



# Motor Imagery Neurofeedback: From System Conceptualization to Neural Correlates

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## Abstract

**Purpose of Review** As a topic review on neurofeedback and motor imagery, this work revises the overall foundations and conceptualization of neurofeedback training (NFBT), focusing on its current trends and applications in the field of motor imagery (MI). This paradigm consists of imagined execution of motor action, without the explicit motor output and has potential beneficial applications in motor rehabilitation protocols. Given the complexity of MI, aiming to also provide an entry-level basis in the subject, we have compiled basic aspects of movement execution as well, to support better understanding of the covert aspects of the processes involved in its planning stages.

**Recent Findings** We have explored recent trends regarding the individualization of MI protocols for NFBT and brain-computer interfaces, which seems to be an emerging branch of evaluations in the field. After establishing a fundamental basis on motor functions, the conceptualization of MI is explored through the contrast of the cognitive and motor models for explaining the task. Research evidence for both models are discussed through reviewing the main areas involved, as revealed by functional neuroimaging studies.

**Summary** Finally, we discuss recent trends in NFBT-MI practice.

**Keywords** Neurofeedback · Brain-computer interfaces · Motor imagery · Electroencephalography · fMRI neural correlates

## What is Neurofeedback?

In neurofeedback training (NFBT), the goal is to improve cognitive capabilities or the symptomatology of a specific neural or mental condition through self-modulation of brain signals [1]. This technique assumes that such signals inherently contain a set of features that relate to the targeted training condition, and, thus, improvements should be possible if the user learns to modulate these features appropriately.

A general NFBT pipeline is shown in Fig. 1. Signals are acquired and preprocessed, and suitable features are extracted and fed back to the user through efferent

stimulation, which generally consists of a graphical interface, although other stimuli, such as sounds and tactile sensations, could be used as well. Based on this feedback, the user's brain should develop strategies of self-modulation—i.e., self-adjustment of the training feature—by achieving a specific goal, such as changing an object's position on a computer screen. Feedback can be computed in several manners, including machine learning classification algorithms or other predetermined quantitative criteria neural signals must satisfy (such as the feature being above or below a given threshold).

As an example, a possible NFBT protocol could attempt to improve a user's attention capability. In this situation, neural signals underlying attention tasks could be monitored to identify a relevant feature for this scenario, which would then be mapped into a screen through the position of a cursor. The user could be instructed that entering a more attentive state would result in the cursor moving toward a target. Hence, compelled to evaluate the cursor's position in real-time, the user should develop strategies to modulate the training features to achieve the task's goal (which, in this case, could be reaching the target with the cursor).

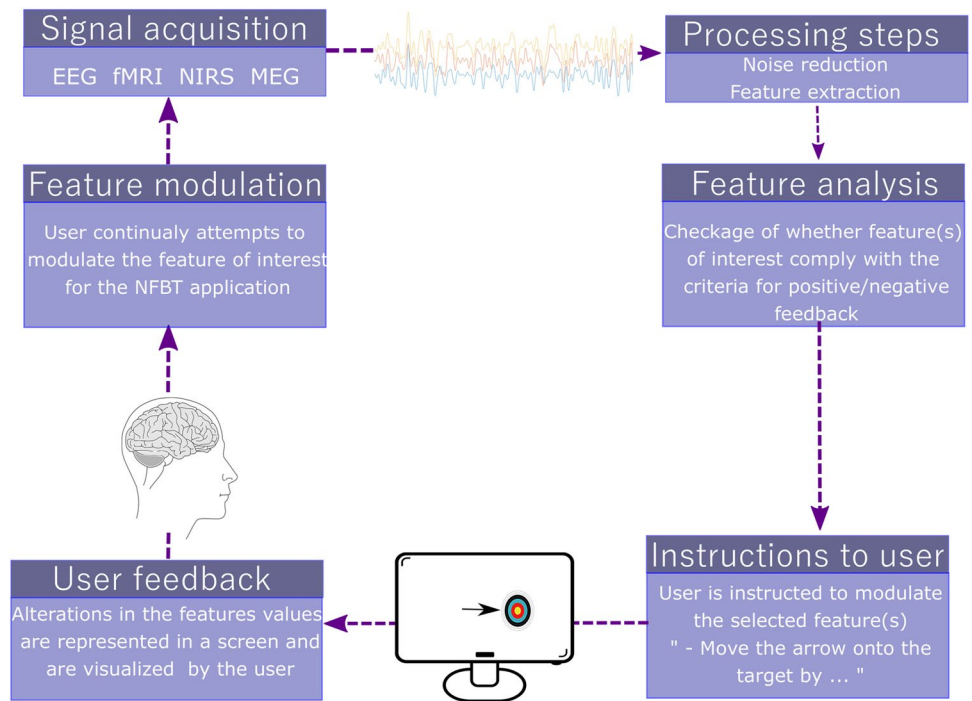
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**Fig. 1** Schematics of neurofeedback training. The NFB loop involves the following steps: feature modulation by the user, signal acquisition, preprocessing, feature extraction, and, finally, the feedback to the user. Generally, the subject should learn to self-modulate their brain signals guided by this feedback



Although NFBT may be implemented with a variety of neural signal acquisition techniques, such as near-infrared spectroscopy (NIRS) [2–4], functional magnetic resonance imaging [5–7], magnetoencephalography [8, 9], among others, electroencephalography (EEG) is usually the technique of choice, due to its low cost, high temporal resolution, and portability [10]. In addition, EEG provides a direct measure of neuronal activity, unlike other techniques, such as fMRI and NIRS, which rely on inferences based on under-verified assumptions regarding the neurovascular coupling phenomenon. On the other hand, EEG does present some drawbacks, such as the inability to provide measurements of sub-cortical structures appropriately. Applications that aim to modulate signals from these areas would thus better benefit from other neuroimaging modalities.

Regardless of the chosen technique, it is reasonable to expect that training can only be successful if informative features are extracted from the recorded signals. In the case of EEG, this usually translates into identifying electrodes and frequency bands of interest as candidate features, since the signal oscillations and their spatial specificity have been related to a variety of cognitive and/or motor states, as well as serving as biomarkers to a few neurological conditions [11–13].

In clinical applications, NFBT has been used as an alternative or complementary technique to treat a series of neural conditions, such as attention deficit and hyperactivity disorder (ADHD), Parkinson's, autism spectrum disorders [14], epilepsy [15], depression [16], and drug addiction [17]. Although studies generally reported good results and

expectations for implementing NFB treatments in practice [18], even comparing them to standardly used drugs in some instances such as psychostimulants for ADHD treatment [19], other numerous works claim that the technique is ineffective or merely relies on the placebo effect [20, 21]. Moreover, there is no standardization between studies, making it difficult to compare distinct works even when results are favorable. Generally, there is no agreement on the number of sessions, subjects, or even on the protocol (i.e., what is to be considered the training feature of the signal, an essential aspect of any NFBT application).

Currently, the state of research on NFBT remains markedly controversial [22], with several researchers increasingly highlighting the need for conducting more rigorous studies. A review published in 2019, for example, indicated several other review studies that discarded the majority of available works due to methodological issues. Even though the authors recognize that the methodology indeed improved over time [23], important issues persist. In 2016, Thibault and colleagues had already argued that despite the escalation in cumulative knowledge toward NFBT, whether feedback propels, neural changes is still a matter of discussion. They specifically suggested that control and sham groups should be imperative in NFBT studies and that such groups should be matched at a level of non-obvious factors, such as the amount of received positive feedback [24].

Other research teams raised similar concerns. For example, in 2017, Orndorff-Plunkett and colleagues proposed an empirically based approach to assess the efficacy of NFBT in social and clinical Neuroscience, emphasizing

that biomarkers at distinct levels (biological, neuropsychological, and behavioral) should be sought to appropriately assess the methodology's effects [25]. That is to say that, although clinical scales may provide important insights into symptomatology improvement, they do not supply specific information regarding possible underlying neuroplasticity mechanisms. Even more recently, an editorial publication by Franchi, Jeunet, and Lotte identified that “well-designed studies for neurofeedback are urgently needed,” underlining as key factors: “double-blind, randomized controlled trials” and the “clinical neurophysiological relevance of the mechanism through which neurofeedback might have a therapeutic benefit” [26]. Several other issues could be raised, involving the lack of randomized and control trials [27] and clear knowledge concerning how factors such as age, gender, training schedule, and feedback type influence the training's outcome [28]. It thus becomes clear that, despite constant advice from the scientific community, meticulous research regarding NFB is still needed.

Furthermore, adding to the non-standardized area of NFB, many studies usually do not clarify their pre-processing steps. Given the highly noisy nature of the EEG signal, this stage is aimed at improving the signal-to-noise ratio (SNR) and diminishing artifacts arising from movement or external sources. Therefore, the presented findings could be misleading without a proper pre-processing description (or even the mention of it). NFBT remains very controversial [1], even though a large number of clinics offer treatment sessions for sharp prices worldwide.

Notwithstanding, the technique has found a less dubious field of applications when allied to motor rehabilitation protocols and brain-computer interfaces (perhaps due to the problem being relatively more well-described in the literature and to neural correlates being more established). Since, in this case, the user's motor capabilities would be impaired due to lesions or neural damages, the general idea is to use NFBT to train the user to imagine their movements rather than actually perform them, thus modulating their EEG signals associated with motor imagery activity (and, hence, to motor-related functions). In the next section, we briefly review general neuroanatomical aspects regarding movement organization that will be relevant for further discussing this less controversial type of application.

