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Review

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Towards neuromorphic neurotechnologies: integrating brain-inspired computing with brain-computer interfaces

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Neurological disorders pose a growing global health burden, motivating advances in neural interfacing and artificial intelligence (AI). This review surveys state-of-the-art approaches for neural recording, stimulation and signal decoding and encoding across brain–computer interfaces, neuroprosthetics, and neuromodulation systems aimed at restoring function and treating neurological disorders. It highlights recent progress in AI, particularly neuromorphic computing and spiking neural networks (SNNs), and introduces Brain-Inspired Brain–Computer Interfaces (BI-BCIs) as a unifying framework for low-power, closed-loop, and miniaturized neuromorphic neurotechnologies.

Neurotechnology: the future game changer

Neurodegenerative disorders such as Parkinson's Disease (PD), Epilepsy, Multiple Sclerosis (MS), Alzheimer's, and Dementia are incurable and debilitating conditions caused by gradual damage or loss of the nervous system structure and function. They lead to cognitive, sensory, and motor dysfunctions. As the world's population ages and life expectancy increases, age-related neurodegenerative diseases are becoming more prevalent, and the risk of being affected by them is dramatically increasing[1,2]. Such diseases are responsible for the greatest economic burden and influence the lives of millions of people worldwide, considering that, in 2010, more than 179 million people in Europe were affected by brain disorders with an associated bill of around 800 billion euros[2,3]. According to the Global Burden of Disease Injuries, and Risk Factors Study (GBD) in 2016, neurological disorders were reported as the top leading causes of disability in the globe with 11.6% Disability-Adjusted Life Years (DALYs) (~276 million per year), and second leading cause of deaths after cardiovascular diseases with 16.5% of all deaths (~9 million)[2,3]. Table 1 provides a general summary of prevalent neurological disorders, outlining their impacts and economic implications. Currently, there is no effective therapeutics to cure such disorders, except for some traditional pharmaceutical drugs that could reduce the symptoms severity such as dopaminergic treatment for PD and movement disorders, cholinesterase for cognitive disorders, anti-inflammatory and analgesic for neuronal infections and pain, antipsychotic for dementia, etc[4,5]. To this end, a substantial amount of research is currently dedicated to developing innovative therapeutic tools and strategies rooted in neurotechnologies, such as Deep Brain Stimulation (DBS)[6–8], offering an alternative to traditional pharmaceutical interventions.

In the last 20 years, neurotechnologies aimed at interfacing the brain with machines and computers have emerged as interesting tools, enabling paralyzed people to communicate and interact with the external world[9]. Simultaneously, they have begun to be used for investigating brain functions in different experimental conditions. Neurotechnologies encompass any method or electronic device (e.g., electrodes, computers, robotic arm, etc.) capable of interfacing with the nervous system to monitor and/or alter its neural activity. This enables them to either record and decode the brain signals into control commands or electrically stimulate the brain to modulate its activity. Several neurotechnologies developed in the past few decades proved to be useful for both assistive and rehabilitative applications, for example cochlear implants for restoring hearing[10], retinal implants for restoring vision[11,12], and Brain Machine/Computer Interfaces (BMIs/BCIs) for brain-controlled applications[13]. Nevertheless, given the intrinsic complexity of the brain, we are still far from completely understanding the neural code, a challenge whose resolution would benefit both the neuroscience and engineering communities. In support of this, vast

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Table 1 | Top prominent neurodegenerative diseases (NDs) based on world health organization (WHO) reports[2,3]

Neurodegenerative Diseases (NDs)	Facts and Symptoms	Percentages and economic Burden
Dementia and Alzheimer's Disease (AD)	– Dementia causes symptoms that affect memory, thinking, and social abilities severely enough to interfere with a patient's daily life. – Memory loss, planning difficulties, mood changes, personality changes, confusion about time and place.	– Over 50 million people worldwide were living with dementia in 2020 (will double every 20 years). – ~10 million new cases every year (one every 3 seconds). – 7th leading cause of death. – Estimated cost: ~1 trillion USD in 2018, projected to reach $2 trillion USD by 2030.
Parkinson's Disease (PD)	– Rigidity, postural disturbance, rest tremor, slow movement, anosmia in early stages.	– 10 million patients affected globally (1.5x more likely men than women) – The prevalence ranges from 41 per 100,000 among people in their thirties to more than 1900 per 100,000 among those who are over 80. – In 2016, it accounted for 3.2 million DALYs and 211.96 thousand deaths. – USA economic burden: $51.9 billion USD in 2021, nearly doubled previous estimates.
Multiple Sclerosis (MS)	– Multiple sclerosis is a disease with unpredictable symptoms that can also vary in intensity. Different symptoms can manifest during relapses or attacks. – Pain from spasticity, impaired ambulation, depression, cognitive impairment, ataxia, and tremors.	– Around 2.8 million people worldwide registered. – Women four times more likely to have MS than men. – Mean costs of MS ~37,100 USD annually per patient with moderate disease in EU.
Epilepsy	– Recurrent seizures, which are brief episodes of involuntary movement that may involve a part of the body or the entire body and are sometimes accompanied by loss of consciousness and control of bowel or bladder function.	– ~ 50 million people worldwide have epilepsy (most common neurological disease globally). – Up to 70% of people living with epilepsy could be seizure-free if properly diagnosed and treated. – Premature death in people with epilepsy is up to three times higher than for the general population. – Active epilepsy (i.e., continuing seizures or with the need for treatment) is estimated to affect 4–10 individuals per 1000 of the general population.

resources have been assigned to study, model, and map the brain and its fundamental mechanisms along with Neurotechnology development. The Brain Research through Advancing Innovative Neurotechnologies (BRAIN) initiative in 2013, supported by the United States (USA) government, the Brain/MINDS (Brain Mapping by Integrated Neurotechnologies for Disease Studies) project launched in 2014 by Japan, and the Human Brain Project (HBP) funded by the European Commission ($703 million) are a few examples. In Dec 2020, HBP launched the EBRAINS platform, which grants access to datasets and digital tools for analysis and experiment conduction[14]. Due to its high potential for treating neurological disorders, neurotechnology research has significantly become an attractive field for industry in the past decade (e.g., © Neuralink[15], ©Paradromics[16], ©Synchron[17], ©Blackrock Neurotech[18], ©Neurable[19], ©Thync[20], ©Medtronic[21], ©kernel[22], etc.). For instance, ©NeuroPace developed a brain-responsive neurostimulator called the RNS System for treating adults with drug-resistant focal epilepsy, using feature thresholding over 4 channels to detect seizures[23,24]. Also, ©Medtronic developed the Percept PC DBS system, which implements 4 Channels[25] and ©Neuralink developed a 1024-channel closed-loop Brain Machine Interface (BMI) implantable chip integrating neural recording and spike detection circuitry while using external devices for motor intention decoding[26]. The first human implant was reported and announced in March 2024[15]. Collectively, these neurotechnologies are considered potential game changers for the diagnosis, treatment, and even prediction of neurological and psychiatric disorders[27–29].

Notwithstanding the great progress in the field, most of the current developments remain confined to laboratory settings, and their performance must be enhanced to enable their application in real-life scenarios[29]. Artificial intelligence (AI) and Machine Learning (ML) techniques can offer support in this regard, empowering neurotechnologies to become more intelligent and achieve enhanced performance in real-world scenarios[30–33]. In this paper, we aim to review the current state of applied research in Neurotechnology, focusing on neuroprostheses and BMIs/BCIs, and to discuss potential future developments and clinical applications stemming from it. As a perspective, we will specifically emphasize the inherent potential of integrating Brain-Inspired AI-based processing with Neurotechnologies. In this context, we use the *"BCI"* term to refer to any Neurotechnology that communicates directly with the brain, either to extract information from it, or to feed information into it by means of brain stimulation. Also, we use the term *"BCI"*, or Brain-Computer Interface, as inclusive of both Brain-Machine and Neural Interfaces.

The paper is organized as follows: *Section "Neural Interfaces: The Brain Editors"* provides a comprehensive overview of methodologies employed to extract and transmit information to and from the brain. *Section "Brain-inspired Intelligence: Merging Neuroscience with AI"* scrutinizes the emerging generation of AI systems known as Spiking Neural Networks (SNN) or spiking neuromorphic architectures. *Section "From open-loop to close-loop intelligent BCIs"* delves into the application of SNNs in Neurotechnology. Finally, the concluding section presents our reflections and outlines our perspective and vision regarding the integration of brain-inspired computing with neural interfaces to develop Brain-Inspired Brain-Computer Interfaces/ Implants (BI-BCIs). These BI-BCIs would represent a novel generation of low-power, intelligent, and compact therapeutic devices with the potential to address a broad spectrum of neurological and psychiatric disorders.

Neural interfaces: the brain editors

Connecting brain to computers: BCI history and outlook

BCI is a general term for any technology that directly communicates with the brain and extracts information from it either by observing its unperturbed electrical signal or by eliciting a measurable neural response (evoked potential) through sensory stimulation (Fig. 1). This terminology was introduced by Vidal in 1970s, who first attempted to create a system capable of translating EEG signals (i.e., Electroencephalography, non-invasive method that records neural activity from the scalp) into computer control signals[34]. Research applications of BCI technology have evolved substantially over the past two decades[35]. Research and development of BCI technologies was boosted by the technological advancement of

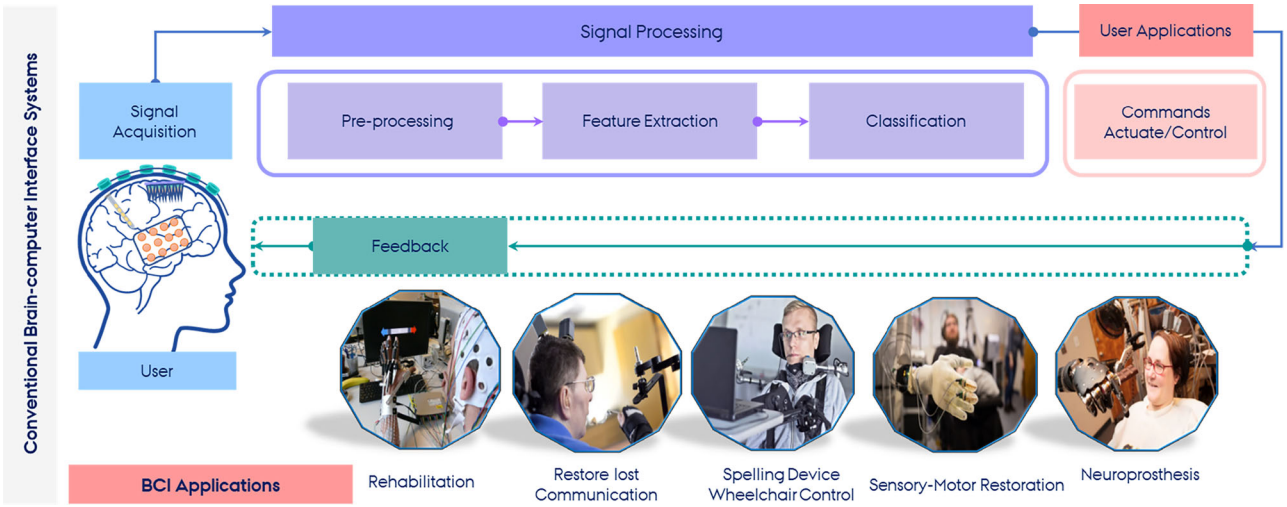

Fig. 1 | Generalized schematic for Brain Computer Interface (BCI) System. Neural signals are recorded from the scalp, cortical surface, or from within the brain by electrodes, etc. These signals are processed to extract the correlated features with the user's intentions. Subsequently, the extracted features are translated into commands to control/actuate a wide range of applications (Could be used to control devices, artificial limbs, or obtain knowledge of the user's intentions). Then, sensory information is fed back to the user either invasively or non-invasively.

microelectrode and single neuron recordings, both in rodent[36] and non-human primates[37,38]. Researchers used electrode arrays and implanted them in the parietal or motor cortex of patients with severe paralysis and tetraplegia to perform skilled motor movements with a robotic arm[39–41]. BCIs could be used to *restore* (e.g., unlock patients with locked-in syndrome), *replace* (e.g., BCI-controlled neuroprosthesis), *enhance* (e.g., user experience enhancement through computer games), *supplement* (e.g., VR, virtual reality, and AR, augmented reality, glasses), *improve* (e.g., lower limb rehabilitation after stroke), and as a *research tool* (e.g., coding and decoding brain activity with real-time feedback)[35,42–44]. BCIs can record and decode cortical activity while performing or imagining performing a task. The neural signals related to the intended movement can be transformed into visual[45], auditory[46–48], or haptic feedback of the movement[35,49]. Figure 1 illustrates the generalized schematic for classical BCIs and common state-of-the-art (SoA) applications.

BCIs can be classified into two main categories, depending on the way they interact with the brain. Specifically:

- *Active BCIs* employ either consciously induced brain activity from users, such as Motor Imagery (MI)[47,50,51] or brain activity induced by external stimuli (e.g., visual, auditory, or somatosensory stimuli)[35,44,50].
- *Passive BCIs* decode unconscious brain psychological states and do not require active participation from the user[52,53]. They have been used to monitor users' cognitive states including intentions, emotional states, situational interpretations[46,53], and drowsiness[54,55].

From the brain to external devices: recording and decoding

Recording techniques. Several techniques are employed to gather metabolic and electrophysiological signals from the brain, each offering distinct temporal and spatial resolution. Intracellular recordings measure the voltage across the cell membrane of a single neuron by placing electrodes inside and outside the membrane; they also capture the sub-threshold variations from resting potential. Extracellular recordings capture the summation of signals by nearby neurons, and they provide lower neural signal amplitudes in comparison to intracellular recordings, but they cover larger neural areas[56]. Based on electrode location, extracellular recording techniques can be categorized into either invasive or non-invasive methods[13,35]. Figure 2 presents commonly used neural recording electrodes for extracting neural signals from the central and peripheral nervous system. Furthermore, the most relevant non-invasive and invasive recording techniques, respectively, and their BCI applicability are summarized in Tables 2 and 3.

Non-invasive methods used for neural signals recording comprise electroencephalography (EEG)[57], magnetoencephalography (MEG)[58,59], and metabolic signals recorded either by functional near-infrared spectroscopy (fNIRS)[60], or functional magnetic resonance imaging (fMRI)[61]. EEG is the most employed technique in clinical setups for diagnosis purposes due to its non-invasive nature and ease of use. However, this technique captures only collective information from the top cortical layers of the brain, and it suffers from low spatial resolution, poor contact between the electrode and the scalp and low signal quality[57]. Wet EEG electrodes are typically made of metals and gels and mounted in elastic caps to enhance the signal quality. Dry electrodes (i.e., without gels) are more favorable and have a comparable performance with wet electrodes, yet they are less robust to moving artifacts and show higher electrode-tissue impedance[62,63]. To address these challenges, active electrodes with integrated preamplifiers have been developed; new materials have also been used to design EEG electrodes such as polymer foam electrodes, soft conductive textile electrodes, and others[62,63].

fMRI, another non-invasive technique, relies on blood-oxygen-level-dependent (BOLD) signals to capture changes in deoxyhemoglobin driven by localized variations in brain blood flow and oxygenation. This process, known as neurovascular coupling, links these changes to underlying neuronal activity. Although fMRI is more costly in the clinical setting, it provides significantly higher spatial resolution of metabolic signals (~1 mm) and greater sensitivity to subcortical regions compared to electrophysiological signals. fMRI is extensively used in cognitive research[64]. Researchers successfully reconstructed perceived visual images by analyzing fMRI signals obtained from the visual cortex[65]. Using comparable approaches, studies have shown that patients in a vegetative or minimally conscious state are able to comprehend and respond to instructions[66,67] (Table 2).

