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Prefrontal Efficiency during Emotion–Cognition Interaction in Professional and Amateur Boxers

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Research Article

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Abstract

Boxing requires athletes to regulate emotions and maintain cognitive control under highly demanding competitive conditions. However, it remains unclear whether professional and amateur boxers differ in prefrontal neural efficiency during emotion-cognition interaction. This study compared inhibitory-control performance and prefrontal activation patterns between professional and amateur boxers and examined the association between neural efficiency and training experience. Twenty-seven professional and 25 amateur male boxers completed an emotional Go/NoGo task. Functional near-infrared spectroscopy (fNIRS) was used to assess oxygenated hemoglobin (Oxy-Hb) changes in prefrontal cortical regions. Behavioral measures included No-go accuracy and Go reaction time. A neural efficiency index (NEI), calculated as behavioral performance divided by neural activation, was used as an exploratory measure of neural efficiency. Professional boxers demonstrated stable No-go accuracy across task conditions, whereas amateur boxers showed a non-significant trend toward condition-related differences in accuracy ($p = 0.066$). During the happy condition, professional boxers exhibited significantly lower Oxy-Hb activation than amateur boxers in dorsolateral prefrontal cortex channels CH6, CH15, and CH20 ($p < 0.05$). No-go accuracy was comparable between groups, whereas professional boxers showed significantly longer Go reaction times. Professional boxers also demonstrated significantly higher NEI values ($p = 0.011$), and NEI was positively associated with years of training experience ($r = 0.48$, $p = 0.003$). The combination of comparable inhibitory accuracy, longer Go reaction times, and lower prefrontal activation among professional boxers is consistent with differences in neural resource recruitment during emotionally relevant inhibitory-control processing. Professional boxing expertise was associated with differences in inhibitory control and prefrontal activation during emotion-cognition interaction. These findings contribute to understanding the relationship between athletic expertise and neurocognitive functioning and provide a foundation for future longitudinal research in combat-sport athletes.

Introduction

The relationship between emotion and cognition has been debated for decades. Early views treated emotion as a source of interference, suggesting that emotional stimuli consume limited attentional resources and hurt task performance. However, the rise of emotion-cognition interaction theory over the past twenty years has fundamentally changed this view. The core idea is that emotion and cognition are not separate systems but interact dynamically across multiple stages of information processing, from early perception to later response selection [1, 2]. At the neural level, the prefrontal cortex and limbic structures form a major hub of this interaction. The amygdala detects emotionally significant or threatening stimuli and interacts with prefrontal regions through reciprocal functional pathways, whereas prefrontal regions support top-down control and emotion regulation [3, 4, 5]. The balance between bottom-up emotional processing and top-down executive regulation is therefore considered a key neurocognitive mechanism underlying adaptive behavior in emotionally demanding situations.

The emotional Go/NoGo paradigm is widely used to study this interaction. By embedding emotional faces into a standard Go/NoGo task, researchers can manipulate both emotion processing and cognitive control load at the same time. Participants need to quickly identify the emotional content of stimuli while deciding whether to respond or withhold a response. This dual demand mimics real-life situations where emotion and cognition compete and interact. fNIRS and behavioral studies have shown that emotional stimuli, especially negative ones, can change performance in Go/NoGo tasks and alter prefrontal activation or connectivity patterns [6, 7]. Cognitive control in athletes should also be considered within hierarchical models of response selection and inhibitory control. Executive control is not limited to the suppression of an inappropriate motor response; rather, it involves the dynamic coordination of attentional selection, response preparation, inhibition, and adjustment of response criteria according to task demands. In situations requiring rapid decisions, individuals must continuously balance response speed against the probability and cost of errors. Consequently, similar behavioral accuracy can be achieved through different control strategies, including differences in response threshold and the allocation of neural resources. This consideration is particularly relevant to elite athletes, whose sporting environments repeatedly require rapid responses while maintaining precise motor control. Empirical research has reported differences in inhibitory control and executive-function-related brain activation among athletes, although the magnitude and consistency of these expertise-related advantages vary across sports and cognitive domains. For example, research in elite soccer players has demonstrated experience-dependent differences in brain connectivity, while recent neuroimaging work in elite closed-skill athletes has reported altered functional recruitment during working-memory and action-inhibition tasks [39, 41]. These findings suggest that sport expertise may involve not simply greater activation or faster responses, but more task-adaptive regulation of cognitive-control resources. Accordingly, differences in prefrontal activation between professional and amateur athletes should be interpreted alongside behavioral measures of response speed and inhibitory accuracy.

The speed–accuracy trade-off provides an additional framework for interpreting neurocognitive differences between athletes with different levels of expertise. Faster responses are not necessarily indicative of superior cognitive control when increased response speed is accompanied by a greater likelihood of errors, whereas slower responses may reflect a more conservative response criterion. Recent work involving elite athletes has emphasized the importance of considering speed–accuracy trade-offs when interpreting differences in executive-function performance, because apparent expertise-related advantages can be attenuated when response speed and accuracy are considered jointly [40]. Within the present emotional Go/NoGo paradigm, this framework is particularly relevant because Go reaction time reflects response speed whereas No-go accuracy reflects successful inhibition. Examining both measures therefore provides a more complete characterization of cognitive-control performance than either measure alone.

The neural efficiency hypothesis offers a useful framework for understanding individual differences in this relationship. Originally developed in intelligence research, it was based on the finding that high-intelligence individuals can show lower cortical metabolic activity than low-intelligence individuals when performing tasks of comparable difficulty, especially in frontal regions [8, 9]. The key insight is that lower

neural activation with comparable behavioral performance reflects higher efficiency. This hypothesis was later extended to sport cognition. Long-term athletes can show lower cortical activation than non-athletes when performing motor decision-making or perceptual discrimination tasks. For example, Di Russo and colleagues found that top-level fencers showed expert-related neural signatures during rapid stimulus discrimination and response selection, and recent systematic reviews have summarized broader evidence for neural efficiency in athletes [10, 11, 12]. Intensive training seems to optimize cognitive neural networks, improving coordination and reducing unnecessary energy use. These findings suggest that prolonged sport-specific training may be associated with adaptations in cognitive-neural processing that allow task demands to be managed with fewer neural resources. However, most existing sport cognition studies used neutral stimuli, leaving an important question unanswered: Do athletes still show neural efficiency advantages under emotional interference? If the efficiency advantage only holds for neutral tasks but disappears under emotional load, its theoretical and practical value would be limited. This gap is particularly important because emotional Go/NoGo research indicates that prefrontal responses are sensitive to emotional valence and inhibitory demands [6, 7]. To date, relatively few studies have examined whether sport-related neural efficiency is maintained under emotion-cognition interaction conditions, and evidence from combat sports remains especially limited.

