The influence of multiple cognitive workload levels of an exergame on dorsal attention network connectivity at the source level

Ghani, Usman; Niazi, Imran; Signal, Nada; Kumari, Nitika; Amjad, Imran; Haavik, Heidi; Taylor, Denise

Published in:
Physiology & Behavior

DOI (link to publication from Publisher):
10.1016/j.physbeh.2024.114628

Publication date:
2024

Document Version
Accepted author manuscript, peer reviewed version

The Influence of multiple cognitive workload levels of an exergame on Dorsal Attention Network Connectivity at the Source Level

Usman Ghani [a,b*], Imran Niazi [a,b,c], Nada Signal [b], Nitika Kumari [a], Imran Amjad [a], Heidi Haavik [a], Denise Taylor [b]

a. Centre for Chiropractic Research, New Zealand College of Chiropractic, Auckland, New Zealand
b. Department of health and sciences, Auckland University of Technology (AUT), New Zealand
c. Department of Health Science and Technology, Aalborg University, Aalborg, Denmark

Abstract

This study investigates how adding a cognitive task on a balance board (exergame) affects connectivity in the dorsal attention network (DAN) during an exergame task. Healthy young adults performed a soccer ball-moving task by tilting a balance board with their feet while their brain activity was measured using electroencephalography (EEG). In this exergame, the speed of obstacles in front of the goal manipulated the cognitive workload. Higher speed means a higher cognitive workload. The study found significant changes in functional connectivity within DAN regions, specifically in the alpha band. During the shift from easy to medium cognitive task, we observed a significant increase in connectivity (p = 0.0436) between the right inferior temporal (ITG R) and the Left middle temporal (MTG L). During the transition from easy to hard cognitive tasks, strengthened interactions (p = 0.0324) between inferior temporal (ITG) and parsopercularis (pOPPER) were found. This suggests that the proposed balanceboard-based exergame enhances the functionality of specific brain regions, such as ITG and MTG regions, and improves connectivity in the frontal cortex. We also found a correlation between brain activity and performance data, highlighting that increased cognitive workload resulted in decreased performance and heightened frontal alpha activity. These findings align with research suggesting that adding cognitive games to physical activity-based tasks in rehabilitation programs can boost brain activity, resulting in improved decision-making and visual processing skills. This information can help clinicians tailor rehabilitation methods that target specific brain regions.

Keywords: Dorsal Attention Network (DAN); Cognitive workload; Electroencephalogram (EEG), Exergame, and Phase lag index (PLI)

1. Introduction

Neurorehabilitation focuses on the recovery and rehabilitation of individuals who have suffered from brain injury, disease or other neurological disorders (Levine et al., 2011). In recent years, there has been a growing interest in using cognitive workload evaluation in neurorehabilitation, particularly for developing effective rehabilitation strategies (Tunik et al., 2013). The cognitive workload of patients is an important factor to consider, as it can impact the effectiveness of neurorehabilitation programs (Ghani et al., 2020a; Mark et al., 2004). Although several objective measures of cognitive workload evaluation with EEG have been proposed (Ghani et al., 2020b; Ghani et al., 2021; Zhou et al., 2022), it remained unclear how different brain regions communicate under different workload levels or how the underlying mechanisms work. Such information can help develop more robust methods of cognitive workload evaluation. Therefore, in this study, more emphasis was placed on connectivity analysis and source

localisation in cognitive workload evaluation, as it can provide important insights into the neural mechanisms underlying cognitive function and help develop more effective rehabilitation strategies for patients (Schoffelen & Gross, 2009).

Connectivity analysis is a powerful method for examining the communication and collaboration between different brain regions during complex cognitive tasks (Šverko et al., 2022). Connectivity analysis can be done at the sensor level (Duan et al., 2021) or the source level (Hassan & Wendling, 2018). Due to volume conduction, EEG signals at the sensor level express a complex mixture of overlapping signals from other EEG sensors (Rutkove, 2007). Therefore, EEG source reconstruction is considered more robust for calculating functional connectivity between the sources (Hassan & Wendling, 2018). Irrespective of sensor and source-based approaches, two widely used approaches to measure functional connectivity are 1) Coherence and 2) Phase lag index (PLI). Coherence, a widely used approach, evaluates linear associations between signals by measuring the consistency of phase differences between two signals over time (Briels et al., 2020). In contrast, PLI assesses non-linear relationships by quantifying the asymmetry of the distribution of phase differences between signals, focusing on true interactions and avoiding spurious correlations due to volume conduction effects (Briels et al., 2020). Both coherence and PLI have been employed in attention-related studies, offering valuable insights into the communication between brain regions under varying levels of attention and cognition (Mateos et al., 2022; Ueda et al., 2020). Thus, these techniques can enhance our understanding of the intricate dynamics of the brain's functional connectivity during cognitive tasks.

Recently, PLI has been used extensively to study the dorsal attention network (DAN), a network of brain regions critical for attention and cognitive control (Dixon et al., 2017; Rohr et al., 2017). The DAN includes brain regions such as the superior parietal lobe and the frontal eye fields, which are involved in spatial attention and eye movements (Szczepanski et al., 2013). These brain regions are shown in **Figure 1**. Understanding how these regions communicate with each other and with other brain networks is crucial for understanding how the brain supports attention and cognition. One important question is how the DAN operates under different levels of cognitive workload. Previous research has shown that the DAN is activated during tasks requiring high attention, such as visual search and working memory tasks (Corbetta & Shulman, 2002). However, it is still unclear how the network adapts to changing levels of cognitive demand and how this affects its communication patterns. In this study, we used an exergame as a task with multiple levels of cognitive workload to see how the connectivity of source reconstructed EEG changes in DAN with variation in cognitive workload.

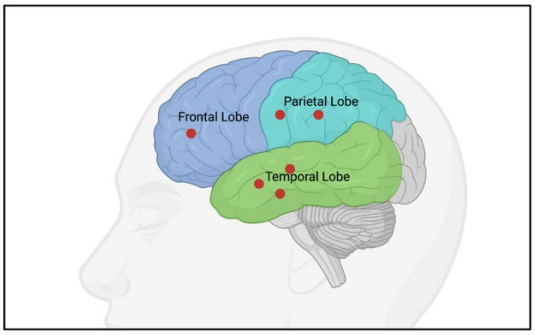

Figure 1: Brain (sagittal right view) with DAN regions Created with BioRender.com

Exergames, which combine physical activity and cognitive challenges, have emerged as a useful tool for investigating cognitive processes during complex tasks (Maillot et al., 2012). In this context, the current study aimed to examine the impact of cognitive workload changes on the connectivity within the DAN during an exergame. We will use the data collected during our previous work, which validated that the exergame provided three distinct levels of cognitive workload (Ghani et al., 2021). In this previous study, EEG was employed to measure brain activity in twenty-four healthy adults who completed an exergame task that involved moving a soccer ball into a highlighted goal by tilting a balance board with their feet. The task's cognitive workload was manipulated by adjusting the speed of obstacles in front of the goal, creating three distinct workload levels (more details on the task can be found at (Ghani et al., 2021). Participants were presented with three cognitive workload levels (easy, medium, and hard) and task-irrelevant auditory tones to generate event-related potentials (ERPs). In our previous studies, we looked at the amplitude change of these ERPs with cognitive workload and found that the amplitude of these ERPs decreased with an increase in cognitive workload (Ghani et al., 2020b; Ghani et al., 2021). This suggested an increase in attention towards the task and a decrease in attention towards the auditory tone with an increase in cognitive workload. In this study, we wanted to look at the change in connectivity between brain regions with an increase in cognitive workload. Based on the literature and previous findings, we hypothesised that the connectivity between brain regions will increase with increased cognitive workload. We will also correlate performance data collected during the study, such as the number of goals scored and subjective ratings of task difficulty, with changes in brain activity (PLI).

