Human-in-the-Loop Robot Learning for Smart Manufacturing: A Human-Centric Perspective

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***Abstract*— Robot learning has attracted an ever-increasing attention by automating complex tasks, reducing errors, and increasing production speed and flexibility, which leads to significant advancements in manufacturing intelligence. However, its low training efficiency, limited real-time feedback, and challenges in adapting to untrained scenarios hinder its applications in smart manufacturing. Introducing a human role in the training loop, a practice known as human-in-the-loop (HITL) robot learning, can improve the performance of robots by leveraging human prior knowledge. Nonetheless, the exploration of HITL robot learning within the context of human-centric smart manufacturing remains in its infancy. This study provides a holistic literature review for understanding HITL robot learning within an industrial context from a human-centric perspective. A united structure is presented to encompass different aspects of human intelligence in HITL robot learning, highlighting perception, cognition, behavior, and notably, empathy. Then, the typical applications in manufacturing scenarios are analyzed to expand the research landscape for smart manufacturing. Finally, it introduces the empirical challenges and future directions for HITL robot learning in the next industrial revolution era.**

***Note to Practitioners*—This review is motivated by the emergence of the next generation of smart manufacturing, which emphasizes the coexistence of humans and robotics in the manufacturing workstation to mitigate inherent limitations of each. It presents an overview of HITL robot learning-related works to identify state-of-the-art and significant focuses for human-centric smart manufacturing. It classifies representative studies into detailed sub-categories based on various facets of human intelligence, highlighting perception, cognition, behavior, and empathy, providing a complete and detailed survey of this field. The applications in manufacturing scenarios are analyzed, and we discuss the possible challenges and future directions. This paradigm has the potential to revolutionize manufacturing operations, enhancing flexibility, and resilience in supply chains, and efficiency for self-organizing collaborative intelligence and cyber-physical systems toward human-robot coevolution. The goal is to attract scholars in broader research fields to contribute to the development of HITL robot learning for smart manufacturing.**

***Index Terms*— Robot learning, smart manufacturing, human-in-the-loop, human guidance.**

I. Introduction

The design and development of manufacturing systems has undergone a significant transformation with the integration of state-of-the-art technologies such as robotics and artificial intelligence (AI) [1]. The integration and deployment of advanced technologies foster the development of systems that are intelligent, interconnected, and highly automated while providing a significant impact on smart manufacturing [2]. Especially, robots are regarded as a fundamental pillar in achieving outstanding efficiency and capacity, but conventional robots are proficient at performing repetitive and predefined tasks, they lack the ability to adapt to dynamic and unstructured environments [3]. Due to their limited capabilities and intelligence, traditional learning-based methods cannot fully satisfy production needs and handle diverse scenarios in smart manufacturing [4], thereby precluding their ability to entirely supplant human roles in real-world applications. Therefore, it is crucial to incorporate human intelligence into the training loop of robot learning, leveraging human expertise to enhance learning-based algorithms, as humans demonstrate remarkable robustness and adaptability in complex scenarios [5].

As a promising learning paradigm in the fields of robot systems, human-in-the-loop (HITL) robot learning can integrate human intelligence, creativity, and adaptability with the strength and accuracy of robotics to achieve superior performance in manufacturing tasks [6], [7], [8]. By integrating their expertise into automation, smart manufacturing systems can adapt to changing production requirements and handle variability in product specifications. This approach leverages the intelligence of human workers to provide guidance,

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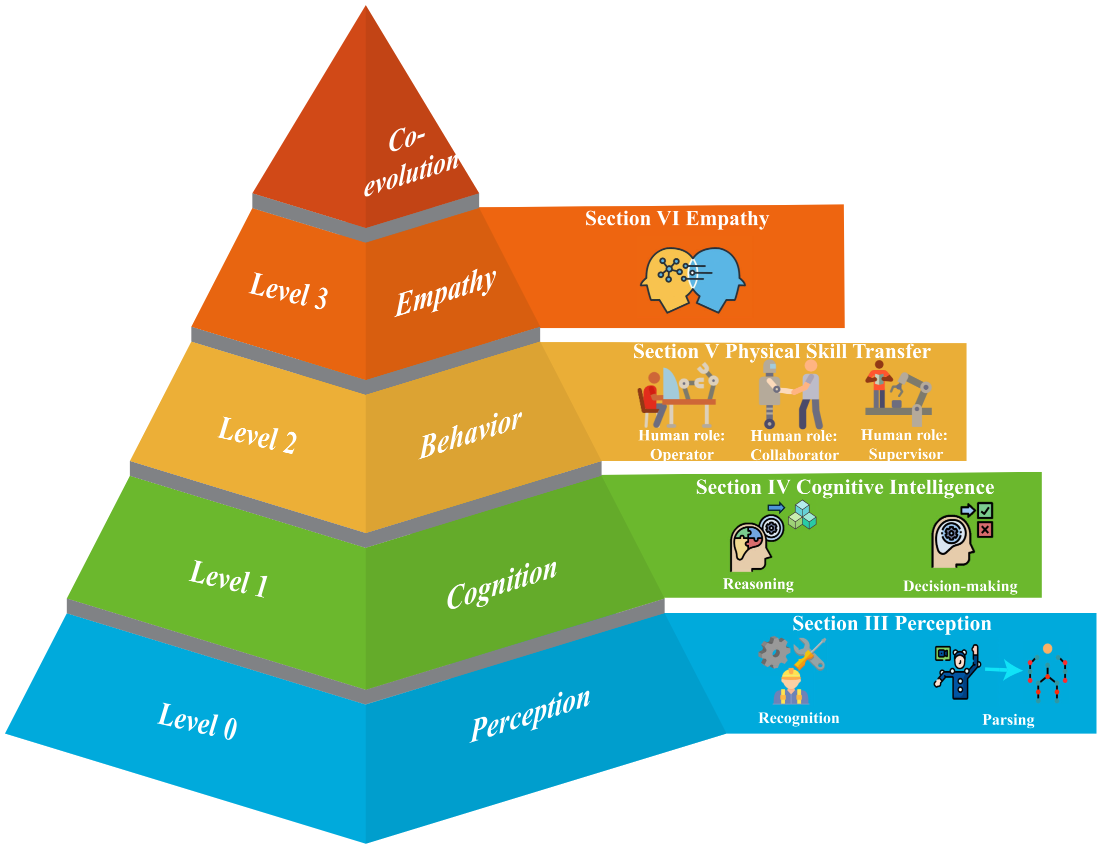

Fig. 1. Overview of the brief categorization of HITL robot learning in this review.

supervision, and feedback to robots, to further advance current abilities of automation systems [9].

The integration of HITL robot learning in smart manufacturing has the potential to revolutionize the way manufacturing operations are conducted [10], [11]. These approaches play a crucial role in facilitating robotics to obtain human prior knowledge, especially in HITL robot systems, allowing humans to focus mainly on higher-value cognitive tasks such as decision-making and problem-solving [12]. This not only improves the overall work environment for human workers but also enhances the degree of informational advancement, manufacturing automation, and digital transformation [13], [14].

Some review papers about similar topics have been published [15], [16], [17], but most concentrate on studies of the characteristics of control and learning methods, often neglecting the critical role and intelligence of human beings in the closed-loop system. To address this shortage, we will present recent works on learning methods, taking into account human intelligence, and summarize domain knowledge beyond previous reviews by presenting a new perspective. The categorization of HITL robot learning in this review is based on different aspects of human intelligence [18], [19], [20], such as perception, cognition, behavior, and empathy (see Fig. 1). Collectively, these elements can help the robotic system become safe, efficient, intelligent, and empathy under the guidance of human in the training loop to achieve ergonomic and self-organizing human-robot coevolution. Although primarily applied within the industrial context, this review extends beyond the limit of the manufacturing sector and sprawls across fields such as healthcare, surgery, intelligent construction, smart agriculture, and social service.

The rest of this paper is organized as follows: Section II outlines an overview and introduces our literature search approach. Section III introduces perception methodologies and technologies, enabling robotics to learn from human guidance. Section IV focuses on facilitating the robots to build cognitive intelligence. Section V summarizes physical skill transfer based on human guidance. Section VI concentrates on how to incorporate the capacity of empathy into HITL robot learning. Section VII delves into HITL robot learning application in smart manufacturing. The current challenges and future perspectives are given in Section VIII. Section IX concludes the main contributions of this review.

II. Overview

A. Robot Learning for Smart Manufacturing

Robotic equipment has been crucial since the first integration of robot manipulators into industrial production lines, presenting infinite potential for industrial automation evolution [21], [22]. Robots like collaborative manipulators, soft robots, automated guided vehicles (AGVs), and unmanned aerial vehicles (UAVs) are widely used to empower the manufacturing system. Towards the next generation of smart manufacturing, the industrial system positions individuals at

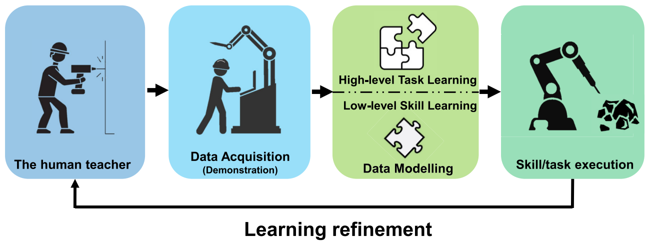

Fig. 2. Workflow illustration of imitation learning.

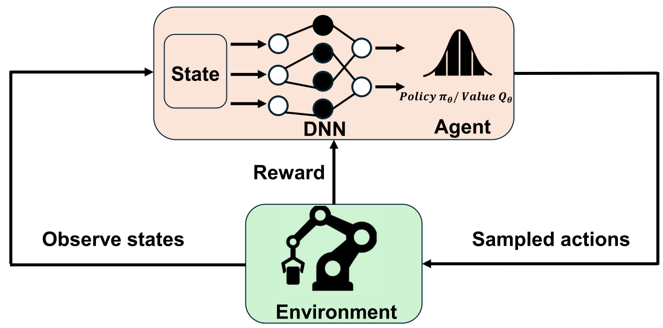

Fig. 3. Learning framework of deep reinforcement learning.

the epicenter of the production ecosystem, utilizing a synergistic combination of humans and robots to augment the well-being and safety conditions of the workforce [23]. Therefore, robots should be released from the limits of old-fashioned hard-programmed solutions and point at more complicated and flexible environments to cater to personal necessities and uphold the manufacturing landscape's imperative for adaptability, nimbleness, and resilience [15], [24].

As the synthesis of diverse machine learning methodologies with robot systems, robot learning is becoming the dominant approach, facilitating robots to learn physical skills with the assistance of humans and enhance their intelligence [25], [26]. While common machine learning pays attention to identification and prediction, robot learning focuses more on generating accurate motions or reactions as the output through perceiving the environment. Concretely, the leading technologies in robot learning consist of two aspects: imitation learning (IL) [17] and deep reinforcement learning (DRL) [27]. For IL, it is also called behavior cloning or learning from demonstration. In this process, a human expert demonstrates the desired skills to robots by providing examples via motion capture, teleportation, or video without programming. The outcome is a policy that guides the robot's actions, aiming to replicate the demonstrated behavior with as much accuracy as possible (see Fig. 2). As for DRL, it combines deep learning (DL) with reinforcement learning (RL) principles to enable autonomous systems to learn optimal behaviors through trial-and-error interactions with the environment or humans in Fig. 3 [28].

In smart manufacturing, robot learning has already demonstrated its initial strength to enable robots to handle more complex industrial operations with a higher degree of collaborative intelligence and natural human-robot interaction (HRI) [19]. Towards more dynamic and stochastic manufacturing environments, robot systems are expected to behave and think more like human beings to relieve humans from heavy workloads significantly [29].

B. Human-in-the-Loop Robot Learning

Since the limited abilities of robot learning are unable to handle various situations and provide personalized production, it is vital to introduce human intelligence into the learning cycle of AI, leveraging human intelligence for further advanced robot learning algorithms to improve the robustness and adaptability of the robot systems in complex scenarios [30], [31].

