

EEG Neurofeedback research: a fertile ground for psychiatry?

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1 **Abstract**

2 The clinical efficacy of neurofeedback is still a matter of debate. This paper analyzes the
3 factors that should be taken into account in a transdisciplinary approach to evaluate the use of
4 EEG NFB as a therapeutic tool in psychiatry. Neurofeedback is a neurocognitive therapy
5 based on human-computer interaction that enables subjects to train voluntarily and modify
6 functional biomarkers that are related to a defined mental disorder. We investigate three kinds
7 of factors related to this definition of neurofeedback. We focus this article on EEG NFB. The
8 first part of the paper investigates neurophysiological factors underlying the brain
9 mechanisms driving NFB training and learning to modify a functional biomarker voluntarily.
10 Two kinds of neuroplasticity involved in neurofeedback are analyzed: Hebbian
11 neuroplasticity, i.e. long-term modification of neural membrane excitability and/or synaptic
12 potentiation, and homeostatic neuroplasticity, i.e. homeostasis attempts to stabilize network
13 activity. The second part investigates psychophysiological factors related to the targeted
14 biomarker. It is demonstrated that neurofeedback involves clearly defining which kind of
15 relationship between EEG biomarkers and clinical dimensions (symptoms or cognitive
16 processes) is to be targeted. A nomenclature of accurate EEG biomarkers is proposed in the
17 form of a short EEG encyclopedia (EEGcopia). The third part investigates human-computer
18 interaction factors for optimizing NFB training and learning during the closed loop
19 interaction. A model is proposed to summarize the different features that should be controlled
20 to optimize learning. The need for accurate and reliable metrics of training and learning in
21 line with human-computer interaction is also emphasized, including targeted biomarkers and
22 neuroplasticity. All these factors related to neurofeedback show that it can be considered as a
23 fertile ground for innovative research in psychiatry.

24

25 **Keywords**

26 Neurofeedback; EEG; Neurophysiology; Psychophysiology; Brain Computer Interface;
27 Training; Learning

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1 Introduction

2 Neurofeedback (NFB) is a neurocognitive therapy based on human-computer interaction. The
3 objective of NFB is to enable subjects to voluntarily train and modify functional biomarkers
4 that are specific to mental disorders, in order to improve symptoms or cognitive processes. In
5 psychiatry, a biomarker is usually a psychophysiological variable that is objectively measured
6 and evaluated as an indicator of pathogenic processes or therapeutic responses [71]. However,
7 most of the current electroencephalographic (EEG) NFB protocols are not based on the
8 modulation of disorder-specific biomarkers but on the modulation of a few spontaneous *brain*
9 *rhythms*, mainly defined by the frequency of their oscillation [2, 55, 57]. This strategy is
10 prevalent since spontaneous brain rhythms demonstrate a high signal-to-noise ratio in EEG
11 recordings, and because they can be disrupted in some mental disorders, *e.g.* increased theta
12 and reduced beta power in patients with Attentional Deficit and Hyperactivity Disorder
13 (ADHD) when compared to healthy controls [3]. However, the clinical efficacy of this
14 approach remains a controversial and delicate issue even for well-investigated applications,
15 such as the therapeutic use of EEG NFB in ADHD [14, 54]. Indeed, the effectiveness of
16 neurofeedback is largely debated [22, 56, 79, 80]. In this paper, we propose that several
17 factors related to the concept of biomarker may be responsible for the conflicting results in
18 the EEG NFB literature:

- 19 (i) Limited understanding of the brain mechanisms driving NFB learning to modify a
20 functional biomarker voluntarily, *i.e. neurophysiological factors* [22],
- 21 (ii) The inconsistent relationship between EEG biomarkers and clinical dimensions
22 (symptoms or cognitive processes), potentially due to the symptom-based
23 classification of psychiatric disorders and the heterogeneity of diagnostic
24 categories, *i.e. psychophysiological factors* [25]
- 25 (iii) Superficial knowledge of how best to measure and optimize NFB learning during
26 the closed loop interaction, *i.e. human-computer interaction factors* [36].

27 This paper investigates these factors (*neurophysiological, psychophysiological and human-*
28 *computer interaction*) in a critical review of the existing literature on EEG NFB. The
29 objective is to integrate these interdependent issues into a general NFB framework in order to
30 demonstrate that EEG NFB can be considered as fertile scientific ground for psychiatry and to
31 provide a roadmap for future research in this field.

32

1 Neurofeedback and its neurophysiological 2 foundations

3 From electroencephalographic oscillations to neurofeedback

4 The EEG may be recorded via non-invasive electrodes placed on the scalp as a result of
5 intracranial fluctuations of electromagnetic field potentials, which are generated by ionic
6 exchanges at cell membranes and synapses during neuronal activity. When neuronal activities
7 occur in a circumscribed region and become temporally synchronized, their local field
8 potentials (LFPs) are then spatially summated, giving rise to large fluctuations of the EEG
9 signal [84]. Hence, changes in EEG oscillation amplitude essentially reflect the degree of
10 synchronization of intracortical neuronal populations. Synchronization is influenced by both
11 the intrinsic excitability of the neuronal population and the synaptic input it receives from
12 other regions. Hence, intra- and inter- electrode EEG measures of amplitude and coherence
13 indicate neuronal excitability within and functional segregation/integration between cortical
14 regions, respectively [17]. Moreover, this dynamic activity can occur simultaneously on
15 different timescales (i.e. frequencies): infraslow (<1 Hz), delta (1–4 Hz), theta (4–8 Hz), alpha
16 (8–12 Hz), sigma (12–15 Hz), beta (15–30 Hz), and gamma (>30 Hz). Studies involving
17 patients with mental disorders have reported significant deviations in a host of task-related
18 and resting-state EEG parameters (e.g. amplitude, coherence) compared to healthy controls
19 [13].

20 Thus, NFB has been developed in these patients mostly to correct notable deviations of
21 cortical oscillations by training subjects to modify their EEG activities. In this perspective, the
22 impact of NFB is thought to be based on the training and subsequent normalization of specific
23 “targeted” neurophysiological signatures to reduce the clinical symptoms related to a given
24 disorder. It has been also postulated that, to achieve therapeutic efficacy with NFB, it is
25 important to demonstrate significant *online* self-regulation of the trained parameter(s) (i.e.
26 during NFB). After which, long-term *offline* changes might be induced through mechanisms
27 of neuroplasticity (i.e. of functionally persistent brain reorganization after termination of NFB
28 training) [74]. Thus, in the simplest scenario, the incremental process of NFB “learning” can
29 be seen as the direct sum of two principal factors:

30 1) the online component, i.e. the within-session change of the trained signal relative to its
31 resting-state baseline, also called “performance” in the field of Brain Computer Interface -
32 BCI, and

1 2) the offline component, i.e. the absolute change of the between-session resting-state
2 baseline, which may be related to “skills acquisition”.
3 Surprisingly however, there is a scarcity of BCI/NFB studies that examine these online and
4 offline criteria in combination. Moreover, a better definition of online/offline metrics would
5 enable a more rigorous assessment of NFB protocols and BCI training [46] together with their
6 impact on brain plasticity [67] (see last section on *human-computer interaction factors*) and
7 the impact of structural and functional brain traits on plasticity [28]. This first section focuses
8 on the basis of neuroplasticity during NFB.

