Unraveling the relation between EEG-correlates of attentional orienting and sound localization performance: a diffusion model approach

Laura-Isabelle Klatt*[1], Daniel Schneider[1], Anna-Lena Schubert[2], Christina Hanenberg[1], Jörg Lewald[1,3], Edmund Wascher[1], Stephan Getzmann[1]

[1]Leibniz Research Centre for Working Environment and Human Factors, TU Dortmund
[2]Institute of Psychology, Heidelberg University
[3]Department of Cognitive Psychology, Faculty of Psychology, Ruhr University Bochum

* Address of correspondence:
Laura-Isabelle Klatt, M.Sc.
Leibniz Research Centre for Working Environment and Human Factors
Ardeystraße 67
44139 Dortmund
Germany
Tel.: +49 / 231 1084 260
E-mail: klatt@ifado.de

Abstract

Understanding the contribution of cognitive processes and their underlying neurophysiological signals to behavioral phenomena has been a key objective in recent neuroscience research. Using linear mixed modeling and a diffusion-model framework, we investigated to what extent well-established correlates of spatial attention in the electro-encephalogram contribute to behavioral performance in an auditory free-field sound-localization task. Younger and older subjects were instructed to indicate the horizontal position of a pre-defined target among three simultaneously presented distractors. Both age groups showed a comparable neural signature of attentional orienting within the auditory scene: Neither the amplitude of the anterior contralateral N2 subcomponent (N2ac) nor the magnitude of posterior alpha power lateralization differed significantly between groups. The central question of interest was whether posterior alpha lateralization and N2ac amplitudes predict sound localization performance (accuracy and mean reaction time) and/or diffusion model parameters (drift rate, boundary separation, and non-decision time). Linear mixed modeling revealed that N2ac amplitudes significantly predicted drift rate and accuracy, whereas alpha lateralization was not related to behavioral or diffusion modeling parameters. The results indicate that a more efficient attentional filtering and selection of information within an auditory scene, reflected by increased N2ac amplitudes, was associated with a higher speed of information uptake (drift rate) and better localization performance (accuracy), while the underlying response criteria (threshold separation), mean reaction times, and non-decisional processes remained unaffected. The lack of a behavioral correlate of post-stimulus alpha power lateralization questions the well-established notion that alpha power modulations reflect a functionally relevant attentional mechanism.

Keywords: attentional orienting; sound localization; N2ac; alpha power lateralization; diffusion model; brain-behavior relationship

1. Introduction

When multiple sources of acoustic information are simultaneously present, selective filtering of the available information is necessary to, for instance, focus on a talker of interest while ignoring traffic noise, music playing in the background, or other peoples' conversations. This capacity of the human auditory system is especially astonishing, given that the incoming auditory signals often overlap in time, space, or spectral content. The behavioral effects of such selective orienting of attention in noisy, multi-speaker environments, usually referred to as '*cocktail-party scenarios*' (Cherry, 1953), have been studied for decades (for review, see Bronkhorst, 2015). However, the contribution of neural signals to observable behavioral performance and its underlying cognitive processes is still poorly understood. Here, we investigated the relationship between well-established correlates of spatial attention in the electro-encephalogram (EEG) and behavioral performance in an auditory sound localization task using a linear mixed modeling approach. In particular, we specified the role of modulations in the alpha frequency band as well as an anterior contralateral N2 subcomponent (N2ac; Gamble & Luck, 2011) with respect to sound-localization performance in younger and older adults.

Lateralized modulations of alpha power amplitude have been shown to reflect the orienting of spatial attention in visual (Foster, Sutterer, Serences, Vogel, & Awh, 2017; Ikkai, Dandekar, & Curtis, 2016; Rihs, Michel, & Thut, 2007; Worden, Foxe, Wang, & Simpson, 2000), tactile (Haegens, Handel, & Jensen, 2011; Haegens, Luther, & Jensen, 2012), and auditory space (Klatt, Getzmann, Wascher, & Schneider, 2018b; Wöstmann, Herrmann, Maess, & Obleser, 2016; Wöstmann, Vosskuhl, Obleser, & Herrmann, 2018). Typically, alpha power is shown to decrease contralaterally to the attended location (Kelly, Gomez-Ramirez, & Foxe, 2009; Sauseng et al., 2005) or to increase contralaterally to the unattended or ignored location (Kelly, Lalor, Reilly, & Foxe, 2006; Worden et al., 2000). Consistently across different modalities, this lateralized pattern of alpha-band activity has been shown to be linked to visual detection performance (Händel, Haarmeier, & Jensen, 2011; Thut, Brandt, & Pascual-Leone, 2006; van Dijk, Schoffelen, Oostenveld, & Jensen, 2008), tactile discrimination acuity (Craddock, Poliakoff, El-deredy, Klepousniotou, & Lloyd, 2017; Haegens et al., 2011), and listening performance (Tune, Wöstmann, & Obleser, 2018; Wöstmann et al., 2016). Going beyond a mere correlational approach, recent studies applying stimulation techniques, such as transcranial magnetic stimulation (TMS) or continuous transcranial alternating current stimulation (tACS), suggest a causal role of alpha oscillations

in the processing of incoming information (Romei, Gross, & Thut, 2010; Wöstmann et al., 2018). Two major (not necessarily mutually exclusive) mechanisms have been proposed to underlie those asymmetric modulations of alpha power oscillations: target enhancement (Noonan et al., 2016; Yamagishi, Goda, Callan, Anderson, & Kawato, 2005) and distractor inhibition (Kelly, Lalor, Reilly, & Foxe, 2006; Rihs et al., 2007; Schneider, Göddertz, Haase, Hickey, & Wascher, 2019; Worden et al., 2000). While the majority of previous studies investigated pre-stimulus alpha oscillations as an index of anticipatory allocation of spatial attention in young adults, we focused on post-stimulus alpha lateralization in a sound-localization task, simulating a '*cocktail-party scenario*'. Such an experimental setup more closely resembles frequent real-life situations, in which a person searches for a sound of interest (e.g., a voice or a ringing phone) without knowing in advance where to look for it. In fact, a recent study provided first evidence that distinct attentional mechanisms contribute to the preparation for as opposed to the ongoing processing of a stimulus (van Ede, Szebényi, & Maris, 2014). In addition, we asked whether the proposed mechanistic function of alpha oscillations extends to samples of older subjects, which remains an ongoing matter of debate (Hong, Sun, Bengson, Mangun, & Tong, 2015; Mok, Myers, Wallis, & Nobre, 2016; Tune et al., 2018; Vaden, Hutcheson, McCollum, Kentros, & Visscher, 2012).

A second neural measure of interest, indicating the allocation of attention within an auditory scene, is the N2ac. The N2ac has been shown to be evoked in the N2 latency range (starting at around 200 ms) when detecting or localizing a target sound in the presence of one or multiple distractor stimuli, using artificial sounds (Gamble & Luck, 2011), animal vocalizations (Klatt, Getzmann, Wascher, & Schneider, 2018a; Lewald & Getzmann, 2015), or spoken numerals (Lewald, Hanenberg, & Getzmann, 2016). While the N2ac was originally suggested to reflect the allocation of selective attention to the target (Gamble & Luck, 2011), analogously to the visual posterior contralateral N2 subcomponent (N2pc; Eimer, 1996; Luck & Hillyard, 1994), its functional significance remains ambiguous. Here, we aimed to provide further evidence on the functional significance of the N2ac by investigating its relationship to sound localization performance.

In the present study, the diffusion modelling approach (Ratcliff, 1978) was applied, allowing for a more detailed understanding of behavioral patterns in discrimination tasks (for recent reviews, see Ratcliff & McKoon, 2008; Voss, Nagler, & Lerche, 2013). Although diffusion models are still only rarely used in cognitive neuroscience research (see, e.g., (Nunez, Vandekerckhove, & Srinivasan, 2017; Philiastides, Ratcliff, & Sajda, 2006; Ratcliff, Philiastides, & Sajda, 2009; Schubert, Hagemann, Voss, Schankin, & Bergmann, 2015;

Schubert, Nunez, Hagemann, & Vandekerckhove, 2018), the interest in and the application of this methodological approach has increased considerably during the past decade. The general purpose of diffusion models is, to decompose the cognitive processes underlying a binary decision. As one of the major advantages of the diffusion model, the estimation procession is not limited to single mean or median values, but takes the whole reaction time (RT) distribution into account. Specifically, the resulting separation of processing components offers an enormous potential to provide more detailed descriptions of cognitive processes and to generate more accurate predictions for behavioral and neurophysiological data (Ratcliff & McKoon, 2008; Turner, Rodriguez, Norcia, McClure, & Steyvers, 2016).

The diffusion model assumes that in order for a decision to be made and a reaction to be executed, evidence for either response is accumulated in the course of a noisy process until it reaches either the decision boundary of response A or response B (see figure 2 in Voss et al., 2013 for an illustration of this evidence accumulation process). The basic diffusion model includes the following parameters: The drift rate v describes the speed at which evidence is accumulated (or "the rate of accumulation of information", Ratcliff & McKoon, 2008, p. 3), with higher drift rates resulting in shorter RTs and fewer errors. Threshold separation a indicates the amount of information considered until a decision is made. That is, conservative response criteria that are associated with slower but more accurate responses, result in large estimates of a, while more liberal response criteria result in smaller estimates of a. Threshold separation and drift rate have been shown to be negatively correlated, due to the fact that individuals with higher drift rates tend to allow more liberal response criteria (i.e., smaller threshold separation values; Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007). A priori biases towards one of the decision thresholds are reflected by starting point z. Beyond that, the model also includes non-decisional processing, such as response execution, working memory access, or stimulus encoding. The latter is indicated by the non-decision time constant t_0. Typically, older adults show a slowing in this decision-unrelated domain (Ratcliff, Thapar, & McKoon, 2001; Thapar, Ratcliff, & McKoon, 2003). Finally, trial-to-trial variability in drift rate (s_v), non-decision time (s_{t0}), starting point (s_z), and the proportion of contaminated trials (p_{diff}; e.g., underlying non-diffusion like processes) can be accounted for.

Here, using linear mixed modeling, we aimed at further characterizing the relation between electrophysiological correlates of attentional orienting within a complex auditory scene (i.e., alpha lateralization and N2ac) and sound-localization performance, which was assessed by classical RT and accuracy measures as well as by diffusion modeling parameters. We hypothesized that, if the cognitive processes reflected by alpha power modulations and

N2ac amplitudes contribute to the successful selection of the target from a sound array containing simultaneously present distractors, they should in turn contribute to the information accumulation process that results in the localization of the target. Hence, alpha power modulations and N2ac amplitudes should predict drift rate (i.e., the speed of information accumulation), and in turn, RT and accuracy.

2. Materials and methods

The raw data analyzed in this study were taken from a separate study that investigated the influence of an auditory training on cocktail-party listening performance in younger and older adults (Getzmann, Hanenberg, & Lewald, 2018). The original experiment comprised three (training) sessions on three days (audiovisual congruency; visual feedback; control), including three experimental blocks per session (15 min pre-training; 15 min post-training; 1 h post-training). For the present re-analysis, exclusively the data obtained in the pre-training blocks, pooled across the three sessions, were used.

2.1 Participants

The original sample included 28 older adults and 24 younger adults. Data for three younger subjects were discarded because of technical problems with EEG recording. In addition, two older subjects were excluded from analysis since their performance was below (14% correct) or very close to (30%) chance level (25%). Consequently, the final sample included 26 older adults (mean age 69 yrs, range 56–76 yrs, 13 female) and 21 younger adults (mean age 24 yrs, range 19–29 yrs, 11 female). All participants were right-handed as assessed by the Edinburgh Handedness Inventory (Oldfield, 1971).