By classifying different roles, individuals can identify their main works in the training loop for more efficient and effective learning of robots. Human roles in the training loop, categorized into supervisor, operator, and collaborator, have been adapted from past research [5], [32] (see Fig. 1):

- *Operator*: The operator can demonstrate the correct way to perform a task or adjust the parameters of data-driven algorithms, enabling robots to learn more effectively.
- *Collaborator*: The collaborator can cooperate alongside robots and provide real-time feedback during joint actions, helping the robot to learn contextually appropriate behaviors and cooperative strategies.
- *Supervisor*: The supervisor can monitor the training process and score the robots' performance, adjusting learning towards better outcomes.

In Fig. 1, HITL robot learning is broadly classified as follows, including levels 0-3:

- *Level 0–Perception*: The robot can comprehensively understand human instructions through a precise sensing and perception system for efficient HRI and communication.
- *Level 1–Cognition*: Leveraging human cognitive intelligence to improve robot learning, the robot can conduct complex reasoning and make appropriate decisions.
- *Level 2–Behavior*: Humans can transfer physical skills or motion to the robot accurately by incorporating their demonstration, collaboration, and supervision.
- *Level 3–Empathy*: Humans can help robots learn how to respond to human emotions appropriately, enhancing the capacity for social empathy with humans.

Level 0 emphasizes providing an overview of the different strategies and interfaces to endow the robot with interaction capabilities, which is regarded as the crucial and preliminary prerequisite to learning from human behavior and intelligence. With the development of learning-based methods, robots are expected to learn from human thought, such as reasoning and decision-making, which is also what *Level 1* concentrated on. *Level 2* focuses on physical skill transfer to create more intuitive ways for robots to learn from human examples, which is regarded as the expression of cognitive processes. In the last two decades, there have been numerous research contributions for it to achieve precise and dexterous operation. For *Level 3*, robots could involve an understanding of users' moods and the capacity to provide human-like empathy to improve user

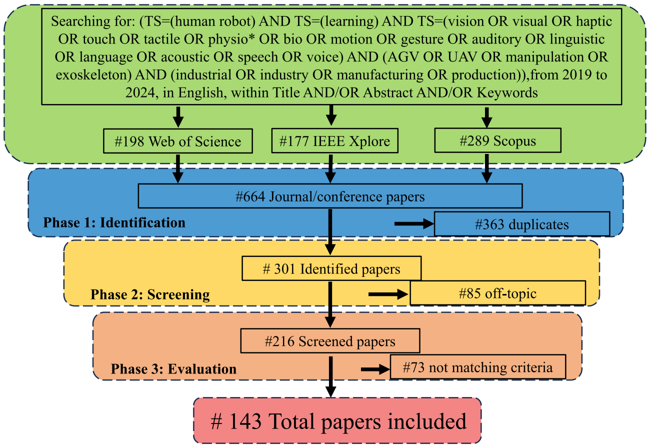

Fig. 4. Searching process and filtering result in this review.

enjoyment and human-robot teaming. In this way, human-robot agents can provide bi-directional learning and co-exploration experiences to promote the human-robot relationship towards coevolution.

C. Literature Review Process

To achieve the systematic literature search and collection of relative research papers, Web of Science (WOS) (https://webofscience.com), Scopus (http://www.scopus.com/) and Institute of Electrical and Electronics Engineers (IEEE) Xplore (https://ieeexplore.ieee.org/) are chosen since they index the high-quality and peer-reviewed publications comprehensively in the engineering field.

Over 20 top-tier journals are highlighted according to their relevance to human factors/intelligence and robot learning, screened based on the Journal Citation Reports in Web of Science. These journal publications include various research areas, such as information science, automation, robotics, and industrial manufacturing. In addition, some significant works should be spotlighted, with published in prominent AI and robotic conferences, like the IEEE International Conference on Robotics and Automation (ICRA) and the Conference on Robot Learning (CoRL).

The initial paper collaboration and the searching process is demonstrated in Fig. 4. In this review paper, two key dimensions are covered: human factors/intelligence and robot learning. Specifically, the search phrase can be duplicated with the following search sentence (WOS version): (TS = (vision OR haptic OR touch OR tactile OR physio* OR emotion OR cognitive OR empathy) AND (human-robot OR “human robot” OR “human factors”) AND (robot learning) AND (industry OR manufacturing OR production) AND (AGV OR UAV OR manipulation OR exoskeleton) AND (PY = 2019 AND 2020 AND 2021 AND 2022 AND 2023 AND 2024))’ (The review only embraces publications available online before May 2024).

According to preliminary searching from databases, WOS, Scopus, and IEEE Xplore provide 198, 289, and 177 papers, respectively. To systematically narrow the scope and generate a high-value review, we identified and excluded working papers, preprints, and duplicates. Then, we screened all the peer-reviewed papers and filtered out works that were off the objective scope based on the abstract. Until this step, there were initially 216 papers in the scope or correlated to our topic. Finally, the main contributions of these papers were evaluated through the methodology and experiment details browsing in articles, leading to only 143 journals and conferences as the reference for our review.

D. Preliminary Results

The gathered literature performed an analysis of HITL robot learning for smart manufacturing. The extended findings, as depicted in Fig. 5 (a), show the number of research works related to HITL robot learning published over the past decade. It can be easily identified that this area has obtained popularity among scholars in recent years due to the consistent rise in the volume of research publications.

Fig. 5 (b) highlights the top three countries in publications’ number ranking: China, the USA, and Germany. It is worth mentioning that all three countries are manufacturing powerhouses and have their own promising blueprints for the next generation of industrial automation. Thus, there is a higher demand for robotics and a growing interest in smart manufacturing in these countries. Besides, Fig. 5 (c) presents the distribution of different human roles for the robot training process in the last five years of studies. *Operator* used to be the predominant role since kinesthetic teaching was the key approach to the early stage of imitation learning. However, from 2021, *supervisor* has obtained more attention and increased significantly since imitation learning hardly fulfills the requirements of training long-horizon tasks. It also stems from the fact that numerous DRL-based or hybrid learning-based methods have been applied to assist robots in learning dexterous manipulation in recent years.

III. Perception

Perception plays a critical and basic role in HITL robot learning, as it enables the robot to receive and interpret inputs from a human trainer. It contains awareness of the environment, humans, and objects and communication with task-related information accurately and efficiently. As a cornerstone of human-robot coevolution, the ability of robots to perceive objects and human factors provides the sensory foundation necessary for safe, effective, and natural interactions between humans and robots.

Object recognition and classification, including workpieces, tools, etc, can provide the necessary tools for environmental understanding, decision-making, and adaptive learning in manufacturing scenes. It enables robots to operate in dynamic environments where conditions and requirements change rapidly [33], [34]. Advanced methods in object recognition and classification often leverage deep learning techniques, particularly Convolutional Neural Networks (CNNs) [35], which excel in handling visual data and can identify intricate patterns and features in images far beyond traditional algorithms. Additionally, techniques such as transfer learning enable these models to apply knowledge gained from one task to improve

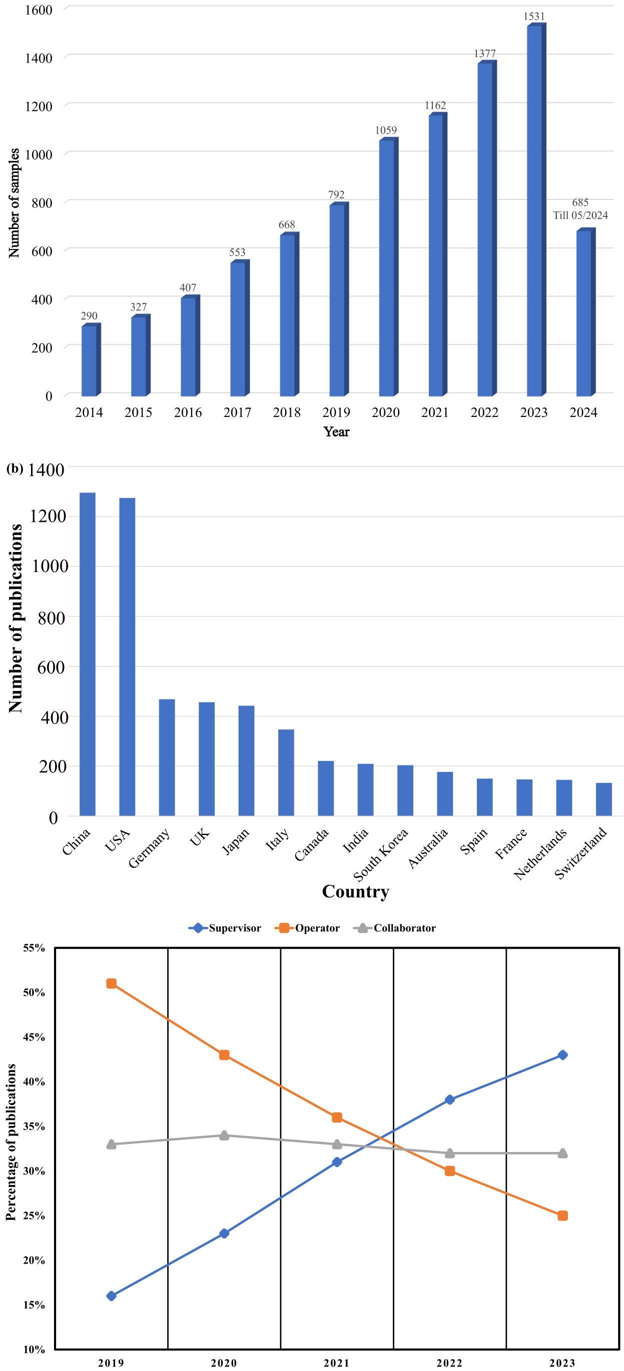

Fig. 5. Preliminary results: (a) Number of annual relative publications; (b) Distribution of literature by countries; (c) Percentage of publications of human roles related to HITL robot learning.

performance on new, but similar tasks, significantly enhancing both the efficiency and accuracy of object recognition systems in diverse environments [36]. Some relative review papers about object and scene perception can be found in [3], [37], and [38].

Since this paper is centered on introducing human intelligence into the robot training loop, our focus in this section is robot perception of human motion, intentions, and emotions, rather than the environment and objects. Humans, as the most important participants of HITL robot learning, have been considered the key research subject by numerous research findings. The following discussion of robot perception to humans in HITL robot learning is divided into two key aspects: *Recognition* and *Parsing*.

A. Recognition

In the context of HITL robot learning, recognition plays an essential role and lays the foundation for the robot's ability to interact with humans and adapt to complex working environments. Multimodal recognition via diverse sensory modalities, such as vision, audio, and haptics, allows a robot to identify human factors and gain detailed human guidance for better performance. A comprehensive summary of recent multimodal recognition studies in HITL robot learning is compiled in Table I and Fig. 6.

1) Vision-Based Technologies: In recent years, vision-based technologies based on machine learning have received unprecedented attention. The typical visual devices include RGB-D camera, event camera, and opti-track system for robot vision. They are instrumental in teaching robots how to adapt accurately to complex environments, interact with humans and other objects, and rapidly obtain new skills under human guidance according to high-resolution and multidimensional visual information.

