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REVIEW PAPER

Emerging Frontiers in Human–Robot Interaction

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Abstract
Effective interactions between humans and robots are vital to achieving shared tasks in collaborative processes. Robots can utilize diverse communication channels to interact with humans, such as hearing, speech, sight, touch, and learning. Our focus, amidst the various means of interactions between humans and robots, is on three emerging frontiers that significantly impact the future directions of human–robot interaction (HRI): (i) human–robot collaboration inspired by human–human collaboration, (ii) brain-computer interfaces, and (iii) emotional intelligent perception. First, we explore advanced techniques for human–robot collaboration, covering a range of methods from compliance and performance-based approaches to synergistic and learning-based strategies, including learning from demonstration, active learning, and learning from complex tasks. Then, we examine innovative uses of brain-computer interfaces for enhancing HRI, with a focus on applications in rehabilitation, communication, brain state and emotion recognition. Finally, we investigate the emotional intelligence in robotics, focusing on translating human emotions to robots via facial expressions, body gestures, and eye-tracking for fluid, natural interactions. Recent developments in these emerging frontiers and their impact on HRI were detailed and discussed. We highlight contemporary trends and emerging advancements in the field. Ultimately, this paper underscores the necessity of a multimodal approach in developing systems capable of adaptive behavior and effective interaction between humans and robots, thus offering a thorough understanding of the diverse modalities essential for maximizing the potential of HRI.

Keywords Human–Robot Interaction · Human–Robot Collaboration · Brain-Computer Interface · Emotional Intelligent Perception · Computer Vision

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1 Introduction

Human–Robot Interaction (HRI) focuses on designing, evaluating, and understanding of robotic systems intended for interaction with humans. This field overlaps various disciplines, such as social sciences, cognitive sciences, robotics, engineering, and human–computer interaction, to examine the interaction between humans and robots. However, the central focus of HRI is on how humans and robots interact, whether between one person and one robot or multiple individuals and multiple robots [1].

This study concentrates on three emerging interaction channels between robots and humans. First, we examine research that enhances our understanding of human robot collaboration, specifically by exploring the field of human–robot cooperative control, an emerging field in robotics that enables interaction through the combination of human and robot action. Next, we examine using Brain-Computer Interfaces (BCI) to enhance interaction between

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humans and robots by utilizing bio-signals. Finally, we explore emotional intelligent perception for transferring emotions to a robot. We review some recent advances in the above three areas; then, we discuss the future directions of these fields and their role in human–robot interaction.

Effective Human–Robot Collaboration (HRC) integrates human skills and robotic capabilities for tasks requiring joint effort, such as co-manipulation and haptic interaction. Advances in this area are leading to more user-friendly robots, capable of tasks like assisting with manual labor or workspace organization. Additionally, Brain-Computer Interfaces (BCI) are evolving as vital tools in HRI, enabling direct communication between humans and machines through brain signals [2]. Moreover, according to multiple research studies [3, 4], nonverbal elements convey two-thirds of human communications. The development of emotional intelligence in robots, which involves recognizing human emotions through nonverbal cues like facial expressions and body language, is crucial for more nuanced and effective human–robot interactions. This paper underscores the necessity of a multimodal approach in developing systems capable of adaptive behavior and effective interaction between humans and robots, thus offering a thorough understanding of the diverse modalities essential for maximizing the potential of HRI.

As depicted in Fig. 1, our primary objective in this study is to examine recent advances in human–robot collaboration, brain-computer interface, and emotional intelligent perception. In addition, we aim to present a roadmap for future Human–Robot Interaction (HRI) advancements by drawing upon these three interrelated areas. By thoroughly investigating these subjects, we strive to gain a comprehensive understanding of the underlying principles and challenges of human–robot cooperative actions, all viewed from three distinct viewpoints. The following Section 2, we elucidate the utilization of these three directions while examine their potential impact on outcomes. Next, Section 3 explores three emerging frontiers in Human–Robot Interaction (HRI). We first delve into human–robot collaboration in Section 3.2, highlighting the various methods used, including compliance control-based, human performance-based, model learning-based, synergy-based methods, and newer techniques such as learning from demonstration, active learning, and learning from complex tasks. Next, in Section 3.3, we examine the brain-computer interface (BCI) field, focusing on its applications in rehabilitation, robotics, brain state detection, communication, and emotion recognition. We then delve into emotional intelligent perception in Section 3.4, explicitly focusing on facial expression recognition and emotion recognition through body gestures and eye-tracking. Finally, in Section 3.5, we bring these three areas together to offer insights into the future directions of HRI.

2 Converging Humanity and Robots

There are different diversions such as Human–Robot Interaction (HRI), Brain computer interface (BCI) and Emotional intelligence (EI), these framework stands at the forefront of technological advancement, holding the potential to revolutionize the dynamics between humans and robots. By delving into the depths of HRI, researchers and engineers are paving the way for a future where robots become indispensable companions, assistants, and collaborators, seamlessly integrated into the fabric of our lives.

In our research, Mitra [5], a humanoid robot, has been chosen as our foundational framework, driven by the vision of enhancing its capabilities to encompass Emotion Detection, Brain-Computer Interface (BCI), and advanced Human–Robot Collaboration, with a specific focus on creating an emotionally intelligent robot. While Mitra's current capabilities may not include these facets, our goal is to propel Mitra towards a future where it becomes proficient in understanding emotions, interacting through BCI, and engaging in nuanced human–robot partnerships. By imbuing Mitra with these advanced attributes, we aim to forge

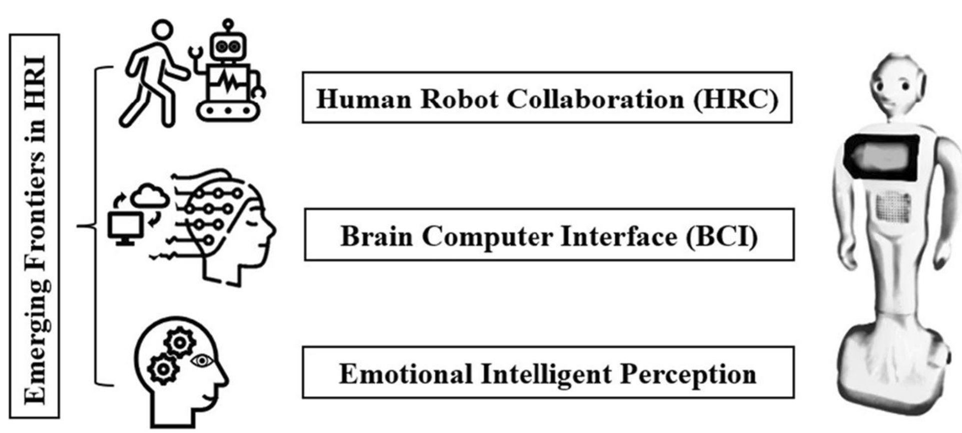

Fig. 1 Three Emerging Frontiers in Human–Robot Interaction (HRI): Human–Robot Collaboration, Brain-Computer Interface, and Emotional Intelligence Perception

a path towards the realization of an emotionally intelligent robot that excels in perceiving, responding to, and collaborating with humans on a deeper level. A compelling facet of our work involves crafting responses based on users' emotional cues. By discerning and interpreting these cues, Mitra adjusts its interactions coherently, exhibiting empathy and synchronizing with the user's emotional state. This multifaceted approach epitomizes our dynamic utilization of Mitra's potential within our research, paving the way for a future where human–robot interactions seamlessly blend complexity with intuition. Instead of starting the learning process from scratch, the artificial intelligence learns from the complex nuances of behavior demonstrated by the"teacher," allowing it to skillfully repeat and achieve relatively successful results. As depicted in Fig. 1, our research trajectory aligns harmoniously with these innovations.

The use of HRI to develop intuitive robots capable of understanding human gestures and facial expressions has been transformative. Consider, a situation where a Mitra robot equipped with an advanced HRI mechanism can understand users' subtle movements and accurately interpret their intentions. This feat allows the Mitra robot to seamlessly adapt to the user's movements, creating an effortless and natural experience. With the progression towards increasingly intuitive interactions, users experience a reduction in their learning curve, enabling seamless utilization of the complete capabilities offered by Mitra's robotic systems.

However, the range of possibilities extends far beyond simple gestures and expressions. Emotional intelligence (EI) emerged as a cornerstone, giving robots like Mitra the ability to recognize and respond to a wide range of human emotions. In this case, we plan to make Mitra robot emotionally intelligent by using eye tracking or by face recognition. Suppose a person is happy Mitra makes it movement fast or slows down when a person is sad. Recent research discusses the advances in emotional intelligence in robotics by being able to allow robots with empathetic behavior and its capabilities of human [6]. This type of emotional intelligent information helps robot better understand the human and make it more interactive. The integration of EI helps robots gain the ability to connect with humans on a deeper level and move beyond their utilitarian role to become empathetic companions. This dimension of empathy created through EI not only enhances Mitra's social abilities, but also allows it to understand and respond to the user's needs, from assistance to companionship.

