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Large scale investigation of the effect of gender on mu rhythm suppression in motor imagery brain-computer interfaces

Valentina Gamboa von Groll[a], Nikki Leeuwis[a], Sébastien Rimbert[b], Aline Roc[b], Léa Pillette[c], Fabien Lotte[b] and Maryam Alimardani[a]

[a]Department of Cognitive Science and AI, Tilburg University, Tilburg, Netherlands; [b]Inria Center at the University of Bordeaux / LaBRI, Talence, France; [c]Department of Virtual Reality, Virtual Humans, Interactions and Robotics, University of Rennes, Inria, CNRS, France

ABSTRACT
The utmost issue in Motor Imagery Brain-Computer Interfaces (MI-BCI) is the BCI poor performance known as 'BCI inefficiency'. Although past research has attempted to find a solution by investigating factors influencing users' MI-BCI performance, the issue persists. One of the factors that has been studied in relation to MI-BCI performance is gender. Research regarding the influence of gender on a user's ability to control MI-BCIs remains inconclusive, mainly due to the small sample size and unbalanced gender distribution in past studies. To address these issues and obtain reliable results, this study combined four MI-BCI datasets into one large dataset with 248 subjects and equal gender distribution. The datasets included EEG signals from healthy subjects from both gender groups who had executed a right- vs. left-hand motor imagery task following the Graz protocol. The analysis consisted of extracting the Mu Suppression Index from C3 and C4 electrodes and comparing the values between female and male participants. Unlike some of the previous findings which reported an advantage for female BCI users in modulating mu rhythm activity, our results did not show any significant difference between the Mu Suppression Index of both groups, indicating that gender may not be a predictive factor for BCI performance.

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1. Introduction

Brain-Computer Interfaces (BCIs) allow controlling external devices using brain activity signals only [1,2], most often recorded by electroencephalogram (EEG). A widely used BCI paradigm is Motor Imagery BCI (MI-BCI) which relies on the active imagination of a movement by the user [1]. By mentally rehearsing the visual or kinesthetics of a movement, the user engages in the Motor Imagery (MI) task, which leads to event-related desynchronization (ERD) and synchronization (ERS) of the EEG signals in the mu (8-13 Hz) frequency band [3,4] as well as the beta (13–30 Hz) band in some reports [1,5]. The attenuation of mu band power following the MI task is known as mu suppression. Mu suppression is stronger for the brain hemisphere contralateral to the imagined body movement hence it is often used by the MI-BCI classifiers to distinguish between left versus right MI [3,6].

Since MI-BCIs rely on the active involvement of the user and their ability to execute the MI task, they suffer from the issue of BCI inefficiency [7,8]. BCI inefficiency, also known as BCI illiteracy in older articles [9], refers to the problem where up to 50% of BCI users are unable to reach a desirable performance (70% accuracy) on their first interaction with the system [10–12]. In addition, 15 to 30% of this population remains unable to reach the threshold of 70% accuracy after standard training [7,8]. BCI inefficiency is one of the reasons why MI-BCI systems are still restricted to laboratories and controlled scenarios. Although the notion of BCI inefficiency has been criticized by some scholars as it puts the locus of deficiency on the user [7], it is still a relevant approach to address this issue by identifying the factors that influence an individual's ability to generate distinguishable neural patterns when performing a MI task. Consequently, adapting the training protocols or using smart algorithms that consider these influential factors can expedite the training process [2,13,14].

Past research has already investigated some of the factors that could influence MI-BCI performance [6,13–15]. The factors that have been examined in the literature can be divided into five categories (Table 1).

The first category refers to neurophysiological differences between subjects, e.g., the amplitude of their

CONTACT Maryam Alimardani m.alimardani@tilburguniversity.edu Department of Cognitive Science and AI, Tilburg University, De Boelelaan 1111, Amsterdam 1081 HV, the Netherlands

Table 1. Factor categories influencing MI-BCI performance and studies that support those findings.

Factor categories	Studies
Neurophysiology	Blankertz et al. [10] Grosse-Wentrup et al. [16], Ahn et al. [17] Thompson [7] Tzdaka et al. [18], Leeuwis et al. [19]
Mental states	Jeunet et al. [13] Leeuwis et al. [14] Zhang et al. [8] Myrden & Chau [20] Mladenovic et al. [21] Rimbert et al. [22]
Cognitive skills	Hagedorn et al. [15] Jeunet et al. [13] Jeunet at al [23]. Leeuwis et al. [14] Leeuwis & Alimardani [24] Hammer et al. [25] Rimbert et al. [26] Rimbert et al. [27]
Personality dimensions	Jeunet et al. [13] Leeuwis et al. [14] Mladenovic et al. [21] Rimbert et al. [27]
Demographics	Randolph [28] Alimardani & Gherman [6] Leeuwis et al. [14] Cantillo-Negrete et al. [29] Zapała et al. [30] Pillette et al. [31]