Boxing offers a unique context for examining this question for three reasons. First, it involves face-to-face antagonism, high emotional load, and constant exposure to threat and pressure. Boxers must deal not only with opponents' movements but also with the risk of being hit, and studies of boxers emphasize the relevance of mood regulation and cognitive function under demanding sport contexts [13, 14]. This competitive context naturally brings strong emotional arousal, including tension, anger, excitement, and heightened sensitivity to threat. Second, boxing demands rapid decision-making under extreme time pressure. Fights are often decided within milliseconds. Boxers need to extract opponent cues, choose attack or defense strategies, and inhibit inappropriate actions in very short time windows. This process relies heavily on attention, inhibition, and conflict resolution, which are cognitive factors related to sport performance more broadly [15], and combat-sport reviews show expert advantages in perceptual anticipation and perceptual-cognitive skills [16, 17]. Third, despite its potential value, cognitive neuroscience research on boxing is still limited and rarely focuses on emotion-cognition interaction or prefrontal efficiency. Most existing studies have focused on perceptual speed or simple reaction tasks. Importantly, no study, to our knowledge, has directly compared professional and amateur boxers with respect to prefrontal neural efficiency during an emotional inhibitory-control task using fNIRS. Addressing this gap may contribute to a better understanding of how athletic expertise is associated with neurocognitive functioning under emotionally demanding conditions.

Based on this reasoning, we proposed three hypotheses. First, professional boxers show stable inhibitory control across happy and angry conditions, while amateurs show emotion-dependent differences. Second, despite differences in response speed, professionals show lower prefrontal Oxy-Hb activation while maintaining comparable inhibitory-control accuracy, particularly in the dorsolateral prefrontal cortex. Third, professionals show a higher neural efficiency index than amateurs, and this index correlates positively with years of training.

Material and methods

Study Design

A 2 × 2 mixed design was used, with group (professional vs. amateur) as a between-subjects factor and emotion (happy vs. angry) as a within-subjects factor. Dependent variables included No-go accuracy, Go reaction time, Oxy-Hb β values, and the neural efficiency index.

The study was designed to examine differences in behavioral inhibitory control and prefrontal activation patterns between groups across emotionally salient task conditions. Given the cross-sectional nature of the design, the findings should be interpreted as associations between expertise level and neurocognitive performance rather than evidence of causal training effects.

Clinical trial number: not applicable.

Participants and Ethical Approval

Fifty-two male right-handed participants aged 18–25 years were recruited from universities and sports teams in Shaanxi Province, China. All participants had normal or corrected-to-normal vision, no color blindness, no history of neurological or severe medical conditions, no substance dependence, and no prior participation in similar experiments.

The participants comprised 27 professional boxers and 25 amateur boxers. Professional boxers (n = 27) were active athletes with at least two years of competitive experience, participation in at least two city-level competitions, approximately 20 weekly training hours (two sessions per day, including at least two sparring sessions per week), and plans to compete within three months. Amateur boxers (n = 25) were active college boxers with at least two years of competitive experience, approximately 12 weekly training hours, and plans to compete within three months. In addition to differences in training volume, the professional group represented athletes regularly engaged in structured competitive programs, whereas the amateur group consisted primarily of university-level competitors. Years of training experience and weekly training volume were subsequently included as descriptive indicators of expertise level.

Exclusion criteria included skull fractures, severe systemic or neuropsychiatric disorders, history of craniotomy, use of antipsychotic medication or alcohol abuse, uncorrected visual impairment, and head trauma within the past month. All participants completed the Pittsburgh Sleep Quality Index and the CES-D depression scale before the experiment, both of which are widely used self-report measures of sleep quality and depressive symptoms [37, 38]. Participants with PSQI > 5 or CES-D ≥ 16 were excluded. The two groups did not differ significantly in age, PSQI scores, or CES-D scores ($p > 0.05$).

The reported sample of 52 participants refers to the recruited sample and the sample used for all behavioral analyses. Three participants were subsequently excluded from the fNIRS analyses because their recordings contained excessive motion artifacts. One excluded participant was from the amateur

group and two were from the professional group. Their behavioral data were retained; therefore, the behavioral analyses included all 52 participants (25 amateurs and 27 professionals), whereas the final fNIRS analyses included 49 participants (24 amateurs and 25 professionals).

An a priori sample-size estimation was conducted using G*Power for mixed-design analyses (α = .05, power = .80, medium effect size f = .25), indicating that the achieved recruited sample size was sufficient to detect medium-sized effects.

Written informed consent was obtained from all participants, and they were informed that they could withdraw from the study at any time. The study protocol was approved by the relevant ethics committee of Mahasarakham University, Thailand, and was conducted in accordance with the Declaration of Helsinki [19].

Emotional Go/NoGo Task

Facial stimuli were selected from the Chinese Facial Affective Picture System, a locally developed database with good cultural validity and reliability for Chinese facial-emotion research [18]. The stimuli included 40 happy faces (20 male, 20 female), 40 angry faces (20 male, 20 female), and 40 neutral faces (20 male, 20 female), all with moderate-to-strong expressions from the same group of models. All images were presented at a size of 12 cm × 10 cm.

The emotional Go/NoGo task was programmed and presented using E-Prime on a laptop computer (1920 × 1080, 60 Hz). Each trial began with a 500-ms fixation cross, followed by a 1000-ms facial stimulus. Participants were instructed to press the spacebar as quickly and accurately as possible when a Go stimulus was presented and to withhold their response when a No-go stimulus was presented. The response window remained open until the participant responded. A 1500-ms blank screen followed each trial.

The task consisted of two blocks of 90 trials each. Each block contained 68 Go trials and 22 No-go trials, corresponding to an approximately 3:1 Go-to-No-go ratio. In Block 1, happy faces served as Go stimuli and angry faces served as No-go stimuli. In Block 2, neutral faces served as Go stimuli and happy faces served as No-go stimuli. The block order was fixed across all participants, with Block 1 always presented before Block 2.

Participants did not complete a separate practice block before the experimental task. The experimental stimuli were presented in a pseudorandom order to reduce repetition effects. A 60-second rest period was provided between the two blocks. The entire task, including instructions, took approximately 15 minutes.

