Spontaneous alpha and theta oscillations are related to complementary aspects of cognitive control in younger and older adults

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Abstract

The resting-state human EEG power spectrum is dominated by alpha (8-12 Hz) and theta (4-8Hz) oscillations, and also includes non-oscillatory broadband activity inversely related to frequency (1/f activity). Gratton (2018) proposed that alpha and theta oscillations are both related to cognitive control function, though in a complementary manner. Alpha activity is hypothesized to facilitate the *maintenance* of representations, such as task sets in preparation for *expected* task conditions. In contrast, theta activity would facilitate *changes* in representations, such as the *updating* of task sets in response to *unpredicted* task demands. Therefore, theta should be related to reactive control (which may prompt changes in task representations), while alpha may be more relevant to proactive control (which implies the maintenance of current task representations). Less is known about the possible relationship between 1/f activity and cognitive control, which was analyzed here in an exploratory fashion. To investigate these hypothesized relationships, we recorded eyes-open and eyes-closed resting-state EEG from younger and older adults and subsequently tested their performance on a cued flanker task, expected to elicit both proactive and reactive control processes. Results showed that alpha power and 1/f slope were smaller in older than younger adults, whereas theta power did not show age-related reductions. Resting alpha power and 1/f slope were predictive of proactive control processes, whereas theta power was related to reactive control as measured by the cued flanker task. All predictive associations were present over and above the effect of age, suggesting that these resting-state EEG correlates could be indicative of trait-like individual differences in cognitive control performance, which may be already evident in younger adults, and are still similarly present in healthy older adults.

Keywords: EEG alpha power, EEG theta power, cognitive control, proactive control, reactive control, aging

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1. Introduction

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48   Three main features dominate the resting-state EEG power spectrum: alpha oscillations (8-12

49 Hz; e.g., Hanslmayr, Gross, Klimesch, & Shapiro, 2011; Jensen & Mazaheri, 2010; Mathewson et al.,

50 2011), theta oscillations (4-8 Hz; e.g., Jaušovec, Jaušovec, & Gerlič, 2001; Pscherer et al., 2019;) and

51 non-oscillatory broadband activity inversely related to frequency, known as 1/f slope (e.g., He, 2014).

52 Other frequency bands have also been identified and investigated, such as beta, gamma, etc., but their

53 amplitude is smaller. Alpha and theta oscillations have been extensively investigated in relation to

54 cognition, whereas the relationship between 1/f activity and cognition is emerging (Cavanagh & Frank,

55 2014; Clayton, Yeung, & Kadosh, 2015; Cohen, 2014; Voytek et al., 2015). Alpha and theta power are

56 most often measured during tasks to elucidate moment-to-moment neural variability yoked to certain

57 stimuli or conditions. For instance, posterior alpha has been related to the inhibition of the processing

58 of visual stimuli (e.g., Jensen & Mazaheri, 2010; Klimesch, Sauseng, & Hansilmayr, 2007; Lőrincz et

59 al., 2009; Mathewson et al., 2009; 2011) and can be suppressed by incoming visual stimulation that

60 needs attending (Morrell & Ross, 1953; Williamson et al., 1997). This suggests that alpha may be

61 related to a processing mode geared at limiting the progression of perceptual information through the

62 brain to avoid interfering with currently active representations.

63   In contrast, task-related activity in theta power shows marked, short-lived increases in response

64 to stimuli with high levels of conflict or when task settings require updating (Cavanagh & Frank, 2014;

65 Cavanagh et al., 2009; Clayton, Yeung, & Kadosh, 2015; Cohen, 2014; Cooper et al., 2016, Cohen &

66 Donner, 2013). In this context, theta activity may be associated with the adjustment of settings related

67 to how stimulus information needs to be processed (Cavanagh et al., 2009). Thus, in task-related

68 conditions, both alpha and theta are thought to be associated with mechanisms regulating the flow of

69 information, a set of processes often labeled cognitive control (for a review, see Gratton et al., 2018).

70   Providing a unified view of this evidence for alpha and theta, Gratton (2018) hypothesized that

71   these oscillations exert complementary roles in cognitive control, with alpha associated with the

72   maintenance of currently active representations (in order to protect their processing from interference;

73   *proactive control*, Braver, 2012) and theta associated with the disruption/updating of representations,

74   when attention needs to shift to incoming information (and alpha is therefore suppressed; *reactive*

75   *control*, Braver, 2012).   While largely proposed on the basis of stimulus-related activity, such

76   complementary roles for alpha and theta could also occur spontaneously, outside of the influence of

77   externally defined tasks, and therefore be related to trait-like *individual differences* in cognitive control.

78   If this were the case, then alpha activity at rest could be *predictive* of the propensity of an individual

79   to exert proactive control, which requires the maintenance of representations or goal-states.   Similarly,

80   the extent to which theta activity is exhibited at rest could be *predictive* of a person's ability to detect

81   and resolve interference, and therefore to exert reactive control.   In addition, because cognitive control

82   is known to vary with age (Braver & Barch, 2002, Braver, 2012; Bugg, 2014; Manard, Francois,

83   Phillips, Salmon, & Collette 2017), we were also interested in determining whether aging would

84   modulate these hypothesized relationships.   Specific evidence for these hypotheses is reviewed in the

85   remainder of this introduction.

86   *Alpha and theta power at rest*.   At rest, alpha power decreases with open eyes and is correlated

87   with many cognitive processes, including working memory and IQ (Doppelmayr, Klimesch, Stadler,

88   Pöllhuber, & Heine, 2002; Oswald et al., 2017). Further, it is well documented that alpha power

89   decreases with age (e.g., Polich, 1997) and also in various stages of clinical impairments as dementia

90   develops (Babiloni et al., 2006).   Healthy older adults have been shown to have greater resting-state

91   alpha power compared to those with Mild Cognitive Impairment (MCI), and they, in turn, have greater

92   alpha power than those with Alzheimer's Disease (AD; Moretti et al., 2004; Babiloni et al., 2006).

93   Thus, resting-state alpha power has already been used as a biomarker for individual differences in older

94   adults, due to its clinical relevance in distinguishing various degrees of age-related cognitive

95   pathologies. Additionally, Mahjoory et al. (2019) have shown that resting-state alpha power in younger

96   adults is related to attention span, indicating that alpha at rest may be a useful tool to understand

97   cognitive variability in younger adults. By-and-large, these data indicate that high resting-state alpha

98   power is associated with higher cognitive abilities, suggesting that resting-state alpha manifests a brain

99   mechanism of significant importance for cognition.

100   The relationship between *resting-state* theta activity and cognitive control is less clear.

101   Pscherer et al. (2019) found that individuals with low eyes-open resting-state theta power had poorly

102   controlled conflict-related response inhibition during a Go/No-Go task compared to those with high

103   resting theta power. They also found that participants with low resting-state theta power had more total

104   task-based theta power on incompatible than compatible trials. This was not true for participants who

105   had high resting-state theta power. These data suggest that resting theta power (just as theta power

106   during tasks) is related to inhibitory control, particularly during conflict, and that theta at rest may

107   predict cognitive control theta activity during a task. Surprisingly, however, theta at rest has also been

108   negatively associated with lower IQ (Jaušovec, et al., 2001).

109   These seemingly contradictory findings suggest that, although theta oscillations may represent

110   cognitive-control-related processes even in the absence of a task (but see Gordon et al., 2018), the exact

111   nature of these processes is still unclear. They may reflect periodic disengagement from established

112   representations to monitor the environment for changes, or the excessive occurrence of shifting or

113   updating operations (Miyake & Friedman, 2012), which may characterize highly distractible

114   individuals. Differently from alpha, the evidence for resting-state theta changes with age is mixed

115   (Babiloni et al., 2006; Finnigan & Robertson, 2011). Theta power has been reported not to differ

116   between healthy older adults and individuals with MCI or AD (Babiloni et al., 2006), but also to

117   undergo a relative *increase* with disease progression (Kwak, 2006).

Resting-state EEG and cognitive control

118   *1/f activity*. In recent years it has become clear that the resting-state EEG spectrum contains

119   not only recurrent oscillatory activity, but also activity of a non-recurrent (or non-oscillatory) nature.

120   These non-oscillatory phenomena typically produce a broadband effect, which is more visible at low

121   than at high frequencies, likely because the longer the duration of these deflections, the greater their

122   summation in the EEG spectrum. This type of activity is referred to as 1/*f* noise, 1/*f* slope or 1/*f* activity,

123   because its power decreases as a function of frequency (*f*) following a power-law function (He, 2014;

124   Voytek & Knight, 2015). Research on 1/*f* slope suggests that it could be related to task performance

125   and cognitive state (Miller et al., 2015; Ouyang et al., 2020; Pertermann et al., 2019). It has also been

126   recently shown that 1/*f* may be affected by age (Voytek et al., 2015; Dave et al., 2018;). Because 1/*f*

127   is a substantial component of the resting EEG power spectrum, and may vary with age, we decided it

128   would be important to separately estimate its role and predictive value in a set of exploratory analyses.

