MOTOR IMAGERY VIVIDNESS AND NATURALISTIC INNER SPEECH HABITS IN IMAGINED SPEECH CLASSIFICATION

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ABSTRACT: Research on BCI-illiteracy in the imagined speech domain has been scarce. In the current study, we therefore investigate the relationships between both motor imagery vividness as well as inner speech habits, and classification accuracy based on the neural activity evoked by speech imagination. For this purpose, we classified electroencephalography-derived brain activity with respect to four imaginatively spoken phonemes: /a/, /i/, /b/ and /k/. We found that individuals who engaged more frequently in dialogic inner speech exhibited significantly higher classification accuracies, while motor imagery vividness showed no effects. Neurophysiological findings indicate that a higher expression of dialogic inner speech is associated with a suppression of redundant or counteractive neural information. These findings extend our understanding of the substrates of classification performance, respectively, BCI-illiteracy in speech imagery-based systems.

INTRODUCTION

Imagery vividness and inner speech habits Brain-computer interfaces (BCIs) rooted in electroencephalography (EEG) attempt to enable individuals with motor impairments to control a certain device by leveraging electrophysiological brain signals. Motor imagery has been used extensively for this purpose [1,2]. The classification of imagined speech emerged more recently and is considered an intuitive means for the development of speech prostheses [3]. Irrespective of whether one imagines movements or speech, some individuals fail to control BCIs via own brain signals. This phenomenon is referred to as BCI illiteracy. An estimated 15-30% of BCI-users are affected by this [4]. Regarding the roots of the illiteracy phenomenon, structural brain heterogeneity, insufficiently discriminative classification algorithms and a lack of neuroimaging diversity have been discussed in the literature [5]. Furthermore, associations between motor imagery vividness and classification performance [6–8] or corticomotor excitability [9] have been reported. Vuckovic [7], for example, showed that kinesthetic motor imagery vividness was highly correlated with the classification accuracies of a kinesthetic motor imagery task. Visual motor imagery vividness also was positively correlated with the classification outcome, but to a lesser extent. Despite being a motor imagery process, the role of motor imagery vividness has not yet been investigated in speech imagery. Corresponding questionnaires, however, may not accurately capture the full dynamics of the underlying ability to vividly imagine speaking, as they neglect the auditory component thereof entirely. Since no speech imagery vividness questionnaire exists, previous studies [10,11] alternatively used the Varieties of Inner Speech Questionnaire (VISQ) [12] to quantify the degree to which individuals "mentally" talk to themselves on an everyday basis. However, it is important to note that conceptual and procedural discrepancies between naturalistic inner speech and experimentally manipulated imagined speech exist [13]. The former is produced naturally and spontaneously, while the latter is elicited as part of an investigation. The former often serves a function, e.g. to remind oneself of something or to monitor one's actions, while the latter frequently consists of isolated stimuli, such as phonemes [3] and yes/no contrasts [14]. For this reason, we refer to experimentally elicited imagined speech as imagined speech and to naturally occurring inner speech as inner speech throughout the rest of this paper. Despite the differences, naturalistic inner speech habits may represent a more suitable proxy for speech imagery vividness compared to motor imagery vividness, as they capture the predominant auditory component of imagined speech.

Neural substrates of imagined/inner speech Neural correlates of imagined speech have been researched thoroughly over the last decades. Evidence derived from reviews [15,16] suggests the involvement of an extensive perisylvian, respectively, sylvian network including the left pars opercularis, premotor cortex (especially ventral portions), insula, supplementary motor area, inferior parietal gyrus and superior and middle temporal gyri. Similarly, findings of a recent fMRI study [11] indicate the recruitment of left-hemispheric areas, including the inferior frontal gyrus, medial frontal gyrus, insula and nucleus caudatus regarding both dialogic and monologic inner speech. Additionally, the authors found significant correlations between the activation contrast Dialogic>Monologic inner speech and self-reported

dialogic inner speech usage as assessed by the corresponding VISQ subscale in the right medial temporal gyrus as well as the right precuneus. The remaining subscales were not associated with any voxel activity cluster. With respect to identifying the drivers of BCI-illiteracy in imagined speech classification problems, discovering the neural markers of imagined speech discriminability might be of higher relevance than those of imagined speech per se. For this purpose, imagined speech classification studies frequently reported the discriminative power of features. In terms of frequency bands, higher frequency components (beta, gamma) have been shown to hold a larger amount of discriminative information [14,17,18]. Regarding the role of brain areas, respectively, EEG channels, evidence suggests that, similarly to the neural correlates of imagined speech in general, perisylvian areas, consisting of inferior frontal, inferior parietal and superior temporal channels, provide the most discriminative information [14,18]. However, it is difficult to draw general conclusions from the literature, as feature types, neuroimaging methods and classification algorithms vary strongly between studies [17].