2. Method

2.1. Participants and task

Twenty-four young, healthy adults (11 females, age range: 20–30 years, mean age: 25 ± 3.4 years) were recruited via advertisements through university networks and word of mouth. The task was a tilt-ball game that participants played while standing on a balance board (for details on the study procedure, see (Ghani et al., 2021)).

2.2. EEG data processing

The overall flow graph of the EEG data processing for the study is shown in Figure **2**. The EEG data was acquired using a 64-channel Brainwave EEG cap coupled with a REFA amplifier (TMSi, Twente, Netherlands) at a sampling rate of 2,048 Hz. The recordings were obtained from 64 scalp sites, following the 10-20 electrode system (Homan et al., 1987), with the ground electrode situated at AFz and both mastoids (M1 and M2) employed as reference points. Electrode impedance was consistently maintained below 10 kΩ. Additionally, online filter settings were adjusted to a range of DC-100 Hz, incorporating a 50 Hz notch filter during the raw data acquisition process. The raw EEG data were preprocessed offline using EEGLAB (version 14.1.1) (Delorme & Makeig, 2004) and ERPLAB (version 6.1.4) (Lopez-Calderon & Luck, 2014) running on MATLAB (2015b) (The MathWorks, Inc, Natick, MA, United States).

For the EEG preprocessing, 62 electrodes were re-referred to achieve a common average reference excluding the two mastoids. We used the PREP pipeline (version 0.55.1) (Bigdely-Shamlo et al., 2015) to remove and interpolate bad channels and line noise.

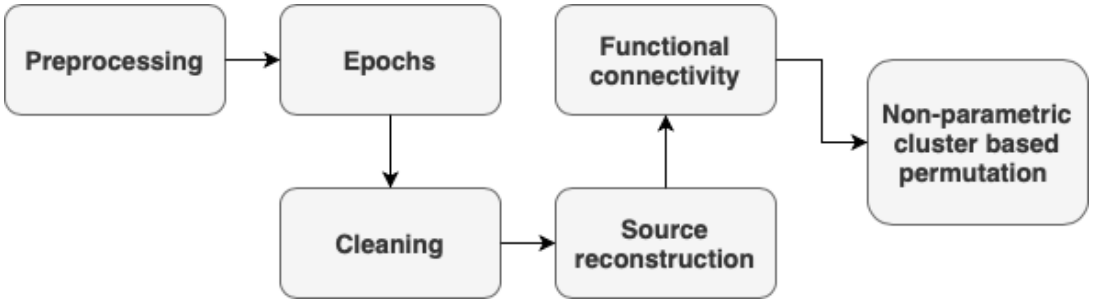

Figure 2: EEG data processing pipeline

After running the PREP pipeline, epochs were extracted from −200 to 1500 ms to the stimulus and corrected baseline using the pre-stimulus period. The bad channels were visually marked from the data before running the independent component analysis (ICA). Custom-written ICA code was then used to remove bad components from the data. The data obtained after epoching and ICA were subjected to the ERPLAB artifact detection algorithm of moving window threshold (Lopez-Calderon & Luck, 2014). A 200 ms window width and a 100 ms step were defined with a threshold of ±100 μV. The epochs in which the signal exceeded ±100 μV on any channel were rejected. This preprocessed data (interpolated to full channels) was then loaded into Brainstorm for source estimation.

2.3. Source reconstruction

EEG source reconstruction was performed using Brainstorm (Tadel, 2011) in MATLAB R2022a. Source reconstruction is a method used in neuroscience to estimate the location and activity of underlying neural sources based on measurements obtained from multiple sensors or electrodes (Hämäläinen & Ilmoniemi, 1994). Using advanced mathematical models and algorithms, source reconstruction can provide a more comprehensive understanding of brain activity by identifying the specific regions and networks involved in specific tasks or behaviours (Friston, 2011). There are two main problems in EEG source reconstruction: forward modelling and inverse modelling, both dependent on each other for accurate source reconstruction (Sadleir & Argibay, 2007). Forward modelling involves the human head, including its scalp, skull, cortex, and electromagnetic properties (Hassan & Wendling, 2018). The inverse modelling problem uses the information about cortical activity from forward modelling to identify the most likely locations and strengths (Sadleir & Argibay, 2007). In subsequent sub-sections, forward and inverse modelling will be explained in detail. The overall process of source reconstruction is shown in Figure **3**.

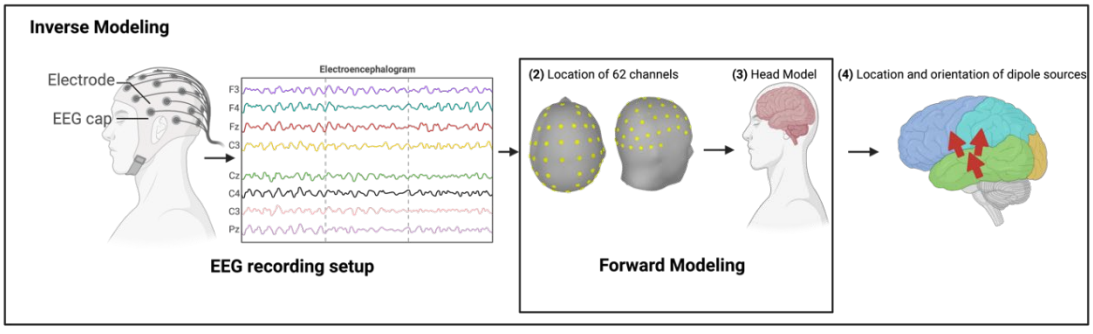

Figure 3: Source reconstruction pipeline

2.3.1. Forward Modelling

This section outlines the forward modelling process for EEG source reconstruction. Our goal was to determine the location and orientation of EEG sensors relative to the cortical source, which required defining the location and orientation of current dipole fields (Sadleir & Argibay, 2007; Tadel et al., 2011). We accomplished this by placing source dipoles on a voxel grid space approximating the cortical space, ensuring they were oriented perpendicular to the cortex. We used the symmetric boundary element method (Open MEEG BEM) to model the dipoles for all subjects (Tadel et al., 2011). We employed a default generic head model from Brainstorm May 2023, which featured 15,000 vertices and a three-layer compartment (scalp, skull, and brain). Tissue conductivities were set based on a previous study by R.J Sadlier (Sadleir & Argibay, 2007): scalp = 1, skull = 0.0125, and brain = 1. We calculated the forward model after defining the 64 electrode locations (including ref: M1 and M2) on the scalp using the 10-20 electrode placement system and the Colin27 Neuroscan Quick-Cap 64.