129   Crucially, separating 1/*f* from the remainder of the spectrum is important to accurately estimate the

130   power of oscillatory activity such as alpha and theta (Haegens, Cousijn, Wallis, Harrison, Nobre, 2014;

131   Nikulin & Brismar, 2006; Voytek et al., 2015).

132   *Assessment of proactive and reactive control*. To provide an independent assessment of an

133   individual's ability to exert proactive and reactive cognitive control, we employed a cued flanker task

134   (Eriksen & Eriksen, 1974). In a flanker paradigm, a central target stimulus is flanked by irrelevant

135   distractors that are either congruent (e.g., >>>>> or <<<<<) or incongruent with the target (e.g., <<><<

136   or >><>>). The participant's task is to ignore the flankers and respond based on the direction of the

137   central arrow. In the *cued* version of this paradigm used in the current study, the reaction stimulus

138   arrays are preceded by a cue that indicates the probability that the array will contain congruent flankers.

139   The difference in performance between incongruent and congruent trials, known as the *congruency*

140   *effect* (CE), reflects the extent to which distractor information is processed up to the point it influences

141   responses. The less the distractor information is processed, the smaller the congruency effect, which

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142   is taken as a measure of *reactive control*. Smaller congruency effects indicate more effective reactive

143   control.

144   Gratton, Coles, & Donchin (1992) showed that probability cues influence the size of the

145   congruency effect, with cues indicating a high probability of congruency leading to larger congruency

146   effects. In other words, when participants are warned that distractors are likely to be incongruent, they

147   adopt a strategy that limits the influence of the distractor information, reducing the congruency effect.

148   In contrast, when they are informed that irrelevant distractors are likely to be congruent, they adopt a

149   strategy that allows for more distractor information to be processed, because on the majority of trials

150   this information will facilitate performance. This is of course at the cost of hindering performance on

151   the infrequent incongruent arrays, leading to a larger congruency effect in such instances. These effects

152   are similar to the conflict adaptation effect (also called the congruency sequence effect, or the Gratton

153   effect) which is characterized by a reduced congruency effect on trials immediately following an

154   incongruent, as opposed to a congruent, array (e.g., Egner, 2007; Ullsperger, Bylsma, & Botvinick,

155   2005). We refer to the difference in probability cue-based congruency effects as the *conflict*

156   *expectation effect* (CEE), which is taken here as a measure of *proactive control*. Age should lead to a

157   reduction in the efficiency of both modes of control (i.e., an increase in CE and a decrease in CEE),

158   although potentially less so for reactive control (Bugg, 2014). Using a cued-flanker task, we

159   investigated the relationship between cognitive control processing and resting-state alpha power, theta

160   power and 1/*f* slope in a sample of younger and older adults.

161   **2. Materials and Methods**

162   *2.1 Participants*

163   Twenty-one younger and 20 older adults were recruited and underwent the procedures

164   described below[1]. Participants reported no history of psychiatric or neurological disorders and had no

165   signs of dementia (scores ≥51 on the modified Mini-Mental Status Examination [mMMSE]; Mayeux,

166   Stern, Rosen, & Leventhal, 1981), or depression (younger adults assessed with the Beck's Depression

167   Inventory, Beck, Steer, & Brown, 1996; and older adults with the Geriatric Depression Scale, Yesavage

168   et al., 1983; Yesavage & Sheikh, 1986). The study received ethical approval from the Institutional

169   Review Board at the University of Illinois Urbana-Champaign. All participants provided written

170   informed consent and were compensated for their time.

171   One younger adult and one older adult were excluded for excessive EEG artifacts: eye

172   movements, muscle activity, and/or amplifier saturation. The remaining 20 younger adults (age range

173   = 18-30, 14 females) and 19 older adults (age range = 65-80, 11 females) constituted the final sample.

174   See Table 1 for age-group characteristics. Older and younger adults were well matched in cognitive

175   status, although older adults, as is typical, had a slight advantage over younger adults in tests relying

176   on vocabulary knowledge[2], $t(35) = 4.29$, $p = .0001$. Older adults had slightly more years of education,

177    $t(37) = -2.15$, $p = .04$, as expected, given that most younger adults were college students. Older adults

178   also had higher composite age-adjusted IQ, $t(37) = -2.25$, $p = .03$, than younger adults.

179   INSERT TABLE 1 ABOUT HERE

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[1] The sample size reflects predicted effects for this task. To illustrate that the data is suitable for the analysis of individual differences we provide a reliability analysis on the EEG effects reported here.

[2] Two older adults did not take the Shipley Vocabulary Scale, resulting in fewer degrees of freedom for this *t*-test.

180   *2.2 Data Acquisition and Analysis*

181   Participants underwent two separate sessions: a resting-state EEG recording session, followed by a

182   behavioral testing session.

183   *2.2.1 Resting-State EEG*

184   Participants sat in a dimly lit, sound- and electrically attenuated recording chamber, and were

185   instructed to sit quietly and not think about anything in particular. Each session included a 1-minute

186   recording of resting EEG with eyes-open followed by 1-minute with eyes-closed. These recording

187   periods were conducted at the beginning of a recording session that involved other experiments that

188   will not be reported here.

189   *2.2.2 EEG Recording and Analysis*

190   EEG and EOG were recorded continuously from 64 active electrodes in an elastic cap (Acti-

191   Cap) using BrainAmp amplifiers (BrainVision Products GmbH). EEG was recorded from scalp

192   electrodes referenced to the left mastoid, with off-line re-referencing to the average of the two

193   mastoids. Two electrodes placed above and below the left eye measured vertical EOG to detect blinks

194   and vertical eye movements. Two electrodes placed approximately 1 cm to the left and right of the

195   outer canthi of the eyes measured horizontal eye-movements (saccades). Impedance was kept below

196   10kΩ. The EEG was filtered on-line using a 0.1-250 Hz bandpass and sampled at 500Hz.

197   Off-line EEG processing was done using EEGLAB Toolbox (version: 13.6.5b; Delorme &

198   Makeig, 2004), ERPLAB Toolbox (version: 6.1.3) and custom Matlab16a scripts (The MathWorks,

199   Inc., Natick, Ma, USA). A 30 Hz low-pass filter was applied. The data were epoched into 4096 ms

200   contiguous segments to facilitate usage of our artifact detection scripts. Epochs with amplifier

201   saturation were discarded. Ocular artifacts were corrected using the procedure described in Gratton et

202   al. (1983). After eye movement correction, epochs with voltage fluctuations exceeding 200µV were

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203 excluded from further analysis to minimize the influence of any remaining artifactual activity. This

204 resulted in the exclusion of 1.26% of the epochs.

205   Power spectral densities were determined using a fast Fourier transform with Welch's method

206 at parietal (Pz, POz, P1, P2, PO3, PO4) and frontocentral (Fz, FCz, Cz, CPz, FC1, FC2, C1, and C2)

207 electrode clusters. The segments were zero-padded and multiplied with a Hamming taper, with 0%

208 overlap. These clusters were selected because alpha power is largest at parietal locations (e.g., Haegens,

209 Cousijn, Wallis, Harrison, & Nobre, 2014), and 1/*f* slope and theta are typically largest at frontocentral

210 locations (Pertermann, Mückschel, Adelhöfer, Ziemssen, & Beste, 2019). This was confirmed in our

211 sample by a review of topographical plots.

212   For the purposes of the current study, we modeled the observed power spectrum as formed by

213 the sum of non-oscillatory activity (1/*f*), alpha and theta oscillatory peaks, and noise using the following

214 equation. Because there was no observable peak in the beta band, beta was not included in the model:

215      $Power(f) = 1/f\ effect\ (f) + theta\ power(f) + alpha\ power(f) + \varepsilon$

216   where *f* is frequency and ε is noise.

217   To ensure that our measures of alpha and theta oscillatory power were not confounded with

218 non-oscillatory activity, the 1/*f* component was removed from the spectrum prior to calculating mean

219 narrowband power. We first modeled the 1/*f* component on the raw power spectrum, excluding 4-13

220 Hz, which represents most oscillatory power in the spectrum, using a least-squares linear regression

221 with 1/*f* predicting power (see **Figure 1**; frequencies up to the Nyquist frequencies were used to model

222 1/*f*, frequencies up to 30 Hz were plotted). The slope of the 1/*f* component – i.e., the ß weight of

223 predictor 1/*f* in the equation – was retained for analysis. Note that the exponent of the *f* predictor was

224 fixed at -1 (i.e., f^{-1}). In other words, we did not use a log-log transform to fit the exponent of the 1/*f*

225 function to the data, as done in other studies (e.g., Voytek et al., 2015). Rather, we transformed the

226   frequency values into their inverse, and then regressed the power values for each frequency onto this

227   new axis (excluding power values between 4 and 13 Hz). This procedure was used because it is less

228   sensitive to very small variations in power for high frequencies, which in the EEG spectrum (compared

229   to the ECoG spectrum) have very low power. Because of these procedures, the interpretation of the

230    $1/f$ slope as computed in this fashion is different than that used by Voytek and colleagues (2015).

