

Circadian alignment modulates mental tasks BCI performance

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ABSTRACT: Active brain–computer interfaces (aBCIs) exhibit substantial performance variability both across and within participants. While many sources of variability have been investigated, circadian influences remain largely unexplored in aBCI control. We investigated whether time of day and chronotype (individual’s circadian preference for sleep and activity timing across the day) jointly modulate BCI performance (classification accuracy). Twelve participants completed 6 EEG-based BCI sessions each alternating between morning and afternoon sessions, performing 3 mental tasks (motor imagery, mental calculation, letter/word association). Online performance was analyzed using generalized linear mixed models with binomial distribution and random intercepts for participants and sessions. Overall performance was above chance level, with a significant decrease across runs but no linear trend across sessions. A significant interaction between time of day and chronotype was observed: morning-type participants tended to perform better in the morning, whereas evening-type participants showed relatively higher performance in the afternoon, consistent with the circadian alignment.

INTRODUCTION

Active brain–computer interfaces (aBCIs) allow users to voluntarily modulate their brain activity to control external devices, often via electroencephalography (EEG) [1]. While highly promising for assistive and rehabilitation applications, BCIs are still limited by substantial performance variability [2], both across users and within the same user across sessions [3]. The current literature suggests that performance variability arises from multiple interacting sources [4], including experimental settings such as task design, feedback modality, electrode montage or environmental context [5, 6], as well as stable individual characteristics such as cognitive abilities [7], motor imagery capacity, personality traits, and structural brain properties [8]. Physiological artifacts [9], or psychological states (fatigue, attention, motivation) [10] and intrinsic neurophysiological dynamics [11] (e.g., spontaneous oscillatory power and connectivity fluctuations) further contribute to performance variability over time. Despite this growing understanding of performance vari-

ability, one potentially important factor has received little attention in active BCI research: circadian modulation [12]. Human cognition is regulated by the interaction between homeostatic sleep pressure, which increases with time spent awake, and endogenous circadian processes that follow a near 24-hour rhythm [13]. Together, these mechanisms create daily fluctuations in alertness, attention, inhibition, and working memory. As a result, cognitive performance is not stable from morning to evening. Importantly, these daily changes do not affect all individuals in the same way. The chronotype reflects an individual’s preferred timing of activity and alertness, with some people functioning optimally in the morning and others later in the day [14, 15]. When task timing aligns with chronotype, performance tends to improve and this alignment is known as the synchrony effect [16]. A recent systematic review by Chauhan et al., highlights that this synchrony effect is frequently observed in cognitive tasks involving attention and executive control in healthy adults, and appears to be even more pronounced in older populations, with up to 83% of studies reporting such an effect [17, 18]. Other experimental studies also showed neurophysiological correlates of this effect, indicating that time-of-day and chronotype are associated with measurable changes in EEG oscillatory activity and ERP dynamics [19, 20]. Salehinejad et al.[21] further reported that cortical excitability and neuroplasticity show circadian modulation depending on chronotype, and that performance in several cognitive domains, including motor learning, working memory, and attention, tends to be optimal when tasks are performed at an individual’s preferred time of day.

These findings are highly relevant for active BCI control which requires sustained attention, mental engagement, and reliable modulation of sensorimotor rhythms [22]. All these processes are sensitive to the ongoing brain state and inherently variable throughout the day, leading to a fluctuation of BCI performance accordingly. Despite this theoretical coherence, circadian factors remain largely unexplored in active BCI studies. Most BCI experiments are conducted at a single, often unspecified, time of day without considering chronotype and time-of-day alignment. One of the few study addressing this question is Aricò et al. (2012), who reported preliminary

evidence that chronotype may modulate P300-BCI performance depending on time of day [23].