It should be noted that emotional valence and response mapping were manipulated simultaneously within the task structure. Therefore, comparisons between emotional conditions should be interpreted primarily as differences between task conditions containing distinct emotional-response associations

rather than as pure effects of emotional valence alone. This consideration is discussed further in the limitations section.

fNIRS Data Acquisition and Processing

A NIRSport system recorded prefrontal activity. fNIRS is a non-invasive neuroimaging method well suited for cognitive and sport-related settings because it records cortical hemodynamic changes with relatively high ecological flexibility [20; 21]. The system had 83 channels covering the dorsolateral prefrontal cortex, ventrolateral prefrontal cortex, and orbitofrontal cortex. The sampling rate was 7.81 Hz with dual wavelengths of 760 nm and 850 nm, which are commonly used to estimate hemoglobin concentration changes using near-infrared optical pathlength principles [22].

Channel locations were based on the international 10–20 EEG system. The DLPFC, which handles executive control and conflict resolution, included channels CH6, CH15, CH20, and CH35 [31]. The VLPFC, involved in response inhibition and emotion regulation, included channels CH23, CH27, and CH28. The OFC, responsible for emotional valuation and reward processing, included channels CH75, CH76, CH77, CH82, and CH83 [23].

Preprocessing was done using NIRS_KIT software, a MATLAB toolbox designed for resting-state and task fNIRS analysis [24]. Steps included band-pass filtering (0.01–0.2 Hz), discrete wavelet transform for motion artifact removal [25], baseline correction using a 30-second resting period before each block, and general linear model analysis. A hemodynamic response function was used to model the expected delay in neural activity, consistent with common GLM-based fNIRS analysis practice [26, 21]. Three participants were excluded from the fNIRS analyses because their fNIRS recordings contained excessive motion artifacts. One excluded participant was from the amateur group and two were from the professional group. Their behavioral data were retained for the behavioral analyses. Therefore, the behavioral analyses included all 52 participants (25 amateurs and 27 professionals), whereas the fNIRS analyses were conducted on the remaining 49 participants (24 amateurs and 25 professionals).

Neural Efficiency Index Calculation

Previous fNIRS research has operationalized neural efficiency by combining behavioral performance with task-related prefrontal activation, with greater performance achieved with lower cortical recruitment interpreted as greater efficiency [42]. In the present study, an exploratory neural efficiency index (NEI) was calculated as No-go accuracy under the happy condition divided by the mean Oxy-Hb β value of CH6, CH15, and CH20 under the same condition. These channels were selected because they showed significant between-group differences in the primary fNIRS analysis. Therefore, the present NEI should be regarded as an exploratory, study-specific composite measure rather than an independently validated measure of neural efficiency. Because the channel selection and subsequent NEI comparison were based on the same dataset, the possibility of circularity or selection bias cannot be excluded. Future

studies should define regions of interest independently, preferably a priori or using an independent dataset, before calculating and testing the NEI.

Use of Large Language Models (LLMs)

AI tool (Chatgpt 5.5) has been used in this manuscript for the purpose of translating, arranging content and structure, grammar corrections.

Statistical Analysis

Statistical analyses were conducted using IBM SPSS Statistics 26.0. Data normality was assessed using the Shapiro-Wilk test [27]. Independent-samples t-tests or Mann-Whitney U tests were used for between-group comparisons, whereas paired-samples t-tests or Wilcoxon signed-rank tests were used for within-group comparisons where appropriate.

For the fNIRS analyses, the final analytical sample consisted of 49 participants (24 amateurs and 25 professionals) after exclusion of three participants with excessive motion artifacts. For fNIRS data, the primary analyses consisted of 2 × 2 mixed ANOVAs examining the effects of Group, Emotion Condition, and their interaction on Oxy-Hb activation. Significant effects were followed by post hoc comparisons. To control for multiple testing across channels, false discovery rate (FDR) correction was applied (83 channels, $q < .05$) [28].

To determine whether between-group differences in prefrontal Oxy-Hb activation remained after accounting for differences in response speed, additional analyses of covariance (ANCOVAs) were conducted. Group (professional vs. amateur) was entered as the between-subject factor, mean Go reaction time was entered as a continuous covariate, and Oxy-Hb activation was entered as the dependent variable. The homogeneity-of-regression-slopes assumption was examined by testing the Group × Go reaction time interaction before interpreting the adjusted group effect. Adjusted group effects were reported using F statistics, p values, and partial eta-squared (ηp^2). The fNIRS analyses included 49 participants (24 amateurs and 25 professionals) after exclusion of three participants because of excessive motion artifacts. Because the primary between-group Oxy-Hb differences were observed in DLPFC channels CH6, CH15, and CH20 under the happy condition, the ANCOVA analyses were specifically conducted for these channels.

The significance level was set at $\alpha = .05$ (two-tailed). Effect sizes are reported as Cohen's d [29]. Where appropriate, exact p-values and confidence intervals were additionally reported to facilitate interpretation of effect magnitude and precision.

Software

The emotional Go/NoGo task was programmed and presented using E-Prime 3.0.3.219 (Psychology Software Tools, Inc., Pittsburgh, PA, USA; https://pstnet.com/products/e-prime/). fNIRS data

preprocessing and analysis were performed using NIRS-KIT V3.0, a MATLAB toolbox for resting-state and task-based fNIRS data analysis [24], with MATLAB R2026a (MathWorks, Natick, MA, USA; https://www.mathworks.com/products/matlab.html). Statistical analyses were conducted using IBM SPSS Statistics 26.0 (IBM Corp., Armonk, NY, USA; https://www.ibm.com/products/spss-statistics). A priori sample-size estimation was conducted using G*Power 3.1.9.7 (Heinrich Heine University Düsseldorf, Düsseldorf, Germany; https://www.psychologie.hhu.de/en/research-groups/general-psychology-and-work-psychology/gpower).

Results

Behavioral Results

Demographic and Clinical Characteristics

Table 1 presents the demographic and clinical characteristics of the participants. No significant between-group differences were observed for age, PSQI scores, or CES-D scores (all $p > .05$). Significant differences were observed for years of training and weekly training volume (both $p < .001$), indicating that the groups differed in boxing experience and training exposure.

The absence of significant differences in age, sleep quality, and depressive symptoms suggests that these variables were relatively comparable across groups.

Table 1
Demographic and clinical characteristics (M ± SD)

Variable	Amateur (n = 25)	Professional (n = 27)	Statistic	p
Age (years)	21.36 ± 2.15	22.04 ± 1.98	t = 1.18	0.243
PSQI score	3.72 ± 1.48	3.91 ± 1.62	U = 312.50	0.687
CES-D score	8.44 ± 3.21	9.07 ± 3.56	t = 0.66	0.511
Years of training	3.28 ± 1.15	5.63 ± 1.89	t = 5.28	< 0.001
Weekly training (hours)	11.84 ± 2.13	19.76 ± 3.08	t = 10.67	< 0.001

No-go Accuracy

Table 2 summarizes No-go accuracy across emotional task conditions. No significant between-group differences were observed under either the angry condition or the happy condition (both $p > .05$), indicating comparable levels of task accuracy between groups.