2.3.2. Inverse Modelling

The inverse problem is a technique used in neuroscience to estimate activity from the brain based on measurements taken from electroencephalography (EEG) sensors (Schoffelen & Gross, 2009). This technique solves an underdetermined and ill-posed problem where the number of estimated sources exceeds the number of electrodes used to record the data. To achieve a solution, the method of minimum-norm estimation is utilised, which involves applying a linear kernel to the spatial data at each point in time (Grech et al., 2008). This technique estimates cortical current source densities by minimising the overall power of the estimated sources while using an identity matrix as the noise covariance matrix (Tadel et al., 2011). However, the minimum-norm estimate tends to locate sources in the superficial regions of the cortex, leading to inaccurate results. We, therefore, used the standardised low-resolution brain electromagnetic tomography (sLORETA) method to adjust current density maps of source dipoles, representing them as normalised current densities perpendicular to the cortex (Brunovsky et al., 2008). To efficiently assess functional connectivity, we grouped the high-resolution sources based on the Desikan Killiany atlas, which defines 68 regions of interest (ROIs) on the cortex surface. Averaging the time series within each ROI, we formed a [ROIs x time] matrix. As suggested by the literature, we also flipped the sign of dipoles with opposite directions before averaging to prevent activity cancellation. This approach enabled accurate estimation of brain activity and an understanding of how different brain regions are connected.

2.4. Functional Connectivity

2.4.1. Dorsal Attention Network

DAN is a neural network involved in attentional control and spatial processing. Table 1 shows key brain regions, subregions within the DAN, and their common abbreviations taken from (Kabbara et al., 2017).

Table 1: Brain sub-regions within DAN

Brain Regions	Abbreviations	Brain Regions
cAUDalanteriorcingulate L	cACC L	Cingulate
cAUDalanteriorcingulate R	cACC R	Cingulate
inferiortemporal L	ITG L	Temporal

inferiortemporal R	ITG R	Temporal
middletemporal L	MTG L	Temporal
middletemporal R	MTG R	Temporal
parsopercularis L	pOPPER L	Frontal
parsopercularis R	pOPPER R	Frontal
parsorbitalis L	pORB L	Frontal
parsorbitalis R	pORB R	Frontal
parstriangularis L	pTRI L	Frontal
parstriangularis R	pTRI R	Frontal

Before the functional connectivity calculation, the DAN was derived from the sources only considering brain regions within this network.

2.4.2. Phase Lag Index

PLI is a measure of connectivity that quantifies asymmetry based on the phase difference distribution between two signals, denoted as 'x(t)' and 'y(t)'. We first calculated the average phase difference using Equation (1) to compute the PLI. This requires obtaining the signal's phase information, which is derived from the phase of the ratio between the signal's Hilbert transform and the signal itself.

$$PLI_{x,y} = \left| \frac{1}{N} \sum_{t=1}^{N} sign\left[sin\left(\emptyset_x(t) - \emptyset_y(t) \right] \right| \right. \quad (1)$$

The resulting phase difference can be positive, negative, or zero, depending on the sign. The phase differences were evaluated across a specific window to determine the PLI and the calculation was performed over N total samples contained within that window. This process enabled us to quantify the extent of connectivity and asymmetry between the signals, providing valuable insights into the functional interactions of brain regions.

This study divided the data into narrow-band signals using a 4th-order Butterworth filter before PLI computation. This step allowed us to extract specific frequency bands: alpha (7.5–12.5 Hz), beta (12.5–30 Hz), and gamma (30–40 Hz), based on the ranges reported in the study Newson and Thiagarajan (2019). The computation of PLI was done between every reconstructed EEG source signal in a pair. The result of the computed PLI lies in the interval from zero to one, where zero indicates no connectivity, and one indicates maximum connectivity between signals. After the computation of PLI between every source pair, the PLI data were stored in an adjacency matrix of dimension 12 x 12 with zeros along the diagonal, giving a symmetric square matrix corresponding to the number of sources. We had three 12 x 12 adjacency matrices corresponding to easy, medium and hard within alpha in the DAN. We used non-parametric cluster-based permutations to find significant source pairs when we compared different workload levels.

2.4.3. Non-parametric cluster-based permutation

We employed a non-parametric cluster-based permutation test to handle the multiple comparison problem and control the familywise error (Maris & Oostenveld, 2007). Using a within-study design, this test compared the calculated PLI values within the adjacency matrices across multiple workload levels (easy vs medium, easy vs hard, and medium vs hard). The non-parametric cluster-based permutation test was conducted using the Field Trip toolbox provided by the Donders Institute, Brain, Cognition, and Behavior in Nijmegen, the Netherlands. For each pairwise comparison (easy vs. medium, easy vs. hard, medium vs. hard), we calculated

cluster-level statistics. The largest cluster-level statistic served as the critical t-value for determining significant clusters. To create a null distribution, we conducted 5000 permutations by randomly shuffling the data labels for each comparison. We then recalculated cluster-level statistics for each permutation, reflecting the expected distribution of results under the null hypothesis of no differences in functional connectivity between conditions.

The *p*-value for each observed cluster was computed as the proportion of permutations where the cluster-level statistic was more extreme (either larger or smaller, depending on the directionality) than the observed cluster-level statistic. A significant positive cluster (+cluster) indicated increased functional connectivity, whereas a significant negative cluster (-cluster) indicated decreased functional connectivity in one condition. This analysis allowed us to identify brain regions where functional connectivity significantly changed between conditions, shedding light on the impact of cognitive workload on brain network interactions. The results were visualised within the cortex using EEGNET version 1 (Hassan et al., 2015); where statistically significant results were illustrated as red spheres representing the brain region and connecting lines representing statistical dependencies from the functional connectivity metrics between brain regions (Hassan et al., 2015).

2.4.4. Correlation Analysis

The brain regions within the DAN were categorised into three main regions: Frontal, Temporal, and Cingulate, based on the assignments outlined in Table 1. We then calculated the mean PLI values for each of the three main brain regions (Frontal, Temporal, and Cingulate) for every participant to examine the relationship between task performance (goals scored and ratings) and brain activity (PLI values). After that, we performed Pearson correlation analyses to explore the connections between goals scored, ratings, and the mean PLI values in each brain region. This correlation analysis was aimed to determine how brain activity patterns corresponded to performance and perceived task difficulty across different brain regions.

3. Results

3.1. Cluster-based Permutation:

We analysed EEG data from 24 subjects. The analysis revealed that higher cognitive workload resulted in increased functional connectivity within the DAN in various brain regions within the alpha frequency band calculated from the PLI.

A non-parametric cluster-based permutation test compared the PLI values between different workload levels (easy, medium, and hard). In this test, a cluster was defined as a set of spatially adjacent connections that showed significant differences between these workload levels. The test controlled for multiple comparisons and familywise errors. Four positive clusters were found when comparing easy and medium workload levels ($t = 3.945$, $p = 0.0436$), indicating increased connectivity. Similarly, six positive clusters were observed when comparing easy and hard levels ($t = 7.43$, $p = 0.0324$), indicating increased connectivity. However, no significant clusters were observed when comparing medium to hard workload levels for both positive ($t = 2.82$, $p = 0.6399$) and negative ($t = -2.18$, $p = 0.9$) clusters. The reported t-statistic and p-value for each condition in Table 2 represent the largest cluster's t-statistic and associated p-value derived from the cluster-level permutation test, ensuring that they reflected the most significant change within the identified clusters.

