

Attentional Modulations of Alpha Power Are Sensitive to the Task-relevance of Auditory Spatial Information

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1 **Abstract**

2 The topographical distribution of oscillatory power in the alpha band is known to vary
3 depending on the current focus of spatial attention. Here, we investigated to what extent
4 univariate and multivariate measures of post-stimulus alpha power are sensitive to the
5 required spatial specificity of a task. To this end, we varied the perceptual load and the
6 spatial demand in an auditory search paradigm. A centrally presented sound at the
7 beginning of each trial indicated the to-be-localized target sound. This spatially unspecific
8 pre-cue was followed by a sound array, containing either two (low perceptual load) or four
9 (high perceptual load) simultaneously presented lateralized sound stimuli. In separate task
10 blocks, participants were instructed either to report whether the target was located on the
11 left or the right side of the sound array (low spatial demand) or to indicate the exact target
12 location (high spatial demand). Univariate alpha lateralization magnitude was neither
13 affected by perceptual load nor by spatial demand. However, an analysis of onset latencies
14 revealed that alpha lateralization emerged earlier in low (vs. high) perceptual load trials as
15 well as in low (vs. high) spatial demand trials. Finally, we trained a classifier to decode the
16 specific target location based on the multivariate alpha power scalp topography. A
17 comparison of decoding accuracy in the low and high spatial demand conditions suggests
18 that the amount of spatial information present in the scalp distribution of alpha-band power
19 increases as the task demands a higher degree of spatial specificity. Altogether, the results
20 offer new insights into how the dynamic adaption of alpha-band oscillations in response to
21 changing task demands is associated with post-stimulus attentional processing.

22 *Keywords: alpha oscillations, EEG, multivariate pattern analysis, selective attention, spatial*
23 *specificity, sound localization*

24 **1. Introduction**

25 In everyday environments, containing multiple competing sensory inputs, focusing spatial
26 attention on relevant information while ignoring or suppressing irrelevant information is
27 crucial to engage in goal-directed behaviour. Consistently, covert shifts of spatial attention
28 have been shown to improve various aspects of behavioural performance, including visual
29 spatial acuity (reviewed by Anton-Erxleben & Carrasco, 2013), contrast sensitivity (Carrasco,
30 Penpeci-Talgar, & Eckstein, 2000), or the rate of information accumulation (Carrasco &
31 McElree, 2001). On the electrophysiological level, asymmetric modulations of parieto-
32 occipital alpha-band power present a robust signature of spatial attentional orienting.
33 Typically, alpha-band power decreases contralateral to the attended location and / or
34 increases over ipsilateral scalp sites. This phenomenon of alpha power lateralization has
35 been found in response to anticipatory shifts of attention (Foxe, Simpson, & Ahlfors, 1998;
36 Worden, Foxe, Wang, & Simpson, 2000), when retro-actively attending to working memory
37 representations (Poch, Capilla, Hinojosa, & Campo, 2017; Schneider, Mertes, & Wascher,
38 2016), as well as during post-stimulus attentional processing (e.g., in auditory or visual
39 search paradigms; Bacigalupo & Luck, 2019; Klatt, Getzmann, Wascher, & Schneider, 2018b).

40 Accumulating evidence suggests that scalp-level alpha-band activity not only reflects
41 the attended hemifield but is tuned specifically to the attended visual field location
42 (Bahramisharif, Heskes, Jensen, & van Gerven, 2011; Rihs, Michel, & Thut, 2007). Moreover,
43 this spatial selectivity is also reflected in the retinotopic organization of alpha sources
44 (Popov, Gips, Kastner, & Jensen, 2019). First evidence for comparable ‘spatial tuning’ of
45 alpha-band oscillations in the auditory domain comes from a recent study by Deng and
46 colleagues (Deng, Choi, & Shinn-Cunningham, 2020) who found that the topographic
47 distribution of posterior alpha-band lateralization changes monotonically as the focus of
48 auditory spatial attention shifts in space.

49 Notably, recent evidence suggests that the degree of spatial specificity reflected in
50 the scalp distribution of alpha-band power also depends on the current task demands
51 (Feldmann-Wüstefeld & Awh, 2019; Voytek et al., 2017). Specifically, two studies of visual
52 anticipatory spatial attention, using multivariate inverted encoding models (IEM),
53 demonstrated that the spatial selectivity of alpha activity increased when participants
54 voluntarily focused on a narrow rather than a broad region of space (Feldmann-Wüstefeld &

55 Awh, 2020) and scaled to the degree of certainty of a central cue that indicated the location
56 of an upcoming target (Voytek et al. 2017).

57 Consistently, in an auditory spatial attention study, focusing on post-stimulus
58 attentional processing, we found that task-demands shape the reliance on alpha-band
59 mediated post-stimulus processing. That is, auditory post-stimulus alpha lateralization was
60 only present in a spatially specific sound localization task, whereas it was absent in a simple
61 sound detection paradigm (Klatt et al. 2018b, see also Deng et al. 2019). In the present
62 study, we set out to further investigate to what extent attentional modulations of post-
63 stimulus alpha power capture the spatial demands of a sound localization task on a more
64 fine-grained scale. To this end, we varied both the perceptual load and the spatial demand of
65 the task. That is, participants were asked to localize a target sound among a set of either two
66 (low perceptual load) or four (high perceptual load) concurrently presented sounds in a
67 lateralized sound array. In separate task blocks, they either indicated (a) whether the target
68 was present on the left or the right side (i.e., two response options, low spatial demand) or
69 (b) reported the exact target location (i.e., four response options, high spatial demand). On
70 the behavioural level, we expected that high perceptual load (compared to low load) and
71 high spatial demand (compared to low spatial demand) would present the more challenging
72 listening situation, resulting in slower response times and lower sound localization accuracy.
73 Beyond that, attempting to replicate previous results, we hypothesized that post-stimulus
74 modulations of alpha-band power should index the attended target location, while the
75 magnitude thereof should not be affected by perceptual load (Klatt et al., 2018b). This
76 should be evident in a hemispheric lateralization of alpha-band power over parieto-occipital
77 electrode sites in both low and high perceptual load trials.

78 Further, the critical aim of this study was to assess whether the required degree of
79 behavioural spatial specificity (low vs. high spatial demand) affects the spatial specificity of
80 the alpha power signal. If this is the case, this should be either evident in a modulation of
81 alpha lateralization magnitude and / or captured by the scalp distribution of alpha-band
82 power. Hence, we applied both univariate as well as multivariate analysis techniques to
83 evaluate alpha-band power modulations depending on the spatial (and perceptual) demands
84 of the task. Finally, we assessed alpha lateralization onset latencies to explore whether the
85 time course of alpha-band activity is likewise modulated by the required degree of spatial
86 specificity or perceptual load. Specifically, if slower sound localization performance in high

87 spatial demand or high perceptual load conditions coincides with slower post-stimulus
88 attentional processing, this should be reflected in delayed onset latencies of alpha
89 lateralization. Such a time-resolved modulation of attentional alpha-band activity is, for
90 instance, suggested by Foster and colleagues (Foster, Sutterer, Serences, Vogel, & Awh,
91 2017), who showed that the onset latency of location-selective alpha-band channel tuning
92 functions (reconstructed from the topographic distribution of alpha-band oscillatory power)
93 occurred later in time for trials with slow compared to fast responses as well as for a hard
94 compared to an easier search condition.

95

96 **2. Methods**

97 *2.1 Ethics statement*

98 The study was approved by the Ethical Committee of the Leibniz Research Centre for
99 Working Environment and Human Factors and conducted in accordance with the Declaration
100 of Helsinki. All participants provided written informed consent prior to the beginning of the
101 experimental procedure.

102

103 *2.2 Participants*

104 19 participants were recruited to take part in the study. Hearing acuity was assessed using a
105 pure-tone audiometry (Oscilla USB 330; Inmedico, Lystrup, Denmark), presenting eleven
106 pure-tone frequencies in-between 125 Hz and 8000 Hz. One participant had to be excluded
107 due to a unilateral, mild to moderate hearing impairment in the right ear (hearing thresholds
108 of up to 35 – 50 dB hearing level). All other participants showed no signs of hearing
109 impairment (hearing thresholds \leq 25 dB). Another participant did not correctly follow the
110 task instructions and was also excluded. Thus, the final sample included 17 subjects (mean
111 age 23.29 years, age range 19- 30, 9 female), all of which were right-handed as indicated by
112 the Edinburgh Handedness Inventory (Oldfield, 1971). The sample size we aimed at was
113 chosen to be comparable to previous publications from the lab that investigated similar
114 electrophysiological measures (e.g., Klatt, Getzmann, Wascher, & Schneider, 2018b, 2018a).
115 All participants had normal or corrected-to-normal vision, reported no history of or current
116 neurological or psychiatric disorders and received course credit or financial compensation
117 (10€/hour) for their participation.

118

119 2.2 Experimental setup and stimuli

120 The experiment was conducted in a dimly illuminated, anechoic, and sound-attenuated
121 room ($5.0 \times 3.3 \times 2.4\text{m}^3$). Pyramid-shaped foam panels on ceiling and walls and a woolen
122 carpet on the floor ensure a background noise level below 20dB(A). Participants were seated
123 in a comfortable chair with their head position held constant by a chin rest. A semicircular
124 array of nine loudspeakers (SC5.9; Visaton, Haan, Germany) was mounted in front of the
125 subject at a distance of ~1.5 meters from the subject's head and at a height of ~1.3 meters
126 (approximately at ear level). Only five loudspeakers, located at azimuthal positions
127 of -90° , -30° , 0° , 30° , and 90° respectively, were used for the present experimental setup. A
128 red, light-emitting diode (diameter 3 mm) was attached right below the central loudspeaker.
129 The diode remained turned off during the experiment, but served as a central fixation target.

130 As sound stimuli, eight familiar animal vocalizations ('birds chirping', 'dog barking',
131 frog croaking', 'sheep baaing', 'cat meowing', 'duck quacking', 'cow mooing', 'rooster
132 crowing') were chosen from an online sound archive (Marcell, Borella, Greene, Kerr, &
133 Rogers, 2000). The original sounds were cut to a constant duration of 600 ms (10 ms on/off
134 ramp), while leaving the spectro-temporal characteristics unchanged. The overall sound
135 pressure level of the sound arrays, containing either two or four concurrently present
136 sounds, was about 63 dB(A) and 66 dB(A), respectively. The target sounds, presented in
137 isolation from a central position, had a sound pressure level of 60 dB(A).

138

139 2.3 Procedure, task, and experimental design

140 The experiment consisted of an auditory search paradigm implementing a sound localization
141 task. The sequence of events in a given trial is depicted in Figure 1. Each trial began with a
142 silent period of 500 ms. Then a sound stimulus (i.e., a target cue) was presented from a
143 central position (0° azimuth angle) for 600 ms, indicating which animal vocalization will serve
144 as a relevant target sound in a given trial. The latter was followed by a 1000 ms silent inter-
145 stimulus-interval and a sound array (600 ms). The sound array contained either two (i.e., *low*
146 *perceptual load*, 50%) or four (i.e., *high perceptual load*, 50%) simultaneously present
147 lateralized sound stimuli. Sound array presentation was followed by a 1600 ms response
148 interval and a 300 ms silent interval. In total, each trial lasted for 4600 ms.

