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Long-term kinesthetic motor imagery practice with a BCI: Impacts on user experience, motor cortex oscillations and BCI performances

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ABSTRACT

Kinesthetic motor imagery (KMI) generates specific brain patterns in sensorimotor rhythm over the motor cortex (called event-related (de)-synchronization, ERD/ERS), allowing KMI to be detected by a Brain-Computer Interface (BCI) through electroencephalographic (EEG) signal. Because performing a KMI task stimulates synaptic plasticity, KMI-based BCIs hold promise for many applications requiring long-term KMI practice (e.g., sports training or post-stroke rehabilitation). However, there is a lack of studies on the long-term KMI-based BCI interactions, especially regarding the relationship between intrapersonal factors and motor pattern variations. This pilot study aims to understand better (i) how brain motor patterns change over time for a given individual, (ii) whether intrapersonal factors might influence BCI practice, and (iii) how the brain motor patterns underlying the KMI task (i.e., ERDs and ERSs) are modulated over time by the BCI user's experience. To this end, we recruited an expert in this mental task who performed over 2080 KMIs in 26 different sessions over a period of five months. The originality of this study lies in the detailed examination of cross-referenced data from EEG signals, BCI data performance, and 13 different surveys. The results show that this repetitive and prolonged practice did not diminish his well-being and, in particular, generated a sense of automatization of the task. We observed a progressive attenuation of the ERD amplitude and a concentration in the motor areas as the sessions accumulated. All these elements point to a phenomenon of neural efficiency. If confirmed by other studies, this phenomenon could call into question the quality of the BCI in providing continuous stimulation to the user. In addition, the results of this pilot study provide insights into what might influence the response of the motor cortex (e.g. emotions, task control, diet, etc.) and promising opportunities for improving the instructional design of BCIs intended for long-term use.

1. Introduction

Brain-computer interfaces (BCI) are communication and control systems that enable end-users to interact with a computer using modulation of brain activities, usually measured with electroencephalography (EEG) signals [115, 59]. One of the most prominent BCI types of interaction is Motor Imagery (MI)-based BCI, which allows users to control a system by performing MI tasks, e.g., imagining hand or foot movements detected from EEG signals [59]. Indeed, movement and imagination of movement activate similar neural networks [22, 83], enabling the MI-based BCI to exploit the modulation of SensoriMotor Rhythms (SMR) over the motor cortex [82]. Such modulations are respectively known as Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS), coming from the mu (7-13 Hz) and beta (15-30 Hz) frequency bands [80, 79] to control the BCI system (see related section 2.6.3 below). Then, MI-based BCI relies on classical machine learning algorithms (i.e., Linear Discriminant Analysis, Support Vector Machine; [60]) or Riemannian framework, the current state-of-the-art EEG classifiers [120], to discriminate several mental states between them [58] and enable user interaction.

Currently, synaptic plasticity stimulation resulting from the practice of Kinesthetic Motor Imagery (KMI) opens up

promising fields, mainly to control assistive technologies [64, 106, 57], for sport training [42, 68], for e-sport [118] or even for post-stroke motor rehabilitation [13, 5, 88]. A KMI consists of imagining a movement without execution, focusing on the haptic sensations experienced during the actual movement (e.g., tactile, proprioceptive, and kinesthetic) [28, 71]. Because a KMI corresponds to the recall of a motor act, this mental task activates the primary motor cortex and the additional motor areas in the same way as a real movement would [35]. Indeed, it is well known that KMI generates a bilateral [92, 113] or contralateral [82] ERD during the task followed by a contralateral ERS afterward [94, 117, 84], thereby enabling KMI to be detected by a BCI.

Although very promising for many applications, interacting with a BCI through KMI is a complex task [63, 41], and therefore relatively difficult for the user to perform [89, 36]. In contrast, Visual Motor Imagery (VMI) is usually easier to carry out because it is more intuitive [37]. KMI requires a reactivation of many perceptions usually present during the movement, to which we typically do not pay attention. Consequently, KMI leads to mental fatigue [105, 38], requires a high level of cognitive availability [38], and cannot be performed during too long sessions [27]. This complexity can lead to highly variable KMI-based BCI results [1, 98, 66, 95], degrading the BCI interaction's quality and, consequently, limiting the potential benefits sought (e.g., stimulating brain plasticity).

If several studies have proposed learning protocols for

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the KMI-based BCI interaction [89, 66, 121], works studying the training and mastery of the KMI task in the long term are still lacking [97]. For most of the targeted applications (e.g., post-stroke rehabilitation, sports training, control), the use of a KMI-based BCI requires, after the period necessary for its learning, regular and continuous training for a long time to expect an effect on brain plasticity (i.e., daily or weekly use over several months) [5]. Beyond the fact that this period of continuous training can be felt as repetitive [99] and tedious [119, 99], data on the long-term practice of KMI are still lacking to properly understand the processes engaged by the users and the factors that may influence their performance throughout their practice. Indeed, due to ethical and pragmatic limitations, most MI-BCI studies are carried out over a single day or few sessions, usually with novice users. On the other hand, the effect of long-term practice of KMI is complex to quantify when users may not have similar levels of KMI control. Nevertheless, the resulting confusing knowledge are used for long-term applications by the BCI community.

One particular issue needs to be further investigated: how brain motor patterns (i.e., ERD and ERS) evolve for a given person during a regular practice of KMI. Do the patterns fluctuate depending on the experimental condition or the user training level? Does the repetition of KMI tasks lead to stability, an increase in BCI performance, or, on the contrary, to a decrease? However, variation in the nature or quality of brain inputs can affect the overall quality of the BCI itself, and thus the corresponding user experience, and vice versa, creating a potential mutual degradation of the BCI loop. This directly raises the issue of better understanding the variability of ERD and ERS over one or different sessions. Numerous studies have previously shown that there is much inter-subject and intra-subject variability [98], especially concerning the ERDs and ERSs patterns [78, 40]. Still, difficulties remain in understanding the origin of such phenomenon [117] during a long-term practice. Unfortunately, how the user is changing in terms of mastery of the task, acceptability, emotional state, and subjective perception of continued use of the interface are poorly investigated in the literature. While many studies have shown the relevance of considering the psychological state and motivation of the BCI user [49, 72, 121, 3, 41, 2, 93, 69], empirical user-centered studies are still needed. Moreover, individual activation patterns during KMI are largely neglected in most studies, which have mainly focused on identifying patterns common to all participants. As well as Wriessinger et al., we believe that a better understanding of the intra-individual variability during long-term use of the BCI is crucial for developing efficient interfaces [117, 81].

This study investigates the within-subject effects of performing a KMI task, via a BCI, over a long period. In particular, we investigated three main questions: (i) how brain motor patterns change over time for a given individual, (ii) whether within-subject factors can influence BCI practice, and (iii) whether the brain motor patterns underlying the KMI task (i.e., ERDs and ERSs) are modulated by the user's ex-

perience with the BCI over time. The originality of our approach relies on an in-depth study of the dataset provided by a subject who performed 26 KMI sessions of a right-hand grasp task with a BCI over five months. Although this approach needs to be replicated, this unique database includes over 2080 KMIs performed under similar controlled conditions by a pre-trained subject proficient in the KMI task. In addition, we combined the user's neurological motor patterns (i.e., ERDs and ERSs) with the user's perception of their general state of well-being (e.g., tiredness, stress, emotional state) and KMI training experience collected during each of the 26 sessions via 13 different self-report surveys. An approach with such fine granularity is quite rare.

2. Material and method

In detail, we combined two methods:

- a so-called objective method, which describes the situation by its environmental and physiological characteristics [61];
- a so-called subjective method, which tends to collect the experience perceived by a subject via perception questionnaires and explanatory feedback in the form of open questions and a log book. The objective here is to complete and cross-reference the previous data via a point of view directly from the user, more intimate and not only inferred [8, 112, 17, 16, 19].

Our approach is grounded on the phenomenological theoretical principle that the subject transforms, actualizes, and evolves in concert with what it perceives of the situation during the experiment [24].

2.1. Ethical approach

The experiment follows the statements of the WMA Declaration of Helsinki on ethical principles for medical research involving human subjects [116]. The subject signed an informed consent approved by the local ethical committee of Inria (COERLE, approval number: 2016-011/01).

2.2. Participant

One right-handed participant (male, age 32 years) was recruited for this study. He was selected because of his familiarity with BCI technologies and expertise in performing kinesthetic motor imagery. As evidence, he had consistently demonstrated excellent classification performance (>80%) in more than ten BCI studies using the right-hand KMI task. Thus, he had already received feedback on his past performance, which allowed him to self-assess his task level. Before this experiment, he completed a progressive training program (described in [89]) and used the BCI interface (see below), which ensured that he became familiar with its design. The participant never had any information regarding the hypotheses of the study in order to ensure that the research was not biased. The participant's education level is post-high school diploma, ensuring he understood the experiment's instructions. To identify participant's motivational

profile, we asked him to answer the Situational Motivation Scale (SIMS) [26] and the New General Self-Efficacy scale (NGSE) [14] questionnaires during the appropriation period. His Intrinsic Motivation (IM-SIMS score=5.25 when max score=7) and Identified Regulation scores were high (IR-SIMS score=6.25) towards how he generally works or carries out activities, professional tasks (calculated with the SIMS survey [26]), and his general self-efficacy perception is moderate to high (NGSE score=3.5, std=0.53 - [14]). These results ensure the subject's initial motivation for such a study. The subject had no medical history that could influence the task (i.e., diabetes, antidepressant treatment, or neurological disorders). The study's objective (i.e., to evaluate the evolution of ERD and ERS patterns in the motor cortex over time) justifies the decision to involve an experienced rather than naive user in the KMI task. Indeed, training of the task is a confounding factor that could change the activation of the motor cortex throughout the sessions and prevent any conclusion [75]. Moreover, it has been previously shown that experience in motor imagery significantly reduces the effort and resulting fatigue [73], which in our experience, could be significant considering the high number of trials (>160) performed for each session.

