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Research Report

Slow-wave brain connectivity predicts executive functioning and group belonging in socially vulnerable individuals

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ARTICLE INFO

Article history:
Received 20 July 2023
Reviewed 21 November 2023
Revised 19 January 2024
Accepted 5 March 2024
Action editor Jordan Grafman
Published online 26 March 2024

Keywords:
Neural connectivity
Executive function
Social vulnerability
EEG
Phase synchrony

ABSTRACT

Important efforts have been made to describe the neural and cognitive features of healthy and clinical populations. However, the neural and cognitive features of socially vulnerable individuals remain largely unexplored, despite their proneness to developing neurocognitive disorders. Socially vulnerable individuals can be characterised as socially deprived, having a low socioeconomic status, suffering from chronic social stress, and exhibiting poor social adaptation. While it is known that such individuals are likely to perform worse than their peers on executive function tasks, studies on healthy but socially vulnerable groups are lacking. In the current study, we explore whether neural power and connectivity signatures can characterise executive function performance in healthy but socially vulnerable individuals, shedding light on the impairing effects that chronic stress and social disadvantages have on cognition. We measured resting-state electroencephalography and executive functioning in 38 socially vulnerable participants and 38 matched control participants. Our findings indicate that while neural power was uninformative, lower delta and theta phase synchrony are associated with worse executive function performance in all participants, whereas delta phase synchrony is higher in the socially vulnerable group compared to the control group. Finally, we found that delta phase

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https://doi.org/10.1016/j.cortex.2024.03.004

synchrony and years of schooling are the best predictors for belonging to the socially vulnerable group. Overall, these findings suggest that exposure to chronic stress due to socioeconomic factors and a lack of education are associated with changes in slow-wave neural connectivity and executive functioning.

1. Introduction

Social and economic factors can play a crucial role in people's mental well-being by easing or hampering their access to education, healthcare, social security, and work opportunities. Socioeconomically vulnerable individuals typically struggle at getting access to such resources, which may lead to chronic stress, oftentimes precluding them from a healthy cognitive development (Cermakova et al., 2018; Migeot et al., 2022). Indeed, they frequently experience a higher rate of domestic problems and live in areas with higher crime and drug abuse rates, and scarce recreational spaces (De Nadai et al., 2020; Engelberg et al., 2016; Giles-Corti & Donovan, 2002). Many studies have thoroughly characterised cognitive functioning in groups that present risk factors for developing psychiatric disorders (i.e., clinical populations), finding a generalisable decrease in their executive functioning (Romer & Pizzagalli, 2021; Testa & Pantelis, 2009). However, studies characterising cognitive functioning in healthy but socially vulnerable groups are still lacking, even though such groups are particularly at risk of chronic stress and mental illness (Baum et al., 1999).

Executive function encompasses a set of cognitive skills crucial for the control of behaviour, including focussing attention, planning, remembering relevant recent information, thinking flexibly, and inhibiting impulses (Diamond, 2013; Ferguson et al., 2021). Multiple studies have found that, to different extents, impairments in executive function are present in various neuropsychiatric conditions such as schizophrenia (Haugen et al., 2021; Raffard et al., 2009; Wobrock et al., 2009), bipolar disorder (Cotrena et al., 2020; Koene et al., 2022), substance abuse (Hester & Garavan, 2004; Kim-Spoon et al., 2017), traumatic brain injury (McDonald et al., 2002), and personality disorders (Gvirts et al., 2012; Koudys & Ruocco, 2022). Similar to the impairments identified in executive functions associated with psychiatric disorders, comparable deficits have been observed in socially vulnerable populations characterised by low socioeconomic status, poverty, and a history of early social deprivation (Bernier et al., 2012; Jensen et al., 2017; Lipina & Posner, 2012; Noble et al., 2015). Importantly, poor executive functioning typically correlates with symptom severity and social maladaptation (Drakopoulos et al., 2020; Simon et al., 2003). The intricate interplay among executive functioning, socioeconomic status (SES), and social adaptation is inherently complex. Individuals in socially vulnerable contexts, characterised by low SES contend with heightened stressors that impact executive function-related cognitive processes such as social cognition and intelligence. The resulting executive function deficits may give rise to maladaptive behaviours, thereby impeding adaptive capacities within their living environments (Blair et al., 2011; Evans & Schamberg, 2009; Huepe et al., 2011; Mani et al., 2013; Schulte et al., 2022). Essentially, chronic stress induced by socioeconomic factors can hinder executive functioning, even in the absence of a neuropsychiatric condition.

Electroencephalographic (EEG) studies have found an association between executive function impairment and alterations in alpha, theta, delta, and beta frequency bands (Bong et al., 2020; Chen et al., 2016). More specifically, researchers have reported an increase in power in slow-wave oscillations such as delta and theta bands during resting state in individuals who have been diagnosed with traumatic brain injury (Dunkley et al., 2015), mild cognitive impairment (Musaeus et al., 2019), Alzheimer's disease (Babiloni et al., 2020), autism spectrum disorder (J. Wang et al., 2020), and attention deficit hyperactivity disorder (Morillas-Romero et al., 2015), and a decrease in power in such frequency bands in healthy older individuals (Vlahou et al., 2014). Furthermore, cognitive decline in dementias such as Alzheimer's disease has been associated with an increase in delta-frequency functional connectivity (Babiloni et al., 2004, 2006, 2009; Brunovsky et al., 2003; Cheng et al., 2020; Comi et al., 1998; Locatelli et al., 1998; Meghdadi et al., 2021; Schreiter-Gasser et al., 1994), which has been attributed to an impairment in the neural mechanisms that regulate delta-band coupling. Thus, both slow-wave power and functional connectivity exhibit dynamic changes in the presence of neurological or psychiatric ailments.

