

Event-related desynchronization in motor imagery with EEG neurofeedback in the context of declarative interference and sleep

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ABSTRACT

Motor imagery (MI) in combination with neurofeedback (NF) is a promising supplement to facilitate the acquisition of motor abilities and the recovery of impaired motor abilities following brain injuries. However, the ability to control MI NF is subject to a wide range of inter-individual variability. A substantial number of users experience difficulties in achieving good results, which compromises their chances to benefit from MI NF in a learning or rehabilitation context. It has been suggested that context factors, that is, factors outside the actual motor task, can explain individual differences in motor skill acquisition. Retrospective declarative interference and sleep have already been identified as critical factors for motor execution (ME) and MI based practice. Here, we investigate whether these findings generalize to practicing MI NF.

Three groups underwent three blocks of practicing MI with NF, each on two subsequent days. In two of the groups, MI NF blocks were followed by either immediate or delayed declarative memory tasks. The control group performed only MI NF and no specific interference tasks. Two of the MI NF blocks were run on the first day of the experiment, the third in the morning of the second day. Significant within-block NF gains in mu and beta frequency event-related desynchronization (ERD) were evident for all groups. However, data did not provide evidence for an impact of immediate or delayed declarative interference on MI NF ERD. Also, MI NF ERD remained unchanged after a night of sleep.

We did not observe the expected pattern of results for MI NF ERD with regard to declarative interference and a night of sleep. This is discussed in the context of variable experimental task designs, inter-individual differences, and performance measures.

1. Introduction

The acquisition of new movements or improving existing motor skills is a significant part of everyday life. It is known that motor acquisition is mainly achieved by repeatedly physically executing the target movements, incorporating the external sensory input, and adapting subsequent movement attempts (Adams, 1971; Hikosaka et al., 2002; Willingham, 1998). In addition to this motor execution (ME) practice loop, motor acquisition can be supported by motor imagery (MI) (e.g., Guillot et al., 2013; Ruffino et al., 2017). MI is a dynamic mental state,

which involves a systematic internal simulation process to rehearse a target movement without overtly executing it (Decety, 1996; Di Rienzo et al., 2016). The neural simulation of action theory provides a theoretical framework for the interplay between ME and MI (Jeannerod, 2001). It postulates that imagined movements are functionally equivalent to executed ones not only in terms of overt motor stages, as e.g., motor planning, but also with regard to the underlying neural networks (for a critical review, see O'Shea and Moran, 2017). Remarkably, the activation of these specific networks strongly depends on the MI strategy, i.e., the activity of sensorimotor areas is predominantly induced by

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kinaesthetic MI (internal perspective) and less by visual MI (external perspective) (Annett, 1995; Héту et al., 2013; Neuper et al., 2005; Stinear et al., 2006).

MI practice is suitable to facilitate the acquisition of new motor skills and the improvement of already existing motor skills in healthy subjects (Kraeutner et al., 2018; Schack et al., 2014; Wriessnegger et al., 2018). Furthermore, MI practice is considered as a promising tool to complement motor rehabilitation interventions after a brain injury, such as stroke, by facilitating the relearning of lost motor skills (Bajaj et al., 2015; Maier et al., 2019; Malouin et al., 2013). To overcome the lack of sensory feedback in MI and so to enhance its positive effects, MI can be combined with neurofeedback (NF).

NF serves as a channel for feeding back information about brain activation resulting from MI to the subject and can be utilized to enhance adaptive activation patterns (Braun et al., 2016; Ietswaart et al., 2011; Zich et al., 2015a), motor skill acquisition, and motor recovery (for a review, see Pichiorri and Mattia, 2020). Paradigms that combine MI and NF are typically controlled by event-related (de)synchronization (ERD/S), reflecting task related power changes of rhythmic brain activity recorded within the mu (8–12 Hz) and beta (13–30 Hz) frequency range over sensorimotor areas contralateral to the target limb. Specifically, during MI (similar to ME) power decreases (ERD) and post movement power increases (ERS), relative to a given baseline (Cheyne, 2013; Lopes da Silva & Pfurtscheller, 1999; Pfurtscheller and Aranibar, 1979).

The active self-regulation of the ERD/S evoked during MI, and the closely interrelated ability to control an MI NF, can be considered as skills that can be acquired and that are subject to principles of learning (Lotte et al., 2015; Lotte et al., 2013). For ME and MI skill acquisition it has been shown that they are influenced by task context (Brown and Robertson, 2007; Debarnot et al., 2012; Debarnot et al., 2011a; Schlatter et al., 2020). Based on this it can be hypothesized that also for acquiring MI NF control, the context in which MI NF practice takes place matters (e.g., Daeglau et al., 2020a; Roc, Pilette, N'Kaoua and Lotte, 2019).

Very little is known about what aspects of task context relevant for ME or MI skill acquisition are also of relevance for acquiring MI NF control (for a review, see Daeglau et al., 2021). The present study focused on the context factors declarative interference through a subsequent non-motor task and a night of sleep (e.g., Brown and Robertson, 2007; Debarnot et al., 2012; Debarnot et al., 2011b), both of which are so far unexplored for MI NF control. Debarnot et al. (2012) found that declarative interference after MI practice of a finger tapping task negatively affects subsequent physical task performance. This finding was based on the hypothesis that the explicit memory trace induced by MI practice may rely more heavily on the declarative than the procedural memory system (Debarnot et al., 2012). The impairment in physical task performance was observed both over intervals of sleep and wakefulness. Notably, this contrasts with ME practice, where declarative interference similarly impairs the consolidation of a motor task over wakefulness, whereas sleep has been shown to support performance recovery (Brown and Robertson, 2007; but see, Rothkirch et al., 2018). Studies on the role of sleep in ME motor skill acquisition and without specific interference tasks have indicated that sleep following ME skill acquisition leads to additional gains in the practised motor skill (for a review, see King et al., 2017). Other studies however challenge this notion (Brawn et al., 2010; Hotermans et al., 2006; Nettersheim et al., 2015). Using a finger-tapping task, Nettersheim et al. (2015) showed that the supposedly sleep related gain is not really a gain but rather a stabilisation of task performance at the early boost level. The early boost describes an offline gain in performance that can be measured around 5–30 min after the motor task and then decays over the next 4–12 h of wakefulness (Brawn et al., 2010; Hotermans et al., 2006). Gains in performance following a sleep period have also been reported for MI practice (Debarnot et al., 2011b; Debarnot et al., 2009a; Debarnot et al., 2009b). This has been interpreted as follows: motor consolidation and associated delayed offline gains in ME performance acquired through MI

practice profit from sleep or even depend on it. Yet it seems possible that this interpretation needs to be reconsidered, and that also for MI skill acquisition sleep does not result in an additional gain but rather in a consolidation at the early boost level. Supporting this assumption, an early boost can also be found for MI skill acquisition (Debarnot et al., 2011a).

To date, it has not been studied whether declarative interference affects MI NF skill acquisition and if so, how the effect would evolve over a night of sleep. Also, it is unknown whether MI NF skill acquisition is subject to an early boost and subsequent decay effects. Providing evidence for any of those effects could help to optimally schedule MI NF interventions and therefore aid patients to receive the best possible treatment. In the present study, three groups underwent three MI NF blocks each, which took place over two consecutive days. In the two experimental groups, two of the three MI NF blocks were arranged such that each MI NF block was followed by tasks tapping declarative memory resources (immediate interference) or such that the interference tasks followed a day of wakefulness (late interference). In the control group MI NF blocks were combined with control tasks and no explicit declarative interference task was performed (no interference). ERD of the MI NF blocks was used as a quantifiable feature for describing MI NF performance related to MI NF skill acquisition. Regarding immediate declarative interference, we hypothesized it to have an adverse impact on MI NF performance compared to no interference, as evident in reduced contralateral ERD within the mu and beta frequency range in the group receiving immediate declarative interference. We additionally hypothesized that after a night of sleep these adverse effects of declarative interference on MI NF ERD would not be reversed. Further, regarding late interference, we expected to observe an early boost in MI NF ERD from the first to the second MI NF block that would not be affected by late interference but rather remain stable after a night of sleep.

