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Abstract.
Mental-Tasks based Brain-Computer Interfaces (MT-BCIs) allow their users to interact with an external device solely by using brain signals produced through mental tasks. While MT-BCIs are promising for many applications, they are still barely used outside laboratories due to their lack of reliability. MT-BCIs require their users to develop the ability to self-regulate specific brain signals. However, the human learning process to control a BCI is still relatively poorly understood and how to optimally train this ability is currently under investigation. Despite their promises and achievements, traditional training programs have been shown to be sub-optimal and could be further improved. In order to optimize user training and improve BCI performance, human factors should be taken into account. An interdisciplinary approach should be adopted to provide learners with appropriate and/or adaptive training. In this article, we provide an overview of existing methods for MT-BCI user training - notably in terms of environment, instructions, feedback and exercises. We present a categorization and taxonomy of these training approaches, provide guidelines on how to choose the best methods and identify open challenges and perspectives to further improve MT-BCI user training.

Keywords: Brain-Computer Interfaces (BCI), Electroencephalography (EEG), mental imagery, mental task, feedback, training tasks, instructions, learning, user.

1. Introduction

Brain-computer interfaces (BCIs), also referred to as neural interfaces or brain-machine interfaces (BMIs), enable a direct communication pathway between one's brain and an external device [127, 194, 250]. Non-invasive BCIs based on electroencephalography (EEG) [9, 224] have proven promising for numerous applications [250], ranging from rehabilitation (e.g. motor rehabilitation after a stroke) [238] and assistive technologies (e.g. communication or smart wheelchair control) [75, 127, 128, 192] to non-medical applications (e.g. video games) [73, 112, 125].

EEG-based BCIs can rely on a variety of neural mechanisms. One of the most common active BCI paradigms [218] measures the Event Related De/Synchronization (ERD/ERS) of oscillatory EEG activity [10, 16, 46, 48, 50] generated during the performance of cognitive tasks [26]. BCIs based on this paradigm have sometimes been referred to as Mental Imagery-based BCIs. Here, we will rather use the term Mental Task (MT-)based BCIs as some of these tasks may not always involve imagery. To control MT-BCIs, users are instructed to perform MTs such as, for instance, mental rotation (e.g. of 3D shapes), mental calculation [79] or Motor Imagery (MI) [17, 29, 42]. The latter consists in mentally rehearsing movements without performing them [116].

While promising, MT-BCIs are not reliable enough yet for being used in *real-world* applications, outside laboratories. Indeed, the decoding of users' mental commands is subject to high error rates [87, 89]. Moreover, it is estimated (based on experiments performed mainly on healthy naive participants with current standard training protocols) that 10 to 30% of BCI users would not be able to control current MT-BCI applications at all [32, 87, 89, 165]. The literature often refers to these unsuccessful interactions as BCI deficiency, BCI inefficiency, or "illiteracy" [59, 89, 111, 136] - although labeling users this way erroneously suggest that the problem necessarily comes from them [259].

In order to increase MT-BCI reliability, BCI researchers have dedicated a lot of efforts to the improvement of both hardware (e.g. sensors) and software (e.g. signal processing algorithms) solutions. It has led to the broad adoption of machine learning approaches [44, 71, 244] which rely on a decoder/classifier "trained" on user data collected beforehand and/or over the course of the training for co-adaptive MT-BCIs [51, 53, 63, 82]. The use of such classifiers has enabled BCI researchers to shorten the user training duration compared to the first MT-BCIs where users had to adapt themselves to a fixed system [7, 9, 21, 23] through a trial-and-error operand conditioning approach [1].

Although these efforts reduced the time required to achieve a given classification accuracy, they may not be sufficient to enable MT-BCIs to be used in practice. Extensive studies dedicated to the decoding of BCI commands from EEG signals may have overshadowed the importance of user training, whose purpose is to enable users to develop or improve their BCI control skills. Indeed, the efficiency of MT-BCIs inherently depends on the users' ability to successfully encode mental commands into their brain signals. In other words, it relies on the users' ability to produce EEG patterns which are stable each time they intend to send one same command, and distinct between the different mental commands [193]. If the user cannot produce distinct EEG patterns, then no machine learning algorithm would be able to detect them. Stability, on the other hand, seems essential for mental commands to be efficiently decoded by current systems, although the need for completely stable patterns may be overtaken by future decoding algorithms (e.g. by considering past and present brain states).

As human learning appears very relevant for BCI reliability, there is a growing interest in user training. Improving user training, and thereby MT-BCI reliability, requires understanding the cognitive and neurophysiological processes underlying this ability to efficiently encode mental commands through the performance of MTs, i.e. to produce stable and distinct EEG patterns. In addition, it also requires understanding the human-computer interaction processes involved in training procedures, and their influence on users' performances and processes underlying learning. Studying MT-BCI user training is crucial to better apprehend the extent to which MT-BCI users can learn when and how to modify their MT strategy, and thereby their brain patterns, so that their mental commands are recognized as well as possible by the system.

Efforts have already been made to investigate these various aspects and to summarize the advances on the topic, notably in an introductory paper on MT-BCI human learning [199] and in a short review specifically addressing motor imagery [236]. The present

paper aims to provide a broader, comprehensive review of the MT-BCI training procedures which have been reported in the literature. The efficiency of these procedures is described as reported in the papers, and analysed based on learning models from the fields of psychology and instructional design in order to provide recommendations for the design of future training procedures.

This paper is organized as follows. First, Section 2 sets the background by presenting a framework of MT-BCI user training and by addressing the existing models related to the MT-BCI user learning process which led to this framework. Based on this framework, the review is afterwards organized in the major components of MT-BCI user training, namely: environment (Section 3), instructions (Section 4), feedback (Section 5), and training exercises (Section 6). Finally, we provide a summary of the guidelines and open challenges in this field of research in Section 7, some perspectives in Section 8 and conclude the paper in Section 9.

2. Learning to control MT-BCIs

In this first part, the framework used to organize this review is presented. Then, we discuss the existing models related to MT-BCI user learning and MT-BCI training procedures. Discussing these models and theories is fundamental in order to contextualize the components of BCI training in relation to user learning.

2.1. A Framework to study BCI user training

We provide a general framework and taxonomy to summarize and compare existing BCI training methods, as well as to identify gaps in the existing literature.

In the framework introduced in Figure 1, the MT-BCI training program is structurally represented through different nested stages related to the time period, i.e. sessions, runs, and trials. BCI training is composed of one or more sessions that are composed of runs, which are themselves a sequence of trials.

Sessions refer to specific training days with a given BCI setup (e.g. sensors' type, location, number). For example, [252] reported 35 training sessions over seven months, approximately twice a week, to train a competitor for the BCI Cybathlon race. Each *run* is a sequence of trials. Here, the term *trial* refers to a defined time window associated with one specific command, during which the user should perform an MT. The MT execution can be, for a synchronous training sequence, preceded by a cue, i.e. a stimulus at the beginning of a trial associated with the expected command.

In a given MT-BCI training procedure, we identified four main components that define this training: environment, instructions, feedback and training exercises.

The *environment* refers to the context in which training takes place, e.g. with the user alone or with other BCI trainees, in the lab or out-of-the-lab. The *instructions* refer to information provided to BCI users to explain them about how to use the BCI and about the tasks to be performed. For instance users can be instructed to perform visual or kinesthetics MI. The *feedback* refers to how users are informed about how well they can control the MT-BCI. For instance, users can receive either a continuous visual feedback (e.g. using a visual gauge) or a discrete tactile feedback (e.g. a vibration on the hand) to inform them about which MT was recognized by the BCI. Finally, MT-BCI *training exercises* refer to what MT-BCI users are expected to do, i.e. what control skill they should practice, and how to practice it. For instance, a given training exercise can consist in having users practice left hand MI versus rest, in a synchronous way, whereas another exercise would have them practice left hand versus right hand MI together, in a self-paced way, to control a specific application. Exercises can vary across trials, runs or sessions.

In the remainder of this paper, we will review existing MT-BCI user training works along these four main components.

2.2. Learning involved

Unfortunately, while studied for a long time [21, 31], the cognitive processes underlying the ability to learn to self-regulate specific brain patterns, and thereby to learn to control an MT-BCI, are not yet fully understood [201, 231].

This learning process is still unclear and improvements in BCI performance over time are not always observed in recent MT-BCI experimental studies with few sessions [95]. However, it is widely acknowledged that the ability to use an MT-BCI is a skill involving learning [31, 35, 83, 86, 114, 248, 252, 270] and thus that it seems to require *deliberate practice*, i.e. users intentionally engaging their efforts in structured activities/tasks in order to improve their level of performance in a specific domain [11]. Indeed, it seems that the more MT-BCI users practice, the better they can master the system through the self-regulation of specific brain patterns [161]. This was demonstrated in the competitive training described in [252] where statistically significant differences are shown in mean command accuracy between the first and last sessions (from 53.8% to 93.8% and from 81.9% to 96.8% for both pilots respectively).

In MT-BCI user-training programs, the goal

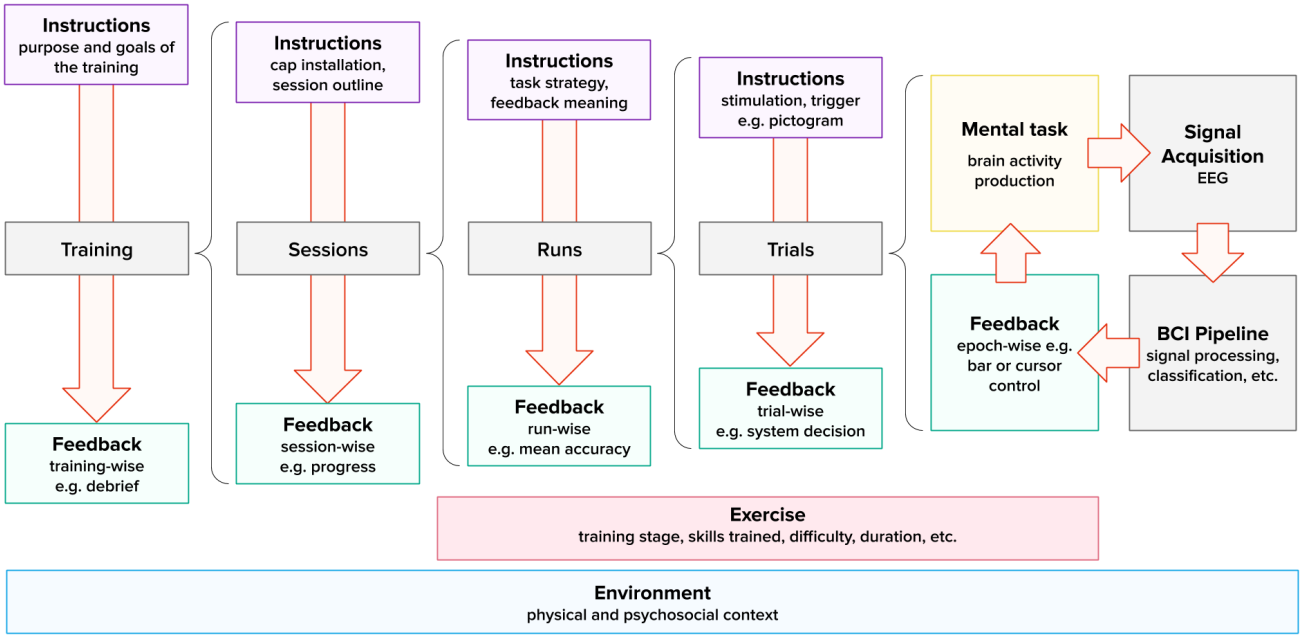

Figure 1. A representation of a taxonomy of MT-BCI control training construction, according to the time scale of each component (training, sessions, runs, trials). Based on this framework, we afterwards present a review of the major components of MT-BCI user training, namely : environment (Section 3), instructions (Section 4), feedback (Section 5), and training exercises (Section 6).

is to provide the user with the opportunity to practice through the use of a neurofeedback, i.e. a feedback representing the modulations of one's brain activity. User learning can be reinforced using various behavioral learning paradigms such as operant conditioning [1].