For instance, Algabri and Choi [49] designed a new human-following framework for mobile robots in HRI. Through this framework, the robot can detect humans and follow the target via an RGB-D camera, according to CNNs and Single Shot Detector (SSD). A hand-action recognition solution is presented in [39] extracting from human skeleton activity sequences. The skeleton activity representation model applied a Temporal Convolutional Network (TCN) that describes actions and generalizes to invisible target motion domains. As for human gestures, Zhang et al. [50] proposed a dynamic recognition method for natural robot perception. Hand gestures are acquired by video input, and outputs are fed into long short-term memory (LSTM)-CNN. According to this method, humans can communicate with robots in a more natural and intuitive way, reducing the need for complex programming or control devices. Some useful technologies only apply digital images as input. Hwang et al. [51] created a facial emotion recognition for human-robot collaboration (HRC) using an omnidirectional service robot. It achieves a higher recognition rate of dynamic mapping of human mood and prevents the overfitting issue in a noisy environment effectively by sequential recurrent convolution network (SRCN). Another novel recognition approach is introduced by Islam and Iqbal in [52] to enable seamless HRC. LSTM-recurrent neural network (RNN) is employed to capture learning robust features for recognizing human motion accurately. In [53], Gao et al. proposed a feature-map-fused single-shot detector (FF-SSD) to deal with complex gesture detection. Mounted into the assistant robot, it can achieve satisfactory recognition accuracy while ensuring high efficiency. Different from the RGB-D camera, the OptiTrack system is a classic tool for motion capture by a series of high-speed cameras positioned around an area to track the movement of reflective markers. Based

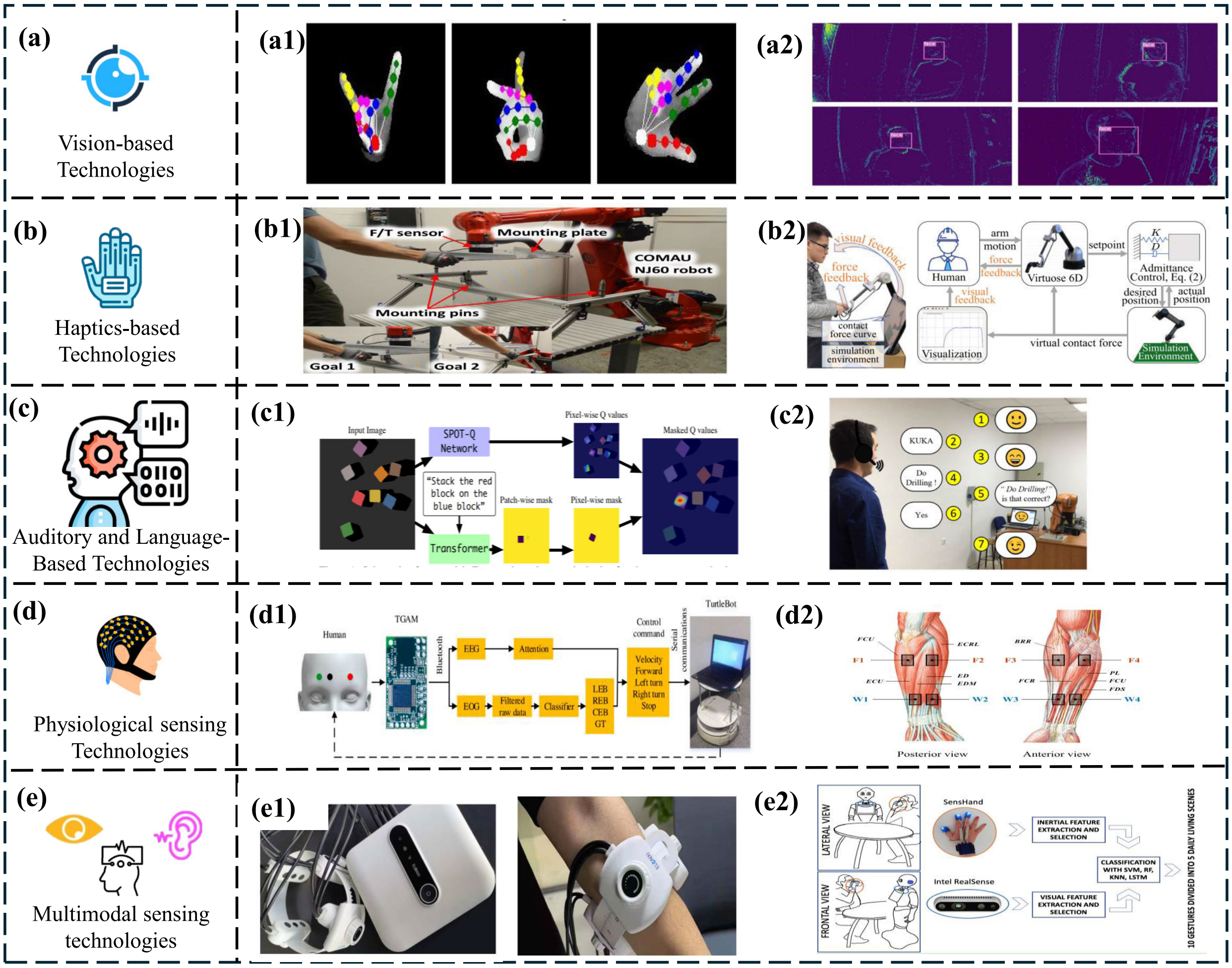

Fig. 6. Diverse recognition methodologies of perception. (a) Vision-based Technologies. (a1) Hand-action recognition by TCN using RGB-D camera [39]. (a2) Facial microexpression identification using CNN and LSTM with event camera [40]. (b) Haptics-based Technologies. (b1) Force recognition and reaction based on F/T sensors with GPM [41]. (b2) Force control impedance skills transferring to robots by F/T sensors and Haption Virtuose 6D device [42]. (c) Auditory and Language-Based Technologies. (c1) Guiding tasks with natural language instructions [43]. (c2) Speech analysis for performing predefined tasks with microphones [44]. (d) Physiological sensing Technologies. (d1) Interaction with mobile robot based on EEG signal [45]. (d2) Gesture recognition by EMG signal with SVM [46]. (e) Multimodal sensing technologies. (e1) Gesture recognition with sEMG and A-Mode ultrasound sensing [47]. (e2) Gesture recognition through hybrid vision and wearable systems [48].

on this device, Khadivar and Billard [54] built a coupled dynamical system to track fingers' desired velocity for dexterous manipulation. They regulated the hierarchical Dirichlet process (HDP)- hidden Markov models (HMM) to identify the segments of the task to improve the robustness of grasping. The event camera is a bio-inspired and dynamic vision sensor, unlike the traditional camera. Instead of capturing frames at a fixed rate, it emits a series of spatio-temporally localized events. Becattini et al. [40] utilized it to detect human micro-expressions to evaluate if humans are mentally and physically fit to work. CNN and LSTM are used to generate frame representations, leading to better recognition of underlying sentiments of human faces.

Although vision-based technologies are increasingly being used in HITL robot learning, where humans provide direct or indirect input to help robots acquire new skills or adapt to new environments, they come with certain limitations in this context, including occlusions, complex backgrounds, and limited fields of view. Additionally, the ambiguity of human gestures and the need for generalization across different settings pose difficulties if robot recognition of humans only relies on vision sensors.

2) Haptics-Based Technologies: Haptics offer crucial value in HITL robot learning by providing tactile feedback to humans and enhancing the active and bidirectional interaction between humans and robots (see Fig. 6(b)). This kind of technology can facilitate the transfer of skills from humans to robots, where the robot learns the nuances of a task by recording the force and motion patterns applied by the human user.

For example, Force/Torque (F/T) sensors enable robots to feel and react to physical forces, leading to smoother and more natural movements. Haninger et al. [41] developed a novel approach for physical human-robot interaction (pHRI) that models the human force as the Gaussian process model (GPM) in collaborative assembly. The largest functional value of this approach is in the human model, in staying the robot near the training data from F/T sensors. Besides,

TABLE I
RECOGNITION

Sensing	Perception interface	Category	Method	Year	Ref.
Vision	RGB-D camera	Human pose	CNNs+SSD	2020	[49]
		Hand action	TCN	2021	[39]
		Human gesture	LSTM-CNN	2021	[50]
	RGB camera	Human mood	SRCN	2023	[51]
		Human motion	LSTM-RNN	2021	[52]
		Human gesture	FF-SSD	2020	[53]
	OptiTrack system	Human motion	HDP-HMM	2023	[54]
	Event camera	Human facial expression	CNN+LSTM	2023	[40]
Haptic	F/T sensor	Human motion	GPM+Bayesian interface	2022	[41]
		Human activity	WRF	2021	[55]
	Bionic soft sensor	Human activity	DNN	2022	[56]
	MS HoloLens 2	Eye gaze	RetinaNet	2021	[57]
	FT sensors+ Haption Vir tuose 6D	Human motion	CDS-based control	2023	[42]
Auditory/ Language	Text instruction	Human intention	dLSTMPB	2022	[58]
		Human activity	Transformer-based Q-learning	2021	[43]
	Microphone	Human attention	DNN	2020	[44]
	Dialogue system	Human intention	FSM+NPC	2022	[59]
Physiological signals	Wrist surface EMG channels	Hand gesture	SVM	2022	[46]
	ThinkGear Asic Module (EEG)	Human intention	CNN with residual block model	2022	[45]
Multimodal	sEMG and AUS fusion device	Hand gesture	CNN-LSTM	2023	[47]
	RGB-D camera+ SensHand	Hand gesture	KNN+LSTM-RNN	2021	[48]
	Omega 3+ HoloLens 2	Human motion and intention	DMP	2023	[60]

Al-Yacoub et al. [55] applied haptic information captured from human guidance interpreting human motion and generating equivalent robot trajectory. Weighted Random Forest (WRF) with stochastic regression is proposed to enhance the generalization capabilities of the approach for co-assembly tasks. With the development of advanced haptic sensing technologies, mixed reality (MR) is becoming an important tool to offer the user with more natural HRI. Park et al. [57] implemented the wearable MR equipment to capture human gestures and eye gaze. In this way, RetinaNet [61] in this system can generate more effective and intuitive task assistance according to the precise perception of humans and environments. In addition, Ge et al. [42] designed a compliant dynamical system to transfer users' variable force control impedance skills to robots according to F/T sensors and Haption Virtuose 6D device. Lyapunov theory in this work ensures force control stability for dual-arm manipulation transportation. with the realms of bionic and soft materials witnessing exponential advancement, a kind of bionic skin equipped with robots is invented to improve the robot perception in [56]. By using a novel deep neural network (DNN), this system can recognize touch stimulus and tactile modalities for natural HRI.

Haptic-based technologies in HITL robot learning provide immersive feedback but face limitations such as finite resolution and sensitivity, potential latency issues, high complexity, and costs that restrict widespread adoption. Despite these limitations, ongoing technological advancements are anticipated to mitigate many of these issues, thereby enhancing the effectiveness and applicability of haptic systems in HITL applications.

3) Auditory and Language-Based Technologies: Audio or language, as ubiquitous in daily human communication, is an invaluable asset for HITL robot learning due to its roles in facilitating perception, instruction, and interaction. These technologies enable intuitive and natural interactions with humans in the robot training loop, allowing for real-time feedback and adaptation and facilitating the understanding of complex commands. Besides, human audio or language recognition enhances a robot's ability to follow vocal commands, learn from human dialogue, and adapt to social and cultural contexts (see Fig. 6(c)). In [58], the method can generate motions in real-time for robots based on language instruction. Description Long Short-Term Memory with Parametric Bias (dLSTMPB) is employed to train a time series of language information and extract the location information of the object. Following the above language interface, another novel framework is presented in [43] to enable users to interact with robots. A new Transformer-based model in this work can ensure humans guide a robot manipulator by a 3D multi-step operation task with natural language commands. Besides, Bingol and Aydogmus [44] focus their work on natural speech/audio extraction and parsing for robot control without any prior knowledge or experience of robotics. People who are not experts can use microphones to take direct voice commands based on DNN for efficient HRI. As for dialogue systems, they enable robots to answer human queries accurately and maintain friendly interactions. Suddrey et al. [59] introduced a well-built control architecture of robotics for the Pick-and-place task. They showed how behavior trees, can be utilized in conjunction with language instruction in this system to provide a robust control strategy for autonomous agents. Although language or audio instructions can support the development of robots that are more relatable and capable of providing personalized responses by grasping the nuances, intent, and sentiment behind spoken words, it also presents several limitations when integrated into robot systems, including ambiguity and variability in speech, difficulties in noise discrimination, and the dynamic nature of language that requires continuous learning.