mu rhythm at rest [10]. These differences can facilitate or impede the BCI system from detecting the appropriate neural signals needed to distinguish changes in the EEG patterns [7,10,17–19]. The second category entails the subject's mental state while executing the MI task and how it affects the BCI performance [13,14]. Through extensive research, it has been shown that some intra-subject variability can be explained by changes in the subject's attention level, fatigue, frustration, relaxation, and motivation [8]. However, these are factors that vary by subject and depend on the temporal course of study, making them difficult to control or monitor during the training process. The third category considers the subject's cognitive skills, e.g., spatial ability, vividness of visual imagery, visuospatial memory, and visuomotor coordination skills. Researchers have found that subjects with a high BCI performance tend to have a different cognitive profile than low performers [13–15,22,23]. Personality traits (e.g., orderliness, autonomy, self-reliance, emotional stability) compose the fourth category of factors influencing BCI performance [13,14]. It has been argued that personality traits affect MI-BCI performance because they influence users' response to the training protocol and hence their MI learning [13]. Having a tense personality reflects an impatient and frustrated subject with a lower BCI performance, while a self-reliant subject that has a high ability to learn autonomously can achieve a higher BCI performance after training [13,14]. This type of information about a subject can be useful when assigning them to adaptive training protocols or when predicting their response to the training [20,32].

The last category focuses on the effect of demographics on BCI performance. Although some research has been done on the effect of age, education, gender, and other demographic factors [6,14,27,28], there is no consensus on whether these factors influence BCI performance. One factor with contradictory findings is gender. According to the study of Randolph [27] which employed 80 subjects (45 females), the participant's sex is a fundamental factor for BCI performance, with females being better at modulation of mu suppression. These findings were corroborated by later research of Cantillo-Negrete et al. [28] and Alimardani and Gherman [6] who compared BCI performance between the two gender groups using data from 32 (16 females) and 54 (23 females) subjects, respectively. On the contrary, Jeunet et al. [13] did not find a gender difference based on the BCI classification accuracy of 18 users (9 females). Similarly, the study performed by Hagedorn et al. [15] did not discover a significant difference in mu suppression values between genders (36 females vs. 19 males). Therefore, the existing evidence does not allow drawing a conclusion on the impact of gender on MI-BCI performance, although gender seems to impact neural activity during motor planning [33] as well as motor execution [34].

Given the above-mentioned gap in the literature, this study aimed to extend the analysis done by Alimardani & Gherman [6] to elucidate the effect of gender on MI-BCI performance using a large dataset, with equal gender distribution. By combining four openly available EEG datasets ($n = 248$) that followed a left- vs. right-hand motor imagery paradigm, we compared males' and females' ability to modulate mu rhythms. This extension of the analysis aimed to increase the robustness and reliability of the previous findings since it tackled two main issues in past research: small sample sizes and unequal gender distribution [6,14]. A sufficiently large sample size allows for isolating the gender effect, even in the presence of other factors.

In sum, we pursued to answer the following research question: 'Does an individual's gender relate to their ability to perform the motor imagery task for BCI control?' To quantify motor imagery performance, we extracted mu suppression patterns from EEG signals as this has been previously identified as one of the main features associated with MI-BCI control [3,6,28,34]. This study is the first of its kind in BCI user training research to combine various online-available datasets that satisfy a given selection criteria. This will make it a valuable contribution to the current methodology in the field, by encouraging open science practices such as sharing and reusing datasets to increase the reliability and generalization of past findings.

2. Method

2.1. Dataset selection

This research combined all datasets that followed a similar MI-BCI protocol and were available online. The datasets were chosen following six selection criteria (see Table 2), which were basic guidelines the datasets had to comply with for the EEG data to be comparable after applying the same processing steps.

The most critical criteria for selection of datasets was the experimental paradigm that was followed during the recording of the EEG signals. While there are a considerable number of MI-EEG datasets available online, we only included MI-BCI datasets that followed the standard Graz protocol with abstract feedback strategy (explained in section 2.2). In order to have sufficient samples for mu suppression analysis, the MI task should have lasted at least 3 seconds. In addition, to prevent any effect of neuromuscular disorders on brain signals, all recruited subjects should have been healthy and neurotypical. For this specific research, the gender of each subject needed to be documented, in order to classify the combined datasets into two groups of females and males. The EEG channels C3 and C4 must have been recorded in order to obtain the mu suppression values associated with the MI task. These two channels were essential to the computation of Mu Suppression Indices [6], as they are the primary left and right electrodes placed above the sensorimotor area of the brain. Finally, we only included openly available datasets to ensure their accessibility as well as the replicability of this study.

This led to a total of four datasets included in this study. Detailed description of these datasets is provided in 2.3.