Alternatively, *invasive* methods such as electrocorticography (ECoG or μEoG)[68,69] and intracortical recordings (IR)[70–72] provide higher signal-noise ratio and higher-frequency signal bands, as well as better localization of brain activity as they enable more direct interaction with the brain. For instance, flexible μECoG electrodes have pushed spatial resolution down to 1 mm even in the sub-mm range[73], unlike conventional ECoG electrodes which have a pitch of around 1 cm. Transistor multiplexed ECoG arrays managed to increase the electrode density and channel count and reduce the area for routing wires[74,75]. Both ECoG and μECoG are used in preclinical and clinical research settings[76,77]. Lately, bundled arrays of microwires were used to interface with up to 1 million neurons through a neural input-output bus (NIOB) funded by DARPA[78]. Despite the improved performance in spike sorting and mechanical stability offered by microwires, this method still

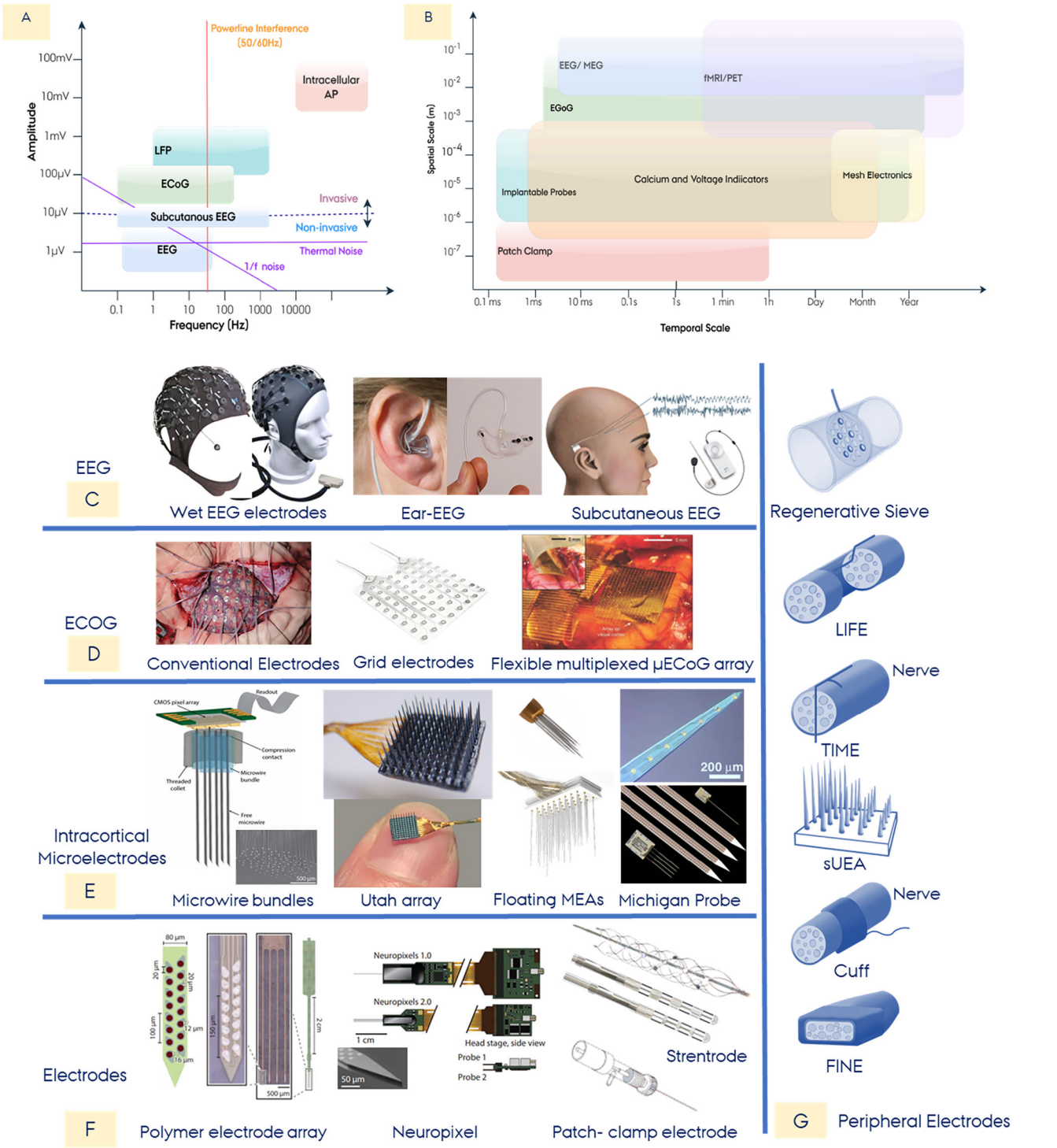

Fig. 2 | Neural signals and electrodes. A Common extracted neural signals; the vertical and horizontal solid lines represent the amplitude (V) and frequency (Hz) range of the extracted neural signals. The purple lines represent the thermal and 1/f noise from the circuit itself, while the red line represents the external powerline interference, which may degrade the neural signal. The shaded areas represent the span of each recording technique. AP action potential, LFP local field potential, ECoG electrocorticography, EEG electroencephalography[397]. **B** Spatiotemporal limitations of the various neurotechnologies, the rectangular shapes represent the spatiotemporal span of each neurotechnology. **C** Typical non-invasive electrodes wet EEG electrodes (128- Channels Quick cap by Neuvo), Ear EEG[398], subcutaneous EEG[399]. **D** Conventional invasive non-penetrating electrodes for ECoG recording, e.g., Flexible grid ECoG electrode array[400,401], transistor- multiplexed µECoG array[75,76,402]. **E** Intracortical penetrating needle shaped microelectrodes for recording e.g., microwire bundles integrated with CMOS chips for bundles[78], Utah array by Blackrock neurotech[80], floating microelectrodes array (MEA), planar Michigan probe[81]. **F** Commonly used recording neural electrodes: High density polymer-based electrode array for electrophysiological recordings[83], Neuropixel for long term Brian recoding[89,366], Stentrode - minimally invasive endovascular arrays for chronic recordings[357], patch-clamp electrode. **G** Peripheral nerve electrodes[403], e.g., TIME[87], LIFE[86].

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Table 2 | Non-Invasive Recording Methodologies and neurotechnological applications

Techniques Definition	Type	Resolution		Portable	Application	Publication
		Temporal	Spatial			
EEG **A method to record the electrical activity of the brain with electrodes placed on the scalp. It represents the macroscopic activity of the surface layer of the brain underneath.**	Electrical	~0.05 s	~10 mm	Yes	Epilepsy	314
					Motor learning & plasticity induction	334
					Multimodal BCI for psychological prediction (Attention, motivation, memory load, fatigue)	51,335,336
					Motor recovery after stroke	337
					Transfer learning (Inter-subject BCI)	338
					Motor rehabilitation (Parkinson's disease)	339
MEG **A neuroimaging method that uses SQUID to measure weak magnetic fields outside the head. It reflects the magnetic changes arising from cortical neural activity.**	Magnetic	~0.05 s	~5 mm	No	Multimodal BCI for motor rehabilitation	340
					Assistive technology (BMI for paralysis)	340
					MEG-based brain–computer interface (BCI)	58
					Real time control of neuroprosthetic hand	341
fMRI **Uses magnetic resonance imaging to detect local brain activity by measuring the changes in the BOLD signal.**	Metabolic	~1 s	~1 mm	No	Multimodal BCI for Psychological prediction (Attention, motivation, memory load, fatigue)	335,342
					Brain activity Regulation	45
					Neuroplasticity Rehabilitation of attention deficit	343
fNIRS **Measures the concentration variation of oxygenated and deoxygenated hemoglobin respectively HbO and HbR in brain tissue depending on changes of the exiting photon intensity and incident -photon intensity, then characterizes the local neural activity.**	Metabolic	~1 s	~5 mm	No	Multimodal BCI for Gait rehabilitation	60
					Robotic control	344
					Motor Rehabilitation	345
					Intention detection	346
PET **An imaging procedure. It is a combination of nuclear medicine and biochemical analysis. PET studies evaluate the metabolism of a particular organ or tissue, so that information about the physiology (functionality) and anatomy (structure) of the organ or tissue is evaluated, as well as its biochemical properties.**	Metabolic	~1-2 min	~4 mm	No	Limit potential Diagnostic tools of neurological disorders such as dementia, epilepsy	347
MRI **An imaging technique that combines strong magnetic fields, electrical gradients, and radio waves to measure the biological tissue composition and derive its structure.**	Hybrid (magnetic + electrical+ radio waves)	~1 s	~1 mm	No	Locked In syndrome.(Somatosensory Rehabilitation in stroke and phantom limb pain)	348
					Neurofeedback	64

EEG (Electroencephalography), MEG (Magnetoencephalography), *fMRI* (Functional Magnetic Resonance Imaging), fNIRS (Functional Near-infrared Spectroscopy), *MRI* (Magnetic Resonance Imaging), *BMI* (Brain Machine Interface), *BOLD* (Blood Oxygenation Level Dependent, *SQUID* (Superconducting Quantum Interference Device).

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Table 3 | Invasive Recording Methodologies and neurotechnological applications

Techniques Definition	Type	Resolution		Portable	Application	Publication
		Temporal	Spatial			
ECoG **Uses flexible subdural grid or strip electrodes that directly interface with the brain surface to measure cortical activity. It exhibits higher spatio-temporal resolution than EEG, larger bandwidth, and excellent signal-to-noise ratio (SNRs)**	Electrical	~0.003 s	~1mm (subdural ECoG ~1.25mm) (epidural ECoG ~1.4 mm)	Yes	Assistive technology neuroprosthetic control	68,349
					Motor learning and rehabilitation	69
					Intracranial BCI for severely motor-impaired patients	77,350
					Neural decoding and encoding (speech synthesis, text translation)	351,352
IRI **(Intracortical recording interfaces) are critical components of BCIs and consist of arrays of penetrating electrodes that are implanted into the motor cortex of the brain.**	Electrical	~0.003 s	LFP ~ 0.5mm MUA ~ 0.1 mm SUA ~ 0.05 mm)	Yes	BCI for ALS, Diagnostics, Therapeutic Treatments	353
					Neural decoding and stimulation, robotic prosthetics control	354,355
					Assistive technologies and clinical BCI	41,71
					Restoration of mobility and communication, cursor control, epilepsy monitoring	41,71
Endovascular recording (Stentrodes)	Catheter angiography guided implantation	-	At least 2.4 mm-	Yes	Minimally invasive BCIs (Ongoing Human trails) Motor neuroprosthesis	356,357
					Endovascular Brain-Computer Interfaces in Poststroke Paralysis	358
Neural Dusts	-	-	-		Optogenetics Parkinson	359–365
Neuropixel	High density probe for stable long-term brain recording	-	-	-	Recording thousands of individual neurons in living brain (Freely moving animals and recently tested in humans)	89,366,367

ECoG (Electrocorticography), *PET* (Positron Emission Tomography), *IRI* (Intracortical Recording Interfaces), *iMEA*, (intracortical Microelectrode Array), *ALS* (Amyotrophic Lateral Sclerosis).

faces challenges in signal attenuation and crosstalk. To overcome these limitations, silicon-based needle-shaped microelectrodes enabling multisite recording were proposed[79–81]. Yet, rigid probes may lead to tissue damage and inflammation, which may degrade the recorded neural signal[82]. Differently, polymer-based flexible electrodes ensure tight and conformable geometries, which make them more suitable for chronic long-term implants[83]. Despite their flexibility, their insertion can be challenging as they are prone to bending and deflecting. To address this issue, a robotic insertion method for polymer electrodes has been introduced[84], also carbon fiber high-density arrays have been developed[85]. Flexible intra-fascicular electrodes such as LIFE (Longitudinally Intra-Fascicular Electrodes)[86]and TIME (Transverse Intra-fascicular Multi-channel Electrodes)[87] have been used in the peripheral nervous system, and they are showing a promising future for neuroprosthetic applications[88].

The latest advances in CMOS enabled the fabrication of high-density micro-electrode arrays/probes, allowing simultaneous recording from hundreds of neurons in the brains of humans and monkeys. Unlike conventional electrodes, the novel electrode technologies based on organic material, multifunctional flexible polymer fibers and meshes, offer increased spatial integration (e.g., Neuropixels[89], NeuroGrid[90]and SiNAPS[91]), long-term temporal stability (e.g., mesh electronics), and improved biocompatibility[92]. In parallel, advances in optical cellular imaging have shifted the number of neural recordings by several orders of magnitude. For example, Kim et al. used such a technique to optically record the activity of up to one million neurons in a single rodent[93]. While numerous studies utilize transgenic mice with constitutive GECI (genetically encoded calcium indicators) expression, modified viruses have been employed to introduce a genetic construct inducing expression in non-transgenic animals. Likewise, viral delivery methods have been used in humans for gene therapy. Despite the challenges posed by such technologies (e.g., optical access to neural tissues, need for high-precision microscopes), the combination of these and other methods holds the potential to facilitate the recording of millions of neurons in humans in the future[94] (Table 3).

A major application of invasive BCIs is assisting paralyzed people, for example by implanting subdural electrodes over the cortex[77]. Higher bandwidths could be achieved by implanting electrode arrays deeper into different areas of the cortex to record neuronal spiking activity[39,95]. The recorded spiking activity can be used to decode user's intention to move the hand in a certain direction or control a robotic arm for skilled movements[39,95]. Bouton et al. demonstrated that a quadriplegic patient with a 96-electrode array implanted in the motor cortex's hand area managed to utilize cortical signals to electrically activate/stimulate muscles in his paralyzed forearm. This process enabled him to execute six distinct movements involving the wrist and hand[96]. Also, Lajoie, G., et al. used bidirectional BCI to artificially induce task-related neuroplasticity[97]. In summary, such BCI methods mainly target brain regions that represent low-level and high-level motor commands to restore motor control in patients. In addition, these methods could be used to read the neural codes associated with perceptions[98], attention[99], and decisions[100]. Recently, invasive BCIs enabled researchers to decode the thoughts of a person from the activity of their "concept cells", which were discovered for the first time in the temporal lobe of patients implanted with electrodes to identify brain regions responsible for intractable epilepsy[101]. They also found out that these cells represent abstract concepts about specific places and people, and they get activated when the person thinks, sees, or retrieves memories about such concepts[102,103]. While this study recorded only a single cell or a few neurons at a time, the potential for clearer monitoring of thoughts exists through the simultaneous recording of larger numbers of concept neurons. Enhanced capability in extracting complex intentions could potentially revolutionize communication BCIs, particularly in decoding the intentions of patients with locked-in syndrome, such as in the case of Amyotrophic Lateral Sclerosis (ALS)[13,104].