149 In low perceptual load trials, the two sounds could occur at either of the four
150 lateralized loudspeaker positions (-90° , -30° , 30° , 90° azimuth), with the restriction that the

151 two sounds (i.e., the target and a non-target sound) were always present in different hemi-
152 fields. Accordingly, in high perceptual load trials all four lateralized active loudspeakers (-90°,
153 -30°, 30°, 90° azimuth) were used. Depending on the task condition, participants received
154 slightly different task instructions: In the *low spatial demand (lsd)* condition, participants
155 were instructed to indicate whether the target sound was present on the left versus right
156 side (i.e., two response options: left vs. right) or to withhold their response if the target
157 sound was not present (i.e., target-absent trials). In the *high spatial demand (hsd)* condition,
158 participants were asked to indicate the exact target location (i.e., four response options:
159 inner-left, outer-left, inner-right, outer-right) or to withhold their response if the target
160 sound was not present. Target-absent trials were included to ensure that selectively listening

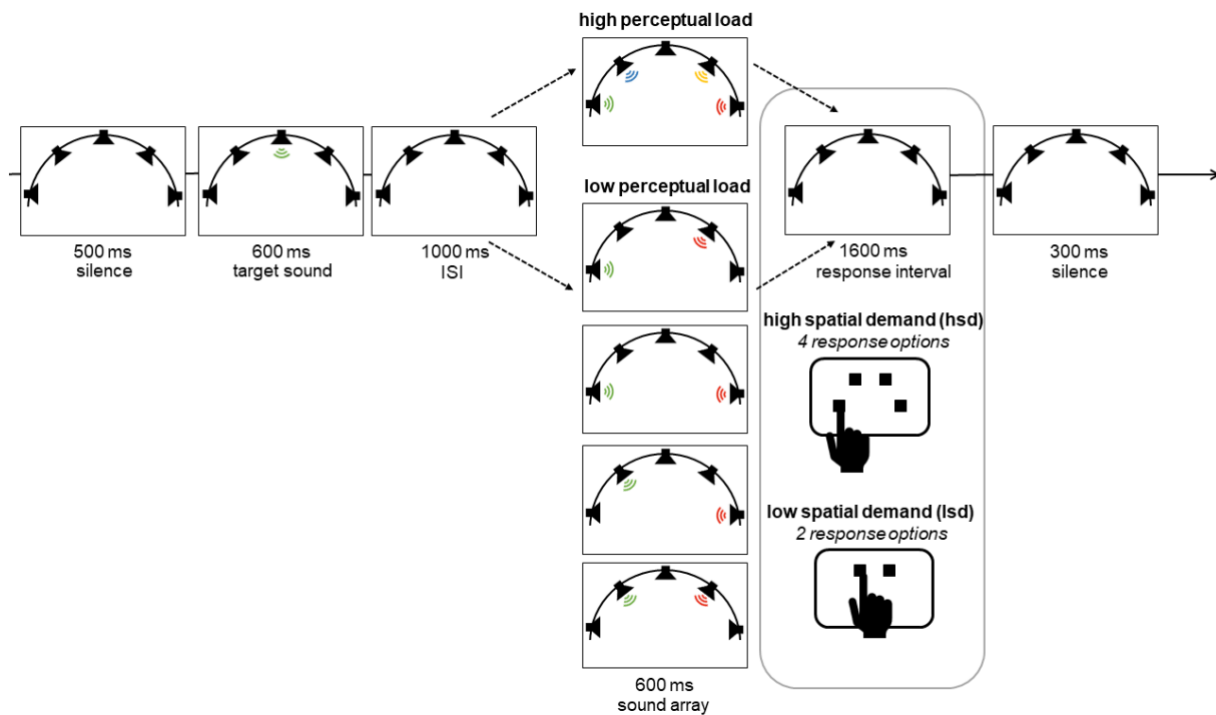


Figure 1. Schematic illustration of the experimental design. A centrally presented target cue indicated the relevant target in a given trial. Then, a sound array appeared, containing either two or four simultaneously present sounds from lateralized positions. In different task blocks, participants were asked to either indicate whether the target was presented on the left or the right side (low spatial demand) or to report the exact target location (high spatial demand). In both task blocks, it was also possible that the sound array did not contain the target (i.e., target-absent trial). In this case, participants withheld their response. ISI = inter-stimulus-interval.

161 to the input from only one side of the stimulus array (i.e., left or right) presented no viable
162 strategy in low spatial demand task blocks. Specifically, if the sound array always contained a
163 target sound in low spatial demand blocks, subjects could be inclined to simply infer that the
164 target was located on the left side solely because they didn't perceive it on the right side (or
165 vice versa).

166 Participants indicated their response by pressing one out of four buttons, arranged in a semi-
167 circular array on a response pad. In the high-spatial demand condition, each button
168 corresponded to one of the loudspeaker positions, such that participants had to press the
169 left-most button when the target was presented at the left-most loudspeaker and so on. In
170 low spatial demand trials, participants only used the two inner response buttons (i.e., the
171 left button for left-target responses, the right button for right-target responses). Participants
172 were instructed to always respond as accurately and as fast as possible, using the index
173 finger of their right hand. To minimize horizontal eye movements during the EEG-recording,
174 participants were instructed to fixate a centrally positioned LED.

175 Each of the spatial demand conditions (i.e., low vs. high spatial demand) consisted of
176 672 trials, containing both low (50%) and high (50%) perceptual load trials in randomized
177 order. Short, self-paced breaks after every 224 trials and in-between conditions were
178 conducted to prevent fatigue. The order of conditions was counterbalanced across
179 participants, such that $n = 8$ subjects first completed the low-spatial demand condition and n
180 $= 9$ subjects first completed the high-spatial demand condition. Prior to the beginning of
181 each condition participants completed 40 practice trials to familiarize with the task. All
182 participants were presented with the same semi-randomized selection of trials. Critically, in
183 both spatial demand conditions the same selection of 672 trials was presented, but in a
184 different, randomized order. This assured that all differences between conditions could be
185 ascribed to the task manipulations rather than differences in the stimulus materials. Each of
186 the eight animal vocalizations served as the target equally often (i.e., 84 times per
187 condition). In addition, the target sound appeared equally often at each of the four possible
188 sound speaker locations (i.e., 56 times per location and perceptual load per condition). This
189 also ensured that the number of left (1/3) vs. right (1/3) responses in low-spatial demand
190 trials as well as the number of outer-left (1/5), inner-left (1/5), inner-right (1/5), and outer-
191 right (1/5) responses in high-spatial demand trials was counterbalanced across subjects.
192 Target-absent trials constituted 1/3rd and 1/5th of all trials in low and high spatial demand
193 task blocks, respectively. The timing of the stimuli was controlled by custom-written
194 software. Participants did not receive feedback during the experiment.

195 Taken together, the present study comprised a 2 x 2 repeated-measures design,
196 including the within-subject factors *spatial demand* (low vs. high spatial demand) and
197 *perceptual load* (low vs. high perceptual load). Note that there are different ways of defining

198 perceptual load (for a review see Murphy, Spence, & Dalton, 2017). Here, we refer to
199 *perceptual load* as the number of items in the search display.

200

201 *2.4 EEG data acquisition*

202 The continuous EEG data were recorded from 58 Ag/AgCl passive scalp electrodes (ECI
203 Electrocap, GVB-geliMED GmbH, Bad Segeberg, Germany) as well as from left and right
204 mastoids. Electrode positions corresponded to the international 10-10 system. The
205 electrooculogram (EOG) was simultaneously recorded from four additional electrodes,
206 placed lateral to the outer canthus of each eye as well as below and above the right eye. The
207 ground electrode was placed on the center of the forehead, right above the nasion. The
208 average of all electrodes served as the online-reference. The data were recorded using a
209 QuickAmp-72 amplifier (Brain products, Gilching, Germany) and digitized at a sampling rate
210 of 1 kHz. During the preparation of the EEG cap, all electrode impedances were kept below
211 10 k Ω .

212

213 *2.5 Data analysis*

214 If not stated otherwise, all data analyses were performed using custom MATLAB (R2018b)
215 code and built-in functions from the *Statistics and Machine Learning Toolbox*. In a few
216 specific cases, R (v3.6.1) and RStudio (v1.2.1335) were used (see references to specific R
217 packages below). The significance of all tests was evaluated at an alpha level of .05. Because
218 the *F*-distribution is always asymmetric, reported *p*-values associated with repeated-
219 measures analysis of variance (ANOVA) are directional (Winter, 2011). Partial Eta Squared
220 (η_p^2) and Hedges' *g* (denotes as *g*, Hentschke & Stüttgen, 2011) are provided
221 as standardized measures of effect size for ANOVAs and follow-up paired sample *t*-tests.

222

223 *2.5.1 Behavioral*

224 The behavioral parameters that were analyzed were response times (RT) and accuracy (i.e.,
225 percentage of correct responses). Only target-present trials were considered. For accuracy
226 measures, this selection of trials was required because in target-absent trials a correct
227 target-absent-categorization (i.e., a volitional omission of a key press) could not be reliably
228 dissociated from an incorrect, missing response. Mean RTs and accuracy measures per

229 subject and condition were submitted to a repeated-measures ANOVA. Spatial demand and
230 perceptual load served as within-subject factors.

231 2.5.2 EEG

232 All EEG data processing was performed using the open-source toolbox EEGLAB (v14.1.2;
233 Delorme & Makeig, 2004) in combination with custom MATLAB (R2018b) code.

234

235 *Preprocessing.* Initially, continuous segments of -1 to +1 seconds surrounding boundary
236 events as well as the DC offset were removed from the data. Then, the continuous EEG data
237 were band-pass filtered, using a non-causal, high-pass and a low-pass Hamming windowed
238 sinc FIR filter (*pop_eegfiltnew* function). The lower edge of the frequency pass band was set
239 to 0.1 Hz (filter order: 33000, transition band-width: 0.1 Hz, -6dB cutoff: 0.05 Hz) and the
240 higher edge of the frequency pass band to 30 Hz (filter order: 440, transition band-width: 7.5
241 Hz, -6dB cut-off: 33.75 Hz). Early-stage preprocessing was then performed using the PREP
242 pipeline (Bigdely-Shamlo, Mullen, Kothe, Su, & Robbins, 2015), which essentially consists of
243 three steps: it performs an initial clean-up, determines and removes a robust reference
244 signal, and interpolates bad channels with a low signal to noise ratio. For an extensive
245 documentation of the single steps, please see Bigdely-Shamlo et al. (2015). Only scalp EEG
246 channels were used for evaluation of noisy channels and for computation of the robust
247 reference, while all channels (including mastoids and EOG channels) were re-referenced. On
248 average, 3.7 channels (SD = 2.2) were identified as bad and interpolated prior to subtracting
249 the computed “true” reference. This includes a total of three channels (across two subjects)
250 that were manually interpolated prior to running the PREP algorithm, because the latter did
251 not identify the respective channels as flat channels. For channel interpolation, the PREP
252 pipeline applies spherical spline interpolation as implemented in the *eeg_interp()* function
253 (Perrin, Pernier, Bertrand, & Echallier, 1989). The same algorithm was used to manually
254 interpolate the three channels that were not identified as flat channels by the PREP
255 algorithm. A total of three channels (in two subjects) belonging to the posterior electrode
256 cluster of interest that was used for statistical analysis (see section on *Alpha Laterlization*)
257 were marked as bad and thus, interpolated during this procedure.

