EEG Correlates of cognitive demand in experts chess players

Hugo Marte-Santana[1,2]* and M. Isabel García-Ogueta[2]

[1] Vicerectoria de Investigacion e Innovacion, Universidad Iberoamericana (UNIBE), Santo Domingo, Dominican Republic, [2] Department of Basic Psychology, Psychobiology, and Methodology at the University of Salamanca, Salamanca, Spain.

*Corresponding Author: Hugo Marte-Santana, Department of Basic Psychology, Psychobiology, and Methodology at the University of Salamanca. Vicerectoria de Investigacion e Innovacion, Universidad Iberoamericana (UNIBE).
Email: Hugo.marte@usal.es

Abstract

The game of chess involves cognitive demands that are experienced as effort. It has been proposed that these cognitive resources consumption have a metabolic dimension on the nervous tissue so that it would be a physiologically measurable phenomenon. In the present work we studied the effect of different attentional and cognitive demands within the game of chess have on behavioral and electroencephalographic measurements. We designed a chess problem, to be solved by chess expert players (N = 18), with differnet levels of difficulty. In our results, an increase in reaction times and accuracy were related to attentional demand increase. An increase in Alpha band power in parieto-occipital regions was observed, indicating a posible greater involvement of these areas in overall task processing.

Keywords: **Cognitive demand; attention demand; chess; EEG;**

1. Introduction

Chess is a two-player strategy board game played on a checkered board with 64 squares arranged in an 8x8 grid (Simon & Schaeffer, 1992).

Chess has traditionally been used as a framework in the study of cognitive processes such as memory, attention or executive functions (Postal, 2012; Sheridan & Reingold, 2014). Similarly, owing to the requisite planning skills inherent in attaining an expert level of proficiency, extensively trained chess players have actively participated in studies investigating the impact of training on chess strategies, as well as the augmentation of memory capacity and mental calculation (Kazemi et al., 2012; Sala et al., 2015).

The concept of task demands is intricately connected to that of cognitive load or workload, denoting the extent of information processing resources requisite for achieving the optimal performance level demanded by a task (Teh et al., 2014). This concept emanates from the framework of attentional resources and their finite capacity, acknowledging that attention modulates cognitive systems to facilitate information processing (Kahneman, 1997; Wickens, 2008; Young et al., 2015). In this context, any dynamic task subject to variations necessitates attentional control to dynamically adapt performance to new circumstances, thereby representing a substantial cognitive demand (Aricò et al., 2015; Iqbal et al., 2020a).

Bruya & Tang (2018) contend that the consumption of cognitive resources (Kahneman, 1997) may have metabolic implications for brain tissue. Such implications could impact brain electrical patterns, which are quantifiable through techniques like electroencephalography (EEG), in terms of electrical intensity (amplitude) and oscillations per second (Hertz). These oscillations are categorized into frequency blocks known as frequency bands, namely: Theta (3–7Hz), Alpha (8–12Hz), and Beta (13–30Hz) (Gutmann et al., 2018).

EEG measurements of cognitive resource consumption are frequently assessed in high-responsibility contexts, such as air traffic control or aircraft piloting (Aricò et al., 2015; Shou & Ding, 2013) This evaluation aims to gauge cognitive overload, with the ultimate goal of mitigating fatigue and preventing human error (Iqbal et al., 2020b).

Increases in task difficulty, memory load, rule complexity, sharing of attention, or attentional control, ultimately resulting in cognitive load, have demonstrated correlations with different brain frequencies. A direct relationship has been observed between activity in the Theta band in frontal areas and the escalation of cognitive load (Borghini et al., 2014; Fuentes-García et al., 2020; Katahira et al., 2018; Wang & Hsu, 2014). Similarly, an inverse relationship has been noted between Alpha activation in parietal areas and the augmentation of attentional load in the task (Gulbinaite et al., 2017; Kamzanova et al., 2014) and working memory load (Pergher et al., 2019). Babiloni et al. (2012), for instance, reported smaller Alpha band amplitudes with the increase in brain overall activation.

Concerning the Beta frequency, a connection has been identified between its amplitude and the elevation of cognitive load in tasks involving inhibitory control (Karch et al., 2016), multitasking (Lim et al., 2018), or mental calculation tasks (Plechawska-Wójcik et al., 2018). Similarly, the activity of this frequency band has demonstrated associations with various cognitive processes, including working memory, language processing, long-term memory, and decision-making (Chikhi et al., 2022; Spitzer & Haegens, 2017).

This observation lends support to Bruya and Tang's notion of the metabolic implications of cognitive resource consumption. EEG measurements assessing cognitive demand are commonly employed in contexts of high responsibility, such as air traffic control or aircraft piloting (Aricò et al., 2015; Hamann & Carstengerdes, 2022; Shou & Ding, 2013). Extensive research has been conducted on the mental effort required for optimal performance in expert domains where errors can have substantial security implications. Continuous EEG measurement serves as a foundational element for the development of assistive systems. However, there is a notable gap in research regarding other domains of expert performance that are more prevalent in the general population, such as chess.