Given the gap identified in the current literature, and the limited investigation of circadian influences in active BCI research, the present study investigates whether time of day and chronotype modulate active BCI performance. We designed a repeated-measures protocol in which participants completed both morning (AM) and afternoon (PM) sessions on different days. Chronotype was assessed using the reduced French version of the Morningness–Eveningness Questionnaire (MEQ) [14, 24], and the wake up hour was self reported before each session. BCI performance resulted of the classification accuracy of three different mental tasks. These results were analyzed using generalized linear mixed models to account for the hierarchical and repeated-measures structure of the data. We hypothesized that BCI performance would not depend only on time of day, but on its interaction with chronotype, reflecting a synchrony effect in active BCI control. The remainder of this paper presents the experimental protocol, the statistical modeling approach, results, and implications of circadian influence as a potential factor of variability in active BCI performance.

MATERIALS AND METHODS

Participants:

This paper reports the results obtain from twelve (12) participants who completed the full BCI experiment protocol, (5 women / 7 men; age 19-44, $M = 29.2$, $SD = 7.4$). They were required to be between 18 and 60 years old, have normal or corrected vision, and report no history of neurological or psychiatric conditions. No authority relationship existed between the experimenters and the volunteers. All procedures followed the relevant ethical research guidelines set out in the Declaration of Helsinki [25]. Each participant signed a consent form confirming their agreement to participate and to allow the use of their EEG recordings and behavioral data. The research protocol received approval from the Inria ethics committee, the COERLE (Approval number: 2023-13).

EEG data acquisition:

Participants were seated comfortably in front of a computer screen during the experiment. Brain signal activity was recorded using 41 active scalp electrodes positioned according to the international 10–10 system (AF3, AF4, F5, F3, F1, Fz, F2, F4, F6, FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, TP7, CP5, CP3, CP1, CPz, CP2, CP4, CP6, TP8, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8). Signals were referenced to the left mastoid, while the ground electrode was placed at the FPz location. Electromyographic (EMG) activity was recorded with 2 active electrodes from both hands (EMGr and EMGI) and electrooculography (EOG) signals was recorded with four active electrodes: two placed above the eyes (FP1 and FP2) and two located below and lateral to the left eye (EOG2 and EOG3). All signals were acquired using an actiCHamp amplifier sys-

tem (Brain Products GmbH, Gilching, Germany) with a sampling rate of 500 Hz. Online signal processing and experimental control were implemented using the open-source BCI software OpenViBE 3.6.0 [26]. The vast majority of electrodes had an impedance below 20k Ω , with a few more difficult electrodes occasionally reaching higher impedances. Throughout each run, the experimenters continuously monitored the EEG signals to ensure stable acquisition quality at all time.

Experimental design:

Each participant completed six experimental sessions conducted on different days in the same room. Sessions alternated between morning (AM) and afternoon (PM) in a counterbalanced order to investigate potential circadian influences on BCI performance. Morning sessions were conducted between approximately 9:30 and 12:10 (mean = 10:48, $SD = 1.33$ h), corresponding to the start of BCI data acquisition following approximately one hour of preparation (equipment setup, instructions, and baseline recordings). Afternoon sessions began between approximately 13:10 and 15:40 (mean = 14:24, $SD = 1.24$ h). Chronotype was assessed prior to the experiment using the reduced French version of the Morningness–Eveningness Questionnaire (MEQ) [14, 24]. Before each session, participants reported their wake-up time. This information was used to compute the duration between wake-up and the start of the BCI acquisition (Time Awake). This variable was treated as a self-reported proxy of time since awakening, providing an indirect estimate of the homeostatic sleep pressure component, which has been shown to influence EEG activity and cognitive performance [13]. Each session included six runs counterbalanced between two experimental contexts. The first corresponded to the A) Classical Graz paradigm, a low-stimulation visual interface [27]. The second environment was a gamified interface, B) Brain-Hero, developed within our research group, enriched with visual elements and background auditory noise designed to approximate real-world conditions. These two contrasted interfaces allowed us to experimentally manipulate the environmental context and assess its potential influence on BCI performance.

