



# Aperiodic neural activity during speech comprehension in aging: Insights into cognitive effort

Sarah J. Woods<sup>1</sup> · Jack W Silcox<sup>1</sup> · Brennan R. Payne<sup>1,2,3</sup>

Received: 27 June 2025 / Accepted: 17 September 2025  
© The Psychonomic Society, Inc. 2025

## Abstract

Though largely ignored in the past, aperiodic (i.e., irregular, non-oscillatory) activity is emerging as an important element of the electroencephalography (EEG) signal. Certain characteristics of broadband aperiodic activity have been shown to reflect dynamic neurophysiological states that are sensitive to cognitive task demands and predictive of individual differences in cognitive capacity. In the current study, we test whether aperiodic neural activity can be used to index cognitive effort during speech comprehension in older listeners. Older adults with varying hearing acuity ( $N=48$ ) listened to sentences in quiet and in background noise while EEG was recorded. Consistent with listening effort, aperiodic neural activity was sensitive to increased acoustic challenge such that the aperiodic slope flattened and offset was reduced with increasing noise. Moreover, noise-induced changes in aperiodic activity were greater for older adults with poorer hearing acuity. In an age-comparative analysis using additional data from young normal hearing adults ( $N=35$ ), age-related reductions in aperiodic slope and offset were observed, replicating past work, while sensitivity to background noise was observed in both age groups. These findings highlight the importance of considering aperiodic EEG activity in assessing cognitive listening effort specifically, and in challenging cognitive tasks more generally.

**Keywords** Listening effort · Electroencephalography · Aging · Speech comprehension

## Introduction

Real-world situations where listening can become difficult abound, such as trying to hear an announcement in a crowded train station, understand the dialogue in a movie with explosions or loud background music, have a conversation in a restaurant during the dinner rush, or even getting directions in a new place where people speak with an unfamiliar accent. The aforementioned situations can introduce acoustic challenges that compete for attention or mask portions of the speech signal of interest, both of which require a listener to engage in more effortful processing of the speech signal. While these situations can be difficult for

individuals with normal hearing acuity, these challenges are further compounded for individuals with age-related hearing loss (Barker et al., 2017; Heine & Browning, 2004). This increased difficulty can make common social situations incredibly taxing and often leads to social withdrawal and isolation (Hughes et al., 2018; Shukla et al., 2020). In fact, a frequent complaint among audiology patients is the feeling that conversations are hard even if word recognition is relatively good because they feel “left behind” in the conversation due to the additional time needed to understand what is being said (Hughes et al., 2018). Furthermore, as the population ages, conditions such as sensorineural hearing loss are becoming increasingly prevalent (Alexander & Harris, 2013). Therefore, in order to address patient concerns and improve the scientific understanding of everyday speech understanding, it is critical that we have a way to assess the cognitive effort involved in speech perception and comprehension.

Several potential measurements of listening effort have been proposed in the literature including but not limited to cardiovascular measures, electrodermal activity, pupillometry, functional magnetic resonance imaging and

✉ Sarah J. Woods  
sarah.woods@psych.utah.edu

<sup>1</sup> Department of Psychology, University of Utah, 380 S 1530 E, Salt Lake City, UT 84112, USA

<sup>2</sup> Department of Communication Sciences and Disorders, Salt Lake City, UT, USA

<sup>3</sup> Interdepartmental Program in Neuroscience, Salt Lake City, UT, USA

electroencephalography (EEG; see Keur-Huizinga et al., 2024, for a complete review). We focus on EEG measures in the current study because EEG is noninvasive, relatively inexpensive, can be collected in quiet, and importantly is already present in many audiology clinics because EEG is used to test auditory neural function (e.g., brainstem auditory-evoked responses) generally as well as for individuals who cannot tolerate behavioral audiometry assessments (Woods et al., 2025).

In the listening effort literature, the most commonly studied EEG measure is alpha activity, which is usually defined as oscillatory, or periodic, activity within the ~8–13 Hz frequency range. There are strong theoretical reasons to link alpha activity to listening effort. Alpha power is strongly related both to attention and to the suppression of competing sensory input in vision (Foxe & Snyder, 2011) and audition (Strauß et al., 2014; Wöstmann et al., 2015). For example, Strauß and colleagues (2014) provided a framework for characterizing increases in alpha oscillatory power during effortful speech comprehension as reflecting increased inhibition of non-task-relevant auditory channels during auditory selective attention. In their framework, the auditory system processes overlapping features of goal-relevant speech and noise as distinct processing channels. Alpha power is then up-regulated via top-down attentional control mechanisms to suppress the noise channel(s) in order to “protect” the goal-relevant speech signal and maintain optimal task performance. This is broadly consistent with our growing understanding of the role of alpha in sensory suppression of distractors in vision as well (Jensen, 2024).

At the same time, listening effort studies have not found a consistent relationship between alpha power and listening effort (Ala et al., 2020; Alhanbali et al., 2019; Dimitrijevic et al., 2019; Fiedler et al., 2021; Miles et al., 2017; Paul et al., 2021; Waschke et al., 2019). Whereas a number of studies have found an increase in alpha power in response to increased acoustic challenge, consistent with the suppression framework discussed above (Jafari et al., 2019; Obleser & Weisz, 2012; Wöstmann et al., 2015), other data patterns have been reported, including decreases (McMahon et al., 2016; Miles et al., 2017), non-linear relationships (Paul et al., 2021), or variability in the direction of changes in alpha across different participants within the same study (Petersen et al., 2015). Some of these differences could potentially be attributed to methodological differences across studies, including the use of different types of stimuli (e.g., digits vs. words vs. sentences) and different task demands. However, it is also possible that these differences could be due to unaccounted for differences in stimulus-evoked changes in non-oscillatory contributors to spectral neural activity (Woods et al., 2024).

The EEG power spectrum is made up of two physiologically distinct sources: aperiodic activity and

periodic activity. Aperiodic activity is broad-band or scale-free (He, 2014) neural activity driven by irregular and non-oscillatory sources. These sources of activity are considered broad band or scale free because they impact power across all frequencies and contribute to the overall  $1/f$ -like inverse scaling between spectral power and frequency (i.e., power decreases with increasing frequency). In contrast, periodic activity is narrow-band (i.e., frequency-band specific) activity driven by oscillatory sources and observed as “bumps” riding on top of the power spectrum (Donoghue et al., 2020). The most consistently observed of these clear oscillatory signals is the alpha rhythm, which appears in the power spectrum as a peak between ~8 and 13 Hz riding on top of the broadband aperiodic slope. Despite the fact that aperiodic activity dominates cortical activity (from local field potentials to non-invasive EEG/MEG recordings; Buzsáki et al., 2012), until recently, this broadband non-oscillatory activity has not received much direct attention – with it often being treated as a nuisance factor with a non-physiological source to be brought under statistical control (e.g., via baseline dB scaling, see Gyurkovics et al., 2021, for a discussion).

Critically, a more recent but rapidly growing literature has begun to reconsider the role of broadband aperiodic activity both in its physiological origins (Akbarian et al., 2023; Gao et al., 2017) and as a factor that is related to cognitive state and arousal (Ouyang et al., 2020; Podvalny et al., 2015; Waschke et al., 2021). For example, a number of studies have shown that the aperiodic slope (i.e., the exponent of the  $1/f^x$ -scaling of broadband power spectral density) becomes flatter with increasing age (Bódizs et al., 2021; Cellier et al., 2021; Dave et al., 2018; Voytek et al., 2015; Waschke et al., 2017), and that individual differences in this slope are related to cognitive task performance. Voytek and colleagues (2015) for example found that flatter spectral slopes are related to worse visual working memory (WM) performance in aging. Related, Dave and colleagues (2018) replicated this age-related spectral flattening in older adults performing a language comprehension task and further showed that individual differences in the aperiodic exponent (i.e., slope) partially explained the magnitude of linguistic prediction effects on the N400 ERP component, a component associated with lexical-semantic access and retrieval (Federmeier, 2022).

