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Mind Meets Robots: A Review of EEG-Based Brain-Robot Interaction Systems

Yucong Zhang[a], Nona Rajabi[a], Farzaneh Taleb[a], Andrii Matviienko[a], Yong Ma[b], Mårten Björkman[a], and Danica Kragic[a]

[a]KTH Royal Institute of Technology, Stockholm, Sweden; [b]University of Bergen, Bergen, Norway

ABSTRACT

Brain-robot interaction (BRI) empowers individuals to control (semi-)automated machines through brain activity, either passively or actively. In the past decade, BRI systems have advanced significantly, primarily leveraging electroencephalogram (EEG) signals. This article presents an up-to-date review of 87 curated studies published between 2018 and 2023, identifying the research landscape of EEG-based BRI systems. The review consolidates methodologies, interaction modes, application contexts, system evaluation, existing challenges, and future directions in this domain. Based on our analysis, we propose a BRI system model comprising three entities: *Brain, Robot, and Interaction*, depicting their internal relationships. We especially examine interaction modes between human brains and robots, an aspect not yet fully explored. Within this model, we scrutinize and classify current research, extract insights, highlight challenges, and offer recommendations for future studies. Our findings provide a structured design space for human-robot interaction (HRI), informing the development of more efficient BRI frameworks.

KEYWORDS

EEG based; brain-robot interaction; interaction mode; comprehensive review

1. Introduction

With the rapidly evolving development of human–computer interaction (HCI) and robotics, the overlapping realm of human-robot interaction (HRI) has attracted significant attention (Sheridan, 2016), especially manifested in CHI for the recent years (Carros et al., 2020; Esterwood et al., 2021; Winkle et al., 2023). Nowadays, the inclusion of neuroscience into HCI scenarios has led to an era that transcends traditional boundaries. For instance, the advent of brain–computer interfaces (BCIs) originated in the 1970s (Vidal, 1973) has linked the human brain with external intelligent agents by harnessing physiological signals. BCIs are intricate systems capable of circumventing traditional communication pathways to establish direct interaction and control between the human brain and external agents. This is achieved by instantaneously transcribing brain signals from brain activities into operable commands (Millán et al., 2010). Various approaches exist to measure human biological activities, such as bioelectric signals: electroencephalogram (EEG) (Minguillon et al., 2017), electrooculogram (EOG) (Fatourechi et al., 2007), electromyogram (EMG) (Fatourechi et al., 2007), and electrocardiogram (ECG) (Perrin, 2009), or neuroimaging techniques: functional magnetic resonance imaging (fMRI) (Sitaram et al., 2007) and functional near-infrared spectroscopy (fNIRS) (Naseer & Hong, 2015). Among these, using EEG-based measurements for BCIs and relevant usage has emerged as the predominant approach due to its affordability and exceptional convenience (Bi et al., 2013; Xia et al., 2024).

Over the past few decades, we have witnessed an evident growth in the development and integration of robots into our daily lives, such as offering assistance in public or at home (Bauer et al., 2008; Mahdi et al., 2022; Zhang et al., 2024). Robots, as (semi-)automated agents with manifold capabilities, are unexpectedly favored in the industry owing to their exceptional proficiency in movement and operations (Goodrich & Schultz, 2008; Zhang et al., 2024). As humans and real robots coexist in reality, there arises a necessity for instantaneous mutual understanding, enabling both roles to leverage their unique capabilities and achieve the desired synergy (Rajabi et al., 2023; Wallace et al., 2024; Zhang et al., 2024). The integration of robots has significantly enriched the field of HRI, fostering a deeper comprehension and the development of purposeful robotic systems, whether the humans are in close proximity or spanning distances (Adams, 2005; Zhang et al., 2024). Specifically, the dedicated area brain-robot interaction (BRI) has gone through remarkable advancement over the last decade, with a discernible and increasingly pronounced trend emerging, particularly in the last five years. Extensive research efforts have been conducted to uncover novel approaches in diverse aspects of BRI to enhance the seamlessness of interaction between human brains and physical robots. The involved robots

CONTACT Yuchong Zhang yuchongz@kth.se KTH Royal Institute of Technology, Stockholm, Sweden

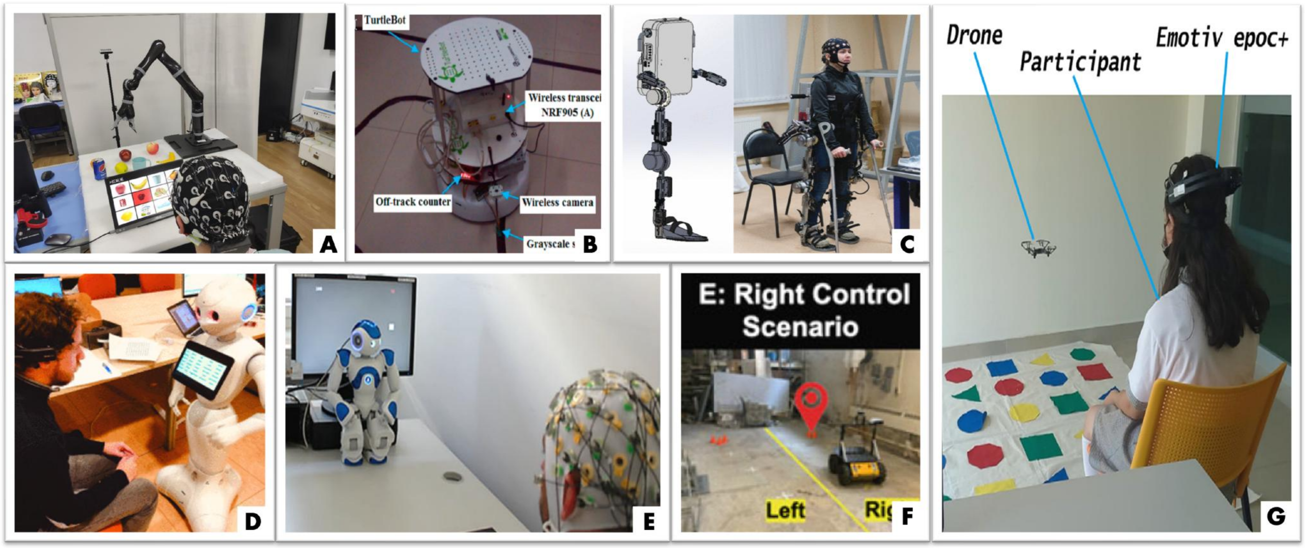

Figure 1. Samples from the reviewed studies in our corpus regarding BRI systems with different robots. (a) Industrial robot (Chen et al., 2021) (b) Service robot (Wang et al., 2018) (c) Medical robot (Ghosh & Orlando, 2019) (d) Social robot (Staffa & Rossi, 2022) (e) Educational robot (Ehrlich & Cheng, 2019) (f) Exploratory robot (Liu & Jebelli, 2021) (g) Autonomous vehicle (Cervantes et al., 2023).

showcase a wide range of forms and configurations, such as robotic arms (Rodriguez, 1988), humanoid robots (Kajita et al., 2014), and mobile robots (Tzafestas, 2013). Meanwhile, the collaboration between humans and robots based on complete BRI systems is depicted in various contexts, i.e., guided navigation (Chang & Sun, 2021), knowledge learning (Wang & Sugaya, 2021), and socializing (Staffa & Rossi, 2022).

Notably, the predominant focus within the aforementioned time frame has shown to be on EEG-based BRI which employs nonintrusive technology, ranging from clinical usage to academic research (Coyle et al., 2004; Ibáñez et al., 2013). EEG is a non-invasive technique employed for the assessment of the brain electrical activity, using multiple electrodes attached to the scalp, which offers high temporal resolution but comparatively low spatial resolution. As a result, BCIs utilizing EEG signals to capture brain electrical activities have gained widespread popularity (Vaughan et al., 2003). The unique BRI area has experienced incredible advancements at the intersection of cognitive science, technology, and engineering in the past decade, especially has shown advantages in assistive techniques (Chang & Sun, 2021; Ghosh & Orlando, 2019; Zhang et al., 2021) and healthcare (Boonarchatong & Ketcham, 2023; Braun et al., 2019; Jo et al., 2022; Xu et al., 2018). Thus, more up-to-date literature overview must be formulated on the latest in-depth advancements in EEG-based BRI systems since there were no constructed review articles addressing the research status since 2018, when relevant publications started to thrive unprecedentedly. To address this gap, in this article, we provide an exhaustive analysis of the current research landscape, encompassing crucial techniques, potential challenges, and prospective research directions for the future development of EEG-based BRI systems (Figure 1). A BRI framework consistently involves interactions with robots which require complex communication and physical interaction while monitoring brain signals within the connections between human brains and robots. A typical tool for this connection is BCIs. Therefore, we exclusively focus on pragmatic BRI systems with EEG, rather than general EEG-BCIs or BCIs activated by other signals. We specifically concentrate more efforts on the analysis of interaction modes and techniques so as to illuminate the future possibilities for the HRI community. The conceptualization of our BRI context is displayed in Figure 2. Specifically, we intend to answer the following research questions (RQs):

- **RQ1**: What are the pivotal techniques, application areas, and evaluation methods used in complete EEG-based BRI systems?
- **RQ2**: What is the nature of the interaction between human brains and robots within the context of EEG?
- **RQ3**: What key insights should be distilled for effective interaction between brain and robot with EEG?
- **RQ4**: What are challenges/limitations and open problems associated with current EEG-based BRI systems?

To answer these questions, we examined 87 studies published over the past five years (2018–2023) that explore EEG-based BRI systems. Our contributions are manifested in two aspects: (1) providing an overview with in-depth meta-analysis regarding the research landscape of EEG-based BRI (research techniques, application contexts and evaluation methods) as well as guiding the way for future researchers (challenges and outlook), and (2) offering a theoretical contribution in the form of an EEG-based BRI system model and detail the three entities (*Brain*, *Robot*, and *Interaction*) included, with a primary concentration on the interaction between human brains and robots.

The rest of the article is elaborated as follows. Section 2 elucidates the background and related work. In Section 3, we describe the methods used in our review, encompassing our search strategies and data extraction processes. Section 4 outlines the devised BRI system model developed based on

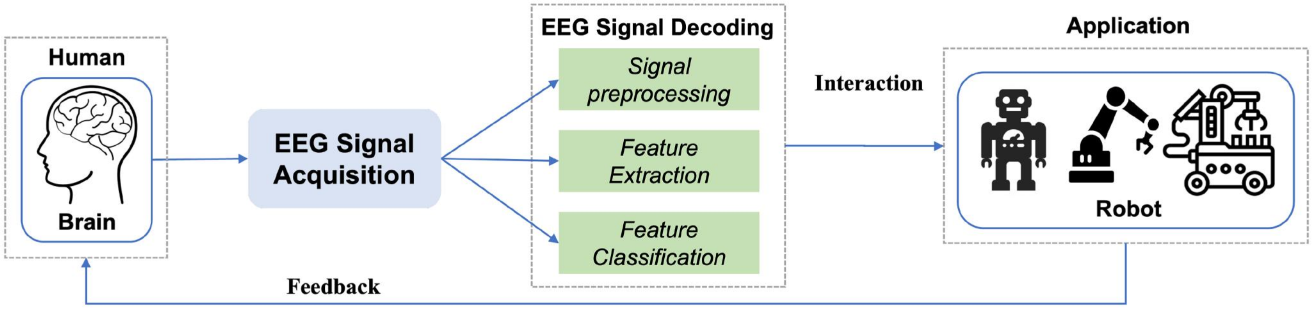

Figure 2. The common framework of a complete BRI system utilizing EEG.

the meta-analysis of our final corpus with the three entities. For *Brain* entity, the dimensions, namely, signal acquisition and decoding are introduced. For *Robot* entity, a diverse range of dimensions entailing robots are summarized. Section 5 provides an extended analysis of the *Interaction* entity with four dimensions included. In particular, two additional sub-dimensions of Proactive Control are elicited. Section 6 presents the identified challenges and future directions while Section 7 shows the discussion of our findings together with the principal limitations. A succinct summary of our article is encapsulated in Section 8.

2. Background and related work

2.1. Brain robot interaction and EEG signals

The term "brain-robot interaction" has yet to achieve a universally accepted definition, although it is generally considered a derivative field of HRI (Bozinovski & Bozinovski, 2015). This emerging area that establishes a cutting-edge communication bridge between humans and robots particularly through brain signals, holds promise in enhancing the daily lives of individuals with disabilities (McFarland & Wolpaw, 2008; Zhao et al., 2015). A typical BRI system operates as a closed-loop control mechanism, integrating human brain signals with contextual feedback. This entails deciphering captured signals from brain activities to formulate commands, thereby instructing the contextual robots to perform desired tasks. Simultaneously, the robot thereby conveys the environmental feedback to the human brain, aiding informed decision-making processes (Mao et al., 2017). In most BRI systems, human intelligence is highly relied upon to monitor the robot motions based on visual feedback in traditional setups, but machine intelligence has started to flourish and gained significant recognition in recent years (Lei et al., 2019). Most of the seamless functioning of BRI systems can be attributed to the success of intelligent BCIs integrated with cognitive models tailored for controlling robots (Crawford et al., 2015; Chen et al., 2016; Gui et al., 2017).

A complete BRI system collects brain signals as the original input to generate further operations, which can be categorized as invasive and non-invasive. Under invasive context, the brain signals are much stronger while they must be captured inside the brain and always need surgery (Aljalal et al., 2020). Although non-invasive brain signal acquisition results in weaker outcomes, it merely requires the capture outside the brain with little harm to the human body. In addition, the affordable cost, lower risk, and superior portability comprise other reasons why non-invasive brain signal capturing is preferred in most cases (Hwang et al., 2013; Lin et al., 2010; Zhu et al., 2010). This exploration adopts the extensive utilization of EEG, a non-invasive neuroimaging technique that captures the electrical activity of the brain (Alimardani & Hiraki, 2020; Nwagu et al., 2023; Torres et al., 2020). EEG offers a window into investigating the human mind, enabling the extraction of emotional states and even intentions. Thus, EEG-based BRI systems where the robot/robotic system dominantly employs EEG-based BCIs to interact with humans, have become the most prevailing mechanism in manifold application scenarios (Douibi et al., 2021; Fan et al., 2015; Li et al., 2013; Neuper et al., 2003). Integrating EEG technology with robots paves the way for a new era of interaction between humans and intelligent agents, where neural patterns serve as the central axis of communication.

2.2. Current EEG-based BRI systems

Several reviews have mapped the terrain of EEG-based BRI and associated fields. In 2010, Zhang et al. (2010) provided a summary of BCI's evolution in industrial robotics and evaluated new commercial BCI products. Subsequently, Si-Mohammed et al. (2017) conducted a literature review merging BCI with augmented reality (AR), a technology that superimposes digital elements onto real-world environments via specialized devices (Van Haastregt et al., 2024; Zhang et al., 2023), covering applications in medicine, robotics, home automation, and brain activity visualization. Hwang et al. (2013) provided a detailed account of EEG-based BCI studies from 2007–2011, and Cao (2020) later updated this landscape in 2020, with a focus on integrating EEG-based BCI and artificial intelligence (AI). In robotics, Bi et al. (2013) comprehensively reviewed EEG-driven control for mobile robots, addressing systems, techniques, and evaluations, while Krishnan et al. (2016) focused on EEG control for assistive robots aiding the disabled and elderly. Aljalal et al. (2020) surveyed EEG signal processing for robot control, highlighting challenges in noninvasive BCI systems. They highlighted encountered challenges of brain-controlled systems at the time. Huang and Wang (2021) delved into EEG signal processing methods, spotlighting neural network

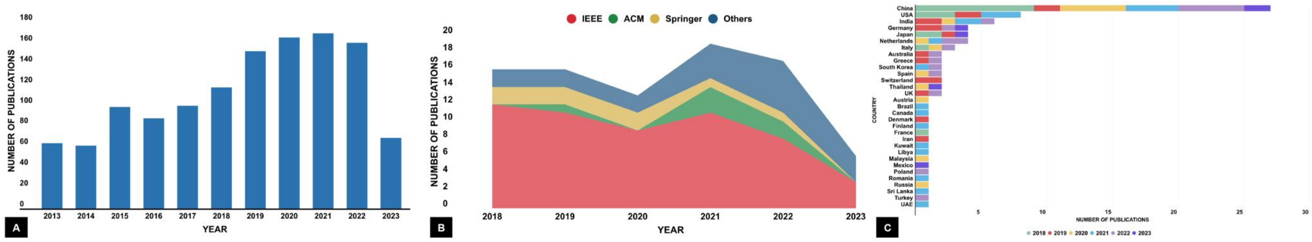

Figure 3. The research agenda of EEG-based BRI in the last few years: (a) The number of publications (2013–2023) related to the search results of "EEG-based," "brain," "robot," and "interaction" in the four tested databases. An apparent growing trend is identified especially from 2018. (b) The number of papers in our corpus for each year with publishers. For convenience, we listed three main publishers: IEEE, ACM, and springer, while other publishers are noted as others. (c) The number of studies published for each year with countries.

and deep learning (DL) techniques for signal classification. In 2017, Mao et al. (2017) reviewed the research output generated from the past years with a precise emphasis on EEG-based BRI interactive systems, which aligns with the thematic intent of our article the most so far. They identified the key techniques and BCI paradigms, but without focusing on the interaction between brains and robots. In fact, none of the previously mentioned papers investigated the brain-robot interaction mode, a critical subject in the HRI community. Moreover, our observation indicates that research in this area has notably increased since 2018 (Figure 3(a)), yet reviews synthesizing these recent advances are still missing. While some have then explored EEG-based robot-assisted rehabilitation (Berger et al., 2019), or EEG-based BCI interaction with virtual reality (VR) and AR (Nwagu et al., 2023), there's an urgent need for a current review that consolidates the latest EEG-based BRI techniques, highlighting the interaction between human brains and robotic systems. Table 1 showcases the extensive advancements our article offers over prior similar reviews. We've concentrated on inclusive BRI systems, provided search strategy, integrated in-depth insights on key techniques, robot categorization, interaction modes, application contexts, challenges, and future directions in novel formats.

3. Method

3.1. Search strategy

The inspiration obtained by methodologies outlined in previously published literature reviews in CHI and other top HCI venues (Baytas et al., 2019; Nwagu et al., 2023; Pascher et al., 2023; van den Oever et al., 2024) laid the foundation for our systematic exploration. We adhered to the guidelines set forth by the Preferred Reporting Items for Systematic Reviews (PRISMA) with the updated statement of guidelines (Page et al., 2021), as well as the extended framework for scoping reviews (Tricco et al., 2018). Four databases, including Web of Science (one of the most comprehensive academic literature databases (Chadegani et al., 2013)), IEEE Xplore (provides access to more than four million full-text documents from some of the world's most highly cited publications (Tomaszewski, 2021)), ACM Digital Library (a well-known source incorporating numerous computer science research), and Scopus (a large-scale database containing massive research articles that complement WoS (Burnham, 2006)), were exhaustively scoured, employing a strategic blend of keywords and controlled vocabulary terms. We first established a reference literature dataset by accessing these four databases with the searching the keywords "EEG," "brain," "robot," and "interaction" during the period of 2013–2023. After excluding the repetitions, we obtained 1223 papers in total, which is visualized in Figure 3(a). As mentioned, we found the publication trend had an obvious increase from 2018 and continued to flourish in the following years. Then, we commenced with the formal literature selection within the scope of our article (2018–2023). Please refer to Figure 4 for an illustrative breakdown of our article selection process. Five authors were involved in the procedure of paper searching and selection. Elaborations on each distinct stage in this process will be shown in the subsequent sections. During the querying, we incorporated different categories of papers: we unified research articles, conference full papers, and conference proceedings with substantial contributions and advisable pages as full papers, while short papers, posters, late-breaking results as short papers.

3.2. Search terms

The formulation of our search strings revolved around the foundational constructs of "EEG," "brain," "robot," and "interaction," along with their complete names and corresponding synonyms. To ensure an expansive coverage reflecting the multifaceted notion of "robot," we extended our purview to encompass related terms such as "exoskeleton" and "wearable" that embody certain robotic attributes. We intentionally avoid using "brain-computer/machine interface" and "BCI/BMI" since these queries would lead to incorrect searching results, with massive papers exclusively focusing on BCI after a few attempts. Below, we present the five search strings harnessed in our search procedure, which were devised and crafted by two authors and subsequently endorsed by the entire author group. These strings were strategically employed in the titles, keywords, and abstracts across the array of four databases:

- EEG **OR** EEG-based **OR** electroencephalogram **OR** electroencephalogram-based **AND** robot

Table 1. Comparison of contributions between previous similar EEG-based review papers and our article.

Paper	Objectives	Search strategy	Key techniques	Robot categorization	Interaction mode	Application contexts	Identified challenges	Research outlook
Bi et al. (2013)	Mobile robot control	–	Classic brain signal depiction	–	–	–	Mostly in BCI development	Implicit description
Krishnan et al. (2016)	Assistive mobile robot control	–	Classic brain signal depiction	–	–	–	–	–
Mao et al. (2017)	Mind-robot control	–	Classic brain signal depiction	Partial; based on classic design	–	–	Mostly in BCI development	Implicit description
Aljalal et al. (2020)	Mobile robots and arm control	–	Classic brain signal depiction	–	–	–	Control effectiveness	Limited details
Huang & Wang (2021)	Robot control	–	Classic brain signal depiction	–	–	–	–	Very limited details
Zhang et al. (2025) (Ours)	Inclusive BRI systems	Scientific strategy and exclusion criteria	Novel summarization for brain signals	Complete; based on function and objectives	Novel taxonomy based on interconnectedness	Novel taxonomy with hierarchical information	BRI including human-centric and ethic issues	Explicit and complete elaboration

- EEG **OR** EEG-based **OR** electroencephalogram **OR** electroencephalogram-based **AND** brain robot interaction **OR** BRI **OR** human robot interaction **OR** HRI
- EEG **OR** EEG-based **OR** electroencephalogram **OR** electroencephalogram-based **AND** exoskeleton **OR** wearable robots **OR** wearables
- EEG **OR** EEG-based **OR** electroencephalogram **OR** electroencephalogram-based **AND** brain machine interaction **OR** brain computer interaction
- EEG **OR** EEG-based **OR** electroencephalogram **OR** electroencephalogram-based **AND** robot interaction **OR** interactive robot **OR** robot communication **OR** communicative robot

3.3. Filtering, pre-selecting, and manual screening

This phase began with a specialized process that included filtering duplicates, assessing relevance, and evaluating accessibility within the initial dataset yielding 1108 papers, which were formulated by three authors via initial querying. After excluding duplicates and removing irrelevant papers based on titles, keywords, and abstracts, we retained 141 papers (Figure 4), which were accomplished by five authors. Regarding the full-text screening (achieved by four authors), each paper from the resultant pool was scrutinized against two fundamental exclusion criteria, which were intentionally designed to advance the HRI/HCI community, rather than the traditional BCI/BMI community, with an emphasis on interaction mode that was previously unexplored:

1. Does the paper pertain directly to a fully or predominantly EEG-based context? Consequently, any works that mainly revolved around non-EEG-based scenarios or only tangentially touched upon EEG signals were excluded from our consideration (i.e., Alimardani et al., 2021; Kremenski & Lekova, 2022; Liu et al., 2020; Li et al., 2022; Stanković et al., 2023; Wang et al., 2020; Zhao et al., 2020).
2. Does the paper explicitly detail studies specifically intertwined with human brain robot interaction? This led, for example, to the exclusion of topics that lacked well-defined interaction modalities connecting the human brain and specific robotic systems (i.e., Nemati et al., 2022; Rodriguez et al., 2022; Rekrut et al., 2022; Shi et al., 2021; Xu et al., 2022), and studies that do not involve the physical, real robotic systems (i.e., Holloman et al., 2019; Li et al., 2020; Manjunatha et al., 2020; Omer et al., 2022; Tan et al., 2021; Wang et al., 2018).