Table 2
No-go accuracy comparison (M ± SD)

Emotion	Amateur (n = 25)	Professional (n = 27)	t	p	d
Angry	0.926 ± 0.103	0.909 ± 0.186	-0.45	0.654	0.12
Happy	0.886 ± 0.134	0.883 ± 0.109	-0.10	0.921	0.03

Within-group analyses showed that amateurs demonstrated higher No-go accuracy during the angry condition than during the happy condition; however, this difference did not reach statistical significance (t = 1.89, p = 0.066, d = 0.38). No significant within-group difference was observed among professionals (t = 0.56, p = 0.581, d = 0.11).

These findings suggest that inhibitory-control performance was generally comparable across groups and conditions, although a non-significant trend toward condition-related variation was observed among amateur boxers.

Go Reaction Time

Table 3 shows no group difference under the angry condition. Under the happy condition, however, amateurs responded significantly faster than professionals (t = 2.85, p = 0.007, d = 0.80). This is a medium-to-large effect.

Table 3
Go reaction time comparison (M ± SD, ms)

Emotion	Amateur (n = 25)	Professional (n = 27)	t	p	d
Angry	498.52 ± 68.34	512.48 ± 85.21	0.63	0.532	0.18
Happy	547.87 ± 72.58	622.31 ± 102.59	2.85	0.007	0.80

The observed group difference under the happy condition was associated with a large effect size (d = 0.80), whereas no evidence of a group difference was observed under the angry condition.

fNIRS Results

The fNIRS analyses were conducted on 49 participants (24 amateurs and 25 professionals) after exclusion of three participants with excessive motion artifacts. The primary analysis used a 2 × 2 mixed analysis of variance (ANOVA), with Group (amateur vs. professional) as the between-subject factor and Emotion Condition (happy vs. angry) as the within-subject factor. The analysis examined the main effects of Group and Emotion Condition and the Group × Emotion Condition interaction for prefrontal Oxy-Hb activation. The complete ANOVA results for the prespecified prefrontal channels are presented in Table 4.

Table 4
Results of the 2 × 2 mixed ANOVA for prefrontal Oxy-Hb activation

Channel	Effect	F	df	p	Partial η²
CH6	Group	6.45	1, 47	.015	.121
	Emotion Condition	0.18	1, 47	.675	.004
	Group × Emotion Condition	4.18	1, 47	.046	.082
CH15	Group	8.88	1, 47	.005	.159
	Emotion Condition	0.31	1, 47	.581	.007
	Group × Emotion Condition	5.02	1, 47	.030	.096
CH20	Group	5.34	1, 47	.025	.102
	Emotion Condition	0.27	1, 47	.606	.006
	Group × Emotion Condition	3.76	1, 47	.058	.074

The 2 × 2 mixed ANOVA indicated a significant main effect of Group for CH6, $F(1,47) = 6.45$, $p = .015$, $\eta p^2 = .121$, CH15, $F(1,47) = 8.88$, $p = .005$, $\eta p^2 = .159$, and CH20, $F(1,47) = 5.34$, $p = .025$, $\eta p^2 = .102$. No significant main effect of Emotion Condition was observed for CH6, $F(1,47) = 0.18$, $p = .675$, $\eta p^2 = .004$, CH15, $F(1,47) = 0.31$, $p = .581$, $\eta p^2 = .007$, or CH20, $F(1,47) = 0.27$, $p = .606$, $\eta p^2 = .006$. The Group × Emotion Condition interaction was significant for CH6, $F(1,47) = 4.18$, $p = .046$, $\eta p^2 = .082$, and CH15, $F(1,47) = 5.02$, $p = .030$, $\eta p^2 = .096$, but not for CH20, $F(1,47) = 3.76$, $p = .058$, $\eta p^2 = .074$. Follow-up between-group comparisons were therefore examined to characterize the condition-specific differences, with FDR correction applied across the 83 fNIRS channels.

Happy Condition

Among the participants included in the fNIRS analysis (n = 49) 24 amateurs and 25 professionals, professionals showed significantly lower Oxy-Hb activation than amateurs in DLPFC channels CH6, CH15, and CH20, as shown in Table 4. Additional channels, including CH35 and CH75, demonstrated similar directional trends but did not remain significant following FDR correction and therefore are not interpreted further.

Table 5
Oxy-Hb activation under happy condition (β values, M ± SD)

Channel	Region	Amateur (n = 24)	Professional (n = 25)	t	df	p	FDR-adjusted q	d
CH6	DLPFC	0.024 ± 0.019	0.008 ± 0.022	2.54	47	0.0145	0.014	0.72
CH15	DLPFC	0.018 ± 0.015	0.006 ± 0.013	2.98	47	0.0046	0.004	0.85
CH20	DLPFC	0.021 ± 0.022	0.009 ± 0.017	2.31	47	0.0253	0.025	0.65

Table 6
ANCOVA of Oxy-Hb activation controlling for Go reaction time

Channel	Adjusted Mean Oxy-Hb Amateur	Adjusted Mean Oxy-Hb Professional	F	df	p	Partial η^2
CH6	0.024	0.009	5.87	1, 46	.019	.113
CH15	0.018	0.007	7.42	1, 46	.009	.139
CH20	0.021	0.010	4.91	1, 46	.032	.096

ANCOVA was conducted with group as the fixed factor, Go reaction time as the covariate, and Oxy-Hb activation as the dependent variable. To determine whether the observed differences in prefrontal Oxy-Hb activation were independent of response speed, ANCOVAs were conducted with Go reaction time entered as a covariate. The homogeneity-of-regression-slopes assumption was supported because the Group × Go reaction time interaction was not statistically significant for CH6, $F(1,45) = 0.84$, $p = .364$, CH15, $F(1,45) = 0.71$, $p = .404$, or CH20, $F(1,45) = 1.03$, $p = .315$. After adjustment for Go reaction time, the between-group effect remained significant for CH6, $F(1,46) = 5.87$, $p = .019$, $\eta p^2 = .113$, CH15, $F(1,46) = 7.42$, $p = .009$, $\eta p^2 = .139$, and CH20, $F(1,46) = 4.91$, $p = .032$, $\eta p^2 = .096$. These findings indicate that the observed group differences in prefrontal Oxy-Hb activation were not fully attributable to differences in Go reaction time.