To better understand and describe it, the BCI learning process can be related to learning processes of other complex cognitive tasks in other fields with which it seems to share similarities such as verbal learning [210, 231] or motor learning [117, 142, 231]. Hammer *et al* suggested to bring together elements from operant identification of a latent strategy and motor learning [117] using Lacroix's dual process theory [6]. As it is extensively described by Wood *et al* [161], learning self control of brain activity might not only involve automatic processes. Thus, dual-process models might be a good framework to describe BCI learning. In dual process theory [6], type I (non-conscious, e.g. demonstrated in [134]) processes are supplemented by type II processes (controlled processes), i.e. regulated self-instruction which relies on metacognitive abilities. In this framework, users' conscious efforts (declarative knowledge, motivational processes) are part of BCI learning.

These comparisons might not be perfectly accurate since, in contrast to learning situations such as motor learning, BCI learners do not usually get examples nor corrections of a properly executed mental task. In addition, they do not perceive any internal feedback (e.g. visual, auditory, proprioceptive, etc.) [120]. Nonetheless, mental imagery of motor tasks was extensively studied in sport psychology and related to motor learning [69]. Finally, as discussed as perspectives at the end of the paper (Section 8), major questions remain open regarding the links between machine learning and user learning, how they influence each other, and how to quantify user learning independently of machine performances.

2.3. Modelling MT-BCI users

The typical/standard model of a BCI is the one which represents the "BCI loop" and focuses almost exclusively on the machine: it generally depicts the interaction pipeline which contains signal acquisition, signal pre-processing (e.g. artifacts removal), feature extraction and selection, classification/decision, followed by another round of acquired neural activity, and so on [30, 86, 151]. This representation pays little attention to how users produce mental commands or how they process/react to feedback. Yet the user is a fundamental element in Brain-Computer Interactions.

This is why a couple of user-oriented models have been developed based on instructional design [110, 173, 199], which led to the development of a cognitive model [91] by [219]. Such conceptual modelling enables a clear visualization of the cognitive processes which seem to be involved in MT-BCI learning, the extrinsic/intrinsic factors affecting them [201], consequently allowing for the design of training procedures adapted to each user.

To include user-related factors in this type of

model, it is required to investigate *predictors of performance*, i.e. factors which may explain users' MT-BCI performances generally measured with classification accuracy [165, 173, 201]. These predictors can be included in (computational) models of MT-BCI user training which could predict users' performance or progress over time, based on different factors, e.g. user-technology relationship, attentional and motivational traits or states or previous performances [117, 149, 201, 219, 265, 271].

However, predicting performance through such human predictors has yielded inconclusive results, which would require further studies in order to determine reliable prediction models [237]. Some findings could not be replicated, e.g. kinesthetic imagination score used in [104, 141] is not a performance predictor in [255]. Similarly, opposite effects could be found for the same factor, e.g. the locus of control positively [45] or negatively [144] correlated with performance. Finally, disparities across experiments make it difficult to reliably predict performance based on users' traits [265]. Finally, disparities across experiments make it difficult to reliably predict performance based on users' traits [265]. There is no gold standard for quantifying human learning in MT-BCIs and few studies are conducted on the topic. Currently, performances are reported in terms of classification accuracy and progression is often estimated by analysing the slope of this classification accuracy's regression line computed across runs or sessions. However, classification accuracy mixes both user and machine performances. Thus, as discussed further in section 8, future research should define more user-related metrics such as signal stability [245] to evaluate a user's BCI proficiency and progress specifically.

Furthermore, the numerous states depicted in user models are most probably not independent from one another, nor from longer-lasting attributes (e.g. psychological profile), nor from the environment (e.g. social context, see Section 3) or from system and task properties such as feedback or instructions. Some of them also depend on the time of measurement or the measurement method (e.g. physiological metrics or self-assessment questionnaires).

2.4. Adaptive training procedures

Other conceptual models raised the possibility of adapting BCI training tasks to directly affect users' states and in turn steer the neurophysiological changes in the direction in which both performances and satisfaction (e.g. ease of use) would increase [249].

There is evidence that BCI self-regulation learning is influenced by subjective psychological factors, i.e. the cognitive processes and states experienced by MT-BCI users during their training. These include motivation [99, 109, 157], or flow [225], *inter alia*. Instructional design literature states that the amount of guidance provided during training should be adapted to the expertise of the learner [153]. This relates to concepts such as Flow theory [3, 130] or the Zone of Proximal Development [5]. These concepts suggest that the users' skills must match the challenge of the activity, which implies that learning progress may generate intrinsic motivation [58, 119, 203]. Learners are more intrinsically motivated to accomplish the task if they are confident they would eventually succeed at it. Accordingly, enhanced expectancy or *prospective confidence* has been linked to motor skill acquisition [213, 221]. In other words, the learning progress is intertwined with users' perception of the task outcomes.

Another user state worth considering is (perceived) mental fatigue, which correlates to a decrease in MI EEG separability [278]. Statement from instructional design suggests that the interface content and task difficulty should be adapted if the user is in a state of fatigue. Indeed, an overload of the learner's cognitive system might lead to negative effects on learning, performance and motivation [20, 57]. Recommendations from this field and applied to MT-BCIs were extensively discussed in [136, 176, 199].

2.5. Challenges and perspectives

Overall, three approaches to improve BCI training tasks and programs intertwine and complement each other.

The first approach aims to *refine* training parameters by capturing the key characteristics of effective training procedures developed outside the field of BCIs (e.g. human-computer interactions, instructional design) in order to formulate guidelines and implement recommendations [136]. The second approach aims at *reshaping* training procedures through a whole training-wise user-centered approach [152, 241, 254]. The third approach is to *personalize* training procedures, particularly by taking into account the users' skills or profile (session-wise *adapted* training) or states (run-wise or trial-wise *adaptive* training) when designing tasks and feedback [219, 249].

Modelling users could enable researchers to design training procedures which yield better MT-BCI usability and performance, as they would be tailored specifically to each user. The final step would be implementing (mathematically and computationally) such conceptual models, as data-driven, action-perception models (e.g. machine actions depend on the user reactions to feedback), as suggested in [287].

In this section, we introduced the background

of user-training and learning in MT-BCI. The rich literature on user learning supports the importance of well-designed BCI training procedures. We argue that identifying and defining the various parameters composing a BCI training (and their interaction), as represented in Figure 1, might shed light on the gaps in user training and provide levers to positively impact users' understanding, perceptions, motivation, etc.

For this reason, we conducted a review on the training components we presented (Section 2.1). In the following sections, we provide an overview of the existing practices, challenges and perspectives for MT-BCI user-training environment (Section 3), instructions (Section 4), feedback (Section 5), and exercises (Section 6).

Presumably, the reported practices should apply to all types of users, as they target BCI learning in general and do not focus on a specific application. On the other hand, the vast majority of BCI studies reviewed in this paper are conducted on healthy naive users with motor-imagery (MI) tasks and with few (often one) sessions.

3. Environment in MT-BCI training

In the fields of psychology and ergonomics, it is understood that users' activity takes place in a context. This context is one of the components of the interaction [64] and as such plays a role on users' perceptions and emotions. As shown in Figure 1, our MT-BCI user training framework identified the training environment, i.e. the context in which the training takes place, as one of the key elements to consider for designing MT-BCI training protocols. Although the environment as a training parameter is generally not apparent in BCI models, it can be found for example in a recent framework for BCI systems usability evaluation [254]. However, their model includes the modality (specific to the task feedback) which is not encompassed in what we describe as the *"training environment"*.

In this section, we discuss two main aspects: first, the physical characteristics of the environment (e.g. temperature or auditory/visual distractors) and in a second part, the psycho-social context in which the training takes place.

3.1. Physical environment

First of all, we discuss the physical environment in which the training session takes place. Apart from the extensively studied issue of electrical and magnetic signals which may interfere with EEG recording [202], the influence of the contextual environment on MT-BCI training is not well established.

From a theoretical point of view, beyond the BCI sphere, it has been shown that contextual/environmental factors (e.g. acoustical, thermal, lightning or olfactory comfort, air quality, ergonomics, aesthetics) could together explain up to 16% of the variation in pupils' academic progress achieved in classroom [166]. Thus, these many aspects of actual and perceived conditions of physical environment can influence human proficiency and this may apply to some extent to a MT-BCI context.

In the BCI field, there are some other contextual variables whose effects have been discussed. Regarding the perceived qualities of the environment, one of the perspectives identified in [179] was the positive role of aesthetics in MT-BCI technology acceptance. Furthermore, the training environment could induce cognitive overload and thereby prevent BCI users from learning or controlling efficiently the BCI. For example, some task-irrelevant visual and auditory stimuli could have a detrimental effect on training. It has been shown that the perceived cognitive load induced by visual distractors had a strong negative correlation with classification accuracy for low-performance participants [284]. It has also been shown that background music may be responsible for decreasing performance in an experiment [225].

However, BCI studies rarely report this kind of environmental variables. This thus makes it difficult to study their effects since the physical environment is generally not the object of dedicated research questions in BCI, at least not yet.

3.2. Psycho-social environment

Another important aspect of the environment is the psycho-social context, notably the social presence, i.e. the subjective experience of being in presence of a person with thoughts and emotions [251]. Indeed, studies in social neuroscience have shown that social presence, e.g. a person or android, favours learning [186].

Both theoretical [122, 136, 186] and experimental [289] research stressed out that social presence is an important element in BCI training and recommended to further take advantage of the potential benefits it could bring, such as improving the user-experience, effectiveness and engagement of BCI users [129, 289]. For this purpose, multiplayer and collaborative BCI games were explored. Collaborative and competitive training procedures , involving several users [129, 180] or a single BCI user and an artificial agent [252] have been designed. One study showed an increase in BCI performance and motivation for the best performing users [129] but further experiments are required to investigate the influence of BCI multi-user training. We also designed a social agent [289] providing social

presence and (positive) emotional feedback through spoken sentences and facial expressions (see Section 5).

In addition to social contexts where one would interact with other BCI users, we argue that experimenters are a main source of social presence and emotional feedback in experimental settings throughout the user training. Some experimenters report acting on cognitive and motivational factors, e.g. "*we tried to keep the subjects motivated and attentive by providing non-alcoholic beverages, sweets and fresh air*" [117]. Other experimental protocols directly include the social feedback given by the therapist [178, 181]. Though, the influence of experimenters on experimental outcome has only recently been explored for MT-BCI user training, showing that an interaction between the experimenters' and participants' gender could influence the evolution of the participants' performance [275]. In addition, a recent study on neurofeedback suggests that psycho-social factors such as locus of control in dealing with technology, i.e. how strongly people believe they have control over technology, could have a different influence depending on the experimenters' and participants' gender [260].

3.3. Guidelines for the MT-BCI training environment

Overall, several recommendations can be made about the environment.

First, regarding the physical environment, users should not be disturbed or overloaded by task-irrelevant stimuli [225, 284]. When designing new training programs, the guidelines from BCI user-centered design literature can be applied [152, 241, 254] to assess the influence of the learning context on usability and user experience.

Concerning the social context, the idea that trainer-trainee interpersonal relations seem to be decisive for learning progress was suggested in Neurofeedback [158]. However, it remains difficult to provide evidence-based recommendations on *how* to optimize MT-BCI training environment since very few BCI studies formally addressed this aspect. Nonetheless, it is recognized that the overall social environment (e.g. significant others) influences the patients' BCI learning [174]. Therefore, it is important to take into account psychosocial context while designing experimental protocol. In addition, assessing and reporting its influence on BCI performance would increase the reproducibility of studies as it has been suggested to have a differential impact depending on the characteristics of the participants, e.g. gender or autonomy [275, 289]. Furthermore, when enough data is available on the matter, it will enable a rigorous estimation of the influence that social interactions have on BCI learning and performance.

3.4. Open Challenges and perspectives regarding MT-BCI training environments

So far, the environment and its effect on MT-BCI training has not been extensively studied and how much benefit could arise from this is still mostly unknown. Therefore, there are several open challenges which could be addressed on this topic.

Notably, such open challenges include identifying which training environment parameters are relevant for BCI user training, and to understand their influence on users' performance and learning-related states, e.g. motivation or cognitive load. One could theoretically use the environment as a lever to adaptively influence users [271]. The psychosocial context should also be investigated further to determine its precise influence on users' experience, learning and performance. The next step is therefore to formally identify the effects of each parameter. This involves controlling the physical aspects in usability studies, but also controlling the psychosocial aspects as described in the guidelines section.

4. Instructions in MT-BCI training

Although not systematically detailed in BCI papers, user training requires information about how the interaction should be done or the system operated. In this section, we thus formalize what these instructions given to users can be by suggesting a categorization. We also discuss what has been explored so far, and then provide guidelines, challenges and perspectives based on this literature review.