Review and perspective papers lacking practical BRI implementations, such as (Hernandez-Cuevas et al., 2020), were excluded, leaving us with 79 full papers (referred to as "papers" hereafter). Reference crawling added 8 more, totaling 87 papers. Expanding our search to Google Scholar with the same terms yielded no new relevant findings. Our search parameters remained confined to studies published in English within the last five years (1 January 2018 to 31 July 2023), executed by two authors from 8 to 20 August 2023.

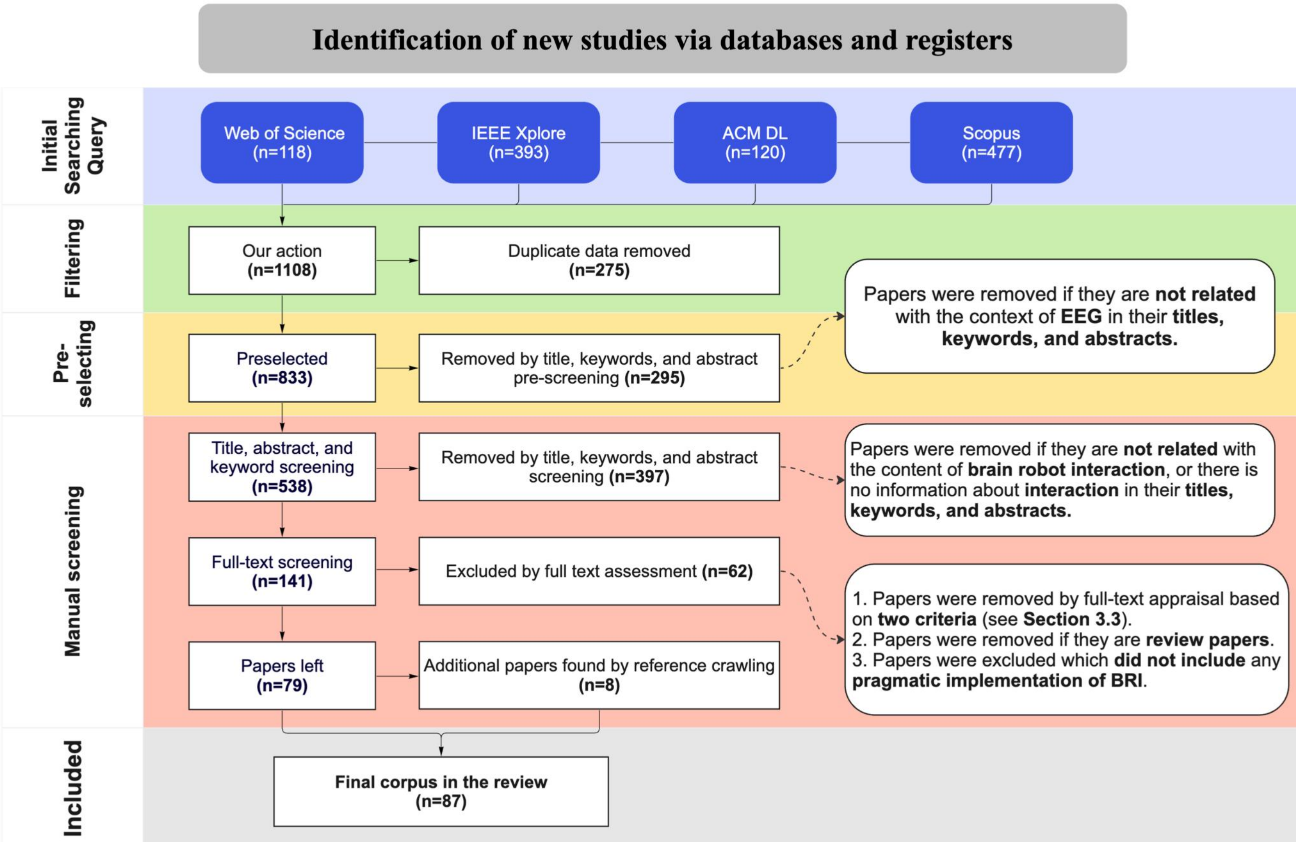

Figure 4. Flow chart of the corpus formulation process with the identification of databases and the initial search query (see Sections 3.1 and 3.2), and filtering, pre-selecting, and the manual screening (see Section 3.3), which resulted in 87 full papers.

This compilation encapsulates works emanating from three key publishers, namely IEEE, ACM, and Springer, alongside other publishers (see Figure 3(b)). Notably, China emerged as a prominent contributor in this field, as depicted in Figure 3(c).

3.4. Data extraction

Data extraction involved gathering essential details from each study using a standardized form that included objectives, EEG hardware/software, experimental setup, task paradigms, signal processing techniques, robot types, applications, results, and limitations. Through initial readings of these 87 papers, a series of questions crystallized to facilitate the summarization, consolidation, and comparative analysis of the presented studies:

1. What are the key research questions investigated within the context of the EEG signal?
2. What types of robots/robotic systems are featured in the study?
3. What are the interaction modes employed between the brain and the robot?
4. Which kind of EEG signals are used and what is the methodology for signal acquisition?
5. What methods are applied in signal decoding?
6. How are these BRI systems assessed, and what metrics are used for evaluation?
7. In what application scenarios are the EEG-based BRI systems explored?
8. What specific tasks are executed within these BRI systems? (Note: In some cases, this aligns with (7)).
9. What findings and outcomes emerge from the research study?
10. How do these outcomes contribute to knowledge acquisition, offering insights, lessons, or guidelines in the field of BRI? (Note: In some papers, this may overlap with (9)).
11. Does the paper present challenges and outline future research directions?

4. The BRI system model

Our literature review aimed to deeply understand the brain-robot communication explored in research over five years by analyzing 87 studies. For this, we developed a BRI system model consisting of three key entities (Brain, Robot, and Interaction) as displayed in Figure 5, two of which we discuss in detail in this section, starting with *Brain* and two dimensions Signal Acquisition and Signal Decoding, followed by *Robot* that covers seven dimensions. Additionally, we provide a detailed analysis of application contexts and evaluation methods derived from our corpus. This section tends to address **RQ1**. The subsequent section presents the analysis of the third entity of *Interaction*.

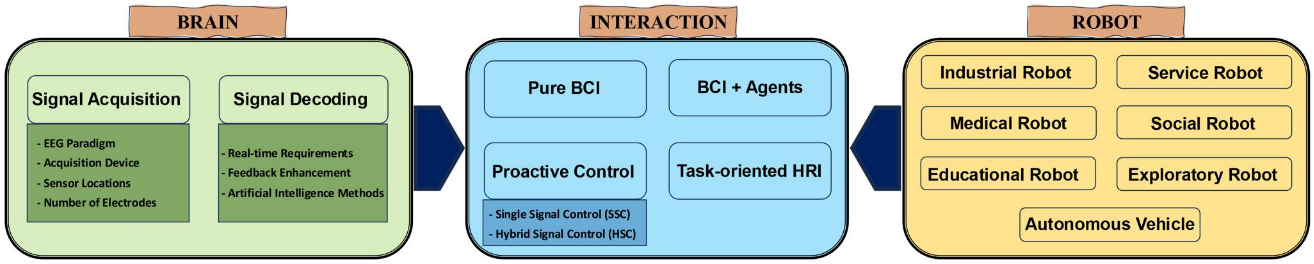

Figure 5. Overview of the BRI system model. The three entities: *Brain*, *interaction*, and *robot*, are distilled from our corpus. Human brains and robots are intercorrelated by the *interaction* entity. Each entity is affiliated with several dimensions, while some of them are comprised of extra sub-dimensions.

4.1. Brain

The brain is defined as the source of brain EEG signal extraction and transmission. In the context of a complete EEG-based BRI system, establishing an interactive connection between the human brain and the robot is crucial, which heavily relies on signal (1) acquisition and (2) decoding (Figure 2) which we discuss in this part. Table 2 indicates the relevance of this entity within our corpus.

4.1.1. Signal acquisition

The first dimension involves the acquisition of EEG signals, collected using a number of electrodes placed on the scalp by employing a variety of biosignal hardware. The acquisition is typically done through either a wired EEG electrode cap connected to an amplifier or a wireless EEG device. Our review revealed a gap in prior BRI literature, as none thoroughly addressed the four sub-dimensions we identified: EEG paradigms, acquisition devices, sensor locations, and the number of electrodes used across our corpus. Table 3 outlines the specific details identified in our corpus, aligning with the sub-dimensions.

4.1.2. EEG paradigms

Various EEG paradigms have been developed and utilized in research. Following the newest classification proposed by Yadav et al. (2023), we identified several paradigms in our corpus: sensory and motor-related, including event-related desynchronization (ERD) and event-related synchronization (ERS), and motor imagery (MI); vision-related, specifically steady-state visually evoked potentials (SSVEP); and cognition-related, encompassing P300 BCI, event-related potential (ERP), and task-based approaches. Our analysis merely reveals one study employing hybrid paradigms while the task-based paradigm (where participants perform a specific task or set of tasks, i.e., grasping task (Jo et al., 2022) or conversational task (Baka et al., 2019)) is the most prevalent, with MI and SSVEP following in popularity. We found that task-based paradigms are particularly advantageous in applications related to cognitive neuroscience (i.e., Lyu et al., 2022; Zhang et al., 2021) and HCI (i.e., Fang et al., 2023; Si-Mohammed et al., 2020). In contrast, MI paradigms are extensively employed in rehabilitation (i.e., Guo et al., 2020; Li et al., 2019), while SSVEP was predominantly favored for communication control (i.e., Aznan et al., 2019; Farmaki et al., 2022).

4.1.3. Acquisition device

Numerous bio-signal devices were employed for EEG data collection in our review. These ranged from EEG electrode caps linked to amplifiers to independent EEG units. We identified over 30 distinct EEG acquisition devices across the examined studies and provide an overview of the studies that utilized them underlying wire/wireless connections (Wang et al., 2018). Particularly, we found that the Emotiv EPOC was the preferred device spanning 19 studies due to its portability and consistent signal quality.

4.1.4. Sensor locations

The sensors of EEG acquisition devices are typically positioned on various scalp areas, adhering to established standards that correlate electrode placement with the underlying cerebral cortex regions. The most widely recognized standard is the international 10–20 system (Jasper, 1958) but we also found instances of the 10–10 system (Araujo et al., 2021; Gordleeva et al., 2020). Typically, device sensors are positioned on the scalp to cover key brain regions such as frontal (F), temporal (T), parietal (P), and occipital (O) (Cobb et al., 1958). In certain instances, earlobe areas (A/M) or the midline sagittal plane (Z) are also utilized for grounding or referencing. We categorized sensor locations based on the use brain areas and the inclusion of ground/reference points. As shown in Table 3, we identified six sensor location categories, marking, to our knowledge, the first such classification in EEG device sensor location within review literature. We observed that most studies did not encompass all brain regions with device sensors, while many utilized ground/reference points for accurate signal acquisition.

4.1.5. Number of electrodes

We aimed to determine the specific number of electrodes utilized in the signal acquisition, however, several studies did not provide precise details. According to Montoya-Martínez et al. (2021), 64 electrodes are typically adopted in practical cases, however, 20 and 32 electrodes are observed to yield distinctively desired results in subject-independent cases. Since our observation revealed that many studies employ fewer than 10 electrodes, leading to the classification into five categories based on electrode count: 10, 20, 32, and 64 (Table 3). The majority of studies prefer fewer electrodes, with 37 studies using less than 10, and only 8 studies utilizing more than 32 electrodes.

Table 2. The overview of the BRI model with (sub)dimensions identified in our corpus.

	Brain Signal Acquisition				Brain Signal Decoding			Interaction				Robot						
Literature	EEG Paradigm	Acquisition Device	Sensor Locations	Numbers of Electrodes	Real-time Requirements	Feedback Enhancement	AI Methods	Pure BCI	Auxiliary BCI	Proactive Control	Task-oriented HRI	Industrial Robot	Service Robot	Medical Robot	Social Robot	Educational Robot	Exploratory Robot	Autonomous Vehicle
Qian et al. (2018)	√	√	◇	√	√	√	√	×	×	×	√	√	×	×	×	×	×	×
Ogino & Mitsukura (2018)	√	√	√	√	√	√	√	×	×	√	×	√	×	×	×	×	×	×
Chu et al. (2018)	√	√	√	√	√	√	√	√	×	√	×	×	√	√	×	×	×	×
Kilmarx et al. (2018)	√	√	◇	√	√	√	×	√	×	√	×	√	×	×	×	×	×	×
Wang et al. (2018)	√	√	√	√	√	√	◇	√	×	√	×	×	√	×	×	×	×	×
Cao & Liu (2018)	√	√	√	√	√	√	√	×	×	×	×	×	√	×	×	×	×	×
Penaloza et al. (2018)	√	√	√	√	√	√	√	√	×	×	√	×	√	×	×	×	×	×
Xu et al. (2018)	√	◇	√	√	√	√	√	×	×	√	×	×	√	×	×	×	×	×
Kompatsiari et al. (2018)	√	√	√	√	√	√	×	×	×	×	√	×	×	×	√	×	×	×
Si-Mohammed et al. (2020)	√	√	√	√	×	√	√	√	√	√	√	√	×	×	×	×	×	×
Kuffuor & Samanta (2018)	√	√	√	√	√	√	√	×	√	√	×	√	×	×	×	×	×	×
Yuan & Li (2019)	√	√	√	√	◇	√	√	×	√	√	×	√	×	×	×	×	√	×
Jiang et al. (2018)	√	◇	√	√	◇	√	√	√	×	√	×	×	×	×	√	×	×	×
Wang et al. (2018)	√	√	√	√	√	√	√	×	√	√	×	√	×	×	×	×	×	×
Ai et al. (2018)	√	√	√	√	◇	√	×	×	√	√	×	×	◇	√	×	×	×	×
Memar & Esfahani (2018)	√	√	◇	×	√	√	×	√	×	√	×	√	×	×	×	×	×	×
Hernandez-Carmona & Penaloza (2019)	√	√	√	√	√	√	◇	×	×	√	×	√	×	×	×	×	×	×
Yu et al. (2019)	√	√	√	√	◇	√	×	×	×	×	√	√	√	×	×	×	×	×
Li et al. (2019)	√	√	√	√	√	√	√	×	√	√	×	×	√	√	×	√	×	×
Chiuzbaian et al. (2019)	√	√	√	√	√	√	◇	√	×	√	×	×	√	×	×	×	×	√
Bahman & Shamsollahi (2019)	√	√	√	√	√	√	×	√	×	√	×	×	√	×	×	×	×	×
Aznan et al. (2019)	√	√	√	√	√	√	√	×	√	×	√	×	√	×	×	×	×	×
Ghosh & Orlando (2019)	√	√	√	√	√	√	√	√	×	√	×	×	√	◇	×	×	×	×
Baka et al. (2019)	√	√	√	√	√	√	◇	×	×	×	√	×	×	×	√	×	×	×
Ehrlich & Cheng (2019)	√	√	√	√	√	√	√	◇	×	√	×	×	×	×	◇	√	×	×
Braun et al. (2019)	√	√	√	√	√	√	√	√	×	×	◇	×	×	√	×	×	×	×
Aldini et al. (2019)	√	√	√	√	√	√	×	×	×	√	√	√	×	×	×	×	×	×
Rahul & Sharma (2019)	√	√	√	√	√	√	√	×	×	√	×	×	√	×	×	×	×	×
Long et al. (2019)	√	√	√	√	√	√	√	√	√	√	√	×	√	√	×	×	×	×
Iwane et al. (2019)	√	×	√	√	√	√	√	√	×	√	×	√	×	×	×	×	×	×
Memar & Esfahani (2020)	√	×	×	√	×	√	√	×	×	◇	√	√	×	×	×	×	×	×
Korovesis et al. (2019)	√	√	√	√	√	√	√	×	×	√	×	×	√	×	×	×	×	×
Chhabra et al. (2020)	√	√	√	√	√	√	√	√	×	√	×	×	◇	√	×	×	×	×
Martínez-Cagigal et al. (2020)	√	√	◇	√	√	√	×	√	×	√	×	×	√	×	×	×	×	×
Alimardani et al. (2020)	√	√	◇	√	×	√	×	√	×	×	√	×	◇	√	◇	×	×	×
Rashid et al. (2020)	√	√	√	√	√	√	√	×	√	√	×	√	×	×	×	×	×	×
Zhao et al. (2020)	√	×	√	×	√	√	√	√	×	√	×	√	×	×	×	×	×	×
Guo et al. (2020)	√	√	√	√	√	√	√	√	×	√	×	×	×	×	√	×	×	×
Gordleeva et al. (2020)	√	√	◇	√	√	√	√	×	×	√	×	×	◇	√	×	×	×	×
Nann et al. (2021)	√	√	√	√	√	√	×	×	×	√	×	×	◇	√	×	×	◇	×
Chen et al. (2020)	√	√	√	√	√	√	√	×	√	√	×	√	×	×	×	×	×	×
Lu et al. (2020)	√	√	√	√	√	√	√	×	×	√	×	×	√	×	×	×	×	×
Sanguantrakul et al. (2020)	√	√	√	√	√	√	√	√	×	√	×	×	√	◇	×	×	×	×
Mondini et al. (2020)	√	√	◇	√	√	√	×	×	×	√	×	×	√	×	×	×	×	×
Shao et al. (2020)	√	√	√	√	◇	√	√	×	×	√	×	×	√	×	×	×	×	×
Abougarair et al. (2021)	√	√	√	√	√	√	×	×	×	√	×	√	×	×	×	×	×	×
Zhang et al. (2021)	√	◇	◇	√	√	√	√	×	×	√	×	×	√	√	×	×	×	×
Du et al. (2021)	√	√	√	√	√	√	√	×	×	√	×	×	√	◇	×	×	×	×
Magee & Givigi (2021)	√	√	√	√	√	√	√	×	×	√	×	√	×	×	×	×	×	×
Roshdy et al. (2021)	√	√	◇	√	√	√	√	√	×	√	×	×	×	×	√	×	×	×
Wei et al. (2021)	√	◇	√	√	√	√	√	×	×	√	×	×	√	◇	×	×	×	×
Araujo et al. (2021)	√	√	√	√	√	√	√	×	×	√	×	×	◇	√	×	×	×	×
Ali et al. (2021)	√	√	◇	√	√	√	×	×	×	√	×	×	√	×	×	√	×	×
Francis et al. (2021)	√	×	×	√	√	√	√	×	×	√	×	×	√	◇	×	×	◇	×
Belkacem & Lakas (2021)	√	√	√	√	√	√	√	√	×	√	×	×	×	×	×	×	√	√
Kim et al. (2021)	√	√	◇	√	√	√	×	×	×	√	×	√	×	×	×	×	×	×
Chang & Sun (2021)	√	√	√	√	√	√	√	×	×	√	×	×	×	×	√	×	×	×
Toichoa Eyam et al. (2021)	√	√	◇	√	√	√	×	×	×	√	×	√	×	×	×	×	×	×
Wang & Sugaya (2021)	√	√	√	√	◇	√	◇	√	×	×	×	×	×	×	◇	√	×	×
Yoon et al. (2021)	√	√	◇	√	√	√	◇	√	√	√	√	×	×	◇	√	×	×	×
Liu & Jebelli (2021)	√	×	◇	√	√	√	×	√	×	√	×	◇	×	×	×	×	√	×
Karunasena et al. (2021)	√	√	√	√	√	√	×	√	×	√	×	◇	√	×	×	×	×	×
Kar et al. (2022)	√	√	√	√	√	√	√	×	√	×	×	×	×	×	×	√	×	×
Chen et al. (2021)	√	√	√	√	√	√	√	×	×	√	×	√	×	◇	×	×	×	×
Prinsen et al. (2022)	√	√	√	√	√	√	×	√	×	×	√	×	×	×	◇	√	×	×
Alimardani et al. (2022)	√	√	√	√	×	×	×	√	×	×	√	×	×	×	◇	√	×	×
Quiles et al. (2022)	√	√	√	√	×	√	√	√	×	√	×	◇	√	×	×	×	×	×
Ak et al. (2022)	√	√	√	√	×	√	×	×	√	√	×	√	×	×	×	×	×	×
Farmaki et al. (2022)	√	√	√	√	√	√	√	√	×	√	×	×	√	×	×	×	×	×
Fang et al. (2023)	√	√	√	√	×	√	√	×	×	√	×	√	×	◇	×	◇	×	×
Lyu et al. (2022)	√	√	◇	√	◇	√	√	×	×	√	×	√	×	×	×	×	×	×
Wu et al. (2022)	√	◇	◇	√	√	√	√	√	×	√	×	×	√	√	×	×	×	×
Dissanayake et al. (2022)	√	√	√	√	√	√	×	√	×	√	×	×	√	×	×	×	×	×
Staffa & Rossi (2022)	√	√	√	√	√	√	√	√	×	×	×	×	×	×	√	×	×	×
Tang et al. (2022)	√	√	√	√	√	√	√	√	√	√	√	×	√	√	×	×	×	×
Pawuś & Paszkiel (2022)	√	√	◇	√	√	√	√	×	×	√	×	√	×	×	×	×	×	×
Li et al. (2022)	√	√	√	×	√	√	◇	×	×	√	×	×	×	√	×	×	×	×
Roy & Bhaumik (2022)	√	×	√	√	√	√	√	×	×	√	×	×	×	√	×	×	×	×
Jo et al. (2022)	√	√	◇	√	√	√	√	√	×	√	×	×	×	√	×	×	×	×
Aldini et al. (2023)	√	√	◇	√	√	√	√	×	×	×	√	√	×	×	×	×	×	×
Lu et al. (2022)	√	√	√	√	√	√	×	×	×	√	×	√	×	×	×	×	×	×
Sugiyama et al. (2023)	√	×	◇	√	√	√	×	√	×	√	×	√	×	×	×	×	×	×
Richter et al. (2023)	√	√	◇	√	√	√	×	×	×	×	√	×	×	×	√	×	×	×
Boonarchatong & Ketcham (2023)	√	√	◇	×	×	√	√	×	×	√	×	√	×	×	×	×	×	×
Li et al. (2023)	√	√	√	√	√	√	√	√	×	√	×	×	√	◇	×	×	×	×
Cervantes et al. (2023)	√	√	√	√	√	√	×	×	×	√	×	×	×	√	×	×	×	√
Cheng et al. (2024)	√	×	√	×	×	√	√	√	√	√	√	×	◇	×	√	×	×	×

(*continued*)

Table 2. Continued.