2.2. Motor imagery (MI) task

To minimize variation across datasets, this research only focused on MI-EEG datasets that were collected using the standard MI-BCI paradigm described by Pfurscheller & Neuper [36]. This paradigm, also known as the Graz protocol, consists of a binary MI task, in which subjects are instructed to imagine either a right-hand or a left-hand movement. To execute the imaginary movement, there is an externally paced time protocol, presented on a computer screen, that guides the subject through the trial (see Figure 1). Every single trial lasts around 8 seconds, starting with a fixation cross in the center of the screen. After that, a left- or right-pointing arrow is presented for 1.25 sec to indicate the hand for which the subject should imagine the movement. The subject is instructed to continue the imagination until the fixation cross disappears. Normally, for calibration of the BCI system, the first run consists of multiple non-feedback or sham-feedback trials with equal distribution of right-hand and left-hand MI. Following calibration of the system, subjects practice the MI task with feedback runs. In feedback runs, the trials follow the same 8-second protocol, only that at second 4.25, a horizontal feedback bar appears indicating the classifier output. The direction and length of the bar represent the classifier output, i.e., the recognized MI task and the confidence in that decision, based on the produced EEG sensorimotor activity. The bar is presented to the user until the trial ends [35].

2.3. Dataset description

This section provides information about each dataset, such as the dataset's descriptive statistics, sample size, sampling frequency, and researchers who collected the data. A summary of the dataset information is provided in Table 3. For a more detailed description of each dataset and experimental procedure, refer to the corresponding source.

The first dataset was shared by Leeuwis et al. [37]. The dataset collected EEG signals from 55 novice BCI users (36 females, 19 males, $M_{\text{age}} = 20.71$, $SD_{\text{age}} = 3.52$), during a two-class MI task. Sixteen electrodes were placed according to the 10–20 international system.

Table 2. Selection criteria employed during screening of MI-BCI datasets in this study.

Number	Criterion
1	The experimental paradigm followed the standard MI paradigm in Graz protocol (see section 2.2).
2	The MI task was at least 3 sec long.
3	The dataset consisted of only healthy subjects.
4	The dataset had documented the gender for each subject.
5	EEG channels C3 and C4 were recorded.
6	The dataset is openly available.

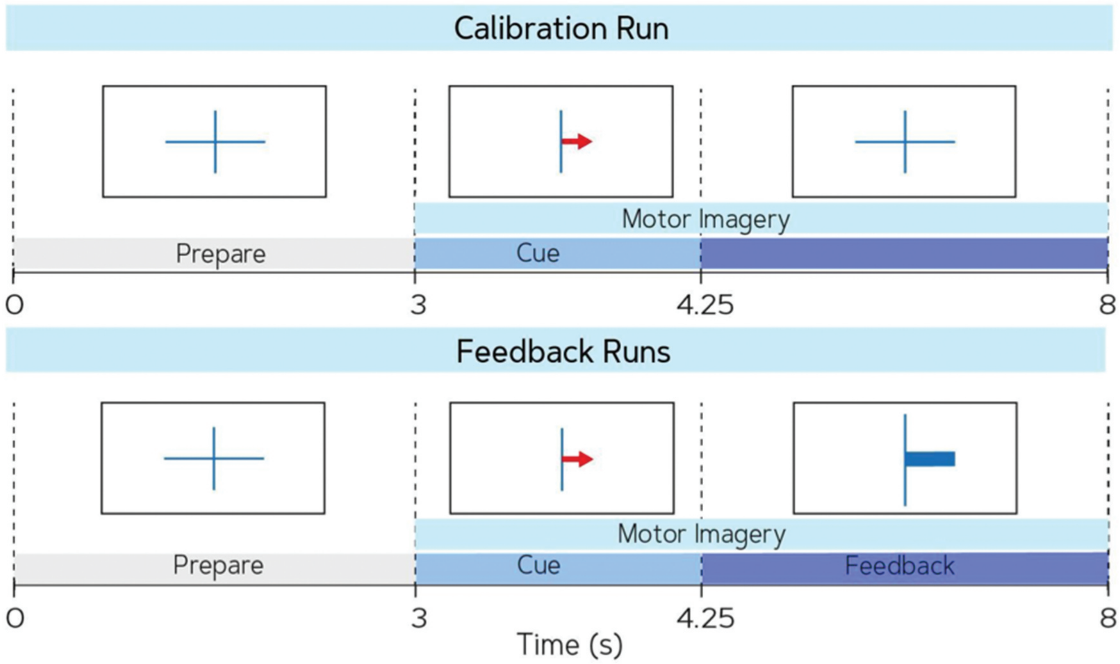

Figure 1. An illustration of the motor imagery BCI task according to the Graz protocol as employed in Leeuwis et al. [35]. Each trial lasts 8 sec, starting with a fixation cross in the center of the screen, followed by an arrow-shaped cue that guides the MI task. A right-pointed arrow signals the subject to imagine a right-hand movement (Right MI) and a left-pointed arrow signals the imagination of a left-hand movement (Left MI). In the first run, subjects do not receive any feedback or sham feedback only, and the collected data is used for calibration of the BCI system. In the following runs, subjects receive feedback in the form of a horizontal bar that extends to the right or left depending on the classifier output. Subjects should continue imagination of the movement until the fixation cross and feedback disappear.

Table 3. An overview of the datasets included in the current study.