4.1. A categorization of instructions

To categorize instructions, we argue that they can be divided into several concepts according to the time scale at which they are provided as shown in Figure 1. For example, instructions provided at the training level, e.g. during presentation of the BCI system, can be distinguished from those given at the session or exercise level, e.g. explanations regarding the session outline or the behavior users should adopt. Herein-after we suggest a categorisation of the instructions which are provided along an MT-BCI training procedure.

First, *general instructions* refer to the instructions given at the training and session level, e.g. the presentation of the system, the description of what the training will be, etc. Although it might differ from one exercise to another, we also include the explanations about the meaning of feedback and stimuli, e.g. what will be on the screen throughout the session.

Then, *instructed task* and *guidance* are directly associated with the mental tasks, hence the BCI

control commands. The *instructed task* refers to a more or less precisely-defined instruction about *what* mental task(s) users will have to perform, e.g. "performing right hand motor imagery". The *guidance* refers to instructions on *how* to shape the cognitive strategy associated with an instructed mental task, e.g. timing, perspective, along with dimensional, emotional or sensory characteristics of the task. It is common for the number of *instructed tasks* to change, for example between a screening exercise and subsequent BCI exercises. In a BCI with multiple commands, controls generally differ in terms of *instructed tasks* (e.g. hand imagery vs. mental calculation). However, it is also possible to encode commands by using two identical instructed tasks with different *guidance* (e.g. short duration vs. long duration of left-hand imagery [98]).

The following sub-sections discuss these different types of instructions, i.e. first the general instructions (Section 4.2), then *what* mental tasks can be instructed (Section 4.3) and what guidance can be given on *how* to perform these mental tasks (Section 4.4).

4.2. General instructions

As defined herein-before, *general instructions* do not directly apply to the mental task being performed, but rather to the training as a whole. Although these instructions may have an influence on user understanding and technology-related stereotypes, these practices are usually not reported in papers and their potential influence on MT-BCI training has not been formally assessed yet.

First, the presentation of the BCI technology made before experimental or clinical experiments may trigger technology-related stereotypes, i.e. preconceived ideas or images of a specific type of person regarding the technology. This could prove important, especially since ethical questions raised by the field [239, 268, 276, 279] or some technical achievements may have reached the media with varying degrees of distortion or misrepresentation. Thus, new BCI users may arrive with damaging misconceptions [126], e.g. on the accuracy which can be achieved. It has been suggested by studies relying on P300-BCIs that explaining the relevance of the experimental protocol for BCI research could induce greater intrinsic motivation for the participants [133, 157]. It has also been hypothesized [160] that showing live recordings of EEG data could influence the sense of agency of MT-BCI users, i.e. how much they feel in control of the system's output.

Then, the general instructions also include details about the exercise as a whole, e.g. what goal should be achieved, when should the user send commands, what will appear on the screen and what is its meaning, etc. However, a vast majority of papers do not report if and how the BCI technology was introduced to the participants. In other words, the instructions provided to explain the meaning of the cues/stimulations and of feedback (e.g. content, modality, timing, as detailed in Section 5), the functioning of the BCI system and the goals and performance criteria, are most often not reported. Satellite instructions, such as remaining still to minimize EEG noise, or meta-information such as the duration of a given exercise or the differences with a previous exercise, are usually not reported neither.

Broadly speaking, there is a lack of knowledge on how to design a presentation of the system (training level), but also explanations regarding training goals or feedback meaning (at the session and exercise levels).

4.3. Instructed mental tasks

In contrast to *guidance* which will be discussed in the next sub-section, we described the notion of "instructed task" as *what* mental task(s) users will have to perform, e.g. mental rotation (e.g. of 3D shapes), mental calculation [79] or limb motor imagery [17, 29, 42]. In this subsection, we first discuss the presence and the role of this instructed task in MT-BCI training, and then present an overview of the tasks which have been explored so far.

4.3.1. Why giving instructions at all?

Depending on the BCI purpose, the question of the instructed task does not exactly arise in the same way.

First, when it comes to acting directly on the control of brain rhythms (NeuroFeedback (NF) training), it has been suggested that explicitly instructing users not to force mastery but instead to aim at a state of effortless relaxation may improve their performance [144] for sensori-motor rhythms (SMR) regulation. However, NF training does not always involve mental tasks. The goal of NF training, most of the time, is to improve the clinical condition of patients (e.g. cognitive abilities or emotional state). Therefore, operant conditioning is used in order to enable them to define cognitive strategies which induce modulations of the target brain patterns underlying a specific condition.

Second, for MT-BCIs used for control applications, the goal is to determine cognitive strategies which enable users to produce stable and distinct brain patterns in order to provide reliable mental commands to an application. Here, unlike NF training, the EEG rhythm modulated does not matter so much as long as different strategies induce distinct modulations. Therefore, the aim is primarily to differentiate the commands sent, often with machine learning. As such, the instructed tasks are generally pre-defined, reported in

papers, and associated with specific brain area, as detailed in subsequent sections. The following sections show that MT-BCI performance seems to benefit from explicitly instructed MI tasks, which are known to be (theoretically) underlain by distinct brain patterns.

It was showed in P300 studies that congruent control-display mapping (CDM) is necessary between the tasks users have to perform and the final application (i.e. commands output) in order to reduce error numbers, to quicken response time and reduce cognitive load [124], hence potentially making the learning process easier. However, even in BCI aiming for control, using a specific task might be a starting point and not an end since proficient users (10+ sessions) tend to report not using explicit imagery anymore [97, 134, 248].

4.3.2. Motor-imagery tasks

Motor imagery [18, 29] is a very common and widely used command for BCI applications [164]. The range of possible instructed imagined motor tasks is very wide, including "imagined hand movement" commands [17], but also for example imagined tongue or feet movements [43, 52, 66, 70, 97]. Other imagined movements, such as swallowing, were proven to be detectable by EEG [162].

Recently, MT-BCI researchers also explored "high-level commands" based on complex imagined movements, arguing that these control tasks would be more natural, intuitive, and would allow for a greater number of MI tasks. Examples include MI tasks of the right hand such as flexion, extension, supination and pronation [77, 169], MI tasks of the entire right limb such as hand grip, forearm flexion/extension and full-arm target reaching/grasping [281], or MI tasks based on hand swings, such as left and right hand swings clock-wise and anticlockwise [282]. All MT described in this paragraph relate to "what" should be performed. The variations within a given instructed motor task will be further explored in the subsection focused on *guidance* (Section 4.4).

Finally, although the task may no longer be strictly a *pure mental command*, there are contexts where some users may be asked to perform quasi-movements (maximally reduced movements indistinguishable through ElectroMyoGraphy (EMG) measures [74]), which seems promising to gradually train users to perform motor imagery. In the context of neuroprostheses or stroke-rehabilitation applications, users suffering from motor impairments can also be asked to perform attempted movements instead of imagined movements [272]. However, it is uncertain how the recommendations reported in the present review apply to training non-mental tasks.

4.3.3. Task association

In order to increase the number of commands without increasing the number of unique mental imagery tasks, it is possible to associate commands to different combinations of these mental tasks. Task combination can be performed in two different ways. First, by performing tasks simultaneously [68, 102, 175, 277], e.g. with only 2 MI tasks (left and right hand MI), 4 combinations (and therefore 4 commands) can be defined: left only, right only, both, none. Second, mental tasks can be performed sequentially, e.g. by using two different MI tasks for a 3-class BCI: both hands, both feet, and a quick sequence of both hands then both feet [227, 252]. However, adding more classes tend to decrease the overall accuracy [222]. Although the associations we described are for imagined motor tasks, the concept of task combination could also be applied to cognitive (non-motor) tasks such as those described in the following paragraph.

4.3.4. Cognitive tasks

There are numerous mental tasks which are not motor imagery, apart from the relax state usually used as no-control command/state. Examples of these cognitive tasks include mental problem solving such as mental subtraction, letter-cued silent word generation or name generation, mental counting, mental writing of a letter to a friend or relative, human face imagery, auditory imagery (melody of a familiar tune), spatial navigation (orientation task), speech imagery (reciting a poetry, vowel speech imagery), dynamic visualization (mental rotation of a 3-dimensional figure). For typical applications of these tasks, see, e.g. [8, 28, 33, 37, 78, 131]. It has been suggested that spatial navigation around a familiar environment or auditory imagery tasks may yield better results than motor imagery paradigms [37], and more importantly that multiclass BCI would benefit from involving both imagined motor task and cognitive ones [131] as described in the subsection dedicated to the screening (Section 4.3.5).

The efficiency of other types of cognitive tasks to control an MT-BCI have been assessed in the literature. Some seem to be showing promising results such as Somatosensory attentional orientation (SAO) tasks, i.e. imagined tactile sensation of left hand, right hand or both hands [214]. Other approaches, such as self-induced emotions, seem to lead to lower BCI decoding performances than motor imagery [283]. Another approach is visual motion imagery. While pure visual imagery of dots motion [232] classified offline seems to be promising, recent studies [269] suggest that further research on the brain areas to be targeted should be conducted in order to achieve classification of visuospatial information such as motion imagery. Other studies trained participants

to perform conceptual visual imagery [243] which resulted in quite low accuracy, i.e. the two visual imagery tasks used could only be distinguished with 52% classification accuracy, which is under the 65% statistical chance level reported in the paper. In addition to all these tasks studied in MT-BCI, some other tasks seem to be detectable by EEG, such as olfactory imagery [170, 182], although there is a lack of BCI studies on the subject.

4.3.5. Screening

Screening corresponds to a preliminary stage of training for which user-centered adaptation of instructed mental tasks is made. The different training stages are described in more detail in Section 6.

Overall, it is globally understood that different users will obtain better BCI performances with different BCI tasks. In other words, the MI tasks which will lead to an optimal BCI control are specific to each user [131, 183]. This means it is relevant to select an instructed task (or pair of tasks, triplet, etc.) among several predefined ones through a screening phase before the training. As described in [30], the standard Graz BCI protocol starts with a preliminary step during which the user tries several mental tasks, e.g. motor imagery of right hand, left hand, feet or tongue movements. A number of studies report selecting a subject-specific task pair out of three motor tasks, e.g. [54] or [117].

Task selection as a BCI optimization problem was the subject of different research works [78, 132, 154, 183]. Among the general findings, it has been suggested that "hand vs. feet" seem to lead to better classification compared to "right vs. left hand" motor imagery [98] and that a pair-wise combination of "brain-teaser" (cognitive tasks) and "dynamic imagery" (motor imagery) might increase classification performance compared to paired tasks inside these categories [183]. In [154], the study notably showed that the optimal task pair in two-class BCI seems to vary intra-subject between sessions, although these variations (inter-session transfer loss) are reduced as the subject learns. In any case, user-specific mental task selection proved promising both for healthy users [131, 132] and motor-impaired ones [183] for whom the classical MI task pair (hand vs. feet) lead to 15% lower classification accuracy than user-specific instructed tasks.

In addition to knowing whether a task (or pair) is the most efficient from an analysis and classification point of view, the user's choice may also come into play. Though it was not the focus of these studies and has not been formally tested, there are some examples of papers reporting a protocol where users themselves "chose to work" with two tasks out of five (two motor imagery tasks and three cognitive tasks) suggested instructed tasks [41]. In another study [103], a mix of the two approaches is used: the two chosen tasks (out of three) are selected via prior data for some participants and are chosen by the subjects for novices. The exact effect of choice on performance, learning, engagement, perceived load or judgment of control is not known. In a research on a MT-BCI BCI game [90], the authors compared different tasks and indicated that user preference for certain mental tasks is based on: the recognition of the mental activity by the system, the effort it takes to execute the task, and the immersion / mapping between the task and its effect, i.e. how easy is the task to interpret and how well it fits with the context, e.g. a game.

Such a screening step allows for potentially more adapted practice runs in which users could learn more efficiently.

4.4. Guidance

In our categorisation, *guidance* refers to instructions on how to perform the task such as timing (e.g. speed) or perspective (e.g. first vs. third person), along with emotional and sensory characteristics of the task. In this section we discuss five main aspects of guidance: level of specificity, complexity, familiarity, focus and context.

