Contents lists available at ScienceDirect

Neuropsychologia

Frontoparietal network and neuropsychological measures in typically developing children

Isabel Solis [a,b], Jacki Janowich [a,b], Felicha Candelaria-Cook [b], William Collishaw [b], Yu-Ping Wang [c], Tony W. Wilson [d], Vince D. Calhoun [b,e,f], Kristina R.T. Ciesielski [a,g], Julia M. Stephen [b,*]

[a] *Department of Psychology, University of New Mexico, 2001 Redondo S Dr, Albuquerque, NM, 87106, USA*
[b] *Mind Research Network and Lovelace Biomedical and Environmental Research Institute, 1101 Yale Blvd N.E., Albuquerque, NM, 87106, USA*
[c] *Department of Biomedical Engineering, Tulane University, 6823 St. Charles Ave, New Orleans, LA, 70118, USA*
[d] *Department of Neurological Sciences, University of Nebraska Medical Center, 988440 Nebraska Medical Center, Omaha, NE, 68198, USA*
[e] *Department of Electrical and Computer Engineering, University of New Mexico, 498 Terrace St NE, Albuquerque, NM, 87106, USA*
[f] *Tri-institutional Center for Translational Research in Neuroimaging and Data Science (TReNDS), Georgia State University, Georgia Institute of Technology, Emory University, 33 Glimer St SE, Atlanta, GA, 30303, USA*
[g] *MGH/MIT A. A. Martinos Center for Biomed. Imaging, Dept of Radiology, Harvard Medical School, 149 Thirteenth St, Suite 2301, Charleston, MA, 02129, USA*

ARTICLE INFO

ABSTRACT

Resting-state activity has been used to gain a broader understanding of typical and aberrant developmental changes. However, the developmental trajectory of resting-state activity in relation to cognitive performance has not been studied in detail. The present study assessed spectral characteristics of theta (5–8 Hz) and alpha (9–13 Hz) frequency bands during resting-state in *a priori* selected regions of the frontoparietal network (FPN). We also examined the relationship between resting-state activity and cognitive performance in typically developing children. We hypothesized that older children and children with high attentional scores would have higher parietal alpha activity and frontal theta activity while at rest compared to young children and those with lower attentional scores. MEG data were collected in 65 typically developing children, ages 9–14 years, as part of the Developmental Chronnecto-Genomics study. Resting-state data were collected during eyes open and eyes closed for 5 min. Participants completed the NIH Toolbox Flanker Inhibitory Control (FICA) and Attention Test and Dimensional Change Card Sort Test (DCCS) to assess top-down attentional control. Spectral power density was used to characterize the FPN. We found during eyes open and eyes closed, all participants had higher theta and alpha power in parietal regions relative to frontal regions. The group with high attentional scores had higher alpha power during resting-state eyes closed compared to those with low attentional scores. However, there were no significant differences between age groups, suggesting changes in the maturation of neural oscillations in theta and alpha are not evident among children in the 9-14-year age range.

1. Introduction

The human brain is consistently active even in the absence of a task. Magnetoencephalography (MEG) and electroencephalography (EEG) have long been used to record this resting brain activity. These resting-state recordings are undemanding and involve no explicit task beyond the participants resting quietly with their eyes open or closed for a relatively short time. Neural oscillations measured during these resting-state recordings are recognized as an important metric of brain function in both children and adults (Chapman et al., 1962; Volavka et al., 1967; Srinivasan, 1999; Barry et al., 2007, 2009). Therefore, characterizing the developmental progression of neural oscillations during resting-state may assist in our understanding of brain development and its relation to behavioral and cognitive performance.

Resting-state studies have revealed consistent and repeatable correlations between brain regions. Functional magnetic resonance imaging

(fMRI) studies have extended our understanding of the resting-state using functional connectivity, which is typically defined as coordinated fluctuations in BOLD signal between spatially separated brain regions. These functionally connected regions are in turn referred to as networks. Resting-state fMRI studies have identified resting-state networks including the frontoparietal network (FPN) (Raichle et al., 2001; Calhoun et al., 2002; Greicius et al., 2003), which has also been observed in MEG studies (Brookes et al., 2011).

The FPN is connected to various brain regions that are active during task engagement (Corbetta and Shulman, 2002; Fan et al., 2005) and is functionally associated with attentional performance (Fox et al., 2005; Vincent et al., 2008; Markett et al., 2014; Visintin et al., 2015). The FPN has been specifically associated with top-down attentional control (Corbetta and Shulman, 2002; Bressler et al., 2008; Ciesielski et al., 2010; Lückmann et al., 2014) and it may alter the functional connectivity to other networks according to task requirements (Cole et al., 2013). The FPN has also been implicated in other functions, including initiating and adjusting cognitive control abilities (Corbetta and Shulman, 2002; Dosenbach et al., 2007; Fair et al., 2007; Cole et al., 2014; Lückmann et al., 2014) and working memory performance (Barnes et al., 2016; Astle et al., 2015). Prior studies indicate that changes in the organization or maturation of the FPN parallel cognitive development (Luna et al., 2015).

Neural oscillations are a mechanism by which network connectivity is facilitated (Engel et al., 2013; Fries, 2015) and may be used to assess the FPN during resting-state. Theta (5–8 Hz) and alpha (9–13 Hz) oscillations specifically map onto the FPN and are also related to attention, memory, affect, and cognitive processing (Klimesch, 1999; Aftanas et al., 2001; Başar et al., 2001a, 2001b; Klimesch et al., 2007; Ciesielski et al., 2010). Both are involved in long-distance integration of neuronal activity (von Stein & Sarnthein, 2000; Donner and Siegel, 2011). In contrast to alpha power, which is strongest in parietal cortex during eyes closed rest, frontal theta power *increases* during task-performance (Klimesch, 1999).

Prior MEG and EEG studies have found a decrease in power spectral density (PSD) with increasing age in lower frequencies (delta 1–4 Hz, theta 5–8 Hz) (Cragg et al., 2011; Gómez et al., 2017; Brookes et al., 2018) and an increase in PSD with increasing age in higher frequencies (alpha 9–13 Hz, beta 4–29 Hz, gamma 31–58 Hz) (Gasser et al., 1988a; Klimesch, 1999; Clarke et al., 2001; Cragg et al., 2011; Gómez et al., 2017; Anderson and Perone, 2018; Perone et al., 2018). Measuring the underlying PSD changes may be done at the source or sensor level with most studies examining PSD at the sensor level. Examining PSD at the source level remains a strength for MEG (Pathak et al., 2016; Khan et al., 2018) and is increasingly being used for EEG (Rodríguez-Martínez et al., 2015; Pani et al., 2020). Using source PSD to characterize developmental change is a reliable method given that MEG spectral measures have good to excellent test-retest reliability (Candelaria-Cook et al., 2019). However, little is known about how source PSD is related to behavioral and cognitive measures in children.

Alpha reactivity, which is an estimate of alpha power reduction from eyes closed to eyes open conditions, is also associated with cognitive health; prior MEG/EEG studies identified systematic differences in alpha reactivity in clinical populations (Stam et al., 2005; Ciesielski et al., 2007; Cornew et al., 2012; Wilson et al., 2013; Wang and Meng, 2016; Hassan et al., 2017). For instance, alpha reactivity may be a marker of cholinergic system integrity (Wan et al., 2019). In children, alpha reactivity increases with age (Somsen et al., 1997) and decreases in late adulthood and in neurodegenerative disorders like Alzheimer's disease and Lewy body dementia (Schumacher et al., 2020). However, the relationship between alpha reactivity and attention in childhood has yet to be examined.

