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Investigating the Relationship Between Resting-state EEG Frontoparietal Coherence, Visuospatial Ability, and Motor Skill Acquisition: A Retrospective Analysis

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Abstract

Introduction: Visuospatial ability may explain individual differences in the extent of motor skill learning. This study tested whether frontoparietal functional connectivity at rest, measured by resting-state electroencephalography (EEG) coherence, is related to both visuospatial performance and motor skill acquisition (an early stage of motor learning). **Methods:** Across 21 participants, the following data were retrospectively analyzed: 2-min eyes-closed resting-state EEG, the Visuospatial/Constructional Index score from the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS), and five practice trials of a functional motor task. Right frontoparietal coherence in the alpha band (8–12 Hz) was computed with imaginary coherence (IC) between electrodes F4 and P4, with ICs from left and midline electrodes included as negative controls. **Results:** F4–P4 alpha IC was highly correlated with the RBANS Visuospatial/Constructional Index, while left and midline alpha ICs were not. However, there was no correlation between right frontoparietal alpha IC with skill acquisition. **Conclusion:** This study supports that right frontoparietal IC is positively related with visuospatial function, yet the limited dose of motor practice (five trials) in the retrospective dataset was not inherently designed to investigate motor skill acquisition per se. However, results show proof of concept for developing right frontoparietal alpha IC-based neurofeedback applications for visuospatial training.

Keywords: visuospatial function; EEG; imaginary coherence; motor learning

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Introduction

The process of motor skill learning has widespread implications across motor rehabilitation, sports, surgical training, and brain–computer interface control. However, some individuals learn slower than others with the same amount of practice, or not at all (e.g., Brooks et al., 1995). Recently, we have demonstrated that individual differences in the extent of motor skill learning can be explained by variation in visuospatial ability, such that better visuospatial scores correlate with more skill retention (Lingo VanGilder, Hengge, et al., 2018; Lingo VanGilder, Lohse, et al., 2021; Regan et al., 2021; Wang et al., 2020).

A potential underlying mechanism may be the degree of connectivity between right frontoparietal network, which may be critical for the interaction between motor learning and visuospatial processes. Frontoparietal neural structures, such as the superior longitudinal fasciculus, have been shown to underlie skilled motor performance (Steele et al., 2012), and both cognitive and visuomotor control (Brandes-Aitken et al., 2019). Further, neuropsychological findings suggest that many visuospatial processes are specialized to the right parietal cortex (Corbetta et al., 2000; Foxe et al., 2003). Based on the structural findings, this study aimed to test whether functional connectivity between right frontal and parietal regions at rest, measured by resting-state electroencephalography (EEG) coherence, is related to both visuospatial function and motor skill acquisition, which is an early stage of motor learning. EEG coherence is a correlation measure based on the frequency spectrum, which measures the degree of synchronization between oscillations of different neuronal ensembles underlying any two scalp electrodes (Nunez & Srinivasan, 2009). Recent studies have suggested that resting-state EEG coherence is linked to motor learning (Wu, Knapp, et al., 2018; Wu, Srinivasan, et al., 2014; Zhou et al., 2018). Coherence in the alpha band (8–12 Hz) is of particular interest in this study, because higher alpha power has been linked with improved performance in a spatial rotation task (Zoefel et al., 2011), while resting-state EEG coherence of the motor network in the mu (11–14 Hz) frequency band may also predict motor skill acquisition (i.e., within-session changes; Wu, Srinivasan, et al., 2014).

Methods

Experimental Design

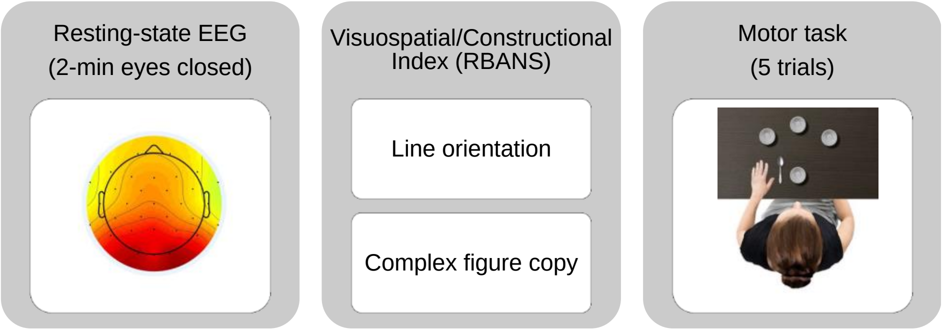
This study utilized an existing dataset (Pathania et al., 2022). The original data collection was approved by the University of Utah Institutional Review Board (IRB), in which participants provided informed consent prior to study enrollment. This retrospective analysis was approved by the Arizona State University IRB.

The dataset contained data from 21 healthy younger adults (aged 23.29 ± 3.47 years, 10 females). Eyes-closed resting-state EEG data was recorded for 2 min prior to completing the RBANS test battery and five trials of a functional motor task, as illustrated in Figure 1. More detail about the EEG data collection and processing is provided below. Visuospatial ability was measured using the Visuospatial /Constructional Index of the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS; Randolph et al., 1998), which was scored according to the test manual.