4) Physiological Sensing Technologies: Physiological sensing technologies enrich the interaction between humans and robots by providing real-time, objective signals on the human physiological state, such as Electroencephalography (EEG) and Electromyography (EMG) signals (see Fig. 6(d)). These data allow for adaptive learning, performance optimization, and enhanced safety through the detection of stress, fatigue, and emotional states. By enabling robots to respond to human cognitive and physical cues, these technologies foster a more intuitive and personalized learning experience. Lu et al. [45] created an online brain-computer interface (BCI) system by EEG signals to detect human intention. The system based on CNN with residual block model realized the accurate control of the TurtleBot mobile robot for efficient HRI. Another pattern recognition system was developed in [46] on the basis of the design of wrist-based EMG. Support vector machine (SVM) is set as the classification model for hand gesture extraction from EMG signals. However, physiological signals can be noisy and subject to artifacts from movement, electrical interference, or other sources. While many physiological sensors are non-invasive, they may still be uncomfortable for users to wear for extended periods. This can affect the quality of data and the user's willingness to participate in HITL tasks. Despite these limitations, ongoing advancements in sensor design, data analysis, and adaptive algorithms offer prospects for overcoming these hurdles and enhancing the symbiosis between humans and robots in collaborative environments.

5) Multimodal Sensing Technologies: Multimodal sensing technologies bring together diverse sensing inputs, such as visual, auditory, tactile, and physiological data, to create a well-rounded perception of both human beings and the surrounding environment. Wei et al. [47] illustrated a multimodal gesture recognition method through A-mode ultrasound (AUS) and surface electromyography (sEMG) signals. CNN can extract the hidden features of the AUS signal, and CNN-LSTM can extract some spatial-temporal features from the sEMG signal to generate hybrid features of different modalities. In [48], Fiorini et al. combined vision with haptic information to recognize human gestures by RGB-D camera and a wearable device, SensHand. K-Nearest Neighbor (KNN) and LSTM are used to process multimodal signals to gain precise classification. Indeed, the cameras could get the obvious motions of the body, whereas the SensHand can catch subtle movements of the hand, especially when they are not within the vision sensor's field of view in this method. To enrich data for learning algorithms, Yan et al. [60] designed a mixed interaction interface with augmented reality (AR) and haptic equipment for safe HRC. In this framework, dynamic movement primitives (DMPs) assisted robots in learning the user's demonstration from multimodal sensing input. Despite of numerous merits of multimodal sensing technologies, integrating and making sense of heterogeneous data from different modalities can be challenging. Besides, it is very difficult to ensure that all sensors are properly calibrated and synchronized, which is critical for accurate data collection.

B. Parsing

Unlike recognition, extraction and parsing implies a deeper level of robot perception, referring to the ability of a robot to not only detect and identify human guidance and features within its environment but also to comprehend their significance, purpose, and context in which they exist. Bolstered by advances in relevant algorithms, the parsing of human factors is discussed from three critical aspects: human activity, human intention, and human emotion, which is compiled in Table II and Fig. 7.

1) Human Activity: By analyzing human activity, robots can achieve a higher level of perceptual intelligence that allows for more fluid and adaptable interactions in complex and dynamic environments. By incorporating motion perception, robots can offer more intuitive and effective services, particularly in collaborative, social, and healthcare settings (see Fig. 7(a)). For example, Hara et al. [63] applied end-to-end (E2E) learning to develop a haptic-based control system of humanoid Robots for the cloth folding/unfolding task. Geomagic Phantom Omni is used to demonstrate human motion for teleoperation and skill learning through Gaussian mixture models (GMMs), leading to higher task execution efficiency. In [68], Latifee et al. also employed a similar haptic device to extract and analyze human activity with kinesthetic coupling between humans and robots by Dynamic Authority Distribution (DAD). Some research works pay more attention to human motion analysis by multimodal sensing. Zhang et al. [62] adapt sENG signal and F/T sensors to identify human motion for collaborative saw work. Deep Deterministic Policy Gradient (DDPG) RL is proposed for human-centric collaborative control, performing satisfied coordination ability between precise tracking and comfortable collaboration. In addition, Shao et al. [69] reported one new idea that agents are endowed to learn a single multi-task policy by leveraging large-scale vision demonstration of humans performing operation motion and natural language instructions according to the integration of DDPG and the cross entropy method (CEM). However, similar movements might have different meanings depending on the context, cultural background, or individual preferences. This can lead to misinterpretation by robots that do not have the capability to extract these nuances completely.

2) Human Intention: Human intention for robot perception refers to the ability of a robot to recognize and analyze the goals or desired outcomes that a human has in a given context. Robots can observe and learn from human behavior by analyzing the intentions behind actions in HITL systems, where human feedback helps to shape and refine robot learning

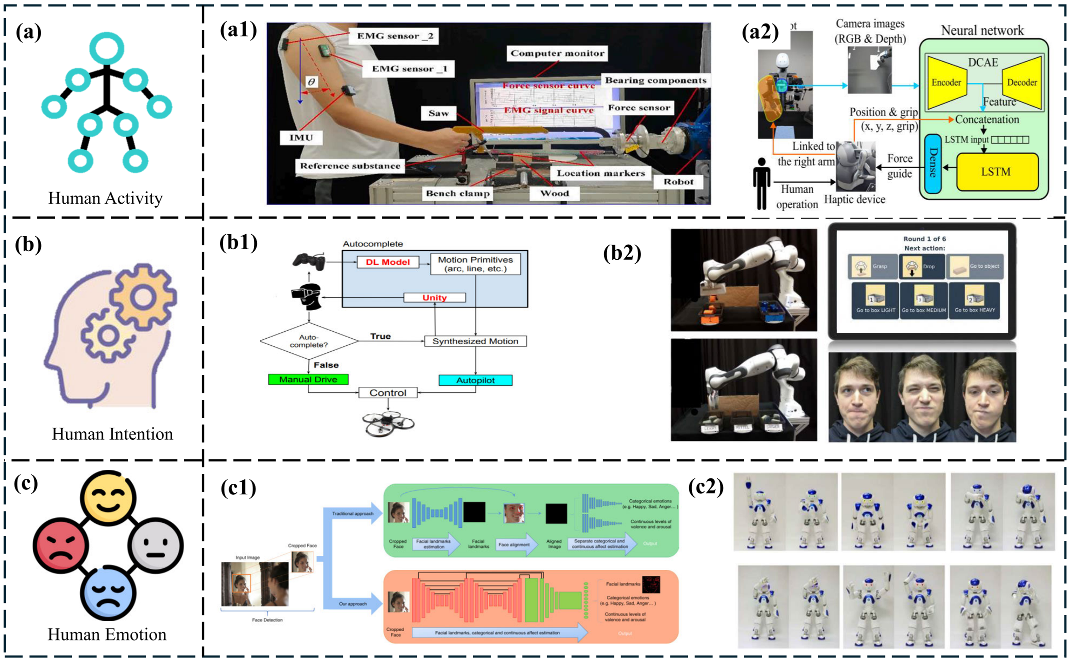

Fig. 7. Parsing different human factors for robot systems. (a) Human Activity. (a1) HRC based on human activity recognition and estimation by sEMG signal [62]. (a2) Flexible object manipulation with haptic shared control by human motion guidance [63]. (b) Human Intention. (b1) Drone teleoperation system supported by an MR user interface to demonstrate human intention [64]. (b2) Learning from human intention and action advice in interactive reinforcement learning [65]. (c) Human Emotion. (c1) Categorical and continuous human emotion parsing with face alignment by EmoFAN [66]. (c2) Robot body-language expressions with multimodal emotional HRI [67].

TABLE II
PARSING

Category	Perception interface	Method	Year	Ref.
Human activity	Geomagic Phantom Omni	GMMs	2023	[63]
	SensAble PHANToM Omni	GMMs+EM+DAD	2020	[68]
	F/T sensor + sEMG signal	DDPG	2022	[62]
	RGB-D camera+text instruction	DDPG+CEM	2021	[69]
Human intention	Text instruction	BERT+Bi-LSTM	2022	[70]
	PS3 controller + MR headset	CNNs and GRUs	2021	[64]
	PS3 controller	Koopman operator-based model	2020	[71]
	Binary feedback	LUNAA	2022	[65]
Human emotion	Text/audio input	AIA-Net	2023	[72]
	RGB cameras	EmoFAN	2021	[66]
	RGB cameras + Microphone	Bayesian Network + HMM	2021	[67]

to ensure the alignment of robot actions with human goals and preferences (see Fig. 7(b)). A human intention analysis system was established by spoken language in [70]. In the intent parsing part, bidirectional LSTM (Bi-LSTM) encodes the shared tokenwise representations with a language model BERT. Zein et al. [64] developed a solution for the teleoperation of robots based on the combination of CNNs and Gated Recurrent Units (GRUs). The training was built on a dataset of motion primitives for drones with the MR headset and the PS3 joystick demonstrating human intention. Broad et al. [71] focus on the problem of how automation can be used to adjust to the specific capabilities of a human partner for control allocation. Koopman operator-based control is used to allocate control authority for higher efficiency of HITL paradigm. In [65], human intention about motion preference is potentially inaccurate human input, so learning from unreliable action advice (LUNAA) is developed to evaluate human uncertainty in the training cycle for the robotic sorting skill.

3) Human Emotion: Parsing human emotion in robot perception refers to the process by which a robot interprets and understands human emotional states through facial expressions, vocal tones, body language, or other sensory inputs. Robots can distinguish between positive reinforcement, frustration, or satisfaction through parsing human emotion and precise human feedback interpretation, allowing for more nuanced and effective learning from human inputs (see Fig. 7(c)). In [72], an adaptive interactive attention network (AIA-Net) was developed to analyze human emotion with

TABLE III
REASONING

Robot platform	**Method**	**Method type**	**Key result**	**Ref.**
Turtlebot 2	CNN+MPC	DRL	The robot can navigate around humans and avoid dynamic obstacles	[74]
Kinova Jaco	Bayesian inference+POMDP	IL+DRL	It assists the robot in better learning when it cannot explain the human input.	[81]
Franka Panda	ResNet18+ MLP+ LSTM	IL+DRL	The system accomplishes up to 70% success on the task of extracting keys by vision and sound even with visual occlusion.	[77]
UR5	PPO	DRL	The framework can complete complex manipulation tasks specified by abstract and long-horizon semantics.	[73]
Franka Panda	R3M+DINOv2's ViT-B	DL+IL	NOIR enables intention prediction through few-shot learning, facilitating a more efficient collaborative interaction.	[78]
Everyday Robots 2	Instruct-GPT+PALM	DRL	LLMs reasoning improves high-level instruction completion on long-horizon manipulation tasks.	[81]
UR5	Transformer	DRL	Our method can learn an action planning sequence and recover the human decision-making process.	[82]
Embodied 3D scene	Transformer + BERT	DRL	This method enables building an agent that performs hierarchical reasoning to execute long-term tasks effectively.	[80]

linguistic instruction and audio input as multimodal parsing. This architecture adjusted textual and acoustic features and learned multimodal interactive relations based on the auxiliary structure, which provides a novel emotional representation. Toisoul et al. [66] paid more attention to facial affect parsing to better analyze a person's emotional state. The proposed method applied the features extracted by a face-alignment network (FAN) to analyze both categorical and continuous human moods in a single pass with face alignment in a high level of accuracy. Hong et al. [67] proposed a new emotional HRI framework to achieve bidirectional emotional communications. A multimodal affect classification system focused on the combination of body language and vocal intonation using a Bayesian network to determine the robot's emotional behavior.

IV. Cognitive Intelligence

Cognitive intelligence refers to the human mental abilities involved in reasoning, decision-making, abstract thinking, complex idea comprehension, and learning from experience. Through human-centric data-driven methods, the integration of cognitive intelligence from humans can significantly enhance the capabilities of robots with the development of human-inspired brains in HITL systems, allowing robots to learn in a manner similar to humans, which includes understanding concepts, generalizing from examples, and learning from less structured data. These abilities not only enable robots to learn new skills from humans but also allow them to make appropriate adjustments in different environments and changes, thereby achieving higher levels of autonomy and functionality. Ultimately, it is crucial to develop robots that can seamlessly integrate into human environments, making them more intuitive and effective partners to boost self-fulfillment goals and collaborative intelligence in human-robot coevolution.