Concerning the examination of cognitive demand in chess players, studies have revealed fluctuations in Theta amplitudes corresponding to heightened game demands, suggesting a strategic adjustment to address the increased demand (Fuentes-García et al., 2020, 2018; Silva et al., 2018). Additionally, a decrease in Alpha amplitude has been reported with demand escalation in expert chess players (Villafaina et al., 2021).

Fuentes-García et al. (2020) documented a decrease in Beta power among a group of chess players who experienced losses in their games. The study posits that this decline in Beta power reflects a challenge in coping with the demands posed by a more skilled opponent.

Nevertheless, these studies have centered their difficulty manipulations on factors such as increases in opponent skill levels or variations in the strategic positions of the participants. Strategic advantage manipulations are predicated on the type, quantity, and position of pieces held by participants at the commencement of execution. Specifically, if participants possess a greater number of superior pieces arranged more favorably on the chessboard compared to their opponents, they are deemed to be in a strategically superior position, making it easier for them to secure victory. However, it is plausible that these demands fluctuate over time. Upon obtaining a strategic advantage, chess experts may experience a decrease in cognitive demand owing to their capability to predict the game several moves ahead (Fuentes-García et al., 2020; Silva et al., 2017). A strategic advantage, even against high-level opponents, could represent a relief for the participant, resulting in a diminished demand for cognitive resources.

The purpose of our study was to examine the behavioral and neural activation patterns associated with varying attentional demands, particularly their influence on behavioral execution and the fluctuations in EEG frequency band amplitudes. We hypothesized that cognitive workload escalation would result in increased amplitudes in the Theta and Beta bands, alongside a decrease in the amplitudes of the Alpha frequency band.

2. Methods

2.1. Participants

20 participants affiliated with the International Chess Federation, healthy, with normal or corrected vision, volunteered to participate in this study (18 men, 2 women; mean age 31.3 years, with a standard deviation of ±12.02; 2 of them left-handed).

Unfortunately, two participants had to be excluded due to technical issues in collecting Electroencephalographic (EEG) information, resulting in a final sample of 18 participants (17 men, 1 woman; mean age 30.67 years, standard deviation ±11.28; 2 of them left-handed). Exclusion criteria during sample selection included individuals with psychological, psychiatric, or neurological diagnoses and those with an ELO score[1] below 1600 points.

2.2. Task Design

The task comprised a set of independent and unrelated chess scenarios, each requiring solution based on specific rules. The study incorporated three experimental conditions: (1) No cue (NC), (2) Piece cue (PC), and (3) Piece movements cue (PMC). This design followed a within-subject structure.

In the No Cue (NC) condition, participants were tasked with identifying the most senior threatened piece and the corresponding response square. In the Piece Cue (PC) condition, the piece to move was specified for participants, but information about possible movements was not provided. In the Piece Movements Cue (PMC) condition, participants were informed about both the threatened piece and all the viable solutions.

To successfully accomplish the task, participants were required to identify the piece with the highest hierarchy that was under threat from an opponent's piece and relocate it to a square where it was out of danger. While there was only one safe square on the board to which the threatened piece could be moved, adhering to traditional rules of movement, participants had multiple possible movement options.

The scenarios were created using Shane's Chess Information Database (Scid) software (v.4.6.4, S. Hudson, 2016). Specifically, scenarios where the threatened piece had only one viable solution were chosen for the study.

[1]The Elo score was developed by the physicist Arpart Elo (1903-1992) and is a numerical scoring system, based on the statistical calculation of the games a participant plays, which attempts to determine the relative ability of chess players on a scale upward.

The scenarios were designed to have between 2 and 8 possible solutions, evenly distributed among the three experimental conditions. These scenarios were presented randomly on the computer screen in images measuring 24.37 x 24.37 cm. Additionally, the number of pieces on the board was controlled, ranging between 15 and 25.

To introduce variations in the strategic components of the game, moving the threatened figure to a square where it was defended by an allied piece was not considered a correct move.

The hierarchy of pieces was intentionally modified slightly from traditional chess to induce attentionally controlled execution. In this adaptation, the rook and the bishop exchanged positions in the hierarchical order, deviating from the standard sequence (King, Queen, Rook, Knight, Bishop, Pawn) to the altered order: King, Queen, Bishop, Knight, Rook, and Pawn, arranged in descending order.

2.3. Procedure.

Upon signing the consent form, participants were escorted to the experimental room, which was equipped with the task presentation computer and the EEG recording device. Each participant was allotted 30 minutes to solve 120 individual scenarios, with 40 scenarios assigned to each experimental condition. The presentation order of the experimental conditions was counterbalanced among the participants.