The choice to involve one single subject might be discussed. However, it should be noted that involving a cohort of users for weeks on end in a time-consuming task, generating, as a minimum, fatigue, and lassitude, poses ethical problems. In addition, it is very complex to motivate a group of participants to be available for months (i.e., half a day per week for five months). These factors increase the risk that many participants will withdraw during the protocol. Therefore, this study should be considered a pilot study to expand knowledge about the possible effects of performing a BCI based on KMI in the long term before undertaking more extensive studies.

2.3. Protocol description

The experiment took place in a quiet, confined room and was conducted by the same researcher throughout the entire study (i.e., to avoid any bias related to the placement of the headset, or the EEG signal acquisition). In addition, the researcher was previously trained in the good practices required to install the Biosemi EEG cap. During the experiment, the subject sat comfortably on a chair, with their right arm leaning on an armrest and their hand resting on an ergonomic pillow (Figure 1A). All sessions were carried out in very similar conditions, both in terms of the time of the session [114], positioning of the subject, and the experimenter.

2.3.1. The *Grasp-IT* device

The *Grasp-IT* environment (for "Grasp a KMI in an Interactive and Tangible manner") was used for this long-term KMI practice program. *Grasp-IT* is a BCI designed to make KMIs more tangible, understandable, and easy to implement. Its design followed three main criteria: the affordance effect of a common object, facilitating visual cues, and challenging feedback (The latter element was deactivated during this experimentation), to provide a positive and effective KMI

experience. A previous study highlighted the usability of the interface and the appropriateness of design choices to support the performance of KMI tasks [89].

The non-immersive VR environment of *Grasp-IT* provides visual cues through a traffic light, allowing the subject to easily identify when to start and stop performing the KMI (i.e., during the green light) and then rest for the duration of the red light (Figure 1). In addition, an orange light indicates to the user for two seconds that he should prepare before performing the KMI. This latency ensures that he is fully relaxed during the resting task and avoids any motor preparation during the resting state. In addition, between each trial, we randomly allowed a time of around two seconds to prevent the subjects from anticipating the task.

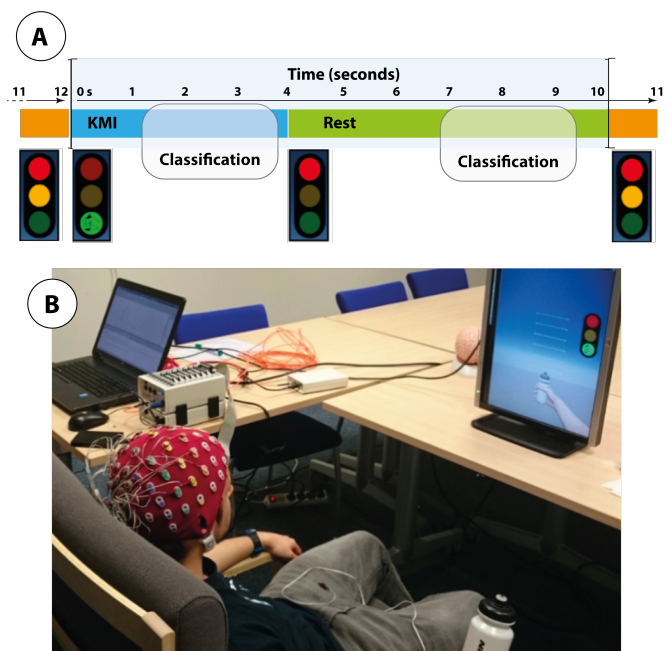


Figure 1: (A) Timing scheme for each trial: the subject was in a resting state when the light was red. The participant performed a right-hand KMI during 4 s when the light was green. We segmented each trial into a kinesthetic time for classification and a rest time for classification. (B) Representative photo of the experimental configuration: the subject is seated comfortably in front of a non-immersive virtual environment. The non-immersive virtual environment was composed by a three-color traffic light corresponding to the cues and a virtual right-hand corresponding to the feedback.

The *Grasp-IT* BCI is based on two distinct mental tasks: kinesthetic motor imagery and resting state. These two mental tasks are known to generate, respectively, ERD and ERS modulations [82] that can be easily detected by a BCI using machine learning algorithms [59] (see related section 2.6.3 below). The recognition of right hand MI and rest is particularly interesting for stroke rehabilitation and athletes [90].

2.3.2. The KMI task

Support by the graphical interface of *Grasp-IT* presenting a bottle in hand viewed in "first-person shooter" mode,

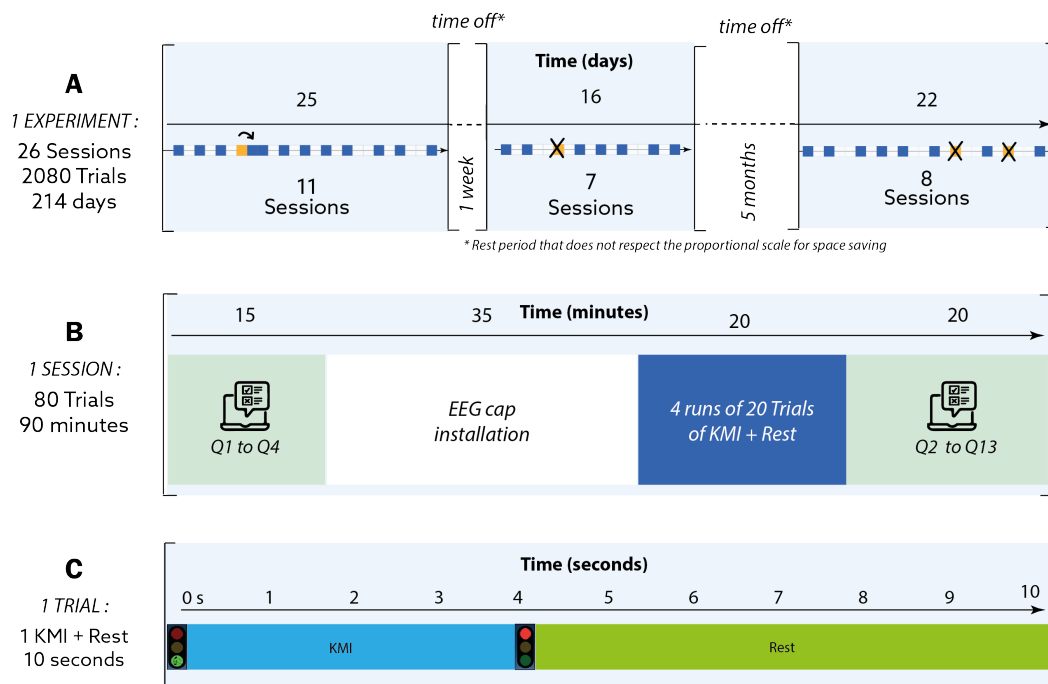


Figure 2: (A) Timing scheme for the experiment including 26 different sessions over 214 days. A blue cube represents each session. Some sessions were rescheduled or canceled by the subject (in orange). Two breaks of one week and five months were taken. (B) Representing scheme describing the procedure of a session (about 90 minutes). Each session started with completing the first four questionnaires, then the EEG headset's installation, the performance of 80 trials (KMI and rest), and completing questionnaires Q2 to Q13. (C) Timing scheme for each trial: the subject was in a resting state when the light was red. The participant performed a right-hand KMI during 4 s when the light was green.

the user had to imagine squeezing the physical bottle in his hand as if he wanted to produce a powerful jet of water (Figure 1.B). To do this, he had to recall all the sensations of muscle contractions, warmth, and perceptions in the fingers that are usually present during natural movement but without actually doing the movement. He should focus on the sensation of activation of the peripheral nerve pathway, which allows for better delivery of the KMI [89]. No neurofeedback or performance feedback was given to the subject. He could, therefore, only situate himself in his achievement of the KMI by his self-perception. The user ensured that he breathed slowly and was adequately relaxed during the resting time for the resting state. He ensured that he *"tried as much as possible to remove the muscle tension in his hand and arm consecutive to the KMI"*. To avoid tension in the participant's arm, the pillow was placed to hold the elbow and forearm, and the participant's hand was slightly open to the side so that the bottle rested in his hand. This approach is supposed to ensure that the ERD generated during the KMI does not continue after the task.

2.3.3. Describing timing and number of sessions

To assess the long-term effect of KMI practice, the subject performed 26 sessions under similar conditions. The 26 sessions were conducted for 214 days, in 3 different periods separated by a break (see, Figure 2.A). The first 11 ses-

sions were carried out over 25 days and were followed by a one-week break. Then seven sessions were conducted for 16 days, followed by a more consistent break of 5 months. Finally, eight more sessions were carried out over 22 days. The difference in pause duration between periods 1-2 and 2-3 is intended to determine whether a longer pause would affect the results compared to a shorter pause (between periods 1 and 2). A daily follow-up was set up to ensure the subject's well-being throughout the experiment. Three sessions were thus shifted or removed to account for the subject's needs (see Figure 2. A).