Motor Task

As described previously (Lingo VanGilder, Hengge, et al., 2018; Lingo VanGilder, Lohse, et al., 2021; Regan et al., 2021; Wang et al., 2020), the functional motor task in this study involves reaching and fine motor control. Briefly, the experimental apparatus is comprised of four plastic cups adhered to a board; three of the cups are "target" cups that are located radially around a center "home" cup that is aligned with the participant's midline (Figure 1, right panel). The participant must use a standard plastic spoon with their nondominant hand to acquire two beans at a time from the home cup and transport them to one of the target cups. The participants are instructed to transport the beans first to the target cup located ipsilateral to the participant's nondominant hand. They then scoop two more beans from the home cup and transport them to the middle target cup, then another two beans to the contralateral cup. The home cup contains 30 beans, resulting in 15 total reaches (five target cycles) per trial. Trial time is the measure of performance for each trial, which is the elapsed time from when the participant picks up the spoon until the last of the beans are deposited into the last target cup. In this dataset, participants completed five training trials only.

Figure 1. *Experimental protocol.*



Modeling Motor Skill Acquisition

To quantify motor skill acquisition, trial time data (in seconds) from each individual were fit with a linear model[1]:

$$Trial\ Time_i = A_i - B_i t \quad (1)$$

where *t* is trial number, *A* intercept term, and *B* the slope term. Individual participant was specified as *i*. Initial performance was estimated with *A*, where smaller *A* values indicates better initial performance. The rate of improvement was estimated with *B*, where larger *B* values indicates a faster rate of improvement.

EEG Acquisition and Preprocessing

Scalp EEG was collected from 32 electrodes of a 64-channel EEG cap housing a Brain Vision actiCAP system (Brain Products GmbH, Gilching, Germany), labeled in accord with an extended International 10–20 system (Oostenveld & Praamstra, 2001) and amplified and digitized using a BrainAmp DC amplifier (Brain Products GmbH, Gilching, Germany) and BrainVision Recorder software (Brain Products GmbH, Gilching, Germany). Eyes-closed resting-state EEG data were collected for 2 min. Data were online referenced to the right earlobe, and the ground electrode was placed on the left earlobe. Sampling rate was 1000 Hz. Preprocessing was done via the EEGLAB toolbox (Delorme & Makeig, 2004) and the ZapLine package (de Cheveigné, 2020) in MATLAB. Continuous data were high-passed at 1 Hz with a zero-phase noncausal window sinc FIR filter (EEGLAB function “pop_eegfiltnew”), which had a filter order of 3300 and a cutoff of 0.5 Hz at 6 dB.

As the current dataset contains heavy line noise, ZapLine was used to remove line for its superiority in specifically cleaning 60 Hz noise while preserving signals at other frequencies (de Cheveigné, 2020). Faulty channels and data segments with heavy muscle artifacts were manually rejected. Channels whose power spectrum did not demonstrate 1/f decline or with power less than other channels were removed. This resulted in 1.94 ± 1.24 removed channels for each participant, mostly temporal electrodes (T7, T8, TP9 & TP10, 83.9%) and FT electrodes (FT9 & FT10, 9.7%). The continuous data were then visually inspected to reject segments with spatially widespread muscle artifact. This resulted in average data length of 107.63 ± 8.61 s for the sample. Following data rejection, data were then submitted to an infomax ICA (Delorme et al., 2007). The validity of ICA artifact removal (e.g., eye movement artifact, muscle artifact) has been tested via numerous publications (Delorme et al., 2007; Hoffmann & Falkenstein, 2008; Plöchl et al., 2012) and recommended by consensus guidelines (Keil et al., 2014). In one paper (Plöchl et al., 2012), comparing ICA-identified artifacts with real eye tracking data, the authors concluded that rejecting ICs from the data resulted in complete removal or significant reduction of the eye and eyelid movement artifacts, while leaving the relevant signal emerging from neural sources intact. Furthermore, previous research that inspired this study (Wu, Knapp, et al., 2018; Wu, Srinivasan, et al., 2014) have used ICA analysis along with visual inspection. Therefore, this study utilized ICA as recommended by guidelines and to be consistent in preprocessing methods with similar studies. ICLabel (Pion-Tonachini et al., 2019) was used to identify and remove independent component(s) with eye artifacts and muscle artifacts. Any IC components with eye and muscle artifacts over 90% probability as identified by ICLabel were removed. On average, 2.3 ± 1.5 independent components were removed from the sample. After ICA artifact correction, rejected channels were interpolated with spherical splines interpolation (Perrin et al., 1989). Data were then segmented into nonoverlapping 1-s epochs.

Lastly, to appropriately perform electrode-level connectivity with EEG, the preprocessed data (scalp potentials) were submitted to a reference-free surface Laplacian algorithm to mitigate volume conduction (Kayser & Tenke, 2015). The surface Laplacian is a current source density measure that estimates the spatial second derivatives of scalp EEG potentials as an approximation for the amplitudes of underlying current generators (Tenke & Kayser, 2012). Due to the nature of taking derivatives, the EEG data at this point were reference free. A spline Surface Laplacian was used with default flexibility (m = 4) and regularization (lambda = 10^{-5}) parameters (Cohen, 2015; Perrin et al., 1989). The Surface Laplacian step was completed in MATLAB with code from Cohen (2014).