2. Material and methods

2.1. Participants

We collected data from 66 healthy, young participants. All participants reported normal or corrected-to-normal vision. None of the participants reported a current or previous history of psychiatric or neurological conditions or use of psychoactive medication. As indicated by the Edinburgh Handedness Inventory (Oldfield, 1971), all participants were right-handed. Participants did not participate in previous MI NF studies. Explicit information about the purpose of the conducted experiments were not provided. Participants were informed about MI processes in general and specifically about the characteristics of visual and kinaesthetic MI. Every participant read and signed an institutionally approved consent form prior to the experiment. A total of 13 data sets were discharged from analyses. Three data sets were discarded due to technical issues during data collection, six data sets due to participant's early drop out, one data set due to non-compliance to task instructions (i.e., moving during MI blocks), and three data sets because post-hoc analysis of self-report questionnaires indicated that participants did not comply with the general instruction to stay drug free between the three experimental sessions.

The final sample consisted of 53 participants with three sessions each. Final group sizes were 17 participants in *group late-interference* (14 women, aged 20–32 years, M and SD : 24.3 ± 3.5 years), 19 participants in *group immediate-interference* (17 women, aged 21–35 years, M and SD : 25.1 ± 3.9 years) and 17 participants in *group no-interference* (10 women, aged 23–32 years, M and SD : 25.8 ± 2.5 years).

The study protocol was approved by the Commission for Research Impact Assessment and Ethics of the University of Oldenburg.

2.2. Study layout

The study design is illustrated in Fig. 1A. The study consisted of three experimental sessions spread across two successive days. Two sessions were run in the morning of the first and the second day (8:30–12:00), and one in the evening (18:00–21:30) of the first day. Sessions consisted of a combination of three out of four different blocks (motor imagery, interference, control, break). Motor imagery or MI blocks consisted of one run MI without NF (referred to as training run because data collected here were used to train the classifier used in NF), preceding

two MI NF runs (for details see section 3.3.1 Motor Imagery Neurofeedback Paradigm). Interference blocks encompassed four different cognitive demanding non-motor tasks (for details see section 3.3.2 Interference-, Break- and Control-Blocks). In control blocks and break blocks participants passively watched a nature documentary. Each block lasted about 30 min.

Participants were assigned in alternation on a rolling basis to either group *late-interference*, group *immediate-interference* or group *no-interference*. The first experimental session of group *late-interference* comprised two blocks of MI NF (MI1, MI2), separated by a break block. For group

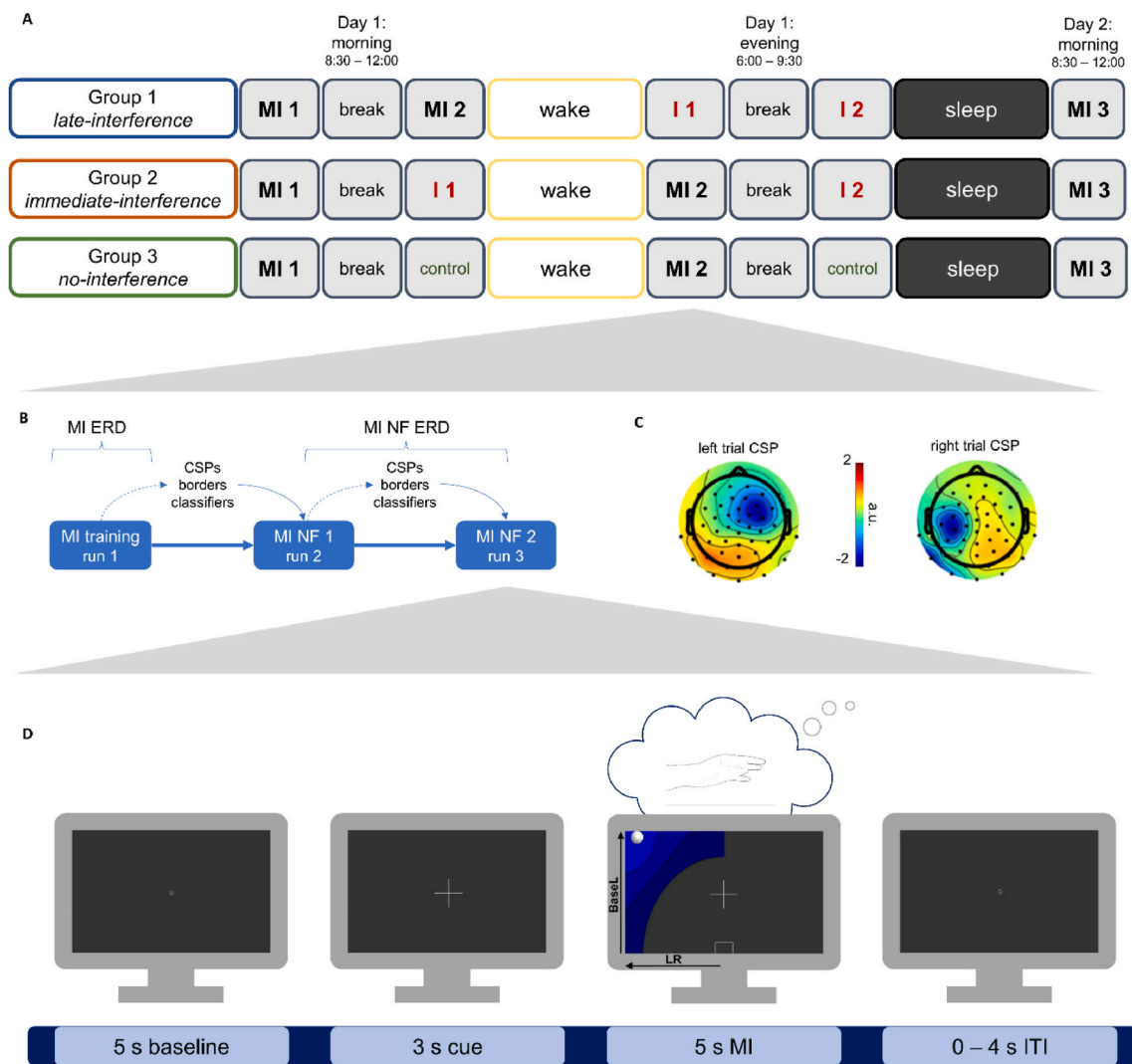


Fig. 1. Experimental Hierarchy. A. Study Design. The first session in the morning of day 1 began with a block of MI NF practice (MI1) followed by a break of 30 min (watching a documentary). Afterwards group *late-interference* performed another block of MI NF practice (MI2), group *immediate-interference* completed a block of declarative non-motor interference (I1) and group *no-interference* continued watching the documentary as a control condition. Participants then followed their daily life routine. However, daytime naps or excessive sport activities were not allowed, which was monitored by an activity tracker. In the evening of the same day, group *late-interference* completed its first interference block (I1), while group *immediate-interference* and group *no-interference* completed their second MI NF block (MI2). After a break group *late-interference* and group *immediate-interference* had their second interference block (I2) and group *no-interference* proceeded with its control condition. After a night of sleep all groups returned for a final session with a single block of MI NF practice (MI3). **B. Flowchart MI NF block.** Each MI block encompassed three runs consisting of 40 trials each (20 left hand, 20 hand right trials). After the training run, where no feedback was provided, NF parameters common spatial patterns (CSPs), classifier, and border were calculated and set for the second run (MI NF1). After this first feedback run (MI NF1), the NF parameters were renewed and set for the third run (MI NF2). For offline evaluation, the event-related-desynchronization (ERD) was calculated from EEG data obtained from MI NF 1 and MI NF 2 and averaged (MI NF ERD). **C. Representative single subject CSPs.** CSPs shown are based on left hand and right-hand trials of one MI run. **D. Structure of a left-hand motor imagery (MI) neurofeedback (NF) trial.** Each trial began with a baseline period of 5 s showing the outline of a small circle. Afterwards a fixation cross displayed for 3 s indicated the imminent start of the MI task period. The onset of a graphic comprising 3 different shades of blue indicated the beginning of the task period (duration 5 s). The location of the graphic indicated which hand to use for MI. During the NF runs a white ball moved along the horizontal (LR for left vs. right MI) and vertical (BaseL for baseline vs. left MI) axes according to the classifier output magnitudes. In the training runs the ball remained motionless in the centre of the screen. The inter-trial-interval (ITI) comprised 0–4 s connecting to the next baseline period. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

