

1 **Event-Induced Modulation of Aperiodic Background EEG:**
2 **Attention-Dependent and Age-Related Shifts in E:I balance,**
3 **and Their Consequences for Behavior**

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Abstract

The broadband shape of the EEG spectrum, summarized using a $1/f^x$ function, is thought to reflect the balance between excitation and inhibition in cortical regions (E:I balance). This balance is an important characteristic of neural circuits and could inform studies of aging, as older adults show a relative inhibitory activity deficit. Thus far, no studies have leveraged the event-related temporal dynamics of $1/f^x$ activity to better understand the phases of information processing, especially in the context of aging. Here, for the first time, we examined variations of this activity during the foreperiod of a cued flanker task in younger (YA) and older adults (OA), with picture cues varying in task relevance, relative novelty, and valence. We report a biphasic change in the spectral exponent (corresponding to negative slopes in log-log space) after cue presentation, independent of cue-elicited ERPs, with an initial period of increased negativity (indicating cortical inhibition, similar in YA and OA) followed by decreased negativity (indicating cortical excitation, especially in OA). The decrease in the exponent negativity was associated with lower performance and greater congruency costs in the flanker task. Finally, more novel cues reduced the shift towards excitation in OA, partly restoring their E:I balance, and diminishing congruency costs. These findings demonstrate that the broadband shape of the EEG spectrum varies dynamically in a manner that is predictive of subsequent behavior. They also expand our understanding of how neural communication shapes cognition in YA and OA and have implications for neuroscientific models of cognitive processing and age-related cognitive decline.

Keywords: broadband EEG; $1/f$ activity; aging; neural noise; excitation:inhibition (E:I) balance; aperiodic activity

55

1. Introduction

56 The brain constantly exhibits a repertoire of complex dynamics related to behavior in
57 health and disease. In the electrophysiological power spectrum, brain dynamics are expressed in
58 the form of oscillatory/periodic voltage fluctuations, emerging against non-oscillatory/aperiodic
59 background activity. Despite accounting for a substantial portion of the neural signal, the
60 aperiodic component has, until recently, received limited attention in cognitive neuroscience,
61 often being considered “noise” devoid of any functional significance. Recent theoretical and
62 methodological advances, however, have begun to provide evidence in support of the functional
63 relevance of the aperiodic component in explaining brain dynamics and human behavior
64 (Donoghue et al., 2020; Gyurkovics et al., 2022; Voytek et al., 2015; Waschke et al., 2021). A
65 significant breakthrough in this research is the observation of a reduction in the exponent of the
66 aperiodic activity (i.e., a flatter spectrum) in older adults, consistent with the idea of increasing
67 neural noise in aging (Cremer & Zeef, 1987; Salthouse, 2010; Salthouse & Lichty, 1985; Voytek
68 & Knight, 2015), and suggesting an age-related shift in the balance between excitation and
69 inhibition (E:I balance, Gao et al., 2017). In this article, we underscore the rich exogenous and
70 endogenous features of scalp-recorded aperiodic neural activity and show, for the first time,
71 evidence for its dynamic alternations over time. Crucially, these dynamics differ between
72 younger and older adults and correlate with behavioral performance.

73 Aperiodic neural activity (also called $1/f$ noise) is characterized by a progressive decrease
74 in power across increasing frequencies, which follows a $1/f^x$ function, where f denotes frequency,
75 and x is a spectral exponent that can be estimated from the steepness of the power decay in log-
76 log space. Because the aperiodic component follows an inverse power function, its parameters
77 (exponent and offset) are best characterized by using log-log power spectra, where they can be
78 estimated from the negative slope and the intercept of the background spectrum (once periodic
79 components are subtracted). In this article, spectral exponents x were characterized in log-log
80 space following the equation of $\log(1/f^x) = -x \cdot \log(f)$. Therefore, a more negative exponent value
81 is associated with a steeper slope, reflecting a shift in power from high to low frequencies, and a
82 less negative value, indicating a shift from low to high frequencies. These exponent changes can
83 also be described as rotations of the log-log power spectrum that are either clockwise (more

84 negative exponent, steeper spectrum) or counterclockwise (less negative exponent, flatter
85 spectrum).

86 Recent *in silico* modeling, supported by *in vivo* experiments (Ahmad et al., 2022; Cohen
87 & Maunsell, 2011; Gao et al., 2017; Harris & Thiele, 2011; Kanashiro et al., 2017) has shown
88 that the spectral exponent can provide information about the balance between excitatory and
89 inhibitory synaptic circuits (E:I balance), with more or less negative exponents reflecting
90 increased inhibition or excitation, respectively. The spectral exponent x can also be interpreted as
91 an index of the degree of synchronization of neural networks during their firing. This suggests
92 that a less negative exponent (i.e., *relatively* greater power at high frequencies) reflects more
93 asynchronous (i.e., noisier) neural communication (Chini et al., 2022; B. J. He, 2014; W. He et
94 al., 2019; Voytek & Knight, 2015). The presented interpretations complement each other and
95 together provide a more complete explanation of the spectral exponent function.

96 Within these synergistic frameworks, accumulating evidence shows that the spectral
97 exponent obtained from noninvasive EEG recordings can reliably and validly reflect the
98 functional properties of aperiodic neural activity across broad regions of the human cortex
99 (Donoghue et al., 2020; Waschke et al., 2021; Zhang et al., 2023). Consistent with a neural noise
100 hypothesis of aging (Cremer & Zeef, 1987; Salthouse & Lichy, 1985; Voytek & Knight, 2015),
101 several studies have shown a reduced (less negative) exponent for older compared to younger
102 adults, indicating disrupted (noisier) neural communication with advancing age (Clements et al.,
103 2021; W. He et al., 2019; Hill et al., 2022; Merkin et al., 2023; Ostlund et al., 2022). Drawing on
104 the E:I balance framework, the reduced exponent for older adults suggests *an age-related*
105 *counterclockwise spectral rotation*, signifying an increasing E:I ratio in the aging brain, possibly
106 reflecting a deficit of inhibitory circuits in older adults (see also Gordon et al., 2014).

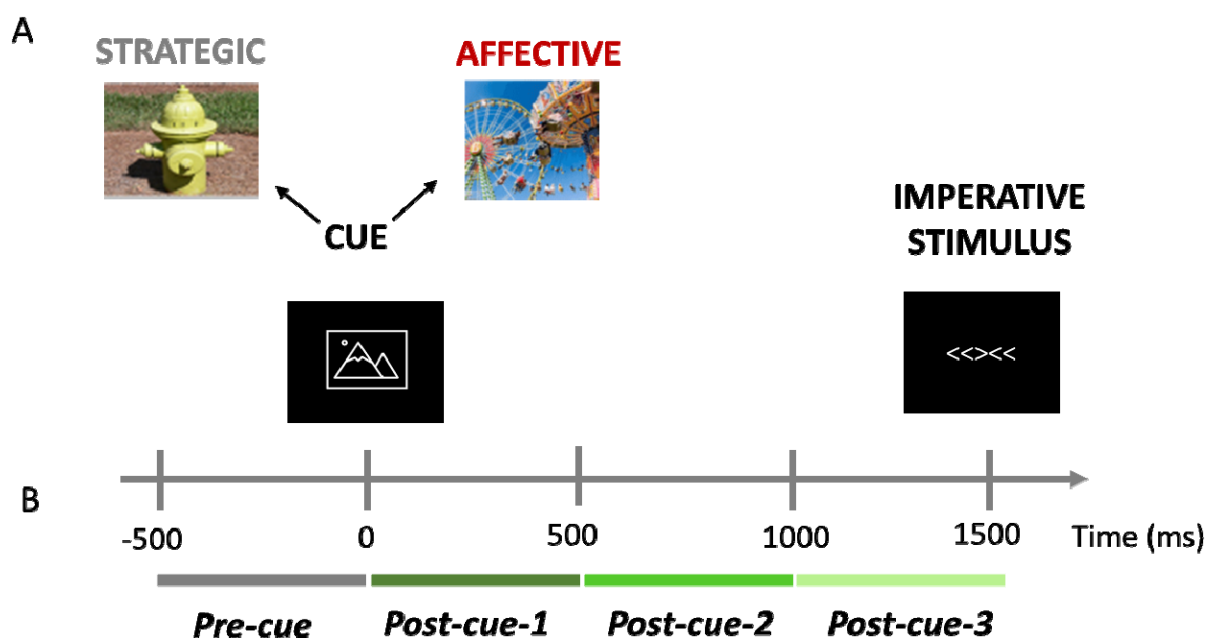
107 There is also emerging evidence suggesting that individual differences in the spectral
108 exponent may contribute to age-related cognitive decline, with a reduced exponent associated
109 with poorer outcomes across the adult lifespan (e.g., Dave et al., 2018; Tran et al., 2020; Voytek
110 et al., 2015). This evidence suggests that the increase in neural noise observed in aging – indexed
111 by a decreasing exponent and an increasing E:I ratio – may hamper older adults' ability to
112 process information. However, the mechanisms behind these phenomena remain elusive, as
113 aperiodic activity is typically derived from the EEG signal in the absence of experimentally
114 manipulated stimuli, which limits its interpretation with respect to information processing. Taken

115 together, this body of research motivates the need for a methodological framework that classifies
116 task-induced broadband EEG into periods of inhibition and excitation. This would greatly
117 increase our understanding of the sequence of processing events that precede or follow a
118 stimulus, allowing this activity to be related to other types of brain measurements, such as
119 single/multiple units or neuroimaging recordings. In the current study, we expand on this idea in
120 a paradigm that includes different phases of information processing performed by younger and
121 older adults.