Do these dynamic changes also manifest in individuals without medical conditions? Moreover, there is evidence linking brain markers with EEG to poverty, low socioeconomic status, and social disparity (in socially vulnerable populations; for a review, see Pavlakis et al., 2015). EEG studies highlight disparities in neural function associated with socioeconomic status, including lower frontal gamma power in infants (Tomalski et al., 2013), higher low-frequency power (Harmony et al., 1990; Otero, 1994, 1997; Otero et al., 2003), and higher theta power when ignoring stimuli (D'angiulli et al., 2012), prefrontal activation differences during attentional tasks (Kishiyama et al., 2009; Moriguchi & Shinohara, 2019), variations tied to mothers' education (Stevens et al., 2009) and mental health (Tomarken et al., 2004), and infants' cognitive abilities (Brito et al., 2016). These findings contribute to the theoretical framework, accentuating the intricate relationship between SES and neural development (Pavlakis et al., 2015; Pietto et al., 2017).

Socially vulnerable populations include individuals residing in contexts with limited access to economic resources due to their low-income range (Evans & English, 2002; Evans et al., 2005; Henoch, 2010). These populations are predominantly concentrated in social risk neighbourhoods (Mechanic & Tanner, 2007) and lack the necessary social resources to effectively cope with the impacts of external stressors (Schulte et al., 2022). The cumulative number and intensity of stressors experienced by these individuals, coupled with their inadequate access to stress management resources, contribute to conditions that are conducive to poor mental health and chronic stress (Evans & France, 2022; Evans & Kim, 2010).

In this study, we investigate the EEG spectral and connectivity signatures within a socially vulnerable group, taking into account the specific stressors they face. Specifically, we examine the differences in executive function and its association with neural measures between two distinct groups: healthy individuals who are socially vulnerable and those who are socioeconomically stable.

2. Materials and methods

2.1. Participants

The sample consisted of 76 healthy participants, with 38 individuals in the socially vulnerable group and 38 in the control group. Participants' ages ranged from 34 to 47 years ($M_{total} = 39.6$; [$SD_{total} = 3.58$]; $M_{soc.\ vul.} = 40.3$; [3.68]; $M_{control} = 39$; [3.41]), with 43 of them being female (comprising 24 females in the socially vulnerable group and 20 in the control group). On average, they had 15 years of formal education ($M_{total} = 16.0$ [3.65]; $M_{soc.\ vul.} = 13.8$ [2.09]; $M_{control} = 18.2$ [3.55]), equivalent to completing primary and secondary education, and no history of psychiatric or neurological conditions. Eligibility criteria for the socially vulnerable group required being a member of a household meeting the 40th percentile qualification for the lowest income range (stretch 1 of 7) of the Chilean Welfare Programme (Ministerio de Desarollo Social y Familia - Gobierno de Chile, 2020). The socioeconomic classification is determined based on several criteria, including (a) the sum of income derived from labour, pension, and capital sources for all individuals within the household; (b) the overall count of household members; (c) specific attributes of household members, such as age, disability, or dependency; and (d) an assessment of the possessions and services accessible or owned by the household. This assessment facilitates the inference of the household's socioeconomic status in relation to its actual income. Control participants were recruited from the general population based on accessibility and did not belong to the 40th percentile of the lowest income range.

2.2. Data collection

The Social Protection Sheet, issued by the Ministry of Social Development and Family of the Chilean government (Ministerio de Desarollo Social y Familia - Gobierno de Chile, 2020), was used to determine the socioeconomic status of participants in the vulnerable group. This sheet includes comprehensive information on the combined income from labour, pensions, and capital for all household members, as well as the number of individuals within the household and their respective characteristics such as age, disability, or dependency (see Supplementary material). Additionally, the sheet assesses the access to and ownership of goods and services by the household, enabling an inference of its socioeconomic status based on a comparison with the actual household income received. Individuals included in the vulnerable group were exclusively selected from the Social Registry of households. In Chile, similar to social security systems in other countries, there is a socioeconomic status registration system. This system facilitates the targeted implementation of public subsidy policies for populations located in more disadvantaged socioeconomic contexts (Ministerio de Desarollo Social y Familia – Gobierno de Chile, 2020).

In accordance with the aforementioned criteria, a brief semi-structured interview was conducted prior to the commencement of the study to assess the level of exposure to long-term social vulnerability for each individual. Only participants who met this criterion were included in the study. Participation was voluntary, and all data were anonymised to ensure confidentiality. Individuals with visual or hearing impairments, who indicated an inability to complete the assessment battery (e.g., difficulty reading or responding to verbal information or following oral instructions provided by the evaluator), were excluded from participation. Furthermore, individuals with psychiatric or neurological conditions were not included in the study. Prior to their participation, all individuals provided informed consent and signed a consent form. The study received ethical approval from the Adolfo Ibáñez University Ethics Committee (Santiago, Chile) and adhered to the protocols outlined in the Declaration of Helsinki.

2.3. INECO frontal screening (IFS)

All participants completed the IFS, which measures four different executive function components: working memory, motor inhibition, verbal inhibition, and abstraction capacity through eight subtests. The IFS incorporates various tasks, including the Luria motor series (3 points), Conflicting instructions (3 points), Go-no go test (3 points), Months backward task (2 points), Backward digit span (6 points), Modified Corsi tapping test (4 points), Proverb interpretation (3 points), and Modified Hayling Test (6 points). As a result, the IFS possesses a maximum attainable score of 30 points (overall raw score). The IFS has shown good internal consistency, high reliability, and high concurrent validity (Ihnen et al., 2013; Torralva et al., 2009). IFS performance correlates with other executive function tests too, such as the Frontal Assessment Battery, the Trail Making Test (Part B), the Wisconsin Card Sorting Test, and the verbal phonological fluency test (Baez et al., 2014; Custodio et al., 2016; Gleichgerrcht et al., 2011; Ihnen et al., 2013; Torralva et al., 2009). While the IFS was initially designed for detecting executive dysfunction in dementia, it has proven useful in assessing healthy young and older individuals as well (Fittipaldi et al., 2020; García-Cordero et al., 2017; Sierra Sanjurjo et al., 2019), demonstrating high sensitivity (Moreira et al., 2014; Torralva et al., 2009).

2.4. EEG data collection and pre-processing

Data collection occurred within the designated time frame of 10:00 to 16:00. To minimise the potential impact of fatigue or energy fluctuations, participants from each group were evenly distributed. Throughout the EEG data collection, participants maintained a seated position. Clear instructions were provided, directing them to refrain from engaging in specific thoughts, aligning with the methodology commonly employed in resting-state EEG studies (e.g., Chennu et al., 2014; Elliott et al., 2005).