The session began with the acquisition phase, with 2 acquisition runs with sham feedback. These 2 runs were used to compute three-band Common Spatial Pattern (CSP) (in theta, alpha, beta bands) and then classified using Linear Discriminant Analysis (LDA) before online control. The training phase then followed and participants performed 4 online runs with real-time feedback: two runs in the Graz interface and two with Brain Hero interface in counterbalanced order across sessions. Within each context, participants performed three mental tasks: (i) kinesthetic motor imagery: Imagination of performing specific non dominant hand movements (e.g., clenching your fist) while focusing on all the sensations associated with the real movement. (ii) mental calculation: mental subtraction tasks of a given subtraction and (iii) letter/word association: generating as many

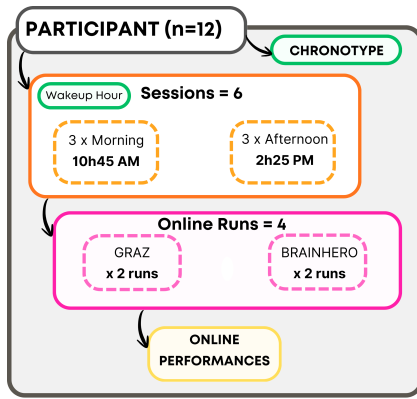


Figure 1: Experimental protocol of the BCI experiment.

words as possible starting with a given letter. Each run consisted of 30 trials (10 per class). Each trial began with a visual cue displayed for 3 s that indicated the required mental task, and participants were instructed to perform the task continuously during the 5-s feedback period. However, due to a technical issue, for some sessions, classifier training was performed using data from the Graz run only. Consequently, contextual differences in this subset may partly reflect calibration constraints rather than purely interface-related effects. Importantly, participants still performed runs in both contexts during the experiment, only the classifier calibration relied exclusively on the Graz data for some sessions.

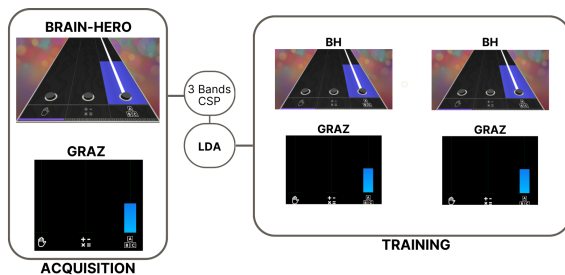


Figure 2: Overview of the acquisition and training procedure. During the acquisition phase, participants performed runs in both contexts (BrainHero and Graz), with sham feedback. EEG data from the acquisition runs were used to compute spatial filters using a three-band CSP and then classified using LDA. For a subset of sessions, classifier training relied on data from the Graz run only but then applied online in both contexts during the training phase with real feedback.

BCI pipeline and performance metric:

The classification model was trained separately for each participant and session using data from both BrainHero and Graz acquisition runs. As mentioned above, in some sessions the model was trained using only the Graz run. First, 39 EEG channels were selected, excluding TP7 and TP8 from the available EEG channel pool. No artifact removal was applied. A fifth-order Butterworth band-pass filter was applied in the forward direction to obtain data in three frequency bands (theta: 4–8 Hz, alpha: 8–12 Hz, and beta: 12–30 Hz). The following processing steps were applied independently to each frequency band.

EEG signals for each task were segmented into epochs. For model training, epochs from 0.5–9.5 s after the onset of the visual cue of each task were extracted. In contrast, for the online experiment, data from 3.0–8.0 s after the visual cue onset (i.e., feedback presentation period) were used.