	Brain Signal Acquisition				Brain Signal Decoding			Interaction				Robot						
Literature	EEG Paradigm	Acquisition Device	Sensor Locations	Numbers of Electrodes	Real-time Requirements	Feedback Enhancement	AI Methods	Pure BCI	Auxiliary BCI	Proactive Control	Task-oriented HRI	Industrial Robot	Service Robot	Medical Robot	Social Robot	Educational Robot	Exploratory Robot	Autonomous Vehicle
Belkacem & Lakas (2021)	√	√	√	√	√	√	√	√	×	√	×	×	×	×	×	×	√	√
Kim et al. (2021)	√	√	◇	√	√	√	×	×	×	√	×	√	×	×	×	×	×	×
Chang & Sun (2021)	√	√	√	√	√	√	√	×	√	√	√	×	×	×	√	×	×	×
Toichoa Eyam et al. (2021)	√	√	◇	√	√	√	×	×	√	√	×	√	×	×	×	×	×	×
Wang & Sugaya (2021)	√	√	√	√	◇	√	◇	√	×	×	√	×	×	×	◇	√	×	×
Yoon et al. (2021)	√	√	◇	√	√	√	◇	√	√	√	√	×	×	◇	√	×	×	×
Liu & Jebelli (2021)	√	×	◇	√	√	√	×	√	×	√	×	◇	×	×	×	×	√	×
Karunasena et al. (2021)	√	√	√	√	√	√	×	√	×	√	×	◇	√	×	×	×	×	×
Kar et al. (2022)	√	√	√	√	√	√	√	×	√	×	×	×	×	×	×	√	×	×
Chen et al. (2021)	√	√	√	√	√	√	√	×	×	√	×	√	×	◇	×	×	×	×
Prinsen et al. (2022)	√	√	√	√	√	√	×	√	×	×	√	×	×	×	◇	√	×	×
Alimardani et al. (2022)	√	√	√	√	×	×	×	√	×	×	√	×	×	×	◇	√	×	×
Quiles et al. (2022)	√	√	√	√	×	√	√	√	×	√	×	◇	√	×	×	×	×	×
Ak et al. (2022)	√	√	√	√	×	√	×	×	√	√	×	√	×	×	×	×	×	×
Farmaki et al. (2022)	√	√	√	√	√	√	√	√	×	√	×	×	√	◇	×	◇	×	×
Fang et al. (2023)	√	√	√	√	×	√	√	×	√	√	×	√	×	×	×	×	×	×
Lyu et al. (2022)	√	√	◇	√	◇	√	√	×	√	√	×	√	×	×	×	×	×	×
Wu et al. (2022)	√	◇	◇	√	√	√	√	√	×	√	×	×	√	√	×	×	×	×
Dissanayake et al. (2022)	√	√	√	√	√	√	×	√	×	√	◇	×	√	×	×	×	×	×
Staffa & Rossi (2022)	√	√	√	√	√	√	√	√	×	×	◇	×	×	×	√	×	×	×
Tang et al. (2022)	√	√	√	√	√	√	√	√	√	√	√	×	√	√	×	×	×	×
Pawuś & Paszkiel (2022)	√	√	◇	√	√	√	√	×	×	√	×	√	×	×	×	×	×	×
Li et al. (2022)	√	√	√	×	√	√	◇	×	×	√	×	×	×	√	×	×	×	×
Roy & Bhaumik (2022)	√	×	√	√	√	√	√	×	×	√	×	×	×	√	×	×	×	×
Jo et al. (2022)	√	√	◇	√	√	√	√	√	×	√	×	×	×	√	×	×	×	×
Aldini et al. (2023)	√	√	◇	√	√	√	√	×	×	×	√	√	×	×	×	×	×	×
Lu et al. (2022)	√	√	√	√	√	√	×	×	×	√	×	√	×	×	×	×	×	×
Sugiyama et al. (2023)	√	×	◇	√	√	√	×	√	×	√	×	√	×	×	×	×	×	×
Richter et al. (2023)	√	√	◇	√	√	√	×	×	×	×	√	×	×	×	√	×	×	×
Boonarchatong & Ketcham (2023)	√	√	◇	×	×	√	√	×	×	√	×	√	×	×	×	×	×	×
Li et al. (2023)	√	√	√	√	√	√	√	√	×	√	×	×	√	◇	×	×	×	×
Cervantes et al. (2023)	√	√	√	√	√	√	×	×	×	√	×	×	×	√	×	×	×	√
Cheng et al. (2024)	√	×	√	×	×	√	√	√	√	√	√	×	◇	×	√	×	×	×

√: completely relevant; ×: not relevant or did not mentioned; ◇: relevant either indirectly, implicitly, partially, or mentioned but lacked detailed descriptions.

4.1.6. Signal decoding

The traditional decoding process involves several key steps: preprocessing to remove any artifacts from the data, feature extraction to capture relevant signal information, and feature classification where labels are assigned to features based on predefined classes. Common techniques like band-pass (Aldini et al., 2019; Kompatsiari et al., 2018; Staffa & Rossi, 2022) and notch filters (Chu et al., 2018; Roy & Bhaumik, 2022; Zhang et al., 2021) for preprocessing, and Canonical Correlation Analysis (CCA) (Chen et al., 2021; Du et al., 2021; Zhang et al., 2021) and Common Spatial Patterns (CSP) (Araujo et al., 2021; Wei et al., 2021) for feature extraction and classification, are well-documented in prior literature. Besides, the recent surge in AI like DL related technologies has introduced novel advancements in this area. However, the real-time requirements and feedback enhancement of the decoding process have not yet been investigated in any previous reviews (Table 1). Our article have exclusively identified the three sub-dimensions: real-time requirement, feedback enhancement and AI methods from the reviewed studies, as displayed in Table 4.

4.1.7. Real-time requirements

In the majority of the studies reviewed, EEG signals were processed in real-time, meaning the brain's electrical activity was analyzed instantly or with negligible delay, facilitating immediate device interaction or interpretation. Our corpus provided a rich source of information, from which we distilled five types of requirements, highlighting the critical factors that contribute to the successful implementation of EEG-based BRI systems.

- Low Latency: To maintain a natural and intuitive user experience (UX), the latency from signal acquisition to action or feedback should be minimal, ranging from a few to several hundred milliseconds. This requirement emerged as the second most prevalent in our corpus, as 23 studies involved it.
- High Accuracy: Decoding algorithms need to precisely translate EEG signals into accurate commands or responses, reducing errors and misunderstandings for effective interaction. This is crucial for applications where incorrect interpretations can lead to potentially dangerous outcomes ($n = 15$).
- High Temporal Resolution: The EEG system requires a high sampling rate to accurately record the brain's fast-changing activity, essential for effective real-time signal decoding. Only a few studies successfully met this criterion ($n = 8$).
- Seamless Feedback: Immediate and intuitive feedback from EEG signals to users is crucial for practical applications, especially for neurofeedback and BCI used cases (Long et al., 2019; Ogino & Mitsukura, 2018), so as to

Table 3. Overview of the signal acquisition dimension in *brain* entity in our corpus.

Sub-dimension	Category	Connection	Papers (%)	References
EEG Paradigm	Sensory and motor-related, SMR/ERD	—	1 (1.1%)	Nann et al. (2021)
	Sensory and motor-related, MRCP	—	1 (1.1%)	Sugiyama et al. (2023)
	Sensory and motor-related, MI	—	21 (24.1%)	Liu & Jebelli (2021); Xu et al. (2018); Boonarchatong & Ketcham (2023); Li et al. (2019); Guo et al. (2020); Gordleeva et al. (2020); Araujo et al. (2021); Cheng et al. (2024); Tang et al. (2022); Roy & Bhaumik (2022); Martínez-Cagigal et al. (2020); Penaloza et al. (2018); Hernandez-Carmona & Penaloza (2019); Wei et al. (2021); Francis et al. (2021); Ak et al. (2022); Zhao et al. (2020); Kuffuor & Samanta (2018); Jiang et al. (2018); Wang et al. (2018); Ai et al. (2018)
	Vision-related, SSVEP	—	17 (19.5%)	Chen et al. (2021); Zhang et al. (2021); Farmaki et al. (2022); Aznan et al. (2019); Chhabra et al. (2020); Chu et al. (2018); Abougarair et al. (2021); Du et al. (2021); Chiuzbaian et al. (2019); Shao et al. (2020); Karunasena et al. (2021); Yuan & Li (2019); Chen et al. (2020); Quiles et al. (2022)
	Cognition-related, P300	—	8 (9.2%)	Braun et al. (2019); Belkacem & Lakas (2021); Cao & Liu (2018); Li et al. (2023); Magee & Givigi (2021); Bahman & Shamsollahi (2019); Rahul & Sharma (2019); Ali et al. (2021)
	Cognition-related, ERP	—	2 (2.2%)	Aldini et al. (2023); Kompatsiari et al. (2018)
	Cognition-related, ErrP	—	1 (1.1%)	Iwane et al. (2019)
	Cognition-related, task-based	—	33 (37.9%)	Cervantes et al. (2023); Chang & Sun (2021); Wang & Sugaya (2021); Jo et al. (2022); Baka et al. (2019); Prinsen et al. (2022); Wu et al. (2022); Richter et al. (2023); Memar & Esfahani (2018); Dissanayake et al. (2022); Aldini et al. (2019); Toichoa Eyam et al. (2021); Memar & Esfahani (2020); Lu et al. (2022); Alimardani et al. (2022); Alimardani et al. (2020); Long et al. (2019); Yoon et al. (2021); Ogino & Mitsukura (2018); Pawuś & Paszkiel (2022); Kilmarx et al. (2018); Li et al. (2022); Lu et al. (2020); Roshdy et al. (2021); Sanguantrakul et al. (2020); Yu et al. (2019); Mondini et al. (2020); Rashid et al. (2020); Korovesis et al. (2019)
	Cognition-related, IAPS	—	1 (1.1%)	Kim et al. (2021)
	Hybrid	—	1 (1.1%)	Kar et al. (2022)
Acquisition Device	ADS1299	Wired/wireless	2 (2.2%)	Li et al. (2022); Sanguantrakul et al. (2020)
	BIOPAC MP150	Wired	1 (1.1%)	Ghosh & Orlando (2019)
	BioRadio system	Wireless	1 (1.1%)	Karunasena et al. (2021)
	Biosemi ActiveTwo	Wired	3 (3.4%)	Lyu et al. (2022); Tang et al. (2022); Long et al. (2019)
	BrainProducts MOVE	Wireless	1 (1.1%)	Aldini et al. (2023)
	BrainProducts ActiChamp	Wired	1 (1.1%)	Ehrlich & Cheng (2019)
	BrainProducts ActiCap	Wired/wireless	4 (4.6%)	Araujo et al. (2021); Martínez-Cagigal et al. (2020); Kompatsiari et al. (2018); Mondini et al. (2020)
	BrainProducts LiveAmp	Wireless	1 (1.1%)	Nann et al. (2021)
	BrainProducts others	Wired	2 (2.2%)	Aldini et al. (2019); Kim et al. (2021)
	Cognionics HD-72	Wireless	1 (1.1%)	Qian et al. (2018)
	Cognionics Quick-20	Wireless	1 (1.1%)	Aznan et al. (2019)
	EGI system	Wired	1 (1.1%)	Alimardani et al. (2022)
	Emotiv EPOC	Wireless	19 (21.8%)	Staffa & Rossi (2022); Chang & Sun (2021); Braun et al. (2019); Kuffuor & Samanta (2018); Chiuzbaian et al. (2019); Shao et al. (2020); Li et al. (2023); Bahman & Shamsollahi (2019); Ali et al. (2021); Toichoa Eyam et al. (2021); Pawuś & Paszkiel (2022); Kilmarx et al. (2018); Lu et al. (2020); Roshdy et al. (2021); Yu et al. (2019)
	g.HIAMP	Wired	1 (1.1%)	Richter et al. (2023)
	g.MOBIlab+	Wireless	1 (1.1%)	Dissanayake et al. (2022)
	g.Tec Nautilus	Wired	1 (1.1%)	Hernandez-Carmona & Penaloza (2019)
	g.USBamp	Wired/N.S.	3 (3.4%)	Si-Mohammed et al. (2020); Alimardani et al. (2020); Yoon et al. (2021)
	Neuracle	Wired/N.S.	3 (3.4%)	Chen et al. (2021); Abougarair et al. (2021); Chen et al. (2020)
	Neuroelectrics	Wireless	1 (1.1%)	Quiles et al. (2022)
	NeuroScan SynAmps	Wired	2 (2.2%)	Jo et al. (2022); Fang et al. (2023)
	NeuroScan NuAmps	Wireless	4 (4.6%)	Baka et al. (2019); Li et al. (2019); Guo et al. (2020); Yuan & Li (2019)
	NeuroScan Others	Wired/wireless/N.S.	4 (4.6%)	Wang et al. (2018); Du et al. (2021); Cao & Liu (2018); Magee & Givigi (2021)
	NeuroSky Mindwave	Wireless/N.S.	6 (6.9%)	Wang & Sugaya (2021); Boonarchatong & Ketcham (2023); Ak et al. (2022); Rahul & Sharma (2019); Ogino & Mitsukura (2018); Rashid et al. (2020)

(*continued*)

Table 3. Continued.

Sub-dimension	Category	Connection	Papers (%)	References
	NeuroSky TGAM	Wireless	1 (1.1%)	Lu et al. (2022)
	Nexus 32	Wireless	1 (1.1%)	Cervantes et al. (2023)
	Nihon Kohden	N.S.	1 (1.1%)	Kar et al. (2022)
	NVX 52	Wired	1 (1.1%)	Gordleeva et al. (2020)
	OpenBCI Cyton	Wireless	1 (1.1%)	Farmaki et al. (2022)
	OpenBCI Ganglion	N.S.	1 (1.1%)	Korovesis et al. (2019)
	Unicorn Hybrid Black	Wireless	2 (2.2%)	Belkacem & Lakas (2021); Prinsen et al. (2022)
Sensor Locations	One of F,T,P,O Involved	—	14 (16.1%)	Ghosh & Orlando (2019); Wang & Sugaya (2021); Guo et al. (2020); Farmaki et al. (2022); Cheng et al. (2024); Martínez-Cagigal et al. (2020); Kuffuor & Samanta (2018); Chiuzbaian et al. (2019); Belkacem & Lakas (2021); Li et al. (2023); Memar & Esfahani (2018); Sanguantrakul et al. (2020); Korovesis et al. (2019); Kar et al. (2022)
	Two of F,T,P,O Involved	—	21 (24.1%)	Chen et al. (2021); Zhang et al. (2021); Si-Mohammed et al. (2020); Araujo et al. (2021); Jiang et al. (2018); Abougarair et al. (2021); Du et al. (2021); Cao & Liu (2018); Bahman & Shamsollahi (2019); Rahul & Sharma (2019); Kompatsiari et al. (2018); Iwane et al. (2019); Dissanayake et al. (2022); Lu et al. (2022); Ogino & Mitsukura (2018); Yu et al. (2019); Rashid et al. (2020)
	Three of F,T,P,O Involved	—	9 (10.3%)	Fang et al. (2023); Aznan et al. (2019); Nann et al. (2021); Penaloza et al. (2018); Wei et al. (2021); Chu et al. (2018); Quiles et al. (2022); Magee & Givigi (2021); Prinsen et al. (2022)
	All of F,T,P,O Involved	—	13 (14.9%)	Staffa & Rossi (2022); Ehrlich & Cheng (2019); Cervantes et al. (2023); Chang & Sun (2021); Baka et al. (2019); Tang et al. (2022); Ak et al. (2022); Zhao et al. (2020); Wang et al. (2018); Ai et al. (2018); Chhabra et al. (2020); Alimardani et al. (2022); Long et al. (2019)
	Earlobe (A/M) Involved	—	21 (24.1%)	Wang et al. (2018); Staffa & Rossi (2022); Cervantes et al. (2023); Wang & Sugaya (2021); Aznan et al. (2019); Martínez-Cagigal et al. (2020); Ak et al. (2022); Zhao et al. (2020); Kuffuor & Samanta (2018); Wang et al. (2018); Ai et al. (2018); Chhabra et al. (2020); Chu et al. (2018); Du et al. (2021); Rahul & Sharma (2019); Kompatsiari et al. (2018); Dissanayake et al. (2022); Long et al. (2019); Ogino & Mitsukura (2018); Yu et al. (2019); Korovesis et al. (2019)
	Midline Sagittal Plane (Z) Involved	—	22 (25.3%)	Staffa & Rossi (2022); Cervantes et al. (2023); Zhang et al. (2021); Li et al. (2019); Aznan et al. (2019); Araujo et al. (2021); Nann et al. (2021); Martínez-Cagigal et al. (2020); Penaloza et al. (2018); Shao et al. (2020); Karunasena et al. (2021); Chen et al. (2020); Quiles et al. (2022); Rahul & Sharma (2019); Kompatsiari et al. (2018); Dissanayake et al. (2022); Yoon et al. (2021); Rashid et al. (2020); Korovesis et al. (2019)
Number of Electrodes	No. $\leq$ 10	—	37 (42.5%)	Chen et al. (2021); Ghosh & Orlando (2019); Wang & Sugaya (2021); Zhang et al. (2021); Xu et al. (2018); Gordleeva et al. (2020); Nann et al. (2021); Roy & Bhaumik (2022); Hernandez-Carmona & Penaloza (2019); Kuffuor & Samanta (2018); Dissanayake et al. (2022); Lu et al. (2022); Ogino & Mitsukura (2018); Sanguantrakul et al. (2020); Yu et al. (2019); Rashid et al. (2020); Korovesis et al. (2019); Kar et al. (2022)
	10 $<$ No. $\leq$ 20	—	23 (26.4%)	Staffa & Rossi (2022); Cervantes et al. (2023); Chang & Sun (2021); Braun et al. (2019); Aznan et al. (2019); Araujo et al. (2021); Sugiyama et al. (2023); Wei et al. (2021); Cao & Liu (2018); Li et al. (2023); Toichoa Eyam et al. (2021); Memar & Esfahani (2020); Alimardani et al. (2022); Alimardani et al. (2020); Yoon et al. (2021); Kilmarx et al. (2018); Lu et al. (2020); Roshdy et al. (2021)
	20 $<$ No. $\leq$ 32	—	14 (16.1%)	Wang et al. (2018); Ehrlich & Cheng (2019); Liu & Jebelli (2021); Jo et al. (2022); Lyu et al. (2022); Penaloza et al. (2018); Ak et al. (2022); Shao et al. (2020); Aldini et al. (2023); Aldini et al. (2019); Long et al. (2019); Pawuś & Paszkiel (2022); Kim et al. (2021); Qian et al. (2018)
	32 $<$ No. $\leq$ 64	—	5 (5.7%)	Baka et al. (2019); Tang et al. (2022); Martínez-Cagigal et al. (2020); Kompatsiari et al. (2018); Richter et al. (2023)
	No. $>$ 64	—	3 (3.4%)	Farmaki et al. (2022); Francis et al. (2021); Mondini et al. (2020)

N.S.: not specified.

enhance user controllability. The understandable is normally facilitated by preprocessing, feature extraction, and classification. This requirement was present in nearly half of the studies (n = 42).
- Computational Efficiency: Decoding algorithms should be computationally efficient for real-time processing, often necessitating optimized software and specialized hardware. Notably, only four studies fulfilled this requirement.

4.1.8. Feedback enhancement

Feedback enhancement in EEG signal decoding involves integrating feedback loops to elevate the user-system interaction within EEG-based platforms, for instance, BCIs. Such feedback mechanisms empower users to more adeptly adjust their brain activities, thereby boosting the system's effectiveness and ease of use. Additionally, this feedback plays a crucial role in managing particular functions, enabling and facilitating the real-time control of these operations via EEG signals (Qin et al., 2023). In our corpus, we identified six types of feedback.

- Visual Feedback: The typical EEG feedback, which involves users receiving visual cues related to their brain activity or commands, such as moving objects on a screen or graphical representations of brainwave patterns (n = 28). For example, video stimuli showcasing robot movements are frequently employed (Quiles et al., 2022; Sugiyama et al., 2023).
- Auditory Feedback: Provides users with auditory signals matching their brain activity or command success, including beeps, volume changes, or complex audio information for different states or outcomes. Three studies adopted standalone audio feedback.
- Multimodal Feedback: Combines multiple feedback types (visual, auditory, haptic …) for an enriched user experience, potentially enhancing control efficiency. The combination of visual and auditory feedback are the preferred option (Braun et al., 2019). Seven studies in our corpus involved multimodal feedback.
- Direct Feedback: Direct feedback corresponds to the user's immediate actions (n = 22). For instance, in BCI-controlled robotic arm scenario, the arm movement is the direct feedback of user's commands (Martínez-Cagigal et al., 2020; Wei et al., 2021).
- Performance Feedback: Refers to performance metrics such as algorithm accuracy and error rates, are utilized to evaluate system control and progress during training sessions (n = 18).
- Neurofeedback: Neurofeedback provides users with real-time information about specific brainwave patterns or mental states, allowing them to learn how to enhance their cognitive abilities by modulating these patterns or states. This is the second most prevalent feedback in our corpus (n = 22).

4.1.9. Artificial intelligence methods

The swift advancement of AI technologies in recent years has led to the creation of more sophisticated algorithms that deliver impressive performance. DL techniques, such as deep neural networks and their variations, have shown exceptional proficiency, even surpassing ML algorithms. While traditional ML methods like linear discriminant analysis (Jo et al., 2022) and support vector machine (Francis et al., 2021) remain popular in EEG-based BRI studies for their reliability and robustness, there is a growing trend towards advanced DL techniques, particularly in EEG signal decoding tasks such as feature extraction and classification. For example, a combination of graph convolutional networks and gated recurrent unit networks was used for feature classification in Tang et al. (2022), and a blend of long-short term memory networks with convolutional neural networks was utilized for both feature extraction and classification in Cheng et al. (2024). In our analysis, we categorized the studies based on their usage of traditional ML, DL, or non-ML/DL approaches instead of enumerating specific algorithms that have been exhaustively listed previously (literature in Table 1). In addition, we intend to generalize and compare the trends between exploiting ML and DL for signal decoding. Despite the advent of new AI methods, our findings (Table 4) indicate a continued preference for conventional ML algorithms in the majority of the studies (n = 42).