EEG Coherence

Imaginary coherence (IC) was chosen as the primary coherence measure because it avoids inflated and artifacted coherence values caused by volume conduction, and thus provides a robust estimate of EEG connectivity (Nolte et al., 2004). IC was estimated with the frequency spectrum, and

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[1] A mixed-effect model was not used here because it failed to capture the individual variabilities for the slope term (B). That is, the random effect of slope is zero for all subjects when the data were fit with a mixed-effect linear model.

reflects the amount of phase synchronization between two time series. However, IC only measures time-lagged synchronizations by taking only the imaginary part of the complex cross-power spectrum of the two EEG signals (see Equation 3). IC was computed using customized codes in MATLAB as described in the following paragraphs.

Laplacian-referenced, preprocessed 1-s data segments were submitted to Fourier transforms using the MATLAB *fft* function and normalized by segment length to yield Fourier coefficients. No windowing function was used. Frequency resolution was 1 Hz. The Fourier coefficients were then used to calculate auto- and cross-power spectra via Welch's method:

$$S_{xy}(f_n) = \frac{2}{K} \sum_{k=1}^{K} X_k(f_n) Y_k^*(f_n) \quad n = 1, 2, \dots, \frac{N}{2} - 1 \quad (2)$$

where n stands for the index of frequencies after the Fourier transform, N is the total number of time points for each segment, k indicates the index of segments, and K the total number of segments. $X_k(f_n)$ is the complex Fourier coefficients of time series $x(t)$ at frequency f_n, whereas $Y_k^*(f_n)$ is the conjugated complex Fourier coefficients of time series $y(t)$ at frequency f_n. The notation and definition for S_{xy} is consistent with that from Nunez (Nunez & Srinivasan, 2009) in which a factor of two of only the positive frequencies (as the corresponding negative frequencies have the same Fourier coefficients) was included and the DC signal ($f = 0$) and Nyquist frequency ($f = N/2$) were omitted.

Thus, the cross-power spectrum Sxy between signals x and y was estimated from the average of individual power spectra of all segments. This estimation can increase signal-to-noise ratio and, therefore, obtains robust estimates (Nunez & Srinivasan, 2009). When the two signals are the same, $x(t) = y(t)$, the complex-valued cross spectrum S_{xy} is reduced to a real-valued auto spectrum for that signal, noted as S_{xx}.

IC is calculated with the magnitude of the imaginary part of cross-power spectrum normalized by the square root of both auto power spectra (Nolte et al., 2004):

$$IC_{xy} = \frac{Im\left(S_{xy}(f_n)\right)}{\sqrt{S_{xx}(f_n) S_{yy}(f_n)}} \quad n = 1, 2, \dots, \frac{N}{2} - 1 \quad (3)$$

where Im denotes taking the imaginary part of the complex cross spectrum. IC reflects the level of consistency of the phase difference between two channels of interest and is valued from 0 to 1. A higher IC value indicates that the two channels are more connected. By definition, the IC between a channel and itself is zero, because there is no time-lagged coherence. Thus, IC avoids inflated and artifacted coherence values caused by volume conduction, and can provide a robust estimate of EEG connectivity. Based on Zoefel et al. (2011), only the alpha band was examined in this study.

Statistical Analysis

Brain-behavior correlations between coherence and motor or visuospatial variables were tested with bivariate correlation. All bivariate correlation analyses were tested using Spearman Rank correlation. Significance level was set to 0.05. Multiple comparisons were not adjusted for to minimize the potential of rejecting true positives in this proof-of-concept study with a relatively small sample size. Instead, statistics are reported comprehensively for all analyses, including those for null results.

Results

Data from 21 participants were analyzed. One participant was excluded for missing motor performance data and four participants were excluded due to substantial artifacts in the EEG data (neither alpha peaks in power spectra nor not following typical 1/f shape). This resulted in a final sample of 15 participants (8 females; age 22.73 ± 2.69 years old).

On average, motor performance improved from the first trial to the fifth trial by a reduction of 9.15 ± 4.77 in trial time, $t(14) = 7.42$, $p < .001$, 95% CI [6.50, 11.79] seconds. The distribution of trial times is presented in Figure 2, showing that motor performance improved across participants with considerable individual variability. Individual model fits (Figure 3) demonstrated an average intercept of 52.05 ± 5.97 s for baseline performance, and an average slope of 1.80 ± 1.30 for rate of improvement over trials. Modeled baseline performance and slope were correlated ($r = 0.78$, $p < .001$).