immediate-interference it consisted of a block of MI NF (MI1), a break block, and an interference block (I1), and for *group no-interference* of one block of MI NF (MI1), a break block and a control block. Participants were instructed to follow their regular daily routine in-between sessions, except for taking naps and exhausting sport activities. Adherence to these instructions was monitored using an actigraphy watch (Motion-Watch8, CamNtech Ltd., Cambridgeshire, UK) and queried by the experimenters. We did not explicitly control for declarative interference tasks since we were solely interested in effects of immediate declarative interference in this study. The second experimental session was performed in the evening of the first day. For *group late-interference* it covered two blocks of interference (I1, I2) and a break block in-between, for *group immediate-interference* one block of MI NF (MI2), a break block and an interference block (I2) and for *group no-interference* one block of MI NF (MI2), a break block and a control block. Participants were instructed to get at least 8 h of sleep, which was confirmed by the actigraphy watch. The third experimental session was conducted the next morning and consisted of a single block of MI NF (MI3) for all three groups.

In both morning sessions, participants completed the Stanford Sleepiness Scale (SSS; Hoddes et al., 1972) questionnaire, which provides a subjective measure of alertness. The SSS is a 7-point scale, with 1 being the most alert state. The SSS was applied to ensure an adequate state of alertness prior to each session for all participants. For each of the three sessions, participants had to rate their current alertness at least a 4 (“Somewhat foggy, let down”) but not below for their dataset to be included in analysis. Prior to the first experimental session the short version of the kinaesthetic and visual imagery questionnaire (KVIQ; Malouin et al., 2007) was conducted to emphasize the difference between visual and kinaesthetic MI (see Table S1 supplemental material for details). After MI NF blocks participants rated their motivation on a visual analogue scale, and perceived vividness and easiness of MI on a 5-point Likert scale. Participants further completed the Pittsburg Sleep Quality Index to assess sleep quality and quantity (PSQI; Buysse et al., 1989) and the Epworth Sleepiness Scale (ESS; Johns, 1991) to assess their ‘daytime sleepiness’. The PSQI examines retrospectively over a period of four weeks about the frequency of sleep disturbing events, the assessment of sleep quality, the usual sleeping times, sleep latency and duration, the intake of sleep medication and daytime sleepiness. A total of 18 items are used for quantitative evaluation and assigned to seven components, each of which ranges from 0 to 3. The total score is the sum of the component scores and can vary from 0 to 21, whereby a higher score corresponds to a lower quality of sleep. The ESS is a self-administered questionnaire covering eight questions. Participants had to rate their usual chances of dozing off or falling asleep while performing eight different activities (4-point scale: 0–3). The ESS score ranges from 0 to 24. The higher the ESS score, the higher that person’s average sleep propensity in daily life, or their ‘daytime sleepiness’. As part of a different research question, participants also performed a limb lateralization task (LLT; Ter Horst, Van Lier and Steenbergen, 2010) and the nine-hole-peg test (NHPT; Kellor et al., 1971).

Participants were instructed to be free of drug, alcohol, and caffeine for 24 h prior to and during each experimental session.

2.3. Experimental procedure

2.3.1. Motor Imagery Neurofeedback Paradigm

A previously established MI NF paradigm (Braun et al., 2017; Meekes et al., 2019) showing reliably changes in NF performance measures both within a session (Zich et al., 2017a) and over several days (Zich et al., 2015b; Zich et al., 2017b) was adapted for the present study. In the present implementation, in each MI block participants performed one run of MI without NF (referred to as training run) followed by two runs of MI NF (cf. Fig. 1B). Each run had a duration of about 10 min. The imagined movement was sequential thumb to finger opposition either with the left or the right hand starting with the little finger. Prior to the

first run, the movement was demonstrated by the experimenter. The participant was verbally instructed to copy the movement and practice it with both hands until they felt sufficiently familiarized. Movements were performed at a rate of about 1 Hz. Participants were instructed to hold this pace during kinaesthetically performing MI. In the training run, that is, the first MI run of each MI block, no NF was presented. The EEG data recorded in the training run were used to set up the NF parameters for the NF in the second MI run. In turn, EEG data acquired in the second MI run served for calibrating the parameters used for the NF in the third MI run. Each MI run including the training run consisted of 20 left and 20 right hand trials presented in pseudo-randomized order.

Stimulus presentation was controlled with OpenViBE 0.17.1 (Renard et al., 2010). The NF was based on the adapted Graz MI protocol as implemented in OpenViBE (Renard et al., 2010; Zich et al., 2015a). Each trial began with a baseline period of 5 s showing a small, outlined circle. The circle was replaced by a fixation cross displayed for 3 s, indicating the imminent start of the MI task period. The start of the MI task period was signalled by a blue graphic displayed in addition to the fixation cross. The blue graphic was placed either on the left or right half of the screen (see Fig. 1D). The on-screen location of the blue graphic signalled the hand to be used during the MI task period. Each task period had a duration of 5 s. In the last two MI blocks NF was included in the task period. The NF was visualized as a white ball moving along two dimensions on either the left or right half of the screen. The horizontal position of the ball reflected the degree of ERD lateralization, the vertical position the degree of contralateral ERD (see Fig. 1D). The exact horizontal and vertical positions of the ball were determined by the output of two classifiers. One classifier reflected the difference between contralateral and ipsilateral EEG activity and the other between baseline and contralateral EEG activity (see section EEG analysis for details). Participants were informed that navigating and maintaining the ball in the upper left or right corner of the screen, depending on the location of the graphic, reflected an appropriate task performance. The NF screen was updated at a frequency of 16 Hz. During the inter-trial interval, the screen showed a small, outlined circle presented pseudo-randomly for 0–4 s (increments of 1 s). Participants were instructed to sit still but relaxed with their eyes open. NF borders, representing the maximum reachable edges on screen for both the vertical and horizontal dimensions of the NF, were kept constant within a run and defined as the upper quartile of the classifier output from the previous run.

2.3.2. Interference-, break- and Control-Blocks

Declarative interference blocks had a duration of 30 min and comprised four different non-motor tasks: a word list recall, an n-back task, a face-name matching task, and a modified version of the Paced Auditory Serial Addition Test (PASAT; Gronwall, 1977). This is in contrast to other studies (e.g., Debarnot et al., 2012; Rothkirch et al., 2018).

Where only a single task was used but here served to ensure that participants would stay engaged over the whole period. Interference tasks were chosen to cover a wide range of declarative memory associated abilities. All declarative interference tasks covered working memory resources, which have been proposed to be closely related to declarative memory (Botvinick, Carter, Braver, Barch, & Cohen, 2001; Buckner, Kelley, & Petersen, 1999) and to demand attention processes, which are crucial resources for both memory formation and retrieval as well as MI NF practice (Moran & O’Shea, 2020). Additionally, the Names-Faces-Task is an associative memory task, testing the ability of participants to recall unrelated pairs of items Sperling et al., 2003. The PASAT requires arithmetic capabilities Cragg et al., 2017.