9 From electroencephalographic oscillations to neuroplasticity

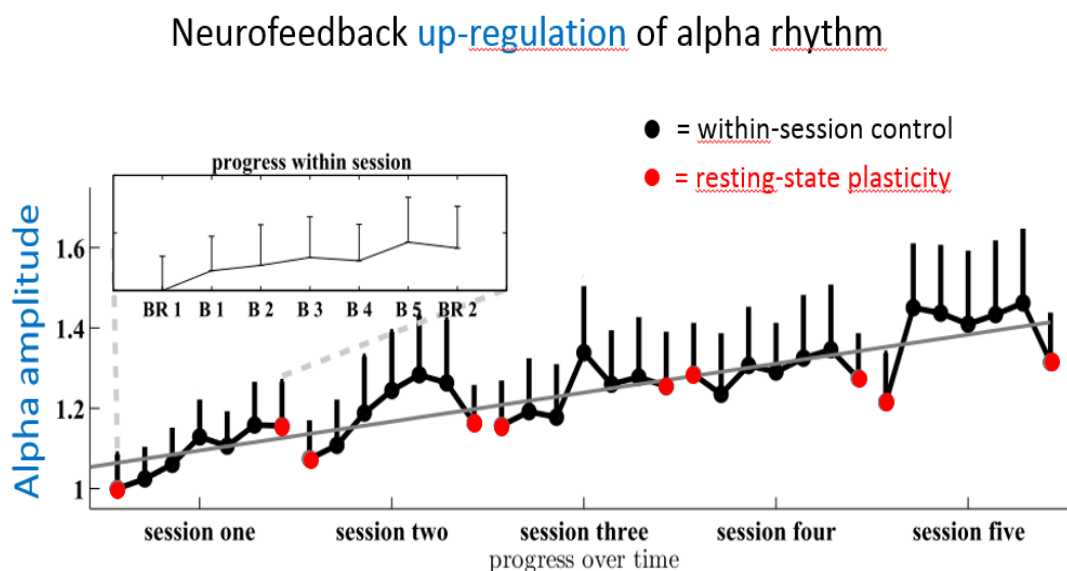
10 The dynamic modulation of EEG oscillations using NFB may induce different types of
11 neuroplasticity [67]. Neuroplasticity in general may be defined as a durable (i.e. long-term)
12 change in neural function outlasting the training period itself, underpinned by long-term
13 modification of neural membrane excitability and/or synaptic potentiation. In practice, one
14 may expect long-term plasticity to manifest itself during resting-state EEG recording(s)
15 *outside of* training sessions (i.e. offline), and/or as progressive changes *during* repeated
16 training sessions (i.e. online). Based on the neuroscience literature, there are two main forms
17 of neuroplasticity: the Hebbian type and the homeostatic type.

18 The underlying mechanism of Hebbian plasticity is *correlation-based*. Hence, NFB-induced
19 Hebbian plasticity may be expected to produce functional changes that occur *in the same*
20 *direction* as that dictated by the NFB protocol (e.g. long-term alpha increase following alpha-
21 upregulation NFB) [92]. On the other hand, since homeostasis attempts to stabilize network
22 activity within a bounded range, homeostatic plasticity is not correlation-based and may be
23 expected to produce changes in the opposite direction of NFB training (e.g. long-term alpha
24 increase following alpha-downregulation NFB) [40]. Generally, synaptic potentiation brain
25 oscillations are closely linked, given that changes in neuronal coupling directly affect levels
26 of neuronal synchronization, and vice-versa.

27 Hebbian plasticity and neurofeedback

28 Historically speaking, pioneering experiments in the 1960s that demonstrated self-regulation
29 of the EEG [39] were followed by reports that NFB training of spindle oscillations during
30 wakefulness may result in their stronger expression during sleep [77]. Recent studies provide
31 convincing data that NFB can be used to induce plastic *increases of theta, alpha, beta,* and

1 *gamma* rhythms, as well as their corresponding *decreases* [74]. However, the exact
 2 neurophysiological mechanism(s) behind the long-term conditioning of brain rhythms remain
 3 unclear.
 4 Given common observations that plasticity manifests in the same direction/frequency targeted
 5 by the NFB protocol, Ros and colleagues proposed a mechanism based on associative (i.e.
 6 Hebbian) plasticity and encapsulated by the phrase [67]: “synapses that fire together wire
 7 together, and synapses that fire apart wire apart”. This type of correlation-based plasticity
 8 occurs when connectivity is reinforced by temporally-coincident neuronal activation. As
 9 explained in the section above, EEG oscillatory amplitude positively covaries with the degree
 10 of synchronized neurons/synapses, see **Figure 1**.



Plasticity of resting-state is Hebbian since it occurs in the direction of NFB training.

11
 12 **Figure 1:** An example of Hebbian-type neuroplasticity mechanism subsuming neurofeedback
 13 training with experimental data on alpha rhythm up-regulation (adapted to experimental data
 14 from [20]).

15
 16 Hence, during amplified oscillations, synchronized neural populations involved in generating
 17 this oscillatory pattern would, after some time, strengthen the connections between
 18 themselves, and further facilitate the oscillation to emerge in the future. Conversely,
 19 maintaining a cortical region in a low-amplitude (“desynchronized”) state would reduce
 20 synaptic correlations and weaken the connections that give rise to synchronization.
 21 Encouragingly, recent experimental work provides support for this mechanism outside of

1 NFB, reporting up-regulation and down-regulation of cortical oscillations using synchronizing
2 and desynchronizing patterns of stimulation, respectively [67, 74].

3 Homeostatic plasticity and neurofeedback

4 Animal research has consistently revealed the presence of an additional form of plasticity
5 referred to as ‘homeostatic’ plasticity, which actively counteracts the Hebbian type so as to
6 prevent its unlimited expression [67]. Otherwise, unchecked Hebbian plasticity would
7 inevitably lead to pathologically high or low neural connectivity, firing or synchronization.
8 Hence, from the point of view of NFB, one would anticipate homeostatic forms of plasticity
9 to produce changes opposite to the direction of training. Early observations within this context
10 were made by Kluetsch and colleagues [40], who reported that following down-training of
11 alpha rhythm, patients with Post Traumatic Stress Disorder (PTSD) displayed a paradoxical
12 increase in alpha rhythm above and beyond its resting-state value. Since PTSD patients are
13 found to exhibit significantly low alpha amplitude at baseline relative to healthy subjects, a
14 recent framework proposed that this might reflect homeostatic regulation of the excitation/
15 inhibition balance [67, 68].