For each session, the participant took part in one experiment of 90 min divided into six parts: (1) Fill in the first questionnaires (15 min); (2) EEG cap installation (35 min); (3) Complete 80 trials of KMI and rest (20 min); (4) Fill the post-experiment questionnaires (20 min) and uninstallation. Each trial consisted of performing the KMI of grasping continuously for 4 seconds as the light turns green and a rest condition indicated by red light (Figures 1.A and 2.C). During each session, the subject performed four runs with 20 trials of KMIs and resting state, i.e., 80 KMIs of each mental state (see, Figure 2B - 2C). Considering the literature on ERD/ERS [47, 82] and the classification performance used in BCI [60, 58], 80 trials of each class is relevant to estimate the accuracy. The total represents more than 2080 KMIs and resting states over the 26 sessions, which is substantial for

Table 1

Detailed list of the surveys targeting the subject's well-being and emotional state evolution.

D.S. = Designed for the Study

Q.N*	Name	Authors	Description	Questions	Pre	Post
Q1	Quality of life	D.S.	6-item survey (4-point Likert scale) on selected elements of personal quality of life as perceived by the subject	In the 24 hours before the session, I have (a) consumed alcohol, (b) consumed exciting beverages, (c) eaten a balanced diet, (d) had a quality sleep, (e) eaten salty food, (f) drunk water	X	-
Q2	Brief Fatigue Inventory	[65]	Two short questions (10-point Likert scale)	I rate my perception of fatigue, (a) in the 24 hours before the session, (b) Right now, before the session (<i>after</i> for the post-test)	X (a+b)	X (b)
Q3	Stress level	D.S.	Two short questions (10-point Likert scale)	I rate my perception of stress, (a) in the 24 hours before the session, (b) just now, before the session (<i>after</i> for the post-test)	X (a+b)	X (b)
Q4	Medical Emotion Scale	[20]	20-item questionnaire (5-point Likert Scale) assessing emotional state during training in a medical environment. Single emotion scores can be used solely or averaged by valence (positive, negative) and by the potential for activation (Activating, Deactivating)	Right now, I feel "emotions/feelings"	X	X
Q5	Personal feedback	D.S.	Open-ended question allowing the subject to give qualitative information about his conditions	Personal elements that I think are important to mention	X	-

the intra-individual variability in the database. During each trial, the user was invited to perform the KMI of grasping continuously for 4 seconds as soon as the light turned green and while it remained so.

2.4. User's perception assessment

In this experiment, we used thirteen surveys to track the participants' subjective perceptions across the different KMI sessions. In addition, the subject filled in a digital logbook (Padlet) freely before and after each session. These approaches pursued three main goals:

1- Monitor the subject's way of life throughout the experiment, estimate the effect of the sessions on this wellness and emotional state, and control a possible intra-subject impact on the EEG oscillations. To that aim, the subject completed five surveys before each session (see Q1 to Q5 - Table 1). They cover different aspects of life (fatigue, quality of sleep and food, stress, daily professional constraints, etc.) and the emotional state, as perceived by the subject.

2- Estimate the ergonomics and usability of the perceived environment throughout the protocol to control a possible context effect and, more generally, estimate the user's experience in front of a KMI-based BCI situation executed repetitively. The questionnaires commonly used to assess the usability and attractiveness of a system (e.g., SUS [12], AttrakDiff [31, 52], MeCUE [67]) do not cover the dimensions that

we are interested in (specifically for this type of BCI environment) or could be too long to fill in. Therefore, we designed three short surveys (see Q6 to Q8 more detailed in the table 2); covering the perceived quality of the overall environment, the reliability of the system and its ergonomic qualities.

3- Estimate the subject's perception of the KMI task, performance, expertise, and possibly progress (see Q9 to Q13 - Table 2).

The researcher was never present with the subject during the completion of the pre- or post-sessions questionnaires so as not to influence the subject. All the specifically designed surveys (*D.S.* in the Tables 1 and 2) were only used here to explore possible links between the participant's feelings, environmental conditions, and neuromotor performance and patterns. They still need to be statistically validated for wide use. The subject was asked to complete these questionnaires online before and/or after each session. The different questionnaire results were coupled with the EEG results. In addition to being analyzed in isolation, they were correlated with EEG signals collected and BCI data.

2.5. Electrophysiological recordings

EEG signals were recorded through the OpenViBE software platform with a Biosemi Active Two 64-channel EEG system. Following the international 10-20 system, the EEG

Table 2

Detailed list of surveys targeting different dimensions that can influence KMI execution and control, including user experience. *D.S.* = *Designed for the Study*

Q.N°	Name	Authors	Description	Questions	Pre	Post
Q6	Environment quality	D.S.	4-item survey on the perceived quality of the environment during the session (5-point Likert scale)	I found the context and the material to do my KMI session (a) comfortable, (b) ergonomic, (c) conducive to concentration, (d) pleasant	-	X
Q7	System reliability	D.S.	One question on the general quality of the system's performance (5-point Likert scale)	The system's functioning has been optimal (from not at all to totally)	-	X
Q8	Ergonomic properties of the system	D.S.	20 items of contrasting word pairs, inspired from the AttrakDiff [31] and the MeCUE [67], covering four dimensions, i. e., attractiveness, practicality, reliability, and motivational properties of the system	Right now, I found the system used to perform my KMI session: (e.g., hazardous/reliable; uninteresting/interesting; inaccurate/accurate; boring/stimulating; etc.)	-	X
Q9	KMI Task Expertise Level	D.S.	One question (one item; 10-point Likert scale)	From 1 to 10, I estimate my level of mastery of the KMI tasks	-	X
Q10	Sense of progress	D.S.	One question on the perceived progress since the previous session (10-point Likert scale)	Right now, from 1 to 10, I encode my feeling of progress since the previous session	-	X
Q11	KMI skills and Challenge level	D.S.	8-item survey assessing the extent to which performing the KMI task was personally challenging and required specific skills	During the KMI, I felt (a) immersed in the task, (b) able to maintain sustained attention, (c) able to channel my distracting thoughts, (d) challenged, (e) consistent, (f) competent, (g) mastering the task, (h) automated my actions	-	X
Q12	NASA-TLX	[110]	7-point workload index questionnaire (21-point scale)	Mental, physical and temporal demand, Performance, Effort, Frustration	-	X
Q13	Personal notebook	D.S.	Open expression if needed	the subject described, for example, the possible dysfunctions of the system, the KMI strategies used, or the feeling of learning or not something during the session.	-	X

was recorded from 64 sites localized around the sensorimotor area. An external electromyogram (EMG) electrode was used during the experiment to verify no movement during the KMI task.

2.6. Electrophysiological analysis

2.6.1. Pre-processing

All offline analyses were performed using the EEGLAB toolbox 14.1 [18]. The data were processed in General Data Format (GDF). Considering the large number of electrodes used in this study (eg. =64) and the purpose of this research (motor patterns over the motor cortex) we chose to use a common average referencing (CAR) [39, 54]. The EEG data were resampled at 256 Hz, high-pass filtered at 0.5 Hz using a FIR filter, and divided into 11 seconds epochs corresponding to 3 seconds before and 8 seconds after the KMI for each run.

2.6.2. Event-related spectral perturbation

To analyze the differences between each session, we performed an event-related spectral perturbation (ERSP) between 8-35 Hz. We compute the ERSPs using the gain model approach equivalent to the *band power method* [82]. In this model, the ERSP at each time-frequency point is divided by the average spectral power in a 2.5s pre-stimulus baseline period for each frequency band. Then, a log-transformed ERSP measure was used to highlight our results (Eq. 1). The mean ERSP for frequency f and time point t is defined as:

$$ERSP_{log}(f, t) = 10 \log_{10}(ERSP_{\%}(f, t)) \quad (1)$$

We used a 256-point sliding fast Fourier transform (FFT) window (padding 4) and we computed the ERSP for the whole period.

2.6.3. Topographic ERD/ERS map

Brain topography allows us to display the possible changes over different electrodes on the scalp to localize which part of the brain was involved when the subject performed the requested task. As a reminder, typically, motor imagery is preceded by an ERD in the mu and beta frequency bands. This gradual decrease in power starts in the preparatory phase of the motor task and reaches a maximum during its execution [82]. After the motor imagery, an ERS, also called post-movement beta rebound, occurs mainly in the beta frequency band while the ERD in the mu band slowly returns to the baseline [84]. During the imagination of movement, the ERD occurs bilaterally around the sensorimotor cortex and has a somatotopic cortical distribution of the engaged limb [102], but can also have a contralateral predominance, especially in the beta frequency band [47]. In many cases, the ERD has a larger amplitude in the mu-band than in the beta-band and seems to be modulated according to the experimental criteria (e.g., the uncertainty of the direction of movement, attention in the task, type of movement performed; [108, 47]).

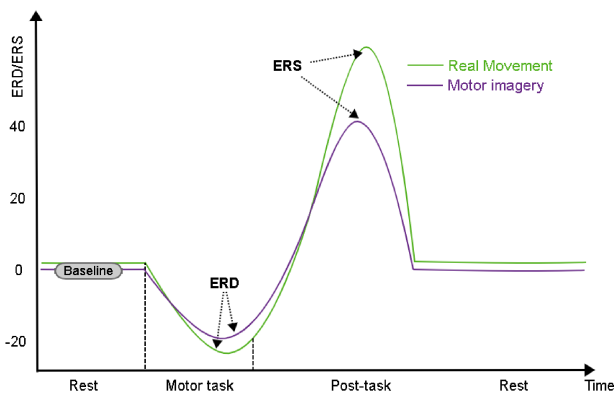


Figure 3: Illustration of the timings and amplitudes of the desynchronization and the followed synchronization induced by a real movement or motor imagery according to [94] in the mu and beta frequency bands

In this article, we computed the topographic ERSPs (which is equivalent to ERD and ERS) in the mu + beta (8-30 Hz) during and after the KMI task (Figure 10).