For the word list recall task, lists of 24 words were presented visually three times. Words were presented for 3 s without an inter-trial-interval. Participants were instructed to remember as many words as possible. After a break of 15–20 min, participants had to identify remembered words among distractor words via a button press as fast and accurate as possible. Wordlists were retrieved from Salvideoitia and colleagues

(Piñeyro Salvadegoitia et al., 2019; CELEX online lexical database, Max Planck Institute for Psycholinguistics, 2001, available at <http://celex.mpi.nl/>).

The n-back task consisted of one training block (eight trials) to familiarize participants with the task followed by two blocks (120 trials). Participants had to indicate whether the current letter was identical to the previous one (1-back task) as fast and accurate as possible. Each letter was presented for 600 ms.

The face-name matching task was designed based on the corresponding subtest from the memory assessment scales (MAS; Williams et al., 1991). The procedure started with a learning phase, where participants were successively presented 20 faces in combination with a name (each 5 s). They were asked to remember each name-face combination. Thereafter, they were shown one of the 20 faces at once and three names at the bottom, one being the correct name and two previously learned but incorrect names. Participants were asked to indicate the location of the correct name via a button press on the keyboard. This procedure was repeated for all 20 faces. Images for the faces were retrieved from pics.stir.ac.uk.

The PASAT was conducted following the instructions in the manual (Gronwall, 1977) except that digits were not presented verbally but visually for 2 s each without ISI. A total of 122 digits were presented in two blocks. Participants were asked to add up the last two digits and say the result out loud. As soon as the next number was shown, it had to be added to the previous one again.

Each interference task was performed once per interference block. To minimize task familiarization effects across sessions various versions were created for all interference tasks. Interference tasks were presented in pseudo-randomized order across participants within each interference block. Results were not of interest for the present study, but they were recorded and are reported in the supplemental material (Table S3).

Break and control blocks consisted of 30-min sections of various nature documentaries each with male narrators and ambient music, but no visible human interaction. The same set of documentaries was shown to all participants, but each documentary was shown to each subject only once. All tasks were controlled by customized scripts implemented in Presentation software (Version 17.0, Neurobehavioral Systems, Inc., Berkeley, CA, USA, RRID:SCR_002521).

2.4. Data acquisition

EEG data were acquired from 65 sintered Ag/AgCl electrodes using an equidistant infracerebral electrode layout with a central frontopolar site as ground and a nose tip reference (EasyCap, Herrsching, Germany). In addition, bipolar surface EMG was recorded from both hands and arms by placing sintered Ag/AgCl electrodes over the muscle belly and the proximal base of the Flexor digitorum superficialis and the Abductor pollicis longus with reference and ground on the collarbone. Both EEG and EMG data were recorded using a BrainAmp amplifier system (Brain-Products, Gilching, Germany). Data were obtained with an amplitude resolution of 0.1 μ V and a sampling rate of 500 Hz with online analogue filter settings of 0.016–250 Hz. Electrode impedances were maintained below 10 k Ω for the EEG and below 100 k Ω for the EMG before data acquisition. Data acquisition was performed using the OpenViBE acquisition server 0.17.1. In addition, resting state EEG recordings of 2 min each were obtained before and after each session using BrainVision recorder software (Version 1.20.0506, Brain-Products GmbH, Gilching, Germany).

2.5. Data analysis

2.5.1. Online processing

Online EEG data analyses for providing NF comprised three parts and was performed after the first and second MI run (i.e., training run and MI NF1). In the first and second part of the analyses subject-specific parameters for the subsequent MI NF blocks were determined by means of

common spatial pattern (CSP) analysis in MATLAB (Version 9.3; MathWorks, Natick, MA, USA, RRID:SCR_001622), and classifier training and border computation in OpenViBE (Renard et al., 2010). The third part encompassed the actual NF delivery during the second and third experimental runs through OpenViBE using the results of the previous parameter estimation.

For the CSP analysis, EEG data from the central 49 channels were high-pass filtered at 8 Hz (finite impulse response, filter order 826) and subsequently low-pass filtered at 30 Hz (finite impulse response, filter order 220) using EEGLAB toolbox Version 14.1.1 (Delorme and Makeig, 2004) for MATLAB (Version 9.3; MathWorks, Natick, MA, USA, RRID:SCR_001622). This filter range was set to encompass the sensorimotor rhythms μ (8–12 Hz) and β (13–30 Hz), to which the neural correlate of interest, the event-related desynchronization or ERD, is highly specific to (Cheyne, 2013; Lopes da Silva and Pfurtscheller, 1999). Epochs were extracted from 0.5 to 4.5 s relative to MI onset, separately for left- and right-hand trials. Segments containing artifacts were rejected (EEGLAB function `pop_jointprob.m`, $SD = 3$) and the remaining data submitted to a CSP analysis pipeline (Ramoser et al., 2000). CSP analysis is a common approach to obtain spatial filters optimized for the detection of power differences between two classes (i.e., left vs right hand MI) by maximizing the variance of the signal for one class (i.e., left hand MI) while simultaneously minimizing the variance of the signal for a second class (i.e., right hand MI). For each class, of the three filters with the highest variance segregation for the class the most neurophysiologically plausible filter was selected, and the filter coefficients of the two selected CSPs (one for each class) were submitted to OpenViBE. Exemplary single subject CSPs for one MI NF run are shown in Fig. 1C.

For the classifier training in OpenViBE (Bougrain & Serrière, 2016; Renard et al., 2010), EEG raw data were spatially filtered using the selected CSPs and temporally filtered using a 4th-order Butterworth band-pass filter (8–30 Hz, 0.5 dB pass band ripple). Epoching in left- and right-hand MI periods was done from 0.5 to 4.5 s relative to the onset of MI and, also relative to MI onset from -7 to -3 s for the corresponding baseline intervals. The resulting intervals were subdivided into 1 s time bins overlapping by 0.9375 s. The logarithmic power of the band-pass-filtered 1 s time windows represented the features for linear discriminant analysis classification using sevenfold cross-validation (Fisher, 1936). For the online NF, two classifiers per active side were trained: either left motor imagery vs. baseline (BaseL) or right motor imagery vs. baseline (BaseR), representing the vertical component of the feedback (contralateral ERD), and left motor imagery vs. right motor imagery (LR), controlling the horizontal component of the feedback (degree of lateralization). Based on the results of the cross-validation three border values were calculated, corresponding to the upper quartiles of the three classification distributions. These border values were used to determine the range of the display for the horizontal and vertical axis for the online NF. CSPs, classifiers and borders were updated for the second MI NF run of a MI NF block based on data of the first MI NF run. Obtained parameters were applied to the respective successive run.

The reported online classification accuracy corresponds to the percentage of trials that have been correctly classified, relative to the number of total trials per class for each MI run (Bougrain & Serrière, 2016). Since differences in online classification accuracies within each block were not of interest and to provide a stable estimate of online performance, we averaged across MI NF runs for each block (see Table S2 supplemental material, for details). Online classification accuracies ($M \pm SD$) were for *group late-interference* MI NF block 1 $69.2 \pm 6.3\%$, MI NF block 2 $69.4 \pm 5.7\%$ and MI NF block 3 $70.6 \pm 6.2\%$, for *group immediate-interference* MI NF block 1 $70.3 \pm 8.0\%$, MI NF block 2 $70.2 \pm 6.4\%$ and MI NF block 3 $70.1 \pm 7.3\%$, and for *group no-interference* MI NF block 1 $66.3 \pm 6.4\%$, MI NF block 2 69.6 ± 5.9 and MI NF block 3 $67.4 \pm 6.1\%$. With 40 trials per MI NF run, online classification accuracies were significantly above the chance level of 62.5% (Combrisson and Jerbi, 2015).