An audiometry, including eleven pure-tone frequencies (0.125 - 8 kHz; Oscilla USB100, Inmedico, Lystrup, Denmark) was conducted. Hearing thresholds in the speech frequency range (< 4kHz) indicated normal hearing (≤ 25 dB) for all younger subjects and mild impairments for older subjects (≤ 40 dB). The study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethical Committee of the Leibniz Research Centre for Working Environment and Human Factors. All participants gave their written informed consent for participation.

2.2 Experimental setup, procedure, and stimuli

The experiment was conducted in a dimly lit, echo-reduced, sound-proof room. Participants were seated in a comfortable chair that was positioned with equal distances to the

left, right, and front wall of the room. Participants' head position was stabilized by a chin rest. A semicircular array of nine broad-band loudspeakers (SC5.9; Visaton, Haan, Germany; housing volume 340 cm^3) was mounted in front of the subject at a distance of 1.5 meters from the subject's head. Only four loudspeakers, located at azimuthal positions of -60°, -20°, 20°, and 60°, were used for the experimental setup of the present study. A red light-emitting diode (LED; diameter 3 mm, luminous intensity 0.025 mcd) was attached right below the central loudspeaker in the median plane of the subject's head at eye level. The LED was continuously on and served as a central fixation point.

The sound localization task applied in the present study was a modification of the multiple-sources approach that has been used in several previous studies on auditory selective spatial attention in "cocktail-party scenarios" (Lewald, 2016, 2019; Lewald & Getzmann, 2015; Zündorf, Karnath, & Lewald, 2011, 2014; Zündorf, Lewald, & Karnath, 2013). Details of the present task version have been previously described in detail (Lewald et al., 2016) Briefly, participants indicated the position of a pre-defined target numeral that was presented simultaneously with three distractor numerals (Figure 1a). The target was kept constant for each subject and was counterbalanced across subjects. Four one-syllable numerals ("eins", 1; "vier", 4; "acht", 8; "zehn", 10), spoken by two male (mean pitch 141 Hz) and two female (mean pitch 189 Hz) native German speakers, served as sound stimuli (Lewald et al., 2016). All numerals were presented equally often at each of the four possible loudspeaker positions. Numerals presented in each trial were spoken by four different speakers. The overall sound pressure level of the sound arrays was 66 dB(A), as measured at the position of the subject's head using a sound level meter with a ½" free-field measuring microphone (Types 2226 and 4175, Brüel & Kjær, Nærum, Denmark).

The target was present in each trial, with target position, distractor positions, and speakers varying between trials following a fixed pseudo-random order. The stimulus duration was 600 ms, followed by a response period of 2 s and an inter-trial interval of 525 ms, resulting in a total trial duration of 3.125 s. The response was given by pressing one out of four response buttons with the index finger of the right hand. The response buttons were arranged in semi-circular array, related to the four possible target locations (i.e., far left, inner left, inner right, far right). Each block consisted of 288 trials, resulting in a duration of 15 minutes per block. As already mentioned above, data from three blocks, assessed on different days, were pooled. Thus, there was a total of 864 trials per subject. On each of the three days, participants completed a short training sequence of ten trials prior to the experiment to familiarize themselves with the task.

2.3 EEG recording and pre-processing

The continuous EEG was recorded from 58 passive Ag/AgCl electrode cap at a sampling rate of 1 kHz using a QuickAmp-72 amplifier (Brain products, Gilching, Germany). The electrode montage was arranged according to the international 10/10 system. Two electrodes were positioned on the left and right mastoid, respectively. In addition, two horizontal and two vertical electro-oculography (EOG) electrodes were placed below and above the right eye and at the outer canthi of the left and right eye, respectively. The ground electrode was positioned right above the nasion, in the center of the forehead. The average of all electrodes served as an online-reference. Electrode impedances were kept below 10 kΩ.

Offline pre-processing of the data was conducted using the open-source toolbox EEGLAB (v14.1.2b, Delorme & Makeig, 2004) for Matlab (R2018a). The continuous EEG data were high-pass filtered at 0.5 Hz (6601-point FIR filter, band width 0.5 Hz, cut-off frequency 0.25 Hz) and low-pass filtered at 30 Hz (441-point FIR filter, transition band width 7.5 Hz, cut-off frequency 33.75 Hz). The filtered data were re-referenced to the average of 58 channels (56 EEG and 2 mastoid electrodes) and segmented into epochs ranging from -1000 to 3125 ms, relative to sound array onset. For epoched data, the 200 ms time window prior to sound array onset served as a baseline. Independent component analysis (ICA) was run on a subset of the original data, downsampled to 200 Hz and containing only every second trial. The derived independent component (IC) decomposition was then projected onto the original dataset with a 1 kHz sampling rate comprising all trials. Using the DIPFIT plugin of the EEGLAB toolbox, a single-equivalent current dipole model was computed for each of the independent component scalp maps by means of a spherical head model (Kavanagh, Darcey, Lehmann, & Fender, 1978). Artefactual ICs were identified and excluded in two subsequent steps: The automated algorithm ADJUST (Mognon, Jovicich, Bruzzone, & Buiatti, 2011) was applied to identify and reject components related to blinks, eye movements, and generic discontinuities. In addition, because artefactual independent components usually do not resemble the projection of a single dipole (Onton & Makeig, 2006), all components with a residual variance exceeding 40% of the dipole solution were rejected. The resulting IC solution was visually inspected for any additional artefactual components that were not detected by this automated rejection procedure. On average, 28 independent components (out of 51 to 58 ICs) were rejected for each participant (range: 12 – 40). Finally, the automated artifact rejection procedure implemented in EEGLAB (threshold limit: 1000 μV, probability threshold: 5 standard deviations) was performed. On average, the procedure rejected 207 trials

(range: 92 – 317), that is, 23% of trials (range: 10.6 – 36.6%). Only trials with correct responses were submitted to further analyses of EEG data (cf. 2.4).

2.4 Data analyses

2.4.1 Behavioral data

Behavioral performance was quantified by means of mean RTs and mean accuracy (proportion of correct trials) as well as diffusion model parameters. Proportion of correct trials included only responses that were given within the maximum response period of 2 seconds. A total of 83 trials (i.e., on average 2 trials per subject, range = 0 – 16, median = 1) were rejected as incorrect due to missing responses and responses that exceeded the maximum response period.

The diffusion modeling framework was applied to the present auditory localization task, in which participants were instructed to localize the position of a given target within a four-sound array of one-syllable spoken numerals. Because the diffusion model is originally based on a two-choice decision task, the decision process is here assumed to present a continuous accumulation of evidence for the true target location relative to the three non-target locations. Previous applications of the diffusion model have shown that it can validly described decision making in four-choice alternative response tasks (Schubert et al., 2015, 2018). To eliminate outliers that could bias model results (Voss, Voss, & Lerche, 2015), extremely fast (< 150 ms) and extremely slow (> 3000 ms) RTs were discarded. Subsequently, data were log-transformed and *z*-standardized in order to exclude all trials with RTs exceeding ± 3 standard deviations of the mean for each individual subject.

The free software fast-dm (Voss & Voss, 2007) was used to fit a diffusion model to the RT distributions of the present data. The model parameters were estimated based on an iterative permutation process using the Kolmogrov Smirnov test statistic. The starting point *z* was set to 0.5, presuming that participants were not biased towards one of the two response categories (correct target location versus distractor location). The parameters *a*, *v*, and t_0 were allowed to vary freely. In addition, parameters s_v and st_0 were estimated because they led to a notable improvement of model fit. Trial-to-trial variability of starting point (s_z), the difference in speed of response execution (*d*), as well as the measure for the percentage of contaminants (p_{diff}) were set to 0.

To graphically evaluate model fit, we plotted observed versus predicted accuracy as well as observed versus predicted values of the RT distribution for the first (.25), second (.50), and third (.75) quartile. Predicted parameter values were derived using the *construct-samples* tool of fast-dm (Voss & Voss, 2007). That is, 500 datasets were generated for each

participant based on each individual's empirical parameter values and number of trials. Finally, the mean quartile values and mean response accuracy were calculated for each subject. Pearson correlations were calculated to quantify the relationship between empirical data and model predictions for both age groups. If the majority of data points lies close to the line of perfect correlation, good model fit can be assumed.

2.4.2 ERP analysis

In order to investigate the N2ac component (Gamble & Luck, 2011), we computed the mean contralateral and ipsilateral ERP amplitude at fronto-central electrodes FC3/4. The contralateral portion comprised the average signal at electrode FC3 in right target-trials and electrode FC4 in left-target trials, whereas the ipsilateral portion included the average signal at electrode FC3 in left-target trials and electrode FC4 in right-target trials. Mean amplitude was measured from 466 ms to 566 ms relative to sound array onset. The measurement window was based on a 100 ms time window set around the 50% fractional area latency (FAL; Hansen & Hillyard, 1980; Luck, 2014) in the grand average contralateral minus ipsilateral difference curve averaged across age groups (50% FAL = 516 ms). To determine the FAL, first, the area under the difference curve was measured in a broad time window ranging from 200 to 600 ms relative to sound array onset. The latency at which this area is divided in two equal halves denotes the 50% FAL. The present electrodes of interest have been previously chosen in reports of N2ac amplitudes (Gamble & Woldorff, 2015; Klatt, Getzmann, Wascher, & Schneider, 2018).

2.4.3 Time-frequency data

To obtain time-frequency representations of the single-trial oscillatory power, we convolved the epoched, stimulus-locked EEG data with three-cycle complex Morlet wavelets. The number of cycles increased with frequency by a factor of 0.5, that is, half as fast as the number of cycles in the respective fast-fourier transformation (FFT). This resulted in 3-cycle wavelets at the lowest frequency (4 Hz) and 11.25-cycle wavelets at the highest frequency (30 Hz). To quantify asymmetries in the attentional modulation of oscillatory power, the alpha lateralization index (ALI) was calculated (e.g., Haegens et al., 2011; Thut, 2006; Wildegger, van Ede, Woolrich, Gillebert, & Nobre, 2017; Wöstmann et al., 2016). The latter quantifies the strength of the ipsilateral minus contralateral difference in alpha power relative to the total power across both hemispheres:

$$ALI = \frac{(ipsilateral\ alpha\ power - contralateral\ alpha\ power)}{(ipsilateral\ alpha\ power + contralateral\ alpha\ power)}$$

Mean ipsilateral and contralateral power was extracted in the alpha frequency band (8-12 Hz) at electrodes PO7/PO8 in a time window ranging from 705 to 902 ms relative to the onset of the sound array. The measurement window was based on a 200 ms time window set around the 50% FAL in the ALI difference curve averaged across age groups (50% FAL = 804 ms). The 50% FAL was calculated based on a broad time window ranging from 300 to 1400 ms relative to sound array onset. The electrodes sites were selected based on a range of previous studies (e.g., Gould, Rushworth, & Nobre, 2011; Klatt et al., 2018; Myers, Walther, Wallis, Stokes, & Nobre, 2015; Thut, 2006; Van Der Lubbe, Bundt, & Abrahamse, 2014; van Driel, Gunseli, Meeter, & Olivers, 2017; van Ede, Niklaus, & Nobre, 2017), showing PO7/8 to be a representative choice of electrodes when measuring posterior alpha lateralization. To minimize the family wise error rate, we chose to limit the analysis to one pair of electrodes. The ALI is positive when alpha power is higher over the ipsilateral hemisphere (relative to the target sound) and/or lower over the contralateral hemisphere. In contrast, negative values indicate higher alpha power contralateral to the target and/or lower alpha power over ipsilateral electrode sites. The lateralization index was calculated using the raw, baseline-uncorrected power values. ALI values for younger and older adults were submitted to parametric two-sample *t*-tests, using Satterthwaite's approximation to assess degrees of freedom. Subsequently, one-sample *t*-tests were conducted to tests for significance of alpha lateralization within or across age groups.