Table 2: The non-parametric cluster-based permutation test results comparing functional connectivity within the dorsal attention network for PLI. The PLI metric was compared for Easy vs Medium, Easy vs Hard, and Medium vs Hard within the Alpha band. Positive an

Condition	+Clusters	t-value	p-value	-Clusters	t-value	p-value
Easy vs Medium	4	3.945	**0.0436**	0	-	-
Easy vs Hard	6	7.43	**0.0324**	0	-	-
Medium vs Hard	4	2.82	0.6399	4	-2.18	0.9

Within identified significant clusters, several brain regions were involved, and Figure 4 illustrates these brain regions whose functional connectivity from the PLI metric was significantly increased from (A) easy to medium and (B) easy to hard. The results were visualised at the cortex level with the connected brain regions using EEGNET (version 1) (Hassan et al., 2015) and custom-written MATLAB code for the circular graph plots to better understand the significant changes found. Furthermore, a circular graph highlighted connectivity (PLI values) between the brain regions. This circular graph is shown in Figure 5.

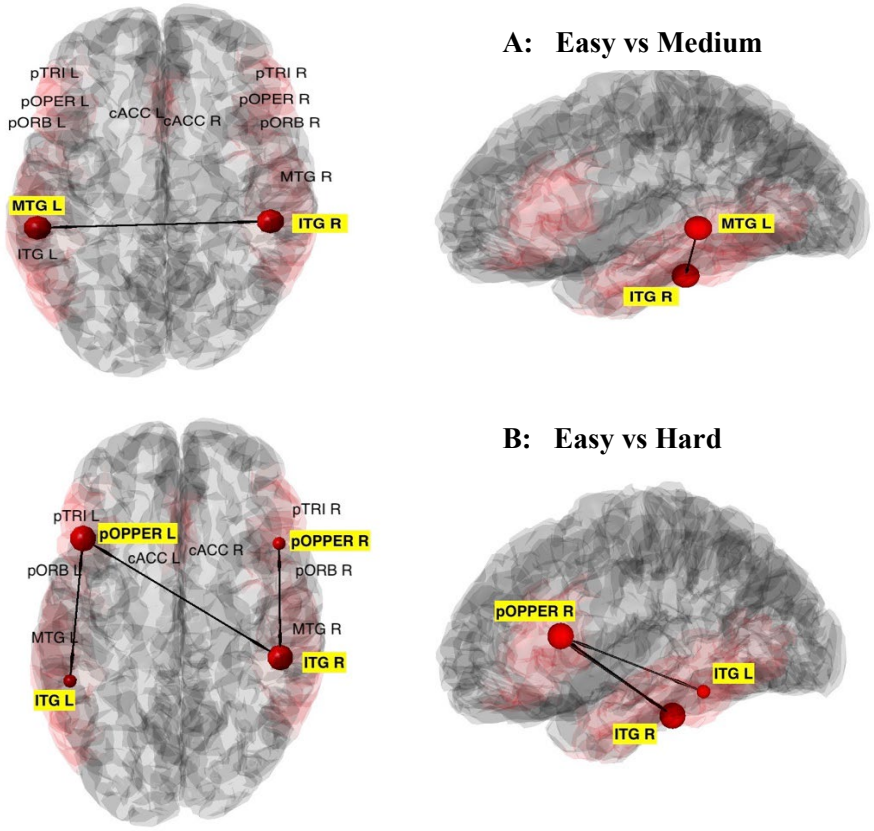

Figure 4: Alpha functional connectivity changes in brain regions when transitioning from **A:** Easy to Medium, and **B:** Easy to Hard. The cortex visualisation displays networks and connectivity, with red highlighted areas indicating the DAN and labelled brain regions. Significant results are represented by bold labels and yellow highlights, with red dots representing brain regions and lines showing functional connectivity via PLI metrics. Mentioned brain regions are cAUDalanteriorcingulate L (cACC L), cAUDalanteriorcingulate R (cACC R), inferiortemporal L (ITG L), inferiortemporal R (ITG R), middletemporal L (MTG L), middletemporal R (MTG R), parsopercularis L (pOPPER L), parsopercularis R (pOPPER R), parsorbitalis L (pORB L), parsorbitalis R (pORB R), parstriangularis L (pTRI L), parstriangularis R (pTRI R).

The functional connectivity matrix PLI increased significantly in the alpha band in inferior temporal R (ITG R) and middle temporal L (MTG L) brain regions within the DAN as we moved from easy to medium. Similarly, PLI increase in the following brain regions was observed as we moved from easy to hard cognitive workload. 1) inferiortemporal L (ITG L)

and parsopercularis L (pOPPER L), 2) inferiortemporal R (ITG R) and parsopercularis R (pOPPER R), and 3) inferior temporal R (ITG R) and parsopercularis L (pOPPER L). These interactions with corresponding effect sizes (cohen's d) are shown in Table 3.

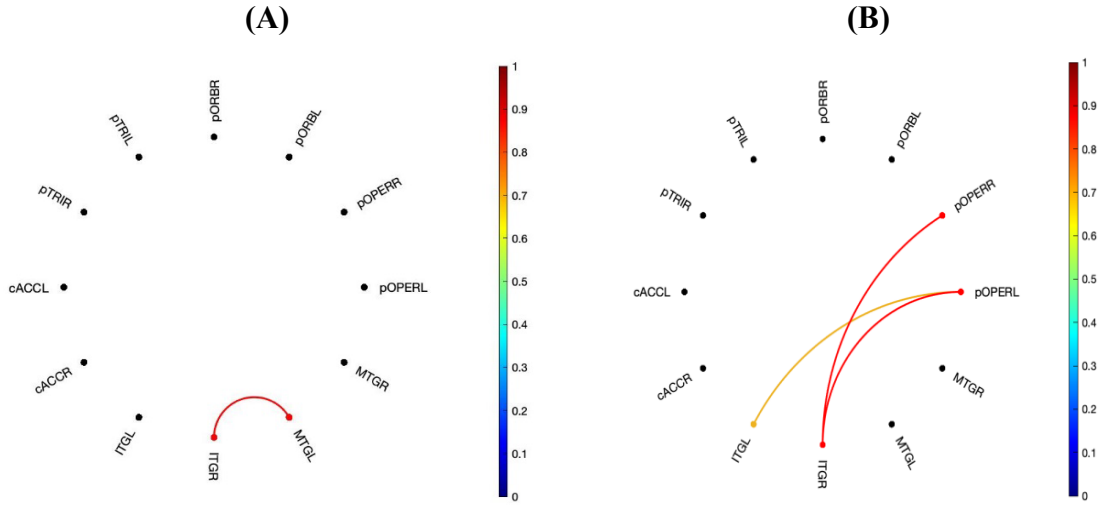

Figure 5: The circular graph shows PLI connectivity between brain regions A) Easy vs Medium and B) Easy vs Hard. A higher PLI value means higher connectivity.