Decoding neural signals for BCI applications

Neural decoding methods focus on extracting information from neural activity, either to reconstruct the event or stimulus that generated it, or to predict the actions that it might elicit. For classical BCIs, a decoder typically includes three main procedures: *signal preprocessing, feature extraction, and pattern classification*, as shown in Fig. 1. *Signal preprocessing*, such as artifact reduction methods, aims to eliminate the noise from the recorded neural signals and extract useful components. *Feature extraction* entails identifying the most relevant features linked to the subject's intention from the neural activity. These features could include spectral power, event-related potentials (ERPs), firing rates of individual neurons, etc. *Pattern classification*, on the other hand, differentiates the diverse classes of users' intentions based on the extracted features. Among these processes, pattern classification stands as the pivotal algorithm in decoding brain signals[77,95,105].

Various approaches have been explored for neural decoding, including linear models, Kalman filters[106], state-space models, Bayesian decoding, information theory[107] and more advanced techniques based on Artificial Neural Networks (ANNs) like Deep Learning models such as Recurrent Neural Networks (RNNs) or Convolutional Neural Networks (CNNs)[108] to produce accurate predictions using spikes[109] or intracortical LFPs[110,111]. Several attempts have been made to employ non-linear methods for neural decoding, such as particle filter and unscented Kalman filter. Most of the non-invasive BCIs are based on classification of mental states rather than on decoding kinematic parameters, as is typically the case for invasive BCIs. F Lotte et al. present an updated review of EEG-based BCIs classification algorithms and distribute them over four main classes: adaptive classifiers, matrix and tensor classifiers, transfer learning and deep learning, plus a few other classifiers[112].

Despite the success of traditional linear decoding methods, recent advances in AI and ML have led to even more effective techniques[108], which have been employed for brain signal decoding and classification[100,101]. For example, Deep Neural Networks (DNNs) have been used to interpret activity patterns elicited by visual stimuli and predict them with a remarkable precision close to 90%. Interestingly, lower layers in DNNs represent simple features while higher layers represent conceptual information, which in turn can be mapped to different brain regions[113]. Therefore, the development of novel technologies for recording and decoding neural activity could enable researchers to decipher the human brain, unveiling subjects' intentions, preferences, thoughts, and emotions. However, this raises concerns regarding privacy, security, and mental ownership.

From external device to the Brain: Stimulating and Encoding

Stimulation techniques. Several technologies have been developed to influence neural activity. Technologies in this context encompass a broad spectrum, ranging from those focused on repairing and replacing impaired neural functions, such as neuroprosthetics, to those aimed at regulating dysfunctional neural activity, known as neuromodulation techniques[114,115]. Indeed, modulation of neural activity can be done either by stimulation (i.e., by applying physical energy e.g., electrical, magnetic, optical, acoustic, directly to brain regions) or by neurofeedback (i.e., without direct brain stimulation).

Neuromodulation can be administered through diverse methods, including *non-invasive* techniques such as transcranial magnetic stimulation (TMS)[116,117], transcranial direct current stimulation (tDCS)[118], transcranial electrical stimulation (TES)[118], Focused Ultrasound Stimulation (FUS)[119], and transcranial focused ultrasound (tFUS)[120], as well as *invasive methods* such as Surface Cortical and IntraCortical Micro-Stimulation (ICMS)[70] both focusing on the cortex, Deep Brain Stimulation (DBS)[6,7] which focuses on deep brain tissue, Spinal Cord Stimulation (SCS)[121], and Vagus Nerve Stimulation (VNS)[122,123] (Fig. 3).

Non-invasive brain stimulation approaches offer distinct advantages as they obviate the need for surgery and most patients prefer it, yet they often entail the use of bulky wearable devices or uncomfortable wearability features, which can result in skin irritation and damage. They typically offer limited spatial resolution compared to invasive methods, and their precise effects on brain activity remain to be fully elucidated. For example, tDCS still encounters the challenge of avoiding skin irritation, whereas TMS uses current pulses to generate magnetic fields that stimulate the nervous

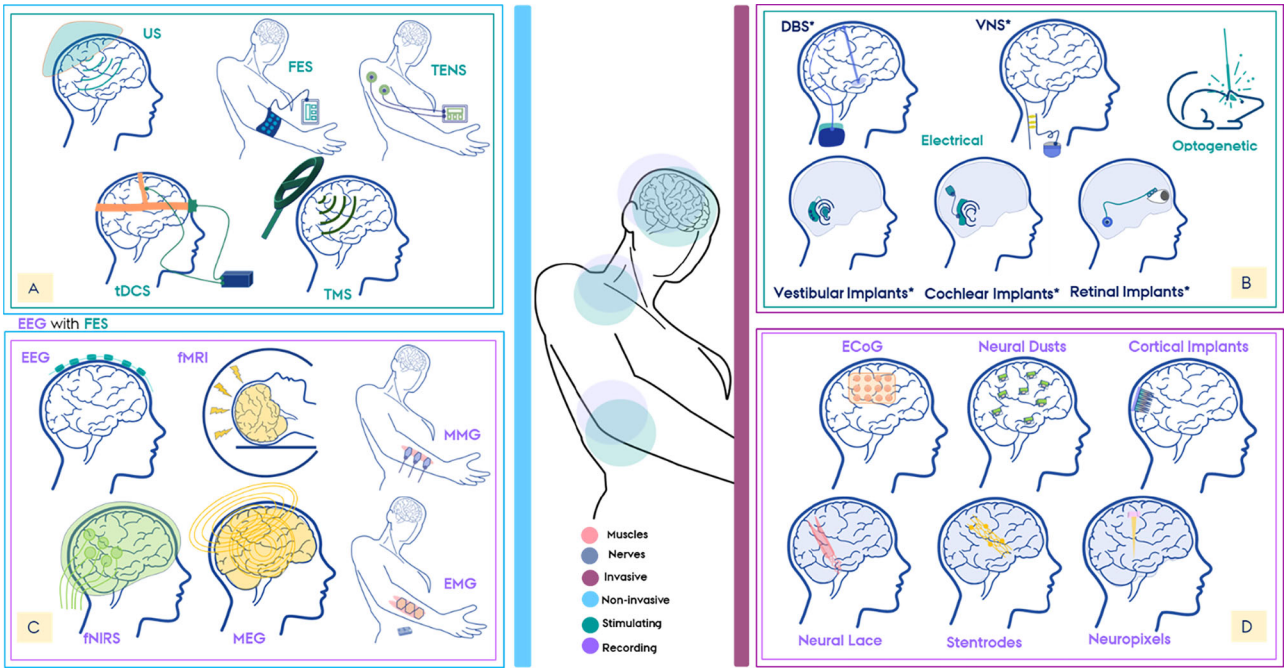

Fig. 3 | Neural stimulation and recording methodologies: Invasive vs. Non-invasive. On the left, in blue represents the non-invasive interfaces, while on the right, in red represents the invasive interfaces. Stimulation vs. Recording interfaces: **A**, **B** represent some of the stimulation interfaces. **C**, **D** Represent some of the recording neural interfaces. FES: Functional Electric Stimulation, TENS: Transcutaneous Electrical Nerve Stimulation, tDCS Transcranial Direct Current Stimulation, TMS: Transcranial Magnetic Stimulation, US: Ultrasonic stimulation, EEG: Electroencephalography, fMRI: Functional Magnetic Resonance, fNIRS: Functional Near infrared Spectroscopy, MEG: Magnetoencephalography, EMG: Electromyography, MMG: Mechanomyography, ECoG: Electrocorticography, DSB: Deep Brain Stimulation, VNS: Vagus Nerve Stimulation.

system[115]. Focused ultrasound stimulation (FUS), a non-invasive method to stimulate the brain acoustically, although it typically requires an external ultrasound transducer. More advanced neuromodulation techniques such as paired stimulation and temporal interference[124], could be used to synchronize various brain regions and administer therapy deeper into the brain. Stimulation could be adapted according to biological rhythms; some devices can even adjust stimulation on a pulse-by-pulse basis[114].

On the other hand, *invasive methods* provide higher spatial specificity and longer-term interaction and require less patient interaction. Electrical stimulation-based approaches have been extensively developed, and many such as DBS, SCS, and VNS are clinically approved for treatment[114]. For instance, spinal cord implants allow patients to relieve chronic neuropathic pain by sending low-level electrical impulses directly into the spinal cord[121,125] and closed-loop VNS has demonstrated its eligibility in restoring neural connectivity and motor control after spinal cord injuries, as presented in[126]. Also, DBS has been used to treat neurological and neuropsychiatric disorders by modulating or regulating internal brain states rather than controlling external motor movements[127,128]. It has been clinically tested for treating psychiatric disorders including depression and obsessive-compulsive disorder (OCD)[129,130]. ICMS has been applied to elicit sensory feedback with high spatiotemporal accuracy[70,131–133]. Modulation entails creating potential gradients across neurons to elicit functional responses, such as triggering action potentials, by depolarizing the cell membrane for stimulation and hyperpolarizing it for inhibition. The modulation of the stimulation parameters (i.e., amplitude, polarity, frequency, pulse width, etc.) affects outcomes like the rate of nerve excitation; it also influences the spatial selectivity within the nerve bundle. Currently used stimulation patterns are still considered rudimentary due to electrodes' large contact point surface areas. In addition, long-term implantations can develop scar tissue and fibrotic response, which in turn leads to time-varying contacting interface properties and the required stimulation parameters[134]. Another constraint for using electrical stimulation for neuromodulation is limited control of targeted therapeutic outcomes due to difficulty in selectively stimulating specific cells and regions[135]. Future technological advancement is needed to augment the electrodes' precision and maximize the therapeutic output while minimizing risks[136].

Taking a longer-term perspective, optogenetics, a newly developed invasive optical-based method for modulating neurons' activity through light and genetic modification, may offer higher specificity in neural modulation, thereby enabling direct inhibition or excitation of activity in specific cells[137,138]. This technique involves the implantation of an optical fiber to deliver light to specific areas within the brain, which is known for its highly scattering tissue. It has enabled neuroscientists to explore neural microcircuits in mice that were previously uncharted. It mainly depends on bulky photo microscopes, which makes it impractical for clinical. Till now, it is only been utilized in animal studies[139,140]. Researchers believe that increasing optical methods precision, quality, and bandwidth could shift the brain stimulation techniques therapeutic potential significantly by utilizing its ability to activate specific subsets of neurons[137,141]. Researchers demonstrated that the activation of higher brain regions by stimulation may lead to a change in the subject's behavior and emotional state[142]. For instance, A recent study shows that optogenetic stimulation could steer complex behaviors such as attacking a prey[143], eating, drinking, and sexual behavior in rodents and other animals[144]. Also, functions like memory and attention can be influenced[145]. For instance, the stimulation of the parietal cortex or frontal eye field modulates visuo-spatial attention[146,147], likewise electrical stimulation of the temporal lobes induces vivid recollection of memories of a patient's past[148]. Several BCI applications instead target behavior change to avoid certain diseases, for example, Lipsman et al. used it for the treatment of refractory anorexia nervous[149]. Researchers could also suppress or reinforce certain behavior by inhibiting or activating a set of neurons (e.g., activation of dopamine neurons in the ventral tegmental area, activation of circuits that mediate aversion in the lateral habenula)[150,151].

Despite its high potential, optogenetic stimulation is still not ideal for neuromodulation in humans. Several efforts have been made to develop a non-invasive cell type-selective stimulation method. Researchers investigated alternative stimulation methods that are more sensitive than optogenetic mediators and less penetrating than light. Sonogenetics - a

noninvasive stimulation method- employs ultrasound waves to activate exogenous ultrasound-sensitive mediators or actuators within specific neurons or cell types, allowing for the manipulation and control of their activity. Its therapeutic ability has been tested in animals. The results show that sonogenetic stimulation of the visual cortex of the rodents induces a behavioral response associated with light perception[152,153]. This discovery could be used to restore vision in blind people. Also, it has been clinically tested for treatment of neurodegenerative diseases such as Parkinson[152,153]. Figure 3 presents the SoA of existing invasive and non-invasive neurotechnologies for stimulation and recording.

Encoding neural signals for BCI applications

Researchers have been exploring techniques to encode and deliver information in a biomimetic or artificial fashion by stimulating neuronal networks inside the brain and in other parts of the nervous system. These efforts encompass various sensory modalities, including auditory[10,154], visual[155,156], proprioceptive[157], and tactile perception[158–160].

As regards the restoration of sensory modalities, the first attempts were made with cochlear implants, which electrically stimulate the inner ear (i.e., spiral ganglion nerves) and meanwhile became the common treatment for deafness[161]. The implant consists of an array of electrodes implanted along the cochlea such that each section stimulates a region corresponding to a specific frequency. Most encoding strategies are based on amplitude modulation of a biphasic current pulse train. Yet, recent work used a bio-inspired encoding strategy based on the electrically evoked compound action potentials, showing better representation of spectral and temporal information[161]. Recently, researchers have been focusing on the development of event-based cochlea using FPGA[162], CMOS[163], or neuromorphic microelectromechanical systems[164].

Also, restoring vision in patients with damaged retina has been realized, either by electrical stimulation of living cells through retinal chips[155] or by chemical or optogenetic stimulation that re-establish retina's light sensitivity[165–167]. Scientists implanted stimulation electrodes in the visual cortex to activate the neurons nearby (tens of micrometers around the electrode) and then evoke visual percepts in the brain[155,168]. Such a visual cortical prosthesis uses a camera mounted on a pair of glasses to capture visual information. The information is processed by a BCI system and translated into stimulation patterns that are delivered to the cortex through microelectrodes. Each stimulation electrode evokes a phosphene (i.e., the percept of light) to later build a visual image (pixel by pixel)[12]. Stimulating higher visual cortical areas elicits more detailed percepts like motion or depth, as well as shapes of faces[169] and spatial layout of scenes[170] by stimulating the temporal cortex. Despite advancements, the sensations elicited by these devices are still perceived as artificial and distorted. Hence, understanding the effects of stimulation on the nervous system could lead to breakthroughs in the field of neuroprosthetics. For instance, in visual implants, altering the stimulation waveform by adjusting the threshold can influence the response of retinal ganglion cells, leading to improved spatial resolution in shape recognition. Another limitation of stimulation is the spread of activation for each electrode (as it is not point t-like), which can be mitigated by shaping algorithms that adjust the current flow[171]. Different strategies exist to create effective stimulation techniques. For example, deep neural networks- based approaches can be trained to mimic the underlying biological system to construct end-to-end neural prostheses[172]. Also, convolutional neural networks are employed to predict electrode activation patterns necessary for generating desired visual stimuli[173].