2.5.2. Offline analysis

2.5.2.1. EMG analysis. EMG data were filtered with a cut-off frequency of 25 Hz using a high-pass finite-impulse response filter with a hamming window (filter order: 264). Noise removal was conducted via wavelet denoising (wavelet signal denoiser toolbox, MathWorks, Natick, MA, USA) with a Daubechies 4 (dB4) wavelet. EMG data were then segmented from -9 s relative to $+7$ s. For each trial, the standard deviation and the 250-samples centred moving standard deviation were calculated. Trials in which the moving standard deviation exceeded the standard deviation of the trial by the factor 2.5 at any point were considered to contain movement artifacts and excluded from further analyses (M and SD: 49 ± 35.6 trials, range: 1–141 trials for a total of 360 trials).

2.5.2.2. EEG analysis. EEG data were preprocessed with the EEGLAB toolbox Version 14.1.1 (Delorme and Makeig, 2004) for MATLAB (Version 9.3; MathWorks, Natick, MA, USA). For artifact correction independent components analysis (ICA) was performed. The EEG data of all three runs within one experimental block, i.e., training, MI NF1 and MI NF2, were appended for further processing. Identification of improbable channels was conducted using the EEGLAB extension trimOutlier (https://sccn.ucsd.edu/wiki/EEGLAB_Extensions) with an upper and lower boundary of two standard deviations of the mean standard deviation across all channels (channels identified M and SD: 1.9 ± 0 channels, range 0–4 channels). Channels exceeding this threshold were removed accordingly. A copy of the data was first low-pass filtered (40 Hz, FIR, hamming window, filter order: 166), down-sampled to 250 Hz and high-pass filtered (1 Hz, FIR, hamming window, filter order: 414). Afterwards data were segmented into consecutive 1-s epochs and segments containing artifacts were removed (EEGLAB functions `pop_jointprob.m`, `pop_rejkurt.m`, both $SD = 3$). Remaining data were submitted to the extended infomax ICA to estimate the unmixing weights of 45 independent components. The unmixing matrix obtained from this procedure was applied to the original unfiltered EEG dataset for selection and rejection of components representing stereotypical artifacts. Components reflecting eye, muscle and heart activity were identified using ICLabel (Pion-Tonachini et al., 2019), and by the Eye-Catch approach (Bigdely-Shamlo et al., 2013) and controlled by visual inspection. Components flagged as artifacts were removed from further analysis. Artifact corrected EEG data were low-pass filtered with a finite-impulse response filter and a cut-off frequency of 30 Hz (hamming window, filter order 220, $F_s = 500$ Hz), and subsequently high-pass filtered with a finite-impulse response filter and a cut-off frequency of 8 Hz (hamming window, filter order 826, $F_s = 500$ Hz). After the data were re-referenced to common average, and bad channel signals were replaced by spherical interpolation. Data were segmented from -7 s to 9 s relative to the start of the task interval, separately for left and right trials, and baseline corrected (-6 to -4 s). Artefactual epochs as indicated by the joint probability within each of the experimental runs (EEGLAB function `pop_jointprob.m`, `pop_rejkurt.m`, both $SD = 3$) and epochs flagged by the EMG analysis (see 2.5.2.1 EMG Analysis) were discarded from further analyses. In parallel to the online analysis, EEG data were reduced to the central 49 channels. CSP filters were calculated offline following the same procedure as described for the online EEG analysis, except that data based on all three MI runs was used. Likewise, two filters were selected, one for left and one for right hand MI. Contralateral activity was obtained by multiplying CSP filters with corresponding trials (i.e., right filters with right trials EEG data, left filters with left trials EEG data) and ipsilateral activity by multiplying CSP filters with respective opposite trials (i.e., right filters with left trials EEG data, left filters with right trials EEG data). Thereafter, task-related event-related desynchronization (ERD) was extracted following the procedure proposed by Lopes da Silva and Pfurtscheller (1999). Since hemispheric differences were not of interest in the present study,

relative ERD contralateral to the target hand was averaged for left- and right-hand trials. On average, a total of 31.1 ± 4.5 trials per subject and condition (range 24–40 trials) were used for analysis. For the statistical analyses, contralateral relative ERD was averaged within MI runs across a time window of 0.5–4.5 s with respect to the onset of the MI task interval. For the evaluation of MI NF runs, contralateral relative ERD was additionally averaged across MI NF1 and MI NF2, resulting in MI NF ERD. MI NF ERD served as the sole feature of MI NF performance for statistical analyses. The acquisition of the MI NF skill was accordingly expected to be expressed as stronger MI NF ERD over MI blocks.

2.6. Statistical analyses

Questionnaire data (motivation, tiredness, MI vividness/easiness, sleep scores) and MI NF ERD of the first MI block were analysed by means of separate Bayes ANOVAs with between-subject factor group to ensure that groups were initially comparable in these measures.

To confirm the effect of NF on MI ERD, we performed paired *t*-tests within each group and block comparing the training run MI ERD with MI NF ERD, obtained from both MI NF runs. This was followed by a mixed 3x3-ANOVA with group as between-subject factor and block as within-subject factor to explore how the NF-related gain in MI ERD evolved over time. The dependent variable in this analysis was the difference between training run (MI ERD) and both NF runs (MI NF ERD) within one block.

Hypotheses were tested in planned comparisons. Frequentist statistics were used whenever a difference was expected, Bayes statistics were used when no difference was expected. For interference it was hypothesized that immediate declarative interference has an adverse impact on MI NF performance compared to no interference. This was tested with an independent samples *t*-test between MI NF ERD of block 2 of group *immediate-interference* and MI NF ERD of block 2 of group *no-interference*.

We further hypothesized that after a night of sleep the expected adverse effects of declarative interference on MI NF performance would not be eliminated, that is, we hypothesized that for group *immediate-interference* MI NF performance would not be higher after a night of sleep. This was tested with a Bayes paired *t*-test between MI NF blocks 2 and 3 of group *immediate-interference*.

For group *late-interference* we expected to observe an early boost effect in MI NF performance as well as a consolidation of this performance level after a night of sleep. This was tested in a repeated measures ANOVA comprising MI NF blocks 1–3 for group *late-interference*. The ANOVA was complemented by a Bayes paired *t*-test between MI NF block 2 and MI NF block 3.

In case that sphericity was violated Greenhouse–Geisser–correction was applied as implemented in the R-package `ez` (Version 4.4-0; Lawrence, 2016). Post hoc comparisons were conducted using two-tailed *t*-tests. Multiple pairwise comparisons were corrected for by the Holm-Bonferroni method according to the number of performed tests (Holm, 1979). All numerical values are reported as mean \pm SE, except where otherwise stated. Effect sizes are reported as Eta-squared (η^2) for ANOVAs and Cohen's *d* (*d*) for *t*-tests. Confidence intervals (CI) were calculated using 90% for η^2 and 95% for *d* (Steiger, 2004). If Frequentist statistics showed non-significant results, they were followed up by Bayes statistics to test the confidence in the Null hypothesis (Keysers et al., 2020; Quintana and Williams, 2018).

All Frequentist statistics were conducted as implemented in RStudio (Version 1.1.463; Team, 2018). All Bayes statistics were performed with the free software JASP (Version 0.9.2.0; JASP Team, 2019) using default priors to make as less assumptions about the data as possible, reporting Bayes Factor (BF_{10}) and for interaction effects Bayes Factor inclusion ($BF_{inclusion}$).