3.2. Correlation Analysis

A series of Pearson correlation analyses were performed to investigate the connections between Goals, Ratings, and PLI across three brain regions: Cingulate, Frontal, and Temporal. **Goals vs PLI:** For the Goals and PLI analysis, the Cingulate region showed a weak positive correlation ($r = 0.09, p = 0.561$). The Frontal region exhibited a moderate negative correlation, $r = -0.48$ $p < 0.001$). The Temporal region had a weak negative correlation ($r = -0.06$, $p = 0.698$.) **Ratings vs PLI:** In the Ratings and PLI analysis, the Cingulate region displayed a very weak positive correlation ($r = 0.06$, $p = 0.683$). The Frontal region showed a moderate to strong positive correlation ($r = 0.63$, $p < 0.001$). The Temporal region demonstrated a weak positive correlation ($r = 0.28$, $p = 0.052$). These results are shown in Table 4 and Figure 6.

Table 3: Effect size (Cohen's d) for significant clusters within the alpha band. For easy vs medium, inferiortemporal R (ITG R) and middletemporal L (MTG L). For easy vs hard, inferiortemporal R (ITG R), inferior temporal L (ITG L), parsopercularis L (pOPPER L)

Condition	Regions	Condition 1	Condition 2	Cohen's d
Easy vs Hard		**Easy**	**Hard**	
	ITG L- pOPPER L	0.05	0.1754	0.42
	ITG R - pOPPER R	0.04	0.08	0.17
	ITG R - pOPPER L	0	0.28	-
		Easy	**Medium**	
Easy vs Medium	ITG R – MTG L	0.01	0.13	0.32

Table 4: Performance vs Brain data (Correlation analysis)

Brain Regions	Correlation	Pearson Correlation (r)	p-value
Frontal*	PLI vs Goals	-0.48	<0.001*
	PLI vs Ratings	0.63	<0.001*

Cingulate	PLI vs Goals	0.09	0.561
	PLI vs Ratings	0.06	0.683
Temporal	PLI vs Goals	-0.06	0.698
	PLI vs Ratings	0.28	0.052

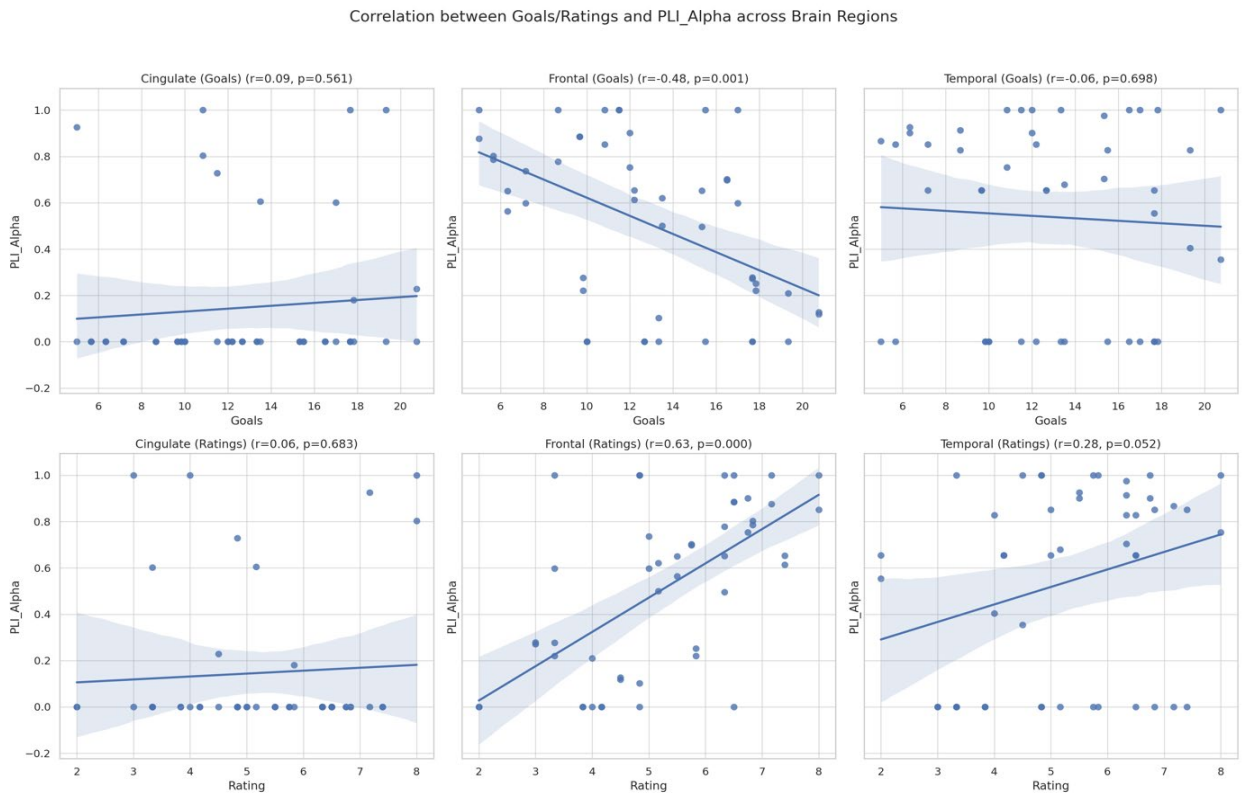

Figure 6: Correlation analysis of performance data with the brain data (PLI).

4. Discussion

This study investigated how varying cognitive workload levels affect neural dynamics during an exergame task. Building upon previous research showing that the amplitude of N100 ERPs decreases as cognitive workload increases (Ghani et al., 2020a, 2020b; Kok, 2001), our study explored the connectivity changes based on the PLI applied to sources within the Dorsal Attention Network (DAN). During the shift from easy to medium cognitive workload, we observed a significant increase in connectivity within the alpha band between inferiortemporal R (ITG R) and middletemporal L (MTG L) within the DAN. On the other hand, during the transition from easy to hard cognitive workload, several significant changes in alpha band connectivity were observed within the DAN. These included the strengthened interactions between inferiortemporal L (ITG L) and parsopercularis L (pOPPER L), as well as the increased connectivity between parsopercularis R (pOPPER R) and inferiortemporal R (ITG R), and lastly, the heightened connectivity between parsopercularis R (pOPPER R) and inferiortemporal L (ITG L). furthermore, A correlation analysis revealed a negative correlation between performance and brain activity, as well as a positive correlation between perceived difficulty and brain activity.

We found significant changes only within the alpha frequency band. The absence of significant findings in the other frequency bands, such as beta and gamma bands, aligns with some studies that suggest task-specific and context-dependent variations in EEG responses (Molteni et al.,

2008). For example, Coelli et al. (2015) reported increased beta activity with cognitive workload and concentration, but these effects were not universally observed across all tasks or cognitive demands, a finding also supported by Molteni et al. (2008). Therefore, the exergame used in our study often requires motor coordination, cognitive processing, and attentional control (Fitzgerald et al., 2010), eliciting a different pattern of neural activation, predominantly reflected in the alpha band and not in the other frequency bands. Furthermore, the alpha band has been shown to be associated with attentional processes (Klimesch, 1997), which could be highly engaged during the exergame tasks. Hence, It's plausible that the nature of the exergame encouraged participants to allocate attention and resources to the task, resulting in significant changes in the alpha band activity. Within the alpha band, multiple brain regions were involved in this attention allocation as the cognitive workload increased. Understanding the functionality of different brain regions is essential for gaining a more detailed interpretation of the results.