However, advances in human–computer interaction continue to push past current boundaries, reflecting the ever-changing nature of the field. Brain-computer interface (BCI) technology is becoming a channel through which people can seamlessly connect intentions and actions. This research are being done in order to make Mitra interact with human by using brain signals. Different studies are done where an EEG signal extracted from human brain are used to interact with robots by passing these extracted brain signals to the robots. EEG-based Brain-Computer Interfaces (BCIs) for locomotion and mobility rehabilitation, focusing on applications like wearable exoskeletons, orthosis, prosthesis, and assistive robots [7]. It is expected that robots respond accordingly as the passed signals. This makes a deeper connection between a robot and a human with disabilities reaching new levels of autonomy by mind-controlling the movements of the Mitra robot. BCI is changing the concept of interaction and ushering in an era where human–robot interaction goes beyond traditional methods, opening up possibilities like never before. Mitra robots can be an extension of user intent, building the foundation not only for accessibility, but for deep intuitive engagement driven by the power of the mind.

In addition to these remarkable advances, the convergence of artificial intelligence (AI), virtual reality (VR), and augmented reality (AR) facilitates the transformation of the Mitra robot into an autonomous, immersive, and information-rich device. Artificial intelligence allows the Mitra robot to learn from experience, adapting its behavior and actions based on the accumulated knowledge. VR puts a robot in an immersive environment that allows it to hone skills and navigate complex scenarios in virtual space before performing real-world tasks. AR overlays a layer of digital information on the physical world, allowing Mitra's robots to help users identify objects, provide navigational advice or provide context-sensitive data.

These three directions when combined, bridges the gap between human desires and technological capabilities. Humans can directly translate mental commands into actions performed by robots, allowing for personal control and management of the technology. The synergy between human–robot interaction, brain-computer interfaces, and emotional intelligence has the capacity to create a more harmonious and productive integration of technology into our lives, bridging the gap between human desires and technological capabilities. It shows the potential of human ingenuity, giving us a glimpse of a future where machines seamlessly fit into our lives, empowering us, enriching our experiences, and creating connections that redefine the boundaries between the artificial and the human.

3 Emerging Frontiers in HRI

This section presents an overview of popular approaches in human–robot collaboration, brain-computer interfaces (BCI), and emotional intelligent perception. Our investigation begins with a comprehensive examination of various methods used for human–robot collaboration. Subsequently, we analyze the potential for improving interactions between robots and humans, emphasizing the utilization of brain signals. Finally, we review the current methods for emotion recognition, including the state-of-the-art techniques for extracting human emotions from vision interfaces.

3.1 Human–Robot Collaboration

In general, humans teach robots to assist in solving a complex problem leading to a goal. The underlying impression of this interaction is considered as the relationship between the master and his apprentice. Ideally, the robot must adapt to different needs based on the context. Traditionally, human engineers predicted all these probable interaction parameters and implemented routines to generate appropriate robot responses. But with the advances in human–robot interaction (HRI), systems are now being developed based on spatiotemporal adaptations of recorded human–human interaction such as learning from demonstration (LfD) [8] or programming by demonstration (PbD). These methods allow the natural and intuitive transfer of human knowledge about a task to a collaborative robot [9]. For example, multi-agent imitation learning leads to a responsive robot that learns to react to human movements and gestures [10]. Research studies on human–robot collaboration have been under investigation as early as the 1980s. Since then, the field has undergone rapid developments based on the following approaches. Broadly, one can categorize these approaches as control-based, human performance-based, learning-based, and synergy-based. Table 1 presents different methods for controlling human–robot collaboration, along with their descriptions and references to the research for each approach.

3.1.1 Compliance Control-based Approaches

Compliance control-based approaches were widely used during the early stages of human–robot collaboration studies. In this category, we group those works that utilize impedance and admittance control to interact with the robot. In impedance-controlled robots, the robot's behavior is characterized by an impedance matrix, which describes the relationship between applied forces/torque and the resulting motion of the robot. Typically, a spring-damper system analogy is used where the "spring" denotes the robot's stiffness. This indicates the robot resistance to deformation when subjected to external forces whereas the "damper" represents damping, signifying the robot resistance to motion in response to external forces. Thus, by modulating the impedance matrix, the robot can display compliance similar to a physical spring, enabling it to absorb and respond to external forces in a controlled manner. In the case of admittance-controlled robots, the focus shifts to the robot's response to external displacement. An admittance matrix is used to characterize the behavior of the robot that represents the relationship between the external displacements applied to the robot's end effector and the resulting forces/torques produced by the robot. Using the same spring-damper system analogy, in this case, the "spring" represents the robot's compliance to external displacements while the "damper" represents the damping, indicating how the robot resists abrupt changes in positions. Therefore, by adjusting the admittance matrix, the robot tends to exhibit compliance when an external force displaces the robot's end effectors similar to a physical spring-damper system.

Generally, in compliance control-based research studies, the human performed the role of a master, whereas the robot acted as a follower. In [11, 12], the robot's controllers received the force applied by the master, allowing the human to direct the object's motion while the robot worked as a follower. Hence, it was proposed to adopt an admittance control approach that focuses on the mechanical impedance or resistance of the object manipulated by the human and robot. [13, 14] used a variable impedance control to model human–robot cooperation. This study used force information to estimate human intention and modified the robot to act cooperatively. [15] proposed to use the equilibrium trajectory hypothesis to control the robot action in a cooperative environment. Similar to this approach, [16] developed a model based on the task and visual feedback to an admittance controller. The authors reported that a force-based controller might not be sufficient for human–robot collaboration; as a result, they included visual information to improve the robot's performance in a cooperative environment.

Table 1 Human–Robot Collaboration Approaches

Approach	Description
Compliance control-based	Uses impedance control and admittance control for HRI. [11–16]
Human performance-based	Studies human–human collaboration to design robots. [13, 17–20]
Model learning-based	Uses algorithms like Gaussian Mixture Models and Regression and Dynamic Movement Primitives to train robots to perform tasks. [21–23]
Synergy-based	Uses human interaction as an inherent part of designing the HRI. [24–31]

3.1.2 Human Performance-based Approaches

Human performance-based approaches involved human–human collaboration, which was initially studied to understand the intrinsic details during assistive experiments and then designed to translate that into robot controllers. Through the use of a variable admittance control, [13] proposed to estimate human cooperation from data collected through experimental trials. The experiments included two humans jointly carrying an object. A minimum jerk model [32] has been an inspiration for much research. [17] used the minimum jerk model as a reference and modeled an admittance-controlled robotic assistant. Similarly, the minimum jerk model was used in [18] to approximate the human hand position during a human–robot collaboration experiment of transporting an object. This approximation of hand position was used as a reference for the robot controller. Tsumugiwa et al. proposed an admittance controller by varying the damping according to the approximation of human arm stiffness. Moreover, a similar approach by varying the robot's damping according to the human arm stiffness, at a low velocity, was also developed [19]. Yang et al., in [20] proposed a robot controller that reproduced how humans adapt to interaction forces and instability. The robot controller learned to adjust to unaccounted deviations using feedback and feedforward parameters and minimized the motion errors achieving a variable impedance behavior.

3.1.3 Model Learning-based Approaches

We aim to categorize those research studies that use different algorithms to achieve interactive robots. [21] demonstrated master and apprentice roles in a cooperative task where Gaussian Mixture Models (GMM) and Gaussian Mixture Regression (GMR) encode and recreate collaborative behaviors in robots. The GMM captures the robot motion and the different forces and the GMR generates the reference force during replication. In [22], a new framework was presented to recognize human intentions as early as possible in order to generate safe robot motions when human and robot are working together in close proximity. In this study, GMM representations simulate human coworker's motion and GMR predicts the coworker's future motions. [33] proposed a hybrid structure built on programing by demonstration (PbD) and adaptive control. Some researchers employ the interaction forces using dynamic movement primitives (DMP) introduced by Schaal et al. [34–36]. DMPs combine optimal control theory and nonlinear dynamical systems for trajectory control and planning. A probabilistic encoding of the DMP parameters that let the robot's movements be adapted and correlated depending on the assumptions about human intentions made from partial observations was proposed in [23]. Ben Amor et al. suggest the use of dynamic time warping for structuring future robot movements in accordance with the human partner's timing. [37] took this idea one step further by modeling the collaborative interaction using the probabilistic motion primitives that were introduced by [38]. In this model, the correlation between the trajectories of the human and the robot is used to carry out coordinated tasks in which the action of the robot is completely conditioned by the human partner's motion. Recently, Rozo et al., [39] proposed an approach that combined probabilistic learning, dynamical systems and stiffness estimates to encode the robot's behavior from human demonstrations. Their method allowed the robot partner to learn both trajectories following skill and impedance behaviors.