We collected a minimum of 10 min of resting-state EEG data using a 128-channel high-density EEG system, sampled at 250 Hz and re-referenced to the vertex using a Net Amps 300 amplifier (Electrical Geodesics Inc., USA). EEG data were obtained from both the socially vulnerable group and its matched control group in a state of relaxed wakefulness with eyes open while looking at a fixation cross to minimise eye movement. Eye-blinks were individually assessed to ensure that both groups had their eyes open throughout the recording session.

We measured both eye-blink and eye-movement-related EEG activity. We derived left and right vertical bipolar electrooculographic (EOG) channels from the raw EEG data by subtracting channels 25 versus 127, and 8 versus 126, respectively (Cologan et al., 2013). Next, we filtered the resulting derived channels with 1–3 Hz to focus on eye-movement-related activity by calculating their standard deviations (SD) using a 1-sec non-overlapping sliding window, which was normalised by the mean SD over all windows.

We excluded 36 electrodes located on non-scalp surfaces, such as the neck, cheeks, and forehead. This decision was based on the well-established knowledge that these locations primarily contribute to movement-related noise rather than to neural signals (see Chennu et al., 2014, 2016). EEG data from the remaining 91 scalp electrodes were selected for further analysis (for a map of these electrode locations, see Supplementary material). Continuous EEG data were filtered between .5 and 45 Hz and segmented into sixty 10-sec epochs. Thus, each epoch was baseline-corrected relative to the mean voltage of the entire epoch. Epochs that contained excessive eye-movement or muscular artefacts were rejected using a quasi-automated procedure whereby abnormally noisy channels and epochs were identified by quantifying their normalised variance – by visual inspection, they were next rejected or kept.

We employed independent-component analysis (ICA) with the Infomax ICA algorithm (Bell & Sejnowski, 1995) to identify and select components related to artefacts. ICA was performed following data filtering and segmentation into 10-sec epochs, as previously described. Components associated with EEG activity related to eye-blinks, eye movements, heartbeats, and body movements were classified as artifacts and subsequently removed from the signal. A maximum of five components per participant and condition were removed based on visual inspection. Under 6% of the epochs were rejected. An analysis of variance (ANOVA) revealed no significant difference between the number of epochs selected for each group. Finally, we interpolated the channels that were rejected by using spherical spline interpolation, and the data were re-referenced to the mean across all channels.

All pre-processing and analysis steps were implemented using MATLAB and the EEGLAB toolbox (Delorme & Makeig, 2004). The procedures of the study were not pre-registered.

2.5. Spectral power and phase synchrony analysis

We calculated spectral power and phase synchrony using the MOHAWK-pipeline v1.2 (available from https://github.com/srivaschennu/MOHAWK; e.g., see Chennu et al., 2017; Rosenfelder et al., 2023). This pipeline employs functions from both EEGLAB (Delorme & Makeig, 2004) and FieldTrip (Oostenveld et al., 2010) to calculate, analyse, and visualise EEG-power and scalp-level brain connectivity.

We calculated spectral power values between .5 and 30 Hz, with a resolution of .1 Hz from the clean EEG datasets (see below), using a multitaper method with five Slepian tapers. We calculated the absolute power magnitude for each canonical frequency band: delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz). For each band, the absolute power values were also converted to relative power contributions to the total power within the .5–30 Hz range.

Phase synchrony is considered a measure of information exchange between neuronal populations and is often calculated from the phase or the imaginary component of the complex cross-spectrum between the signals measured at each pair of channels. For instance, its predecessor, the Phase Locking Value (PLV; Lachaux et al., 1999) is obtained by averaging the exponential magnitude of the imaginary component of the cross-spectrum. However, many of the phase coherence indices derived from EEG data can be affected by differences in volume conduction (Nunez et al., 1997, 1999). As a consequence, a single dipolar source rather than a pair of interacting sources may lead to spurious coherence between spatially disparate EEG channels.

The Phase Lag Index (PLI; Stam et al., 2007) aims at minimising the impact of volume conduction and common sources found in the EEG data by averaging the signs of phase differences, thus ignoring average phase differences of 0 or 180°. The rationale behind it is that such phase differences may be likely to be due to volume conduction of single dipolar sources.

Formally, the PLI is defined as the absolute value of the sum of the signs of the imaginary part of the complex cross-spectral density S_{xy} of two real-valued signals $x(t)$ and $y(t)$ at time point or trial t:

$$\mathrm{PLI} = \left| \frac{\sum_{t=1}^{n} sgn\left(imag\left(S_{xy,t}\right)\right)}{n} \right|$$

However, PLI has two important limitations: it is very sensitive to noise, and it shows a strong bias towards strong coherences when calculated on small samples. The weighted PLI index (wPLI; Vinck et al., 2011) addresses the former problem by weighting the signs of the imaginary components based on their normalised absolute magnitudes, which yields a dimensionless measure of connectivity unaffected by differences in spectral or cross-spectral power:

$$\mathrm{wPLI} = \left| \frac{\sum_{t=1}^{n} \left|imag\left(S_{xy,t}\right)\right| sgn\left(imag\left(S_{xy,t}\right)\right)}{\sum_{t=1}^{n} \left|imag\left(S_{xy,t}\right)\right|} \right|$$

In addition, the dwPLI addresses the latter problem by decreasing its bias when the number of epochs is small. Therefore, we employed the dwPLI measure introduced by Vinck et al. (2011) to estimate functional connectivity.

We quantified the dwPLI peak across all time and frequency bins within each frequency band, for each pair of channels. Thus, we obtained subject-wise and band-wise dwPLI connectivity matrices.