4.2. Robot

The *Robot* entity characterizes the autonomous or semi-autonomous machines that are capable of performing tasks or actions on their own or offering help with a degree of programmable intelligence. In our corpus, we classified robots into eight categories, focusing on their functionality, objectives, application domains, and implementation scenarios rather than traditional design aspects like robot arms or mobile robots. This approach moves beyond superficial classifications commonly found in previous reviews, offering a deeper understanding of robots' roles and uses. The entire distribution of robot usage across the reviewed papers is exhibited in Table 2, while examples of each type of robot are displayed in Figure 1. It's crucial to realize that in our categorization, the dimensions were not exclusively mapped with the papers. For example, one study may involve multiple types of robots (i.e., Yuan & Li, 2019; Zhang et al., 2021) or the single robot used may be considered to have a (partial) relation to other types (i.e., Nann et al., 2021; Prinsen et al., 2022). This recognition underscores the overlapped and interconnected nature of the dimensions (robots) and facilitates an in-depth understanding of the variability and nuance within the reviewed studies.

4.2.1. Industrial robot

Industrial robots, often employed in manufacturing settings, are engineered to execute operations like welding, painting, assembly, and product handling. Renowned for their precision, speed, and durability, these robots typically manifest as

Table 4. Overview of the signal decoding dimension in the *Brain* entity.

Sub-dimension	Category	Papers (%)	References
Real-time requirements	Low Latency	23 (26.4%)	Ehrlich & Cheng (2019); Liu & Jebelli (2021); Xu et al. (2018); Jo et al. (2022); Guo et al. (2020); Sugiyama et al. (2023); Tang et al. (2022); Francis et al. (2021); Zhao et al. (2020); Wang et al. (2018); Chhabra et al. (2020); Karunasena et al. (2021); Chen et al. (2020); Belkacem & Lakas (2021); Bahman & Shamsollahi (2019); Aldini et al. (2023); Prinsen et al. (2022); Wu et al. (2022); Toichoa Eyam et al. (2021); Roshdy et al. (2021); Mondini et al. (2020); Rashid et al. (2020); Korovesis et al. (2019)
	High Accuracy	15 (17.2%)	Chen et al. (2021); Wang et al. (2018); Jo et al. (2022); Guo et al. (2020); Nann et al. (2021); Roy & Bhaumik (2022); Martínez-Cagigal et al. (2020); Penaloza et al. (2018); Francis et al. (2021); Abougarair et al. (2021); Cao & Liu (2018); Magee & Givigi (2021); Rahul & Sharma (2019); Aldini et al. (2023); Rashid et al. (2020)
	High Temporal Resolution	8 (9.2%)	Ehrlich & Cheng (2019); Baka et al. (2019); Li et al. (2019); Farmaki et al. (2022); Aznan et al. (2019); Zhao et al. (2020); Pawuś & Paszkiel (2022); Kim et al. (2021)
	Seamless Feedback	42 (48.3%)	Chen et al. (2021); Ghosh & Orlando (2019); Staffa & Rossi (2022); Cervantes et al. (2023); Chang & Sun (2021); Zhang et al. (2021); Braun et al. (2019); Li et al. (2019); Farmaki et al. (2022); Gordleeva et al. (2020); Araujo et al. (2021); Nann et al. (2021); Roy & Bhaumik (2022); Penaloza et al. (2018); Hernandez-Carmona & Penaloza (2019); Wei et al. (2021); Kuffuor and Samanta (2018); Chu et al. (2018); Abougarair et al. (2021); Du et al. (2021); Chiuzbaian et al. (2019); Li et al. (2023); Bahman & Shamsollahi (2019); Ali et al. (2021); Kompatsiari et al. (2018); Iwane et al. (2019); Prinsen et al. (2022); Richter et al. (2023); Memar & Esfahani (2018); Dissanayake et al. (2022); Aldini et al. (2019); Long et al. (2019); Yoon et al. (2021); Ogino & Mitsukura (2018); Kilmarx et al. (2018); Li et al. (2022); Lu et al. (2020); Roshdy et al. (2021); Sanguantrakul et al. (2020); Kim et al. (2021); Kar et al. (2022); Qian et al. (2018)
	Computational Efficiency	4 (4.6%)	Araujo et al. (2021); Rahul & Sharma (2019); Richter et al. (2023); Lu et al. (2022)
Feedback enhancement	Visual Feedback	28 (32.2%)	Wang et al. (2018); Ghosh & Orlando (2019); Ehrlich & Cheng (2019); Zhang et al. (2021); Baka et al. (2019); Si-Mohammed et al. (2020); Farmaki et al. (2022); Aznan et al. (2019); Sugiyama et al. (2023); Cheng et al. (2024); Penaloza et al. (2018); Hernandez-Carmona & Penaloza (2019); Yuan & Li (2019); Kompatsiari et al. (2018); Prinsen et al. (2022); Alimardani et al. (2022); Kilmarx et al. (2018); Yu et al. (2019); Mondini et al. (2020)
	Auditory Feedback	3 (3.4%)	Wang & Sugaya (2021); Richter et al. (2023); Kar et al. (2022)
	Multimodal Feedback	7 (8%)	Chen et al. (2021); Braun et al. (2019); Li et al. (2019); Roy & Bhaumik (2022); Li et al. (2023); Dissanayake et al. (2022); Li et al. (2022)
	Direct Feedback	22 (25.3%)	Staffa & Rossi (2022); Ehrlich & Cheng (2019); Cervantes et al. (2023); Zhang et al. (2021); Jo et al. (2022); Fang et al. (2023); Aznan et al. (2019); Araujo et al. (2021); Martínez-Cagigal et al. (2020); Chhabra et al. (2020); Aldini et al. (2023); Prinsen et al. (2022); Memar & Esfahani (2018); Lu et al. (2022); Alimardani et al. (2022); Pawuś & Paszkiel (2022); Sanguantrakul et al. (2020); Rashid et al. (2020); Kar et al. (2022)
	Performance Feedback	18 (20.1%)	Liu & Jebelli (2021); Cervantes et al. (2023); Boonarchatong & Ketcham (2023); Lyu et al. (2022); Guo et al. (2020); Kuffuor & Samanta (2018); Jiang et al. (2018); Wang et al. (2018); Ai et al. (2018); Shao et al. (2020); Chen et al. (2020); Iwane et al. (2019); Wu et al. (2022); Aldini et al. (2019); Memar & Esfahani (2020); Long et al. (2019); Lu et al. (2020); Qian et al. (2018)
	Neurofeedback	22 (25.3%)	Staffa & Rossi (2022); Chang & Sun (2021); Xu et al. (2018); Lyu et al. (2022); Guo et al. (2020); Gordleeva et al. (2020); Nann et al. (2021); Tang et al. (2022); Ak et al. (2022); Zhao et al. (2020); Chu et al. (2018); Karunasena et al. (2021); Ali et al. (2021); Richter et al. (2023); Alimardani et al. (2020); Yoon et al. (2021); Ogino & Mitsukura (2018); Roshdy et al. (2021); Korovesis et al. (2019); Kim et al. (2021)
Artificial Intelligence Methods	Traditional Machine Learning (ML)	42 (48.3%)	Chen et al. (2021); Ehrlich & Cheng (2019); Chang & Sun (2021); Lyu et al. (2022); Si-Mohammed et al. (2020); Gordleeva et al. (2020); Araujo et al. (2021); Roy & Bhaumik (2022); Penaloza et al. (2018); Wei et al. (2021);

(*continued*)

Table 4. Continued.

Sub-dimension	Category	Papers (%)	References
			Francis et al. (2021); Chhabra et al. (2020); Chu et al. (2018); Du et al. (2021); Shao et al. (2020); Magee & Givigi (2021); Aldini et al. (2023); Iwane et al. (2019); Memar & Esfahani (2020); Long et al. (2019); Ogino & Mitsukura (2018); Lu et al. (2020); Rashid et al. (2020); Kar et al. (2022); Qian et al. (2018)
	Deep Learning (DL)	19 (21.8%)	Ghosh & Orlando (2019); Staffa & Rossi (2022); Aznan et al. (2019); Cheng et al. (2024); Tang et al. (2022); Li et al. (2023); Magee & Givigi (2021); Rahul & Sharma (2019); Aldini et al. (2023); Wu et al. (2022); Pawuś & Paszkiel (2022); Lu et al. (2020); Roshdy et al. (2021); Sanguantrakul et al. (2020); Korovesis et al. (2019); Kar et al. (2022)
	Non-ML/DL	7 (8%)	Wang et al. (2018); Wang & Sugaya (2021); Baka et al. (2019); Hernandez-Carmona & Penaloza (2019); Chiuzbaian et al. (2019); Yoon et al. (2021); Li et al. (2022)

robotic arms or mobile robots, catering to the rigorous demands of industrial applications for desired task performance. This type of robot emerged as the second most utilized in our corpus (n = 32).

4.2.2. Service robot

Service robots are designed to aid humans in tasks beyond manufacturing realms which can be embodied in any shapes. In personal service contexts, they facilitate household chores, provide entertainment, or serve as personal aides. Conversely, in professional settings, they find application across various sectors such as healthcare, where they assist in surgeries and patient care; agriculture, through harvesting robots; and logistics, with delivery drones, among others, showcasing their versatility and utility in both personal and professional spheres. Particularly, a wheeled robot with a robot arm was harnessed for assisting disabled individuals in Du et al. (2021). This robot category emerged as the most favored in our analysis, with 38 studies featuring it.

4.2.3. Medical robot

Medical robots are specifically designed for healthcare applications, encompassing surgical robots that aid in procedures, rehabilitation robots for therapeutic use, and diagnostic robots for medical assessments. Common examples include wearable exoskeletons (Chu et al., 2018) for mobility support and prosthetic devices (Ghosh & Orlando, 2019) for limb replacement, illustrating their critical role in enhancing patient care and medical outcomes. 27 studies were identified in this dimension.

4.2.4. Social robot

Social robots are engineered to engage with humans on an interpersonal level, possessing the ability to recognize and respond to human emotions, partake in conversations, and emulate social behaviors. Typically designed as humanoid robots, these machines are crafted to closely resemble human appearance and mannerisms, facilitating natural and intuitive interactions (n = 11).

4.2.5. Educational robot

Educational robots serve as interactive teaching aids, designed to assist in learning languages, programming, mathematics, and science subjects. They are specifically engineered to be engaging and interactive, making the learning experience more effective and enjoyable for students. Similarly, it is often engineered as humanoid robots to mimic human teacher actions (n = 9).

4.2.6. Exploratory robot

Exploratory robots are deployed in environments deemed inaccessible or hazardous for humans, contrasting with the typical use of industrial robots. These include rovers navigating in the inaccessible places, exploring underwater regions, and searching and rescuing operations in disaster-stricken areas, showcasing their critical role in extending human reach and capabilities (n = 4). Especially, a swarm robot was employed for exploratory purposes in Belkacem and Lakas (2021).

4.2.7. Autonomous vehicle

This innovative approach has transformed human society in recent years, introducing autonomous systems like self-driving cars, drones, and unmanned aerial vehicles (UAVs). These robots operate independently of human intervention, serving critical roles in transportation and conducting aerial surveys, marking a significant leap forward in technology and its applications (n = 3). Drones were the predominant type of autonomous vehicle observed in our corpus.

In addition to robot categories and EEG devices, several studies in our corpus also detailed the technologies utilized to bridge brains and robots. For hardware, Arduino (i.e., Abougarair et al., 2021; Farmaki et al., 2022; Pawuś & Paszkiel, 2022) and Raspberry Pi (i.e., Belkacem & Lakas, 2021; Kilmarx et al., 2018; Tang et al., 2022) (as well as their derivatives) were the most frequently mentioned. On the software side, the robot operating system (ROS) (i.e., Chhabra et al., 2020; Du et al., 2021; Qian et al., 2018; Richter et al., 2023; Zhang et al., 2021) emerged as the predominant robotic platform, with some studies also employing MATLAB (Simulink) (i.e., Ehrlich & Cheng, 2019; Lu et al., 2022; Prinsen et al., 2022) for robot integration. Regarding communication protocols, the most commonly used option was transmission control protocol (TCP) (i.e., Cao & Liu, 2018; Fang et al., 2023; Quiles et al., 2022; Tang et al., 2022; Xu et al., 2018) while some studies included user datagram protocol (UDP) (i.e., Prinsen et al., 2022), secure shell protocol (SSH) (Ali et al., 2021), message queuing telemetry transport (MQTT) (i.e., Sugiyama et al., 2023), and custom-developed protocols (i.e., Chu et al., 2018; Si-Mohammed et al., 2020; Wang et al., 2018).

4.3. Application contexts and evaluation techniques

4.3.1. Application contexts

Based on the level of direct human control over robots, we uncovered two overarching application contexts: Human Control Concern (HCC) and Robot Design Concern (RDC). We then delineated eight more specific, but rather high-level application categories lying either on HCC or RDC contexts. Further, we defined more specific application domains with detailed descriptions. Each study was primarily classified under either HCC or RDC (Table 5). Our goal is to harness this hierarchical knowledge to motivate future researchers to consider the function and role of robots prior to constructing a complete BRI system under EEG.

4.3.1.1. HCC. In this context, the BRI system is tailored for situations in which humans intentionally control, direct, or guide the robots to achieve specific objectives.

4.3.1.2. RDC. In this context, humans intentionally controlling the robots is not the main concern; instead, the robots serve as external agents that provide assistance in carrying out specific tasks or achieving predefined goals.

Moreover, upon revisiting all studies, we identified eight application categories, with the majority present in both HCC and RDC contexts. Notably, Military Usage was uniquely associated with HCC, whereas Education was exclusively linked to RDC. Some studies extended across multiple application domains. For example, Wang et al. (2018) was classified under HCC while also incorporating application categories of assistance and healthcare. Similarly Alimardani et al. (2020), belonged to RDC, spanned education and social interaction.

- *Human-centric Technology:* This category (n = 28 in HCC and n = 9 in RDC) investigates innovative, human-centered approaches in EEG-based BRI to enhance human interactions with robots, mutual task collaboration, and UX. A majority of the studies were research-oriented introducing new tools or methodologies to advance the field. For instance, several studies harnessed AR for enhanced robotic control (Chen et al., 2020; Si-Mohammed et al., 2020).
- *Assistance:* Aims to leverage robotics in aiding individuals with disabilities or motor impairments, facilitating physical tasks like walking or navigation and enabling control over robots for task execution without physical movement, i.e., steering a mobile robot using solely brain signals (Rashid et al., 2020). 28 studies were identified with this category linked with HCC while 5 with RDC.
- *Healthcare:* Focuses on employing advanced robotics, such as exoskeletons or prostheses, for rehabilitation and therapeutic purposes in patients with mobility disorder issues, as well as supporting individual mental recovery and meditation. In this category, 16 studies were identified under HCC and only three under RDC.
- *Education* Targets cognitive development and skill improvement through BRI, with specific emphasis on language acquisition of gaining the ability to understand and communicate in a non-native language; and self-directed learning of obtaining knowledge or skills with self-supervision. This category was merely associated with RDC (n = 5).
- *Entertainment:* Summarizes research where BRI systems are designed or evaluated with relaxation, fun, and leisure activities, utilizing EEG technology. One study was found in each of HCC and RDC.
- *Safety and Security:* Investigates strategies for enhancing safety in shared human-robot environments and ensuring secure operations to boost productivity. Likewise, only one study was identified both in HCC and RDC.
- *Social Interaction:* Encompasses studies on communication, collaboration, and companionship with robots designed to simulate more human-like interactions, focusing on robots' ability to recognize and respond to human emotions and intentions. Mostly, humanoid robots were engaged such as Pepper robot (Staffa & Rossi, 2022) or Nadine robot (Baka et al., 2019). This category includes five studies, with four in RDC and only one in HCC.
- *Military Usage:* Explores the application of EEG-based BRI systems in military settings, with merely one study in this area associated with HCC.

4.3.2. Evaluation techniques

System evaluation is pervasively used in research papers to examine the developed systems. It was observed that nearly all the reviewed studies employed this methodology to evaluate their designed BRI systems. The evaluation methodologies within our corpus were categorized into six groups: performance metrics, user experience (UX) metrics, signal information, surveys, interviews, and not specified. Some studies employed multiple categories for system evaluation (Table 6).

4.3.2.1. Performance metrics. Traditional performance metrics, as typical objective measurements in EEG-based BRI system evaluation, vary depending on the specific applications and goals. This category represents the predominant evaluation method employed in 57 studies (i.e., Penaloza et al., 2018; Sanguantrakul et al., 2020; Yu et al., 2019), focusing on accuracy, response time, task completion time, error rate, and information transfer rate, with workload and efficiency serving as supplementary considerations.

Table 5. Application contexts with category and domain information in our corpus.

Context	Category	Domain	Description	Papers (%)	References
Human Control Concern (HCC)	Human-centric Technology	Usability and user experience	Exploring better UX for effective interactions	7 (8%)	Fang et al. (2023); Martínez-Cagigal et al. (2020); Kuffuor & Samanta (2018); Yuan & Li (2019); Iwane et al. (2019); Memar & Esfahani (2020); Kim et al. (2021)
		Research and innovation	Exploring new advancements for research needs	18 (20.7%)	Chen et al. (2021); Si-Mohammed et al. (2020); Guo et al. (2020); Sugiyama et al. (2023); Hernandez-Carmona & Penaloza (2019); Wei et al. (2021); Ak et al. (2022); Zhao et al. (2020); Jiang et al. (2018); Yuan & Li (2019); Chen et al. (2020); Cao & Liu (2018); Pawuś & Paszkiel (2022); Kilmarx et al. (2018); Lu et al. (2020)
		Mutual collaboration	Collaborating with robots to enhance task performance by control	3 (3.4%)	Liu & Jebelli (2021); Lyu et al. (2022); Memar & Esfahani (2018)
	Assistance	Physical movement	Aiding people with motor disorders for physical movements	19 (21.8%)	Wang et al. (2018); Ghosh & Orlando (2019); Zhang et al. (2021); Li et al. (2019); Farmaki et al. (2022); Tang et al. (2022); Wei et al. (2021); Francis et al. (2021); Wang et al. (2018); Abougarair et al. (2021); Du et al. (2021); Chiuzbaian et al. (2019); Li et al. (2023); Magee & Givigi (2021); Bahman & Shamsollahi (2019); Rahul & Sharma (2019); Ali et al. (2021); Long et al. (2019); Mondini et al. (2020)
		Communication	Motionless control from people for intended actions	7 (8%)	Boonarchatong & Ketcham (2023); Shao et al. (2020); Karunasena et al. (2021); Quiles et al. (2022); Bahman & Shamsollahi (2019); Rashid et al. (2020); Korovesis et al. (2019)
	Healthcare	Rehabilitation	Rehabilitation for people with mobility impairment	15 (17.2%)	Wang et al. (2018); Xu et al. (2018); Jo et al. (2022); Gordleeva et al. (2020); Araujo et al. (2021); Nann et al. (2021); Tang et al. (2022); Roy & Bhaumik (2022); Ai et al. (2018); Chhabra et al. (2020); Chu et al. (2018); Wu et al. (2022); Dissanayake et al. (2022); Li et al. (2022); Sanguantrakul et al. (2020)
		Therapy	Therapeutic process	1 (1.1%)	Roshdy et al. (2021)
	Entertainment		Engagement in entertaining activities	1 (1.1%)	Cervantes et al. (2023)
	Safety and Security		Exploration for safe and secure needs	1 (1.1%)	Lu et al. (2020)

(*continued*)

Table 5. Continued.

Context	Category	Domain	Description	Papers (%)	References
	Social Interaction		Robots as companions for social communications	1 (1.1%)	Toichoa Eyam et al. (2021)
	Military Usage		Exploration intended for military cases	1 (1.1%)	Belkacem & Lakas (2021)
Robot Design Concern (RDC)	Human-centric Technology	Usability and user experience	Exploring better UX for effective interactions	2 (2.3%)	Cheng et al. (2024); Aldini et al. (2019)
		Research and innovation	Exploring new advancements for research needs	5 (5.7%)	Penaloza et al. (2018); Kompatsiari et al. (2018); Richter et al. (2023); Lu et al. (2022); Ogino & Mitsukura (2018)
		Mutual collaboration	Collaborating with robots to enhance task performance	2 (2.3%)	Aldini et al. (2023); Aldini et al. (2019)
	Assistance	Physical movement	Aiding people with motor disorders for physical movements	3 (3.4%)	Aznan et al. (2019); Yoon et al. (2021); Yu et al. (2019)
		Communication	Aiding motionless people for intended actions	2 (2.3%)	Wang & Sugaya (2021); Braun et al. (2019)
	Healthcare	Rehabilitation	Rehabilitation for people with mobility impairment	1 (1.1%)	Cheng et al. (2024)
		Mental recovery	Supports mental recovery	1 (1.1%)	Yoon et al. (2021)
		Meditation	Help with mindfulness and meditation process	1 (1.1%)	Yoon et al. (2021)
	Education	Language learning	Supports exclusively in language learning	2 (2.3%)	Prinsen et al. (2022); Alimardani et al. (2022)
		Self-learning	Support self-learning for skill enrichment	3 (3.4%)	Wang & Sugaya (2021); Alimardani et al. (2020); Kar et al. (2022)
	Entertainment		Engagement in entertaining activities	1 (1.1%)	Kar et al. (2022)
	Safety and Security		Exploration for safe and secure needs	1 (1.1%)	Qian et al. (2018)
	Social Interaction		Robots as companions for social communications	4 (4.6%)	Staffa & Rossi (2022); Chang & Sun (2021); Baka et al. (2019); Alimardani et al. (2020)

4.3.2.2. UX metrics. UX metrics, usually as subjective measurements, focus on gauging UX and user satisfaction when humans interact with a product within BRI. These metrics rely on the user's opinions and feelings to evaluate aspects such as usability, engagement, and perception of the system's quality. In our corpus, we spotted numerous UX metrics exploited in designing and examining the BRI systems, such as emotional states (happiness, fatigue, sorrow, excitement), usability (system usability score), and cognitive workload (NASA task load index). 16 studies embraced UX metrics for systematic evaluation (i.e., Alimardani et al., 2020; Staffa & Rossi, 2022; Toichoa Eyam et al., 2021).

4.3.2.3. Signal information. This category constitutes another preferred evaluation methodology in our corpus. Many reviewed studies chose the information gleaned from brain signals employed within their BRI systems for assessment, which in the majority of the cases, were EEG signals. This signal information encompasses various elements, including extracted features and other pertinent data. This category of evaluation methods ranked as the second most preferred approach among the studies (n = 20). For instance, in Chu et al. (2018), information regarding steady-state visually evoked potential (a type of EEG) was extracted for evaluation, while Ehrlich and Cheng (2019) used error-related potential (observed through EEG) for assessing their designed BRI systems.

5. Analysis of the interaction entity

The aim of this article is to investigate the recent research status with respect to EEG-based BRI systems especially to identify the interaction between brains and robots. Thus, the *Interaction* entity becomes the pivotal component in our BRI system model. As aforementioned, we established theoretical innovation regarding the communication between the brain and the robot under EEG. The relevant information pertaining to the interaction mode was based on how the brain and the robot were interconnected, mutually influenced, and provided reciprocal feedback. In most instances, robots were linked with BCIs, which have previously shown high efficiency in seamless control. BCIs act as a crucial intermediary, facilitating connections between humans and

Table 6. The evaluation methods identified in our corpus.

