark, E.A. Topp, From Demonstrations to Skills for High-Level Programming of Industrial Robots, in: AAAI Fall Symposia, 2016.
- [147] E.A. Topp, M. Stenmark, A. Ganslandt, A. Svensson, M. Haage, J. Malec, Ontology-Based Knowledge Representation for Increased Skill Reusability in Industrial Robots, in: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018, pp. 5672-5678.
- [148] L. Rozo, M. Guo, A.G. Kupcsik, M. Todescato, P. Schillinger, M. Giftthaler, M. Ochs, M. Spies, N. Waniek, P. Kesper, M. Burger, Learning and Sequencing of Object-Centric Manipulation Skills for Industrial Tasks, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020, pp. 9072-9079.
- [149] G. Bruno, D. Antonelli, Dynamic task classification and assignment for the management of human-robot collaborative teams in workcells, The International Journal of Advanced Manufacturing Technology, 98 (2018) 2415-2427.

- [150] M.R. Pedersen, D.L. Herzog, V. Krüger, Intuitive skill-level programming of industrial handling tasks on a mobile manipulator, in: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2014, pp. 4523-4530.
- [151] M.R. Pedersen, L. Nalpantidis, R.S. Andersen, C. Schou, S. Bøgh, V. Krüger, O. Madsen, Robot skills for manufacturing: From concept to industrial deployment, *Robotics and Computer-Integrated Manufacturing*, 37 (2016) 282-291.
- [152] C. Cai, Y. Liang, N. Somani, Y. Wu, Inferring the Geometric Nullspace of Robot Skills from Human Demonstrations, 2020 IEEE International Conference on Robotics and Automation (ICRA), (2020) 7668-7675.
- [153] L. Johannsmeier, S. Haddadin, A Hierarchical Human-Robot Interaction-Planning Framework for Task Allocation in Collaborative Industrial Assembly Processes, *IEEE Robotics and Automation Letters*, 2 (2017) 41-48.
- [154] R.E. Andersen, E.B. Hansen, D. Cerny, S. Madsen, B. Pulendralingam, S. Bøgh, D. Chrysostomou, Integration of a Skill-based Collaborative Mobile Robot in a Smart Cyber-physical Environment, *Procedia Manufacturing*, 11 (2017) 114-123.
- [155] V. Krueger, A. Chazoule, M. Crosby, A. Lasnier, M.R. Pedersen, F. Rovida, L. Nalpantidis, R. Petrick, C. Toscano, G. Veiga, A Vertical and Cyber-Physical Integration of Cognitive Robots in Manufacturing, *Proceedings of the IEEE*, 104 (2016) 1114-1127.
- [156] V. Krueger, F. Rovida, B. Grossmann, R. Petrick, M. Crosby, A. Charzoule, G. Martin Garcia, S. Behnke, C. Toscano, G. Veiga, Testing the vertical and cyber-physical integration of cognitive robots in manufacturing, *Robotics and Computer-Integrated Manufacturing*, 57 (2019) 213-229.
- [157] L. Johannsmeier, M. Gerchow, S. Haddadin, A Framework for Robot Manipulation: Skill Formalism, Meta Learning and Adaptive Control, in: 2019 International Conference on Robotics and Automation (ICRA), 2019, pp. 5844-5850.
- [158] L. Heuss, G. Reinhart, Integration of Autonomous Task Planning into Reconfigurable Skill-Based Industrial Robots, in: 2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2020, pp. 1293-1296.
- [159] N.M. Ceriani, A.M. Zanchettin, P. Rocco, A. Stolt, A. Robertsson, Reactive Task Adaptation Based on Hierarchical Constraints Classification for Safe Industrial Robots, *IEEE/ASME Transactions on Mechatronics*, 20 (2015) 2935-2949.
- [160] F. Rovida, V. Krüger, Design and development of a software architecture for autonomous mobile manipulators in industrial environments, in: 2015 IEEE International Conference on Industrial Technology (ICIT), 2015, pp. 3288-3295.