4.4.1. Specificity and familiarity

Depending on the research, the specificity of the instructions can vary significantly. Consider the example of a very common yet rather vague instructed control task: hand motor imagery. There are multiple ways of performing hand motor imagery, e.g. visual/kinesthetic, first/third perspective, different types of movements with different amplitudes and frequency. The strategy adopted by the BCI user will most likely be influenced by the users' habits/expertise, but also depend on the instructions they have been provided with, e.g. typically orienting the choice by asking users *"whether they are familiar with specific movements from sport-related activities or playing a musical instrument"* [183]. User strategies can also be limited with guidelines, e.g. asking users *"to keep their attention on the MI task and avoid imagining very fast or very slow movements"* [183]. Note that the degree of freedom and specificity in the instructed task can vary according to the modality of trial cues or feedback since realistic feedback implies a specific task.

It is often recommended to instruct familiar mental tasks, presented to the subjects according to their daily manual tasks, to improve training. Indeed, familiarity with the task was shown to positively influence BCI classification in some cases (e.g. Chinese character writing [228]) or not to

influence it alone but only when coupled with task complexity [147]. It has also been suggested [167] that both impersonal arbitrary instructed tasks with specific guidance (*"squeeze a stress ball in your hand"*) and personalized hand imagery tasks (selected by the subjects before the experiment) might yield better results than an unspecific and undefined instructed *"hand imagination task"*. These results suggest that guidance in instructions is highly relevant in MT-BCIs training, although more formal testing is needed with more subjects and more trials/sessions.

4.4.2. Complexity

Complexity can vary for cognitive tasks, for example, the number of digits in a calculation task, as in motor imagery tasks. It has for example been suggested that mental imagery of complex motor actions, i.e. mental tasks which involve both sequences of movements and more than one body part, seems to result in significantly better classification performances (69.6%) compared to simpler MI tasks (66.34%) [147].

4.4.3. Focus

Even within a given task, e.g. hand imagery, not all strategies may be equally effective and it is possible to direct the focus of users' attention towards a specific aspect of the mental task.

It has been mentioned earlier that variations in the same task can be differentiated, for example in motor imagery when users are asked to vary imaginary hand movements [169, 281, 282] or to change other parameters such as the imagined speed [139], which could be better discriminated than changes in the nature of movement [80]. In addition, motor imagery can rely on different perspective modalities (independently or by combining them): "*kinesthetic (based on sensory information normally generated during actual movement), haptic (using cutaneous information to recreate the interaction with external objects), visual (with external and internal perspectives), or auditory*" [230]. Studies have found that first-person kinesthetic motor imagery (KMI) induces more distinct patterns, in contrast to third-person visual imagery (VMI) [42] and allowed better classification rates for KMI (67%) than for VMI (56%). The most commonly used mental task instruction is therefore to kinesthetically imagine body part movements. Hence, involving the sensory part of the imagination task is potentially valuable. This is supported by recent studies on non-motor paradigms discussed earlier in the paper. For example, recent work from [263] showed that a combination of two hand-related tasks, left hand somatosensory attentional orientation [214] and right hand MI, led to greater classification accuracies than the MI paradigm alone for both hands.

Regarding the different modality approaches on attentional orientation, further studies are needed to assess to what extent they can be distinguished, differentiated, combined. The focus matter naturally extends to other cognitive tasks, although this was not explored yet to our knowledge.

4.4.4. Context

The context might potentially be an important guidance parameter. For example, in [167], subjects in the "participant specific" task group were asked to describe a hand motor task they typically preform, i.e. a preferred movement or a familiar movement from daily activity, and then asked to bring an object associated with the chosen task, which was placed in front of the participants to aid them in their imagination of this specific movement. The task was therefore coupled with a context. In recent years, several studies in motor imagery addressed this question and showed that the involvement of objects in the MI tasks led to more vivid tasks and broader activation in motor-related areas. Interestingly enough, this is dependant on the type of object, whether it is abstract or real, e.g. in EEG [211] and functional Magnetic Resonance Imaging (fMRI) [257], manipulable or not, e.g. in EEG [123] and fMRI [24], within range/graspable or not [229], affective or not, e.g. inducing pain or disgust in fMRI [261], etc. The inclusion of another person in the imagery might also matter since clear distinct neural patterns were found for joint vs. single action MI in fMRI [212].

4.5. Guidelines for the instructions in MT-BCI training

In this section, we present a number of guidelines for MT-BCI training instructions.

First of all, in order to avoid the introduction of negative biases and perhaps exploit the positive effects of the general instructions, standardized approaches to introduce the participants to the technology should be developed and assessed in the future. Theoretical recommendations on user training [57, 76] suggest that MT-BCI control training might benefit from being goal-oriented since it is considered important to present tasks with clear learning objectives [136], and the meaning of feedback should be explained, particularly for non-intuitive feedback such as classifier output [136]. Likewise, cognitive support such as offering examples is theoretically encouraged [171]. Furthermore, taking into account the potential influence of general instructions on technology-related stereotypes might contribute to diminish misconceptions [126], induce greater intrinsic motivation [133, 157] or judgment of agency [160].

Overall, concerning the instructed task, many factors have been explored and the wide number of parameters makes it difficult to extract guidelines since there is a lack of formal comparisons. We do advise if possible to conduct screening (user-centered task selection) with a set of tasks, including motor imagery and cognitive tasks [37, 78, 131]. It is also recommended to activate prior knowledge instead of asking the user to perform an unfamiliar task [228], possibly to instruct complex tasks [147] and to use specific rather than a vague instruction [167]. Finally, although the nature of appropriate guidance is still unclear and might depend on users' individual characteristics, one aspect which received some attention is the focus in motor imagery, where it seems that kinesthetic imagery is better than purely visual imagery [42].

4.6. Open Challenges for the instructions in MT-BCI training

First, one of the major challenges lies in the general instructions, i.e. how to introduce the BCI system and session outline to foster users' understanding and engagement. The influence that instructions might have on users, for example in relation to the technology-related stereotypes, has not been really evaluated yet. It is not clear yet what a good overall instruction design could look like in BCI and it would be beneficial to instigate this further, for example by drawing on theoretical recommendations from other areas. Note that another challenge, closely related to the first, involves the evaluation of users' reaction to instructions, such as ensuring understanding and memorization - which is under-explored so far.

Concerning task-related instructions, many instructions were experimented, but the link between the instructed task, the guidance, users' cognitive strategy and the EEG patterns stability and distinctiveness is still unclear and should be further studied. Thus, we do not yet know what a properly executed mental task should be for a BCI to successfully decode it, partly because users' precise cognitive strategies are scarcely assessed or reported in papers. However, we do not know what is the most appropriate method to retrieve users' strategies, neither do we fully know the way MT strategies relate to performances or to the states of the user.

This general lack of knowledge on the right strategies limits our insight on which instructions are best adapted globally, but there is also a lack of knowledge about how to adapt the instructions individually (cf. next section). It can also be added that it is not known yet whether or how instructions could be adapted throughout the training, e.g. based on learning progress.

4.7. Perspectives for the instructions in MT-BCI training

In the following subsections, we describe four perspectives axis which could improve the effectiveness of instructions for MT-BCI user training.

4.7.1. Adapted instructions

Instructions can for example vary in terms of modality (e.g. oral vs. written) and narrative. Since there is little or no mention of these procedures in BCI papers, no further inquiry was conducted into them to our knowledge. However, theoretical evidence in the literature indicate that the instructions currently in use may not be appropriate enough [136, 176, 198]. Indeed, literature in educational design states that the amount of guidance provided during the training should be adapted to the experience of the learner (expertise reversal effect, [153]). Furthermore, different people do not learn in the same manner. The study in [36] has shown for example that, when learning to use a video game, strategy can be internally or externally oriented (i.e. reading a manual vs. asking for help, respectively). Similarly, BCI learners may prefer explanations provided by the system or the experimenter according to personality or psychosocial factors, e.g. anxiety [289] or gender interactions [260, 275]. Furthermore, in some contexts, it might be possible to leave the choice to the user on what they want to do or in which order they will do it (e.g. allowing patients to choose between different training modes according to their needs in upper limb rehabilitation [280]) although the effect of choice was not assessed.

4.7.2. Understanding

In order to improve instructions, one approach could be to evaluate users' understanding of what has been explained. Similarly, formalizing the presence (or absence) of re-explanation periods between runs or at the beginning of a new session could improve reproducibility and cross-subject comparisons. In fact, the evaluation of the learnability/memorability of the BCI skills and instructions is very rare [198, 223]. On a related topic, [160] discussed the availability of the instructions during the experiment. In their study (with auditory feedback), they allowed the participant to look at a paper to see what needed to be imagined when a certain instruction was heard. They hypothesised that it may compensate for the lack of transparency between the mental task and performed action by reducing the memory load. However, this was not formally tested.

4.7.3. Strategy variations

As described in Section 2.2, conscious efforts (declar-

ative knowledge, motivational processes) influence MT-BCI learning, thereby highlighting the importance of direct external guidance such as self-instructions or cognitive feedback to find a good strategy. One research direction would therefore be to explore the possibility of facilitating these conscious processes. Indeed, in MT-BCI/NF studies, users are generally instructed to find the "right" task. In doing so, they establish some kind of control-of-variables strategies (CVS) [4], i.e. the cognitive and procedural skills associated with being able to isolate and select good parameters in MT execution out of different trials. The idea that users dispose of a motor activation model for the task which evolves according to their findings is defended in [134]. However, there has not been any attempt to our knowledge to support the process of strategy adoption/rejection on the user side. Such cognitive support (i.e. "guidance to find a good strategy") was encouraged in recent papers [219, 253] in line with theoretical evidence [136, 176, 198] that instructions should include clear goals of progressing complexity. As pointed out in [253], this could be done with direct semiotic training. Such a training, as described in [188, 210], consists in assisting users to establish the connection between the "signifier" (the chosen MT strategy as conceptualized by the user), the "meaning" (the effective desired command) and the "reference" (resulting behavioral BCI response, e.g. feedback). The authors provide a comparison between learning self-regulation of brain activity and language learning, highlighting the importance of "training introspection" [188], or metacognition. Reporting users' strategy selection and strategy variations is all the more crucial since researchers have very little information on users' behavior (which is a covert behavior) in the context of BCI training.

4.7.4. Task selection

User-centered screening phases, aimed at selecting the best (set of) task(s), generally involve broad (unspecific) instructions. It could be interesting to consider changing the granularity of the instructions during this screening phase, with guidance variation leading to an appropriate pair-wise combination of cognitive strategies possibly showing more discriminative EEG patterns.

Finally, it is worth mentioning that user-centered task selection, when it occurs, is mostly done offline. For example, [79] proceeded by comparing (offline) several classifiers, choosing the best one for each subject, and then selecting the most discriminatory task based on the best classifier. On the contrary, online automatic selection of mental tasks was scarcely explored in the BCI field outside of [132]. This work showed it was possible to automatically select a task for a single brain-controlled switch during the course of the training but it has not been done yet for the selection of a pair (or a triplet) of tasks.

5. Feedback in MT-BCI training

Feedback provides an information to the learners regarding aspects of their performances or their understanding of the task/skills to learn [57]. Depending on the theory on the underlying mechanisms of MT-BCI process which is considered, feedback aims at consciously or unconsciously enabling the learners to produce a brain activity which is recognizable by the computer [273]. It is a fundamental component of MT-BCI protocols [101, 290].

A typical MT-BCI feedback consists of a rapidly extending bar or moving cursor which represents how well the system recognizes the task performed by the learner and how confident the system is in its recognition (see Figure 2).

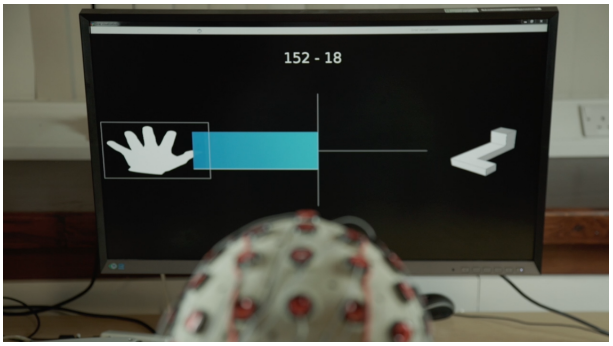

Figure 2. Example of feedback often provided to users during MT-BCI training. In this example, the user has to train to imagine left-hand movement, performing mental calculation and imagining an object rotating [171]. At the moment the picture was taken, the user had to imagine moving their left-hand. The blue bar location and direction indicates the task which has been recognized. The bar length indicates how confident the system is in its recognition: the longer the bar, the more confident the system. Here the system correctly recognizes the task that the user is performing and is quite confident about it.