258 For artifact rejection, an independent component analysis (ICA) was run on the
259 dimensionality reduced data (using a basic PCA implementation). To speed up and improve

260 ICA decomposition, the continuous data were down-sampled to 200 Hz and high-pass
261 filtered at 1 Hz (Winkler, Debener, Muller, & Tangermann, 2015), using a non-causal
262 Hamming windowed sinc FIR filter (filter order: 3300, transition band-width: 1 Hz, -6dB
263 cutoff: 0.5 Hz) prior to running the ICA algorithm. Then, data epochs were extracted, ranging
264 from -1000 to 4500 ms relative to target cue onset. In addition, major artefacts and
265 extremely large potential fluctuations were removed before running ICA, using the
266 automatic trial-rejection procedure implemented in EEGLAB (i.e., function *pop_autorej*). The
267 latter rejects data epochs, containing data values exceeding a given standard deviation
268 threshold by means of an iterative procedure (probability threshold: 5 SD, maximum
269 proportion of total trials rejection per iteration: 5%, threshold limit: 500 μ V). Because
270 interpolating channels prior to ICA introduces rank-deficiency, the number of to-be
271 extracted ICs was manually reduced by the number of interpolated channels + 1 (to account
272 for the dependency introduced by the average reference). The obtained ICA decomposition
273 was back-projected onto the original, continuous dataset (band-pass filtered and re-
274 referenced) with a 1 kHz sampling rate. The latter was segmented into epochs ranging from -
275 1000 to 4500 ms relative to target cue onset and baseline-corrected, using the pre-stimulus
276 period of -200 to 0. To identify artefactual independent components (ICs), the EEGLAB plug-
277 in ICLabel (v1.1, Pion-Tonachini, Kreutz-Delgado, & Makeig, 2019), was applied. ICLabel
278 assigns a label vector to each IC, indicating the probability that an IC belongs to any of seven
279 possible categories: brain, muscle, eye, heart, line noise, channel noise, or other. All ICs that
280 received a probability estimate below 50% for the brain category were considered
281 “artefactual” and subsequently subtracted from the data. On average 34.82 ICs (SD = 4.26)
282 were removed per participant (i.e., 59.67 %, SD = 7.85). Finally, the automatic trial rejection
283 procedure implemented in EEGLAB was performed, setting the probability threshold to 5 SD,
284 the maximum proportion of total trials to-be-rejected per iteration to 5 % and the threshold
285 limit to 1000 μ V. On average, 177 (lsd-low, SD = 23), 182 (lsd-high, SD = 20), 162 (hsd-low, SD
286 = 19), and 166 (hsd-high, SD = 18) *target-present-trials* passed artefact correction per
287 subject. Specifically, 174 (lsd-low, SD = 22), 160 (lsd-high, SD = 20), 156 (hsd-low, SD = 18),
288 and 136 (hsd-high, SD = 19) of those target-present trials were correct trials, and thus
289 entered the univariate EEG analysis. This corresponds to, on average, 87 (lsd-low, SD = 11),
290 80 (lsd-high, SD = 10), 78 (hsd-low, SD = 9), and 68 (hsd-high, SD = 10) trials per target
291 hemifield (left vs. right).

292 *Time-frequency decomposition.* The time-frequency decomposition of the processed EEG
293 data was computed using Morlet wavelet convolution as implemented in the build-in
294 EEGLAB STUDY functions (i.e., *newtimef.m*). Specifically, the segmented EEG signal was
295 convolved with a series of complex Morlet wavelets. The frequencies of the wavelets ranged
296 from 4 Hz to 30 Hz, increasing logarithmically in 52 steps. A complex Morlet wavelet is
297 defined as a complex sine wave that is tapered by a Gaussian. The number of cycles, that
298 defines the width of the tapering Gaussian, increased linearly as a function of frequency by a
299 factor of 0.5. This procedure accounts for the trade-off between temporal and frequency
300 precisions as a function of the frequency of the wavelet. The number of cycles at the lowest
301 frequency was 3; the number of cycles at the highest frequency was 11.25. The time period
302 in-between -400 and -100 ms relative to target cue onset served as a spectral baseline.

303
304 *Alpha power lateralization.* Spatial shifts of attention following the onset of the sound array
305 were quantified by assessing lateralized modulations of posterior alpha-band power (8-12
306 Hz). Specifically, the difference between contralateral and ipsilateral alpha power at a cluster
307 of posterior electrodes, comprising PO7/8, P7/8, P3/4, and PO3/4, was calculated separately
308 for each condition and each subject. The selection of electrodes was based on previous
309 studies of post-stimulus, posterior alpha lateralization (Klatt, Getzmann, Begau, & Schneider,
310 2019; Schneider, Göddertz, Haase, Hickey, & Wascher, 2019), except that P5/P6 were not
311 part of the present electrode setup and thus, electrodes P3/4 were included in the electrode
312 cluster instead. Given that post-stimulus alpha power asymmetries have been shown to
313 appear as a relatively long-lasting, sustained effect (Klatt et al., 2018a), the mean
314 contralateral-minus-ipsilateral differences in power were extracted in a broad 400 ms-time
315 window, ranging from 532 to 937 ms following sound array onset. The time window was set
316 around the peak in the grand average contralateral minus ipsilateral difference waveform
317 across all conditions and subjects. The peak was defined as the point in time at which the
318 difference waveform (following sound array onset, 1600 ms – 3000 ms) reached its most
319 negative amplitude value. The resulting analysis time window is consistent with our earlier
320 work (Klatt et al., 2018a). Notably, although this approach to determine the analysis time
321 window is data-driven, the comparisons between conditions remain unbiased (Luck &
322 Gaspelin, 2017). The mean power values per subject and condition were then submitted to a
323 repeated-measures ANOVA, including the within-subject factors *spatial demand* and

324 *perceptual load* to assess their effect on alpha lateralization magnitude.

325

326 *Alpha lateralization onset latencies.* To quantify alpha lateralization onset latency, we used a
327 combination of the fractional area technique (Kiesel, Miller, Jolicœur, & Brisson, 2008; Luck,
328 2014) and a jackknife approach (Luck, 2014; Miller, Patterson, & Ulrich, 1998). That is, for
329 each condition, n subaverage contralateral minus ipsilateral difference waveforms were
330 created, using a subsample of $n-1$ waveforms (i.e., each participant was omitted once). In
331 each of these subaverage waveforms, the point in time at which the negative area under the
332 curve reached 20% and 50%, respectively (i.e., Fractional Area Latency, denoted as FAL) was
333 measured, using the MATLAB function *latency.m* by Liesefeld (2018). Negative area was
334 measured relative to zero and in-between a broad time window from 1600 to 3000 ms post-
335 cue-onset (i.e., 1600 ms corresponds to sound array onset). Note that reported mean
336 latency differences (denoted as D) correspond to the differences in onset latency between
337 conditions, measured in the condition-grand averages. According to Miller, Patterson, &
338 Ulrich (1998), the jackknife-based SE_D was calculated as follows:

339

$$340 \quad SE_D = \sqrt{\frac{N-1}{N} \sum_{i=1}^N (D_{-i} - \bar{J})^2}.$$

341

342 D_{-i} (for $i = 1, \dots, N$, with N representing the sample size) denotes the latency difference for
343 the subsample, including all subjects except for subject i . \bar{J} is the mean difference across all
344 subsamples (i.e., $\bar{J} = \sum D_{-i} / N$).

345 The 20%-FAL and 50%-FAL values were submitted to separate repeated-measures
346 ANOVAs, including the within-subject factors *spatial demand* and *perceptual load*. Because
347 the use of subsample average measures artificially reduces the error variance, the error
348 terms in the respective ANOVA will be underestimated, while the F-values will be
349 overestimated. To account for this bias, the F -correction according to Kiesel, Miller, Jolicœur,
350 & Brisson (2008) was applied. Corrected F -values are denoted as F_{corr} . The corresponding p -
351 value for the corrected F statistic was computed using the online calculator by Soper (2020).

352 Please note that the main aim of the present analysis of onset latency measures was
353 to assess differences in onset latency between the experimental conditions. However, the
354 estimated onset latency measures should not be interpreted as reflecting the true onset

355 time of the underlying attentional process. This precaution applies for two reasons: First, the
356 temporal resolution of event-related spectral perturbations is considerably lower compared
357 to standard ERP analysis. Second, non-causal filters, as applied here to the continuous raw
358 EEG data, have been shown to affect the onset latency of time-series data considerably
359 (VanRullen, 2011, but see also Rousselet, 2012). Critically, as the filter should affect all
360 conditions to the same extent, the differences between conditions can still be reliably
361 interpreted.

362

363 *Brain-behavior correlations.* To investigate to what extent the timing of alpha lateralization
364 was related to behavioral performance, we used a repeated-measures correlation approach
365 and the R package *rmcorr* (Bakdash & Marusich, 2017). *Rmcorr* determines “the relationship
366 between [...] two continuous variables, while controlling for the [...] between-participants
367 variance” (Bakdash & Marusich, 2017, p. 3). We obtained FAL-measures from the single-
368 subject waveforms (i.e., contralateral minus ipsilateral alpha power) for each of the four
369 conditions and correlated those with condition-specific mean response times. Here, the
370 latter were estimated, including only the (correct) trials that remained after EEG-artefact
371 rejection. Three subjects did not show an alpha lateralization effect (i.e., there was no
372 negative area) and were thus, excluded from the correlation analysis. The repeated-
373 measures correlation coefficient r_{rm} as well as a 95% confidence interval will be reported.
374 The corresponding degrees of freedom are calculated as follows (Bakdash & Marusich,
375 2017):

376

$$377 \quad df_{rmcorr} = N(k - 1) - 1,$$

378

379 where k is the number of repeated measures per participant (i.e., 4) and N is the total
380 number of participants (i.e., 14).