Further progress has been made on restoring tactile feedback in upper limb prostheses either by directly stimulating the residual peripheral nerves with electrical stimulation[174,175] or by stimulating the somatosensory cortex of non-human primates[158] and humans[70,131,176]. However, the primary challenge remains the necessity for a comprehensive understanding of how complex thoughts are encoded in brain activity as well as the technical capability to evoke activity patterns essential for direct communication of information to higher-order cortices, such as the parietal and temporal cortex.

Currently, in the field of neuroprosthetics, the common approach to neural stimulation primarily involves modulating the pulse waveform of the stimulation train, often utilizing a single parameter coding method mostly applied to individual channels of the neural interface. The employed encoding functions modulate the injected charge by manipulating pulse amplitude[177], pulse width, or pulse frequency of the neurostimulation pulse-train based on values obtained from prosthetic sensors[178,179]. This encoding typically follows a linear and proportional relationship with sensor readings (i.e., as the measured pressure increases, the stimulation charge/ intensity increases). Consequently, the perceived sensation is proportionally associated with both the stimulation charge and frequency (i.e., higher injected charges lead to higher perceived sensations). However, this approach frequently results in sensations that feel unnatural, commonly described as vibrations, electricity, tingling, or paresthesia by users[177,180].

An alternative approach known as biomimetic encoding[181–183], which employs tailored transfer functions derived from perceptual representations of natural sensory processing, has been implemented in PNS for both upper and lower limb prostheses. This approach has shown its effectiveness in replicating more natural sensations[183] with minimal learning and providing more informative feedback to perform functional tasks[181]. In particular, the artificial readouts from the prosthetic sensors are converted into biomimetic neurostimulation patterns. These translated signals are subsequently converted into current impulses, which are then delivered to the residual peripheral nerve via electrodes implanted (such as TIME, LIFE, etc.) directly into the nerve itself[181,183]. Furthermore, within the CNS, multichannel biomimetic ICMS has been deployed and assessed in a bionic hand. The results indicate that it conveys finely graded force feedback in BCI that more closely approximates the sensitivity conferred by natural touch[184].Table 4 summarizes the developed brain stimulation technologies and their BCI applicability.

Brain-inspired intelligence: merging neuroscience with AI

Neuromorphic computing

With the rapid growth of AI and development of neural networks, AI technologies nowadays display outstanding abilities in multiple cognitive tasks such as large language models (LLMs) like OpenAI's GPT series that generate text in a human-like fashion and AlphaZero that overcomes human players at several strategic games like the board game Go, chess, etc[185]. Though such performance is outstanding, the key question is still how to reduce the computational cost of these algorithms and how to get brain-like efficiency? The human brain is one of the most fascinating organs. It is a remarkable information storage and processing system with impressive computation-per-volume efficiency. The raw computational power of the human brain ranges between 10^{13} to 10^{16} operations/sec[186,187]. It performs diverse operations such as recognition, reasoning, control movement with a power budget of about 20 W (like a lightbulb)[188] and a power density of $1.1–1.8 \times 10^4$ w/m^3 at an operating temperature of 37 °C[187]. In contrast, running AlphaGo requires power of approximately 170 KW (it uses around 1202 CPUs (central processing units) and 176 GPUs (graphics processing units)). Neurons and synapses constitute the fundamental computational units and storage of the human brain[189]. Brain neural networks are formed by billions of neurons ($\sim 9 \times 10^9$ neurons) interconnected with trillions of synapses ($\sim 3 \times 10^{14}$ synapses). Neurons are responsible for transferring information through discrete action potentials or 'spikes, while synapses are the intrinsic elements for temporal information processing, long-term and short-term memory storage, and deletion. Also, synapses act as signal transducers and plasticity mediators. Apart from neurons and synapses, studies have also revealed that several elements such as dendritic trees, axons, proteins, and neural microtubules contribute to the brain storage and computation capabilities[190–193]. Based on the discovery that dendrites generate 10 times more spikes than neurons and that they are hybrids that could process both analog and digital

Table 4 | Stimulation Techniques and BCIs' applicability

Techniques Definition	Invasiveness	Context of Application	Publication
DBS **Surgical procedures chronically implant electrodes into the brain to allow stimulation of deep structure.**	Invasive	Chronic pain treatments	368
		Treatment of resistant movement and neuropsychiatric disorders	130
		Parkinson disease	7
		Obsessive-compulsive disorder (OCD)	129
		Treatment of psychiatric disorders (depression)	8,130
ICMS **Intracortical Microsimulation**	Invasive	Modulation of cortical activity	369
		Restoration of tactile feedback	70,132
		Restoration of vision	370,371
FUS **Non-Invasive neuromodulation method that focuses on a beam of high-frequency sound waves to synchronize at a specific location of the brain to influence neuronal activity.**	non-Invasive	Modulation of brain and behavior	120
		Brain modulation (Human somatosensory cortex activity modulation)	120,372
Sonogenetics **A method used to selectively control neural activity through genetically encoded ultrasound-responsive mediators or actuators. It is feasible both in vitro and in vivo and has sub-mm spatial and sub-sec temporal resolution.**	Non-Invasive	Neuromodulation	152,373,374–376
		Drug delivery	
OS **A method for controlling cellular activity using light. It involves genetically modified neurons to express light-sensitive ion channels or pumps which can be opened or closed with light of specific wavelengths.**	Invasive (minimally invasive)	Choice biasing in primates	146
		Restoration of light sensitivity of the retina	12,165
		Behavioral control (e.g., pursuit of prey)	143
		Optogenetics, electrophysiology and pharmacology with an ultrasonically powered DUST for Parkinson's disease	360,361,363
tDCS **Non-invasive brain stimulation method in which a low constant direct current is applied to electrodes on the skull to elicit current flow in the underlying brain tissue.**	Non-invasive	Behavior modulation, neuroplasticity	118,377,378
		Hyper interaction (Brain to brain interface)	379,380
TMS **Non-invasive brain stimulation technique that uses a changing magnetic field outside the skull to generate a localized electric current in the brain via electromagnetic induction.**	Non-invasive	Cognitive and clinical neuroscience	116,117,381

FES (Functional Electrical Stimulation), *TMS* (Transcranial Magnetic Stimulation), *DBS* (Deep Brain Stimulation), *ICMS* (IntraCortical MicroStimulation, *FUS* (Focused Ultrasound Stimulation), *OS* (Optogenetic Stimulation), *tDCS* (transcranial Direct Current Stimulation).

signals, the estimated human brain computational capacity rises 10 times higher than previously thought[186,187,194].

These intertwined networks of neurons and synapses, along with the temporal spiking processing, enable the fast and efficient transfer of information between the brain's various areas. State-of-the-art artificial intelligence is intrinsically based on neural networks, which are inspired by the brain's hierarchical structure and neuro-synaptic architecture. Deep Neural Networks (DNN) are hierarchical structures composed of multiple layers or transformations that represent variable features within input data. For example, deep convolutional neural networks are multilayered models inspired by the primate visual cortex[195,196] and utilize synaptic storage and neuronal nonlinearity to learn representative features. These neural networks are powered by conventional hardware computing systems based on CMOS transistors. Billions of transistors can be integrated on a single silicon chip for enormous computing platforms. Such platforms have been a key enabler in the current machine learning revolution. Today's DNNs are trained on powerful cloud servers, yielding incredible accuracy although incurring huge energy consumption. For instance, the deployment of a deep network on an embedded smart-glass processor would drain its battery (2.1 Wh) within 25 minutes[197]. It may be possible to enable energy-efficient machine intelligence by designing full-custom hardware that mimics the dynamics and architecture of biological brains, achieving greater power efficiency. Nevertheless, obtaining a high degree of connectivity in neuronal networks and replicating their time-dependent plasticity of synapses are the biggest challenges in this endeavor.

In the 1980s, neuromorphic computing was introduced to mimic human brain functionality by exploiting the similarity between ionic transport across the neuron membrane and carrier diffusion in the transistor channel[198]. A key characteristic of neuromorphic computing that distinguishes it from conventional computing is its spike/event-driven nature of information representation and communication[198]. Currently, researchers are exploring the advantages of using spike-driven computations to promote scalable, energy-efficient SNNs. In this regard, the neuromorphic computing field could be described as a synergetic domain that focuses on both hardware and software tools to enable spike-based artificial intelligence[199]. It has become an appealing paradigm to overcome the von-Neumann bottleneck and accelerate computing efficiency[199]. Brain-inspired computing systems and conventional digital (von-Neumann) computing architectures present the following key contrasting characteristics: (1) Neuromorphic computing systems (NCSs) exhibit highly parallel operation; thus, neurons and synapses operate in parallel, even though the computations performed by neurons and synapses are still simple in comparison to von Neumann systems[200–202]. (2) Both the processing unit (i.e., neurons) and memory (i.e., synapses) are co-located on the same hardware unit, which reduces data communication and improves throughput. (3) NCSs are inherently scalable. In other words, adding more neuromorphic chips could increase the number of neurons and synapses implemented without incurring significant technical obstacles. Several neuromorphic chips can also be combined and treated as a single neuromorphic implementation, such as in SpiNNaker[203,204], Loihi[205], and mixed-signal chips[206,207]. (4) Some NCSs display stochasticity which may be

exploited for computation. (5) Moreover, NCSs use asynchronous, event-driven computations (i.e., it computes only when the data are available), which allows them to be more energy efficient and have lower latency than conventional systems[208]. Table 5 presents a short comparison between conventional (Von-Neuman) architecture and bio-inspired (non-Von-Neuman, e, g., neuromorphic) architectures.

Hardware implementation: CMOS neuromorphic chips

Neuromorphic computing systems could become natural platforms for future AI and machine learning applications, as they inherently operate at extremely low power and implement neural network computation style. Both industry and academic researchers have keen interest in developing and implementing neuromorphic systems. Notable examples of industrial neuromorphic chips include IBM's TrueNorth[209] and Intel's Loihi[205]. In academia, many groups aim to build large-scale neuromorphic chips, for instance, BrainScales[210,211], SpiNNaker[203,204], NeuroGrid[212], IFAT[213] and DYNAPs[206]. These chips have their own specific end-to-end software toolchains and applications. Different tasks, such as keyword spotting, medical image analysis and object detection, have been successfully implemented on existing platforms like Intel's Loihi and IBM's TrueNorth, showing the efficiency of the neuromorphic hardware platforms for specific applications[214,215]. Alternatively, there is research emerging to create general-purpose neuromorphic platforms that connect hardware and software frameworks for wider classes of applications[199,200]. For example, Tianjic is a hybrid neuromorphic chip that was developed to support both neuromorphic SNNs and traditional ANNs[216]. The previously mentioned large-scale neuromorphic chips are silicon-based and implemented with conventional Complementary metal oxide semiconductor (CMOS) technology either in digital (synchronous or asynchronous), analog (subthreshold or super-threshold), or mixed signal (where, in general, neurons are implemented in analog and synapses and learning are implemented in the digital domain)[199,200].

Despite remarkable progress in CMOS-based neuromorphic computing systems, they are far from the brain's energy- and area efficiency, which limits the scalability of such networks[217]. This has driven a significant effort to investigate non-CMOS implementations of ANNs using emerging technologies such as memristors[218,219], magnetic tunnel junctions (MTJs) and spin Hall nano-oscillators (SHNOs)[220], etc., as synapses, and MTJs[221,222], spin-torque nano-oscillators (STNOs)[223–225], SHNOs[226], phase change materials (PCM), ferroelectric, topological insulators, biomolecular memristor, no-filamentary, etc[227,228]. as artificial neurons. Meanwhile, memristive technologies are used to build resistive memories to collocate both processing and memory units (in-memory computing)[200,229]. On the other hand, spintronics is a strong contender as it is CMOS-compatible, multifunctional, and extremely versatile, with features like non-volatility, plasticity, and oscillatory behavior which can be exploited to implement both artificial neural components (i.e., neuron and synapse) to develop energy-efficient ANNs. Each of these technologies has shown unique features that significantly improved energy efficiency with comparable footprints as biological counterparts. Figure 4 (adapted from[201]) represents the structural organization of the central nervous system from carriers (1A°) until the brain and the most common methods used to study it (top-down analysis), alternatively, it shows the equivalent neuromorphic systems used to mimic

Table 5 | Fundamental differences between conventional architecture and neuromorphic architecture

	Conventional architecture	Neuromorphic architecture
Organization	Separated Computation and Memory units	Collocated processing and memory
Operation	Sequential processing	Parallel processing
Timing	Synchronous (clock-driven)	Asynchronous (event-driven)
Communication	Binary	Spikes
Programming	Digital (code with binary instructions)	Spiking neural network (SNN)
Learning	Non- local	Local

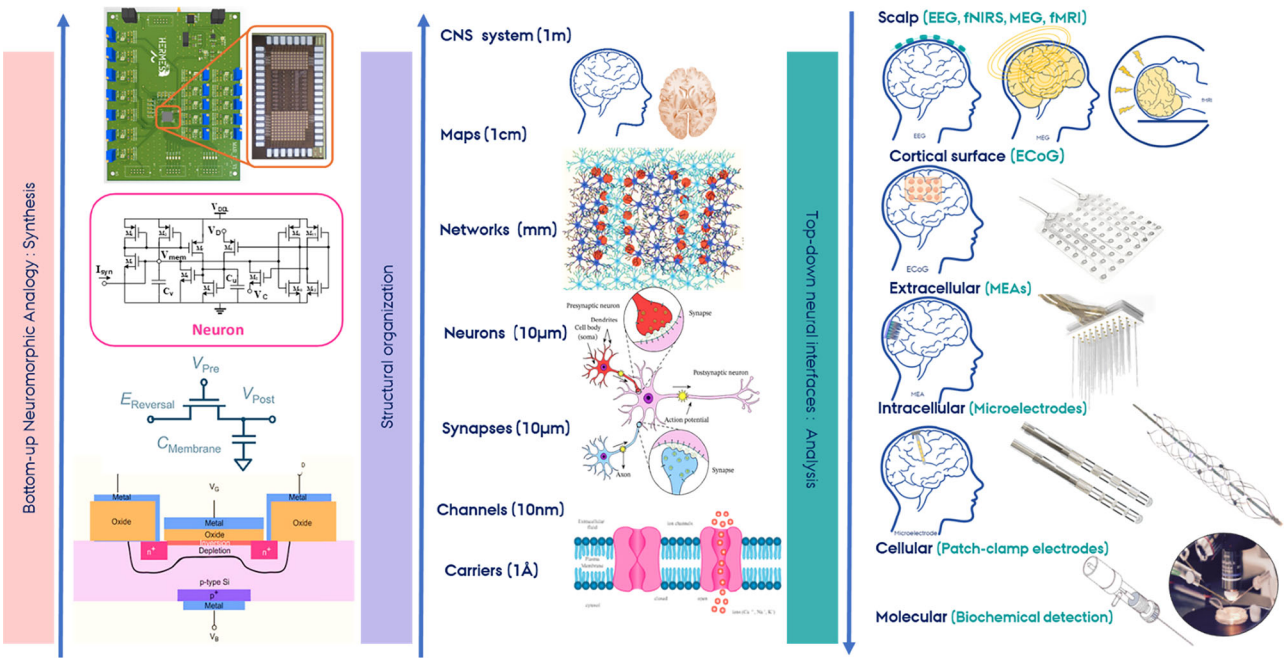

Fig. 4 | Multiscale structural organization of the central nervous system (CNS) with its corresponding neuromorphic equivalents and neural interfaces used for its investigation. The middle section shows the structural organization of the CNS. The rightmost side illustrates the methods used to interface with and investigate the CNS, spanning from the molecular level to scalp-level modalities, whereas the left side shows the corresponding neuromorphic equivalents, ranging from ionic channels at the bottom to large-scale neural networks implemented on neuromorphic chips at the top.