While it is acknowledged that feedback can improve the learning outcome, its effects are variable and can even be detrimental [92]. These variations in the efficiency of feedback have notably been associated with its different characteristics [136, 273]. Based on our study of the literature, we argue that feedback can be defined using three main characteristics: (1) its content, i.e. which information it conveys (2) its modality of presentation, i.e. how this information is provided and (3) its timing, when and how frequently this information is provided [273].

It is recommended for feedback to have (1) a content that is both informative (provide advice) and supportive (have a social presence/emotional feedback)

(2) to be multimodal (provided on several modalities) and finally (3) to be timely (provided when the learners most need it). However, the most current typical MT-BCI feedback is evaluative, non-supportive, unimodal and highly frequent [136, 273].

While the typical feedback presented above is broadly used by the MT-BCI community, other types of feedback have been tested in order to improve the user training outcomes, i.e. MT-BCI performances and user-experience. The following subsections focus on each of the three characteristics of feedback, i.e. its content, modality of presentation and timing. We first provide a definition of the characteristic. Then, based on a review of the literature we provide insights regarding the leads that were explored in order to improve each characteristic of feedback. Finally, in the last section, we present the main open challenges which hamper the improvement of feedback.

5.1. Feedback content

First of all, feedback can be defined by its content, which varies depending on the information that feedback conveys to the learner regarding the task or their comprehension of the task. We have distinguished at least two types of information that MT-BCI feedback conveys. First, it conveys information regarding the results/performances of the users. If feedback conveys information regarding an achieved result or a deviation from the desired result, then it is called "feedback of results" [14]. However, if feedback provides specific information on how to improve the results, then it is called a "feedback of performances" [14]. Second, it can also convey a supportive content, i.e. social presence and emotional feedback. The two following subsections present results from the literature regarding these types of feedback content.

5.1.1. Feedback of results

During MT-BCI training, current standard feedback is mostly about results as it conveys information regarding how well the system recognizes the task performed by the learner, and how confident the system is in its recognition. Research on skill learning in other fields informs us that feedback of results is particularly useful to skilled learners who already possess a sufficiently elaborated cognitive model of the task to interpret feedback and translate it into relevant adaptations of their cognitive strategy [14]. During MT-BCI user training, feedback is generally based on the BCI classifier output, which is typically some form of probability that the current trial belongs to a given MI class [199, 245]. However, most MT-BCI users are not familiar with the notion of classifier output. It does not represent anything concrete for the learner who has to understand and interpret feedback. Therefore, users might particularly struggle to interpret feedback and translate it into the necessary behavioral modifications [198].

Several leads have been explored in order to improve the content of such cognitive feedback. One of them consists in biasing feedback, i.e. in artificially increasing or decreasing the users' (perceived) performances. In line with the literature regarding flow and the zone of proximal development, the use of such feedback which adapts the (perceived) difficulty of the task is expected to impact the immersion and intrinsic motivation of the users [88, 225]. Influencing the perceived difficulty of the task has been done by providing positive feedback only [27] or by biasing feedback [88, 258]. Biased feedback seems to benefit novice users but impede the performances of experts [27, 88, 249]. In this regard, researchers suggested to adapt feedback to the expertise of the users [184]. Though further research using a control group is necessary to evaluate the efficiency of such feedback. Some research also focused on enriching feedback, for instance by adding information related to muscular relaxation [185] or the stability of the EEG signals [208]. A two-dimensional feedback encompassing information regarding contra vs ipsilateral activity and contralateral activity during rest vs during mental imagery was also used in a neurofeedback study [190]. Studies with control groups found mixed results [185, 208]. Schumacher et al. did not find any significant influence on the performances [185]. Sollfrank et al. found that a more complex feedback enabled significantly better performances during the first session but this difference did not last for the next four sessions [208]. While assessing the influence on the user-experience, Sollfrank et al. found that their complex feedback enhanced motivation and minimized frustration throughout the sessions [208].

5.1.2. Supportive feedback

Another approach to improve the feedback content has been explored by providing some support to the users. Social presence and emotional feedback are considered as supportive content [273].

Currently, BCI feedback contains little or no supportive content. Few studies have used smileys to provide supportive content during MT-BCI training [27, 60, 264]. Only one has formally compared such feedback to a plain one [264]. Their results do not indicate any improvements of the performances or control over SMR with the use of a smiley. However, neurophysiological studies as well as theoretical MT-BCI studies demonstrate the importance of a supportive content [177, 186].

Recent studies have explored the impact of more complex forms of supportive feedback [253, 275, 289].

For instance, we designed and tested a learning companion dedicated to MT-BCI user training [289]. It was called PEANUT for Personalized Emotional Agent for Neurotechnology User Training. PEANUT provided a social presence and an emotional feedback to the users in between trials through interventions which were composed of both spoken sentences and displayed facial expressions. Its interventions were selected based on the performances and progress, i.e. evolution of performances, of the users. The results indicated that PEANUT had a beneficial impact on the perception that users had of their ability to learn and memorize how to use MT-BCI, which is a component of the user-experience [197]. PEANUT also had a different influence on MT-BCI performances depending on the level of autonomy of the participants. Non-autonomous participants, i.e. participants who would rather learn in a social context, had worse performances than autonomous participants when PEANUT was not present. However, when PEANUT was present, non-autonomous participants had better performances than autonomous participants.

In another recent study, we investigated the impact that experimenters had on their own experimental results [275]. Indeed, experimenters are the main source of social presence and emotional feedback during a MT-BCI user training. Our results indicate a differential evolution of trial-wise MT-BCI performances over a session depending on experimenters' and participants' gender. An interaction of experimenters' and participants' gender has also been found in a neurofeedback study [260]. Though, whereas we found a positive effect of women experimenters on the evolution of BCI users' performances over a training session, they found that women participants training with women experimenters tended to have lower performances than the other participants. Therefore, this interaction should be further explored in future studies.

5.2. Feedback modality

The second main characteristic of feedback is its modality, i.e. how the information is presented to the user.

Standard feedback for MT-BCI user training is often conveyed through the visual modality, e.g. a moving object or an extending bar, that users learn to control (see Figure 2). Nevertheless, realistic and embodied feedback, including 3D realistic visualisations [187], seems to be associated with better performances [138] or at least better subjective experience [191].

Vision is the sense on which daily life perception relies the most. It is also the modality which is the most represented at the cortical level and one for which we have the most finesse in the distinction of information [13]. Such characteristics make this modality very relevant to provide feedback. Though, in an ecological settings, visual resources dedicated to vision, visual attention or gaze focus, would be engaged by the interaction with the environment. For example, when controlling a wheelchair, a great amount of visual resources are dedicated to the monitoring of the surroundings. Therefore, relying on visual feedback only might not be suitable for the application phase of the MT-BCI. However, visual feedback can be used during the training phase with an adaptation and transition of feedback before moving to the application phase.

Numerous research studies have been led to assess the efficiency of providing feedback through other modalities than the visual one, i.e. auditory feedback [72], proprioceptive feedback [189, 285] or vibrotactile feedback [55, 172, 247]. Overall, vibrotactile feedback may be comparable to visual feedback [55] and even improve MT-BCI performances when the visual attention or cognitive load is high [55, 148, 172]. However, auditory feedback seems to enable comparable [155] or worse performances [49] than visual feedback in healthy controls.

The modality of feedback presentation for MT-BCI user training can also be adapted to the sensory abilities of the target population. For example, the choice of auditory feedback was made for people with visual impairments [163].

Studies led in motor skill learning have shown that the complexity of the motor task to be learnt, as well as the skills of the learner, have a major influence on the type of modalities to favour [140]. The more complex a motor task, the more effective the use of multimodal feedback [140]. In everyday life, the brain relies on information arising from multiple senses which often complement and confirm each other. This redundancy increases the degree of confidence associated with the perception [12]. Different studies explored the use of multimodal feedback for MT-BCI training [168, 208, 215]. Combining visual and proprioceptive feedback seems to improve the classification accuracy [106, 118, 168, 215] and enable more stable ERDs [215]. However, the results of combining visual and auditory feedback seem less conclusive. It might impede the learning [39] or be as efficient as unimodal visual feedback [208] in terms of performances. Finally, a congruence between task and feedback is highly important [124]. The integration of the multiple and incongruent sources of information can increase the amount of cognitive load and errors [124].

5.3. Feedback timing

The third and final dimension of feedback that we analysed is its timing, i.e. when and how often

feedback is provided.

Usually, feedback is continuously presented to the MT-BCI learners while they train and it is updated very frequently [273]. The frequency depends on the amount of acquired data related to the performances of the learner. For MT-BCIs, the amount of data depends on the sampling rate used to record the brain activity from the participant. Most often, it ranges from around one data per second in fMRI to hundreds or thousands of samples per second in EEG. Feedback is based on the processing of a time-window including several samples of these brain data. Feedback is considered discrete, or terminal, if it is provided at the end of one or several trials. It is considered continuous, or concurrent, if participants receive information during the trial, while they are performing the mental imagery task. There is little information in the MT-BCI literature regarding the timing that feedback should have. One study suggests that continuous feedback is more efficient for MT-BCI user training than a discrete feedback [22]. Further research is needed to confirm this result and investigate at which frequency feedback should be provided depending on the expertise of the MT-BCI user. Studies on motor learning have shown that the frequency of feedback should decrease with the increasing skills of the learners [140]. A study in neurofeedback with participants up regulating their alpha rhythm during ten sessions also indicates that providing feedback at the end of a session regarding the trial-by-trial performances in addition to some feedback after each trial seems beneficial [2].

Also, feedback might benefit from taking into account the cognitive state of MT-BCI users, e.g. attention or workload. For instance, the more frequent feedback is, the more attentional resources are necessary to process it [65]. Previous MT-BCI studies indicate that participants' attentional skills have an influence on their ability to control MT-BCIs [108, 115, 149]. It has been hypothesised that continuously adjusting the frequency of feedback according to the users' attentional states could improve the training outcome. According to the model of van Zomeren and Brower there are four different attentional states, e.g. selective or divided attentional states are respectively involved when one or several stimuli are monitored [15]. One of our study suggests that the attentional states described in this model can be distinguished with an accuracy of 67% using only EEG data [273]. Such a result could be used in the future to adapt the timing of the feedback to the attentional state of the users.

5.4. Guidelines for feedback in MT-BCI training

In the introduction of this section, we argued that it is recommended for feedback to be informative (provide advice), supportive (have a social presence/emotional feedback), multimodal (provided on several modalities) and timely (provided when the learners most need it). All of these recommendations can be drawn from fundamental and/or experimental research in education and MT-BCIs [136, 273].

Currently, MT-BCI users are provided with feedback of results. However, the literature in skill learning indicates that such feedback does not benefit every learner. For instance, novice users may not yet have the skills to translate feedback of results into the necessary corrections to make to their behavior [14]. It is recommended to use informative feedback also known as "feedback of performances" [219, 273]. In other words, feedback should provide information to the users regarding why a task has been recognized and how to improve their performance. Though, very few studies have explored the use of feedback that can be considered as feedback of performances, and did so with a low number of training sessions only [185, 208]. Overall, their results do not reveal much influence on MT-BCI performances compared to traditional feedback. More development on this matter is necessary (see next section: "Open Challenges"). When keeping feedback based on MT-BCI performances, biasing feedback seems promising for novice users [88, 258].

Recent MT-BCI experimental results indicate that using a learning companion to provide a feedback with supportive content can be useful for non-autonomous users [289]. The few studies testing the influence of supportive feedback indicate that the profile of the learners should particularly be assessed to prevent any bias and to adapt the supportive feedback [275, 289].

The recommendation concerning the use of multimodal feedback over unimodal one is more debatable. The experimental results are in accordance when considering multimodal feedback composed of both visual and tactile or somatosensory stimuli compared to unimodal visual one [106, 118, 168, 215]. However, multimodal feedback composed of both visual and auditory stimuli does not seem more appropriate than unimodal visual one [39, 113, 208]. When considering visual feedback, an embodied and realistic feedback seem more effective [138, 191]. All of these results should be considered with care as the presence or absence of a difference between two feedback presented on different modalities might also be associated to other characteristics of feedback, e.g. its content, presentation or timing.