3.1.4 Synergy Model-based Approaches

Synergy model-based approaches have recently been explored toward a human-inspired solution where the robot performs with human dexterity and flexibility. Generally, a synergy-based approach involves human-in-the-loop integration where human interaction is an inherent part of designing the HRI framework. One key limitation of this approach is that for a natural interaction between human and robot, neural signals generated from the human should communicate with the machine. Recent studies [40] demonstrated that human motion intentions can be detected with good accuracy through surface electromyography (sEMG). Several research studies [24–26] have implemented sEMG based motion intention recognition for human lower limb and gait recognition and their corresponding prediction model. With the introduction of the concept of synergies by Bernstein in 1966 [41], which hypothesized the human brain controls the human hand from a lower dimensional space, several attempts have been made to extend it in HRI. A 3D printed soft hand exoskeleton was introduced that provided 5 degrees of freedom (DoF) [30]. The goal of this Hand Exoskeleton with Embedded Synergies (HEXOES) was to train subjects in executing kinematic synergy-based grasping motions during rehabilitation. In a later version, the system enabled 10 DoF of the metacarpophalangeal joints (MCP) and proximal interphalangeal joints (PIP) and interphalangeal joints (IP) of each finger and thumb [31]. In this study, muscular control of three functional synergies were used in control of 10 DoF HEXOES, thus demonstrating low dimensional control imposed on a high dimensional system. Multi modal data fusion techniques that involve combining sEMG signals with finger joints kinematics were implemented recently in the studies [27–29] to improve the decoding performance. These fusion models have the potential to enhance synergy-based grasping movements.

3.2 Human–Robot Collaboration by Learning Methods

Robots must possess the ability to react to changes in their environment and exhibit adaptive behavior in response to unknown objects and circumstances while working in collaboration with human partners. To address these challenges, various interactive machine learning techniques such as"imitation learning", "learning from demonstrations", "learning from critique","programming by demonstration","teaching by showing", and "active learning" have been proposed to imitate human skills through demonstration. In this section, we provide an exploration of various learning techniques that have been developed to enable effective human–robot collaboration. Our discussion covers a range of research in this area, including Learning from Demonstration (LfD), as well as active learning and learning from complex tasks. Table 2 provides an overview of learning-based techniques for human–robot collaboration, accompanied by descriptions and examples for each approach.

3.2.1 Learning from Demonstration

Learning from Demonstration (LfD) approach is particularly useful as it does not require expert knowledge of robotics technology, enabling end-users to instruct the robots according to their specific requirements and workflows. Furthermore, from a human–robot interaction perspective, this method effectively allows robots to learn impractical tasks to automate through other means, resulting in a more efficient learning process.

Rather than developing a technique to transfer knowledge from a human to a robot for replicating certain motion, [42] focuses on designing to help a human coworker understand their robotic partner. Several studies [10, 43, 44] suggest detecting social cues of human coworkers such as facial expression, the direction of gaze, verbal cues, and body postures to understand the human's mental states. [45] categorizes learning from demonstration (LfD) based on the technique by which demonstrations are performed as kinesthetic teaching, teleoperation, and passive observation. In kinesthetic teaching [39, 46, 47], the user can demonstrate by physically moving the robot through the desired movements. The onboard sensors capture the robot's state during the interaction such as joint angles and torques providing the machine-learning models with training data. Due to the intuitive approach and minimal user training requirements, kinesthetic teaching is popular for manipulative robots.

Teleoperation has been used in trajectory learning, task learning, grasping and high-level tasks as a commonly used demonstration input [48–51]. It uses a joystick, a graphical user interface, or other external inputs from the robot. Using interfaces through haptic devices and virtual-reality interfaces is currently the subject of ongoing research. One key advantage of teleoperation over kinesthetic learning is that this demonstration technique does not require the user to be present alongside the robot. In the passive observation technique the robot learns by passively observing the user [10, 52–54]. The user performs the task equipped with additional sensors to make tracking easier. The robot only acts as a passive observer and takes no part in the demonstration. This technique is suitable for applications with robots with a very large number of degrees of freedom where kinesthetic teaching is difficult.

3.2.2 Active Learning

Active learning is a machine learning methodology that enables a robot to solicit information from a human user

Table 2 Learning techniques for enhancing human–robot collaboration, with the goal of adapting to changes in the environment and responding appropriately to unknown circumstances

Learning Technique	Description	Examples
Learning from Demonstration (LfD)	Kinesthetic teaching	User physically moves robot through desired movements. [39, 46, 47]
	Teleoperation	Robot is controlled by a joystick, GUI or other external inputs. [48–51]
	Passive observation	Robot learns by observing the user perform a task. [10, 52–54]
Active Learning	Active Learning	Solicit information from a human user when uncertain about the next task during its learning process. [55]
	Learning from Critique	A technique that enables the robot to learn from feedback provided by a human. [56]
Learning from Complex Tasks	BP-AR-HMM and DMPs	Offer four essential requirements for learning complex tasks from unstructured demonstrations. [57]
	BP-AR-HMM, GTW, and DMP	Incorporate alignment phase to improve learning and generalization of complex tasks. [58]
	BP-HMM	Segment and identify action primitives for complex sequential tasks, evaluated on pizza dough rolling task. [59]

when uncertain about the next task during its learning process. Cakmak and Thomas [55], for example, used three types of queries were used during both human–human and human–robot collaboration scenarios, including label queries, demonstration queries, and feature queries. The results indicated that, similarly to humans, robots can effectively learn by inquiring in uncertain situations and were perceived as most intelligent when they utilized feature queries.

3.2.3 Learning from Complex Tasks

The focus of much of the learning from demonstration (LfD) research has been on scenarios in which a robot learns a policy by performing simple tasks with clear start and end points. As tasks become more complex, it becomes increasingly more work to model a policy, and such methods often fail. Subsequently, structured LfD studies often employ a decomposition technique, which involves breaking down the simple task into more minor sequences of skills. These sequences or subtasks are easier to learn and generalize, and solutions to these subtasks are combined to teach the collaborative robot to interact with humans in a smooth manner [60]. In the field of Learning from Demonstration (LfD), learning complex tasks has proven to be a difficult challenge. Consequently, limited studies have explored using LfD for the purpose of facilitating human–robot collaboration in such complex scenarios [61]. Niekum et al., proposed a novel framework that combines the benefits of Beta Process Autoregressive Hidden Markov Model (BP-AR-HMM) and DMPs [57]. This approach suggests segmenting the tasks, recognize repeated skills and generalize complex tasks from unstructured demonstrations. Through this framework the robot is enabled to learn complex demonstrations from multiple subtasks. The authors offer four essential requirements for the robust learning of complex tasks from unstructured demonstrations: The robot must (i) possess the ability to identify recurring skills and apply them in new environments; (ii) be capable of segmentation without prior knowledge; (iii) be able to recognize a general class of skills; and, (iv) the skill policies of the robot must be represented in a manner that allows for easy generalization and improvement through practice. The framework addresses these requirements and enables the robot to learn a multi-step task from unstructured demonstrations. A recent study by [58] aimed to enhance the BP-AR-HMM framework by incorporating an alignment phase along with the demonstration, segmentation, and generalization phases. To align the demonstration profiles with the key requirements, the authors utilized the generalized time warping (GTW) algorithm. By integrating BP-AR-HMM, GTW and DMP into a unified framework, the robot was able to effectively regulate each segment of the demonstrated profiles and learn a vast collection of skills, encompassing both movement and stiffness primitives. In a separate study by [59], an extension of the BP-HMM model was utilized to segment and identify action primitives, allowing the robot to learn a complex sequential task, specifically pizza dough rolling, through human demonstrations. The authors extracted action primitives and the transition probabilities of these action primitives and then trained the model on human demonstrations. The proposed framework was evaluated with a robot on a pizza dough rolling task and the robot was able to make the pizza dough with consistent shapes and desired size. Over the past decade, there has been a steady increase in the number of publications in the areas of human–robot collaboration, imitation learning, and learning from demonstration (LfD), demonstrating a growing research interest in teaching robots through example. The significant growth in publications within the last five years further highlights the growing emphasis on this approach to robot learning.