16 Towards new neurophysiological measures of neuroplastic 17 effects of neurofeedback

18 In addition to EEG-based measures, the neuroplastic effects of NFB have started to be
19 explored using several other techniques, including transcranial magnetic stimulation (TMS),
20 functional magnetic resonance imaging (fMRI) and diffusion tensor imaging (DTI). For
21 example, a single 30-minute session of NFB alpha downregulation has been found to enhance
22 cortical excitability, as measured by a plastic (>20 minute) increase in TMS-induced motor
23 evoked potentials after training [69]. Of note is also the observation of reduced intracortical
24 inhibition, in view of its established association as a cortical state that facilitates plasticity and
25 learning [8]. Elsewhere, fMRI has shown that NFB may induce plastic changes in cortical
26 hubs responsible for cognitive control such as the dorsal anterior cingulate [30], which was
27 associated with improvements in symptoms of ADHD [42] or on-task mind wandering [70].
28 fMRI studies shown also that NFB training can induce plasticity in patients with mental and
29 brain disorder that may engage other regions and circuits implicated in the physiopathology
30 [61] and that may be correlated with clinical amelioration [91]. Lastly, data from a DTI study
31 make an encouraging case for NFB affecting white matter and grey matter [27].

1 In closing, this first section has focused on the neurophysiological foundations of EEG NFB,
2 which enable it to be used as a unique therapeutic tool for targeting specific neural activities
3 and inducing neuroplasticity. However, beyond basic up- or down- regulation of brain
4 rhythms, the central challenge of NFB is to target clinically relevant biomarkers that are
5 consistent with the psychophysiological foundations of mental and brain disorders. The
6 following section focuses on this challenge.

7 Neurofeedback and its psychophysiological 8 foundations

9 Dimensional approach for neurofeedback in psychiatry

10 Because the psychiatric nosology has weak biological grounds, on the one hand, and because
11 the link between biomarkers (electrophysiologic biomarkers in particular with EEG or
12 metabolic biomarkers with functional neuroimager) and cognitive processes remain mostly
13 unraveled, on the other hand, it is impossible to confirm the functional specificity of current
14 NFB EEG biomarkers. In fact, contemporary psychiatry is undergoing a taxonomic crisis that
15 is characterized by the poor diagnostic power of current nosology [15]. Interestingly, in 2010,
16 the National Institute of Mental Health (NIMH) proposed a dimensional approach to
17 circumvent this issue. For Insel et al., the current symptom-based classification probably does
18 not reflect the pathophysiological mechanisms that underlie mental disorders [31]. The aim of
19 the Research Domain Criteria (RDoC) project is to conceptualize mental illnesses as brain
20 disorders with pathophysiological features represented by a reliable and validated continuum
21 from the clinical to the genetic, all defined by tools from neuroscience [31]. Such an approach
22 could be very useful in the field of NFB research applied to mental disorders. By targeting
23 specific biomarkers related to well identified symptoms or cognitive processes, the
24 psychophysiological rationale underlying NFB therapy should be stronger and its efficacy
25 probably greater. Importantly, although the quality of EEG recordings and the design
26 parameters of NFB protocols (e.g. the number of sessions per week) are essential variables to
27 be optimized to foster training, their optimization will never overcome the putative
28 deleterious effects of our current lack of precise knowledge about the underlying brain/mental
29 processes. We advocate here that acknowledging this fundamental limitation is a useful
30 starting point to guide the research and development of future NFB therapies. Furthermore,

1 this limitation holds whatever the functional modality used to record brain activity
2 (electrophysiology, fMRI, fNIRS, etc.).

3 As the first step to overcome this limitation, we consider it essential to inventory and refine
4 the existing list of EEG biomarkers and associated cognitive functions. In the following
5 section, we propose an “EEGcopia” to illustrate the need to rely on EEG biomarkers that are
6 strongly linked to symptoms or cognitive processes. We discuss this concept of EEGcopia
7 below and provide a preliminary list that highlights the need to link psychiatric nosology and
8 putative biomarkers with clinical dimensions such as executive function, emotion regulation
9 and reward processing (see **Supplementary material**). The opportunity to construct new
10 therapeutic hypotheses based on other EEG and putatively more specific biomarkers than
11 those used so far in NFB is illustrated in two concrete and very topical fields of
12 NFB/psychiatric research: depression and ADHD.

13 A proposed EEGcopia for neurofeedback in psychiatry

14 Most NFB investigations to date have focused on a limited set of EEG frequency ranges (the
15 two most famous being the θ/β ratio and the Sensory Motor Rhythm - SMR). However, there
16 are several other known correlates of cognitive functions that could be used as potential target
17 biomarkers. Indeed, one can extract numerous biomarkers from EEG signals such as discrete
18 EEG events like event-related potentials (ERP), measures of complexity, or local and long
19 distance neural synchrony, which could have potential NFB applications. The use of these
20 EEG biomarkers for NFB has received little attention until now. We introduce here a brief
21 nomenclature of cognitive functions (see **Supplementary material**), together with their
22 known EEG biomarkers. Dimensional EEG biomarkers of cognitive functions with known
23 neural correlates of sensory processing, executive functions, emotional cognition, memory,
24 embodied cognition and social cognition are presented. This short EEG encyclopedia
25 (EEGcopia) reflects the main theories linking EEG and cognitive dimensions in
26 neurophysiology. A more complete and exhaustive EEGcopia would be of great help to the
27 NFB community.

28 Among the different biomarkers listed, Event Related Potentials (ERP) for NFB open up new
29 avenues for application. The numerous publications on BCI based on the real-time detection
30 of P300 demonstrate the feasibility of this approach [87]. Recent studies have generalized
31 these results to other ERP components, such as error negativity (ERN) [9] and auditory
32 mismatch negativity (MMN) [7]. However, each ERP has its specific properties, such as

1 differences in refractoriness [88], which may limit their detection rate for real-time
2 applications and make them usable only for discrete delayed feedback. Another promising
3 candidate is the use of classification algorithms targeting specific dimensions. For instance,
4 arousal detection using the VIGALL algorithm [60] was recently used to investigate brain
5 mechanisms, and it can also be used to design efficient NFB strategies [29].

6 Linking brain / mental processes and psychiatric disorders

7 The emblematic research field of depression

8 Which innovative biomarker could be relevant to treat depression? Recently, Rayner et al.
9 published a comprehensive review of cognition-brain related networks of depression [65].
10 This neurocognitive hypothesis of depression could be an interesting basis for an applied
11 reflection on the choice of the most relevant target for NFB. Three main networks are
12 involved: autobiographical memory (AMN), affective (AN) and cognitive control networks
13 (CCN) [65]. The former is involved in self-referential cognitive processing and the latter in
14 the ability to perform goal-directed tasks. The authors postulated that AMN is hyperactivated
15 (self-referential cogitation and congruent emotional processing) over the CCN, which is
16 deactivated during a mood depressive episode. This state is also associated with AN
17 overactivation which is linked with deficit of cognitive control network activity and
18 postulated having a key role in dysfunction of mood regulation. This model highlights the
19 central role of cognition (and its neural substrates) in regulating affective symptoms and
20 autobiographical memory in depression [65]. This cognitive dimension could be a promising
21 therapeutic target for NFB instead of more conventional therapeutics. However, the best
22 psychophysiological signal related to this cognitive dimension remains to be determined.