## Neuroanatomical Correlates of Motor Functions

### Existence of a Motor Cortex

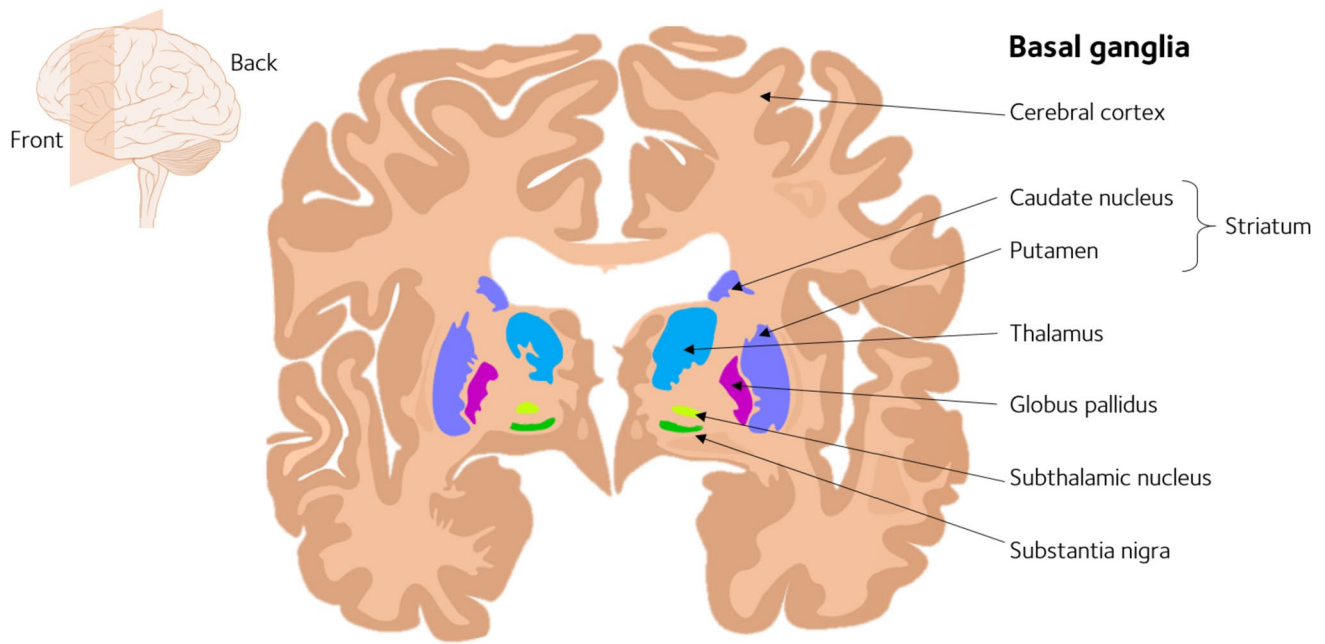
Neuroimaging techniques enable neuroanatomical studies that can yield strong evidence of the participation of brain areas and circuitry involved in various tasks, including

motor execution. Even though these tools were not available until recent years, the association between the brain and motricity outputs can be traced back to ancient times. At that time, however, the forthcoming knowledge was accumulated by case studies of brain lesions. The *Edwin Smith Surgical Papyrus*, for example, is a document over 4000 years old that contains considerable descriptions of brain damage and the corresponding impaired motor functions [29]. A lot had to be learned merely by observing real examples of lesions and how they would produce specific impairments.

In this context, animal studies played a major role in further pushing the boundaries of our understanding of the brain. Works involving decerebration on birds and mammals conducted in the first half of the nineteenth century by Marie Jean Pierre Flourens began to suggest that willing motor execution originated in the cortex and (as would be corroborated by future studies) that this type of activity is essentially distinct from more automated motor responses (such as reflexes). Nevertheless, at that time, there was still a lack of understanding of the actual cortical areas involved in movement execution. Some scientists even defended the idea that the cortex was an unexcitable structure, with the role of movement relying mainly on the cerebellum and subcortical structures involving some basal ganglia [29].

The debate of the actual role, and even the existence, of a motor cortex, endured sometime in the history of Neuroscience. John Hughlings Jackson was the first person to suggest the existence of such a structure. As a doctor who began to show interest in the nervous system, he started writing as a medical reporter about epilepsy in 1861, describing what would later become known as Jacksonian epilepsy: incomplete and unilateral seizures that do not cause unconsciousness, with the abnormal electrical activity being localized in a small portion of the brain. At that time, the idea of a motor cortex was not established, and the centers for movement were supposedly located on the corpus striatum, a part of the basal ganglia (Fig. 2), which was also believed to be the uppermost part of the motor tract [29]. The idea that the striatum was the origin of movement has its roots in Thomas Willis' observations, a physician who, performing post-mortem analyses, found that this region was more softened than any other brain area in patients who died from paralysis. His notion was prominent for about 200 years [30].

The shift from Jackson's idea of the striatum was influenced by his post-mortem analyses of his patients' brain, which indicated an apparent connection between the damaged contralateral brain hemisphere and the epileptic convulsive behavior. In fact, by 1865, Jackson had studied several hemiplegia patients. He was interested in the time-spreading of the seizure, that is how it propagated from its origin to the final destination (for example, from the hand to the arm and, further, to the face). He also noted that his patients did not generally present sensory deficits and that some parts of



**Fig. 2** Illustration of the basal ganglia. The striatum, or corpus striatum, encompasses the putamen and the caudate nucleus. Extracted from <https://commons.wikimedia.org/>; created by Waddie96

the body, such as the trunk, were unaffected by the seizures. Although his inspections suggested that not all muscles were affected the same, Jackson did not propose any cortical organization at that point. He was indeed struggling to abandon the idea of the striatum's role in these seizures. His idea shift became more evident a few years later, in 1870, when he partially attributed the cause of severe convulsions to a cortical area and suggested that different sites of this area should be somatotopically organized. In other words, this means that specific sites of this cortical area should be directly related to specific muscles. For him, this type of organization was the only manner to explain the progression of the seizure [29]. Nevertheless, his observations were not seen as proof of the existence of a motor cortex.

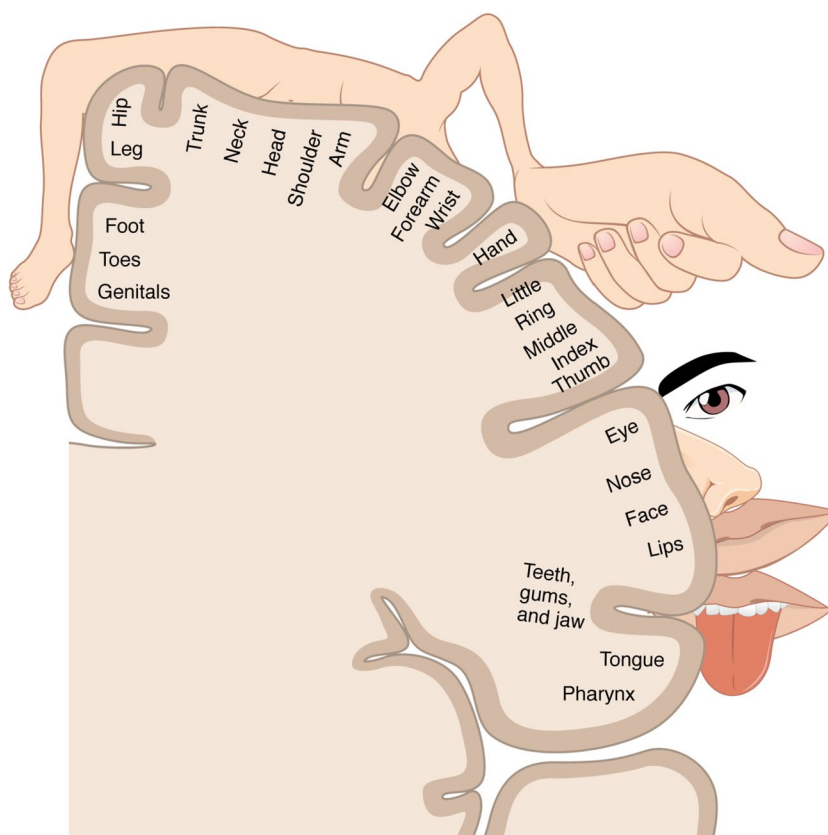
Concomitantly, in 1870, Gustav Theodor Fritsch and Eduard Hitzig performed experiments on dogs and found that electrical stimulation of their frontal cortex induced discrete contralateral movements on the face or limbs. At this time, with improvements in anesthesia and aseptic surgical techniques, they were also able to surgically damage and remove parts of the cortex, observing that it affected the dogs' motion. They also noticed that, although no paralysis was observed, the animals displayed significant motor deficits: what the scientists mostly observed was that the dogs still moved actively but with awkward or unsuitable movements in a given situation. They also often reported some motor recovery on the lesioned animals. Therefore, Fritsch and Hitzig proposed that there could be more than one motor center, providing solid evidence for a motor cortex that did

not work by itself [29]. Their findings were later confirmed by David Ferrier, who applied similar techniques to study monkeys, obtaining analogous results [29, 31]. Finally, their experiments also indicated the existence of a somatotopic organization of the motor cortex, as stimulation of adjacent cortical areas resulted in movements in adjacent muscles [31], agreeing with the ideas proposed by Jackson.

Some years later, in the first half of the twentieth century, Wildon Penfield tested the functional organization of neurosurgical patients. He and his colleagues applied more focal stimulation experiments to their patients' brains and built a map relating specific sites of the cortical motor area and the muscles they ultimately connected to. Woolsey and his colleagues performed similar studies, but with several species of mammals, reporting analogous findings. These enabled the construction of somatotopic maps—see, for example, Fig. 3. All researchers also noted that distinct muscle-related areas in these maps had different size representations. Generally, movements that require more fine tuning (such as hands and feet) had a bigger representation over the motor cortex, which is associated with the density of neurons of that population that are necessary for performing that specific task [31].

Hence, at that moment, evidence regarding the existence of a motor cortical area, as well as findings about the corresponding somatotopic organization, was accumulating. The idea of a cortical area for central motor control was eventually accepted. This area is referred to as the *primary motor cortex* and is usually represented by M1, corresponding to

**Fig. 3** Illustration of the somatotopic organization of the motor cortex. Distinct limbs and organs are mapped accordingly in the cortex. Movements that require a higher level of fine-tuning are usually mapped over a larger area of the cortex—see, for example, the extent of the fingers and mouth area representation for the human brain. Extracted from wikimedia.org; created by CFCF



the Brodmann area number 6 in the Brodmann cytoarchitecture's nomenclature. In the following subsection, we briefly review how motor tasks are output from the brain, setting the basis for better understanding the imagery of this type of activity.