More recently, a number of studies have begun to show that characteristics of aperiodic activity (e.g., the slope) are not just stationary traits of individuals but vary in a dynamic, stimulus-induced manner during cognitive task performance (Gyurkovics et al., 2022; Jia et al., 2024; Kałamała et al., 2024). For example, Gyurkovics and colleagues (2022) showed that the aperiodic exponent showed greater event-related increases (i.e., steeper slope) for task-relevant stimuli during an auditory oddball task. In contrast, Kałamała and

colleagues (2024) recently showed evidence of event-related flattening of the spectral slope in a cognitive control (i.e., flanker) task, with greater event-related spectral flattening in older adults. Moreover, they showed that the magnitude of aperiodic changes predicted overall task behavior (overall accuracy and flanker congruency reaction time effects). The authors argued that these effects are likely driven by shifts in the balance of cortical excitation and inhibition (E:I balance, see also Ahmad et al., 2022; Gao et al., 2017) due to increased attentional task demands. Collectively, these findings suggest that aperiodic activity is directly related to arousal and cognitive task performance, making it a suitable candidate neural marker for studying cognitive effort allocation in speech listening.

Critically, most prior work examining the effects of acoustic challenge on spectral EEG/MEG activity (i.e., via spectral or time–frequency methods) has not considered the role of task-induced aperiodic shifts during speech listening. In our recent work, we examined whether aperiodic activity was sensitive to acoustic challenge during speech listening in young normal-hearing listeners (Woods et al., 2024). Continuous EEG was recorded while young adult participants ( $N=35$ ) listened to individual sentences presented in quiet or with speech-shaped background noise at +3 dB SNR. We used the specparam (previously known as “fitting oscillations and one-over-f” or FOOOF; Donoghue et al., 2020) algorithm to decompose EEG power spectral densities into aperiodic and periodic components separately for trials in quiet and noise. We observed evidence of broadband spectral flattening, particularly over prefrontal electrodes, with increases in background noise, consistent with the claim that aperiodic activity may be sensitive to changes in listening effort. Moreover, we showed that accounting for this aperiodic activity improved measurement of alpha such that accounting for spectral flattening led to an increased effect size of background noise on parietal alpha power. Indeed, because broadband activity effects were overall negative (i.e., the slope flattened with increasing noise) whereas induced alpha effects were positive (i.e., alpha power increased with increasing noise), these effects partially cancelled out, leading to null results in a traditional analysis that did not adjust for aperiodic activity.

In the current study, we performed a secondary analysis on previously collected data from Silcox and colleagues (2024) where older adults with a variety of hearing acuities listened to sentences in quiet and background noise while continuous EEG was recorded. In our prior work in young adults, we found flattening of the spectra in response to background noise. Therefore, we predicted that older adults would also show a reduction in the aperiodic offset (i.e., similar to a y-intercept parameter) and spectral slope when listening to speech in background noise as compared to quiet. Consistent with prior studies, we also expected older adults to have a

flatter broadband spectral slope and an overall shift downwards in the spectrogram as compared to the younger adult sample (Dave et al., 2018; Voytek et al., 2015). While validation of the sensitivity of aperiodic measures in older adults is an important extension of prior work, a good measure of listening effort needs to be compatible with theoretical models of listening effort which acknowledge not just background noise as a source of increased acoustic challenge (i.e., environmental factors) but also individual listener factors such as hearing acuity and age of the listener (Peelle, 2018). Therefore, we also examined whether acoustic-challenge induced changes in the spectral slope relate to participant hearing acuity and age, which we predicted given the established finding of compounding effects of listening effort in older adults with hearing loss (Anderson Gosselin & Gagné, 2011). Finally, we compared the explanatory and predictive power of changes in aperiodic activity to the more traditional measurement of EEG alpha power in younger and older adults. This analysis provides not only a new potential measure of cognitive effort allocation in speech comprehension but also provides insight into how listening effort changes across the adult lifespan.

## Methods

### Participants

Forty-eight community dwelling older adults (age range: 60–85 years) participated in the experiment. All participants were right-handed as determined by the Edinburgh Handedness Inventory (Oldfield, 1971) and were screened for potential cognitive decline using the Montreal Cognitive Assessment (MoCA; mean = 25.2, range = 23–30; Carson et al., 2018). One participant did have a MoCA score of 21, which is lower than traditional cut-off scores (of 25). However, recent work has advocated for a lower cut-off (Dautzenberg et al., 2021; Waldron-Perrine & Axelrod, 2012) and the participant scored within the normal range on all other outcomes (see Silcox et al., 2024, for more details). Therefore, we chose to retain their data.

Pure-tone averages (PTA) were calculated for each participant and values for their better-hearing ear were used for the purpose of later analysis. Pure-tone detection thresholds were found at octave intervals from 250 to 8,000 Hz and at 6,000 Hz for each ear. If participant thresholds jumped more than 20 dB HL, inter-octaves were also assessed. Mean three-frequency (1,000–4,000 Hz), PTA thresholds were 27.0 dB HL (range = 8.3–56.7) for right ears and 27.8 dB HL (range = 8.3–62.5) for left ears. Speech reception thresholds (SRTs) were also tested and were highly correlated with PTA ( $r = .86$ ,  $p < .001$ ; mean right ear = 25.2 dB HL, mean left ear = 26.1 dB HL).

For age-group comparisons, a sample of 35 younger adults with normal hearing (age range 18–36 years) from the University of Utah participant pool were included in later analysis. For more information about the younger adults, see Woods et al. (2024). The exact same exclusion criteria were used for the participants analyzed here (e.g., excessive artifacts, not completing the experiment, and not being a native English speaker) resulting in a final dataset of 35 subjects. Silcox and colleagues collected data on 44 young adult participants, but a total of 39 were analyzed for the EEG data after screening for excessive artifacts or missing data. Because the analysis for the current work uses a different (and longer) time epoch and is examining different outcomes from the original Silcox and Payne study (i.e., aperiodic and periodic neural activity vs. target word ERPs) we ended up needing to reject an additional four participants compared to Silcox and Payne (2021) for excessive artifacts, yielding a final sample size for young adult analyses of  $N=35$ . Note that this young adult dataset is identical to the one reported in Woods and colleagues (2024).

## Procedure

Participants were screened using the MoCA before proceeding to the hearing assessments and finally the experimental listening task. Older adults were presented the experimental stimuli in their better-hearing ear, whereas younger adults were presented with the stimuli in both ears. Older adults were presented with stimuli at a level of 40 dB HL over their personal speech-reception threshold, up to a maximum level of 70 dB HL. This was done to accommodate the participants' range of hearing acuities without risking discomfort (Dubno et al., 2005). To ensure the task was not too difficult, three test sentences were presented to participants before beginning the main experimental task and they were asked to do a speech-shadowing task. The speech-shadowing task sentences were from the same talker that recorded the other experimental stimuli with the same background noise and the participant specific presentation level. Performance on the task was near the ceiling. The young adult comparison sample underwent the same procedure with a few minor deviations. Younger adults were not screened with the MoCA and they were presented with the stimuli binaurally at a level of 65 dB HL for all participants.

## Materials

All participants listened to 240 sentences, 120 in quiet and 120 presented with +3 dB SNR speech-shaped background noise. This level of noise was selected to maintain intelligibility while still increasing acoustic challenge (e.g., Payne et al., 2022; Silcox & Payne, 2021; Silcox et al.,

2024). The stimuli were identical for all participants. For more information about stimuli and its creation see Silcox and Payne (2021) and Silcox and colleagues (2024), which report on the original data collection for the older adult sample. Sentences were on average ten words long and consisted of items varying in contextual constraint as well as the expectancy of the sentence-final word. However, for the purposes of this study, we did not focus on the effects of sentential constraint nor final-word expectancy. Therefore, the sentence final word was trimmed from sentences (to remove the expectancy condition) and the data were collapsed across contextual constraint conditions to focus our analysis on the main effect of noise. Note therefore that while this study is a secondary analysis of Silcox and Payne (2021) and Silcox et al., 2024, it does reflect data from the pre-target word interval only, and thus is distinct from the target-word ERP results previously reported.

## EEG recording and processing

EEG recording and processing procedures are briefly described below but were identical to Woods et al. (2024), which previously reported the results of the younger adult sample. While listening to sentences, participants' continuous EEG was recorded using a 32-electrode active system by Brain Products (Brain Vision, LLC, Morrisville, NC, USA) using the standard international 10–20 localization montage (Jasper, 1958). Impedances for the electrodes were kept below 20 kOhms. Electrodes were referenced online to electrode TP10, which is close to the right mastoid and then re-referenced offline to the average of TP9 and TP10.