122 A fundamental step in classifying aperiodic activity into periods of inhibition and
123 excitation is to establish *whether*, *when*, and *how* the appearance of a stimulus affects the
124 ongoing aperiodic activity. However, a serious challenge to this endeavor is the need to separate
125 the task-induced (non-phase-locked) aperiodic component from other task-evoked (phase-
126 locked) EEG activity (i.e., event-related potentials, ERPs, in the time domain), both of which
127 display a broadband distribution in the frequency domain. Gyurkovics et al. (2022) were the first
128 to address this methodological issue using scalp EEG data collected from young adults. Their
129 study showed reliable and systematic stimulus-induced changes in the aperiodic component,
130 which were independent of the concurrent ERPs and scaled with the attentional demands of the
131 task. The reported *stimulus-induced clockwise spectral rotations* are consistent with a decreased
132 E:I ratio (increased inhibition) following stimulus onset and likely reflect a disruption of ongoing
133 excitatory activity proportional to processing demands (Gratton, 2018; see also Zhang et al.,
134 2023). However, the Gyurkovics et al. (2022) study was conducted using simple paradigms with
135 minimal quantification of the participants' performance, thus making it difficult to determine the
136 behavioral consequences, if any, of the stimulus-induced spectral exponent shifts. Moreover,
137 event-related spectrograms were quantified using a time window extending more than 1,000 ms,
138 which precludes the detection of rapid changes in aperiodic activity accompanying information
139 processing over time. Crucially, that study did not investigate the effects of age, which is
140 expected to modulate the E:I balance. These three issues are addressed in the current study.

141 To summarize, the current study sought to determine the role of the aperiodic component
142 – indexed by the spectral exponent – in the relationship between aging and cognitive processing
143 while considering the temporal dynamics of this component. To this end, we analyzed scalp EEG
144 data from younger and older adults performing a cued flanker task (**Fig. 1A**). We capitalized on
145 changes in the aperiodic background activity induced by cues, which do not require any overt

146 responses but provide information to prepare for the upcoming target stimuli (Bowie et al., 2021;
147 Gratton et al., 1992). To capture the temporal dynamics of aperiodic activity, the cue-related
148 EEG was divided into a pre-cue time window and three consecutive post-cue time windows (**Fig.**
149 **1B**). The pre-cue window, being free of any cue processing, served as a baseline. The three
150 subsequent post-cue windows were intended to capture different phases of information
151 processing (early, middle, and late).



152
153 **Figure 1.** Behavioral task design and time windows for the EEG analyses. (A) Participants performed a cued flanker task. The
154 warning cue presented at the beginning of the trial was followed by the imperative stimulus. Cues were images from the
155 International Affective Picture System (Lang et al., 2008) and from an additional database (Jordan & Dolcos, 2015); images in
156 this figure are for reference only. The cues were repetitive, task-relevant, and neutral (strategic blocks) or novel, task-irrelevant,
157 and of variable valence (affective blocks); for details, see the text. (B) The cue-locked EEG recorded during the task was divided
158 into four consecutive 500-ms time windows.

159 The results reveal hitherto unreported features of the aperiodic EEG, which allowed us to
160 estimate shifts in the E:I balance as a function of the processing phase and age. As such, these
161 findings expand our understanding of how dynamic neural communication shapes cognition in
162 younger and older adults and have direct implications for neuroscientific models of cognitive
163 processing and age-related cognitive decline. Given that aperiodic neural activity is considered a
164 key biomarker of healthy neural networks (Ahmad et al., 2022; Chini et al., 2022; Gao et al.,
165 2017), this study could also have important implications for all neurocognitive domains
166 examining normative and abnormal brain dynamics.

167 2. Methods

168 2.1. Participants

169 The study was conducted at the Beckman Institute of the University of Illinois at Urbana-
170 Champaign. Forty-eight participants took part in the study. Two participants were excluded
171 because spectral parameterization failed to provide converging solutions for them. Data from
172 three additional participants had poor quality of the EEG power spectrum (the standard
173 deviation, *SD*, of power across frequencies for each of these three participants was three times
174 higher than the average *SD* of power across all participants). Although the inclusion/exclusion of
175 these three participants did not significantly change the results, $1/f^x$ analyses require data of the
176 highest quality to be reliable, given that *all* frequencies (including those with very small power)
177 are considered. Therefore, we limited the analyses presented in this article to the 43 participants
178 with the highest data quality: 21 younger adults (mean age \pm *SD* = 21.52 \pm 2.82, 13 females) and
179 22 older adults (mean age \pm *SD* = 71.23 \pm 4.25, 10 females). The study was approved by the
180 Institutional Review Board of the University of Illinois at Urbana-Champaign and followed the
181 Declaration of Helsinki. Written informed consents were obtained from all participants. ERP
182 analyses from a subset of these data, unrelated to the current report, were published by Bowie et
183 al. (2021).

184 2.2. Experimental Task and Procedure

185 Participants performed a cued flanker task. The task design is presented in **Figure 1A**.
186 The imperative stimulus array consisted of five horizontal arrows that were either congruent
187 (e.g., <<<<<<) or incongruent (e.g., <<<><<). Participants indicated, as quickly and accurately as
188 possible, which direction (left or right) the central (target) stimulus was pointing by pressing one
189 of two keypads located on either side of the participant. Stimulus-response mapping was fixed
190 (i.e., a left-pointing target stimulus always required a left-button press, and vice versa).

191 Images from the International Affective Picture System database (Lang et al., 2008)
192 supplemented with images of neutral scenes from an additional database (Jordan & Dolcos,
193 2015) served as cues, preceding the presentation of the imperative stimulus array (their catalog
194 numbers along with valence and arousal data are provided in the project repository at
195 <https://osf.io/dfbwa/>). The pictorial cues were split into two sets to establish two different

196 contexts for performing the flanker task: strategic and affective. In strategic blocks, cues were
197 three neutral, low-arousal images (screw, fire hydrant, dresser), each of which indicated the
198 probability of presenting a congruent stimulus array: Predict-Congruent had a $p(\text{congruent})$ of
199 75%; Predict-Incongruent had a $p(\text{congruent})$ of 25%; and No-Prediction had a $p(\text{congruent})$ of
200 50%. The cue types were equiprobable within each strategic block, and participants were
201 explicitly told the probability of a congruent stimulus represented by each cue before
202 commencing the task. Predict-Congruent and Predict-Incongruent images were counterbalanced
203 across participants. In affective blocks, 288 images of varying arousal and valence served as
204 cues. None of them indicated the probability of the imperative stimulus' congruency. Instead,
205 there were three task-irrelevant cue conditions that differed in valence while being equated in
206 terms of arousal (low/high): Positive, Negative, and Neutral. All valence-arousal combinations
207 were equiprobable and intermixed within a single affective block.

208 Each trial began with a 499-ms cue, followed by a 999-ms fixation period. Afterward, the
209 imperative stimulus array appeared for 149 ms, followed by 1848 ms of fixation before the onset
210 of the next trial. The response window began with the onset of the imperative stimulus and
211 continued until the onset of the next trial. The imperative stimulus arrays were presented in white
212 typeface on a black computer screen and subtended $2.23^\circ \times 0.46^\circ$. Each cue overlaid a gray
213 background with uniform dimensions such that each composite image subtended $6.98^\circ \times 5.35^\circ$.
214 All stimuli were presented on a monitor (19-inch CRT, refresh rate 60 Hz, screen resolution
215 1280×960 ; Dell Computer, Round Rock, TX, USA) using the E-Prime 2.0 software
216 (Psychology Software Tools, Pittsburgh, PA, USA). Participants were seated 100 cm in front of a
217 computer monitor centered at eye level.

218 There were three strategic blocks (288 trials each) and three affective blocks (288 trials
219 each), yielding 1728 trials in total. The probability of a congruent trial within a single block was
220 50%. The strategic and affective blocks were alternated, and their order was counterbalanced
221 across participants. All participants completed a set of practice trials prior to the task.

222 **2.3. EEG Data Acquisition and Preprocessing**

223 Scalp EEG was recorded from 59 Ag/AgCl active electrodes using a BrainAmp recording
224 system (BrainVision Products). The electrodes were secured in an elastic cap according to the
225 extended 10-20 international electrode placement system (Acharya et al., 2016). Horizontal and

226 vertical electrooculograms (EOGs) were also recorded to monitor ocular artifacts. During
227 recording, the data were filtered with a 0.10-250 Hz bandpass, digitized at a sampling rate of 500
228 Hz and referenced to the left mastoid. Impedance was kept $< 10 \text{ k}\Omega$.

229 The data were preprocessed using custom MATLAB 2022b codes (The MathWorks)
230 incorporating EEGLAB 13.6.5 (Delorme & Makeig, 2004) and ERPLab 6.1.3 (Lopez-Calderon &
231 Luck, 2014). The EEG was first re-referenced to the average mastoids and bandpass filtered with
232 0.5 and 50 Hz cut-off frequencies (to eliminate contamination from the power supply at 60 Hz).
233 The data were then segmented into 2000-ms long epochs relative to the cue onset (-500 to 1500
234 ms). After excluding epochs with amplifier saturation and performing ocular correction (Gratton
235 et al., 1983), epochs with peak-to-peak voltage fluctuations at any EEG channel exceeding 200
236 μV (600-ms window width, 100-ms window step) were discarded. Data from electrodes Fp1 and
237 Fp2 were excluded as they often contain small residual ocular artifacts even after ocular
238 correction. Epochs for which response latency in the preceding trial exceeded 1400 ms were also
239 excluded, as late response-related activity from the previous trial could overlap with the baseline
240 of the current trial, thus distorting the measurement of pre-cue activity. Since the accuracy of
241 responses is not directly related to cue processing, epochs with both correct and incorrect
242 responses were included¹. The average number of artifact-free epochs per cue type across all
243 participants was 221 ($SD = 50$, $min = 73$, $max = 282$).