Table 6 | Summary of state-of-the-art for designing neuromorphic systems from materials to applications

Materials	Technology	Circuits Micro-architecture System architecture	Algorithms	Applications
1. Phase-change materials 2. Ferromagnetic materials 3. Ferroelectric materials 4. Non-filamentary RRAM materials 5. Topological insulator materialsChannel-doped bio-membrane	1. Electrochemical transistors 2. Spintronic 3. Memristors 4. Optical devices 5. Charge-trapping transistors 6. Phase-change memories 7. Ferroelectric transistors 8. Threshold switching devices	1. Digital 2. Analog 3. Mixed signal	1. Feed-forward neural network 2. Recursive neural network 3. Reservoir computing 4. Spike-based backpropagation 5. Mapping (conversion-based) 6. STDP 7. Graph-based 8. Evolutionary based	1. Control 2. Classification 3. Security 4. Benchmarks 5. Neural signal processing 6. Forecasting 7. Edge-computing

the brain (bottom-up analogy). Also, Table 6 presents a summary for designing neuromorphic systems from materials to applications[199,200,228].

Spiking Neural Networks SNNs: analogy, overview, and perspectives

SNNs are considered as the third generation of ANNs[230]. Bearing in mind that neurons communicate via electric pulses or action potentials (AP) called spikes. It was only in the early 90's that neuroscientists discovered that biological brains use the exact timing of spikes to encode information[231]. This, in turn, boosted the development of spike-based neural networks to further understand the information processing skills of the brain. SNNs provide a more biologically realistic, brain-like approach compared to ANNs by incorporating spatial and temporal considerations through neural connectivity and plasticity. Their ability to deal with precisely timed spikes makes them competitive with traditional ANNs in terms of accuracy and computational power, and in some cases, better suited for hardware implementation[232,233]. Table 7 presents a concise comparison between ANNs and SNNs.

Neuron--The basic computational unit for ANNs is the artificial neuron, and its input is processed by an activation function *f (-)*, while the SNN unit is the spiking neuron, which is expressed by a set of differential or difference equations ($x_t = f(x_{t-1})$). SNNs employ various spiking neuron models to simulate nervous system dynamics and neuronal properties underlying the generation of electrical potential across the cell membrane (Fig. 5). Neuron models implemented in SNNs in the literature range from simple linear models with a fixed threshold and non-linear models with a spiking mechanism, to more complex and biologically plausible models[234] (Fig. 6). The representative neuron models used in literature are: (i) Leaky Integrate-and-Fire (*LIF*)[234], (ii) Hodgkin–Huxley (HH)[235], (iii) Izhikevich[236], and (iv) FitzHugh Nagumo[237]. In the LIF model, a charge is integrated over time until a threshold value is reached. In brief, a neuron emits a spike each time its membrane potential gets to a specific threshold, after which it enters a hyperpolarization state during which it is impossible to emit another spike for a certain time (i.e., absolute refractory period). This can be modeled by an electrical circuit consisting of a capacitor in parallel with a resistor and driven by current I(t). The Hodgkin–Huxley model also approximates the neuron action potential generation mechanism by a simulation of ion channel dynamics. On the other hand, the Izhikevich neuron is claimed to be as biologically plausible as the Hodgkin–Huxley model and computationally effective as the LIF model[199,234]. SNNs use mainly event-driven and clock-driven dynamics, in contrast with ANNs, which use a step-by-step stimulation process[233]. Figure 6 presents the most representative neuron models (adapted from ref. 234).

While most of the existing neuromorphic chips focus on point neurons, there is a renewed interest in multicompartment neurons that can emulate dendritic processes to enhance the processing ability of SNNs. These approaches exploit the spatial and temporal dynamics observed in biological neurons and dendrites[190,191], such as *N*-methyl-d-aspartate (NMDA) plateau potentials or back-propagating action potentials. Computationally, these dynamics can facilitate learning[190,238] and increase the computational capacity of the neuron[239]. The multi-compartment configurability in neuromorphic hardware is generally achieved by adjustable connectivity between local neuron compartments. Such dynamics have been readily implemented in analog and mixed-signal hardware[193,240–242], and digital hardware[205,243] proposes a design that emulates the dendritic processing in an array of ferroelectric devices. In this design, a segment of a dendrite would be implemented by adjacent devices, which, when biased in the programmed sequence, would activate a transistor. Other approaches focus on the spatial layout of dendritic dynamics, as achieved, for example, in memristive arrays[244].

Another related and actively researched approach, inspired by the spatiotemporal complexity of neurons, is the implementation of delays in neuromorphic systems for information processing. In ref. 245, delays are realized using capacitors and programmed via the conductance of Resistive Random-Access Memories (RRAMs). Hierarchical address event representation (AER) architectures[206,246] implemented in many neuromorphic systems use some form of hierarchical communication, which allows for the distribution of synaptic and axonal delays across the communication fabric. This approach is attracting increasing interest, driven by recent advances in training delays that have enabled highly efficient SNNs to achieve state-of-the-art accuracy in temporal signal processing tasks.

Spike encoding-- To apply the neuron model, the input data must be encoded into spike trains before feeding it to SNNs. Neuroscience is still grappling with several significant questions about the encoding part, including: what information is included in these spatio-temporal spike patterns? What code is used by neurons to transmit information by neurons? Also, how do other neurons receive this information and communicate? It is necessary to create spike patterns that preserve most of the task- related information in the input stimuli. Early studies have found that such information is merely embedded in the mean firing rate of neurons[247].

In the literature, there are two main encoding schemes (a) *rate-based encoding* and (b) *temporal encoding* (see Fig. 7)[248,249]. The first scheme is based on a spiking characteristic within an interval of time (such as frequency), while the latter is based on spike timing. Several neuron models use rate codes to explain computational processes in the brain. Rate-based schemes include three different notions of mean firing rate "rate as a spike count", "rate as a spike density" and "rate as a population activity". However, spiking neuron models can model more complex processes that depend on the relative timing between spikes or timing relative to a reference signal, such as network oscillation. Taking as a reference the encoding mechanism of biological neurons to specific stimulus signals, researchers have come up with many temporal encoding strategies, such as "time-to-first spike", "latency phase," population encoding", "correlations and synchrony", and "Ben's spiker algorithm"[247,248]. Often decisions must be made before a reliable estimate of a spike rate can be computed; therefore, temporal codes are highly interesting where even a single spike or small-scale temporal variation in the firing time of a neuron may trigger a different reaction. Figure 7 shows the difference between the two encoding schemes.

https://doi.org/10.1038/s44385-026-00074-w

Table 7 | Comparison between ANNs and SNNs[230,382]

	ANNs 1st gen.	ANNs 2nd gen.	SNNs 3rd gen.	Biological systems
Computational units	Perceptron neuron	Artificial Neuron	Spiking Neuron	
Function	Performs thresholding in a digital (1,0) output	Sigmoid unit or a rectified linear unit (*ReLU*), adds continuous nonlinearity to the neural unit, which enables it to evaluate a continuous set of output values	Mainly based on the integrate-and-fire type that exchanges information via spikes	
Neuron Model	$y = f\left(\sum_{i=1}^{n} w_i x_i - \theta\right) = \begin{cases} 0, \wedge \sum_{i=1}^{n} w_i x_i - \theta < 0 \\ 1, \wedge \sum_{i=1}^{n} w_i x_i - \theta \geq 0 \end{cases}$	$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$ *f y:neuron output* x_i*:neuron input* n *: numberofneurons* w_i *: synapticweight* θ *: Activation threshold* b *: Bias*	$\begin{cases} \frac{dX}{dt} = f(X) \\ X \leftarrow g_i(X) \end{cases}$ *X: vector of state variablesofneurons f for stateofvariable evolution* g_i *variables due spikes a neuron*	
Encoding Scheme	Rate encoding	Rate encoding	Temporal encoding	
Information representation	Scalar values	Scalars values	Spike trains	
Computation mode	Activation function	Activation function	Differential equations	
Network simulation	Step-by-step	Step-by-step	Clock-driven and event-driven	
Input vs Output	Binary, Binary	Real, Real	Real, Real	
Neural Networks architecture	1. Perceptron 2. Multilayer Perceptron (MLP)	1. Conventional Neural networks (CNNs) 2. Recurrent neural networks (RNNs)	Spiking Neural Networks (SNNs)	
Pros	1. Intuitive interpretation as spikes 2. Few parameters to be optimized	1. Higher biological plausibility than **1st** gen. 2. Large scale gradient base optimization techniques 3. Higher computational power than **1st** gen. 4. Implicit time notion, codes fire rates	1. Higher biological plausibility than 2nd gen. 2. Massive parallelization and powerful computation 3. Successful hardware implementation (Neuromorphic VLSI) 4. Excels with spatio and Spectro-temporal data treatment (SSDT) 5. Explicit time notion, codes fire rates	
Cons	1. Only binary outputs 2. Limited analog implementation 3. No time notion (coding spikes)	1. No direct Hebbian learning; it only computes fire rates instead of fires. 2. No intuitive interpretation for spikes 3. Moderate parallelization and spatio and spectro-temporal data treatment (SSDT) 4. VLSI Hardware implementation 5. More parameters to be optimized and high sensitivity to its values	1. Biological insights still not sufficient to develop a rigid theory. 2. Unknown behavior with spatio-temporal data 3. More parameters to be optimized and high sensitivity to their values. 4. Lack of a common framework for the different models and coding schemes	

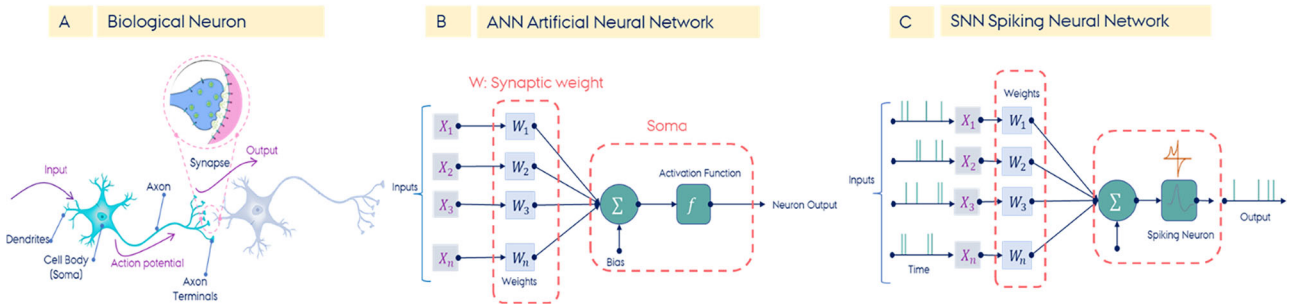

Fig. 5 | Comparison between biological neuron, artificial neuron and spiking neuron. A Simplified diagram of a typical structure of the biological neural cell. The soma receives synaptic signals from other neurons through its dendrites, and the axon propagates signals to other neurons. A synapse is a contact between the axon of one neuron and the dendrite of another. The soma maintains a voltage gradient across the neuron membrane. If the voltage changes by a large enough amount, an action potential (spike) may be elicited. The action potential then travels along the axon and eventually activates synaptic connections with other cells. B Artificial neural network (ANNs), and C Artificial spiking neural network (SNNs) are only active when it receives or emit spikes, which make it energy efficient over a given period.

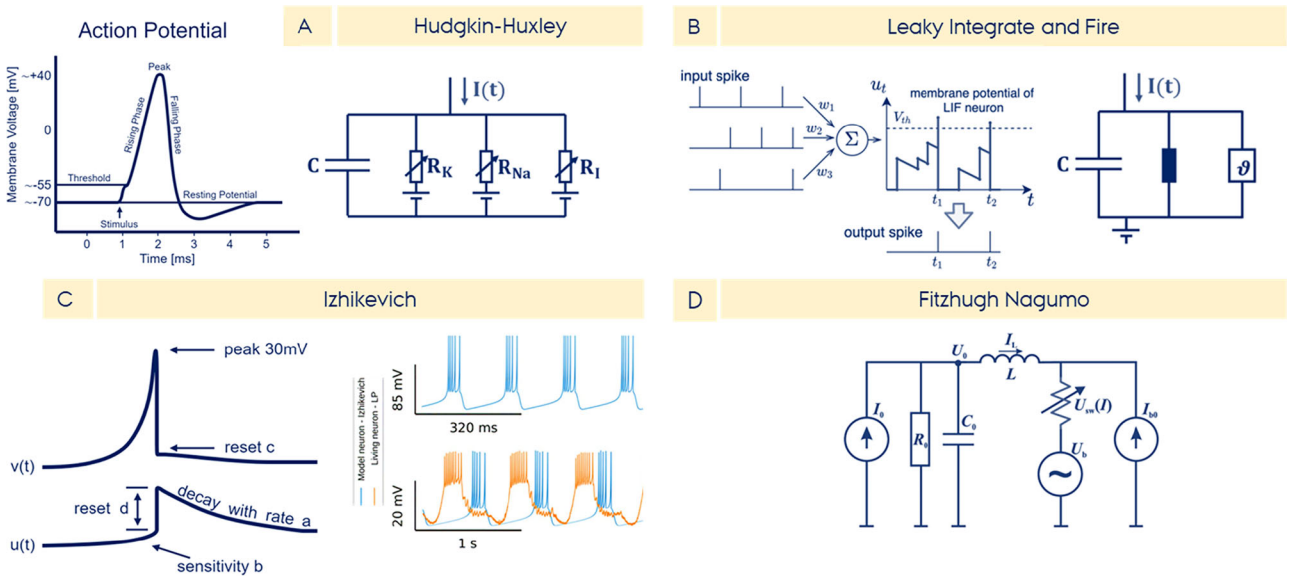

Fig. 6 | Representative neuron models used in computational neuroscience and neuromorphic systems. A Hudgkin-Huxely (HH), **B** Leaky Integrate and Fire (LIF), **C** Izhikevich, and **D** Fitzhugh-Nagumo.