Dataset	Source	Sample size (female, male)	Number of trials per subject	Sampling rate
1	Leeuwis et al. [35]	55 (36 f, 19 m)	160	250 Hz
2	Lee et al. [12]	54 (23 f, 31 m)	100	1000 Hz
3	Cho et al. [36]	52 (19 f, 33 m)	160 or 240	512 Hz
4	Dreyer et al. [37]	87 (45 f, 42 m)	240	512 Hz

The sampling rate of the recorded EEG signals was 250 Hz. A bandpass filter from 0.5 to 30 Hz was applied during the recording, to reduce the noise. The MI-BCI task was repeated in 4 runs (one calibration run without feedback and consequently three runs with feedback). Each run consisted of 40 MI trials (20 right and 20 left), with a random order of right-hand or left-hand MI. Feedback was based on online classification from Common Spatial Patterns (CSP) + Linear Discriminant Analysis (LDA) that was recalibrated between every run.

The second dataset was made available on GigaScience by Lee et al. [12]. The dataset consists of EEG data from 54 subjects, among them 38 were novice users (23 females, 31 males, $M_{age} = 24.24$, $SD_{age} = 3.01$). The EEG signals were recorded from 62 electrodes, placed following the international 10–20 system. The sampling rate was set to 1000 Hz. This dataset contains signals from three different paradigms. According to the selection criteria, only trials from MI-BCI sessions were considered for this research, which led to a total of 50 right-hand and 50 left-hand MI trials per subject. Subjects did not receive any feedback during these trials.

The third dataset also came from the open repository GigaScience and was created by Cho et al. [38]. For this dataset, 52 subjects took part in the experiment of whom 5 had BCI experience before (19 females, 33 males, $M_{age} = 24.8$, $SD_{age} = 3.86$). The EEG signals were recorded from 62 electrodes, placed according to the international 10–10 system, at a sampling rate of 512 Hz. For each subject, there were 4 or 6 runs of 40 trials combining both tasks (left-hand vs. right-hand). Subjects did not receive any feedback during these trials.

The fourth dataset was shared on Zenodo by Dreyer et al. [39]. It consists of EEG signals from 87 novice participants (45 females, 42 males, $M_{age} =$

28.22, $SD_{age} = 9.06$) who participated in three different experiments with the same MI-BCI protocol [31,40]. The signals were recorded from 27 electrodes, placed around motor and somatosensory cortices according to the international 10–20 system. The signals were recorded at a sampling rate of 512 Hz. Each participant conducted 40 trials (20 left-hand and 20 right-hand MI) per run in a total of 6 runs, i.e. a total of 240 trials. The first two runs were calibration runs where the subject received sham feedback. Consequently, a CSP+LDA classifier was trained on this data and provided online classification in the following 4 runs. Notably, only positive feedback was shown.

The above four datasets were combined into one large dataset, composed of 248 subjects (123 females, 125 males, $M_{age} = 24.39$). To date, this makes it the largest dataset used to study the relationship between gender and BCI control. The following section describes the preprocessing and analysis steps applied to this large dataset.

2.4. Data processing and analysis

All data analysis including signal preprocessing, spectral analysis, and statistical testing were performed in Python 3 (version 3.9.12), using NumPy (version 1.22.3), Pandas (version 1.3.4), SciPy (version 1.7.1) and MNE (version 0.24.1) libraries. A pipeline was created as a guideline to be followed during the data processing and data analysis (see Figure 2). The pipeline was based on the methodology presented by Alimardani & Gherman [6] and details all stages and steps required for the computation of Mu Suppression Indices from the combined dataset.

The pipeline outlined the creation of a Python script used to perform all processing steps. Due to the combination of multiple datasets, all data was converted into MNE-raw objects respecting the different loading methods depending on the data format. The first preprocessing step was to resample all EEG recordings to a frequency of 250 Hz. Additionally, a 4th order IIR Butterworth filter was applied to bandpass filter the