381

382 *Non-lateralized, posterior alpha power desynchronization.* Event-related desynchronization
383 of alpha-band activity resulting in low levels of alpha power has been linked with states of
384 high excitability and thus, is thought to reflect functional engagement and information
385 processing (see e.g., Fukuda, Mance, & Vogel, 2015; Krause et al., 2000; Hanslmayr, Spitzer,
386 & Bäuml, 2009). Hence, in the present study, posterior alpha ERD served as a measure of

387 cognitive task demands. Mean alpha ERD amplitude per condition and subject was measured
388 in-between 2144 and 2244 ms relative to target cue onset (i.e., 544 – 644 ms relative to
389 sound array onset) at electrode Pz. The time window that served as the basis for the
390 statistical analysis was determined using a collapsed localizer approach (Luck & Gaspelin,
391 2017). That is, we assessed the negative peak in the grand average waveform across
392 conditions in a broad time-window from 1600 ms to 3000 ms (relative to target cue onset;
393 i.e., the same time window used to measure the area under the curve for fractional area
394 latency measurement). A 100 ms time window (i.e., +/- 50 ms) around the resulting peak
395 value of 2194 ms (i.e., 594 ms following sound array onset) constituted the measurement
396 time window. Mean alpha power values were then submitted to a repeated-measures
397 ANOVA, including the within-subject factors *spatial demand* (high vs. load) and *perceptual*
398 *load* (high vs. low).

399

400 *Decoding analysis.* We attempted to decode the exact location (i.e., outer-left, inner-left,
401 inner-right, outer-right) of the target sound based on the scalp distribution of alpha-band
402 EEG power. The decoding procedure was applied separately for the *low* vs. the *high spatial*
403 *demand* condition to investigate whether the ‘amount’ of spatial information reflected in the
404 scalp topography of alpha-band power is modulated by the spatial demands of the task. The
405 factor *perceptual load* was not considered in the decoding analysis. The decoding analysis
406 described below was adapted from the analysis code and method provided by Bae & Luck
407 (2018). For the present decoding analysis, the preprocessing pipeline described above was
408 modified as follows to retain a maximum number of trials and to prevent spurious decoding
409 due to high-pass (van Driel, Olivers, & Fahrenfort, 2021) or low-pass (Grootswagers, Wardle,
410 & Carlson, 2017) filtering. Specifically, the continuous data was high-pass filtered at 0.01 Hz
411 (i.e., the cut-off that was deemed as acceptable by van Driel et al., 2021), while no low-pass
412 filter was applied. Following ICA-based artefact correction, trials that still contained large
413 voltage fluctuations of $\pm 200 \mu\text{V}$ (e.g., due to muscle activity that was not removed by ICA)
414 were rejected using the *pop_eegthresh()* function. All other preprocessing steps were left
415 unchanged.

416 To improve the signal-to-noise ratio, after extracting alpha power from the signal, the
417 data belonging to a given target location category were averaged across multiple trials.
418 These averages (rather than single-trial data) served as the input for the to-be-trained

419 classifier. The classifier was trained to discriminate between each target location and all
420 other possible locations. To compute decoding accuracy, the classifier was then applied to
421 the average of a set of trials for each location that was not part of the training data.
422 Decoding was considered correct if the classifier correctly determined which one of the four
423 possible locations was the target location. Thus, chance level decoding accuracy was at 25%.

424 Specifically, analogous to Bae & Luck (2018), the following decoding procedure was
425 applied: The segmented EEG at all scalp electrodes was bandpass filtered at 8 to 12 Hz, using
426 EEGLAB's *eegfilt()* function, which applies two-way least-squares finite impulse response
427 (FIR) filtering. Then, we submitted the bandpass filtered EEG data to a Hilbert transform to
428 obtain the magnitude of the complex analytic signal. The latter was squared to compute the
429 total power in the alpha frequency band (i.e., 8-12 Hz) at each time point. Subsequently, to
430 increase the efficiency of the analysis and decrease computation time, the data was
431 subsampled, keeping only every 20th data point in-between -500 and 4500 ms relative to
432 target sound onset (i.e., corresponding to a sampling rate of 50 Hz). This results in a 4-
433 dimensional data matrix for each participant, including the dimensions of time (250 time
434 points), location (4 different categories), trial (varies depending on the subject, in-between
435 64 and 110 trials for each location), and electrode site (the 57 scalp channels). To classify the
436 location of the target sound based on the scalp topography of the alpha power signal over
437 the 57 scalp electrodes (i.e., mastoids and EOG electrodes were excluded), we used a
438 combination of a support vector machine (SVM) and error-correcting output codes (ECOC;
439 Dietterich & Balkiri, 1995). The ECOC model, implemented using the MATLAB function
440 *fitcecoc()*, combines the results from multiple binary classifiers and thus, solves multiclass
441 categorization problems.

442 Decoding was performed separately for each of the 250 time points in-between -500
443 and 4500 ms relative to target sound onset. At each time point, separate trials were used to
444 train and test classifier performance, respectively. Specifically, a threefold cross validation
445 procedure was applied: First the data were sorted into four 'location bins', containing only
446 trials with the same target location. In each location bin, the trials were divided into three
447 equally sized sets of trials, each of which contained in-between 21 and 36 trials (depending
448 on condition and subject, $MDN_{[lsd]} = 32$, $MDN_{[hsd]} = 30$). That is, to ensure that an equal
449 number of trials was assigned to each of the three sets for each location bin, the minimum
450 number of trials per subject for a given location bin was determined (denotes as n), and $n / 3$

451 trials were assigned to each set. In case the total trial number for a given location was not
452 evenly divisible by three, excess trials were randomly omitted. The trials for a given location
453 bin were averaged, resulting in a matrix of 3 (subsample averages) x 4 (location bins) x 57
454 (electrodes) to be analyzed for each time point. Notably, two of the three subsample
455 averages served as the training set, while the remaining group average served as a testing
456 dataset. In the training phase, the data from the two (of the total three) subsample averages
457 was simultaneously submitted to the ECOC model with known location labels to train four
458 SVMs (one for each location). A one-versus-all approach was chosen such that each SVM was
459 trained to perform a binary classification, that is, to discriminate one specific location from
460 all other locations. Subsequently, in the test phase the unused data (i.e., the subsample
461 average that were reserved for testing) was fed into the set of four trained SVMs to classify
462 which of the 4 locations served as the target location in each of the subsample averages.
463 Specifically, the MATLAB *predict()* function was used to classify the input data by minimizing
464 the average binary loss across the four trained SVMs. Essentially, the output of the *predict()*
465 function provides a location label for each of the two input subsample averages. By
466 comparing the true location labels to the predicted location labels, decoding accuracy was
467 computed.

468 This training-and-testing process was applied three times such that each subsample
469 average served as the testing dataset once. Further, the entire procedure was iterated 10
470 times. On each iteration, the trials in each location bin were randomly assigned to the five
471 sets (i.e., to create new subsample averages). Finally, decoding accuracy was collapsed
472 across the four locations, the three cycles of partitioning trials into sets, and the 10
473 iterations, resulting in a decoding percentage for each time point. After obtaining a decoding
474 percentage for all time points of interest, a five-point moving average was applied to smooth
475 the averaged decoding accuracy values and to minimize noise.

476

477 *Statistical analysis of decoding accuracy.* Although decoding was performed for all time
478 points in-between -500 to 4500 ms relative to sound onset, the statistical analysis focused
479 on the time interval following sound array presentation until the end of the maximal
480 response interval (i.e., 1600 – 3800 ms relative to sound onset). We restricted the statistical
481 analysis to this time interval because the goal was to test decoding accuracy during the post-
482 stimulus interval (i.e., when post-stimulus attentional processing takes place). In addition,

483 because participants did not have any knowledge about *where* the target is going to appear
484 prior to sound array onset, there should be no location-specific information present in-
485 between target cue and sound array-onset. Briefly, the statistical analysis of decoding
486 accuracy comprised two separate approaches: First, to confirm that the scalp topography of
487 post-stimulus alpha-band power contains information about the target location, we
488 compared decoding accuracy to chance level (i.e., 25% – because we used 4 locations) at
489 each time point. This was done separately for the two spatial demand conditions. Second,
490 we compared decoding accuracy in the low and high spatial demand condition to evaluate
491 whether the amount of spatial information that is reflected in the scalp topography of alpha-
492 band power is sensitive to the spatial demands of the task. At both stages, we controlled for
493 multiple comparisons (see below for details).

494

495 *Decoding accuracy within conditions.* We used a non-parametric cluster-based permutation
496 analysis to compare decoding accuracy to chance level (i.e., 25%) at each time point. Here,
497 we adopted the corrected analysis code provided by Bae & Luck (2019), accounting for the
498 presence of autocorrelated noise in the data. Using one-sided one sample *t*-tests, the
499 average decoding accuracy across subjects was compared to chance level, separately for
500 each time-point. Because SVM decoding does not produce meaningful below-chance
501 decoding results, a one-sided *t*-test is justified. Then, clusters of at least two adjacent time
502 points with a significant single-point *t*-test (i.e. $p < .05$) were identified. The *t*-values within a
503 given cluster were summed, constituting the so-called cluster mass. To determine whether a
504 given cluster mass is greater than what can be expected under the null hypothesis, we
505 constructed a null distribution of cluster-level *t*-mass values using permutation tests.
506 Critically, to reduce computation time, we randomly permuted the target labels at the stage
507 of testing the decoding output, rather than prior to training the classifier. Specifically, from
508 an array containing all possible target labels (1, 2, 3, 4), we randomly sampled an integer as
509 the simulated response of the classifier for a given target location. If the response matched
510 the true target value, the response was considered correct. This yields an estimate of the
511 decoding accuracy values that would be obtained by chance if the decoder randomly
512 guessed the target location. Critically, to reflect the temporal auto-correlation of the
513 continuous EEG data, the same randomly sampled target position label was used for all time
514 points in a given trial. Overall, this sampling procedure was repeated 120 times (4 locations x

515 3 cross-validations x 10 iterations) and for each time point of interest in-between 1600 ms to
516 3800 ms. The 120 scores for each time point were averaged to obtain the mean simulated
517 decoding accuracy, resulting in a time series of decoding accuracy values. Analogous to the
518 procedure that was applied to the actual EEG data, the latter was smoothed using a five-
519 point running average filter. The procedure was repeated 17 times, to obtain a simulated
520 decoding accuracy time series for each of our 17 participants. Then, using the simulated
521 decoding accuracy time series, the maximum cluster mass was computed, using the
522 procedure described above. That is, if there was more than one cluster of significant t -
523 values, the mass of the largest cluster was selected.

524 Finally, this procedure (i.e., simulating decoding accuracy that would be obtained by
525 chance) was iterated 10,000 times to produce a null distribution of cluster mass values. For
526 each cluster in the decoding results, the obtained cluster t mass was compared to the
527 distribution of cluster t mass values that was constructed under the assumption that the null
528 hypothesis is true. If the observed cluster t mass value was in the top 95% of the null
529 distribution (i.e. $\alpha = .05$, one-tailed), the null hypothesis was rejected and decoding accuracy
530 was considered above chance. Note that this procedure was separately applied to both the
531 low spatial demand condition and the high spatial demand condition.