The developmental trajectory of FPN is not well understood, limiting our ability to identify how aberrant maturation of this circuit may be associated with developmental psychopathologies and other behavioral/cognitive challenges. Further, the association between resting-state activity and neuropsychological task performance during development is unclear. Based on the literature we examined the spectral characteristics of theta (5–8 Hz) and alpha (9–13 Hz) activity across *a priori* regions of interest (ROIs) of FPN in younger children versus older children. We also examined the relationship between PSD across FPN during resting-state and individual differences in top-down attentional control as measured by neuropsychological tests. We hypothesized that while at rest, older children and children with high attentional skills would have higher parietal alpha and frontal theta activity compared to young children and children with low attentional skills. We also expected that older children would have lower theta and alpha power across FPN while at rest compared to younger children.

2. Material and methods

2.1. Participants

As part of a larger longitudinal study on neurodevelopment, the present study included 65 typically developing children, ages 9–14 years ($M_{age} = 11.34$, $SD = 1.76$; 31 females). Participant characteristics are presented in Table 1. To consider developmental stages, children were separated into two groups to assess differences between younger children (9–11 years) and older children (12–14 years).

The sample characteristics, sampling, and methods of the Developmental Chronnecto-Genomics (DevCog) study, a longitudinal developmental study, are described in depth in a separate manuscript (see Stephen et al., 2021). Of the original 102 participants enrolled at the New Mexico site, 26 data sets were not yet processed due to missing MEG and/or MRI scans at the time of this analysis, three were removed due to noisy data and eight were excluded due to disclosure of exclusionary criteria following participation. Exclusionary criteria included history or current clinical diagnosis of any DSM-5 disorder, developmental and neurodevelopmental disorders based on parent-report, medication affecting the central nervous system (e.g. Ritalin, SSRIs), parental history of psychiatric disorders, and parental-report of prenatal exposure to drugs or alcohol. This research was approved by the Chesapeake IRB and conforms with the Declaration of Helsinki. All participants and their parent/legal guardian gave assent/informed consent prior to the performance of any study procedures.

2.2. Measures

2.2.1. Neurobehavioral measures

Neurobehavioral data were collected after the MEG scan. Participants completed the NIH Toolbox Cognition Battery, of which two tasks were used to assess top-down attentional control: The Flanker Inhibitory Control and Attention Test (FICA; Zelazo et al., 2013) and the Dimensional Change Card Sort Test (DCCS; Frye et al., 1995; Zelazo, 2006). FICA is derived from the original Eriksen flanker test (Eriksen and Eriksen, 1974) and the Attention Network Test (Fan et al., 2002; Rueda et al., 2004), which measures attention and executive function. Participants were asked to focus upon an arrow located in the middle of the

Table 1
Participant demographics.

Group	n	Age Mean	(SD)	IQ Mean	(SD)
Younger Children	35 (16F)	10.27	(0.88)	111.4	(11.63)
Older Children	30 (14F)	13.45	(0.97)	107.6	(15.72)
FICA-L	16 (6F)	12.03	(1.82)	100.8	(15.11)
FICA-H	45 (23F)	11.60	(1.86)	112.4	(12.08)

Note. FICA = NIH Toolbox - Flanker Inhibitory Control and Attention Test; L = Low attentional group; H = High attentional group; F = Female.

screen while inhibiting attention to stimuli nearby (e.g. flanking arrows). Participants responded by pressing buttons to congruent and incongruent signals (20 mixed trials). DCCS measures task switching or set shifting (i.e., the capacity for switching among strategies or tasks). Participants were shown two target cards (i.e. brown boat and a white rabbit) and were asked to sort them based on one dimension (i.e. color or shape) and then switch dimensions throughout the task. Performance scores for both FICA and DCCS, were normed ($M = 50$, $SD = 10$) and fully corrected for age, educational attainment (parent's education used; education may be used as a proxy for socioeconomic status, SES), and race/ethnicity (e.g. White, Asian, Black, Hispanic, multiracial). Participants were placed into low (scores $<$ 42) and high (scores $\geq$ to 42) attentional groups for both FICA and DCCS.

The NIH Toolbox is one of the few batteries that is well-standardized and normed across multiple demographic variables in a large sample (Casaletto et al., 2015), which decreases the false positive rate of abnormal responses in underrepresented groups (i.e. most norms are based on typical, neurologically-healthy White, North Americans) (Heaton et al., 2009; Lezak et al., 2012; Casaletto et al., 2015).

2.2.2. MEG behavioral tasks

All participants attended a 75-min-long MEG visit which included 5 min of eyes open and eyes closed resting-state (10 min of total resting-state). The other tasks are described elsewhere (Stephen et al., 2021). The order of eyes open/eyes closed was randomized across participants. In the eyes open condition, participants were asked to gaze at a fixation cross projected onto a screen placed 100 cm in front of them. In the eyes closed condition, participants were instructed to rest quietly and remain with their eyes closed until they were instructed to open them. During both conditions the participants were instructed to rest quietly without thinking of anything in particular.

2.3. MEG data acquisition and processing

MEG data were collected using the Elekta Neuromag (Elekta Oy, Helsinski, Finland) 306-channel whole-head biomagnetometer in a magnetically shielded room (Vaccumschmelze-Ak3B; Hanau, Germany) at the Mind Research Network in Albuquerque, New Mexico. Electro-oculogram (EOG) electrodes (placed above the left eyebrow and lateral to the right outer canthi) and electrocardiogram (ECG) electrodes (placed on the left and right clavicle) were used to provide signals for artifact rejection of eye-blinks, eye movement, and heartbeat. Four head position indicator (HPI) coils were placed on the participants' left and right mastoid bone and forehead to determine head position while in the MEG scanner. The locations of these HPI coils were registered to the head shape/size and position of three fiducial points (left and right preauricular and nasion) using 3D digitization equipment (Fast Trak; Polhemus, Colchester, VT). Participants sat upright during recording and were monitored using audio and video link between the magnetically shielded room and control room. Continuous HPI monitoring was enabled throughout MEG data collection to allow for motion correction.

The head center for each participant was identified using the Neuromag MRIlab software by co-registering each participant's structural MRI with the MEG HPI data. Structural MRIs were obtained from 52 of the 65 (80%) participants. Source locations for the other 13 participants for whom no structural MRIs were available were mapped onto structural volumes obtained from participants with similar head size, age, and gender who had successfully completed the MRI scan. This method has been found to produce low source estimation errors of approximately 5–10 mm using a participant's MRI and the best-fit MRI (Holliday et al., 2003). Sagittal T1-weighted anatomical MR images were obtained using a Siemens TIM Trio 3T MRI system with a 32-channel head coil.

The MEG data were collected at a sampling rate of 1000 Hz with an anti-aliasing filter with a passband of 0.1–330 Hz. Raw MEG data were filtered for noise sources and corrected for head motion with the Neuromag Maxfilter 2.1 software using the temporal extension of signal space separation (t-SSS) method and movement compensation (Taulu and Kajola, 2005; Taulu and Hari, 2009). Eye blink and cardiac artifacts were automatically identified from the EOG and ECG channels, respectively, and eliminated using signal space projection (SSP) (Uusitalon and Ilmoniemi, 1997) in MNE software (Gramfort et al., 2014). The continuous data obtained for each rest condition (eyes open, eyes closed) were then segmented into 2 s duration epochs. Data epochs with large amplitude artifacts with the magnetic field at any sensor exceeding 5 pT were rejected.

Next, cortical source analysis of the MEG data was performed using the FreeSurfer, Neuromag, and MNE software packages. We began with an automatic cortical reconstruction and subcortical segmentation from MPRAGE MRIs using the FreeSurfer software recon-all function. Then, a bilateral hemisphere surface-based source space was created using eight times recursively subdivided octahedron spacing. Next, boundary element model (BEM) meshes were created automatically using the watershed algorithm (Ségonne et al., 2004) from the MNE python software package which produces brain, inner skull, outer skull and outer skin surface triangulation. Each surface triangulation was isomorphic with an icosahedron, which was recursively subdivided, yielding 5120 triangles. The inner skull file was used for the single compartment BEM forward model.