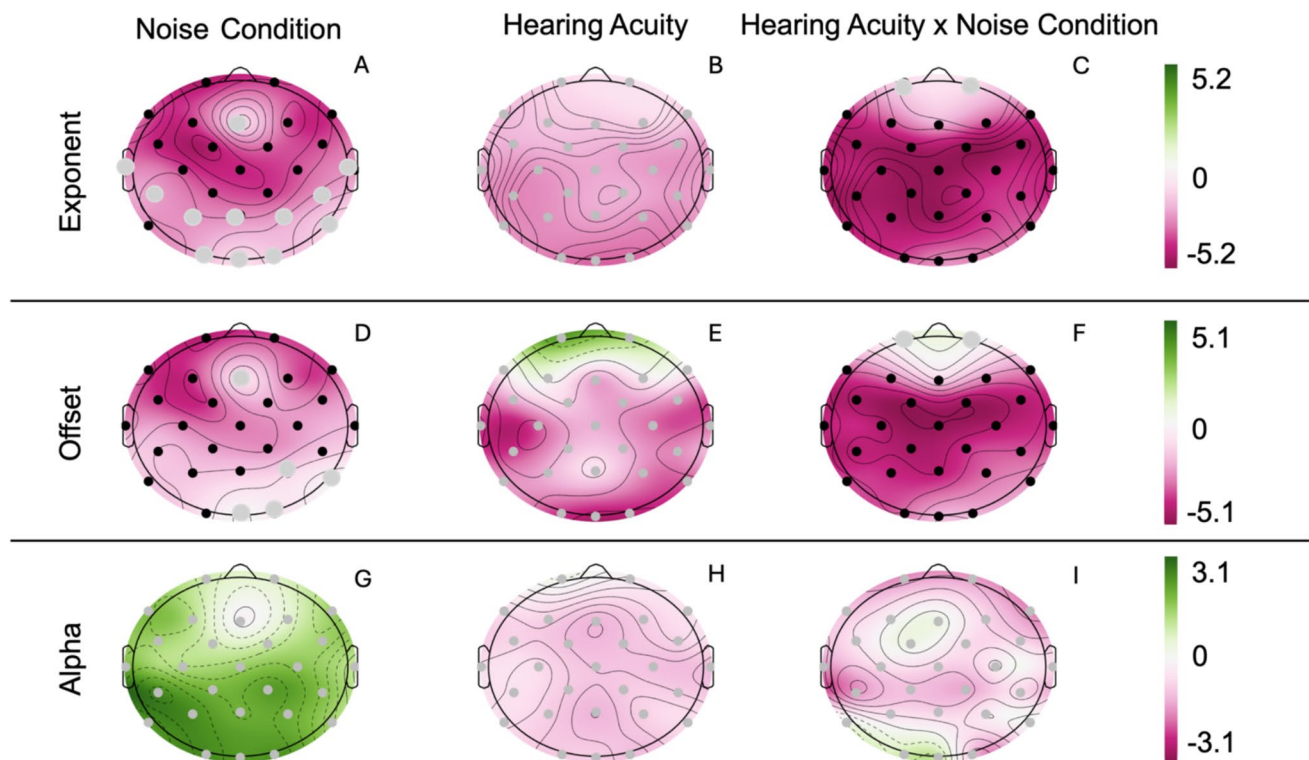
Initial data processing was conducted in MATLAB. Data were first divided into 3,000 ms non-overlapping epochs suitable for Independent Component Analysis (ICA; Luck, 2022). Resulting components were then individually manually inspected using ICLabel (Pion-Tonachini et al., 2019) to ensure that only blink- and muscle-related artifacts were being isolated. We adopted a conservative approach of ICA artifact correction, such that a maximum of two components were selected for removal for each participant to ensure that ICA selection did not distort the cortical activity of interest (e.g., Pontifex et al., 2017). After the completion of artifact correction, data were downsampled to 250 Hz to reduce processing time and re-epoched to 1,000 ms before the sentence final word to 10 ms after the offset of the penultimate word of the sentence. This epoch timing excluded the sentence final word which had been recorded separately to avoid coarticulation effects (Silcox & Payne, 2021). Trials were then binned according to the noise manipulation. Epoched EEG data were then algorithmically inspected for any artifacts that may have survived ICA artifact correction (e.g., flat lines, signal drift, etc.) using artifact detection algorithms in ERPLAB (Lopez-Calderon & Luck, 2014). Once preprocessing was completed, epoched EEG data

were transformed via the Fast Fourier Transformation (FFT) using the `fourieeg()` function in ERPLAB to create single-sided power spectral densities (PSDs) for each channel and participant in both quiet and noise conditions. There were no significant differences in the number of rejected trials across the two conditions for any participants, and all participants had less than 40% of trials rejected due to artifacts, so data from all participants were retained. These PSDs were saved as matrices and then exported to Python for spectral parameterization to separately estimate the periodic and aperiodic components of the spectra. Parameters for the `specparam` algorithm were set identically as Woods et al. (2024): peak width limits: [0.5,12]; max number of peaks: 4; minimum peak height: 0; peak threshold: 2.0; and aperiodic mode: fixed. Power spectra were parameterized across the frequency range of 1–40 Hz. The alpha band was defined as peaks detected in the frequency range from 8 to 13 Hz.

### Data analysis

A mass-univariate linear mixed effects modeling analysis was run for the older adult group to explore where across the scalp the aperiodic components (exponent of the spectral slope and offset of the spectrogram) and alpha power were predicted by hearing acuity, the presence of background noise

and their interaction. Three different linear mixed effects models, using `lme4` (Bates et al., 2015), were fit separately for each electrode: one with spectral slope as the outcome variable, one with offset as the outcome variable, and one with alpha power as the outcome variable. Each of these models used centered hearing acuity (continuous covariate, measured by the average 1–4 kHz PTA of the better ear), noise condition (effect coded as  $-0.5$  for quiet and  $+0.5$  for noise), and their interaction as predictor variables. A random intercept across participants was also added to account for repeated measures. Inferential tests for fixed effects were conducted using  $t$ -tests with Satterthwaite degrees of freedom approximations computed using the `lmerTest` package (Kuznetsova et al., 2017). Satterthwaite degrees of freedom have been shown to be effective at controlling for Type I error rates when used with multilevel models (Luke, 2017). These  $t$ -values were then collected for each of the estimates and each of the electrodes and were controlled for multiple comparisons using the Benjamini and Hochberg method for control of false discovery rate (FDR; Benjamini & Hochberg, 1995). The  $t$ -values were then used to create scalp topographies for each of the fixed effects estimates from the mixed models. Electrodes that were statistically significant after controlling for multiple comparisons were then marked on each scalp topography plot (see Figs. 1 and 3).



**Fig. 1** Effects of noise, hearing acuity, and their interaction on aperiodic and periodic neural activity in older adults. Scalp topographies for the  $t$ -values of the linear mixed effect models run with older par-

ticipants. Channels that remained significant after false discovery rate correction indicated with a black dot

Next, we explored age group differences on each of these three outcome variables (i.e., exponent of the spectral slope, offset, and alpha power). To do this, we combined our older adult dataset with a dataset of young normal hearing adults listening to the same items (from Silcox & Payne, 2021, see *Participants* section for more information). This dataset comprises the young normal hearing data reported in Woods et al. (2024), allowing for a direct comparison with our prior work on listening effort and aperiodic activity. Our analysis followed the exact same approach as described above. That is, we fit three models separately across each electrode (one for each outcome), calculated the  $t$ -values for each fixed effect, controlled for multiple comparisons and plotted the results as scalp topography plots. The only difference was in the predictor variables used. For each model, we used age group (coded as  $-0.5$  for younger adults and  $+0.5$  for older adults), noise condition (coded as  $-0.5$  for quiet and  $+0.5$  for noise), and their interaction as predictor variables. We also included a random intercept for participants.