	Metrics	Papers (%)	References
Evaluation methods	Performance metrics	57 (65.6%)	Chen et al. (2021); Staffa & Rossi (2022); Jo et al. (2022); Gordleeva et al. (2020); Araujo et al. (2021); Penaloza et al. (2018); Wei et al. (2021); Francis et al. (2021); Chhabra et al. (2020); Chu et al. (2018); Memar & Esfahani (2018); Long et al. (2019); Pawuś & Paszkiel (2022); Kilmarx et al. (2018); Kar et al. (2022); Qian et al. (2018)
	UX metrics	16 (18.4%)	Staffa & Rossi (2022); Cervantes et al. (2023); Chang & Sun (2021); Baka et al. (2019); Lyu et al. (2022); Fang et al. (2023); Nann et al. (2021); Cheng et al. (2024); Martínez-Cagigal et al. (2020); Chhabra et al. (2020); Li et al. (2023); Richter et al. (2023); Memar & Esfahani (2018); Toichoa Eyam et al. (2021); Alimardani et al. (2020); Ogino & Mitsukura (2018)
	Signal information	20 (23%)	Ehrlich & Cheng (2019); Wang & Sugaya (2021); Li et al. (2019); Cheng et al. (2024); Roy & Bhaumik (2022); Penaloza et al. (2018); Ai et al. (2018); Chu et al. (2018); Chiuzbaian et al. (2019); Karunasena et al. (2021); Yuan & Li (2019); Aldini et al. (2023); Dissanayake et al. (2022); Aldini et al. (2019); Lu et al. (2022); Alimardani et al. (2022); Li et al. (2022); Yu et al. (2019); Mondini et al. (2020); Kim et al. (2021)

Table 7. The overview of the interaction entity with the dimensions as well as the categories identified in our corpus.

Dimension	Sub-dimension	Papers (%)	References
Pure BCI		34 (39.1%)	Wang et al. (2018); Staffa & Rossi (2022); Liu & Jebelli (2021); Wang & Sugaya (2021); Braun et al. (2019); Jo et al. (2022); Guo et al. (2020); Farmaki et al. (2022); Sugiyama et al. (2023); Cheng et al. (2024); Penaloza et al. (2018); Zhao et al. (2020); Jiang et al. (2018); Chhabra et al. (2020); Chu et al. (2018); Chiuzbaian et al. (2019); Karunasena et al. (2021); Quiles et al. (2022); Cao & Liu (2018); Li et al. (2023); Bahman & Shamsollahi (2019); Memar & Esfahani (2018); Dissanayake et al. (2022); Kilmarx et al. (2018); Roshdy et al. (2021); Sanguantrakul et al. (2020)
BCI + Agents		17 (19.5%)	Zhang et al. (2021); Aznan et al. (2019); Ak et al. (2022); Kuffuor & Samanta (2018); Wang et al. (2018); Ai et al. (2018); Abougarair et al. (2021); Du et al. (2021); Yuan & Li (2019); Chen et al. (2020); Toichoa Eyam et al. (2021); Rashid et al. (2020); Kar et al. (2022)
Proactive Control	Single Signal Control (SSC)	47 (54%)	Chen et al. (2021); Zhang et al. (2021); Lyu et al. (2022); Fang et al. (2023); Guo et al. (2020); Farmaki et al. (2022); Sugiyama et al. (2023); Roy & Bhaumik (2022); Martínez-Cagigal et al. (2020); Hernandez-Carmona & Penaloza (2019); Iwane et al. (2019); Wu et al. (2022); Memar & Esfahani (2018); Dissanayake et al. (2022); Toichoa Eyam et al. (2021); Memar & Esfahani (2020); Ogino & Mitsukura (2018); Kilmarx et al. (2018); Li et al. (2022); Lu et al. (2020); Roshdy et al. (2021); Sanguantrakul et al. (2020); Rashid et al. (2020); Kim et al. (2021)
	Hybrid Signal Control (HSC)	9 (10.3%)	Wang et al. (2018); Jo et al. (2022); Li et al. (2019); Gordleeva et al. (2020); Nann et al. (2021); Tang et al. (2022); Lu et al. (2022); Pawuś & Paszkiel (2022); Korovesis et al. (2019)
Task-oriented HRI		17 (19.5%)	Staffa & Rossi (2022); Chang & Sun (2021); Wang & Sugaya (2021); Braun et al. (2019); Baka et al. (2019); Aznan et al. (2019); Penaloza et al. (2018); Aldini et al. (2023); Kompatsiari et al. (2018); Prinsen et al. (2022); Richter et al. (2023); Dissanayake et al. (2022); Aldini et al. (2019); Alimardani et al. (2022); Alimardani et al. (2020); Yu et al. (2019); Qian et al. (2018)

external devices. However, we noted that some studies either did not employ BCIs for interaction or did not specify their involvement. In this chapter, we address the exhaustive details behind this entity, describing the definitions of the four dimensions (Pure BCI, BCI+Agents, Proactive Control, and Task-oriented HRI) with two derived sub-dimensions generated from our corpus. We illustrate their application scenarios with the practical deployment in the BRI system, featuring a particular emphasis of the control part. The overall distribution of the relevance of these dimensions within our corpus is displayed in Table 2 while the details of sub-dimensions mapping the specific references and number of papers enumerated are presented in Table 7. In addition, a schematic illustration of the four dimensions is displayed in Figure 6. To note, the four dimensions with the two sub-dimensions are not exclusively mapped with any individual papers. Rather, one paper may traverse multiple dimensions, reflecting the nuanced and multifaceted nature of the interactions examined. For instance, a single paper could contribute to both Pure BCI and Proactive Control (i.e., Chu et al., 2018; Cao & Liu, 2018; Kilmarx et al., 2018), showcasing the overlap and integration of these dimensions in one study. We envision this curated knowledge being capable of benefiting future HRI research with

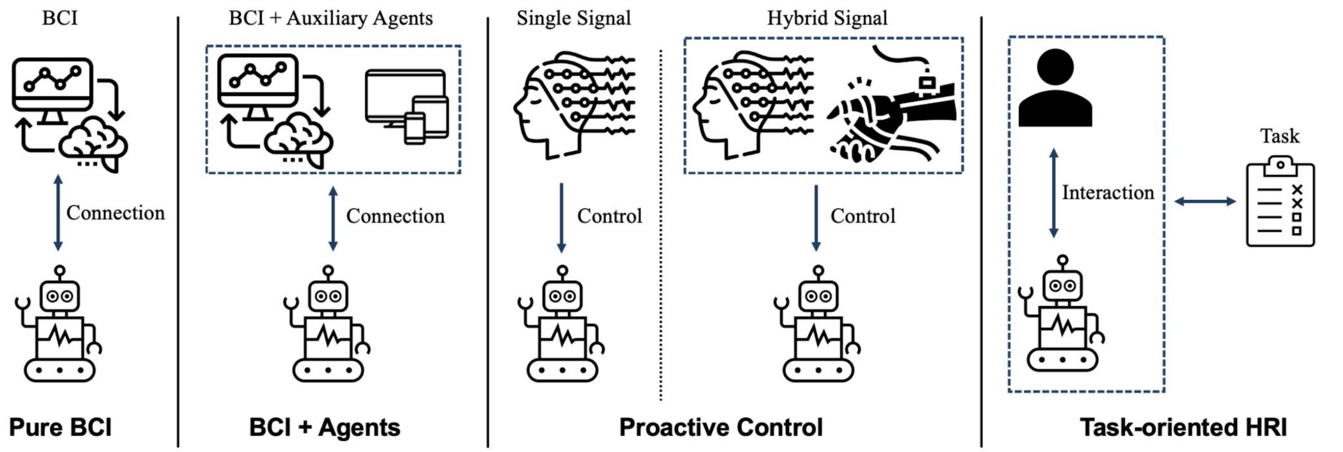

Figure 6. A schematic illustration of the *interaction* entity with the four dimensions proposed.

efficient communication design. This chapter is crafted particularly for interpreting **RQ2** and **RQ3**.

5.1. Pure BCI

In the EEG-based HRI context, BCI is yet the most adopted tool which focuses on enabling direct communication between the brain and robotic systems, allowing individuals to control external devices by brain signals. A fine-designed BRI system takes this concept a step further by integrating brain signals with robotic systems, empowering humans to not only control robots through the collected brain signals but also receive sensory feedback. We found that in the majority of the examined studies, BCI was extensively exploited to build the interaction between the brain and the robot. While certain studies exclusively employed BCI, others integrated BCI with complementary techniques. Hence, the first dimension of the *Interaction* entity is Pure BCI, entailing those papers where the BCI was harnessed without other auxiliary technologies in bridging the connection. Almost 40% of the studies exploited only BCIs for linking human brains and robots, yielding a dominant usage of robot arms. For example, Kilmarx et al. (2018) constructed the connection between the brain and a robot arm for manipulation rooted in a single BCI, while Alimardani et al. (2022) managed to create an assistive learning environment with the same mechanism as the robot. Particularly, exoskeletons are connected with a single BCI in two studies (Chu et al., 2018; Ghosh & Orlando, 2019).

5.2. BCI+Agents

In some of the studies, BCI was employed not in isolation but in conjunction with one or more supplementary technologies. We define the second dimension of this entity as BCI+Agents, where additional technologies are seamlessly integrated with BCI to enhance control and interaction with robots. From our corpus, we identified 15 studies which employed external agents either physical devices or artificial technologies. In Toichoa Eyam et al. (2021), the interactions were designed and conducted under the support of both BCIs and an emotion recognition sector by using the accumulated EEG signals. Whereas, some computer vision use cases such as object detection was probed with BCI, enhancing robotic precision in human-centered service designing (Du et al., 2021). Some studies (Chen et al., 2020; Si-Mohammed et al., 2020) acknowledged VR, AR, and mixed reality (MR) have flourished as the state-of-the-art technologies enabling immersive interactions in recent years and then applied XR (the catch-all term of these three techniques) with BCIs to initiate the advisable interaction in the developed BRI systems. In addition Abougarair et al. (2021) linked BCI with an extra Arduino Uno microcontroller to build interaction while Aznan et al. (2019) leveraged an object detection architecture to establish interaction between human brains and robots.

5.3. Proactive control

The synergy between BRI systems and robot control has emerged as a breakthrough in the field of robotics. Through BRI, humans and autonomous/semi-autonomous machines are connected in unprecedented ways, enabling intuitive, and precise control of robots across a spectrum of applications. In most of the structured BRI systems (including our corpus), EEG signals are compiled for directing the explicit control to robots by conveying commands. Similarly, we revealed that the majority of the studies included in our corpus had the intention to purposefully control the robots, which formed the third dimension of the *Interaction* entity – Proactive Control. The two sub-dimensions formulated according to the number of biosignals used are described in the following two sub-sections.

5.3.1. Single signal control

The main body the research studies in our corpus coincided with the condition that the EEG signal was merely engaged in flowing from brains to robots, promoting the formation of the first sub-dimension – Single Signal Control (SSC). While a diverse array of usage relating to realistic application situations was observed, those papers conforming to SSC did not involve other physiological signals except EEG (i.e., Guo et al., 2020; Jiang et al., 2018; Kuffuor & Samanta, 2018; Karunasena et al., 2021; Quiles et al., 2022; Yuan & Li, 2019). In total, 39 papers were determined in accordance with SSC, where their main purpose was to achieve spontaneous robot control to meet predefined goals. Most of the studies were intended to engage merely EEG as the stimulation, to proactively control, i.e., robotic arms for grasping (Hernandez-Carmona & Penaloza, 2019) or mobile robots for navigating (Magee & Givigi, 2021).

5.3.2. Hybrid signal control

While we narrated before that the ultimate corpus in this article was determined in a fully or dominantly EEG-based context, some of the reviewed studies ($n = 9$) leveraged multiple biosignals together with EEG for efficacious control of robots. Another sub-dimension affirmed is Hybrid Signal Control (HSC), where the compatible papers employed various types of brain signals aside from EEG to attain hybrid control with high robustness. For instance, in Wang et al. (2018), the EOG signals were acquired together with EEG signals to blendedly supervise a mobile robot for home auxiliary. However, it's worth noting that EMG signals emerged as the most commonly employed modality in conjunction with EEG signals for HSC in our corpus (Gordleeva et al., 2020; Jo et al., 2022; Pawuś & Paszkiel, 2022). Notably, almost half of the HSC studies ($n = 4$) concentrated on wearable robots, i.e., exoskeletons for healthcare situations (Gordleeva et al., 2020; Jo et al., 2022; Nann et al., 2021; Tang et al., 2022).

5.4. Task-oriented HRI

HRI, as the precise term describing the collaboration between human cognition and robotic capabilities has redefined industries, enhancing productivity, safety, and adaptability. As BRI technology continues to advance, the potential for more seamless and natural interactions between humans and robots expands, promising to reshape the future of automation and human-robot partnerships. A certain number of reviewed studies ($n = 13$) were found where the primary objective of the BRI systems was not formulated to control and instruct the robots. Instead, most of them fabricated a synergistic environment where the robots were served as an external intermediaries for human (brain) interaction, fulfilling designated tasks or operations, i.e., robot navigation (Aznan et al., 2019; Chang & Sun, 2021; Yu et al., 2019) and cognitive task collaboration (Aldini et al., 2023). Nonetheless, we found that a small number of studies belonging to Task-oriented HRI either with a full extent or an emerging fashion also corresponded to other dimensions (i.e., Pure BCI (Wang & Sugaya, 2021), BCI+Agents (Aznan et al., 2019), and Proactive Control (Aldini et al., 2019)).

6. Challenges and outlook

In the following parts, we list and elaborate on the challenges faced and potential directions for future research within EEG-based BRI that warrant exploration, based on our reviewing process. From the analysis grounded by our three inclusive entities *Brain*, *Robot*, and *Interaction*, we realize that our corpus has indicated the up-to-date technological advancements made in the domain. Whereas, there remain several unavoidable challenges that have yet to be comprehensively discussed in previous literature, including issues related to hardware, signal techniques, human-centric, and ethical concerns. We envision the following problems along with the research outlook derived would be valuable for future investigators in this field and with the derived challenges we aim to pose the future directions of the EEG-BRI research body to benefit the HRI community. This chapter answers **RQ4**.

6.1. Signal quality and acquisition

1. Low Spatial Resolution: While EEG excels in its temporal resolution, capturing rapid changes in brain activity, it offers a notably lower spatial resolution (Toichoa Eyam et al., 2021). This challenge becomes particularly evident when researchers aim to identify precise brain regions involved in advanced brain imaging modalities such as functional magnetic resonance imaging or positron emission tomography scans. This drawback restricts our ability to precisely pinpoint the specific anatomical location of neural activity within the brain. For future direction, this challenge can be addressed by providing complementary techniques or localization methods to enhance the spatial precision of EEG data analysis.
2. Signal Quality: EEG signals are vulnerable to noise from a variety of sources, which can significantly affect signal quality (Ghosh & Orlando, 2019). The presence of noise stemming from muscle activity and eye movements whether voluntary or involuntary, can contaminate EEG recordings. Additionally, even environmental factors such as electromagnetic interference or ambient electrical noise, can infiltrate EEG data. Therefore, the challenge is find a way to consistently maintain a high signal-to-noise ratio in EEG-based BRI research.
3. Individual Variability: Another challenge lies in the considerable individual variability revealed in EEG signals (Quiles et al., 2022; Wang et al., 2018). Different human brains possess unique physiological and functional characteristics, which inevitably result in distinct EEG patterns. This individual variability can complicate the development of BCIs that work universally for others. Consequently, customization and calibration processes are ubiquitously imperative to enable BCIs to accommodate the specific neurophysiological human traits.
4. Interference and Artifacts: External sources of interference, range from everyday electrical appliances to the presence of other individuals in the vicinity, pose a substantial challenge to the integrity of EEG signals (Ghosh & Orlando, 2019; Mondini et al., 2020). These disruptions act as interfering artifacts in EEG acquisition, which can obscure the genuine neural signals of interest. For future research, detecting and mitigating

external interference is of paramount importance in EEG-based applications.

6.2. BCI development

1. Real-time Processing: BCIs rely on the smooth and real-time processing of EEG data to facilitate timely interactions between the human brain and the robot (Francis et al., 2021; Korovesis et al., 2019). As discussed in Section 4.1.2, the significance of low latency, high accuracy, high temporal resolution, and computational efficiency in EEG-based BRI cannot be ignored, particularly with the latter two factors only evident in several studies. BCIs are increasingly employed in applications that require rapid and accurate translation of neural activity into actionable commands to be conveyed to environmental robots. Therefore, the challenge lies in minimizing the delay between the human brain signal generation and the subsequent response of the BCI-controlled agents to deliver a seamless and intuitive experience. Achieving this low latency processing with high accuracy necessitates a robust pipeline that can swiftly acquire and decode EEG signals.
2. Training and Adaptation: Realizing the full promise of BCIs hinges on their ability to be user-friendly and adaptive (Memar & Esfahani, 2020; Richter et al., 2023). Currently, many BCIs demand humans to undergo extensive training to attain proficiency in operating the developed BRI systems effectively. This training process often involves repeated mental tasks or motor imagery to establish a reliable communication with robots. While humans may initially achieve proficient control, maintaining a high level of human performance over time can be challenging. Factors such as fatigue and "Gorilla effect (Feuchtner & Müller, 2018)" can lead to performance deterioration. Therefore, the adaptivity in BCI research is the central development of continuously learning and evolving alongside humans.
3. Integration with Other Technologies: The integration of BCIs with other technologies represents another existing challenge in HCI/HRI. This synergy is reliant on complex hardware and software systems, need to effortlessly interface with external tools or platforms, holding the potential to revolutionize a wide range of applications from healthcare to gaming and beyond (Ali et al., 2021; Lyu et al., 2022). For example, even we identified few studies that embraced XR technique in our corpus, integrating XR into EEG-based BRI systems still remains challenging. By incorporating XR, BCIs can enable more immersive and intuitive experiences by translating human thoughts into actions within virtual environments or objects. For future avenue, selecting appropriate technologies with BCIs for interdisciplinary collaboration is crucial for expanding the horizons of HCI.
4. User Feedback and Control: BCIs are supposed to equip humans with comprehensive feedback and precise control over the BRI systems' operations (Cheng et al., 2024; Toichoa Eyam et al., 2021). However, achieving this goal can be particularly challenging, especially when BCIs primarily rely on neural signals. To develop intelligent interfaces that interpret biosignals and provide real-time feedback to humans still remains challenging. The future research should formulate the feedback to be both informative and user-friendly, ensuring that individuals of varying technical backgrounds can effectively interact with the BCIs.

6.3. Safety and ethical concerns

1. Privacy and Security: The emergence of signal acquisition tools has given rise to concerns regarding the privacy and security of human neural data (Wu et al., 2022). As, i.e., BCIs continue to advance, the need for robust safeguards and ethical considerations becomes increasingly evident. While our study focuses on EEG-based BRI, the biosignal data used is highly personal and can potentially reveal intimate details about individuals' thoughts, emotions, and even medical conditions (Ma et al., 2024; Zhang et al., 2020). In further investigation, ensuring the secure and safe handling of human biosignal data is challenging.
2. Ethical and Legal Issues: Similarly, the rapid growth of biometric data capture tools brings a multitude of ethical and legal considerations that require careful attention in BRI systems (Belkacem & Lakas, 2021; Korovesis et al., 2019; Magee & Givigi, 2021). The foremost concern revealed is the issue of informed consent. The tools used involve the acquisition and utilization of highly personal and private biosignal data, while each person involved must be provided with clear, comprehensive information about how their data will be used and the potential conflicts of interest. Furthermore, the concept of data ownership in signal-acquiring tools is a complex matter. Who has the rightful claim to the neural data generated by these BRI systems – the individuals, the technology provider, the researchers, or a combination of them all? Another critical aspect is safeguarding against potential misuse of the technology. As these tools gain the potential to influence human thoughts and behaviors, there is a growing concern about unauthorized access and manipulation of personal body signal data. Thus, establishing proper ethical guidelines to mitigate the risks and ensuring biosignals are being used for responsible purposes remains challenging.
3. Invasive vs Non-invasive BCIs: The last challenge discovered from our corpus regarding BCI development is the choice between invasive and non-invasive BCIs (Quiles et al., 2022; Si-Mohammed et al., 2020). Invasive BCIs, which oblige the implantation of electrodes directly into the human brain present numerous ethical and safety concerns. Implanting electrodes might cause infection and tissue damage, which must be carefully pondered with the potential benefits. On the other hand, non-invasive BCIs (for EEG signals) are more accessible and safer in terms of physical risks, typically

deliver lowering signal quality as mentioned before. This limitation can hinder their precision and reliability, impacting practical applications such as high-precision robotic control. Hence, selecting between invasive and non-invasive BCIs is challenging since it ultimately depends on the specific scenarios, with considering and equalizing the need of signal quality with the corresponding ethical and safety issues.

6.4. User acceptance and accessibility

1. User Acceptance and Comfort: For meticulously designed EEG-based BRI systems aiming at gaining widespread acknowledgement and adoption, it is challenging to insert BRI system with high user acceptance and comfort (Bauer et al., 2008; Bahman & Shamsollahi, 2019; Si-Mohammed et al., 2020). EEG electrodes typically require close contact with the scalp, which can be discomforting especially when it is required to wear the electrodes for extended durations, such as in rehabilitation studies. Therefore, the generated user fatigue will not only diminish the UX but can also impact the accountability and reliability of the EEG signals obtained. To address this challenge, more concentration should be devoted in developing more ergonomic and unobtrusive EEG devices that minimize discomfort while maintaining signal quality, and promoting human-centered design that fosters greater user engagement and acceptance.
2. Cost and Accessibility: Precise EEG acquisition devices are expensive, which poses challenges both for research institutions and individuals interested in designing BRI systems (Braun et al., 2019; Magee & Givigi, 2021; Prinsen et al., 2022). The prohibitive cost can potentially limit the scope of BRI research, excluding smaller laboratories with budget constraints from contributing to the advancements of this field. Thus, providing access for those who could benefit greatly from the equipment is challenging, especially for people with motor disabilities seeking to enhance their communication with assistive devices or robots. As a result, there's a growing emphasis on democratizing the devices used in EEG-based BRI systems by making them more affordable and accessible.

6.5. Medical and clinical considerations

1. Clinical Validation: Healthcare applications are getting more attention in the EEG-based BRI context, with the potential to revolutionize patient care and improve the quality of life (Rahul & Sharma, 2019). However, realizing this potential which mainly relies on involving BCIs for clinical usage, needs to undergo rigorous testing and regulatory validation to demonstrate their efficacy and safety. Conducting extensive clinical trials and accumulating empirical evidence to support the use in medical contexts still remains challenging.
2. Long-term Reliability: Ensuring the reliability and safety of the tested apparatuses over extended periods is a significant challenge, particularly when considering chronic medical applications where patients may rely on apparatuses for a lengthy duration spanning months or even years (Cervantes et al., 2023; Yoon et al., 2021). The longevity and sustained performance of, i.e., BCIs are crucial for patients with chronic physiological conditions, as any deterioration in device performance can have serious consequences for their health. This challenge entails addressing issues related to signal quality and stability, skin interfaces, and the overall robustness of the BRI system, etc., in upcoming related research endeavors.