### Movement Organization

Our motor actions emerge as a response to external stimulation, whether it is an automated response to some threatening situation, such as quickly and promptly retreating our hands when in contact with a hot surface, or consciously setting and modifying movements, such as adjusting our arm's amplitude and range in a given direction to reach for an object we seek. To enable this, the nervous system relies on specific afferent and efferent pathways, responsible for bringing information from the environment to the peripheral and, further, to the central nervous system, and from the latter to the peripheral nervous system, respectively (see Fig. 4).

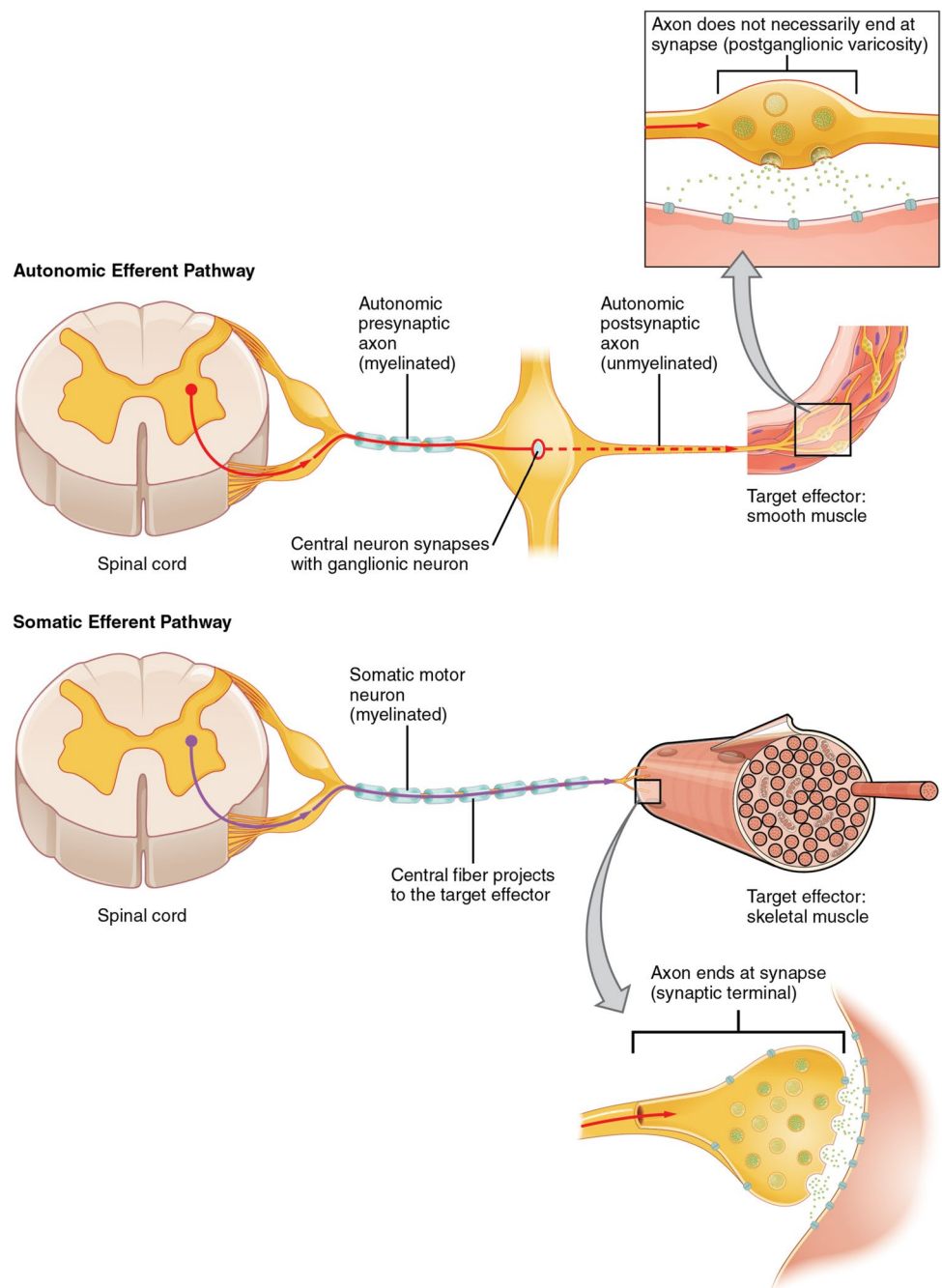
Afferent pathways generally receive external stimulation (heat, pain, touch, light, sound, and so) from the environment through specific neurons that specialize in receiving this type of information; for example, *neuromuscular fuses* are proprioceptive sensory receptors located in muscle cells; the so-called *mechanoreceptors* are neurons responsible for

receiving touch information and transmitting it to deeper structures of the nervous system. On the other hand, efferent pathways are responsible for relaying information from the central nervous system to the peripheral nervous system, mainly as a behavioral response (for instance, a reflexive or intentional motor action).

Intentional and reflexive motor responses, however, differ in nature. Whereas cortical structures mainly generate the first, the latter usually do not reach the cerebral cortex, controlled by sub-cortical structures, such as the cerebellum and the spinal cord. Additionally, intentional movements are goal-directed actions. In other words, they occur to achieve specific purposes and are supposedly accompanied by executive functions involving judgment and decision-making, even if we are not entirely aware of them. Hence, it is reasonable to expect that motor actions also demand the participation of cognitive and sensory centers of the brain.

For intentional limb motor action, the chief output command originates in the primary motor cortex (M1): efferent pathways leave M1, travelling through the internal capsule. Most of them subsequently decussate at the medulla, which is the reason why the motor cortical control is contralateral to the movement performance (i.e., the right motor cortex controls the motor action of the smooth muscles on the left side of the body, behind the head, and vice-versa). This group of fibers corresponds to the *corticospinal tract* and

**Fig. 4** Basic scheme of afferent and efferent pathways. Top illustration: external stimulation is gathered by the sensory, afferent fibers, being further relayed to the central nervous system, entering it through the spinal cord. Bottom illustration: the efferent fibers are responsible for transmitting information from the central nervous system to the peripheral neurons. Extracted from <http://commons.wikimedia.org>; created by CFCF



ultimately makes synapses with motor neurons on the spinal cord, which will relay information to the muscles, thus finally executing the motor action (Fig. 5) (there are other motor tracts that, however, are unrelated to limbs motion. The corticobulbar tract, for example, relays information from the cranial nerves to the brain stem and is thus vital for commanding movements involving muscles of the neck, mouth, and eyes, such as mastication and swallowing). Additionally, since this bundle of fibers passes through a medulla region known as the pyramids, it composes the so-called *pyramidal system* of the motor tracts.

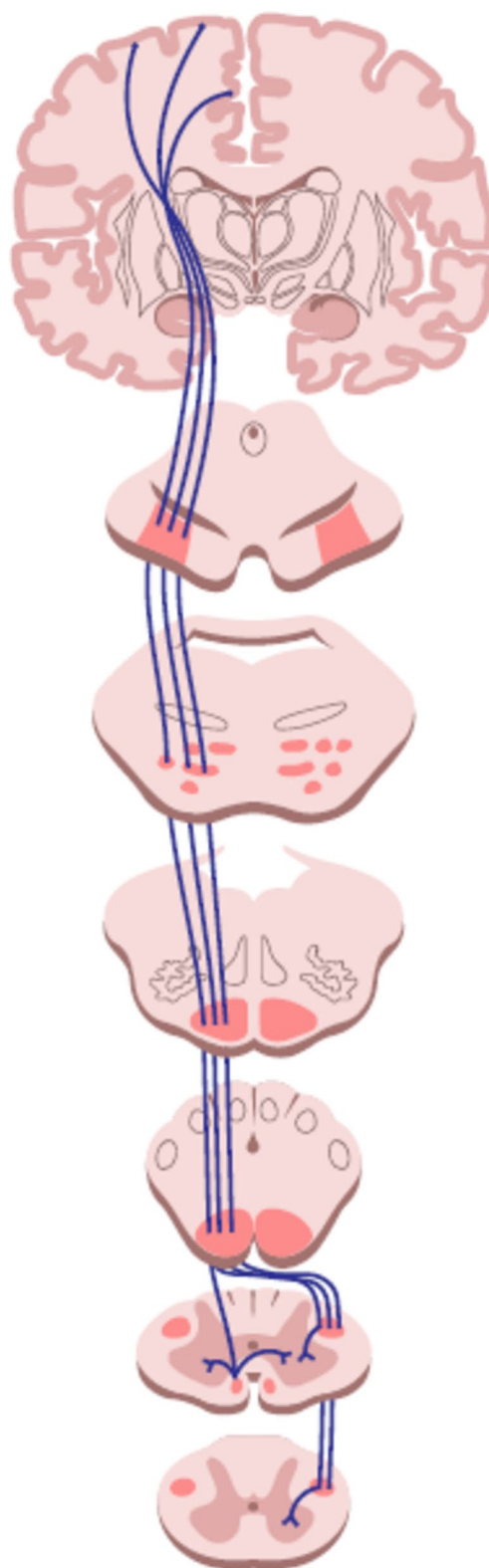
The primary motor cortex does not work alone: various other structures generate activity regarding motor planning, an essential stage (even if unconscious) that precedes motor volitional control. In this sense, motor planning and execution can be regarded as two separate, although intrinsically related, processes. Experiments that aim to identify both processes commonly design motor tasks, introducing a delay between the planning and execution stages. By doing so, researchers found that, even though there is not a homogeneous distribution of neuronal activity, some neurons of specific cortical areas are only activated during

**Fig. 5** Example of an efferent fiber shown as a part of the corticospinal tract. In this example, the fiber leaves the primary motor cortex, travels through white matter structures (posterior limb of the internal capsule), through the structures of the brain stem (midbrain, pons, and medulla), decussates at the pyramidal decussation, and ultimately makes synapses with motor neurons on the spinal cord. These, in turn, connect to the finger's muscles and relay the final step of the information for executing a motor action. Figure extracted from <http://commons.wikimedia.org>; created by Togopic