231   Rather than reflecting the shape (i.e., the exponent) of the $1/f$ function, the slope of the $1/f$ function in

232   the current study is related to *power at very low frequencies* – and thus corresponds more closely to

233   the *intercept* of the $1/f$ function in log-log space as reported by Voytek and coll. (2015).

234   The $1/f$ trend was then subtracted from the spectrum, allowing for more reliable alpha and theta

235   estimates (Nikulin & Brismar, 2006; Haegens et al., 2014). Mean alpha and theta power were

236   quantified on the detrended spectra and then log-transformed. The log transformed data were used for

237   analysis because power has a positively skewed distribution. Using the logarithm attenuates the

238   skewness of the power distributions and allows for an ANOVA to be performed without violating the

239   assumption of normality. Similarly, the $1/f$ slope was also log-transformed.

240   INSERT FIGURE 1 ABOUT HERE

241   Assessment of alpha power scalp topographies separately at 8, 9, 10, 11, and 12 Hz revealed

242   low power across the scalp at 8 Hz and 12 Hz in both younger and older adults. Thus, we estimated

243   alpha power based on the average power between 9-11 Hz. For theta, which did not show a prominent

244   peak in the spectra, we used a broader frequency window encompassing the full, canonical theta band,

245   4-8 Hz.

246   *2.2.3 Behavioral Task Session, Stimuli, and Related Analyses*

247   At the beginning of testing, participants were seated 100 cm in front of a computer monitor

248   centered at eye-level and were read instructions by the experimenter to supplement on-screen

249   instructions. The imperative stimulus consisted of five horizontal arrows that were either congruent

250   (<<<<< or >>>>>) or incongruent (<<><< or >><>>) on any given trial. Participants indicated, as

251   quickly and accurately as possible, which direction (left or right) the central, target stimulus was

252   pointing by pressing one of two keypads located on either side of the participant. Stimulus-response

253   mapping was constant across all participants (i.e., a left-pointing target stimulus always required a left-

254   button press, and vice versa) to eliminate the possibility of a confounding Simon effect in some

255   participants (Simon, 1969).

256   Three neutral, low-arousing images of inanimate objects (fire hydrant, dresser, and screw, from

257   the International Affective Picture System database, IAPS; Lang, Bradley, & Cuthbert, 2008) served

258   as cues and preceded the imperative stimulus array. These images represented a 75% (predict-

259   congruent; PC), a 50% (predict-neutral; PN), and a 25% (predict-incongruent; PI) probability of a

260   congruent stimulus array, respectively. The three cue types were equiprobable and participants were

261   explicitly told the congruency probability represented by each cue prior to commencing the task. PC

262   and PI cue images were counterbalanced across subjects.

263   Each trial began with a 499 ms cue, followed by a 999 ms fixation. Then, the imperative

264   stimulus appeared for 149 ms and was followed by 1848 ms of fixation before the onset of the next

265   trial. The response window began with the onset of the imperative stimulus and continued until the

266   onset of the next cue (i.e., the next trial). The global probability of a congruent trial within each block

267   was 50%. The imperative stimulus arrays were presented in white typeface on a black computer screen

268   and subtended $2.23° \times 0.46°$. Each cue overlaid a gray background with uniform dimensions such that

269   each composite image subtended $6.98° \times 5.35°$. All stimuli were presented on a monitor (19-in. CRT,

270   refresh rate 60 Hz, screen resolution 1280×960; Dell Computer, Round Rock TX) using the E-Prime

271   2.0 software (Psychology Software Tools, Pittsburgh, PA).

272   Accuracy feedback was displayed on-screen at the end of each block. If accuracy was below

273   75% across all trial types, participants saw a message that read "respond more slowly and more

274   accurately." If they scored between 75 and 95%, they saw "continue to respond as quickly and

275   accurately as you can." If they scored above 95%, they saw "respond more quickly". The feedback

276   was designed to encourage participants to prioritize speeded responses and elicit a reasonable number

277   of errors, a requirement for accurately assessing speed of processing. Participants could take breaks

278   between blocks, as needed.

279   Before the flanker task, younger adults completed 96 practice trials at the experimental speed.

280   Older adults completed two sets of practice trials. Additional practice was added for older adults to

281   offset difficulties (apparent in preliminary data) for them to complete the task at the experimental

282   speed. As such, we added a slower-paced practice block to familiarize this group with the task. In the

283   first set (48 trials), the inter-stimulus interval (ISI) was increased by 30%, but the cue and imperative

284   stimulus presentation times remained at experimental speed. In the second set (96 trials), each trial ran

285   at the experimental speed. Subsequently, all participants completed three blocks of 288 experimental

286   trials.

287   Incorrect trials and all trials with reaction times ≤ 200 ms (i.e., fast guesses) were discarded

288   before statistical analysis. Data were collapsed across target stimulus direction (i.e., response hand) to

289   create six trial-types: 3 cue types (PC, PI, PN) × 2 flanker congruency conditions (congruent,

290   incongruent). In addition to recording reaction time (RT) and calculating error rates for each trial-type,

291   the inverse efficiency score (IES), an integrated measure of RT and accuracy, was also calculated

292   (Townsend & Ashby, 1978, 1983; Bruyer & Brysbaert, 2011). IES is insensitive to speed-accuracy

293   tradeoffs and results in a measure of RT that is not biased by fast decisions. IES is computed by dividing

294   the mean RT of correct responses by the proportion of correct responses for each trial type (IES =

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295   RT/proportion correct), thereby providing an index of processing speed that estimates the "true"

296   processing speed when the effects of speed-accuracy tradeoffs are minimized.

297   For our measure of reactive control, we calculated the congruency effect (CE) by subtracting

298   congruent trials from incongruent trials (Incongruent - Congruent), so smaller differences in RT, error

299   rate, and IES indicate greater reactive control. For the measure of proactive control, we calculated the

300   conflict expectation effect (CEE) by subtracting the predict incongruent CE from the predict congruent

301   CE (PC_{CE} - PI_{CE}). Here, a larger difference indicates greater proactive control.

302   *2.4 Statistical Analyses*

303   Two-way mixed ANOVAs were computed, with age (young, old) as a between-subjects factor,

304   eye status (open, closed) as a repeated measure, and alpha power, theta power, or $1/f$ slope as dependent

305   variables. Alpha analyses were restricted to the parietal cluster, whereas theta and $1/f$ analyses were

306   restricted to the frontal cluster. Spearman's *rank-order* correlation coefficients were computed between

307   alpha power, theta power, $1/f$ slope and behavioral performance measurements (CE and CEE for error

308   rate, RT, and IES) across participants, in order to assess the effects of individual variability in resting-

309   state EEG parameters and subsequent cognitive control processing. Spearman's rho was used instead

310   of Pearson's *r* because assessment of normality with the Shapiro-Wilk test indicated that the behavioral

311   measures were not normally distributed. These correlations were calculated both with and without

312   partialing out the effects of age. The CEs were assessed with age (young, old), cue-type (PC, PI, PN),

313   and trial-type (congruent, incongruent) in three-way mixed ANOVAs. The CEE was assessed by

314   comparing the predict-incompatible to the predict-compatible dependent variables (error rate, RT, and

315   IES) in a 2 x 2 ANOVA with age as the between-subjects factor. To address the non-normality,

316   behavioral data were log-transformed prior to computing the ANOVAs. Significance levels were

317   corrected for multiple comparisons as noted in the results.

318   Given the relatively small sample size, we computed intrasubject reliability for alpha and theta

319   power and 1/f slope across the recording period, to show the consistency of the measurements. This

320   was done by comparing alpha power and theta power (after removing the 1/f effect) and 1/f slope

321   during even and odd epochs (each 4096 ms in length). Spearman's rho was calculated between these

322   values for even and odd epochs for each participant.

323   **3. Results**

324   *3.1 EEG Power Spectrum Decomposition*

325   After decomposing the power spectrum into alpha power, theta power and 1/f slope we

326   quantified the variance in the power spectrum captured by these components across participants. To

327   do this, we partitioned each individual's power spectrum into four components: the power accounted

328   for using the 1/f slope, alpha power, theta power, and the remaining, residual power not captured by

329   the model. Together, these should capture 100% of the variance in the power spectrum, given that

330   power itself is a measure of variance of the EEG time-series. Taking the sum of power accounted for

331   with 1/f slope, alpha, and theta and dividing it by the sum of all four components will yield the amount

332   of variability in the power spectrum accounted for by the non-oscillatory and main oscillatory features

333   of the EEG power spectrum. This was done for each participant and then averaged across participants

334   to give an overall estimate of captured variance. With eyes open, these three parameters (alpha power,

335   theta power, and 1/f slope) accounted for 90% of the spectral variance at the parietal electrode cluster

336   and 93% at the frontocentral cluster. Alpha, theta, and 1/f slope accounted for slightly less variance

337   with eyes closed: 89% at both the parietal and frontocentral electrode clusters. Therefore, although the

338   EEG signal is rich and complex, it can be largely described by these parameters. Power spectra (after

339   removing 1/f slope) for each electrode cluster are shown in Figure 2.