2.6. Data analysis

To scrutinise our hypotheses and delve deeper into the dataset, we employed a comprehensive set of statistical analyses, including mixed ANOVA, bivariate correlation, analysis of covariance (ANCOVA), Bayes factor analysis, and binomial logistic regression models. Our first objective was to examine whether discernible differences existed in phase-synchrony connectivity and spectral power for each frequency band of interest between groups. To address this objective, we compared the phase synchrony and spectral power values for each frequency band between groups using two different mixed ANOVA models. In one mixed ANOVA model, we entered phase synchrony values (dwPLI) per frequency band as within-subject factors (delta, theta, alpha, and beta), and group (socially vulnerable and control) as a between-subject factor. In a different but equivalent mixed ANOVA model, we entered the spectral power values. Having found that only phase-synchrony connectivity differed between groups, our second objective was to elucidate the cognitive and demographic factors contributing most significantly to these observed neural connectivity variations. To address this objective, we first conducted correlation analyses between delta, theta, alpha, and beta phase synchrony, and IFS score, age, schooling, and gender; we further examined these relationships within a Bayesian framework, providing a nuanced understanding of the interplay between these variables. Our third objective was to test whether the observed between-group differences in IFS, delta-, and theta-band phase synchrony persisted when accounting for differences in age, schooling, and gender. To address this objective, we compared the IFS scores, delta-band phase connectivity, and theta-band connectivity between groups using three separate ANCOVA models, each of which considered age, schooling, and gender as covariates. Finally, our fourth objective was to determine the factors with the highest predictive power for classifying individuals as socially vulnerable. To address this objective, we entered IFS score, delta-band phase synchrony, theta-band phase synchrony, age, schooling, and gender into a binomial logistic regression model. This last analysis allowed us to discern which variables played a paramount role in determining social vulnerability in our cohort. Statistical tests were run using Jamovi (The jamovi project, 2020) and JASP (JASP Team, 2023). Data and analysis code are publicly available on the Open Science Framework: https://osf.io/j2zb9/.

3. Results

3.1. Socially vulnerable and non-vulnerable individuals differ in phase-synchrony connectivity but not in spectral power

To test whether global dwPLI connectivity (i.e., connectivity across all electrodes) differed between groups at any specific frequency band, we entered the dwPLI means into a 4 (frequency band: alpha, beta, theta, delta) $\times$ 2 (group: socially vulnerable, control) mixed ANOVA (Fig. 1A). We found a main effect of frequency band ($F_{(3,108)} = 68.87, p < .001$) and a main effect of group ($F_{(1,36)} = 5.64, p = .023$). Crucially, we found an interaction between these factors ($F_{(3,108)} = 3.46$, $p = .019$). Holm–Bonferroni-corrected pairwise comparisons revealed a significantly higher dwPLI connectivity in delta ($t(74) = 4.008$, $p < .001, d = .92$), theta ($t(74) = 2.54, p = .018, d = .583$), and beta ($t(74) = 2.557, p = .018, d = .587$) bands in favour of the socially vulnerable group. We found no significant difference in alpha band ($t(74) = -.47, p = .639$).

Is this increase in phase synchrony connectivity accompanied by an increase in spectral power? To test this, we entered the power values into a 4 (frequency band: alpha, beta, theta, delta) $\times$ 2 (group: socially vulnerable, control) mixed ANOVA (Fig. 1B). We found no main effects or interactions (all p-values > .101).

Together, these results indicate that socially vulnerable individuals exhibit higher resting-state phase synchrony connectivity in delta, theta, and beta frequency bands than controls, and that these two groups do not differ in by-frequency-band spectral power.

3.2. Executive function and phase synchrony connectivity: bivariate correlations

To test whether executive function correlates with spectral connectivity, we ran a series of (uncorrected) exploratory Pearson correlations between IFS scores, dwPLI scores, and demographic data (Table 1). We found that delta- ($r = -.321, p = .006$) and theta-band dwPLI connectivity ($r = -.241, p = .043$) negatively correlate with IFS score, irrespective of group, meaning that the lower the IFS score, the higher the dwPLI connectivity score. Next, we found that years of schooling positively correlate with IFS score ($r = .284, p = .017$) and negatively correlate with dwPLI connectivity in delta ($r = -.328, p = .004$) and theta ($r = -.245, p = .034$) bands, indicating that participants with more years of schooling have lower phase synchrony connectivity in these bands (Fig. 2).

3.3. Controlling for age, schooling, and gender further supports differences between groups in executive function and delta phase-synchrony connectivity

3.3.1. IFS performance

To further explore the effects of group and phase synchrony connectivity, we ran an ANCOVA whereby age, years of schooling, and gender were included as covariates. First, we further explored the difference in IFS score between groups (Fig. 3A). We found again that the socially vulnerable group (M = 22.5 [CI = 21.2, 23.8]) performed worse at the IFS than the control group (25[23.7, 26.2]), ($F_{(1,65)} = 5.613, p = .021$). We did not find significant effects of age ($F_{(1,65)} = 1.465, p = .144$), years of schooling ($F_{(1,65)} = .152, p = .698$), or gender ($F_{(1,65)} = 2.192$, $p = .230$).

3.3.2. Phase synchrony connectivity

Next, we ran a series of ANCOVA models to test the effects on dwPLI connectivity for each frequency band, separately. The ANCOVA model for delta-band connectivity (Fig. 3B) showed