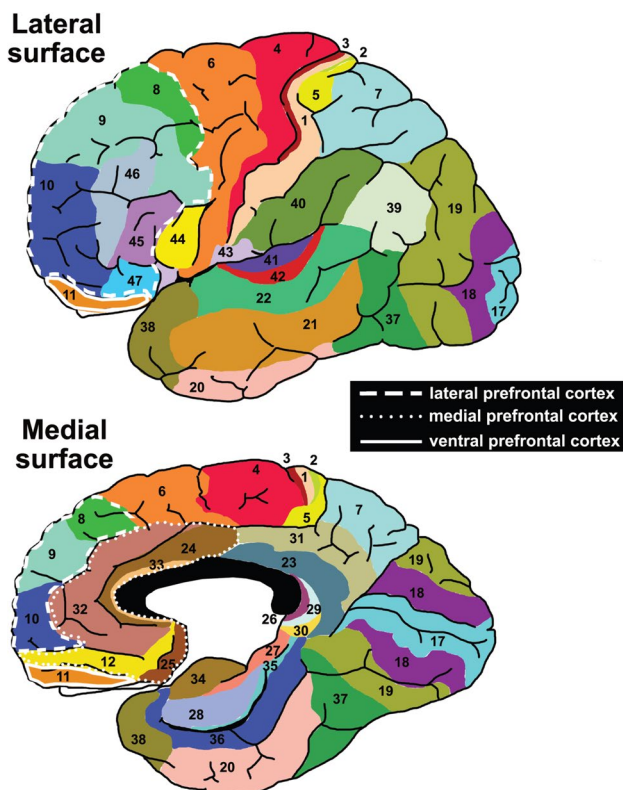
the planning stage, whereas others do so for the execution; however, some populations are always activated. Regardless, differences rely on how most of a population is activated during a certain condition (planning or execution). Previous studies have found that the pre-motor and parietal cortices encompass more neurons related to the planning stages [31]. Note that planning a movement would require much input information regarding, for example, spatial sensory encoding and proprioception and higher cognitive functions involving selection and judgment. This, thus, evidences that a motor action, which inherently comprises a planning stage, would also require other areas beyond M1 to transpire fully.

Several smaller “building blocks” contribute to movement outputs. For example, neurons in the forebrain structures are responsible for more cognitive aspects of movement, involving decision-making and motivation for performing a motor action. Such structures involve complex communication mechanisms and neural circuitry and encompass several basal ganglia. Complementarily, an intricate set of cortical-thalamic interactions participate in this picture and are modulated by the basal ganglia. Final motor commands are output by M1 into the spinal cord and, subsequently, to the skeletal musculature. Furthermore, the cerebellum has a central role in fine-tuning the coordination of movements and in movement learning. On the other hand, other structures in the inferior parietal and ventral premotor cortex participate in even supplementary aspects of movement, including the representation of peripersonal space [32]. Said structures also draw visual information related to this representation. Therefore, although seemingly basic, motor actions, in reality, require a sophisticated set of interactions across a large variety of neuronal populations that are involved in distinct facets of movement.

Voluntary movements can be divided into three fundamental stages: planning, initiation, and execution. As mentioned, the appropriate implementation of each movement stage depends upon complex interactions between distinct brain regions mediated through *corticocortical pathways*, which rely on how anatomical areas are hierarchically organized. In this sense, motor functions can be divided into *primary* and *non-primary* anatomical areas [33]. Both are encompassed by Brodmann areas 4, 6, and 8 (Fig. 6). Area 4 is the primary motor cortex (M1); area 6 is composed of the supplementary motor area (SMA) and the premotor cortex



(PMC); and area 8 contains the frontal eye field, which is important for eye movements. The motor areas are known to receive sensory inputs from the postcentral gyrus (primary sensory cortex) and Brodmann areas 5 and 7 (parietal lobe)



**Fig. 6** Brodmann areas division of the brain. This figure was extracted from <https://commons.wikimedia.org/>; created by Vysha

[33]. As mentioned, said inputs can aid in tuning movements toward their goal based on this sensory input, updated as the movement goes on, and on the visuospatial information output from the parietal cortex. Motor outputs are majorly originated at M1, although SMA and PMC also bear indirect connections to the spinal cord. M1 also reciprocates connections with the secondary motor areas [33], which all connect to the basal ganglia and form an intricate set of loops and connections, yielding the final result of motor outputs.

It is currently accepted that motor control involves cognitive and sensory processes as well, with the planning stages of a movement involving more frontal and parietal areas, whereas M1 would be involved in integrating information originating from these areas and further relaying the final motor commands to the peripheral nervous system [34]. Indeed, a recent review thoroughly highlighted the influence of elaborate circuits involving the SMA, thalamic projections, and basal ganglia in planning and executing movements [35].

With the above description, it becomes clear that there is a complex set of structures perfectly tuned together to yield even simple movements. Therefore, injuries in some of these structures may compromise the correct or desired movement output. In more severe cases, all of the patient's movements can be impaired. In others, some of the activities

may be recovered through physical therapy and other newer approaches that employ, for instance, motor imagery practice and virtual reality. Indeed, since the conventional pathways have been damaged for these patients, the imagery of movement, rather than actions themselves, has been increasingly explored.

## Motor Imagery

Motor imagery (MI) is the mental rehearsal of a movement task without overt execution [36]. To appropriately interpret this activity and improve on its applications, it is crucial to comprehend its neurophysiological correlates. Therefore, this section reviews functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) studies that attempt to delineate the main areas involved in MI. Subsequently, we discuss how the activity of these areas has been measured through EEG and, finally, how it has been applied to MI learning protocols.

## Neuroanatomical Correlates of Motor Imagery

MI has been the subject of debate for decades. One of the enduring themes concerns the debate surrounding the *functional equivalence* and the *motor cognitive* models. The first suggests that both MI and motor execution (ME) involve the same neural state, with the only difference being the motor output response [37] (i.e., the extent to which the motor action is performed, which is overt, in the case of ME, and covert, for MI). In contrast, the *motor cognitive model* specifies that MI also relies on executive control processes much more than ME, thus demanding the involvement of the functionally corresponding frontal brain areas [38]. The latter, proposed by Glover and Baran in 2017, materialized from the lack of theoretical development regarding MI and the compelling evidence they presented, which conflicted with the functional equivalence model [39]. Glover and Baran proposed that their model, besides explaining the similarities between MI and ME, would be more complete since it could also account for the differences between ME and MI [39].

From the perspective of neural correlates of MI, the topic's relevance can be seen from the considerable amount of neuroimaging research devoted to understanding the similarities and differences between MI and ME. Ingvar and Philipson performed functional mapping of regional cerebral blood flow (rCBF) during MI tasks for the first time in humans [36]. In their study, the researchers contrasted the imagined and actual movement of the subject's right hand, measuring rCBF in the left hemisphere. They reported that MI induced increases in rCBF mainly in frontal and temporal areas, in the dominant (left) hemisphere, whereas such behavior was observed on M1 for ME [40]. To further



complement the picture, in 1996, Decety provided important contributions to whether imagined and executed actions shared the same neural substrates [36]. He gathered evidence of MI neural correlates through chronometric studies and autonomic and rCBF measurements. Specifically regarding the latter, the researcher outlined several evidence indicating that mainly the frontal and parietal areas, especially the SMA, were involved in MI [36]. Interestingly, Decety also outlined that, even though MI involves executive functions, researchers should be able to dissociate MI's working memory and attention aspects [36] so that motor-intrinsic aspects of the task can be adequately investigated. On the other hand, mental tasks, such as attention, have been reported to affect movement performance—see, for example, [41]. Thus, we could expect the neural mechanisms involving the interaction between MI's motor and cognitive aspects to be very intricate, and attempting to separate such aspects might be considerably challenging.

In any case, the involvement of the brain areas outlined by Decety in 1996 would be consistently evidenced in similar studies throughout the years. In 1999, Lotze and colleagues examined ten healthy right-handed subjects performing ME and MI of the left and right hands in an MRI scanner. Overall, the authors found that both tasks activated similar areas for all subjects, namely, the SMA, the premotor area, and M1. Nonetheless, they reported that M1 was significantly activated only during actual ME. The authors also described similarities and a few differences in the cerebellum activation. Even with the contrasting behaviors in some instances, their overall conclusion was that MI and ME shared similar neural substrates [42]. Subsequently, in 2003, Nair and colleagues studied the cortical and cerebellar activity during the execution and imagining of unimanual and bimanual finger movements [43]. They reported consistent networks involving the SMA, the superior parietal lobule, and the cerebellum for both MI and ME; however, cerebellar activity was mostly absent for MI [43]. Several works have consistently indicated the involvement of these areas during MI, in particular, the SMA and the parietal lobule [44–65]. A considerable portion of this branch of studies favored the functional equivalence model. However, an appreciable amount of research also evidences differences between MI and ME [64, 66–68], including the extent of the M1's involvement in the imagery tasks [69, 70].

A 2006 review that examined MI as an emerging strategy for the rehabilitation of stroke patients summarized conflicting evidence on this topic (i.e., on the activation of M1 during MI in healthy subjects). The authors stated that the reviewed studies “highlighted robust and consistent activation of the secondary motor network and ipsilateral cerebellum during motor imagery, but only weak or inconsistent M1 activation” [71]. In other words, the extent to which M1 is involved in MI, at least from a purely executive performance,

was still questionable. Secondary areas, such as SMA and PMC, were consistently activated across subjects.