Angry Condition

Among the participants included in the fNIRS analysis (24 amateurs and 25 professionals), channel CH6 showed numerically greater activation among professional boxers than amateur boxers. However, this difference did not reach statistical significance after hypothesis testing ($t = 1.92$, $p = 0.060$, $d = 0.54$).

Table 7
Oxy-Hb activation under angry condition (β values, M ± SD)

Channel	Region	Amateur (n = 24)	Professional (n = 25)	t	df	p	d
CH6	DLPFC	0.007 ± 0.018	0.015 ± 0.021	1.92	47	0.060	0.54

Although the effect size was moderate, this result did not meet the predefined threshold for statistical significance and should therefore be interpreted cautiously.

Correlation analysis revealed a significant positive association between NEI and years of training ($r = 0.48$, $p = .003$). The correlation analysis included the 49 participants with usable fNIRS data.

Given that the NEI was constructed as an exploratory composite measure integrating behavioral performance and neural activation, because the channels contributing to the NEI were selected on the basis of the same between-group fNIRS differences used to motivate the index, the observed NEI group difference may be subject to circularity and selection bias. Accordingly, the NEI findings should be considered exploratory and hypothesis-generating rather than independent confirmation of neural efficiency. Independent ROI selection and preregistered validation in a new sample are needed to establish the reliability and validity of this composite measure. Replication using inde-pendently defined regions of interest and prospective analytical approaches is warranted. The ANCOVA analysis described above was conducted on the Oxy-Hb activation measures and was separate from the exploratory neural efficiency index (NEI) analysis.

Discussion

This study examined whether boxing expertise was associated with differences in inhibitory control and prefrontal recruitment during an emotionally relevant Go/NoGo task. The findings are most informative when considered together rather than as isolated behavioral or neural effects. Overall, the pattern suggests that professional and amateur boxers may differ in how cognitive-control resources are recruited under emotional task demands, particularly in the relationship between inhibitory performance and DLPFC activation. However, the cross-sectional design and the structure of the emotional task require caution when interpreting these differences as consequences of training.

The behavioral findings provide evidence that emotional context may interact with the way inhibitory control is expressed in boxers. Amateur boxers showed a non-significant tendency toward higher No-go accuracy under the angry condition than under the happy condition, whereas professionals did not show a significant within-group difference. Because neither within-group comparison reached statistical significance, these findings should not be interpreted as definitive evidence that professional boxers possess more stable inhibitory control. Rather, they suggest a possible difference in the pattern of condition-related variation that warrants further investigation.

From the perspective of emotion-cognition interaction theory, negative emotional stimuli such as anger may increase alertness, attentional capture, and conflict monitoring. Angry facial expressions can engage attentional and emotion-regulation systems involving interactions between prefrontal regions and emotion-related neural circuitry [3, 5]. One possible explanation is that the greater salience of angry stimuli increased cognitive-control demands for less experienced athletes, potentially leading to more cautious response inhibition. However, this mechanism was not directly measured in the present study. The observed behavioral pattern therefore provides only indirect support for this interpretation, and alternative explanations involving task context, response strategy, or individual differences cannot be excluded.

Repeated exposure to emotionally demanding competitive situations may also influence how athletes regulate cognitive control. Professional boxers typically accumulate substantially greater training and competitive experience than amateur boxers, including repeated exposure to sparring, opponent-related threat cues, competitive pressure, and fluctuating emotional states. Such experience could potentially alter the relationship between emotional arousal and cognitive control. Sport emotion-regulation research similarly indicates that emotion-regulation strategies are relevant to competitive functioning and psychological adaptation in athletes [30, 14]. Nevertheless, the present cross-sectional comparison cannot determine whether differences in emotional control resulted from boxing experience or contributed to athletes reaching different levels of expertise.

The behavioral findings should also be interpreted in conjunction with response speed. Professional boxers showed longer Go reaction times under the happy condition while maintaining comparable No-go accuracy. This combination is relevant because cognitive performance is not adequately characterized by response accuracy or speed alone. Contemporary models of cognitive control emphasize the adjustment of response selection and response criteria according to task demands. In sport settings, rapid responding must often be balanced against the consequences of inappropriate responses. Thus, the longer Go reaction time among professionals should not automatically be interpreted as poorer cognitive performance. It may reflect a different balance between response speed and response control. However, because the present study did not directly estimate response thresholds or computational measures of speed-accuracy adjustment, this explanation remains tentative.

The principal neural finding was the lower DLPFC Oxy-Hb activation observed among professional boxers under the happy condition despite comparable No-go accuracy. The persistence of the between-group neural differences after adjustment for Go reaction time further indicates that the observed DLPFC differences were not fully explained by the difference in response speed. This pattern is consistent with predictions derived from the neural efficiency hypothesis, according to which comparable behavioral performance accompanied by lower task-related neural activation may reflect more economical recruitment of task-relevant neural resources [8, 9].

The present finding is broadly consistent with previous research examining neural efficiency in cognitive and sport contexts. The neural efficiency hypothesis was initially developed in research showing that

individuals with higher cognitive ability may exhibit lower metabolic or neural activation during demanding cognitive tasks [8, 9]. Subsequent research has extended this framework to sport cognition, with highly trained athletes showing differences in cortical recruitment during perceptual, motor, and decision-making tasks [11, 12]. The current findings extend this literature by examining prefrontal recruitment during inhibitory control in the presence of emotional stimuli. Previous emotional Go/NoGo research has demonstrated the involvement of prefrontal activation and connectivity in emotional inhibitory control [6, 7], providing a relevant framework for interpreting the present DLPFC findings.

The lower activation observed in professional boxers may reflect more economical recruitment of prefrontal resources during the task. One possible explanation is that extensive practice may contribute to more efficient coordination of task-relevant neural systems, allowing experienced athletes to perform familiar control operations with reduced recruitment of some prefrontal resources. Repeated engagement in cognitively demanding sport situations may also contribute to more efficient coordination between perceptual processing, response selection, and inhibition. DLPFC involvement in executive control provides a plausible neural substrate for such adaptation [31]. In addition, adaptive neural efficiency accounts propose that expertise may involve adjusting neural recruitment according to task demands rather than maintaining uniformly high or low activation [32, 12].

These mechanisms, however, should be regarded as plausible interpretations rather than demonstrated mechanisms of the present findings. The study did not directly measure synaptic plasticity, neural connectivity, metabolic expenditure, or longitudinal training-related changes. Therefore, the observed reduction in Oxy-Hb activation cannot by itself establish that professional boxing training caused more efficient neural processing. Pre-existing individual differences, selection into higher levels of competition, and differences in competitive experience may also contribute to the observed pattern.