- [161] N. Wantia, M. Esen, A. Hengstebeck, F. Heinze, J. Rossmann, J. Deuse, B. Kuhlenkoetter, Task planning for human robot interactive processes, in: 2016 IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA), 2016, pp. 1-8.
- [162] L. Heuss, D. Gebauer, G. Reinhart, Concept for the automated adaption of abstract planning domains for specific application cases in skills-based industrial robotics, *Journal of Intelligent Manufacturing*, 35 (2024) 4233-4258.
- [163] T. Hoebert, W. Lepuschitz, M. Vincze, M. Merdan, Knowledge-driven framework for industrial robotic systems, *Journal of Intelligent Manufacturing*, 34 (2023) 771-788.
- [164] S. Bøgh, O.S. Nielsen, M.R. Pedersen, V. Krüger, O. Madsen, Does your Robot have Skills, in, 2012.

- [165] J. Michniewicz, G. Reinhart, Cyber-Physical-Robotics – Modelling of modular robot cells for automated planning and execution of assembly tasks, *Mechatronics*, 34 (2016) 170-180.
- [166] T. Wiese, J. Abicht, C. Friedrich, A. Hellmich, S. Ihlenfeldt, Flexible skill-based control for robot cells in manufacturing, *Frontiers in Robotics and Ai*, 9 (2022).
- [167] P. Koch, P. Rawal, N. Töpfer, T. Haß, C. Böhlmann, W. Hintze, Modular lightweight robot system for aircraft production using a generic OPC UA skill concept, *Production Engineering*, 17 (2023) 329-339.
- [168] C. Li, T. Yu, Q. Chang, Robot Learning from Demonstration based on Human-in-the-loop Reinforcement Learning, in: 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE), 2024, pp. 2633-2638.
- [169] C. Eymüller, J. Hanke, A. Poeppel, W. Reif, Towards Self-Configuring Plug & Produce Robot Systems Based on Ontologies, in: 2023 9th International Conference on Automation, Robotics and Applications (ICARA), 2023, pp. 23-27.
- [170] K. Chen, Z. Bing, F. Wu, Y. Meng, A. Kraft, S. Haddadin, A. Knoll, Contact-Aware Shaping and Maintenance of Deformable Linear Objects With Fixtures, in: 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2023, pp. 1-8.
- [171] Q. Yang, J.A. Stork, T. Stoyanov, Learn from Robot: Transferring Skills for Diverse Manipulation via Cycle Generative Networks, in: 2023 IEEE 19th International Conference on Automation Science and Engineering (CASE), 2023, pp. 1-6.
- [172] K. Wang, Y. Zhao, S. Dai, M. Yang, Y. He, N. Zhang, Learning Hierarchical Robot Skills Represented by Behavior Trees from Natural Language, *Cooperative Information Systems: 29th International Conference, CoopIS 2023, Proceedings. Lecture Notes in Computer Science (14353)*, (2024) 366-383.
- [173] Y.M. Ning, T.J. Li, C. Yao, W.Q. Du, Y. Zhang, Y.H. Huang, MT-RSL: A multitasking-oriented robot skill learning framework based on continuous dynamic movement primitives for improving efficiency and quality in robot-based intelligent operation, *Robotics and Computer-Integrated Manufacturing*, 90 (2024).
- [174] I. Kessler, A. Perzylo, Flexible modeling and execution of semantic manufacturing processes for robot systems, 2024 IEEE 29th International Conference on Emerging Technologies and Factory Automation (ETFA), (2024) 1-8.
- [175] Z. Dong, S. Liu, T. Zhou, H. Cheng, L. Zeng, X. Yu, H. Liu, PPR-Net: Point-wise Pose Regression Network for Instance Segmentation and 6D Pose Estimation in Bin-picking Scenarios, in: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019, pp. 1773-1780.