532 To find the p -value associated with a specific cluster, we examined where within the
533 null distribution does each observed cluster t mass value fall. That is, the p -value was based
534 on the inverse percentile (computed using the *invprctile()* function) of the observed cluster-
535 level t mass within the null distribution. If the observed cluster-level t -mass value exceeded
536 the maximum cluster-level t -mass of the simulated null distribution, the respective p -value is
537 reported as $p < 10^{-4}$. The latter corresponds to the resolution of the null distribution (i.e., 1 /
538 number of permutations).

539

540 *Decoding Accuracy in low vs. high spatial demand blocks.* To investigate, whether or not the
541 amount of spatial information reflected by the scalp topography of alpha power differs
542 depending on the spatial demands of the task, decoding accuracy in the two task conditions
543 was compared, using a cluster-corrected sign-permutation test. To this end, the
544 *cluster_test()* and *cluster_test_helper()* functions provided by Wolff, Jochim, Akyürek, &
545 Stokes (2017) were applied. The sign-permutation test is a non-parametric test that makes
546 no assumption of the distribution of the data. As input data, the same time window that was

547 also used for the statistical analysis of decoding accuracy within conditions was selected (i.e.,
548 1600 – 3800 ms). Specifically, the *cluster_test_helper()* function generates a null distribution
549 by randomly flipping the sign of the input data of each participant with a probability of 50%.
550 This procedure was repeated 10,000 times. The resulting distribution served as input to the
551 *cluster_test()* function, identifying those clusters in the actual data that are greater than
552 would we expected under the null hypothesis. The cluster-forming threshold as well as the
553 cluster significance threshold were set to $p < .05$. Because we had a clear hypothesis
554 regarding the direction of the effect (that is, decoding accuracy in the high spatial demand
555 condition should be higher compared to the low spatial demand condition), the cluster-
556 corrected sign-permutation test was one-sided.

557 In addition, to assess the overall difference in decoding ability within the post-
558 stimulus period, the decoding accuracy was averaged across time in the approximate time
559 window that resulted in significant within-condition decoding results (i.e., 1940 – 3340 ms)
560 and submitted to a one-sided permutation test. To this end, the *GroupPermTest()* function
561 provided by Wolff et al. (2017) was applied (using $nSims = 10,000$ permutations).

562

563 *2.6 Data/code availability statement*

564 Stimuli and code for this study can be found at <https://osf.io/a8f6y/>. Data will be publicly
565 stored in a Zenodo repository with restricted access. Access will be granted upon signing a
566 data user agreement.

567

568 **3. Results**

569 *3.1 Behavioral data*

570 Behavioral results are displayed in Figure 2. The analysis of response times revealed a main
571 effect spatial demand, $F(1,16) = 68.75$, $p < .001$, $\eta_p^2 = 0.81$, with slower responses in high
572 spatial demand blocks ($M = 834.79$ ms, $SD = 92.89$) compared to low spatial demand blocks
573 ($M = 713.61$ ms, $SD = 123.94$). In addition, there was a significant main effect of perceptual
574 load, $F(1,16) = 161.57$, $p < .001$, $\eta_p^2 = 0.91$, with slower responses in high-load trials ($M =$
575 843.92 ms, $SD = 116.19$) compared to low-load trials ($M = 704.48$ ms, $SD = 98.47$). For
576 response times, there was no significant interaction of spatial demand and perceptual load,
577 $F(1,16) = 2.59$, $p = .13$, $\eta_p^2 = 0.14$. A nearly analogous pattern of results was revealed by the
578 analysis of the percentage of correct responses. That is, participants responded more

579 accurately in low spatial demand blocks ($M = 92.54\%$, $SD = 4.63$) compared to high spatial
580 demand blocks ($M = 88.84\%$, $SD = 4.80$), $F(1,16) = 21.58$, $p < .001$, $\eta_p^2 = 0.57$). In addition,
581 the percentage of correct responses was higher in low-load trials ($M = 96.57\%$, $SD = 2.72$),
582 compared to high-load trials ($M = 84.81\%$, $SD = 7.32$), $F(1,16) = 53.70$, $p < .001$, $\eta_p^2 = 0.77$.
583 Further, a significant interaction of spatial demand and perceptual load, $F(1,16) = 10.78$, $p =$
584 $.005$, $\eta_p^2 = 0.40$, complements the descriptive observation that the difference in accuracy
585 between low and high perceptual load was slightly greater in high spatial demand blocks (M
586 $= 13.66\%$, $SD = 7.24$) than in low spatial demand blocks ($M = 9.87\%$, $SD = 6.82$).

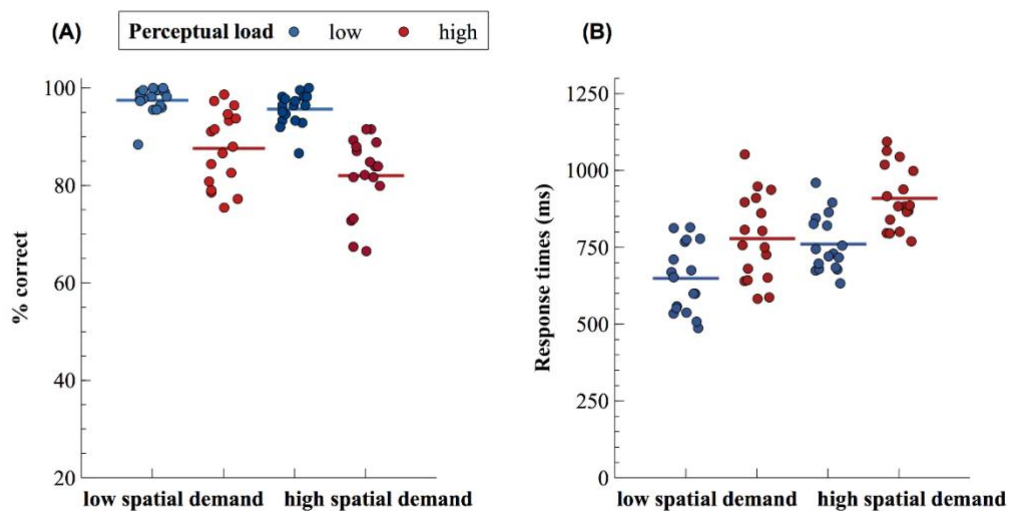


Figure 2. Behavioral performance. Solid, horizontal lines indicate the mean percentage of correct responses (A) or mean response times (B) in a given condition. Colored dots correspond to individual response measures. Please note that the y-axis for the % of correct responses does not originate at 0.

587 3.2 Alpha power lateralization

588 Figure 3A illustrates the time course of the contralateral minus ipsilateral differences in
589 alpha power at a cluster of posterior scalp electrodes. A repeated-measures analysis of the
590 mean alpha power amplitudes in-between 532 to 937 ms post-sound array onset revealed
591 no significant modulation by spatial demand, $F(1,16) = 0.04$, $p = .842$, $\eta_p^2 = 0.003$, neither by
592 perceptual load, $F(1,16) = 0.03$, $p = .862$, $\eta_p^2 = 0.002$, nor an interaction between the two
593 factors, $F(1,16) = 0.03$, $p = 0.854$, $\eta_p^2 = 0.002$. Time-frequency plots, illustrating contralateral,
594 ipsilateral, as well as contralateral minus ipsilateral power for a broader frequency range (4 –
595 30 Hz) are available in the supplementary material. Further, the supplementary material
596 includes a post-hoc analysis, including the factor target eccentricity (inner vs. outer targets).