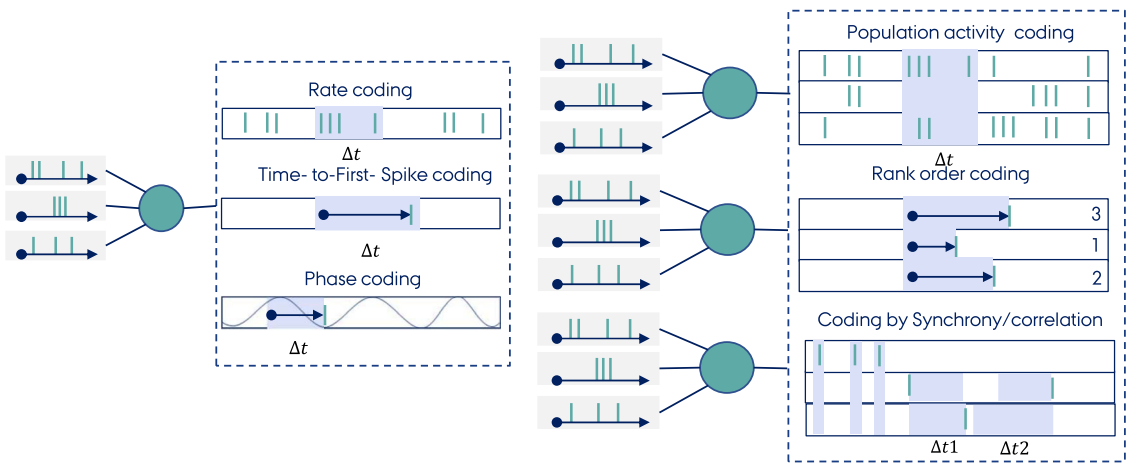

Fig. 7 | Rate-based encoding versus temporal encoding. Schematic representation of some neural codes: neurons are the green circles; the simplified spike coding types and the actual coding schemes are shown respectively on the left and the right © computation by Time by Walter et al.[248].

Learning methods in SNNs

Synaptic plasticity refers to the ability of synaptic connections to change their strength (i.e., modulation of synaptic weights) over time based on network activities. Synaptic plasticity is believed to be a key mechanism of learning and memory processes in the brain. There are various schemes of synaptic plasticity such as Hebbian[249], non-Hebbian[250] and neo-Hebbian[251,252] schemes, differing primarily in their time scales and induction conditions. The timescales of synaptic plasticity scale from dozens of milliseconds to hours (e.g., Long-Term Potentiation (LTP) or Long- Term-Depression (LTD). Depending on induction conditions, some synaptic plasticity rules apply depending on the relative timing of the pre- neuron and post-neuron synaptic spikes, the temporal order of spikes, and on certain factors like specific chemical ion concentrations. Other models rely only on prior presynaptic stimulation, disregarding the postsynaptic response. Neural circuits are either inhibited or excited depending on the type of synaptic input they receive[234,253]. Choosing a proper spiking neuron model with appropriate synaptic plasticity, along with exploiting event-based, data-driven updates (with event-based sensors) are essential factors to enable computationally efficient intelligence applications such as inference and recognition. A full review on learning rules in SNNs has been presented in ref. 254. SNNs have used two major learning schemes so far: *conversion-based* and *spike-based schemes*, which are explained below.

Conversion-based schemes-- are based on converting a trained equivalent DNN into SNNs using weight rescaling and normalization to adapt the attributes of the nonlinear continuous output of the artificial neurons with those of the spiking neuron (e.g., leak time constant, refractory period, membrane threshold, firing rate, etc.)[255–257]. They tend to achieve better accuracies on large-scale spiking networks in image classification like ImageNet dataset[256,258,259], but are less resource-efficient compared to spike-based training schemes. Commonly, DNNs are trained on frame-based data such as TensorFlow[260], which gives them a high training-associated flexibility. Conversion needs parsing of the trained DNNs on event-based data (generated by rate-coding of a static image dataset) and then applying parameter conversions. The conversion-based scheme has the merit of removing training burden in the temporal domain. It achieves the same accuracy for image-recognition tasks as that obtained from image classification in traditional deep learning neural networks (DNNs)[257,259,261], however, it shows intrinsic limitations as follows. The non-linear neuron output value could take both positive and negative values, while the rate of a spiking neuron can only be positive. Therefore, all the negative values are excluded, which lessens the accuracy of converted SNNs. Another issue with conversion-based is the difficulty of achieving an optimal firing rate at each layer without sacrificing performance. Researchers recently proposed new methodologies to optimize the firing rates; for example, leaky ReLUs were introduced during DNN training to better match the spiking neuron's firing rate[262]. Furthermore, the inference time for converted SNNs is generally large, resulting in higher latency and lower energy efficiency[257]. A new mapping strategy was proposed by Stockl et al., in which SNNs use the Few Spikes neuron (FS-neuron) model to represent complex activation functions with two spikes at most. The proposed strategy exhibited similar deep learning accuracy with fewer time steps per inference in comparison to typical conversion- based techniques[263]. Applications such as keyword detection, medical image analysis, and object detection have used those mapping strategies and were implemented on existing neuromorphic hardware platforms (e.g., Intel's Loihi, IBM's True North)[214,215,264]. However, conversation-based methods- although they are used as approximators of ANNs- still miss the main goal of SNNs by achieving greater computational efficiency.

Spike-based schemes-- fall into three main categories, including supervised (training with labeled data), unsupervised (training without labeled data), and reinforcement learning[264]. The supervised Hebbian learning (SHL) rule is one of the most straightforward spike-based learning processes; it is usually supervised by an extra teaching signal that drives the postsynaptic neuron to fire at targeted time intervals and to remain silent at other times[253,264,265]. Remote Supervised Method (ReSuMe)[266], and tempotron[267] are two of the earliest representative works in supervised learning for single-layered SNNs to perform classification. Researchers have been focusing on integrating spike-based quasi-backpropagation error gradient descent to deploy supervised learning in multi-layered SNNs[268,269]. For instance, SpikeProp[270] -a learning rule based on gradient descent for training SNNs- and some of created a new backpropagation rule for SNNs by fixing a target spike train at the output layer[269,270]. Recent works adapted deep-learning training style using surrogate gradient and smoothed activation function to compute the error gradients when adjusting weights in each of the successive layers[271,272]. There have also been some approaches that perform stochastic gradient descent on real-valued membrane potentials to get more random spikes from the correct output neuron[273,274]. These few demonstrations show close to state-of-the-art classification performance on the Modified National Institute of Standards and Technology (MNIST) handwritten digits dataset[275]. Backpropagation through time and real-time recurrent learning approaches have been applied in neuromorphic datasets such as the Spiking Heidelberg Digits (SHD) and the Spiking Speech Command (SSC) datasets[276,277].

In unsupervised learning, the neural connections are reorganized depending on the modification of synaptic weights of the Hebbian processes[249], leading to new functions, for example, input clustering, pattern recognition, source separation, dimensionality reduction, associative memory formation, etc. Spike-timing-dependent plasticity (STDP)- a learning strategy based on varying the synaptic weights according to the relative spiking timing from pre- and postsynaptic neurons - is the most widely implemented synaptic plasticity in neuromorphic literature. It assimilates more brain-like architectures, due to the possibility of bringing both memory and computation units closer. This, in turn, induces more energy-efficient on-chip implementations. Diele et al. were among the first groups that demonstrated fully unsupervised learning on an SNN, leading to analogous accuracy to deep learning on the MNIST database[272,278]. Deep SNNs - Spiking Convolutional Neural Network (SCNN)- are one of the recent scenarios that have shown that adding random error signals through feedback connections enhances learning[279,280]. It depends on training a multilayer SNN network with local spike-based learning per layer, then following it up with global backpropagation for classification. An additional class of SNNs is the recurrent networks with delays and synaptic plasticity and used for modeling dynamical systems. Alemi and colleagues applied a local learning rule with recurrent SNNs with fewer spikes to demonstrate non-linear dynamical systems[281]. These recurrent SNNs display greater classification capacity with winner-take-all models[282,283]. An alternative algorithm used in SNNs is reservoir computing or liquid state machines (LSM). It is considered as Spiking Recurrent Neural networks (SRNN), as it uses sparse and recurrent connections with synaptic delays in spiking neural networks to shape the input into a higher-dimensional space spatially and temporally[284]. In addition to the liquid or reservoir, which is the SNN component and untrained, the reservoir computing methods include a readout mechanism that is trained to realize the output of the reservoir. The main advantage of spike-based reservoir computing is the elimination of training in the SNN component, and it has shown its effectiveness at processing temporally varying signals in a wide range of applications such as bio-signal processing and prosthetic applications[285,286]. Tables 8 and 9 summarize the learning methods in both ANNs and SNNs and give comments on their usage. In another flip, neuromorphic systems have recently considered a few Non-Machine Learning based learning algorithms such as those arising from graph theory[287] and Markov chains[288]. For instance, neuromorphic computing together with graph theory was used as a tool for analyzing Covid-19 disease spread[289]. Neuromorphic deployment of discrete-time Markov chains was used by Smith et al. to estimate particle transport problems and heat flow on complex geometries[290]. Figure 8 depicted the different SNN algorithms.

In conclusion, given the features of SNNs as brain-inspired computing for processing data, especially with temporal content, the idea of bringing SNNs to BCIs, can be a potential game changer in this field, although it requires more effort to understand the strong link, if any, between SNNs and

Table 8 | Learning Methods for both ANNs and SNNs based on[254]

Learning models	ANNs	SNNs	Comments
Self-supervised supervised			- Learning without labels and works better than unsupervised
Supervised Learning	- Gradient descent	- **SPAN**: Spike Pattern Association Neuron - Surrogate Gradient Descent - SRM Spike Response Model (Gradient descent supervised learning)	- Requires labeled data to fit a mapping of the input features to the output by minimizing a loss function (error function) - Two main categories: Classification and regression. - Labels in ANNs are represented as integers (classification) or real numbers (regression), while in SNNs it is represented as spike trains with spatio-temporal properties
Unsupervised Learning	- **Autoencoder**: Neural network model that encodes the features of the input data in a latent space (encoding) and uses latent vectors to reconstruct the original inputs (decoding). - **Generative adversarial network (GAN)** consists of two networks, a generative network and a discriminative network. The two networks are trained to "fool" the discriminative network. - **Self-organizing map (SOM):** A method of dimension reduction using competitive learning in which output neurons compete for activation, with a subset of neurons being activated at any given time, e.g., through a winner-takes-all neuron.	- Hebbian Learning - **STDP Spike-Timing Dependent Plasticity**: A synaptic plasticity rule that captures the spike timing effects in synaptic plasticity. It may lead to either long-term potentiation (LTP) or long-term depression (LTD) of the weights. - **Triplet STDP**: LTP is constructed as a combination of one presynaptic and two postsynaptic spikes. While LTD is based on two presynaptic and one postsynaptic spike. It takes in account the spiking timing interaction	- Unsupervised learning works with unlabeled data.
Reinforcement learning	- **Value-based**: Learns the state or state-action value. Q- learning is the most classic value-based algorithm. DeepMind proposed a combination between RL and deep neural networks (Deep Q-Network algorithm) - **Policy-based**: Maps the state space to the action space, then take best action to maximize its return.	- **Three-factor learning rules**: Synaptic updates depend on three factors: a presynaptic trace, a postsynaptic scalar or trace, and an extrinsic reward (third factor). - **ANNs to SNNs**: Conversion-based learning approaches. It matches the firing frequency of the firing neurons and the successive analog neurons. The training phase is done on ANNs and then converted to SNNs.	- RL was inspired by reward-based learning in animals. - In ANNs, RL based algos learns from feedback through iterative trials that are simultaneously sequential. It uses nonlinear function approximations. - RL is biologically interpretable. RL in deep learning is time-consuming

Table 9 | Neural networks in SNNs

Neural Networks	Feedforward Neural Network (FNN)	Convolutional Neural Networks (CNN)	Recurrent Neural Network (RNN)
Definition	Feedforward Neural networks or Multilayer perceptron (MLP) map input x to the output y(x) through a series of non-linear transformations. Elements of network: input layer (1st layer), output layer (last layer), hidden layers (in between layers), perceptron,	CNNs represent the spatial patterns in an image. A convolutional layer convolves the input with the cross-correlation operation followed by a nonlinear activation function. The pooling layer downsamples the spatial dimensions and so reduces the number of parameters. Generally, final fully connected layers transform the output of the feature extraction layer into class representations. The last layer classifies the output using a SoftMax function. They are used to process visual information, especially images. Multiple layers are used to process the gridded data, such as convolutional, pooling, and fully connected layers.	RNNs process the information in the most recent time step in the learning process based on an internal state. The internal state is updated to memorize task-relevant information. RNN-based Gated recurrent unit (GRU) and long short-term memory (LSTM) have been used in real-life applications. They are used to process sequential data or time series data, and to solve ordinal or temporal problems, such as language translation, speech recognition, etc.
SNNs	**Spiking Feedforward Neural Networks (SFNNs)** are SNNs based on STDP learning and backpropagation-based supervised learning used for pattern recognition. Using a two-layer SNN, based on the biological properties of excitatory-type neurons and inhibitory neurons as the processing layer, using lateral inhibition as well as winner-take-all properties, enabling the neurons in the processing layer to extract features with significant characteristics from the input signal based on STDP learning rules or Surrogate gradients, with optimal performance of 95% on the MNIST dataset.	**Spiking Convolutional Neural Network (SCNN)** Converted SCNNs are close in performance to CNNs and could perform inference tasks on neuromorphic hardware and consume less time and energy. Difference-of-Gaussian kernel for the input image, followed by unsupervised STDP-based training of the convolutional layer as well as the pooling layer, and finally, the extracted features are passed into the classifier	**Spiking Recurrent Neural Networks (SRNNs)** SRNNs have complex nonlinear dynamics and are usually used to study biological neural networks in specific microcircuits of the brain. Excitatory and inhibitory neurons connect to form a neural network that is chaotic yet in an equilibrium state machine. LSM Liquid State Machine is used for computational modeling. It is made of three layers: the input layer, the reservoir or the liquid layer, and the memoryless readout layer. It transforms the time-varying input information into higher-dimensional space to express temporal and spatial properties of neuronal dynamics, thus memorizing the input information. Eprop that perform RNNs with surrogate gradients.