- [176] L. Zeng, W.J. Lv, Z.K. Dong, Y.J. Liu, PPR-Net++: Accurate 6-D Pose Estimation in Stacked Scenarios, *IEEE Transactions on Automation Science and Engineering*, 19 (2022) 3139-3151.
- [177] H. Zhang, H. Liang, L. Cong, J. Lyu, L. Zeng, P. Feng, J. Zhang, Reinforcement Learning Based Pushing and Grasping Objects from Ungraspable Poses, in: 2023 IEEE International Conference on Robotics and Automation (ICRA), 2023, pp. 3860-3866.
- [178] L. Zhao, M. Sun, W.J. Lv, X.Y. Zhang, L. Zeng, Domain Adaptation on Point Clouds for 6D Pose Estimation in Bin-Picking Scenarios, in: 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2023, pp. 2925-2931.

- [179] D.T. Huang, E.T. Lin, L. Chen, L.F. Liu, L. Zeng, SD-Net: Symmetric-Aware Keypoint Prediction and Domain Adaptation for 6D Pose Estimation In Bin-picking Scenarios, in: 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024, pp. 2747-2754.
- [180] M. Krä, L. Vogt, C. Härdtlein, S. Schiele, J. Schilp, Production planning for collaborating resources in cyber-physical production systems, *Procedia CIRP*, 93 (2020) 192-197.
- [181] R. Lankin, K. Kim, P.C. Huang, ROS-Based Robot Simulation for Repetitive Labor-Intensive Construction Tasks, in: 2020 IEEE 18th International Conference on Industrial Informatics (INDIN), 2020, pp. 206-213.
- [182] X.H. Jing, X. Xiong, F.H. Li, T. Zhang, L. Zeng, A Two-Stage Reinforcement Learning Approach for Robot Navigation in Long-range Indoor Dense Crowd Environments, in: 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2024, pp. 5489-5496.
- [183] Y.F. Tang, C. Tai, F.X. Chen, W.T. Zhang, T. Zhang, X.P. Liu, Y.J. Liu, L. Zeng, Mobile Robot Oriented Large-Scale Indoor Dataset for Dynamic Scene Understanding, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), 2024, pp. 613-620.
- [184] F. Rovida, D. Wuthier, B. Grossmann, M. Fumagalli, V. Krüger, Motion Generators Combined with Behavior Trees: A Novel Approach to Skill Modelling, in: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018, pp. 5964-5971.
- [185] I. Lopez-Juarez, Skill acquisition for industrial robots: From stand-alone to distributed learning, in: 2016 IEEE International Conference on Automatica (ICA-ACCA), 2016, pp. 1-5.
- [186] A.T. Le, M. Guo, N.v. Duijkeren, L. Rozo, R. Krug, A.G. Kupcsik, M. Bürger, Learning Forceful Manipulation Skills from Multi-modal Human Demonstrations, in: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2021, pp. 7770-7777.
- [187] A. Lämmle, P. Tenbrock, B. Bálint, F. Nägele, W. Kraus, J. Váncza, M.F. Huber, Simulation-based Learning of the Peg-in-Hole Process Using Robot-Skills, in: 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2022, pp. 9340-9346.
- [188] S.C. Akkaladevi, A. Pichler, M. Plasch, M. Ikeda, M. Hofmann, Skill-based programming of complex robotic assembly tasks for industrial application, *e & i Elektrotechnik und Informationstechnik*, 136 (2019) 326-333.
- [189] K. Karacan, R.J. Kirschner, H. Sadeghian, F. Wu, S. Haddadin, Tactile Robot Programming: Transferring Task Constraints into Constraint-Based Unified Force-Impedance Control, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), 2024, pp. 204-210.
- [190] W. Li, F. Li, X. Jing, P. Feng, L. Zeng, Dual-Alignment Domain Adaptation for Pedestrian Trajectory Prediction, *IEEE Robotics and Automation Letters*, (2024).