In the current study we examine the relationships between motor imagery vividness as well as inner speech habits and classification performance regarding "mentally" spoken phonemes /a/, /i/, /b/ and /k/. In a second step we attempt to establish associations between dialogic inner speech and the discriminability of features, as quantified by mutual information scores, provided that a substantial relationship between the Dialogic inner speech subscale and classification performance emerges in step one. This choice was based on Alderson-Day and colleagues [11], who demonstrated significant associations between the Dialogic subscale and fMRI activity clusters for both dialogic and monologic inner speech. In a third step, we identify features that are significantly associated with classification accuracy. Finally, we enter them into a multiple regression model alongside dialogic inner speech in order to get insights into whether inner speech habits uniquely predict classification performance beyond the influence of neurophysiological features. Through this, we intend to provide preliminary evidence regarding the role of motor imagery vividness and - with a main focus - naturalistic inner speech habits in imagined speech classification paradigms and, consequently, imagined speech based BCI illiteracy.

MATERIALS AND METHODS

Participants Twenty-seven individuals participated in this study. Due to technical errors during measurements and noisy EEG signals, five participants had to be excluded. Thus, the data of 22 individuals between the ages of 19 and 37 ($M = 25.41$, $SD = 4.02$) were subjected to the analyses. 10 of them were male and 12 were female. All were native German speakers, right-handed and had normal or corrected-to-normal vision. Participants reported no psychiatric or neurological disorders, or medical diseases. Further, no use of medication that could influence the central nervous system was reported. Recruiting was performed via university-wide mailing distribution. Compensation in the form of either 28 Euros (8 Euros per hour) or course credit for psychology students was offered. To participate, individuals had to sign an informed consent document. This study was approved by the ethics committee of the University of Graz, Austria and conforms to the ethical principles of the Declaration of Helsinki.

Procedure Participation comprised attendance on two sessions with 1 hour and 45 minutes each (3.5 hours in sum) on two separate days. Participants were seated in a comfortable armchair approximately 100 cm in front of a 24.5-inch computer screen. A COVID-19 questionnaire, the German version of the Vividness of Movement Imagery Questionnaire 2 (VMIQ-2) [19], the Varieties of Inner Speech Questionnaire – Revised (VISQ-R) [10] and sociodemographic questions were answered prior to the beginning of the study paradigm. Instructions and test trials were presented on the computer screen. In this phase, participants were exposed to audio recordings of all four phonemes. These were carried out via near field studio monitors at a constant volume of approximately 75db at the position of the participants. Audio stimuli were self-recorded and digitally manipulated to exhibit a fundamental frequency in the gender-ambiguous range of 140-170 Hz. Two conditions were embedded into the study paradigm: Phoneme imagination and phoneme perception. However, as the phoneme perception data are not relevant for the current study and merely derived as part of a larger investigation, they were not subjected to the analyses. All participants engaged in the mental speaking of four phonemes: /a/, /i/, /b/ and /k/. The reason for this is the articulatory differences, as well as phonetic dissimilarities between these phonemes [20]. Although no specific imagination instructions were provided, the imagination condition was consistently referred to as "imagining speaking something" throughout the entire paradigm. We did not provide any specifics about the imaginative content, as we wanted to ensure that participants apply their most natural form of speech imagination. Trials consisted of 5 seconds of visual phoneme presentation. Phonemes occurred once per second for 0.5 s. Prior to and after trials a fixation cross was displayed for 1 and 2–4 s, respectively. 20 trials of the same phoneme represented one block. Eight phoneme imagination blocks (2 repetitions * 2 conditions * 4 phonemes) were presented in each session. An inter-block break of 15 s was incorporated. With this design 80 trials were carried out for each imaginatively spoken phoneme. The paradigm was constructed and presented in PsychoPy2 (version 1.85).