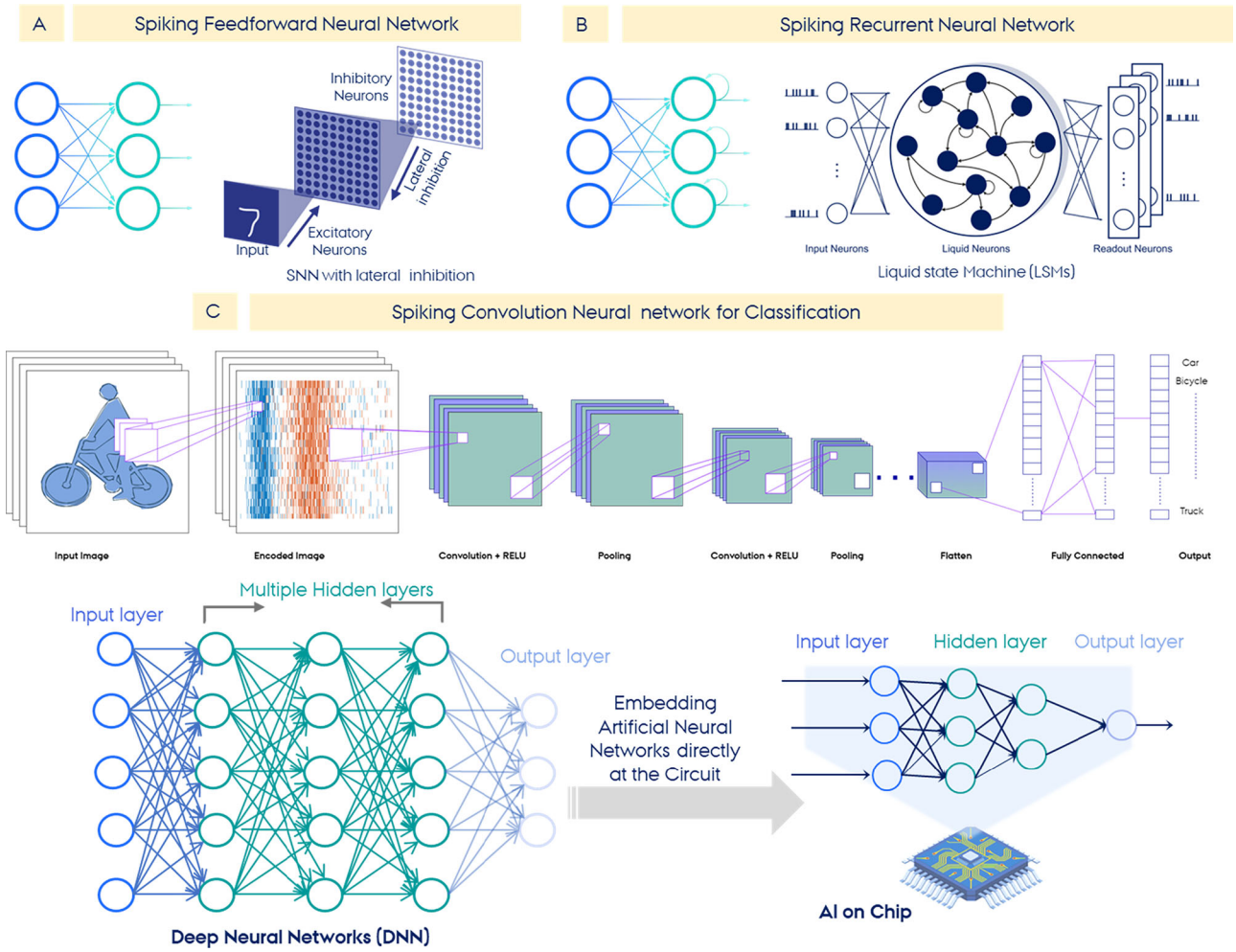

Fig. 8 | Representative neural network architectures in spiking neural networks. A Spiking feedforward Neural network (SFNN), **B** Spiking Recurrent Neural networks (SRNNs), **C** Spiking Convolutional Neural network (SCNN), on-chip Machine learning (ML) implementation.

BCIs. Therefore, based on the hypothesis of the ease of linking between a brain-inspired computing system and the brain, we discuss our perspective and potentially the path towards brain-inspired BCIs in the following sections. First, an overview of the use of AI in BCIs is provided. Then, the importance of processing the neural data on hardware for making a decision in different forms in a closed-loop configuration is presented. Finally, we discuss why SNNs, and more broadly brain-inspired computing systems, represent a promising approach for processing and interfacing with neural data, combining low-power, energy-efficient computation with a biologically grounded framework.

SNNs in BCIs: spiking neural networks in brain-computer interfaces

ML algorithms commonly learn to identify categories or predict unknown future conditions starting from data. ML methods allow the prediction and progression of brain degenerative disorders such as Alzheimer's disease, dementia, schizophrenia, multiple sclerosis, cancer, etc[30]. As an example, an ML approach combining multiple biomarkers of tremors in LFP, such as multi-band spectral power, phase-amplitude coupling, and high-frequency oscillations ratio, with a smoothing Kalman filter, achieved 89.2% sensitivity in detecting rest-state tremor in Parkinson disease patients[32,291,292]. Further exemplars were reported in the detailed systematic review paper on AI for Brain diseases published by Segato et al[33]. In addition, approaches for segmentation and detection of brain structures, as well as pathological tissues, are also widely studied. For instance, a subject-specific logistic regression model was applied to predict memory encoding state from brain-wide ECoG recordings and activate closed-loop stimulation to improve memory anchoring in humans[145]. Nevertheless, it is worth noting that, because of the complexity and the amount of brain data, ML methodologies usually comprise several steps to perform a task. For example, image pre-processing, feature selection and ranking, and dimensionality reduction are often required as initial stages to improve performance to adequate levels. Several low-power, area-efficient digital/mixed signal systems-on-chip (SoC) with embedded ML have been reported in the literature for neural signal acquisition and treatment. Zhang et al. developed the first- in- literature real-time SoC with both online tuning and one-shot learning for a patient-specific closed-loop epilepsy tracking system[293]. Work[294] developed a neural interface processor for brain-state classification (NuriP), it implemented an exponentially decaying-memory support vector machine (EDM-SVM) classifier combined with a neural network autoencoder to lower the dimensionality of input data. Alternatively, Wang et al. presented a low-power closed-loop neuromodulation chipset for epilepsy with high common-mode interference tolerance that integrates a two-level classifier[295]. Most of these systems were verified offline on human epilepsy data and in closed-loop seizure control in animal models of epilepsy. ML SoCs also used DDNs (deep neural networks) for emotion detection of autistic children[296], and CNNs (Convolutional Neural Networks) with online training for emotion recognition from EEG- based data[297].

Brain-inspired neuromorphic architectures have been used in several fields of application such as image recognition, decision making and action

Table 10 | EEG- based Recording Technologies and BCIs applications

EEG-based BCIs Definition	Modulation	Application		Publication
P300 ERP-based BCI **P300- event related potential based BCI: Based on P300 event-related potential, which is a positive deviation that occurs at approximately 300 ms after a rare and relevant stimulus happens. P300 signals could have higher amplitudes when a specific stimulus acquires higher attention.**	P300 signals could have higher amplitudes when a specific stimulus acquires higher attention	vibrotactile stimulation	Spinal cord injury rehabilitation	49,383
		Driving scenario in virtual reality	Drowsiness detection	54,55
		Amyotrophic lateral sclerosis (ALS)	Visual P300 speller, Brain painting	384,385
		Cerebral palsy	Cognitive assessment	386
		Brain fingerprinting	Lie Detection	387
		Assistive technology	Wheelchair control	388
SMR-based BCI **Sensorimotor rhythms Based BCI: Based on mu (8–12Hz) and Beta (18–26Hz) oscillations in EEG signals recorded over the sensorimotor cortex.**	The amplitude of SMRs could be modulated using the mental strategy of motor imagery	Motor learning Brain plasticity	Motor Rehabilitation Lower limb rehabilitation	47,389
		Robotics and Assistive technology (ALS, Stroke)	Hand prosthesis control	43,44,340
		Assistive technology	Wheelchair navigation	319
		Motor training with proprioceptive feedback	Upper limb rehabilitation	390
		Plasticity Induction	Stroke rehabilitation	334
		Neuroanatomical predictor	Motor rehabilitation	389
SCP- based BCI **Slow-cortical potential-based BCI: Based on very slow variation of the cortical activity.**	Positive SCPs correlate with mental inhibition and relaxation, while negative SCPs correlate with mental preparation.		Biofeedback in epilepsy	318,391
SSVEPs-Based BCI **Steady-state visually evoked Potential-based BCI: Based on periodic brain responses induced by repeated visual stimulation.**	SSVEPs appear as an increase in brain activity at the stimulation frequency and its harmonics	Dry and non-contact sensors	Typical BCI applications	320,392
		Motor plasticity	Upper extremity Rehabilitation combined with FES	393
		Assistive technology	Video Games, Text speller	394,395
VEP **Visual evoked potential**			Epilepsy, Hybrid and multimodal BCI applications	46,396

P300 (an event-related potential), *SSVEP* (steady-state visual evoked potential), *VEP* (visual evoked potential), *SMR* (sensorimotor rhythms), *SCP* (slow-cortical potential).

selection, spatial navigation, and environment exploration, rehabilitation and motor control, robotic control based[298], etc. For example, the iCub Humanoid robot was able to develop brain -inspired cognitive abilities like memory and learned to interact and respond to a dynamic environment through SNNs-based controllers[299,300]. Additionally, SNNs have also been used for brain disease diagnosis and prognosis, motor imagery signal classification, and cognitive process measurement. For example, Capecci et al. proposed a method based on a NeuCube spiking neural network to classify brain EEG data from patients of Alzheimer's Disease and subjects diagnosed with mild cognitive impairment and analyze the functional changes in their brain activity[301]. Also, Ghosh-Dastidar et al. investigated SpikeProp, Quik-Prop, and RProp SNN's classification algorithms to detect epileptic seizures from EEG[268,302]. Wang et al. suggested an alternative approach for multiple motor imagery decoding based on SNNs. They used a filter with a one-vs-rest (OVR) strategy to extract the spatio-temporal-frequency features of multiple imagery after preprocessing. Then, they applied F-score to optimize and select these features, which in turn were fed for SNN for classification[303]. Some SNN accelerators take advantage of weight sparsity to efficiently reduce the model size, computation, and data transfer energy. They are commonly implemented in Application Specific Integrated Circuit (ASIC) with either offline[199,200,206] or on-chip learning[304–306].

Thanks to their low power, high adaptability through online learning, and ability to emulate the nervous system functionality implemented in analog, digital, or mixed-signal hardware, neuromorphic systems (SNNs) are receiving more attention in BCIs and neural prostheses systems[201]. For instance, the neuromorphic system in reference[232] used an analog Spiking Neural Network (SNN) classifier and demonstrated an STDP rule for spike sorting in BCI applications[187]. Similarly, combinations of spiking reservoirs and STDP have been used in an SNN architecture called NeuCube[307], which was used to process EEG signals and functional magnetic resonance imaging (fMRI) signals in applications such as sleep state detection[308] and prosthetic controllers[309]. Indiveri et al. developed an event-based neuromorphic system with on-line learning for classifying auditory stimuli[310]. Likewise, the neuromorphic processor was implemented in a modular closed-loop BCI for decoding motor intentions and delivering sensory stimuli to the brains of anesthetized rats[207,311]. Another method based on spiking activity used LFP features to evoke somatosensory feedback in closed-loop BCI in rodents[72]. A related method used a wireless, battery-powered neural implant to stimulate the somatosensory cortex in response to spikes detected in the premotor cortex in a rat model with brain injury[312]. Neural chips can be applied too in bidirectional closed-loop prostheses for brain disorder treatment such as epilepsy[312]. Recently, Moradi et al. built a CMOS-based neuromorphic device for the detection of epileptic seizures from local field potential (LFP) signals from brain slices[313]. Also, a mixed-signal multi-core neuromorphic processor (DYNAPs) exploiting event-based communication was used to detect High-Frequency Oscillations (HFO) as a biomarker of seizure events[206,314]. A high-density retinal implant with in-pixel neuromorphic image processing and temperature-regulation circuits, mimics human retinal operation[315]. Neuromorphic platforms such as IBM's TrueNorth processor were used to implement CNNs that treat electrophysiological signals[316,317].

From Open-loop to Closed-loop intelligent BCIs

With the advancement of BCI technology, there has been a significant evolution from conventional open-loop systems to more advanced closed-loop intelligent BCIs. Initially, *classical BCIs* operated as one-way

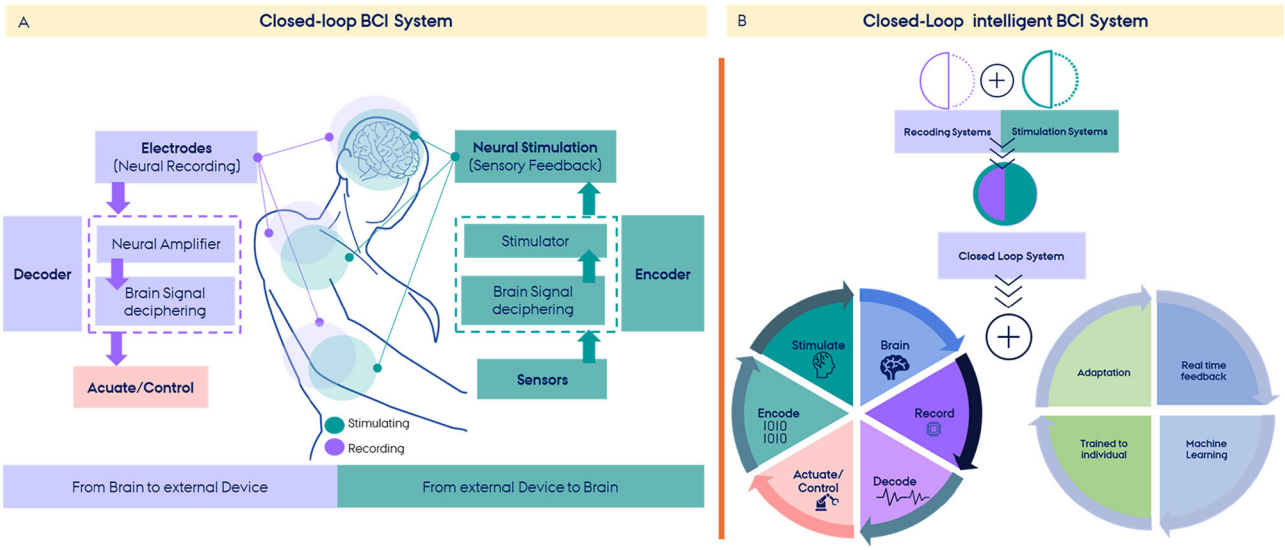

Fig. 9 | Closed-loop brain interface: BCI is a general term for any technology that communicates with the brain either to extract information from it or to inject information into it by means of brain stimulation. A Closed-loop BCI systems: Two complementary routes: in purple the controlled actuator (from brain to device) and in green the modulated brain state (from device to brain), **B** Closed-loop intelligent BCI system: The recording and the stimulation interfaces will be combined to formulate a closed-loop system. To implement a closed-loop intelligent interactive BCI system, several features need to be added, such as adaptation, real-time feedback, AI, and training for individual use.

feedforward systems primarily utilized in control and communication applications[13]. Early BCIs predominantly relied on different types of EEG signals such as slow cortical potentials (SCP)[318], sensorimotor rhythms (SMRs)[319], P300 event-related potentials (ERPs), and steady-state visual evoked potentials (SSVEPs)[320] as input signals to realize brain-computer communication. Table 10 offers a comprehensive overview of conventional EEG-based Brain-Computer Interfaces (BCIs) and their respective applications. To improve the performance of such systems, new paradigms have emerged, including *hybrid BCIs* that integrate additional physiological signals with classical EEG-based BCIs. Concurrently, various open-loop invasive BCIs have been developed based on spikes and intracortical LFP signals, with the overarching objective of controlling external devices/actuators and modulating neural activity based on the interaction with the external world. These classical systems enable generation, acquisition, and decoding of brain signals. However, a paradigm shift occurs when feedback is employed to alter/modulate neural or behavioral activities and control external devices, thereby transforming them into *Closed-loop brain-computer systems*[321].