- [191] F.x. Chen, Y. Tang, C. Tai, X.p. Liu, X. Wu, T. Zhang, L. Zeng, FusedNet: End-to-End Mobile Robot Relocalization in Dynamic Large-Scale Scene, *IEEE Robotics and Automation Letters*, 9 (2024) 4099-4105.
- [192] A. Curtis, N. Kumar, J. Cao, T. Lozano-Pérez, L.P. Kaelbling, Trust the P_{Ro}C3S: Solving long-horizon robotics problems with llms and constraint satisfaction, *arXiv preprint arXiv:2406.05572*, (2024).
- [193] M.G. Arenas, T. Xiao, S. Singh, V. Jain, A. Ren, Q. Vuong, J. Varley, A. Herzog, I. Leal, S. Kirmani, M. Prats, D. Sadigh, V. Sindhwani, K. Rao, J. Liang, A. Zeng, How to Prompt Your Robot: A PromptBook for Manipulation Skills with Code as Policies, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), 2024, pp. 4340-4348.

- [194] R. Wiemann, N. Terei, A. Raatz, Large Language Model for Intuitive Control of Robots in Micro-Assembly, in: 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE), 2024, pp. 3957-3962.
- [195] K. Obata, T. Aoki, T. Horii, T. Taniguchi, T. Nagai, LiP-LLM: Integrating Linear Programming and Dependency Graph With Large Language Models for Multi-Robot Task Planning, IEEE Robotics and Automation Letters, 10 (2025) 1122-1129.
- [196] A. Deursen, P. Klint, J. Visser, Domain-Specific Languages: An Annotated Bibliography, SIGPLAN Notices, 35 (2000) 26-36.
- [197] A. Nordmann, N. Hochgeschwender, D. Wigand, S. Wrede, A Survey on Domain-Specific Modeling and Languages in Robotics, Journal of Software Engineering for Robotics, 7 (2016) 75-99.
- [198] B. Siciliano, Springer Handbook of Robotics, in, 2008.
- [199] I. Lanese, U.P. Schultz, I. Ulidowski, Reversible Execution for Robustness in Embodied AI and Industrial Robots, It Professional, 23 (2021) 12-17.
- [200] M. Schäfer, P. Moll, L. Brocke, S. Coutandin, J. Fleischer, Model for Web-Application based Configuration of Modular Production Plants with automated PLC Line Control Code Generation, Procedia CIRP, 83 (2019) 292-297.
- [201] W. Koehler, Y. Jing, A Novel Block-Based Programming Framework for Non-programmers to Validate PLC Based Machine Tools for Automotive Manufacturing Facilities, in: 2018 11th International Conference on Developments in eSystems Engineering (DeSE), 2018, pp. 202-207.
- [202] R. Wang, Y. Wei, H. Song, Y. Jiang, Y. Guan, X. Song, X. Li, From Offline Towards Real-Time Verification for Robot Systems, IEEE Transactions on Industrial Informatics, 14 (2018) 1712-1721.
- [203] J.P. De la Rosa, J. Solis, K. Nakamori, G.A.G. Ricardez, J. Håkansson, A.S. Sorensen, T.R. Silva, From Gestures to Behaviours: An Empirical Study on Behaviour-Driven Development Scenarios to Support End-User Programming of Collaborative Robots, in: 8th IFToMM International Symposium on Robotics and Mechatronics (ISRM), Djerba, TUNISIA, 2024, pp. 369-381.
- [204] V.J.E. Jiménez, H. Zeiner, A Domain Specific Language for Robot Programming in the Wood Industry <i>A Practical Example</i>, in: 14th International Conference on Informatics in Control, Automation and Robotics (ICINCO), Madrid, SPAIN, 2017, pp. 549-555.
- [205] T. Bolwerk, M. Alonso, M. Schuts, Using a Textual DSL With Live Graphical Feedback to Improve the CPS' Design Workflow of Hardware Engineers, 2024 19th Conference on Computer Science and Intelligence Systems (FedCSIS), (2024) 301-312.