## Results

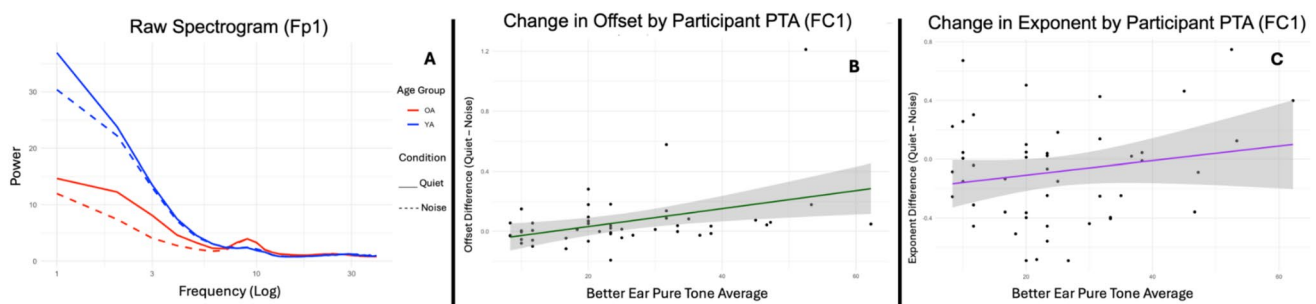
### Older adults hearing acuity exponent results

The results of the model fits using the exponent (i.e., slope of the broadband spectrogram) as the outcome variable can be observed in the scalp topographies in Figs. 1A–C. Each statistically significant electrode (after controlling for multiple comparisons) is indicated by a black dot whereas each electrode that was not significant is indicated by a gray dot. We found that there was a main effect of noise condition on the exponent of the spectral slope across 19 channels that remained significant after multiple comparison correction. These electrodes were generally frontally distributed, replicating the frontal distribution of this effect previously observed in younger normal hearing adults (Woods et al., 2024). There were no channels

that were significant for the main effect of hearing acuity on the exponent of the spectral slope. However, we did observe a robust and spatially diffuse interaction of hearing acuity and noise condition across 27 channels (after correction for multiple comparisons) occurring across almost the entire scalp. The direction of this interaction was such that increased hearing loss was associated with *increased* noise-induced spectral flattening (i.e., reduced offset and slope) across all significant electrodes. This effect can be visualized in Fig. 2C, which plots the noise effect (quiet – noise) on aperiodic activity as a function of hearing acuity for a representative fronto-central electrode (FC1). As can be seen, increasing hearing loss (i.e., larger PTAs) in older adults was associated with a larger noise-induced reduction in the aperiodic offset and slope.

### Older adults hearing acuity offset results

The results for the models fit using aperiodic offset as the outcome variable can be observed in Figs. 1D–F. Generally, the pattern of results for the offset of the spectral slope are very similar to that of the exponent. This is not surprising given that offset and slope are often highly correlated (Gao, 2016). Nevertheless, there were some differences in terms of both magnitude and distribution of the effects, as noted below. There was a main effect of condition on the offset of the spectral slope across 26 channels that remained significant after multiple comparison correction. Again, there were no channels that remained significant for the main effect of hearing acuity on the offset of the spectral slope. However, there was a significant interaction between hearing acuity and noise condition across 28 channels (after FDR correction). This effect was such that increased hearing loss was associated with increased noise-induced spectral flattening across all significant electrodes. To visualize this effect, see Fig. 2B which presents the scatterplot between the noise effect (quiet—noise) and hearing acuity for a representative fronto-central electrode (FC1). This shows that increasing



**Fig. 2** Spectrogram for all participants and relationships between change in aperiodic components and individual participant hearing acuity. **(A)** Raw spectrogram for quiet and noise conditions for older adults (red) and younger adults (blue) for channel Fp1. **(B)** Change

(quiet condition—noise condition) in offset for channel FC1 plotted by each participant's PTA. **(C)** Change (quiet condition—noise condition) in exponent for channel FC1 plotted by each participant's PTA

hearing loss, as measured by increasing PTAs in older adults was associated with a larger noise-induced reduction in the aperiodic offset.

### Older adults hearing acuity alpha power results

The results for the models using alpha power as the outcome variable are displayed in Figs. 1G–I. Across all models, we found that there was no significant main effect of noise condition, hearing acuity, nor the interaction across any channel in older adults (after FDR correction).

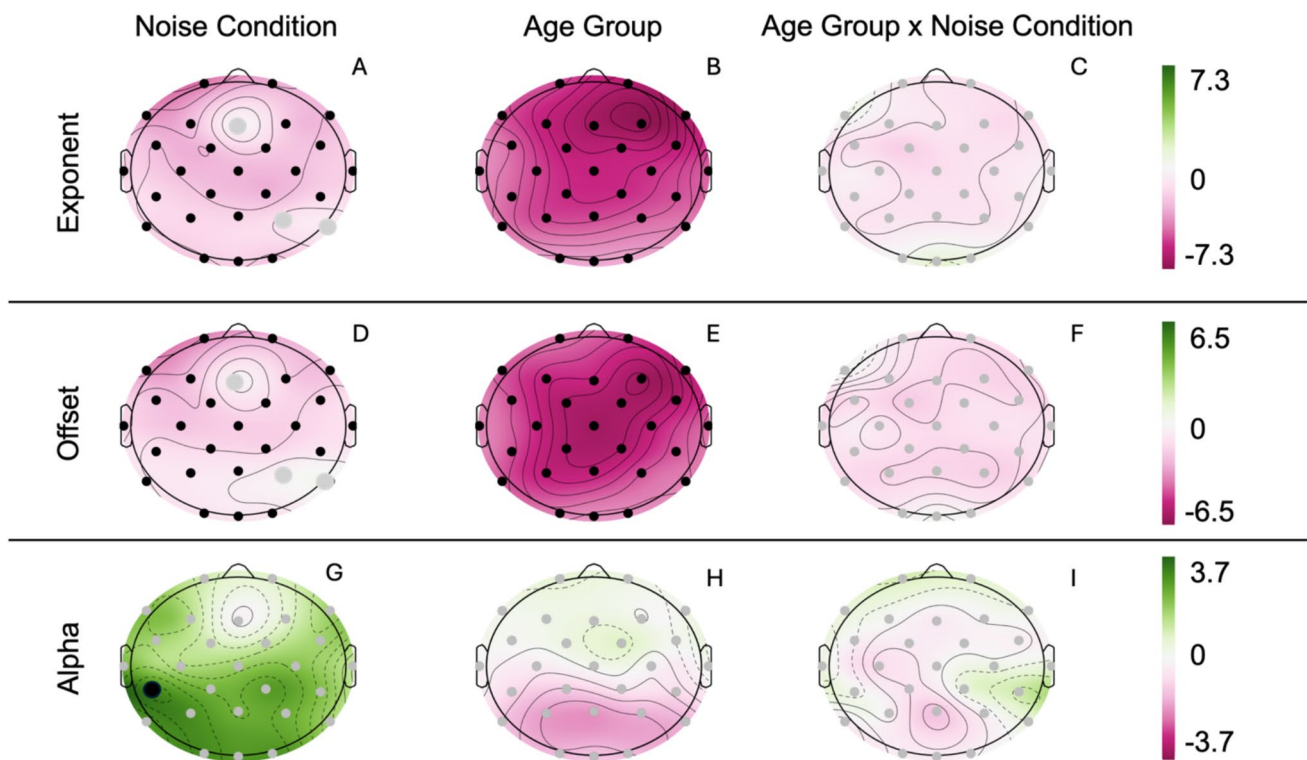
### Age group comparisons exponent results

To directly compare potential age-group differences in the effects of acoustic challenge on aperiodic and periodic brain activity, the reported results below pool the data from older adults reported above with a young normal hearing sample (reported in Woods et al., 2024). The results of the models using the exponent of the spectral slope across both groups of participants can be seen in Figs. 3A–C. There was a main effect of age group across all 32 electrode channels that maintained significance after correction for multiple comparisons. Consistent with our predictions, across all channels, spectral slope was flatter

for older adults than younger adults, replicating past work (e.g., Dave et al., 2018; Voytek et al., 2015). There was also a significant main effect of noise condition on 26 channels such that, across all participants, spectral slope was flatter in background noise as compared to quiet. The interaction between background noise condition and age group was not significant across any channels. To better visualize these two main effects, the average raw spectrogram for younger and older adults is plotted separately for quiet and noise channels for a representative pre-frontal channel (Fp1) in Fig. 2A.

### Age group comparisons offset results

The results of the models using the offset of the spectral slope as the outcome variable across both groups of participants can be seen in Figs. 3D–F. There was a significant main effect of age group across 28 channels such that spectral offset was lower for older adults as compared to younger adults. There was also a significant main effect of noise condition across 30 of the 32 electrodes. These two main effects can also be seen in the raw spectrogram presented in Fig. 2A. The interaction of background noise and age group was not significant for any channel.