Finally, very few recommendations can be drawn from the literature regarding the timing that feedback should have. Initial results indicate that continuous feedback could be more efficient for MT-BCI user training than discrete feedback [22]. Providing

feedback at the end of a session in addition to feedback after each trial could also be beneficial [2].

5.5. Open challenges for feedback in MT-BCI training

In the previous section we have recommended the development of feedback of performances that provides specific information on how to improve the results. Though, we currently lack the necessary knowledge regarding the underlying mechanisms of MT-BCI skills acquisition as well as knowledge on how to improve this skills acquisition to provide such feedback of performances. Furthermore, the content of feedback is currently based on the classifier output, which may not be appropriate to assess the users' acquisition of MT-BCI related skills [245]. Therefore, we first need to deepen our understanding of the skills that are acquired throughout the training. There is also a need for new metrics enabling to better evaluate the acquisition of such skills. Finally, we need to have a better understanding of how the characteristics of feedback impact the acquisition of such skills.

Furthermore, an impact of the learners' characteristics has been found on the efficiency of different feedbacks [273]. For instance, the users' expertise might need to be taken into account when biasing feedback [27, 88, 271]. Therefore, in order to have an adapted and adaptive feedback, we need a comprehensive model encompassing how the characteristics of the users and of the feedback interact with the acquisition of MT-BCI skills. However, to have a comprehensive model of the learners, numerous states might need to be monitored. Assessing states using EEG presents some challenges that remain to be overcome. First, the states that influence MT-BCI training must be defined and identified despite the inter and intra personal variability. Then, behavioural, neurophysiological and physiological markers must be identified to assess these states. Reliable methods must be found to assess these markers. Finally, the different states and their evolution throughout the training must be included in models to improve the feedback and the training accordingly.

Also, new forms of feedback are often compared to simple and traditional forms of visual feedback. This is a first step toward a comprehensive view of the impact of the different characteristics of feedback and their interaction. Future studies should provide more information on how to combine the different characteristics of feedback.

5.6. Perspectives for feedback in MT-BCI training

In previous sections, we have stated that the development of feedback of performances is limited by the lack of knowledge regarding the advice which should be provided to the learners to improve the acquisition of MT-BCI related skills. Learning companions, which we introduced previously for their usefulness in providing a social presence and emotional feedback during MT-BCI training, could also be used for developing feedback of performances, i.e. informative feedback. Indeed, example-based learning companions elaborate their feedback by comparing the current strategy of the user with some previous correct and incorrect strategies [81]. Such companions could be used despite the current lack of information regarding MT-BCI skills acquisition. Furthermore, researchers working on learning companions have being developing methods to adapt the behavior of their companions to the learners' states [196]. It might be worth leveraging such knowledge to adapt MT-BCI user training to the learners' states [200].

6. Exercises in MT-BCI training

6.1. A taxonomy and survey of MT-BCI exercises

While it has not been really formalized so far, and while their impact was not much formally studied yet, MT-BCI training exercises can come in a variety of types and formats, with different goals and effects. Thus, this section formalizes what these *training exercises* can be by suggesting a taxonomy. We also survey the types of BCI exercises which have been explored so far, and what influence they have on BCI user performances and learning, if feasible.

In terms of taxonomy, we argue that BCI training exercises can vary along three main dimensions: the training stage, the skill(s) trained and the parameters of this training. The training stage refers to the advancement of the trainee, and thus to whether the exercises are initial and/or introductory, for ongoing BCI training or for the final application control training. The skill(s) to be trained refer to what BCI skill or BCI-related skill the exercise is dedicated to. For instance, what mental command, set of mental commands or characteristic of that mental command the exercise trains. Finally, the training parameters provide additional information about how this training is presented, e.g. in open or closed-loop, with which type of feedback, or in a self-paced or system-paced manner. These dimensions and their elements are represented on Figure 3 and are described herein-after.

6.1.1. Training stage

Regarding the training stage targeted by the exercise, we identified 3 main stages: familiarization and screening, MT-BCI control training and application control training.

Familiarization and screening: This first stage usually aims at getting a new BCI user familiar with what

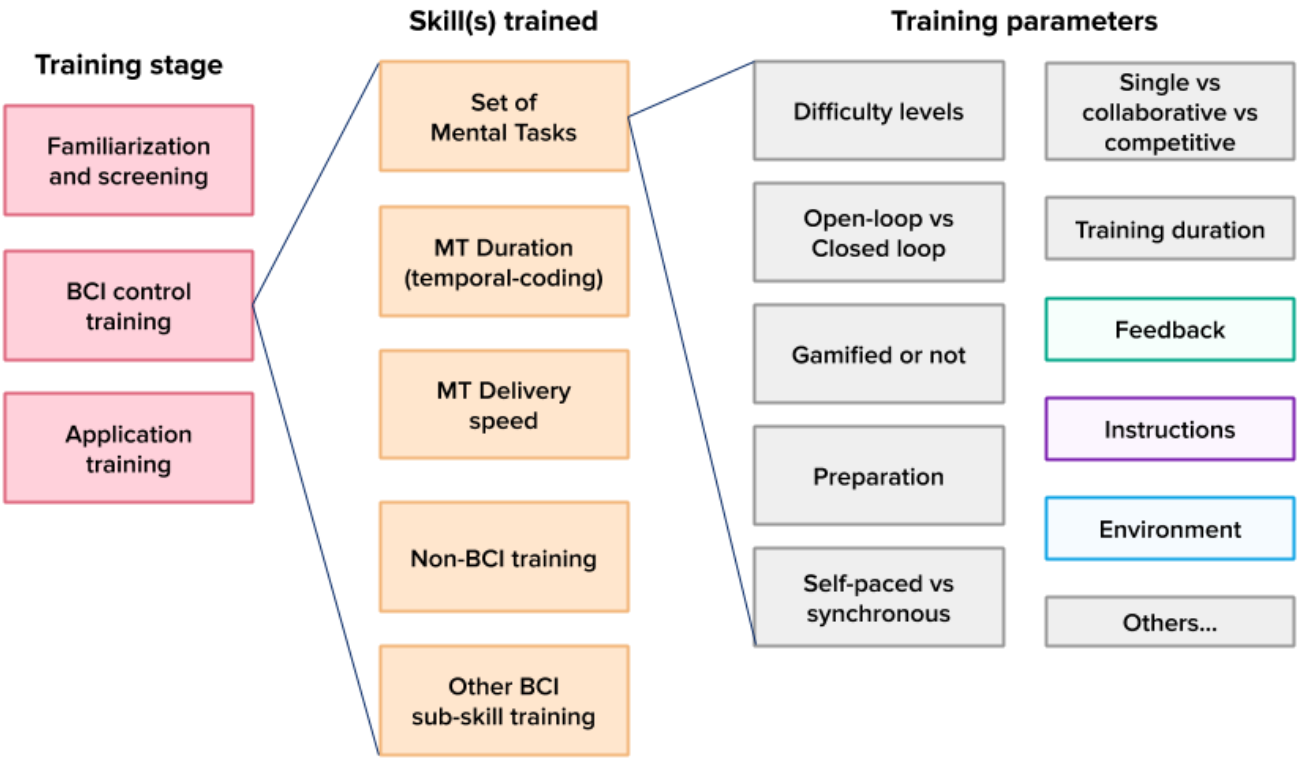

Figure 3. A representation of a taxonomy of BCI training exercises, according to the stage of training (section 6.1.1), the skill being trained (section 6.1.2) and the parameters of the exercise (section 6.1.3). Each stage can target several skills and the training of these skills can vary according to the indicated parameters.

a BCI is, and at identifying whether this user can use a given BCI and/or what type of BCI this user would be the most proficient with, see, e.g. [98, 233, 252]. Typically, the user may be asked to perform different types of mental tasks [131], in order to identify which subset of them can be discriminated the most accurately in EEG signals. Interestingly enough, this screening for the best mental tasks for a given user can be done manually by systematically testing each mental task for a given number of trials, or can be quickened by using machine learning (e.g. bandit algorithms) to present mental tasks in an order and amount maximizing the likelihood of quickly identifying the best ones [132].

MT-BCI control training: MT-BCI control training could be considered the main stage of the training. It consists in training the BCI user to get control over the selected MT-BCI system in a generic way, i.e. to learn to perform the selected mental tasks so that they would be accurately recognized by the BCI. This training is application-independent and often based on simple bar or cursor control feedback [9, 29].

Application control training: Finally, once users acquired some control over the selected MT-BCI, they can be trained to control a specific application using it. For instance, the user can be trained to control a prosthesis [98] or an asynchronous multi-class racing game [252] using the BCI. This stage is an application-specific, goal-oriented training, which often requires more advanced MT-BCI control, e.g. multiclass, multicommand and/or asynchronous control [98, 252]. Note that this stage is also very important, as application-independent training (the previous training stage) may not transfer immediately to application control training, and usually requires additional specific training. Indeed, Perdikis et al [252] explicitly showed that standard MT-BCI control training and application control training both led to measurable and substantial learning effects. The authors argued that both BCI user training exercises were key elements that led to their victory at the Cybathlon BCI competition 2016.

6.1.2. Skill(s) trained

During the MT-BCI control training stage, as well as during the application control stage (although to a lesser extent), the exercises can be made to train different skills. We describe herein-after what skills have been or could be trained.

Set of mental tasks: A given MT-BCI is controlled by using several mental tasks. When training users to control an MT-BCI, it might be too hard to start

training all mental tasks at once (see also Section 6.2). Thus, a given training exercise can consist in training a subset or even a single one of them, while more advanced exercises would later include more mental tasks. This was for instance explored in [135] and [97], who used training exercises with 1D, 2D and 3D BCI-based control, in a progressive way.

MT temporal-coding training: In addition to training users to perform mental tasks so that they are correctly classified by the BCI, users can also be trained to sustain the mental task (and thus the associated brain activity pattern) for a specific targeted duration. For instance, users could perform a MT so that it is recognized for either a short or long time. This is called "temporal coding" of MT patterns in [98]. This makes it possible to design a BCI with multiple commands from a single MT: the same MT can be associated to different commands depending on the duration for which the MT was sustained (and detected by the BCI).

Delivery speed training: Another MT-BCI skill that can be trained is the speed of delivery at which a given MT will be performed and recognized by the BCI. Indeed, for ideal MT-BCI control, the MT performed by the user should not only be recognized accurately and robustly by the BCI, but also as fast as possible, so that the BCI control is both effective and efficient [207, 252]. MT-BCI users can thus be trained explicitly for that, to send MI-based BCI commands as fast as possible. The goalkeeper paradigm was introduced for that purpose in [84]. With this approach, the user can move a bar (acting as a goalkeeper) left or right, only once per trial, using left or right hand MI, to catch a ball going left or right. The ball goes increasingly faster as training goes on, thus forcing the user to issue increasingly faster MI-BCI commands. Such training could indeed increase the command delivery speed as well as the command accuracy for most users [84].

Non-BCI training: Since different predictors of performance have been identified in the literature (e.g. spatial or attentional abilities) [201], several non-BCI training tasks might prove useful to improve non-BCI skills associated to those predictors, and thus, possibly to good BCI performances. For instance, attentional abilities could be trained using mind-body awareness or mindfulness meditation training. Interestingly enough, several studies showed that meditators tend to have better MI-BCI performances than non-meditators or that mindfulness meditation training could improve MI-BCI performances [38, 40, 47, 67, 146, 159]. On the contrary, short or long (week-long) progressive muscle relaxation training or visuo-motor coordination training did not improve BCI performances, even though the ability to concentrate on a task and two-hand visuo-motor error duration were both found to be predictors of SMR-BCI performance [216, 266]. It has also been shown that the ability to gain control over brain activity with SMR-Neurofeedback [220] is facilitated for people who engage in more regular spiritual practice (prayers).

After results suggesting that fronto-parietal gamma-range oscillations was a predictor of MI-BCI performance [108, 115], Grosse-Wentrup *et al* trained gamma-power attenuation using neurofeedback [107] with three subjects and showed with offline analysis that it might be beneficial for SMR modulation and thus potentially MI-BCI.

Finally, spatial abilities (SA) were found to be positively related to MT-BCI performances [171, 198]. Thus, an attempt was made to train BCI users' SA in [209]. However, this pilot study could not show any improvement in MT-BCI performances with SA training, which might be due to the very small number of participants or to the significant difference in their initial mental rotation score [209].