Later, in 2008, Kasess and colleagues modelled effective brain connectivity through dynamic causal modelling (DMC) to investigate causal communication mechanisms during MI [72]. Their results indicated that SMA had a suppressive role in the activation of M1 during MI [72]. Additionally, a recent meta-analysis of functional neuroimaging studies compared the networks involved in MI, action observation (AO), and ME [64]. The authors performed a careful selection of studies indexed in the PubMed database seeking similar types of tasks for the three approaches, and only studies that provided coordinates in the standard stereotaxic space were included. The researchers employed the activation likelihood estimation (ALE) analysis to infer the regions and networks involved in the three tasks. Hardwick and colleagues found consistent brain areas at premotor, parietal, and somatosensory networks recruited across ME, MI, and AO. However, the authors specified that only the MI task consistently recruited the dorsolateral prefrontal cortex and the corresponding regions on the frontal thalamus, which, according to them, could be due to how these areas are involved in working memory mechanisms or in the suppression of overt ME [64]. Moreover, their meta-analysis revealed that the premotor-parietal network is predominantly engaged in MI [64]. Besides, importantly, M1 was consistently recruited only during ME [64]. These studies exemplify that, besides being commonly considered very similar tasks, MI and ME bear their particularities and might not be regarded as yielding the same type of brain response at distinct degrees. This could be expected since the cognitive processes involved in both tasks differ, at least at a conscious level. One could also argue that the aforementioned studies could be used to support the motor cognitive model.

Most recently, the researchers who proposed the motor cognitive model explored three experiments with MI in which they contrasted their ideas with the widely accepted functional equivalence model [73]. Their goal was to analyze how each model accounted for the interference of cognitive functions in the performance of MI tasks. Their work consisted of three experiments in which 32 participants were divided into two groups: one performed ME, whereas the other performed the covert counterpart of the motor actions. Glover and colleagues had subjects undergo three experiments in which they mainly measured the time of execution of the motor tasks when participants were submitted to external conditions that should demand the use of their executive functions, which included performing calculations, low-load repetitions, and word generation tasks concomitantly to the motor activities. The researchers reported similar findings for all conditions, with execution times being substantially altered for the MI condition; only a much more modest impact was observed for overt ME [73]. Glover

and colleagues thus reinforced evidence favoring the motor cognitive model, given that the higher cognitive demand on executive functions affected MI much more significantly than it did for ME. Interestingly, EEG studies in our group have also repeatedly indicated that features from frontal and parietal cortical areas are much more consistent, over time, for distinguishing MI tasks [74–77].

In any case, regardless of the most appropriate model for describing MI and its corresponding neural correlates at the moment, from the amount of evidence exposed in this subsection, what we can more assuredly presume is that MI requires mechanisms of both motor and executive functions, which manifest through the recruitment of cortical networks comprising frontal cortical areas such as the SMA and the parietal lobule. Subcortically, MI mostly demands the participation of basal ganglia and thalamic pathways. These considerations should prove important for appropriately delineating MI practice protocols and for better understanding and isolating this complex task's motor and non-motor aspects. In the following subsection, we review studies that targeted delineating protocols for quantifying the MI response from the EEG signal.

### EEG MI Biomarkers

In 1997, Pfurtscheller and Neuper recorded three healthy subjects performing hand MI tasks with a dense array of EEG electrodes. They observed significant EEG changes only over the primary sensorimotor cortex, with slightly varying patterns. They described event-related desynchronizations (ERDs; that is, a decrease in the signal's power) on the contralateral side of the imagined hand movement for the  $\alpha$  band on two subjects, and in the  $\beta$  band, for the remaining participant. During some cases, synchronization patterns (ERS; event-related synchronization) were also observed at the ipsilateral primary sensorimotor cortex [78]. At the time, Pfurtscheller and other researchers had already described similar ERD patterns during voluntary movement and its planning stages [79–81], leading the authors to conclude that similar activation patterns between imagined movement and the planning of motor actions should be in place.

Although the number of subjects for the aforementioned study was small, their conclusions would be further supported by various fMRI works (such as the ones presented in the previous subsection), favoring the functional equivalence model. In the following years, Pfurtscheller's group continued to elaborate on their findings and suggested, for example, employing ERD/ERS patterns for functional brain imaging studies [79], linking them to activated/deactivated brain areas in some contexts [80] and arguing on their possible uses for activation of brain areas affected by strokes, allied with brain-computer interfaces (BCIs) [81].

In 1999, Pfurtscheller and Lopes da Silva summarized important principles for calculating ERD/ERS patterns in EEG signals [82]. The authors outlined essential distinctions between event-related potentials (ERPs) and the ERD/ERS patterns. According to them, the first is generated as a result of afferent stimulation and thus chiefly involves the interaction between afferent pathways and the subsequent thalamic-cortical relay fibers to the cerebral cortex; on the other hand, an ERD/ERS materializes from a more local interaction usually involving thalamic-cortical and cortico-cortical pathways [82], as illustrated by Fig. 7. These intricate neural communication mechanisms, associated to membrane potentials and the modulation of neuronal signals from neurotransmitters, would result in the EEG patterns observed macroscopically.

Pfurtscheller and Lopes da Silva indicated that ERD/ERS patterns are frequency-specific and summarized the following guidelines for their calculation (summarized in Fig. 8) [82]:

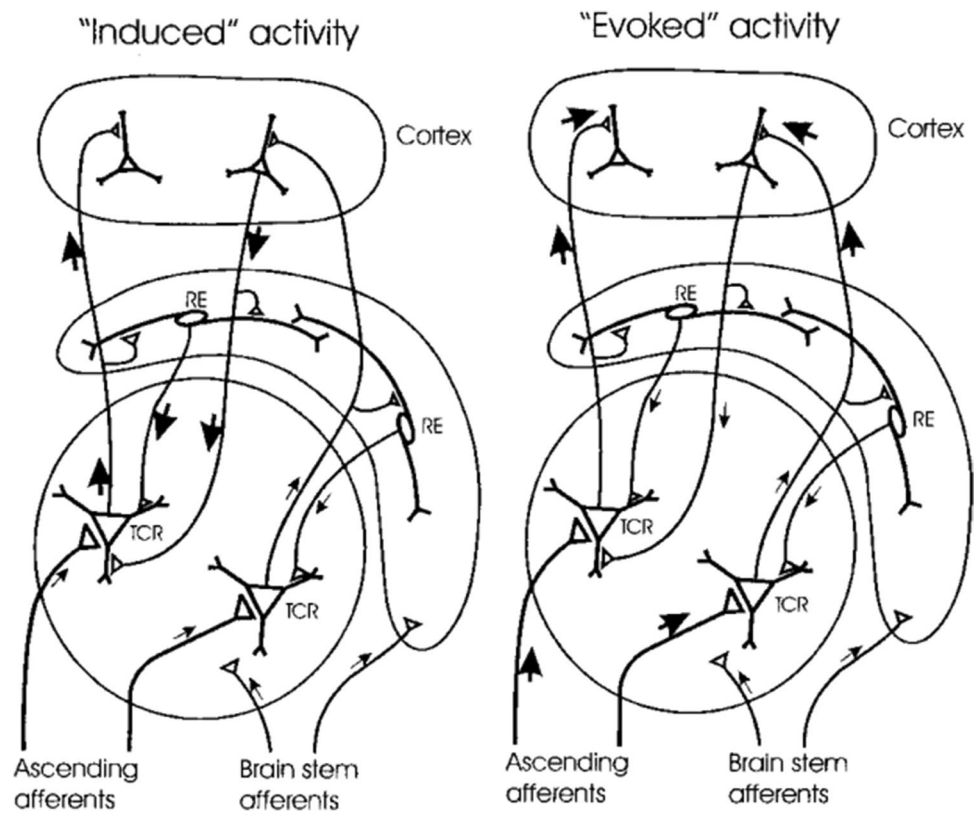
- (i) band-pass filtering the raw EEG signals to the frequency bands of interest;
- (ii) squaring the samples' amplitudes (which yields quantities proportional to the signals' power);
- (iii) averaged power samples over time (trials)

In this manner, ERD/ERS patterns can be calculated for each frequency band of interest.

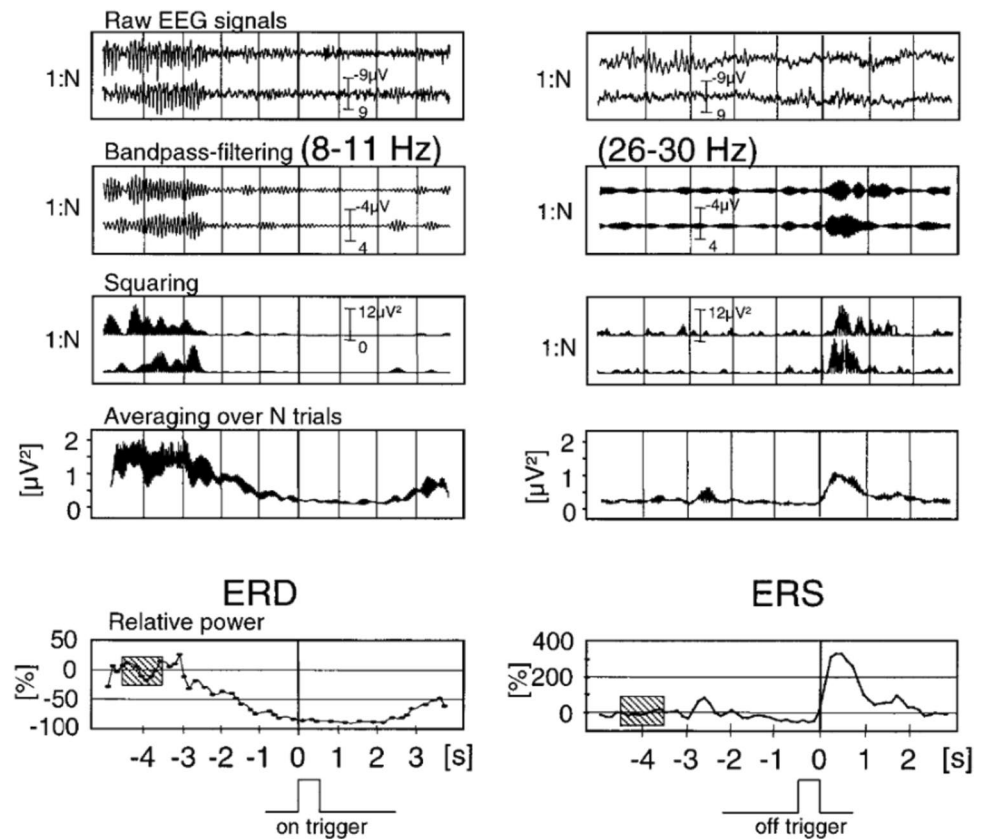
The proposed ERD/ERS methodology was generally well received by the research community, in such a manner that numerous studies have based their MI applications on these guidelines, as well as seeking the corresponding mental patterns on the central electrodes (C-labeled sensors in EEG positioning systems), which are generally above the primary sensorimotor area [83–87]. Nevertheless, as highlighted by the MRI studies in the previous subsection that began favoring the motor cognitive model for MI, disregarding the contribution that other EEG sensors and frequency bands can provide for MI can cause the loss of important information.