A forward solution was calculated using a single layer BEM. The loose variable was set to 0.2 which is the MNE default for surface-oriented source space. For depth weighting the default coefficient, 0.8, was used with cortical patch statistics to define normal orientations. The inverse operator previously calculated was applied to each epoch in the MEG data using dynamic statistical parametric mapping (dSPM) (Dale et al., 2000) an anatomically constrained linear estimation with a regularization parameter with a signal to noise ratio of 3. Next, a time course for each label and source estimate was extracted with the mean flip method which averages the source estimates within each label with sign flips to reduce signal cancellation.

Normalized power per frequency band was obtained by calculating the total power across the frequency range of interest (1–58 Hz) and dividing the power within frequency band by the total 1–58 Hz power. Five individual files were created, delta (1–4 Hz), theta (5–8 Hz), alpha (9–13 Hz), beta (14–29 Hz), and gamma (31–58 Hz) for each participant. Alpha reactivity was used as a measure of arousal and was calculated using normalized spectral power. The following formula was used for each ROI: Alpha reactivity = (eyes closed – eyes open)/eyes open. Therefore, the greater the alpha reactivity index, the greater the difference between eyes open and eyes closed alpha reactivity.

ROI analysis was used to examine statistical significance between groups in select regions. Data from *a priori* ROIs in FPN were analyzed, which included two frontal regions, i.e., rostral middle frontal (rMF) and rostral anterior cingulate cortex (rACC) and two posterior regions, i.e., inferior parietal (IP) and precuneus (PC). The ROIs were selected using the DKT atlas (Klein and Tourville, 2012), which cover 62 regions and is the standard choice for MEG analysis. All spectral data were exported to MATLAB (2018a, MathWorks) and run through custom scripts to summarize measures.

2.4. Statistical analysis

All statistics were performed using SPSS (version 26). Outliers for PSD and neuropsychological scores were removed by converting data to z-scores and replacing absolute values that were 3.29 or greater with the average score of the participant's age and gender group (Field, 2009). Repeated Measures Analysis of Variance (RM-ANOVAs) were calculated to test group differences with statistical thresholds set at p < .05, unless otherwise noted. When applicable, Greenhouse-Geisser corrections were made to account for violations of sphericity. Effect sizes are reported using partial eta^2. Pairwise comparisons were adjusted for multiple comparisons by Bonferroni correction.

Spectral data were analyzed using omnibus RM-ANOVA with age group (9–11 years & 12–14 years) as between-subject factor, and the eight regions (Left, Right hemisphere: rMF, rACC, IP, & PC) as repeated measures. Each resting-state (eyes open, eyes closed) and frequency band (theta, alpha) was analyzed separately based on *a priori* hypotheses.

3. Results

To test whether older children had higher parietal alpha (9–13 Hz) and frontal theta (5–8 Hz) spectral power, RM-ANOVAs were calculated on normalized PSD values with age group as the between-subjects factor. Separate analyses were performed for eyes open and eyes closed.

3.1. Eyes open

There was a significant main effect for PSD across regions within

theta ($F_{(3.2, 203.6)} = 27.64$, $p < .001$, $\eta p^2 = 0.305$) and alpha ($F_{(1.8, 114.1)} = 26.95$, $p < .001$, $\eta p^2 = 0.300$) frequency bands. Pairwise comparisons, adjusted for multiple comparisons by Bonferroni correction, revealed greater theta and alpha power in parietal regions relative to frontal regions, Fig. 1. There were no significant differences between age groups. To examine whether children with higher attentional skills had higher parietal alpha and frontal theta activity, RM-ANOVAs were performed within theta and alpha bands. There were no theta or alpha significant differences for either low/high FICA and DCCS performance.

3.2. Eyes closed

There was a significant main effect for PSD across regions within theta ($F_{(2.8, 179.2)} = 34.08$, $p < .001$, $\eta p^2 = 0.351$) and alpha ($F_{(2.0, 127.6)} = 37.41$, $p < .001$, $\eta p^2 = 0.373$). Bonferroni adjusted pairwise comparisons revealed greater theta and alpha power in parietal regions relative to frontal regions. Additionally, the left rMF ($M = 0.016$, SEM =
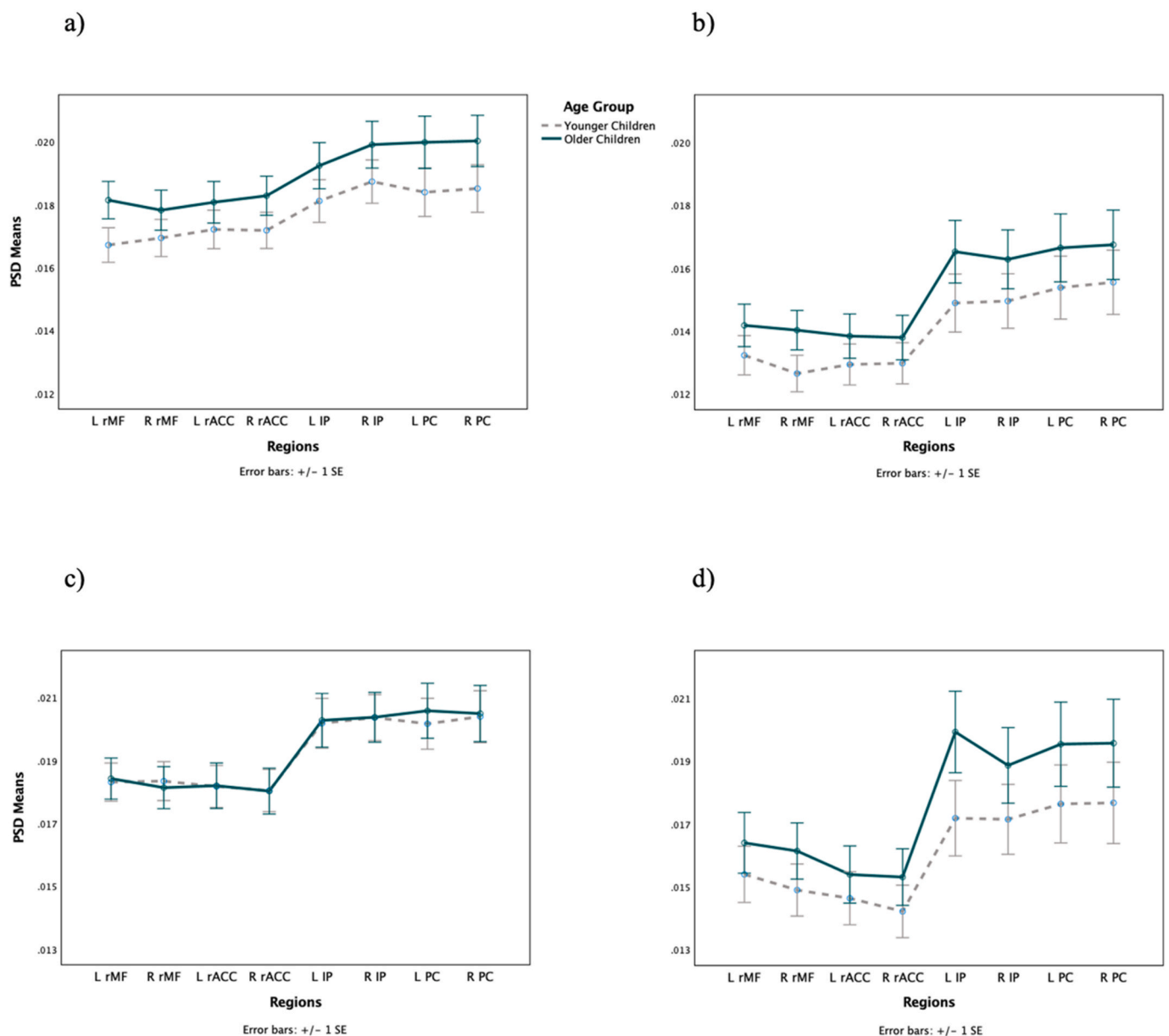

Fig. 1. Mean spectral power in a) theta (5–8 Hz) and b) alpha (9–13 Hz) frequency bands, eyes open and c) theta and d) alpha frequency bands, eyes closed across younger and older children. Frontal regions had significantly lower power spectral density (PSD) compared to parietal regions in both frequency bands in both conditions. L = left; R = Right; rMF = rostral middle frontal; rACC = rostral anterior cingulate cortex; IP = inferior parietal; PC = precuneus.