Next, regularized CSP filters [28] (shrinkage coefficient: 1×10^{-6} , without Tikhonov regularization and with trace normalization) were trained. Since a three-class classification was performed, CSP was trained and applied using a one-vs-all approach, with two filters (one pair) per class. The CSP components of each epoch were then segmented into sub-epochs using a sliding window with a length of 1 s and a step size of $1/16$ s. The data of each sub-epoch were transformed into mean log-power values. Next, the data from the three frequency bands were concatenated for each sub-epoch and used as feature vectors for shrinkage-regularized Linear Discriminant Analysis (LDA) training and classification. These resulted in 18 features per sub-epoch (2 spatial filters, for each of the 3 classes and each of the 3 frequency bands). LDA was trained and applied using the one-vs-all approach. The class of each trial was estimated as follows. For each sub-epoch $n \in \{1, \dots, N\}$, let $a_{n,k}$ denote the probability output of the LDA classifier for class k vs. all. Then, $p_{n,k} = (a_{n,k}) / \sum_{k=1}^N a_{n,k}$ was defined. Using the $p_{n,k}$ obtained from the 128 sub-epochs, the class label of each trial was estimated as $y = \operatorname{argmax}_k \sum_{n=1}^N p_{n,k}$. Trial-wise classification accuracy was the used performance metric.

Statistical modeling:

Statistical analyses aimed to identify the factors associated with variability in online BCI performance, while accounting for the hierarchical and repeated structure of the data. In particular, the analyses tested whether temporal factors (run and session progression, time of day), and participants characteristics (chronotype) were associated with changes in online BCI performance. They were conducted in R (version 4.5.2) implemented in the lme4 package (R). Online BCI performance was modeled using generalized linear mixed models (GLMMs) with a binomial distribution and logit link, appropriate for modeling the number of correct classifications out of a fixed number of trials [29, 30].

The dependent variable, Online BCI performance, was defined as the number of correctly classified trials out of the total number of trials per run (30 trials), modeled as a binomial outcome. The fixed-effects structure included experimental factors defined by the protocol. These included experimental context (BrainHero vs. Graz), run index (within-session progression), session index (between-session progression), Time Awake (TimeAwake: time between waking up and the start of BCI acquisition, within-subject centered), and the interaction between time of day (AM vs. PM) and chronotype (MEQ score, standardized), to test the synchrony effect.

Random-effects structures were selected using a hierarchical model-comparison approach based on likelihood-ratio tests (LRTs) and Akaike Information Criterion

(AIC) [29, 30]. The baseline model (Table 1: P0), specified in R as $(1|SUBJECT) + (1|SUBJECT : SESSION)$, included random intercepts for participants and sessions nested within participants to account for the repeated-measures structure of the protocol. Because the study specifically aimed to investigate potential intra-user variability in performance dynamics across runs, a theoretically motivated model including a random slope for run at the participant-session level was additionally tested (Table 1: Prunin). This model assessed whether the effect of run progression varied across sessions within participants. However, it did not significantly improve model fit relative to the baseline model. Additional random slopes for run progression and session progression at the participant level were also explored (Table 1: Prun and Psess, respectively), but neither structure provided a significant improvement in model fit.

Table 1: Comparison of candidate random-effects structures for the GLMM analyses.

Model	AIC	logLik	LRT (χ^2 , p)	Decision
P0	1520.6	-750.31	—	Retained
Prunin	1521.1	-748.57	3.47, $p = 0.18$	Rejected
Psess	1521.5	-749.73	1.15, $p = 0.28$	Rejected
Prun	1522.6	-750.31	0.00, $p = 1$	Rejected

Model adequacy was evaluated using simulation-based residual diagnostics (DHARMA package) and confirmed adequate fit. Multicollinearity among fixed effects was assessed using variance inflation factors (VIFs), all point estimates were below 2.1, indicating no meaningful collinearity. Profile likelihood confidence intervals were computed for fixed effects.

RESULTS

The final model retained random intercepts for participants and sessions nested within participants (Table 1: P0), capturing both inter-user variability in BCI performance and session-to-session variability within participant while providing a parsimonious representation of the hierarchical structure of the data [29]. Overall the average BCI performance from 12 participants across session is above chance level 46.67% at $p < 0.001$ (see Fig. 3). The global median performance reached 66.7% indicating that most participants achieved reasonable control of the system. Because classifier training was partially performed on Graz's run only for a subset of sessions (see: Experimental design), the context was not interpreted as a main outcome variable, but retained in the statistical model as a fixed effect to control for structured sources of variance [29].