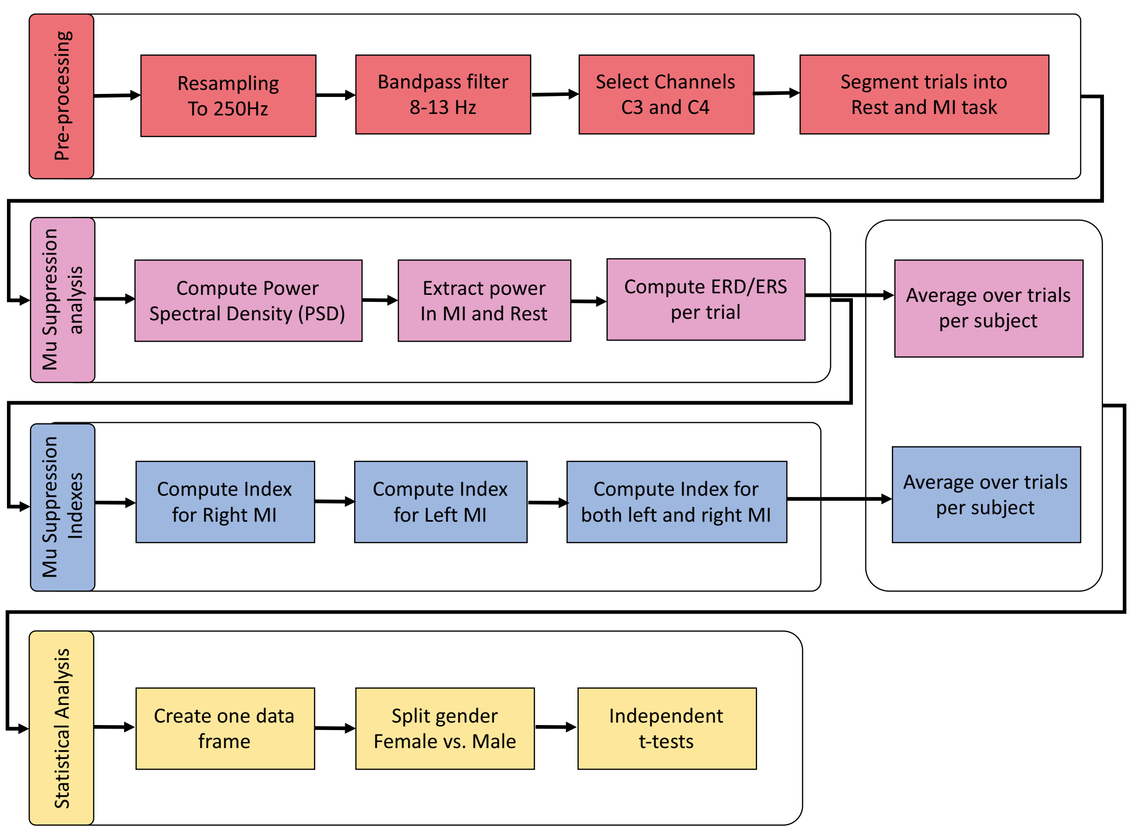

Figure 2. Data processing pipeline. All EEG signals were resampled at 250Hz and bandpass filtered to the mu band (8–13 Hz). The filtered signals from C3 and C4 were selected and segmented into MI task (3 sec) and resting state (Rest: 2 sec) per each trial. Next, the power spectral density (PSD) in MI and Rest segments were extracted and used in the computation of Mu Suppression Indices. Finally, all obtained indices were averaged across corresponding trials to have one value per index per subject. The values were then compared between gender groups (females vs. males) using independent t-tests.

signals within 8–13 Hz, and then EEG channels C3 and C4 were selected to compute the changes of the mu band oscillations in the sensorimotor cortex.

Next, the data was segmented to extract the windows of interest from the signals. The EEG recordings had four markers indicating the start of trials, the end of trials, the time at which the arrow cue was presented, and the MI class that the trial corresponded to (i.e. left or right). This allowed segmentation of the time series into individual trials and consequently segmentation of trials into resting state (Rest) and motor imagery (MI) epochs. The MI window was selected as the 3 seconds after the appearance of the arrow, and the Rest window was considered the first 2 sec from the start of a trial. The length of windows was chosen based on the available timeframe in all datasets.

To compute the Mu Suppression Index, it was necessary to extract the power spectral density (PSD). The PSD values were extracted from every window of every trial using the SciPy.signal.spectrogram function. Consequently, Equation 1 was used to calculate ERD/ERS (mu suppression) per each trial using the average power in the mu band during the resting state and motor imagery windows [3,6].

$$\frac{ERD}{ERS} = \frac{AveragePowerDuringMI - AveragePowerDuringRest}{AveragePowerDuringRest} \tag{1}$$

The mu suppression pattern following the MI task depends on the MI class, where it is prominently observable in the hemisphere contralateral to the imagined movement. To distinguish between the left and right MI trials, we looked at the lateralization of mu suppression for each class. That is, we extracted the above ERD/ERS from both C3 and C4 channels and subtracted their values to obtain a lateralization index for mu suppression. Two different formulas were used to calculate the Mu Suppression Index specific to each MI task (Equation 2 and 3). The goal of the Mu Suppression Index is to compare the mu band power drop (negative values) in the ipsilateral hemisphere as opposed to the contralateral one. Since this drop is expected to be stronger in the hemisphere contralateral to the MI task, the index defined by Equations 2 and 3 yields mostly positive values. Additionally, the larger this positive value, the better the subject could generate distinguishable MI patterns [6].

$$\text{Right} - \text{hand(RH)MI Mu Suppression Index}: \frac{ERD_{RH}}{ERS_{RH\ C4}} - \frac{ERD_{RH}}{ERS_{RH\ C3}} \tag{2}$$

$$\text{Left} - \text{hand(LH)MI Mu Suppression index}: \frac{ERD_{LH}}{ERS_{LH\ C3}} - \frac{ERD_{LH}}{ERS_{LH\ C4}} \tag{3}$$

For all Left-hand and Right-hand MI trials, the Mu Suppression Index was obtained, and the values were averaged across runs, in order to get one Mu Suppression Index per class for every subject. Additionally, to acquire one index reflecting subjects' MI performance regardless of the imagined hand, an Overall Mu Suppression Index (Equation 4) was generated by summing the Left- and Right-hand MI Mu Suppression Indices [6].