0.002) had significantly higher alpha power relative to the left rACC (M = 0.015, SEM = 0.001, p = .003) and right rACC (M = 0.015, SEM = 0.001, p < .001). There was no significant difference between age groups.

Within alpha, there was a significant attentional group difference in FICA ($F (1, 59)$ = 4.90, p = .031, ηp^2 = 0.077), indicating the high attentional group had higher PSD mean (M = 0.018, SEM = 0.001) relative to the low attentional group (M = 0.014, SEM = 0.001), see Fig. 2. There was no significant difference between the DCCS attentional groups.

3.3. Alpha reactivity

Alpha reactivity index was calculated to measure the difference between eyes open and eyes closed. There was a significant difference in alpha reactivity across regions in all participants ($F (2.2, 141.2)$ = 3.60, p = .025, ηp^2 = 0.054). One sample t-test indicated alpha reactivity in parietal region was significantly higher compared to alpha reactivity in frontal regions. Bonferroni adjusted pairwise comparisons revealed a significantly greater alpha reactivity in the right rMF (M = 0.198, SEM = 0.035) compared to left rACC (M = 0.136, SEM = 0.034, p = .04) and right rACC (M = 0.115, SEM = 0.033, p = .002). There were no other significant differences in alpha reactivity found across age groups or attentional groups (FICA and DCCS groups).

4. Discussion

The FPN is involved in top-down attentional control (Corbetta and Shulman, 2002; Bressler et al., 2008) and has a protracted development through adolescence and early adulthood (Ciesielski et al., 2006; Chai et al., 2017). However, the developmental patterns in FPN using spectral power and its relation to neuropsychological performance are not well understood. We focused on four ROIs (rMF, rACC, IP, & PC) based on previous studies (Fox et al., 2005; Fair et al., 2007; Berry et al., 2017) identifying these regions as being part of the FPN. We found that younger children (ages 9–11 years) and older children (ages 12–14 years) did not differ significantly in spectral power in the theta (5–8 Hz) or alpha (9–13 Hz) frequency bands across FPN in either eyes open or eyes closed during resting-state. However, all participants had significantly higher theta and alpha spectral power in parietal regions compared to frontal regions during both eyes open and eyes closed. This finding is in line with previous work showing high alpha power in posterior regions (Gasser et al., 1988a, 1988b; Wada et al., 1996). High theta power in parietal regions has also been observed among infants and young children (Clarke et al., 2001; Orekhova et al., 2001), thus showing a maturation progression from parietal to anterior regions (Matousek and Petersen, 1973; Gasser et al., 1988b). This suggests that children at this age range (9–14) may be primarily using parietal regions compared to frontal regions and the progression may shift during adolescent years.

During eyes closed, the high attentional FICA group had significantly higher alpha power compared to the low attentional FICA group during resting-state. That is, participants with higher alpha spectral power during resting-state had higher performance scores on FICA. Increased alpha power at rest may assist with subsequent neuropsychological tasks which is similar to previous studies examining ongoing brain recordings during cognitive task performance (Klimesch, 1999, 2012, 2012; Hanslmayr et al., 2005, 2007; van Dijk et al., 2008; Mathewson et al., 2009). Further, others have found that larger resting-state alpha power may be related to a person's increased inhibitory control (MacLean et al., 2012) by pre-activating task-relevant networks that leads to greater efficiency in selecting relevant stimuli (Jann et al., 2010). Similarly, Bonnefond and Jensen (2012) found that alpha power predicted the participants' task performance during a modified Sternberg working memory task measured with MEG and alpha power increased prior to an anticipated distractor. These findings suggest that resting-state activity may be able to predict cognitive abilities in subsequent tasks.

It is important to note that the low and high attentional FICA groups differed in their IQ performance, where the low attentional group had significantly lower IQ scores than the high attentional group. This is in line with other studies suggesting that attention is associated with intelligence (Schweizer and Moosbrugger, 2004; Cowan et al., 2006). It has been long debated whether attention is related to intelligence but through structural examination of attention there is evidence for a degree of overlap between both (Schweizer et al., 2005; Schweizer, 2010). Therefore, the current study did not covary for intelligence as selective attention may be a constituent of intelligence. The current results should be interpreted with caution given that we cannot separate these two variables.

We examined alpha reactivity which revealed no significant difference between age groups. This finding differs with previous studies that have found an increase with age (Somsen et al., 1997) in children 5–12 years. The largest change was detected between 6-7 and 9–11 year olds. The difference in age between the two studies may explain the lack of age-related changes in alpha reactivity reported here. Furthermore, our finding is in line with others who have suggested that low alpha reactivity may be associated with neuropsychiatric disorders (Besthorn et al., 1997). For instance, children with ADHD had significantly less alpha reactivity in the frontal regions compared to typically developing children (Fonseca et al., 2013). Additionally, adults with cognitive decline (van der Hiele et al., 2008), Alzheimer's disease (Besthorn et al., 1997; Babiloni et al., 2010; Mcbride et al., 2014), and schizophrenia (Candelaria-Cook et al., 2019) have been associated with reduced alpha reactivity. Since this cohort was exclusively composed of children with healthy development, low variation in alpha reactivity is expected.

However, there was greater alpha reactivity in the right rMF region compared to the left and right rACC across all participants. The rMF has been associated with inhibition in children, ages 9–12 (Heitzeg et al., 2014). These authors found that children with poor inhibitory control performance on an fMRI go/no-go task had reduced activity in the left rMF. Furthermore, adolescents with autism spectrum disorders utilized frontal regions and failed to recruit parietal regions while performing inhibitory tasks (Vara et al., 2014). Conversely, controls recruited both frontal and parietal regions and this pattern was associated with better performance on inhibitory tasks. Collectively, these data suggest that typical development of the rMF may lead to greater inhibitory control which may be associated with greater alpha reactivity in the rMF region.
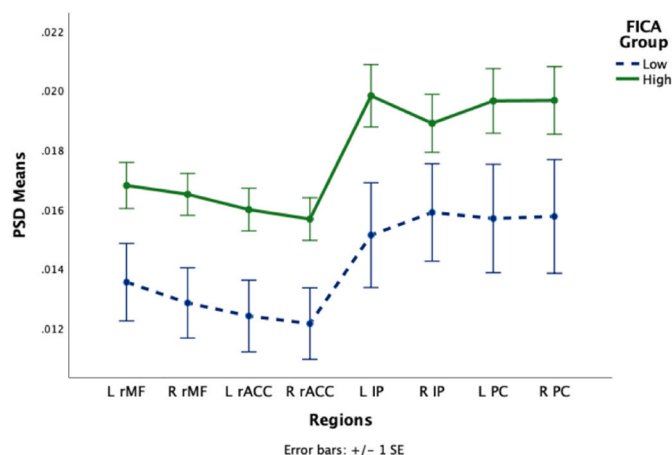

Fig. 2. Eyes closed, mean alpha (9–13 Hz) spectral power across the Flanker Inhibitory Control and Attention Test (FICA) attentional groups. A significant difference found in eyes closed resting-state, revealing greater alpha in higher attentional group compared to low attentional group. PSD = power spectral density; L = left; R = Right; rMF = rostral middle frontal; rACC = rostral anterior cingulate cortex; IP = inferior parietal; PC = precuneus.

It is important to address the limitations of the current study. First, the narrow age range (9–14 years) limits the broader understanding of neurodevelopment of spontaneous neural activity and resting-state connectivity. However, major developmental changes occur within this age range (Eccles, 1999; Fair et al., 2009; Barber et al., 2013; Anderson and Perone, 2018; Marek et al., 2018) including a period of increased onset of psychopathology (Walker, 2002; Rutter, 2007). Thus, by studying typically developing youth, we may then better understand how brain development differs in youth with developmental disorders. Secondly, the study used an *a priori* ROI approach to examine the FPN which limits the analysis of whole-brain connectivity. Future studies are needed to examine the role of other networks in brain development.