**Fig. 3** Effects of noise, age, and their interaction on aperiodic and periodic neural activity. Scalp topographies for the t-values of the linear mixed effect models run with both groups of participants. Chan-

nels that remained significant after false discovery rate correction indicated with a black dot

## Age group comparisons alpha power results

The results of the models using alpha power as the outcome variable across both groups of participants can be seen in Figs. 3G–I. The main effect of age group was not significant across any channel. The main effect of background noise was marginally significant only for one channel, CP5 ( $t(61) = 3.32$ ,  $q = .049$ ), after correcting for multiple comparisons, such that alpha increased for this channel in background noise as compared to quiet. The interaction between noise condition and age group was not significant for any channel. Note that Woods et al. (2024), reporting on the YA results only, observed a robust noise effect on posterior alpha. Despite the lack of a noise effect in the older adult analysis (see *Older adults hearing acuity alpha power results*) we did not observe that this difference between “significant” in the young adults and “not significant” in the older adults was robust enough to produce a significant age  $\times$  noise interaction (see also Gelman & Stern, 2006) after correction for multiple comparisons. Given the lack of age group interaction, we caution any strong age-group comparative interpretation of noise effects on alpha.

## Discussion

The aim of the current study was to characterize the potential for aperiodic spectral EEG activity to index listening effort during speech comprehension in older adults. Our findings suggest that aperiodic neural activity is a promising candidate marker for the study of listening effort in speech comprehension, in part due to its emerging sensitivity to cognitive task demands as well as its sensitivity to individual differences (Ouyang et al., 2020). Extending our prior work in young normal hearing adults (Woods et al., 2024), we found that aperiodic neural activity was sensitive to the addition of acoustic challenge in the form of background noise in older adults. Most importantly, aperiodic neural activity also showed a relationship with individual differences in hearing acuity, such that noise-induced flattening of the aperiodic activity was *larger* for adults with greater hearing loss. This pattern is consistent with our listening effort-based predictions that effects of acoustic challenge should be compounded for adults with greater sensorineural hearing loss (Hussein et al., 2022; Peelle, 2018). Critically, only the aperiodic components showed such selective effects of interactions between hearing loss and acoustic challenge; in contrast, alpha power, the primary periodic measure that has been widely studied in listening effort research, failed to show such an effect, suggesting it may have more limited translational potential for work on listening effort in age-related hearing loss.

Importantly, we found that the relationship between hearing acuity and aperiodic activity was selective to interactions with acoustic challenge, as opposed to the overall aging-related aperiodic flattening, which appeared to be more general. While aging and hearing acuity are strongly correlated (Peelle & Wingfield, 2016), it is important to note that the age-related flattening we observed (replicating past work; Dave et al., 2018; Voytek et al., 2015) was observed as a main effect, occurring in trials with both high and low perceptual demands (i.e., regardless of acoustic challenge), whereas the hearing acuity related flattening interacted with noise, such that increased hearing loss was associated with increased flattening in the background noise condition as compared to quiet. This finding is pivotal in moving forward with aperiodic activity as a sensitive indicator of listening effort, as several theories of listening effort (e.g., Peelle, 2018; Pichora-Fuller et al., 2016) point to the importance of considering the joint effects of extrinsic-environmental drivers of acoustic challenge (i.e., increased background noise) as well as intrinsic, individual listener-level sources of acoustic challenge (i.e., sensorineural hearing loss).

Increases in EEG alpha power with increasing task demands have been theorized to reflect the suppression of task irrelevant information, such as the inhibition of visual or auditory distractors (Noonan et al., 2018; Obleser & Weisz, 2012). However, this relationship between listening effort and increased alpha power is not always consistent, even within the same study. For instance, Peterson and colleagues (2015) found that alpha power increased for participants with hearing loss under low and medium task demands (working memory load and background noise) but decreased for participants with more severe hearing loss under the highest levels of task demand. In Woods and colleagues (2024), we argued that one possible contributor to variability in alpha effects in the literature was the fact that prior work had not separately decomposed the spectral response into periodic (e.g., alpha) and aperiodic components. Given that the effects of acoustic challenge have opposing influences on alpha power (increases) and aperiodic activity (broadband flattening), it is possible that variability in the literature could be driven by differences across studies in the confounding effects of aperiodic activity to alpha power measurement. However, in the current study, we separated both aperiodic and periodic effects of acoustic challenge in older listeners via the specparam algorithm and did not observe that aperiodic adjusted alpha power was a sensitive indicator of listening effort – it was not sensitive to acoustic challenge nor was it sensitive to hearing loss or aging. At the same time, we caution against the over-interpretation of possible age-group differences in noise effects on alpha, as the age  $\times$  noise interaction failed to reach statistical significance after correction for multiple comparisons. We also cannot rule out the possibility that the lack of age  $\times$  noise

interactions (on alpha or aperiodic outcomes) is idiosyncratic to our sample. It is the case that we recruited older adults with a considerable range in hearing acuity (including older adults with excellent hearing). It is possible that the lack of age  $\times$  noise interactions may be due to statistical power limitations in detecting a comparatively small effect size. Note that this was a secondary data analysis and not originally designed to detect age  $\times$  condition differences. Nevertheless, we were able to detect overall age-related main effects on aperiodic activity in the combined sample (replicating prior work). In addition, we did observe statistically significant effects for the overall larger hearing acuity  $\times$  noise effect sizes within the (smaller) older adult sample, suggesting that the effects of noise on aperiodic activity are more strongly correlated with hearing acuity than they are with age. The key for fully disentangling the effects of age and hearing loss in future work would be to collect larger developmental datasets with a wide range of hearing acuity across the lifespan.

While there is not a current consensus on the cognitive nor biological mechanisms behind changes in spectral slope and offset, we think that our current and previous results along with other recent work have begun to tell a compelling narrative about aperiodic sensitivity to cognitive effort. That is, in effortful situations – like listening with background noise or if a listener has a hearing impairment – domain-general brain networks may be recruited to help support processing and comprehension, consistent with neuroimaging studies of effortful speech comprehension (Erb & Obleser, 2013; Peelle, 2018). By combining computational modeling with measures of local field potentials (LFPs) in animal models, Gao and colleagues (2017) found that proportional increases in cortical excitability (relative to inhibition; i.e., E:I balance) resulted in a flattening of the spectral slope. Assuming that this same mechanism accounts for a flattening of spectral slope in humans, Kałamała and colleagues (2024) recently argued that the flattening of slope they observed on conflict trials in a flanker task reflected increased cortical excitability which was indicative of attempted recruitment of domain-general attention-related neural resources. Consistent with this view, others have likewise observed that a  $1/f$  flattening is related to increased task difficulty in challenging cognitive tasks (Akbarian et al., 2023; Dave et al., 2018). Taken together with the findings from the current study, we speculate that the flattening of the spectral slope we observe in the current study with the addition of noise (and decreased hearing acuity) could likewise reflect an increase in cortical excitability representing the attempted recruitment of domain general networks in response to acoustic challenge. We have previously argued (Woods et al., 2024) that this frontal sensitivity of aperiodic activity to increases in acoustic challenge may reflect compensatory recruitment of

domain-general fronto-parietal neural networks (such as the Multiple Demand network; Duncan, 2010; Duncan & Owen, 2000) to attempt to maintain optimal speech perception, consistent with the functional neuroimaging literature on listening effort (Erb & Obleser, 2013; Peelle, 2018) and age-related effort-effects more broadly (e.g., Reuter-Lorenz & Cappel, 2008).

However, it seems like this effort is not equally rewarded across age groups. Wöstmann and colleagues (2017) argued that increases in alpha reflect the inhibition of non-goal relevant sensory information (which is triggered by a top-down cognitive control process). Aperiodic activity could reflect that top-down “call” for additional domain-general resources (consistent with Woods et al., 2024), whereas the increase in alpha could represent the result of that additional effort-related response – successfully bringing online systems to suppress the irrelevant background noise. Taking this account into interpretation of our current findings, it may be that younger normal hearing adults trigger top-down attentional control mechanisms successfully (leading to broadband shifts in aperiodic activity) and this frontally mediated attentional recruitment leads to successful sensory inhibition of noise, reflected by increases in parietal alpha activity. However, for older adults, while they do show a noise-induced listening effort response of (frontally-distributed) spectral flattening, we observed that there is no commensurate increase in alpha activity reflecting successful noise suppression. Put simply, both older and younger adults exhibit this same effort signalling, but only younger adults are able to successfully “answer the call” with an increase in parietal alpha, indicative of successful noise suppression. This could be one reason why older adults overall do not perform well in effortful listening scenarios, even when they allocate additional attentional resources. We again stress that this putative mechanistic interpretation is currently uncertain due to the overall lack of an age  $\times$  noise interaction and thus requires replication in a larger sample that is better powered to detect possible age group differences.