2.6.4. Classification

In this study, we decided not to provide online feedback to the participant because we wanted to evaluate only the effect of long-term KMI practice. We used the EEG data underlying the generation of each KMI during the sessions to calculate the theoretical BCI performance using a so-called offline method.

The recorded EEG signals were bandpassed using a 5th-order Butterworth filter between 8 and 30 Hz. Each trial was segmented into a kinesthetic time for classification (KTC) during the KMI and a rest time for classification (RTC) during the resting state, both lasting 3.5s (Figure 1C). The EEG segment corresponding to the KMI task started 0.5 s after the

go signal (green light), while EEG segment corresponding to the resting state started 2.5 s after the stop signal (red light) (Figure 1C). Thus, we collected 80 EEG segments for the KMI task and 80 EEG segments for the resting state, therefore a total of 160 EEG segments for each task and sessions. This number of EEG segments is considered sufficient to achieve a classification and has been used in similar studies [58]. We computed the performance of the classification methods in a 4-fold cross-validation scheme. We proceed to detail the feature extraction and classification step of the two methods used in this paper.

The classifier used in this study is Riemannian Geometry based classification method, whose popularity has risen in the BCI community due to their easy implementation and enhanced performances [58, 94]. Riemannian geometry-based methods work with the spatial covariance matrices of each trial, which live on the Riemannian manifold of symmetric positive definite matrices [6]. Hence, the features we used in following classification method is the sample spatial covariance matrices $\Sigma_i \in \mathbb{R}^{C \times C} = \frac{1}{T-1} X_i X_i^T$ of each trial X_i . We used the Tangent Space and Logistic Regression (TS + LR) technique, which allows projecting the feature space, that is the Riemannian manifold, onto a Euclidean space. To do so, we compute the Riemannian barycenter of the covariance matrices in the training set, and project the training and testing covariance matrices onto the tangent space at that point. Choosing the training set Riemannian mean as the projection point implies that the resulting tangent space is the best possible approximation of the original Riemannian space [107, 7]. Then, since the tangent space is a Euclidean space, we train and used a Linear Regression classifier.

2.7. Statistical analysis

A surrogate permutation test ($p < 0.05$; 3000 permutations) from EEGLAB toolbox was used to validate the difference in terms of time-frequency ERSPs and localization of these ERSPs with sufficient alpha level ($< 5\%$). In addition to this analysis, we applied a false discovery rate (FDR) correction test to clarify how the false discovery rate was controlled for multiple comparisons. This test performed the drawing of data samples without replacement.

Statistics were performed using SPSS software. We chose to apply a paired t-test (two-sided) to show the significant difference in subject' experience variations before and after the sessions. Then, considering using Likert scales in the questionnaires, we computed Pearson's correlation to establish a correlation between sessions accumulation and answers and ERD/ERS variations over sessions (p -value < 0.05). A Bonferroni correction was applied in the case of multiple correlations.

3. Results

First, this study aims to identify the effects of repeated KMI sessions over time on the participant, their experience, and second, on neuromotor patterns. In addition, we investigate the potential influence of the salient factors in subject's

feedback on EEG results.

3.1. Repeating KMI sessions and user-experience quality

Based on the subject's responses to the surveys (see Tables 1 and 2), we assessed the influence of repeating KMI trials over a long period of sessions on the user experience at three levels: general well-being, emotional states, and the perception of the system used.

3.1.1. Overall context and well-being evolution

The participant reported healthy and relatively consistent eating habits (see Q1 - Table 1). His sleep quality was consistently moderate (Mean Score=2.23; std=0.58), leading, according to the subject, to greater fatigue on certain days (7 or 6 out of 10, for a mean score = 4.89; std=1.37). No major deterioration in the subject's general condition throughout the sessions was noticed. However, on a few days, he reported having overindulged the day before (alcohol, poor diet, higher salt intake). Interestingly, there is a lack of correlation between those days and the subject's emotions or sense of tiredness the following day. Comparing results before and after each session, no significant impact on his perceived stress (Q3) was noticed, as opposed to the fatigue (Q2), which was judged significantly higher after a session (Figure 4). Performing this type of KMI session appears to be an exhausting task for the subject. However, this perceived fatigue did not increase with the number of sessions. The results analysis of the Q6 and Q7 questionnaires, and the open questions (Q13 - see 2), state that the subject never complained of any particular discomfort or difficulties related to the context that would have impacted his experience. The reported problems on certain days were always associated with his job constraints. Thus, with the exception of punctual fatigue after each session, the subject's general state was not affected by the accumulation of sessions, and vice versa.

3.1.2. Emotional states evolution

We first compared the subject's emotional state (Q4) before and after each KMI session to see if there was any difference. In the short term, the participant remained positive throughout the sessions (see Figure 5). There was no significant change in his before/after state. Based on the detailed MES results (Q4), the only difference is that the subject reported feeling significantly more joyful after the sessions than before (t-test; paired sample with p-value <0.01). No other emotional indicator is correlated with achieving a KMI session. Presumably, these conditions did not significantly disrupt the participant's emotional state, despite the tiring and repetitive trials over a session. Secondly, we examined the long-term effect, i.e., the influence of the accumulation of sessions over time (26 sessions over 214 days). As the sessions progress, the subject appears significantly more and more proud ($r=0.670$, $p<0.001$) and serene ($r=0.600$, $p=0.001$). These could suggest that the task has not lost its appeal and indicate that the experience of the KMI BCI-based was not

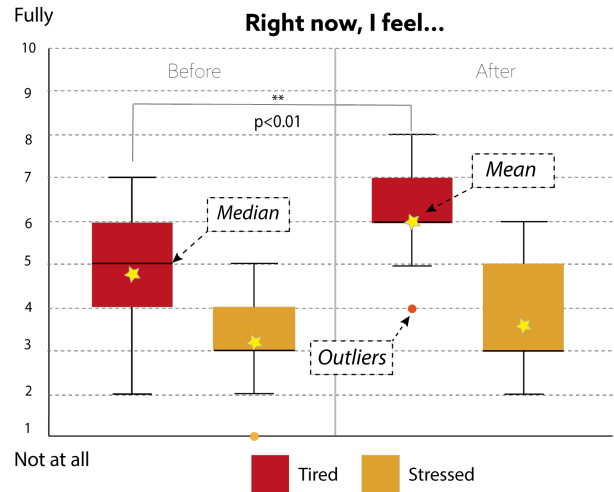


Figure 4: Boxplot representing the perceived fatigue (red - Q3b) and stress (yellow - Q2b) by the subject before (left) and after (right) each KMI session. Significant differences ($p<0.01$) are shown by t-test paired sample.

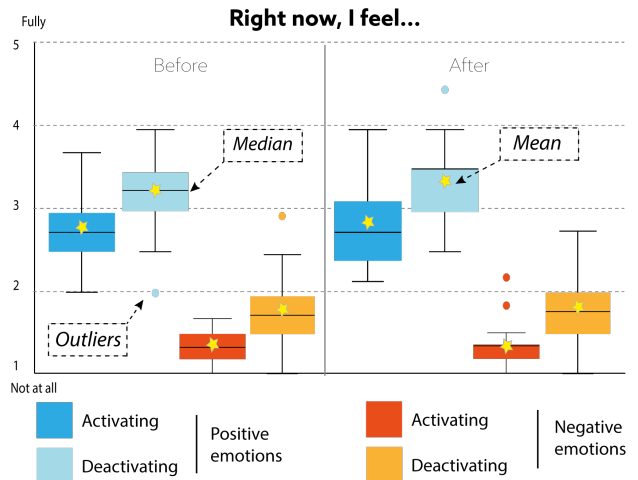


Figure 5: Boxplot representing positive (blue) and negative (orange), activating or deactivating emotions measured via the MES survey (Q4 - [20]) and reported by the subject before (left) and after (right) each KMI session.

without effect on the subject's eudemonic emotions (i.e., feelings of fulfillment, well-being, and meaning that result from experiences that align with personal values. This includes the contentment, satisfaction, and joy that come from achieving goals or experiencing growth).

3.1.3. Evolving perceptions of the system and subject's direct environment

During the sessions, the participants positively considered the *Grasp-IT* functioning (Q7 - Mean Score=3.81; std=0.93). However, the system's ergonomic qualities (Q8) remained moderate (Global Mean Score=1.47; std=0.42), particularly concerning its motivational and practical properties (Figure 6). No incident was reported (Q13) that could have affected the quality of the results. There is no correlation between

BCI performances, workload, sense of progress, or well-being and the system's functioning or ergonomic qualities. However, as the sessions accumulated, the system was perceived as more engaging ($r=0.603$ $p<0.01$), and more usable ($r=0.757$ $p<0.01$), suggesting an increase in the system confidence. In the same line, the subject judged his immediate environment to be more conducive to concentration (Q6) over the sessions ($r=0.429$ $p<0.05$). However, he always performed in the same place and under the same conditions. These last elements could indicate a form of habituation and/or acculturation.