4.1. Conclusion

In this study, we demonstrate that developmental changes are not evident in the FPN across theta (5–8 Hz) and alpha (9–13 Hz) frequency bands in this age group. Furthermore, resting alpha power during eyes closed is greater in children with better performance in the FICA attention task relative to lower performing children. Resting-state cortical networks have been mostly examined using fMRI, but the current findings support the use of MEG with its higher temporal resolution to study the role of spontaneous neural activity and brain networks in cognitive development.

Funding

Credit author statement

Isabel Solis – Investigation, Formal analysis, Visualization, Data curation, Writing - original draft, Jacki Janowich – Investigation, Writing - review & editing, Felicha Candelaria-Cook – Formal analysis, Writing - review & editing, William Collishaw – Software, Writing - review & editing, Yu-Ping Wang – Conceptualization, Funding acquisition, Writing - review & editing, Tony W. Wilson – Conceptualization, Resources, Supervision, Project Management, Funding acquisition, Writing - review & editing, Vince D. Calhoun – Conceptualization, Resources, Project Management, Funding acquisition, Writing - review & editing, Kristina R.T. Ciesielski – Conceptualization, Writing - review & editing, Julia M. Stephen - Conceptualization, Resources, Supervision, Project Management, Funding acquisition, Writing - review & editing.

Acknowledgements

References

Aftanas, L., Varlamov, A., Pavlov, S., Makhnev, V., Reva, N., 2001. Event-related synchronization and desynchronization during affective processing: emergence of valence-related time-dependent hemispheric asymmetries in theta and upper alpha band. Int. J. Neurosci. 110 (3–4), 197–219. https://doi.org/10.3109/00207450108986547.
Anderson, A.J., Perone, S., 2018. Developmental change in the resting state electroencephalogram: insights into cognition and the brain. Brain Cognit. 126, 40–52. https://doi.org/10.1016/j.bandc.2018.08.001.
Astle, D.E., Luckhoo, H., Woolrich, M., Kuo, B.C., Nobre, A.C., Scerif, G., 2015. The neural dynamics of fronto-parietal networks in childhood revealed using magnetoencephalography. Cerebr. Cortex 25 (10), 3868–3876. https://doi.org/10.1093/cercor/bhu271.
Babiloni, C., Lizio, R., Vecchio, F., Frisoni, G.B., Pievani, M., Geroldi, C., Rossini, P.M., 2010. Reactivity of cortical alpha rhythms to eye opening in mild cognitive impairment and Alzheimer's disease: an EEG study. J. Alzheim. Dis. 22 (4), 1047–1064. https://doi.org/10.3233/JAD-2010-100798.
Barber, A.D., Caffo, B.S., Pekar, J.J., Mostofsky, S.H., 2013. Developmental changes in within-and between-network connectivity between late childhood and adulthood. Neuropsychologia 51 (1), 156–167. https://doi.org/10.1016/j.neuropsychologia.2012.11.011.
Barnes, J.J., Woolrich, M.W., Baker, K., Colclough, G.L., Astle, D.E., 2016. Electrophysiological measures of resting state functional connectivity and their relationship with working memory capacity in childhood. Dev. Sci. 19 (1), 19–31. https://doi.org/10.1111/desc.12297.
Barry, R.J., Clarke, A.R., Johnstone, S.J., Brown, C.R., 2009. EEG differences in children between eyes-closed and eyes-open resting conditions. Clin. Neurophysiol. 120 (10), 1806–1811. https://doi.org/10.1016/j.clinph.2009.08.006.
Barry, R.J., Clarke, A.R., Johnstone, S.J., Magee, C.A., Rushby, J.A., 2007. EEG differences between eyes-closed and eyes-open resting conditions. Clin. Neurophysiol. 118 (12), 2765–2773. https://doi.org/10.1016/j.clinph.2007.07.028.
Başar, E., Başar-Eroglu, C., Karakaş, S., Schürmann, M., 2001a. Gamma, alpha, delta, and theta oscillations govern cognitive processes. Int. J. Psychophysiol. 39 (2–3), 241–248. https://doi.org/10.1016/S0167-8760(00)00145-8.
Başar, E., Schürmann, M., Sakowitz, O., 2001b. The selectively distributed theta system: functions. Int. J. Psychophysiol. 39 (2–3), 197–212. https://doi.org/10.1016/S0167-8760(00)00141-0.
Berry, A.S., Sarter, M., Lustig, C., 2017. Distinct frontoparietal networks underlying attentional effort and cognitive control. J. Cognit. Neurosci. 29 (7), 1212–1225. https://doi.org/10.1162/jocn_a_01112.
Besthorn, C., Zerfass, R., Geiger-Kabisch, C., Sattel, H., Daniel, S., Schreiter-Gasser, U., Förstl, H., 1997. Discrimination of Alzheimer's disease and normal aging by EEG data. Electroencephalogr. Clin. Neurophysiol. 103 (2), 241–248. https://doi.org/10.1016/S0013-4694(97)96562-7.
Bonnefond, M., Jensen, O., 2012. Alpha oscillations serve to protect working memory maintenance against anticipated distracters. Curr. Biol. 22 (20), 1969–1974. https://doi.org/10.1016/j.cub.2012.08.029.
Bressler, S.L., Tang, W., Sylvester, C.M., Shulman, G.L., Corbetta, M., 2008. Top-down control of human visual cortex by frontal and parietal cortex in anticipatory visual spatial attention. J. Neurosci. 28 (40), 10056–10061. https://doi.org/10.1523/jneurosci.1776-08.2008.
Brookes, M.J., Groom, M.J., Liuzzi, L., Hill, R.M., Smith, H.J., Briley, P.M., Liddle, P.F., 2018. Altered temporal stability in dynamic neural networks underlies connectivity changes in neurodevelopment. Neuroimage 174, 563–575. https://doi.org/10.1016/j.neuroimage.2018.03.008.
Brookes, M.J., Hale, J.R., Zumer, J.M., Stevenson, C.M., Francis, S.T., Barnes, G.R., Nagarajan, S.S., 2011. Measuring functional connectivity using MEG: methodology and comparison with fcMRI. Neuroimage 56 (3), 1082–1104. https://doi.org/10.1016/j.neuroimage.2011.02.054.
Calhoun, V.D., Pekar, J.J., McGinty, V.B., Adali, T., Watson, T.D., Pearlson, G.D., 2002. Different activation dynamics in multiple neural systems during simulated driving. Hum. Brain Mapp. 16 (3), 158–167. https://doi.org/10.1002/hbm.10032.
Candelaria-Cook, F.T., Schendel, M.E., Ojeda, C.J., Bustillo, J.R., Stephen, J.M., 2019. Reduced parietal alpha power and psychotic symptoms: test-retest reliability of resting-state magnetoencephalography in schizophrenia and healthy controls. Schizophr. Res. https://doi.org/10.1016/j.schres.2019.10.023.
Casaletto, K.B., Umlauf, A., Beaumont, J., Gershon, R., Slotkin, J., Akshoomoff, N., Heaton, R.K., 2015. Demographically corrected normative standards for the English version of the NIH Toolbox Cognition Battery. J. Int. Neuropsychol. Soc. 21 (5), 378–391. https://doi.org/10.1017/S1355617715000351.
Chai, L.R., Khambhati, A.N., Ciric, R., Moore, T.M., Gur, R.C., Gur, R.E., Bassett, D.S., 2017. Evolution of brain network dynamics in neurodevelopment. Netw. Neurosci. 1 (1), 14–30. https://doi.org/10.1162/NETN_a_00001.
Chapman, R.M., Armington, J.C., Bragdon, H.R., 1962. A quantitative survey of kappa and alpha EEG activity. Electroencephalogr. Clin. Neurophysiol. 14 (6), 858–868. https://doi.org/10.1016/0013-4694(62)90136-0.
Ciesielski, K.T., Ahlfors, S.P., Bedrick, E.J., Kerwin, A.A., Hämäläinen, M.S., 2010. Top-down control of MEG alpha-band activity in children performing Categorical N-Back Task. Neuropsychologia 48 (12), 3573–3579. https://doi.org/10.1016/j.neuropsychologia.2010.08.006.
Ciesielski, K.T., Hämäläinen, M.S., Geller, D.A., Wilhelm, S., Goldsmith, T.E., Ahlfors, S. P., 2007. Dissociation between MEG alpha modulation and performance accuracy on visual working memory task in obsessive compulsive disorder. Hum. Brain Mapp. 28 (12), 1401–1414. https://doi.org/10.1002/hbm.20365.
Ciesielski, K.T., Lesnik, P.G., Savoy, R.L., Grant, E.P., Ahlfors, S.P., 2006. Developmental neural networks in children performing a Categorical N-Back Task. Neuroimage 33 (3), 980–990. https://doi.org/10.1016/j.neuroimage.2006.07.028.
Clarke, A.R., Barry, R.J., McCarthy, R., Selikowitz, M., 2001. Age and sex effects in the EEG: development of the normal child. Clin. Neurophysiol. 112 (5), 806–814. https://doi.org/10.1016/S1388-2457(01)00488-6.
Cole, M.W., Bassett, D.S., Power, J.D., Braver, T.S., Petersen, S.E., 2014. Intrinsic and task-evoked network architectures of the human brain. Neuron 83 (1), 238–251. https://doi.org/10.1016/j.neuron.2014.05.014.
Cole, M.W., Reynolds, J.R., Power, J.D., Repovs, G., Anticevic, A., Braver, T.S., 2013. Multi-task connectivity reveals flexible hubs for adaptive task control. Nat. Neurosci. 16 (9), 1348–1355. https://doi.org/10.1038/nn.3470.
Corbetta, M., Shulman, G.L., 2002. Control of goal-directed and stimulus-driven attention in the brain. Nat. Rev. Neurosci. 3 (3), 201. https://doi.org/10.1038/nrn755.