23 Most of the literature on EEG-NFB has focused on alpha asymmetry but with controversial
24 results concerning its efficacy. In fact, EEG-NFB protocols on depression enhance cognitive
25 functioning [20] but have failed to have any effect on emotional and mood features (for
26 review; see Arns et al., 2017 [2]). As alpha asymmetry protocol is identified as a promising
27 EEG-biomarker for depression [12], one recent open label trial proposed to work on another
28 psychophysiological signal such as beta power band and alpha/theta training [11]. This latter
29 has shown that combined NFB on EEG-biomarkers of cognitions could be critical in
30 depression. Mehler and colleagues has questioned the specificity of EEG NFB from emotion-
31 regulating areas and its efficacy on depressive symptoms. Interestingly, fMRI-NFB has been
32 described as an effective treatment for depression by targeting limbic areas involved in

1 emotional processing [43]. Through a single-blind trial, they have highlighted that
2 experiencing self-regulation may probably be therapeutic, irrespective of brain areas targeted
3 (emotional or higher visual area) [53]. Elsewhere, Young and colleagues has exhibited that
4 amygdala fMRI NFB upregulation in a task of autobiographical memory is linked with
5 decreased of anxiety and increase of happiness ratings [90]. They have confirmed this result
6 in a randomized control trial in which residualized amygdala activity is a mediator of the
7 relationship between residualized positive specific autobiographical memory recall and
8 residualized MADRS score at follow-up [89].

9 Taken together, these data highlight that both cognitive and emotional/limbic areas might be
10 relevant for therapeutic NFB-protocols in depression. But to date, there is a lack of data on the
11 effect of EEG NFB working on both sides of depression, emotion and its cognitive regulation.
12 Based on the cognitive dimension of depression [65], it can be hypothesized that the ultimate
13 NFB should disengage the emotional cognitive processes of AMN, strengthen cognitive
14 processes oriented to external stimuli (CCN), and strengthen working memory. Therefore,
15 NFB targeting both AMN and CCN should fit this issue well. Some recent work on NFB has
16 proposed to combine EEG and fMRI in order to provide a more specific self-regulation of
17 these targets [50, 62]. These studies suggest that bimodal/simultaneous EEG and fMRI NFB
18 could be more specific and more engaging than EEG-NFB alone. Zotev et al. have
19 demonstrated its feasibility and potential in depression [93, 94]. This perspective seems to be
20 of great interest for targeting complex psychophysiological processes involved in mental
21 disorders such as depression.

22 The emblematic research field of ADHD and P300-based training

23 Which innovative biomarker could be relevant to treat ADHD? The effectiveness of classical
24 EEG NFB, targeting the $\frac{\theta}{\beta}$ ratio and the Sensory Motor Rhythm – SMR, in ADHD remain
25 debated [5, 10, 16, 75, 81, 82]. Four meta-analyses studies analysed the therapeutic usefulness
26 of EEG NFB in ADHD [4, 14, 54, 76]. The results of these meta-analyses depend of the
27 choice of studies included, in particular if a criteria concerning the training during the
28 neurofeedback protocol was added to include a study in the meta-analysis. Moreover, it
29 should be noted that the classical EEG biomarker chosen in ADHD is probably not the most
30 valid concerning the physiopathology of the disorder. Thus, P300 based training has been
31 recently proposed.

1 The P300 is a large positive complex that reaches its peak at approximately 300 milliseconds
2 after stimulus onset and is composed of two subcomponents, a frontal P3a reflecting
3 attentional capture by some external stimulation, followed by a parietal P3b elicited by the
4 voluntary orientation of attention [64]. The amplitude of the P300 grows with the amount of
5 attentional resources engaged in processing the external event [37]. Although this biomarker
6 has never been used for NFB, it is very much used online for controlling BCI applications
7 such as the P300 speller [51]. With this interface, items are selected on screen based on the
8 orientation of spatial attention. Interestingly, the same principle can be used in engaging
9 EEG-controlled video games [49]. Such games offer a motivating training environment, may
10 include strategic components (e.g. “Connect Four”) and rely on clear instructions about the
11 requested mental effort to be produced in order to control the game and possibly win (e.g.
12 focus spatial attention and avoid being distracted). Interestingly, the P300 is known to be
13 altered in children with ADHD [38]. It is also a marker of treatment efficacy as P300
14 amplitude has been shown to return to normal levels in patients who respond positively to
15 methylphenidate [72]. This has led to an ongoing clinical trial to evaluate the usefulness of
16 P300-based training in children with ADHD [21]. If successful, this trial will support the
17 extension of this kind of training to other pathological states associated with impairment in
18 selective attention.

19

20 This second section has focused on the psychophysiological foundations of NFB applied to
21 mental disorder and has demonstrated how it should be related to a better definition of
22 biomarker in order to target neural activities specific to symptoms or cognitive processes.
23 However, even if the chosen biomarker is strictly related to symptoms or cognitive processes,
24 it should also be verified that it is effectively modified during the NFB sessions. Moreover, it
25 should be studied the impact of control beliefs [86], i.e., participants’ beliefs that their efforts
26 to learn would result in a positive outcome, and self-efficacy [6], which can be defined as
27 participants’ beliefs in their own abilities to manage future events, on the NFB training.
28 Surprisingly, this domain on which the following section focuses remains a major challenge
29 for NFB, and the field of BCI is of great interest to enhance knowledge on optimized training
30 and learning for NFB in psychiatry [22].

31 NF and BCIs are traditionally underlain by different methods. In NF, the target
32 neurophysiological pattern (location, frequency) is usually defined in advance. Users are
33 asked to figure out by themselves how to self-regulate this pattern. In BCI however, a
34 machine learning approach is most of the time employed. Such an approach consists in using

1 signal processing algorithms in order to determine the location and frequency of the target
2 neurophysiological pattern that enables the best discrimination between different states (e.g.,
3 motor-imagery task vs. rest). In case of a BCI involving left vs. right-hand motor imagery
4 tasks, these EEG patterns would theoretically correspond to modulations of sensorimotor
5 rhythms. However, when a pure machine learning approach is used (i.e., without any a priori
6 on the location/frequency of the pattern), as is mostly the case in BCIs, other EEG patterns
7 could be selected.