2.4.4 Linear Mixed-Effects Models

To investigate to what extent alpha lateralization and N2ac amplitudes predict behavior in the given auditory localization task, we applied a linear mixed-effects (LME) model analysis. While a conventional (multiple) regression only includes fixed effects, LME modeling allows for the inclusion of random effects, thereby taking into account group differences or differences across individual subjects.

Analyses were conducted using the *fitlme* function implemented in the MATLAB Statistics and Machine Learning toolbox (R2018a). Model parameters were estimated using a maximum likelihood algorithm. Separate LME analyses were conducted for mean RT, accuracy, drift rate v, threshold separation a, and non-decision time t_0 as response variables. Reported p-values for fixed effect model estimates were derived using the Satterthwaite

approximation for degrees of freedom (Luke, 2017; Tune et al., 2018) and corrected for multiple comparisons using the Bonferroni-Holm correction procedure (Holm, 1979).

An iterative model fitting procedure was applied, starting with a baseline model including fixed effects for N2ac amplitudes and alpha lateralization indices, respectively. Note that we did not exclude insignificant fixed effects, even if it would have improved model fit, to be able to quantify the effect of both N2ac and alpha power irrespective of significance. Random effects, such as a random intercept for age or random slopes, were only included if they improved the model (Matuschek, Kliegl, Vasishth, Baayen, & Bates, 2017). Since *fitlme* does not provide p-values for random effects, we report the respective 95% confidence intervals (CIs) for models making significant predictions with respect to behavioral outcomes. Age, if included in the model, was considered as a categorical variable (older vs. younger age group). Improvements of model fit were assessed using simulated likelihood ratio tests (number of iterations: 1000).

2.4.5 Statistical tests and effect sizes

Data were considered normally distributed if the Lilliefors test (Lilliefors, 1967) yielded insignificant results ($p > .05$). For normally distributed data, parametric two-sample Welch's *t*-test was applied. Degrees of freedom were estimated using Satterthwaite's approximation, assuming unequal variances. Wilcoxon rank-sum test served as the non-parametric counterpart in case of non-normality. Measures of effect sizes were calculated using the MES toolbox provided by Hentschke and Stüttgen (2011). For parametric one- and two-sample *t*-tests, g1 and Hedge's g (in the following referred to as g) are reported, respectively. For both measures, effect sizes of ±0.2 are typically referred to as small, values of ±0.5 as medium, and values of ±0.8 as large. For non-parametric *t*-tests, Cohen's U3 is reported. Cohen's U3 is a measure of overlap of two distributions, with 0.5 indicating minimal overlap and 0 or 1 indicating maximal overlap. The significance of effects was assessed at a significance level of $\alpha = .05$. The Bonferroni-Holm correction procedure was applied to correct for multiple comparisons when appropriate (Holm, 1979). Adjusted *p*-values are denoted as p_{adj}.

3. Results

3.1 Behavioral results

Figure 1 shows the proportion of correct responses (Figure 1b) as well as mean RTs (Figure 1c) separately for both age groups. Diffusion parameters are depicted in Figure 2. On

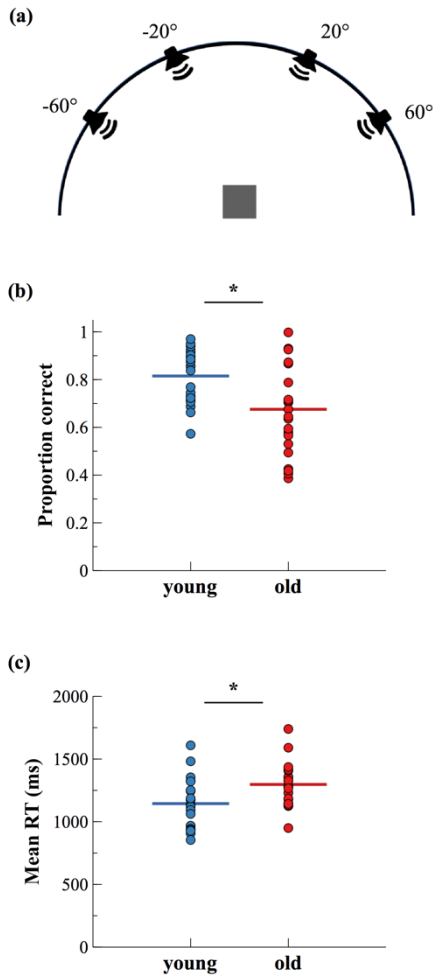

Figure 1. Correct responses and reaction times. (a) illustrates the arrangement of loudspeakers used for the task. The square indicates the subject's approximate position. (b) and (c) illustrate the proportion of correct responses and reaction times (RT), respectively.

average, younger adults showed higher accuracy ($t_{(43.05)}$ = -3.36, p = .002, p_{adj} = .01, g = 0.92) and faster responses than older adults ($t_{(38.56)}$ = 2.80, p = .008, p_{adj} = .038, g = -0.83). While mean RTs do not offer any insights into the underlying causes of prolonged response times, diffusion parameters allow for a closer look at different possible explanations for the observed difference between age groups, including a slowdown of information update (i.e., higher drift rate v), a more conservative response criterion (i.e., higher threshold separation a), or delayed response execution (i.e., higher response constant t_0). In our sample, older adults showed a significantly reduced drift rate ($t_{(44.89)}$= -2.51, p = .016, p_{adj} = .047, g = 0.70) as well as a higher non-decision time ($t_{(41.31)}$= 2.81, p = .008, p_{adj} = .038, g = -0.82), while threshold separation values did not differ between age groups ($t_{(44.24)}$ = -0.66, p = .513, p_{adj} = .513, g = 0.19). Younger and older adults did not differ in their trial-to-trial variability of drift rate (z = -1.21, p = .226, p_{adj} = .453, U3 = 0.29). The variability of non-decision time, however, was significantly higher for older adults ($t_{(40.26)}$ = 5.25, p < .001, p_{adj} < .001, g = -1.43). In order to graphically assess the fit of the estimated diffusion model, observed RT quartiles (.25, .5, .75) and observed accuracy were plotted against the corresponding value of the predicted distribution. As can be seen in Figure 3, the majority of data points lies close to the line of perfect correlation, indicating adequate model fit.

3.2 N2 anterior contralateral component

Figure 4 presents the event-related potentials at fronto-central electrodes FC3/4 and the corresponding topographies for left minus right target trials in the analysis time-window, separately for both age groups. N2ac amplitudes (i.e., contralateral minus ipsilateral difference) did not differ significantly between age groups ($t_{(44.20)}$ = - 0.59, p = .559, g = 0.17).

A one-sample t-test confirmed that across both age groups, N2ac amplitudes were significantly different from zero ($t_{(46)}$ = -6.20, p < .001, g_1 = -0.90).

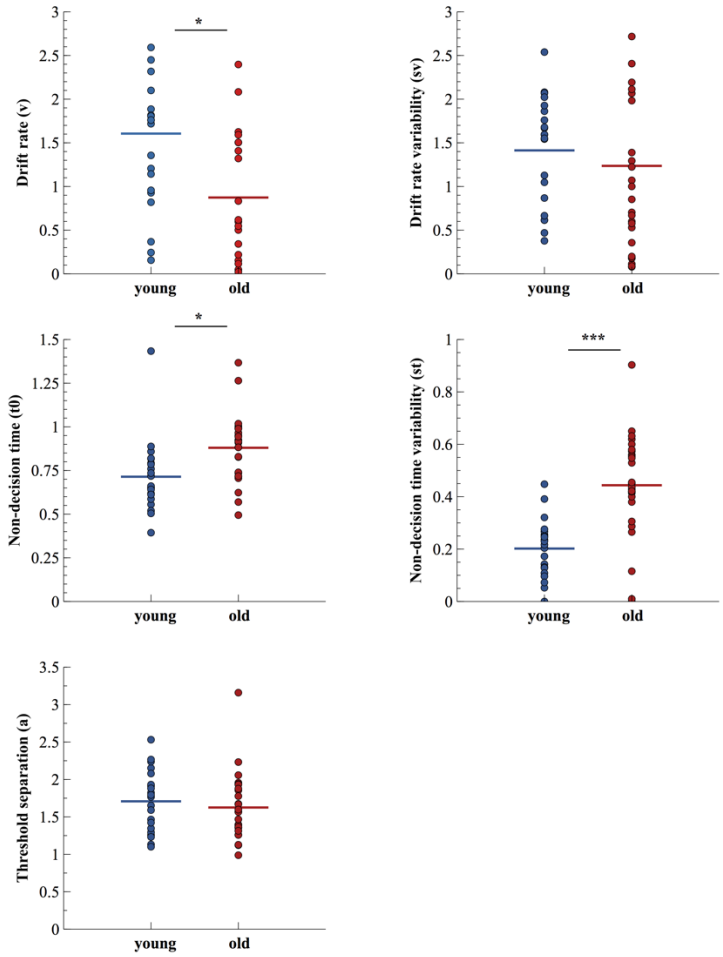

Figure 2. Diffusion model parameter estimates for younger and older participants. Dots represent single subject data. Colored horizontal lines show the mean model parameters within age groups. * p < .05, *** p < .001.

3.3 Alpha Lateralization

The time-frequency plot in figure 5 illustrates the asymmetric modulation of alpha power (8-12 Hz) at electrodes PO7/8 time-locked to sound-array onset, for younger (Figure 5a) and older adults (Figure 5b), respectively. In addition, the corresponding topographies of left minus right target trials are depicted. Although younger adults appeared to show larger alpha power lateralization than older adults, the analysis revealed no significant difference in alpha power lateralization between age groups ($t_{(41.23)}$ = -1.43, p = .161, g = 0.42). A one sample t-test confirmed that alpha lateralization across both age groups was significantly different from zero ($t_{(46)}$ = 6.07, p < .001, g_1 = 0.89).