The subject's overall condition and context remained thus favorable, with no major deterioration. Therefore, the results obtained in the BCI performance and ERSPs patterns cannot be explained by elements external to the subject. However, some aspects of the subject's quality of life and emotion related to the task fluctuated.

Right now, I find the system used ...

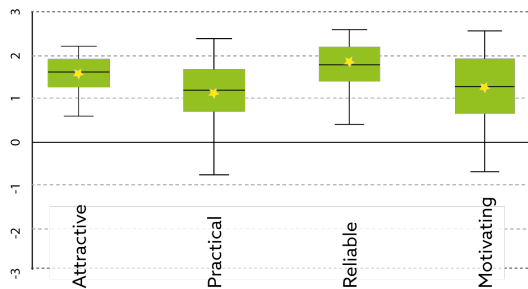


Figure 6: Boxplots representing the user's perception of the ergonomic proprieties of the system through 4 dimensions from Q8: attractiveness, practicality, reliability, and motivation.

3.2. Repeating KMI sessions and sense of competence

3.2.1. KMI and cognitive workload

The NASA-TLX scores (Q12) associated with performing the KMI sessions without feedback were, on average, judged to be high on average (Mean Score = 54.37; Std = 11.8 [110]). Among the different dimensions measured (see Figure 7), the mental demand (Mean=65.8, Std=12.9), the need to make an effort (Mean=69.0, Std=12.4), but also, more surprisingly, for a KMI task, the physical demand (Mean=59.2, Std=12.6) were rated as high. On the other hand, the time pressure (Mean=47.2, Std=20.8) and the level of frustration (Mean=44.4, Std=18.0) were rated relatively high. The lowest workload dimension is the impression that the session was useless (reverse dimension - Mean=40.6, std=18.3). These results are generally consistent with previous research [38]. In addition, there was no correlation between workload (nor any of its sub-dimensions) and the accumulation of sessions over time, nor with the fatigue (pre- or post-session) or any other dimension of the other surveys.

3.2.2. Perceived progress and mastery of the KMI

The subject's sense of progress from one session to the next (Q10) was irregular between sessions, especially at the

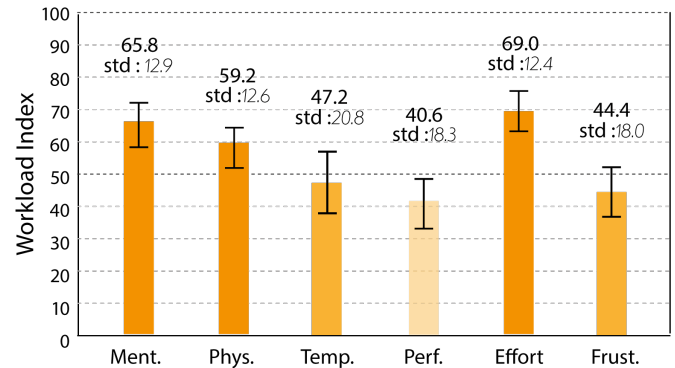


Figure 7: Bar graph of the workload index for the six NASA-TLX dimensions (Q12). The darker the bar, the higher the load.

beginning, peaking at the midpoint and then decreasing significantly (Figure 8). Except for session 6, his perceived personal expertise (Q9) in the KMI task remained moderate to high (Mean score=7.77 Std=1.33; for a min score=1, max score=10), and gradually increased over the sessions ($r=0.759$ $p<0.01$). Although the subject received no feedback on his performance, there are strong correlations between the accumulation of sessions over time and his sense of mastery (Q11-g), which increased significantly over the sessions ($r=0.804$ $p<0.01$), as did his sense of competence (Q11-f $r=0.666$; $p<0.01$), and his ability to automate his actions (Q11-h; $r=0.757$ $p<0.01$). The other items of Q11 were more irregular,

Figure 9 shows that the subjective sense of proficiency in the KMI task increased over the sessions (average score of Q11 e/f/g/h). Furthermore, our results show that during the first 14 sessions, the feeling of being challenged increases as the sessions progress (average score of Q11 a/b/c/d), consistent with the sense of proficiency in the KMI task. These two subjective factors gradually dissociate from session 14 onward. Then, the subject seems to reach a ceiling in his feeling of proficiency in the KMI tasks. This observation is also consistent with the maximum plateau in his sense of being an expert (Figure 8); from this point on (session 22), the sessions no longer seemed to stimulate the subject. The lack of feedback could have made the task less motivating.

3.3. Repeating KMI sessions and motor cerebral patterns modulations

We investigated the average ERD/ERS modulations for all the sessions (Figure 10) and the separate average ERD and ERS for each session (Figure 11 and 12) to determine their evolution according to the condition of the subject and also to assess the effect of time on the motor patterns (see also Table 3).

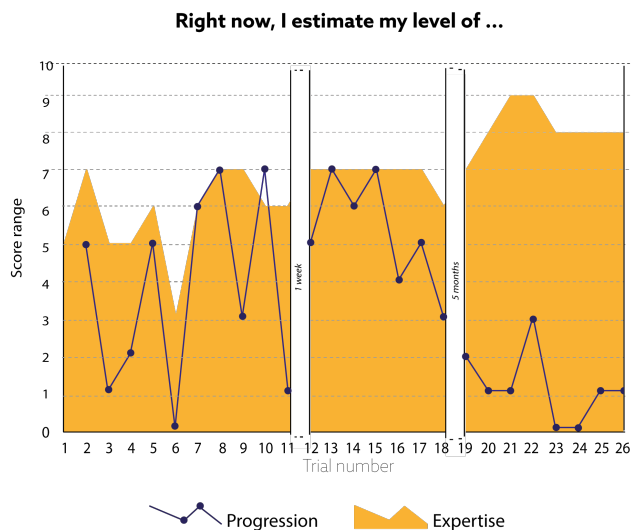


Figure 8: Diagram showing the feeling of expertise (yellow - Q9) and progress (blue line - Q10) and after each of the 26 sessions. A double vertical bar indicates break times.

3.3.1. ERD/ERS grand average over all sessions

Following the methodology used in the literature, the grand average ($n=26$ sessions) of ERD and ERS modulations have been computed for the μ + β (8-30 Hz) band. Our results show activation of the motor cortex with a bilateral ERD, i.e., covering both right and left-hand motor areas, during the 4s of green light onset when the KMI task was performed. Then, following the end of the task, when the bilateral ERD decreases, this is replaced by the contralateral ERS for several seconds. These results are in harmony with the literature: the ERD phase is mainly expressed during the KMI motor task and represents an activation of the motor cortex. After the end of the KMI task, the motor cortex re-synchronizes significantly to allow a new movement.

3.3.2. ERD modulations over time

Figure 11 presents the average ERD produced during 4s of KMI for each of the 26 sessions separately. As observed in the grand average figure, the ERD during the KMI were bilateralized for almost all sessions (except session 50). Indeed, we have already mentioned that the ERD generated during the KMI could affect both hemispheres (see section 3.3.1). Moreover, these results show that a significant ERD was generated for each session, showing that the mental task was performed correctly for all sessions, in line with the subject's expertise. The analysis of the evolution of the ERD over time and across sessions showed a significant correlation between the amplitude of the ERD and the number of cumulative sessions (see Table 3.4.1). This seems to indicate that as the sessions accumulate, the amplitude of the ERD decreases. We also observed they became more focused around electrodes C3 and C4, no matter what breaks the subject took. Indeed, after a one-week or a 5-month break, the ERD amplitudes rapidly return to the same location and amplitude as noticed before the pause.

The BCI performance, calculated using the offline accu-

racy score (TS+LR method, see section 2.6.4), shows the same tendency. This measures the degree of accuracy with which the online BCI could recognize the two mental tasks (KMI and rest). Our results show that the accuracy obtained is significantly correlated to the amplitude of the ERD, both when considering contralateral and ipsilateral electrodes. Indeed, we have already mentioned that the ERD generated during the KMI affects both hemispheres (see section 3.3.1). However, the accuracy scores are not significantly correlated with the ERS, whatever the electrodes analyzed. Indeed, as the sessions progress, the accuracy shows a gradual decline from 97% average performance (first five sessions) to 92% (last five sessions) (see Table 4 and Figure 9). Moreover, there is a significantly strong negative correlation between the accumulation of sessions and the accuracy scores ($r=-0.604$ $p=0.001$). BCI performance was not significantly reduced when the subject reported fatigue but is moderately anti-correlated to the sense of KMI task proficiency ($r=-0.443$ $p<0.05$). In addition, no plateaus or gaps were observable such as those noted by the subject regarding his feeling of proficiency and facing a challenge (see Figure 9).

3.3.3. ERS modulations over time

Figure 12 presents the average ERS produced during 3s after the KMI for each of the 26 sessions. We observed that the ERS after the KMI is contralateral for all sessions, but the amplitude differs according to the session. Sometimes the ERS is large (sessions 19, 25, 50, and 52), sometimes minimal (sessions 1, 22, 13, and 26). The contralateral ERS is most often associated with an ipsilateral ERD, most pronounced in sessions 15, 21, 25, and 26. Note that there is no significant correlation between the power of the contralateral ERS and the ipsilateral ERD. This will be specifically commented on in the discussion section (see section 4.1.2 below). We also observe that the ERS focuses on the motor electrodes around C3, demonstrating that the rebound is subsequent to the KMI task. In contrast to the ERD-related results (Figure 11), the analysis of the evolution of the ERS over time and across sessions showed no significant correlation between the ERS amplitudes and the number of sessions.