Cornew, L., Roberts, T.P., Blaskey, L., Edgar, J.C., 2012. Resting-state oscillatory activity in autism spectrum disorders. J. Autism Dev. Disord. 42 (9), 1884–1894. https://doi.org/10.1007/s10803-011-1431-6.

Cowan, N., Fristoe, N.M., Elliott, E.M., Brunner, R.P., Saults, J.S., 2006. Scope of attention, control of attention, and intelligence in children and adults. Mem. Cognit. 34 (8), 1754–1768. https://doi.org/10.3758/BF03195936.

Cragg, L., Kovacevic, N., McIntosh, A.R., Poulsen, C., Martinu, K., Leonard, G., Paus, T., 2011. Maturation of EEG power spectra in early adolescence: a longitudinal study. Dev. Sci. 14 (5), 935–943. https://doi.org/10.1111/j.1467-7687.2010.01031.x.

Dale, A.M., Liu, A.K., Fischl, B.R., Buckner, R.L., Belliveau, J.W., Lewine, J.D., Halgren, E., 2000. Dynamic statistical parametric mapping: combining fMRI and MEG for high-resolution imaging of cortical activity. Neuron 26 (1), 55–67. https://doi.org/10.1016/S0896-6273(00)81138-1.

Donner, T.H., Siegel, M., 2011. A framework for local cortical oscillation patterns. Trends Cognit. Sci. 15 (5), 191–199. https://doi.org/10.1016/j.tics.2011.03.007.

Dosenbach, N.U., Fair, D.A., Miezin, F.M., Cohen, A.L., Wenger, K.K., Dosenbach, R.A., Schlaggar, B.L., 2007. Distinct brain networks for adaptive and stable task control in humans. Proc. Natl. Acad. Sci. 104 (26), 11073–11078. https://doi.org/10.1073/pnas.0704320104.

Eccles, J.S., 1999. The development of children ages 6 to 14. Future Child. 9 (2), 30–44. https://doi.org/10.2307/1602703.

Engel, A.K., Gerloff, C., Hilgetag, C.C., Nolte, G., 2013. Intrinsic coupling modes: multiscale interactions in ongoing brain activity. Neuron 80 (4), 867–886. https://doi.org/10.1016/j.neuron.2013.09.038.

Eriksen, B.A., Eriksen, C.W., 1974. Effects of noise letters upon the identification of a target letter in a nonsearch task. Percept. Psychophys. 16 (1), 143–149. https://doi.org/10.3758/BF03203267.

Fair, D.A., Cohen, A.L., Power, J.D., Dosenbach, N.U., Church, J.A., Miezin, F.M., Petersen, S.E., 2009. Functional brain networks develop from a "local to distributed" organization. PLoS Comput. Biol. 5 (5) https://doi.org/10.1371/journal.pcbi.1000381.

Fair, D.A., Dosenbach, N.U., Church, J.A., Cohen, A.L., Brahmbhatt, S., Miezin, F.M., Schlaggar, B.L., 2007. Development of distinct control networks through segregation and integration. Proc. Natl. Acad. Sci. 104 (33), 13507–13512. https://doi.org/10.1073/pnas.0705843104.

Fan, J., McCandliss, B.D., Fossella, J., Flombaum, J.I., Posner, M.I., 2005. The activation of attentional networks. Neuroimage 26 (2), 471–479. https://doi.org/10.1016/j.neuroimage.2005.02.004.

Fan, J., McCandliss, B.D., Sommer, T., Raz, A., Posner, M.I., 2002. Testing the efficiency and independence of attentional networks. J. Cognit. Neurosci. 14 (3), 340–347. https://doi.org/10.1162/089892902317361886.

Field, A., 2009. Discovering Statistics Using SPSS, third ed. SAGE, London.

Fonseca, L.C., Tedrus, G.M., Bianchini, M.C., Silva, T.F., 2013. Electroencephalographic alpha reactivity on opening the eyes in children with attention-deficit hyperactivity disorder. Clin. EEG Neurosci. 44 (1), 53–57. https://doi.org/10.1177/1550059412445659.

Fox, M.D., Snyder, A.Z., Vincent, J.L., Corbetta, M., Van Essen, D.C., Raichle, M.E., 2005. The human brain is intrinsically organized into dynamic, anticorrelated functional networks. In: Proc. Of the Natl. Acad. of Sci., vol. 102, pp. 9673–9678. https://doi.org/10.1073/pnas.0504136102, 27.

Fries, P., 2015. Rhythms for cognition: communication through coherence. Neuron 88 (1), 220–235. https://doi.org/10.1016/j.neuron.2015.09.034.

Frye, D., Zelazo, P.D., Palfai, T., 1995. Theory of mind and rule-based reasoning. Cognit. Dev. 10, 483–527. https://doi.org/10.1016/0885-2014(95)90024-1.

Gasser, T., Jennen-Steinmetz, C., Sroka, L., Verleger, R., Möcks, J., 1988b. Development of the EEG of school-age children and adolescents II. Topography. Electroencephalogr. Clin. Neurophysiol. 69 (2), 100–109. https://doi.org/10.1016/0013-4694(88)90205-2.

Gasser, T., Verleger, R., Bächer, P., Sroka, L., 1988a. Development of the EEG of school-age children and adolescents. I. Analysis of band power. Electroencephalogr. Clin. Neurophysiol. 69 (2), 91–99. https://doi.org/10.1016/0013-4694(88)90204-0.

Gómez, C.M., Rodríguez-Martínez, E.I., Fernández, A., Maestú, F., Poza, J., Gómez, C., 2017. Absolute power spectral density changes in the magnetoencephalographic activity during the transition from childhood to adulthood. Brain Topogr. 30 (1), 87–97. https://doi.org/10.1007/s10548-016-0532-0.