8 Neurofeedback and its human-computer 9 interaction foundations

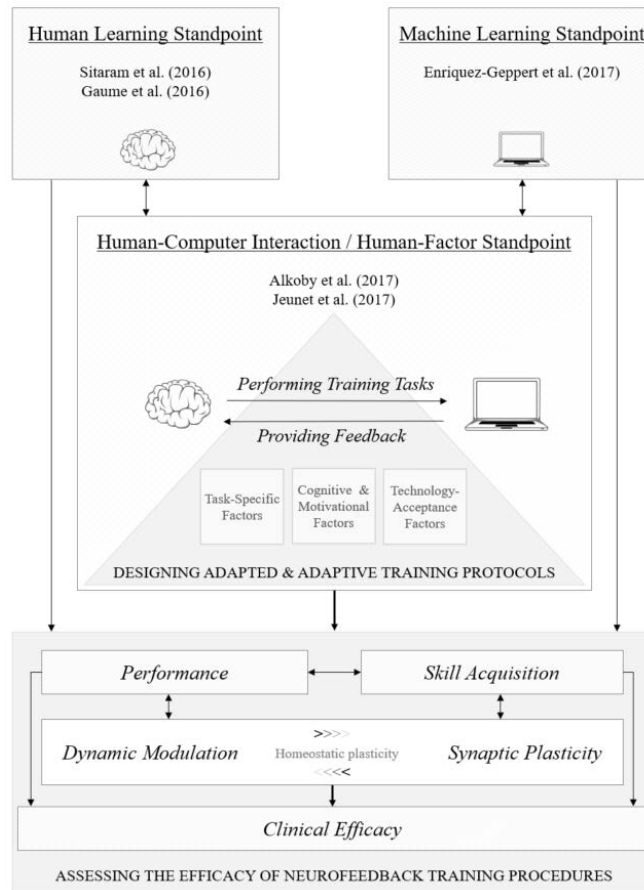
10 A human computer interaction model for neurofeedback

11 To globally improve NFB efficacy in patients, it is necessary to understand and then reduce
12 its variability. To this end, Sitaram et al. (2016) and Gaume et al. (2016) have reviewed the
13 neurophysiological [74] and neuropsychological [25] mechanisms underlying NFB training
14 procedures. In addition, Enriquez-Geppert et al. (2017) have proposed a tutorial explaining
15 how to design rigorous NFB training protocols [19]. While Sitaram et al. (2016) and Gaume
16 et al. (2016) adopted a standpoint purely centered on “human learning” (*i.e.* centered on the
17 psychological and neurophysiological mechanisms that enable patients to learn how to self-
18 regulate specific neural substrates), Enriquez-Geppert et al. (2017) focused on “machine
19 learning” (*i.e.* centered on the technological factors, especially signal processing and machine
20 learning, potentially impacting performance). These papers offer insightful elements to
21 understand and reduce the variability of clinical NFB efficacy.

22 When studying user training in NFB and BCI, it is indeed essential to consider the impact that
23 both machine and user learning can have, and how they interact with each other. In the EEG-
24 based NFB/BCI context, machine learning usually aims at learning from examples of EEG
25 data the user-specific EEG patterns corresponding to the target to self-regulate [44]. For
26 instance, machine learning can be used to identify the spectral and spatial components of a
27 user EEG signals that vary with different attention level (e.g., for ADHD NFB). Most BCI
28 and most fMRI-NFB use machine learning techniques, while most EEG-NFB do not [35, 74].
29 When machine learning is used, the success of the NFB/BCI training thus depends in part on
30 the machine learning algorithms used. On the other hand, user learning is involved in both
31 NFB and BCI, in particular in Mental Imagery BCI [32]. User learning refers to the user

1 learning to self-regulate increasingly better the target neurophysiological pattern by learning
2 from the feedback she receives during NFB/BCI training. The success of the NFB/BCI
3 training thus also depends on the quality of the user learning, which in turns depends on the
4 feedback and training tasks used. If machine learning is used, both machine learning and user
5 learning interact: the machine learns to recognize the EEG patterns of the user, while the user
6 learns to produce EEG patterns that will be recognized by the machine. This is a form of co-
7 adaption or co-learning between the machine and the user [83]. Unfortunately, while this co-
8 learning is very common in BCI and NFB, how it works and how its impacts NFB/BCI
9 training is still mostly unknown. An open challenge is thus to understand and model this co-
10 learning, in order to design BCI/NFB training with feedbacks and machine learning
11 algorithms whose interaction will favor an effective self-regulation and clinical outcome [47].
12 Thus, as illustrated in **Figure 2**, uni-centered approaches are not sufficient to reach a deep
13 understanding of the NFB training process. “A human-computer interaction/human-factor
14 standpoint”, like the one proposed by Alkoby et al. (2017) [1] and Jeunet et al. (2017&2018)
15 [34, 35], is also needed to understand how, depending on their profile (i.e., psychological,
16 cognitive and neurophysiological states and traits), patients interact with the training protocol
17 and what the consequences of this interaction on learning and on clinical efficacy are. In fact,
18 we have proposed a model combining factors that influence learning in Brain Computer
19 Interface (BCI) and NFB (NF) [34]. The model is based substantially on the BCI literature
20 and more specifically on Mental-Imagery-based BCIs (MI-BCIs) [33, 36]. MI-BCIs are
21 neurotechnologies that enable a user to control an application through the completion of
22 mental-imagery tasks such as imagining movements, *i.e.*, motor-imagery, that are associated
23 with a specific modulation of the user’s brain activity. Therefore, as is the case in NFB
24 applications, MI-BCI users have to learn to modulate a target neurophysiological substrate.
25 Consequently, the literature on BCI is of interest to better understand the factors influencing
26 learning in NFB.

27



1
2 **Figure 2:** Schematic representation of proposed approach. While some studies contribute to
3 improving the efficacy of neurofeedback procedures by adopting either purely “human-
4 learning” or “machine learning” standpoints, we posit that a “human-computer interaction /
5 human-factor” approach would enable deeper understanding of the processes subsuming
6 neurofeedback-related performance and skill acquisition, and thus improve its clinical
7 efficacy. This would provide insights into how users’ traits and states impact the efficacy of
8 neurofeedback, notably through three types of factors, and allow training tasks and feedback
9 to be adapted in order to better grasp the interaction and improve the efficacy of
10 neurofeedback. For an extensive description of the factors involved in the model, see [54, 55].
11 Moreover, we believe that neuroplasticity indicators are important intermediate variables to
12 be considered between NFB training/learning and clinical efficacy. We distinguish two kinds
13 of neuroplasticity indicators: dynamic modulation indicators and synaptic plasticity (also
14 called Hebbian plasticity) indicators. For an extensive discussion on neuroplasticity and
15 neurofeedback, see [17, 19].

16
17 The model in **Figure 2** includes three categories of factors: task-specific,
18 cognitive/motivational and technology-acceptance related factors. As this model focuses on

1 MI-BCIs, the task-specific factors refer to spatial abilities, *i.e.*, the ability to produce,
2 transform and manipulate mental images. It is likely that in other kinds of BCI or NFB
3 paradigms, different task-specific factors related to the targeted neurophysiological will have
4 to be identified. The other two families of factors are more generic and do not depend upon
5 the BCI/NFB paradigm used. They include, on the one hand, factors related to cognitive and
6 motivational traits and states, and on the other hand, factors related to patients' acceptance of
7 the technology, *i.e.*, the way they perceive the technology and consequently the way they will
8 interact with it, *e.g.*, to what extent they feel in control as well as their anxiety or confidence.
9 The model suggests that the learning process during BCI or NFB training procedures is
10 influenced by patients' traits and states, which in turn are modulated by the perception of the
11 technology. By considering these factors, one could design training protocols and feedback
12 adapted to the profile of each patient and adaptive to the evolution of their states and skills as
13 they evolve during the course of BCI or NF. Both the training tasks and the feedback can be
14 adapted (*i.e.*, specific to the patient's profile - traits and states - estimated at the beginning of
15 training) and adaptive (*i.e.*, modified dynamically during training to fit the evolving state of
16 the patient) in order to optimize the learning process. The first subsection is dedicated to a
17 review of the literature on how to design efficient adapted and adaptive training tasks and
18 feedback. Then, to evaluate the efficacy of NFB training procedures, relevant metrics of
19 performance, skills acquisition and clinical efficacy are needed. However, to date such
20 relevant metrics have received little attention. Thus, the second subsection describes some
21 metrics dedicated to assessing users' performance and skills and then discusses the
22 relationship between these metrics and the clinical efficacy of NFB procedures.