In 2014, Castro and colleagues analyzed four types of MI with an electroencephalogram, mapping the brain activity to clarify the possible involvement of different cortical areas in these tasks. The authors modelled the brain of a healthy subject as a Distributed Intelligent Processing System, placing eight electrodes over F3, F4, C3, C4, P3, P4, O1, and O2. Although minor activation of M1 was detected for all MI activities, distinct areas were involved depending on the task. Even though one could argue that such differences could be related to the topological distribution of the cortical system innervation on M1, they were not restricted to this brain area. Castro and her colleagues found that the main areas activated involved frontal and parietal sites [88], thus complementing results previously described by Pfurtscheller's

**Fig. 7** Illustration of the mechanisms of generation of ERPs and ERD/ERS patterns. On the left, “induced” neural activity would be generated locally and relayed through thalamo-cortical and cortico-cortical pathways. On the other hand, “evoked” activity would be triggered due to external afferent stimulation. Reprinted from *Clinical Neurophysiology*, Vol 110, Issue 11, G. Pfurtscheller, F.H. Lopes da Silva, *Event-related EEG/MEG synchronization and desynchronization: basic principles*, 16 pages, Copyright 1999, with permission from Elsevier



**Fig. 8** Illustration of the traditional steps for ERD/ERS estimation, according to the guidelines presented in (Pfurtscheller; Silva, 1999). First, EEG signals must be filtered in the frequency band of interest. Subsequently, squaring samples would provide a quantity proportional to the signals’ power, which can be analyzed to explore the time course of average ERD/ERS patterns over N trials. Reprinted from *Clinical Neurophysiology*, Vol 110, Issue 11, G. Pfurtscheller, F.H. Lopes da Silva, *Event-related EEG/MEG synchronization and desynchronization: basic principles*, 16 pages, Copyright 1999, with permission from Elsevier



group that were essentially restrained to M1 (whereas also agreeing with results that favored the motor cognitive model for MI). However, in this study, only data from one subject was collected, preventing the authors' conclusions to be generalized. Moreover, since the electrode array was relatively small (8 channels), there is a higher chance of one single electrode standing out.

On the other hand, branches of studies employing connectivity analysis and graph measures have also found important distinctions between ME and MI and, even further, provided supplementary information regarding the cortical areas involved in MI. For instance, in 2014, Xu and colleagues measured the importance of graph nodes representing functional networks of the brain through the *betweenness centrality*. This metric quantifies how important a node is within a network based on how often it acts as a “bridge” between two other nodes (measured through shortest paths). In their work, the researchers reported that the key node for ME was located at the SMA, whereas, for MI, it was over the PMC [89]. These results, once again, agree with the hypothesis regarding frontal areas' involvement in motor planning during MI. Additionally, this study reinforces this involvement under a completely different analysis approach (functional connectivity). Furthermore, the authors did not outline key nodes over M1 for either ME or MI. Indeed, given the interpretation of the betweenness centrality, a possible explanation of their findings would be that, although, especially for ME, M1 is of ultimate importance (as it relays the information for the movement output), its relevance when measured under the sense of acting as a necessary mediator for information flow within the network is reduced when compared to the other regions (i.e., the SMA and PMC). This suggests the participation of the more frontal areas concerning the functional mediation of information regarding both ME and MI (with, anew, the key region for the ME tasks being at the SMA and, for the MI, at the PMC).

Work from our group also has tended to support the participation of areas beyond M1 in MI, especially highlighting the participation of both frontal and parietal involvement in motor imagery. In 2017, we investigated possible linear relations between the power differences induced by MI and variations in the degree of 64 nodes of a functional network obtained by modelling the brain as a graph. For both the  $\mu$  and  $\beta$  bands, frontal and parietal electrodes displayed statistically significant correlations more often than for sensors located over the primary sensorimotor cortex. In particular, the most prominent electrodes were placed at Fz, F5, F6, P5, P6, and POz [90]. A 2019 work employing functional connectivity analysis (through the Pearson and Spearman correlations and mean phase coherence) investigated the classification scenario of four MI tasks using distinct graph metrics as features for a classifier. When further exploring optimal electrodes for classification

based on their eigenvector centrality, frontal and parietal electrodes proved relevant. Moreover, interestingly, the C-labeled electrodes were not necessarily the ones that provided the best classification features for all subjects [76]. Even in studies that did not involve the functional connectivity approach, the computation of the most recurrent electrodes along a large number of 12 MI data acquisition sessions revealed that 25% of the study's participants displayed preferences on frontal and parietal electrodes rather than on the primary sensorimotor cortex [74]. In addition, in 2020, we used this same database under different approaches, obtaining similar results, and explicitly showed that restraining classification scenarios to features only from C3 and C4 yielded the lowest accuracy outputs when comparing to choosing features from all electrodes ensemble or even excluding C3 and C4's altogether [75]. This does not mean that information on C3 and C4 is not important, but rather that it is necessary to explore further possible MI-induced patterns in other cortical areas, particularly in the frontal and parietal cortices.

Most recently, Lubbe and colleagues contrasted MI, ME, and motor preparation (MP) tasks to investigate whether the functional equivalence or the motor cognitive model would be better suitable for describing MI [38]. In their paper, Van der Lubbe and colleagues studied ERD patterns during finger-tapping tasks' ME, MI, and MP. The researchers reported the most pronounced ERDs in the  $\beta$  band were observed over M1 for the ME paradigm, whereas a posterior ERD in the  $\alpha$  band was found for both ME and MP but not for MI. Moreover, MI yielded major increases in frontal  $\theta$  activity, which were milder for the ME and MP tasks. The authors thus concluded that their results support the motor cognitive model [38].

The evidence mentioned above makes it clear that although MI shares similarities with ME, the two tasks differ. Also, even in the first ERD/ERS studies published by Pfurtscheller's group, each subject displayed its particularities. Regardless, to this day, there is a large body of literature that seems to overlook each participant's individuality in motor imagery detection and training, employing the same features in the practice protocol (see, for example, [91–93]).

Based on the aforementioned evidence, this paper argues that MI practice should be subject-specific by appropriately targeting optimal responses for that subject and that each participant's particularities should be incorporated into training protocols rather than being merely treated as “noise.” With this subsection, we aimed to emphasize the current knowledge regarding the differences between MI and ME and that the signal from other EEG sensors not restricted to the C-labeled electrodes seems relevant for a more complete understanding of the MI task.

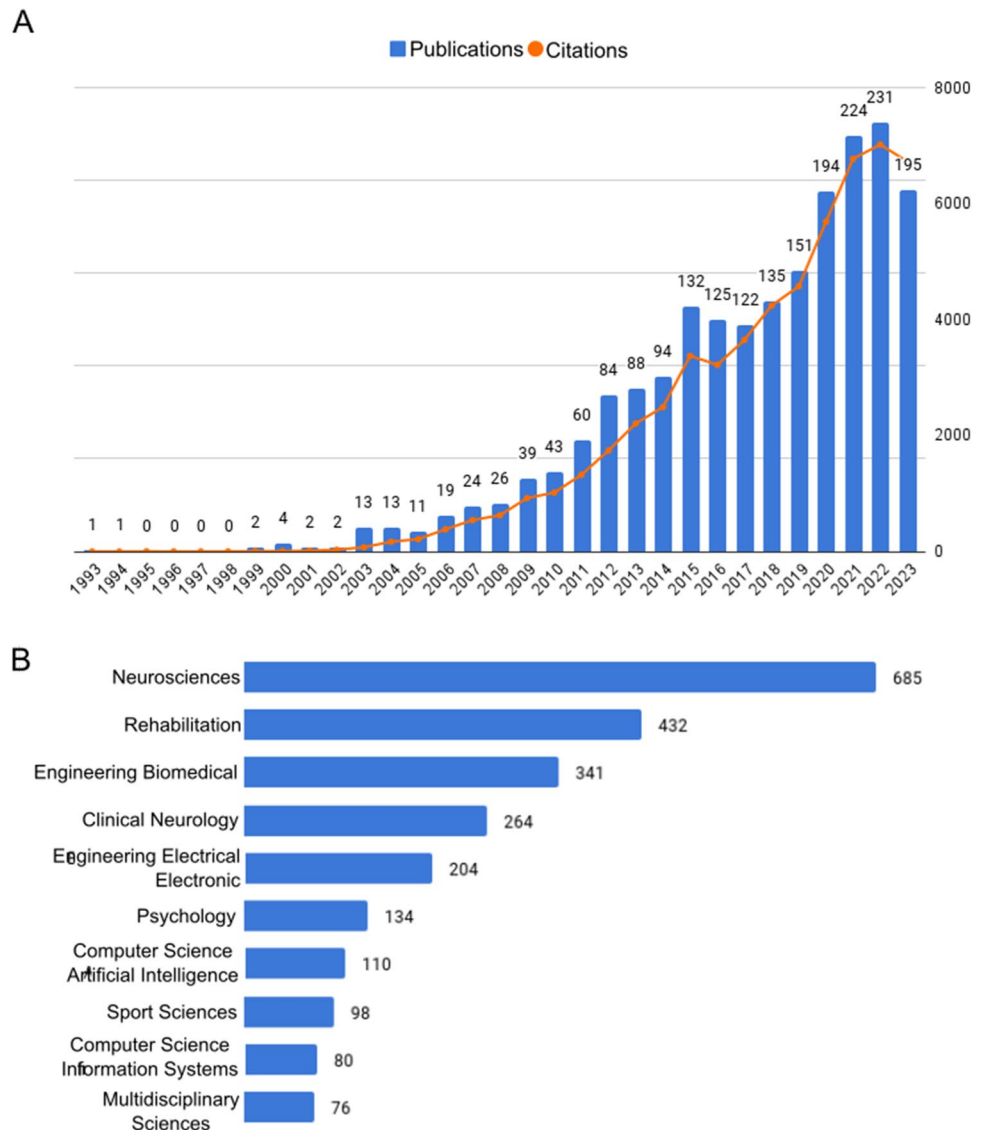
### Applications and Brain-Computer Interfaces