3.2.4 Metrics in Human Robot Collaboration

As depicted in Table 3, in the realm of robotic learning approaches, diverse algorithms rely on specific metrics to evaluate their performance and effectiveness. In the compliance control-based approach, key metrics such as the difference between reference and achieved frames, stiffness estimation, force-torque correlations, and motion accuracy against desired trajectories are used to gauge the algorithm's ability to interact safely and accurately within its environment. In the human performance-based approach, metrics include motion estimations for effective human–robot collaboration, the evaluation of recursive least square methods for continuous improvement, and the accuracy of stiffness estimation for adaptive interactions. The model-learning approach employs metrics like component correlations, motion recognition rates, and mean squared error to assess the cohesion, adaptability, and predictive accuracy of the algorithm. The synergy-based approach utilizes metrics such as Mean Squared Error (MSE), cepstrum distance-based endpoint detection, recognition accuracy, and cancellation index to evaluate the algorithm's proficiency in pattern recognition and control. In the learning from demonstrations approach, metrics revolve around skill reproduction and imitation, ensuring that robots can successfully replicate human actions. Teleoperation's likelihood of movement metric quantifies the accuracy of operator-guided actions. Active learning involves querying participants for feedback and using Euclidean distance for similarity assessment. Lastly, learning from complex tasks encompasses metrics such as complex skill reproduction, stiffness indication, and log-likelihood measurement, offering insights into the algorithm's understanding of intricate tasks. These diverse metrics collectively form a comprehensive framework for assessing the capabilities of various human robot collaboration

Table 3 Metrics in Human Robot Collaboration

Approach	Metrics	Sources
Compliance Control-based	a. Difference between the reference frame and the given frame b. Stiffness estimation c. Force and torque correlations d. Motion generated by admittance controller against the desired trajectory	[11–16]
Human Performance-based	a. Motion estimations – enables robots to follow the motion of its human partner b. Recursive least square method c. Accuracy of stiffness estimation	[17–20]
Model-learning	a. Correlation between components b. Motion recognition rate c. Mean Squared Error	[21–23]
Synergy-based	a. Mean Squared Error (MSE): Difference between the recorded pattern and the reconstructed pattern b. Cepstrum distance-based endpoint detection method c. Recognition accuracy: (Same as accuracy in neural networks) d. Cancellation index	[24–31]
Learning from Demonstrations	a. Skill reproduction to check whether the robots have performed the desired task successfully or not b. Kinesthetic teaching metric of Imitation: a time dependent similarity measure c. Teleoperation—Likelihood of movement	[39, 46, 47]
Active Learning	a. Querying participants for feedback, Euclidean distance measure	[55]
Learning from Complex Tasks	a. Complex skill reproduction b. Stiffness indicator c.Log-likelihood measure	[56–59]

algorithms. Table 2 shows a comparison of learning techniques aimed at enhancing human–robot collaboration.

3.3 Brain-Computer Interfaces

During the early 1970s, researchers discovered a way to enable real-time communication that allowed a person to control the movement of a cursor within a maze using the event-related potentials (ERPs) found in human EEG signals [62]. In the 1990s, researchers developed a complex model that translated brain signals from rats into real-time commands for controlling a robotic arm [63, 64]. In the early twenty-first century, BCI has grown rapidly, with more researchers dedicating themselves to the field. Birbaumer et al. demonstrated an alternative communication method for a paralyzed patient using the slow cortical potential in EEG [65]. Taylor and her colleagues were able to decode real-time movement intentions from cortical neurons in monkeys, using the decoded information to control a neuroprosthetic device [66]. Schwartz et al. achieved a milestone by demonstrating that monkeys could learn to feed themselves by controlling a mechanical arm with their brain activity [67]. Later, noninvasive EEG based BCI was used to detect different human intentions, which were then applied to control a robotic arm [68]. A telepresence [69] robot assisted humans in completing complex tasks in a short amount of time, specifically for disabled individuals. Recently, robotic arms not only receive output from the brain but also feed sensory signals back to the brain, which stimulates the sensory cortex. This allows paralyzed patients to experience the sensation of touch through a robotic arm for the first time [70]. In addition to assisting patients with motor disorders, BCI systems have become a useful tool for improving the quality of life for elderly people [71].

Although invasive BCI renders more accurate and precise control, noninvasive BCI is more feasible for humans due to its lower risk of causing permanent damage to the brain. Furthermore, the evolution of noninvasive BCIs, specifically EEG-based systems, has been complemented by the development of advanced engineering algorithms, such as machine learning [72], that help address the challenges of low resolution and high signal-to-noise ratio in brain signals.

BCIs have been applied to various fields to expedite human-robotic interaction. One of their major applications is in rehabilitating individuals with motor impairments, such as paralysis. BCI systems allow such individuals to interact with and control external prosthetics using their own neural activity, which facilitates an increase in mobility restoration and rehabilitation. Moreover, there has been a growing interest in exploring the potential of human–robot collaboration in recent years. Furthermore, BCIs are not only capable of fostering interaction among those who have lost their ability to communicate to restore communication functionality but also provide a promising strategy for increasing information transmission rates between humans and robots. Additionally, the latest advancements in BCI technology have allowed for more intuitive and human-like communication between humans and robots by detecting cognitive mental states such as attention, workload, and emotions, which correspond with affective states. These breakthroughs in BCI research have led to a greater potential for future applications in the field of human–robot interaction.

3.3.1 Brain-Computer Interface Prosthetic in Rehabilitation

Compared to traditional rehabilitative methods that require long-term training with a physical therapist, BCI-assisted rehabilitation has shown promising results in aiding stroke recovery [73] and increasing the accuracy of repetitive rehabilitative and assistive motions. Furthermore, BCIs remove limitations on the time and capabilities of the therapist, making it a more efficient and accessible rehabilitation option. Specifically, BCIs focusing on motor neuro-prosthetics, such as interfaces with computers or robotic arms, aim to either restore movement in paralyzed individuals or provide assistive devices to improve their mobility. The development of a low-cost and portable assistive BCI system [74] has benefited more individuals in the recovery process, providing a more user-friendly and affordable alternative that can be adopted by a wider range of potential users. The BCI-rehab system can establish a continuous link between neural activity and robotics, enhancing the mobility of physically disabled individuals. The system's robust and reliable decoding strategy translates the intention of gait initiation to an autonomous ambulatory robot, thus promoting the recovery of lower-limb function [75]. Robotic-assisted BCI devices can aid in the recovery of walking ability for individuals who have experienced a stroke or spinal cord injury.

These devices achieve this through intensive and task-oriented training [76], as well as by regulating a functional electrical stimulation system for ankle movement [77]. In contrast to lower-limb rehabilitation, upper-limb recovery demands more complex and precise movements. Therefore, BCI-robotic systems developed for upper-limb recovery must control higher degrees of freedom to provide potential motor assistance and rehabilitation. Experimental results have demonstrated that BCI-based robotic assistance allows patients to perform self-initiated, real-time upper-limb reaching movements with continuous control after experiencing a stroke [78]. In a study by [79] the correlation between particular EEG rhythms in the brain and upper limb motor recovery in stroke patients was examined. The study also revealed that BCI systems coupled with robotic assistive devices provided passive assistance to hand movements and showed potential for clinical rehabilitation. Bidirectional BCI has improved the performance of robotic arms by enabling not only top-down neural control of prosthetic arms, but also by stimulating the somatosensory cortex of the human brain to generate natural tactile sensations [80, 81]. The Table 4 provides a summary of the different approaches and their applications in BCI-assisted rehabilitation and robotic devices for human motor function recovery.

The remarkable finding is that humans can experience an illusion of body ownership when operating robots, even when there is a time discrepancy. This phenomenon, termed the 'ownership illusion,' involves a perceptual trickery that convinces the brain of ownership or agency over non-human bodies, such as robots or avatars in virtual environments, often induced through visual or haptic feedback. Furthermore, this sense of ownership is stronger in cases where the robot is controlled through BCI, as opposed to motion control [82]. The intention to move and receiving feedback on performance can increase the sense of ownership that humans feel towards prosthetic or robotic devices, which provides positive encouragement to users and could potentially impact the development of BCI systems for neuroprosthetics.

3.3.2 Brain-Computer Interface in Robotics

BCI extends beyond assisting and compensating impaired patients. Mobility BCI systems not only compensate for mobility impairments but also promote cooperation and collaboration between humans and robots in various fields.

Table 4 Approaches for BCI-assisted rehabilitation and robotic devices

Approaches	Description
BCI-assisted rehabilitation	Aiding stroke recovery and increasing the accuracy of repetitive rehabilitative and assistive motions. [73]
	Providing a more user-friendly and affordable alternative in the recovery process [74]
	Decoding strategy translates the intention of gait initiation to an autonomous ambulatory robot and promoting the recovery of lower-limb function. [75]
Robotic-assisted BCI devices	Aiding recovery of walking ability for individuals who have experienced a stroke or spinal cord injury [76]
	Perform self-initiated, real-time upper limb reaching movements with continuous control after experiencing a stroke [78, 79]
Bidirectional BCI	Improved the performance of robotic arms by enabling top-down neural control of prosthetic arms and stimulating the somatosensory cortex to generate natural tactile sensations [80, 81]

Currently, a lot of research is focused on the development of BCI-controlled, especially teleoperated, mobile robots for commercial use [83, 84]. BCI technology makes it possible for a human to directly control a humanoid robot in remote locations with their intentions, with mental synchronization between the human operator and robot and minimized the operation bias, if the speed and accuracy requirements are met. By using EEG signals as a command, a humanoid robot can be controlled to pick up a user-selected object and navigate to a specific location [85]. Chae et al. described a new BCI system for controlling humanoid navigation through asynchronous EEG [86], which offers flexible direct control to navigate a humanoid robot with real-time feedback from camera vision and dynamic mental status recorded from EEG. Kubacki and Jakubowski investigated the possibility of using a hybrid of brain signals and eye movements to control a robot, enabling the manipulation of objects while avoiding obstacles [87]. Steady-state visual evoked potentials (SSVEPs) have proven to be effective in BCI systems due to their ease of use and high accuracy. In 2022, Farmaki et al. developed a system for navigating a robotic car using an online SSVEP-based BCI [88]. Users could drive this robotic car in real-world conditions with flexible movement and precise collision avoidance. The use of SSVEP-based BCI has been shown to offer promising accuracy and fast information transfer rates (ITRs) even for new users without prior training [89]. Therefore, synchronous SSVEP-based systems, which usually need a synchronization cue for the beginning of each task, are frequently employed in telepresence scenarios where the robot is pre-trained using programming by demonstration (PbD). Programming by demonstration (PbD) introduces imitation learning to the robot [90], which is independent of the BCI system. As a result, the robot can be effectively trained in the factory, and there is no need for users to undergo any training sessions while using the BCI system. Table 5 summarize various approaches for BCI applications in robotic devices.