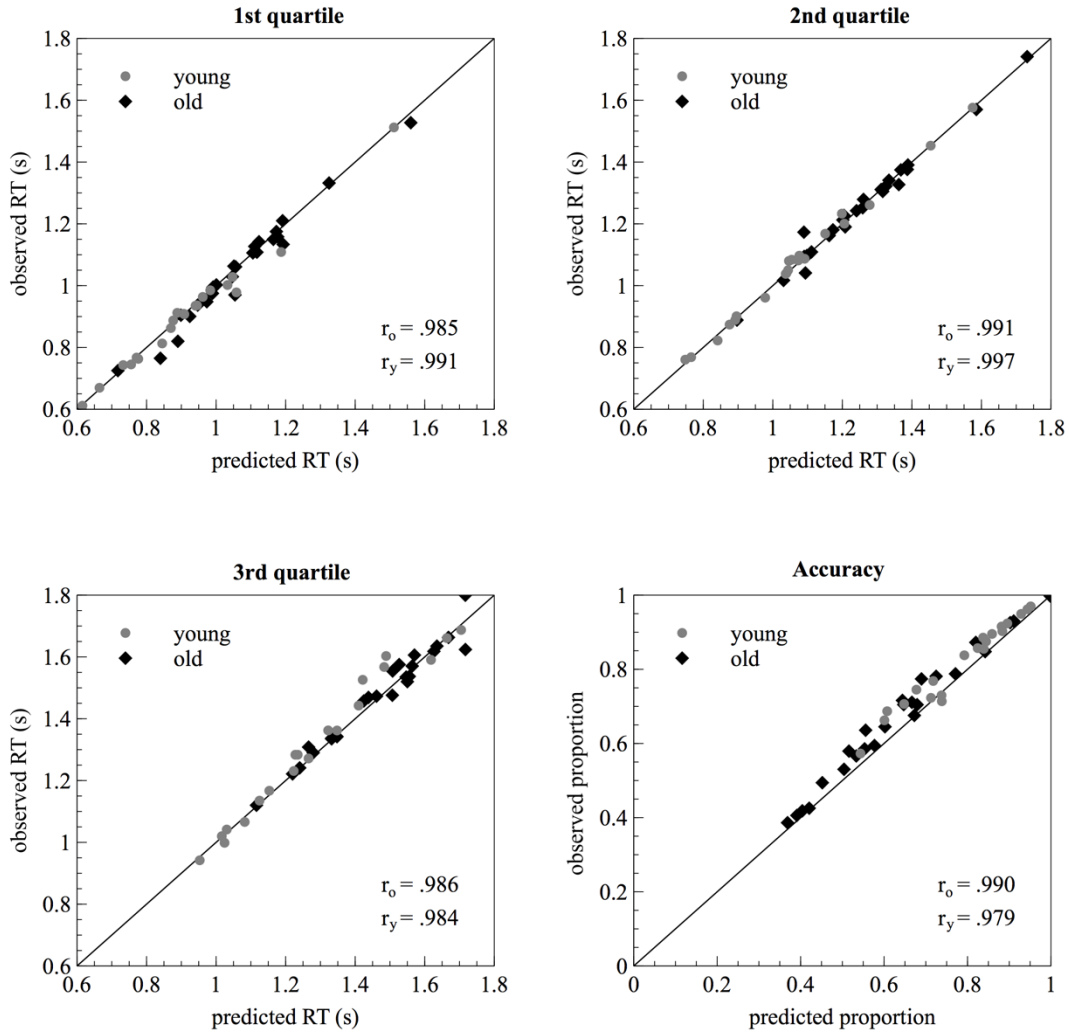

Figure 3. Graphical analysis of model fit. Scatter plots show the observed proportion of correct responses as well as the first three quartiles (.25, .5, .75) of the observed RT distribution as a function of the corresponding value from the predicted distribution. Dots and diamonds represent single subject data for younger and older participants, respectively. r_o and r_y indicate Pearson correlations between observed and predicted values for older and younger participants.

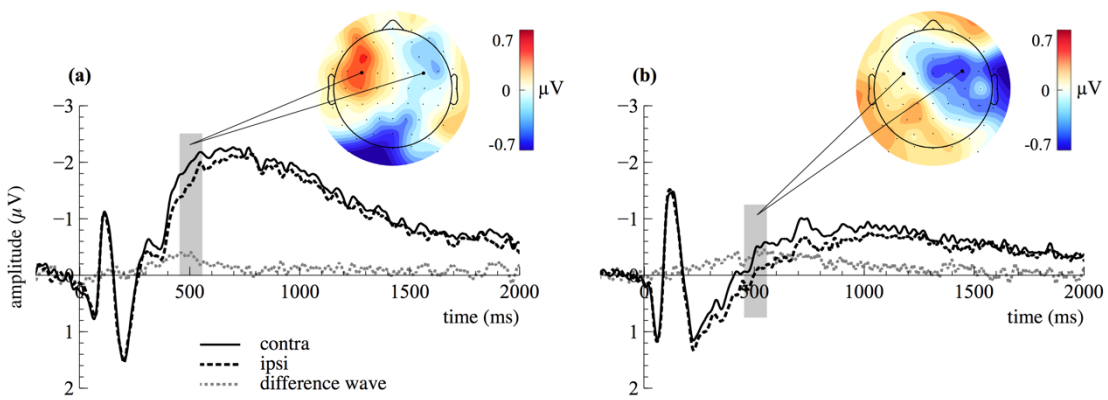

Figure 4. N2ac component at electrodes FC3/4 for younger (a) and older (b) participants. Contralateral and ipsilateral portions of the signal as well as the resulting difference wave (contralateral minus ipsilateral) are depicted. Scalp topographies show the distribution of voltage differences for left minus right target trials in the time window used for statistical analysis (highlighted in grey in ERP figures).

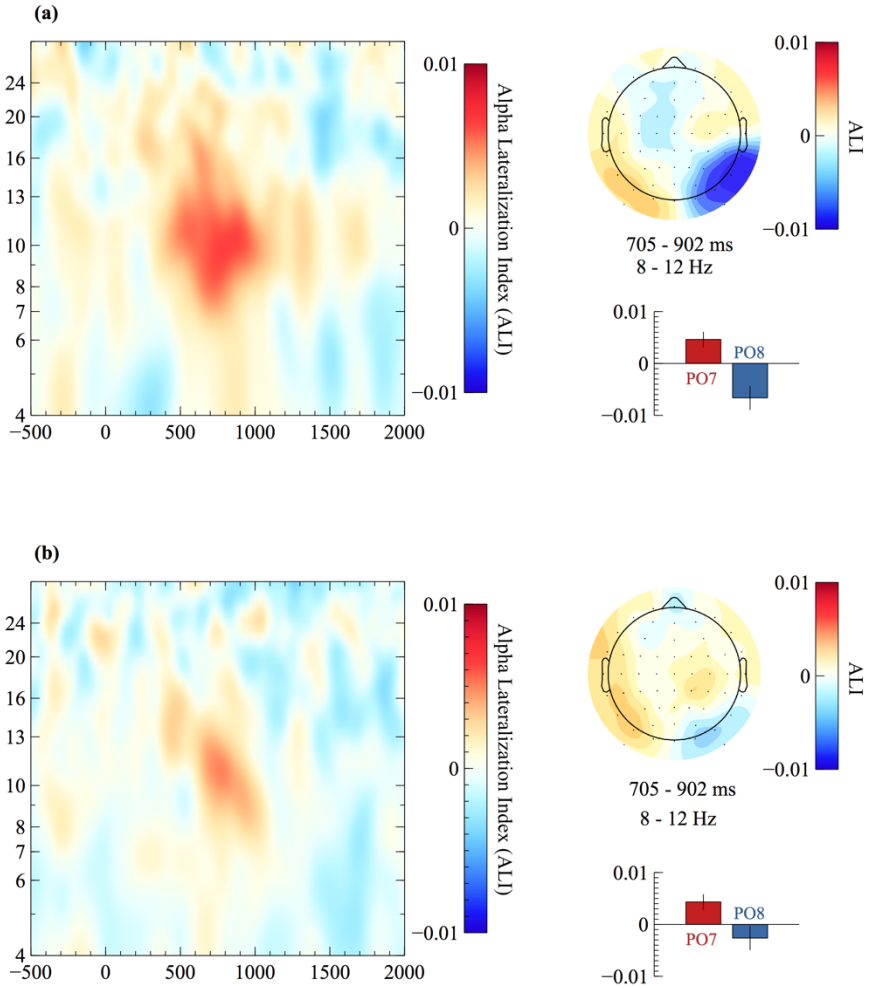

Figure 5. Grand average time-frequency plots of alpha lateralization indices (ALI) at electrodes PO7/8 (cf. left panel) for younger (a) and older (b) adults, respectively. The scalp topographies are based on normalized differences of left minus right target trials (i.e., left – right / left + right) in the time window used for statistical analysis. Bar graphs show the mean difference (left minus right) for the left (i.e., PO7) and right (i.e., PO8) hemisphere. Error bars indicate the standard error of the mean.

3.4 Linear Mixed Effects Models

We examined the relationship between mean alpha power lateralization, N2ac amplitudes, and behavioral performance (including diffusion model parameters) using linear mixed effects (LME) modeling. Fixed effect estimates from best-fitting models are presented in Table 1. LME analysis revealed that greater N2ac amplitudes were associated with higher accuracy ($F_{(1,45.17)} = 17.4$, $p < .001$, $p_{adj} = .001$) and higher drift rate ($F_{(1,45.35)} = 9.82$, $p = .003$, $p_{adj} = .027$), while there was no significant effect of alpha lateralization (accuracy: $F_{(1,45.51)} = 0.74$, $p = .40$, $p_{adj} = 1.98$; drift rate: $F_{(1,46.00)} = 0.01$, $p = .928$, $p_{adj} = 2.50$; note that using Bonferroni-Holm correction, p_{adj} can be greater than 1). For both models, the inclusion of a random intercept for age resulted in a significant improvement of model fit (accuracy: $\chi^2(1) = 9.16$, p

= .002; drift rate: $\chi^2(1) = 3.14$, $p = .003$]). The random intercept accounted for significant variance across age groups for accuracy (SD = 0.08, 95% CI [0.03, 0.23]) and drift rate (SD = 0.35, 95% CI [0.10, 1.28]). Adding random slopes for ALI and N2ac did not improve the model, neither for accuracy ($\chi^2(2) = -1.42 \times 10^{-14}$, $p = .36$), nor for drift rate ($\chi^2(2) = -2.84 \times 10^{-14}$, $p = .20$), suggesting a similar relationship for both younger and older adults. For all other models tested (cf. Table 1), neither N2ac amplitudes nor alpha power lateralization served as significant predictors. Figure 6 visualizes the reported results for those outcomes that were significantly predicted by N2ac amplitudes.

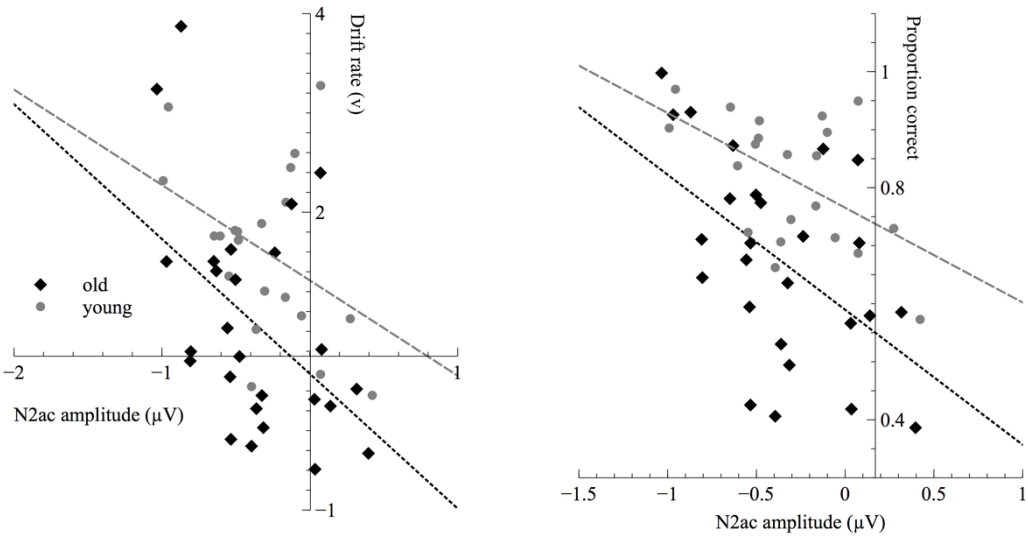

Figure 6. Single subjects' drift rate (a) and mean accuracy (b) as a function of mean N2ac amplitude. Circles represent younger subjects (n = 21), diamonds represent older subjects (n = 26). Short-dashed and long-dashed lines indicate regression lines for older and younger groups, respectively. For drift rate and accuracy, older and younger subjects showed comparable slopes, but different intercepts.