Right Frontoparietal Imaginary Coherence Did Not Correlate with Motor Variables

Right frontoparietal (F4-P4) imaginary coherence, the primary coherence measure of interest, did not correlate with the modeled initial performance ($p = .271$) or the rate of improvement ($p = .474$)

Figure 2. *Progression of motor performance over five trials.*

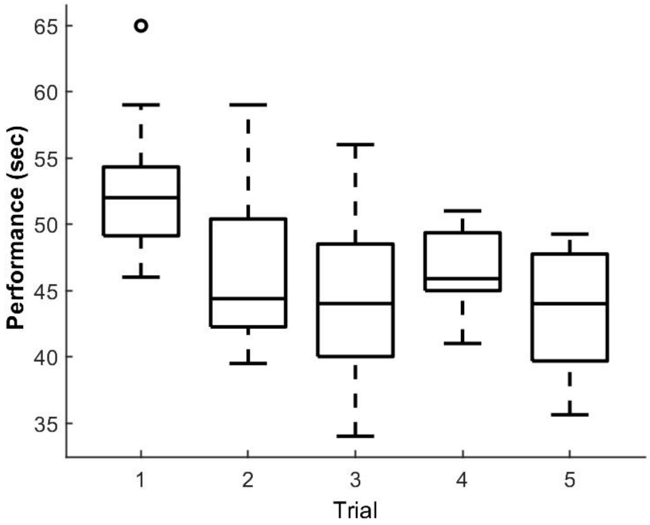
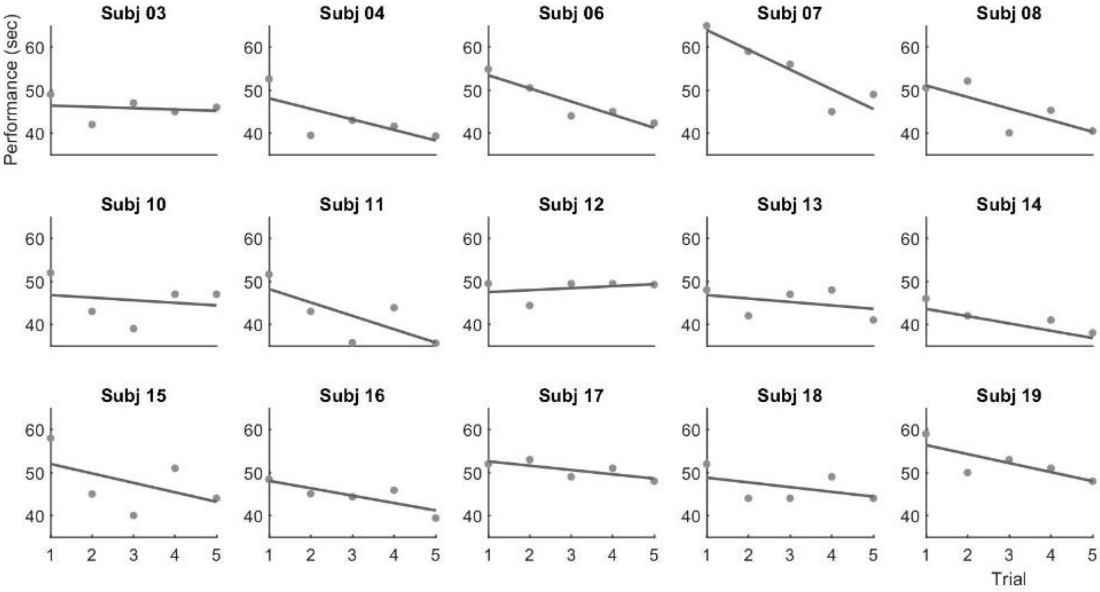
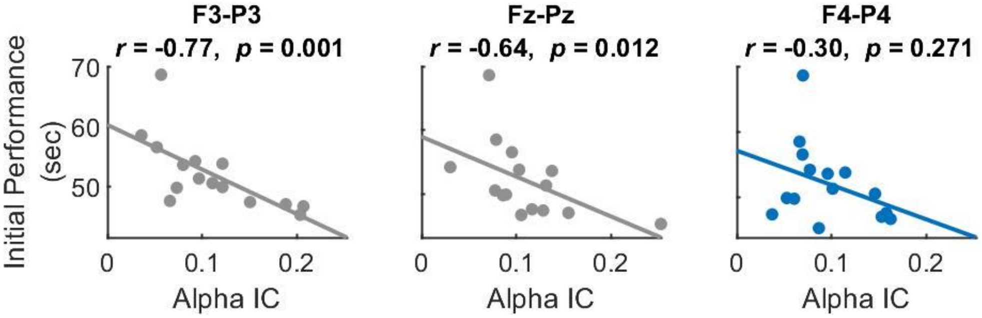


Figure 3. *Individual model fits for motor performance over five trials.*



On the contrary, initial motor performance was strongly correlated with both control imaginary coherence measures (Figure 4, middle and right column). Left frontoparietal (F3-P3) imaginary coherence correlated with initial motor performance ($r = -0.77$, $p = .001$). Midline frontoparietal (Fz-Pz) imaginary coherence also correlated with initial performance ($r = -0.64$, $p = .012$). Although two control ICs also demonstrated correlations with rate of improvement ($r = -0.51$, $p = .052$ for left imaginary coherence; and $r = -0.52$, $p = .051$ for midline imaginary coherence), this relationship was driven by the innate relationship between initial performance and rate of learning. When follow-up regression analyses used both IC and baseline performance to predict rate of improvement, IC was no longer correlated to the rate of improvement ($p = .812$ for left IC, $p = .712$ for midline IC) while baseline performance was (beta = 0.74, $p = .019$; and beta = 0.83, $p = .005$ for the two models separately).