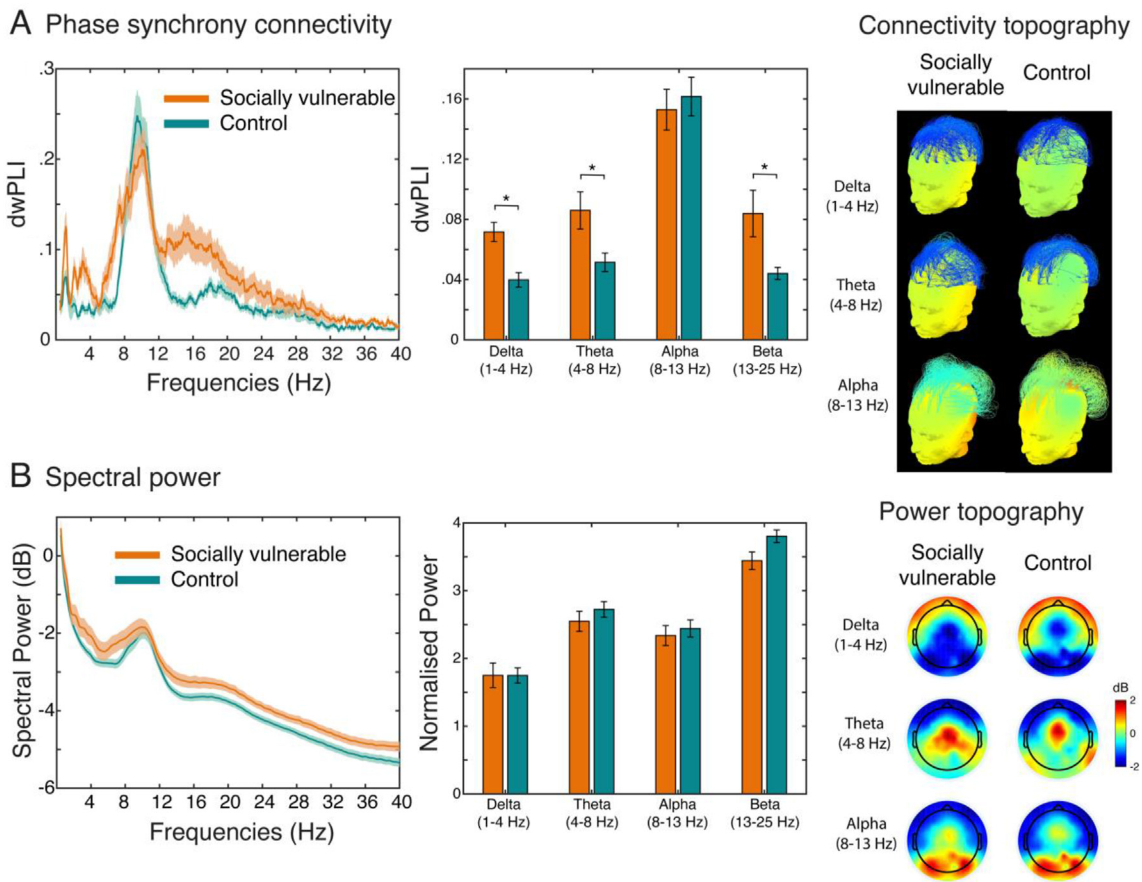

Fig. 1 — Band-wise phase synchrony connectivity and spectral power in socially vulnerable and control groups. (A) Phase synchrony connectivity. (Left) dwPLI connectivity comparison between groups across frequency bands. (Middle) Differences in dwPLI connectivity between groups: the socially vulnerable group exhibits higher dwPLI connectivity in delta, theta, and beta frequency bands. (Right) Connectivity topographies. Topographic colour maps depicting dwPLI connectivity between pairs of electrodes. (B) Spectral power. (Left) Spectral power comparison between groups across frequency bands. (Middle) We found no spectral power differences between groups. (Right) Power topographies. Topographic colour maps depicting spectral power between pairs of electrodes. Asterisks denote significant differences between conditions. Shaded areas and error bars denote 95% confidence intervals (CI).

Table 1 — Bivariate correlation analysis. Bold and asterisks denote significance: *p < .05, **p < .01, ***p < .001.

		IFS	Delta dwPLI	Theta dwPLI	Alpha dwPLI	Beta dwPLI	Age	Schooling	Gender
IFS	Pearson's r	–							
	p-value	–							
Delta dwPLI	Pearson's r	**−.321****	–						
	p-value	.006	–						
Theta dwPLI	Pearson's r	**−.241***	**.483*****	–					
	p-value	.043	<.001	–					
Alpha dwPLI	Pearson's r	.179	.097	**.420*****	–				
	p-value	.136	.402	<.001	–				
Beta dwPLI	Pearson's r	−.031	**.442*****	**.575*****	**.375*****	–			
	p-value	.800	<.001	<.001	<.001	–			
Age	Pearson's r	−.229	.106	.206	.144	.163	–		
	p-value	.053	.364	.074	.216	.160	–		
Schooling	Pearson's r	**.284***	**−.328****	**−.245***	−.005	−.163	−.081	–	
	p-value	.017	.004	.034	.963	.162	.486	–	
Gender	Pearson's r	−.212	.085	−.067	−.047	−.118	.181	−.067	–
	p-value	.073	.467	.566	.689	.310	.115	.565	–