Fixed-effect estimates are reported as log-odds coefficients (β), together with odds ratios (OR) and their 95% confidence intervals (Table 2). OR values above 1 indicate increased odds of correct BCI classification, whereas OR values below 1 indicate decreased odds of success.

Table 2: Fixed effects estimates from the GLMM predicting BCI performance. Regression coefficients (β) are reported on the log-odds scale, with corresponding odds ratios (OR) and 95% confidence intervals. Significant effects (95% CI not including 1 and $p < .05$) are highlighted in bold. Positive and negative coefficients indicate increased or decreased odds of success respectively.

Predictor	β	OR	95% CI (OR)	p
Context (Graz)	0.246	1.28	[1.17, 1.40]	<.001
run	-0.062	0.94	[0.90, 0.98]	.004
session	0.040	1.04	[0.99, 1.10]	.144
TimeAwake (z)	-0.094	0.91	[0.80, 1.04]	.162
TIME (PM)	0.130	1.14	[0.87, 1.48]	.338
MEQ (z)	0.121	1.13	[0.84, 1.51]	.416
TIME (PM) $\times$ MEQ(z)	-0.283	0.75	[0.63, 0.91]	.003

Within-session progression showed a significant negative linear effect of run (OR = 0.94, 95% CI [0.90, 0.98], $p = .004$; Table 2), reflecting a progressive decrease in BCI performance across successive runs within a session (see Fig. 3).

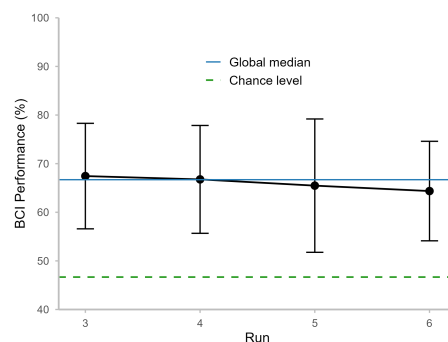


Figure 3: Mean BCI performance for each of the 4 runs in all BCI sessions across the 12 participants. The blue line correspond to the global median (66.7%), and the green one is the chance level (46.67% at $p < 0.001$)

In contrast, no significant linear effect of session was observed (OR = 1.04, 95% CI [0.99, 1.10], $p = .144$). To isolate within-participant variability across sessions, Time awake was centered within each participant and standardized before inclusion in the model. The main effect of time awake was not statistically significant (OR = 0.91, 95% CI [0.80, 1.04], $p = .162$). Neither the main effect of Time of day (PM vs AM) (OR = 1.14, 95% CI [0.87, 1.48], $p = .338$) nor chronotype (MEQ) (OR = 1.13, 95% CI [0.84, 1.51], $p = .416$) reached statistical significance. However, a significant Time $\times$ MEQ interaction was observed (OR = 0.75, 95% CI [0.63, 0.91], $p = .003$).

To facilitate interpretation of this interaction in the GLMM, predicted probabilities were computed on the response scale and visualized across a continuous range of chronotype values (see Fig. 4). This significant interaction indicates that the effect of time of day modulates BCI performance depending on individual chronotype. Specifically, the difference between PM and AM performance becomes increasingly negative as MEQ scores increase. For participants with higher MEQ scores (oriented morning-type), performance tended to be lower in the afternoon compared to the morning. In contrast, par-

ticipants with lower MEQ scores (oriented evening-type) showed relatively higher performance in the afternoon compared to the morning.

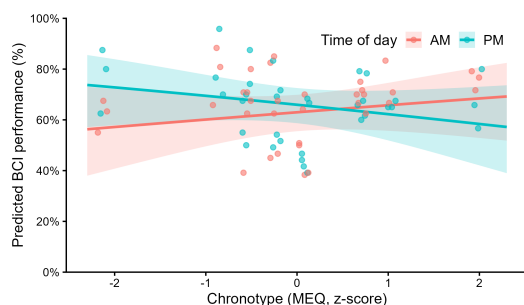


Figure 4: Predicted probability of BCI performance as a function of chronotype (MEQ, z-score) and time of day (AM vs PM), derived from the glmm. Lines represent predicted probabilities (fixed effects only), and shaded areas indicate 95% confidence intervals. The crossing of the AM and PM curves reflects the interaction between chronotype and time of day.