Gramfort, A., Luessi, M., Larson, E., Engemann, D.A., Strohmeier, D., Brodbeck, C., Hämäläinen, M.S., 2014. MNE software for processing MEG and EEG data. Neuroimage 86, 446–460. https://doi.org/10.1016/j.neuroimage.2013.10.027.

Greicius, M.D., Krasnow, B., Reiss, A.L., Menon, V., 2003. Functional connectivity in the resting brain: a network analysis of the default mode hypothesis. In: Proc. Of the Natl. Acad. of Sci., vol. 100, pp. 253–258. https://doi.org/10.1073/pnas.0135058100, 1.

Hanslmayr, S., Aslan, A., Staudigl, T., Klimesch, W., Herrmann, C.S., Bäuml, K.H., 2007. Prestimulus oscillations predict visual perception performance between and within subjects. Neuroimage 37 (4), 1465–1473. https://doi.org/10.1016/j.neuroimage.2007.07.011.

Hanslmayr, S., Sauseng, P., Doppelmayr, M., Schabus, M., Klimesch, W., 2005. Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. Appl. Psychophysiol. Biofeedback 30 (1), 1–10. https://doi.org/10.1007/s10484-005-2169-8.

Hassan, M., Chaton, L., Benquet, P., Delval, A., Leroy, C., Plomhause, L., Defebvre, L., 2017. Functional connectivity disruptions correlate with cognitive phenotypes in Parkinson's disease. Neuroimage: Clinical 14, 591–601. https://doi.org/10.1016/j.nicl.2017.03.002.

Heaton, R.K., Ryan, L., Grant, I., 2009. Demographic influences and use of demographically corrected norms in neuropsychological assessment. In: Grant, I., Adams, K.M. (Eds.), Neuropsychological Assess. Of Neuropsychiatric and Neuromed. Disord, vol. 3. Oxford University Press, pp. 127–155.

Heitzeg, M.M., Nigg, J.T., Hardee, J.E., Soules, M., Steinberg, D., Zubieta, J.K., Zucker, R.A., 2014. Left middle frontal gyrus response to inhibitory errors in children prospectively predicts early problem substance use. Drug Alcohol Depend. 141, 51–57. https://doi.org/10.1016/j.drugalcdep.2014.05.002.

Holliday, I.E., Barnes, G.R., Hillebrand, A., Singh, K.D., 2003. Accuracy and applications of group MEG studies using cortical source locations estimated from participants' scalp surfaces. Hum. Brain Mapp. 20 (3), 142–147. https://doi.org/10.1002/hbm.10133.

Jann, K., Koenig, T., Dierks, T., Boesch, C., Federspiel, A., 2010. Association of individual resting state EEG alpha frequency and cerebral blood flow. Neuroimage 51 (1), 365–372. https://doi.org/10.1016/j.neuroimage.2010.02.024.

Khan, S., Hashmi, J.A., Mamashli, F., Michmizos, K., Kitzbichler, M.G., Bharadwaj, H., Gollub, R.L., 2018. Maturation trajectories of cortical resting-state networks depend on the mediating frequency band. Neuroimage 174, 57–68. https://doi.org/10.1016/j.neuroimage.2018.02.018.

Klein, A., Tourville, J., 2012. 101 labeled brain images and a consistent human cortical labeling protocol. Frontiers in Neuroscience 6, 171. https://doi.org/10.3389/fnins.2012.00171.

Klimesch, W., 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Res. Rev. 29 (2–3), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3.

Klimesch, W., 2012. Alpha-band oscillations, attention, and controlled access to stored information. Trends Cognit. Sci. 16 (12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007.

Klimesch, W., Sauseng, P., Hanslmayr, S., 2007. EEG alpha oscillations: the inhibition–timing hypothesis. Brain Res. Rev. 53 (1), 63–88. https://doi.org/10.1016/j.brainresrev.2006.06.003.

Lezak, M.D., Howieson, D.B., Bigler, E.D., Tranel, D., 2012. Neuropsychological Assessment, fifth ed. Oxford University Press, New York, NY.

Lückmann, H.C., Jacobs, H.I., Sack, A.T., 2014. The cross-functional role of frontoparietal regions in cognition: internal attention as the overarching mechanism. Prog. NeuroBiol. 116, 66–86. https://doi.org/10.1016/j.pneurobio.2014.02.002.

Luna, B., Marek, S., Larsen, B., Tervo-Clemmens, B., Chahal, R., 2015. An integrative model of the maturation of cognitive control. Annu. Rev. Neurosci. 38, 151–170. https://doi.org/10.1146/annurev-neuro-071714-034054.

MacLean, M.H., Arnell, K.M., Cote, K.A., 2012. Resting EEG in alpha and beta bands predicts individual differences in attentional blink magnitude. Brain Cognit. 78 (3), 218–229. https://doi.org/10.1016/j.bandc.2011.12.010.

Marek, S., Tervo-Clemmens, B., Klein, N., Foran, W., Ghuman, A.S., Luna, B., 2018. Adolescent development of cortical oscillations: power, phase, and support of cognitive maturation. PLoS Biol. 16 (11) https://doi.org/10.1371/journal.pbio.2004188.

Markett, S., Reuter, M., Montag, C., Voigt, G., Lachmann, B., Rudorf, S., Weber, B., 2014. Assessing the function of the fronto-parietal attention network: insights from resting-state fMRI and the attentional network test. Hum. Brain Mapp. 35 (4), 1700–1709. https://doi.org/10.1002/hbm.22285.

Mathewson, K.E., Gratton, G., Fabiani, M., Beck, D.M., Ro, T., 2009. To see or not to see: prestimulus α phase predicts visual awareness. J. Neurosci. 29 (9), 2725–2732. https://doi.org/10.1523/JNEUROSCI.3963-08.2009.

Matousek, M., Petersen, I., 1973. Frequency analysis of the EEG background activity by means of age dependent EEG quotients. In: Kellaway, P., Petersen, I. (Eds.), Automation of Clinical Electroencephalography. Raven Press, New York, pp. 75–102. https://doi.org/10.1016/0013-4694(73)90213-7.

Mcbride, J.C., Zhao, X., Munro, N.B., Smith, C.D., Jicha, G.A., Hively, L., Jiang, Y., 2014. Spectral and complexity analysis of scalp EEG characteristics for mild cognitive impairment and early Alzheimer's disease. Comput. Methods Progr. Biomed. 114 (2), 153–163. https://doi.org/10.1016/j.cmpb.2014.01.019.

Orekhova, E.V., Stroganova, T.A., Posikera, I.N., 2001. Alpha activity as an index of cortical inhibition during sustained internally controlled attention in infants. Clin. Neurophysiol. 112 (5), 740–749. https://doi.org/10.1016/S1388-2457(01)00502-8.

Pani, S.M., Ciuffi, M., Demuru, M., La Cava, S.M., Bazzano, G., D'Aloja, E., Fraschini, M., 2020. Subject, session and task effects on power, connectivity and network centrality: a source-based EEG study. Biomed. Signal Process Contr. 59, 101891. https://doi.org/10.1101/673343.

Pathak, Y., Salami, O., Baillet, S., Li, Z., Butson, C.R., 2016. Longitudinal changes in depressive circuitry in response to neuromodulation therapy. Front. Neural Circ. 10, 50. https://doi.org/10.3389/fncir.2016.00050.

Perone, S., Palanisamy, J., Carlson, S.M., 2018. Age-related change in brain rhythms from early to middle childhood: links to executive function. Dev. Sci. 21 (6) https://doi.org/10.1111/desc.12691.

Raichle, M.E., MacLeod, A.M., Snyder, A.Z., Powers, W.J., Gusnard, D.A., Shulman, G.L., 2001. A default mode of brain function. Proc. Natl. Acad. Sci. Unit. States Am. 98 (2), 676–682. https://doi.org/10.1073/pnas.98.2.676.