3.4. Exploring potential cross-influences

Brain activity and subjective metrics are not disconnected. Given the previous results, we questioned the potential influence of factors that occurred in one way or another during the subject's experience on the motor cerebral patterns. Indeed, we have seen that some specific elements of the subject's quality of life, emotional state, or perceived KMI competence may have fluctuated over sessions. Therefore, in an exploratory approach, three domains of potentially influential variables were tested: the KMI task sense of proficiency of Q11, quality of life events (salty food, alcohol consumption, fatigue before starting), and previously highlighted emotions (joy and serenity before and pride after the sessions).

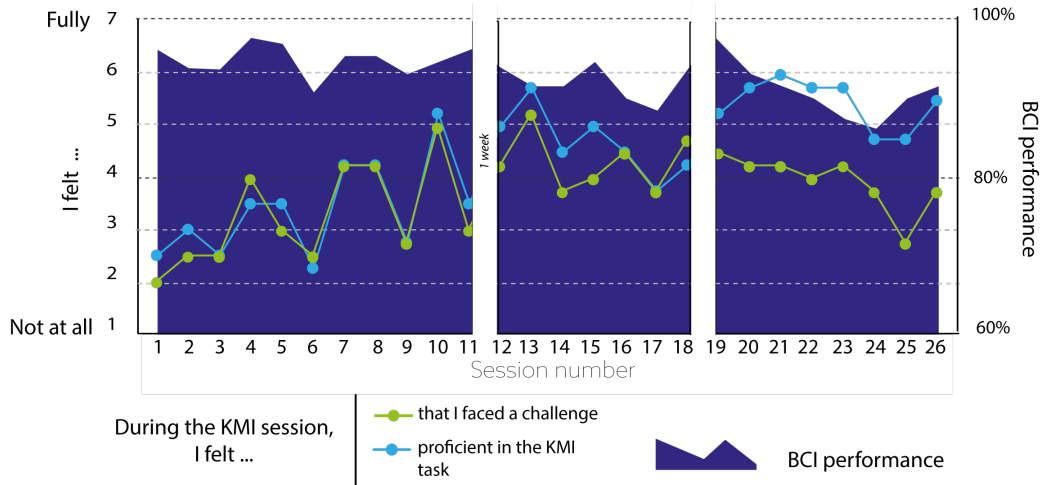


Figure 9: Diagram describing the BCI performance of accuracy (TS+LR method) and the feeling of the KMI task proficiency (average score of Q11-e/f/g/h) and of being faced with a challenge for all sessions (average score of Q11-a/b/c/d).

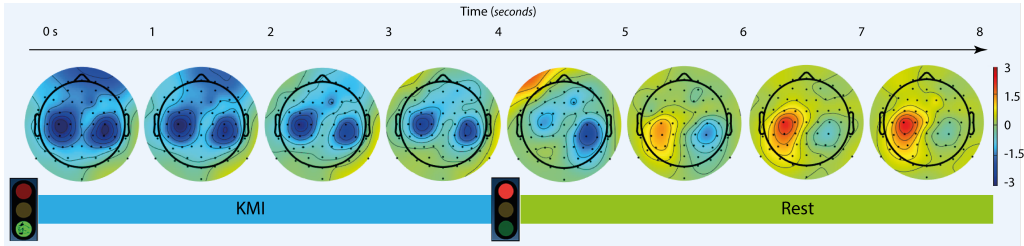


Figure 10: Topographic map of ERD/ERS% (grand average, n=26 sessions) in the mu+beta band during the KMI task. A blue color corresponds to a strong ERD, and a red one to a strong ERS.

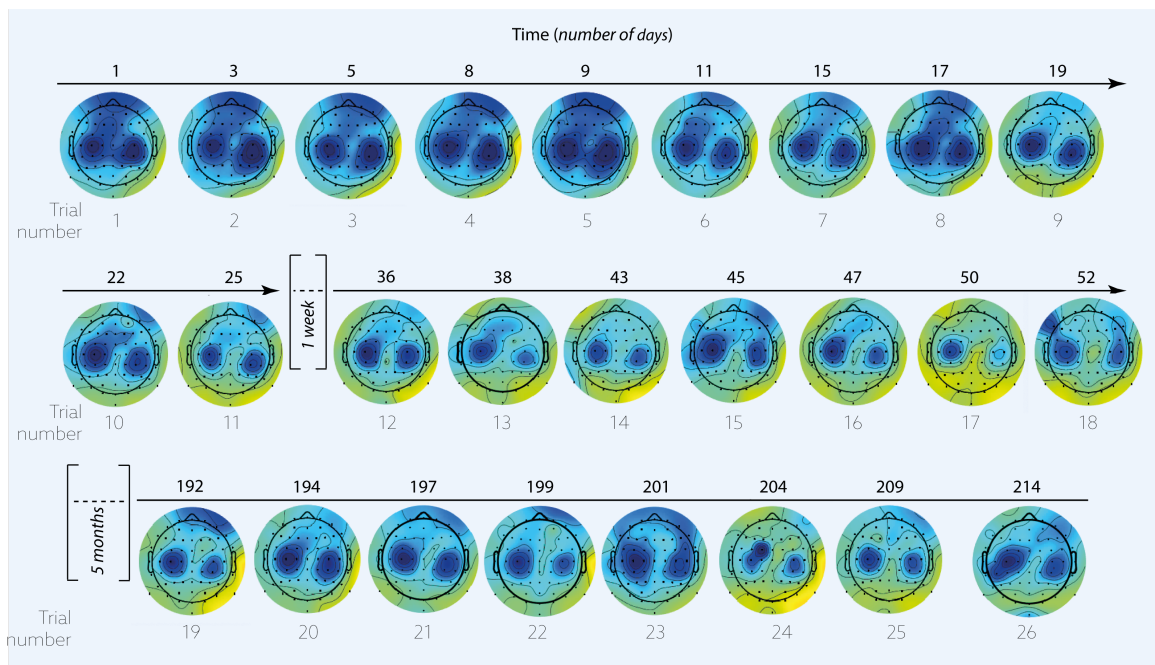


Figure 11: Evolution of the Event-Related Desynchronization (ERD) phase for the 26 sessions in the mu+beta band during the KMI task. A blue color corresponds to a strong ERD. The top indicates the number of days, and the bottom indicates the session number.

Table 3

Correlation coefficients between the number of sessions and the amplitude of desynchronization for the eight electrodes associated with the motor area (contralateral = ERD 4, 7, 8 -C3- and 9 / ipsilateral = ERD 21, 22, 23 -C4- and 27)

	ERD4	ERD7	ERD8	ERD9	ERD21	ERD22	ERD23	ERD27
r (Pearson)	0.411	0.617	0.351	0.622	0.661	0.720	0.591	0.793
p.value	0.037*	<.001***	0.079	<.001***	<.001***	<.001***	0.001***	<.001***

Table 4

Evolution of offline computed BCI performance throughout the sessions

sessions	1	2	3	4	5	6	7	8	9	10	11
BCI perf.	97.5	95.6	95.5	98.7	98.1	93.1	96.9	96.9	95.0	96.2	97.5
sessions	Break	12	13	14	15	16	17	18			
BCI perf.	1 week	95.6	93.7	93.7	96.2	92.5	91.2	95.6			
sessions	Break	19	20	21	22	23	24	25	26		
BCI perf.	5 months	99.4	95.0	93.7	92.5	90.4	89.4	92.5	93.7		

3.4.1. Influences on ERD amplitude

The first domain of interest is related to the sense of competence. Two of the eight items seem to significantly correlate with the ERD amplitudes attenuation of several electrodes associated with premotor, motor control, and especially somesthetic areas (see Figure 13). Thus, ERD amplitudes appear to be strongly anti-correlated contralaterally, but even more so ipsilaterally with the feeling of having better automated one's actions. The sense of task mastery also confirmed an anti-correlation with the ipsilateral CP and P electrodes. For domain 2, which is related to the quality of life, only the feeling of fatigue before the sessions ap-

pears moderately correlated with the CP3 and CP1 ERDs on the ipsilateral electrodes. For domain 3, pre-session serenity seems to be the only emotion moderately correlated with ERD amplitudes at the ipsilateral level (Figure 13). However, these latter results show only moderate significance.