A. Reasoning

To bridge the gap between scenario understanding and proactive decision-making, robots must have a reasoning mechanism for higher-level cognitive intelligence. Robot reasoning ability in HITL environment refers to a robot's capacity to process information, draw inferences, and judge better solutions that are not explicitly programmed but derived from the logical processing of data, experiences, and human input. This cognitive capability is essential for robots to operate in complex, unpredictable environments and perform tasks that require more than just mechanical execution. Related works about introducing the capacity for reasoning into the training loop are listed in Table III.

Reasoning allows robots to navigate and solve complex problems that require logic and understanding beyond simple rule-following, such as identifying causal relationships and planning a sequence of actions to achieve a goal. To finish partially-observed gripping tasks amidst occlusion, Du et al. [77] proposed one interactive learning policy via audio-vision modalities and corrections from users. The robot applies memory to encode the history of observations for completing these complex tasks. In [73], an embodied representation and reasoning architecture (ERRA) is presented to enhance the ability of reasoning in robotic systems for long-horizon manipulation tasks (see Fig. 8(a)). Through this system, robots can reason in the scenes with diverse basic cues between objects under semantics understanding in language-conditioned instructions. Zhang et al. [78] an intelligent BCI-controlled robot system with the prediction of users' intention by few-shot learning. In this system, their brain signals assist robots in completing diverse tasks, consisting of cooking, table cleaning, personal care, and entertainment. Another closed-loop control strategy is demonstrated in [79] with the natural language instructions as the reasoning model. Therefore, the robot platform can accomplish complex and unseen tasks with pre-trained robot skills in a kitchen scene. Likewise, Blukis et al. [80] designed a series of persistent representations for bridging the gap between language commands and long-horizon robot motion. It also can empower robots with the ability of hierarchical reasoning to finish complex tasks effectively with spatial semantic understanding.

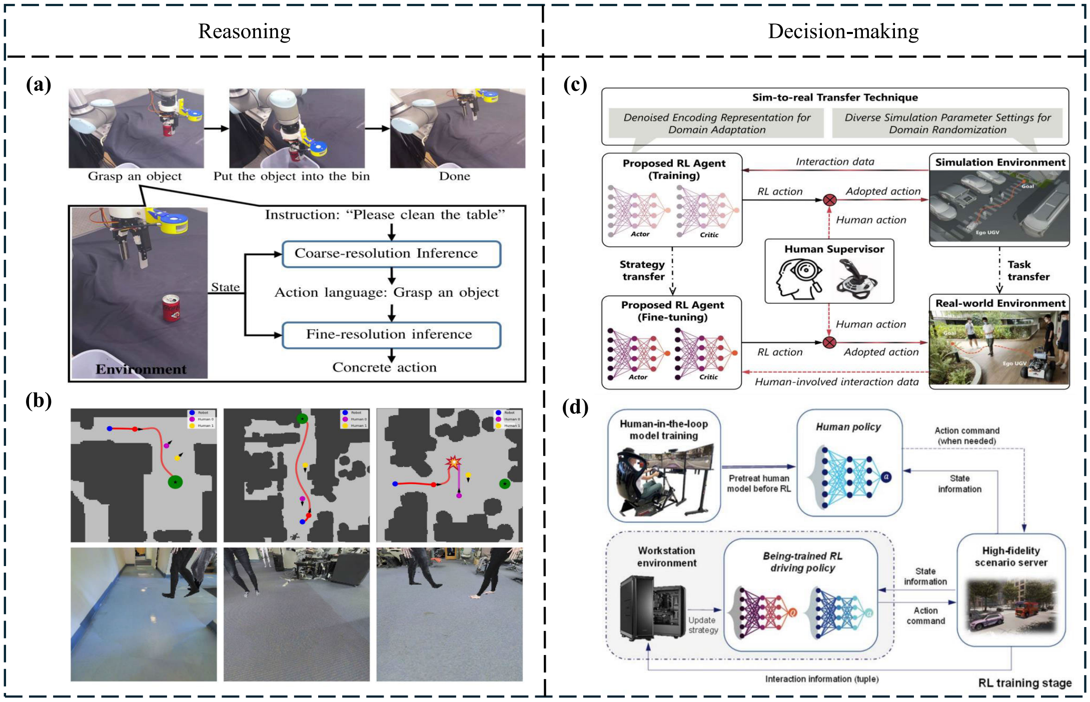

Fig. 8. The improvement for robot learning leveraging human cognitive intelligence. (a) Long-horizon language-conditioned manipulation tasks based on the representation and reasoning architecture [73]. (b) Visual navigation based on optimal control of humans as a supervisor in the loop [74]. (c) RL method with sim-to-real transfer for autonomous driving [75]. (d) Prioritized experience-based RL strategy with human supervision [76].

Robots equipped with reasoning abilities can generalize learned knowledge to new and unforeseen situations, adapting their behavior in dynamic environments without explicit instructions. Tolani et al. [74] focused on how to visual navigation in an unfamiliar dynamic environment and proposed an autonomous navigation system by self-supervised training loop, which achieves zero-shot transfer from simulation to the real context (see Fig. 8(b)). Bobu et al. [81] formalized how to reason about how well human inputs can be explained and introduced a novel framework to quantify the dynamic scene misspecification to help robots understand when they cannot explain human guidance. In [82], Sun et al. established the Planning Transformer network(PlaTe) for procedure planning with learning cross-modal correspondence to achieve intelligent reasoning.

B. Decision-Making

The ability to learn the human decision-making process in HITL brings substantial value by leveraging human cognitive strengths to train robotic systems. The process harnesses human judgment and intuition to inform and shape the decision-making capabilities of robots, resulting in machines that are more intuitive, context-aware, and capable of conforming to the complex fabric of human-centric environments. Some typical frameworks are provided in Table IV for reference.

Robots can learn to make judgments that emulate human decision-making processes, allowing them to handle complex tasks and reducing their reliance on constant human supervision and intervention. Chen et al. [83] applied deterministic learning to control an unmanned ground vehicle (UGV) with probabilistic analysis for human intention by testing the strategy inside a maze. In [84], a bidirectional translation model is utilized to transform the pre-trained semantic embeddings to generate some precise actions from unseen words. In [75], the RL policy applied a denoised representation for spatial adaptation to bridge the sim-to-real gap with the most relevant and informative features from robot perception to enhance the ability of decision-making in navigation (see Fig. 8(c)). Lombardi et al. [85] presented a minor game with action coordination of cyber-players based on Markov chains to build one agent to finish complex human-like motion or virtual games cooperated with other agents or individuals.

By learning from human decisions, robots become more flexible and can adapt to a variety of situations. In this way, this kind of ability enables robots to navigate unforeseen risks more effectively. Jin et al. [86] developed a method based on the cutting plane method with clear geometric representations to enable a robot to train around an objective function using human directional corrections. Taniguchi et al. [87] proposed a method to enable a mobile platform to learn complex spatial concepts in a domestic context. They combined probabilistic inference in the Bayesian model and RL for decision-making in navigation. In [5] and [88], Wu et al. leveraged human-guidance-based (Hug)-DRL to optimize the performance and efficiency of agent training to achieve intelligence transfer between humans and automation in an end-to-end self-driving case.

V. Physical Skill Transfer

Skill transfer in human-centric robot learning is a learning paradigm where robots acquire new skills through human

TABLE IV
DECISION-MAKING

Robot platform	Method	Method type	Key result	Ref.
CHRONOS platform	Markov chain	DRL	A virtual agent can mimic the behavior of a specific human performing a joint motor task	[85]
Parrot Mambo	POMDP	DRL+IL	The scheme only requires the user's directional corrections, which do not necessarily need to be magnitude-specific.	[86]
UGV	RBFNN	DL	The vehicle can be successfully moved through a maze by human guidance.	[83]
Toyota's Robot	Bayesian generative model	DRL	Our method can estimate the trajectory to a place instructed by a speech instruction.	[87]
Mobile robot simulator	Hug-DRL	DRL	Humans could correct the agent's unreasonable DRL actions in real-time during the training process.	[5]
Mobile robot simulator	CNN	DRL	The model identifies the probability of accidents in addition to considering the emotions of the driver	[89]
HUNTER UGV	MDP+PER	DRL	The architecture can solve low-cost navigation with human prior knowledge	[75]
Driving simulator	D3QN	DRL	The strategy exhibits a better target achievement ability when tackling the safe lane-change problem	[88]
NAO	rPRAE	DRL	It allow the robot to properly generate actions from unseen words	[84]
Driving simulator	PHIL-TD3	DRL	It discriminate the quality of various human guidance to relieve humans by less requiring on human proficiency	[76]

guidance. In this context, "Physical skill" refers to actions that require movement and manipulation, such as handling tools, assembling parts, or performing delicate maneuvers. The transfer of these skills involves a process where the robot learns to mimic or reproduce human movements and actions to perform a specific task. By integrating advanced perception and cognitive capabilities, robots can improve the accuracy and efficiency of skill learning, improve adaptability to various tasks, and enable robots to adjust and optimize their actions in complex environments in real-time. Instead of programming every potential action and decision, a robot can learn from human examples, which is often more efficient and effective, especially for complex or artful tasks that require a level of dexterity and adaptability that is difficult to achieve through traditional programming methods. Skill transfer for robots in HITL systems will be discussed in this section regarding different human roles in the training cycle described in Section II-B specifically.

A. Human Role: Operator

In HITL robot learning, the human operator is pivotal in bridging the gap between complex human skills and a robot's ability according to precise demonstration. Operators in HITL robot systems, regarded as proactive roles, can convey the task objectives clearly and interact with the robot in a way that promotes efficient learning with their expertise and skill, ensuring that the machine adapts to new challenges and variations in the environment (see Fig. 9(a)).

Physically demonstrating the correct way to perform a skill by operators involves manually guiding the robot's limbs (kinesthetic teaching), operating the robot remotely via joysticks, gloves, or VR interfaces (teleoperation), and performing the task themselves while being monitored by the robot's sensors (observational learning). Through this direct demonstration, the robot can learn the desired movements and actions by imitating the human operator, which is the main function of IL. As shown in Table V, Su et al. [90] presented a novel methodology for robot-assisted minimally invasive surgery to deal with the kinematic constraint for the remote center of motion (RCM) in laparoscopic surgery. Combining dynamic time warping (DTW) with GMM-based DMP, the developed strategy enables surgical manipulation skill modeling after many demonstrations. Similarly, Zhang et al. [108] utilized DMP and GPR to facilitate efficient surgical performance, which is tested on the da Vinci Research Kit. In [97], a spatial iterative learning control (sILC) is proposed to train a precise task execution path according to online human corrections when meeting uncertainties in the environment. This control method is applied on a Sawyer robot for robot-assisted welding, with a better path-tracking property and training efficiency. To ensure that robots can reproduce behavior by visual imitation with inconsistent contexts, Qian et al. [99] applied three different models that transform human demonstration from coarse to fine and imitate motions after aligning the robot and human at the current state. As for kinesthetic teaching, Duan et al. [103] developed a structured prediction method for trajectory imitation via direct physical guidance. To address the limitations of learning complex skills for kinesthetic demonstration, Guo and Bürger, [106] presented a HITL coordination framework to improve the flexibility of new scenes while teaching complex industrial tasks. According to the incorporation of spatial and temporal demonstration modulation; it facilitates adaptation to the difference in working environments. In [104] and [107], these works both used DMP due to the high calculation efficiency and the excellent ability of generalization to improve the trajectory accuracy for uncertainty in domestic tasks respectively.