Importantly, similar arguments have been made in the literature. For example, Silcox and Payne (2021) found age-related differences in the trade off between effort allocation and language-related ERPs when listening to sentences in noise. For younger adults, (pupil-mediated) arousal increases in response to background noise were associated with the recovery of language-related ERPs such as the N400, which came at the cost of poorer subsequent memory. However, for older adults, Silcox and colleagues (2024) did not find a recovery of the N400 with increases in pupil size in noise, but still observed the same costs to memory. An open question for future research is *why* this breakdown between top-down recruitment and successful suppression is happening in aging. However, it is important to note that this explanation is consistent

with other work more broadly showing that older adults do struggle with perceptual inhibition in the visual domain as well (Campbell et al., 2020; Fabiani et al., 2006).

The current study not only replicated our past work showing sensitivity of aperiodic neural activity to acoustic challenge, but extended it in multiple dimensions (e.g., effects of aging and hearing loss). While this replication and extension is promising, there are multiple future directions that need development to address the role of aperiodic activity in effortful speech comprehension. It will be critical to establish the relationship between aperiodic neural activity and other theoretically important dimensions of listening effort (e.g., motivation, emotion, speech rate, speaking style). For example, we predict, based on our current understanding, that faster speech rates and certain speaking styles (e.g., unfamiliar accented speech, under-articulated speech) would increase listening effort and result in similar spectral flattening that occurs in response to additional background noise (Simantiraki et al., 2023). However, certain emotional or highly motivating speech, which has been shown to reduce perceived effort, may result in the opposite pattern—spectral steepening (Francis & Oliver, 2018). Considering listening effort is likely a multidimensional construct and there is still a great deal of individual variability in offset and slope measurements, we aim to continue to explore correlates between aperiodic neural activity and other behavioral, neural, and physiological correlates of listening effort (e.g., Alhanbali et al., 2019) in future work. Furthermore, given this possible disconnect between effort-recruitment and sensory suppression, future investigations could use more time-resolved methods (which are currently being developed) to attempt to establish the time course of these effects to better understand what might be driving this breakdown.

The findings of the current study contribute to the growing literature indicating that aperiodic activity is not only a source of meaningful variability and needs to be controlled for in studies of neural oscillations in speech comprehension (Woods et al., 2024), but that it is *itself* a functionally important measure that is sensitive to effort during the performance of cognitively demanding tasks in speech comprehension and perhaps in cognitively challenging tasks more broadly. In particular, our data show that differences related to acoustic challenge, aging, and hearing loss have distinct influences on aperiodic neural activity across the lifespan, making it a clear and unique candidate neural correlate of listening effort across the adult lifespan. Our findings demonstrate that aperiodic activity is able to index listening effort in situations where previously used measurements have failed to show a significant difference. This highlights the importance of considering aperiodic activity not just in language and speech studies,

but for any cognitive tasks where we expect effort to be a critical factor.

**Funding** This research is supported by the National Science Foundation Graduate Research Fellowship Program (GRFP) awarded to S. Woods [Award ID: 2024370971].

**Data availability** This was a secondary data analysis. Original data and materials for both experiments are available at [osf.io/de4b9](https://osf.io/de4b9).

**Code availability** Code is available upon request from the corresponding author.

## Declarations

**Competing interests** The authors have no relevant financial or non-financial interests to disclose.

**Ethics approval** Approval was obtained from the Institutional Review Board (IRB) of University of Utah. The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

**Consent to participate** Informed written consent was obtained from all individual participants included in the study.

**Consent for publication** Written informed consent was obtained from all participants for publication of this study's findings. All identifying information has been removed from the data.

**Open practices** This was a non-preregistered secondary data analysis of two previously preregistered experiments. The original OSF pre-registration for each study: Silcox et al., 2024 – <https://osf.io/7p5r6> and Silcox & Payne, 2021 <https://osf.io/5kmbh>.

## References

- Ahmad, J., Ellis, C., Leech, R., Voytek, B., Garces, P., Jones, E., Buitelaar, J., Loth, E., Dos Santos, F. P., Amil, A. F., Verschure, P. F. M. J., Murphy, D., & McAlonan, G. (2022). From mechanisms to markers: Novel noninvasive EEG proxy markers of the neural excitation and inhibition system in humans. *Translational Psychiatry*, 12(1), Article 467. <https://doi.org/10.1038/s41398-022-02218-z>
- Akbarian, F., Rossi, C., Costers, L., D'hooghe, M. B., D'haeseleer, M., Nagels, G., & Van Schependom, J. (2023). The spectral slope as a marker of excitation/inhibition ratio and cognitive functioning in multiple sclerosis. *Human Brain Mapping*, 44(17), 5784–5794. <https://doi.org/10.1002/hbm.26476>
- Ala, T. S., Graversen, C., Wendt, D., Alickovic, E., Whitmer, W. M., & Lunner, T. (2020). An exploratory study of EEG alpha oscillation and pupil dilation in hearing-aid users during effortful listening to continuous speech. *PLoS One*, 15(7), Article e0235782. <https://doi.org/10.1371/journal.pone.0235782>
- Alexander, T. H., & Harris, J. P. (2013). Incidence of sudden sensorineural hearing loss. *Otology & Neurotology*, 34(9), 1586–1589. <https://doi.org/10.1097/MAO.0000000000000222>
- Alhanbali, S., Dawes, P., Millman, R. E., & Munro, K. J. (2019). Measures of listening effort are multidimensional. *Ear and Hearing*, 40(5), 1084–1097. <https://doi.org/10.1097/AUD.0000000000000697>
- Anderson Gosselin, P., & Gagné, J.-P. (2011). Older adults expend more listening effort than young adults recognizing speech in