- [206] P. Detzner, T. Kirks, J. Jost, A Novel Task Language for Natural Interaction in Human-Robot Systems for Warehouse Logistics, in: 2019 14th International Conference on Computer Science & Education (ICCSE), 2019, pp. 725-730.
- [207] C.J. Sutherland, B. MacDonald, Ieee, <i>RoboLang</i>: A Simple Domain Specific Language to Script Robot Interactions, in: 16th International Conference on Ubiquitous Robots (UR), South Korea, 2019, pp. 265-270.
- [208] T. Elliott, M. Alshiekh, L.R. Humphrey, L. Pike, U. Topcu, Salty-A Domain Specific Language for GR(1) Specifications and Designs, in: 2019 International Conference on Robotics and Automation (ICRA), 2019, pp. 4545-4551.
- [209] A.C. Jiménez, J.P. Anzola, V. García-Díaz, R.G. Crespo, L.P. Zhao, PyDSLRep: A domain-specific language for robotic simulation in V-Rep, Plos One, 15 (2020).
- [210] D. Fogli, L. Gargioni, G. Guida, F. Tampalini, A hybrid approach to user-oriented programming of collaborative robots, Robotics and Computer-Integrated Manufacturing, 73 (2022) 102234.

- [211] M. Rizwan, C. Reichenbach, R. Caldas, M. Mayr, V. Krueger, EzSkiROS: enhancing robot skill composition with embedded DSL for early error detection, *Frontiers in Robotics and Ai*, 11 (2025).
- [212] B. Ridge, T. Gaspar, A. Ude, Rapid state machine assembly for modular robot control using meta-scripting, templating and code generation, in: 2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids), 2017, pp. 661-668.
- [213] T.B. Ionescu, Assembly: A Web-Based Multi-Robot Programming and Simulation Tool, *IFAC-PapersOnLine*, 55 (2022) 313-318.
- [214] B. Wesselink, K. de Vos, I. Kuertev, M. Reniers, E. Torta, Ieee, RoboSC: a domain-specific language for supervisory controller synthesis of ROS applications, in: IEEE International Conference on Robotics and Automation (ICRA), London, ENGLAND, 2023, pp. 9090-9096.
- [215] M. Ghallab, C. Knoblock, D. Wilkins, A. Barrett, D. Christianson, M. Friedman, C. Kwok, K. Golden, S. Penberthy, D. Smith, Y. Sun, D. Weld, PDDL - The Planning Domain Definition Language, (1998).
- [216] W. Barnett, A. Cavalcanti, A. Miyazawa, Architectural modelling for robotics: RoboArch and the CorteX example, *Frontiers in Robotics and Ai*, 9 (2022).
- [217] S. Wanna, F. Parra, R. Valner, K. Kruusamae, M. Pryor, Unlocking underrepresented use-cases for large language model-driven human-robot task planning, *Advanced Robotics*, 38 (2024) 1335-1348.
- [218] L.C. Xiao, L. Zeng, Z.B. Xu, X.P. Liu, Assembly language design and development for reconfigurable flexible assembly line, *Robotics and Computer-Integrated Manufacturing*, 80 (2023).
- [219] L. Xiao, X. Jing, L. Zeng, X. Liu, A flexible control system for reconfigurable assembly lines, in: *Journal of Physics: Conference Series*, IOP Publishing, 2021, pp. 012001.
- [220] Z. Xu, C. Zhang, S. Hu, Z. Han, P. Feng, L. Zeng, Reconfigurable flexible assembly model and implementation for cross-category products, *Journal of Manufacturing Systems*, 77 (2024) 154-169.
- [221] J. Gan, L. Zeng, F. Shi, Reconfigurable Flexible Assembly Line Balancing Problem Based on Reinforcement Learning, in: 2022 IEEE 9th International Conference on Industrial Engineering and Applications (ICIEA 2022), 2022.
- [222] N. Koenig, A. Howard, Design and use paradigms for Gazebo, an open-source multi-robot simulator, in: 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566), 2004, pp. 2149-2154 vol.2143.