Besides physical skill teaching, operators can also adjust the training factors in the DRL-based framework, such as tuning reward functions and data labeling. There are some examples of combining IL-based and DRL-based methods to

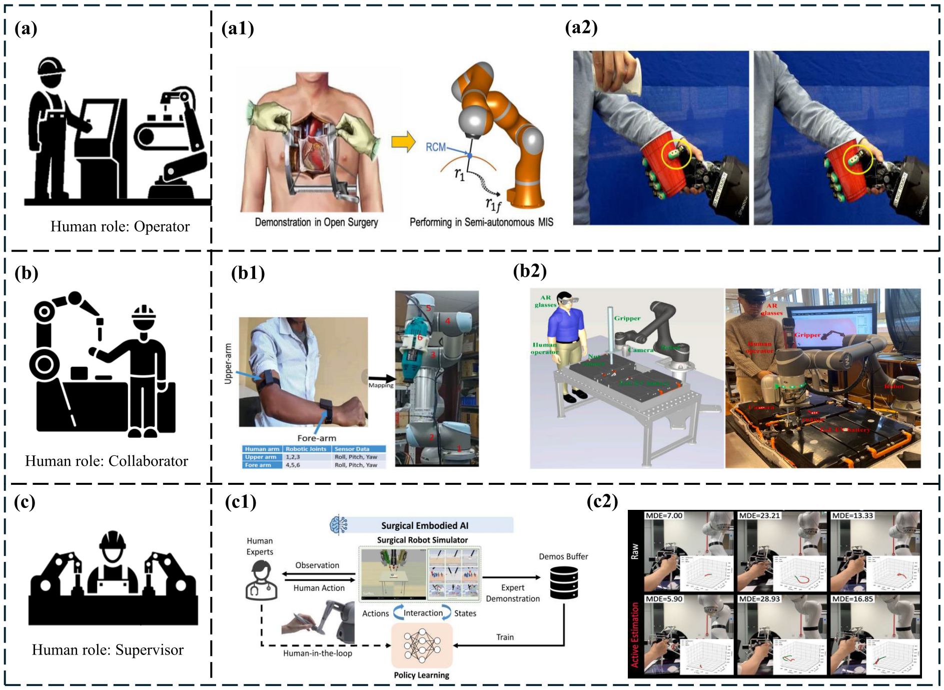

Fig. 9. Physical skill transfer for robots in HITL robot learning. (a) Human Role: Operator. (a1) Kinesthetic teaching for minimally invasive surgery [90]. (a2) Multifingered robot hand learning by vision-based demonstration [91]. (b) Human role: Collaborator. (b1) Skill learning with HRI based on DMP [92]. (b2) HRC framework for disassembly based on YOLOv5+CNN [93]. (c) Human Role: Supervisor. (c1) Interactive sim-to-real learning for surgical robots in SurRoL simulator [94]. (c2) Modified bilateral active estimation for robotic tele-control [95].

TABLE V
HUMAN ROLE: OPERATOR

Robot platform	Application	Method	Method type	Year	Ref.
KUKA LWR4+	Minimally invasive surgery	DTW+GMM-DMP	IL	2021	[90]
Baxter + da Vinci	Minimally invasive surgery	HMM+ RNN	IL	2021	[96]
Sawyer	Robot-assisted welding	sILC with visual assistance	IL	2023	[97]
KUKA iiwa	Peg-in-hole task	LSTM+BRNN	IL+DL	2021	[98]
UR5	Pick-and-place	FVTrans+RANet+IDNet	IL	2023	[109]
NAO Robot	Parallel HRI	DTW+LWR+CNNs	IL+DRL	2023	[100]
KUKA iiwa	Pick-and-place	MPC	IL	2023	[101]
Shadow Dexterous Hand	Pick-and-place	TeachNet+GMM	IL+DRL	2023	[91]
Kinova Gen3 robot	Holding hammering	CoVGS-IL	IL+DRL	2022	[102]
KUKA iiwa	Obstacle avoidance	KRM +MDP	IL	2023	[103]
Sawyer	Precise drawing-a-Line Task/ Writing-Letter	DMP	IL	2022	[104]
ROKAE Xmate3	Safe HRC	MLP	IL	2021	[105]
Franka-Panda	Bin sorting and assembly	TP-HSMM+GTN	IL	2022	[106]
Baxter	Box flipping	OLC-DMP	IL	2022	[107]
da Vinci	Minimally invasive surgery	DMP+GPR	IL	2022	[108]

enhance adaptability and robustness. Chen et al. [98] used a BiLSTM-based method to identify and segment motion primitives after kinesthetic teaching to reconstruct the movement information. Zeng et al. [91] focused on how to get compliant behaviors for dexterous manipulation and showed a markerless vision-based learning system that an end-to-end neural network model (TeachNet) is trained to reflect the hand poses to the joint angles of the multi-fingered robot hand. In [100], human behavior imitation can be provided by 2D vision images According to CNNs, human pose can be estimated and transferred to robot space for IL via DTW and Locally Weighted Regression (LWR).

B. Human Role: Collaborator

The role of a collaborator in HITL robot learning can teach robots how to interact and cooperate with humans in dynamic environments. This collaborative learning approach is particularly relevant in fields such as healthcare, education, manufacturing, and service industries where robots

TABLE VI
HUMAN ROLE: COLLABORATOR

Robot platform	Application	Method	Method type	Year	Ref.
Dual-arm exoskeleton	Human locomotion assistance	DMP+GMM	IL	2021	[109]
UR5-e	Robot-assisted driliing	DMP	IL	2023	[92]
Upper Limb Musculoskeletal System	Human locomotion assistance	TMS+PPO	DRL	2023	[110]
Hydraulic manipulators	Pick-and-place	LWCC + Bayesian clustering	IL	2022	[111]
UR10	Multimodal HRC	MDP	IL	2022	[112]
Kinova Gen3 robot	Safe HRI	ErrP-Classification+LinUCB	DRL	2020	[113]
Dexterous robot hand	Multi-fingered hand teleoperation	AdaRL-MDF+DCNN+Q-learning	DRL	2023	[114]
Techman-14	Robotic disassembly	YOLOv5+CNN	DL	2023	[93]
Franka Panda	Stacking of crates	GGP	IL	2023	[115]
Kinova Gen3 robot	Water pumping	DMP	IL	2022	[116]
ARoA platform	Teleoperation+ambidextrous grasp	RF+CNN	DL	2022	[117]
Pepper and Yumi robot	Safe and multimodal HRI	HSMMs	IL+DRL	2022	[118]
Franka-Panda	Bimanual valve turning	TR-based DMP	IL	2022	[119]
Mobile cobot Assistant	Table cleaning	GMM+GMR	IL	2022	[120]

are expected to work in close proximity with humans (see Fig. 9(b)). Real-time human feedback helps the robot to develop a nuanced understanding of varying contexts and to adjust its actions accordingly.

As delineated in Table VI, the robot learns by working alongside humans on tasks, adapting to their actions, and learning from the collaboration in some learning scenarios. One of the most typical examples is the exoskeleton-based robot. Relative data-driven methods, such as DMP-GMM [109] and proximal policy optimization (PPO) [110], perform well in collaborative settings through a learning and control system that responsively adapts to compliant interactions between the robot and the human participant. Besides, multimodal data fusion technologies can enable a robot to adapt and react to a human's actions and intentions during the collaboration procedure via deep convolutional neural network (DCNN) [114] and Hidden Semi-Markov Models (HSMMs) [118] separately. Yu et al. [116] paid more attention to how to learn human-like adaptive impedance behavior. Regarding movement and impedance features, DMPs are employed to estimate human upper limb stiffness via EMG signals to achieve diverse impedance skill learning.

In addition, humans engage with the robot as equals in a shared task, with the robot learning from the joint activity as a collaborator. Luo et al. [111] developed a blended human-robot coordination method based on Bayesian clustering with fewer collision accidents for safe HRC. In another article [119], Target-Referred DMP (TR-DMP) is exploited for training bimanual skills of telemanipulation to enhance generalization capacities for different scenes.

Besides, collaborators can provide context-rich and real-time feedback and guidance, which can significantly speed up the learning process for robots. Halim et al. [112] created one method for no-code robotic teaching. Depending on the vision system, spatial movement information can be transferred through hand gestures to the robot for intuitive robot control in natural HRI. In [115], efficient corrections of the learning strategy can be provided from kinesthetic real-time feedback. Thanks to this policy, the user can demonstrate single arms' motion and fine-tune them before transferring the training onto a bimanual task. Zhao et al. [120] applied an admittance-type physical approach to get simplified human teachings and GMMs to model human motion for providing desired trajectories to meet the task requirements.

C. Human Role: Supervisor

A supervisor in HITL robot learning brings human expertise, safety, and ethical considerations into the robot's learning process by overseeing the training process and evaluating the robot's performance. They can assign scores or ratings based on predefined criteria to measure how well the robot is accomplishing its tasks. With human evaluation, the supervisor can identify areas where the robot's performance is lacking and direct the learning process toward improvements. Humans can steer the robot's development towards better outcomes by providing additional data, and modifying the learning algorithm, ensuring that the robot's behavior becomes more refined, efficient, and aligned with human expectations (see Fig. 9(c)).

Specifically, the supervisor actively watches the robot's actions, ensuring that it follows the correct procedures and behaves as human anticipation. The recent relative research works are indicated in Table VII. Sun et al. [121] proposed a motion planner to generate a path following kinematics and human behavioral norms under human monitoring. An open-loop strategy for teleoperation is introduced in [95], with the user as a passive supervisor in this system. This method can cope with the problem of high latencies with unstable trajectories. Shridhar et al. [129] presented a framework for learning a mapping from vision-language training to action primitives of household tasks. Humans can watch the robots' real-time motion in this environment, which narrows the difference between agents in simulation and robot movement in the real world.

The supervisor assesses the robot's performance against a set of criteria or benchmarks to improve motion accuracy.

TABLE VII
HUMAN ROLE: SUPERVISOR

Robot platform	**Application**	**Method**	**Method type**	**Year**	**Ref.**
Differential drive mobile system	Motion planning+obstacle avoidance	MDP+A*	DRL	2020	[121]
Franka-Panda	Pick-And-Place + household tasks	VDM+CNN	DRL	2021	[122]
Matlab simulink	Muti-robot coordition picking	RBFNN	DRL	2023	[123]
UR5	Pick-And-Place and pour	GWE+Faster R-CNN+RBF	DRL+IL	2020	[124]
Franka-Panda	Household tasks	ResNet18+ ResNet34+ Ego4D	DL	2022	[125]
SurRoL simulator	Minimally invasive surgery	MLPs with ReLU activations	DRL	2023	[94]
KUKA iiwa	Peg-in-hole teleoperation	m-BAEM	IL+DL	2023	[95]
Force Dimension Omega 7	Pick-and-placement + letter-writing	HSMM +TP-HSMM	IL+DL	2023	[126]
UR5	Pick-And-Place	LSTM	DL	2021	[127]
UE4 simulator	Collision avoidance for motion	CNN+DDPG	DRL	2023	[128]
AI2-THOR simulator	Household tasks	CNN-LSTM	DRL	2020	[129]
Simulated 8-DOF robot	Pick-and-place	Multicontext LMP	DL+IL	2021	[130]
Kinova Gen3	Collision avoidance for motion	PPO+ ACKTR+A2C	DRL+IL	2022	[131]

Stepputtis et al. [124] designed a model for language-based robot control. This strategy, combining vision and language, results in more fine-grained control with decreasing situational ambiguity. In [94], an interactive learning paradigm is used to improve training accuracy for surgical robots. High-quality human interaction can accelerate the process of trial-and-error in the DRL-based method. The learning policies can be used in the real world to achieve sim-to-real transfer In the open-source simulator SurRoL, where humans may provide reward signals or additional examples that help guide the robot's learning process. Nair et al. [122] deal with the problem of learning a series of vision-based tasks from a large offline dataset by crowd-sourced language annotation which provides a reward function for multi-task training. The knowledge in pre-trained models can efficiently learn grounded language in this framework. Wang et. al [127] developed an immersive teleoperation system for skill/task auto-correction. According to predicting human intention, the model tweaks the relative parameters for the precise pick-and-place task. In [128], a DRL-based method endows the UAV for avoidance automatically with reward functions based on relevant domain knowledge. In this training loop, humans can dynamically adjust reward functions for better performance on obstacle avoidance. Lynch and Sermanet [130] applied free-form natural language instruction into IL. Although lots of language-condition commands were added to this system, the cost of language annotation takes up less than 1% of the total data to improve the feasibility and efficiency.

VI. EMPATHY

Incorporating the capacity of empathy into HITL robot learning augments the quality of human-robot interactions by enabling robots to recognize, understand, and respond to human emotions, which fosters a more intuitive, socially harmonious, and user-friendly experience. For example, this empathetic approach can lead to increased trust and acceptance of robotic systems, as people tend to respond positively to entities that appear to understand and consider their emotional states. It stands as a critical component in advancing the sophistication and societal integration of robotic systems within HITL paradigms, offering significant benefits for human-robot coevolution. Table VIII outlines a compendium of papers proposing learning-based methods to develop the ability for empathy in HITL robot systems.