- noise. *Journal of Speech, Language, and Hearing Research*, 54(3), 944–958. [https://doi.org/10.1044/1092-4388\(2010/10-0069\)](https://doi.org/10.1044/1092-4388(2010/10-0069))
- Barker, A. B., Leighton, P., & Ferguson, M. A. (2017). Coping together with hearing loss: A qualitative meta-synthesis of the psychosocial experiences of people with hearing loss and their communication partners. *International Journal of Audiology*, 56(5), 297–305. <https://doi.org/10.1080/14992027.2017.1286695>
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1). <https://doi.org/10.18637/jss.v067.i01>
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society, Series B: Statistical Methodology*, 57(1), 289–300. <https://doi.org/10.1111/j.2517-6161.1995.tb02031.x>
- Bódzits, R., Szalárdy, O., Horváth, C., Ujma, P. P., Gombos, F., Simor, P., Pótári, A., Zeising, M., Steiger, A., & Dresler, M. (2021). A set of composite, non-redundant EEG measures of NREM sleep based on the power law scaling of the Fourier spectrum. *Scientific Reports*, 11(1), Article 2041. <https://doi.org/10.1038/s41598-021-81230-7>
- Buzsáki, G., Anastassiou, C. A., & Koch, C. (2012). The origin of extracellular fields and currents—EEG, ECoG, LFP and spikes. *Nature Reviews Neuroscience*, 13(6), 407–420. <https://doi.org/10.1038/nrn3241>
- Campbell, K. L., Lustig, C., & Hasher, L. (2020). Aging and inhibition: Introduction to the special issue. *Psychology and Aging*, 35(5), 605–613. <https://doi.org/10.1037/pag0000564>
- Carson, N., Leach, L., & Murphy, K. J. (2018). A re-examination of Montreal Cognitive Assessment (MoCA) cutoff scores. *International Journal of Geriatric Psychiatry*, 33(2), 379–388. <https://doi.org/10.1002/gps.4756>
- Cellier, D., Riddle, J., Petersen, I., & Hwang, K. (2021). The development of theta and alpha neural oscillations from ages 3 to 24 years. *Developmental Cognitive Neuroscience*, 50, Article 100969. <https://doi.org/10.1016/j.dcn.2021.100969>
- Dautzenberg, G., Lijmer, J., & Beekman, A. (2021). Clinical value of the Montreal Cognitive Assessment (MoCA) in patients suspected of cognitive impairment in old age psychiatry. Using the MoCA for triaging to a memory clinic. *Cognitive Neuropsychiatry*. <https://doi.org/10.1080/13546805.2020.1850434>
- Dave, S., Brothers, T. A., & Swaab, T. Y. (2018). 1/f neural noise and electrophysiological indices of contextual prediction in aging. *Brain Research*, 1691, 34–43. <https://doi.org/10.1016/j.brainres.2018.04.007>
- Dimitrijevic, A., Smith, M. L., Kadis, D. S., & Moore, D. R. (2019). Neural indices of listening effort in noisy environments. *Scientific Reports*, 9, Article 11278. <https://doi.org/10.1038/s41598-019-47643-1>
- Donoghue, T., Haller, M., Peterson, E. J., Varma, P., Sebastian, P., Gao, R., Noto, T., Lara, A. H., Wallis, J. D., Knight, R. T., Shestyuk, A., & Voytek, B. (2020). Parameterizing neural power spectra into periodic and aperiodic components. *Nature Neuroscience*, 23(12), 1655–1665. <https://doi.org/10.1038/s41593-020-00744-x>
- Dubno, J. R., Horwitz, A. R., & Ahlstrom, J. B. (2005). Word recognition in noise at higher-than-normal levels: Decreases in scores and increases in masking. *The Journal of the Acoustical Society of America*, 118(2), 914–922. <https://doi.org/10.1121/1.1953107>
- Duncan, J. (2010). The multiple-demand (MD) system of the primate brain: Mental programs for intelligent behaviour. *Trends in Cognitive Sciences*, 14(4), 172–179. <https://doi.org/10.1016/j.tics.2010.01.004>
- Duncan, J., & Owen, A. M. (2000). Common regions of the human frontal lobe recruited by diverse cognitive demands. *Trends in Neurosciences*, 23(10), 475–483. [https://doi.org/10.1016/S0166-2236\(00\)01633-7](https://doi.org/10.1016/S0166-2236(00)01633-7)
- Erb, J., & Obleser, J. (2013). Upregulation of cognitive control networks in older adults' speech comprehension. *Frontiers in Systems Neuroscience*, 7. <https://doi.org/10.3389/fnsys.2013.00116>
- Fabiani, M., Low, K. A., Wee, E., Sable, J. J., & Gratton, G. (2006). Reduced suppression or labile memory? Mechanisms of inefficient filtering of irrelevant information in older adults. *Journal Of Cognitive Neuroscience*, 18(4), 637–650. <https://doi.org/10.1162/jocn.2006.18.4.637>
- Federmeier, K. D. (2022). Connecting and considering: Electrophysiology provides insights into comprehension. *Psychophysiology*, 59(1), Article e13940. <https://doi.org/10.1111/psyp.13940>
- Fiedler, L., Seifi Ala, T., Graversen, C., Alickovic, E., Lunner, T., & Wendt, D. (2021). Hearing aid noise reduction lowers the sustained listening effort during continuous speech in noise—A combined pupillometry and EEG study. *Ear and Hearing*, 42(6), 1590–1601. <https://doi.org/10.1097/AUD.0000000000001050>
- Foxe, J. J., & Snyder, A. C. (2011). The Role of alpha-band brain oscillations as a sensory suppression mechanism during selective attention. *Frontiers in Psychology*, 2. <https://doi.org/10.3389/fpsyg.2011.00154>
- Francis, A. L., & Oliver, J. (2018). Psychophysiological measurement of affective responses during speech perception. *Hearing Research*, 369, 103–119. <https://doi.org/10.1016/j.heares.2018.07.007>
- Gao, R. (2016). Interpreting the electrophysiological power spectrum. *Journal of Neurophysiology*, 115(2), 628–630. <https://doi.org/10.1152/jn.00722.2015>
- Gao, R., Peterson, E. J., & Voytek, B. (2017). Inferring synaptic excitation/inhibition balance from field potentials. *Neuroimage*, 158, 70–78. <https://doi.org/10.1016/j.neuroimage.2017.06.078>
- Gelman, A., & Stern, H. (2006). The difference between “Significant” and “Not Significant” is not itself statistically significant. *The American Statistician*, 60(4), 328–331. <https://doi.org/10.1198/000313006X152649>
- Gyurkovics, M., Clements, G. M., Low, K. A., Fabiani, M., & Gratton, G. (2021). The impact of 1/f activity and baseline correction on the results and interpretation of time-frequency analyses of EEG/MEG data: A cautionary tale. *Neuroimage*, 237, Article 118192. <https://doi.org/10.1016/j.neuroimage.2021.118192>
- Gyurkovics, M., Clements, G. M., Low, K. A., Fabiani, M., & Gratton, G. (2022). Stimulus-induced changes in 1/f-like background activity in EEG. *The Journal of Neuroscience*, 42(37), 7144–7151. <https://doi.org/10.1523/JNEUROSCI.0414-22.2022>
- He, B. J. (2014). Scale-free brain activity: Past, present, and future. *Trends in Cognitive Sciences*, 18(9), 480–487. <https://doi.org/10.1016/j.tics.2014.04.003>
- Heine, C., & Browning, C. J. (2004). The communication and psychosocial perceptions of older adults with sensory loss: A qualitative study. *Ageing and Society*, 24(1), 113–130. <https://doi.org/10.1017/S0144686X03001491>
- Hughes, S. E., Hutchings, H. A., Rapport, F. L., McMahon, C. M., & Boisvert, I. (2018). Social connectedness and perceived listening effort in adult cochlear implant users: A grounded theory to establish content validity for a new patient-reported outcome measure. *Ear and Hearing*, 39(5), 922. <https://doi.org/10.1097/AUD.0000000000000553>
- Hussein, A. B., Lasheen, R. M., Emara, A. A., & El Mahallawi, T. (2022). Listening effort in patients with sensorineural hearing loss with and without hearing aids. *The Egyptian Journal of Otolaryngology*, 38(1), Article 99. <https://doi.org/10.1186/s43163-022-00288-w>
- Jafari, M. J., Khosrowabadi, R., Khodakarim, S., & Mohammadian, F. (2019). The effect of noise exposure on cognitive performance and brain activity patterns. *Open Access Macedonian Journal of Medical Sciences*, 7(17), 2924–2931. <https://doi.org/10.3889/oamjms.2019.742>