$$\text{Overall Mu Suppression Index}: \frac{ERD_{LH}}{ERS_{LH\ C3}} - \frac{ERD_{LH}}{ERS_{LH\ C4}} + \frac{ERD_{RH}}{ERS_{RH\ C4}} - \frac{ERD_{RH}}{ERS_{RH\ C3}} \tag{4}$$

Finally, the subjects were divided into two groups: Female ($n = 123$) and Male ($n = 125$), and their ERD/ERS values as well as Mu Suppression Indices were compared using independent t-tests. To perform a parametric independent t-test, the dataset needs to fulfill certain assumptions. However, this study has more than 30 samples per group, for which the central limit theorem (CLT) states that the assumptions can be dismissed [43,44].

3. Results

In this section, the findings obtained through statistical analysis are discussed. The statistical analysis consisted of independent samples t-tests comparing the ERD/ERS values, Right-hand MI Mu Suppression Index, left-hand MI Mu Suppression Index, and the Overall Mu Suppression Index between gender groups. As specified in the Methods section, Mu Suppression Indices indicate the lateralization of the ERD/ERS values between the two brain hemispheres and are used by this study to define a subject's ability to perform the MI task.

3.1. ERD/ERS

Figure 3 presents the ERD/ERS values associated with right-hand MI trials (measured at EEG channel C3) and left-hand MI trials (measured at EEG channel C4) for Female and Male groups. The more negative the ERD/ERS values, the higher the event-related desynchronization caused by the MI task. Levene's test confirmed the homogeneity of variances between groups for both RH-MI trials ($p = .65$) and LH-MI trials ($p = .83$). Therefore, independent t-tests were conducted with the assumption of equal variances. The results yielded no significant effect for gender when subjects performed right-hand MI as can be seen in Figure 3(a) (Female: $M = -0.29$, $SD = 0.22$, Male:

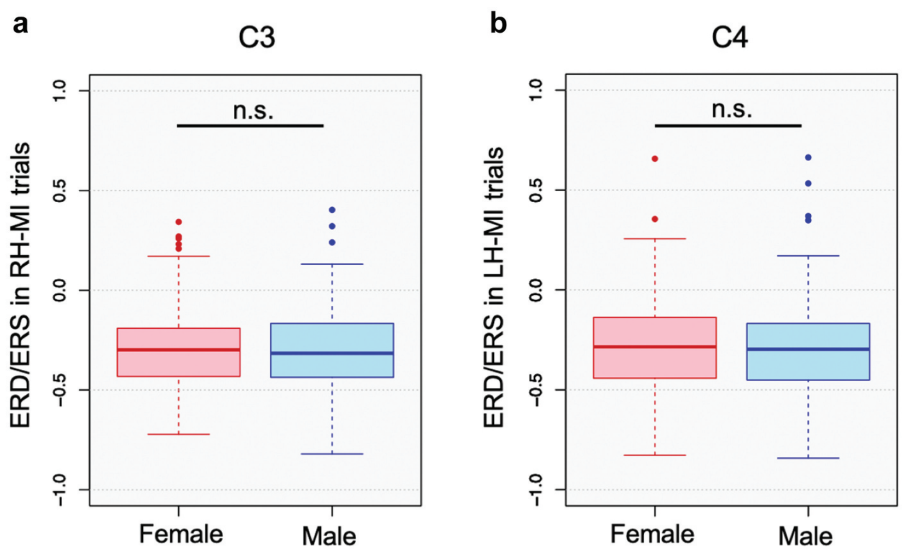

Figure 3. ERD/ERS values calculated based on Equation 1 for both Female and Male groups at (a) EEG channel C3 representing mu suppression values for right-hand MI tasks, and (b) EEG channel C4 representing the values associated with left-hand MI tasks.

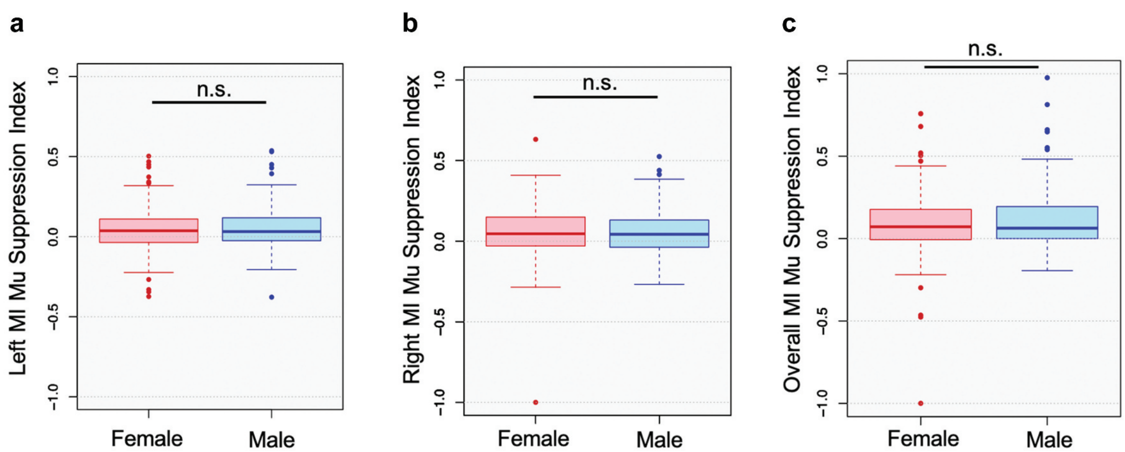

Figure 4. Mu Suppression Indices in Female and Male groups for (a) Left-hand MI, (b) Right-hand MI and (c) both hands.