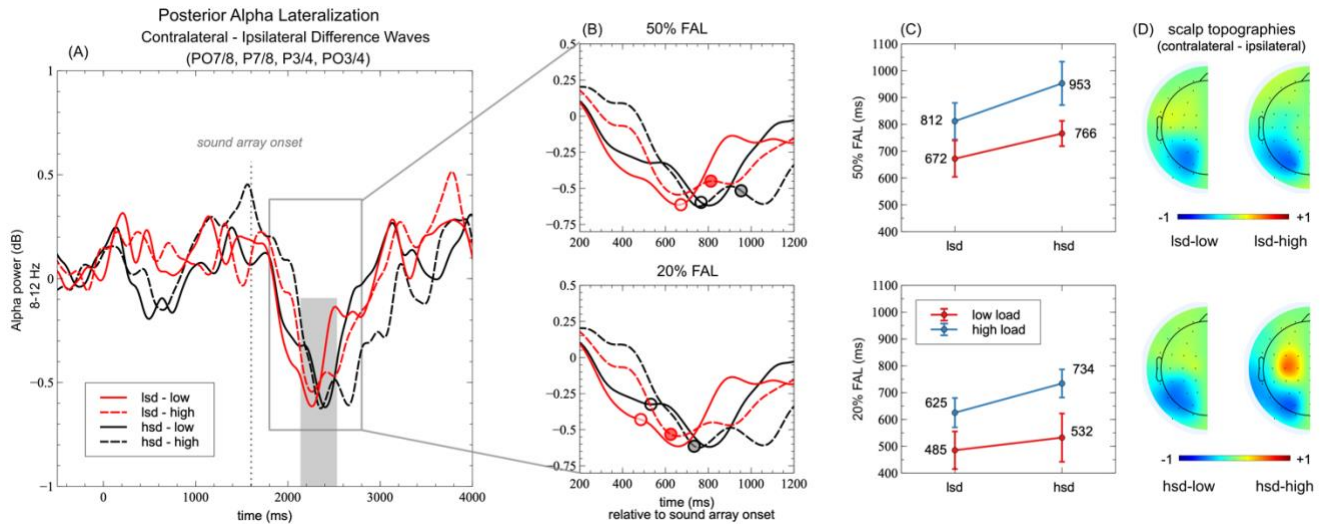


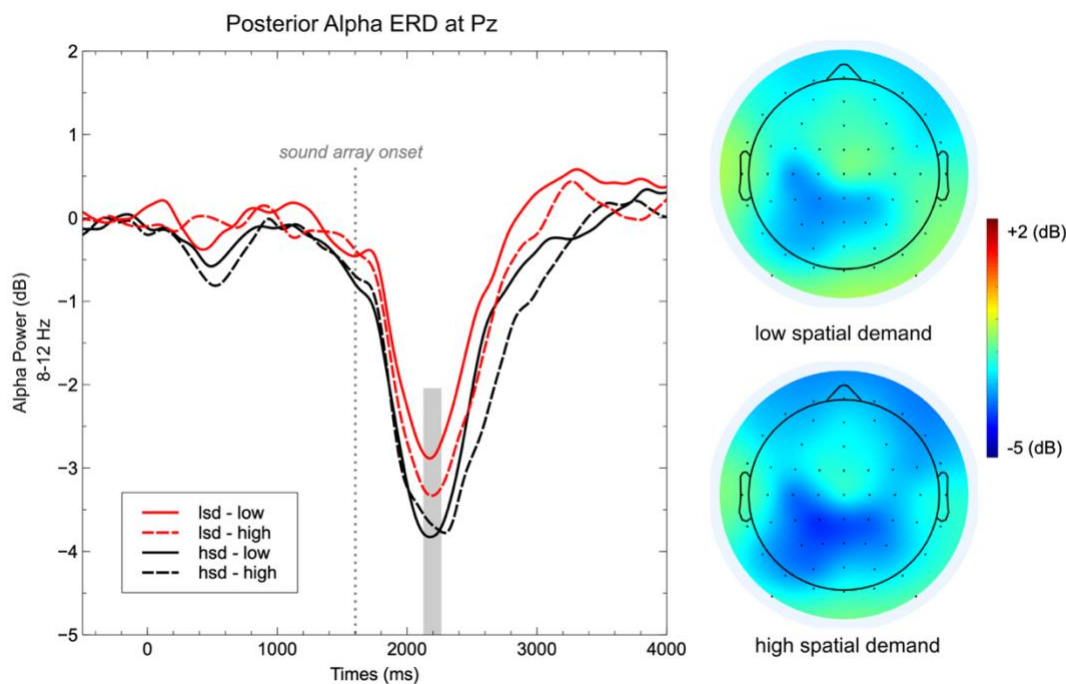
Figure 3. Alpha Power Lateralization. (A) Time course of contralateral minus ipsilateral differences in alpha power across a cluster of parieto-occipital scalp electrodes. The grey-filled rectangle highlights the time window used for statistical analysis of mean alpha lateralization magnitude. (B) A close-up view of the contralateral minus ipsilateral difference waveforms in-between 1800 and 2800 ms (i.e., 200 – 1200 ms relative to sound array onset). The x-axis denotes time (ms) relative to sound array onset. Circles mark the 50% (top) and 20% (bottom) fractional area latency (FAL) measures for each condition. (C) A line plot of the respective 50%-FAL (top) and 20%-FAL (bottom) values, depending on spatial demand and perceptual load. Y-axis values denote FAL relative to sound array onset. Error bars depict the standard error according to Miller et al., 1998 (formula 2) (D) Scalp topographies based on the contralateral minus ipsilateral differences in alpha power in-between 532 to 937 ms following sound array onset (i.e., the time window used for statistical analyses).

598 3.3 Alpha lateralization onset latencies

599 To investigate whether the time-course of alpha lateralization was affected by the task
600 demands, we assessed alpha lateralization onset latencies. Figure 3B and C illustrate the
601 points in time where the area under the condition-specific difference curves reaches 20%
602 and 50%, respectively (i.e., the 20% FAL and the 50% FAL). The analysis of fractional area
603 latency (FAL) measures revealed a significant main effect of perceptual load for the 20%-FAL,
604 $F_{\text{corr}}(1,16) = 7.90, p = .013$, and the 50%-FAL, $F_{\text{corr}}(1,16) = 11.39, p = .004$. That is, alpha
605 lateralization emerged earlier in low perceptual load compared to high perceptual load trials
606 ($D_{20\%} = 171 \text{ ms}, SE_{D-20\%} = 60.15, D_{50\%} = 163.5 \text{ ms}, SE_{D-50\%} = 48.78$). A significant main effect of
607 spatial demand was only evident for the 50%-FAL, $F_{\text{corr}}(1,16) = 4.82, p = .043$, indicating
608 earlier alpha lateralization onset latencies in low spatial demand blocks compared to high
609 spatial demand blocks ($D_{50\%} = 117.5 \text{ ms}, SE_{D-50\%} = 51.69$). There were no significant
610 interactions (all $F_{\text{corr}} < 0.27$). Alpha lateralization onset latency was not significantly related
611 to response times, $r_{\text{rm-20\%}}(41) = .139, p = .373, 95\% \text{ CI } [-0.18 \text{ } 0.43]$, $r_{\text{rm-50\%}}(41) = .170, p = .277,$
612 $95\% \text{ CI } [-0.15 \text{ } 0.453]$.

613 3.4 Non-lateralized, posterior alpha power desynchronization

614 Figure 4 depicts the time-course of posterior alpha power at electrode Pz, separately for
615 each of the four conditions. The analysis revealed a significant main effect of spatial
616 demand, $F(1,16) = 6.94$, $p = .018$, $\eta_p^2 = 0.30$, reflecting greater alpha ERD (i.e., more negative
617 power) in the high spatial demand condition ($M = -3.74$ dB, $SD = 2.48$) compared to the low
618 spatial demand condition ($M = -3.08$ dB, $SD = 2.14$). While the main effect perceptual load
619 was not significant, $F(1,16) = 0.79$, $p = .388$, $\eta_p^2 = .05$, there was a significant interaction
620 between spatial demand and perceptual load, $F(1,16) = 5.49$, $p = .032$, $\eta_p^2 = 0.26$. Follow-up
621 paired sample t -tests revealed that the difference between low and high perceptual load
622 trials fell short of significance in both the low spatial demand condition, $t(16) = 1.74$, $p =$
623 $.101$, $p_{adj} = .304$, $g = 0.21$, and the high spatial demand condition, $t(16) = -0.74$, $p = .469$, p_{adj}
624 $= .704$, $g = -0.05$.

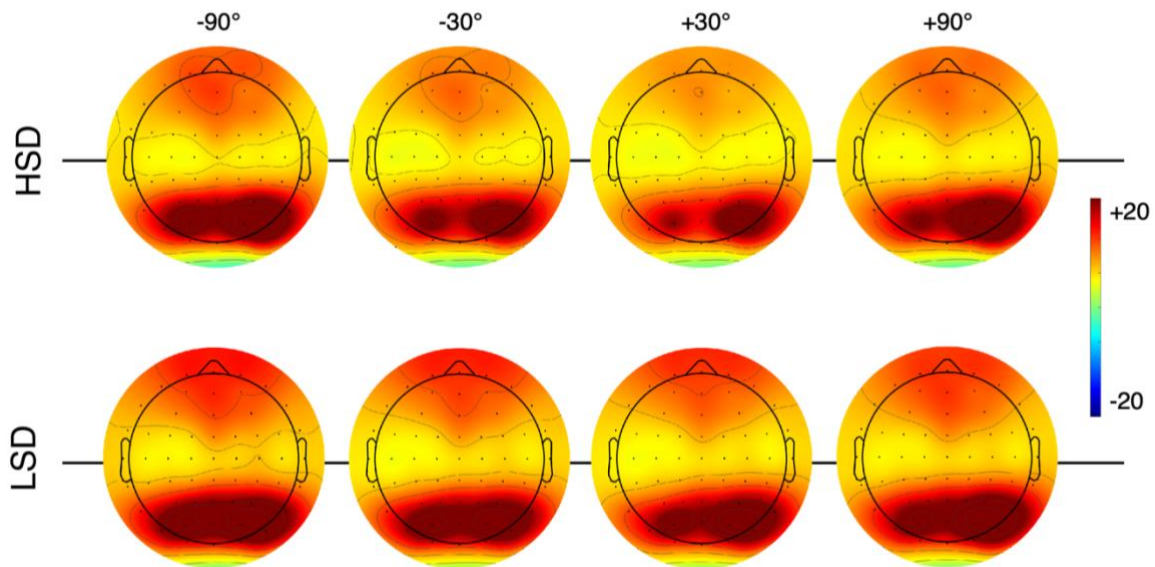


625
626 **Figure 4. Event-related desynchronization (ERD) of alpha power at Pz.** The line plot illustrates the condition-
627 specific averages depending on spatial demand and perceptual load. lsd-low = low spatial demand / low
628 perceptual load, lsd-high = low spatial demand / high perceptual load, hsd-low = high spatial demand / low
629 perceptual load, hsd-high = high spatial demand / high perceptual load. The grey rectangle indicates the
630 approximate time window used for statistical analysis (i.e., 2144 - 2244 ms relative to target cue onset or 544 - 644
631 ms relative to sound array onset). Scalp topographies are based on the average alpha power in the respective
632 analysis time window.

633 3.5 Decoding analysis

634 We decoded the exact spatial location (i.e., outer-left, inner-left, inner-right, outer-right) of
635 the target sound based on the scalp distribution of alpha-band EEG power. Figure 5 shows
636 the grand average scalp topography for each target location, separately for the two spatial
637 demand conditions (and averaged across the two perceptual load conditions). Figure 6A
638 shows the time-course of decoding accuracy for the low vs. high spatial demand condition,
639 as well as the difference in decoding accuracy between conditions. Decoding accuracy starts
640 to rise above chance level (i.e., 25%) at around 1960 ms (i.e., 360 ms following sound array
641 onset) and at first, increases continuously in both spatial demand conditions. In the low
642 spatial demand condition, decoding accuracy reaches a peak at around 2200 ms (i.e., 600 ms
643 post-sound onset) and then gradually decreases throughout the remainder of the response
644 interval; in the high spatial demand condition, decoding accuracy continues to rise beyond
645 the peak in the low spatial demand condition until around ~2360 ms (i.e., 760 ms post-
646 sound onset). The decoding accuracy remains at this level for a couple hundred milliseconds
647 and declines thereafter, although it remains on a higher level compared to the low spatial
648 demand condition. Toward the end of the response interval (i.e., around 3800 ms), decoding
649 accuracy approaches chance level in both conditions. The cluster mass test revealed that
650 decoding was significantly greater than chance in both spatial demand conditions. We
651 identified a significant cluster following sound array onset in each of the two conditions (all p
652 $< 10^{-4}$, see Figure 5A, solid green and yellow lines). In the high spatial demand condition, the
653 cluster extends from around 1980 ms to ~3340 ms relative to cue onset (i.e., ~380 – 1740
654 ms relative to sound array onset); in the low spatial demand condition, the cluster spans a
655 comparable time period in-between ~1940 ms and 3340 ms relative to cue onset (i.e., ~340
656 – 1740 ms relative to sound array onset). Note, however, that cluster-based permutation
657 test results should not be used to derive conclusions about the specific onset or offset of a
658 certain effect (Sassenhagen & Draschkow, 2019).

659 The black, dashed line in Figure 6A illustrates the difference in decoding accuracy
660 between the two spatial demand conditions. A cluster-corrected sign-permutation test
661 indicated significant differences in decoding ability ($p < .01$, one-sided test, cluster extending
662 from ~2340 – 2820 ms relative to cue onset, i.e., ~740 – 1220 ms relative to sound array
663 onset), with higher decoding accuracy in the high spatial demand condition compared to the
664 low spatial demand condition.



665

666 **Figure 5. Scalp topographies of instantaneous alpha power for each of the target locations.** Alpha power
 667 was averaged across a broad time interval following sound array onset (i.e., 340 – 1740 ms post sound array
 668 onset), averaged across subjects as well as across the two perceptual load conditions. The top row depicts the
 669 scalp topographies for the high spatial demand (HSD) condition, the bottom row shows the low spatial demand
 670 (LSD) condition.