244 **2.4. Statistical Analyses**

245 The data were analyzed and visualized in R 4.0.3 (R Core Team, 2021). *p*-values for *F*-
246 tests were based on permutations for mixed ANOVA (Frossard & Renaud, 2021; Kherad-Pajouh
247 & Renaud, 2015). We used 10,000 permutations, and the sign for a given parameter was reversed
248 for a random half of the data points in each iteration (an equivalent approach was adopted in our
249 previous work, Gyurkovics et al., 2022). Only planned comparisons were tested. *p*-values < 0.05
250 were considered significant. The materials, data, and R code for this project will be openly
251 available in the project repository (<https://osf.io/dfbwa/>).

¹ The pattern of results replicates when incorrect trials are excluded.

252 **2.4.1. Behavioral Analysis**

253 Dependent variables (DVs) were mean reaction time (RT), mean error rate (ERR), and
254 mean inverse efficiency score (IES, i.e., $RT/p(\text{correct})$; Townsend & Ashby, 1978). Fast guesses
255 (i.e., $RT \leq 200$ ms) and timeouts were discarded. Trials with incorrect responses were excluded
256 from computing RT and IES. Since the EEG data were trimmed to epochs with $RT < 1400$ ms
257 (for rationale, see section 2.3), this criterion was also applied to the behavioral data to maintain
258 consistency across analyses. On average, 12% of trials ($SD = 10\%$) were excluded, leaving
259 approximately 1,520 trials per participant for analysis. The analyses replicated previously
260 reported effects (Bowie et al., 2021; Gratton et al., 1992), indicating that data trimming did not
261 impact the results.

262 To evaluate results within the strategic and affective contexts separately (within-context
263 ANOVAs, hereafter), DVs were subjected to mixed ANOVAs with Age Group as a between-
264 subject factor (younger, older) and two within-subject factors: Congruency (congruent,
265 incongruent) and Cue Type (predict-congruent, no-prediction, predict-incongruent, for the
266 strategic context; positive, neutral, negative, for the affective context). To compare results across
267 task contexts, data were collapsed across task contexts, and the cue type factor was replaced with
268 the within-subject Task Context factor (strategic, affective) (between-context ANOVA,
269 hereafter).

270 **2.4.2. Spectral Analysis**

271 To investigate the temporal variation of the aperiodic component, the cue-locked epochs
272 were divided into four successive time windows of equal length, representing, respectively, pre-
273 cue activity (-501 – -1 ms; pre-cue/baseline), activity directly after the cue (0 – 500 ms; post-cue-
274 1), mid-interval activity (500 – 1000 ms; post-cue-2), and activity directly before the target
275 stimulus (1000 – 1500 ms; post-cue-3) (see **Fig. 1B**). Single-trial total power spectra were then
276 computed for each time window, electrode, and participant, using MATLAB's built-in fast
277 Fourier transform (FFT) function. Before FFT, the signal was zero-padded to 256 points to
278 ensure that signal length was a power of 2 for the FFT. The spectral resolution was 1.95 Hz.
279 Frequencies < 1.95 and > 44.92 Hz were removed to avoid frequencies whose power estimates
280 were based on < 2 cycles and to ensure frequencies affected by the low-pass filter were omitted.
281 The resulting total power spectra were then averaged across trials for each time window (pre-

282 cue, post-cue-1, post-cue-2, post-cue-3), EEG channel (57 in total after excluding Fp1 and Fp2),
283 and cue type (Predict-Congruent, No-Prediction, Predict-Incongruent, Positive, Neutral,
284 Negative) within each participant separately. To account for the presence of ERPs in the post-cue
285 windows, the spectra of the ERPs (i.e., the cross-trial time-domain averages) were also
286 quantified for each time window \times electrode \times cue type \times participant. These spectra were then
287 subtracted from the total power spectra to yield power spectra after ERP removal, using the
288 procedure described by Gyurkovics et al. (2022).

289 To separate oscillatory and aperiodic spectral components, single-electrode power spectra
290 before and after ERP removal were then parametrized using the *specparam* algorithm (version
291 1.0.0; Donoghue et al., 2020) with the following settings: peak width limits = 3-8 Hz; the
292 maximum number of peaks = 3; peak threshold = 2 *SD*; aperiodic mode = ‘fixed’. These
293 parameters were determined on the basis of a preliminary analysis on a random sample of 20
294 participants, following guidelines by Ostlund et al. (2022). The aperiodic component at each
295 electrode for each participant and time window was then reconstructed in linear space as
296 $10^{(\beta+x\log_{10}(f))}$, where β is the offset in log space, f is frequency, and x (with a negative sign) is the
297 exponent. The exponent values were retained for further analyses, with more negative values
298 indexing steeper spectra (clockwise rotation) and decreased E:I ratio (increased inhibition).

299 The quality of spectral parametrization was assessed using *specparam*’s model R^2 . Since
300 14 parieto-temporal electrodes near the edge of the electrode cap showed relatively poorer fit
301 (median of participants’ average $R^2 < 0.90$ for any time window \times cue type), they were excluded
302 from all analyses. Their reduced fit was likely due to muscle artifacts, affecting the estimation of
303 high-frequency power. To balance the statistical power of the different levels of the electrode
304 cluster factor, the four outermost parietal electrodes (P7, P8, PO7, PO8) were also excluded. The
305 remaining 39 electrodes with satisfactory fit are shown in **Figure 4B**. Average R^2 s were 0.95 (SD
306 = 0.05) for the younger group and 0.93 ($SD = 0.03$) for the older group. While younger
307 participants showed a relatively higher *specparam* R^2 than older adults [$F(1,41) = 4.05$, $p =$
308 0.05], the fit was satisfactory in both age groups.

309 Given the novelty of the procedures used by Gyurkovics et al. (2022) to remove the ERP
310 spectra, we first performed two auxiliary analyses to replicate their findings. First, to examine
311 whether the ERPs contributed to the cue-locked background activity, the exponents estimated on
312 the spectra after ERP removal were compared with those estimated on the spectra before ERP

313 removal. Second, to assess whether the cue induced a change in the aperiodic component (*cue-*
314 *induced spectral shift*, hereafter), post-cue exponents after ERP removal were compared against
315 the pre-cue exponents. These analyses were performed on the exponent values averaged across
316 electrodes and cue types for each time window separately using a series of one-way within-
317 subject ANOVAs.

318 As the pre-cue window served as a baseline in the analyses, we also tested whether the
319 pre-cue exponent (averaged across electrodes) showed any within-subject effects of Cue Type or
320 Task Context that could obscure the experimental effects in the post-cue period. The between-
321 subject Age Group factor was also included to assess age-related changes in baseline aperiodic
322 activity.

323 Afterward, we analyzed the temporal dynamics and effects of experimental manipulation
324 on cue-induced spectral shifts. To this end, the post-cue spectral exponents after ERP removal in
325 each of the three post-cue windows (i.e., post-cue-1, post-cue-2, and post-cue-3) were subtracted
326 from the pre-cue exponent for each electrode \times cue type \times participant, yielding Shift1, Shift2,
327 and Shift3, respectively. These cue-induced spectral shifts were then subjected to the within-
328 context and between-context ANOVAs, all of which included Age Group as a between-subject
329 factor and two within-subject factors: Cue Type/Task Context and Time Window (Shift1,
330 Shift3). Cue Type and Task Context levels were the same as in the behavioral analyses. Shift2
331 was deliberately excluded from these analyses as we did not observe a significant group-level
332 Shift2 (see section 3.2). To investigate possible differences in scalp distribution, the data were
333 averaged over two electrode clusters covering fronto-central and centro-parietal regions (**Fig.**
334 **4B**), constituting an additional within-subject factor in these analyses.

335 **2.4.3. Neuro-Behavioral Correlations**

336 Multiple rank-based regression – a non-parametric, robust alternative to the traditional
337 likelihood or least-squares estimators (Kloke & Mckean, 2012) – was used to determine the
338 effects of aging and aperiodic activity on overall performance (indexed by the IES) and
339 magnitude of the congruency effect (indexed by incongruent minus congruent IES), for each
340 time window separately (pre-cue, post-cue-1, post-cue-2, post-cue-3). The *simple model* included
341 the one of the aperiodic predictors (pre-cue exponent, Shift1, Shift2, or Shift3, depending on the
342 time window), whereas the *additive model* additionally included continuous age. Although Shift2

343 was excluded from the ANOVAs, as there was no significant difference between post-cue-2 and
344 pre-cue exponents (see section 3.2), we chose to re-include it in the correlation analyses. This is
345 because a non-significant group-level effect might reflect large inter-individual variability in the
346 post-cue-2 window, which could be potentially interesting for an individual-difference
347 perspective.

348 The model including the interaction between the predictors was discarded as it did not
349 perform better than the additive model for any DV in any time window (non-significant
350 dispersion-reduction tests, an equivalent of χ^2 in classic regression; $F_s \leq 3.81$). Since the effects
351 showed relatively widespread scalp distributions and analyses for strategic and affective contexts
352 produced largely consistent results, the statistics are reported for the data averaged across all 39
353 electrodes and both task contexts. For visualization purposes, the figures present the regression
354 *beta* estimates on single electrodes. All variables were mean centered prior to these analyses.