$M = -0.30$, $SD = 0.22$, $t(245) = 0.35$, $p = .72$) nor did it when they performed left-hand MI trials (see Figure 3(b), Female: $M = -0.28$, $SD = 0.23$, Male: $M = -0.29$, $SD = 0.25$, $t(245) = 0.54$, $p = .59$).

3.2. Mu Suppression Indices

The Mu Suppression Indices for Right-hand MI, Left-hand MI, and both hands (Overall Index) are illustrated in Figure 4 for both gender groups. In contrast to the ERD/ERS values, Mu Suppression Indices are mostly positive because of the way they were defined in Equations 2, 3, and 4. Three independent t-tests were performed to examine whether the difference in Mu Suppression Indices between Female and Male groups was significant. Homogeneity of variances was confirmed in all cases using the Levene's test (LH-MI: $p = .35$, RH-MI: $p = .66$, Overall MI: $p = .48$). Thus, independent t-tests were conducted with the assumption of equal variances. The tests revealed no significant effect of gender on the Left-hand MI Mu Suppression Index (Female: $M = 0.04$, $SD = 0.16$, Male: $M = 0.06$, $SD = 0.14$, $t(246) = 0.99$, $p = .32$), nor did it when comparing Right-hand MI Mu Suppression Index between the two groups (Female: $M = 0.05$, $SD = 0.17$, Male: $M = 0.06$, $SD = 0.14$, $t(246) = 0.45$, $p = .65$). Similar outcome was obtained for the Overall Mu Suppression Index (Female: $M = 0.08$, $SD = 0.22$, Male: $M = 0.12$, $SD = 0.20$, $t(246) = 1.32$, $p = .19$), indicating that the null hypothesis cannot be rejected, hence, the lateralization of ERD/ERS values during the MI task was not statistically different between the two genders.

4. Discussion

This research aimed to investigate the impact of users' gender on their mu rhythm modulation during motor imagery BCI interaction. By combining four MI-BCI datasets, we gathered EEG signals from 248 subjects (123 females and 125 males) who performed a right- vs. left-hand motor imagery task according to the standard Graz protocol. Following past research, ERD/ERS values indicating mu suppression in the contralateral hemisphere [3] as well as the hemispheric lateralization of ERD/ERS obtained by the Mu Suppression Indices [6] were calculated per subject and compared between gender groups during motor imagery of the left hand, right hand, and both hands. The results showed no significant differences in ERD/ERS values nor Mu Suppression Indices between female and male users in none of the MI tasks, providing evidence that gender has no impact on the user's ability to modulate mu rhythm activity during MI-BCI control.

The outcome of the current study is contradictory to the results of Alimardani & Gherman [6] and Randolph (2102), who reported an advantage for females in producing mu suppression patterns when performing the motor imagery task. However, it resonates well with the reports of other studies (e.g., [13,15,27,,]) that did not find gender influence on MI-BCI control. Indeed, this study embarked on the collection and analysis of an extremely large dataset to address these inconsistencies that existed in previous reports with respect to the impact of gender in MI-BCIs. A sufficiently large sample size allows the isolation of the gender effect, even in the presence of other factors that have been identified as potential contributors to the MI-BCI performane and BCI inefficiency problem (see Table 1). Thus, the results of the current study can be deemed more reliable as the limitations of past research such as small sample size and an unequal gender distribution in the dataset were addressed.

The existence of a gender difference in brain anatomy, neurophysiology, and cognition has been considerably debated and studied in the past. According to a mini review by [41], the reported differences between sex/gender groups are not compelling enough to support a clear classification of 'female brains' vs. 'male brains'. Similarly, [42] state that although some anatomical and functional features occur statistically more often in females and some features are typical of males, these features often overlap far too much, making the impact of gender irrelevant. During the motor imagery task for BCI control, there are various individual factors (e.g., age, sports experience, etc.) as well as psychological (e.g., attention, motivation, etc.) and cognitive factors (e.g., visuospatial memory, etc.) that could influence a person's ability to modulate mu band oscillations [8,17,23]. When the recruited sample consists of a modest number of participants, the impact of one or more of these factors might prevail in one gender group, resulting in a significantly higher BCI performance for that group. However, our results confirm that when the sample is large enough to include a diverse population, the effect of gender on MI-based mu suppression no longer holds.