Leveraging the progress made in neural decoding and encoding, researchers have begun to explore bidirectional closed-loop BCIs, which seamlessly integrate decoding and encoding in a unified single system. Such systems could be extremely influential, as they would enable *real-time* and *co-adaptive feedback* between the brain and the external devices (i.e., the encoding stimulation could be conditioned on the current state of the brain). For instance, neuroprostheses serve as an exemplary illustration of closed-loop BCI systems that integrate both motor outputs and sensory input. These systems not only read/decode neural activity from the primary motor cortex and translate it to movement commands but also provide somatosensory feedback by delivering external sensory information from the neuroprosthesis back to the somatosensory cortex through electrical microstimulation[70,133]. This stimulation enhances control precision and offers feedback about touched objects. Furthermore, closed-loop BCIs aim to modulate the brain's state to augment human performance such as the modulation of brain activity for treating neurological disorders or boosting the cognitive capacity of healthy subjects[321]. Closed-loop DBS is another example of a bidirectional neurotechnology system, where stimulation relies on simultaneous monitoring of brain activity. In patients with Parkinson's disease, LEP oscillations recorded from the subthalamic nucleus provide real-time information about clinical state, which can be used to adjust electrical stimulation settings and deliver stimulation only when needed (i.e., specific time slots). By limiting the application time, the battery life is extended, and the potential occurrence of adverse effects is decreased. Similarly, closed-loop brain stimulation has been used to detect early epileptic seizures and preemptively interrupt them by electrically stimulating either the anterior thalamus or deep cerebellum nuclei before the seizures progress[322]. More recently, electrical stimulation has been applied to the temporal cortex to improve memory encoding in users exhibiting deficits in memory function[145].

Based on what was previously discussed, the realization of robust and effective closed-loop neurotechnologies necessitates three key elements: *neuromodulation, real-time co-adaptive interaction*, and *close-loop construction*. This framework enables the brain to adapt to external stimuli and continuously optimize task execution, while the decoders/actuators learn to tailor their responses according to the changes in neural activity and the user's intentions, as depicted in Fig. 9-B. However, the major challenge lies in establishing effective methods to deliver feedback directly to the brain. Also, several unresolved issues persist, including the longevity of implanted electrodes, electrical stimulation artifacts, and the electrochemical safety of the electrode-tissue interface, etc[323]. Addressing these challenges requires interdisciplinary collaboration among neuroscientists, engineers, and clinicians, as well as ongoing advancements in materials science, signal processing, and neurotechnology design.

Concurrently, as BCI technology advances swiftly alongside the progress in AI, scientists have initiated efforts to foster collaborative synergies between these domains, giving rise to what is commonly referred to as "intelligent BCIs". On one hand, AI can be used to interpret the wide variety of recorded multimodal neural signals in BCIs, while on the other hand, AI-based intelligent devices can encode and provide feedback to the users. This synergy could improve the performance and broaden the applicability of BCI systems. Moreover, they postulate that AI can complement human cognitive abilities, thereby enabling the development of hybrid intelligence driven by direct brain interfaces. To realize closed-loop intelligent BCIs, it is necessary to integrate human cognitive abilities with the AI computing systems and exploit their rapid processing and storage capabilities. Additionally, it should establish human-AI co-adaptive learning mechanisms to ensure adaptive, dynamic, and personalized interaction between the brain

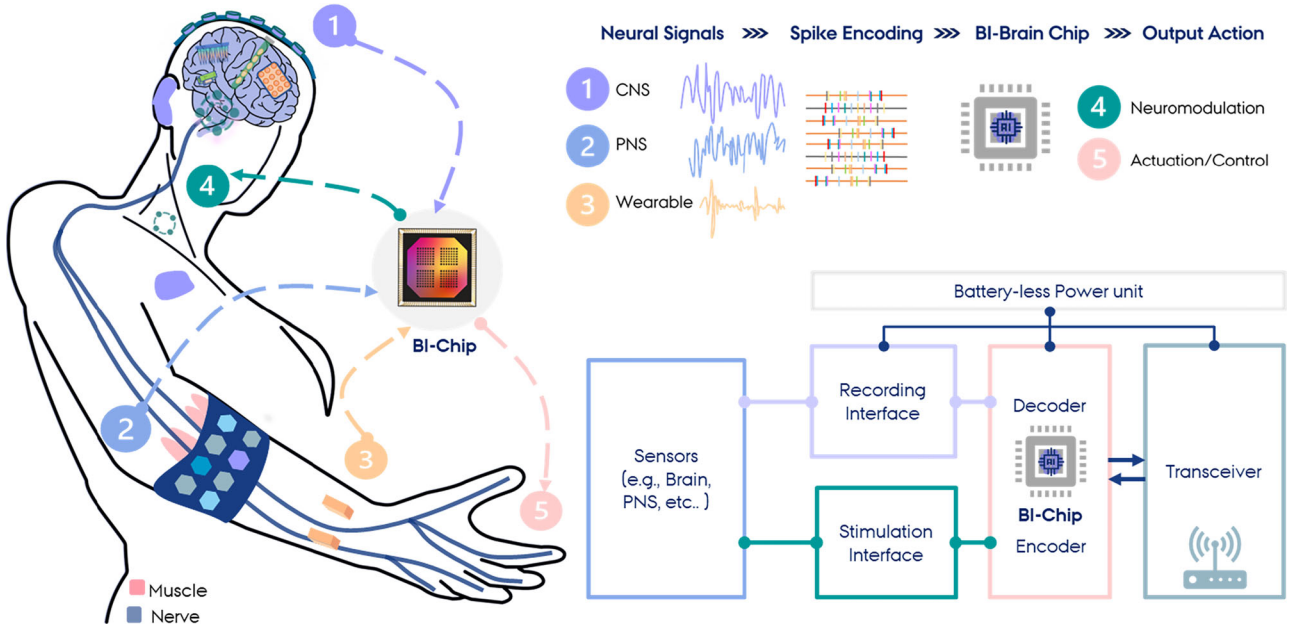

Fig. 10 | Conceptual illustration of our approach on the integration of neuromorphic technology with existing brain interfacing technology to develop novel closed-loop intelligent BCIs called Brain Inspired- Brain Computer Interfaces (BI-BCIs). The system consists of three fundamental neurotechnological modules: the Recording Neural Interface, the Decoding and Encoding Unit, and the Stimulation Neural Interface. Initially, neural signal recording and decoding are accomplished using a fully embedded wearable or implantable neuromorphic system known as the BI-Chip (Brain-Inspired Chip). This chip also functions as an encoding unit, enabling the execution of output actions such as modifying brain activity or controlling external devices.

and the BCI system[324] as illustrated in Fig. 9-B. In a similar vein, we envision the development of a closed-loop intelligent BCI system called BI-BCI (*Brain Inspired- Brain Computer Interface*) that merges the latest iterations of AI with advanced BCI technologies as detailed in "*Toward Brain inspired-Brain Computer Interfaces (BI-BCIs)*".

Ultimately, regardless of whether BCI systems are used for recording brain activity, stimulating/modulating it in an open-loop fashion, or combining both in a closed-loop system, their fundamental objective remains the assistance of patients. Nevertheless, the concept of enhancing human cognition for healthy subjects through direct brain interfacing remains merely an abstract and fictional idea. We will explore the potential advantages and drawbacks of employing brain-computer interfaces for augmenting human cognition in subsequent discussions.

Toward Brain-inspired Brain-computer Interfaces (BI-BCIs)

Based on the work reviewed so far, there is evidence that neuromorphic computing embedded into neural interfaces can play an important role in future technologies for monitoring, diagnosis, and treatment of neurological disorders. Although the feasibility of such systems has been demonstrated, there are still major questions that need to be resolved at the hardware and software levels.

Currently, the existing encoding systems[13,35,43,325,326] suffer from high latency due to the large amount of data fed into these systems. To improve the latency of such systems, it is crucial to reduce the volume of unnecessary information to be processed. Although recently the encoding speed as well as the accuracy of BCIs have been improved due to advances in ML/AI algorithms and more optimized hardware[199–201,327–332], we are still far from the realization of a real-time BCI interfacing the brain and communicating with it.

As discussed, SNNs provide a powerful framework for modeling complex information processing in the brain, owing to their ability to simulate the rich dynamics of biological neurons and to represent and integrate different information dimensions, including time, frequency, and phase. SNNs use spike information representation, in which binary events partly resemble biological action potentials, particularly in the analog form. Moreover, SNNs can exploit biologically plausible local learning rules such as STDP, Hebbian learning, and three-factor rules, which allow for fast real-time learning and low computational complexity. SNNs offer several advantages such as flexible, reconfigurable, and adaptable structure, incremental life-long learning, temporal, or spatio-temporal associations between input variables, event-based or asynchronous learning leading to less volume of data, interpretability of the model due to its simplicity that is built from basic elements, low- power and computational demand, more energy-efficient communication through spikes as they can be compressed and they are more sparse and event-based compared to fixed sampling frequencies, and fault tolerance. Building on the synergy and complementarity between SNNs and human intelligence, we postulate that integrating SNNs into BCIs, particularly in implantable or wearable platforms where low-power and event-driven processing are critical, to communicate with the brain would radically change the neuroscience research field and push it further to attain better results than any classical BCI system[333].

Our future vision is to create an intelligent BCI system that would merge AI with neural interface technologies in what so-called Brain Inspired- BCI (BI-BCI) which interacts with the brain in the most natural way as it should (Fig. 10). Our approach integrates neuromorphic technology with existing brain interfacing technology to develop novel closed-loop BI-BCIs. The system consists of three fundamental neurotechnological modules: the Recording Neural Interface, Decoding and Encoding Unit, and Stimulation Neural Interface. In our envisioned future system, the decoding and encoding of neural signals are achieved using a fully embedded wearable or implantable neuromorphic system known as the BI-Chip (Brain-Inspired Chip). This innovative chip serves as both a recording interface and decoding unit, enabling not only the interpretation of neural signals but also the delivery of stimuli to modulate brain activity or control external devices in a closed-loop manner. Such systems can also be an enabler for monitoring system which requires continuous recording of the data from the brain for clinical purposes in a wireless mode, in either implantable or wearable form. This approach is useful as spike-based data representations can substantially reduce data volume compared with conventional BCIs, potentially

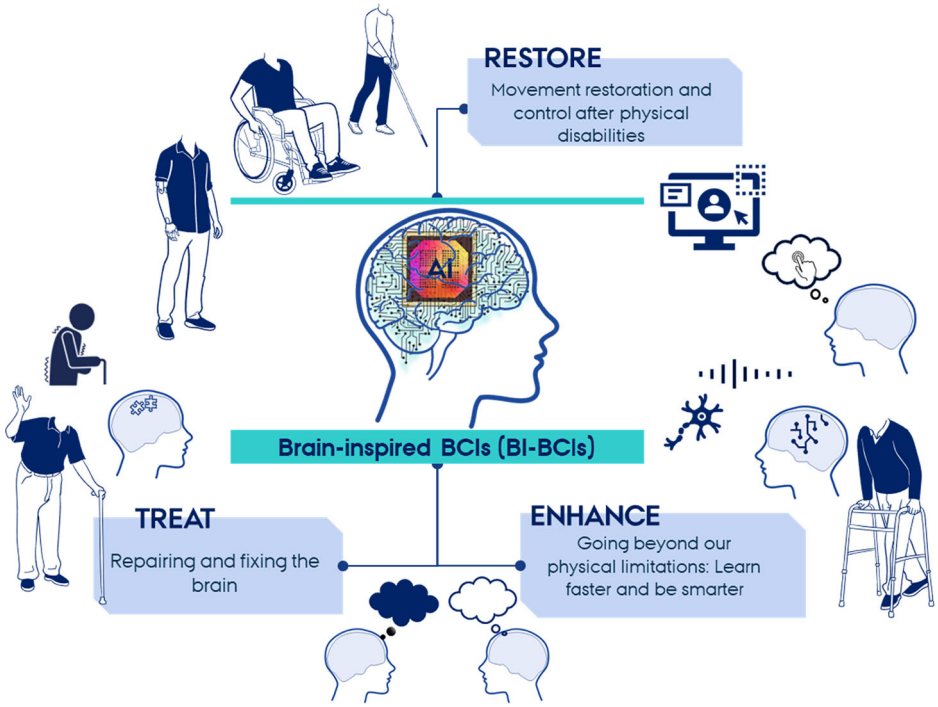

Fig. 11 | Envisioned Future Applications and perspectives of Brain Inspired- Brain Computer Interfaces (BI-BCIs) that links the human intelligence with AI-neural Implants.

enabling low-power wireless wearable and implantable neurotechnologies with extended battery life.

This paper reviewed the most recent developments in neurotechnology domain, with a particular emphasis on brain-inspired computing techniques and their implementations. Merging brain-inspired neuromorphic computing with BCIs creates a human-in-loop system, in which both technologies interwind to alleviate disabilities and impairments and to restore human performance. The joint interaction between the human and the machine could lead us to realize augmented human intelligence, which in turn is one of the main endeavors for future BCI research. Furthermore, we envisage that these integrated systems will pave the way for a new generation of intelligent brain interfaces, offering unprecedented therapeutic efficacy for a wide spectrum of neurological and mental disorders, as illustrated in Fig. 11.

In conclusion, BCI represents an interdisciplinary research field of research, and its advancement depends on the collaboration between neuroscience and engineering technologies. From the neuroscience standpoint, we need to understand better the function and the working mechanisms of the brain. While from an engineering standpoint, we need to create new intelligent miniaturized low-power neural implants that allow us to access deep brain structures, brain- inspired neural algorithms to analyze neural activity and encode it efficiently to acquire real-time interaction, and spike-based energy-efficient hardware.

Data availability

No datasets were generated or analyzed during the current study.

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Author contributions

Hoda F. and Farshad M. formulated the concept and structure of the paper. Hoda F. wrote the original draft and designed the figures. Hoda F., Margherita R., Milad Z., Hooman F., Michela C., Emre N. and Farshad M. reviewed the manuscript. Hoda F., Michela C., Emre N. and Farshad M. edited and approved the final version of the manuscript. Hoda F. and Farshad M. managed the project.

Competing interests

The authors declare no competing interests.

Additional information

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