Figure 4. *Relationship between frontoparietal alpha ICs and initial motor performance.*

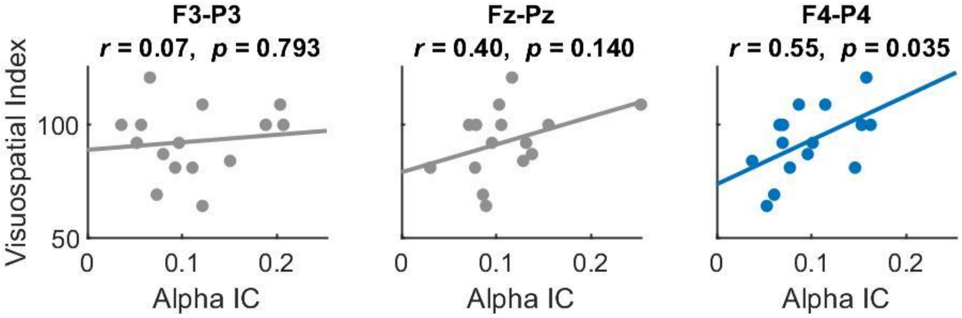


Note. Color blue indicates the analysis between the right frontoparietal coherence (primary IC measure) and motor performance. Color grey indicates control analyses with left and midline frontoparietal coherence.

Right Frontoparietal Imaginary Coherence Correlated with RBANS Visuospatial Index

Spearman Rank correlation revealed that right frontoparietal (F4-P4) alpha IC correlated with the RBANS Visuospatial Index (*r* = 0.55, *p* = .035; Figure 5 left column). Control analyses using left (F3-P3) and midline (Fz-Pz) alpha IC did not reveal any correlations between ICs and the RBANS Visuospatial Index (all *ps* > .140; Figure 5 middle and right column).

Figure 5. *Relationship between frontoparietal alpha ICs and Visuospatial Index.*



Note. Color blue indicates the analysis between the right frontoparietal coherence (primary IC measure) and visuospatial performance. Color grey indicates control analyses with left and midline frontoparietal coherence.

Discussion

This study tested whether right frontoparietal EEG resting-state connectivity was associated with visuospatial function (measured as the RBANS Visuospatial/Constructional Index) and motor skill acquisition. F4-P4 alpha IC, measured at rest with eyes closed, was highly correlated with the RBANS Visuospatial/Constructional Index, while left and midline alpha ICs were not. In terms of motor skill acquisition, F4-P4 IC did not correlate with motor skill acquisition (measured as within-session rate of improvement), nor with baseline motor performance. However, F3-P3 and Fz-Pz IC were highly correlated with baseline motor performance. No IC measure correlated with rate of improvement (i.e., how quickly motor performance improved).

Current results indicate that the right frontoparietal coherence, not left or midline coherence, is highly correlated with visuospatial function. This study extends previous structural neuropsychological findings that frontoparietal networks underlie visuospatial function (Brandes-Aitken et al., 2019; Corbetta et al., 2000; Foxe et al., 2003; Steele et al., 2012) by showing that functional connectivity at rest between right frontal and parietal cortical regions also predicts visuospatial function. This study provides support that the link between alpha coherence and visuospatial function could be causal. Rizk et al. (2013) showed that continuous theta-burst stimulation (cTBS, which is thought to be inhibitory) to the right posterior parietal cortex reduced visuospatial attention and induced neglect-like behavior, with fewer cumulative fixations in the leftward direction (selective-focused attention was not considered in this cited study); the same cTBS stimulation to the right frontal eye field did not show the same effect. After right posterior parietal cortex cTBS stimulation, alpha coherence between the parietal stimulation site and other cortical regions decreased, suggesting that right frontoparietal coherence may be an important visuospatial biomarker with clinical implications. For example, F4-P4 alpha coherence (8–12 Hz) could be a therapeutic target in neurofeedback training for patients with visuospatial deficits, in which they could learn to self-regulate the coherence signal directly and potentially improve visuospatial function. Neurofeedback approaches that provide feedback of dynamic brain networks (such as coherence signals) are considered to be more effective in achieving neural regulation than those providing signals from one single brain region (Sitaram et al., 2017). The feasibility and efficacy of alpha imaginary coherence neurofeedback has been demonstrated previously (Mottaz, Corbet, et al., 2018; Mottaz, Solcà, et al., 2015). Alpha coherence can be successfully modulated via neurofeedback (Mottaz, Solcà, et al., 2015) and upregulating alpha coherence between the motor cortex and the rest of the cortical regions can improve motor performance after stroke (Mottaz, Corbet, et al., 2018). Given the prevalence of visuospatial deficits following stroke (Jokinen et al., 2015; Jongbloed, 1986) and in preclinical Alzheimer’s disease (Caselli et al., 2020; Johnson et al., 2009), there is a clinical need for effective visuospatial training paradigms. Results from the current study warrant follow-up studies that directly test the feasibility of a frontoparietal alpha neurofeedback intervention for improving visuospatial function.