- [223] Y. Zhang, L. Li, M. Ripperger, J. Nicho, M. Veeraraghavan, A. Fumagalli, Gilbreth: A Conveyor-Belt Based Pick-and-Sort Industrial Robotics Application, in: 2018 Second IEEE International Conference on Robotic Computing (IRC), 2018, pp. 17-24.
- [224] D. Marek, P. Biernacki, J. Szyguła, A. Domański, General Concepts of a Simulation Method for Automated Guided Vehicle in Industry 4.0, in: 2022 IEEE International Conference on Big Data (Big Data), 2022, pp. 6306-6314.
- [225] G. Tuo, T. Li, H. Qin, B. Huang, K. Liu, Y. Wang, Control of Nameplate Pasting Robot for Sand Mold Based on Deep Reinforcement Learning, in: H. Yu, J. Liu, L. Liu, Z. Ju, Y. Liu, D. Zhou (Eds.) *Intelligent Robotics and Applications*, Springer International Publishing, Cham, 2019, pp. 368-378.
- [226] M. Aksu, J.L. Michaloski, F.M. Proctor, Asme, VIRTUAL EXPERIMENTAL INVESTIGATION FOR INDUSTRIAL ROBOTICS IN GAZEBO ENVIRONMENT, in: ASME International Mechanical Engineering Congress and Exposition (IMECE2018), Pittsburgh, PA, 2018.
- [227] E. Todorov, T. Erez, Y. Tassa, Mujoco: A physics engine for model-based control, in: 2012 IEEE/RSJ international conference on intelligent robots and systems, IEEE, 2012, pp. 5026-5033.

- [228] W. Tang, Y. Jiang, C. Zeng, H. Zhang, H. Zhong, A reinforcement learning based control framework for robot gear assembly with demonstration learning and force feedback, in: 2024 IEEE International Conference on Industrial Technology (ICIT), 2024, pp. 1-6.
- [229] Q. Liu, Z. Ji, W. Xu, Z. Liu, B. Yao, Z. Zhou, Knowledge-guided robot learning on compliance control for robotic assembly task with predictive model, *Expert Systems with Applications*, 234 (2023) 121037.
- [230] E. Rohmer, S.P.N. Singh, M. Freese, V-REP: A versatile and scalable robot simulation framework, in: 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2013, pp. 1321-1326.
- [231] D. Bringas-Posadas, H.D. Devillet-Castellanos, C.E. Cruz-González, I.G. Flores, B.V. Arista, E.A. Franco-Urquiza, Development of a digital twin and lab-scale manufacturing system for production sequences planning, *The International Journal of Advanced Manufacturing Technology*, 136 (2025) 5515-5530.
- [232] Y. Yuan, S. Wang, Y. Mei, W. Zhang, J. Sun, G. Wang, Improving world models for robot arm grasping with backward dynamics prediction, *International Journal of Machine Learning and Cybernetics*, 15 (2024) 3879-3891.
- [233] J. Huanca, J. Zamora, J. Cornejo, R. Palomares, Mechatronic Design and Kinematic Analysis of 8 DOF Serial Robot Manipulator to Perform Electrostatic Spray Painting Process on Electrical Panels, in: 2022 IEEE Engineering International Research Conference (EIRCON), 2022, pp. 1-4.
- [234] E. Coumans, Y. Bai, Pybullet, a python module for physics simulation for games, robotics and machine learning, in, 2016.
- [235] H. Sun, Z. Zhang, H. Wang, Y. Wang, Q. Cao, A Novel Robotic Grasp Detection Framework Using Low-Cost RGB-D Camera for Industrial Bin Picking, *IEEE Transactions on Instrumentation and Measurement*, 73 (2024) 1-12.
- [236] Y.J. Zang, P.F. Wang, F.S. Zha, W. Guo, C. Zheng, L.N. Sun, Peg-in-hole assembly skill imitation learning method based on ProMPs under task geometric representation, *Frontiers in Neurorobotics*, 17 (2023).