340   Alpha, theta and 1/f scalp distributions are presented in Figure 3. As shown in these maps,

341   younger and older adults had a posterior alpha scalp distribution, and a more anterior theta, as typically

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342   observed. The scalp distribution of 1/*f* had both anterior and posterior aspects. All effects were larger

343   around the midline.

344   INSERT FIGURES 2-3 ABOUT HERE

345   Alpha power at the parietal cluster was positively correlated with theta power at the

346   frontocentral cluster with eyes open, $r(37) = .344$, $p = .032$, [$r(36) = .345$, $p =.034$ after partialing out

347   age], and with eyes closed, $r(37) = .423$, $p = .007$, [$r(36) = .386$, $p = .017$ after partialing out age].

348   Thus, theta and alpha power were correlated with each other at rest, both before and after accounting

349   for age effects and in both eye conditions.

350   Neither alpha nor theta power were correlated with 1/*f* slope [alpha, eyes open, $r(37) = .087$, p

351    $= .600$ or eyes closed, $r(37) = .172$, $p = .295$; theta, eyes open, $r(37) = .185$, $p = .260$, or eyes closed,

352    $r(37) = .132$, $p = .423$]. All of these correlations remained non-significant after partialing out age.

353   *3.2 Reliability Analyses Within Individuals*

354   To show the consistency of the measurements, we computed intrasubject reliability for alpha

355   and theta power and 1/*f* slope across the recording period, by comparing even and odd epochs (each

356   4096ms in length). [3] We found that alpha power was highly consistent within individuals both with

357   open ($r_s (37) = .922$, $p < .00001$, average rho across participants) and closed eyes ($r_s (37) = .980$, $p <$

358    $.00001$, average rho across participants). Similarly, theta power was highly reliable both with open (r_s

359    $(37) = .774, p < .00001$) and closed eyes ($r_s (37) = .816, p < .00001$). Lastly, 1/*f* slope was also consistent

360   within individuals with open ($r_s (37) = .931$, $p < .00001$) and closed eyes ($r_s (37) = .854$, $p < .00001$).

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[3] To ensure that the correlations between even-odd epochs were not an effect of temporal continuity between power or 1/*f* in these epochs and to clarify whether power or 1/*f* changed as a result of participant fatigue, we also computed these correlations between the first and second half of the recording periods. They were all highly correlated: alpha power $r_s = .909$, theta power, $r_s = .963$; 1/f slope $r_s = .910$. These correspond well to the even-odd reliability analysis reported in the results section.

361   *3.3 Effects of age and eye status on alpha, theta, and 1/f*

362   A 2(age) × 2(eye status) mixed effects ANOVA was run for alpha power at the parietal

363   electrode clusters. As expected, alpha power was greater with closed compared to open eyes, $F(1, 37)$

364   = 24.865, $p < .001$, partial $\eta^2 = .402$ (see Figures 2-3). Although there was no main effect of age $F(1,$

365    $37) = 1.056$, $p = .311$, partial $\eta^2 = .208$, there was an age by eye status interaction, $F(1, 37) = 10.260$,

366    $p = .003$, partial $\eta^2 = .217$. Assessing the simple effects with eyes open, there was little difference in

367   alpha power between younger and older adults, $F(1, 37) = .255$, $p = .616$, partial $\eta^2 = .007$ but when

368   they closed their eyes, younger adults had significantly higher alpha power than older adults, $F(1, 37)$

369   = 11.225, $p = .002$, partial $\eta^2 = .233$. This may indicate that older adults modulate their resting-state

370   alpha power less than younger adults, which, in turn, may reflect a weakening of the neural system

371   giving rise to the alpha rhythm, or of the mechanisms for controlling it.

372   A similar analysis was run for theta power measured at the frontocentral cluster. The results

373   indicated a main effect of eye status, $F(1,37) = 25.438$, $p < .001$, partial $\eta^2 = .407$ with greater power

374   with closed than open eyes. However, there was no significant difference between the two age groups,

375    $F(1,37) = 0.064$, $p = .801$, partial $\eta^2 = .002$, and the interaction between age and eye condition was not

376   significant, $F(1,37) = 2.850$, $p = .100$, partial $\eta^2 = .072$. Thus, the data suggest no effect of age on theta

377   power at rest.

378   The 1/f slope was analyzed with a 2(age) × 2(eye status) mixed ANOVA at the frontocentral

379   cluster to determine potential group differences and the effect of eye condition on 1/f slope. The

380   ANOVA revealed that 1/f slope was greater with closed than open eyes, $F(1, 37) = 8.223$, $p = .007$,

381   partial $\eta^2 = .182$. There was also a main effect of age, $F(1, 37) = 12.363$, $p = .001$, partial $\eta^2 = .250$,

382   such that younger adults had higher levels of 1/f activity than older adults and this effect did not interact

383   with eye status, $F(1, 37) = .173$, $p = .680$. An age-related reduction in 1/f slope had been previously

384   shown during visual working memory tasks (Voytek et al., 2015; note however, that in their study this

385 was labeled 1/f intercept, see Methods section) and language processing tasks (Dave et al., 2018), but

386 to our knowledge this is the first time this age-related reduction has been demonstrated at the scalp in

387 the absence of an explicit cognitive task.

388 We performed some additional ancillary analyses, reported in **Supplementary Materials,** to

389 establish whether the timing patterns of theta and alpha occurrence at rest are similar to those observed

390 during tasks. Specifically, we sought to investigate whether frontocentral theta *at rest* occurs in short

391 bursts, as it typically does in tasks in response to the onset of attention-catching stimuli (Cavanagh &

392 Frank, 2014; Cohen & Donner, 2013). Task-recorded alpha, instead, is often present before stimulus

393 onset, with theta bursts typically occurring simultaneously with the alpha suppression that follows

394 stimuli that capture attention. Thus, we predicted alpha to be present in a higher proportion of the time

395 during the resting-state recording than theta. The results of these supplementary analyses are overall

396 consistent with these hypotheses, supporting the idea that similar temporal patterns characterize the

397 resting-state spectrum for theta and alpha compared to their task-based counterparts.

398 *3.4. Behavioral Effects*

399 Evidence from behavioral ANOVAs replicated the well-established CE for error rate [$F(1, 37)$

400 $= 24.708, p < .001$, partial $\eta^2 = .381$], RT [$F(1, 37) = 272.342, p < .001$, partial $\eta^2 = .88$], and IES [$F(1,$

401 $37) = 147.599, p < .001$, partial $\eta^2 = .800$]. There was a main effect of age on the CE when measured

402 with RT, $F(1, 37) = 22.514, p < .001$, partial $\eta^2 = .378$ and IES $F(1, 37) = 22.797, p < .001$, partial η^2

403 $= .381$ such that older adults had a larger CE than younger adults.

404 The probability cues also influenced the size of the CE. This was reflected in a CEE for RT

405 [$F(1, 37) = 6.042, p = .035$, partial $\eta^2 = .140$] and IES [$F(1, 37) = 5.070, p = .047$, partial $\eta^2 = .121$],

406 where CE's were larger following predict congruent compared to predict incongruent trials. The CEE

407 was not apparent for error rate, $F(1, 37) = 2.412 , p = .177$, partial $\eta^2 = .061$ and there was no age by

408   CEE interaction for any of the 3 behavioral measures: error rate [$F(1, 37) < 0.001$, $p > .999$, , partial

409   $\eta^2 = 0.0$], RT [$F(1, 37) = 1.853$, $p = .222$, partial $\eta^2 = .048$] or IES [$F(1, 37) = 0.001$, $p > .999$, partial

410   $\eta^2 = 0.0$]. All reported p-values for the predicted main effects in this section were corrected for multiple

411   comparisons using FDR.

412   *3.5 Correlations between Cognitive Control and Resting-State Alpha Power, Theta Power and 1/f*

413   *Slope*

414   Critically, the current study explored the relationship between alpha power, theta power and

415   1/f slope and proactive and reactive cognitive control processes. The results reported here are

416   exclusively for the eyes open condition, as the eyes closed condition did not predict behavior (it should

417   be noted that this is not surprising, as the behavioral measures were obtained with the eyes-open). All

418   correlations were corrected for multiple comparisons using family-wise FDR to control the expected

419   proportion of false positives in our results. As shown in Figure 4A, alpha power predicted the size of

420   the CEE for IES, $r_s (37) = .491$, $p = .024$. This is consistent with the prediction that alpha is related to

421   individual differences in proactive control. Alpha predicted RT CEE prior to multiple comparisons

422   correction, $r_s (37) = .321$, $p = .046$, but not after: $p = .183$. The relationship between IES CEE and alpha

423   remained significant even after partialing out the effects of age, IES CEE: $r_s (36) = .487$, $p = .024$,

424   suggesting that the ability to engage proactive control is not driven by age per se, and may instead

425   reflect individual differences in proactive cognitive control capacity that may be maintained in healthy

426   aging. In contrast, alpha power did not predict the size of the IES CE, $r_s (37) = .118$, $p = .630$ (with or

427   without partialing out the effects of age). Thus, alpha power appears specifically related to proactive

428   control abilities rather than to cognitive control in general, with greater proactive control in individuals

429   with larger alpha power at rest.