Questionnaires The German version of the VMIQ-2 was used in the current study. It measures the vividness of motor imagery and is comprised of three subscales: internal visual (In), external visual (Ex) and kinesthetic

(Ki) imagination. Each of the three factors has high internal consistency (α > .7). Test-retest-reliability of .69 is moderate. The VISQ-R assesses the phenomenological varieties of inner speech and consists of five factors: 'Dialogic' (D), 'Evaluative/Critical' (E), 'Other People' (O), 'Condensed' (C) and 'Positive/Regulatory' (P) inner speech. Dialogic inner speech denotes talking to oneself in a discursive manner, a recurring back and forth. Condensed inner speech, on the other hand, implies a rather short, fragmented inner speech rather than complete dialogue. The "Evaluative/Critical" scale comprises items that measure to which degree one tends to mentally criticize and evaluate oneself, whereas the "Positive/Regulatory" scale represents a self-praising, comforting inner speech variant. The "Other People" Scale assesses to which degree individuals experience the voices of others in their inner speech. Internal consistency is excellent, ranging from .80 to .91 across subscales.

Data Acquisition EEG was derived from 45 electrodes distributed across the whole scalp. Electrode positions conformed to the international 10-5 system to facilitate an even whole-head distribution. EEG was recorded by using actiCAP active wet Ag/AgCl electrodes (Brain Products GmbH), a BrainAmp EEG amplifier (Brain Products GmbH) and the accompanying recording software BrainVision Recorder (version 1.21) at a sampling rate of 500 Hz. The average of the left and right mastoid signal was used as a reference. The ground was placed at Fpz. Three ocular signals were derived from 1 cm above the nasion (vertical eye movements) and the lateral canthi (horizontal eye movements). Furthermore, fNIRS signals were concurrently acquired. However, as they are not relevant for the research questions of the current study and merely derived as part of a larger investigation, they were not subjected to the analyses.

Preprocessing Bandpass filtering was conducted with a 1 Hz high-pass and a 70 Hz low-pass setting. A notch filter at 50 Hz was also applied. Ocular artifacts were addressed by regressing the EOG signals out of the EEG data [21]. Subsequently, EEG data were visually inspected to mark artifact corrupted trials and channels for removal. Finally, the data were segmented into 5 s epochs (0 to 5 s) with adjacent baselines of 1 s (-1 to 0 s).

Feature selection and classification Power spectral densities (PSDs) were calculated for the predefined frequency bands alpha (8-12 Hz), beta (12-30 Hz) and gamma (30-70 Hz). This selection was grounded on the results of Preedapirat and Wongsawat [18] and Sereshkeh and colleagues [14], who identified higher discriminative potentials of the alpha, beta, and gamma frequency range with respect to an imagined speech classification problem. This resulted in a total of 135 features per trial (45 EEG channels * 3 frequency bands), provided that no channels were excluded. By using 5-fold cross-validation on the training data, the number of used features was optimized. The k = 10, 15, 20, 25, 30

features with the highest mutual information scores were subjected to this. Classification was performed by means of a multilayer perceptron. Individual classification results, however, are not reported; the focus of this study exclusively lies on the relationship between classification performance and motor imagery vividness, respectively, inner speech habits. However, we do want to emphasize that all classification accuracies exceeded chance level by more than 25% and exhibited an average accuracy > 70%.

Statistical analyses To quantify the relationships between motor imagery vividness, inner speech habits, feature discriminability and classification accuracies simple bivariate Pearson classification coefficients are reported. These underwent bootstrapping with 20000 iterations to test them for significance. In an integrative data-driven effort multiple linear regression analysis was conducted to identify more robust, unique effects. Predictors for this were selected as follows: The dialogic inner speech subscale was incorporated if it showed a substantial correlation with classification accuracy. Again, this was based on the findings of Alderson-Day and colleagues [11]. Further, features that showed significant correlations with classification accuracy were also entered. Due to large intercorrelations between features, gamma and beta features were averaged, resulting in one consolidated gamma and beta predictor each. Variance inflation factor was below 5 for all predictors.