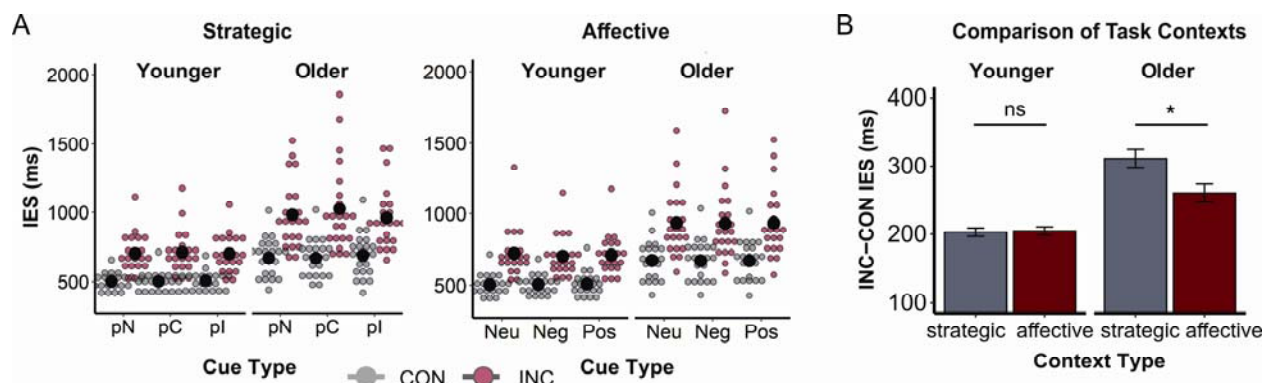
355 3. Results

356 3.1. Contextual Variability Supports the Behavioral Performance of Older Adults.

357 RT, ERR, and IES were subjected to mixed ANOVAs to test the experimental effects of
358 Age Group, Congruency, and Cue Type/Task Context. Since the results were largely consistent
359 across all DVs, the statistics are reported for IES only, as this DV combines both speed and
360 accuracy information, hence providing a robust summary of performance (Townsend & Ashby,
361 1978). **Figure 2A** presents an overview of the behavioral results.

362 The analysis for the strategic context replicated previously reported effects (Bowie et al.,
363 2021). Participants were more efficient in the congruent vs. incongruent condition [$F(1,41) =$
364 $84.04, p < 0.001, \eta p^2 = 0.67$], and older adults were less efficient than younger adults [$F(1,41) =$
365 $28.85, p < 0.001, \eta p^2 = 0.41$]. Moreover, Congruency interacted with Cue Type in the strategic
366 context [$F(2,82) = 8.76, p < 0.001, \eta p^2 = 0.18$]. Performance was lower in the congruent
367 condition when the incongruent condition was predicted compared to when a congruent stimulus
368 was expected [$t(42) = 2.25, p = 0.03, d = 0.34$], or no congruency prediction could be made
369 [$t(42) = 2.44, p = 0.02, d = 0.37$]. Conversely, performance was lower in the incongruent
370 condition when the congruent condition was predicted compared to when an incongruent
371 stimulus was expected [$t(42) = 2.72, p = 0.01, d = 0.41$] or congruency could not be predicted
372 [$t(42) = 2.08, p = 0.04, d = 0.32$]. While the effects of Congruency and Age Group were

373 replicated in the affective context [$F(1,41) = 89.70, p < 0.001, \eta p^2 = 0.69$, and $F(1,41) = 20.96, p$
 374 $< 0.001, \eta p^2 = 0.34$, respectively], there were no effects of Cue Type ($F_s \leq 1.43$).



375
 376 **Figure 2.** Behavioral results. (A) Inverse efficiency scores (IES) in milliseconds (ms) for the strategic context (left) and affective
 377 context (right). Black circles depict means across participants by cue type and congruency. Colored dots represent individual
 378 participants' scores for the congruent (gray, CON) and incongruent (red, INC) conditions. *pN*, No-Prediction; *pC*, Predict-
 379 Congruent; *pI*, Predict-Incongruent; *Neu*, Neutral; *Neg*, Negative; *Pos*, Positive. (B) Congruency effect (INC-CON) in mean
 380 inverse efficiency score (IES) in milliseconds (ms) by task context and age group. Bars depict the mean across participants \pm
 381 within-subject standard error; *ns*, non-significant; *, $p < 0.05$.

382 A between-context ANOVA was performed to disentangle the global impact of strategic
 383 cues (which were neutral images repeated over trials) and affective cues (which varied in valence
 384 and were unique on each trial within a block). The analysis replicated the Congruency and Age
 385 Group effects described above [$F(1,41) = 89.32, p < 0.001, \eta p^2 = 0.69$, and $F(1,41) = 25.34, p <$
 386 $0.001, \eta p^2 = 0.38$, respectively]. We also observed a significant Task Context effect [$F(1,41) =$
 387 $4.97, p = 0.03, \eta p^2 = 0.11$], which was qualified by Age Group [$F(1,41) = 8.61, p < 0.001, \eta p^2 =$
 388 0.17] and Congruency [$F(1,41) = 5.61, p = 0.02, \eta p^2 = 0.69$]. Interestingly, there was also a
 389 three-way interaction between these factors [$F(1,41) = 6.42, p = 0.01, \eta p^2 = 0.14$]. While
 390 younger participants did not differ significantly in the congruency effect (incongruent *minus*
 391 congruent) between task contexts [$t(20) = 0.20, p > 0.05$], older participants demonstrated a
 392 reduced congruency effect in the affective vs. strategic context [$t(21) = 2.74, p = 0.01, d = 0.58$]
 393 (**Fig. 2B**), that was driven by their faster and more accurate responses in the affective-
 394 incongruent vs. strategic-incongruent condition [$t(21) = 3.19, p < 0.001, d = 0.68$]. Consequently,
 395 there was no significant between-group difference in the congruency effect in the affective
 396 context [$t(28) = 1.15, p > 0.05$].

397 To investigate why older adults performed better in the affective compared to the
 398 strategic context, we tested the Age Group \times Task Context \times Congruency interaction on trials

399 with neutral cues only ('no-prediction' cues from the strategic context and neutral cues from the
400 affective context). These cues differed in terms of novelty (same on every trial in a strategic
401 block vs. unique on every trial in an affective block) but were comparable in terms of valence
402 (all neutral) and task relevance (all unpredictable). A three-way interaction was observed for this
403 limited (neutral only) cue set [$F(1,41) = 6.72, p = 0.01, \eta p^2 = 0.14$], bolstering the interpretation
404 that the greater contextual variability and novelty introduced by repeatedly changing cues in the
405 affective context supports the cognitive performance of older adults. This interpretation is further
406 corroborated by the absence of significant effects of cue valence in the affective ANOVA (see
407 above), as well as the absence of block order or arousal effects in the follow-up analyses (see
408 also Footnote 2 in Bowie et al., 2021).

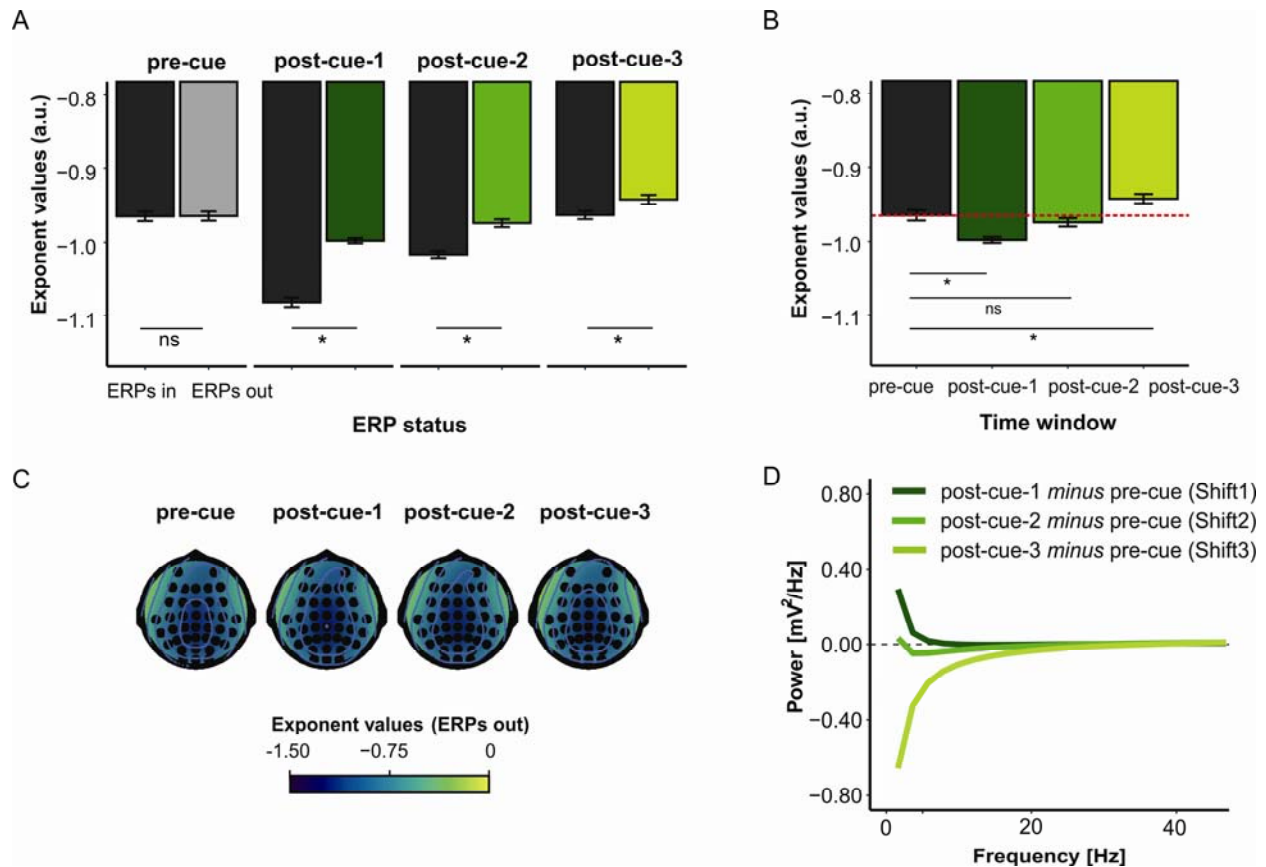
409 **3.2. Cue-Related Changes in Aperiodic Background Activity above and beyond the** 410 **Contribution of ERPs.**

411 Consistent with our previous work (Gyurkovics et al., 2022), the exponent values were
412 significantly reduced (i.e., were less negative, flatter spectrum) when the frequency spectrum of
413 the ERPs was removed in each of the three post-cue windows [$F(1,42) \geq 76.18, p < 0.001, \eta p^2 \geq$
414 0.64], indicating that the ERPs contribute to the shape of the event-locked EEG spectrum and
415 must be removed before estimating aperiodic parameters (**Fig. 3A**). Further analyses focused on
416 the post-cue estimates after ERP removal (**Fig. 3B-C**).