430   For resting theta power, there was a marginal positive relationship with the error rate CE, r_s

431   $(37) = .406$, $p = .06$, which varied little when age was partialed out, $r(36) = .410$, $p = .06$. This effect

19

432   was not present for RT CE, r_s (37) = .020, p = .902 or with IES CE, r_s (37) = .306, p = .183. Theta

433   power was not significantly correlated with the CEE for any of the behavioral measures: error rate, r_s

434   (37) = .226, p = .332 , RT r_s (37) = -.040, p = .883, or IES, r_s (37) = .182, p = .434, and remained non-

435   significant after partialing out age. These results indicate a modest relationship between theta activity

436   at rest and reactive, but not proactive, control. Interestingly, the data indicate that individuals with

437   high theta power at rest are more affected by distractors than individuals with low theta power. These

438   data are shown in Figure 4B.

439   It is important to investigate the dissociation between both alpha and theta power and their

440   relationships to proactive and reactive control, respectively. Therefore, partial correlation analyses

441   were conducted to further illustrate the effect of alpha power on proactive control processes while

442   holding theta power constant and the effect of theta power on reactive control processes while holding

443   alpha power constant. As throughout this section, these analyses were conducted on the eyes-open

444   measurements and corrected for multiple comparisons using family-wise FDR. Alpha power was

445   positively related to the IES CEE [r_s (36) = .464, p = .018] and the RT CEE [r_s (36) = .368, p = .046]

446   after partialing out the effects of theta power. As before, the error rate CEE was not related to alpha

447   power, even after partialing out theta power [r_s (36) = .198, p = .281]. The relationship between theta

448   power and reactive control processes also varied little after partialing out the effects of alpha power.

449   As before, there was a positive relationship between theta power and the error rate CE [r_s (36) = .402,

450   p = .036,]. Taken together, these results indicate that alpha power is indeed related to proactive control

451   processes, in a way that is independent from the contributions of theta power, and, conversely, that

452   theta power may be related to reactive control processes, in a way that is independent from the

453   contributions of alpha (although this result is only marginally significant). This suggests that alpha and

454   theta power *at rest* are uniquely related to proactive and reactive control, respectively. As such, they

455   could be used as separable biomarkers for these two aspects of cognitive control.

456   INSERT FIGURE 4 ABOUT HERE

457   Exploratory analyses of 1/f slope indicated that it marginally predicted the error rate CEE, r_s

458   (37) = .271, p = .096, an effect which reached significance after controlling for age, r_s (36) = .368, p =

459   .023. This may indicate that higher levels of 1/f activity is predictive of greater proactive control (Figure

460   4C). Additionally, 1/f slope was not related to the error rate CE before, r_s (37) = .233, p = .153, or after

461   partialing out age, r_s (36) = .119, p = .477. This suggests that 1/f slope may be more related to proactive

462   rather than reactive control processes. It should be noted, however, that there was no clear *a priori*

463   prediction for the 1/f slope, and that the effects reported were not corrected for multiple comparisons.

464   Therefore, these findings require additional replications.

465   **4. Discussion**

466   Most (~90%) of the resting-state EEG power spectrum can be described by three parameters:

467   the amplitude of the oscillatory spectral activity in the alpha and theta bands and the slope of the non-

468   oscillatory 1/f component. These three spectral features were larger with closed than open eyes.

469   Interestingly, two of these features differed between younger and older adults, such that older adults

470   had less alpha power (at least with closed eyes) and less 1/f activity (i.e., less power at lower

471   frequencies) than younger adults. Both of these findings are consistent with previous reports (Babiloni

472   et al., 2006; Dave et al., 2018; Polich, 1997; Voytek et al., 2015). No age differences were found for

473   theta activity, similarly to some previously reported research (Babiloni et al., 2006; Finely, Angus, van

474   Reekum, Davidson & Schaefer, 2020). Consistent with our hypotheses, these electrophysiological

475   characteristics were related to different aspects of cognitive control processing: increased alpha power

476   (and, to a lesser extent, 1/f slope) predicted greater modulation of distractor processing given the cue

477   information (conflict expectation effects), whereas theta power predicted greater distractor interference

478   in error rates only (congruency effects). Following the dual mechanism framework proposed by Braver

479   (2012), our evidence suggests that resting alpha power (and perhaps 1/f slope) are related to individual

480 differences in proactive control processes, whereas theta power reflects individuals' variations in

481 reactive control. A compelling picture emerges from these data: separate parameters from the

482 decomposed EEG power spectrum *at rest* may predict separable cognitive control processes during a

483 behavioral task, independent of participant's age. The alpha results resonate with previous work, which

484 showed that alpha power predicted subsequent learning in a complex video game task involving

485 multiple aspects of cognition (Mathewson et al., 2012).

486 Resting-state EEG has been previously used to investigate individual variability in cognitive

487 status and cognitive performance, especially in the context of aging and cognitive decline. Most often,

488 these recordings are conducted with eyes closed and have illustrated a shift in the EEG power spectrum

489 as participants progress from a healthy cognitive status to MCI and AD (Babiloni et al., 2006; Kwak,

490 2006). This suggests that, as older adults change in cognitive status, their closed-eyes resting-state EEG

491 spectrum changes concurrently, and that these changes can be used as indices of cognitive performance.

492 In the current study the predictability of the power spectrum characteristics on cognitive control

493 processes occurred in the eyes open condition and in *both* younger and older adults, which suggests

494 that this informative neural variability exists already in younger adults and may continue to provide

495 predictive power as individuals age. This is not equivalent to saying that age has no effect on either

496 alpha/theta amplitude or proactive/reactive control. Rather, it indicates that *mechanistic relationships*

497 between the neural systems represented by alpha and theta and cognitive control functions may be

498 maintained throughout the healthy lifespan, even though the individual component functions of these

499 relationships may weaken (see Fabiani, 2012). As an example, in a study of the relationship between

500 sequential effects in P300 amplitude and working memory function, we showed that the *relationship*

501 was the same for younger and older adults, despite an evident reduction in working memory capacity

502 and a shortening of the sequential activity in aging (Peltz, Gratton, & Fabiani, 2011).

503   As noted, there is an apparent dissociation between the typical age-related resting-state alpha

504   differences observed with closed eyes, and the predictive role of alpha measures taken with open eyes,

505   which is irrespective of age. This may indicate that individual differences in resting-state open-eyes

506   alpha may better predict cognitive control phenomena occurring in tasks where visual attention is

507   required, and eyes are open. It remains to be shown whether age-related differences in alpha obtained

508   with closed eyes are instead more likely to be predictive of cognitive phenomena that do not rely on

509   visual attention and can occur when the eyes are closed. This should be investigated in future research.

510   In many previous studies, alpha power fluctuations were investigated during ongoing cognitive

511   control tasks using a time-frequency approach. These experiments often report alpha blocking during

512   working memory encoding, attentional engagement, and proactive inhibition (Sauseng et al., 2005;

513   Foxe & Snyder, 2011; Vissers et al., 2016; Wöstmann et al., 2019). They also report phasic posterior

514   alpha power reductions following error trials (i.e., Cooper et al., 2016; van Driel, Ridderinkhof, &

515   Cohen, 2012). These decreases in alpha power have been conceptualized as a mechanism associated

516   with the refocusing of attention after an error occurred and when the updating of ongoing working

517   memory task-related representations is needed. Gratton (2018; see also Mathewson et al., 2009; 2011)

518   proposed that a temporary *blocking* of alpha is required for, or at least facilitates, the updating of

519   representations. This is consistent with the idea that alpha per se is associated with the maintenance of

520   existing representations over time (a phenomenon that would resist the updating process). This

521   proposal links alpha mechanisms with the maintenance of representations, which would be required

522   during proactive but not reactive control. This is consistent with the findings of the current study, in

523   which alpha power at rest was predictive of the size of the conflict expectation effect (which requires

524   maintenance of task-related representations in the interval between cues and response stimuli) but not

525   of the congruency effect (which requires direct handling of conflict, without a delay).