ITG R and MTG L are part of the temporal lobe, predominantly involved in visual processing and perception (Kravitz et al., 2013; Mesgarani et al., 2014). The temporal lobe plays a crucial role in processing complex visual stimuli, object recognition, and semantic memory, making it highly relevant to the exergame task used in our study (Ghani et al., 2021). As the exergame involved an increased speed of obstacles, participants encountered more intricate and rapidly changing visual stimuli during a medium cognitive workload compared to the easy one. Consequently, ITG R was more engaged in detailed visual feature processing and object recognition. At the same time, MTG L played a role in integrating visual information and extracting semantic meaning from the stimuli. The heightened connectivity between these visual processing regions within the DAN during medium cognitive workload reflects their concerted effort to manage the increase in cognitive workload of the exergame.

The increased connectivity between ITG L and pOPPER L during hard cognitive workload is noteworthy, as ITG L is implicated in object recognition and visual processing (Vlcek et al., 2020). At the same time, pOPPER L is associated with cognitive control processes and decision-making (Fedorenko et al., 2013; Kravitz et al., 2013). This heightened connectivity indicates a coordinated engagement of these regions in allocating attentional resources and strategic decision-making to optimise task performance under higher cognitive demands. Similarly, the observed increase in DAN connectivity between pOPPER R and ITG R further supports the network's extensive interactions to facilitate attentional control during challenging cognitive tasks (Capotosto et al., 2009). The interaction between pOPPER R and ITG R involves integrating cognitive control processes and visual information processing, enabling effective task engagement and performance during hard cognitive workloads. Lastly, the heightened connectivity between pOPPER R and ITG L highlights the dynamic and interconnected nature of the DAN in managing higher cognitive demands.

When comparing medium workload with hard workload, our results did not show significant differences in connectivity. This lack of significant results could be due to several factors. One possible explanation is the ceiling effect, where participants' cognitive capabilities might have been maxed out during the medium workload, leaving little room for further significant increases during the hard workload. Additionally, the neural mechanisms underlying medium and hard cognitive workloads might involve similar brain regions and connectivity patterns, making it challenging to detect distinct changes. Overall, These results reflected the network's ability to adapt its connectivity flexibly to optimise cognitive performance during complex tasks. The integrated efforts of these regions within the DAN suggest a coordinated system that efficiently allocates attentional resources and facilitates cognitive processing in response to

varying levels of cognitive workload. We also performed a correlation analysis to examine how brain activity relates to the performance metric (goals scored) and perceived difficulty (ratings).

4.1. Correlation Analysis

Our correlation analysis revealed that the number of goals scored decreased as task difficulty increased (increasing PLI). This showed a significant negative correlation with the PLI in the frontal region. These findings align with existing research suggesting that alpha oscillations in the frontal cortex are associated with cognitive control and working memory load. In particular, higher task difficulty has been linked to increased alpha activity in the frontal region, indicating greater cognitive control and attentional demand. This is supported by studies showing that frontal alpha activity tends to increase with greater task complexity and cognitive workload (Katahira et al., 2018). Furthermore, alpha oscillations are known to impact cognitive processes like attention and memory, which are crucial for effectively handling more challenging tasks (Sadaghiani & Kleinschmidt, 2016). A significant positive correlation was also found between subjective ratings and frontal PLI values, which again highlight heightened alpha activity in the frontal region with the increased cognitive workload.

Overall, this study demonstrated that as the difficulty of the task in an exercise-based video game increased, there was a higher phase lag index (PLI) in the alpha band between regions of the DAN. Additional analysis also showed a connection between performance measures and the PLI and reported that increased perceived difficulty rating was associated with heightened alpha activity in the frontal brain region. These findings align with existing research, indicating that frontal alpha oscillations are crucial for cognitive control and managing cognitive load. The study underscores the significant role of the frontal cortex in adapting to varying cognitive demands, highlighting how increased connectivity within this region supports enhanced attentional control and task performance under challenging conditions. Recently, exergames have been increasingly used in neurorehabilitation to accelerate recovery (Goble et al., 2014; Hasselmann et al., 2015; Laufer et al., 2014). This study highlights the importance of adjusting the difficulty level of exergames and how it can impact the engagement of brain resources, involving more areas of the brain. Additionally, identifying the brain regions involved in exergames can help clinicians optimise the task to expedite rehabilitation.

Although the study has revealed significant findings, it is important to consider certain limitations. First, the present study focused on the DAN and its connectivity changes, but other brain networks may also contribute to cognitive workload modulation and attentional control. Future investigations employing a network-level approach could provide a more comprehensive understanding of the brain's response to cognitive demands. Second, the exergame task, while engaging, might not fully capture the complexity and ecological validity of real-world cognitive tasks. Studies using a broader range of cognitive paradigms are needed to generalise the findings to various cognitive activities. Moreover, it is essential to conduct a thorough analysis of the connectivity between different brain regions and its impact on performance measures.

5. Conclusion

Our study investigated neural dynamics linked to cognitive workload variations during an exergame task, building on the established inverse relationship between N100 event-related potential amplitudes and cognitive workload. By utilising connectivity analysis through the PLI within the DAN, we aimed to uncover underlying mechanisms of cognitive workload

modulation. Our results revealed distinct DAN connectivity changes as participants shifted from easy to medium and easy to hard cognitive workloads. During the easy-to-medium transition, enhanced connectivity emerged between the inferiortemporal R (ITG R) and middletemporal L (MTG L), suggesting collaboration in processing complex visual stimuli. Similarly, the easy-to-hard transition showed significant connectivity shifts within the DAN, including strengthened interactions between the inferiortemporal L (ITG L) and parsopercularis L (pOPPER L), increased connectivity between the parsopercularis R (pOPPER R) and inferiortemporal R (ITG R), and heightened connectivity between the parsopercularis R (pOPPER R) and inferiortemporal L (ITG L), showcasing the network's adaptability and attentional engagement under higher demands.

Correlation analysis revealed that as task difficulty increased, goal scoring decreased, with a significant negative correlation between goals and frontal PLI. Subjective ratings were positively correlated with frontal PLI, highlighting the role of frontal alpha oscillations in managing cognitive load. These insights are valuable for optimising rehabilitation tasks and suggest that future studies should integrate broader brain networks and behavioural measures for a comprehensive understanding. Integrating behavioural measures with neural data would enrich interpretations of connectivity changes relative to cognitive performance.

6. Acknowledgment

We thank Brain Research New Zealand (BRNZ) for sponsoring this research.

7. Author Contribution statement

Usman Ghani: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Imran Khan Niazi:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Nada Signal:** Conceptualization, Supervision, Writing – review & editing. **Nitika Kumari:** Writing – review & editing. **Imran Amjad:** Writing – review & editing. **Heidi Haavik:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Denise Taylor:** Formal analysis, Funding acquisition, Supervision, Writing – review & editing.

8. Data availability

The authors will make the numerical data supporting this article's conclusions available without undue reservation. Interested individuals can obtain this data by making a reasonable request to the corresponding author, Usman Ghani. The Local Ethics Committee, adhering to local data protection laws, does not allow sharing of individuals' raw data.