2.4. Data Collection

For the collection of electroencephalographic information, a 64-channel Electro cap helmet (Electro cap international, Inc., Eaton, OH, USA) arranged according to the international 10-20 system was employed. To record eye movement activity, external electrooculogram channels (EOG, EOCG) were utilized. An online filter with a range of 0-73Hz was applied, employing a sampling rate of 500Hz and maintaining impedance below 10KΩ. The data were gathered using Brainvision recorder software (v. 1.20.0601, Brain Products, 2013).

The presentation of items and the collection of behavioral information were conducted using the OpenSesame software (v.3.2.5, Mathôt, S., Schreij, D., & Theeuwes, J. 2012). For this purpose, a desktop computer with the Windows XP Professional operating system, service pack 1 (v2002, Microsoft Corporation, USA, 2002), featuring a 19-inch LG "FLATRON" L1918S screen with a contrast ratio of 700, was utilized. The screen had a 1.83 kHz horizontal refresh rate and a 75 Hz vertical refresh rate.

2.5. Data Processing

The behavioral data collected from participants' task performance were categorized into reaction times (RT), indicating the interval between the presentation of the stimulus and the emission of the response, and the proportion of correct answers. These results were averaged for each participant within each experimental condition for subsequent statistical analysis.

The electroencephalographic information was processed with the EEGLAB® toolbox (v14.1.1, Delorme and makeig 2004) based on MATLAB (R2017a, the MathWorks, Inc., Massachusetts, USA).

To eliminate sources of interference in the electroencephalographic data, a bandpass filter ranging from 0.1 to 35Hz was applied, a notch filter at 50Hz was also implemented, the sampling rate was readjusted to 128 Hz and average reference was used. The collected continuous EEG data was then sliced into 2-second epoch windows (from -0.5 to 1.5 seconds from item appearance).

Segments containing artifactual information were automatically removed using the tool provided by the software for this purpose. Additionally, a visual inspection was conducted, identifying and marking windows deemed inappropriate, which were subsequently compared with those automatically deleted (Cohen , 2014). After segment removal, the number of trials ranged from 33 to 40 for each condition.

To correct artifacts from eye movements (EOG), blinks, or other sources of interference, Independent Component Analysis (ICA) (Jung et al., 2000) was employed. 64 components were extracted for each participant.

Following ICA, the Multiple Artifact Rejection Algorithm (MARA) tool (Winkler, S. Haufe, and M. Tangermann, 2011) was utilized. MARA facilitates the automatic differentiation between cerebral and artifactual sources based on probabilistic principles, enabling the removal of artifactual components. Once again, the automated removal of components was manually supervised by the experimenter (Cohen, 2014). The application of the MARA algorithm resulted in the removal of an average of 8 components (SD=±2).

The electroencephalographic records were subjected to Fourier transform to partition the information into frequency bands for subsequent analysis.

Following the proposal by Katahira et al. (2018), to conduct spectral analyses, a set of electrodes was chosen based on their locations and organized into six regions of interest (ROIs), see: Left frontal: AF3, F3, F7, FC3; Right frontal: AF4, F4, F8, FC4; Left central:

C3, C5, CP3, CP5; Right central: C4, C6, CP4, CP6; Left parieto-occipital: P3, P5, PO3, PO7; Right parieto-occipitial: P4, P6, PO4, PO8.

2.6. Statistical analysis.

Statistical analyses of the data were conducted using SPSS software (Version 25.0, IBM Corp. 2017). For the examination of behavioral data (reaction times and accuracy) derived from participant execution, a priori planned t-comparisons were employed. Given that it involves a single dimension of comparisons, a related samples t-test was applied, incorporating Bonferroni corrections. The three experimental conditions (No Cue (NC), Piece Cue (PC), and Piece and Movement Cue (PMC)) were compared.

Concerning EEG data, differences in amplitudes within the Theta (3 to 7Hz), Alpha (8 to 12Hz), and Beta (13 to 30Hz) frequency bands were analyzed across different experimental conditions, considering both location and laterality. To this end, a repeated measures ANOVA with factors of 3 (Condition: NC, PC, and PMC), 3 (ROIs: Frontal, Central, and Parieto-Occipital), and 2 (Laterality: Left and Right) was performed.

In the event of statistically significant interactions, post hoc contrast analyses were executed using the Bonferroni multiple comparisons test.

3. Results

3.1. Behavioral Results.

In the analysis of reaction times, a t-test revealed significantly higher reaction times in the NC condition compared to both the PC condition ($t(17) = 8.437$, $p < 0.001$) and the PMC condition ($t(17) = 6.314$, $p < 0.001$). Descriptive statistics are presented in Table 1.