- [237] J. Li, H. Shi, K.S. Hwang, Using Goal-Conditioned Reinforcement Learning With Deep Imitation to Control Robot Arm in Flexible Flat Cable Assembly Task, *IEEE Transactions on Automation Science and Engineering*, 21 (2024) 6217-6228.
- [238] V. Makoviychuk, L. Wawrzyniak, Y. Guo, M. Lu, K. Storey, M. Macklin, D. Hoeller, N. Rudin, A. Allshire, A. Handa, Isaac gym: High performance gpu-based physics simulation for robot learning, *arXiv preprint arXiv:2108.10470*, (2021).
- [239] NVIDIA, Nvidia isaac sim: Robotics simulation and synthetic data, in, <https://developer.nvidia.com/isaac-sim>, 2023.
- [240] H.S. Kim, RoboManuGen: Robot Data Generation Using Generative AI for Manufacturing, in: 2024 15th International Conference on Information and Communication Technology Convergence (ICTC), 2024, pp. 2001-2004.
- [241] E. Kolve, R. Mottaghi, W. Han, E. VanderBilt, L. Weihs, A. Herrasti, M. Deitke, K. Ehsani, D. Gordon, Y. Zhu, Ai2-thor: An interactive 3d environment for visual ai, *arXiv preprint arXiv:1712.05474*, (2017).
- [242] X. Puig, K. Ra, M. Boben, J. Li, T. Wang, S. Fidler, A. Torralba, Virtualhome: Simulating household activities via programs, in: *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 8494-8502.

- [243] X. Gao, R. Gong, T. Shu, X. Xie, S. Wang, S.-C. Zhu, Vrkitchen: an interactive 3d virtual environment for task-oriented learning, arXiv preprint arXiv:1903.05757, (2019).
- [244] M. Savva, A. Kadian, O. Maksymets, Y. Zhao, E. Wijmans, B. Jain, J. Straub, J. Liu, V. Koltun, J. Malik, Habitat: A platform for embodied ai research, in: Proceedings of the IEEE/CVF international conference on computer vision, 2019, pp. 9339-9347.
- [245] B. Shen, F. Xia, C. Li, R. Martín-Martín, L. Fan, G. Wang, C. Pérez-D'Arpino, S. Buch, S. Srivastava, L. Tchapmi, igibson 1.0: A simulation environment for interactive tasks in large realistic scenes, in: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2021, pp. 7520-7527.
- [246] C. Li, F. Xia, R. Martín-Martín, M. Lingelbach, S. Srivastava, B. Shen, K.E. Vainio, C. Gokmen, G. Dharan, T. Jain, iGibson 2.0: Object-Centric Simulation for Robot Learning of Everyday Household Tasks, in: Conference on Robot Learning, PMLR, 2022, pp. 455-465.
- [247] C. Gan, J. Schwartz, S. Alter, M. Schrimpf, J. Traer, J. De Freitas, J. Kubilius, A. Bhandwalder, N. Haber, M. Sano, ThreeDWorld: A platform for interactive multi-modal physical simulation, Advances in Neural Information Processing Systems (NeurIPS), (2021).
- [248] KUKA, KUKA.Sim, in, https://www.kuka.com/en-de/products/robot-systems/software/planning-project-engineering-service-safety/kuka_sim.
- [249] ABB, RobotStudio Suite: Visualize your ideas and reduce commissioning time, in, <https://new.abb.com/products/robotics/software-and-digital/robotstudio>.
- [250] FANUC, Simulation Software ROBOGUIDE, in, <https://www.fanuc.eu/eu-en/accessory/software/simulation-software-roboguide>.
- [251] Yaskawa, MotoSim EG-VRC, in, https://www.yaskawa.eu.com/products/software/productdetail/product/motosim-eg-vrc_1686.
- [252] H. Associates, Robotmaster, in, <https://www.robotmaster.com/>.
- [253] RoboDK, RoboDK: Simulator for industrial robots and offline programming, in, <https://robodk.com/>.