417 Cue-induced exponent changes were observed in two of the three post-cue windows.
418 Compared to the pre-cue window, the post-cue-1 exponent was more negative, indicating a
419 clockwise rotational shift [Shift1; $F(1,42) = 28.48, p < 0.001, \eta p^2 = 0.40$], whereas the post-cue3
420 exponent was less negative, indicating a counterclockwise shift [Shift3; $F(1,42) = 4.61, p = 0.04,$
421 $\eta p^2 = 0.10$]. The absence of a significant difference between the pre-cue and post-cue-2
422 exponents indicates that there was no detectable group-level shift in the mid-interval, relative to
423 the pre-cue period [Shift2; $F(1,42) = 0.89, p > 0.05$].

424 Considering the pre-cue (baseline) activity, no effects of Cue Type or Task Context were
425 found [$F_s < 1$], indicating that the pre-cue activity provided an unbiased baseline for post-cue
426 comparisons. At the same time, consistent with research showing an age-related decrease in
427 ongoing (baseline) aperiodic activity (for a review, see Ostlund et al., 2022), the pre-cue

428 exponent was less negative for older compared to younger adults [$F(1,41) \geq 21.43, p < 0.001,$
 429 $\eta p^2 \geq 0.34$] indicating a flatter power spectrum in the former age group.

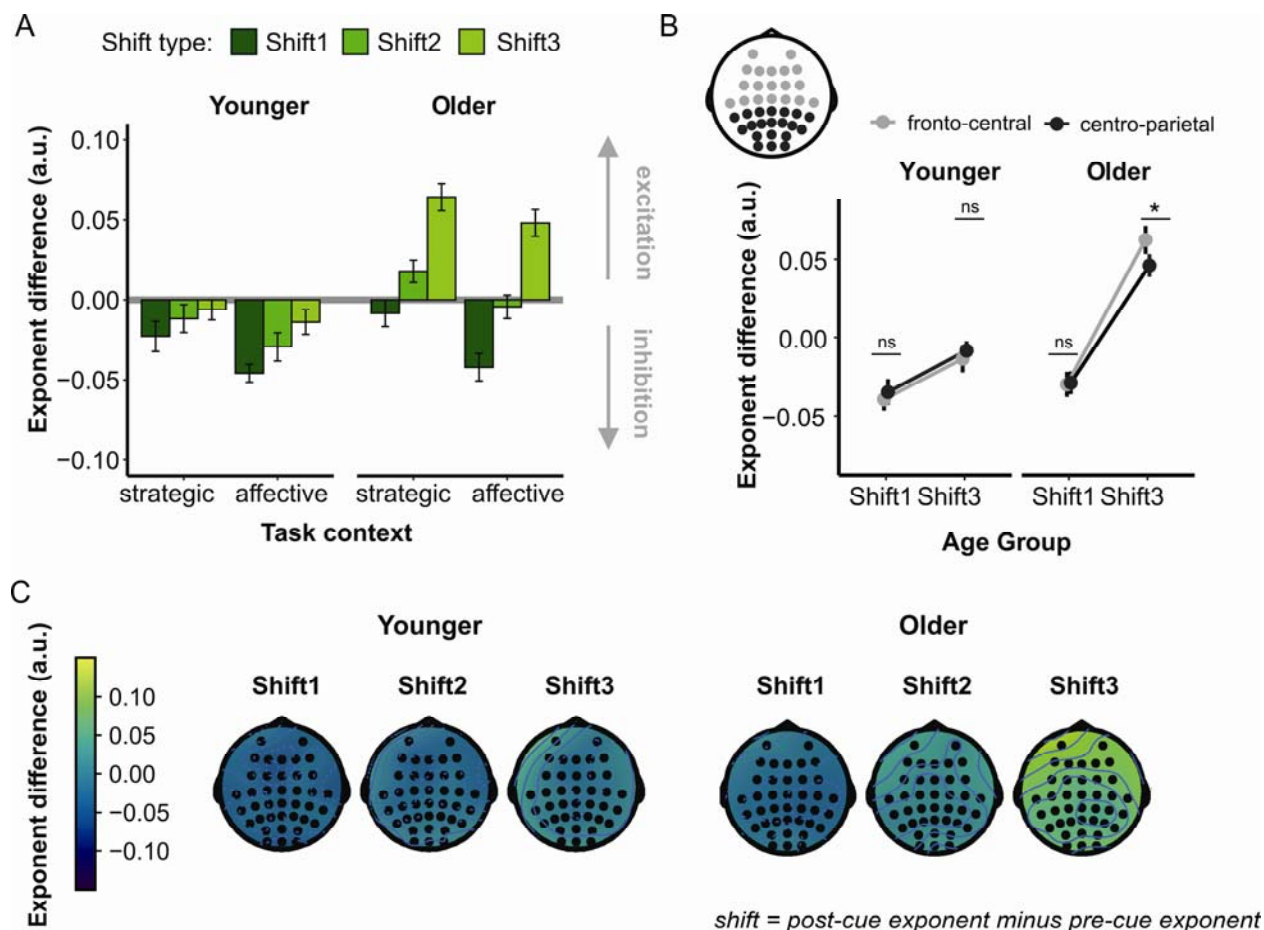


430

431 **Figure 3.** Aperiodic component overview. (A) Average exponent before (black) and after (gray/green) removal of the ERP
 432 spectrum (ERPs in and ERPs out, respectively) by time window. (B) Average exponent by time window. The red dashed line
 433 indicates the mean value of the pre-cue/baseline period. (C) Scalp distribution of the absolute exponent values in each time
 434 window. (D) Cue-induced spectral shifts (post-cue aperiodic components after subtracting pre-cue/baseline component) across
 435 frequencies in each time window, termed *Shift1*, *Shift2*, and *Shift3*. For both (A) and (B), error bars depict the mean across
 436 participants \pm within-subject standard error. ns, nonsignificant, *, $p < 0.05$. For (B), (C), and (D), the post-cue exponent values
 437 are after ERP removal. For all panels, more negative values indicate steeper spectra.

438 3.3. Dynamic Nature of Aperiodic Background Activity and Age-Related Changes

439 **Figures 3D** and **4A** present an overview of cue-induced spectral shifts, referred to as
 440 Shift1 (post-cue-1 *minus* pre-cue), Shift2 (post-cue-2 *minus* pre-cue), and Shift3 (post-cue-3
 441 *minus* pre-cue). These spectral shifts were subjected to strategic, affective, and between-context
 442 ANOVAs. As mentioned, Shift2 was excluded, as we did not find a group-level exponent
 443 difference in the post-cue-2 vs. pre-cue comparison. Statistics are shown in **Table 1**. Since Age
 444 Group and Time Window effects were consistent across these analyses, the follow-up tests are
 445 reported for the between-context ANOVA only.



446
447 **Figure 4.** Dynamic nature of the aperiodic component. (A) Average cue-induced spectral shifts (post-cue after the ERP removal
448 *minus* pre-cue exponent) by age group, task block, and time window, termed *Shift1*, *Shift2*, and *Shift3*. Error bars depict the mean
449 across participants \pm within-subject standard error. (B) Average cue-induced spectral shifts by age group, time window, and
450 electrode cluster. Fronto-central (light gray) and centro-parietal (dark gray) electrode clusters are depicted on the scalp above the
451 line plot. *ns*, non-significant, $*$, $p < 0.05$. (C) Scalp distribution of the cue-induced spectral shifts by time window for younger
452 (left) and older participants (right). For all panels, more negative values indicate steeper spectra.

453 All analyses showed a significant Age Group effect. Compared to younger adults, older
454 adults demonstrated a less negative spectral shift, indicating a counterclockwise spectral rotation
455 and an increased E:I ratio. A Time Window effect was also significant across all analyses,
456 indicating changes in the time course of cue-locked aperiodic activity. The initially negative
457 spectral shift (signifying a clockwise spectral rotation and a decreased E:I ratio for Shift1)
458 decreased over time to become a positive spectral shift before the target appeared
459 (counterclockwise rotation and an increased E:I ratio for Shift3). Moreover, Age Group
460 interacted significantly with Time Window across all analyses (**Fig. 4A**). Interestingly, Shift1 did
461 not differ between younger and older participants (no significant age-group difference in E:I
462 ratio), $t(38.67) = 0.61$, $p > 0.05$. Instead, what differentiated older from younger adults was their

463 greater counterclockwise rotation in time (increased E:I ratio and decreased inhibition), which
 464 emerged as a significant Age Group difference for Shift3, $t(39.77) = 3.56, p < 0.001, d = 1.08$.