RESULTS

Inner speech habits and motor imagery vividness with respect to classification performance Correlative analyses indicated a positive relationship between the Dialogic, the Evaluative/Critical as well as the Condensed inner speech subscale and phoneme classification performance of r = .32 (bootstrap 95% *CI* [-.18, .73]), r = .30 (bootstrap 95% *CI* [-.13, .62]) and r =
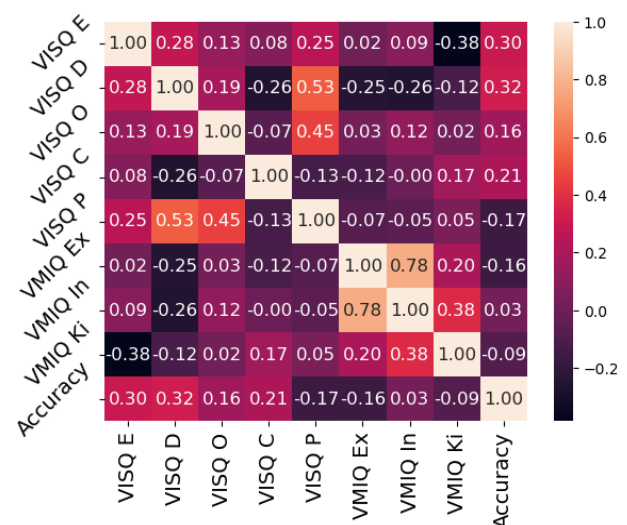

Figure 1: Correlation map containing the variables of interest.

.21 (bootstrap 95% *CI* [-.18, .61]), respectively (Fig. 1). Note that bootstrapping did not attest the correlation coefficients significance. Partial correlation analysis indicated that the correlation between the dialogic inner speech subscale (D) and classification performance (C) persists beyond the influence of Evaluative/Critical inner speech (E) ($r_{DC.E}$ = .26). All other questionnaire scales showed absolute correlation coefficients < .17.

Inner speech and feature discriminability Negative correlations arose between gamma- as well as beta-based mutual information scores, and the Dialogic inner speech subscale (Fig. 2). A fronto-central beta network consisting of FC3 (r = -.54, bootstrap 95% *CI* [-.75, -.19]), FC1 (r = -.44, bootstrap 95% *CI* [-.67, -.03]), FC2 (r = -.57, bootstrap 95% *CI* [-.81, -.18]), C1 (r = -.51, bootstrap 95% *CI* [-.77, -.13]) and Cz (r = -.52, bootstrap 95% *CI* [-.78, -.18]) emerged. Further, in both the gamma and the beta frequency band CPP5h showed a significant correlation (r = -45, bootstrap 95% *CI* [-.69, -.13]; r = -.49, bootstrap 95% *CI* [-.73, -.11] for beta and gamma, respectively). Finally, mutual information values of the gamma frequency band at C4 (r = -.50, bootstrap 95% *CI* [-.74, -.18]) and the beta frequency band at TTP8h (r = -.35, bootstrap 95% *CI* [-.61, -.07] exhibited a significant correlation with Dialogic inner speech. This constitutes a small right-hemispheric centro-temporal cluster. Lastly, O2 beta also showed a significant association (r = -.44, bootstrap 95% *CI* [-.71, -.12]) with the inner speech subscale.

Feature discriminability and classification accuracy Several significant correlations regarding mutual information scores of features and classification accuracy were observed (Fig. 3). A predominant left fronto-central gamma network consisting of F7 (r = .37, bootstrap 95% *CI* [.00, .66]), Fz (r = .50, bootstrap 95% *CI* [.05, .76]), FFT7h (r = .41, bootstrap 95% *CI* [.08, .66]), FC1 (r = .58, bootstrap 95% *CI* [.30, .76]), FCz (r = .51, bootstrap 95% *CI* [.23, .70]), C3 (r = .46, bootstrap 95% *CI* [.06, .71]), C1 (r = .50, bootstrap 95% *CI* [.14, .72]) and Cz (r = .49, bootstrap 95% *CI* [.12, .72]) emerged. Additionally, left parietal and right frontal contribution was observed at P3 (r = .39, bootstrap 95% *CI* [.10, .65]) and FFC6h (r = .43, bootstrap 95% *CI* [.13, .66]), respectively. A more diffuse pattern was found in the beta

band with significant correlations at FFT7h (r = .48, bootstrap 95% *CI* [.10, .73]), Cz (r = -.50, bootstrap 95% *CI* [-.76, -.11]) and CP4 (r = .44, bootstrap 95% *CI* [.10, .77]).