The findings under the angry condition provide a more cautious perspective on the interpretation of neural efficiency. Professional boxers showed numerically greater CH6 activation than amateur boxers, with a moderate effect size, but the between-group difference did not reach statistical significance. Consequently, this result should not be interpreted as evidence that professional boxers definitively increase DLPFC recruitment in response to emotional threat.

Nevertheless, the direction of the finding is compatible with the broader concept of adaptive neural efficiency, in which efficient neural functioning does not necessarily mean uniformly reduced activation. Rather, neural recruitment may vary according to task demands and emotional context [32, 12]. From this perspective, expertise could potentially involve reducing recruitment when task demands can be handled efficiently while increasing recruitment when greater cognitive control is required. The present data raise this possibility but do not establish it because the angry-condition group difference was not statistically significant.

An additional methodological issue is important when comparing the emotional conditions. Angry No-go trials were presented within a block in which happy faces served as Go stimuli, whereas happy No-go trials were presented within a block in which neutral faces served as Go stimuli. Therefore, emotional

valence and response mapping were manipulated simultaneously. Differences between the two conditions may consequently reflect not only the emotional valence of individual stimuli but also sustained block-level context and response-mapping demands. The present findings should therefore be interpreted as condition-specific differences in prefrontal recruitment during emotion-inhibition processing rather than as evidence of a pure neural effect of emotional valence. Future studies should use event-related or fully counterbalanced factorial designs that independently manipulate emotional valence and Go/NoGo status.

This consideration also provides an alternative explanation for the apparent condition-dependent pattern of prefrontal activation. Rather than reflecting a specific professional response to anger, the observed differences could arise from differences in sustained emotional context, response expectations, or task-set maintenance. Accordingly, the present findings support the possibility of context-dependent differences in prefrontal recruitment but do not establish a specific mechanism by which professional boxers respond to angry stimuli.

The exploratory NEI provides a complementary way of considering the relationship between inhibitory-control performance and prefrontal activation. Professional boxers showed higher NEI values, and NEI was positively associated with years of training. Conceptually, this approach is consistent with the neural-efficiency framework because it considers behavioral performance together with the neural resources recruited during task performance rather than treating either behavioral or neural measures in isolation.

However, the NEI requires particularly cautious interpretation in the present study. The channels used to construct the index were selected because they demonstrated group differences in the same dataset. Consequently, the construction of the NEI and its evaluation were not fully independent, creating a potential source of selection bias or circularity. The higher NEI observed among professional boxers therefore should not be interpreted as independent validation of the index or as evidence that it represents a confirmed biomarker of training-related neural plasticity.

The positive association between NEI and years of training is nevertheless potentially informative as an exploratory observation. It is compatible with the possibility that accumulated sport experience is associated with differences in the relationship between cognitive performance and prefrontal activation. However, because years of training and competitive level are closely related in the present sample, the correlation cannot determine whether training duration itself accounts for the association. Longitudinal research with independently defined regions of interest and preregistered analytical procedures will be necessary to determine whether NEI is reliable and sensitive to training-related changes.

The findings have implications for several areas of sport cognitive neuroscience. First, they extend executive-function research by considering inhibitory control in an emotionally relevant rather than exclusively neutral context. Emotional Go/NoGo studies have demonstrated that emotional information can influence prefrontal processes involved in response inhibition [6, 7]. The present findings suggest

that athletic expertise may be relevant to how these processes are recruited during emotionally loaded cognitive control.

Second, the findings contribute to research examining expertise-related differences in neural recruitment. Previous work has reported differences in cortical activation among highly trained athletes during cognitive and perceptual-motor tasks [11, 12], while recent research has further demonstrated altered functional brain activation during working-memory and action-inhibition tasks in highly trained sport populations [33]. The present findings are compatible with this literature in suggesting that sport expertise may be associated with differences in prefrontal recruitment during cognitive control. However, the present cross-sectional design does not establish that these differences represent training-induced neural plasticity.

Third, the findings are relevant to emotion-cognition interaction theory. Emotional stimuli can modify attentional and inhibitory-control demands, while prefrontal systems contribute to the regulation of behavior under emotionally salient conditions [3, 5]. The present results suggest that differences in expertise may be associated with how prefrontal resources are recruited in such contexts. Importantly, the evidence does not support a simple interpretation in which professional boxers always show lower activation. Instead, the findings are more consistent with the possibility that expertise is associated with context-dependent differences in neural recruitment, although this interpretation requires confirmation in experimental designs that more directly manipulate emotional and cognitive demands.

The findings may have several implications for future sport-training research. First, emotion-regulation and inhibitory-control exercises conducted under controlled competitive or emotionally challenging conditions may be useful areas for further investigation. Training situations involving opponent pressure, provocation, score deficits, or other emotionally demanding scenarios could potentially be examined to determine whether cognitive-control training transfers to emotionally loaded competitive situations. Such approaches are consistent with evidence emphasizing the relevance of emotion regulation to athletic functioning [30, 14]. However, the present study did not test the effects of such training and therefore cannot establish their effectiveness.

Second, the combination of fNIRS and exploratory indices such as the NEI may provide a potential framework for future longitudinal investigations of cognitive and neural changes in athletes. At present, the NEI should be regarded as a research measure rather than a validated clinical or monitoring tool. Future studies should establish its reliability, construct validity, sensitivity to longitudinal change, and relationship with independent measures of athletic or cognitive performance. Standardized fNIRS acquisition and analysis procedures will also be important for this work [24, 20, 21].

Third, neurofeedback targeting prefrontal activity represents another possible area for future research. Sport neurofeedback research has suggested potential applications for performance, anxiety regulation, and emotional control, although the methodological evidence remains developing [34, 35, 36]. The present findings do not demonstrate that DLPFC neurofeedback would improve boxing performance.

Rather, they provide a rationale for future controlled studies examining whether targeted modulation of prefrontal activity can influence emotional inhibitory control in athletes.

Limitations

Several limitations should be considered. First, the cross-sectional design prevents causal inference regarding the relationship between boxing expertise and prefrontal activation. The observed differences may reflect training-related adaptations, pre-existing characteristics, or both. Second, the sample consisted exclusively of young male boxers, limiting generalizability to female athletes, other age groups, and other sporting populations. Third, the emotional Go/NoGo paradigm simultaneously manipulated emotional valence and response mapping, limiting the ability to isolate the specific contribution of emotional processing. Fourth, the NEI was an exploratory composite constructed using channels identified from the present group comparisons, creating potential selection bias and requiring independent validation. Fifth, the sample may have had limited power to detect smaller effects, particularly in channel-level analyses. Finally, fNIRS primarily measures cortical hemodynamic activity and does not directly capture deeper structures involved in emotion–cognition interactions. Future studies should therefore use larger and more diverse samples, longitudinal designs, independently defined regions of interest, and experimental paradigms that more clearly separate emotional and cognitive-control demands.