465 **Table 1**

466 *Summary of ANOVA Results for Between-Context, Strategic, and Affective Effects*

Effects	<i>Between-Context</i>			<i>Strategic</i>			<i>Affective</i>		
	<i>F</i>	<i>p</i>	η^2	<i>F</i>	<i>p</i>	η^2	<i>F</i>	<i>p</i>	η^2
Age Group	7.85	0.01	0.16	12.34	0.00	0.23	2.81	0.09	---
Task	13.58	0.00	0.25	0.71	0.49	---	2.08	0.12	---
Age Group \times Task	0.77	0.40	---	0.80	0.46	---	0.95	0.38	---
Time	59.13	0.00	0.59	34.34	0.00	0.46	50.29	0.00	0.55
Age Group \times Time	17.31	0.00	0.30	13.59	0.00	0.25	12.63	0.00	0.24
Cluster	0.00	0.95	---	1.00	0.32	---	0.87	0.33	---
Age Group \times Cluster	2.72	0.11	---	5.09	0.03	0.11	0.66	0.41	---
Task \times Time	4.49	0.04	0.10	0.19	0.82	---	2.42	0.08	---
Age Group \times Task \times Time	0.02	0.90	---	1.22	0.30	---	1.34	0.25	---
Task \times Cluster	3.31	0.08	---	2.51	0.09	---	0.42	0.66	---
Age Group \times Task \times Cluster	0.91	0.36	---	1.32	0.27	---	0.00	1.00	---
Time \times Cluster	6.20	0.02	0.13	6.21	0.02	0.13	2.18	0.13	---
Age Group \times Time \times Cluster	5.98	0.02	0.13	3.28	0.08	---	5.07	0.02	0.11
Task \times Time \times Cluster	1.06	0.31	---	1.07	0.35	---	0.24	0.79	---
Age Group \times Task \times Time \times Cluster	0.04	0.84	---	0.21	0.82	---	0.14	0.87	---

467 *Note.* Task refers to the task context (levels: strategic, affective) or to the strategic/affective cue type (levels: predict-congruent,
 468 no-prediction, predict-incongruent/positive, neutral, negative); degrees of freedom (*dfs*) for all effects are (1,41) except for task
 469 effects in the strategic context and affective context, for which *dfs* are (2,82).

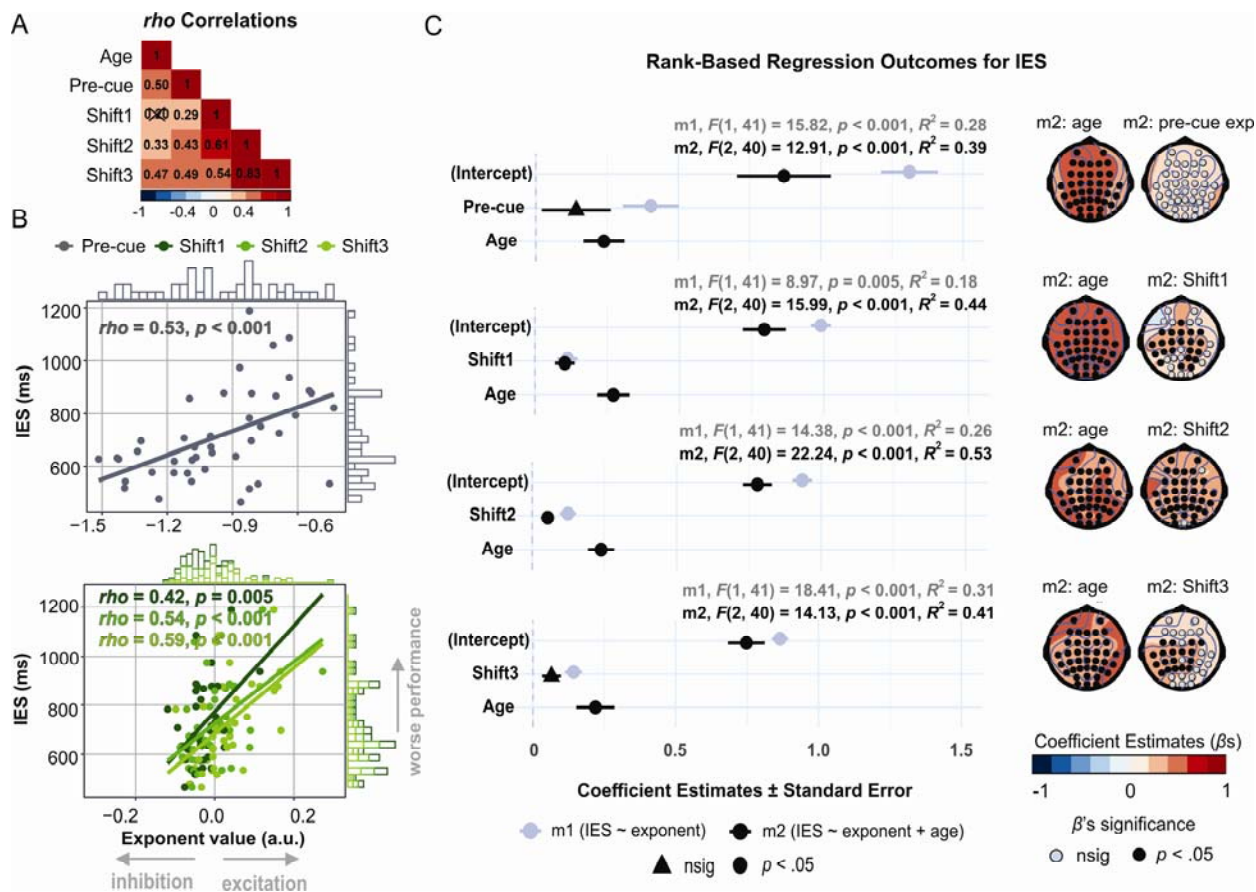
470 The interaction between Age Group and Time Window was further qualified by
 471 significant effects for Electrode Cluster in the between-context and affective-context analyses.
 472 While most spectral shifts showed a widespread distribution in both age groups (no significant
 473 differences between fronto-central and centro-parietal clusters, $t \leq 0.69, p > 0.05$), Shift3 was
 474 larger at the fronto-central than centro-parietal cluster in older adults, $t(21) \geq 2.55, p < 0.01, d \geq$
 475 0.54 (**Fig. 4B**). Collectively, these results point to the dynamic nature of stimulus-related
 476 changes in the aperiodic component, indicating that the feature distinguishing older from
 477 younger adults is a greater counterclockwise power redistribution over time. This indicates an
 478 increasing E:I ratio and decreasing inhibition with advancing age.

479 **3.4. Attention-Dependent Changes in the Aperiodic Background Activity**

480 Although the ANOVAs did not show any Cue Type effects when strategic and affective
481 contexts were considered separately (see **Table 1**), we did observe a significant Task Context
482 effect in the between-context ANOVA, with a more negative spectral shift (i.e., a more
483 clockwise spectral rotation indicating increased inhibition) in the affective compared to the
484 strategic context. This effect was not qualified by Age Group in the between-context
485 comparison. However, a significant Age Group \times Task Context interaction was observed when
486 comparing the *neutral* cues from the two task contexts [$F(1,41) = 6.71, p < 0.001, \eta p^2 = 0.50$].
487 While the spectral shift was less negative in response to repetitive neutral cues in older compared
488 to younger adults (strategic context: $t(35.48) = 3.20, p < 0.001, d = 0.98$), there was no
489 significant difference between the age groups in response to more novel neutral cues (affective
490 context: $t(35.73) = 0.64, p > 0.05$; see **Fig. 4A**). This suggests that the difference in the cue-
491 induced spectral shift between younger and older adults diminished in response to the more
492 novel cues presented in the affective context. This effect is consistent with the behavioral data,
493 showing improved performance in the affective context in older adults, and further indicates that
494 increased contextual variability may support cognitive performance in older adults.

495 **3.5. Neuro-Behavioral Relationships**

496 To further understand the relationships between aging, aperiodic activity, and behavior,
497 we performed a series of neuro-behavioral correlations (**Figs. 5 and 6**). Consistent with the
498 ANOVA results, older age was associated with a less negative pre-cue (baseline) exponent,
499 further supporting the notion that aging is accompanied by an overall increase in the E:I ratio,
500 indicating reduced inhibitory function (Ostlund et al., 2022; Voytek & Knight, 2015).
501 Interestingly, however, when considering the cue-induced spectral shifts, age significantly
502 correlated with Shift2 and Shift3 but not Shift1 (**Fig. 5A**). These results complement the
503 ANOVA findings (significant age-group effect for Shift3 but not Shift1), further suggesting that
504 the initial aperiodic response to the cue (indexed by Shift1) was not associated with age-related
505 changes in the E:I balance, and that age only began to contribute to the cue-induced spectral shift
506 after some time (middle and late post-cue periods in this study, indexed by Shift2 and Shift3,
507 respectively).