526   According to Gratton (2018), bursts of frontocentral theta may provide a mechanism by which

527   alpha is temporarily suspended to facilitate the updating of representations. As such, theta bursts would

528   provide an opportunity for sustained alpha oscillations to be interrupted and for the maintenance of a

529   representation to either be changed in favor of a new task-relevant representation, or in favor of a task-

530   irrelevant distractor. Ancillary analyses, reported as **Supplementary Materials**, investigated whether

531   theta occurs in a more burst-like manner than alpha (*at rest* and after accounting for 1/*f* activity). The

532   results showed that this was indeed the case in the eyes open condition. These exploratory analyses

533   suggest that, even during resting-state and in the absence of discernible external triggering events, theta

534   tends to occur in shorter bursts than alpha. Further, the data suggest that the frequency of occurrence

535   of theta bursts is strongly reflected by the total power across the whole resting-state recording period,

536   whereas this is much less so for alpha. With respect to the functional significance of these bursts, we

537   argue that, although a flexible engagement of theta interruption mechanisms is a useful process, integral

538   to cognitive control, its excessive engagement may lead to maladaptive responses (i.e., distractibility)

539   in conditions in which refocusing is not needed. This effect may be evident during resting-state

540   situations: In such conditions, engagement of theta activity and blocking of alpha activity are not

541   required, and the trait-like propensity to do so may be correlated with lower control abilities during

542   tasks. It may also explain previously reported results, which indicate that IQ is negatively correlated

543   with resting-state theta, and positively correlated with resting-state alpha (Doppelmayr et al., 2002;

544   Jaušovec et al., 2001). Our results also inform the trait-like spectral differences in adults with ADHD,

545   which indicate both increased theta power and decreased alpha power (Woltering, Jung, Liu, &

546   Tannock, 2012), and could explain the tendency for increased distractibility in these individuals. This

547   pattern may develop with the disorder, as Robertson et al. (2019) have shown that unmedicated children

548   with ADHD have similar theta power but more alpha power compared to typically developing children.

549   In the present study, such a propensity may be associated with increased susceptibility to the

550   interference caused by incompatible flankers in the flanker task.

551   As mentioned previously, the evidence for age-related decreases in theta power is mixed

552   (Babiloni et al., 2006; Cummins & Finnigan, 2007; Finely Angus, van Reekum, Davidson & Schaefer,

553   2020). Prichep et al. (2006) reported reductions in resting-state theta power in cognitively typical older

554   individuals with subjective memory complaints seven years later, but only for those individuals whose

555   mental status declined during the seven-year interval. This may address why younger and older adults

556   in our study did not show theta power differences. Our older adults were cognitively intact and not

557   reporting memory complaints. Finnigan and Robertson (2011) reported that relatively higher resting

558   theta power in healthy older adults was related to better performance on verbal recall, attention, and

559   executive function measures. Taken together these results suggest that the relationship between

560   resting-state theta activity and cognitive abilities is complex, and perhaps not monotonic. Perhaps some

561   minimum level of theta function needs to be maintained for appropriate cognition, but an excessive

562   amount may signal a propensity to over-react to contextual changes and distraction, which may also be

563   deleterious for cognition (e.g., Cools & D'Esposito, 2011). Further studies are needed to investigate

564   this hypothesized inverse-U relationship between theta function at rest and cognition.

565   Although we did not find a difference in theta power with age, we did find a reduced $1/f$ slope

566   with age, replicating similar age effects reported by Voytek et al. (2015) and Dave et al. (2018). It is

567   important to note that, as computed in our study, $1/f$ slope is largely determined by low-frequency EEG

568   activity (in a manner more similar to the intercept measures reported by Voytek et al., 2015). Thus,

569   the reduction in $1/f$ slope observed in the current study fits well with other literature reporting reduced

570   delta power across the adult lifespan (Babiloni et al., 2006; Polich, 1997). Interestingly, in both of

571   these studies, alpha power was also shown to decrease with age, which we have reported as well. Here

572   we show, for the first time, a relationship between $1/f$ slope and proactive control processes. This is of

573   interest because it suggests that an additional electrophysiological mechanism may be involved in

574   control processing. We have shown that alpha power and $1/f$ slope are not correlated with each other

575   (in the open eyes condition), indicating that although they both predict proactive control processing,

576   they are likely to be distinct electrophysiological signals. Since the analyses of $1/f$ were largely

577   exploratory, they should be replicated and extended in future research.

578   　　　Some limitations of the current study should be pointed out. First, our study is limited by its

579   sample size. Nonetheless, predictive relationships were still present in this sample, suggesting that

580   their effect size is sufficient. It is clear, however, that further testing with larger samples and other

581   cognitive control tasks may be very useful to further validate the results reported here. Additionally,

582   time-frequency analyses of EEG recorded during rest with different levels of alertness, and compared

583   to diverse cognitive control tasks in a within-subject design would allow us to investigate the dynamics

584   of these electrophysiological parameters and assess whether alpha and $1/f$ slope and theta power

585   selectively mediate proactive and reactive control. These analyses may also be useful to demonstrate

586   that EEG parameters measured at rest are predictive of possible trait-like individual differences in

587   event-related time-frequency phenomena.

588   4.1 *Conclusions*

589   　　　Resting-state EEG contains three dominant – and largely separable – electrophysiological

590   signals: oscillatory alpha and theta power, and non-oscillatory $1/f$ slope. We found independent and

591   separable predictive relationships between *resting-state* alpha power and proactive control, and theta

592   power and reactive control, which existed regardless of participants' age. The fact that these

593   dimensions of cognitive control can be predicted from EEG activity *at rest*, and are therefore unrelated

594   to specific task characteristics, suggests that they may represent important trait-like biomarkers. As

595   such, they may prove useful in understanding life-span individual differences in cognition and may

596   help researchers investigate variability in cognitive aging.

597 **5. Conflict of Interest**
598 The authors declare that the research was conducted in the absence of any commercial or financial
599 relationships that could be construed as a potential conflict of interest.
600
601 **6. Author Contributions**
602 GMC helped design the study, collected and analyzed the EEG data, and wrote the first draft of the
603 manuscript; DCB collected and analyzed the behavioral data; MG helped with the EEG analysis
604 pipeline and execution; KAL helped with experimental design and analyses; MF and GG designed
605 the study, and supervised analyses and writing. All authors edited the manuscript and met to discuss
606 results and theoretical implications.
607
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614

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818   Table 1

819   *Descriptive characteristics of the sample. Mean (SD).*

820

	Younger Adults	**Older Adults**	*p*-value
N	20 (14 females)	19 (11 females)	
Age (years)	22.4 (*3.3*)	69.4 (*4.3*)	< .001
Education (years)	15.6 (*2.4*)	17.3 (*2.4*)	.038
IQ (age-adjusted)*	115.2 (*10.7*)	124.0 (*15.4*)	.030
Shipley's Vocabulary Scale	31.4 (*3.4*)	36.1 (*3.2*)	< .001

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822   **Kaufman Brief Intelligence Test – 2ⁿᵈ edition*

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825 **Figure Legends**

826 **Figure 1: Detrending Procedure:** Raw power spectrum (solid black line), with the characteristic $1/f$
827 phenomenon across the spectrum. The $1/f$ phenomenon was modeled excluding the frequencies 4-
828 13 Hz (dashed black line) and was subtracted from the raw power spectrum, resulting in the
829 detrended power spectrum (solid blue line). Alpha and theta measurements were made on the
830 detrended power spectrum.

831 **Figure 2: Detrended Power Spectra:** Detrended power spectra at the parietal (A-B) and frontocentral
832 (C-D) electrode clusters with eyes closed (A, C) and eyes open (B, D). Shaded gray areas indicate
833 +/- the standard error. Note that younger adults had greater alpha power than older adults with both
834 eyes open and eyes closed. However, theta power was not significantly different between younger
835 and older adults. Both alpha and theta powers were reduced by opening the eyes.

836 **Figure 3: Topographic maps of alpha, theta, and $1/f$ slope:** Alpha and theta amplitude, and $1/f$ slope
837 with eyes open (top) and closed (bottom) are shown for both younger and older adults. Amplitude
838 was used instead of power because power differences between younger and older adults were too
839 large to be plotted meaningfully using the same scale.