Importantly, no significant differences were observed between the PC and PMC conditions (t (17) = 0.557, p = 0.572).

Table 1. *Means and standard deviations of reaction times.*

Reaction Times	mean (sec)	Std.Deviation
NC	7,672	1,634
PC	5,268	1,961
PCM	5,483	1,831

Note. NC (no cue), PC (piece cue), PCM (piece movements cue).

In the analysis of correct answer proportions, we observed a significantly lower proportion in the NC condition compared to both the PC condition (t (17) = -4.528, p < 0.001) and the PMC condition (t (17) = -3.756, p = 0.002). Descriptive statistics can be found in Table 2. Importantly, no significant differences were found between the PC and PMC conditions (t (17) = 0.586, p = 0.565).

Table 2. *Means and standard deviations of the proportion of hits.*

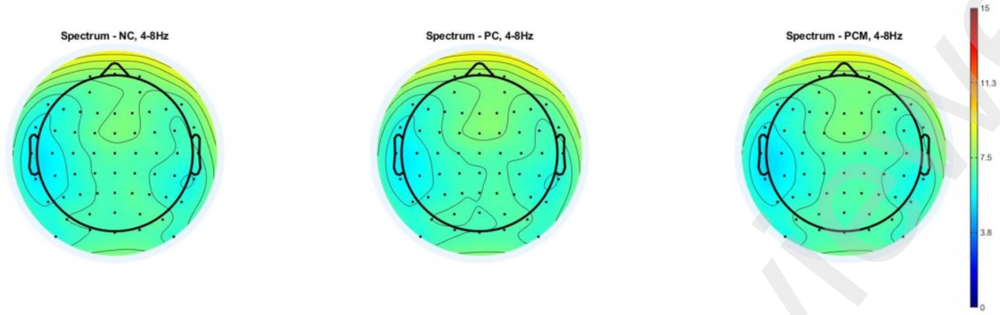
hit ratio	mean	Std.Deviation
NC	0.699	0.202
PC	0.841	0.154
PMC	0.826	0.139

Note. NC (no cue), PC (Piece cue), PMC (piece and movements cue).

3.2. EEG results

In the ANOVA conducted for amplitude differences in the **Theta frequency band**, no significant effects were observed for the variables of interest (F (2, 34) = 0.271, p = 0.686, $\eta^2 = 0.016$). Additionally, there were no significant interactions between conditions and ROIs (F (4, 68) = 2.324, p = 0.106, $\eta^2 = 0.120$), conditions, ROIs, and laterality (F (4, 68) = 0.264, p = 0.833, $\eta^2 = 0.015$), or any other interactions (see Figure 1).

Figure 1. *Scalp map of Theta amplitudes.*



In the **Alpha frequency band**, we observed significant differences in the interaction betewen condition and ROIs (F (4, 68) = 5.270; p = 0.007; $\eta 2$ = 0.237) (figure 2).

This interaction was found to be responsive to amplitude variations recorded in different ROIs across experimental conditions. These differences are attributed not to the effects of the experimental condition, but rather to the effects of ROIs, resulting in amplitude disparities between central and parieto-occipital areas in the three conditions: NC (mean = 1.676; mean = 2.128; p = 0.001), PC (mean = 1.542; mean = 1.947; p = 0.013), and PMC (mean = 1.990; mean = 2.520; p = 0.008), with consistently greater amplitudes in the parieto-occipital areas. No other significant effects were observed in this frequency band (p > 0.05). Additional information can be found in Table 3.

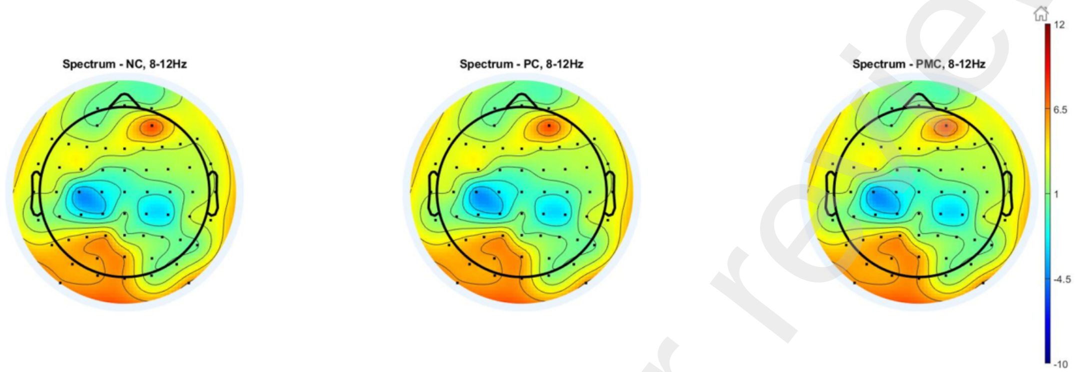
Table 3. *ANOVA of the Alpha frequency band amplitudes.*