4. Discussion

In the present study, we investigated the contribution of post-stimulus alpha power lateralization and N2ac amplitudes to sound localization performance in a sample of younger and older adults. Both measures have been associated with the deployment of attention in auditory space. We hypothesized that if the cortical processes reflected by alpha lateralization and N2ac amplitudes contribute to successful target selection, their magnitudes should be related to the information accumulation process (i.e., drift rate; cf. diffusion model framework in *2.5.2*), and in turn to localization accuracy and RTs. In fact, what we found only partially confirmed this hypothesis. N2ac amplitudes significantly predicted both drift rate and accuracy, while alpha lateralization was not associated with any of the behavioral outcomes. This was true for both age groups that showed a comparable pattern of neural activity. The

Table 1. Fixed effects parameter estimates and confidence intervals from linear mixed effect models.

Outcome	**v**		**a**		**t_0**		**Accuracy**		**RT**	
Predictors	**b (*SE*)**	**95% CI**	**b (*SE*)**	**95% CI**	**b (*SE*)**	**95% CI**	**b (*SE*)**	**95% CI**	**b (SE)**	**95% CI**
N2ac	-1.17* (0.37)	-1.92, -0.42	-0.24 (0.17)	-0.58, 0.10	0.16 (0.08)	0.002, 0.31	-0.21** (0.05)	-0.32, -0.11	0.10 (0.07)	-0.04, 0.25
ALI	2.57 (28.33)	-54.53, 59.68	-2.65 (12.50)	-27.83, 22.54	5.90 (11.77)	-17.83, 29.62	-3.35 (3.91)	-11.23, 4.53	1.67 (5.49)	-9.39, 12.72
Model	v ~ 1 + N2ac + ALI + (1|age)		a ~ 1 + N2ac + ALI		t ~ 1 + N2ac + ALI + (1|age) + (ALI-1|age)		corr ~ 1 + N2ac + ALI + (1|age)		RT ~ 1 + N2ac + ALI + (1|age)	
Adjusted R^2	.21		< 0		.18		.36		.10	

Note. v, a, t0, and RT denote drift rate, threshold separation, non-decision time, and mean reaction times, respectively. *SE* = standard error, CI = confidence interval, corr = proportion of correct responses. Asterisks denote the significance of parameter estimates; * $p_{adj} < .05$, ** $p_{adj} < .01$.

results suggest that N2ac and alpha lateralization reflect distinct aspects of attentional orienting. In the following, we will discuss these findings in more details.

4.1 Diffusion modeling of sound-localization performance in older and younger adults

As expected, older adults showed fewer correct responses and slower response times than younger adults. This age difference in target localization under multi-speaker conditions is in line with the often-described difficulties of older people to follow a conversation in noisy ("cocktail-party") environments, which depends on the integrity of both sensory and cognitive functions (Shinn-Cunningham, 2017). Such a performance deficit in older adults has traditionally been interpreted as a result of a general sensory-cognitive decline (e.g., Pichora-Fuller et al., 2017). More specifically, a slowing effect has been proposed that assumes all aspects of processing in an experimental task to be globally slowed in aging adults (Myerson, Hale, Wagstaff, Poon, & Smith, 1990). The diffusion model allows to differentiate between different aspects of processing that might be affected by age (Ratcliff, Spieler, & Mckoon, 2000): In aging research, the diffusion model has been widely applied to assess age differences across a range of different tasks, such as recognition memory (Ratcliff, Thapar, & McKoon, 2004), associative memory (Ratcliff, Thapar, & McKoon, 2011), long-term-memory-retrieval (Spaniol, Madden, & Voss, 2006), brightness discrimination (Ratcliff, Thapar, & McKoon, 2003), and signal detection (Ratcliff et al., 2001). Across the majority of studies, older adults typically showed an increase in non-decision times and more conservative response criteria (i.e., higher threshold separation). However, the influence of aging on drift rate, that is, the quality of information that drives the evidence accumulation process, is less clear. Some studies find little or no effect of aging on drift rates (Ratcliff et al., 2004; Starns & Ratcliff, 2010, 2012), while others report decreased drift rates for older adults (Ratcliff et al., 2011; Spaniol et al., 2006; Thapar et al., 2003).

Consistent with previous results, we found an increase in non-decision time for older adults. In addition, older subjects varied more strongly in their non-decision time from trial to trial, indicating that this process was noisier in older adults (Spaniol et al., 2006). However, rather untypically, the two age groups did not differ in their threshold separation values. This contradicts the wide-spread assumption that older adults usually aim to minimize errors (leading to more conservative response criteria), while younger adults focus on balancing speed and accuracy (Starns & Ratcliff, 2010). The observed lack of differences in response criteria between older and younger adults could be due to the relatively long response period in the present study, potentially inducing a change in task goals in younger adults. Despite a

nonsignificant difference in boundary separation, the two age groups showed a clear difference in overall task accuracy. Consistently, accuracy has been shown to be relatively unaffected by boundary thresholds (Ratcliff et al., 2004, 2011). In turn, the age difference in task accuracy was consisted with the result that older adults showed smaller drift rates, resulting in higher error rates and slower response time. Hence, the observed difference in mean RTs hinges most likely on the differences in non-decision times and drift rates between the two age groups.

Supporting a line of evidence that shows differences in the rate of information accumulation in some contexts, our older adults showed significantly decreased drift rates. Given the current state of research, the conditions under which drift rate decreases with age are still hard to grasp. Ratcliff, Thapar, and McKoon (2011) were able to show that drift rate varied as a function of age and IQ, and that this relationship was largely different for an associative recognition task as opposed to an item recognition task. Similarly, a comparison of episodic and semantic long-term memory retrieval showed differential behavior of drift rates, depending on the task, suggesting that decreased drift rates in episodic retrieval reflect a deficit to process context details in older adults. In the current sound localization task, drift rate was significantly predicted by N2ac amplitudes. Subjects with higher N2ac amplitudes (i.e., more negative difference waves) showed higher drift rates, while subjects with lower N2ac amplitudes tended to have lower drift rates. This relationship was in general true for both older and younger adults, but shows that differences in drift rate may reflect the differences in the ability to extract relevant information from a perceptual scene (in this case, an array of concurrently presented sounds). The final section of the discussion will address this in more detail.

4.2 Preserved alpha lateralization in older adults

Typically, alpha lateralization manifests in a bilateral decrease of alpha power, that is more pronounced over the contralateral hemisphere (relative to a target or a cue). This spatially specific modulation of oscillatory activity has been repeatedly associated with the top-down controlled voluntary allocation of attention (Foxe, Simpson, & Ahlfors, 1998; Haegens et al., 2011; Ikkai et al., 2016; Thut et al., 2006). Here, we replicate this consistently observed response in the alpha frequency band in a sample of younger and older subjects who performed an auditory localization task, requiring them to indicate the location of a pre-defined target stimulus among three concordantly presented distractors. This preserved correlate of auditory spatial attention in older adults is in line with recent findings, suggesting

that some aspects of spatial attention remain intact or relatively unaffected in ageing populations (Madden, 2007; Mok et al., 2016; Nissen & Corkin, 1985; see Zanto & Gazzaley, 2014, for a comprehensive review). The literature on alpha lateralization, however, presents a rather unambiguous picture: A number of studies has shown a lack or a reduction of alpha lateralization in older adults in the presence of preserved behavioral performance (Hong et al., 2015; Leenders, Lozano-Soldevilla, Roberts, Jensen, & De Weerd, 2018; van der Waal, Farquhar, Fasotti, & Desain, 2017), arguing that tasks involving the deployment of spatial attention might not exclusively rely on mechanisms of alpha lateralization. In contrast, similar to our findings, other studies reported intact alpha power lateralization in older adults (Heideman et al., 2018; Leenders et al., 2018; Mok et al., 2016; Tune et al., 2018). A closer look reveals that a simple all-or-nothing principle does not seem to apply to the question of whether or not the dynamics of alpha lateralization change with age. Sander, Werkle-Bergner, and Lindenberger (2012) showed that task difficulty affected the magnitude of alpha lateralization, with older adults showing most pronounced alpha lateralization under intermediate difficulty conditions that the authors described as "challenging, but not overtaxed". In fact, the task demands in the above cited studies varied considerably. For instance, van der Waal et al. (2017) chose a relatively easy task in which subjects were instructed to count the number of red squares that they had observed on the previously cued side of an alternating stimulus array. Heideman et al. (2018) as well as Leenders et al. (2018) specifically adjusted their paradigm for both groups of participants to achieve a comparable or predefined level of performance, thereby, also modulating task difficulty on an inter-individual level. Thus, task difficulty or more generally attentional task demands could be a potential factor that reconciles the different findings on alpha lateralization in samples of older adults. A further factor that might come into play is the level on which attentional orienting takes places. For instance, Leenders et al. (2018) found preserved alpha lateralization in anticipation of an upcoming lateralized memory array; in contrast, there was no lateralization in the delay period following the stimulus display, as it is typically observed in younger adults (Sauseng et al., 2009; Schroeder, Ball, & Busch, 2018). Our paradigm illustrates alpha lateralization in yet a different context, that is, searching for a predefined target among simultaneously presented distractor sounds. It is important to note that this situation is inherently different from shifts of attention in response to a spatial cue, as in the majority of studies cited above. In addition, a direct comparison to most previous studies might be difficult, as they focus on visual attentional processes.

Taken together, our results suggest that older adults may in principle be able to recruit the same oscillatory mechanisms as younger adults when searching for a target among simultaneously present distractors (Klatt et al., 2018b). This finding of preserved post-stimulus alpha lateralization corroborates a number of studies, showing intact alpha lateralization in older adults when anticipating an upcoming (lateralized) stimulus (Heideman et al., 2018; Leenders et al., 2018; Tune et al., 2018). Yet, recent studies reported no alpha lateralization in older adults, although they were still able to perform the task as good as their younger counterparts (Hong et al., 2015; van der Waal et al., 2017). This poses the question to what extent lateralized alpha dynamics are functionally relevant for behavior.

4.3 Is alpha power lateralization functionally relevant?

It is undisputed that alpha power lateralization tracks the locus and timing of spatial attention (Bae & Luck, 2018; Foster et al., 2017; Samaha, Iemi, & Postle, 2017). In addition, a growing body of evidence supports the notion that the alpha rhythm as a correlate of spatial attention, so far predominantly investigated in the visual attention literature, analogously operates in different modalities (Haegens et al., 2011; Klatt et al., 2018a, 2018b; Thorpe, D'Zmura, & Srinivasan, 2012; Wöstmann et al., 2016, 2018). Yet, what remains a matter of debate is, *how* alpha power lateralization aids selective spatial attention and whether it reflects a necessary prerequisite for successful behavioral performance. Regarding the *how*, two prevailing views exist: The gating by inhibition theory, proposed by Jensen and Mazaheri (2010), suggested that the relative increase of alpha power over the ipsilateral hemisphere inhibits regions processing irrelevant information. Alternatively, it has been suggested that the relative decrease of alpha power over the contralateral hemisphere results in increased cortical excitability, allowing for enhanced processing of the targets (Noonan et al., 2016; Yamagishi et al., 2005). Both mechanisms are not necessarily mutually exclusive. In fact, Foster and Awh (2018) just recently pointed out that a lot of the empirical evidence is compatible with either the target enhancement or the distractor suppression account. Recent evidence suggested that both mechanisms might independently contribute to attentional orienting (Schneider et al., 2019). In line with those latter findings, Capilla, Schoffelen, Paterson, Thut, and Gross (2014) proposed distinct sources and behavioral correlates for the ipsilateral and contralateral portion of the alpha power signal. Somewhat surprisingly, using linear mixed modeling, we found no relationship between alpha lateralization and accuracy, RTs, or any of the diffusion model parameters (i.e., drift rate, threshold separation, or non-decision time).