840 **Figure 4: Relationship between EEG and cognitive control: (A)** Scatterplot of parietal alpha power
841 with the conflict expectation effect (CEE) on the inverse efficiency score (IES). The greater the
842 alpha power, the more these individuals used the cue information (proactive control). **(B)**
843 Scatterplot of frontocentral theta power with the congruency effect (CE) on error rate. The greater
844 the theta power at rest, the greater the distractor interference (reactive control). **(C)** Scatterplot of
845 frontocentral $1/f$ slope with the CEE on error rate. The steeper the $1/f$ slope, the more these
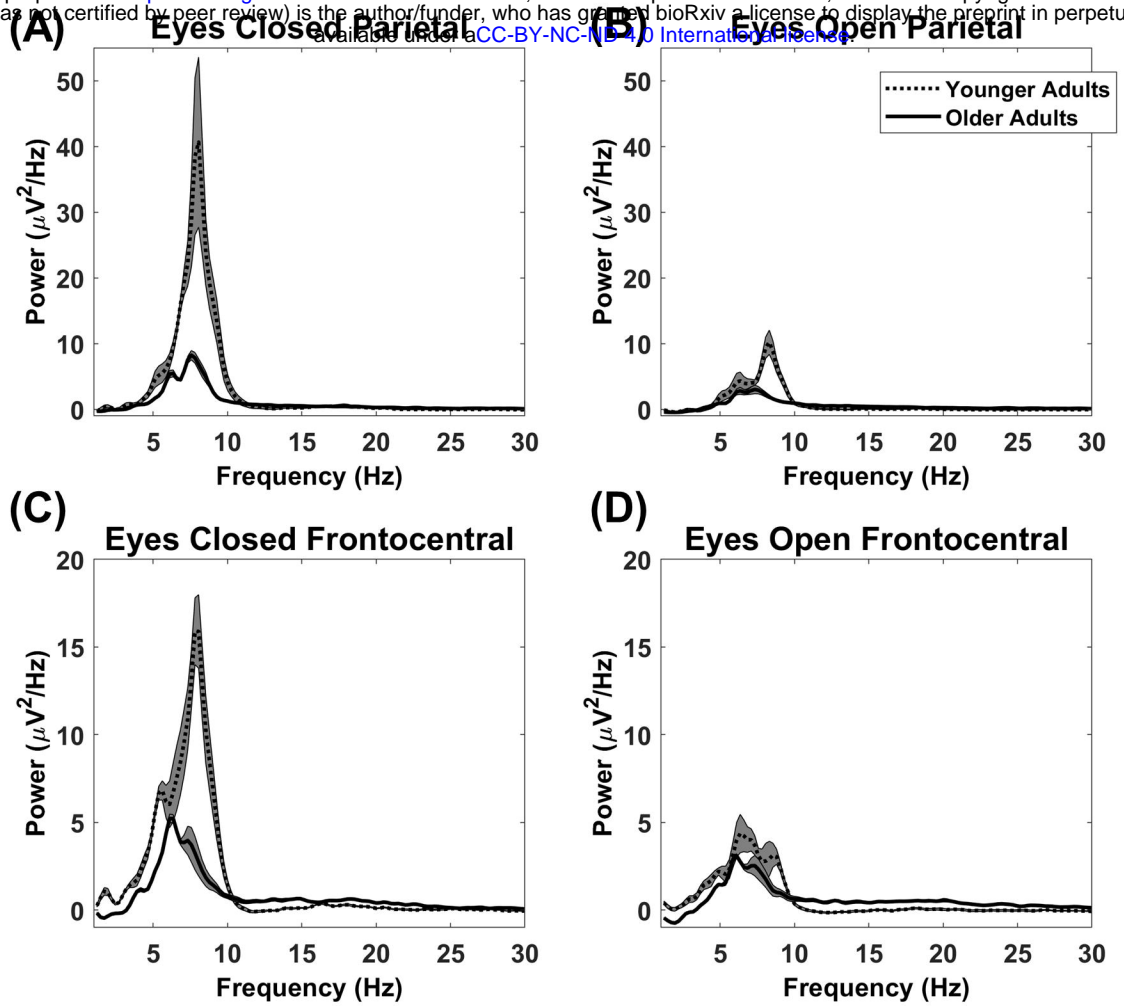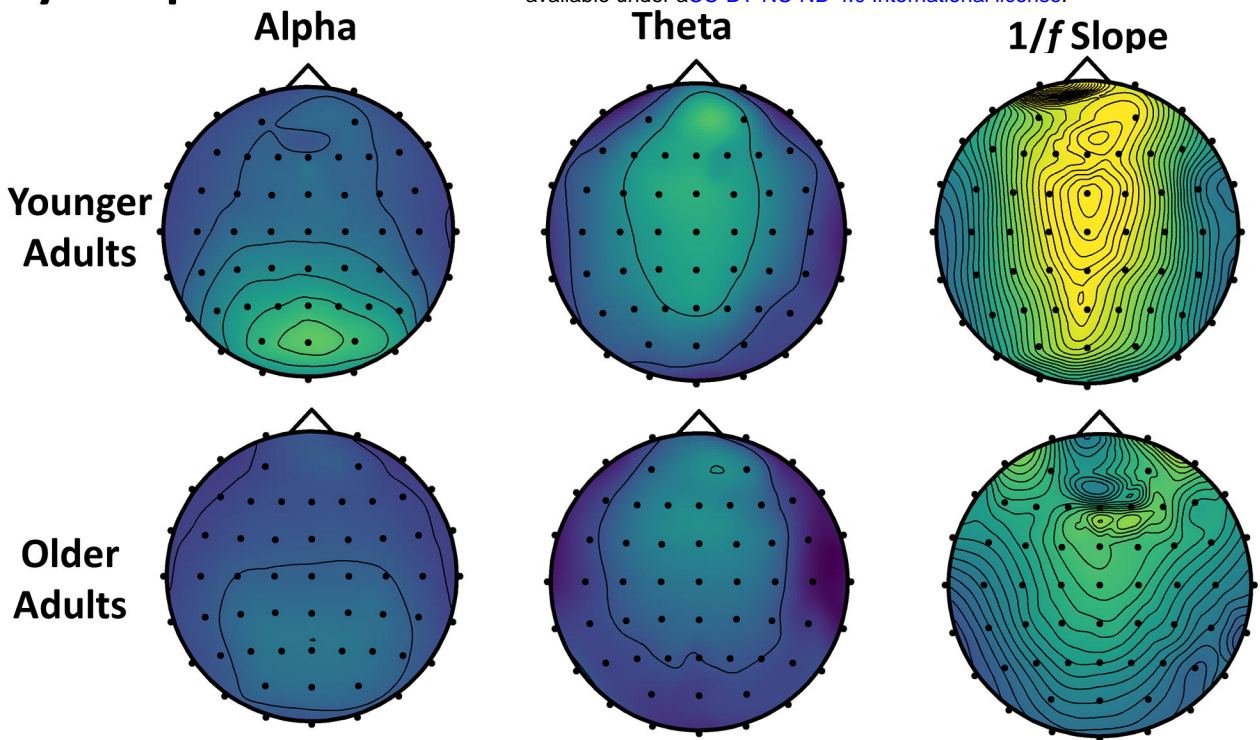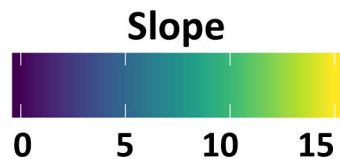846 individuals used the cue information (proactive control).
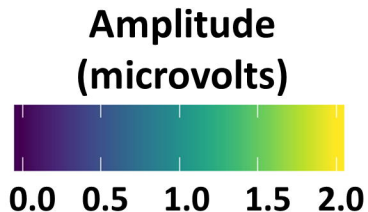
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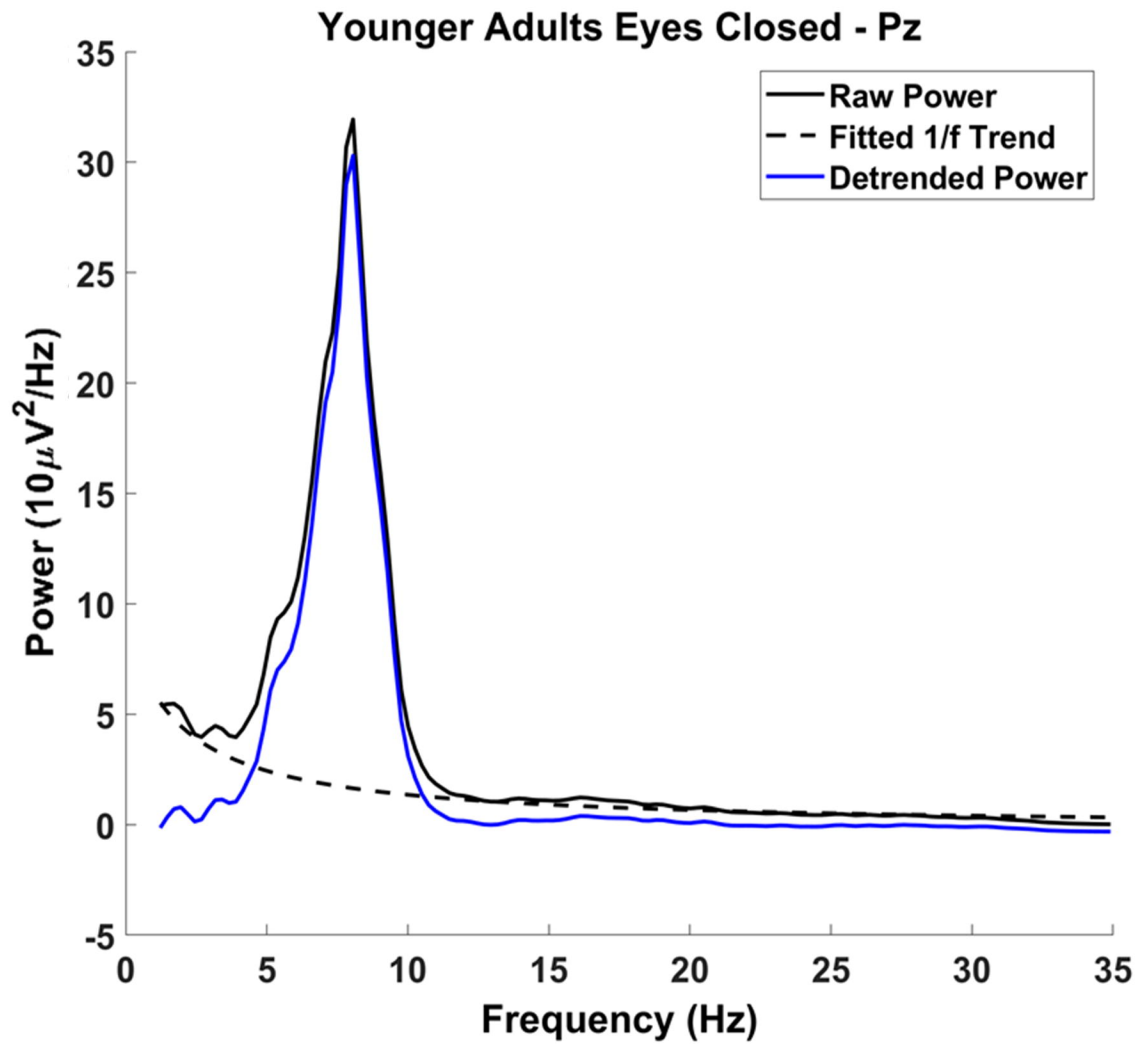
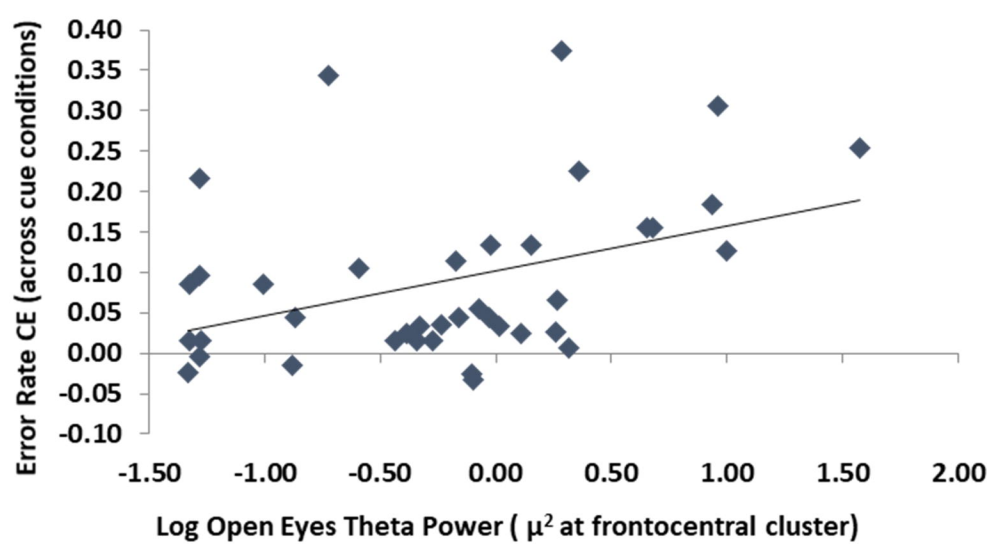# Eyes Open