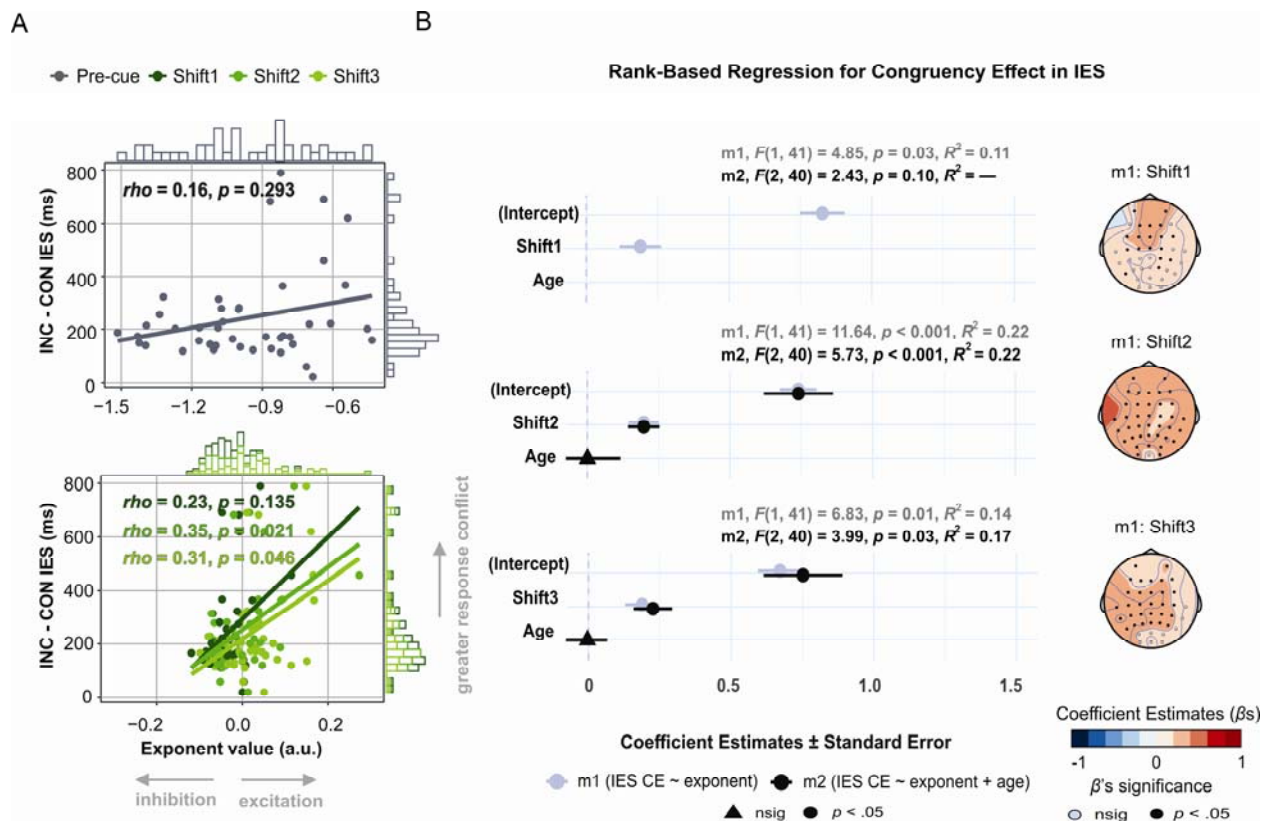
508

509 **Figure 5.** Overall performance as a function of the spectral exponent. (A) Spearman's ρ correlations between continuous age,
 510 pre-cue exponent, and post-cue spectral shifts (post-cue exponent after subtracting the pre-cue value). Non-significant estimates
 511 ($p > 0.05$) were crossed out. (B) Inverse efficiency score (IES) in milliseconds (ms) as a function of absolute pre-cue exponent
 512 (upper) and spectral shifts (post-cue exponents after subtracting the pre-cue exponent; lower). Coefficients are Spearman's ρ s.
 513 (C) Outcomes of rank-based regressions for each time window. The left panel shows regression coefficients (β s) \pm
 514 standard error for the simple model (m1, gray) and additive model (m2, black). The right panel displays the scalp distribution
 515 of regression coefficients (β s) for the effects of age and exponent from m2 (p -values on the scalp maps uncorrected for multiple
 516 comparisons).

517 To determine how the aperiodic activity and aging contributed to overall performance
 518 (indexed by IES) and to the congruency effect (incongruent *minus* congruent IES), we fit a series
 519 of rank-based regression models. Regarding overall performance (**Fig. 5B-C**), a simple model
 520 including the pre-cue exponent or post-cue shift as a predictor of IES was significant across all
 521 time windows, indicating that the more negative the baseline exponent or the more negative the
 522 post-cue shifts (all indicating increased inhibition), the higher the task performance. Models
 523 including age as an additional predictor (additive models, hereafter) were also significant in each
 524 time window and indicated that older age was associated with lower behavioral outcomes.
 525 Importantly, when age was added to the models, the pre-cue exponent and Shift3 no longer
 526 significantly predicted IES, indicating that their associations with IES observed in the simple

527 models could be fully explained by age-related changes in aperiodic activity. At the same time,
 528 Shift1 and Shift2 continued to be significant predictors after the addition of age, indicating that
 529 the cue introduced changes in the aperiodic activity that predicted subsequent performance
 530 regardless of age.

531 Regarding the efficiency of resolving the flanker-induced response conflict, indexed by
 532 the congruency effect (**Fig. 6**), a simple model including the post-cue shift as a predictor of the
 533 congruency effect in IES was significant across all post-cue time windows: the more negative the
 534 post-cue shift (i.e., the greater the shift towards inhibition), the smaller the subsequent
 535 congruency effect. The additive model was significant for Shift2 and Shift3, but the age effect
 536 was non-significant. Neither model was significant for the pre-cue window [$F_s < 1$], indicating
 537 that baseline aperiodic activity, similarly to age, is unrelated to the magnitude of the congruency
 538 effect.



539 **Figure 6.** The magnitude of the congruency effect as a function of the spectral exponent. (A) Congruency effect (INC-CON) in
 540 inverse efficiency score (IES) in milliseconds (ms) as a function of absolute pre-cue exponent (upper) and spectral shifts (post-
 541 cue exponents after subtracting the pre-cue exponent; lower). Coefficients are Spearman's ρ s. (B) Outcomes of rank-based
 542 regressions for each post-cue window (note that the models with the pre-cue exponent were non-significant and are therefore
 543 omitted). The left panel shows regression coefficients (β s) \pm standard error for the simple model (m1, gray)
 544 and additive

545 model (m2, black). The right panel displays the scalp distribution of regression coefficients (β s) for the effect of exponent from
546 m1 (p -values on the scalp maps uncorrected for multiple comparisons).

547 In summary, the analyses reported here suggest that aperiodic neural activity substantially
548 affects subsequent performance on the flanker task. While age contributed to overall
549 performance, cue-induced spectral shifts were not only able to predict overall performance but
550 also the magnitude of the congruency effect. Furthermore, results suggest that the cue-induced
551 spectral shift is a mixture of age-dependent and age-independent processes, whose relative
552 contribution to performance depend on the information processing timescale (**Fig. 5B**).
553 Specifically, since Shift1 did not correlate with age and the addition of age to the IES model
554 hardly changed its estimate ($\Delta\beta = 0.009$), the spectral shift immediately following the cue
555 appears to reflect age-invariant stimulus processing. Conversely, the relationship between the
556 latest shift (Shift3) and overall performance was canceled out when age was added to the IES
557 model, indicating that it was entirely driven by age-dependent changes in information
558 processing. In line with this logic, age-dependent and age-invariant stimulus processing co-
559 contributed to the shift in the mid-interval, as shown by the additional model in which Shift2 still
560 significantly predicted IES after regressing out either age or Shift1 (the latter representing age-
561 invariant stimulus processing). Yet, the explained variance substantially dropped in both cases
562 ($\Delta R^2 = 17\%$ and 15% , respectively). Notably, after regressing out both age and Shift1, this
563 model ceased to be significant [$F(1,41) = 1.84, p > 0.05$], indicating that there was no additional
564 variance in Shift2 that would explain IES over and above the effect of age-dependent and age-
565 invariant cue processing present in the first time window.

566 **4. Discussion**

567 This study provides an in-depth analysis of stimulus- and age-related changes in the
568 spectral exponent, an overarching measure of aperiodic background neural activity, indicating
569 rotational shifts in broadband power. To this end, we analyzed scalp-recorded EEG data from
570 younger and older adults who completed a cued flanker task. In this task, the pictorial cues were
571 either repetitive, neutral, and task-related (creating a strategic context) or relatively novel, of
572 varying valence, and unrelated to the task (affective context). This study extends our knowledge
573 of stimulus-induced changes in the spectral exponent (see Gyurkovics et al., 2022) by showing
574 that cues, signaling upcoming targets, trigger systematic changes in EEG background activity

575 independently from the ERPs elicited by the same stimuli. In addition to the experimental
576 effects, we also observed significant individual variations in the exponent in relation to age,
577 stimulus processing phase, and subsequent behavioral performance. Collectively, the findings
578 extend our current knowledge of the neural dynamics underlying aging and cognitive processing
579 and bring these phenomena together within a unified framework.

580 **4.1. Contextual Variability Supports the Cognitive Functioning of Older Adults by Altering** 581 **Aperiodic Neural Activity**

582 The behavioral analyses revealed some novel, hitherto unreported findings: overall,
583 performance was higher when pictorial cues were relatively novel (affective context) than when
584 they were repeated (strategic context). At the same time, cue valence itself had no detectable
585 effect on behavior. This novelty (task-context) effect was further qualified by age group,
586 indicating that presenting relatively more novel and varied cues made older adults more efficient
587 and, thus, behaviorally more comparable to younger adults (**Fig. 2B**). The data we report,
588 therefore, suggest that the presentation of relatively novel and variable pictorial cues created a
589 task context that helped older adults to maintain increased engagement throughout the task,
590 which consequently resulted in their more efficient performance. In contrast, younger adults
591 were able to maintain high-level performance regardless of cue characteristics.