First of all, robots that can exhibit or interpret emotional cues are more likely to gain trust and acceptance from human users. Narayanan et al. [132], [134] introduced an affect-aware social robot navigation algorithm among pedestrians to keep safe and conformable (see Fig. 10(a)). A new obstacle profile representation is used in this scheme with dynamical adjustment through human pose and affect. For collaborative tasks, one new approach [135] facilitates robots to understand human moods and generate some assisting actions based on the transfer learning to build the trust human-robot partnership.

HITL learning that incorporates empathy allows robots to adjust their learning process based on the user's emotional feedback. Ko et al. [136] developed a method to provide nonverbal social behavior after human motion is understood and emotionally cared for. Two metrics are added to compare the similarity between the generated output and the ground-truth behavior. Cui et al. [137] focus on the issue of learning from implicit human feedback, with mapping hidden human feedback to relative task statistics. In this network, it can judge relative reward ranking from pre-trained human facial reactions. In another work [138], the affective states of humans can be perceived, and the more proper robot motion can be provided by Q-value learning, leading to participants being more comfortable and confident. Yu et al. [139] designed the trust-aware learning-based strategy for multiagent interaction settings. The theory of mind model is applied to predict the human's trust beliefs with the flexible trust-aware reward function to avoid human trust collapse in the human-robot agent.

Besides, robots with empathy can achieve more natural and effective interactions that align with the emotions of humans. In [140], the new behavior transformation model according to human motion is introduced in that robots' gestures reflect users' moods, establishing a positive and

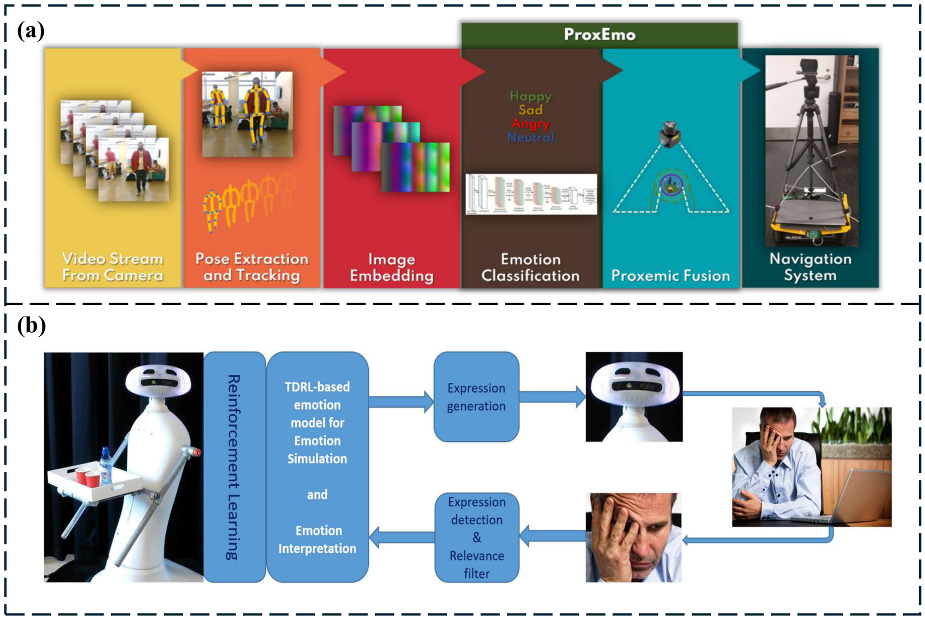

Fig. 10. The enhancement for the capacity of empathy in HITL robot learning. (a) Gait-based emotion learning for socially-aware robot navigation [132]. (b) An emotionally expressive robot interaction with humans by TDRL [133].

long-lasting HRI system. Broekens and Chetouani [133] presented a temporal difference reinforcement learning (TDRL) theory to develop an emotionally expressive robot interaction with humans (see Fig. 10(b)). In this learning loop, appropriate expressions can be chosen to interact with humans for personalized emotion interpretation. To provide affect-driven motion for communicating with humans of social robots, Churamani et al. [141] investigated a framework consisting of intrinsic emotion description and interaction behavior training with self-organizing neural models.

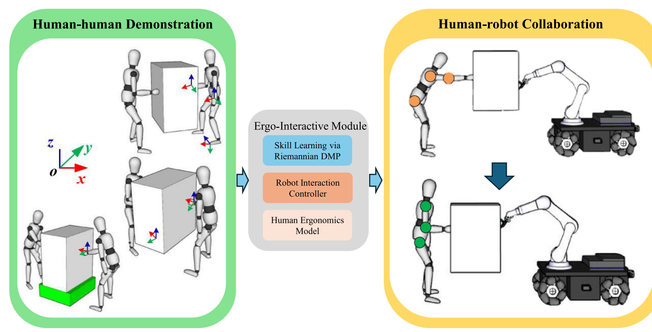

Fig. 11. An illustration showcasing the application of HITL robot learning in the human-robot co-carrying task [142].

VII. HITL Robot Learning Application in Smart Manufacturing

HITL robot systems in smart manufacturing, which leverage human intelligence into the learning cycle of robots, thus not only optimize operational efficiency and product quality but also play a crucial role in workforce development and the sustainable evolution of manufacturing practices.

Fig. 11 encapsulates a typical HITL system in smart manufacturing for the human-robot co-carrying task. In this framework [142], the main content includes three blocks: human-human demonstration, ergo-interactive module, and HRC. In the first step, one worker first finished the co-carry work with another human partner. The trajectories of human joints were captured by the MoCap system. Then, the Riemannian-based DMP is applied to encode the corresponding trajectories in Cartesian space and define reference position and orientation. In the HRC block, a mobile manipulator executed such reference trajectories and completed the task with workers with online adaption with human ergonomics.

With the features of generalization, few-shot learning, and low-code programming in HITL systems, the robots can finish intricate tasks such as inspection in industrial scenarios, co-carrying heavy mechanical components, and robot trajectory planning for complex surfaces in welding, thereby actualizing human-centric smart manufacturing in an intelligence factory. In the section, the value of HITL robot learning is explicated in detail following the above three key features in smart manufacturing applications.

A. Generalization

Generalization refers to the robot's ability to apply learned knowledge or skills to new and unseen situations or tasks that were not part of its original training set, which determines the adaptability and usefulness of a robot in varied and dynamic real-world environments. Essentially, it's the measure of how well a robot can adapt its responses to changes in its contexts or to new tasks that it has not explicitly been programmed to perform [143]. In HITL, generalization facilitates robots to extend their intelligence and skills by integrating human insight and corrective feedback which enables autonomous systems to learn from less data, recognize broader patterns, and establish a human-inspired capacity for problem-solving (see Fig. 12).

TABLE VIII
EMPATHY

Robot platform	Method	Method type	Key result	Ref.
Pepper	DCS+GWR	IL	The robot can express emotions through the imitated motions of the user	[140]
Pepper	Seq2Seq+GAN	IL+DL	The robot could generate and adjust social behaviors according to the user's posture.	[136]
Kinova Gen2	MDPs-based model	IL+DRL	The robot interprets human facial reactions in both the training task and the deployment task	[137]
Pepper	Value-function through TD	DRL	It helps to generate and express emotions for learning robots in a unified way.	[133]
NICO	MCCNN +GWR	DRL	The model can yield intrinsic responses in the robot towards the user that constitute its own affective state	[141]
Pepper	Contextual Q-value	DRL	The robot can provide users comfort and confidence and help them enjoy and feel better	[138]
Mobile robot simulator	EWareNet	DRL	Social robot navigation can adjust based on the pedestrian pose, intent, and affect	[134]
Clearpath Jackal	Graph convolution	DRL	Socially-aware navigation can incorporate constants derived from emotion and view-group predictions	[132]
Franka Panda	VGG16	DRL	The robot can precisely understand human emotions and effectively assist humans in co-assembly tasks.	[135]
Cheat game simulator	Conservative Q-Learning	DRL	The model optimizes the reward function of robot strategy, balancing team benefit and human trust maintenance	[139]

In manufacturing systems, the strength of generalization in robot learning is multifaceted. As the diversity of product offerings expands and the complexity of manufacturing tasks escalates, there is an imperative need for robots to possess the capacity for rapid adaptation to these variations, thereby obviating the necessity for reprogramming or extensive human intervention. Moreover, the array of assembly components, each necessitating unique assembly techniques, demands that robots be endowed with the ability to generalize their learned skills to suit varying assembly requirements effectively. Additionally, within the context of unstructured work environments, robots may be required to navigate and operate absent predefined pathways. This necessitates a robust capability in robots to comprehend and adapt to the inherent randomness and uncertainty characteristic of such environments, to perform tasks efficaciously. Collectively, these factors highlight the critical importance of enhancing the generalization abilities of robots, thus ensuring their capability to execute diverse tasks efficiently in the dynamically evolving and technically demanding landscape of smart manufacturing. In [142], the generalized trajectories were computed online through the robot's current positions and orientations, target pose, and phase variables. Pearson's correlation coefficient is used to evaluate the similarity between the generalization and the demonstration trajectories for the human-robot co-carry task. Every generalization can be achieved from different starts and targets without extra robot teaching. Pérez-Dattari et al. [144] developed a novel contrastive loss for obtaining globally steady motion in dynamical systems, which is verified by the hammer hanging experiment. In this method, actions provided in certain regions with no teaching smoothly generalize the motions generated in the demonstrations. Huang et al. [107] designed an object-level constrained (OLC)-DMP model for the box flipping task, which focused on the improvement of the ability of generalization. Baxter flipped three boxes successfully and steadily with different sizes to verify the skill generalization capability. In addition, the skill generalization ability is widely valuable in many applications in industrial automation, such as robotic grasping [145], industrial HRC [146], and assembly [41].

However, skills or knowledge learned in one task or environment may not always transfer seamlessly to another, particularly when the tasks are very dissimilar or the environments have distinct characteristics. Even with successful transfer, the performance of a robot may vary significantly from one task to another, necessitating additional tuning or training to achieve the desired level of performance. Kim et al. [147] proposed a transfer learning policy based master-to-robot (M2R) system. However, the camera had to be mounted in a fixed position in this system, which means the method could be useless if the manufacturing context is changed with a lack of skill generalization ability.

B. Few-Shot Learning

In traditional machine learning, particularly in DL, models typically require large datasets to generalize well from the training data to unseen data. However, in many real applications, such as in the context of manufacturing systems, obtaining large datasets can be impractical, expensive, or time-consuming. Despite the implementation of Digital Twin (DT) technology, which partially reconstructs real-world scenarios in virtual environments, and the ability of robots to utilize simulations with extensive datasets for improved training, the virtual models may not fully and accurately replicate all physical and environmental details [148], [149], [150]. If the foundational models of DTs are inaccurate, the resultant training or acquired skills could be unsatisfactory, with a relatively high demand for computing resources and data storage for generating large amounts of data through simulation to train models. Few-shot learning, on the other hand, refers to training a model on a small number of examples to quickly

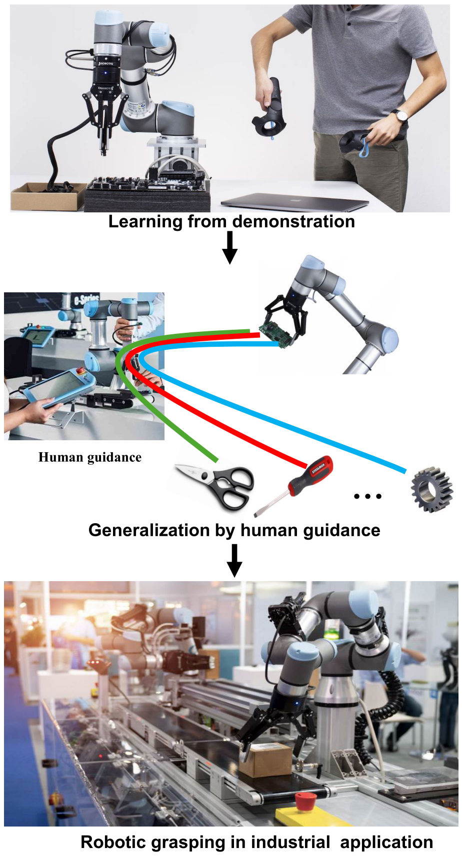

Fig. 12. The application of the skill generalization for robotic grasping in industrial scenarios.

adapt to new scenarios, relying on quickly generalizing from these examples to perform tasks accurately. This approach significantly reduces the time and effort required for traditional robot training methods, relieving the burden on human users. The robot can learn from these few examples with few demonstrations, making the training process more efficient and less time-consuming.