Eyes Closed
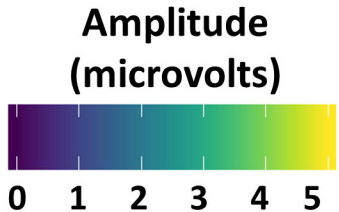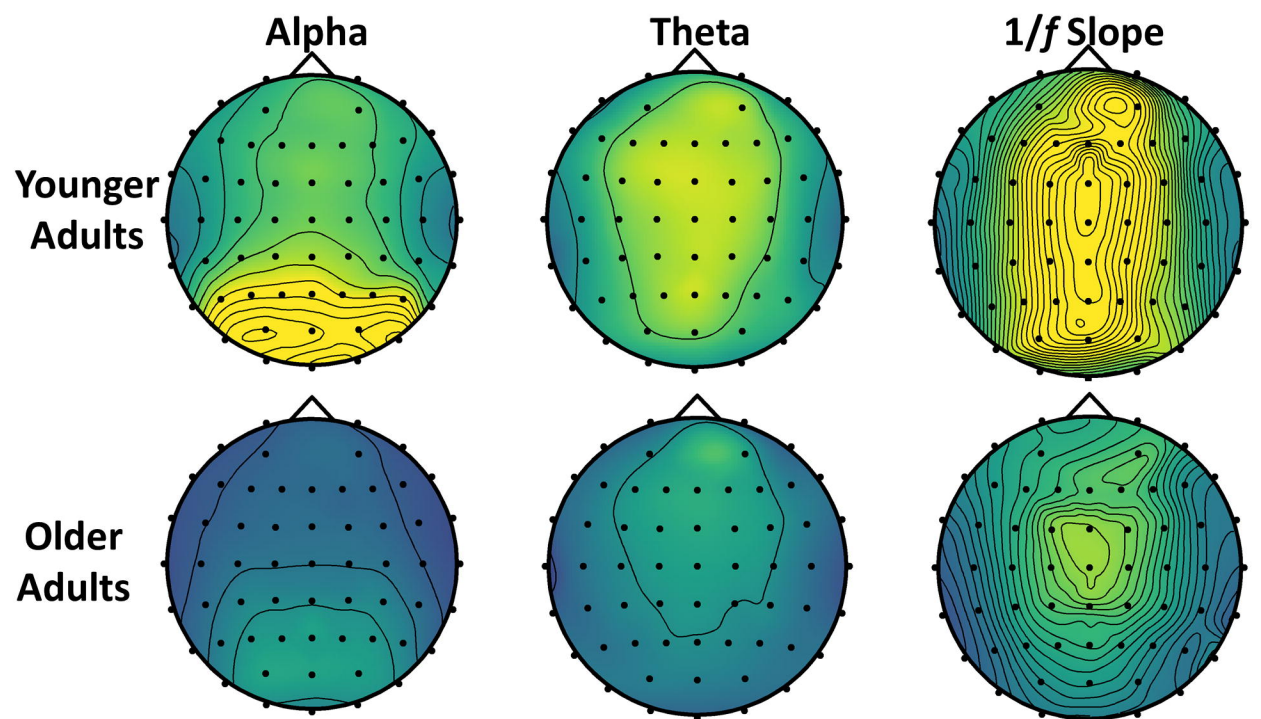
A) **Alpha Power and Conflict Expectation Effect**
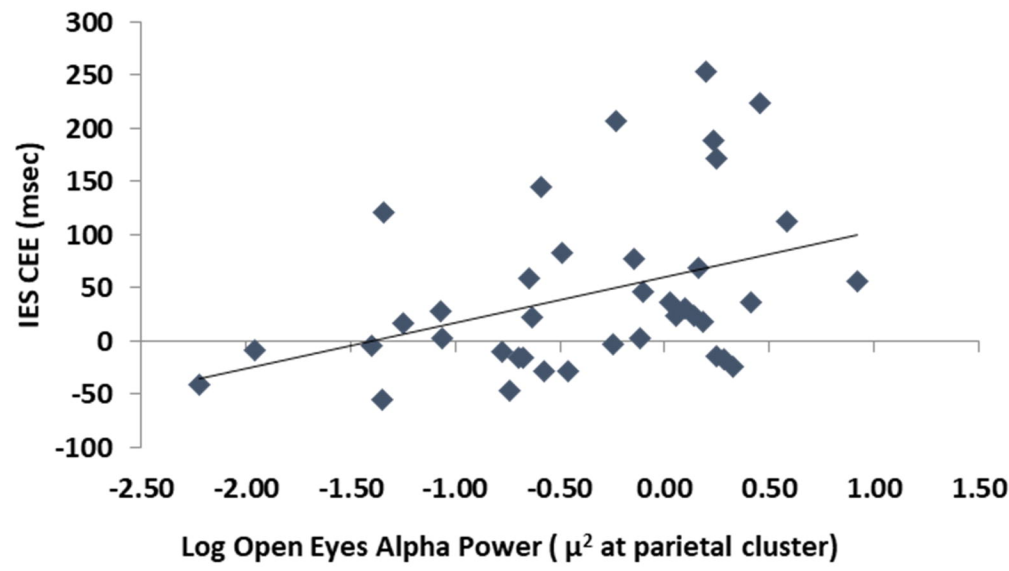
B) **Theta Power and Congruency Effect**

C) **1/f slope and Conflict Expectation Effect**