671

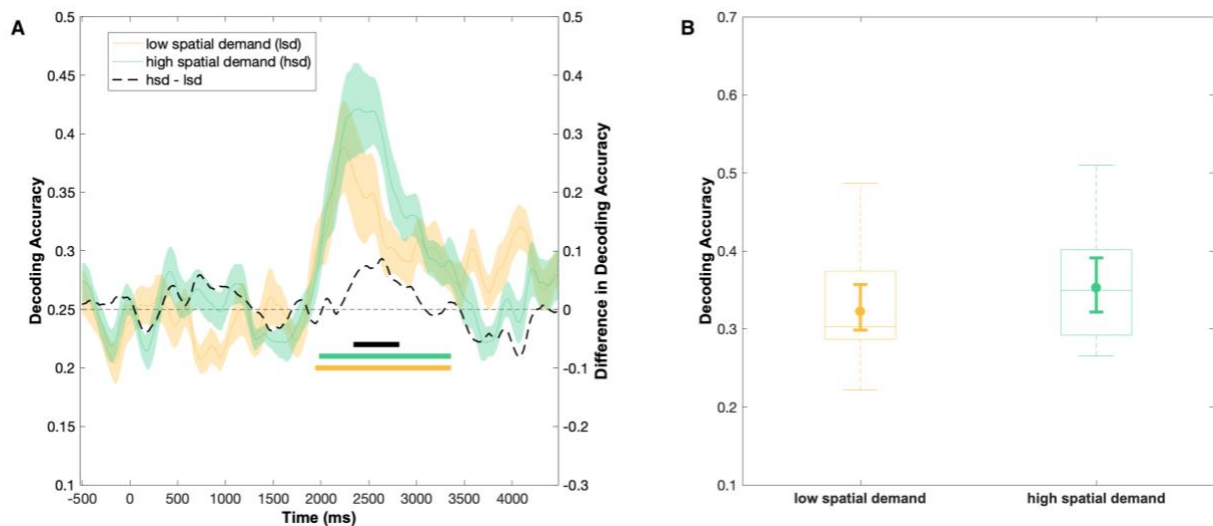


Figure 6. Location decoding based on the multivariate scalp distribution of alpha power. (A) Time-course of the average decoding accuracy results in the low (yellow) and high (green) spatial demand condition, respectively. The colored shading indicates ± 1 SEM. Chance-level performance (i.e., 25%) is indicated by the grey dashed horizontal line. The yellow and green solid bars indicate significant decoding of the target location in the low and high spatial demand condition, respectively. The black solid bar denotes significant differences in decoding ability between the low and the high spatial demand condition. Note that only time-points in-between 1600 – 3800 ms were considered in the statistical analysis. (B) Boxplots refer to the average decoding accuracy in-between 1940 – 3340 ms relative to cue-onset (i.e., 340 – 1740 ms following sound array onset). As per convention, boxplots illustrate the interquartile range and the median. Whiskers extent to the 1.5 times the interquartile range. The superimposed circles show the average decoding accuracy, while the corresponding error bars denote the 95% bootstrap confidence interval of the mean (number of bootstrap samples = 10000).

672 Finally, we assessed the overall difference in decoding ability within the post-stimulus
673 period (specifically, within the approximate time-window that resulted in above-chance
674 decoding accuracy within both spatial demand conditions). A one-sided permutation test of
675 the average decoding accuracy between 1940 – 3340 ms (i.e., 340 – 1740 ms relative to
676 sound array onset) consistently revealed a significant difference in decoding accuracy
677 between the spatial demand conditions ($p = .002$, Fig. 6B).

678 Notably, an additional, exploratory decoding analysis based on alpha power at parieto-
679 occipital scalp sites (rather than the whole scalp), returned very comparable results (see
680 supplementary material, S3).

681

682 3.6 Confusion matrices

683 To provide more detailed insights into the decoding results, here we show the confusion
684 matrices for each combination of target location and classification response, separately for
685 the high and low spatial demand condition. Figure 7 illustrates the probability of each
686 classification response (i.e., predicted location) for a given stimulus category (i.e., true
687 location), averaged over the time interval that resulted in significant within-condition
688 decoding performance and over participants. In both conditions, the highest probability of
689 classification response is evident at the true location. Interestingly, while neighboring
690 positions receive the most classification errors, the least confusion occurs between a true
691 location and the position that is in the opposite hemifield and of opposite eccentricity (e.g.,
692 left-out vs. right-in).
693

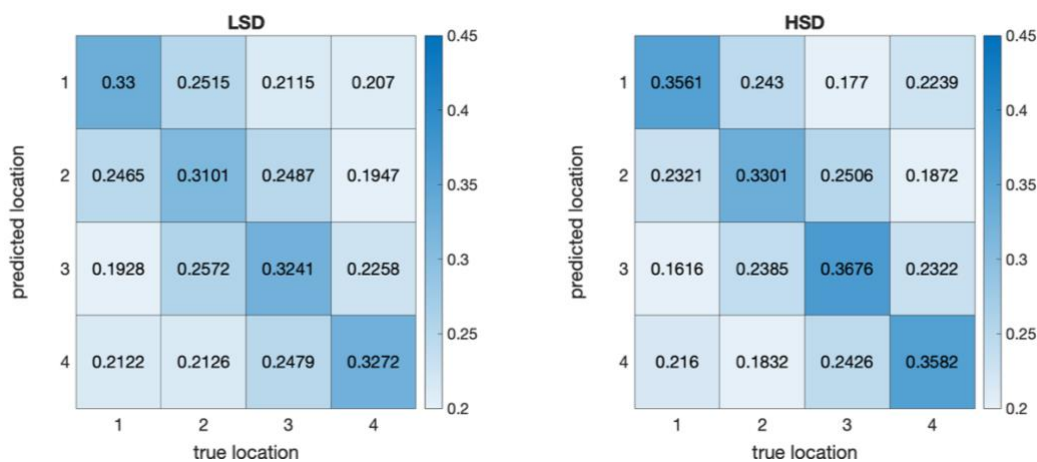


Figure 7. Confusion matrices for the low (LSD) and high (HSD) spatial demand condition. Each cells shows the probability of a given classification response (y-axis) for each stimulus position (x-axis), averaged across subjects and across the entire time-period that resulted in significant within-condition decoding (i.e., 1940-3340 ms relative to cue onset or respectively, 340 -1740 ms relative to sound array onset). Location labels (1-4) correspond to stimulus locations in their order of occurrence from left to right (i.e., left-out, left-in, right-in, right-out).

694 *3.7 Control analyses: eye movements*

695 The ERP signal at horizontal EOG electrodes (LO1, LO2), contralateral and ipsilateral relative
696 to the target location, revealed asymmetric voltage differences, indicative of horizontal eye
697 movements (see supplementary figure 3). That is, despite the instruction to fixate a central
698 fixation point, on average, saccades toward the target sound were present. Notably,
699 saccades appeared to occur more frequently or more strongly in the high spatial demand
700 condition. To verify that eye movements (and the differences in eye movement between
701 conditions) did not impact the univariate alpha lateralization or the multivariate decoding
702 results, we performed a series of post-hoc control analyses. We briefly summarize the main
703 results here. For details, please see the supplementary material.

704 First, to rule out that the overall presence of alpha lateralization was affected by the
705 occurrence of horizontal eye movement, we performed an analysis of covariance (ANCOVA),
706 including alpha lateralization magnitude as the dependent variable. The average hEOG
707 asymmetry (contra minus ipsi) served as a covariate, spatial demand (high vs. low),
708 perceptual load (high vs. low) and asymmetry (contra vs. ipsi) as within-subject factors.
709 While we obtained a non-significant interaction of hEOG asymmetry and alpha asymmetry,
710 $F(1,15) = 0.67$, $p = .425$, the main effect of alpha asymmetry remained significant, $F(1,15) =$
711 12.39 , $p = .003$, after controlling for the effect of saccades.

712 Further, we assessed the potential impact of horizontal eye movements on the decoding
713 results. An exploratory decoding analysis, using the ERP at horizontal EOG channels as input,
714 revealed significant above-chance decoding of target location in both the low and the high
715 spatial demand condition (see supplementary figure 4). However, the difference in decoding
716 accuracy between the high versus low spatial demand condition did not reproduce. Further,
717 overall decoding accuracy was lower for hEOG-based decoding compared to alpha power-
718 based decoding. As an additional control analysis, to clarify whether the apparent
719 differences in hEOG asymmetry between conditions systematically covary with the effect of
720 spatial demand on alpha-power-based decoding accuracy, we performed a post-hoc
721 ANCOVA. The average decoding accuracy in-between 1940 – 3340 ms served as the
722 dependent variable, spatial demand (low vs. high) served as the within-subject factor, and
723 the difference in hEOG lateralization between the spatial demand conditions (hsd minus lsd)
724 was included as a covariate. The covariate was not significantly related to decoding accuracy,
725 $F(1,15) = 0.52$, $p = .481$. Critically, the main effect of spatial demand was still significant after

726 controlling for the effect of saccades, $F(1,15) = 7.14$, $p = .017$. The interaction between
727 saccades and spatial demand was not significant, $F(1,15) = 0.03$, $p = 0.855$. Overall, this
728 suggests that the higher decoding accuracy in high spatial demand conditions is not caused
729 by a potential impact of horizontal eye movements.

730 **4. Discussion**

731 Sensory stimuli and behavioral demands are constantly subject to change, requiring the
732 attentive brain to adapt its response to accommodate to those changes. In this study, we
733 investigated the effects of varying perceptual load and spatial demand in a sound
734 localization task on post-stimulus alpha-band oscillations. The notion that alpha-band
735 oscillations track the currently attended location in a spatially fine-tuned manner is relatively
736 undisputed. However, what remains more elusive is to what degree this spatial specificity
737 depends on the current task demands. Here, we demonstrate that the amount of spatial
738 information reflected in the multivariate scalp distribution of alpha power increases when
739 the task requires a precise sound localization (i.e., indicating the exact stimulus location)
740 compared to when a rather coarse localization judgment is required (i.e., indicating the
741 hemifield). In contrast, these task demand-dependent modulations were not captured by
742 the magnitude of univariate parieto-occipital alpha lateralization. Rather, the time course of
743 alpha power lateralization varied with the task demands.

744 Behaviorally, the pattern of results was consistent with the well-established observation
745 that the detection of a target sound in a cocktail-party scenario suffers from additional
746 concurrent stimuli in the auditory scene (Brungart & Simpson, 2007; Brungart, Simpson,
747 Ericson, & Scott, 2001; Ericson, Brungart, & Simpson, 2004; Klatt et al., 2018b). Accordingly,
748 in the present study, participants' responses were slower and less accurate when the sound
749 array contained four (high perceptual load) instead of just two sounds (low perceptual load).
750 In terms of sound localization accuracy, this difference was even more pronounced when
751 they were asked to report the exact target location (high spatial demand) rather than the
752 target hemifield (low spatial demand). Certainly, the present set size effect cannot be
753 completely disentangled from the effects of energetic masking due to the acoustic overlap
754 between the competing sound sources (cf. Murphy, Spence, & Dalton, 2017). However, most
755 critical for the intended EEG analysis was the manipulation of spatial demand. As expected,
756 indicating the exact sound location was more challenging (i.e., slower and less accurate) than

757 simply determining whether the target was present in the left or right hemispace.
758 Nevertheless, subjects still managed to perform clearly above chance level (i.e., on average >
759 80% correct).