Contrary to a range of spatial-cueing studies investigating the anticipatory modulation of alpha oscillations (Haegens et al., 2011; Kelly et al., 2009; Thut et al., 2006; Wöstmann et al., 2018), the current findings question the notion that alpha power lateralization reflects a behaviorally relevant attentional mechanism. However, as emphasized above, the present study differed from the majority of previous studies in that it investigated alpha power modulations following stimulus presentation. Thus, while alpha lateralization may in fact be necessary to successfully shift one's attention *in anticipation of* an upcoming stimulus, it does not appear to be a required neural response in the attentional processing *following* the presentation of a multi-sound array. This is in line with the proposal previously made by van Ede et al. (2014), who similarly concluded that the relevance of attentional modulations might be "restricted to situations in which attention influences perception through anticipatory processes" (p. 139). However, in contrast to our results, these authors found that alpha lateralization was completely abolished during the processing of an ongoing tactile stimulus.

Alternatively, the lack of a relationship with behavioral performance may be due to the fact that we calculated a relative measure of alpha amplitudes, that is, the difference between contralateral and ipsilateral alpha power. In a cued somatosensory detection task, van Ede et al. (2012) found only contralateral alpha power amplitudes to be related to tactile detection performance, whereas fluctuations in the contralateral minus ipsilateral difference failed to predict performance. Similarly, other studies using a relative index of alpha power modulations did not find a strong relationship with behavioral performance (Limbach & Corballis, 2017; Tune et al., 2018). These findings, or rather null-findings, might strengthen the emerging view that both target enhancement (i.e., contralateral alpha power decrease) and distractor suppression (i.e., ipsilateral alpha power increase) differentially contribute to task performance (Schneider et al., 2019) and that this should be taken into account when analyzing the contribution of alpha power oscillations to behavior. Yet, it should be noted that there are studies that successfully show an effect of the relative strength of alpha lateralization on task performance (Haegens et al., 2011; Kelly et al., 2009), suggesting the reasons for those diverging results are likely to be more complex than just a methodological artifact.

Critically, one question remains unanswered: If alpha lateralization is not a necessary component of post-stimulus attentional processing in an auditory scene, what does it reflect? It might be that post-stimulus alpha lateralization is an "optional response" that may result in more effective target enhancement or distractor inhibition, when a specific strategy is applied. Hence, due to different strategies used by different subjects, there might be no overall relationship between alpha lateralization and behavior when analyzed across all subjects

(Limbach & Corballis, 2017; Rihs, Michel, & Thut, 2009). Alternatively, as shown in a previous study using a very similar task design, auditory post-stimulus alpha lateralization might be more closely related to the spatial-specificity of the task (Klatt et al., 2018b). In the latter study, a lateralization of alpha power was only evident when participants were instructed to localize (instead of to simply detect) a target sound within a multi-sound array. Hence, we proposed that in post-stimulus attentional processing, the lateralization of alpha power indexes the access to a spatiotopic template that is used to generate a spatially-specific response (Klatt et al., 2018b). If alpha lateralization reflects such a process, amplitude would not necessarily be expected to be related to differences in behavioral performance, as even for an incorrect response, subjects would access such a spatial template when generating the false, but still spatially-specific response.

4.4 N2ac amplitudes predict drift rate and accuracy for older and younger adults

Similar to the observed alpha power modulations, N2ac amplitudes were comparable across age groups. To our best knowledge, this is the first study to show an N2ac component in a sample of older adults. Again, this shows that the general capacity to spatially shift attention appears to remain intact in older adults. To date, little is known about the functional relevance of the N2ac component. The linear mixed modeling analysis conducted here revealed that N2ac amplitudes significantly predicted variations in accuracy as well as drift rate, while they were unrelated to mean RTs, threshold separation, or non-decision time. This relationship was true for both older and younger adults. These findings add to the sparse literature that has investigated the N2ac component in different contexts (Gamble & Luck, 2011; Gamble & Woldorff, 2015; Gamble & Woldorff, 2015; Klatt et al., 2018b; Lewald & Getzmann, 2015; Lewald et al., 2016). Gamble and Luck (2011) originally proposed that the N2ac arises in order to resolve the competition between simultaneously present stimuli and reflects the attentional orienting towards a target. They further elucidated that this may be based on the biasing of neural coding towards the attended stimulus, as observed in the visual modality. In fact, the observed relationship of N2ac amplitudes and drift rate may undergird this line of reasoning: Drift rate conceptually reflects the quality of relevant information derived from sensory input that eventually drives the decision process (Ratcliff et al., 2000). Hence, the better participants may be able to resolve competition between concurrent sounds by focusing on the target (i.e., N2ac amplitude), the better the quality of information that prompts participants to make a decision (i.e., drift rate; or in other words, the higher the rate

of evidence accumulation in favor of a given response). In turn, it logically follows that the better or more consistently participants are able to focus their attention onto a relevant target sound (i.e., N2ac amplitude), the higher their overall accuracy.

However, if lower N2ac amplitudes result in lower drift rates and decreased performance, why did older adults not show reduced N2ac amplitudes? First of all, it needs to be emphasized that the random intercept for age in both models accounts for differences in drift rate and accuracy between age groups. Within age groups, however, the same linear relationship between N2ac amplitudes and accuracy or drift rate, emerged, as visualized by the separate, but parallel regression lines (i.e., identical slope) for younger and older adults (cf. Figure 6). Hence, the variance within age groups appears to stronger contribute to the observed relationship than the variance between age groups. The same magnitude of N2ac components in older adults may reflect the failure to or the attempt to compensate for general age-related cognitive decline through the recruitment of additional top-down resources that would allow for more efficient target selection.

5. Conclusion

In this study, we investigated the relationship between neural correlates of attentional orienting to behavioral performance in a sample of younger and older adults, performing a sound localization task. Both younger and older adults showed comparable neural correlates of attentional orienting when localizing a sound among concurrently presented distractors, with similar amplitudes of alpha power lateralization and the N2ac component. For both groups, fluctuations in N2ac amplitude predicted the rate of information accumulation (i.e., drift rate) as well as overall accuracy. We conclude that the N2ac component reflected the participants' ability to resolve competition between co-occurring sounds by focusing on the target. This, in turn, determined the quality of the information accumulated during the decision-making process and thereby affected overall accuracy levels. In contrast, alpha lateralization was unrelated to behavioral performance. We propose that successful attentional orienting within an auditory scene (as opposed to in anticipation of an upcoming target sound), does not rely on alpha lateralization. Instead, based on previous work (Klatt et al., 2018), we suggest that post-stimulus alpha lateralization may reflect the access to spatiotopic representations of the previously encoded sound array, that serves to generate a spatially-specific response. Our findings strengthen the proposal that alpha lateralization is not specific to the visual domain, but may reflect a supramodal attentional mechanism that generalizes to

the auditory domain (Kerlin, Shahin, & Miller, 2010; Thorpe et al., 2012). Yet, we highlight that it is important to distinguish between cue-related, anticipatory modulations of alpha power and post-stimulus alpha power lateralization.

Acknowledgements

The authors are grateful to David Schmude, Jonas Heyermann, Stefan Weber, and Michael-Christian Schlüter for their help in running the experiments and to Peter Dillmann and Tobias Blanke for preparing software and parts of the electronic equipment. This work was supported by the German Federal Ministry of Education and Research in the framework of the TRAIN-STIM project (grant number 01GQ1424E).

Declarations of interest: None.

References

Bae, G.-Y., & Luck, S. J. (2018). Dissociable Decoding of Spatial Attention and Working Memory from EEG Oscillations and Sustained Potentials. *The Journal of Neuroscience*, *38*(2), 409–422. http://doi.org/10.1523/JNEUROSCI.2860-17.2017

Bronkhorst, A. W. (2015). The cocktail-party problem revisited: early processing and selection of multi-talker speech. *Attention, Perception, and Psychophysics*, *77*(5), 1465–1487. http://doi.org/10.3758/s13414-015-0882-9

Capilla, A., Schoffelen, J. M., Paterson, G., Thut, G., & Gross, J. (2014). Dissociated α-band modulations in the dorsal and ventral visual pathways in visuospatial attention and perception. *Cerebral Cortex*, *24*(2), 550–561. http://doi.org/10.1093/cercor/bhs343

Cherry, C. E. (1953). Some Experiments on the Recognition of Speech, with One and with Two Ears. *The Journal of the Acoustical Society of America*, *25*(5), 975–979. http://doi.org/10.1121/1.1907229

Craddock, M., Poliakoff, E., El-deredy, W., Klepousniotou, E., & Lloyd, D. M. (2017). Pre-stimulus alpha oscillations over somatosensory cortex predict tactile misperceptions. *Neuropsychologia*, *96*(September 2016), 9–18. http://doi.org/10.1016/j.neuropsychologia.2016.12.030

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(2004), 9–21. http://doi.org/10.1016/j.jneumeth.2003.10.009

Eimer, M. (1996). The N2pc component as an indicator of attentional selectivity. *Electroencephalography and Clinical Neurophysiology*, *99*(3), 225–234. http://doi.org/10.1016/S0921-884X(96)95711-2

Foster, J. J., & Awh, E. (2018). The role of alpha oscillations in spatial attention: Limited evidence for a suppression account. *Current Opinion in Psychology*, *29*, 34–40. http://doi.org/10.1016/J.COPSYC.2018.11.001

Foster, J. J., Sutterer, D. W., Serences, J. T., Vogel, E. K., & Awh, E. (2017). Alpha-band oscillations enable spatially and temporally resolved tracking of covert spatial attention. *Psychological Science*, *28*(7), 929–941. http://doi.org/10.1177/0956797617699167

Foxe, J. J., Simpson, G. V., & Ahlfors, S. P. (1998). Parieto-occipital ~10 Hz activity reflects anticipatory state of visual attention mechanisms. *NeuroReport*, *9*(17), 3929–3933. http://doi.org/10.1097/00001756-199812010-00030

Gamble, M. L., & Luck, S. J. (2011). N2ac: An ERP Component Associated with the Focusing of Attention Within an Auditory Scene. *Psychophysiology*, *48*(8), 1057–1068. http://doi.org/10.1111/j.1469-8986.2010.01172.x

Gamble, M. L., & Woldorff, M. G. (2015a). Rapid context-based identification of target sounds in an auditory scene. *Journal of Cognitive Neuroscience*, *27*(9), 1675–1684. http://doi.org/10.1162/jocn_a_00814

Gamble, M. L., & Woldorff, M. G. (2015b). The temporal cascade of neural processes underlying target detection and attentional processing during auditory search. *Cerebral Cortex*, *25*(9), 2456–2465. http://doi.org/10.1093/cercor/bhu047

Getzmann, S., Hanenberg, C., & Lewald, J. (2018). Improving auditory spatial attention by non-invasive brain stimulation and training. In *Cognitive Neuroscience Society. 25th Annual Meeting* (p. 62). Boston, MA, USA.