Integrative model Multiple linear regression analysis yielded the following results: gamma-based mutual information scores (b = .069, p = .001) as well as the Dialogic inner speech subscale (b = .047, p = .009) emerged as significant predictors with respect to classification accuracy (Tab. 1). Beta-based mutual information scores did not prove significant (b = .017, p = .332). In sum, the model explained approximately 60% of the variance of classification accuracy (R^2 = .595, p < .001).

Table 1. Multiple linear regression results

	b	SE	t
Gamma	.069**	.017	4.115
Beta	.017	.017	0.996
VISQ D	.047**	.016	2.935
R^2 = .595	R^2 adj. = .527	F = 8.807	$p(F)$ < .001

Note. Gamma: Averaged mutual information values of gamma features. Beta: Averaged mutual information values of beta features. VISQ D: Dialogic inner speech subscale of the VISQ-R
**p < .01

DISCUSSION

Motor imagery vividness and inner speech habits The aim of the current study was to investigate the relationships between motor imagery vividness as well as inner speech habits and classification performance on grounds of neural activity evoked by imaginatively spoken phonemes. Literature suggests that visual [6,8] as well as kinesthetic motor imagery vividness [8,22] have an impact on the classification of neural reaction patterns evoked by motor imagery. Dissonantly, by means of correlative methods, we were unable to establish a connection between visual or kinesthetic motor imagery vividness and classification performance in the imagined speech domain. Despite not withstanding bootstrapping-based significance tests, inner speech habits, however, indicated promising effects: dialogic and evaluative inner
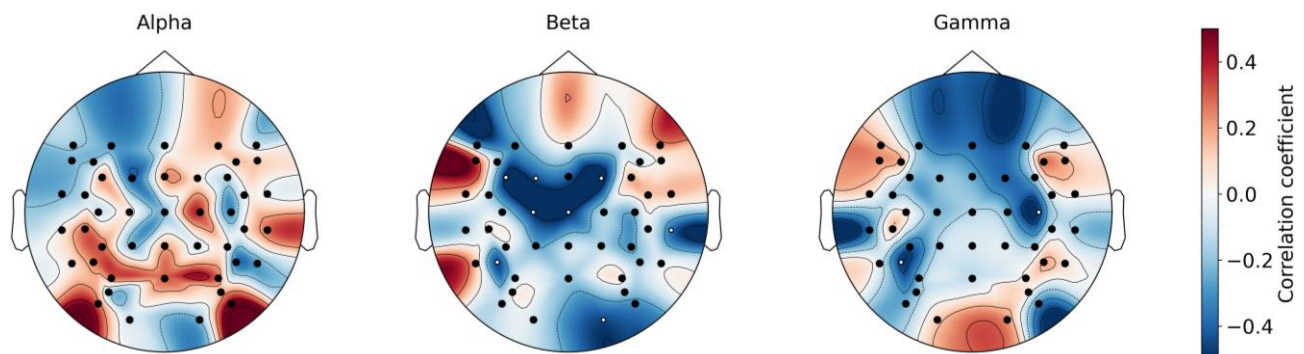

Figure 2. Topo plots of the correlation coefficients between mutual information scores of the frequency bands of interest and the VISQ-R Dialogic subscale. Significant correlation coefficients are marked in white.

speech both showed a moderate, and condensed inner speech exhibited a small to moderate correlation with classification performance. Hence our results suggest that, while individuals who can vividly imagine movements cannot produce more differentiable neural signals on grounds of imaginatively spoken phonemes, individuals engaging frequently in dialogic, evaluative inner speech can. Although, in previous studies, motor imagery vividness was shown to have reliable influence on motor imagery classification, it is not surprising that this mechanism cannot simply be translated to speech imagery. The established motor imagery vividness questionnaires do not assess speech imagery or any other form of imagery with an auditory component. Since the content of imagined speech is considered to be not only of articulatory, but also auditory nature [13], this may explain the larger influence of naturalistic inner speech on classification performance compared to motor imagery vividness.