3. Results

The baseline and task period time-courses of MI NF ERD for all

groups and MI NF blocks are shown in Fig. 2. Clear ERD responses could be confirmed for all groups and blocks.

Fig. 3 shows individual MI NF ERDs split by group and MI blocks. Descriptively, at the group level, MI NF ERD did not differ significantly over MI NF blocks nor between groups. At the single subject level differences across MI NF blocks were present but showed a high variability overall and no clear within-group pattern.

3.1. Group characteristics

Questionnaire scores were compared using Bayesian ANOVAs to ensure comparability across groups, whereby null hypotheses (H0) postulate no differences between the groups. Regarding initial motivation there was moderate evidence¹ for no difference between groups ($BF_{\text{group}} = 0.26$, error% = 0.04; $M \pm SD$: *late-interference*: $70.12 \pm 20.2\%$; *immediate-interference*: $69.84 \pm 18.8\%$; *no-interference*: $76.65 \pm 13.6\%$), meaning that the data are approximately 3.9 times more likely to occur under H0 than under H1.

The same held for the initial tiredness level ($BF_{\text{group}} = 0.26$, error% = 0.04; $M \pm SD$: *late-interference*: $41.65 \pm 17.7\%$; *immediate-interference*: $38.26 \pm 20.2\%$; *no-interference*: $33.06 \pm 22.4\%$) also providing moderate evidence for no initial difference between groups, meaning that the data are approximately 3.9 times more likely to occur under H0 than under H1.

For MI vividness we found anecdotal evidence for no initial difference between groups ($BF_{\text{group}} = 0.39$, error% = 0.02; $M \pm SD$: *late-interference*: 2.97 ± 0.5 ; *immediate-interference*: 3.13 ± 0.5 ; *no-interference*: 3.32 ± 0.9) and for MI easiness moderate evidence for no difference between groups ($BF_{\text{group}} = 0.24$, error% = 0.03; $M \pm SD$: *late-interference*: 2.85 ± 0.8 ; *immediate-interference*: 3.11 ± 0.7 ; *no-interference*: 3.21 ± 1.1), meaning that the data are approximately 2.6 and 4.2 times more likely to occur under H0 than under H1, respectively.

Further, we found marginal anecdotal evidence for no difference in initial Stanford sleepiness scale (SSS; $BF_{\text{group}} = 0.99$, error% = 0.01; $M \pm SD$: *late-interference*: 2.18 ± 0.7 ; *immediate-interference*: 2.42 ± 0.5 ; *no-interference*: 2.00 ± 0.4) and moderate evidence for no difference between groups regarding sleep quality (PSQI; $BF_{\text{group}} = 0.19$, error% = 0.03; $M \pm SD$: *late-interference*: 5.47 ± 2.5 ; *immediate-interference*: 4.90 ± 2.6 ; *no-interference*: 5.06 ± 1.35), meaning that the data are about 1.01 and 5.3 times more likely to occur under H0 than under H1, respectively.

To ensure comparability between groups regarding initial MI NF ERD a 1x3 Bayes ANOVA with between-subject factor group (three levels: *late-interference*, *immediate-interference*, *no-interference*) and MI NF ERD obtained from MI NF block 1 as dependent variable was conducted. The resulting BF of 0.65 suggested anecdotal evidence for H0, that is no initial difference between groups in MI NF ERD, meaning that the data are approximately 1.5 times more likely to occur under H0 than under H1.

3.2. MI NF gain and MI NF performance over blocks

To examine the effect of NF on MI ERD, we performed paired t-tests within each group and block to compare the training run MI ERD with MI NF ERD within the same block (cf. Fig. 4). For each block and group the MI induced ERD was significantly stronger in the MI NF runs

¹ A Bayes factor (BF) of 1 corresponds to no evidence for either H1 or H0. Bayes factors <1 indicate that the data provide evidence in favor of H0. Commonly used categories are: BF 1/3–1 ‘anecdotal evidence for H0’, BF 1/10–1/3 ‘moderate evidence for H0’, BF 1/10–1/30 ‘strong evidence for H0’, BF 1/30–1/100 ‘very strong evidence for H0’ and BF < 1/100 ‘extreme evidence for H0’. BF > 1 indicate evidence ranging from ‘anecdotal’ to ‘extreme’ in favor of H1. The original label for $3 < BF < 10$ was ‘substantial evidence’, which was changed by Lee and Wagenmakers (2013) to ‘moderate’. ‘Anecdotal’ was formerly known as ‘Barely worth mentioning’.

compared to the training run (see Table 1 for details).

To explore how this NF gain evolves over blocks and across groups, we performed a 3x3 mixed ANOVA with group as between-subject factor (three levels: *late-interference*, *immediate-interference*, *no-interference*), MI NF block as within-subject factor (three levels: 1, 2, 3). MI ERD NF gain, i.e., the difference between training run MI ERD and MI NF ERD, was the dependent variable. We did not find significant effects (group: $F_{2,50} = 0.37$, $p = .69$, $\eta^2 = 0.02$, 90% CI [0 0.08]; block: $F_{1,77,100} = 0.25$, $p = .75$, $\eta^2 = 0.01$, 90% CI [0 0.03]; group x block: $F_{3,54,100} = 0.69$, $p = .58$, $\eta^2 = 0.03$, 90% CI [0 0.06]). As this exploratory ANOVA did not indicate significant effects, an additional Bayes ANOVA was conducted with the same parameters to determine the degree of evidence for the null hypothesis. It provided moderate evidence for no differences between groups and blocks as well as for the absence of an interaction effect ($BF_{\text{group}} = 0.22$, error% = 0.80; $BF_{\text{block}} = 0.08$, error% = 1.47; $BF_{\text{inclusion}} = 0.11$), meaning that the data are approximately 4.6, 12.5 and 9.1 times more likely to occur under H0 than under H1, respectively.

3.3. Effect of immediate declarative interference on MI NF ERD

To test whether performing interference tasks immediately after an initial block of MI and MI NF reduced MI NF ERD in a subsequent block of MI and MI NF, for the second MI NF block (MI2) MI NF ERD was compared between groups *immediate-interference* and *no-interference* in an independent samples t-test. We did not find a significant effect ($t_{1,34} = 0.58$, $p = .57$, $d = 0.19$, 95% CI [−0.46 0.85], post-hoc power 0.083, for post hoc power curves see supplemental materials; all power calculations with G*Power 3.1.); *immediate-interference*: $M = -35.64\%$, $SD = 16.77\%$, *no-interference*: $M = -32.01\%$, $SD = 20.77\%$). To determine the degree of evidence for this null-effect, an additional Bayes t-test was conducted with the same parameters. The Bayes t-test indicated that evidence for no difference in MI NF block 2 between both groups was anecdotal ($BF = 0.37$, error% = 0.01), meaning that the data are approximately 2.7 times more likely to occur under H0 than under H1. Thus, our data provide no evidence for the hypothesis that immediate interference after MI NF practice reduced MI NF ERD after a period of wakefulness.

There was no evidence for an adverse effect of immediate declarative interference on MI NF ERD after a period of wakefulness. Nonetheless, the Bayes paired t-test between MI NF blocks 2 and 3 of group *immediate-interference* was run as planned to confirm that there was also no change after a night of sleep. Results again suggested no difference in MI NF ERD ($BF = 0.32$, error% = 0.03; moderate evidence for no difference between MI NF blocks 2 and 3, meaning that the data are approximately 3.1 times more likely to occur under H0 than under H1.).