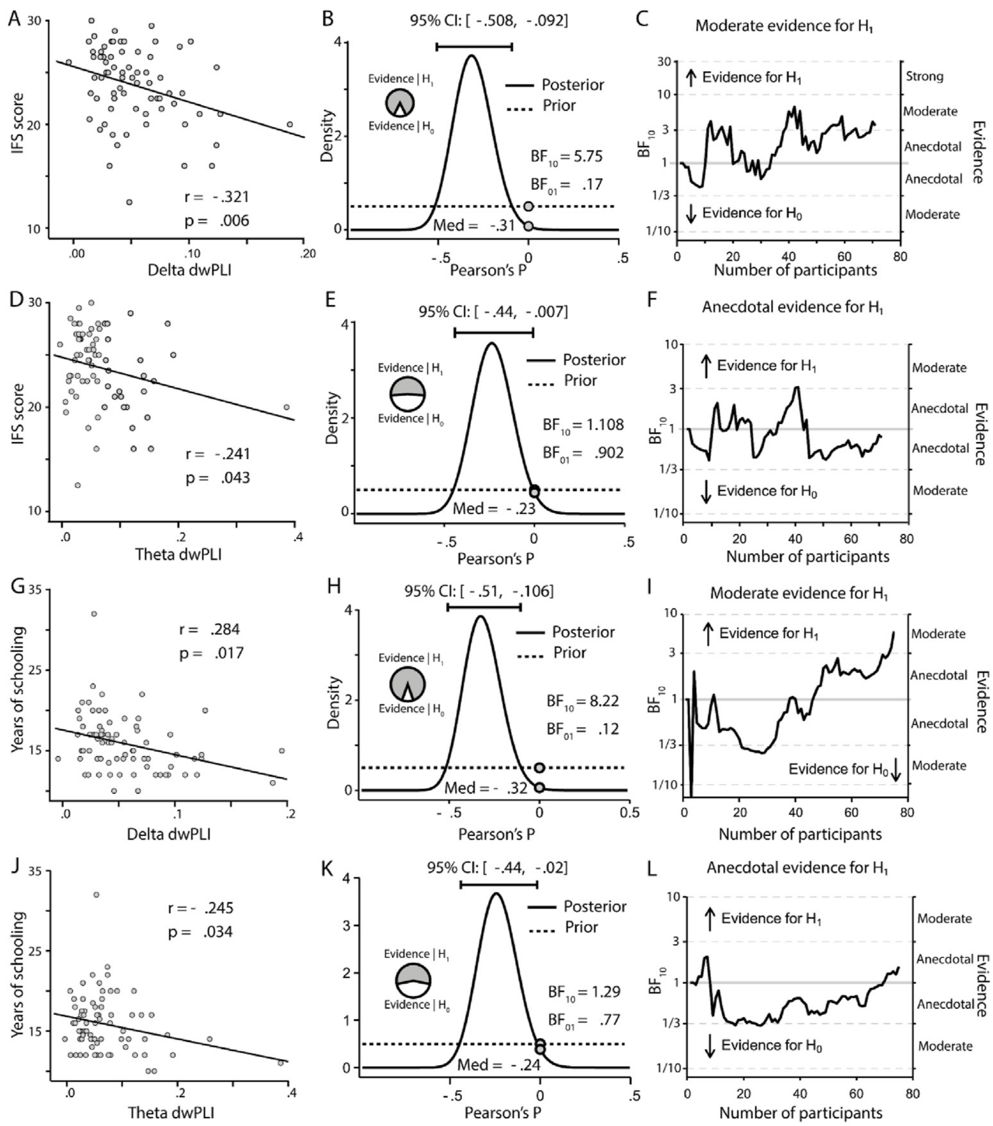

Fig. 2 – Scatterplots and Bayesian assessment of the evidence. (A–C) IFS score and delta-band dwPLI. (A) IFS score and delta dwPLI showed a significant negative correlation. (B) Bayes factors provided moderate evidence in favour of the alternative hypothesis model (i.e., IFS score and delta dwPLI correlate), which is depicted by the estimated population effect size, with a median of −.31 and a 95% central credible interval of −.508 and −.092. (C) Sequential analysis shows that most participants give moderate or anecdotal support to the alternative hypothesis model. (D–F) IFS score and theta-band dwPLI. (D) IFS score and theta dwPLI showed a significant negative correlation. (E) Bayes factors provided anecdotal evidence in favour of the alternative hypothesis model (i.e., IFS score and theta dwPLI correlate), which is depicted by the estimated population effect size, with a median of −.23 and a 95% central credible interval of −.44 and −.007. (F) Sequential analysis shows that all participants give anecdotal support either in favour or against the alternative hypothesis model. (G–I) Years of schooling and delta-band dwPLI. (G) Years of schooling and delta dwPLI showed a significant negative correlation. (H) Bayes factors provided moderate evidence in favour of the alternative hypothesis model (i.e., years of schooling and delta dwPLI correlate), which is depicted by the estimated population effect size, with a median of −.32 and a 95% central credible interval of −.51 and −.106. (I) Sequential analysis shows that most participants give moderate or anecdotal support to the alternative hypothesis model. (J–L) Years of schooling and theta-band dwPLI. (J) Years of schooling and theta dwPLI showed a significant negative correlation. (K) Bayes factors provided anecdotal evidence in favour of the alternative hypothesis model (i.e., years of schooling and theta dwPLI correlate), which is depicted by the estimated population effect size, with a median of −.24 and a 95% central credible interval of −.44 and −.02. (L) Sequential analysis shows that most participants give anecdotal support to the null hypothesis model.

higher dwPLI for the socially vulnerable group (.067[.054, .08]) compared to the control group (.042[.03, .06]), ($F_{(1,69)} = 5.77, p =$ .019). We did not find any other significant effects (all p-values > .263).

The ANCOVA model applied to theta-band dwPLI connectivity (Fig. 3C) did not detect a significant group effect ($F_{(1,69)} =$ $1.28, p = .261$). No other significant effects were found (all p-values > .108). Given the association of theta-band neural dynamics with learning (Begus & Bonawitz, 2020; Herweg et al., 2020; Verbeke et al., 2021), we hypothesised that the variable 'years of schooling' could potentially moderate any between-group differences in theta-band connectivity, assuming such differences exist. To explore this hypothesis, we removed years of schooling from the ANCOVA model and found differences between groups ($F_{(1,71)} = 4.96$, $p = .029$), which suggests that theta-band connectivity may be moderated by schooling (see further below).

3.4. Delta-band synchrony and years of schooling predict membership in either the vulnerable or control groups

To determine the likelihood of belonging to either the vulnerable or control group, a binomial logistic regression was conducted, with several variables of interest serving as predictors ($F_{(1,71)} = 4.96, p = .029$), including IFS score, delta-band dwPLI, theta-band dwPLI, years of schooling, and age. This regression model enabled us to statistically predict which cognitive, demographic, and neural parameters could effectively classify participants into their respective groups and with what degree of accuracy. The model provided an explanation for 54% (R^2_{CS}) to 72% (R^2_N) of the variance in the dependent variable, resulting in a classification precision of 86%, exhibiting a sensitivity of 82% and a specificity of 89% (Table 2). Notably, two predictors significantly contributed to this model: delta-band dwPLI ($X^2(1) = 12.39, p < .001$) and years of schooling ($X^2(1) = 22.21, p < .001$) (Fig. 4).

Together, these results indicate that years of schooling and delta-band dwPLI connectivity contribute the most to predicting an individual's group (i.e., socially vulnerable or control).

4. Discussion

Socially vulnerable individuals often experience chronic stress due to limited access to education, healthcare, safe environments, and work opportunities, which poses a threat to their cognitive development and mental health (Cermakova et al., 2018; De Nadai et al., 2020; Engelberg et al., 2016; Giles-Corti & Donovan, 2002; Migeot et al., 2022). In this study, we explored how social vulnerability affects executive functioning and investigated its relationship with resting-state neural activity, analysing neural spectral power and connectivity measures in a group of healthy individuals. Our main findings revealed that socially vulnerable individuals display higher delta, theta, and beta functional connectivity compared to controls. Additionally, both delta- and theta-band functional connectivity exhibited a negative association with executive functioning, indicating that connectivity increases as executive functioning scores decrease. Interestingly, we observed no difference in power across frequency bands between the two groups. Finally, after accounting for covariates such as age, years of schooling, and gender, we found that only the increase in delta-band connectivity predicted social vulnerability, while theta-band connectivity was associated with years of schooling.