9. References

Bigdely-Shamlo, N., Mullen, T., Kothe, C., Su, K. M., & Robbins, K. A. (2015). The PREP pipeline: standardized preprocessing for large-scale EEG analysis. *Front Neuroinform, 9*, 16. https://doi.org/10.3389/fninf.2015.00016

Briels, C. T., Schoonhoven, D. N., Stam, C. J., de Waal, H., Scheltens, P., & Gouw, A. A. (2020, 2020/06/03). Reproducibility of EEG functional connectivity in Alzheimer's disease. *Alzheimer's Research & Therapy, 12*(1), 68. https://doi.org/10.1186/s13195-020-00632-3

Brunovsky, M., Krajca, V., Diblikova, F., Bartos, A., Zavesicka, L., & Matousek, M. (2008, 2008/04/17). Standardized low-resolution brain electromagnetic tomography (sLORETA) in the prediction of response to cholinesterase inhibitors in patients with Alzheimer's disease. *Annals of General Psychiatry, 7*(1), S277. https://doi.org/10.1186/1744-859X-7-S1-S277

Capotosto, P., Babiloni, C., Romani, G. L., & Corbetta, M. (2009, May 6). Frontoparietal cortex controls spatial attention through modulation of anticipatory alpha rhythms. *J Neurosci, 29*(18), 5863-5872. https://doi.org/10.1523/jneurosci.0539-09.2009

Coelli, S., Sclocco, R., Barbieri, R., Reni, G., Zucca, C., & Bianchi, A. (2015). *EEG-based index for engagement level monitoring during sustained attention* (Vol. 2015). https://doi.org/10.1109/EMBC.2015.7318658

Corbetta, M., & Shulman, G. L. (2002, Mar). Control of goal-directed and stimulus-driven attention in the brain. *Nat Rev Neurosci, 3*(3), 201-215. https://doi.org/10.1038/nrn755

Delorme, A., & Makeig, S. (2004, Mar 15). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods, 134*(1), 9-21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Dixon, M. L., Andrews-Hanna, J. R., Spreng, R. N., Irving, Z. C., Mills, C., Girn, M., & Christoff, K. (2017, Feb 15). Interactions between the default network and dorsal attention network vary across default subsystems, time, and cognitive states. *NeuroImage, 147*, 632-649. https://doi.org/10.1016/j.neuroimage.2016.12.073

Duan, W., Chen, X., Wang, Y.-J., Zhao, W., Yuan, H., & Lei, X. (2021). Reproducibility of power spectrum, functional connectivity and network construction in resting-state EEG. *Journal of Neuroscience Methods, 348*, 108985.

Fedorenko, E., Duncan, J., & Kanwisher, N. (2013, Oct 8). Broad domain generality in focal regions of frontal and parietal cortex. *Proc Natl Acad Sci U S A, 110*(41), 16616-16621. https://doi.org/10.1073/pnas.1315235110

Fitzgerald, D., Trakarnratanakul, N., Smyth, B., & Caulfield, B. (2010). Effects of a wobble board-based therapeutic exergaming system for balance training on dynamic postural stability and intrinsic motivation levels. *journal of orthopaedic & sports physical therapy, 40*(1), 11-19.

Friston, K. (2011, Sep 15). Dynamic causal modeling and Granger causality Comments on: the identification of interacting networks in the brain using fMRI: model selection, causality and deconvolution. *NeuroImage, 58*(2), 303-305; author reply 310-301. https://doi.org/10.1016/j.neuroimage.2009.09.031

Ghani, U., Signal, N., Niazi, I. K., & Taylor, D. (2020a, Nov). ERP based measures of cognitive workload: A review. *Neurosci Biobehav Rev, 118*, 18-26. https://doi.org/10.1016/j.neubiorev.2020.07.020

Ghani, U., Signal, N., Niazi, I. K., & Taylor, D. (2020b, Dec). A novel approach to validate the efficacy of single task ERP paradigms to measure cognitive workload. *Int J Psychophysiol, 158*, 9-15. https://doi.org/10.1016/j.ijpsycho.2020.09.007

Ghani, U., Signal, N., Niazi, I. K., & Taylor, D. (2021, 2021-September-08). Efficacy of a Single-Task ERP Measure to Evaluate Cognitive Workload During a Novel Exergame [Original Research]. *Frontiers in Human Neuroscience, 15*. https://doi.org/10.3389/fnhum.2021.742384

Goble, D. J., Cone, B. L., & Fling, B. W. (2014, 2014/02/08). Using the Wii Fit as a tool for balance assessment and neurorehabilitation: the first half decade of "Wii-search". *Journal of NeuroEngineering and Rehabilitation, 11*(1), 12. https://doi.org/10.1186/1743-0003-11-12

Grech, R., Cassar, T., Muscat, J., Camilleri, K. P., Fabri, S. G., Zervakis, M., Xanthopoulos, P., Sakkalis, V., & Vanrumste, B. (2008, 2008/11/07). Review on solving the inverse problem in EEG source analysis. *Journal of NeuroEngineering and Rehabilitation, 5*(1), 25. https://doi.org/10.1186/1743-0003-5-25

Hämäläinen, M. S., & Ilmoniemi, R. J. (1994, 1994/01/01). Interpreting magnetic fields of the brain: minimum norm estimates. *Medical & Biological Engineering & Computing, 32*(1), 35-42. https://doi.org/10.1007/BF02512476

Hassan, M., Shamas, M., Khalil, M., El Falou, W., & Wendling, F. (2015). EEGNET: An Open Source Tool for Analyzing and Visualizing M/EEG Connectome. *PLOS ONE, 10*(9), e0138297. https://doi.org/10.1371/journal.pone.0138297

Hassan, M., & Wendling, F. (2018). Electroencephalography Source Connectivity: Aiming for High Resolution of Brain Networks in Time and Space. *IEEE Signal Processing Magazine, 35*(3), 81-96. https://doi.org/10.1109/MSP.2017.2777518

Hasselmann, V., Oesch, P., Fernandez-Luque, L., & Bachmann, S. (2015, Sep 7). Are exergames promoting mobility an attractive alternative to conventional self-regulated exercises for elderly people in a rehabilitation setting? Study protocol of a randomized controlled trial. *BMC Geriatr, 15*, 108. https://doi.org/10.1186/s12877-015-0106-0

Homan, R. W., Herman, J., & Purdy, P. (1987, Apr). Cerebral location of international 10-20 system electrode placement. *Electroencephalogr Clin Neurophysiol, 66*(4), 376-382. https://doi.org/10.1016/0013-4694(87)90206-9

Kabbara, A., El Falou, W., Khalil, M., Wendling, F., & Hassan, M. (2017, 2017/06/07). The dynamic functional core network of the human brain at rest. *Scientific Reports, 7*(1), 2936. https://doi.org/10.1038/s41598-017-03420-6

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. *Front Psychol, 9*, 300. https://doi.org/10.3389/fpsyg.2018.00300

Klimesch, W. (1997). EEG-alpha rhythms and memory processes. *International Journal of Psychophysiology, 26*(1-3), 319-340.