Other MT-BCI sub-skills training: Finally, like any skill, MT-BCI control skills are likely to involve a number of sub-skills, e.g. as strength or flexibility are important sub-skills to master a given martial art. Such MT-BCI sub-skills could be, for instance, how different EEG patterns for different MT tasks are from each other, or how stable a given MT EEG pattern can be produced [245]. To the best of our knowledge, there is currently no BCI training exercise targeted at improving EEG pattern stability for instance. However, it seems relevant to design and study such sub-skills training exercises for improving MT-BCI user training in the future. Also, as discussed in section 4.7.3, the conscious and declarative part of the training (i.e. the set of commands/mental tasks as conceptualized by the user) could be trained separately, at least for BCI applications where users have sufficient ability to report their subjective experience.

6.1.3. Training parameters

Finally, whatever the training stage, or the skill(s) trained, the MT-BCI training exercise can have various properties depending on how the training is conducted. In the following we describe various (non-exclusive) parameters which can be used to describe these properties.

Difficulty levels: First, different exercises can have different difficulty levels, and thus be targeted at beginners or experts for instance. This difficulty can be modulated, e.g. by varying the number of

MT to control simultaneously [97, 135], by reducing the allowed duration for the tasks to be performed (increasing delivery speed) [84], limiting the accuracy needed to complete a trial [150] or by biasing feedback, to make users believe they are doing better or worse than what they are really doing, thus changing the perceived difficulty [88] (see also Section 5.1 on this last point).

Open-loop vs close-loop: Any MT-BCI training task can be performed open-loop, i.e. without any online feedback, or close-loop, i.e. with online feedback. Typically, screening exercises are performed open-loop, as no BCI classifier is available yet [233, 252]. Note, that open-loop exercise could be interesting even when a classifier is available, as it could be a way to test how much users rely on feedback, and whether they can control a BCI without this feedback [19].

Gamified or not: A MT-BCI training exercise, or an application training exercise, can be based on a "classical" BCI environment and feedback, e.g. bar feedback, and/or with the real targeted application. Alternatively, these exercises can be gamified and/or performed in an enhanced environment, e.g. Virtual Reality (VR) [121]. There are indeed many video games which can be controlled using a BCI, see [137, 240] for reviews, and which can thus be used as BCI training exercises. Interestingly enough, using VR and games has been shown to improve BCI user motivation and training performances [85] on average, but may not be suitable for all users [242]. From a theoretical point of view, offering an inherently motivating and relevant environment to the learner is considered important [136] and gamification is a known way to elicit notions such as appeal of novelty, challenge or aesthetic value [25, 61]. However, the supposed positive effects of game-like environment are scarcely studied in BCI applications [242] and there might be some potential unknown shortcomings caused by complex stimuli, e.g. cognitive overload or additional processing effects on the brain [217]. Furthermore, numerous gamified BCI training report used exercises similar to the Graz MT-BCI protocol for calibration data collection, followed by an enhanced environment for the "feedback" exercise. It has been suggested that differences between calibration environment and testing environment might result in decreased performances [51, 225].

Self-paced vs synchronous: Most MT-BCI training exercises are synchronous, a.k.a. system-paced, in the sense that the system imposes to users when they should do which MT. Alternatively, a BCI system or BCI training exercise can be self-paced, i.e. users decide by themselves which MT they want to practice, and when they want to do so [56, 62, 96]. This requires a BCI able to handle such self-paced control, which usually comes at the price of a lower accuracy, and prevents from having a ground truth since we cannot know what the user is trying to do. However, allowing self-paced practice is a general recommendation from instructional design (independently of BCI training) [25, 76]. Furthermore, allowing such self-paced (or "self-managing" [254]) practice proves beneficial for users suffering from motor impairments in [34]. However, whether this is beneficial for all BCI users on average has not been formally tested yet.

Duration: MT-BCI exercises can also have different durations, e.g. to be able to offer short but numerous diverse exercises or to offer long exercise to train user endurance and familiarity with BCI control. In synchronous BCIs, this duration can be modulated by trial parameters, e.g. their own duration or their number. Applied to trials, adaptive decision related to timing were explored, e.g. inhibiting BCI interactions until specific requirements were met using EEG markers correlated to attention level [105] or pre-estimated command delivery time (CDT) as showed in both healthy users [206] or users suffering from motor impairments [207]. Shorter timing could, however, increase workload and/or stress level [207]. Note that the impact of MT-BCI exercises or trial duration has never been formally evaluated, though delayed trials and/or duration manipulation was discussed in several papers [165, 185, 249].

Environment: As mentioned in Section 3, the environment can vary in many ways in MT-BCI training. As such, a given MT-BCI training exercise can vary in contextual parameters, e.g. ambient noise, presence of one or more (un)known individuals in the room, etc.

Instructions: Similarly, as described in Section 4, various instructions can be provided to the user, and these can also vary for different training exercises, e.g. depending on the training stage of users, their past performances, or the information they may need.

Feedback: As mentioned in Section 5, many different feedback types can be used in MT-BCI. As such a given BCI training exercise can vary in which feedback to use, depending, e.g. on feedback content or modality which can benefit the BCI user the most at a given time.

Preparation: Exercises can also vary according to how users are prepared for this exercise or for each MT. Indeed, one method explored to improve MT-BCI

training was to directly induce desirable user states through preparation. For example, suggestive hypnosis has been tested to increase MI-BCI users' attentional focus [274]. However, experimental results found a statistically significant ERD disappearance during the MI task during hypnosis leading to lower classification accuracy. Another type of trial-wise preparation would be "brain tuning", i.e. stimulating users in order to shift their current brain state to a more optimal one using e.g. electrical stimulation. This has been shown to be beneficial for MI-BCI training [143, 234]. Another approach of this kind (i.e. with pre-stimulus) would be to instruct users to perform two consecutive tasks. For example, [145] showed that doing two tasks consecutively (tactile selective attention first, then MI) resulted in a better classification of MI, with a 10% improved classification. Yet another example would be the use of physical preparation: it has been shown that short physical exercise enhances neural correlates of MI in novice participants [262].

Single vs collaborative vs competitive: As discussed in Section 3, while the vast majority of MT-BCI training exercises are performed with the user alone with the MT-BCI exercise (single user mode), some works have explored having the BCI user train by collaborating or competing with another human user.

Other: Finally, there are certainly other parameters which could be used to design and characterise MT-BCI training exercises. We hypothesize that the more we will understand MT-BCI user training, the more refined and specific the training exercises could become, leading to more effective and efficient MT-BCI training. Many other exercise parameters are thus still to be identified and invented.

6.2. MT-BCI training programs: sequencing exercises

To favor training in general, educational science recommends varied and adapted exercises [136, 193]. Thus, to ensure a successful MT-BCI training program, we argue that the BCI training exercises mentioned previously should be arranged and sequenced in an appropriate and adapted way.

To do so, a first idea is to gradually confront the user with the BCI system and intended application. As an example, the study in [235] described distinct exercises, with a first look at brain signal modulation using MI tasks and classical BCI feedback [29], followed by an explanation of the functional role of the MI task and then a transfer task with real online control. Another more extensive example would be the study in [195] in which users were gradually guided towards a control task with different protocol components, including VR interactions and robotic control.

This progressive approach may not be so widespread, although some papers refer to the presence of a familiarization exercise, e.g. a simulation mode with no input from the user [184]. Yet, carrying out a complex control task might prove difficult for novice BCI users attempting to acquire MT-BCI skills. It might thus prove useful to have users practice on simpler elements before asking them to practice on the *whole* control exercise. These simpler elements could be based on the difficulty levels described in Section 6.1.3, for example by training tasks separately in a multi-class BCIs [97, 135].

This modulation of difficulty may not be limited to differences between exercises. This could also, for example, be explored inside a single exercise by training users with a non-random order of MI tasks to practice, as suggested in [249]. However, the BCI literature currently lacks formal comparisons that demonstrate the potential value of these practices.

Finally, while the sequencing of MT-BCI exercises can be done manually as shown in the studies described above, it could also be done automatically, by using Machine Learning tools to identify dynamically the best sequences of exercises for each user. Systems that can do so are known as Intelligent Tutoring Systems (ITS) [100], and their use for MT-BCI user training was first advocated in [200]. Since then, an ITS based on deep reinforcement learning was suggested in [267] to automatically identify the best sequence of MI exercises for MT-BCI user training. When assessed on idealistic simulated BCI users, this ITS proved superior to manual or random task exercise sequencing. However, it is still unclear how it would behave on real data, with noisy and non-stationary brain signals, and with real and thus complex human users.

6.3. Guidelines for the exercises in MT-BCI training

Overall, from this survey of MT-BCI training exercises, we can make the following recommendations. First, screening exercises should be used to identify the best mental tasks for each user [131, 183, 233, 252]. Users should also be trained to both BCI control (application independent) and to BCI-based application control [98, 252]. In terms of skills to be trained, it seems that Non-BCI training exercises improving attentional abilities, notably mindfulness meditation, can be used to increase BCI performances [146, 159]. In terms of exercises parameters, it appears that game-based or gamified BCI training exercise are useful to increase user motivation and engagement [85, 242]. They can also possibly improve MT-BCI performances, at least for relatively young users enjoying games [85]. However, it is not clear yet whether all types of users can benefit from games during BCI training, and if so, from which type of game [242]. In addition,

users' needs may vary according to the population (e.g. the nature of their motivation depending on whether they are patients or not, as shown in a P300 study [94]). Consequently, gamification is not necessarily recommended for all training situations and must be decided through UCD approaches. Then, including self-paced training exercises is theoretically recommended [25, 76] and was shown effective in practice [34]. It has not been yet assessed in controlled studies though.

Providing training exercise with other users in a collaborative way can increase performances and motivation, at least for some of them [129]. Finally, progressive training, with increasing difficulty (notably by increasing the number of MT to train) seems to enable advanced and complex MT-BCI-based control [97, 102, 252]. Note that formal comparisons without such progressive training are missing though.

6.4. Open Challenges for the exercises in MT-BCI training

So far, there have been relatively few studies of different types and/or sequences of training exercises for BCI. Thus, currently very little is known about how to design, choose and arrange training exercises in an optimal way. Consequently, there is a number of open challenges which need to be solved on that topic. Such open challenges include identifying which non-BCI training task could improve skills useful for MT-BCI control, as well as identifying MT-BCI sub-skills and designing appropriate training exercises to improve each of them. We also need to identify which exercises parameters are relevant for BCI user training, and to evaluate what their influence on users' BCI performance, learning and experience is. Future studies should also provide more information on appropriate trade-off between these parameters. Such evaluations should be performed with each exercise both alone and in combination with other exercises.

Furthermore, we have to identify the best sequence of training exercises to train for a specific MT-BCI control, or to design ITS algorithms to optimise that training sequence for each user and MT-BCI type. In the Motor Imagery literature, it has been shown that users' concentration decreases after 60 repetitions of imagined movements [93], that prolonged motor imagery sessions induce mental fatigue [156] and that prolonged sessions might decrease motor imagery accuracy in terms of imagination duration [205]. Consequently, it would seem interesting to investigate the suitable order, speed, duration or number of successive trials and exercises. Last but not least, another challenge is to identify the best exercises and exercise sequences for each users' type, and each user state.

6.5. Perspectives for the exercises in MT-BCI training

Several of the challenges mentioned could be solved by systematic and intensive evaluations of various exercise types, during longitudinal user studies, to formally assess and quantify their effects. However, the number of parameters, exercise types and exercises orders that could be tested is virtually infinite, so the most theoretically promising options should be tested first. Such evaluations should also be used to build models of the effect of various exercises, so that the influence of exercises types and sequences that have not been tested could be predicted by such models. In terms of finding the best exercises sequences for each user, the BCI community should study the work from the ITS community, to borrow tools, algorithms and ideas to do so [100].

7. Discussion

In recent years, MT-BCI research has made significant advances in user training. The variety of methods presented in this paper are promising and there is no doubt that training programs will further improve in future research. In this paper, we introduced a taxonomy of MT-BCI user training, according to the time-scale of each component. We argue that MT-BCI user training is a combination of several distinct aspects: environment, instructions, feedback, exercises. We reviewed the literature on MT-BCI in light of this taxonomy. It appears that, though extensive literature (theoretical or practical) deals with these different aspects and provide guidelines, there are still many challenging questions related to MT-BCI user training methods.

In the remainder of the document, a summary of these guidelines and challenges is therefore provided. Please note that, as research perspectives are rather specific to each aspect (i.e. instructions, feedback, etc.) and are more difficult to summarize, we do not provide a synthesis of the perspectives that are detailed in the respective sections.