- Jasper, H. H. (1958). The ten-twenty electrode system of the international federation. *Electroencephalography and Clinical Neurophysiology*, *10*(2), 371–375. [https://doi.org/10.1016/0013-4694\(58\)90053-1](https://doi.org/10.1016/0013-4694(58)90053-1)
- Jensen, O. (2024). Distractor inhibition by alpha oscillations is controlled by an indirect mechanism governed by goal-relevant information. *Communications Psychology*, *2*(1), 1–11. <https://doi.org/10.1038/s44271-024-00081-w>
- Jia, S., Liu, D., Song, W., Beste, C., Colzato, L., & Hommel, B. (2024). Tracing conflict-induced cognitive-control adjustments over time using aperiodic EEG activity. *Cerebral Cortex*. <https://doi.org/10.1093/cercor/bhae185>
- Kalamala, P., Gyurkovics, M., Bowie, D. C., Clements, G. M., Low, K. A., Dolcos, F., Fabiani, M., & Gratton, G. (2024). Event-induced modulation of aperiodic background EEG: Attention-dependent and age-related shifts in E: I balance, and their consequences for behavior. *Imaging Neuroscience*. [https://doi.org/10.1162/imag\\_a\\_00054](https://doi.org/10.1162/imag_a_00054)
- Keur-Huizinga, L., Huizinga, N. A., Zekveld, A. A., Versfeld, N. J., van de Ven, S. R. B., van Dijk, W. A. J., de Geus, E. J. C., & Kramer, S. E. (2024). Effects of hearing acuity on psychophysiological responses to effortful speech perception. *Hearing Research*, *448*, Article 109031. <https://doi.org/10.1016/j.heares.2024.109031>
- Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). LmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–26. <https://doi.org/10.18637/jss.v082.i13>
- Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: An open-source toolbox for the analysis of event-related potentials. *Frontiers in Human Neuroscience*, *8*. <https://doi.org/10.3389/fnhum.2014.00213>
- Luck, S. J. (2022). Artifact correction with independent component analysis. In LibreTexts social sciences. Applied event-related potential data analysis. University of California, Davis. <https://doi.org/10.18115/D5QG92>
- Luke, S. G. (2017). Evaluating significance in linear mixed-effects models in R. *Behavior Research Methods*, *49*(4), 1494–1502. <https://doi.org/10.3758/s13428-016-0809-y>
- McMahon, C. M., Boisvert, I., de Lissa, P., Granger, L., Ibrahim, R., Lo, C. Y., Miles, K., & Graham, P. L. (2016). Monitoring alpha oscillations and pupil dilation across a performance-intensity function. *Frontiers in Psychology*, *7*. <https://doi.org/10.3389/fpsyg.2016.00745>
- Miles, K., McMahon, C., Boisvert, I., Ibrahim, R., de Lissa, P., Graham, P., & Lyxell, B. (2017). Objective assessment of listening effort: Coregistration of pupillometry and EEG. *Trends in Hearing*, *21*, Article 2331216517706396. <https://doi.org/10.1177/2331216517706396>
- Noonan, M. P., Crittenden, B. M., Jensen, O., & Stokes, M. G. (2018). Selective inhibition of distracting input. *Behavioural Brain Research*, *355*, 36–47. <https://doi.org/10.1016/j.bbr.2017.10.010>
- Obleser, J., & Weisz, N. (2012). Suppressed alpha oscillations predict intelligibility of speech and its acoustic details. *Cerebral Cortex*, *22*(11), 2466–2477. <https://doi.org/10.1093/cercor/bhr325>
- Oldfield, R. C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychologia*, *9*(1), 97–113. [https://doi.org/10.1016/0028-3932\(71\)90067-4](https://doi.org/10.1016/0028-3932(71)90067-4)
- Ouyang, G., Hildebrandt, A., Schmitz, F., & Herrmann, C. S. (2020). Decomposing alpha and 1/f brain activities reveals their differential associations with cognitive processing speed. *Neuroimage*, *205*, Article 116304. <https://doi.org/10.1016/j.neuroimage.2019.116304>
- Paul, B. T., Chen, J., Le, T., Lin, V., & Dimitrijevic, A. (2021). Cortical alpha oscillations in cochlear implant users reflect subjective listening effort during speech-in-noise perception. *PLoS One*. <https://doi.org/10.1371/journal.pone.0254162>
- Payne, B. R., Silcox, J. W., Crandell, H. A., Lash, A., Ferguson, S. H., & Lohani, M. (2022). Text captioning buffers against the effects of background noise and hearing loss on memory for speech. *Ear and Hearing*, *43*(1), 115. <https://doi.org/10.1097/AUD.0000000000001079>
- Peelle, J. E. (2018). Listening effort: How the cognitive consequences of acoustic challenge are reflected in brain and behavior. *Ear and Hearing*, *39*(2), 204–214. <https://doi.org/10.1097/AUD.0000000000000494>
- Peelle, J. E., & Wingfield, A. (2016). The neural consequences of age-related hearing loss. *Trends in Neurosciences*, *39*(7), 486–497. <https://doi.org/10.1016/j.tins.2016.05.001>
- Petersen, E. B., Wöstmann, M., Obleser, J., Stenfeldt, S., & Lunner, T. (2015). Hearing loss impacts neural alpha oscillations under adverse listening conditions. *Frontiers in Psychology*, *6*. <https://doi.org/10.3389/fpsyg.2015.00177>
- Pichora-Fuller, M. K., Kramer, S. E., Eckert, M. A., Edwards, B., Hornsby, B. W. Y., Humes, L. E., Lemke, U., Lunner, T., Matthen, M., Mackersie, C. L., Naylor, G., Phillips, N. A., Richter, M., Rudner, M., Sommers, M. S., Tremblay, K. L., & Wingfield, A. (2016). Hearing impairment and cognitive energy: The framework for understanding effortful listening (FUEL). *Ear and Hearing*, *37*(Suppl 1), 5S-27S. <https://doi.org/10.1097/AUD.00000000000000312>
- Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019). ICLABEL: An automated electroencephalographic independent component classifier, dataset, and website. *Neuroimage*, *198*, 181–197. <https://doi.org/10.1016/j.neuroimage.2019.05.026>
- Podvalny, E., Noy, N., Harel, M., Bickel, S., Chechik, G., Schroeder, C. E., Mehta, A. D., Tsodyks, M., & Malach, R. (2015). A unifying principle underlying the extracellular field potential spectral responses in the human cortex. *Journal of Neurophysiology*, *114*(1), 505–519. <https://doi.org/10.1152/jn.00943.2014>
- Pontifex, M. B., Gwizdala, K. L., Parks, A. C., Billinger, M., & Brunner, C. (2017). Variability of ICA decomposition may impact EEG signals when used to remove eyeblink artifacts. *Psychophysiology*, *54*(3), 386–398. <https://doi.org/10.1111/psyp.12804>
- Reuter-Lorenz, P. A., & Cappell, K. A. (2008). Neurocognitive aging and the compensation hypothesis. *Current Directions in Psychological Science*, *17*(3), 177–182. <https://doi.org/10.1111/j.1467-8721.2008.00570.x>
- Shukla, A., Harper, M., Pedersen, E., Goman, A., Suen, J. J., Price, C., Applebaum, J., Hoyer, M., Lin, F. R., & Reed, N. S. (2020). Hearing loss, loneliness, and social isolation: A systematic review. *Otolaryngology-Head and Neck Surgery*, *162*(5), 622–633. <https://doi.org/10.1177/0194599820910377>
- Silcox, J. W., Bennett, K., Copeland, A., Ferguson, S. H., & Payne, B. R. (2024). The costs (and benefits?) of effortful listening for older adults: Insights from simultaneous electrophysiology, pupillometry, and memory. *Journal of Cognitive Neuroscience*, *36*(6), 997–1020. [https://doi.org/10.1162/jocn\\_a\\_02161](https://doi.org/10.1162/jocn_a_02161)
- Silcox, J. W., & Payne, B. R. (2021). The costs (and benefits) of effortful listening on context processing: A simultaneous electrophysiology, pupillometry, and behavioral study. *Cortex*, *142*, 296–316. <https://doi.org/10.1016/j.cortex.2021.06.007>
- Simantiraki, O., Wagner, A. E., & Cooke, M. (2023). The impact of speech type on listening effort and intelligibility for native and non-native listeners. *Frontiers in Neuroscience*. <https://doi.org/10.3389/fnins.2023.1235911>
- Strauß, A., Wöstmann, M., & Obleser, J. (2014). Cortical alpha oscillations as a tool for auditory selective inhibition. *Frontiers in Human Neuroscience*, *8*. <https://doi.org/10.3389/fnhum.2014.00350>
- Voytek, B., Kramer, M. A., Case, J., Lepage, K. Q., Tempesta, Z. R., Knight, R. T., & Gazzaley, A. (2015). Age-related changes in 1/f neural electrophysiological noise. *Journal Of Neuroscience*, *35*(38), 13257–13265. <https://doi.org/10.1523/JNEUROSCI.2332-14.2015>

- Waldron-Perrine, B., & Axelrod, B. N. (2012). Determining an appropriate cutting score for indication of impairment on the Montreal Cognitive Assessment. *International Journal of Geriatric Psychiatry*, 27(11), 1189–1194. <https://doi.org/10.1002/gps.3768>
- Waschke, L., Donoghue, T., Fiedler, L., Smith, S., Garrett, D. D., Voytek, B., & Obleser, J. (2021). Modality-specific tracking of attention and sensory statistics in the human electrophysiological spectral exponent. *eLife*, 10, Article e70068. <https://doi.org/10.7554/eLife.70068>
- Waschke, L., Tune, S., & Obleser, J. (2019). Local cortical desynchronization and pupil-linked arousal differentially shape brain states for optimal sensory performance. *eLife*, 8, Article e51501. <https://doi.org/10.7554/eLife.51501>
- Waschke, L., Wöstmann, M., & Obleser, J. (2017). States and traits of neural irregularity in the age-varying human brain. *Scientific Reports*, 7(1), 17381. <https://doi.org/10.1038/s41598-017-17766-4>
- Woods, A., Cornejo, J., & Spinner, A. (2025). Auditory brainstem response. In *StatPearls*. StatPearls Publishing. <http://www.ncbi.nlm.nih.gov/books/NBK564321/>
- Woods, S. J., Silcox, J. W., & Payne, B. R. (2024). Evaluating aperiodic and periodic neural activity as markers of listening effort in speech perception. *Auditory Perception & Cognition*, 7(3), 203–218. <https://doi.org/10.1080/25742442.2024.2395217>
- Wöstmann, M., Herrmann, B., Wilsch, A., & Obleser, J. (2015). Neural alpha dynamics in younger and older listeners reflect acoustic challenges and predictive benefits. *The Journal of Neuroscience*, 35(4), 1458–1467. <https://doi.org/10.1523/JNEUROSCI.3250-14.2015>
- Wöstmann, M., Lim, S.-J., & Obleser, J. (2017). The human neural alpha response to speech is a proxy of attentional control. *Cerebral Cortex*, 27(6), 3307–3317. <https://doi.org/10.1093/cercor/bhx074>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.