Neurophysiological contribution To obtain a more comprehensive depiction of the role of naturalistic inner speech habits in an imagined speech classification paradigm, we investigated the embedding of the discriminative power of features. Negative correlations between the mutual information values, i.e., the discriminability of features and dialogic inner speech emerged. A prominent fronto-central network of beta channels emerged, along with isolated significant channels in left superior temporal, right occipital and right medial temporal regions regarding beta, and left superior temporal and right inferior central regions regarding gamma. To our knowledge, only one study exists that investigated associations between VISQ scales and neural data [11]. Our results are only partially overlapping with those reported in the referenced study, as the authors consonantly reported a significant association between the Dialogic subscale of the VISQ and an fMRI cluster in the right medial temporal gyrus, but additionally in two clusters of the right precuneus. Note that the authors did not report the direction of the correlation. Since our network is much more diffuse, caution is advised with respect to interpreting these findings. While being negatively correlated with the discriminability of EEG-channels, dialogic inner speech shows a positive relationship with the overall

classification performance. Consequently, individuals who engage more frequently in dialogic inner speech may be more successful in suppressing redundant neural information, which in turn increases accuracy. We found associations between feature discriminability and classification performance that support this notion. An increased expression of dialogic inner speech suppresses features that show a negative or no influence on classification performance. A higher expression of dialogic inner speech might therefore not only act as a noise cancelling mechanism but also directly suppress the recruitment of counteractive features. However, significant positive correlations between feature discriminability and classification performance were also found. In this regard, a predominantly left-hemispheric frontal gamma network emerged, which is in line with previous literature [11,14,18]. Despite existing findings showing more diffuse discriminability maps [14,18], comparisons are limited, as these reflect mere discriminability values and not correlations. Ultimately, we integrated these results in a data-driven approach by building a multiple linear regression model to predict classification accuracy based on dialogic inner speech and the beta as well as gamma features that showed a significant correlation with classification accuracy. In line with previous findings [14,18], gamma indicated a significant influence on classification performance that is independent from all other predictors. Similarly, dialogic inner speech yielded a significant unique effect that goes beyond the neurophysiological predictive power. As indicated in the bivariate correlative analyses, this supports the notion that a high tendency towards every-day dialogic inner speech acts as a noise cancelling mechanism, inhibiting redundant neural contributions rather than increasing feature discriminability. Lastly, beta features did not influence classification performance.

CONCLUSION

We were able to shed light on the complex action mechanisms surrounding the role of naturalistic inner speech habits and motor imagery vividness in imagined speech classification. In opposition to previous studies, no link between motor imagery vividness and BCI performance was found. Dialogic inner speech, however,
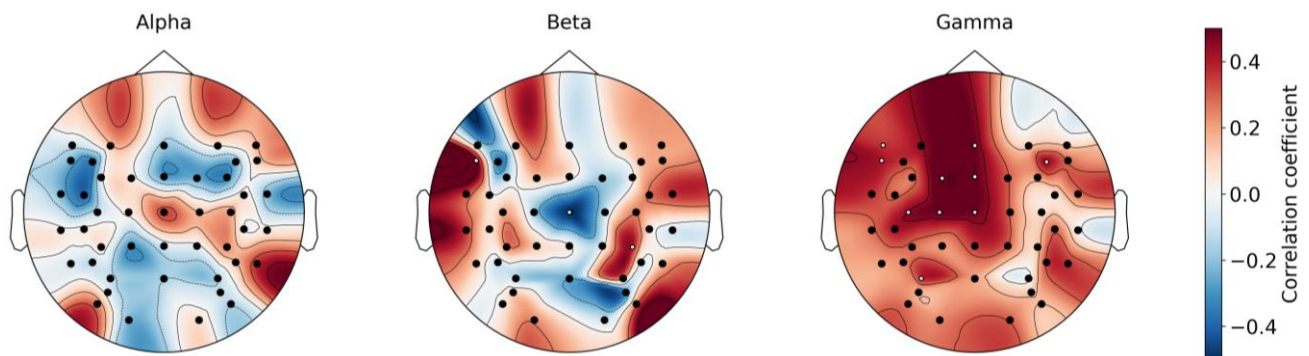

Figure 3. Topo plots of the correlation coefficients between mutual information values of the frequency bands of interest and classification accuracy. Significant correlation coefficients are marked in white.

was found to significantly predict classification accuracy. The auditory imagination component, which might be captured by the inner speech, but not by the motor imagery vividness assessment, may be the reason for this. Although promising, the presented findings are preliminary. Further studies are needed to gain an in-depth understanding about the role of naturalistic inner speech habits in speech imagery based classification performance, respectively, BCI-illiteracy.

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