In manufacturing scenarios, few-shot learning enables manufacturing systems to quickly adapt to new or updated production tasks with minimal training data, minimizing the need for extensive data collection and annotation. Based on this paradigm, robots can rapidly learn new tasks with just a few teachings from human guidance, which is essential in dynamic industrial environments where robots need to adapt to new tasks frequently. Furthermore, this approach facilitates the transfer of skills or capabilities from generalized contexts to specific manufacturing settings through the utilization of limited datasets, which effectively addresses the intricate industrial tasks prevalent within manufacturing environments. In this context, this learning-based method can address the issue that products and processes can change rapidly and allow for the swift integration of new instructions or tasks into a robot's repertoire without the need for extensive retraining, making it a flexible approach for customized manufacturing processes in HITL setups. In [151], Zhu et al. focused on learning task-parameterized behaviors with few-shot demonstrations for deformable objects. Instead of solely learning from the expert's teaching, this method makes the generalization of synthetic demonstrations by augmenting the raw dataset to decrease ambiguous demonstrations in the total dataset. Jang et al. [152] proposed a vision-language framework for few-shot generalization to new tasks for dynamic pick-and-place. A command in the form of language or a video of a user can allow robots to learn a new task quickly without any extra robot data for those tasks, according to this IL policy. A vision-based HRI approach is designed in [153] for indoor goal communication. In this article, metric learning is employed for data augmentation and passive diversification to enhance the training ability of a classifier with few-shot. Besides, many contexts, like navigation [76], collision-free path planning [154], and muti-industrial robot control [155], pay more attention to this few-demonstration method to make robotic systems more adaptable and cost-effective.

Few-shot learning, while powerful, comes with inevitable limitations that can affect its performance. For example, the success of few-shot learning can be sensitive to the choice of model architecture and hyper-parameters, and the quality and extent of the pre-training can significantly impact the model's ability to learn from a small number of examples. Sheidlower et al. [156] developed an interactive RL policy for action-space environments. However, the strategy needs to learn independently from the environment and a teacher, leading to more high-quality demonstration data for this process. If combining both training processes, the model should be selected carefully for better performance.

C. Low-Code Programming

Low-code programming is an approach that simplifies the process of programming robots by reducing the amount of traditional text-based code that needs to be written. Instead, it relies on visual programming interfaces, pre-built templates, user-friendly configuration tools, and multimodal natural HRI that enable developers and even non-technical users to create and customize robotic applications with minimal manual coding. Low-code platforms support iterative development processes, making it easier to refine and optimize robot behaviors based on real-world performance and feedback, which provide a high-level, user-friendly interface that can translate visual and model-driven programming into underlying code [112].

For industrial production, this method opens up robot programming to a broader range of users, decreasing the reliance on specialized programming expertise to gain cost-effectiveness in this process. With low-code platforms, robots can be quickly reconfigured to handle new tasks, supporting an agile manufacturing environment. Besides, engineers and operators on the manufacturing floor can take an active role in programming and fine-tuning robot operations, leading to solutions that are closely tailored to the actual needs and nuances of the manufacturing process. The framework emphasizes the smooth process and generates execution code from the scheduled and optimized manufacturing process, providing significant enhancements to the flexibility and resilience of production processes with the ability to adapt to a variety

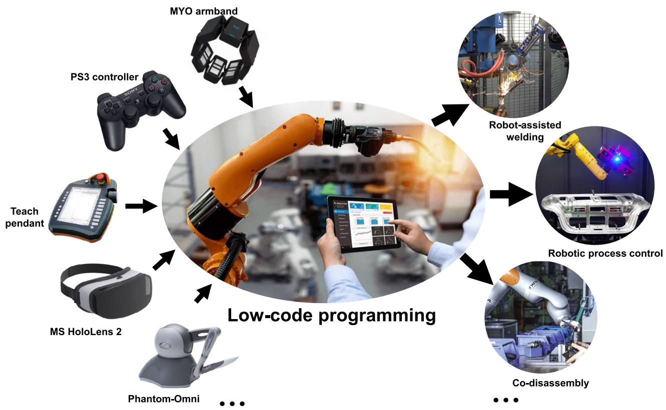

Fig. 13. The application of low-code programming for smart manufacturing.

of tasks swiftly and changing industrial demands. A human-like compliant movement primitives (HL-CMPs) is introduced in [157] to learn compliant behaviors, encoding motion trajectories with task-specific parameters. After the kinematic demonstration, the compliant details are trained according to a biomimetic control policy in the muscle space and tested by the insertion and cutting tasks. Bechtle et al. [101] designed a self-supervised learning strategy from vision-based potential representations. The extended kinematic chain can be applied as a visual predictive model with multimodal keypoint detector on the grasped object placing task with a 7-DoF iiwa Kuka arm. In [158], Du et al. proposed a multimodal learning framework based on EMG and inertial measurement unit (IMU) in human-robot co-sorting. This interface serves to record the real-time poses and grasp forces of human hands so that the robotic limb can mimic the forces for reliable sorting. Beyond the above applications, low-code programming is regarded as one key role in robotic process control [159], robot-assisted welding [97], and co-disassembly [160] (see Fig. 13).

Nevertheless, a robot trained via low-code programming might perform well on tasks that closely mimic the training scenarios but may struggle to generalize to slightly different situations or to handle unforeseen circumstances that were not present in the training data in real-world manufacturing systems, which often involve a degree of variability and noise not present in a controlled learning environment. Lee et al. [161] designed a visual interaction force prediction method for teleoperation systems. In this policy, the generalization of this method for diverse objects or unseen objects is lacking, so it is feasible for online teleoperation in complex manufacturing contexts.

VIII. Challenges and Future Perspectives

In this section, some challenges and future directions for robot learning technologies based on HITL systems will be discussed.

A. Sim-to-Real Transfer

Sim-to-real transfer is to transfer predictive control and learning strategies obtained in simulation directly to the real world. It provides a unique opportunity to train robotic systems in a controlled, risk-free environment before deploying them in the real world in the context of HITL robot learning [162]. When robots learn new tasks, especially complex or potentially dangerous ones, mistakes can have serious consequences. These can range from damage to the robot or its surroundings to potential harm to human operators or bystanders. Training the robot in a simulated environment can significantly reduce the risk of such incidents. However, the challenge of addressing the dynamic domain gap between a simulated environment and the real world remains essential [163]. Looking ahead, the sim-to-real transfer could enhance human guidance to train robotic systems safely and cost-effectively and ensure that robots can generalize their learning effectively. The advent of transfer controllers like OpenAI's Rubik's cube [164] promulgates rapid development in this field.

B. Multi-Agent Learning

Multiple learning agents interact or collaborate to solve a problem in industrial scenarios where every agent is regarded as an independent learner with its method and agents work together to achieve a common goal, such as in team sports or swarm robotics [165]. This allows humans to train multiple robots simultaneously, saving time and resources compared to training each robot individually. Furthermore, it enables human experts to provide high-level guidance to the group of robots as a whole rather than having to micromanage each robot's actions. Na et al. [166] designed a collision avoidance behavior for swarm systems based on a virtual pheromone, making robot navigation and collision avoidance tasks in different scenarios. However, as the number of agents increases, the complexity of the learning problem grows exponentially, and coordinating these robots can be a complex task, especially in dynamic or unpredictable manufacturing environments. Nevertheless, the potential substantial impact on manufacturing systems makes this an inspiring research frontier.

C. Human-Cyber-Physical Systems

Human-cyber-physical systems (HCPS) integrate humans, cyber systems, and physical systems to satisfy the prerequisite of Industry 5.0, which states that humans are placed at the core of the manufacturing system [167]. Besides, HCPS facilitates the customization of robot learning to individual users' or tasks' specific needs and preferences since it enhances workers' abilities to interact with robots via intelligent human-machine interfaces and techniques designed to assist robots in understanding and adapting to the workers' physical and cognitive demands. Nevertheless, increasing acceptance, trust, and transparency between humans and robots is currently crucial under human-centered thought. The coexistence of nonlinearity, large delays, and compliance control amplifies the complexity of the system. Augmented reality (AR) and the metaverse can establish a virtual shared space created by converging virtually enhanced physical and digital reality with the real-world scene [168]. Cloud computing-based AR could give more prominence to the role of humans in robot learning. The next generation of HCPS is supposed to empower further human-robot symbiosis for smart manufacturing.

D. BCI-Controlled Robot

BCI allows robots to be controlled directly by brain neural signals. A BCI is a system that communicates between the brain and a computer mutually [169]. BCIs can capture human intention, emotion, or motion planning and convey this information to robots, enabling them to mimic some specific movements or learn cognitive abilities according to deducing actions the human imagines or positive/negative feedback from brain neural activities. There are a set of challenges to combining BCIs with learning processes. For example, safety is paramount since most brain-robot systems lack natural acceptance. The adaptation of BCIs in robotics, applying brainwaves to guide robots, also requires seamless compatibility of the robot by the brain [170]. Referring to section IV-A, as the recent advance, steady-state visually evoked potential (SSVEP) and motor imagery (MI) are employed to capture the spontaneous activity of the brain under the safety approach with muscle tension from jaw clench [78]. The interplay between BCI and robot learning boosts the development of safe and ergonomic robotic systems.

E. Industrial Embodied Intelligence

Based on the current shortages and outstanding abilities of large language models (LLMs), the opinion of "embodied intelligence" in robotics plays a transformative role in achieving truly smart systems in the Industry 5.0 era [19]. when empowered with multimodal perception, LLMs are regarded as AI agents capable of interacting and learning from humans and the environment. The combination of robot skill training with LLMs has shown that robots can execute precise trajectories and perform complex operational tasks directly from human language guidance. In this context, GPT-4 presents a pioneering opportunity to narrow the bridge gap between human instruction and robotic skill/cognition learning with multi-domain knowledge understanding and reasoning [171]. However, manufacturing scenarios are confined by diverse industrial constraints and standards, so the advancement of industrial embodied intelligence meets unique challenges. For instance, it lacks zero-shot and few-shot learning capabilities when parameters and task-specified configurations are insufficient for providing a complex toolpath for manufacturing processes. Despite the above challenges spanning HRC, trajectory planning, and force control, it is believed to be a promising research direction to satisfy multiple requirements of personalized manufacturing. This concept significantly enhances the coevolution of humans and robots by creating more intelligent, responsive, and efficient industrial systems.

IX. Conclusion

To provide a holistic scene perspective, this paper provides a recent survey paper of HITL robot learning for smart manufacturing. The main contributions of this paper, which set it apart from other review papers, are three-fold: (1) this paper is the first that comprehensively reviewed HITL robot learning-related works from a human-centric perspective, identifying cutting-edge advancements and key areas of focus for human-centric smart manufacturing according to surveying and classifying over 140 representative studies; (2) we present a thorough review from different aspects of human intelligence, such as perception, cognition, behavior, and empathy, and provide the categorization of human roles in the learning cycle; (3) five topics practically limited by certain challenges are discussed in detail to improve the current approaches and seek promising future directions. It is hoped that the insights in this paper will be valuable to both scholars and industry professionals and offer a comprehensive resource to advance HITL robot learning in future human-centric smart manufacturing.

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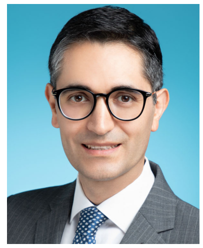

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