DISCUSSION

The present study investigated whether time of day and chronotype contribute to participant variability in aBCI performance. Using a repeated-measures design with alternating morning and afternoon sessions, we observed that average BCI performance was reliably above chance across participants and sessions, confirming that participants were able to achieve effective BCI control. In line with [31], combining mental tasks considered by the authors as "brain teaser" such as mental calculation or word association with more "dynamic imagery tasks" such as motor imagery, could yield higher feature discriminability. Moreover, in a three-class BCI protocol, the probability that at least one pair of tasks produces separable EEG patterns increases, which may partly explain the above, chance performance observed here for all users.

We observed a small linear decrease in performance across runs within sessions, while no clear linear trend emerged across sessions on different days. The within session decline is compatible with accumulating mental fatigue due to the repeated mental tasks, reduced engagement, and is in line with [32], who reported a within-session decrease in motor imagery EEG separability associated with increasing mental fatigue. The absence of a linear improvement across sessions in this preliminary sample could be explained by the classifier training procedures. The classifier was recalibrated at each session, possibly interfering with a potential learning effect across days. Consequently, the lack of a significant session effect should not necessarily be interpreted as the absence of learning, but rather as a limitation inherent to session-dependent classifier training [33].

The main finding is a significant interaction between time of day and chronotype, whereas neither of them individually showed a robust main effect. More morning-type participants tended to perform better in the morning than

in the afternoon, and more evening-type tended to perform better in the afternoon. This result is consistent with the "synchrony effect" described in cognitive psychology, whereby cognitive performance peaks when tasks are performed at an individual's circadian preferred time of day [13, 16]. Here, the predicted probability curves for AM and PM performance cross at intermediate MEQ scores, which is the characteristic signature of this effect and confirms that time-of-day modulation is not uniform across participants but depends on their chronotype. Our findings extend this effect to aBCI, suggesting that BCI control may be optimized when experimental timing is aligned with a participant's chronotype. The potential benefit of scheduling BCI sessions according to participant chronotype, may be particularly relevant for older adults [18] or in clinical populations where reliable control is critical.

Several limitations should be noted. The current results rely on a small sample ($n = 12$ participants, six sessions each), which limits power and generalizability, despite the repeated-measures design. Larger samples are needed to robustly confirm these effects and test interactions with other psychological or physiological factors. Second, while the reduced version of the MEQ questionnaire is validated and widely used, it reflects subjective behavioral preference rather than a precise marker of biological circadian timing [14, 24]. Additional sleep-related factors, including sleep quality and sleep debt, may also influence performance variability alongside circadian effects. Future studies should therefore implement better control of sleep-wake history. Finally, with the rich database collected here, further analyses could integrate multimodal physiological markers (e.g., ocular activity, heart rate variability) [34], which may provide complementary insights into performance variability and user experience [35]. Additional neurophysiological analyses could also explore how oscillatory activity varies with time of day and chronotype.

CONCLUSION

Our results suggest that circadian alignment between session's timing and individual chronotype contributes to intra participant variability in active BCI performance. Neither time of day nor chronotype alone are a robust main effect. Instead, their interaction, consistent with the synchrony effect, appeared to be the main factor associated with performance variability across sessions. These findings highlight the importance of considering chronotype in the design of BCI experiments, alongside factors that are more commonly controlled such as alertness, engagement or motivation. Taking chronotype in to account may offer a yet underexplored factor to improve user-centered BCI design and adaptive strategies. This consideration is particularly relevant in clinical contexts, where the reliability of BCI control at each session is essential.

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