Prior studies have reported an association between both higher resting-state delta-band power and connectivity, and cognitive decline in conditions such as mild cognitive impairment and dementia (Adler et al., 2003; Babiloni et al., 2009; Brunovsky et al., 2003; Kwak, 2006; Locatelli et al., 1998). Although findings in this area are still inconclusive (Wang et al., 2022), an association between slow-wave connectivity and cognitive performance has been established (Laptinskaya et al., 2020). While it is common to encounter studies comparing cognitively impaired patients with healthy controls, demonstrating differences in delta-band power and

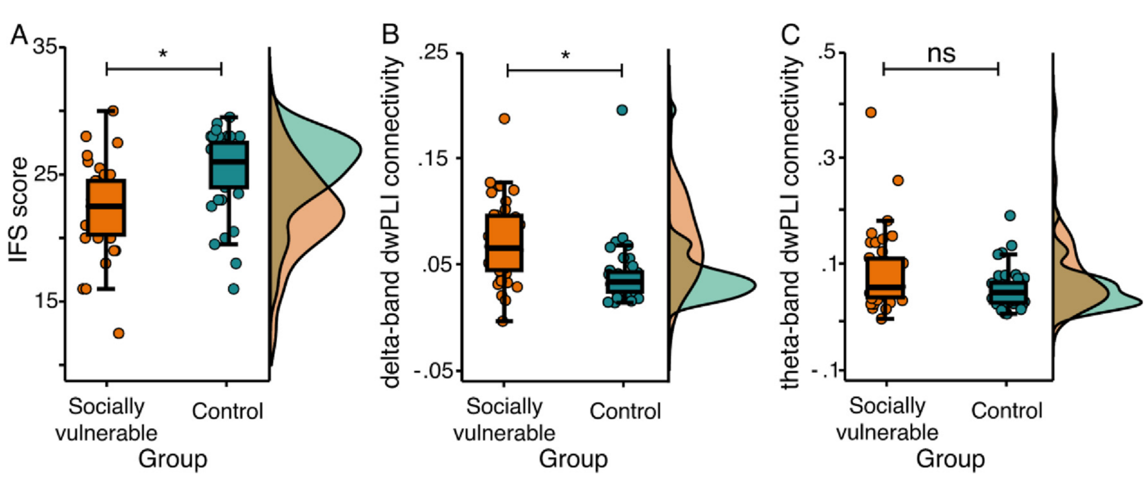

Fig. 3 – Group differences based on the ANCOVA model. (A) IFS scores were significantly lower in the socially vulnerable group compared to the control group. (B) Delta-band phase synchrony connectivity was significantly higher in the socially vulnerable group compared to the control group. (C) Theta-band phase synchrony connectivity did not significantly differ between groups. Asterisks denote significant differences between groups. Error bars denote 95% CI.

Table 2 – Binomial logistic regression model coefficients. Estimates represent the log odds of Socially vulnerable group versus Control group. Estimates represent log odds of "Group = Socially vulnerable" versus "Group = Control". Bold and asterisks denote significance: *$p < .05$, **$p < .01$, ***$p < .001$.

Predictor	Estimate	95% Confidence Interval		SE	Z	*p*	Odds ratio	95% Confidence Interval	
		Lower	Upper					Lower	Upper
Constant	13.55511	.0634	27.0468	6.884	1.9692	.049	770743.573	1.0655	5.58e+11
IFS	−.15251	−.3971	.0920	.125	−1.2224	.222	.859	.6723	1.096
Delta dwPLI	55.71430	17.1421	94.2865	19.680	2.8310	**.005****	1.57e+24	2.78e+7	8.87e+40
Gender:									
Female – Male	−1.06581	−2.8191	.6875	.895	−1.1914	.233	.344	.0597	1.989
Schooling	−.74251	−1.1773	−.3078	.222	−3.3474	<.001***	.476	.3081	.735
Age	.00379	−.2224	.2300	.115	.0328	.974	1.004	.8006	1.259
Theta dwPLI	−8.29594	−28.4988	11.9070	10.308	−.8048	.421	2.50e-4	4.20e-13	148294.659

other bands (Torres-Simón et al., 2022), the emphasis has shifted toward investigating neural networks and connectivity measures (Liu et al., 2023). In our study, we did not find evidence for power differences in any frequency band between socially vulnerable individuals and controls. However, we found connectivity differences between groups and in association with executive function, particularly for slow frequencies. It is important to note that suspected cognitive differences observed in pre-dementia studies and socioeconomic status studies are unlikely to be similar, and the same expectation applies to neural markers. Our findings suggest that the mechanisms by which neurological disorders and socioeconomic factors impact executive functioning are different. On the other hand, based on behavioural evidence, Mani et al. (2013) found that individuals facing poverty or resource scarcity typically exhibit a diminished capacity to make rational decisions and solve complex problems. Persistent concerns about economic matters were observed to adversely affect cognitive abilities, resulting in lower performance on cognitive tasks and a decline in executive function. In other words, the constant preoccupation with resource scarcity may negatively impact brain function, similar to other factors that deplete cognitive capacity, such as sleep deprivation or alcohol consumption. The aforementioned findings support the notion that socioeconomic vulnerability, such as poverty, is associated with lower cognitive performance, given that economic concerns consume cognitive resources. This hypothetical effect could be mirrored at the neural level by a higher predominance of connectivity in low-frequency bands.

Indeed, our findings indicate that the increased delta-band connectivity observed in the socially vulnerable group cannot be accounted for by differences in age, years of schooling, gender, or IFS score – only group membership significantly predicted changes in delta-band connectivity. This raises the question of which specific underlying factor, present among socially vulnerable individuals, drives this effect. While years of schooling may seem like a straightforward factor to predict group membership, as economic and social hardships often lead to school dropout (Adelman & Székely, 2017; Zaff et al., 2017), it is noteworthy that delta-band dwPLI connectivity contributed the most to predicting an individual's group (socially vulnerable or control). This leaves the door open for further research to explore its functional role and potential involvement in the underlying mechanisms of neural reconfiguration in response to hardship.