Conclusions

This study examined inhibitory control and prefrontal activation in professional and amateur boxers during an emotionally relevant Go/NoGo task. The findings indicate that boxing expertise was associated with differences in the relationship between behavioral performance and prefrontal recruitment. Professional boxers showed comparable inhibitory-control accuracy but lower DLPFC activation under the happy condition, a pattern consistent with the neural efficiency hypothesis. The exploratory NEI findings further suggest that integrating behavioral and neural measures may provide a useful framework for studying cognitive control in athletes.

However, these findings should be interpreted as associative rather than causal because of the cross-sectional design, and the NEI requires independent validation. Future longitudinal and experimentally controlled studies should determine whether differences in prefrontal recruitment reflect training-related adaptations and whether they generalize across emotional contexts and athletic populations.

Declarations

Ethics approval and consent to participate

A written informed consent was obtained from all participants and they were informed that they can quit/stop from participating at any time. The study protocol was approved by the relevant ethics committee of Mahasarakham University, Thailand, and followed the Declaration of Helsinki [19].

Consent for publication

Written informed consent was obtained from the patient for publication of this case report and any accompanying images. A copy of the written consent is available for review by the Editor-in-Chief of the journal upon request.

Author Contributions Statement

Y.G. Manuscript writing, data collection

C.C. Data collection, corrections, Supervisions

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Data availability statement

All data presented in this study is available upon a request from the corresponding author (chamnan.c@msu.ac.th)

Competing interests

The authors declare no competing interests.

References

1. Okon-Singer H, Hendler T, Pessoa L, Shackman AJ. The neurobiology of emotion-cognition interactions: Fundamental questions and strategies for future research. Front Hum Neurosci. 2015;9:58. https://doi.org/10.3389/fnhum.2015.00058.
2. Pessoa L. A network model of the emotional brain. Trends Cogn Sci. 2017;21(5):357–71. https://doi.org/10.1016/j.tics.2017.03.002.
3. Berboth S, Morawetz C. Amygdala-prefrontal connectivity during emotion regulation: A meta-analysis of psychophysiological interactions. Neuropsychologia. 2021;153:107767. https://doi.org/10.1016/j.neuropsychologia.2021.107767.
4. Dixon ML, Thiruchselvam R, Todd RM, Christoff K. Emotion and the prefrontal cortex: An integrative review. Psychol Bull. 2017;143(10):1033–81. https://doi.org/10.1037/bul0000096.
5. Kredlow MA, Fenster RJ, Laurent ES, Ressler KJ, Phelps EA. Prefrontal cortex, amygdala, and threat processing: Implications for PTSD. Neuropsychopharmacology. 2022;47(1):247–59. https://doi.org/10.1038/s41386-021-01155-7.

6. Nguyen T, Condy EE, Park S, Friedman BH, Gandjbakhche A. Comparison of functional connectivity in the prefrontal cortex during a simple and an emotional Go/No-Go task in female versus male groups: An fNIRS study. Brain Sci. 2021;11(7):909. https://doi.org/10.3390/brainsci11070909.
7. Sasaki J, Matsubara T, Chen C, Fujii Y, Fujita Y, Nakamuta M, Nitta K, Egashira K, Hashimoto T, Nakagawa S. Prefrontal activity during the emotional Go/No-Go task and computational markers of risk-based decision-making predict future relapse in alcohol use disorder. Front Psychiatry. 2023;13:1048152. https://doi.org/10.3389/fpsyt.2022.1048152.
8. Haier RJ, Siegel BV, Nuechterlein KH, Hazlett E, Wu JC, Paek J, Browning HL, Buchsbaum MS. Cortical glucose metabolic rate correlates of abstract reasoning and attention studied with positron emission tomography. Intelligence. 1988;12(2):199–217. https://doi.org/10.1016/0160-2896(88)90016-5.
9. Neubauer AC, Fink A. Intelligence and neural efficiency. Neurosci Biobehavioral Reviews. 2009;33(7):1004–23. https://doi.org/10.1016/j.neubiorev.2009.04.001.
10. Di Russo F, Taddei F, Apnile T, Spinelli D. Neural correlates of fast stimulus discrimination and response selection in top-level fencers. Neurosci Lett. 2006;408(2):113–8. https://doi.org/10.1016/j.neulet.2006.08.085.
11. Filho E, Dobersek U, Husselman T-A. The role of neural efficiency, transient hypofrontality and neural proficiency in optimal performance in self-paced sports: A meta-analytic review. Exp Brain Res. 2021;239(5):1381–93. https://doi.org/10.1007/s00221-021-06078-9.
12. Li L, Smith DM. Neural efficiency in athletes: A systematic review. Front Behav Neurosci. 2021;15:698555. https://doi.org/10.3389/fnbeh.2021.698555.
13. Korobeynikov G, Korobeinikova L, Raab M, Baić M, Borysova O, Korobeinikova I, Shengpeng G, Khmelnitska I. Cognitive functions and special working capacity in elite boxers. Pedagogy Phys Cult Sports. 2023;27(1):84–90. https://doi.org/10.15561/26649837.2023.0110.
14. Roberts RJ, Lane AM. Mood responses and regulation strategies used during COVID-19 among boxers and coaches. Front Psychol. 2021;12:624119. https://doi.org/10.3389/fpsyg.2021.624119.
15. Kalén A, Bisagno E, Musculus L, Raab M, Pérez-Ferreirós A, Williams AM, Araújo D, Lindwall M, Ivarsson A. The role of domain-specific and domain-general cognitive functions and skills in sports performance: A meta-analysis. Psychol Bull. 2021;147(12):1290–308. https://doi.org/10.1037/bul0000355.
16. Russo G, Ottoboni G. The perceptual-cognitive skills of combat sports athletes: A systematic review. Psychol Sport Exerc. 2019;44:60–78. https://doi.org/10.1016/j.psychsport.2019.05.004.
17. Zhang Z, Piras A, Chen C, Kong B, Wang D. A comparison of perceptual anticipation in combat sports between experts and non-experts: A systematic review and meta-analysis. Front Psychol. 2022;13:961960. https://doi.org/10.3389/fpsyg.2022.961960.
18. Gong X, Huang Y-X, Wang Y, Luo Y-J. Revision of the Chinese facial affective picture system. Chin Mental Health J. 2011;25(1):40–6. https://doi.org/10.3969/j.issn.1000-6729.2011.01.011.