Contrary to the hypothesis, this study did not find a correlation between right frontoparietal alpha IC with motor skill acquisition, or baseline motor performance. One potential reason for this could be the limited dose of motor practice (only five trials) in this retrospective dataset, which was not inherently designed to investigate motor skill acquisition per se. In previous studies using the same motor task, visuospatial function correlated with 1-month motor retention after 50 or more trials of practice (Lingo VanGilder, Lohse, et al., 2021), as well as with 1-week retention after at least 10 trials of practice (Lingo VanGilder, Hengge, et al., 2018; Schaefer & Duff, 2017). The dose of practice in the current dataset may be too small to accurately evaluate motor skill acquisition and the learning process, but future studies are needed to test whether right frontoparietal coherence correlates with skill acquisition over a larger training dose, as suggested by the multisession motor training paradigm reported in Zhou et al. (2018).

This study did, however, identify a relationship between left and midline frontoparietal coherence with baseline motor performance. This is particularly provocative since 14 out of 15 participants used their left (nondominant) hand on the motor task, for whom the dominant (left) cortex is the ipsilateral cortex. Other studies have demonstrated that the alpha coherence in the left, but not right, hemisphere was related to visuomotor learning (Manuel et al., 2018) and motor skill acquisition (Wu, Srinivasan, et al., 2014) when using the right (dominant) hand. Moreover, alpha and beta coherence between left M1 and the rest of the cortical regions predicts motor skill acquisition (Wu, Srinivasan, et al., 2014; Zhou et al., 2018). Because this dataset used in the current study did not include any dominant hand motor data, we cannot directly test whether our data are consistent with these previous studies. However, our data do suggest a left parietal specialization for motor planning regardless of which effector is used, consistent with Kumar et al. (2020).

We acknowledge that the current study only focused on a single EEG frequency band (the alpha band). This was because this retrospective dataset included substantial artifacts that contaminated the beta band even after rigorous preprocessing (described in Methods), preventing the analyses of the beta frequency. Beta-band oscillations are strong sensorimotor rhythms (Hari & Salmelin, 1997; Jensen et al., 2005) that have been shown to predict performance both during task and at rest. Beta coherence at rest may also play a role in predicting motor learning. Wu, Srinivasan, et al. (2014) found that beta coherence from M1 to other parts of the brain predicted motor learning in high accuracy, while alpha coherence demonstrated a weaker correlation. It is worth pointing out that Wu, Srinivasan, et al. (2014) also showed that left premotor-parietal beta coherence was not related to motor learning. In further support of the beta frequency band, beta coherence can predict training-related behavioral gains in stroke patients

(Zhou et al., 2018) and beta oscillations at rest were confined to sensorimotor cortex, inferior parietal lobes, as well as the dorsolateral prefrontal cortex (Hillebrand et al., 2012). These findings suggest that frontoparietal beta coherence should be investigated as a biomarker for motor learning in future studies.

In conclusion, this retrospective analysis used imaginary coherence in the alpha frequency band to measure frontoparietal functional connectivity with EEG, and demonstrated that right frontoparietal connectivity is positively related with visuospatial function. This finding has implications for developing right frontoparietal alpha IC-based neurofeedback applications for improving visuospatial function, which could be used on its own as a form of cognitive training, or as a concurrent therapy to motor rehabilitation that would benefit slow- or nonlearners. Future studies are needed to test the relationship between alpha IC and motor learning with more extensive motor training.

Author Declarations

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References

Brandes-Aitken, A., Anguera, J. A., Chang, Y.-S., Demopoulos, C., Owen, J. P., Gazzaley, A., Mukherjee, P., & Marco, E. J. (2019). White matter microstructure associations of cognitive and visuomotor control in children: A sensory processing perspective. *Frontiers in Integrative Neuroscience, 12*, 65. https://doi.org/10.3389/fnint.2018.00065

Brooks, V., Hilperath, F., Brooks, M., Ross, H. G., & Freund, H. J. (1995). Learning "what" and "how" in a human motor task. *Learning & Memory, 2*(5), 225–242. https://doi.org/10.1101/lm.2.5.225

Caselli, R. J., Langlais, B. T., Dueck, A. C., Chen, Y., Su, Y., Locke, D. E. C., Woodruff, B. K., & Reiman, E. M. (2020). Neuropsychological decline up to 20 years before incident mild cognitive impairment. *Alzheimer's & Dementia, 16*(3), 512–523. https://doi.org/10.1016/j.jalz.2019.09.085

Cohen, M. X. (2015). Comparison of different spatial transformations applied to EEG data: A case study of error processing. *International Journal of Psychophysiology, 97*(3), 245–257. https://doi.org/10.7551/mitpress/9609.001.0001

Cohen, M. X. (2014). *Analyzing neural time series data: Theory and practice*. Cambridge, MA: The MIT Press. https://doi.org/10.1017/CBO9781107415324.004

Corbetta, M., Kincade, J. M., Ollinger, J. M., McAvoy, M. P., & Shulman, G. L. (2000). Voluntary orienting is dissociated from target detection in human posterior parietal cortex. *Nature Neuroscience, 3*, 292–297. https://doi.org/10.1038/73009

de Cheveigné, A. (2020). ZapLine: A simple and effective method to remove power line artifacts. *NeuroImage, 207*, 116356. https://doi.org/10.1016/j.neuroimage.2019.116356