23 BCI principles to adapt training tasks and feedback in 24 neurofeedback

25 Based on an analysis of the literature, the following paragraphs present insights on how a
26 training protocol may be adapted. The protocol comprises two main parts: training tasks and
27 feedback. Indeed, during BCI/NFB training, the patient performs different training tasks
28 according to the instructions provided by the system or experimenter, so as to self-regulate
29 their EEG. They are then provided with feedback from the machine to inform them about the
30 quality of their EEG self-regulation (see **Figure 2**). Thus, training tasks are neurocognitive
31 exercises that the patient will perform, such as trying different mental strategies or trying to
32 self-regulate the targeted EEG feature with various levels of difficulty, *e.g.*, thresholds to

1 reach. The feedback is the information provided by the machine to represent real-time
2 variations in the EEG feature and/or to guide the patient in the training task, *e.g.*, towards a
3 modification of their strategy. For instance, feedback can be a visual gauge or an audio sound
4 of which the size or amplitude varies according to the EEG feature value. The following
5 sections first present various training tasks that have been explored for BCI training, and then
6 present different types of feedback that have been used for the same purpose. They also
7 describe which of these tasks and feedback types are adapted and adaptive according to the
8 users' traits and states, or how they could be made so.

9 Towards adapted and adaptive BCI/Neurofeedback training tasks

10 This subsection analyzes a training task that can be adapted and adaptive in order to optimize
11 the learning process. The type of the task and its difficulty can be adapted [59]. The type of
12 the task comprises the psychophysiological parameter that the user is asked to modulate. This
13 modulation can be used to control various applications. For instance, with motor imagery, the
14 different exercise types would be the possible mental commands; *e.g.*, motor imagery of
15 hands, feet or tongue. The instructions serve to guide the user in knowing which exact mental
16 command he is supposed to perform in real time (trial-by-trial). The type of the task can be
17 adapted or adaptive. So far in the literature, adapted types do not seem to have been explored.
18 However, adaptive BCI/NFB task types have been explored. For instance, the machine could
19 automatically identify which psychophysiological parameter works best for the users to assist
20 them to more easily manipulate the system. For instance, machine learning (Bandit algorithm)
21 has been used to select the MI task type within runs (among hands, feet and tongue) in order
22 to identify as quickly as possible for which one the user has the best performance [24]. The
23 same could apply for NFB tasks, where the user is asked to regulate different EEG patterns
24 from the initial ones if he is unable to regulate or produce them.

25 The difficulty of the task may be defined by the amount of mental resources that the patient
26 needs to engage in it in order to complete it successfully. This is related to the skills of the
27 user at EEG self-regulation. Ideally, to ensure efficient learning, the task difficulty should
28 match the user's skills in order to be neither too easy - which would be boring - nor too
29 difficult - which would be frustrating. The difficulty of the task can be adapted or adaptive,
30 *i.e.*, increased or decreased according to the user's profile and the speed at which he acquires
31 skills. Traditionally, adapted and adaptive task difficulty has been set by using a threshold
32 initially adapted to the user's physiology and regularly updated between sessions. It has not
33 yet been adapted to the user's cognitive profile, which thus remains to be explored.

1 Additionally, recent research is now exploring other ways to dynamically adapt the difficulty
2 instead of changing the threshold between sessions. For instance, in McFarland et al. (2010)
3 motor-imagery task difficulty was increased from 1D, then to 2D, and finally to 3D cursor
4 control within sessions [52]. Another way to increase user performance and motivation is to
5 adapt the perceived task difficulty by providing a feedback which does not comply with the
6 real performance of the user but is positively biased or is adaptively biased [58]. Finally, the
7 difficulty in an experimental context can differ from an ecological one, so virtual reality
8 coupled with NF/BCI could be useful to train the subject in a more realistic environment [45].
9 Indeed, in these types of protocol, the level of the environmental distractors and therefore
10 difficulty can be controlled, *e.g.*, by increasing the speed of instructions or adding distracting,
11 real-life, environmental noise.

12 Adaptive difficulty can be further explored by educational theories. Indeed, instructional
13 design theories and flow theory show that to promote progress and intrinsic motivation, a task
14 should be engaging, often ludic and adapted to the user's skills [48, 58]. This suggests that
15 NFB training tasks could also follow educational theories to foster learning and intrinsic
16 motivation. Moreover, the cognitive strategy of the user, which refers to the way the user tries
17 to modulate the psychophysiological parameter used in the exercise, could be influenced by
18 the instructions as well as by various feedback.

19 Towards adapted and adaptive feedback for BCI/Neurofeedback

20 This subsection analyzed the feedback that can be adapted and adaptive in order to optimize
21 the learning process. Feedback is an indication provided to users that allows them to learn to
22 modulate their brain activity. However, providing feedback that is appropriate and
23 informative is a great challenge [48]. A substantial number of studies on BCI have focused on
24 feedback modality, content and social features.

25 Concerning the feedback modality, the effects of adapted and adaptive classic visual
26 feedback, auditory feedback, tactile feedback or even multiple sensory modalities feedback
27 have been studied. Such feedback can improve control display mapping to further enhance the
28 sense of agency which influences the technology acceptance factor presented in **Figure 2**.
29 Adapting the modality of the feedback also makes it possible to take general cognitive
30 principles into account, *e.g.* the presentation of information on different modalities enables a
31 faster response, related to the “redundant signal effect”, but it also makes it possible to adapt
32 to the sensorial impairments of patients [41]. Moreover, virtual reality can be used to improve
33 training by providing motivating and immersive feedback [45].

1 Concerning the content of feedback, some task-specific elements have been studied. For
2 example, a key element for controlling BCI is for users to understand how their brain activity
3 is modified when performing a task. Such representation of their brain activity can be
4 provided by new visualization tools, e.g., TEEGI [23]. These can show users an engaging
5 visualization of their own brain activity in real time to help them to understand which EEG
6 patterns should be produced.

7 Lastly, concerning social features, some original studies have provided adapted and adaptive
8 emotional support as well as a social presence to compensate for the lack of interaction during
9 BCI/NFB sessions by using a learning companion, see **Figure 3** [63]. Each of the companion
10 interventions was composed of an animation of its face and a spoken sentence. The feedback
11 provided took the performances and progression of the user into account. It focused on the
12 subject's effort and strategy and on reinforcing good performances and progress. Results
13 showed a beneficial impact on the user's experience and might also indicate a differential
14 effect on users that is yet to be verified. These results are encouraging and require further
15 investigation.