19. World Medical Association. (2024). WMA Declaration of Helsinki: Ethical principles for medical research involving human participants. https://www.wma.net/policies-post/wma-declaration-of-helsinki/
20. Pinti P, Tachtsidis I, Hamilton A, Hirsch J, Aichelburg C, Gilbert S, Burgess PW. The present and future use of functional near-infrared spectroscopy (fNIRS) for cognitive neuroscience. Ann N Y Acad Sci. 2020;1464(1):5–29. https://doi.org/10.1111/nyas.13948.
21. Yücel MA, von Lühmann A, Scholkmann F, Gervain J, Dan I, Ayaz H, Boas D, Cooper RJ, Culver J, Elwell CE, Eggebrecht A, Franceschini MA, Grova C, Homae F, Lesage F, Obrig H, Tachtsidis I, Tak S, Tong Y, Wolf M. Best practices for fNIRS publications. Neurophotonics. 2021;8(1):012101. https://doi.org/10.1117/1.NPh.8.1.012101.
22. Delpy DT, Cope M, van der Zee P, Arridge S, Wray S, Wyatt J. Estimation of optical pathlength through tissue from direct time of flight measurement. Phys Med Biol. 1988;33(12):1433–42. https://doi.org/10.1088/0031-9155/33/12/008.
23. Rolls ET, Cheng W, Feng J. The orbitofrontal cortex: Reward, emotion and depression. Brain Commun. 2020;2(2):fcaa196. https://doi.org/10.1093/braincomms/fcaa196.
24. Hou X, Zhang Z, Zhao C, Duan L, Gong Y, Li Z, Zhu C. NIRS-KIT: A MATLAB toolbox for both resting-state and task fNIRS data analysis. Neurophotonics. 2021;8(1):010802. https://doi.org/10.1117/1.NPh.8.1.010802.
25. Molavi B, Dumont GA. Wavelet-based motion artifact removal for functional near-infrared spectroscopy. Physiol Meas. 2012;33(2):259–70. https://doi.org/10.1088/0967-3334/33/2/259.
26. von Lühmann A, Ortega-Martinez A, Boas DA, Yücel MA. Using the general linear model to improve performance in fNIRS single-trial analysis and classification: A perspective. Front Hum Neurosci. 2020;14:30. https://doi.org/10.3389/fnhum.2020.00030.
27. Shapiro SS, Wilk MB. An analysis of variance test for normality (complete samples). Biometrika. 1965;52(3–4):591–611. https://doi.org/10.1093/biomet/52.3-4.591.
28. Benjamini Y, Hochberg Y. Controlling the false discovery rate: A practical and powerful approach to multiple testing. J Roy Stat Soc: Ser B (Methodol). 1995;57(1):289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x.
29. Cohen J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates. https://doi.org/10.4324/9780203771587
30. Bird GA, Quinton ML, Cumming J. Promoting athlete mental health: The role of emotion regulation. J Clin Sport Psychol. 2023;17(2):112–30. https://doi.org/10.1123/jcsp.2021-0022.
31. Friedman NP, Robbins TW. The role of prefrontal cortex in cognitive control and executive function. Neuropsychopharmacology. 2022;47(1):72–89. https://doi.org/10.1038/s41386-021-01132-0.
32. Dunst B, Benedek M, Jauk E, Bergner S, Koschutnig K, Sommer M, Ischebeck A, Spinath B, Arendasy M, Bühner M, Freudenthaler HH, Neubauer AC. Neural efficiency as a function of task demands. Intelligence. 2014;42:22–30. https://doi.org/10.1016/j.intell.2013.09.005.

33. Park I, Kim Y, Kim SK. Athlete-specific neural strategies under pressure: A fNIRS pilot study. Int J Environ Res Public Health. 2020;17(22):8464. https://doi.org/10.3390/ijerph17228464.
34. Cheng M-Y, Yu C-L, An X, Wang L, Tsai C-L, Qi F, Wang K-P. Evaluating EEG neurofeedback in sport psychology: A systematic review of RCT studies for insights into mechanisms and performance improvement. Front Psychol. 2024;15:1331997. https://doi.org/10.3389/fpsyg.2024.1331997.
35. Rydzik Ł, Wąsacz W, Ambroży T, Javdaneh N, Brydak K, Kopańska M. The use of neurofeedback in sports training: Systematic review. Brain Sci. 2023;13(4):660. https://doi.org/10.3390/brainsci13040660.
36. Tosti B, Corrado S, Mancone S, Di Libero T, Carissimo C, Cerro G, Rodio A, da Silva VF, Coimbra DR, Andrade A, Diotaiuti P. Neurofeedback training protocols in sports: A systematic review of recent advances in performance, anxiety, and emotional regulation. Brain Sci. 2024;14(10):1036. https://doi.org/10.3390/brainsci14101036.
37. Radloff LS. The CES-D Scale: A self-report depression scale for research in the general population. Appl Psychol Meas. 1977;1(3):385–401. https://doi.org/10.1177/014662167700100306.
38. Buysse DJ, Reynolds CF, Monk III, Berman TH, S. R., Kupfer DJ. The Pittsburgh Sleep Quality Index: A new instrument for psychiatric practice and research. Psychiatry Res. 1989;28(2):193–213. https://doi.org/10.1016/0165-1781(89)90047-4.
39. Yao ZF, Sligte IG, Moreau D, Hsieh S, Yang CT, Ridderinkhof KR, Muggleton NG, Wang CH. The brains of elite soccer players are subject to experience-dependent alterations in white matter connectivity. Cortex. 2020;132:79–91. Epub 2020 Sep 1. PMID: 32956909.
40. Vona M, de Guise É, Leclerc S, Deslauriers J, Romeas T. Multiple domain-general assessments of cognitive functions in elite athletes: Contrasting evidence for the influence of expertise, sport type and sex. Psychol Sport Exerc. 2024;75:102715. Epub 2024 Jul 22. PMID: 39048061.
41. Yao Z-F, Sligte IG, Ridderinkhof RK. Olympic team rowers and team swimmers show altered functional brain activation during working memory and action inhibition. Neuropsychologia. 2024;203:108974. https://doi.org/10.1016/j.neuropsychologia.2024.108974.
42. Causse M, Chua Z, Peysakhovich V, Del Campo N, Matton N. Mental workload and neural efficiency quantified in the prefrontal cortex using fNIRS. Sci Rep. 2017;7(1):5222. 10.1038/s41598-017-05378-x. Erratum in: Sci Rep. 2018;8(1):7184. doi: 10.1038/s41598-018-25614-2. PMID: 28701789; PMCID: PMC5507990.