Recent studies have brought attention to the early effects of socioeconomic hardship on neural development, specifically in relation to neural markers of power in EEG. For instance, Wilkinson et al. (2023) found associations between family income and neural power in a USA sample, whereas Otero (1997) obtained similar findings in a Mexican sample.

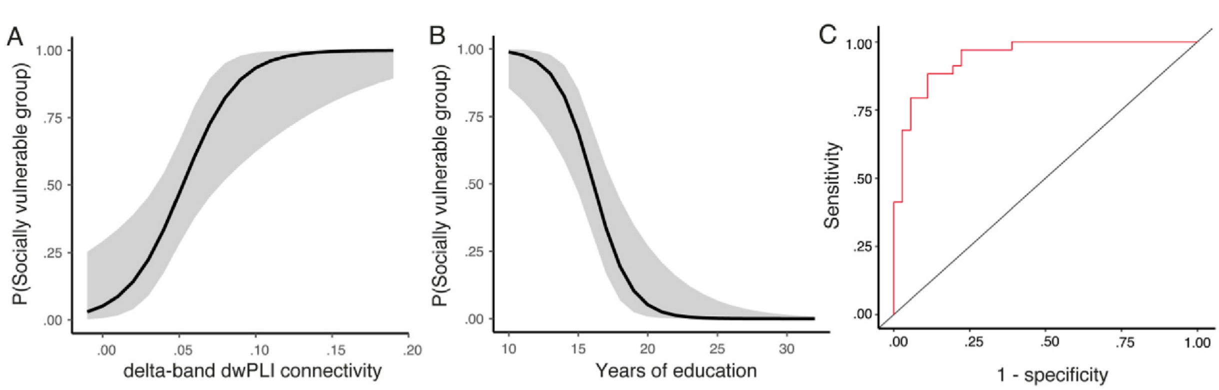

Fig. 4 – Binomial logistic regression model. (A) Performance of delta-band dwPLI connectivity as predictor of group classification. (B) Performance of years of schooling as predictor of group classification. (C) Receiver Operating Characteristic (ROC) curve represents the classification performance of the model (Area Under the Curve = .94).

Interestingly, while these findings support the early effects of hardship on neural development, the evidence for adults is not as conclusive. This suggests that while neural power may capture the initial effects of hardship, other neural signatures likely come into play later in life.

In a recent study, we found that cognitive variables (working memory and fluid intelligence) and socio-affective variables (self-esteem, stress, and locus of control) can predict social adaptation among adults living in vulnerable contexts (Neely-Prado et al., 2019). Specifically, we found that 31.8% of the differences in social adaptation were accounted for by stress, internal locus of control, and self-esteem, while 7% depended on working memory and fluid intelligence. The current study aimed to explore the relationship between neural markers and executive functioning in both socially vulnerable and non-vulnerable groups. Interestingly, some of the results indicate changes in slow-wave connectivity, which may also be related to or underlie socio-affective aspects of cognition. The combined findings of these two studies suggest that public policies could target self-esteem, locus of control, and perceived stress as relevant areas for intervention. Additionally, neural markers may play a role in defining the degree of belonging and could potentially be used to track progress and understand the underlying neural mechanisms of vulnerability in socio-economic hardship.

One limitation of our study is that we did not measure any physiological markers of stress or sleep hygiene. Although there is well-established evidence linking heightened stress levels in socially vulnerable individuals to socioeconomic factors (Cermakova et al., 2018; Migeot et al., 2022), and acknowledging the potential influence of sleep deprivation (a common occurrence in stressed individuals) on EEG signals, this omission hinders our ability to delve deeper into the relationship between executive functioning, neural connectivity, and chronic stress. Nevertheless, it is noteworthy that the participants in our laboratory study were drawn from the same population as those recruited by Neely-Prado et al. (2019). During that collaboration, it was observed that the perception of stress in individuals from socially vulnerable backgrounds emerged as a significant characteristic. Future studies should collect data on physiological markers of stress, allowing for a more comprehensive exploration of statistical nuances that our current analyses may have missed. Moreover, future studies should also investigate the specific executive functions most impacted by social vulnerability and how they evolve throughout childhood and adolescence. Understanding how slow-wave connectivity unfolds during the cognitive development of socially vulnerable individuals may shed light on how social factors affect cognitive development and the emergence of susceptibility to neuropsychiatric disorders among this group.

Another potential limitation of our study pertains to its sample size. While our current sample size is adequately powered to detect within-subject effects, it may be relatively constrained for identifying small between-subject effects. For future investigations seeking to explore more nuanced neural and cognitive distinctions between socially vulnerable and non-vulnerable individuals, larger sample sizes may be needed.

In summary, our study explored the impact of social vulnerability on executive functioning and its association with neural connectivity in healthy individuals, and found that socially vulnerable individuals exhibit higher slow-wave neural connectivity than non-vulnerable individuals.

Author statement

We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study. No part of the study procedures or analysis plans was pre-registered prior to the research being conducted.

Data and code availability statement

The materials, analysis code, and data are publicly available on the Open Science Framework (https://osf.io/j2zb9/).

Open practices

The study in this article has earned Open Data and Open Material Badges for transparent practices. The data and materials used in this study are available at: https://osf.io/j2zb9/.

CRediT authorship contribution statement

Renzo C. Lanfranco: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fabienne dos Santos Sousa:** Writing – review & editing, Investigation, Conceptualization. **Pierre Musa Wessel:** Writing – review & editing, Investigation, Conceptualization. **Álvaro Rivera-Rei:** Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tristán A. Bekinschtein:** Writing – review & editing, Investigation, Conceptualization. **Boris Lucero:** Writing – review & editing, Investigation, Conceptualization. **Andrés Canales-Johnson:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **David Huepe:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Acknowledgements

David Huepe is supported by an ANID/FONDECYT Regular (1231117) research grant and Andrés Canales-Johnson is supported by an ANID/FONDECYT Regular (1240899) research grant. The authors would like to thank Dr. Srivas Chennu for his valuable contribution to the implementation of the dwPLI analyses. The content of this article is solely the responsibility of the authors and does not necessarily represent the official views of their institutions.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cortex.2024.03.004.

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