3.4.2. Influences on ERS amplitude

A similar analysis to the previous section (see section 3.4.1 above) showed correlations between the amplitude of the ERS and items related to the three similar domains (Figure 13). At the contralateral level, feeling challenged during the task and, more significantly, punctual exceeds the day before the session also correlate to lower synchronization. For

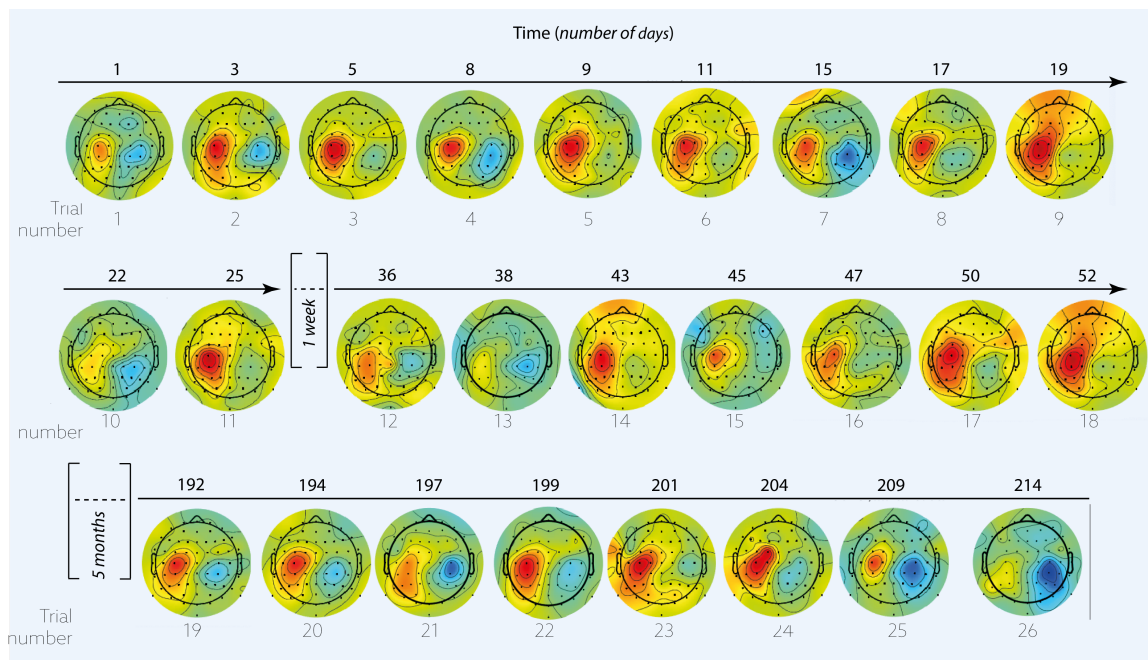


Figure 12: Evolution of the Event-Related Synchronization (ERS) phase for the 26 sessions in the mu+beta band during the KMI task. A red color corresponds to a strong ERS. The top indicates the number of days and the bottom indicates the session number.

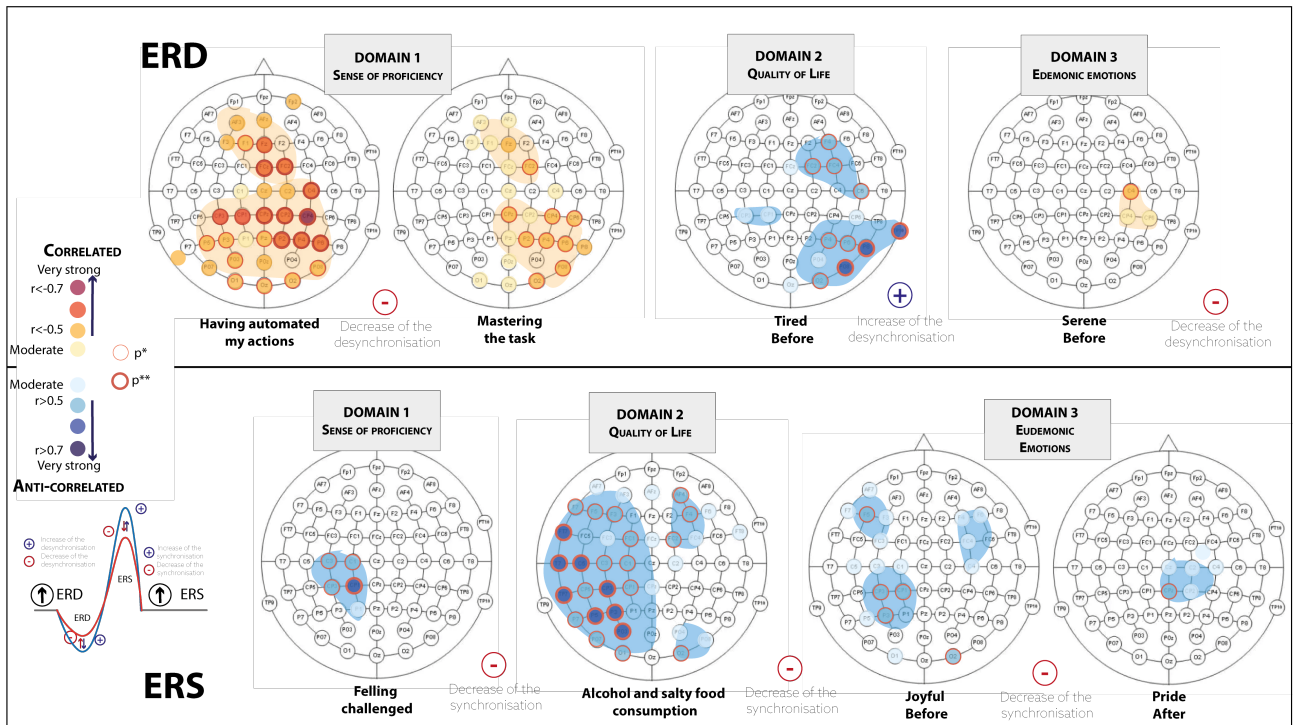


Figure 13: Topographic map representing the correlations between the amplitude of desynchronization of the ERD (Top), ERS (Bottom), and variables of the three domains of interest related to user's perceptions and habits: Domain 1 - Sense of Proficiency; Domain 2: Quality of Life, Domain 3: Eudemonic emotions.

domain 3, feeling joyful before starting the sessions tends to be moderate to strongly anti-correlated with ERS synchronization of motor control area electrodes. Except for feeling pride after sessions, for which a moderate anti-correlation was noticed with a moderate significance, no other emotion was correlated to electrodes amplitudes.

We can observe that correlations with the electrodes at the ipsilateral level remain rare, which is relatively logical considering the topographic figures that show a predominantly contralateral ERS for all sessions (Figure 11).

4. Discussion

4.1. Effect of repetitive KMI on the motor cortex

4.1.1. Decrease and focus of the ERD

The effect of long-term KMI practice on the motor cortex is poorly described in the literature. However, there is considerable knowledge about the practice of voluntary movements. Indeed, it is generally accepted that learning a new movement leads to a progressive increase in the cerebral activity in the primary motor cortex (M1) of the associated limb area (see [46, 32, 23]). Repetition of the same motor task then causes the recruitment of additional neurons to the M1 motor cortex, resulting in greater activation [109]. Thus, learning a sequence over several days was often accompanied by an increase in the size of the motor map and an increase in the cortico-motoneuronal excitability of the limb involved in the motor task [75]. Although learning or repeating a gesture causes an increase in M1 activity, once

the neural process is optimized, it seems that M1 activity is reduced [44, 30, 50]. For example, it has been reported that there is an increase in neural networks, including M1, during initial gesture learning, followed by an attenuation of activity after the consolidation of the motor task [104, 103]. In support of this hypothesis, Picard et al. (2013) examined the effect of sequential motor training from 1 to 6 years of age in primates. They showed that practicing the same gesture over time decreased M1 metabolic activity but not a neuronal activity, suggesting that less synaptic activity was required to activate M1 [85]. In addition, the theory of neural efficiency has also shown that an expert in a motor task (e.g., athlete) displayed less pronounced and more spatially focused mu ERD [4, 56, 77].

Our results show an overall decrease in bilateral ERD in the 8-30 Hz frequency band and a more pronounced spatial localization with repeated KMI (Figure 11). Indeed, although in the first sessions, the electrodes around C3 and C4 showed a strong ERD, as the sessions continued, the location of the ERD remained bilateral but seemed more focused on the electrodes of interest C3 and C4. Such focused activity could be consistent with the reduction in activity and consolidation of the KMI motor program [104, 103, 30] and could show a neural efficiency for the KMI [56]. The bilateralization of activity, i.e., the fact that the ERD occurs in both the contralateral and ipsilateral hemispheres for a right-handed KMI, has already been found in other experiments related to voluntary movement [47] and motor im-

agery [57, 92, 55, 34].

4.1.2. ERD and ERS: questioning the function during and after kinesthetic motor imagery

Many authors have already questioned the functional role of ERD, and ERS phenomena during a motor act (i.e., real movement, motor imagery, somesthetic stimulation) [71, 84, 47, 94]. The evidence suggests that ERD may represent a state of activation of the primary motor cortex [71]. In contrast, the post-movement ERS around 20 Hz may be a temporary deactivation or an active inhibition of the motor cortex that would prepare the motor system for the execution of a new motor task [43, 74].

The results of this study seem to be consistent with a differential function of the ERD and the ERS for three reasons. First, we observed that the amplitude and location of the ERD seem to be more focused on electrodes C3 and C4 with time and the number of sessions performed, in contrast to the ERS, which is not correlated with these two variables (Figure 11 and Figure 12). This is also consistent with the theory of the neural efficiency which seems to affect only the ERD and not the ERS (see section 4.1.1). Several studies have already shown that the experimental context can separately alter the mechanisms of ERD and ERS [47]. For example, a hypnotic state causes a change of state in the sensorimotor cortex with suppression of the ERD while the ERS remains unchanged [96]. Conversely, performing a motor task in the presence of propofol (i.e., a loss-of-consciousness anesthetic) increases the ERS alone [91]. Second, our analyses show a correlation between the ERD and BCI accuracy classification scores, but not for the ERS, confirming the literature results [111, 58, 59]. Finally, no single variable is correlated both with the ERD and the ERS (Figure 13). This observation pleads that these motor patterns do not respond the same way, perhaps suggesting a different role [47, 71]. A better understanding of the functional role of the ERD and the ERS will provide a better understanding of the modulation and variability of these motor brain responses and thus improve the performance of the BCI. As a future perspective, if we know exactly how the ERD or ERS are modulated according to the context of the experiment, the task being performed or the user's feeling, we will be able to design a BCI that could be adapted to the modulations of motor patterns for a better user experience.