Gould, I. C., Rushworth, M. F., & Nobre, A. C. (2011). Indexing the graded allocation of visuospatial attention using anticipatory alpha oscillations. *Journal of Neurophysiology*, *105*, 1318–1326. http://doi.org/10.1152/jn.00653.2010.

Haegens, S., Handel, B. F., & Jensen, O. (2011). Top-Down Controlled Alpha Band Activity in Somatosensory Areas Determines Behavioral Performance in a Discrimination Task. *Journal of Neuroscience*, *31*(14), 5197–5204. http://doi.org/10.1523/JNEUROSCI.5199-10.2011

Haegens, S., Luther, L., & Jensen, O. (2012). Somatosensory anticipatory alpha activity increases to suppress distracting input. *Journal of Cognitive Neuroscience*, *24*(3), 677–685. http://doi.org/10.1162/jocn_a_00164

Händel, B. F., Haarmeier, T., & Jensen, O. (2011). Alpha oscillations correlate with the successful inhibition of unattended stimuli. *Journal of Cognitive Neuroscience*, *23*(9), 2494–2502. http://doi.org/10.1162/jocn.2010.21557

Hansen, J. C., & Hillyard, S. A. (1980). Endogeneous brain potentials associated with selective auditory attention. *Electroencephalography and Clinical Neurophysiology*, *49*(3–4), 277–290. http://doi.org/10.1016/0013-4694(80)90222-9

Heideman, S. G., Rohenkohl, G., Chauvin, J. J., Palmer, C. E., van Ede, F., & Nobre, A. C. (2018). Anticipatory neural dynamics of spatial-temporal orienting of attention in younger and older adults. *NeuroImage*, *178*(March), 46–56. http://doi.org/10.1016/j.neuroimage.2018.05.002

Hentschke, H., & Stüttgen, M. C. (2011). Computation of measures of effect size for neuroscience data sets. *European Journal of Neuroscience*, *34*(July), 1887–1894. http://doi.org/10.1111/j.1460-9568.2011.07902.x

Holm, S. (1979). A Simple Sequentially Rejective Multiple Test Procedure. *Scandinavian Journal of Statistics*, *6*(2), 65–70.

Hong, X., Sun, J., Bengson, J. J., Mangun, G. R., & Tong, S. (2015). Normal aging selectively diminishes alpha lateralization in visual spatial attention. *NeuroImage*, *106*, 353–363. http://doi.org/10.1016/j.neuroimage.2014.11.019

Ikkai, A., Dandekar, S., & Curtis, C. E. (2016). Lateralization in alpha-band oscillations predicts the locus and spatial distribution of attention. *PloS One*, *11*(5), e0154796. http://doi.org/10.1371/journal.pone.0154796

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in Human Neuroscience*, *4*, 186. http://doi.org/10.3389/fnhum.2010.00186

Kelly, S. P., Gomez-Ramirez, M., & Foxe, J. J. (2009). The strength of anticipatory spatial biasing predicts target discrimination at attended locations: A high-density EEG study.

European Journal of Neuroscience, *30*(11), 2224–2234. http://doi.org/10.1111/j.1460-9568.2009.06980.x
Kelly, S. P., Lalor, E. C., Reilly, R. B., & Foxe, J. J. (2006). Increases in Alpha Oscillatory Power Reflect an Active Retinotopic Mechanism for Distracter Suppression During Sustained Visuospatial Attention. *Journal of Neurophysiology*, *95*(6), 3844–3851. http://doi.org/10.1152/jn.01234.2005
Kerlin, J. R., Shahin, A. J., & Miller, L. M. (2010). Attention gain control of ongoing cortical speech representations in a "cocktail party." *Journal of Neuroscience*, *30*(2), 620–628. http://doi.org/10.1523/JNEUROSCI.3631-09.2010.
Klatt, L. I., Getzmann, S., Wascher, E., & Schneider, D. (2018a). Searching for auditory targets in external space and in working memory: Electrophysiological mechanisms underlying perceptual and retroactive spatial attention. *Behavioural Brain Research*, *353*, 98–107. http://doi.org/10.1016/j.bbr.2018.06.022
Klatt, L. I., Getzmann, S., Wascher, E., & Schneider, D. (2018b). The contribution of selective spatial attention to sound detection and sound localization: Evidence from event-related potentials and lateralized alpha oscillations. *Biological Psychology*, *138*, 133–145. http://doi.org/10.1016/j.biopsycho.2018.08.019
Leenders, M. P., Lozano-Soldevilla, D., Roberts, M. J., Jensen, O., & De Weerd, P. (2018). Diminished alpha lateralization during working memory but not during attentional cueing in older adults. *Cerebral Cortex*, *28*(1), 21–32. http://doi.org/10.1093/cercor/bhw345
Lewald, J. (2016). Modulation of human auditory spatial scene analysis by transcranial direct current stimulation. *Neuropsychologia*, *84*, 282–293. http://doi.org/10.1016/j.neuropsychologia.2016.01.030
Lewald, J. (2019). Bihemispheric anodal transcranial direct-current stimulation over temporal cortex enhances auditory selective spatial attention. *Experimental Brain Research*, 1–11. http://doi.org/10.1007/s00221-019-05525-y
Lewald, J., & Getzmann, S. (2015). Electrophysiological correlates of cocktail-party listening. *Behavioural Brain Research*, *292*, 157–166. http://doi.org/10.1016/j.bbr.2015.06.025
Lewald, J., Hanenberg, C., & Getzmann, S. (2016). Brain correlates of the orientation of auditory spatial attention onto speaker location in a "cocktail-party" situation. *Psychophysiology*, *53*, 1484–1495. http://doi.org/10.1111/psyp.12692
Lilliefors, H. W. (1967). On the Kolmogorov-Smirnov Test for Normality with Mean and Variance Unknown Hubert W. Lilliefors. *Journal of the American Statistical Association*, *62*(318), 399–402.
Limbach, K., & Corballis, P. M. (2017). Alpha-power modulation reflects the balancing of task requirements in a selective attention task. *Psychophysiology*, *54*(2), 224–234. http://doi.org/10.1111/psyp.12774
Luck, S. J. (2014). *An introduction to the event-related potential technique* (2nd ed.). MIT Press.
Luck, S. J., & Hillyard, S. A. (1994). Spatial Filtering During Visual Search: Evidence from Human Electrophysiology. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(5), 1000–1014.
Luke, S. G. (2017). Evaluating significance in linear mixed-effects models in R. *Behavior Research Methods*, *49*(4), 1494–1502. http://doi.org/10.3758/s13428-016-0809-y
Madden, D. J. (2007). Aging and visual attention. *Current Directions in Psychological Science*, *16*(2), 70–74. http://doi.org/10.1111/j.1467-8721.2007.00478.x
Mognon, A., Jovicich, J., Bruzzone, L., & Buiatti, M. (2011). ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features. *Psychphysiology*, *48*, 229–240. http://doi.org/10.1111/j.1469-8986.2010.01061.x
Mok, R. M., Myers, N. E., Wallis, G., & Nobre, A. C. (2016). Behavioral and neural markers

of flexible attention over working memory in aging. *Cerebral Cortex*, *26*(4), 1831–1842. http://doi.org/10.1093/cercor/bhw011
Myers, N. E., Walther, L., Wallis, G., Stokes, M. G., & Nobre, A. C. (2015). Temporal dynamics of attention during encoding vs. maintenance of working memory: complementary views from event-related potentials and alpha-band oscillations. *Journal of Cognitive Neuroscience*, *27*(3), 492–508. http://doi.org/10.1162/jocn_a_00727
Myerson, J., Hale, S., Wagstaff, D., Poon, L. W., & Smith, G. A. (1990). The information-loss model: A mathematical theory of age-related cognitive slowing. *Psychological Review*, *97*(4), 475–487. http://doi.org/10.1037//0033-295x.97.4.475
Nissen, M. J., & Corkin, S. (1985). Effectiveness of attentional cueing in older and younger adults. *Journals of Gerontology*, *40*(2), 185–191. http://doi.org/10.1093/geronj/40.2.185
Noonan, M. P., Adamian, N., Pike, X. A., Printzlau, F., Crittenden, B. M., & Stokes, M. G. (2016). Distinct Mechanisms for Distractor Suppression and Target Facilitation. *The Journal of Neuroscience*, *36*(6), 1797–1807. http://doi.org/10.1523/JNEUROSCI.2133-15.2016
Nunez, M. D., Vandekerckhove, J., & Srinivasan, R. (2017). How attention influences perceptual decision making: Single-trial EEG correlates of drift-diffusion model parameters. *Journal of Mathematical Psychology*, *76*, 117–130. http://doi.org/10.1016/j.jmp.2016.03.003
Oldfield, R. C. (1971). The assessment and analysis of handedness: the Edinburgh inventory. *Neuropsychologia*, *9*, 97–113. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/5146491
Onton, J., & Makeig, S. (2006). Information-based modeling of event-related brain dynamics. In C. Neuper & W. Klimesch (Eds.), *Progress in Brain Research* (Vol. 159, pp. 99–120). Elsevier B.V. http://doi.org/10.1016/S0079-6123(06)59007-7
Philiastides, M. G., Ratcliff, R., & Sajda, P. (2006). Neural Representation of Task Difficulty and Decision Making during Perceptual Categorization: A Timing Diagram. *The Journal of Neuroscience*, *26*(35), 8965–8975. http://doi.org/10.1523/JNEUROSCI.1655-06.2006
Pichora-Fuller, M. K., Alain, C., & Schneider, B. A. (2017). Older Adults at the Cocktail Party. In R. F. J. Middlebrooks, J. Simon, A. Popper (Ed.), *The Auditory System at the Cocktail Party* (Vol. 60, pp. 227–259). Cham: Springer. http://doi.org/10.1007/978-3-319-51662-2_9
Ratcliff, R., & McKoon, G. (2008). The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks. *Neural Computation*, *20*(4), 873–922. http://doi.org/10.1162/neco.2008.12-06-420
Ratcliff, R., Philiastides, M. G., & Sajda, P. (2009). Quality of evidence for perceptual decision making is indexed by trial-to-trial variability of the EEG. *Proceedings of the National Academy of Sciences*, *106*(16), 6539–6544. http://doi.org/10.1073/pnas.0812589106
Ratcliff, R., Spieler, D., & Mckoon, G. (2000). Explicitly modeling the effects of aging on response time. *Psychonomic Bulletin and Review*, *7*(1), 1–25. http://doi.org/10.3758/BF03210723
Ratcliff, R., Thapar, A., & McKoon, G. (2001). The Effects of Aging on Reaction Time in a Signal Detection Task. *Psychology and Aging*, *16*(2), 323–341. http://doi.org/10.1037/0882-7974.16.2.323
Ratcliff, R., Thapar, A., & McKoon, G. (2003). A diffusion model analysis of the effects of aging on brightness discrimination. *Perception & Psychophysics*, *65*(4), 523–535. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=2004-14390-004&site=ehost-live&scope=site
Ratcliff, R., Thapar, A., & McKoon, G. (2004). A diffusion model analysis of the effects of