3.4. Early boost and effects of sleep on contralateral MI NF ERD

To test for an early boost effect for MI NF ERD and, if present, its stability over a night of sleep, a 1x3 repeated measures ANOVA with MI NF block (three levels: 1, 2, 3) as within-subject factor and MI NF ERD as dependent variable was performed for group *late-interference*. We did not find a significant effect ($F_{2,32} = 0.09$, $p = .91$, $\eta^2 = 0.01$, 90% CI [0 0.03], post-hoc power 0.13). Bayes paired t-tests were performed in addition to the planned ANOVA to indicate the strength of evidence for this null-finding. Evidence for no difference between blocks was moderate for both MI NF blocks 1 and 2 (1 vs 2: $BF = 0.25$, error% = 0.01) and MI NF blocks 2 and 3 (2 vs. 3: $BF = 0.26$, error% = 0.01), meaning that the data are approximately 4 and 3.8 times more likely to occur under H0 than under H1. Hence, our data do not provide evidence for an early boost effect in MI NF ERD nor for a change in MI NF ERD following a night of sleep.

4. Discussion

This study investigated the effects of declarative interference on MI



Fig. 2. MI NF ERD time courses. MI NF ERD time courses are shown for groups *late-interference* (blue), *immediate-interference* (orange) and *no-interference* (green) for each MI block. Grey areas indicate the baseline (–6 to –4 s before task onset) and the statistically analysed MI interval (0.5–4.5 s after task onset). Data are averaged across MI NF runs within a block. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

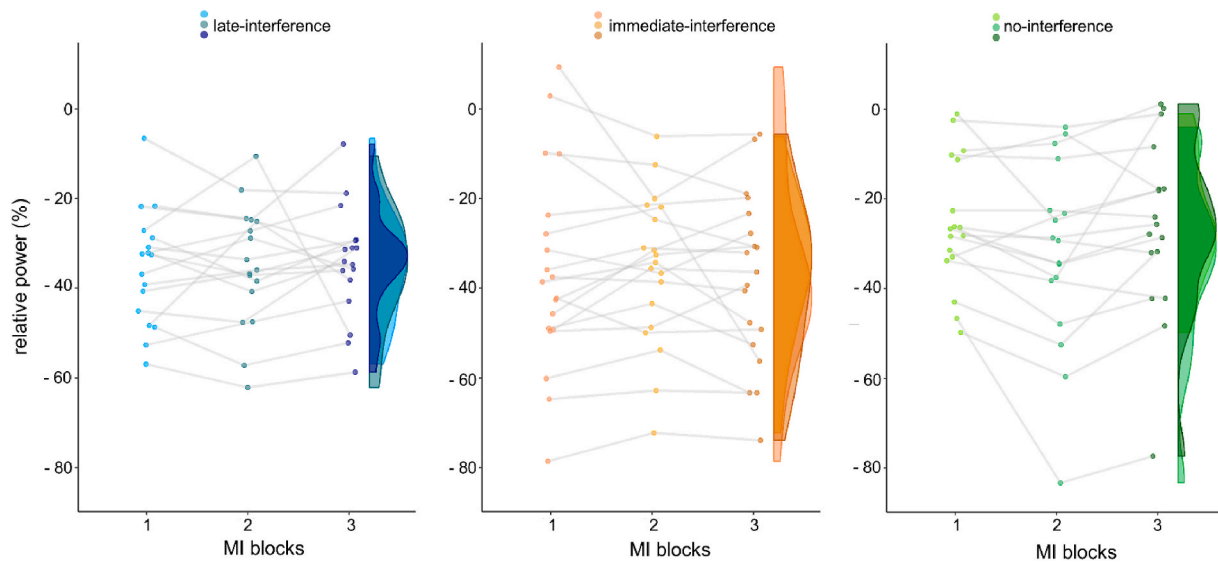


Fig. 3. Single subject MI NF ERD data split by group and MI block. Each dot represents the single-subject ERD power value averaged across MI NF runs within a block. Data distribution is estimated using kernel density estimations as implemented in the van Langen open-visualizations repository (van Langen, 2020). Wider sections represent a higher probability that a data point of the population will take on the given value. Lower probability is reflected by narrower sections.

NF ERD as a measure of MI NF performance and aimed at studying the stability of the effects after a night of sleep. Three groups underwent three MI NF blocks each on two consecutive days. Groups differed regarding the presence and timing of a set of declarative interference tasks. We expected an adverse impact of immediate declarative interference on MI NF ERD that would not recover after a night of sleep. We further anticipated an early boost for MI NF ERD, and if present, we expected a consolidate of the MI NF ERD at this early boost level after a night of sleep. A significant NF effect was present in all three groups and blocks, i.e., ERD was significantly stronger in the MI NF runs when compared to the training run without NF. Inconsistent with our hypotheses, we found no evidence for an impact of immediate declarative interference on MI NF ERD nor for an early boost effect for MI NF ERD. The hypotheses regarding the stability of both effects over a night of

sleep thus became baseless.

Consistent with previous MI NF studies, we found that MI NF resulted in a significantly stronger ERD compared to a training run without NF (see e.g., [Darvishi et al., 2017](#); [Zich et al., 2015](#)). This feedback effect was present for all groups in all MI blocks, suggesting that task-related feedback reliably enhances MI ERD, independent of the implementation of interference (i.e., immediate, late or no interference) or time of day in this study. However, neither the feedback effect or MI ERD NF gain nor MI NF ERD did visibly increase over the course of three MI blocks. This apparent absence of a practice effect over time contrasts with the findings of several other studies (e.g., [Foldes et al., 2020](#); [McWhinney et al., 2018](#); but see [Perronnet et al., 2017](#); [Zich et al., 2015](#); [Kober et al., 2015](#); [Vernon, 2005](#)), though reports in line with the present study’s null-finding exist as well. Although observed effect sizes are

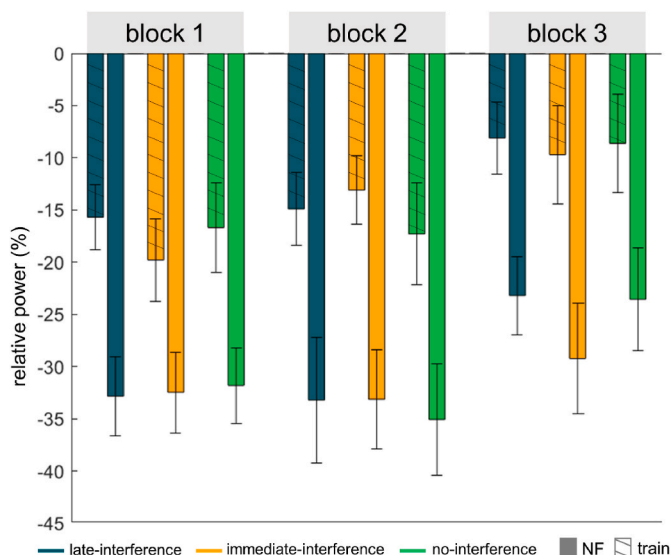


Fig. 4. MI ERD for training and NF blocks. Shown are MI (NF) ERDs separate for MI blocks and groups (means \pm one standard error). For all combinations of block and group, a strong NF effect is evident in the much stronger ERD in the NF compared to the training runs. However, the NF effect (difference between NF and training runs) is comparable between groups and MI blocks.

rather small to basically non-existent, which rules out to draw firm conclusions about this study’s findings, we discuss possible explanations in the following.