592 The EEG data showed systematic cue-induced changes in the ongoing background
593 aperiodic activity (i.e., cue-induced spectral shifts) that varied depending on the task context.
594 Specifically, the cue induced a more pronounced clockwise rotation (i.e., more negative post-cue
595 vs. pre-cue exponent in log-log space) in the affective than in the strategic context. Consistent
596 with previous findings (Gyurkovics et al., 2022), this task-context effect indicates increased
597 inhibition in more novel and variable settings, which require more frequent updating of active
598 representation status (Gratton, 2018; see also Zhang et al., 2023). Interestingly, the observed
599 task-context effect was further qualified by age group when only neutral cues were considered.
600 There was a significant age group difference in the spectral shift for repeated neutral cues used in
601 the strategic context but not for the more novel and variable neutral cues used in the affective
602 context. These findings are consistent with the behavioral results and suggest that the relatively
603 greater inhibition induced by more novel cues helped older participants to overcome, at least in
604 part, the age-related E:I imbalance towards excitation (Merkin et al., 2023; Ostlund et al., 2022;

605 Thuwal et al., 2021; Voytek & Knight, 2015), making their cue-induced aperiodic response, as
606 well as their subsequent performance, more comparable to that of younger adults. Consistent
607 with our previous work (Gyurkovics et al., 2022), the observed cue-induced spectral shifts in the
608 aperiodic component showed broad scalp distributions (no significant effects of electrode cluster
609 were observed), further suggesting that the alternations in the E:I balance involve widespread
610 changes in cortical activity.

611 **4.2. Dynamics of Aperiodic Neural Activity and Their Consequences for Behavior**

612 This study allowed us to examine the temporal dynamics of the aperiodic component
613 related to different phases of stimulus processing. The results revealed that, compared to the pre-
614 cue (baseline) period, the cue initially induced a clockwise shift in the ongoing power spectrum
615 (Shift1), which became counterclockwise over time (Shift3), pointing to the transient nature of
616 the aperiodic neural activity. Notably, there was no difference between age groups in the early
617 phase of cue processing (Shift1). However, older adults (compared to younger adults)
618 demonstrated a greater counterclockwise rotation in the late processing phase (Shift3) (**Fig. 4**).
619 These experimental findings were further supported by significant correlations between age and
620 spectral shifts in the middle and late but not early processing phase (**Fig. 5A**).

621 Similarly to the task-context effects discussed in the previous section, the observed
622 temporal effects can also be explained within the E:I balance framework. The clockwise rotation
623 immediately following the cue (Shift1) is consistent with a shift towards inhibition that
624 temporarily halts ongoing processing to allow for new representations to be established (Gratton,
625 2018; Gyurkovics et al., 2022). Younger and older adults did not differ in the early phase of
626 stimulus processing (Shift1), suggesting that they engage these early inhibitory mechanisms to a
627 similar degree. Notably, the cue-induced spectral shift in the late processing phase (Shift3) was
628 *still negative* (albeit to a lesser extent) in younger adults, suggesting that the momentary
629 inhibition was followed by disinhibition (return to baseline) in this group, which may reflect
630 their need to prepare to shift attention to the upcoming target. Conversely, in older adults, this
631 later change was *positive*, suggesting an increased excitation following the early phase of
632 inhibition. Shift1 showed broad scalp distribution in both age groups. In contrast, Shift3 showed
633 a more fronto-central distribution in older adults (**Fig. 4C**), suggesting that the age-related
634 excitation in the late processing phase involves changes in cortical activity that are more local

635 and can be captured only at fronto-central sites in scalp-recorded EEG. A series of regression
636 analyses shed further light on the mechanisms through which aperiodic activity is related to
637 aging, stimulus processing, and behavior. Cue-induced spectral shifts predicted upcoming
638 performance, with a more clockwise shift related to higher overall performance (as indexed by
639 IES) and more efficient conflict resolution (as indexed by the congruency effect). As such, the
640 regressions converge with the ANOVA findings, further supporting the interpretation of
641 aperiodic activity as a viable marker of information processing that substantially contributes to
642 subsequent behavior. Importantly, the strength of the relationship between the cue-induced
643 spectral shifts and overall performance decreased when age was included in the models (**Fig.**
644 **5C**). This indicates that event-related spectral shifts can be considered a mixture of individual
645 differences related to stimulus processing and aging, which additively shape overall performance
646 (cf. Voytek et al., 2015).

647 **4.3. Theoretical and Methodological Implications**

648 The novel properties of the aperiodic background EEG reported here have important
649 theoretical and methodological implications. First and foremost, the present results contribute to
650 current theories of age-related cognitive decline (for reviews, see Fabiani et al., 2022; Grady,
651 2012; Jiang et al., 2023). In particular, the neural noise hypothesis of aging (Cremer & Zeef,
652 1987; Salthouse & Lichy, 1985; Voytek & Knight, 2015) posits that disrupted neural
653 communication with advancing age and related inhibitory deficits – indexed by greater E:I ratio
654 – become more pronounced after stimulus presentation, thereby reducing older adults' ability to
655 maintain newly formed representations. While several studies have attempted to address this
656 hypothesis (Dave et al., 2018; Ribeiro & Castelo-Branco, 2022; Tran et al., 2020; Voytek et al.,
657 2015), none are conclusive as they have not examined event-related changes in aperiodic
658 activity, which greatly limits their interpretation in terms of information processing. In this study,
659 despite replicating an age-related increase in the E:I ratio at baseline (the pre-cue window), older
660 adults did not show significantly greater E:I ratio in the early phase of stimulus processing
661 compared to younger adults (no age-group difference for Shift1). This indicates that there is no
662 apparent deficit in the initial inhibitory response in older individuals, thus suggesting that the
663 mechanism of age-related cognitive decline speculated so far may require some revision. Based
664 on the observed age-related temporal changes in aperiodic activity and their relationships with

665 performance, we propose that the greater *post-inhibitory excitation* observed in the late phase of
666 information processing in older adults (an increased E:I ratio for Shift3) may be an excessive
667 (i.e., greater than baseline) rebound after inhibition. This is consistent with the E:I framework
668 (Gao et al., 2017; Gyurkovics et al., 2022; Waschke et al., 2021) and sheds new light on the
669 origins of neural noise associated with stimulus processing (Voytek et al., 2015; Voytek &
670 Knight, 2015).

671 Relatedly, the ANOVA results also suggest that the age-related increase in the E:I ratio
672 can be experimentally counteracted by providing older adults with greater contextual diversity
673 and novelty (frequently changing cues in this study), which triggers a heightened level of
674 performance. It will be important for future research to test how long event-induced aperiodic
675 changes persist and what other forms of experimental manipulations can help overcome the age-
676 related E:I imbalance towards excitation. As here we focused on cue-induced (proactive)
677 processes and the target-locked EEG was deliberately excluded (as it was contaminated with
678 manual responses), future research would also benefit from tracking the dynamics of aperiodic
679 activity in response to an imperative stimulus, provided that contamination from motor activity
680 can be excluded.

681 At the methodological level, this study reinforces the notion that the ERPs contribute to
682 the broadband EEG background activity (Gyurkovics et al., 2022), emphasizing the need for
683 their removal before estimating the $1/f^{\alpha}$ (aperiodic) parameters. Furthermore, our findings greatly
684 extend the current understanding of event-related shifts in aperiodic activity by revealing their
685 temporal variability and offering a viable methodological framework for studying dynamic
686 changes in the E:I balance over time. Although the ideal length of the time window for
687 quantifying spectrograms is still an open research question, we demonstrated that a 500-ms
688 temporal integration window provides a robust and effective method for quantifying temporal
689 aperiodic changes in scalp EEG. Moreover, to ensure the highest data quality, we employed
690 rigorous EEG quality control, including careful assessment of spectrograms and spectral
691 parameterization outcomes. We also utilized a relatively large sample size (compared to typical
692 studies in this field), which further increases the statistical power of the analyses and improves
693 the generalizability of our findings. Collectively, the results presented here indicate that a 500-
694 ms temporal integration window, along with strict data quality control and a relatively large
695 sample size, offer a robust and effective framework for quantifying temporal aperiodic changes

696 in the scalp EEG recordings, thus providing a promising avenue to better understand the brain
697 dynamics underlying information processing.

698 Finally, the evidence for dynamic changes in the aperiodic component reconciles
699 seemingly conflicting reports regarding attention-dependent spectral changes in scalp-recorded
700 EEG. While Gyurkovics et al. (2022) reported an attention-dependent exponent *increase*,
701 Waschke et al. (2021) reported an attention-dependent exponent *decrease*. One of the
702 methodological differences between these studies is that they focused on the aperiodic activity
703 from different post-stimulus periods. Gyurkovics and colleagues focused on the immediate
704 response to the stimulus, whereas Waschke and colleagues quantified the spectrum several
705 hundred milliseconds after stimulus onset and did not control for any lingering ERP
706 contributions. The current results suggest that the discrepancy between these two previous
707 studies may only be coincidental. Here, compared to the pre-event period, the exponent was
708 more negative immediately after the stimulus, consistent with Gyurkovics et al., and less
709 negative in the furthest time window, consistent with Waschke et al. (**Fig. 3A**). Given this
710 apparent discrepancy and the risk of misinterpretation, future studies should account for the
711 dynamic nature of the aperiodic activity or at least carefully address the period over which they
712 quantify the spectra. This seems all the more important given that the regression analyses
713 showed that the exponent can convey different information depending on the time window in
714 which it is quantified. Although more research is needed on this topic, aperiodic neural activity
715 immediately after the stimulus seems to be the most sensitive to experimental effects, whereas
716 later activity may also reflect the contribution of individual differences, such as those due to
717 aging.

718 **4.4. Conclusions**

719 To our knowledge, this study is the first to investigate the temporal dynamics of broadband
720 (aperiodic) EEG background activity during stimulus processing in younger and older adults.
721 Our findings show that the spectral exponent – an overarching measure of the shape of the
722 broadband EEG – is not a stationary feature of electrophysiological signals but a dynamically
723 changing phenomenon that provides insights into the neural bases of stimulus processing and its
724 changes with aging. From a theoretical standpoint, these data contribute to neuroscientific
725 models of cognitive processing and age-related cognitive decline. From a methodological

726 standpoint, the study provides a viable framework for investigating the temporal dynamics of
727 aperiodic activity and the alternation of excitation and inhibition in neural circuits, providing
728 cross-scale links with single and multiple-unit activity and imaging research.

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