MI has found many applications ranging from perfecting movement practice and performance in sports [94] to rehabilitation therapies [95–98]. Indeed, as reviewed by Kappes and Morewedge, there is evidence of the efficiency of the mental practice of motor actions (instead of their actual performance) for groups of athletes, musicians, and surgeons. The authors emphasize, however, that mental practice may not be regarded as a perfect substitute for physical practice; instead, “a combination of mental and physical practice [...] can be as or more effective in improving task performance than physical practice alone” [99]. This logic bases the appeal for targeting rehabilitation protocols, which have received increasing interest over the last decades, as can be seen by the rise in the number of studies on the topic of “MI rehabilitation,” as depicted in Fig. 9A. Additionally, research

on rehabilitation-based applications intrinsically involves multiple fields of research (Fig. 9B), making for a highly multidisciplinary area, encompassing more traditional fields such as Neurology and Psychology but also more quantitative and mathematical areas of study, such as Computer Science, Engineering, and Artificial Intelligence (AI).

Not all aspects of MI are still fully understood though. Despite the high level of agreement across studies about the effectiveness of including MI in motor rehabilitation sessions, there is no consensus on session duration, number, or even the MI protocol itself, reinforcing the need for further research in this direction [100]. In addition, many studies usually do not attempt to comprehend the underlying neuronal changes that could justify improvements in the therapy. Movement performance enhancement is often measured through clinical scales (e.g., [101–103]), such as the Fugl-Meyer assessment rather than by direct neural

**Fig. 9** Number of publications and citations **A** and publications per knowledge category **B** under research topic “motor imagery rehabilitation” in Web of Knowledge (at 2024/01/21). A total of 2036 publications since 1993 were found in this query



and more objective measures. Albeit this approach is useful for elucidating issues related to the patients' overall quality of life, it is unspecific as to inform about possible neural plasticity effects.

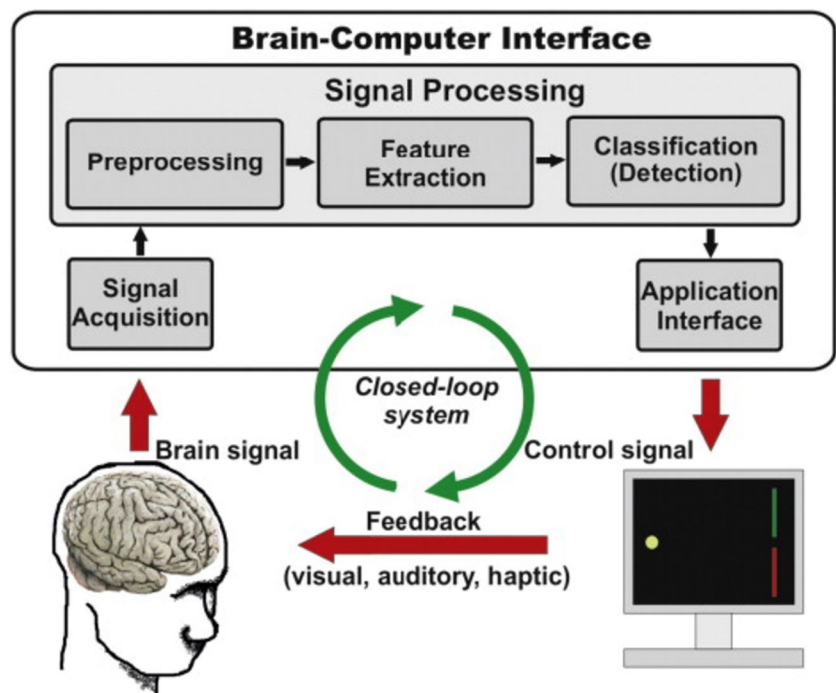
In relation to neural changes, in 2018, Fang Li and colleagues employed magnetic transcranial stimulation to investigate motor-evoked potentials and diffusion tensor imaging (DTI) to assess brain changes in two groups of stroke patients who performed traditional physical therapy with and without MI. All participants underwent a 45-min daily rehabilitation session for 4 weeks, five times a week. The authors observed a larger amplitude and shorter latency in the motor-evoked potentials for the group that performed the physical therapy sessions with MI. Moreover, the DTI data indicated that the MI group exhibited a larger integrity for the dorsal pathway [104]. Furthermore, the Fugl-Meyer Assessment and the Action Research Arm Test showed larger increases for the group that experienced the inclusion of MI in their physical therapy [104]. Therefore, this investigation also considered more objective measures, an approach that, to the best of our knowledge, is still not common in the literature. More recently, another study attempted to establish correlations between clinical and functional scales and EEG metrics. More specifically, the researchers sought relations with the laterality coefficient of the EEG (which is calculated considering ERD and ERS values of both ipsi and contralateral patterns during MI), raising the possibility of using it as a biomarker for functional assessment of stroke patients [105].

Regardless of the final application, proper MI training should involve identifying the task's response, which requires monitoring brain signals (usually with EEG). Feeding back results in real-time to the user enables them to modulate and adjust their corresponding mental strategies accordingly. Hence, brain-computer interfaces (BCIs) can be useful tools for MI training [101, 102, 106] (Fig. 10). These are systems that are used to control an external device, such as a wheelchair or a prosthesis, without relying on the traditional efferent fibers. Instead, these devices are commanded directly by brain signals. As with NFBT, a variety of signal acquisition techniques can be employed to design BCIs, such as fMRI, NIRS, and magnetoencephalography; however, EEG is usually preferred, mainly due to its low cost, portability, and high temporal resolution (even though its spatial resolution is not great, temporal resolution is fundamental for the proper operation of an online BCI). When coupled with this technology, MI training can aid in objectively monitoring brain features related to this type of imagery since researchers can define MI-specific quantitative measures. These measures can then be longitudinally evaluated.

Even though the general schematics of BCIs and NFB are very similar, they differ in their final goal, whereas the first focuses on commanding an external device, and the latter aims to improve the cognitive capability and/or symptomatology of a given neurological condition.

Current state-of-the-art BCIs include three main stimulus types for generating measurable mental responses: the P300 potential, the steady-state visual evoked potential (SSVEP), and MI.

**Fig. 10** Schematics of a BCI encompassing the three essential stages of the technology: signal acquisition, preprocessing, and classification. The first step may be performed with any neural signal acquisition technique; the preprocessing step aims to increase the signal-to-noise ratio to identify features of interest in the signals. Finally, a classification determines the final application of the recorded signals based on the aforementioned features. Reprinted from *NeuroImage*, Vol 85, Part 1, V. Kaiser, G. Bauernfeind, A. Kreilinger, T. Kaufmann, A. Kübler, C. Neuper, G. R. Müller-Putz, Cortical effects of user training in a motor imagery based brain-computer interface measured by fNIRS and EEG, 13 pages, Copyright 2014, with permission from Elsevier



The P300 wave is a positive potential that is evoked during an attentive state due to exposition to an occurring low-probability event. This response is usually employed for designing spellers: characters are displayed, and the system's user is instructed to write a word by focusing on the needed characters. Rows and columns of the character matrix flash at predefined times, and by combining information on the P300 evocation during the corresponding flashes, it is possible to identify the character the P300-BCI user is targeting. This type of BCI is generally well-developed, with characters being recognized with high accuracy, with the main focus now relying on increasing the system's transfer rate since these systems still suffer from relatively longer spelling times. Further information on this type of speller can be found in [103].

SSVEP-BCIs are based on a brain response that arises in the occipital cortex due to exposition to flashing visual stimulation: when the user is exposed to a visual stimulus that flashes at a given frequency, a steady-state visual evoked potential (SSVEP) that oscillates at the same frequency can be recorded in the primary visual cortex. This allows protocol designs involving, for example, a matrix with four distinct stimuli that flash each at its own pace, enabling the mapping of four distinct commands to an external device. SSVEP-BCIs can achieve comparable performances to P300-based systems and generally present the advantage of higher transfer rates [107]. Considerable effort has been invested in even developing a combined SSVEP-P300 BCI system [108–110] limitations of each approach would be attenuated by the other.

Although SSVEP and P300-based BCIs can achieve considerably good accuracies, they require external stimulation, whereas MI could, in principle, be initiated at any given time by the system user. However, this is not a trivial task, with naive users being particularly subject to difficulties performing it at first. Hence, employing MI-NFBT for BCI performance improvement can be of great use if appropriately implemented, possibly aiding in guiding users to understand how to generate (and maintain) identifiable and distinguishable MI patterns. Nevertheless, appropriate learning would only occur if the training feature is related to the task at hand. This emphasizes the importance of studies that still attempt to improve the current literature concerning the exact MI response further, even though the ERD/ERS patterns reported by Pfurtscheller's group have practically constituted a paradigm for the field.

So far, we have reviewed the concepts of NFBT and BCI, as well as relevant findings and considerations for building systems based on them that researchers have found over the years. Although we have distinguished between the two approaches according to their final goals, i.e., the main objective for a BCI is the control of an external device by itself, whereas NFBT is used to improve on some specific

cognitive capability or in the symptomatology of a neural condition, we will use the term “BCI-NFBT” to designate applications that involve controlling an external device as a feedback to improve on a cognitive capability and/or on a specific symptom of a neural condition. In other words, when we use this term, we refer to systems that unify the main goals of BCIs and NFBT.