3.3.3 Brain-Computer Interface in Communication

Communication is a crucial process for expressing oneself and interacting with others. Unfortunately, this process can pose severe challenges for individuals suffering from motor neuron disorders, such as amyotrophic lateral sclerosis (ALS), which progressively disables mobility and impairs communication abilities [91]. BCI presents a promising strategy to restore communication between patients and their environment, providing an alternative solution for improved communication in individuals lacking voluntary muscle control compared to traditional communication technology [2]. A reliable neural speech interface was established for paralyzed and communication impaired individuals by recording single-unit firing from the speech motor cortex. This breakthrough provides a significant opportunity for the development of neural prostheses and improvement of the BCI system [92].

The BCI speller is a commonly used communication interface for individuals with disabilities Improving the communication speed of the BCI is essential and presents a challenge in BCI-speller research. High-performance intracortical BCIs have been identified as potential assistive communication systems, enabling paralyzed individuals to type continuously at a rate of up to 30–40 characters per minute using information transfer rate (ITR) [93]. The fast P300-based BCI speller can achieve an ITR of up to 5.32 bits/second, approximately 60 characters (12 words) per minute [94], which is overwhelming for invasive and noninvasive BCIs. Beyond “spell”, developed a BCI-controlled robot system to “write” characters in a pixel-based interface, enabling the efficient writing of both ideogram and phonogram [95]. Velasco-Alvarez et al. developed a communication system that´ connects the brain and a smartphone, allowing users to open an app, spell out words, and send messages using a BCI speller [96]. Table 6 provides a summary of different methods utilized for implementing BCI applications in communication.

3.3.4 Brain-Computer Interface in Cognition Detection

Human cognitive state detection is an essential field for both humans and robotics. It can help disabled users with active robotic assistance, as well as detect human cognitive states. BCI has also been applied to the recognition of cognitive states, with the goal of improving communication between individuals and machines by recognizing human brain states such as emotions. BCI compensates for disruptions caused by a user's emotional state, allowing intentions to be correctly interpreted. BCI applications that recognize human

Table 5 BCI-based approaches in robotics

Approach	Description
BCI-controlled mobile robots	EEG signals can be used as a command to control a robot to pick up a user-selected object and navigate to a specific location [85–87]
SSVEP-based BCI for robotic car navigation	Online SSVEP-based BCI, allowing for flexible movement and precise collision avoidance [88]
SSVEP-based BCI in telepresence scenarios	Using programming by demonstration, which introduces imitation learning to the robot [89, 90]

Table 6 Approaches for BCI-based communication systems

Approach	Description
BCI for Communication	Improved communication in individuals lacking voluntary muscle control. [2, 91]
Single-Unit Firing Recording	Recording single unit firing from the speech motor cortex. [92]
BCI Speller	Communication interface for individuals with disabilities. [93, 94]
Beyond "spell"	System to "write" characters in a pixel-based interface. [97, 98]
Brain-Smartphone	Connects the brain and a smartphone. [96]

intention adapt to changes in the affective states of humans and thereby facilitate the recognition and detection of human cognitive states, improving the human-robotic interaction.

3.3.5 Brain State Detection

The ideal interaction between humans and robots should resemble human–human interaction, which requires continuous detection and prediction of human intention [99]. An intention detection model has been built using machine learning algorithms, enabling to distinguish user's movement intention from non-invasive EEGs [100]. The detection of fatigue levels is also used in a wide range of applications, as drops in attention levels and increases in cognitive fatigue can affect the accuracy of non-invasive BCIs [101].

Studies have shown that mental fatigue may contribute to poorer BCI performance, highlighting the importance of fatigue detection coupled with a training system to ensure practical clinical efficacy according to the detected or predicted fatigue or mental state [102]. To detect emotional changes and monitor the status of a mobile terminal, Wang et al. designed an intelligent wearable helmet [103]. Three negative emotional levels (anxiety level, fatigue level, concentration level) monitoring using BCI potentially avoid improper operation and improve operation safety. Table 7 provides a summary of various brain state detection methods along with their corresponding descriptions.

3.3.6 Emotion Detection

Comprehensive cognition, including emotions, enables universal social communication, an essential topic in human–robot interaction. Emotions are necessary for cognition to manage human behavior, helping people respond appropriately to their surroundings and make decisions. Emotions can be reflected in facial expressions, body language, and speech, enabling simple communication between humans and machines or robots [105]. One of the differences between humans and robots is that humans have emotions and can hide their feelings. Thus, accurately modeling and quantifying the emotional states are important in the assessment of the emotions of human [110]. BCI system enables emotion detection from human subconsciousness and directly communicates between brain states and the outside world by identifying the positive and negative emotions of the users. When a human controls and monitors robot navigation, the BCI system distinguishes between satisfaction and dissatisfaction based on the correctness of the robot's performance, and the immediate feedback is subsequently conveyed to the robot [106]. This can correct and improve the behavior of the robot to maximize human satisfaction for better interaction between the robot and the human. Furthermore, regarding the collaboration between robots and humans, robots should be able to adapt their behaviors according to the human's mental or physical states and be more socially acceptable. [107] proposed mapping the human brain into intelligent robots by projecting the detected human feelings to a behavioral model of the robot, which allows the robot to detect and react to humans. For the detected signals out of the range of pre-defined categories, the robot will ask the users their feelings and enhance the communication and interaction between humans and robots. Furthermore, researchers suggested that it is helpful that the robot can understand the behavior and internal brain states, especially the stress level of humans, when the robot interacts with humans for effective response [108]. Table 8 provides a summary of various emotion detection methods along with their corresponding descriptions.

Table 7 Brain State Detection utilizing BCIs

Approach	Description
Intention detection model	Detect and predict human intention through non-invasive EEGs [99, 100]
Detection of fatigue levels	The ability to detect changes in attention levels and cognitive fatigue. [101, 102]
Intelligent wearable helmet	Monitoring emotional changes and status of a mobile terminal [104]

Table 8 Emotion detection utilizing BCIs

Approach	Description
Emotion detection through BCI system	EEG signals can be used as a command to control a robot to pick up a user-selected object and navigate to a specific location. [105, 106]
Mapping human feelings to a behavioral model of the robot	Enable robots to detect and react to human feelings. [92, 107]
Understanding human stress levels	Effective response in human–robot interactions [108]

The ability to identify emotions using BCI can provide humans with more natural ways of effectively controlling and interacting with robots. This requires accurate detection algorithms and higher information transfer rates to enrich the entire communication process, leading to a more natural and effective user experience. This potential for improved interaction could open new opportunities for applications. Additionally, recognizing human emotional states would allow for automatic system adaptation to humans or, it may predict their intentions, enhancing usability, and minimizing frustration, leading to an improved human experience with robots.

3.3.7 Metrics in Brain-Computer Interface (BCI) Systems

As depicted in Table 9, in the realm of Brain-Computer Interface (BCI) systems, an array of metrics is employed to evaluate their performance and usability. These metrics encompass various dimensions of system functionality and user experience. Accuracy provides insight into the reliability of the interface. Information Transfer Rate (ITR) quantifies the amount of information successfully transmitted from the user's brain to the computer, indicating the speed and efficiency of communication. Task operation time and Decoding time assess the speed at which users can perform tasks and the system can decode their intentions, respectively. Response time measures the duration between the user's intent and the system's response, influencing real-time interactions. Success attempts gauge the number of accurately completed tasks, reflecting the system's practical usability. Post-session assessment correlations analyze the consistency between users' self-assessments of their experience and objective system performance, providing valuable feedback for system refinement. Collectively, these BCI evaluation metrics offer a comprehensive framework for assessing the effectiveness, efficiency, and user-centered aspects of Brain-Computer Interface systems.

3.4 Emotional Intelligent Perception

The ability of robots to recognize human emotions is a compelling attribute, especially in socially interactive devices such as assistive and educational robots. Emotion perception and recognition from face and body poses are extensively studied in human computer interactions and affective computing. These expressions provide social cues to infer emotions only by computer vision analysis of facial expressions and body movements. In general, there are two model representations for emotion recognition. Some scholars argue that emotions comprise discrete entities and are categorized distinctly [111, 112]; in contrast, others suggest that continuous values define features that describe emotions [113]. Accordingly, facial expression and body gesture recognition methods are developed based on these model representations. This section reviews state-of-the-art algorithms for classifying emotions using facial expressions and body gesture recognition. Finally, we look at eye-tracking emotional-relevant features that can be applied to human–robot interactions.