aging on recognition memory. *Journal of Memory and Language*, *50*(4), 408–424. http://doi.org/10.1016/j.jml.2003.11.002
Ratcliff, R., Thapar, A., & McKoon, G. (2011). The effects of aging and IQ on item and associative memory. *Journal of Experimental Psychology. General*, *140*(3), 464–487. http://doi.org/10.1158/0008-5472.CAN-10-4002.BONE
Rihs, T. A., Michel, C. M., & Thut, G. (2007). Mechanisms of selective inhibition in visual spatial attention are indexed by α-band EEG synchronization. *European Journal of Neuroscience*, *25*, 603–610. http://doi.org/10.1111/j.1460-9568.2007.05278.x
Rihs, T. A., Michel, C. M., & Thut, G. (2009). A bias for posterior α-band power suppression versus enhancement during shifting versus maintenance of spatial attention. *NeuroImage*, *44*(1), 190–199. http://doi.org/10.1016/j.neuroimage.2008.08.022
Romei, V., Gross, J., & Thut, G. (2010). On the Role of Prestimulus Alpha Rhythms over Occipito-Parietal Areas in Visual Input Regulation: Correlation or Causation? *Journal of Neuroscience*, *30*(25), 8692–8697. http://doi.org/10.1523/JNEUROSCI.0160-10.2010
Samaha, J., Iemi, L., & Postle, B. R. (2017). Prestimulus alpha-band power biases visual discrimination confidence, but not accuracy. *Consciousness and Cognition*, *54*, 47–55. http://doi.org/10.1016/j.concog.2017.02.005
Sander, M. C., Werkle-Bergner, M., & Lindenberger, U. (2012). Amplitude modulations and inter-trial phase stability of alpha-oscillations differentially reflect working memory constraints across the lifespan. *NeuroImage*, *59*(1), 646–654. http://doi.org/10.1016/j.neuroimage.2011.06.092
Sauseng, P., Klimesch, W., Heise, K. F., Gruber, W. R., Holz, E., Karim, A. A., … Hummel, F. C. (2009). Brain Oscillatory Substrates of Visual Short-Term Memory Capacity. *Current Biology*, *19*(21), 1846–1852. http://doi.org/10.1016/j.cub.2009.08.062
Sauseng, P., Klimesch, W., Stadler, W., Schabus, M., Doppelmayr, M., Hanslmayr, S., … Birbaumer, N. (2005). A shift of visual spatial attention is selectively associated with human EEG alpha activity. *European Journal of Neuroscience*, *22*(11), 2917–2926. http://doi.org/10.1111/j.1460-9568.2005....Log
Schmiedek, F., Oberauer, K., Wilhelm, O., Süß, H. M., & Wittmann, W. W. (2007). Individual Differences in Components of Reaction Time Distributions and Their Relations to Working Memory and Intelligence. *Journal of Experimental Psychology: General*, *136*(3), 414–429. http://doi.org/10.1037/0096-3445.136.3.414
Schneider, D., Göddertz, A., Haase, H., Hickey, C., & Wascher, E. (2019). Hemispheric asymmetries in EEG alpha oscillations indicate active inhibition during attentional orienting within working. *Behavioural Brain Research*, *359*, 38–46. http://doi.org/10.1016/j.bbr.2018.10.020
Schroeder, S. C. Y., Ball, F., & Busch, N. A. (2018). The role of alpha oscillations in distractor inhibition during memory retention. *European Journal of Neuroscience*, *48*(July 2017), 2516–2526. http://doi.org/10.1111/ejn.13852
Schubert, A.-L., Hagemann, D., Voss, A., Schankin, A., & Bergmann, K. (2015). Decomposing the relationship between mental speed and mental abilities. *Intelligence*, *51*, 28–46. http://doi.org/10.1016/j.intell.2015.05.002
Schubert, A.-L., Nunez, M. D., Hagemann, D., & Vandekerckhove, J. (2018). Individual Differences in Cortical Processing Speed Predict Cognitive Abilities: a Model-Based Cognitive Neuroscience Account. *Computational Brain & Behavior*, 1–21. http://doi.org/10.1007/s42113-018-0021-5
Shinn-Cunningham, B. (2017). Cortical and Sensory Causes of Individual Differences in Selective Attention Ability Among Listeners With Normal Hearing Thresholds. *Journal of Speech, Language, and Hearing Research*, *60*(10), 2976–2988. http://doi.org/10.1044/2017_jslhr-h-17-0080
Spaniol, J., Madden, D. J., & Voss, A. (2006). A Diffusion Model Analysis of Adult Age

Differences in Episodic and Semantic Long-Term Memory Retrieval. *Journal of Experimental Psychology: Learning Memory and Cognition*, *32*(1), 101–117. http://doi.org/10.1158/0008-5472.CAN-10-4002.BONE

Starns, J. J., & Ratcliff, R. (2010). The effects of aging on the speed-accuracy compromise: Boundary optimality in the diffusion model. *Psychology of Aging*, *25*(1), 377–390. http://doi.org/10.1037/a0018022

Starns, J. J., & Ratcliff, R. (2012). Age-related differences in diffusion model boundary optimality with both trial-limited and time-limited tasks. *Psychonomic Bulletin and Review*, *19*(1), 139–145. http://doi.org/10.3758/s13423-011-0189-3

Thapar, A., Ratcliff, R., & McKoon, G. (2003). A diffusion model analysis of the effects of aging on letter Discrimination. *Psychology and Aging*, *18*(3), 415–429. http://doi.org/10.1037/0882-7974.19.2.278

Thorpe, S., D'Zmura, M., & Srinivasan, R. (2012). Lateralization of frequency-specific networks for covert spatial attention to auditory stimuli. *Brain Topography*, *25*(1), 39–54. http://doi.org/1doi:10.1007/s10548-011-0186-x

Thut, G., A., N., Brandt, S. A., & Pascual-Leone, A. (2006). α-Band Electroencephalographic Activity over Occipital Cortex Indexes Visuospatial Attention Bias and Predicts Visual Target Detection. *Journal of Neuroscience*, *26*(37), 9494–9502. http://doi.org/10.1523/JNEUROSCI.0875-06.2006

Tune, S., Wöstmann, M., & Obleser, J. (2018). Probing the limits of alpha power lateralization as a neural marker of selective attention in middle-aged and older listeners. *European Journal of Neuroscience*, *48*(7), 2537–2550. http://doi.org/10.1101/267989

Turner, B. M., Rodriguez, C. A., Norcia, T. M., McClure, S. M., & Steyvers, M. (2016). Why more is better: Simultaneous modeling of EEG, fMRI, and behavioral data. *NeuroImage*, *128*, 96–115. http://doi.org/10.1016/j.neuroimage.2015.12.030

Vaden, R. J., Hutcheson, N. L., McCollum, L. A., Kentros, J., & Visscher, K. M. (2012). Older adults, unlike younger adults, do not modulate alpha power to suppress irrelevant information. *NeuroImage*, *63*(3), 1127–1133. http://doi.org/10.1016/j.neuroimage.2012.07.050

Van Der Lubbe, R. H. J., Bundt, C., & Abrahamse, E. L. (2014). Internal and external spatial attention examined with lateralized EEG power spectra. *Brain Research*, *1583*, 179–192. http://doi.org/10.1016/j.brainres.2014.08.007

van der Waal, M., Farquhar, J., Fasotti, L., & Desain, P. (2017). Preserved and attenuated electrophysiological correlates of visual spatial attention in elderly subjects. *Behavioural Brain Research*, *317*, 415–423. http://doi.org/10.1016/j.bbr.2016.09.052

van Dijk, H., Schoffelen, J.-M., Oostenveld, R., & Jensen, O. (2008). Prestimulus Oscillatory Activity in the Alpha Band Predicts Visual Discrimination Ability. *Journal of Neuroscience*, *28*(8), 1816–1823. http://doi.org/10.1523/JNEUROSCI.1853-07.2008

van Driel, J., Gunseli, E., Meeter, M., & Olivers, C. N. L. (2017). Local and interregional alpha EEG dynamics dissociate between memory for search and memory for recognition. *NeuroImage*, *149*(October 2016), 114–128. http://doi.org/10.1016/j.neuroimage.2017.01.031

van Ede, F., Niklaus, M., & Nobre, A. C. (2017). Temporal expectations guide dynamic prioritization in visual working memory through attenuated α oscillations. *The Journal of Neuroscience*, *37*(2), 437–445. http://doi.org/10.1523/JNEUROSCI.2272-16.2016

van Ede, F., Szebényi, S., & Maris, E. (2014). Attentional modulations of somatosensory alpha, beta and gamma oscillations dissociate between anticipation and stimulus processing. *NeuroImage*, *97*, 134–141. http://doi.org/10.1016/j.neuroimage.2014.04.047

Voss, A., Nagler, M., & Lerche, V. (2013). Diffusion models in experimental psychology: A practical introduction. *Experimental Psychology*, *60*(6), 385–402. http://doi.org/10.1027/1618-3169/a000218

Voss, A., & Voss, J. (2007). Fast-dm: A free program for efficient diffusion model analysis. *Behavior Research Methods*, *39*(4), 767–775. http://doi.org/10.3758/BF03192967

Voss, A., Voss, J., & Lerche, V. (2015). Assessing cognitive processes with diffusion model analyses: A tutorial based on fast-dm-30. *Frontiers in Psychology*, *6*(MAR), 1–14. http://doi.org/10.3389/fpsyg.2015.00336

Wildegger, T., van Ede, F., Woolrich, M., Gillebert, C. R., & Nobre, A. C. (2017). Preparatory α-band oscillations reflect spatial gating independently of predictions regarding target identity. *Journal of Neurophysiology*, *117*(3), 1385–1394. http://doi.org/10.1152/jn.00856.2016

Worden, M. S., Foxe, J. J., Wang, N., & Simpson, G. V. (2000). Anticipatory biasing of visuospatial attention indexed by retinotopically specific α-band electroencephalography increases over occipital cortex. *The Journal of Neuroscience*, *20*(6), RC63. http://doi.org/10.1523/JNEUROSCI.20-06-j0002.2000

Wöstmann, M., Herrmann, B., Maess, B., & Obleser, J. (2016). Spatiotemporal dynamics of auditory attention synchronize with speech. *Proceedings of the National Academy of Sciences*, *113*(14), 3873–3878. http://doi.org/10.1073/pnas.1523357113

Wöstmann, M., Vosskuhl, J., Obleser, J., & Herrmann, C. S. (2018). Opposite effects of lateralised transcranial alpha versus gamma stimulation on auditory spatial attention. *Brain Stimulation*, *11*(4), 752–758. http://doi.org/10.1016/j.brs.2018.04.006

Yamagishi, N., Goda, N., Callan, D. E., Anderson, S. J., & Kawato, M. (2005). Attentional shifts towards an expected visual target alter the level of alpha-band oscillatory activity in the human calcarine cortex. *Cognitive Brain Research*, *25*(3), 799–809. http://doi.org/10.1016/j.cogbrainres.2005.09.006

Zanto, T. P., & Gazzaley, A. (2014). Attention and ageing. In A. C. K. Nobre & S. Kastner (Eds.), *The Oxford Handbook of Attention*. (pp. 927–971). Oxford: Oxford University Press.

Zündorf, I. C., Karnath, H. O., & Lewald, J. (2011). Male advantage in sound localization at cocktail parties. *Cortex*, *47*(6), 741–749. http://doi.org/10.1016/j.cortex.2010.08.002

Zündorf, I. C., Karnath, H. O., & Lewald, J. (2014). The effect of brain lesions on sound localization in complex acoustic environments. *Brain*, *137*(5), 1410–1418. http://doi.org/10.1093/brain/awu044

Zündorf, I. C., Lewald, J., & Karnath, H. O. (2013). Neural Correlates of Sound Localization in Complex Acoustic Environments. *PLoS ONE*, *8*(5). http://doi.org/10.1371/journal.pone.0064259