4.2. KMI-based BCI long-term training and user experience

4.2.1. Feasibility concerning maintaining a positive UX

KMI-based BCIs are typically designed for applications (e.g., poststroke rehabilitation, sports training, control) that will require continuous KMI practice over a long period (i.e., several months). For motor rehabilitation after a stroke, several sessions per week for several months are recommended to recover the motor functions of the hand [5, 13]. In sports training, KMI practice could also last several weeks [33, 113]. As previously observed in short-term studies, the prac-

tice of repetitive KMI sessions (40 KMI per session) here was tiring and generated a high workload at each session, even for our expert [89]. However, in this study, this fatigue type did not accumulate and did not seem to influence the quality of the user's experience or performance. This fatigue related to the task itself requires to be considered when dealing with fatigued patients, for example. Nevertheless, our results suggest that long-term KMI-based BCI practice might be possible without degrading the participant's wellness. Interestingly, with this subject, the task and the BCI system seemed to gain attractiveness, the emotional state was positively maintained (see Figure 5), and eudemonic emotions seemed to be activated. Moreover, the activity experienced by the subject retains its intrinsic value over a long period, even though the lack of feedback may have eroded motivation. It even seems to value its dimensions of action-control expectations (e.g., anticipatory pleasure). Action-control expectations are expectations that an action can be initiated and performed, and imply that one's actions will produce some positive outcome [51, 76]. The high level of concentration and focus required by the KMI may be one explanation for the maintenance of high levels of positive emotion, as noted in a recent study in the field of education [101]. However, our results show that it might also be necessary to challenge the user throughout the practice of KMI (Figure 9). Indeed, the repetition of KMI tasks and the increased feeling of control and competence make KMI less challenging. These results are consistent with the flow theory [70], which requires a balance between the perceived difficulty level and the individual's skills for an optimal learning/training experience. It would be relevant to examine whether this condition is replicated with subjects who have a less favorable foundation in terms of feelings of accomplishment, intrinsic motivation, or self-efficacy.

4.2.2. KMI-based BCI long-term training without feedback

Although the subject received no feedback in our study, he remained able to control the BCI throughout the five months. His offline BCI performance remained very high to high (never below 90% except session 24; see Figure 9 and Table 4). It cannot be excluded that the attenuation of ERD amplitudes over sessions was due to the fact that without feedback the subject did not have a point of reference, lost perspective of the task and did not perform it as strongly as before. However, his sense of expertise remained strong and gradually increased. We might have expected a decline in performance, either a progressive disengagement, boredom or possible learned helplessness [62], due to a loss of marks of success or supportive feedback [25] or lassitude. Associated with the lack of correlation observed between the task-related "challenge" component with accuracy, these results raise the question of the importance of dissociating the effects related to the extrinsic (received feedback) or the intrinsic motivation (positive sense of expertise and eudemonic emotions) on BCI accuracy, all the more so faced with i) a subject who already masters the task, ii) repetitive tasks

performed over a long period. However, this is not always clearly dissociated in the papers that are referenced [48]. Most BCI studies aimed at helping users master the interaction task focus on the BCI neurofeedback to be provided and its situational and motivational features. However, few of them consider other means and, in particular, the possibility of supporting the subject's achievement (see, for a review [97]).

In our case, the subject indicated that he lacked reference points, especially at the beginning of the experiment. Moreover, the gap between his self-assessment and his performance level is significant evidence that he had difficulty self-assessing his abilities. However, it appears that without feedback, the subject remains able to maintain his performance high and almost constant, although slightly decreasing. Moreover, the intrinsic perceived value of the task increases, and the engagement only fades late. Different elements overlapped here could solely or combined explain these observations:

- The systematic stimulation of metacognition (i.e., awareness and understanding of one's thought processes); Indeed, through the questionnaires, the subject was regularly invited to analyze the KMI task systematically engaged and his performance according to different dimensions.
- The affordance of the task provided by the *Grasp-It* BCI-VR environment [89, 90] remains relevant and sufficiently active for the subject to allow him to be systematically successful.

These possible explanations are all perspectives that open up future fields for improving the pedagogical design of BCI. In the future, it would be interesting to test these different hypotheses and verify if, once acquired, the accuracy remains high in a systematic way in front of an environment without affordance and/or without asking the subject to engage in metacognition.

4.2.3. KMI long-term training patterns

Regarding the modalities of long-term KMI mastery, the subject was placed in a situation of implicit learning [45] by a direct accumulation of procedural knowledge. Most results suggest that the subject went through three phases:

- a phase of appropriation, accommodation [86] which the time from session 1 to 13 could cover, and during which probing, trial, and error processes seem to dominate. The subject had difficulty feeling consistent. His intense ERDs suggest a strong solicitation of the sensory-motor area, and he felt less pride at the end of the task during this period.
- a phase of adoption of the process, of confidence and stabilization of his skills, from sessions 15 to 21, during which the subject felt that he was performing well and that he had reached a ceiling in terms of progress, but the task remains a challenge for him.

- a phase of automatization, of procedural routine, seems to set in from session 22. The subject appeared to have come to terms.

Our results align with the observation that skill level and automaticity generally co-develop with training in real motor practice [45]. However, our results also highlight the affirmation differently that the more automatized the motor skill, the more robust performance is. Indeed, the repetition of the KMI task with time and the number of sessions slightly attenuates the amplitude of the ERD, and BCI accuracy, despite completely removing this pattern (Figure 11). Even if a lassitude effect could appear because of the absence of feedback, many results observed (i.e., wellness stability, system acculturation, sense of automatization correlated to ERD amplitude decrease, activity focused on the C3/C4 electrodes, gradual reduction of accuracy) tend to plead for a phenomenon of physiological habituation. As defined by [87], habituation results from repeated stimulation that could lead to a progressive decrease of some parameters of a response to an asymptotic level (from the activation to the body chemical signal, i.e., neuronal, hormonal responses), and does not involve sensory adaptation/sensory fatigue or motor fatigue. In more general terms, habituation is a type of 'single-stimulus' learning that allows animals to avoid costly responses when there is no benefit from responding to repeated stimulation [9]. The persistence of aspects of habituation is called long-term habituation [87]. In our observation, the ERD response decay lasts for weeks.

4.3. Perspectives for the design of KMI-based BCI training motor program

As the sessions progressed, the ERD appeared to have a more accurate localization of motor areas, as previously observed in real movements [53, 23]. It raises two important questions for future investigations:

- Is the fact that the ERD is more minor and more focused beneficial for the user? Indeed, a smaller ERD might be interpreted as less activation of the motor cortex or even optimized processing of the motor program [44]. In motor rehabilitation after a stroke or gesture training for athletes, generating a smaller ERD could be less beneficial for synaptic plasticity [13]. However, a reduced but more focused ERD in the primary motor cortex could result from a specialization of the neural networks involved in the motor control that the subject would benefit from.
- Would a smaller and more focused ERD be a better outcome for BCI usability and reliability? In fact, the ERD influences the accuracy of the BCI. However, this issue implies a long-term adaptation of the BCI for the user, since the reduction of the ERD amplitude and its focus could be analyzed as a poor performance of the subject. On the other hand, it would only result from a natural effect of the sequence of sessions. One solution would be to use transfer learning techniques

before each new session so that the classifier can reorient itself by taking into account the previous sessions [11, 15].

Moreover, placing subjects in challenges that evolve according to set levels and intrapersonal factors could be a key factor, especially in providing a better experience. A positive technology design approach (see, e.g., [10, 100]), adaptive and more human-centered gamification (see, e.g., [21, 29]) of training programs would be a wise choice for KMI-based BCI design in the future.

5. Conclusion

In this pilot study, we investigated the impact of long-term kinesthetic motor imagery (KMI) practice on motor cortex oscillations and brain-computer interface performance by precisely investigating the mental and environmental context in which the subject was. For this purpose, we recruited an expert in this mental task. He performed more than 2080 KMIs in 26 different sessions, during which we measured his motor-brain activity with electroencephalography and assessed his perceptions and habits from several surveys.

Our results show that long-term BCI-based practice produces continuous ERD in the motor cortex without compromising the subjects' well-being. Furthermore, this study allows addressing ethical issues that have limited the implementation of such protocols (i.e., potentially negative effects on the subject, such as accumulated fatigue, deterioration of emotional state, increasing discomfort, and de-motivation). The number of sessions slightly attenuates the amplitude of the ERD, but does not suppress this pattern. As sessions progress, the ERD appears to have a more precise localization of motor areas, raising important questions for future investigation. In addition, our analyses show that it may be necessary to stimulate the user throughout the KMI practice and to help them analyze their activities. In fact, these conditions seem to have compensated for the lack of feedback by maintaining the subject's activity for several weeks and generating a sense of accomplishment. This is an example of an approach that could be used in long-term rehabilitation. These results encourage further studies to design long-term training protocols to improve BCIs and make them promising for targeted applications (e.g., stroke rehabilitation, sports training, and control). We hope these results will allow us to replicate this approach with a larger number of subjects in the future. If these exploratory results are confirmed, it may be possible to implement a motor brain stimulation program using KMI for more than two months and gradually remove the feedback without compromising engagement. We envision that post-stroke patients could become independent in their rehabilitation before leaving rehabilitation centers and returning home, able to continue KMI.

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Author Contributions

SR and SF conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and tables, authored or reviewed drafts of the paper and approved the final draft.

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