	F	*p*	η2
C.	0.165	0.763	0.01
z	2,908	0.096	0.146
L	1,900	0.186	0.101
C*R	5,270	0.007*	0.237
C*L	0.049	0.939	0.003
R*L	0.497	0.562	0.028

C*R*L	0.620	0.591	0.035

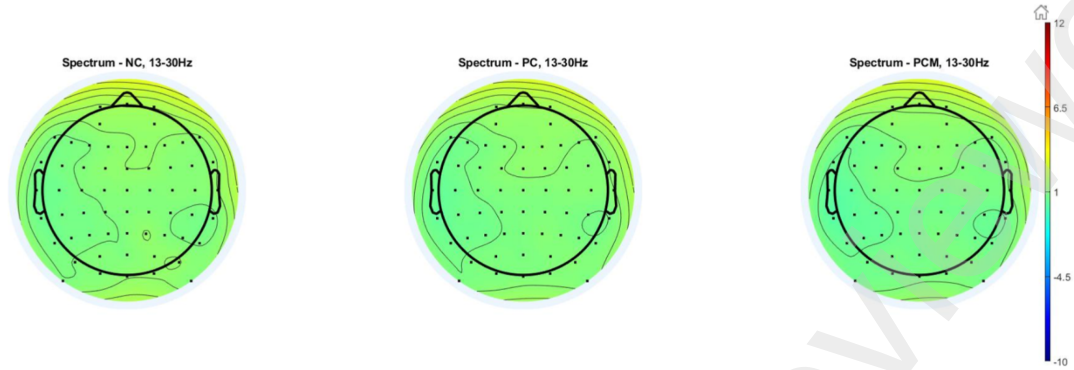
Note. C (Condition), R (ROIs), L (laterality).

Figure 2. *Scalp map of Alpha amplitudes***.**



Conversely, the ANOVA conducted for amplitude variations in the **Beta frequency band** did not yield statistically significant results for any of the variables. No significant effects were observed under different conditions (F (2, 34) = 0.488, p = 0.564, η^2 = 0.028), in the interaction of condition with ROIs (F (4, 68) = 1.546, p = 0.217, η^2 = 0.083), or in the interaction of condition with ROIs and laterality (F (4, 68) = 1.015, p = 0.391, η^2 = 0.056), as well as in any other interaction (see Figure 3).

Figure 3. *Scalp map of Beta amplitudes*



4. Discussion and Conclusions

The modification introduced in the strategic component and traditional rules of chess (hierarchy of the pieces) necessitates the execution of the task with supervisory attentional control, akin to the demands observed during task-related changes (Silva et al., 2018). The aim of this study was to analyze the behavioral and neural activation patterns associated with diverse attentional demands, as reflected in behavioral execution and variations in EEG frequency band amplitudes.

Upon observing the behavioral results, the observed increase in reaction times in the NC condition aligns with the expected decrease in attentional load following the presentation of cues in all experimental conditions. Despite our initial hypothesis that the PMC condition would be less demanding than the PC condition, this was not evident at the behavioral level. This discrepancy can be explained by the chess experts' automation of all possible moves once the piece to be moved is identified. A similar pattern was noted in terms of the proportion of correct answers, where the presentation of any type of cue resulted in an increased proportion of correct responses.

While examining the amplitudes in frequency bands within our results, no significant differences were observed in this experiment regarding the amplitudes of the Theta frequency band. This finding contrasts with the results reported by Fuentes-Garcia et al. (2020),), who identified an increase in Theta frequency band amplitudes correlated with task difficulty, specifically in players who won their games. In a similar vein, Fuentes-Garc et al. (2018) observed an elevation in Theta frequency band amplitudes at the Fz location among professional chess players as the ELO level of their opponents increased in flash games.

In terms of the results obtained for the amplitudes of the Alpha frequency band, lower amplitudes were consistently observed in central areas across all three experimental conditions compared to parieto-occipital areas. This suggests a potential higher involvement of central areas in the overall processing of the task. Fuentes-García et al. (2020), reported a similar pattern of decreasing amplitudes in this band with increasing task demands, but specifically in players who experienced losses at various difficulty levels.

In a recent study, Villafaina et al. (2021) noted a comparable pattern of decreasing Alpha amplitudes in expert chess players. In their specific task, participants were required to achieve a checkmate in as few moves as possible with a limited number of pieces and at two levels of difficulty. The authors observed a reduction in Alpha amplitudes in the most challenging condition when compared to the easiest condition.

Conversely, Fuentes et al. (2018) observed an increase in the Theta Fz/Alpha Pz ratio in a chess master while playing a rapid game, in contrast to the rest condition.