6.6. Reflection of the future trend

6.6.1. Innovative signal acquisition

One of the foremost challenges in EEG-based BRI research lies in improving signal quality and acquisition. Current signal acquisition methods are limited by low spatial resolution, necessitating advancements in hardware to enhance precision and reliability. Similarly, the challenge of maintaining signal quality demands innovative approaches to detect and mitigate noise, ensuring cleaner data for processing and analysis.

6.6.2. Addressing BCI challenges

Several issues persist in BCI development, such as delays in signal generation, sustaining human performance over extended periods, integrating XR into EEG-based BRI systems, and interpreting complex bio-signals. Hardware advancements are crucial to addressing delays and performance maintenance, while integration with existing systems will require seamless solutions. On the other hand, interpreting bio-signals calls for user-friendly methods that can be understood by a wide audience—medical professionals, engineers, and lay users alike. These solutions should simplify bio-signal analysis without sacrificing precision.

6.6.3. Handling ethical considerations

Physiological sensing inherently brings challenges related to data handling and privacy. Future research must prioritize the development of robust ethical guidelines for data processing and storage. Importantly, users should be informed about how and under what conditions their data is used, ensuring privacy is never compromised. This requires creating transparent and secure systems that respect users' rights while enabling effective data utilization.

6.6.4. Designing user-acceptable interactions

For EEG-based BRI systems to achieve widespread adoption, the hardware must prioritize comfort and unobtrusiveness, allowing seamless use in public spaces without disrupting daily routines. Efforts should focus on developing devices that are intuitive, aesthetically acceptable, and user-friendly for diverse real-world contexts. Particular attention should be given to individuals who rely on BCI technology for medical purposes, ensuring these systems are accessible, reliable, and tailored to their specific needs.

6.6.5. Long-term empirical evaluation

Future research should prioritize long-term empirical studies that collect data from participants outside laboratory environments, for instance, for from the medical perspective. Ensuring reliable and safe conditions for such studies is critical to understand the practical utility and performance of BCI systems in everyday settings. These evaluations will not only strengthen the empirical foundation of BRI systems but also provide insights into their usability and accessibility for diverse user groups.

In summary, addressing these challenges will require multidisciplinary efforts to advance hardware, ensure data integrity and ethical compliance, and design systems that are accessible, reliable, and practical for both specialized and everyday use. These trends will shape the next generation of EEG-based BRI systems, paving the way for broader applications in medical, industrial, and public contexts.

7. Discussion

In this section, we discuss key findings and formulate take-away messages for the HRI community aligned with our BRI system model.

7.1. Current research landscape in EEG-based BRI

7.1.1. Application and evaluation

As we have shown in this article, current researcher is increasingly exploring novel applications for brain-interacted robotics, ranging from assistive technologies for healthcare over collaboration and entertainment to education. We grouped these applications contexts into overarching categories of HCC and RDC, which underlines the two primary foci in the current research landscape. Analysis of our corpus reveals that the predominant application context for EEG-based BRI in recent years falls under HCC, specifically involving the control of robots by the human brain to achieve deliberate goals. Notably, scenarios where applications were aligned with human-centric technologies are particularly favored both in HCC and RDC. Healthcare and assistance applications, where robots are manipulated to achieve specific objectives, are mainly attributed to HCC. In contrast, applications for socializing wherein robots are selected and designed without clear indications of spontaneous control, instead offering companionship are mostly correlated with RDC. We believe that HCC will remain the predominant context for future EEG-BRI design, while RCC is expected to gain prominence as well. As for the evaluation methods, most of the reviewed papers ($> 60\%$) employed various performance metrics, such as accuracy, response time, task completion time, and error rate. This indicates that conventional metrics for evaluating task success remain widely adopted. The remaining two categories almost equally cover UX metrics and signal information. This likely reflects the fundamental goals of the research within the field of HCI/HRI, in which researchers often prioritize objective measures to quantitatively assess the performance and efficiency of the systems. The nearly equal distribution of these two metrics may suggest a growing importance of users' subjective experience alongside objective performance measures. UX metrics include subjective assessments, such as user satisfaction, perceived ease of use, and overall user experience, which leads to a more holistic understanding of EEG-based BRI. We recommend that future developments incorporate a combination of different metrics to enhance the robustness of these systems.

7.1.2. Brain

Another line of current research in this field is dedicated to signal acquisition and decoding included in the *Brain* entity. As for the signal acquisition, over 80% of the papers we reviewed focused on three primary paradigms: task-based, MI, and SSVEP, known for their proven efficiency and usability in prior work. Regarding the apparatus, the Emotiv EPOC emerged as the preferred choice, a trend likely to continue until the next generation of advanced devices appear. Sensor location choices indicated a preference for targeting specific brain regions for optimal system performance, with over half of the studies not utilizing all four brain regions for EEG sensor placement. Notably, in determining the number of electrodes, the majority opted for fewer than 32, challenging the conventional wisdom that 64 electrodes are optimal. In the decoding phase, over 40% of the studies emphasized the importance of a seamless feedback mechanism for real-time EEG decoding, enhancing both user control and experience. Whereas, we discovered that computational efficiency remains to be a challenge, possibly requiring more specialized hardware and other resources. For feedback enhancement approaches, visual feedback was the most popular representative for its convenience and intuitiveness. Notably, neurofeedback was featured in about a quarter of the studies (same to direct feedback), where we speculate that, in EEG-based environments, the profound and precise neural signals were collected and deemed to provide effective feedback. In feature extraction and classification, traditional ML algorithms were used in nearly half of the studies, owing to their proven performance in signal processing before the advent of the review papers (2018). Also, the advanced DL methods were in a period of rapid and prosperous development during the period of the examined studies (2018–2023). Hence, many studies incorporated various DL algorithms in signal decoding. In comparison, only several studies employed neither ML nor DL methods. We are confident that future researchers will be able to leverage the information we offered in the *Brain* entity to design different related dimensions.

7.1.3. Robot

In relation to the *Robot* entity, we have identified seven dimensions, correspond to seven types of robots according to their functionality, contextuality, and applicability, surpassing the scope of previous categorization efforts (Aljalal et al., 2020; Mao et al., 2017). We found that service robots were most commonly used, closely followed by industrial robots, likely because many studies focused on using service robots, employed for human-centred services like object delivery or indoor cleaning. The prevalence of industrial robots may stem from numerous studies leveraging neural signals for precise tasks, like operating a robot arm for grasping items or guiding a mobile robot to a specific spot. Medical robots, often wearables, represent another significant dimension, aimed at aiding recovery in individuals with physical disabilities. In addition, the growing interest in social and educational robots reflects the expanding field of social robotics over the past years, with social robots taking diverse forms from humanoid (Staffa & Rossi, 2022) to other designs (Wang & Sugaya, 2021), facilitating interactive functions.

7.1.4. Interaction

We uniquely dissected the essence of the interaction between human brains and robots, formulating the *Interaction* entity which serves as the bridge facilitating mutual communication between the *Brain* and *Robot* entities. This is the most innovative part of our article compared to prior review papers. Within this entity, we have categorized the design strategy into four dimensions, where Proactive Control emerged as the predominant interaction mode in our corpus (64.3%). This might because in prevalent BRI scenarios, the driving objectives are to control and manipulate robots for desired outcomes. Of which, two more sub-dimensions are SSC and HSC. SSC, which involves using EEG signals as the sole biosignal input, constitutes the largest proportion (54%) of brain-to-robot interactions. As a comparison, only a few studies belong to HSC (10.3%) where other types of biosignals are harnesses at the same time. This obvious divergence is likely due to the perceived complexities, potential errors, and challenges associated with managing multi-signal uncertainty in HSC cases. The second most favoured interaction mode is Pure BCI (39.1%), which is twice the number of BCI+Agents (19.5%). This can be attributed to the convenience and ease of control of the singular adoption of BCIs. As a fact, we found that papers spanned over one dimension were predominantly categorized into both Pure BCI and Proactive Control (mostly in SSC). This observation suggests that this combination, particularly within the SSC sub-dimension, has potentially evolved into a standard in designing interaction modes for BRI systems within the reviewed literature. Simultaneously, we have to realize that the tendency of using BCIs with external agents (XR techniques, emotion recognition, etc.) for effective interaction has been affirmed through our observation. About 20% of reviewed studies were classified as Task-oriented HRI, where robots were exploited as more of providing companionship for mutual collaboration, instead of unidirectional control. We believe the similar usage will prosper with a remarkable pace in the future because of the advancements in social robotics.

7.2. Future research directions

Within the scope of this article, we have identified five main direction for future research directions that coincide with aforementioned challenges: (1) signal quality and acquisition, (2) BCI development, (3) safety and ethical concerns, and (4) user acceptance and accessibility, and (5) medical and clinical considerations. Future work on signal quality and acquisition can explore dry electrodes, which are more user-friendly, require less preparation time, and often yield better signal quality over extended periods. Moreover, the development of flexible and wearable electrode arrays conform to the scalp better, providing improved contact and reducing motion artifacts. Another potential direction can focus on utilizing machine learning algorithms that improve the system's ability to decode intentions accurately and enhance the flexibility and adaptability of EEG-robot interaction systems. As for the BCI development, future work should further explore signal processing techniques, such as adaptive filtering and wavelet analysis, to enhance the extraction of relevant information from EEG signals and improve the accuracy of brain signal interpretation. With the raise of ML/DL, future research can further leverage algorithms to adapt and learn user-specific patterns to enhance the system's ability to decode complex brain signals and improve control accuracy. As we have seen from this article, not many works have focused on addressing issues related to safety and ethical concerns, which increases a demand to explore them in the future. For example, it can include feedback and notification mechanisms that ensure users are informed about the data collection, storage, and potential use of their EEG data, since obtaining clear and informed consent is essential to respect users' privacy and autonomy. Moreover, implementation of robust data security measures, including encryption and secure storage, is crucial to protect users' sensitive EEG data from unauthorized access and potential breaches. To address issues related to user acceptance and accessibility, future work should actively engage users in the design process, gather feedback, and iteratively refine the system based on user input, to ensure that the technology aligns with users' needs, preferences, and expectations, for example, by employing user-centered design. Last but not least, as for medical and clinical considerations, future work should perform rigorous clinical validation studies to assess the effectiveness and safety of the EEG-robot interaction system in real-world medical scenarios. For example, clinical trials can provide valuable evidence of the technology's clinical utility and validate its use in healthcare contexts. Additionally, collaboration with healthcare professionals, neurologists, and clinicians should be facilitated to integrate EEG-robot interaction into medical diagnoses and treatment plans. This can ensure that the system aligns with clinical practices and contributes meaningfully to patient care.

7.3. Limitations

However, it's important to acknowledge a significant limitation of the model we developed and employed. This model does not explicitly encompass all the specific and potential components within the *Brain* entity. We have primarily focused on EEG signal acquisition and decoding approaches with proposed dimensions (4 + 3) within the *Brain* entity for coverage and generalizability. However, there may be more aspects not yet explored in this article. Additionally, the associations between HCC and RDC in application contexts often depend on the specific context; for instance, a robot may be chosen to provide feedback to humans during a route guidance task, and its action control may require brain signals to generate directives. However, introducing additional layers of complexity could render both analysis and presentation unwieldy. As for the *Robot* entity, while we admit the possibility of overlooking some robots or robotic systems with specialized usage, we are confident that our coverage incorporates the entirety of robots utilized in the studies published up until our examination date (31 July 2023). Nonetheless, we acknowledge that the dimensions developed in the *Interaction* entity may not be in agreement with some other HRI researchers since they might have different definitions and classifications regarding interaction modes. Simultaneously, a diverse range of modalities may be employed in conjunction with BCIs, which were collectively referred as BCI+Agents in our study, as our intention was to span over a wide range of research.

8. Conclusion

This article delivers two principal contributions: firstly, it offers a comprehensive overview coupled with an in-depth meta-analysis of the EEG-based BRI research landscape, serving as a guiding beacon for future researchers. Secondly, it introduces a theoretical contribution in the form of an EEG-based BRI system model, meticulously delineating the constituent entities, with a primary focus on the intricacies of interaction between human brains and robots. Specifically, our research dissects the EEG-based BRI system into three distinct entities, with a special emphasis on the design facets regarding the interaction between human brains and robots. Our findings illuminate that a significant portion of the reviewed papers prefers proactively controlling robots when establishing this interaction. Simultaneously, others are dedicated to shaping a Task-oriented HRI environment, leveraging pure BCIs, or integrating BCIs with external physical or artificial agents, with a near-even distribution among building up such interactions. Our work aims to provide a valuable compass for future researchers, enabling them to align their investigations with the proposed dimensions and sub-dimensions. This alignment facilitates the comparison of diverse related studies, thereby laying the groundwork for a unified design pipeline in the dynamic realm of EEG-based BRI. From a practical standpoint, the gained knowledge of existing research literature according to our BRI system model empowers both researchers and hands-on practitioners to navigate the design landscape for establishing effective communication between human brains and robots. However, it is crucial to acknowledge that the field of EEG-based BRI is in a state of continuous evolution, with more novel technologies to be developed in the coming future. Nonetheless, we believe that the presented work in this article, along with the BRI system model, offers an empirically grounded foundation that can inspire future endeavors in this domain as well as bringing more possibilities for the HRI/HCI community.

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ORCID

Yuchong Zhang http://orcid.org/0000-0003-1804-6296
Nona Rajabi http://orcid.org/0000-0003-2533-7868
Farzaneh Taleb http://orcid.org/0000-0003-4482-1460
Andrii Matviienko http://orcid.org/0000-0002-6571-0623
Yong Ma http://orcid.org/0000-0002-8398-4118
Mårten Björkman http://orcid.org/0000-0003-0579-3372
Danica Kragic http://orcid.org/0000-0003-2965-2953

References

References marked with • are in our corpus

•Abougarair, A. J., Gnan, H. M., Oun, A., & Elwarshfani, S. O. (2021). *Implementation of a brain-computer interface for robotic arm control* [Paper presentation]. 2021 IEEE 1st International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering MI-STA (pp. 58–63). IEEE. https://doi.org/10.1109/MI-STA52233.2021.9464359

Adams, J. A. (2005). *Human-robot interaction design: Understanding user needs and requirements* [Paper presentation]. Proceedings of the Human Factors and Ergonomics Society Annual Meeting (pp. 447–451). SAGE Publications Sage CA. https://doi.org/10.1177/154193120504900349

•Ai, Q., Wang, L., Chen, K., Chen, A., Hu, J., Fang, Y., Liu, Q., & Zhou, Z. (2018). *Cooperative control of an ankle rehabilitation robot based on human intention* [Paper presentation]. 2018 Joint IEEE 8th International Conference on Development and Learning and Epigenetic Robotics (ICDL-EpiRob) (pp. 181–186). IEEE. https://doi.org/10.1109/DEVLRN.2018.8761006

•Ak, A., Topuz, V., & Midi, I. (2022). Motor imagery EEG signal classification using image processing technique over GoogleNet deep learning algorithm for controlling the robot manipulator. *Biomedical Signal Processing and Control*, *72*, 103295. https://doi.org/10.1016/j.bspc.2021.103295

•Aldini, S., Akella, A., Singh, A. K., Wang, Y.-K., Carmichael, M., Liu, D., & Lin, C.-T. (2019). *Effect of mechanical resistance on cognitive conflict in physical human-robot collaboration* [Paper presentation]. 2019 International Conference on Robotics and Automation (ICRA) (pp. 6137–6143). IEEE. https://doi.org/10.1109/ICRA.2019.8793748

•Aldini, S., Singh, A. K., Leong, D., Wang, Y.-K., Carmichael, M. G., Liu, D., & Lin, C.-T. (2023). Detection and estimation of cognitive conflict during physical human-robot collaboration. *IEEE Transactions on Cognitive and Developmental Systems*, *15*(2), 959–968. https://doi.org/10.1109/TCDS.2022.3205168

•Ali, H. A., Popescu, D., Hadar, A., Vasilateanu, A., Popa, R. C., Goga, N., & Hussam, H. A. D. Q. (2021). EEG-based brain computer interface prosthetic hand using raspberry pi 4. *International Journal* *of Advanced Computer Science and Applications*, *12*(9), 44–49. https://doi.org/10.14569/IJACSA.2021.0120905

Alimardani, M., & Hiraki, K. (2020). Passive brain-computer interfaces for enhanced human-robot interaction. *Frontiers in Robotics and AI*, *7*, 125. https://doi.org/10.3389/frobt.2020.00125

•Alimardani, M., Duret, J. L. P., Jouen, A.-L., & Hiraki, K. (2022). *Robot-assisted language learning increases functional connectivity in children's brain* [Paper presentation]. 2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 674–677). IEEE. https://doi.org/10.1109/HRI53351.2022.9889406

•Alimardani, M., Kemmeren, L., Okumura, K., & Hiraki, K. (2020). *Robot-assisted mindfulness practice: Analysis of neurophysiological responses and affective state change* [Paper presentation]. 2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN) (pp. 683–689). IEEE. https://doi.org/10.1109/RO-MAN47096.2020.9223428

Alimardani, M., van den Braak, S., Jouen, A.-L., Matsunaka, R., & Hiraki, K. (2021). Assessment of engagement and learning during child-robot interaction using EEG signals. *Social Robotics: 13th International Conference, ICSR 2021, Singapore* (pp. 671–682). Springer.

Aljalal, M., Ibrahim, S., Djemal, R., & Ko, W. (2020). Comprehensive review on brain-controlled mobile robots and robotic arms based on electroencephalography signals. *Intelligent Service Robotics*, *13*(4), 539–563. https://doi.org/10.1007/s11370-020-00328-5

•Araujo, R. S., Silva, C. R., Netto, S. P. N., Morya, E., & Brasil, F. L. (2021). Development of a low-cost EEG-controlled hand exoskeleton 3d printed on textiles. *Frontiers in Neuroscience*, *15*, 661569. https://doi.org/10.3389/fnins.2021.661569

•Aznan, N. K. N., Connolly, J. D., Moubayed, N. A., & Breckon, T. P. (2019). *Using variable natural environment brain-computer interface stimuli for real-time humanoid robot navigation* [Paper presentation]. 2019 International Conference on Robotics and Automation (ICRA) (pp. 4889–4895). IEEE. https://doi.org/10.1109/ICRA.2019.8794060

•Bahman, S., & Shamsollahi, M. B. (2019). *Robot control using an inexpensive p300 based BCI* [Paper presentation]. 2019 26th National and 4th International Iranian Conference on Biomedical Engineering (ICBME) (pp. 204–207). IEEE. https://doi.org/10.1109/ICBME49163.2019.9030408

•Baka, E., Vishwanath, A., Mishra, N., Vleioras, G., & Thalmann, N. M. (2019). "Am I talking to a human or a robot?": A preliminary study of human's perception in human-humanoid interaction and its effects in cognitive and emotional states. *Advances in Computer Graphics: 36th Computer Graphics International Conference, CGI 2019, Calgary, AB, Canada* (pp. 240–252). Springer.

Bauer, A., Wollherr, D., & Buss, M. (2008). Human–robot collaboration: A survey. *International Journal of Humanoid Robotics*, *05*(01), 47–66. https://doi.org/10.1142/S0219843608001303

Baytas, M. A., Çay, D., Zhang, Y., Obaid, M., Yantaç, A. E., & Fjeld, M. (2019). The design of social drones: A review of studies on autonomous flyers in inhabited environments. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1–13).

•Belkacem, A. N., & Lakas, A. (2021). *A cooperative EEG-based BCI control system for robot–drone interaction* [Paper presentation]. 2021 International Wireless Communications and Mobile Computing (IWCMC) (pp. 297–302). IEEE. https://doi.org/10.1109/IWCMC51323.2021.9498781

Berger, A., Horst, F., Müller, S., Steinberg, F., & Doppelmayr, M. (2019). Current state and future prospects of EEG and FNIRS in robot-assisted gait rehabilitation: A brief review. *Frontiers in Human Neuroscience*, *13*, 172. https://doi.org/10.3389/fnhum.2019.00172

Bi, L., Fan, X.-A., & Liu, Y. (2013). EEG-based brain-controlled mobile robots: A survey. *IEEE Transactions on Human-Machine Systems*, *43*(2), 161–176. https://doi.org/10.1109/TSMCC.2012.2219046

•Boonarchatong, C., & Ketcham, M. (2023). Green EEG energy control robot for supporting bedfast patients. *Energy Reports*, *9*, 4493–4506. https://doi.org/10.1016/j.egyr.2023.03.100

Bozinovski, S., & Bozinovski, A. (2015). Mental states, EEG manifestations, and mentally emulated digital circuits for brain-robot interaction. *IEEE Transactions on Autonomous Mental Development*, *7*(1), 39–51. https://doi.org/10.1109/TAMD.2014.2387271

•Braun, J. F., Díez-Valencia, G., Ehrlich, S. K., Lanillos, P., & Cheng, G. (2019). *A prototype of a p300 based brain-robot interface to enable multi-modal interaction for patients with limited mobility* [Paper presentation]. 2019 IEEE International Conference on Cyborg and Bionic Systems (CBS) (pp. 78–84). IEEE. https://doi.org/10.1109/CBS46900.2019.9114484

Burnham, J. F. (2006). Scopus database: A review. *Biomedical Digital Libraries*, *3*(1), 1–8. https://doi.org/10.1186/1742-5581-3-1

•Cao, B., & Liu, Y. (2018). *Tactile p300 brain-computer interface paradigm for robot arm control* [Paper presentation]. 2018 Eighth International Conference on Instrumentation & Measurement, Computer, Communication and Control (IMCCC) (pp. 732–736). IEEE. https://doi.org/10.1109/IMCCC.2018.00158

Cao, Z. (2020). A review of artificial intelligence for EEG-based brain-computer interfaces and applications. *Brain Science Advances*, *6*(3), 162–170. https://doi.org/10.26599/BSA.2020.9050017

Carros, F., Meurer, J., Löffler, D., Unbehaun, D., Matthies, S., Koch, I., Wieching, R., Randall, D., Hassenzahl, M., & Wulf, V. (2020). Exploring human-robot interaction with the elderly: Results from a ten-week case study in a care home. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–12).

•Cervantes, J.-A., López, S., Molina, J., López, F., Perales-Tejeda, M., & Carmona-Frausto, J. (2023). CogniDron-EEG: A system based on a brain–computer interface and a drone for cognitive training. *Cognitive Systems Research*, *78*, 48–56. https://doi.org/10.1016/j.cogsys.2022.11.008

Chadegani, A. A., Salehi, H., Yunus, M. M., Farhadi, H., Fooladi, M., Farhadi, M., & Ebrahim, N. A. (2013). *A comparison between two main academic literature collections: Web of science and Scopus databases*. arXiv Preprint arXiv:1305.0377.