7.1. General guidelines

We provide general guidelines extracted from the literature in Table 1. These guidelines are associated to a degree of certainty ranging from (*) to (***), according to whether they are purely theoretical (*) or were shown promising in practice through initial results in a few studies (**), or shown in a controlled experimental context in several studies (***). Note that formal assessments in controlled studies are often missing and that further research based on the challenges raised in the following section is expected to

yield new valuable guidelines. It is also important to keep in mind that most of the reviewed studies were conducted on healthy naive users with MI-BCIs. As a result, some aspects may be less relevant or may apply differently to patients and to non-motor MTs.

7.2. General open challenges

In this paper, we identified and mentioned a number of specific challenges that would need to be solved to improve MT-BCI user training, notably at the environment, instructions, feedback and exercise level. Here, we summarize in Table 2 the main general challenges to solve in order to better describe, understand and improve MT-BCI user training.

8. Perspectives

This article already presented a number of perspectives which are specific to each MT-BCI user training component, i.e. environment, instructions, feedback and exercises. However, there is also a number of relevant perspectives which are more global and which should be considered as well. We describe them hereinafter.

8.1. Defining and quantifying users' MT-BCI skills

In order to understand and improve further user training in MT-BCI, there is a need to be able to define and quantify the skills which are learned during such training [193, 246]. So far, these skills have mostly been quantified by the BCI classification accuracy or other related system performance metrics. These are "behavioral performance" of the system, which depends on neuro-bio-psychological, data analytical and ergonomical aspects [110, 161].

Though, while such types of metrics can tell us how well the user-machine pair performed, i.e. how well the machine can decode the EEG patterns from the user, it still quantifies the overall performance of the interaction and not the performance of the user independently from the system [245]. Yet, rather poor performance with a user can have many possible causes which do not depend on the protocol or on the user MT-BCI skills, e.g. electrodes can sometimes malfunction and EEG signals are likely to be noisy (due to electronic devices, power line noise and subjects' eye movement or muscle activity), or the classifier may not be adapted to the user's current EEG signals. Therefore, it is a poor metric to adequately study BCI users' skills and learning curve.

There is thus a need to define what precisely MT-BCI skills‡ are, and to be able to quantify them, in a way that is as independent of the BCI system (and in particular of the BCI classifier) as possible. A first step in this direction was presented in [245], with a definition of users' MT-BCI skills and some classifier independent metrics. Other types of metrics were used in [252] to quantify user learning at the EEG features level, independently of the classifier. Such efforts should be pursued in order to find relevant metrics to quantify various aspects of MT-BCI skills and user learning progress.

Tracking changes in user-related metrics might enable a more informed decision on whether to switch to a different exercise and/or whether it is possible to move on from feedback training to a transfer task, e.g. real BCI control application. Generally speaking, defining and quantifying users' MT-BCI skills can be useful to refine our understanding of user training, and thus to be able to further optimize it.

8.2. Machine learning and user learning in MT-BCI

This paper focused on various elements which are dedicated to user training in brain-computer interfaces, notably environment, instructions, feedback and training exercises. It was not focused on another key BCI element, that is usually more dedicated to train the machine: the classifier and associated machine learning algorithms. However, since all or part of the feedback provided to MT-BCI users is currently almost always the classifier output, those machine learning algorithms also have a key - although indirect - influence on user training. In particular, there is a need to identify and understand the influence of the classifier properties on the resulting user learning [246]. This notably includes 1) identifying whether using some specific EEG features and classifier types favors or impedes user learning [244, 246] and 2) identifying if, when and how to update classifiers with incoming data.

The influence of the classifier properties on user learning has been barely studied so far, but a handful of studies showed interesting results and raised interesting questions. In particular, the study in [95], based on a meta-analysis from 2010, suggested that for BCIs based on machine learning, users learning effects were essentially not visible in the publications analyzed, as they did not show increasing BCI accuracy with increasing practice. This was in contrast to previous Neurofeedback-based BCI training studies, which did show such users learning effects. This may thus

‡ Note that we are talking of multiple skills, as controlling a BCI is not a single monolithic skill, but most probably a set of multiple (sub-)skills, e.g. a separate set of skills to perform each of the mental tasks, being able to produce EEG patterns which are distinct, but also stable, being able to produce such patterns as fast as possible, etc.

Table 1. General guidelines extracted from the literature, with a degree of certainty ranging from (*) to (***), whether they are purely theoretical (*) or shown promising in practice through initial results in a few studies (**), or shown in a controlled experimental context in several studies (***).

Instructions and social environment	General instructions	(*) clearly explain the BCI technology and the research goal (*) explain the meaning of feedback, convey clear goal (*) demonstrate the skill to be learned
	Instructed task and guidance	(***) adapt the task to the user, e.g. through screening (***) explicitly encourage kinesthetic motor tasks over visual ones (**) provide specific guidance rather than unspecific instructions: activate prior knowledge and use tasks which are familiar for users
Feedback	Content	(**) provide supportive feedback for non-autonomous users (**) provide biased (positive) feedback for novice users (*) provide feedback of performances which is clear, meaningful, explanatory and specific
	Modality	(***) prefer multimodal (visual + tactile/somatosensory stimuli) rather than unimodal
	Timing	(**) for trial wise feedback, provide continuous feedback rather than discrete feedback
Exercises	Training stage	(**) Use screening exercises to identify the best mental tasks for each user (**) train users to both BCI control (application independent) and to BCI-based application control
	Trained skills	(***) offer non-BCI training exercises improving attentional abilities, notably mindfulness meditation, to increase BCI performance.
	Training parameters	(**) provide an engaging environment, e.g. game-based or gamified BCI training exercise to increase user motivation, engagement and possibly improve BCI performances (at least for relatively young users enjoying games) (*) offer a diversified training, include a variety of tasks (**) include self-paced training exercises (**) offer a progressive training, with increasingly difficulty (notably by progressively increasing the number of mental tasks to train)

Table 2. Summary of the General challenges extracted from our analysis of the reviewed articles. In this table, the expression "training characteristics" refers to those described in depth in the article: environment (Section 3), instructions (Section 4), feedback (Section 5), and other characteristics of training exercises (Section 6). To these training methods, other factors can be added such as user profile (discussed in Section 2.3) and elements that are more related to the BCI system such as acquisition and machine learning. Here the challenges are presented in chronological order (i.e. with the first challenges to be solved first).

1	• Identifying MT-BCI sub-skills. • Designing user-related performance metrics. • Studying the way they relate to system behavioral performances, EEG patterns, and user experience (extracted during and after the interaction, e.g. through physiological measures or subjective reports).
2	• Investigating the influence of training characteristics* on MT-BCI performances and sub-skills. • Studying *how* these training characteristics* interact with each other.
3	• Identifying *which* parameters can be manipulated and are relevant to improve MT-BCI sub-skills. • Identifying *what* users' states should be monitored (and how) to provide adapted/adaptive training.
4	• Designing appropriate training exercises and evaluating their effect, both alone and in combination with other exercises. • Adapting training with properties that are best suited for each user type/profile or for each skill to be trained. • Optimising training sequences dynamically, depending on users' states and traits, e.g. by designing ITS algorithms.

suggest that whereas machine learning could help to obtain high classification accuracy quickly, this may also impede user learning over time. This hypothesis was also somehow supported by the results from [270]. Indeed, in their study, the authors compared SMR-BCI training over multiple sessions with either Laplacian band power features or Common Spatial Patterns (CSP) features, i.e. without or with machine learning to define EEG spatial filters. Their results showed that using CSP led to higher first session performances, higher than with Laplacian channels, but that users with a BCI based on Laplacian channels improved over sessions, whereas those with CSP did not.

On the other hand, several recent BCI studies based on machine learning demonstrated clear user learning. Notably, in [252], the authors used fixed classifiers for long term training of two quadriplegic users and could demonstrate a robust learning, both in terms of BCI performance, application performances and neurophysiological changes. The authors argued

that using a fixed classifier was a key element to enable user learning, so as to provide consistent feedback to the BCI users. Rather than using fixed classifiers, another line of works explored co-adaptive methods (reviewed in [256]), in which both the user and the machine are continuously learning and adapting to each other. In these cases, the classifiers and eventually the features are adaptive and update their parameters as new data become available. Such approaches were shown to enable many subjects to reach good BCI control relatively fast, including some users who could not control the BCI with static fixed approaches [103, 256]. This was also recently shown to even lead to quick brain plasticity in a single BCI session [288]. However, such approaches do not work for all users, and notably not for users without any initial relevant EEG patterns among the features used, nor for users who cannot make sense of feedback nor when the adaptation is either too slow or too fast [256]. While co-adaptive approaches can certainly quickly improve BCI performances over time, one study reported it could lead to a decreased quality of users' EEG patterns and thus possibly to users' BCI skills: the users may rely too much on the machine adaptation, and may not try to improve by themselves [204].

Overall, it seems that there are a number of factors that influence whether the machine learning algorithms will enable, favor or impede user learning, notably the type of spatial filtering and classifier used, whether and if so, how and how fast the features and/or classifiers are adapted, whether the user can produce some distinct enough EEG patterns from the start, and whether the user can make sense of the feedback resulting from the machine learning algorithm. So far, there is no formal comparison to identify which machine learning approach enables the most effective and efficient learning, nor how far this learning can go. There is also a lack of metrics, theories and models (an exception is the relevant theoretical model of co-adaptation presented in [226]. It needs to be validated on real data though) to quantify and characterise how the various factors mentioned above influence learning. Such models and theories would enable to design and choose the appropriate classifiers, and appropriate adaptation schemes to ensure effective user learning [246].

8.3. On the need for large scale longitudinal evaluation of MT-BCI user training

As mentioned multiple times in this article, there is still a lot we do not know about MT-BCI user training, e.g. about why some users can learn efficiently to use a BCI and some other cannot, about how to train users effectively, about how to give each of them optimal environment, instructions, feedback and exercises at all time or about how far can MT-BCI users learn and progress with training. This is partly due to a lack of studies on several of these questions, as well as to inconsistent results between studies about them. The latter is probably due to large within and between-user variability typically observed in BCI combined to the often small sample sizes (in number of users and/or training sessions) of current BCI studies. There is thus a need for more experimental studies in MT-BCI user training, and ideally for more extensive and larger scale ones. Such studies should, ideally, train large user populations (i.e. hundreds or thousands), that are diverse in user types, and to train them over multiple sessions (i.e. typically at least 10 sessions if not much more, for each user). They should also record various aspects of users' profile, states and skills. Naturally, if such large scale studies were to share their data in open access, that would enable the whole BCI community to benefit from them, and improve our knowledge.

8.4. On the need for models of MT-BCI user training

With increasing experimental data on MT-BCI user training, the next steps would be to use them to build both theoretical and computational models of MT-BCI user training in order to be able to fully understand and optimize this training. As mentioned in Section 2, there are already some ongoing works on these aspects, e.g. [110, 173, 219, 265]. However, so far, there is still no comprehensive and robust model able to explain BCI user training progress with a given MT-BCI training protocol. Given the very large number of parameters that could be explored and combined in MT-BCI user training, it is virtually impossible to fully optimize this training by following an experiment intensive only approach, hence the need for models that could - hopefully - generalize the obtained experimental data to new situations. To be able to build such models, it should be stressed that we need both positive and negative results, i.e. to know both what works and what does not work to improve training [286].

9. Conclusion

Designing training procedures which take into account the potential effect of all parameters remains a challenge far out of our reach. With this article, we tried to contribute to pull together the varied literature on MT-BCI training into a comprehensive framework, which will hopefully lead to improved training procedures. We attempted at covering the major key components of MT-BCI training (i.e. environment, instruction, feedback, and other characteristics of training exercises) and we provided some suggestions on the potential research avenues

that may contribute to our general understanding of MT-BCI training, learning and performances.

Past and current MT-BCI studies that investigate user learning mostly focus on classification accuracy improvements. Many more studies will be needed in order to be able to mobilize more factors, involve a broader use of User Centered Design (UCD), User eXperience (UX) design, usability studies and subjective assessments [152, 241, 254, 259] and, ultimately, drastically improve BCI effectiveness but also users' experiences. There are still many steps to be taken and it is crucial to keep analysing and improving all training aspects (environment, instructions, exercise design, feedback, signal processing, classification, etc.) in order to achieve useful, usable systems.

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