As for the results obtained from the analysis of Beta frequency band amplitudes, no significant differences were observed. Our hypothesis posited that Beta amplitudes, typically associated with cognitive activity, would increase with an escalating task load. However, contradictory findings have also been reported in this regard. Fuentes-García et al. (2020) observed an opposing pattern, noting a decrease in Beta frequency band amplitudes with an increase in task demand among players who experienced losses in their games.

5. Limitations and Future Research

One of the primary challenges encountered in this research was the difficulty in recruiting expert participants. While it is common for many experiments to rely on small samples, and even single-case studies with experts (Babiloni et al., 2011; Bianco et al., 2018; Calma-Roddin & Drury, 2020; Fuentes-García, Pereira, et al., 2019; Hänggi et al., 2014; Silva et al., 2018) , the sensitivity of our measures may be compromised due to a lack of sample power.

Another limitation involved the low spatial specificity of EEG measurements and the considerable inter-individual variability inherent in EEG data. Future research endeavors should address these methodological challenges in performance contexts by exploring complementary approaches such as integrating EEG measurements with techniques like fNIRS or magnetoencephalography.

Despite these limitations, the present study makes a valuable contribution to our understanding of how the visual scanning strategies employed by expert chess players underlie the development of chunk and template strategies. These cognitive strategies empower players to perceive the chessboard as a cohesive set of functional blocks, rather than viewing individual pieces in isolation with discrete functions. Moreover, the study offers a brief insight into the potential flow state (Csikszentmihalyi, 1988) experienced by these experts during cognitively demanding situations while playing.

6. Conflict of Interest

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

7. Acknowledgments

The authors would like to express their gratitude to Amador González, a FIDE international master, for his assistance in participant recruitment. Special thanks are also extended to Laura Sanchez-Vincitore and Daniel Cubilla for their valuable contributions, comments, and corrections.

8. Data availability statement

The datasets generated for this study can be found in the Open Science Framework as "EEG correlates of cognitive load in musical performance" (https://osf.io/cvbup/).

9. CRediT author statement

Hugo Marte-Santana: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - Original Draft, Visualization. **M. Isabel García-Ogueta**: Conceptualization, Methodology, Writing - Review & Editing, Supervision.

10. References

Aricò, P., Borghini, G., Graziani, I., Imbert, J.-P., Granger, G., Benhacene, R., Pozzi, S., Napoletano, L., Flumeri, G. D., Colosimo, A., & Babiloni, F. (2015). Air-traffic-controllers (ATCO): Neurophysiological analysis of training and workload. *Italian Journal of Aerospace Medicine*, *12*, 35.

Babiloni, C., Buffo, P., Vecchio, F., Marzano, N., Del Percio, C., Spada, D., Rossi, S., Bruni, I., Rossini, P. M., & Perani, D. (2012). Brains «in concert»: Frontal oscillatory alpha rhythms and empathy in professional musicians. *NeuroImage*, *60*(1), 105-116. https://doi.org/10.1016/j.neuroimage.2011.12.008

Babiloni, C., Vecchio, F., Infarinato, F., Buffo, P., Marzano, N., Spada, D., Rossi, S., Bruni, I., Rossini, P. M., & Perani, D. (2011). Simultaneous recording of electroencephalographic data in musicians playing in ensemble. *Cortex; a Journal Devoted to the Study of the Nervous System and Behavior*, *47*(9), 1082-1090. https://doi.org/10.1016/j.cortex.2011.05.006

Bianco, R., Novembre, G., Keller, P. E., Villringer, A., & Sammler, D. (2018). Musical genre-dependent behavioural and EEG signatures of action planning. A comparison between classical and jazz pianists. *NeuroImage*, *169*, 383-394. https://doi.org/10.1016/j.neuroimage.2017.12.058

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience and Biobehavioral Reviews*, *44*, 58-75. Scopus. https://doi.org/10.1016/j.neubiorev.2012.10.003

Bruya, B., & Tang, Y.-Y. (2018). Is attention really effort? Revisiting Daniel Kahneman's influential 1973 book attention and effort. *Frontiers in Psychology*, *9*(SEP). Scopus. https://doi.org/10.3389/fpsyg.2018.01133

Calma-Roddin, N., & Drury, J. E. (2020). Music, Language, and The N400: ERP Interference Patterns Across Cognitive Domains. *Scientific Reports*, *10*(1). Scopus. https://doi.org/10.1038/s41598-020-66732-0

Chikhi, S., Matton, N., & Blanchet, S. (2022). EEG power spectral measures of cognitive workload: A meta-analysis. *Psychophysiology*, *59*(6). Scopus. https://doi.org/10.1111/psyp.14009