•Chang, Y., & Sun, L. (2021). *EEG-based emotion recognition for modulating social-aware robot navigation* [Paper presentation]. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (pp. 5709–5712). IEEE. https://doi.org/10.1109/EMBC46164.2021.9630721

Chen, S.-C., Hsu, C.-H., Kuo, H.-C., & Zaeni, I. A. E. (2016). The BCI control applied to the interactive autonomous robot with the function of meal assistance. In Jengnan Juang (Ed.), *Proceedings of the 3rd International Conference on Intelligent Technologies and Engineering Systems (ICITES2014)* (pp. 475–483). Springer International Publishing.

•Chen, W., Yang, B., Gu, X., Wang, Z., & Li, Y. (2021). *Research on brain-controlled robotic arm based on improved faster-RCNN target detection model* [Paper presentation]. Proceedings of the 2021 10th International Conference on Computing and Pattern Recognition (pp. 136–141). https://doi.org/10.1145/3497623.3497645

•Chen, X., Huang, X., Wang, Y., & Gao, X. (2020). Combination of augmented reality based brain-computer interface and computer vision for high-level control of a robotic arm. *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, *28*(12), 3140–3147. https://doi.org/10.1109/TNSRE.2020.3038209

•Cheng, S., Wang, J., Tian, J., Zhu, A., & Fan, J. (2024). Using humanoid robots to obtain high-quality motor imagery electroencephalogram data for better brain-computer interaction. *IEEE Transactions on Cognitive and Developmental Systems*, *16*(2), 706–719. https://doi.org/10.1109/TCDS.2023.3289845

•Chhabra, K., Mathur, P., & Baths, V. (2020). *BCI controlled quadcopter using SVM and recursive LSE implemented on ROS* [Paper presentation]. 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 4250–4255). IEEE. https://doi.org/10.1109/SMC42975.2020.9282898

•Chiuzbaian, A., Jakobsen, J., & Puthusserypady, S. (2019). *Mind controlled drone: An innovative multiclass SSVEP based brain computer interface* [Paper presentation]. 2019 7th International Winter

Conference on Brain-Computer Interface (BCI) (pp. 1–5). IEEE. https://doi.org/10.1109/IWW-BCI.2019.8737327

•Chu, Y., Zhao, X., Zou, Y., Xu, W., & Zhao, Y. (2018). *Robot-assisted rehabilitation system based on SSVEP brain-computer interface for upper extremity* [Paper presentation]. 2018 IEEE International Conference on Robotics and Biomimetics (ROBIO) (pp. 1098–1103). IEEE. https://doi.org/10.1109/ROBIO.2018.8664812

Cobb, W., Gastaut, H., Hess, R., Jr, Jung, R., Magnus, O. Gt Britain London. (1958). Report of the committee on methods of clinical examination in electroencephalography. *Electroencephalography and Clinical Neurophysiology*, *10*(2), 370–375. https://doi.org/10.1016/0013-4694(58)90053-1

Coyle, S., Ward, T., Markham, C., & McDarby, G. (2004). On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces. *Physiological Measurement*, *25*(4), 815–822. https://doi.org/10.1088/0967-3334/25/4/003

Crawford, C. S., Andujar, M., Jackson, F., Remy, S., & Gilbert, J. E. (2015). User experience evaluation towards cooperative brain-robot interaction. In Masaaki Kurosu (Ed.), *Human-computer interaction: Design and evaluation* (pp. 184–193). Springer International Publishing.

•Dissanayake, U. C., Steuber, V., & Amirabdollahian, F. (2022). EEG spectral feature modulations associated with fatigue in robot-mediated upper limb gross and fine motor interactions. *Frontiers in Neurorobotics*, *15*, 788494. https://doi.org/10.3389/fnbot.2021.788494

Douibi, K., Le Bars, S., Lemontey, A., Nag, L., Balp, R., & Breda, G. (2021). Toward EEG-based BCI applications for industry 4.0: Challenges and possible applications. *Frontiers in Human Neuroscience*, *15*, 705064. https://doi.org/10.3389/fnhum.2021.705064

•Du, S., Wang, F., Zhou, G., Li, J., Yang, L., & Wang, D. (2021). *Vision-based robotic manipulation of intelligent wheelchair with human-computer shared control* [Paper presentation]. 2021 33rd Chinese Control and Decision Conference (CCDC) (pp. 3252–3257). IEEE. https://doi.org/10.1109/CCDC52312.2021.9601850

•Ehrlich, S. K., & Cheng, G. (2019). A feasibility study for validating robot actions using EEG-based error-related potentials. *International Journal of Social Robotics*, *11*(2), 271–283. https://doi.org/10.1007/s12369-018-0501-8

Esterwood, C., Essenmacher, K., Yang, H., Zeng, F., & Robert, L. P. (2021). *A meta-analysis of human personality and robot acceptance in human-robot interaction* [Paper presentation]. Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1–18). https://doi.org/10.1145/3411764.3445542

Fan, J., Wade, J. W., Bian, D., Key, A. P., Warren, Z. E., Mion, L. C., & Sarkar, N. (2015). A step towards EEG-based brain computer interface for autism intervention. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 3767–3770). IEEE.

Fang, B., Ding, W., Sun, F., Shan, J., Wang, X., Wang, C., & Zhang, X. (2023). Brain-computer interface integrated with augmented reality for human-robot interaction. *IEEE Transactions on Cognitive and Developmental Systems*, *15*(4), 1702–1711. https://doi.org/10.1109/TCDS.2022.3194603

•Farmaki, C., Zacharioudakis, N., Pediaditis, M., Krana, M., & Sakkalis, V. (2022). *Application of dry EEG electrodes on low-cost SSVEP-based BCI for robot navigation* [Paper presentation]. 2022 IEEE International Conference on Imaging Systems and Techniques (IST), (pp. 1–6). IEEE. https://doi.org/10.1109/IST55454.2022.9827672

Fatourechi, M., Bashashati, A., Ward, R. K., & Birch, G. E. (2007). EMG and EOG artifacts in brain computer interface systems: A survey. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *118*(3), 480–494. https://doi.org/10.1016/j.clinph.2006.10.019

Feuchtner, T., & Müller, J. (2018). Ownershift: Facilitating overhead interaction in virtual reality with an ownership-preserving hand space shift. *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology* (pp. 31–43).

•Francis, M. J., Preethi Keran, M., Chetan, R., & Krupa, B. N. (2021). EEG-controlled robot navigation using Hjorth parameters and Welch-PSD. *International Journal of Intelligent Engineering & Systems*, *14*(4), 231–240.

•Ghosh, S., & Orlando, M. F. (2019). *Continuous joint angle estimation of an index finger exoskeleton using online EEG signal* [Paper presentation]. 2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) (pp. 808–813). IEEE. https://doi.org/10.1109/AIM.2019.8868794

Goodrich, M. A., & Schultz, A. C. (2008). Human–robot interaction: A survey. *Foundations and Trends® in Human–Computer Interaction*, *1*(3), 203–275. https://doi.org/10.1561/1100000005

•Gordleeva, S. Y., Lobov, S. A., Grigorev, N. A., Savosenkov, A. O., Shamshin, M. O., Lukoyanov, M. V., Khoruzhko, M. A., & Kazantsev, V. B. (2020). Real-time EEG–EMG human–machine interface-based control system for a lower-limb exoskeleton. *IEEE Access*, *8*, 84070–84081. https://doi.org/10.1109/ACCESS.2020.2991812

Gui, K., Liu, H., & Zhang, D. (2017). Toward multimodal human–robot interaction to enhance active participation of users in gait rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, *25*(11), 2054–2066. https://doi.org/10.1109/TNSRE.2017.2703586

•Guo, Y., Wang, M., Zheng, T., Li, Y., Wang, P., & Qin, X. (2020). *Nao robot limb control method based on motor imagery EEG* [Paper presentation]. 2020 International Symposium on Computer, Consumer and Control (IS3C) (pp. 521–524). IEEE. https://doi.org/10.1109/IS3C50286.2020.00141

•Hernandez-Carmona, D., & Penaloza, C. I. (2019). *Deep learning based image reconstruction from brain data during object-grasping task with a BMI* [Paper presentation]. 2019 IEEE International Conference on Advanced Robotics and Its Social Impacts (ARSO) (pp. 335–339). IEEE. https://doi.org/10.1109/ARSO46408.2019.8948782

Hernandez-Cuevas, B., Sawyers, E., Bentley, L., Crawford, C., & Andujar, M. (2020). Neurophysiological closed-loop control for competitive multi-brain robot interaction. *Advances in Human Factors in Robots and Unmanned Systems: Proceedings of the AHFE 2019 International Conference on Human Factors in Robots and Unmanned Systems. Washington DC, USA* (pp. 141–149). Springer.

Holloman, A., Egbert, W., Stegman, P., Cioli, N., & Crawford, C. S. (2019). *Leveraging neurophysiological information to augment interpretation of responses to vulnerable robot behaviors* [Paper presentation]. 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 566–567). IEEE. https://doi.org/10.1109/HRI.2019.8673290

Huang, Z., & Wang, M. (2021). A review of electroencephalogram signal processing methods for brain-controlled robots. *Cognitive Robotics*, *1*, 111–124. https://doi.org/10.1016/j.cogr.2021.07.001

Hwang, H.-J., Kim, S., Choi, S., & Im, C.-H. (2013). EEG-based brain-computer interfaces: A thorough literature survey. *International Journal of Human-Computer Interaction*, *29*(12), 814–826. https://doi.org/10.1080/10447318.2013.780869

Ibáñez, J., Serrano, J. I., del Castillo, M. D., Gallego, J. A., & Rocon, E. (2013). Online detector of movement intention based on EEG—Application in tremor patients. *Biomedical Signal Processing and Control*, *8*(6), 822–829. https://doi.org/10.1016/j.bspc.2013.07.006

•Iwane, F., Srinath Halvagal, M., Iturrate, I., Batzianoulis, I., Chavarriaga, R., Billard, A., & Millán, J. D. R. (2019). *Inferring subjective preferences on robot trajectories using EEG signals* [Paper presentation]. 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER) (pp. 255–258). IEEE. https://doi.org/10.1109/NER.2019.8717025

Jasper, H. H. (1958). Ten-twenty electrode system of the international federation. *Electroencephalography and Clinical Neurophysiology*, *10*, 371–375.

•Jiang, J., Zhao, B., Zhang, P., Bai, Y., & Chen, X. (2018). *Brain-actuated humanoid robot based on brain-computer interface (BCI)* [Paper presentation]. 2018 IEEE International Conference on Automation, Electronics and Electrical Engineering (AUTEEE) (pp. 319–322). IEEE. https://doi.org/10.1109/AUTEEE.2018.8720766

•Jo, S., Jung, J. H., Yang, M. J., Lee, Y., Jang, S. J., Feng, J., Heo, S.-H., Kim, J., Shin, J.-H., Jeong, J. (2022). *EEG-EMG hybrid real-time classification of hand grasp and release movements intention in chronic stroke patients* [Paper presentation]. 2022 International Conference on Rehabilitation Robotics (ICORR) (pp. 1–6). IEEE. https://doi.org/10.1109/ICORR55369.2022.9896592

Kajita, S., Hirukawa, H., Harada, K., & Yokoi, K. (2014). *Introduction to humanoid robotics* (Vol. 101). Springer.

•Kar, R., Ghosh, L., Konar, A., Chakraborty, A., & Nagar, A. K. (2022). EEG-induced autonomous game-teaching to a robot arm by human trainers using reinforcement learning. *IEEE Transactions on Games*, *14*(4), 610–622. https://doi.org/10.1109/TG.2021.3124340

•Karunasena, S. P., Ariyarathna, D. C., Ranaweera, R., Wijayakulasooriya, J., Kim, K., & Dassanayake, T. (2021). *Single-channel EEG SSVEP-based BCI for robot arm control* [Paper presentation]. 2021 IEEE Sensors Applications Symposium (SAS) (pp. 1–6). IEEE. https://doi.org/10.1109/SAS51076.2021.9530189

•Kilmarx, J., Abiri, R., Borhani, S., Jiang, Y., & Zhao, X. (2018). Sequence-based manipulation of robotic arm control in brain machine interface. *International Journal of Intelligent Robotics and Applications*, *2*(2), 149–160. https://doi.org/10.1007/s41315-018-0049-7

•Kim, B. H., Kwak, J. H., Kim, M., & Jo, S. (2021). *Affect-driven robot behavior learning system using EEG signals for less negative feelings and more positive outcomes* [Paper presentation]. 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), (pp. 4162–4167). IEEE. https://doi.org/10.1109/IROS51168.2021.9636451

•Kompatsiari, K., Pérez-Osorio, J., Tommaso, D. D., Metta, G., & Wykowska, A. (2018). *Neuroscientifically-grounded research for improved human-robot interaction* [Paper presentation]. 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 3403–3408). IEEE. https://doi.org/10.1109/IROS.2018.8594441

•Korovesis, N., Kandris, D., Koulouras, G., & Alexandridis, A. (2019). Robot motion control via an EEG-based brain–computer interface by using neural networks and alpha brainwaves. *Electronics*, *8*(12), 1387. https://doi.org/10.3390/electronics8121387

Kremenski, S. E., & Lekova, A. K. (2022). *Brain-robot communications in the internet of things* [Paper presentation]. 2022 International Conference on Information Technologies (InfoTech) (pp. 1–6). IEEE. https://doi.org/10.1109/InfoTech55606.2022.9897117

Krishnan, N. M., Mariappan, M., Muthukaruppan, K., Hijazi, M. H. A., & Kitt, W. W. (2016). Electroencephalography (EEG) based control in assistive mobile robots: A review. In *IOP conference series: Materials science and engineering* (Vol. 121, pp. 012017). IOP Publishing. https://doi.org/10.1088/1757-899X/121/1/012017

•Kuffuor, J., & Samanta, B. (2018). Brain computer interface using motor imagery and facial expressions to control a mobile robot. In *Dynamic Systems and Control Conference* (Vol. 51890, pp. V001T13A006). American Society of Mechanical Engineers.

Lei, C., Jin, J., Duan, F., Chen, S., Mao, X., & Li, W. (2019). A brain–robot interaction system by fusing human and machine intelligence. *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, *27*(3), 533–542. https://doi.org/10.1109/TNSRE.2019.2897323

Li, H., Zhang, X., Lu, Z., Dong, R., & Sun, Q. (2020). *Rp-based voluntary movement intention detection of lower limb using CNN* [Paper presentation]. 2020 10th Institute of Electrical and Electronics Engineers International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER) (pp. 349–353). IEEE. https://doi.org/10.1109/CYBER50695.2020.9279117

•Li, J., Dang, M., Cao, J., & Fan, X. (2022). *A EEG signal extraction algorithm based on DWT-GRUBBS-average for manipulator control* [Paper presentation]. Proceedings of the 2022 2nd International Conference on Control and Intelligent Robotics (pp. 769–773). https://doi.org/10.1145/3548608.3559303

Li, W., Shao, K., Zhu, C., Ma, Y., Cao, W., Yin, M., Yang, L., Luo, M., & Wu, X. (2022). *Preliminary study of online real-time control system for lower extremity exoskeletons based on EEG and SEMG fusion* [Paper presentation]. 2022 IEEE International Conference on Robotics and Biomimetics (ROBIO) (pp. 1689–1694). IEEE. https://doi.org/10.1109/ROBIO55434.2022.10011813

•Li, X., Deng, H., Ouyang, J., Wan, H., Yu, W., & Wu, D. (2023). *Act as what you think: Towards personalized EEG interaction through attentional and embedded LSTM learning* [Paper presentation]. IEEE Transactions on Mobile Computing.

Li, Y., Pan, J., Wang, F., & Yu, Z. (2013). A hybrid BCI system combining p300 and SSVEP and its application to wheelchair control. *IEEE Transactions on Bio-Medical Engineering*, *60*(11), 3156–3166. https://doi.org/10.1109/TBME.2013.2270283

•Li, Z., Yuan, Y., Luo, L., Su, W., Zhao, K., Xu, C., Huang, J., & Pi, M. (2019). Hybrid brain/muscle signals powered wearable walking exoskeleton enhancing motor ability in climbing stairs activity. *IEEE Transactions on Medical Robotics and Bionics*, *1*(4), 218–227. https://doi.org/10.1109/TMRB.2019.2949865

Lin, C.-T., Ko, L.-W., Chang, M.-H., Duann, J.-R., Chen, J.-Y., Su, T.-P., & Jung, T.-P. (2010). Review of wireless and wearable electroencephalogram systems and brain-computer interfaces – A mini-review. *Gerontology*, *56*(1), 112–119. https://doi.org/10.1159/000230807

•Liu, Y., & Jebelli, H. (2021). Enhanced robotic teleoperation in construction using a GAN-based physiological signal augmentation framework. *Canadian Society of Civil Engineering Annual Conference* (pp. 295–307). Springer.

Liu, Y., Yang, C., & Wang, M. (2020). *Human-robot interaction based on biosignals* [Paper presentation]. 2020 International Symposium on Autonomous Systems (ISAS) (pp. 58–63). IEEE. https://doi.org/10.1109/ISAS49493.2020.9378844

•Long, X., Ma, Y., Ma, X., Yan, Z., Wang, C., & Wu, X. (2019). *The EEG-based lower limb exoskeleton system optimization strategy based on channel selection* [Paper presentation]. 2019 IEEE International Conference on Real-Time Computing and Robotics (RCAR) (pp. 1–6). IEEE. https://doi.org/10.1109/RCAR47638.2019.9044090

•Lu, W., Wei, Y., Yuan, J., Deng, Y., & Song, A. (2020). Tractor assistant driving control method based on EEG combined with RNN-TL deep learning algorithm. *IEEE Access*, *8*, 163269–163279. https://doi.org/10.1109/ACCESS.2020.3021051

•Lu, Y., Wang, H., Feng, N., Jiang, D., & Wei, C. (2022). Online interaction method of mobile robot based on single-channel EEG signal and end-to-end CNN with residual block model. *Advanced Engineering Informatics*, *52*, 101595. https://doi.org/10.1016/j.aei.2022.101595

•Lyu, J., Maýe, A., Görner, M., Ruppel, P., Engel, A. K., & Zhang, J. (2022). Coordinating human-robot collaboration by EEG-based human intention prediction and vigilance control. *Frontiers in Neurorobotics*, *16*, 1068274. https://doi.org/10.3389/fnbot.2022.1068274

Ma, Y., Nordberg, O. E., Zhang, Y., Rongve, A., Bachinski, M., & Fjeld, M. (2024). *Understanding dementia speech: Towards an adaptive voice assistant for enhanced communication* [Paper presentation]. Companion Proceedings of the 16th ACM SIGCHI Symposium on Engineering Interactive Computing Systems (pp. 15–21). https://doi.org/10.1145/3660515.3661326

•Magee, R., & Givigi, S. (2021). *A system for p300 detection applied to vehicle navigation* [Paper presentation]. 2021 IEEE International Systems Conference (SysCon) (pp. 1–8). IEEE. https://doi.org/10.1109/SysCon48628.2021.9447129

Mahdi, H., Akgun, S. A., Saleh, S., & Dautenhahn, K. (2022). A survey on the design and evolution of social robots—Past, present and future. *Robotics and Autonomous Systems*, *156*, 104193. https://doi.org/10.1016/j.robot.2022.104193

Manjunatha, H., Distefano, J. P., Jani, A., Ghassemi, P., Chowdhury, S., Dantu, K., Doermann, D., & Esfahani, E. T. (2020). *Using physiological measurements to analyze the tactical decisions in human swarm teams* [Paper presentation]. 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 256–261). IEEE. https://doi.org/10.1109/SMC42975.2020.9282845

Mao, X., Li, M., Li, W., Niu, L., Xian, B., Zeng, M., & Chen, G. (2017). Progress in EEG-based brain robot interaction systems.