3.4.1 Facial Expression Recognition

Facial expressions are an effective nonverbal communication method for conveying emotional information among humans [114, 115]. Additionally, they are reflective of various human emotions and thoughts [116–118]. Consequently, countries across the globe share a high level of agreement in identifying emotions through facial expressions [119]. Recent research has even demonstrated that sixteen facial expressions occur in similar contexts worldwide, showcasing the universality of these expressions [114]. Facial emotion perception is influenced by two contrasting theories: categorical and dimensional. The categorical approach suggests that there are six fundamental emotions that are recognized universally: happiness, anger, sadness, surprise, disgust, and fear [120–124]. In contrast, the dimensional theory describes human emotions using a two-dimensional space, which considers valence and arousal [125, 126]. Valence refers to the level of human pleasure on the pleasantness–unpleasantness continuum, while arousal considers the degree of energy of an emotional experience.

Some studies use a combination of dimensional and categorical theories to detect facial expressions [127–129]. In this section, we will primarily concentrate on deep FER (Facial Emotion Recognition) models that classify emotions categorically.

Table 9 Metrics in Brain-Computer Interface (BCI) systems

BCI Metrics	Applications	Operation tasks	Sources
Accuracy	Rehabilitation	Active walking	[75]
		Passive walking	[76]
		Virtual walking	[77]
		Upper limb motor imagery	[78]
	Robotics	Directional navigation	[83]
		Motor imagery	[84]
		Location navigation	[85]
		Directional navigation	[88]
		Robotic task control	[90]
		Directional navigation	[104]
	Communication	Text spelling	[94]
		Character writing	[95]
	State detection	Limb motor imagery	[100]
		Robot navigation	[106]
		Robotic control	[107]
Information Transfer Rate	Robotics	Motor imagery, directional navigation	[86]
		Directional navigation	[88]
	Communication	Text typing	[93]
		Text spelling	[94]
		Character writing	[95]
		Send and read messages	[96]
Task operation time	Rehabilitation	Drinking	[74]
		Hand motor imagery	[81]
	Robotics	Motor imagery, directional navigation	[86]
		Target navigation	[87]
	Communication	Character writing	[95]
		Send and read messages	[96]
Decoding time	Rehabilitation	Active walking	[75]
Response time	Robotics	Motor imagery	[84]
		Motor imagery, directional navigation	[86]
Success attempt	Robotics	Motor imagery, directional navigation	[86]
		Target navigation	[87]
		Motor Arm control	[109]
	Communication	Character writing	[95]
Post session assessment	Rehabilitation	Hand motor imagery	[79]
		Hand motor imagery	[82]
	State detection	Upper limb rehabilitation	[102]
		Cognitive tests	[108]
Correlations	State detection	Picture stimulation	[103]
		Cognitive tests	[108]

Facial expression recognition (FER) is a computer vision technique used to recognize a human's psychological state and emotions from an image or video sequence [130]. This makes it a practical tool for robots to automatically comprehend and recognize human facial expressions for better interactions. With the popularity of machine learning, recent studies have employed deep neural networks to decipher the emotions conveyed by facial expressions in an image [131]. These networks require large training datasets from real-world scenarios to handle emotion recognition in the wild. Overall, FER holds great potential for advancing the field of human–computer interaction, especially in the development of emotionally intelligent robots. As deep learning techniques continue to improve, we can expect to see even more accurate and effective emotion recognition in the future.

FER2013 is among the most popular databases and contains 35,887 images that have been resized to 48 × 48 pixels.

These images were collected from Google image search API [132]. AffectNet [133] is another significant database that contains both categorical and dimensional models of facial expressions. It comprises over one million images gathered from various search engines on the internet. Most FER databases typically classify emotions into the six fundamental expressions of happiness, anger, sadness, surprise, disgust, and fear, as well as a neutral state. For instance, Extended Cohn-Kanade (CK+) [134], Static Facial Expressions in the Wild (SFEW) [135], and Toronto Face Database (TFD) [136] are a few publicly available databases that contain these basic expressions and serve as benchmarks for FER models. These databases are essential for training and evaluating FER models, and their availability enables researchers to compare the performance of different models. As FER continues to gain popularity in computer vision and human–computer interaction, it is likely that more advanced and diverse databases will become available in the future.

In the past, handcrafted features were typically used in laboratory settings for FER models. However, recent advances in deep learning have enabled us to utilize both neural networks and handcrafted features to learn discriminative representations. For instance, researchers have employed local feature learning using Convolutional Neural Networks (CNN) and handcrafted features calculated by the bag-of-visual words (BOVW) model to classify different emotions in human faces [137]. In addition, experiments with Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (CNN-RNN) have been conducted to classify basic expressions and evaluated on various emotion databases [138]. Similarly, a Compact and Accurate K-dimensional representation of Emotion (CAKE) is used to learn emotions from static images [139]. These approaches have yielded promising results in FER, and as the field continues to evolve, it is likely that researchers will develop even more sophisticated models and techniques to improve the accuracy of facial expression recognition.

Li and Deng categorized deep FER neural networks into two groups based on their representations of static and dynamic features [140]. Static FER models extract spatial features to identify and classify human emotions from a single image without taking temporal information into account. Many static FER systems consider multiple relevant factors, such as head pose, illumination, and facial morphology, for multitask FER learning. Some others leverage special tasks like facial landmark localization to enhance FER performance [141, 142]. For instance, FaceBehaviorNet is a framework designed to analyze faces and extract all facial behavior features [143]. Hybrid Multitask Learning (HMTL) employs self-supervised learning to extract more valuable features in the FER domain [144]. Additionally, Emotion-GCN is a multi-task learning (MTL) framework that leverages expression classifiers, valence-arousal regressors, and a Graph Convolutional Network (GCN) to recognize facial expressions, [145].

Several FER approaches utilize lifelong learning to accumulate information over time through deep networks. For instance, the packing-and-expanding (PAENet) method is a continual learning approach that enables the network to gradually incorporate new facial features such as face recognition, gender identification, and facial expressions [97]. Similarly, Compacting, Picking, and Growing (CPG) is an incremental method that facilitates continual learning of facial expressions and emotions [98].

Certain static FER methods are more attentive and exhibit greater sensitivity to various regions of human face. For instance, the Distract your Attention Network (DAN) leverages underlying similarities in facial appearance and directs attention to multiple facial areas, generating a comprehensive attention map [146]. This allows for precise facial analysis of specific regions for both facial expression and attribute recognition, ultimately improving the accuracy of convolutional neural networks (CNNs) in emotion recognition [147]. The Deep Attentive Center Loss (DACL) method employs an attention mechanism to select significant features and control sparse center loss, effectively classifying facial expressions in wild FER datasets [88]. Moreover, the Facial Motion Prior Networks introduce a new branch to produce a facial mask on facial muscle movements, further enhancing the performance of the FER framework [148].

Dynamic FER models leverage the temporal relations among frames in the facial expression sequence. For instance, EmoAffectNet is an emotion recognition framework that models temporal dependencies across video frames [149]. Additionally, these models prioritize efficiency and are well-suited for real-time applications and video processing. For example, an efficient neural network can extract features from a frame to predict individual emotions, enabling real-time facial expression recognition [147]. Furthermore, efficient facial feature learning with wide ensemble-based convolutional neural networks has been shown to reduce redundancy and computations, resulting in actual ensemble performance improvements [150].

Following an extensive analysis of various real-time semantic segmentation models [151–154], a recent FER model based on the Mix transformer has been developed. This model integrates a self-attention mechanism, focusing on enhancing efficiency while maintaining high accuracy [155].

Some scholars have demonstrated that the performance of multiple networks can exceed that of an individual network [156]. In the context of static FER models, an ensemble ResMaskingNet combined with six other convolutional neural networks outperformed all individual networks on the FER2013 dataset for static images [157]. Ensemble methods are not only used to combine spatial information, but also to integrate temporal information in dynamic FER models. For instance, optic flow and facial landmark trajectories can be fused into a spatial representation using multiple channel networks for dynamic FER systems [158, 159].

Static and dynamic vision-based FER models are complemented by other modalities for recognizing expressions, such as audio or physiological channels. Some scholars consider audio to be a significant element for multi-modal information processing [160, 161]. For instance, the study of audio-visual emotion recognition proposes a visual facial expression feature extraction network that leverages knowledge distillation for FER [162]. Moreover, the fusion of multiple modalities, such as RGB, 3D, and thermal images, can enhance the representation space and improve emotion inference [163].

Modern FER systems encounter several challenges, including issues with illumination, head pose, and identity bias [140]. Among these challenges, occlusion and non-frontal head pose are two main challenges of deep FER models. As a result, various methods have been proposed to mitigate these issues. For instance, the Pyramid with Super Resolution (PSR) proposes a deep network to address the problems associated with pose, direction, and input resolution in the FER task [164]. Similarly, Region Attention Networks (RAN) have been developed to tackle FER issues pertaining to occlusion-robustness and pose-invariance [165]. Figure 1 1 shows the categories of different deep facial recognition methods explained above. Table 10 presents an overview of various deep facial expression recognition (FER) methodologies, providing recent neural networks employed for this purpose.