Csikszentmihalyi, M. (1988). The flow experience and its significance for human psychology. En I. S. Csikszentmihalyi & M. Csikszentmihalyi (Eds.), *Optimal Experience: Psychological Studies of Flow in Consciousness* (pp. 15-35). Cambridge University Press. https://doi.org/10.1017/CBO9780511621956.002

Fuentes, J. P., Villafaina, S., Collado-Mateo, D., de la Vega, R., Gusi, N., & Clemente-Suárez, V. J. (2018). Use of Biotechnological Devices in the Quantification of Psychophysiological Workload of Professional Chess Players. *Journal of Medical Systems*, *42*(3), 40. https://doi.org/10.1007/s10916-018-0890-0

Fuentes-García, J. P., Pereira, T., Castro, M. A., Carvalho Santos, A., & Villafaina, S. (2019). Heart and Brain Responses to Real Versus Simulated Chess Games in Trained Chess Players: A Quantitative EEG and HRV Study. *International Journal of Environmental Research and Public Health*, *16*(24), Article 24. https://doi.org/10.3390/ijerph16245021

Fuentes-García, J. P., Villafaina, S., Collado-Mateo, D., Cano-Plasencia, R., & Gusi, N. (2020). Chess players increase the theta power spectrum when the difficulty of the opponent increases: An EEG study. *International Journal of Environmental Research and Public Health*, *17*(1). Scopus. https://doi.org/10.3390/ijerph17010046

Gulbinaite, R., Van Viegen, T., Wieling, M., Cohen, M. X., & Vanrullen, R. (2017). Individual alpha peak frequency predicts 10 hz flicker effects on selective attention. *Journal of Neuroscience*, *37*(42), 10173-10184. Scopus. https://doi.org/10.1523/JNEUROSCI.1163-17.2017

Gutmann, B., Hülsdünker, T., Mierau, J., Strüder, H. K., & Mierau, A. (2018). Exercise-induced changes in EEG alpha power depend on frequency band definition mode. *Neuroscience Letters*, *662*, 271-275. Scopus. https://doi.org/10.1016/j.neulet.2017.10.033

Hamann, A., & Carstengerdes, N. (2022). Investigating mental workload-induced changes in cortical oxygenation and frontal theta activity during simulated flights. *Scientific Reports*, *12*(1). Scopus. https://doi.org/10.1038/s41598-022-10044-y

Hänggi, J., Brütsch, K., Siegel, A. M., & Jäncke, L. (2014). The architecture of the chess player's brain. *Neuropsychologia*, *62*, 152-162. https://doi.org/10.1016/j.neuropsychologia.2014.07.019

Iqbal, M. U., Srinivasan, B., & Srinivasan, R. (2020a). Dynamic assessment of control room operator's cognitive workload using Electroencephalography (EEG). *Computers & Chemical Engineering*, *141*, 106726. https://doi.org/10.1016/j.compchemeng.2020.106726

Iqbal, M. U., Srinivasan, B., & Srinivasan, R. (2020b). Dynamic assessment of control room operator's cognitive workload using Electroencephalography (EEG). *Computers and Chemical Engineering*, *141*. Scopus. https://doi.org/10.1016/j.compchemeng.2020.106726

Jung, T.-P., Makeig, S., Humphries, C., Lee, T.-W., McKeown, M. J., Iragui, V., & Sejnowski, T. J. (2000). Removing electroencephalographic artifacts by blind source separation. *Psychophysiology*, *37*(2), 163-178. https://doi.org/10.1111/1469-8986.3720163

Kahneman, D. (1997). *Atención y esfuerzo*. http://dialnet.unirioja.es/servlet/libro?codigo=223976

Kamzanova, A. T., Kustubayeva, A. M., & Matthews, G. (2014). Use of EEG workload indices for diagnostic monitoring of vigilance decrement. *Human Factors*, *56*(6), 1136-1149. Scopus. https://doi.org/10.1177/0018720814526617

Karch, S., Loy, F., Krause, D., Schwarz, S., Kiesewetter, J., Segmiller, F., Chrobok, A. I., Keeser, D., & Pogarell, O. (2016). Increased event-related potentials and alpha-, beta-, and gamma-activity associated with intentional actions. *Frontiers in Psychology*, *7*(JAN). Scopus. https://doi.org/10.3389/fpsyg.2016.00007

Katahira, K., Yamazaki, Y., Yamaoka, C., Ozaki, H., Nakagawa, S., & Nagata, N. (2018). EEG correlates of the flow state: A combination of increased frontal theta and moderate frontocentral alpha rhythm in the mental arithmetic task. *Frontiers in Psychology*, *9*(MAR). Scopus. https://doi.org/10.3389/fpsyg.2018.00300