One factor limiting MI ERD NF gain and an increase in MI NF ERD with repeated MI NF practice in the present study may be the break block. The break block consisted of nature documentaries and followed MI blocks in all three groups. Watching nature documentaries is a common control task in (motor) skill acquisition associated studies (Bassolino et al., 2014; Friedrich and Beste, 2020; Ruffino et al., 2019; Ruffino et al., 2017). In the present study it was also integrated in the experimental group procedure as neutral break occupation. However, a recent study on physical practice suggests that watching a documentary over a prolonged duration as a break occupation or control condition might be problematic. Hachard and colleagues observed that unexpectedly, their control condition of watching a documentary had adverse effects on performance in subsequent balance control tests in young, healthy participants (Hachard et al., 2020). The authors discuss that participants’ reduced performance in balance control following the control condition could be due to a deleterious effect of prolonged sitting. While this reasoning cannot be applied to the present study, an alternative explanation was that watching the documentary induced mental fatigue. MI ERD NF gain did however not deteriorate but remained rather stable between MI blocks, arguing against this

possibility. It is however conceivable that participants got distracted by the content of the break documentaries or became drowsy, and that this interfered with the consolidation of the memory trace for the preceding experience of learning to or being able to control the NF with MI. To the best of our knowledge no MI NF literature is available to support this speculation and thus, no firm conclusions can be drawn at this point. Further studies are necessary to systematically study the interplay of MI NF task and control or break tasks.

Immediate declarative interference did not reduce subsequent MI NF ERD when compared to no interference. This result is contrary to our expectation but was statistically confirmed by a Bayes analysis indicating that MI NF ERD in the second MI block did not differ between a group exposed to declarative interference tasks and a group not exposed to these tasks. To the best of our knowledge, no other study has investigated the impact of declarative interference on MI NF ERD. However, the finding of no effect contrasts with recent studies reporting impaired motor consolidation after MI and ME practice following declarative interference, as reflected in reduced physical task performance (Brown and Robertson, 2007; Debarnot et al., 2012; but see Rothkirch et al., 2018). Reasons for this difference might be closely related or even identical to the reasons leading to another unexpected outcome, i.e., the lack of evidence for an early boost effect on MI NF ERD. Bayes analysis showed moderate evidence for the absence of an early boost effect. Here, as before, a direct comparison to other MI NF ERD studies is not possible due to a lack of published research. But the result clearly contrasts with previous ME and MI practice studies showing early boost effects for both (Debarnot et al., 2011a; Nettersheim et al., 2015). One aspect contributing to the deviating results could be the different dependent variables, i.e., MI NF ERD versus physical task performance, and characteristics of these variables, such as test-retest reliability. Another aspect could be unspecific interference through the documentaries used to fill the break block in the present study. If unspecific interference is an issue, it may not only affect MI ERD NF gain over time as discussed above, but also the MI NF ERD early boost and specific, declarative interference effects.

An alternative explanation for the discussed dissociation between the findings of previous studies on ME and MI practice and the present one is task difficulty. It is conceivable that our results differ from the aforementioned studies both regarding interference effects and the early boost effect because of the applied motor task. Studies reporting effects of interference and early boost typically concentrate on motor sequence learning tasks with a resulting increase in motor execution performance (e.g., Brown and Robertson, 2007; Debarnot et al., 2012; Debarnot et al., 2011b). In contrast, we opted for a simple thumb-to-finger-opposition task that has been validated in the context of MI NF for young healthy and older healthy participants (e.g., Nikulin et al., 2008; Zich et al., 2017). This task might however have been too simple to yield measurable ERD effects of interference and early boost in healthy young participants. Indeed, the search for MI paradigms suitable for NF research is an ongoing challenge. Research to date is mostly conducted in healthy, often young volunteers. Yet NF interventions, in particular in the

Table 1
Paired t-tests between training and MI NF runs per block for each group.

group	blocks	t	p	d	95% CI		N	M _{train}	SD _{train}	M _{NF}	SD _{NF}
					lower	upper					
late-interference	1	3.60	.002	0.83	0.29	1.34	19	-16.4	13.7	-36.0	22.5
	2	5.77	<.001	1.32	0.69	1.93	19	-14.4	12.7	-35.6	16.8
	3	4.65	<.001	1.07	0.49	1.63	19	-19.2	19.2	-37.8	19.0
immediate-interference	1	5.15	.001	1.25	0.60	1.88	17	-17.3	12.5	-35.4	12.8
	2	3.03	.008	0.73	0.19	1.26	17	-21.7	15.8	-35.0	13.5
	3	2.89	.008	0.70	0.16	1.22	17	-18.6	17.7	-34.3	12.4
no-interference	1	4.78	<.001	1.16	0.53	1.77	17	-9.4	14.9	-25.3	14.5
	2	4.86	<.001	1.18	0.54	1.79	17	-11.4	20.2	-32.0	20.8
	3	4.87	<.001	1.18	0.54	1.79	17	-10.2	20.4	-26.0	19.9

neurorehabilitation field, are targeted at clinical, often older populations. Tasks showing practice gains in young and healthy volunteers tend to have little every-day relevance or are conceptualized for a specific audience e.g., athletes (Mulder et al., 2004; Paris-Alemanly et al., 2019). Attempts have been made to implement more complex tasks that are both feasible for basic research in non-clinical populations and that have every-day relevance. An example illustrating this is a visuo-motor reach and grasp paradigm with varying levels of difficulty (Allami et al., 2014; Daeglau et al., 2020b). Though the visuo-motor reach and grasp paradigm addresses task complexity and generalizability; it brings about new challenges. So do the variable trial durations that result from the setup complicate the calculation and interpretation of the ERD. Furthermore, more complex tasks also mean an increase in cognitive load during MI. This increase reduces cognitive resources available for processing and incorporating NF while doing MI, creating yet another challenge for future research.

The design of this study regarding the stability of MI NF ERD effects over a night of sleep was inspired by previous studies investigating how motor or motor imagery practice effects evolve over a night of sleep (Debarnot et al., 2011b; Debarnot et al., 2009a; Debarnot et al., 2009b). T. With the present design, we would have been able to test our hypotheses regarding the early boost and the interference MI NF ERD effects after a night of sleep. The design would however not have allowed unequivocal conclusions regarding the role of sleep for any difference observed between Day 1 and Day 2 MI NF ERDs. For this, a matched-control wake group would be a prerequisite, for instance in a sleep deprivation design or a nap/ no nap design (for a review, see King et al., 2017).

Based on experimental groups, MI NF ERD did not change with MI NF practice. In line with this, single subject MI NF ERD shows a remarkable variability over time. Yet nonetheless, visual inspection of MI NF ERDs indicates that all experimental groups contained participants that did not increase their MI NF ERD over MI blocks at all, participants that improved from Block 1 to Block 2 but lost that gain after a night of sleep, and participants improving continuously over the three blocks. This variation can be seen as indication that individual factors play a major role for MI NF skill acquisition (Ahn & Jun 2015; Daeglau et al., 2020b; Jeunet et al., 2015; Roc et al., 2019; Zapala et al., 2019). These individual factors might be more important than the context factors sleep, and declarative interference studied here, or they might interact with them. Future studies should therefore strive to consider individual in addition to context factors instead of looking at both separately.

5. Conclusion

In the present study, we did not observe the expected effects of interference on MI NF ERD or an early boost, and therefore could not test how either effect evolved over a night of sleep. As previously shown, the interplay of MI (NF) and performance increase is complex (Dickhaus et al., 2009; Lotte et al., 2019; Vidaurre and Blankertz, 2010). Context factors are likely contributing to this complexity. In order to better understand their role, it is inevitable to continue to systematically depict common and differing features of MI, MI NF, and ME skill acquisition.

Data availability

The datasets generated for this study are available on request to the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ynirp.2021.100058>.

Author contributions

Mareike Daeglau: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing—original draft, Writing—review and editing; Catharina Zich: Conceptualization, Methodology, Supervision, Writing—review and editing; Julius Welzel: Investigation, Writing—review and editing; Samira Kristina Saak: Investigation, Writing—review and editing; Jannik Florian Scheffels: Investigation, Writing—review and editing; Cornelia Kranczioch: Conceptualization, Funding acquisition, Methodology, Project administration, Writing—review and editing.

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Further reading

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