Rodríguez-Martínez, E.I., Barriga-Paulino, C.I., Rojas-Benjumea, M.A., Gómez, C.M., 2015. Co- maturation of theta and low-beta rhythms during child development. Brain Topogr. 28 (2), 250–260. https://doi.org/10.1007/s10548-014-0369-3.

Rueda, M.R., Fan, J., McCandliss, B.D., Halparin, J.D., Gruber, D.B., Lercari, L.P., Posner, M.I., 2004. Development of attentional networks in childhood. Neuropsychologia 42 (8), 1029–1040. https://doi.org/10.1016/j.neuropsychologia.2003.12.012.

Rutter, M., 2007. Psychopathological development across adolescence. J. Youth Adolesc. 36 (1), 101–110. https://doi.org/10.1007/s10964-006-9125-7.

Schumacher, J., Thomas, A.J., Peraza, L.R., Firbank, M., Cromarty, R., Hamilton, C.A., Donaghy, P.C., O'Brien, J.T., Taylor, J.P., 2020. EEG alpha reactivity and cholinergic

system integrity in Lewy body dementia and Alzheimer's disease. Alzheimer's Research & Therapy 12, 1–12. https://doi.org/10.1186/s13195-020-00613-6.

Schweizer, K., 2010. The relationship of attention and intelligence. In: Handbook of Individual Differences in Cognition. Springer, New York, NY, pp. 247–262. https://doi.org/10.1007/978-1-4419-1210-7_15.

Schweizer, K., Moosbrugger, H., 2004. Attention and working memory as predictors of intelligence. Intelligence 32 (4), 329–347. https://doi.org/10.1016/j.intell.2004.06.006.

Schweizer, K., Moosbrugger, H., Goldhammer, F., 2005. The structure of the relationship between attention and intelligence. Intelligence 33 (6), 589–611. https://doi.org/10.1016/j.intell.2005.07.001.

Ségonne, F., Dale, A.M., Busa, E., Glessner, M., Salat, D., Hahn, H.K., Fischl, B., 2004. A hybrid approach to the skull stripping problem in MRI. Neuroimage 22 (3), 1060–1075. https://doi.org/10.1016/j.neuroimage.2004.03.032.

Somsen, R.J., van't Klooster, B.J., van der Molen, M.W., van Leeuwen, H.M., Licht, R., 1997. Growth spurts in brain maturation during middle childhood as indexed by EEG power spectra. Biol. Psychol. 44 (3), 187–209. https://doi.org/10.1016/S0301-0511(96)05218-0.

Srinivasan, R., 1999. Spatial structure of the human alpha rhythm: global correlation in adults and local correlation in children. Clin. Neurophysiol. 110 (8), 1351–1362. https://doi.org/10.1016/S1388-2457(99)00080-2.

Stam, C.J., Montez, T., Jones, B.F., Rombouts, S., van der Made, Y., Pijnenburg, Y., Scheltens, P., 2005. Disturbed fluctuations of resting state EEG synchronization in Alzheimer's disease. Clin. Neurophysiol. 116 (3), 708–715. https://doi.org/10.1016/j.clinph.2004.09.022.

Stephen, J.M., Solis, I., Janowich, J., Stern, M., Frenzel, M.R., Eastman, J.A., Calhoun, V. D., 2021. The Developmental Chronnecto-Genomics (Dev-CoG) study: A multimodal study on the developing brain. NeuroImage 225, 117438. https://doi.org/10.1016/j.neuroimage.2020.117438.

Taulu, S., Hari, R., 2009. Removal of magnetoencephalographic artifacts with temporal signal-space separation: demonstration with single-trial auditory-evoked responses. Hum. Brain Mapp. 30 (5), 1524–1534. https://doi.org/10.1002/hbm.20627.

Taulu, S., Kajola, M., 2005. Presentation of electromagnetic multichannel data: the signal space separation method. J. Appl. Phys. 97 (12), 124905. https://doi.org/10.1063/1.1935742.

Uusitalo, M.A., Ilmoniemi, R.J., 1997. Signal-space projection method for separating MEG or EEG into components. Med. Biol. Eng. Comput. 35 (2), 135–140. https://doi.org/10.1007/BF02534144.

van der Hiele, K., Bollen, E.L., Vein, A.A., Reijntjes, R.H., Westendorp, R.G., van Buchem, van Dijk, J.G., 2008. EEG markers of future cognitive performance in the elderly. J. Clin. Neurophysiol. 25 (2), 83–89. https://doi.org/10.1097/WNP.0b013e31816a5b25.

van Dijk, H., Schoffelen, J.M., Oostenveld, R., Jensen, O., 2008. Prestimulus oscillatory activity in the alpha band predicts visual discrimination ability. J. Neurosci. 28 (8), 1816–1823. https://doi.org/10.1523/JNEUROSCI.1853-07.2008.

Vara, A.S., Pang, E.W., Doyle-Thomas, K.A., Vidal, J., Taylor, M.J., Anagnostou, E., 2014. Is inhibitory control a 'no-go' in adolescents with autism spectrum disorder? Mol. Autism. 5 (1), 6. https://doi.org/10.1186/2040-2392-5-6.

Vincent, J.L., Kahn, I., Snyder, A.Z., Raichle, M.E., Buckner, R.L., 2008. Evidence for a frontoparietal control system revealed by intrinsic functional connectivity. J. Neurophysiol. (Bethesda) 100 (6), 3328–3342. https://doi.org/10.1152/jn.90355.2008.

Visintin, E., De Panfilis, C., Antonucci, C., Capecci, C., Marchesi, C., Sambataro, F., 2015. Parsing the intrinsic networks underlying attention: a resting state study. Behav. Brain Res. 278, 315–322. https://doi.org/10.1016/j.bbr.2014.10.002.

Volavka, J., Matoušek, M., Roubíček, J., 1967. Mental arithmetic and eye opening. An EEG frequency analysis and GSR study. Electroencephalogr. Clin. Neurophysiol. 22 (2), 174–176. https://doi.org/10.1016/0013-4694(67)90158-7.

Wada, M., Ogawa, T., Sonoda, H., Sato, K., 1996. Development of relative power contribution ratio of the EEG in normal children: a multivariate autoregressive modeling approach. Electroencephalogr. Clin. Neurophysiol. 98 (1), 69–75. https://doi.org/10.1016/0013-4694(95)00187-5.

Walker, E.F., 2002. Adolescent neurodevelopment and psychopathology. Curr. Dir. Psychol. Sci. 11 (1), 24–28. https://doi.org/10.1111/1467-8721.00161.

Wan, L., Huang, H., Schwab, N., Tanner, J., Rajan, A., Lam, N.B., Zaborszky, L., Li, C.R., Price, C., Ding, M., 2019. From eyes-closed to eyes-open: Role of cholinergic projections in EC-to-EO alpha reactivity revealed by combining EEG and MRI. Human Brain Mapping 40 (2), 566–577. https://doi.org/10.1002/hbm.24395.

Wang, B., Meng, L., 2016. Functional brain network alterations in epilepsy: a magnetoencephalography study. Epilepsy Res. 126, 62–69. https://doi.org/10.1016/j.eplepsyres.2016.06.014.

Wilson, T.W., Franzen, J.D., Heinrichs-Graham, E., White, M.L., Knott, N.L., Wetzel, M. W., 2013. Broadband neurophysiological abnormalities in the medial prefrontal region of the default-mode network in adults with ADHD. Hum. Brain Mapp. 34 (3), 566–574. https://doi.org/10.1002/hbm.21459.

Zelazo, P.D., 2006. The Dimensional Change Card Sort: a method of assessing executive function in children. Nat. Protoc. 1, 297–301. https://doi.org/10.1038/nprot.2006.46.

Zelazo, P.D., Anderson, J.E., Richler, J., Wallner-Allen, K., Beaumont, J.L., Weintraub, S., 2013. II. NIH Toolbox cognition Battery (CB): measuring executive function and attention. Monogr. Soc. Res. Child Dev. 78 (4), 16–33. https://doi.org/10.1111/mono.12032.