Computational Intelligence and Neuroscience, *2017*(1). https://doi.org/10.1155/2017/1742862
•Martínez-Cagigal, V., Kobler, R. J., Mondini, V., Hornero, R., & Muller-Putz, G. R. (2020). *Non-linear online low-frequency EEG decoding of arm movements during a pursuit tracking task* [Paper presentation]. 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (pp. 2981–2985). IEEE.
McFarland, D. J., & Wolpaw, J. R. (2008). Brain-computer interface operation of robotic and prosthetic devices. *Computer Magazine*, *41*(10), 52–56. https://doi.org/10.1109/MC.2008.409
•Memar, A. H., & Esfahani, E. T. (2018). *EEG correlates of motor control difficulty in physical human-robot interaction: A frequency domain analysis* [Paper presentation]. 2018 IEEE Haptics Symposium (HAPTICS) (pp. 229–234). IEEE. https://doi.org/10.1109/HAPTICS.2018.8357181
•Memar, A. H., & Esfahani, E. T. (2020). Objective assessment of human workload in physical human-robot cooperation using brain monitoring. *ACM Transactions on Human-Robot Interaction*, *9*(2), 1–21. https://doi.org/10.1145/3368854
Millán, J. D. R., Rupp, R., Müller-Putz, G. R., Murray-Smith, R., Giugliemma, C., Tangermann, M., Vidaurre, C., Cincotti, F., Kübler, A., Leeb, R., Neuper, C., Müller, K.-R., & Mattia, D. (2010). Combining brain–computer interfaces and assistive technologies: State-of-the-art and challenges. *Frontiers in Neuroscience*, *4*(161). https://doi.org/10.3389/fnins.2010.00161
Minguillon, J., Lopez-Gordo, M. A., & Pelayo, F. (2017). Trends in EEG-BCI for daily-life: Requirements for artifact removal. *Biomedical Signal Processing and Control*, *31*, 407–418. https://doi.org/10.1016/j.bspc.2016.09.005
•Mondini, V., Kobler, R. J., Sburlea, A. I., & Müller-Putz, G. R. (2020). Continuous low-frequency EEG decoding of arm movement for closed-loop, natural control of a robotic arm. *Journal of Neural Engineering*, *17*(4), 046031. https://doi.org/10.1088/1741-2552/aba6f7
Montoya-Martínez, J., Vanthornhout, J., Bertrand, A., & Francart, T. (2021). Effect of number and placement of EEG electrodes on measurement of neural tracking of speech. *PloS One*, *16*(2), e0246769. https://doi.org/10.1371/journal.pone.0246769
•Nann, M., Cordella, F., Trigili, E., Lauretti, C., Bravi, M., Miccinilli, S., Catalan, J. M., Badesa, F. J., Crea, S., Bressi, F., Garcia-Aracil, N., Vitiello, N., Zollo, L., & Soekadar, S. R. (2021). Restoring activities of daily living using an EEG/EOG-controlled semiautonomous and mobile whole-arm exoskeleton in chronic stroke. *IEEE Systems Journal*, *15*(2), 2314–2321. https://doi.org/10.1109/JSYST.2020.3021485
Naseer, N., & Hong, K.-S. (2015). FNIRS-based brain-computer interfaces: A review. *Frontiers in Human Neuroscience*, *9*(3). https://doi.org/10.3389/fnhum.2015.00003
Nemati, M., Taheri, A., Ghazizadeh, A., Banitalebi Dehkordi, M., & Meghdari, A. (2022). *Feature selection using EEG signals: A novel hybrid binary particle swarm optimization* [Paper presentation]. 2022 10th RSI International Conference on Robotics and Mechatronics (ICRoM) (pp. 359–364). IEEE. https://doi.org/10.1109/ICRoM57054.2022.10025190
Neuper, C., Müller, G. R., Kübler, A., Birbaumer, N., & Pfurtscheller, G. (2003). Clinical application of an EEG-based brain–computer interface: A case study in a patient with severe motor impairment. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *114*(3), 399–409. https://doi.org/10.1016/s1388-2457(02)00387-5
Nwagu, C., AlSlaity, A., & Orji, R. (2023). EEG-based brain-computer interactions in immersive virtual and augmented reality: A systematic review. *Proceedings of the ACM on Human-Computer Interaction*, *7*(EICS), 1–33. https://doi.org/10.1145/3593226
•Ogino, M., & Mitsukura, Y. (2018). *An EEG-based robot arm control to express human emotions* [Paper presentation]. 2018 IEEE 15th International Workshop on Advanced Motion Control (AMC) (pp. 322–327). IEEE.
Omer, K., Ferracuti, F., Freddi, A., Iarlori, S., Monteriù, A., & Porcaro, C. (2022). *Human-in-the-loop approach for enhanced mobile robot navigation* [Paper presentation]. 2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE) (pp. 416–421). IEEE. https://doi.org/10.1109/MetroXRAINE54828.2022.9967516
Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery (London, England)*, *88*, 105906. https://doi.org/10.1016/j.ijsu.2021.105906
Pascher, M., Gruenefeld, U., Schneegass, S., & Gerken, J. (2023). *How to communicate robot motion intent: A scoping review* [Paper presentation]. Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (pp. 1–17). https://doi.org/10.1145/3544548.3580857
•Pawuś, D., & Paszkiel, S. (2022). Application of EEG signals integration to proprietary classification algorithms in the implementation of mobile robot control with the use of motor imagery supported by EMG measurements. *Applied Sciences*, *12*(11), 5762. https://doi.org/10.3390/app12115762
•Penaloza, C. I., Alimardani, M., & Nishio, S. (2018). Android feedback-based training modulates sensorimotor rhythms during motor imagery. *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, *26*(3), 666–674. https://doi.org/10.1109/TNSRE.2018.2792481
Perrin, X. (2009). *Semi-autonomous navigation of an assistive robot using low throughput interfaces* [PhD thesis]. ETH Zurich.
•Prinsen, J., Pruss, E., Vrins, A., Ceccato, C., & Alimardani, M. (2022). *A passive brain-computer interface for monitoring engagement during robot-assisted language learning* [Paper presentation]. 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 1967–1972). IEEE. https://doi.org/10.1109/SMC53654.2022.9945182
•Qian, C., Hou, T., Lu, Y., & Fu, S. (2018). *Affective recognition using EEG signal in human-robot interaction.* Engineering Psychology and Cognitive Ergonomics: 15th International Conference, EPCE 2018, Held as Part of HCI International 2018, Las Vegas, NV, USA. (pp. 336–351). Springer.
Qin, Y., Zhang, Y., Zhang, Y., Liu, S., & Guo, X. (2023). Application and development of EEG acquisition and feedback technology: A review. *Biosensors*, *13*(10), 930. https://doi.org/10.3390/bios13100930
•Quiles, E., Dadone, J., Chio, N., & García, E. (2022). Cross-platform implementation of an SSVEP-based BCI for the control of a 6-dof robotic arm. *Sensors*, *22*(13), 5000. https://doi.org/10.3390/s22135000
•Rahul, Y., & Sharma, R. K. (2019). EEG signal-based movement control for mobile robots. *Current Science*, *116*(12), 1993–2000. https://doi.org/10.18520/cs/v116/i12/1993-2000
Rajabi, N., Khanna, P., Kanik, S. U. D., Yadollahi, E., Vasco, M., Björkman, M., Smith, C., & Kragic, D. (2023). *Detecting the intention of object handover in human-robot collaborations: An EEG study* [Paper presentation]. 2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN) (pp. 549–555). IEEE. https://doi.org/10.1109/RO-MAN57019.2023.10309426
•Rashid, M., Sulaiman, N., Mustafa, M., Khatun, S., Bari, B. S., Hasan, M. J., & Al-Fakih, N. M. (2020). *Investigating the possibility of brain actuated mobile robot through single-channel EEG headset* [Paper presentation]. In ECCE2019: Proceedings of the 5th International Conference on Electrical, Control & Computer Engineering, Kuantan, Pahang, Malaysia, 29th July 2019 (pp. 579–590). Springer.
Rekrut, M., Selim, A. M., & Krüger, A. (2022). *Improving silent speech BCI training procedures through transfer from overt to silent speech* [Paper presentation]. 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 2650–2656). IEEE. https://doi.org/10.1109/SMC53654.2022.9945447
•Richter, B., Putze, F., Ivucic, G., Brandt, M., Schütze, C., Reisenhofer, R., Wrede, B., & Schultz, T. (2023). EEG correlates of distractions

and hesitations in human–robot interaction: A lablinking pilot study. *Multimodal Technologies and Interaction*, *7*(4), 37. https://doi.org/10.3390/mti7040037

Rodriguez, G. (1988). *Recursive forward dynamics for multiple robot arms moving a common task object*. Technical Report.

Rodriguez, J., Del-Valle-Soto, C., & Gonzalez-Sanchez, J. (2022). Affective states and virtual reality to improve gait rehabilitation: A preliminary study. *International Journal of Environmental Research and Public Health*, *19*(15), 9523. https://doi.org/10.3390/ijerph19159523

•Roshdy, A., Al Kork, S., Karar, A., Al Sabi, A., Al Barakeh, Z., ElSayed, F., Beyrouthy, T., & Nait-Ali, A. (2021). *Machine empathy: Digitizing human emotions* [Paper presentation]. 2021 International Symposium on Electrical, Electronics and Information Engineering (pp. 307–311). https://doi.org/10.1145/3459104.3459154

•Roy, G., & Bhaumik, S. (2022). Classification of MI EEG signal using minimum set of channels to control a lower limb assistive device. *Journal of the Institution of Engineers (India): Series B*, *Series B*, 1–7. https://doi.org/10.1007/s40031-022-00783-x

•Sanguantrakul, J., Soontreekulpong, N., Trakoolwilaiwan, T., & Wongsawat, Y. (2020). *Development of BCI system for walking substitution via humanoid robot* [Paper presentation]. 2020 8th International Electrical Engineering Congress (iEECON) (pp. 1–4). IEEE. https://doi.org/10.1109/iEECON48109.2020.232736

•Shao, L., Zhang, L., Belkacem, A. N., Zhang, Y., Chen, X., Li, J., & Liu, H. (2020). EEG-controlled wall-crawling cleaning robot using SSVEP-based brain-computer interface. *Journal of Healthcare Engineering*, *2020*(1), 6968713. https://doi.org/10.1155/2020/6968713

Sheridan, T. B. (2016). Human–robot interaction: Status and challenges. *Human Factors*, *58*(4), 525–532. https://doi.org/10.1177/0018720816644364

Shi, M., Yang, C., & Zhang, D. (2021). A novel human-machine collaboration model of an ankle joint rehabilitation robot driven by EEG signals. *Mathematical Problems in Engineering*, *2021*(1), 5564235. https://doi.org/10.1155/2021/5564235

•Si-Mohammed, H., Petit, J., Jeunet, C., Argelaguet, F., Spindler, F., Evain, A., Roussel, N., Casiez, G., & Lecuyer, A. (2020). Towards BCI-based interfaces for augmented reality: Feasibility, design and evaluation. *IEEE Transactions on Visualization and Computer Graphics*, *26*(3), 1608–1621. https://doi.org/10.1109/TVCG.2018.2873737

Si-Mohammed, H., Sanz, F. A., Casiez, G., Roussel, N., & Lécuyer, A. (2017). Brain-computer interfaces and augmented reality: A state of the art. *Graz Brain-Computer Interface Conference*.

Sitaram, R., Caria, A., Veit, R., Gaber, T., Rota, G., Kuebler, A., & Birbaumer, N. (2007). FMRI brain-computer interface: A tool for neuroscientific research and treatment. *Computational Intelligence and Neuroscience*, *2007*(1), 25487–25410. https://doi.org/10.1155/2007/25487

•Staffa, M., & Rossi, S. (2022). *Enhancing affective robotics via human internal state monitoring* [Paper presentation]. 2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), (pp. 884–890). IEEE. https://doi.org/10.1109/RO-MAN53752.2022.9900762

Stanković, E., Kljajić, J., Šumarac, J., & Radmilović, M. (2023). *Human motion behavior evaluation: The possibility of improving human-robot collaboration* [Paper presentation]. 2023 10th International Conference on Electrical, Electronic and Computing Engineering (IcETRAN) (pp. 1–6). IEEE. https://doi.org/10.1109/IcETRAN59631.2023.10192194

•Sugiyama, S., Pongthanisorn, G., Aya, S., & Capi, G. (2023). *EEG channel optimization for wireless BMI-based robot interaction for internet of robotic things* [Paper presentation]. 2023 6th Conference on Cloud and Internet of Things (CIoT) (pp. 131–135). IEEE. https://doi.org/10.1109/CIoT57267.2023.10084884

Tan, Y., Liu, G., Chen, L., Sun, Z., & Duan, F. (2021). *Joint distribution adaptation network for multi-source electroencephalogram-based emotion recognition* [Paper presentation]. 2021 IEEE International Conference on Robotics and Biomimetics (ROBIO) (pp. 1077–1082). IEEE. https://doi.org/10.1109/ROBIO54168.2021.9739438

•Tang, Z., Zhang, L., Chen, X., Ying, J., Wang, X., & Wang, H. (2022). Wearable supernumerary robotic limb system using a hybrid control approach based on motor imagery and object detection. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *30*, 1298–1309. https://doi.org/10.1109/TNSRE.2022.3172974

•Toichoa Eyam, A., Mohammed, W. M., & Martinez Lastra, J. L. (2021). Emotion-driven analysis and control of human-robot interactions in collaborative applications. *Sensors*, *21*(14), 4626. https://doi.org/10.3390/s21144626

Tomaszewski, R. (2021). A study of citations to STEM databases: ACM digital library, engineering village, IEEE Xplore, and MathSciNet. *Scientometrics*, *126*(2), 1797–1811. https://doi.org/10.1007/s11192-020-03795-w

Torres, E. P., Torres, E. A., Hernández-Álvarez, M., & Yoo, S. G. (2020). EEG-based BCI emotion recognition: A survey. *Sensors*, *20*(18), 5083. https://doi.org/10.3390/s20185083

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-SCR): Checklist and explanation. *Annals of Internal Medicine*, *169*(7), 467–473. https://doi.org/10.7326/M18-0850

Tzafestas, S. G. (2013). *Introduction to mobile robot control*. Elsevier.

van den Oever, F., Fjeld, M., & Sætrevik, B. (2024). A systematic literature review of augmented reality for maritime collaboration. *International Journal of Human–Computer Interaction*, *40*(15), 4116–4131. https://doi.org/10.1080/10447318.2023.2209838

Van Haastregt, J., Welle, M. C., Zhang, Y., & Kragic, D. (2024). *Puppeteer your robot: Augmented reality leader-follower teleoperation* [Paper presentation]. 2024 IEEE-RAS 23rd International Conference on Humanoid Robots (Humanoids) (pp. 1019–1026). IEEE. https://doi.org/10.1109/Humanoids58906.2024.10769593

Vaughan, T. M., Heetderks, W. J., Trejo, L. J., Rymer, W. Z., Weinrich, M., Moore, M. M., Kübler, A., Dobkin, B. H., Birbaumer, N., Donchin, E., Wolpaw, E. W., & Wolpaw, J. R. (2003). Brain-computer interface technology: A review of the second international meeting. *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society*, *11*(2), 94–109. https://doi.org/10.1109/tnsre.2003.814799

Vidal, J. J. (1973). Toward direct brain-computer communication. *Annual Review of Biophysics and Bioengineering*, *2*(1), 157–180. https://doi.org/10.1146/annurev.bb.02.060173.001105

Wallace, B., van Otterdijk, M., Zhang, Y., Rajabi, N., Marin-Bucio, D., Kragic, D., & Torresen, J. (2024). *Imitation or innovation? Translating features of expressive motion from humans to robots* [Paper presentation]. Proceedings of the 12th International Conference on Human-Agent Interaction (pp. 296–304). https://doi.org/10.1145/3687272.3688302

•Wang, F., Zhang, X., Fu, R., & Sun, G. (2018). Study of the home-auxiliary robot based on BCI. *Sensors*, *18*(6), 1779. https://doi.org/10.3390/s18061779

•Wang, K.-J., & Sugaya, M. (2021). *Focus and concentrate! Exploring the use of conversational robot to improve self-learning performance during pandemic isolation by closed-loop brainwave neurofeedback* [Paper presentation]. 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER) (pp. 928–932). IEEE. https://doi.org/10.1109/NER49283.2021.9441469

Wang, K.-J., Liu, Q., Vhasure, S., Liu, Q., Zheng, C. Y., & Thakur, P. (2018). *EXG wearable human-machine interface for natural multimodal interaction in VR environment* [Paper presentation]. Proceedings of the 24th ACM Symposium on Virtual Reality Software and Technology (pp. 1–2). https://doi.org/10.1145/3281505.3281577

•Wang, Y., Xu, G., Song, A., Xu, B., Li, H., Hu, C., & Zeng, H. (2018). *Continuous shared control for robotic arm reaching driven by a hybrid gaze-brain machine interface* [Paper presentation]. 2018 IEEE/RSJ International Conference on Intelligent Robots and

Systems (IROS) (pp. 4462–4467). IEEE. https://doi.org/10.1109/IROS.2018.8594367
Wang, Y., Zhang, X., Li, K., Wang, J., & Chen, X. (2020). *Humanoid robot control system based on AR-SSVEP* [Paper presentation]. Proceedings of the 2020 6th International Conference on Computing and Artificial Intelligence (pp. 529–533). https://doi.org/10.1145/3404555.3404625
•Wei, X., Chen, K., Liu, Y., Zhao, X., Ma, L., Ai, Q., & Liu, Q. (2021). *Control of multiple DOFs robots using motor imagery EEG combined with Huffman coding* [Paper presentation]. 2021 27th International Conference on Mechatronics and Machine Vision in Practice (M2VIP) (pp. 344–348). IEEE. https://doi.org/10.1109/M2VIP49856.2021.9665060
Winkle, K., Lagerstedt, E., Torre, I., & Offenwanger, A. (2023). 15 years of (who) man robot interaction: Reviewing the h in human-robot interaction. *ACM Transactions on Human-Robot Interaction*, *12*(3), 1–28. https://doi.org/10.1145/3571718
•Wu, D., Ouyang, J., Dai, N., Wu, M., Tan, H., Deng, H., Fan, Y., Wang, D., & Jin, Z. (2022). Deepbrain: Enabling fine-grained brain-robot interaction through human-centered learning of coarse EEG signals from low-cost devices. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *6*(3), 1–27. https://doi.org/10.1145/3550334
Xia, H., Zhang, Y., Rajabi, N., Taleb, F., Yang, Q., Kragic, D., & Li, Z. (2024). Shaping high-performance wearable robots for human motor and sensory reconstruction and enhancement. *Nature Communications*, *15*(1), 1760. https://doi.org/10.1038/s41467-024-46249-0
•Xu, B., Song, A., Zhao, G., Liu, J., Xu, G., Pan, L., Yang, R., Li, H., & Cui, J. (2018). EEG-modulated robotic rehabilitation system for upper extremity. *Biotechnology & Biotechnological Equipment*, *32*(3), 795–803. https://doi.org/10.1080/13102818.2018.1437569
Xu, T., Zhao, T., Cruz-Garza, J. G., Bhattacharjee, T., & Kalantari, S. (2022). Evaluating human-in-the-loop assistive feeding robots under different levels of autonomy with VR simulation and physiological sensors. In *International Conference on Social Robotics* (pp. 314–327). Springer.
Yadav, H., Maini, S., & Kumar, D. (2023). *EEG-based brain-computer interface paradigms: A review*. Available at SSRN 4484352.
•Yoon, S., Alimardani, M., & Hiraki, K. (2021). *The effect of robot-guided meditation on intra-brain EEG phase synchronization* [Paper presentation]. Companion of the 2021 ACM/IEEE International Conference on Human-Robot Interaction (pp. 318–322). https://doi.org/10.1145/3434074.3447184
•Yu, Y.-C., Smith, B., Goreshnik, A., & Gabel, L. (2019). *Design of an affordable brain-computer interface for robot navigation* [Paper presentation]. 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA) (pp. 787–792). IEEE. https://doi.org/10.1109/ICIEA.2019.8833813
•Yuan, W., & Li, Z. (2019). Brain teleoperation control of a nonholonomic mobile robot using quadrupole potential function. *IEEE Transactions on Cognitive and Developmental Systems*, *11*(4), 527–538. https://doi.org/10.1109/TCDS.2018.2869903
Zhang, B., Wang, J., & Fuhlbrigge, T. (2010). A review of the commercial brain-computer interface technology from perspective of industrial robotics. *2010 IEEE International Conference on Automation and Logistics* (pp. 379–384). IEEE.
•Zhang, L., Sun, Z., Duan, F., Zhu, C., & Yokoi, H. (2021). *Mind control of a service robot with visual serving* [Paper presentation]. 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), (pp. 3747–3752). IEEE. https://doi.org/10.1109/IROS51168.2021.9636079
Zhang, Y., Kassem, K., Gong, Z., Mo, F., Ma, Y., Kirjavainen, E., & Häkkilä, J. (2024). *Human-centered AI technologies in human-robot interaction for social settings* [Paper presentation]. Proceedings of the International Conference on Mobile and Ubiquitous Multimedia (pp. 501–505). https://doi.org/10.1145/3701571.3701610
Zhang, Y., Luo, H., Wang, H., Zheng, Z., & Ooi, O. C. (2020). Validation of prognostic accuracy of the SOFA score, SIRS criteria, and qSOFA score for in-hospital mortality among cardiac-, thoracic-, and vascular-surgery patients admitted to a cardiothoracic intensive care unit. *Journal of Cardiac Surgery*, *35*(1), 118–127. https://doi.org/10.1111/jocs.14331
Zhang, Y., Ma, Y., & Kragic, D. (2024). *Vision beyond boundaries: An initial design space of domain-specific large vision models in human-robot interaction* [Paper presentation]. Adjunct Proceedings of the 26th International Conference on Mobile Human-Computer Interaction (pp. 1–8). https://doi.org/10.1145/3640471.3680244
Zhang, Y., Nowak, A., Xuan, Y., Romanowski, A., & Fjeld, M. (2023). *See or hear? Exploring the effect of visual/audio hints and gaze-assisted instant post-task feedback for visual search tasks in AR* [Paper presentation]. 2023 IEEE International Symposium on Mixed and Augmented Reality (ISMAR) (pp. 1113–1122). IEEE. https://doi.org/10.1109/ISMAR59233.2023.00128
Zhang, Y., Vasco, M., Björkman, M., & Kragic, D. (2024). *Will you participate? Exploring the potential of robotics competitions on human-centric topics* [Paper presentation]. International Conference on Human-Computer Interaction (pp. 240–255). Springer.
Zhang, Y., Yadollahi, E., Ma, Y., Fu, D., Leite, I., & Kragic, D. (2024). *The 1st InterAI workshop: Interactive AI for human-centered robotics*. arXiv Preprint arXiv:2409.11150.
Zhao, J., Li, W., Mao, X., & Li, M. (2015). SSVEP-based experimental procedure for brain-robot interaction with humanoid robots. *Journal of Visualized Experiments*, (105), e53558. https://doi.org/10.3791/53558-v
Zhao, X., Huang, J., Zheng, J., Ma, Y., & Tang, H. (2020). *A multi-modal-signals-based gesture recognition method for human machine interaction* [Paper presentation]. 2020 3rd International Conference on Unmanned Systems (ICUS) (pp. 494–499). IEEE. https://doi.org/10.1109/ICUS50048.2020.9274853
•Zhao, X., Liu, D., Xie, S., Liu, Q., Chen, K., Ma, L., & Ai, Q. (2020). *Multiple action movement control scheme for assistive robot based on binary motor imagery EEG* [Paper presentation]. International Conference in Communications, Signal Processing, and Systems (pp. 760–768). Springer.
Zhu, D., Bieger, J., Garcia Molina, G., & Aarts, R. M. (2010). A survey of stimulation methods used in SSVEP-based BCIS. *Computational Intelligence and Neuroscience*, *2010*(1), 702357. https://doi.org/10.1155/2010/702357

About the authors

Yuchong Zhang is a postdoctoral fellow at KTH Royal Institute of Technology in Sweden. He obtained his PhD degree from Chalmers University of Technology in 2023 and MSc. degree from Nanyang Technological University in Singapore in 2017. His research includes human-robot interaction with human-centered design, VR/AR/MR, and human perception.

Nona Rajabi is a doctoral student at KTH Royal Institute of Technology in Sweden. Her primary research areas are brain–computer interfaces, electroencephalogram (EEG) signal analysis, and applied machine learning in neuroscience.

Farzaneh Taleb is a PhD student at KTH Royal Institute of Technology, Sweden. Her research includes understanding the gap between natural and artificial intelligent systems by making the artificial systems closer to the natural ones. She focuses on olfactory perception and making bridges between molecules, human perception, and neural networks.

Andrii Matviienko is an assistant professor in human–computer interaction at KTH Royal Institute of Technology, Sweden. He works at the Department of Media Technology and Interaction Design, where he leads an Immersive Technologies Lab. His research focuses on Extended Reality and assisting technology in urban environments.

Yong Ma is a postdoctoral researcher in medical department and HCI group at the University of Bergen, Norway. His research focuses on speech signal processing, emotion-aware voice interfaces, and innovative applications in dementia healthcare. He holds a PhD in Media Informatics from Ludwig Maximilian University of Munich (LMU), Germany.

Mårten Björkman is an associate professor KTH Royal Institute of Technology, Sweden. His primary research areas are perception and learning, in particular for real-world robotic systems, typically using multi-view computer vision for 3D perception, but often including other modalities such as force-torque sensing.

Danica Kragic is a professor at KTH Royal Institute of Technology, Sweden. She received PhD in 2001. She is a member of the Royal Swedish Academy of Sciences, Royal Swedish Academy of Engineering Sciences and Young Academy of Sweden. She chaired IEEE RAS Technical Committee on Computer and Robot Vision.