3.4.2 Emotional Body Gesture Recognition

In recent years, there has been a growing interest among researchers in the analysis of emotional body language, in addition to facial expressions. It has been observed that emotions can also be conveyed through human body motion and pose [167]. Furthermore, dynamic body language can often provide additional cues for recognizing basic emotions, which complement facial expression recognition [168]. Therefore, the extraction of emotions from body pose can enable robots to better perceive and interact with humans, by being able to recognize emotional body language.

The study of emotions has expanded beyond facial expressions to encompass full body expressions. Recognizing emotions from full-body expressions is more challenging than facial expression recognition (FER) due to the greater freedom of movement and substantial variability in body figures during motion. However, recent advances in computer vision and machine learning have demonstrated promising results in categorizing emotional body language from visual cues. The development of motion capture technologies has enabled automatic recognition of expressive movements [169]. Some methods have been developed that recognize human emotions from body movement and gesture dynamics, which are determined by the dynamics of motion cues such as speed and fluidity of movements [170]. Many researchers have focused on specific body parts for expression recognition, for example, the recent study suggests that there is a universal relationship between emotion and gesture elements, such as handedness [171].

The recognition of emotions from body gestures, or Emotion Body Gesture Recognition (EBGR), involves several steps, including body detection, pose estimation, and learning representation [169]. In the first step, EBGR systems detect the entire body and remove the background to isolate the body gesture. The second step involves detecting and tracking the body pose, which entails estimating the constraints of a body model from a single frame or sequence of frames. Body pose detection and tracking are crucial as the body's position and configuration change over time. The final step is applying learning models such as classification or regression to construct a relevant representation, including feature extraction and emotion recognition. Research on recognizing emotions from body gestures is still in the beginning stages as most studies have focused on analyzing facial expressions. Nevertheless, some methods have been proposed for recognizing emotions from body gestures, and we discuss some of them below.

Empirical evidence suggests that machine learning techniques, such as SVM, ensemble tree, decision tree, 1-nearest-neighbour, k-nearest neighbor, and hidden Na¨ıve Bayes, have been successful in recognizing emotions from body

Table 10 Models and methods in deep facial expression recognition

Approach	Description	Metrics
MultiTask Network	A type of deep neural network that combines the outputs of multiple individual models for enhanced performance. [138, 143–145]	Accuracy
Lifelong Learning	Allowing robots to continuously learn and adapt to new situations and environments. [97, 98]	Accuracy
Attention Models	Focusing on specific parts of an input sequence, such as facial expressions or speech, to improve accuracy and speed. [146, 148, 155, 166]	Accuracy
Ensemble Networks	Combines multiple models to improve accuracy and generalization in emotion recognition and human robot interaction. [157]	Accuracy

gestures. For instance, Saha et al. [172] used these techniques to categorize emotions into five states, namely anger, fear, happiness, sadness, and relaxation. Similarly, Castellano et al. [170] applied these methods to extract dynamic representations of emotional body expressions, such as anger, joy, pleasure, or sadness. Moreover, Bayesian networks have also been utilized to classify upper-body gestures categorically [173]. These traditional methods have demonstrated promising results in the field of emotion recognition from body gestures.

Researchers have identified different categories of basic emotions by tracking body motion trajectories. For instance, Sapin´ski et al. proposed a sequential model that categorizes emotions based on the spatial location and orientation of joints of the skeletal structure, using a sequence of body movements [174]. Similarly, Glowinski et al. applied trajectories of the head and hands from frontal and lateral views to recognize emotions in the dimensional space [175]. Dynamic qualities of gestures are utilized to detect, measure, and group affective behavior based on their valence (positive, negative) and arousal (high, low).

Empirical research has established that real-world images are comprised of a plethora of nonverbal cues, including body gestures and contextual features, such as the background. In recent years, numerous convolutional neural network (CNN) models have been developed and trained to identify and classify human emotions, by combining both spatial and contextual information extracted from images, as well as data extracted from the bounding box. As reported in a recent study by Huang et al., these models have achieved significant success in emotion recognition by leveraging such information [176]. Specifically, the baseline CNN models used in the field of affective computing are typically trained to classify emotions into discrete categories, including but not limited to happiness, anger, and sadness, among others. Additionally, some models incorporate continuous emotion dimensions, such as valence, arousal, and dominance, to provide a more nuanced understanding of the emotional states conveyed by an image, as demonstrated by Kosti et al. [177].

In the realm of emotion recognition, body gestures are often used in conjunction with other modalities to enhance the accuracy of the results. For instance, Inthiam et al. utilized multiple modalities, such as facial expressions, body gestures, and speech, to improve the emotion recognition of a social robot through a Hidden Markov Model [178]. Another study by Yang and Narayanan explored the relationship between speech and body gestures, specifically the head and lower and upper body motions, on emotional expression [179]. Similarly, Vu et al. developed a bi-modal emotional recognition system based on speech and gesture for classifying four emotional states: happiness, sadness, disappointment, and neutrality [180]. In addition, Gunes and Piccardi proposed a bi-modal emotion recognition method that fuses body gestures and facial expression recognition for more accurate results [181]. Psaltis et al. (2016) employed a multi-modal system that combined facial action units and body gestures to classify five emotional states: surprise, happiness, anger, sadness, and fear [182]. Furthermore, Kessous et al. (2010) developed a multi-modal system that incorporated features from facial expressions, body gestures, and audio components to recognize different emotional states of ten people speaking in other languages, such as French, German, and Greek [183]. In addition, they used a Bayesian classifier to recognize the different emotional states of ten people talking in other languages, including French, German, and Greek. Empirical evidence suggests that multimodal systems outperform unimodal systems. Table 11 shows the summary of different emotion body gesture recognition methods that we reviewed in this section.

3.4.3 Emotion Recognition by Eye-Tracking

In the field of emotion recognition, eye-tracking has emerged as a valuable modality alongside facial expressions and body gestures. Eye-tracking technology involves monitoring the point of gaze where the human eyes focus on a visual stimulus [184]. Eye-tracking devices such as desktop eye-tracking and mobile eye-tracking integrated into lightweight glasses or head-mounted displays collect data that

Table 11 Emotional Body Gesture Recognition Methods

Approach	Description	Metrics
Traditional ML Methods	Classification using machine learning algorithms such as SVM, decision tree, 1-nearest neighbor, k-nearest neighbor, and hidden Naive Bayes. [170, 172, 173]	Accuracy
Tracking Body Motion Trajectories	Categorization of emotions based on the spatial location and orientation of joints of the skeletal structure [174, 175]	Accuracy
BodyGesturesand Contextual Features	Classify human emotions, by combining both spatial and contextual information [176]	Accuracy
Multi-Model Systems	Recognition of emotions from body gestures in conjunction with other modalities to enhance the accuracy of the results [178, 179, 181–183]	Accuracy

robots can use to detect human emotions. Robots can utilize various emotional-relevant eye features such as pupil diameter and position, motion speed of the eye, or pupillary responses. Machine learning algorithms, such as support vector machines (SVM) and neural networks, are used to classify emotions based on eye-tracking data. Pupil diameter is associated with changes in emotions and cognitive processing [185]. Zheng et al. combined pupil diameter with EEG signals and used an SVM classifier to classify human emotions [186]. Aracena et al. employed neural networks to classify human emotions while viewing images based on pupil size and position [187]. Pupil motion analysis is another technique used in emotion recognition systems to track the speed of eye movements [188]. In this study, artificial neural networks were used to classify four emotions: neutral, disgust, funny, and interested. In addition, Alhargan et al. recognized the affective state of players interacting with a virtual gaming environment using pupillary response features [189]. The Hilbert transform was employed in this study to improve the emotional recognition performance in the arousal and valence model. Table 12 summarizes the various eye-tracking methods for emotion recognition that we have reviewed in this section.

3.4.4 Metrics in Emotion Recognition Approaches

As depicted in Table 10, 11, and 12, Emotion recognition, a pivotal aspect of human robot interaction, employs a spectrum of metrics across various methodologies to gauge accuracy and effectiveness. In the realm of deep facial expression recognition, diverse approaches harness metrics such as Accuracy to quantify the precision of Multitask Networks, Lifelong Learning paradigms, Attention Models, and Ensemble Networks. In the context of emotional body gesture recognition, traditional Machine Learning methods and models tracking body motion trajectories utilize Accuracy to assess classification performance.

Similarly, strategies incorporating both body gestures and contextual features focus on achieving high Accuracy through combined spatial and contextual information.

Meanwhile, multi-model systems fuse body gesture analysis with other modalities to enhance recognition accuracy. In the realm of eye-tracking based emotion recognition, metrics like Pupil Diameter and Pupillary Response are exploited to infer emotional states. Metrics like Gaze Position and Pupil Size feature prominently in methodologies using pupil size and position as indicators of emotion, and the analysis of Pupil Motion proves essential for classifying emotions based on eye movement speed. These diverse metrics collectively underscore the efficacy and accuracy of varied emotion recognition paradigms across different modalities.