16



17

18 **Figure 3:** Brain Computer Interface training during which PEANUT (on the left) provides
19 user with social presence and emotional support adapted to his performance and progression
20 [64].

21

22

1 A key objective for future research should be to focus on making feedback more informative
2 by better understanding learning processes and improving measures of performances of BCI.
3 Moreover, a challenge arises from enriching the feedback without overloading users with
4 more information than they can process given their capacities. Assessing cognitive abilities
5 such as attention and providing related adaptive feedback would provide interesting insights
6 into this issue. Overall, BCI/NFB would benefit from studies combining several of these
7 factors and assessing the interactions between them. The goal is to provide feedback that is
8 both adapted and adaptive to training tasks, users' profiles, and their social and physical
9 environment, a criterion often forgotten but which should be given more consideration by
10 doing more ecological experiments, *e.g.* by using virtual reality.

11 Redefining the assessment of BCI/Neurofeedback training 12 efficacy

13 The assessment of NFB training efficacy is essential to better understand the clinical efficacy
14 of such therapeutics. Indeed, most studies that investigated the clinical efficacy of NFB did
15 not evaluate or even report the efficacy of training [95]. Thus, it cannot be concluded whether
16 patients gained control over their brain activity during the NFB training procedure or not.
17 However, as learning is the most immediate result of NFB training according to the principle
18 of NFB, it seems essential to measure the learning that takes place across sessions. As
19 Rémond & Rémond stressed: *“Doubting the effectiveness of a biofeedback treatment on a*
20 *physiological variable when this treatment is carried out without previously testing the*
21 *modification of this variable, is the equivalent of doubting the effectiveness of a drug to cure a*
22 *disease when the drug has not been absorbed by the patient”* [66].

23 The principles behind NFB is that self-regulation of a target neurophysiological pattern
24 underlying a cognitive function should lead to clinical benefits linked to that cognitive
25 function. Thus, a positive clinical outcome requires that the user learned to self-regulate the
26 target pattern. Unfortunately, as mentioned before, many NFB publications do not report any
27 metric of user learning [22]. There is also no clear consensus on what these metrics should be.
28 It is thus necessary to identify relevant metrics of performance reflecting user learning of self-
29 regulation. Some metrics of this sort have been recently proposed for BCI for instance [46].
30 Then, we will need to study how these metrics are related to the clinical outcome. Ideally, we
31 need metrics that would enable us to compare how different feedback approaches or machine
32 learning impact user learning, as well as to predict clinical outcome. This would enable us to

1 screen participants that are likely to benefit from neurofeedback as well as to identify the best
2 NFB/BCI training methods.

3 Thus, the following subsections first present how to assess NFB and BCI user learning by
4 distinguishing: (i) how well users can self-regulate their EEG activity at a given time, which
5 represents their current “performance”, and (ii) how well they acquire new skills across
6 sessions to improve this EEG self-regulation, which represents their EEG self-regulation
7 “skill”. The following subsection describes the issues involved in redefining such metrics in
8 order to both (i) improve the design of adapted and adaptive training tasks and feedback in
9 NF, and (ii) better link such metrics to neurophysiological and neuroplasticity indicators.

10 Towards new performance and skill metrics in BCI/Neurofeedback

11 Performance is typically assessed by using success rates as metrics , *i.e.*, how often a) users’
12 NFB features successfully crossed the threshold, or b) users’ mental tasks are successfully
13 recognized by the BCI. In both cases, a threshold is used: generally, a univariate one for
14 classical NFB analysis in mental disorders (*i.e.*, a single value to be crossed by the
15 unidimensional feature value) [2], usually defined manually, or a multivariate one for BCI,
16 the EEG classifier typically used being a multidimensional threshold on all the features used
17 by the BCI to recognize each mental task. While success rates are typically used in NFB/BCI,
18 it can be argued that they are a poor performance metric of user learning. Indeed, success
19 rates are discrete and depend on the data used to determine the threshold/classifier, whereas
20 users’ skills at EEG self-regulation are continuous and threshold/classifier-independent. This
21 means that an improvement in EEG self-regulation might not translate into an improvement in
22 success rates, e.g. if the threshold is too high. This also means that if the threshold or
23 classifier is calibrated on data of poor quality, this will result in poor feedback and in a poor
24 measure of performance based on them. To date, only a few studies have evaluated the
25 relevance of performance metrics in BCI/NFB during a session. Recently, new metrics were
26 proposed to study BCI user training that provide a continuous and threshold-free measure of
27 how stable and distinct EEG patterns for each mental task are [46]. Comparisons showed that
28 such metrics could reveal fast learning of EEG self-regulation in several BCI subjects
29 whereas success rates sometimes did not. NFB success rates very likely have the same
30 limitation and should thus be reconsidered when assessing NFB interventions. In any case,
31 research into more specific and learning-related metrics of performance is needed.

32 Skill metrics are computed to quantify learning across sessions. They are typically based on
33 relevant performance metrics estimated on each session/run. They estimate whether these

1 performance metrics increase over time and sessions, which would indicate learning. An
2 example of such a metric could be the difference between performances obtained during the
3 previous sessions and those obtained during the first ones, or the slope of the regression line
4 passing by the performances across sessions (the steeper the regression line, assuming
5 increasing performances, the faster the learning). Nonetheless, so far there is no gold standard
6 in skill metrics and the ones currently used suffer from several limitations. For instance, the
7 metrics mentioned above are very sensitive to outliers, and a single failed session (*e.g.*, due to
8 a failing sensor or a tired patient) or an overly good one (due, *e.g.*, to chance) may lead to an
9 inadequate corresponding skill metric. Skill metrics also depend typically on the threshold
10 used in the performance metrics. If the threshold changes across sessions, which is typically
11 the case in NF as in BCI if the classifiers are adaptive or recalibrated regularly, then
12 performances are not comparable between sessions and the resulting skill metric may be
13 meaningless. Finally, performance metrics also depend on rest/baseline EEG, such baseline
14 values typically changing at each session. As such, the performance metrics used to compute
15 skill metrics may not be comparable with each other. Overall, there is thus a need for new
16 relevant skill metrics that are stable, meaningful and robust to outliers, as well as for
17 investigation into their impact on clinical efficacy.