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

Delorme, A., Sejnowski, T., & Makeig, S. (2007). Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. *NeuroImage, 34*(4), 1443–1449. https://doi.org/10.1016/j.neuroimage.2006.11.004

Foxe, J. J., McCourt, M. E., & Javitt, D. C. (2003). Right hemisphere control of visuospatial attention: Line-bisection judgments evaluated with high-density electrical mapping and source analysis. *NeuroImage, 19*(3), 710–726. https://doi.org/10.1016/S1053-8119(03)00057-0

Hari, R., & Salmelin, R. (1997). Human cortical oscillations: A neuromagnetic view through the skull. *Trends in Neurosciences, 20*(1), 44–49. https://doi.org/10.1016/S0166-2236(96)10065-5

Hillebrand, A., Barnes, G. R., Bosboom, J. L., Berendse, H. W., & Stam, C. J. (2012). Frequency-dependent functional connectivity within resting-state networks: An atlas-based MEG beamformer solution. *NeuroImage, 59*(4), 3909–3921. https://doi.org/10.1016/j.neuroimage.2011.11.005

Hoffmann, S., & Falkenstein, M. (2008). The correction of eye blink artefacts in the EEG: A comparison of two prominent methods. *PLoS ONE, 3*(8), e3004. https://doi.org/10.1371/journal.pone.0003004

Jensen, O., Goel, P., Kopell, N., Pohja, M., Hari, R., & Ermentrout, B. (2005). On the human sensorimotor-cortex beta rhythm: Sources and modeling. *NeuroImage, 26*(2), 347–355. https://doi.org/10.1016/j.neuroimage.2005.02.008

Johnson, D. K., Storandt, M., Morris, J. C., & Galvin, J. E. (2009). Longitudinal study of the transition from healthy aging to Alzheimer disease. *Archives of Neurology, 66*(10), 1254–1259. https://doi.org/10.1001/archneurol.2009.158

Jokinen, H., Melkas, S., Ylikoski, R., Pohjasvaara, T., Kaste, M., Erkinjuntti, T., & Hietanen, M. (2015). Post-stroke cognitive impairment is common even after successful clinical recovery. *European Journal of Neurology, 22*(9), 1288–1294. https://doi.org/10.1111/ene.12743

Jongbloed, L. (1986). Prediction of function after stroke: A critical review. *Stroke, 17*(4), 765–776. https://doi.org/10.1161/01.str.17.4.765

Kayser, J., & Tenke, C. E. (2015). Issues and considerations for using the scalp surface Laplacian in EEG/ERP research: A tutorial review. *International Journal of Psychophysiology, 97*(3), 189–209. https://doi.org/10.1016/j.ijpsycho.2015.04.012

Keil, A., Debener, S., Gratton, G., Junghöfer, M., Kappenman, E. S., Luck, S. J., Miller, G. A., & Yee, C. M. (2014). Committee report: Publication guidelines and recommendations for studies using electroencephalography and magnetoencephalography. *Psychophysiology, 51*(1), 1–21. https://doi.org/10.1111 /psyp.12147

Kumar, A., Panthi, G., Divakar, R., & Mutha, P. K. (2020). Mechanistic determinants of effector-independent motor memory encoding. *Proceedings of the National Academy of Sciences of the United States of America, 117*(29), 17338–17347. https://doi.org/10.1073/pnas.2001179117

Lingo VanGilder, J., Hengge, C. R., Duff, K., & Schaefer, S. Y. (2018). Visuospatial function predicts one-week motor skill retention in cognitively intact older adults. *Neuroscience Letters, 664*, 139–143. https://doi.org/10.1016/j.neulet.2017.11.032

Lingo VanGilder, J., Lohse, K. R., Duff, K., Wang, P., & Schaefer, S. Y. (2021). Evidence for associations between Rey-Osterrieth Complex Figure test and motor skill learning in older adults. *Acta Psychologica, 214*, 103261. https://doi.org/10.1016/j.actpsy.2021.103261

Manuel, A. L., Guggisberg, A. G., Thézé, R., Turri, F., & Schnider, A. (2018). Resting-state connectivity predicts visuo-motor skill learning. *NeuroImage, 176*, 446–453. https://doi.org/10.1016/j.neuroimage.2018.05.003

Mottaz, A., Corbet, T., Doganci, N., Magnin, C., Nicolo, P., Schnider, A., & Guggisberg, A. G. (2018). Modulating functional connectivity after stroke with neurofeedback: Effect on motor deficits in a controlled cross-over study. *NeuroImage: Clinical, 20*, 336–346. https://doi.org/10.1016/j.nicl.2018.07.029

Mottaz, A., Solcà, M., Magnin, C., Corbet, T., Schnider, A., & Guggisberg, A. G. (2015). Neurofeedback training of alpha-band coherence enhances motor performance. *Clinical Neurophysiology, 126*(9), 1754–1760. https://doi.org/10.1016/j.clinph.2014.11.023

Nolte, G., Bai, O., Wheaton, L., Mari, Z., Vorbach, S., & Hallett, M. (2004). Identifying true brain interaction from EEG data using the imaginary part of coherency. *Clinical Neurophysiology, 115*(10), 2292–2307. https://doi.org/10.1016/j.clinph.2004.04.029