## Strategies for BCIs and NFBT

In the early 2000s, advances in the fMRI field have enabled real-time signal processing and applications. One branch of applications included investigating whether human subjects could self-modulate their fMRI signal. In 2003, Weiskopf and colleagues developed an fMRI-BCI that, based on the BOLD (blood oxygenation level-dependent) signal, would display an activation map of their brain to users. In that study, one male subject was recruited and was trained to modulate his BOLD signal on both “up-regulation” and “down-regulation” tasks. The authors observed a learning effect across sessions, suggesting that self-modulation of brain signals was feasible with fMRI [111]. In the next year, the group further reviewed several studies on this topic [112], reinforcing the feasibility of fMRI-NFBT, which was also strengthened by more recent studies (e.g., as reviewed by [113]).

When comparing EEG and fMRI for NFBT applications, the authors argued in favor of the higher spatial resolution of fMRI, also indicating that the EEG signal is not merely related to the cortical areas directly underneath the sensors (a signal recorded through an EEG electrode is indeed subject to the influence of other brain areas and volume conduction effects throughout the brain and scalp) [112] and, thus, is subject to mixing of signals arising from a variety of sources at the same time. However, it should be noted that the BOLD response is hemodynamic, thus relating to neuronal activity indirectly and with an intrinsic latency. In contrast, EEG sample frequency can reach values of kHz, which should enable real-time applications that are less subject to delays in neural responses. Furthermore, several components of the fMRI signal arise from systemic and non-neural sources [114]. Given the ERD/ERS prior knowledge patterns, common strategies for MI training with EEG-BCIs generally involve user-signal interaction through power-related features.

In 2009, Hwang et al. developed an NFBT interface showing users their real-time activation cortical maps. Ten subjects were asked to participate in this study. Five of them underwent a 30-min NFBT session. After being instructed on the location of the primary sensorimotor cortex, subjects should attempt to generate cortical activations around the area. The authors reported that, although all participants experienced difficulty at first, they were able to generate

such activations successfully during the training. The other five subjects, constituting a control group, did not participate in the training and had their EEG data collected during a 30-min break time. Recordings were also made before and after the training period to explore possible training effects. The authors found a larger number of significant features for data classification for the group that underwent the NFBT and improvements in MI classification accuracy, concluding that their system was efficient in assisting MI activity modulation learning [115]. Regardless, EEG recordings were only of a single session, without mentioning possible long-term effects. Therefore, a few questions remained open: Was the observed improvement maintained in the next days? Or would it return to basal levels over time? Could a single training session be enough for MI learning? Could the type of feedback exert any influence on the training outcome?

In that same year, Neuper and colleagues investigated two groups of participants who performed right- and left-hand MI tasks to control an output signal on a computer screen. Two types of feedback, “realistic feedback” and “abstract feedback,” were evaluated. The first consisted of controlling a virtual hand performing a grasping task, whereas the other involved controlling a moving bar. Band power estimates were employed as features for a Fisher discriminant classifier to distinguish the MI tasks. No difference regarding classification was observed for both groups; instead, significantly larger ERDs were induced during the feedback sessions compared to an initial acquisition without feedback. The authors thus concluded that the feedback presentation form (i.e., abstract versus realistic) played no role in the MI learning process, given that both types of feedback provided equivalent information [116]. Like the previous study, this work recruited more subjects [23] who underwent a larger number of sessions (four days), addressing some of the limitations mentioned above.

Despite these indications of the feasibility of using EEG-based systems for MI learning, some questions were still unclear. Xia et al. investigated whether providing distinct feedback strengths—i.e., associating distinct feedback amplitudes to the strength of the MI response—would yield better results. Their study recruited nine healthy subjects and a progressive muscular atrophy patient with no previous BCI experience. All participants were randomly divided into a control and experimental group that performed the same task but received slightly different feedback. The MI interface displayed the drawing of two bars, representing sinks and an arrow between them. This arrow could point to either right or left, and its direction should induce the subject to perform the MI task of the corresponding hand. When the arrow’s direction was determined, a ball would be displayed at the matching sink, and the correct identification of the MI occurrence by a support vector machine (SVM) classifier should provide the feedback. Features for the classifier

originated from the CSP (common spatial patterns) signal decomposition (CSP decomposes the signal based on its variance, which is calculated through the signal’s squared amplitude and, hence, is related to the power of the measured signal) [117]. User feedback was given through the sink bar being filled with water, consequently raising the ball’s position inside it. The difference between both groups lies in the fact that, for the experimental group, the step at which the ball was raised would vary upon the output SVM classification probability. Conversely, for the control group, the feedback step remained constant during the training sessions. When comparing classification accuracy over 7 training days, the experimental group displayed increases compared to the control group. Moreover, the SVM classification probability also tended to be sharper for the experimental group. The authors thus concluded that the feedback strength also played a role in MI learning [118]. The generalization of their conclusions, however, was precluded by the relatively small (10) number of subjects.

One year later, Lotte et al. elaborated on a review study highlighting human training protocols for spontaneous BCI control flaws. The authors divided their flaws screening into three levels: (1) the feedback, (2) the given instructions, and (3) the training tasks. At each of these levels, a few guidelines were given: for (1), the authors recommended that the feedback should be encouraged toward positive feedback (i.e., only provided when the user performs well), meaningful (e.g., in the machine learning context, the classifier should be carefully trained, preferentially with only relevant features and with trials when the user indeed presented a good performance), and explanatory (i.e., ideally, the given feedback should provide enough information for the user to understand what he/she did wrong, as well as how to improve on the training task). At level (2), the authors stressed that instructions were rarely mentioned in papers and should be provided in detail to the subject, reviewing the influence of kinesthetic MI over the visual strategy. Finally, regarding (3), the authors highlighted that the BCI training should provide an engaging environment for the user [119]. The authors also criticized the fixed and unmodified format BCI training protocols have received over the last few years, indicating that their proposed guidelines should be considered when designing this type of study.

It is also important to consider that MI-BCI applications may be seen as composed of two main approaches: on the one hand, the main neurophysiological correlates of MI in the form of ERD/ERS patterns over the primary motor cortex can be modulated and identified by the system. On the other, feature selection and classification algorithms can gather relevant signal characteristics to detect mental patterns related to MI (that are not necessarily restricted to M1), further employing them in the desired application. Note that this last approach is indirect because it necessarily



involves mathematical combinations and projections of the signal features, thus adding a step that may entangle the neurophysiological meaning of the studied quantities. In addition, the classification approach might detect patterns that are not strictly motor-related. Thus, these methodologies may be regarded separately to target two questions. The first relates to identifying and improving motor-related patterns and should be of larger interest to applications that target the improvement of motor-related functions. The other would verify whether the improvement of BCI control might lead to corresponding enhancements in motor-related aspects. Therefore, one can expect that, although some relationship may exist between both strategies, such a relationship may not always be straightforward. A study published in 2018 already suggested that MI BCI performance may not be correlated with the underlying ERD response despite it being a representative feature of motor imagery [120]. Indeed, recent research has investigated whether functional and structural brain network features at resting state correlate to MI performance [121, 122].

## Current Challenges in MI-NFBT Research

Throughout this review, we delineated several points regarding the main areas involved in MI as measured through functional neuroimaging techniques, which, we argued, can help fine-tuning potential implementations for applications such as motor rehabilitation protocols. Hence, studies that help uncover the underlying neural mechanisms of MI will certainly be useful in the future to improve on the current body of knowledge.

Additionally, we have also reviewed evidence relating to the role of feedback itself in the process. Indeed, the specificity of NFBT in possible improvements on the MI capability is still a topic of discussion. Therefore, studies measuring placebo effects should be encouraged [123]. Indeed, although some studies have used sham groups [75, 124, 125], the body of literature on the subject is still scarce.

We have also previously argued in favor of the individualization of NFBT protocols and on the consideration of specificities for neurologically damaged patients, which seems to be an increasing trend in recent studies, e.g., [126, 127]. In any case, several challenges still remain, as recently pointed out by Almufareh and colleagues, involving the varying proficiency of individuals to appropriately perform MI and, consequently, generate identifiable patterns in functional neuroimaging techniques; the subject-specific training responses; the actual implementation in clinical practice, which is limited due to multiple factors, including insufficient knowledge and awareness of MI among healthcare professionals; and technological constrains, which might hinder the outcome of MI-based interventions [128].

It is also noteworthy that practical studies involving neurological patients in clinical settings are much more difficult to develop than well-controlled studies with healthy subjects in laboratorial environments. However, as the field of NFBT-MI advances, concurrent technological advances in neuroimaging should aid in facilitating measurements in practical clinical settings, which certainly will provide valuable insights in the years to come.

## Conclusions and Overall Perspectives

We reviewed several aspects of the MI tasks, ranging from perspectives on their neural correlates to applications involving BCIs and/or NFBT. Our work exemplifies the complexity of the brain and the MI task.

We have delineated particularities regarding MI's cognitive and motor models, emphasizing the importance of areas that are not strictly motor-related to completely understand this task. In this sense, we have argued for individualized NFBT protocols incorporating users' specificities. At the most general level, experiments should always be thoroughly designed to target specific research questions that will enable a larger picture to improve our understanding of MI.

The topic of motor rehabilitation through MI-NFBT seems promising. However, we cannot simply rush into developing systems and applying expensive treatments without appropriately understanding the foundations and validity of the technique, which is what we attempted to clarify, at least to some extent of the current issues, through the studies reviewed in this work.

**Availability of Data and Materials** Access to the data can be granted by the corresponding author upon request.

**Author Contribution** C.A.S.F. wrote the main text. All authors reviewed the manuscript.

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## Compliance with Ethical Standards

**Conflict of Interest** The authors declare no competing interests.

**Human and Animal Rights and Informed Consent** All reported studies/experiments with human or animal subjects performed by the authors have been previously published and complied with all applicable ethical standards (including the Helsinki Declaration and its amendments, institutional/national research committee standards, and international/national/institutional guidelines). In such cases, studies were approved by the University of Campinas' Ethical Committee (CAAE: 53041616.6.0000.5404). All participants signed an informed consent term, freely agreeing to participate in this research project.

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