18 Towards optimizing clinical efficacy based on new metrics and 19 neuroplastic approaches

20 We need to improve our knowledge about the relevant performance and skill metrics in order
21 to optimize the clinical efficacy of NFB. Indeed, such metrics are essential for designing
22 adapted and adaptive training tasks and feedback in NFB. At present, the task and the
23 feedback are adapted by NFB practitioners before and during the training procedure. An
24 important step for NFB practitioners is determining a threshold and the kind of feedback [73,
25 78, 85]. Adjusting a threshold and a given occupation time determines the number of positive
26 reinforcements. Traditionally, the threshold may be set automatically or manually. When the
27 threshold is determined automatically, it is continuously updated in order to provide patients
28 with a positive reinforcement for a given percentage of occupation time below or above the
29 threshold. The threshold is continuously estimated according to the signal recorded just
30 before. However, the limitation is that the patient is rewarded only for changing his/her brain
31 signal based on the previous averaged time period and not from the starting point, which
32 drastically reduces the chance of learning across NFB sessions [73]. When the threshold is set
33 manually by the professional, it is based on a baseline recorded before the NFB session. If the

1 number of positive reinforcements is too high or too low during the session, the threshold can
2 be adjusted [73]. However, there is a risk of inconsistency between different NFB
3 practitioners, as each one will adapt the task according to their own clinical experience.
4 Moreover, different practitioners will typically take the profile of each patient into account
5 (*i.e.*, psychological, cognitive and neurophysiological states and traits) subjectively according
6 to their global feeling and not according to evidence and objective features. Moreover, the
7 clinician may not be able to evaluate a state or a trait evolution that would be crucial to adapt
8 the training task. Strehl (2014) stressed that “*the therapist will need to know the laws of*
9 *learning as well as how to apply NFB training in order to be a competent partner*”. However,
10 the limitation of this standpoint is that these skills currently rely on clinical experience [26]
11 rather than on scientific knowledge related to NFB learning processes [73, 85, 95]. Thus, the
12 remaining challenge for assessing the efficacy of NFB therapies is to develop rigorous
13 standards that ensure the consistency (*a.k.a.*, fidelity - Gevensleben et al., 2012) of NFB
14 training protocols in order to optimize the potential positive effects of NFB on learning.
15 However, no “optimal” NFB training procedure has yet been defined, and one research
16 challenge is to design and evaluate optimal NFB training based on relevant performance and
17 skill metrics.

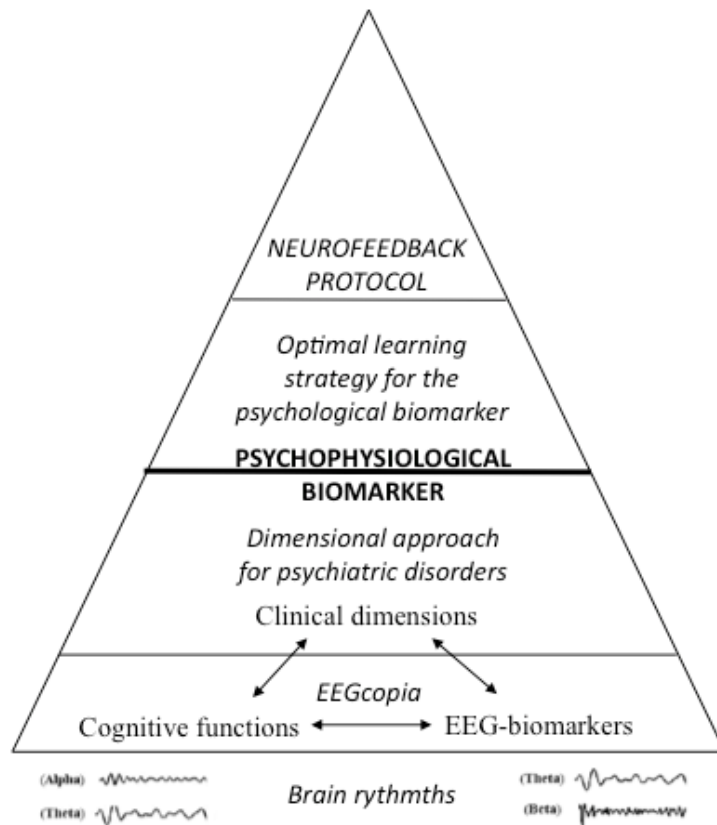
18 The second challenge is to improve understanding about how these metrics and
19 neuroplasticity indicators are linked in order to grasp the underlying neurophysiological
20 mechanisms that explain EEG self-regulation and skills acquisition. If this relationship could
21 be established, it would go a long way to validating such metrics. Indeed, as shown in **Figure**
22 **2**, performance and skills metrics should be understood not only in terms of the training
23 BCI/NFB task but also with regard to indicators of neuroplasticity specific to the trained
24 neural substrate [74]. Furthermore, this relationship could be considered as an important
25 intermediate variable between NFB training/learning and clinical efficacy. As described in the
26 first section of this paper, there are two kinds of indicators: dynamic modulation indicators
27 based on EEG oscillation and Hebbian-type neuroplasticity indicators [67]. Thus, as EEG-
28 based BCI/NFB tasks generally tend to modify EEG oscillations, performance metrics need to
29 be related to dynamic modulation indicators. Maintaining the brain in a persistent oscillatory
30 pattern improves the brain circuit so that it can produce the same pattern with a higher
31 probability in the future [67]. Thus, as BCI/NFB trains the brain to maintain certain
32 oscillatory patterns, skills metrics need to be related to Hebbian neuroplasticity. See **Figure 2**.
33 Very few studies dedicated to the clinical efficacy of NFB have investigated such

1 neurophysiological indicators. Thus, in NFB, the neurophysiological relationship between
2 dynamic modulation and deserves further attention [18, 92].

3 In conclusion, the human-computer interaction foundations of NFB demonstrates that training
4 and learning are central to designing rigorous NFB protocols. Such protocols should be
5 designed so that the induction of neuroplasticity is optimized *i.e.* it produces a lasting change
6 after the training session. The relationship between NFB training performance, skills metrics
7 and neuroplasticity induction is very exciting new ground that must now be explored in order
8 to find new means of optimizing the clinical effect of NFB in the long term.

9 Conclusion

10 This paper investigated the neurophysiological, psychophysiological and human computer
11 interaction foundations of neurofeedback. A transdisciplinary approach is now needed to
12 evaluate rigorously the use of EEG NFB as a therapeutic tool in psychiatry. **Figure 4.**
13 Notwithstanding the debate on the efficacy of NFB for treating mental disorders, this field of
14 research remains fertile ground for innovative research in psychiatry. Neurophysiology,
15 psychophysiology and human-computer interaction approaches of NFB pave the way for
16 innovative research on two levels: for fundamental research attempting to define the
17 mechanisms subsuming NFB training; and for clinical research aiming to establish better
18 designed EEG NFB protocols, control/active groups and clinical criteria that define efficacy
19 in terms of targeted biomarkers.



1

2 **Figure 4:** The quest to optimize neurofeedback protocol according to a transdisciplinary
 3 approach taking into account the neurophysiological, psychophysiological and human
 4 computer interaction bases of neurofeedback.

5

6 **Acknowledgments**

7 We thank Anatole Lecuyer for his participation to the second French congress on
 8 neurofeedback organized by NExT.

9 This work was supported by the French National Research Agency within the REBEL project
 10 (grant ANR-15-CE23-0013-01), the European Research Council with the BrainConquest
 11 project (grant ERC-2016-STG-714567), the Inria Project-Lab BCI-Lift and the EPFL/Inria
 12 International Lab.

13

14 **Conflict of interest**

15 None to declare concerning this paper.

16

17

18

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