To compare gender groups, the current study only employed mu suppression values and indices obtained from two EEG electrode locations (i.e., C3 and C4) as indicators of motor imagery task performance following previous literature [3,6,35]. This choice was made mainly due to the existing inconsistencies across available datasets, namely, the differences in the EEG recording configuration and the number of available trials per individual. Moreover, it has been shown that neurophysiological analysis of motor related EEG patterns is a better metric of MI-BCI users' skills, contrary to classification accuracy which reflects a mix of users' skills and machine learning classifiers' abilities [45]. However, it is likely that for some subjects, the modulation patterns associated with the motor imagery task were reflected in other brain areas or frequency bands. Future research can expand this work by establishing offline BCI classifiers that recruit subject-specific spectral and spatial filters and compare BCI classification accuracy between gender groups [32]. This requires a higher level of homogeneity across selected datasets for instance similar EEG electrode placement over sensorimotor area as well as an equal number of MI trials per subject.

While the outcome of this study does not support the effect of participants' gender on mu rhythm modulation during motor imagery task execution, gender remains a relevant factor in future MI-BCI training protocols. Previously, Pillette et al. [32] reported that the interaction between experimenters' and participants' genders could influence user experience as well as their performance across motor imagery BCI trials. They observed that women experimenters could positively influence the progress of subjects on the task. Another neurofeedback study by Wood and Kober [46] reported the reverse effect where female participants trained by female experimenters showed lower training outcomes compared to male participants. These contradictory findings demonstrate the complex relationship between gender and BCI skill development which deserves future investigation. Particularly in the current work, the gender of experimenters was not specified by all datasets and hence should be considered as a limitation when interpreting the results.

A practical implication of this study is in the design of subject-specific training protocols for MI-BCIs. Cantillo-Negrete et al. [31] argued that gender could be an important factor in developing subject-independent BCI classifiers. Using data from 32 participants, they showed that a gender-specific motor imagery BCI could achieve a better performance than a gender-nonspecific one. However, our results and that of Pillette et al. [32] suggest that the impact of gender on motor imagery performance might be more psychosocial than physiological, hence, the effect of such contextual factors that interact with the user's gender, personality, and psychological states should be considered more earnestly in the design of future MI-BCI training schemes [47]. For instance, the delivery of instructions for the MI task could be adaptive to the user needs depending on their level of autonomy and preference for external or internal guidance [14,23], or the feedback accuracy and visual design during the BCI interaction could be manipulated for each user to optimize their experience and ultimately improve their learning gain [21,31,48,49]. Alternatively, while our study suggested no relationship between gender and sensorimotor activity during MI-BCI use, it could be that there is such a relationship with other EEG patterns, e.g., in frequency bands other than mu or electrodes other than C3 and C4, as discussed before. If that is the case, then gender-specific classifiers could still be useful, to exploit non-SMR-based differences between genders. That would be an interesting research question to investigate in the future.

Another approach to tackle performance variation among BCI users is to employ data-driven methods for the development of better predictive models that identify user-specific EEG patterns associated with the MI task rather than considering mu rhythm modulation as a one-fits-all solution. When comparing low and high-aptitude BCI performers, it was found that other neural metrics such as intra-brain connectivity may differ between the two groups [19], and that end-to-end deep learning methods have an advantage over more traditional (and shallow) machine learning algorithms in extracting subject-specific EEG patterns, thus improving the performance of inefficient users [50]. These findings are aligned with the report of Benaroch et al. [40] who also showed that user-specific frequency band characteristics can predict a person's BCI performance and that to improve BCI classification accuracy in machine learning pipelines, researchers should consider feature selection steps based on neurophysiological prior of the user.

Finally, this study provides a basis for future BCI research by promoting open science and data sharing practices. EEG data collection for BCI experiments is costly, thus oftentimes the research teams report their findings with a modest number of participants. In order to increase the replicability and validity of findings, BCI researchers are encouraged to make their data openly accessible to other researchers [51]. A challenge we faced during dataset screening for this study was the lack of compatibility between MI protocols and data quality in open datasets, as well as missing demographic information such as gender. Future studies should consider a standardization of data collection, curation, and sharing practices for the development of a large reference dataset that could be widely used when investigating inter-subject variability in BCI research.

5. Conclusion

The current study aimed to answer whether gender is an influential factor in determining a user's performance on motor imagery BCIs. By combining four EEG datasets, we compared mu rhythm suppression patterns between two groups of females ($n = 123$) and males ($n = 125$) when they performed a right- vs. left-hand MI task following the Graz protocol. Unlike some previous studies that found an advantage for females in performing the motor imagery task, we found no evidence of such a gender effect on a person's ability to modulate mu band activity during MI-BCI interaction. This leads to the conclusion that a user's gender alone is not a contributing factor to the BCI inefficiency problem. However, more research is required to gain insights into the psychosocial dimensions of gender and how that influences an individual's interaction with the BCI training environment and experimenters.

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Disclosure statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ORCID

Maryam Alimardani http://orcid.org/0000-0003-3077-7657

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