4 Discussion on Future Directions

The development of robots capable of collaborating closely with humans in a shared environment has spurred the emergence of the human–robot interaction, which is still in its early stages. As outlined by [190], several approaches have been proposed that establish general principles of this field. While preliminary investigations have focused on basic motor tasks, such as assisting with object manipulation or robot-patient interaction, more complex applications are envisioned, including working with therapists, guiding individuals with visual impairments, and beyond. While the interaction dynamics for these scenarios may differ from current research outcomes, the theories and insights gained from the study of human–human interaction can provide valuable directions for the advancement of human–robot interaction.

In recent years, the field of human–robot collaboration has shown promising developments in the design of algorithms that can enhance the efficiency of robots operating in the presence of human partners. These advancements have paved the way for robots to assist humans in performing tasks that may be dangerous, repetitive, or require a high degree of precision. The potential applications of such robots span several industries, including manufacturing, healthcare, and logistics, and can significantly improve productivity. Additionally, these robots can significantly reduce the physical demands placed on human workers in hazardous environments, enabling them to work more comfortably and safely.

Table 12 Emotion Recognition (ER) methods using eye-tracking

Approach	Description	Metric
Pupil Diameter	Pupil diameter is associated with changes in emotions and cognitive processing. [185]	Pilot testing
Pupil Size and Position	Pupil size and position are used to classify human emotions while viewing images. [187]	Gaze position and pupil size
Pupil Motion	Pupil motion analysis tracks the speed of eye movements and is used to classify emotions. [188]	Accuracy
Pupillary Response	Pupillary response features are used to recognize the affective state of players interacting with a virtual game. [189]	Accuracy

BCI-based HRI is an emerging field that utilizes human brain activity to control robotic behavior, enabling adaptability to changing collaborative requirements. This technology has the potential to overcome the current limitations of preprogrammed industrial robots, which are only capable of performing fixed, repetitive tasks. However, despite its potential, there are still several challenges that must be addressed. One significant limitation of BCI-based HRI is that the majority of current applications are conducted in laboratory environments under strict condition control, which can limit the generalizability of the findings to real-world scenarios. Additionally, BCI systems are susceptible to interference from the environment, and the real-time decoding of brain signals and information transfer rate can significantly impact the performance of human–robot interactions. In the commercial field, the design and implementation of HRI systems must consider a diverse range of factors specific to the application environment. To improve the collection of brain signals, it is crucial to develop high signal-to-noise ratio data collection and transfer systems. Portable, noise-insensitive, and comfortable headset systems are required to ensure relatively pure brain activity is captured for long-term use. Effective decoding systems require ideal analysis algorithms that can achieve fast and accurate signal processing and information transfer. Despite the limitations of BCI-based HRI, its potential to enhance human–robot collaboration and increase productivity in various industries such as manufacturing, healthcare, and logistics is significant. Further research and development are needed to overcome the current limitations and address the practical challenges associated with the use of BCI-based HRI in real-world applications.

BCI-based HRI presents further limitations related to the performance of human commands decoding and the condition of human mental state level. The requirement of high concentration in control, operation, and communication to the robotics restricts the feasibility of sophisticated interactions in diverse conditions. Moreover, the occurrence of performance degradation under heavy mental tasks is common, making a good mental state a necessary requirement in avoiding performance deterioration. As a compensatory approach, hybrid interfaces in HRI systems have been proposed to improve the accuracy of robotic control and further facilitate the performance of human–robot interaction. With hybrid multimodal bioelectrical signals [87, 191, 192], the interaction can provide more stable motor control of a robotic system. In addition, the combination of BCI and computer vision techniques enables flexible and effective control with real-time visual feedback, leading to the potential of an efficient human and robot interaction through close-loop HRI with neurofeedback [86, 193]. These emerging hybrid interfaces have the potential to overcome the limitations of BCI-based HRI and enhance the overall performance of human–robot interaction.

The development of emotionally intelligent robots has shown great potential in a wide range of fields, including but not limited to education, healthcare, and services. Emotionally intelligent educational robots have the capability to adapt their teaching styles by detecting and interpreting the emotional cues present in the user's facial expressions or body gestures. Furthermore, these robots can play a crucial role in assisting autistic children in understanding and identifying other people's emotions. In a collaborative environment, robots equipped with emotion detection abilities can track the emotional state of users, such as their stress levels and fatigue, and adjust their behaviors accordingly to ensure efficient and effective interaction. Additionally, emotionally aware robots can play a key role in detecting fraud and scams in the service industry by determining the honesty of the human's behavior. As the technology in the field of emotionally intelligent robots continues to evolve, there will be numerous opportunities for further advancement and refinement, leading to a significant impact on the way robots can be utilized to improve human lives.

In the realm of emotionally aware robotics, the integration of multiple channels of communication data has shown great promise for enhancing emotion perception capabilities. By fusing physiological signals from multiple modalities, such as EEG and EMG, with computer vision techniques such as facial expression and body gesture recognition, a multimodal approach has been shown to yield higher accuracy in emotion recognition compared to a unimodal approach. As such, a crucial direction for future research in this field is the development of advanced data fusion techniques that can effectively integrate the data from various modalities to further improve the accuracy of emotion recognition in robots. With the advent of machine learning algorithms and accessible technologies such as affordable cameras, non-invasive EEG, and smart portable devices recognizing and conveying emotions to robots are more feasible. This allows emotionally intelligent robots with the ability to adapt their behaviors according to their social interactions with humans. However, multimodal systems require new deep learning models to apply to heterogeneous data. Also, training such deep learning architectures requires realistic datasets for HRI contexts. As a result, deep learning models adapted for fusing numerous features and new dataset. The integration of human–robot cooperative control, brain-computer interfaces, and emotional intelligent perception has the potential to revolutionize various industries, such as healthcare, manufacturing, and service sectors. The use of robots in rehabilitation can provide patients with the opportunity to practice their motor skills and improve training quality. In manufacturing, tasks that require physical interaction between robots and humans can be made more efficient and of higher quality through the exchange of rich haptic information during compliant movements. However, future directions in this area require the development of new deep learning models and the use of realistic datasets for training such models. The continued advancement of technology and the use of multimodal systems can ultimately facilitate physical and emotional collaboration between humans and robots in a variety of scenarios.

5 Conclusion

This paper provides a comprehensive review of critical approaches to human–robot interaction (HRI), with a particular emphasis on three crucial areas that have significant implications for the future of HRI. The first area examines popular techniques for human–robot collaboration, including compliance control-based, human performance based, model learning-based, and synergy-based methods, as well as newer techniques such as learning from demonstration, active learning, and learning from complex tasks. The second area delves into cutting-edge methods for utilizing brain signals to enhance the interaction between humans and robots, particularly emphasizing areas such as rehabilitation, robotics, communication, brain state detection, and emotion recognition. The third area discusses innovative techniques for transferring emotions from humans to robots, including an explicit focus on facial expression recognition and emotion recognition through body gestures and eye-tracking to create an emotionally intelligent perception for a robot.

These approaches are revolutionizing industries, with applications in healthcare, manufacturing, and domestic settings, demonstrating the significant potential of HRI to transform everyday interactions and operational efficiencies. In healthcare, it enables robots to assist in rehabilitation, offer support in surgeries, assist autistic children, and detect stress levels to improve patient care. In manufacturing, HRI facilitates safer and more precise production processes, enhancing worker productivity and safety. Furthermore, in domestic settings, emotionally intelligent robots are emerging as adaptive home assistants capable of recognizing and responding to user emotions and decoding human commands. These applications demonstrate the significant potential of HRI to transform everyday interactions and operational efficiencies across varied sectors.

Overall, this review provides valuable insights and directions for the field of HRI, laying a solid foundation for future studies. We have identified key modalities for HRI, including control methods for human–robot collaboration, brain-computer interfaces for direct neurological commands, and the recognition of human emotions by robots. Additionally, our paper presents innovative methods to enhance multimodal HRI systems, incorporating brain signals and visual cues for more effective collaboration. By delving into current literature, we have highlighted the latest trends and emerging frontiers in the field. The development of systems capable of accurate perception and response to human emotions, adaptive behavior, and effective interaction necessitates a multimodal approach. Consequently, our work contributes to a comprehensive understanding of the diverse modalities necessary for unlocking the full potential of human–robot interaction, paving the way for groundbreaking advancements in this dynamic and rapidly evolving field.

Authors' Contributions Farshad Safavi helped organize the research paper, collected, and analyzed research studies on emotional intelligence perception, and participated in writing and revising the manuscript. Parthan Olikkal collected and analyzed research studies on human robot collaboration and participated in writing the manuscript. Dingyi Pei collected and analyzed research studies on brain-computing interface and participated in writing the manuscript. Sadia Kamal, Helen Meyerson and Varsha Penumalee contributed toward revising the manuscript. Ramana Vinjamuri directed the review studies, developed the framework, and participated in writing and revising the manuscript.

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Declarations

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