- [254] A. Robotics, Artiminds RPS - Intuitive Robot Software for Advanced Robotics, in, <https://www.artiminds.com/robotics-software-and-services/robot-programming-suite-basic/>.
- [255] D. Systèmes, Global Operations Software | DELMIA, in, <https://www.3ds.com/products/delmia>.
- [256] V. Components, Visual Components - 3D Simulation Software, in, <https://www.visualcomponents.com/products/>.
- [257] Siemens, Tecnomatix digital manufacturing software, in, https://plm.sw.siemens.com/en-US/tecnomatix/?srsId=AfmBOqcCMdYptEBiK_oNNfDAxf3mXC4GaexNR-_spDt9cnrSL0W3j6T.
- [258] D. Alejandro, J. Matos, L. Vences, H. Mirko, Analysis of an Automated System in a Robotized Cell for the Transport, Control, Classification, and Organization of Heterogeneous Packages, in: Y. Iano, O. Saotome, G.L. Kemper Vásquez, C. Cotrim Pezzuto, R. Arthur, G. Gomes de Oliveira (Eds.) Proceedings of the 7th Brazilian Technology Symposium (BTSym'21), Springer International Publishing, Cham, 2022, pp. 470-478.
- [259] R. Holubek, D.R. Delgado Sobrino, M. Matusova, A new approach for creating and testing safety components integrated into a robotic cell simulation scenario in a virtual reality environment, Journal of Physics: Conference Series, 2927 (2024) 012002 (012008 pp.)-012002 (012008 pp.).

- [260] A. Sukhovey, A. Gubankov, Collision Avoidance Method for End Effectors of Industrial Robots with Overlapping Workspaces, in: 2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), 2020, pp. 1-5.
- [261] Y. Haixiang, S. Junfeng, Z. Xuejun, Off-line programming and remote control for a palletizing robot, in: 2011 IEEE International Conference on Computer Science and Automation Engineering, 2011, pp. 586-589.
- [262] R. Raffaelli, P. Bilancia, M. Peruzzini, S. Pisu, G. Berselli, M. Pellicciari, Virtual Prototyping and Commissioning of Manufacturing Cycles in Robotic Cells, in: M. Carfagni, R. Furferi, P. Di Stefano, L. Governi, F. Gherardini (Eds.) Design Tools and Methods in Industrial Engineering III, Springer Nature Switzerland, Cham, 2024, pp. 391-398.
- [263] H. Dai, G. Lv, W. Huang, Q. Qin, Analysis for the Process Planning of the Body Side Welding in Delmia, Journal of Physics: Conference Series, 2198 (2022) 012037.
- [264] R. Benotsmane, A. Trohak, R. Bartók, G. Mélypataki, Transformative Learning: Nurturing Novices to Experts through 3D Simulation and Virtual Reality in Education, in: 2024 25th International Carpathian Control Conference (ICCC), 2024, pp. 1-6.
- [265] L. Ren, H. Wang, J. Dong, Z. Jia, S. Li, Y. Wang, Y. Laili, D. Huang, L. Zhang, B. Li, Industrial Foundation Model, IEEE transactions on cybernetics, PP (2025).
- [266] L. Zeng, Z.-k. Dong, J.-y. Yu, J. Hong, H.-y. Wang, Sketch-based retrieval and instantiation of parametric parts, Computer-Aided Design, 113 (2019) 82-95.
- [267] L. Zeng, W.J. Lv, X.Y. Zhang, Y.J. Liu, Parametricnet: 6dof pose estimation network for parametric shapes in stacked scenarios, in: 2021 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2021, pp. 772-778.
- [268] Y.H. Xie, W.J. Lv, X.Y. Zhang, Y.H. Chen, L. Zeng, ParametricNet++: A 6DoF Pose Estimation Network with Sparse Keypoint Recovery for Parametric Shapes in Stacked Scenarios, in: 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2024, pp. 7181-7188.