Kok, A. (2001, May). On the utility of P3 amplitude as a measure of processing capacity. *Psychophysiology, 38*(3), 557-577. https://doi.org/10.1017/s0048577201990559

Kravitz, D. J., Saleem, K. S., Baker, C. I., Ungerleider, L. G., & Mishkin, M. (2013, Jan). The ventral visual pathway: an expanded neural framework for the processing of object quality. *Trends Cogn Sci, 17*(1), 26-49. https://doi.org/10.1016/j.tics.2012.10.011

Laufer, Y., Dar, G., & Kodesh, E. (2014). Does a Wii-based exercise program enhance balance control of independently functioning older adults? A systematic review. *Clin Interv Aging, 9*, 1803-1813. https://doi.org/10.2147/cia.S69673

Levine, B., Schweizer, T., O'Connor, C., Turner, G., Gillingham, S., Stuss, D., Manly, T., & Robertson, I. (2011, 2011-February-17). Rehabilitation of Executive Functioning in Patients with Frontal Lobe Brain Damage with Goal Management Training [Original Research]. *Frontiers in Human Neuroscience, 5*. https://doi.org/10.3389/fnhum.2011.00009

Lopez-Calderon, J., & Luck, S. J. (2014, 2014-April-14). ERPLAB: an open-source toolbox for the analysis of event-related potentials [Technology Report]. *Frontiers in Human Neuroscience, 8*. https://doi.org/10.3389/fnhum.2014.00213

Maillot, P., Perrot, A., & Hartley, A. (2012, Sep). Effects of interactive physical-activity video-game training on physical and cognitive function in older adults. *Psychol Aging, 27*(3), 589-600. https://doi.org/10.1037/a0026268

Maris, E., & Oostenveld, R. (2007, 2007/08/15/). Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods, 164*(1), 177-190. https://doi.org/https://doi.org/10.1016/j.jneumeth.2007.03.024

Mark, A. G., Mark, A. G., Timothy, D. L., & Timothy, D. L. (2004). Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning. *Journal of Motor Behavior*. https://doi.org/10.3200/jmbr.36.2.212-224

599 Mateos, D. M., Krumm, G., Arán Filippetti, V., & Gutierrez, M. (2022). Power Spectrum and
600 Connectivity Analysis in EEG Recording during Attention and Creativity Performance in
601 Children. *NeuroSci, 3*(2), 347-365. https://www.mdpi.com/2673-4087/3/2/25

602
603 Mesgarani, N., Cheung, C., Johnson, K., & Chang, E. F. (2014). Phonetic Feature Encoding in Human
604 Superior Temporal Gyrus. *Science, 343*(6174), 1006-1010.
605 https://doi.org/doi:10.1126/science.1245994

606
607 Molteni, E., Bianchi, A., Butti, M., Reni, G., & Zucca, C. (2008, 08/01). Combined Behavioral and EEG
608 Power Analysis in DAI Improve Accuracy in the Assessment of Sustained Attention Deficit.
609 *Annals of Biomedical engineering, 36*, 1216-1227. https://doi.org/10.1007/s10439-008-9506-
610 z

611
612 Newson, J. J., & Thiagarajan, T. C. (2019, 2019-January-09). EEG Frequency Bands in Psychiatric
613 Disorders: A Review of Resting State Studies [Review]. *Frontiers in Human Neuroscience, 12*.
614 https://doi.org/10.3389/fnhum.2018.00521

615
616 Rohr, C. S., Vinette, S. A., Parsons, K. A. L., Cho, I. Y. K., Dimond, D., Benischek, A., Lebel, C., Dewey, D.,
617 & Bray, S. (2017, Sep 1). Functional Connectivity of the Dorsal Attention Network Predicts
618 Selective Attention in 4-7 year-old Girls. *Cereb Cortex, 27*(9), 4350-4360.
619 https://doi.org/10.1093/cercor/bhw236

620
621 Rutkove, S. B. (2007). *Introduction to volume conduction* Clinical neurophysiology Primer pp 43-53.

622
623 Sadaghiani, S., & Kleinschmidt, A. (2016, Nov). Brain Networks and α-Oscillations: Structural and
624 Functional Foundations of Cognitive Control. *Trends Cogn Sci, 20*(11), 805-817.
625 https://doi.org/10.1016/j.tics.2016.09.004

626
627 Sadleir, R. J., & Argibay, A. (2007, Oct). Modeling skull electrical properties. *Ann Biomed Eng, 35*(10),
628 1699-1712. https://doi.org/10.1007/s10439-007-9343-5

629
630 Schoffelen, J. M., & Gross, J. (2009, Jun). Source connectivity analysis with MEG and EEG. *Hum Brain*
631 *Mapp, 30*(6), 1857-1865. https://doi.org/10.1002/hbm.20745

632
633 Šverko, Z., Vrankić, M., Vlahinić, S., & Rogelj, P. (2022). Complex Pearson Correlation Coefficient for
634 EEG Connectivity Analysis. *Sensors, 22*(4), 1477. https://www.mdpi.com/1424-
635 8220/22/4/1477

636
637 Szczepanski, S. M., Pinsk, M. A., Douglas, M. M., Kastner, S., & Saalmann, Y. B. (2013). Functional and
638 structural architecture of the human dorsal frontoparietal attention network. *Proceedings of*
639 *the National Academy of Sciences, 110*(39), 15806-15811.
640 https://doi.org/doi:10.1073/pnas.1313903110

641
642 Tadel. (2011). *Brainstorm*. http://neuroimage.usc.edu/brainstorm

643

Tadel, F., Baillet, S., Mosher, J. C., Pantazis, D., & Leahy, R. M. (2011). Brainstorm: a user-friendly application for MEG/EEG analysis. *Comput Intell Neurosci, 2011*, 879716. https://doi.org/10.1155/2011/879716

Tunik, E., Saleh, S., & Adamovich, S. V. (2013, Mar). Visuomotor discordance during visually-guided hand movement in virtual reality modulates sensorimotor cortical activity in healthy and hemiparetic subjects. *IEEE Trans Neural Syst Rehabil Eng, 21*(2), 198-207. https://doi.org/10.1109/tnsre.2013.2238250

Ueda, R., Takeichi, H., Kaga, Y., Oguri, M., Saito, Y., Nakagawa, E., Maegaki, Y., & Inagaki, M. (2020, Feb). Atypical gamma functional connectivity pattern during light sleep in children with attention deficit hyperactivity disorder. *Brain Dev, 42*(2), 129-139. https://doi.org/10.1016/j.braindev.2019.11.001

Vlcek, K., Fajnerova, I., Nekovarova, T., Hejtmanek, L., Janca, R., Jezdik, P., Kalina, A., Tomasek, M., Krsek, P., Hammer, J., & Marusic, P. (2020). Mapping the Scene and Object Processing Networks by Intracranial EEG. *Front Hum Neurosci, 14*, 561399. https://doi.org/10.3389/fnhum.2020.561399

Zhou, Y., Huang, S., Xu, Z., Wang, P., Wu, X., & Zhang, D. (2022). Cognitive Workload Recognition Using EEG Signals and Machine Learning: A Review. *IEEE Transactions on Cognitive and Developmental Systems, 14*(3), 799-818. https://doi.org/10.1109/TCDS.2021.3090217