Nunez, P. L., & Srinivasan, R. (2009). Electric Fields of the Brain: The neurophysics of EEG. *Oxford Scholarship Online*. https://doi.org/10.1093/acprof:oso /9780195050387.001.0001

Oostenveld, R., & Praamstra, P. (2001). The five percent electrode system for high-resolution EEG and ERP measurements. *Clinical Neurophysiology, 112*(4), 713–719. https://doi.org/10.1016/s1388-2457(00)00527-7

Pathania, A., Euler, M. J., Clark, M., Cowan, R. L., Duff, K., & Lohse, K. R. (2022). Resting EEG spectral slopes are associated with age-related differences in information processing speed. *Biological Psychology, 168*, 108261. https://doi.org/10.1016/j.biopsycho.2022.108261

Perrin, F., Pernier, J., Bertrand, O., & Echallier, J. F. (1989). Spherical splines for scalp potential and current density mapping. *Electroencephalography and Clinical Neurophysiology, 72*(2), 184–187. https://doi.org/10.1016/0013-4694(89)90180-6

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage, 198*, 181–197. https://doi.org/10.1016/j.neuroimage.2019.05.026

Plöchl, M., Ossandón, J., & König, P. (2012). Combining EEG and eye tracking: Identification, characterization, and correction of eye movement artifacts in electroencephalographic data. *Frontiers in Human Neuroscience, 6*, 278. https://doi.org/10.3389/fnhum.2012.00278

Randolph, C., Tierney, M. C., Mohr, E., & Chase, T. N. (1998). The repeatable battery for the assessment of neuropsychological status (RBANS): Preliminary clinical validity. *Journal of Clinical and Experimental Neuropsychology, 20*(3), 310–319. https://doi.org/10.1076/jcen.20.3.310.823

Regan, E., Fridriksson, J., Schaefer, S. Y., Rorden, C., Bonilha, L., Lingo VanGilder, J., & Stewart, J. C. (2021). Neural correlates of within-session practice effects in mild motor impairment after stroke: A preliminary investigation. *Experimental Brain Research, 239*(1), 151–160. https://doi.org/10.1007/s00221-020-05964-y

Rizk, S., Ptak, R., Nyffeler, T., Schnider, A., & Guggisberg, A. G. (2013). Network mechanisms of responsiveness to continuous theta-burst stimulation. *European Journal of Neuroscience, 38*(8), 3230–3238. https://doi.org/10.1111/ejn.12334

Schaefer, S. Y., & Duff, K. (2017). Within-session and one-week practice effects on a motor task in amnestic mild cognitive impairment. *Journal of Clinical and Experimental Neuropsychology, 39*(5), 473–484. https://doi.org/10.1080/13803395.2016.1236905

Sitaram, R., Ros, T., Stoeckel, L., Haller, S., Scharnowski, F., Lewis-Peacock, J., Weiskopf, N., Blefari, M. L., Rana, M., Oblak, E., Birbaumer, N., & Sulzer, J. (2017). Closed-loop brain training: The science of neurofeedback. *Nature Reviews Neuroscience, 18*(2), 86–100. https://doi.org/10.1038/nrn.2016.164

Steele, C. J., Scholz, J., Douaud, G., Johansen-Berg, H., & Penhune, V. B. (2012). Structural correlates of skilled performance on a motor sequence task. *Frontiers in Human Neuroscience, 6*, 289. https://doi.org/10.3389/fnhum.2012.00289

Tenke, C. E., & Kayser, J. (2012). Generator localization by current source density (CSD): Implications of volume conduction and field closure at intracranial and scalp resolutions. *Clinical Neurophysiology, 123*(12), 2328–2345. https://doi.org/10.1016/j.clinph.2012.06.005

Wang, P., Infurna, F. J., & Schaefer, S. Y. (2020). Predicting motor skill learning in older adults using visuospatial performance. *Journal of Motor Learning and Development, 8*(1), 38–51. https://doi.org/10.1123/jmld.2018-0017

Wu, J., Knapp, F., Cramer, S. C., & Srinivasan, R. (2018). Electroencephalographic connectivity measures predict learning of a motor sequencing task. *Journal of Neurophysiology, 119*(2), 490–498. https://doi.org/10.1152/jn.00580.2017

Wu, J., Srinivasan, R., Kaur, A., & Cramer, S. C. (2014). Resting-state cortical connectivity predicts motor skill acquisition. *NeuroImage, 91*, 84–90. https://doi.org/10.1016/j.neuroimage.2014.01.026

Zhou, R. J., Hondori, H. M., Khademi, M., Cassidy, J. M., Wu, K. M., Yang, D. Z., Kathuria, N., Erani, F. R., Dodakian, L., McKenzie, A., Lopes, C. V., Scacchi, W., Srinivasan, R., & Cramer, S. C. (2018). Predicting gains with visuospatial training after stroke using an EEG measure of frontoparietal circuit function. *Frontiers in Neurology, 9*, 597. https://doi.org/10.3389/fneur.2018.00597

Zoefel, B., Huster, R. J., & Herrmann, C. S. (2011). Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *NeuroImage, 54*(2), 1427–1431. https://doi.org/10.1016/j.neuroimage.2010.08.078

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