Kazemi, F., Yektayar, M., & Abad, A. M. B. (2012). Investigation the impact of chess play on developing meta-cognitive ability and math problem-solving power of students at different levels of education. *Procedia - Social and Behavioral Sciences*, *32*, 372-379. https://doi.org/10.1016/j.sbspro.2012.01.056

Lim, W. L., Sourina, O., & Wang, L. P. (2018). STEW: Simultaneous Task EEG Workload Data Set. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *26*(11), 2106-2114. https://doi.org/10.1109/TNSRE.2018.2872924

Mike X. Cohen. (2014). *Analyzing Neural Time Series Data*. The MIT Press. https://mitpress.mit.edu/books/analyzing-neural-time-series-data

Pergher, V., Wittevrongel, B., Tournoy, J., Schoenmakers, B., & Van Hulle, M. M. (2019). Mental workload of young and older adults gauged with ERPs and spectral power during N-Back task performance. *Biological Psychology*, *146*. Scopus. https://doi.org/10.1016/j.biopsycho.2019.107726

Plechawska-Wójcik, M., Borys, M., Tokovarov, M., & Kaczorowska, M. (2018). Measuring cognitive workload in arithmetic tasks based on response time and EEG features. *Advances in Intelligent Systems and Computing*, *655*, 59-72. Scopus. https://doi.org/10.1007/978-3-319-67220-5_6

Postal, V. (2012). INHIBITION OF IRRELEVANT INFORMATION IS NOT NECESSARY TO PERFORMANCE OF EXPERT CHESS PLAYERS [1,2]. *Perceptual and Motor Skills*, *115*(1), 60-68. https://doi.org/10.2466/23.04.22.PMS.115.4.60-68

Sala, G., Gorini, A., & Pravettoni, G. (2015). Mathematical Problem-Solving Abilities and Chess: An Experimental Study on Young Pupils. *SAGE Open*, *5*(3), 2158244015596050. https://doi.org/10.1177/2158244015596050

Sheridan, H., & Reingold, E. M. (2014). Expert versus novice differences in the detection of relevant information during a chess game: Evidence from eye movements. *Frontiers in Psychology*, *5*(AUG). Scopus. https://doi.org/10.3389/fpsyg.2014.00941

Shou, G., & Ding, L. (2013). *Frontal theta EEG dynamics in a real-world air traffic control task*. 5594-5597. Scopus. https://doi.org/10.1109/EMBC.2013.6610818

Silva, L. R., Cesar, F. H. G., Rocha, F. T., & Thomaz, C. E. (2017). *EEG and Eye movement maps of chess players*. *2017-January*, 434-441. Scopus. https://doi.org/10.5220/0006191404340441

Silva, L. R., Jr., Cesar, F. H. G., Rocha, F. T., & Thomaz, C. E. (2018). A Combined Eye-Tracking and EEG Analysis on Chess Moves. *IEEE Latin America Transactions*, *16*(5), 1288-1297. Scopus. https://doi.org/10.1109/TLA.2018.8407099

Simon, H. A., & Schaeffer, J. (1992). Chapter 1 The game of chess. En *Handbook of Game Theory with Economic Applications* (Vol. 1, pp. 1-17). Elsevier. https://doi.org/10.1016/S1574-0005(05)80004-9

Spitzer, B., & Haegens, S. (2017). Beyond the Status Quo: A Role for Beta Oscillations in Endogenous Content (Re)Activation. *eNeuro*, *4*(4), ENEURO.0170-17.2017. https://doi.org/10.1523/ENEURO.0170-17.2017

Teh, E., Jamson, S., Carsten, O., & Jamson, H. (2014). Temporal fluctuations in driving demand: The effect of traffic complexity on subjective measures of workload and driving performance. *Transportation Research Part F: Traffic Psychology and Behaviour*, *22*, 207-217. Scopus. https://doi.org/10.1016/j.trf.2013.12.005

Villafaina, S., Castro, M. A., Pereira, T., Carvalho Santos, A., & Fuentes-García, J. P. (2021). Neurophysiological and autonomic responses of high and low level chess players during difficult and easy chess endgames – A quantitative EEG and HRV study. *Physiology and Behavior*, *237*. Scopus. https://doi.org/10.1016/j.physbeh.2021.113454

Wang, C.-C., & Hsu, M.-C. (2014). *An exploratory study using inexpensive electroencephalography (EEG) to understand flow experience in computer-based instruction*. Scopus.

Wickens, C. D. (2008). Multiple resources and mental workload. *Human Factors*, *50*(3), 449-455. Scopus. https://doi.org/10.1518/001872008X288394

Young, M. S., Brookhuis, K. A., Wickens, C. D., & Hancock, P. A. (2015). State of science: Mental workload in ergonomics. *Ergonomics*, *58*(1), 1-17. Scopus. https://doi.org/10.1080/00140139.2014.956151