760

761 **4.1 Decoding of auditory covert attention based on alpha power modulations**

762 The main question of the present study was: Is the difference in spatial task demands
763 also reflected in the neural signal? Strikingly, while the classifier could reliably decode the
764 precise target location in both spatial demand conditions, the amount of spatial information
765 reflected in the scalp distribution of alpha-band power was higher under high spatial
766 demand. It should be emphasized that in both spatial demand conditions, participants were
767 presented with the exact same trials (although in randomly shuffled order). This rules out
768 that differences between conditions were caused by bottom-up perceptual factors. Further,
769 the confusion matrices show most classification errors for neighboring positions and the
770 least confusion between the true target location and the location that is both within the
771 other hemifield and on the opposite side (e.g., left-out vs. right-in). This supports the
772 assumption that in auditory scene analysis the relative location between sounds is coded on
773 a neural level, rather than the mere stimulus position (cf. Shiell et al., 2018).

774 The present results extend previous work, using an analogous auditory search task
775 design, where we demonstrated that the presence of auditory post-stimulus alpha
776 lateralization was dependent on the task-relevance of spatial information. Specifically, Klatt
777 et al. (2018b) showed that alpha lateralization was absent in a simple sound detection task
778 (i.e., when spatial location was completely irrelevant to the task), whereas it reliably
779 indicated the attended location when participants were asked to localize the target. Here,
780 we show that post-stimulus alpha oscillations are not only sensitive to such coarse
781 manipulations of spatial relevance, but rather – when considering the multivariate activity
782 patterns – also capture fine-grained adaptations to the required degree of spatial specificity.
783 However, the curves reflecting decoding accuracy in the low and high spatial demand
784 conditions do not diverge until about 600 ms following sound array onset; in addition,
785 statistically significant differences in decoding accuracy were limited to a relatively late
786 time-window (i.e., > 700 ms following sound array onset; cf. Figure 5A). In contrast, general
787 decodability of spatial location increases above chance level shortly after sound array onset
788 and persists well into the response interval. This suggests that, even though the spatial

789 demand conditions were blocked (i.e., participants knew beforehand which spatial specificity
790 would be required), it took several hundred milliseconds to evoke changes in spatial
791 specificity of the underlying alpha power signal. Such long latencies have also been reported
792 with respect to voluntary adaptations of the alpha-power signal in a visual spatial cueing study
793 paradigm, requiring participants to adopt either a narrow or a broad focus of attention in
794 anticipation of an upcoming search array (Feldmann-Wüstefeld & Awh, 2019). In the latter
795 study, Feldmann-Wüstefeld & Awh (2019) computed spatially selective channel tuning
796 functions (CTF) based on the topography distribution of alpha power and assessed their
797 slope as a measure of spatial selectivity. Notably, differences in the CTF slopes between the
798 narrow-focus cue and the broad-focus cue only emerged at timepoints > 500 ms following
799 cue onset. A previous study by Voytek and colleagues (Voytek et al., 2017) similarly
800 manipulated the breadth of the attentional focus using a central cue, pointing to either the
801 exact location the target will appear in or to an approximate region of varying size.
802 Consistent with Feldmann-Wüstefeld & Awh (2019), an inverted encoding modeling analysis
803 revealed that the spatial selectivity of anticipatory alpha-band activity decreased with
804 greater uncertainty about the upcoming target's location.

805 Critically, the present results add to these previous findings in several ways: First, we
806 demonstrate that just like preparatory attention is finely tuned and spatially sharpened
807 depending on the task demands (Feldmann-Wüstefeld & Awh, 2019; Voytek et al., 2017), the
808 ongoing attentional processing following search array onset is dynamically modulated
809 depending on the required spatial specificity of the task. Further, the present findings
810 complement a growing body of evidence, supporting the assumption that modulations of
811 alpha oscillations represent a ubiquitous top-down controlled mechanism of spatial
812 attention that plays a role across different attentional domains as well as across sensory
813 modalities. Notably, the pattern that decoding accuracy increases if a more precise spatial
814 judgment is required did fully reproduce when using only parieto-occipital channels as
815 classifier input (cf. supplementary material). This suggests that most information that
816 contributes to classification performance, and critically, to the difference in decoding
817 accuracy between conditions, is present at posterior electrode sites. Overall, this is in line
818 with the notion that parieto-occipital cortex subserves a supramodal neural circuit for spatial
819 attention (Popov, Gips, Weisz, & Jensen, 2021).

820 In principle, the notion that attention can improve the information content of a neural
821 code is not novel. In fact, it is well-established that attending to a spatial position or a
822 relevant feature increases single-neuron firing rates in primary and extrastriate visual areas
823 and can result in changes in the size and position of spatial receptive fields (reviewed by
824 (Sprague, Saproo, & Serences, 2015). In the auditory domain, physiological recordings in cats
825 (Lee & Middlebrooks, 2011) revealed similar sharpening of spatial tuning in auditory cortex
826 (i.e., A1) when the animal engaged in a spatial task compared to an off-task “Idle” condition
827 and a non-spatial periodicity detection task (for similar findings in human A1 see van der
828 Heijden, Rauschecker, Formisano, Valente, & de Gelder, 2018). Hence, along with previous
829 studies in the visual modality (Feldmann-Wüstefeld & Awh, 2019; Voytek et al., 2017), the
830 present results extend these findings, showing that such “sharpening” of neural activity
831 occurs not only in tuning functions of single neurons, but is also evident in the adaption of
832 population-level activity patterns.

833

834 **4.2 Alpha power lateralization as a temporally resolved signature of target processing**

835 In addition to the multivariate decoding analysis, we also analyzed alpha lateralization
836 following sound array onset as a ‘classical’ univariate measure of attentional orienting (e.g.,
837 Ikkai, Dandekar, & Curtis, 2016). In the present study, alpha lateralization magnitude did
838 neither vary with perceptual load or spatial demand. The former observation replicates
839 results of a previous study (Klatt et al., 2018b), finding no evidence for differences in alpha
840 lateralization magnitude between a low-load (i.e., two-sound array) and a high-load (i.e.,
841 four-sound array) auditory search condition. In contrast, Bacigalupo and Luck (2019)
842 reported that target-elicited alpha lateralization in a visual search paradigm tended to
843 increase with greater task difficulty. Thus, the authors speculate that alpha lateralization
844 might reflect effort rather than target selection. The present findings do not seem to bolster
845 this claim: Both the behavioral data as well as the complementary analysis of non-lateralized
846 posterior alpha power indicate that task difficulty and required cognitive resources increased
847 with greater spatial demand. Yet, alpha lateralization magnitude was unaffected by the
848 experimental manipulation. An additional study by Wang, Megla, and Woodman (2021)
849 corroborates the present results, showing that the magnitude of stimulus-induced alpha
850 lateralization remains unaffected by an increase in the difficulty of attentional selection (e.g.,
851 through higher distractor numerosity), while global, non-lateralized posterior alpha power

852 suppression did increase with distractor set size (experiment 1 and 2) and with greater
853 distance between the items (experiment 3).

854 Nonetheless, the present findings do substantiate the notion that post-stimulus (or
855 target-elicited) alpha lateralization presents an active signature of target processing in both
856 visual (Bacigalupo & Luck, 2019) as well as auditory search (Klatt et al., 2018b). Bacigalupo
857 and Luck (2019) further dissociate alpha lateralization from a well known ERP-signature of
858 target individuation (i.e., the N2pc), suggesting that alpha lateralization reflects a long-
859 lasting and ongoing attentional processing of the target. Although we do not investigate ERP
860 correlates in the present study, a closer look at the time-course of alpha lateralization
861 supports this assumption: on average, alpha lateralization persist beyond and in fact peaks
862 around the time participants make their response. Different temporal characteristics of N2ac
863 (an auditory analogue of the visual N2pc component Gamble & Luck, 2011) and alpha
864 lateralization have recently also been observed in response to shifts of auditory attention
865 between relevant talkers in a simulated cocktailparty scenario (Getzmann, Klatt, Schneider,
866 Begau, & Wascher, 2020), corroborating the notion that the EEG measures reflect different
867 attentional processes (see also Klatt et al., 2018b).

868 Contrary to alpha lateralization magnitude, alpha lateralization onset latency was
869 linked to task demands. Specifically, alpha lateralization emerged around 165 ms earlier in the
870 less demanding low perceptual load condition relative to the high perceptual load condition
871 and ~115 ms earlier (50%-FAL) in the low spatial demand condition relative to the high
872 spatial demand condition. Overall, the observed modulations of alpha lateralization onset
873 latency are in line with a previous visual search study (Foster et al., 2017), showing that the
874 onset of alpha-based CTFs varied with reaction times as well as search difficulty. That the
875 latency differences reported by Foster et al. (2017) were much larger (i.e., differences of up
876 to 440 ms) could be attributed to the fact that their search conditions differed more strongly
877 (e.g., distractors were all identical vs. heterogenous). In sum, the present findings
878 corroborate the claim that attentional modulations of alpha power not only track the
879 location of covert spatial attention, but also the time-course (i.e., the latency) of post-
880 stimulus attentional processing.

881 Finally, the clear-cut difference between univariate and multivariate measures of
882 alpha power highlights the potential of multivariate decoding for the study of neurocognitive
883 mechanisms. Similarly, when performing a univariate analysis of alpha power, Voytek et al.

884 (2017) did not capture the fine-grained differences in the allocation of attention (depending
885 on the spatial certainty of a cue) that were evident in the multivariate topography of alpha
886 power. Taken together, this illustrates the increased sensitivity of multivariate decoding
887 techniques to reveal complex dynamics that are present in the combined signal across the
888 scalp (Hebart & Baker, 2017).

889

890 **5. Conclusion**

891 In conclusion, our results show that the spatial specificity of post-stimulus alpha-band
892 oscillations can be finely adapted depending on the spatial demands of the task. Notably,
893 this task-dependent adaptation was only evident in the multivariate distribution of the
894 alpha-band signal, whereas the magnitude of univariate parieto-occipital alpha lateralization
895 did not capture those variations in perceptual load and spatial demand. Rather, alpha
896 lateralization onset latency varied with the difficulty of the task, suggesting that the time-
897 resolved modulation of post-stimulus alpha lateralization captures differences in the
898 efficiency of post-attentional processing. These findings improve our understanding of the
899 functional role of alpha oscillations for the ongoing attentional processing of complex
900 auditory scenes and provide new insights into the attentional mechanisms underlying top-
901 down adaptations to changing task demands.

902

903 **6. Competing Interests**

904 Declarations of interest: none.

905

906 **7. Author contributions: CRediT authors statement**

907 **Laura-Isabelle Klatt:** Conceptualization, Formal analysis, Investigation, Writing – Original
908 Draft, Visualization, Project administration **Stephan Getzmann:** Conceptualization, Writing –
909 Review & Editing, Supervision **Daniel Schneider:** Conceptualization, Writing – Review &
910 Editing, Supervision

911

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919 decoding and cluster permutation analyses.

920

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SUPPLEMENTARY MATERIALS FOR

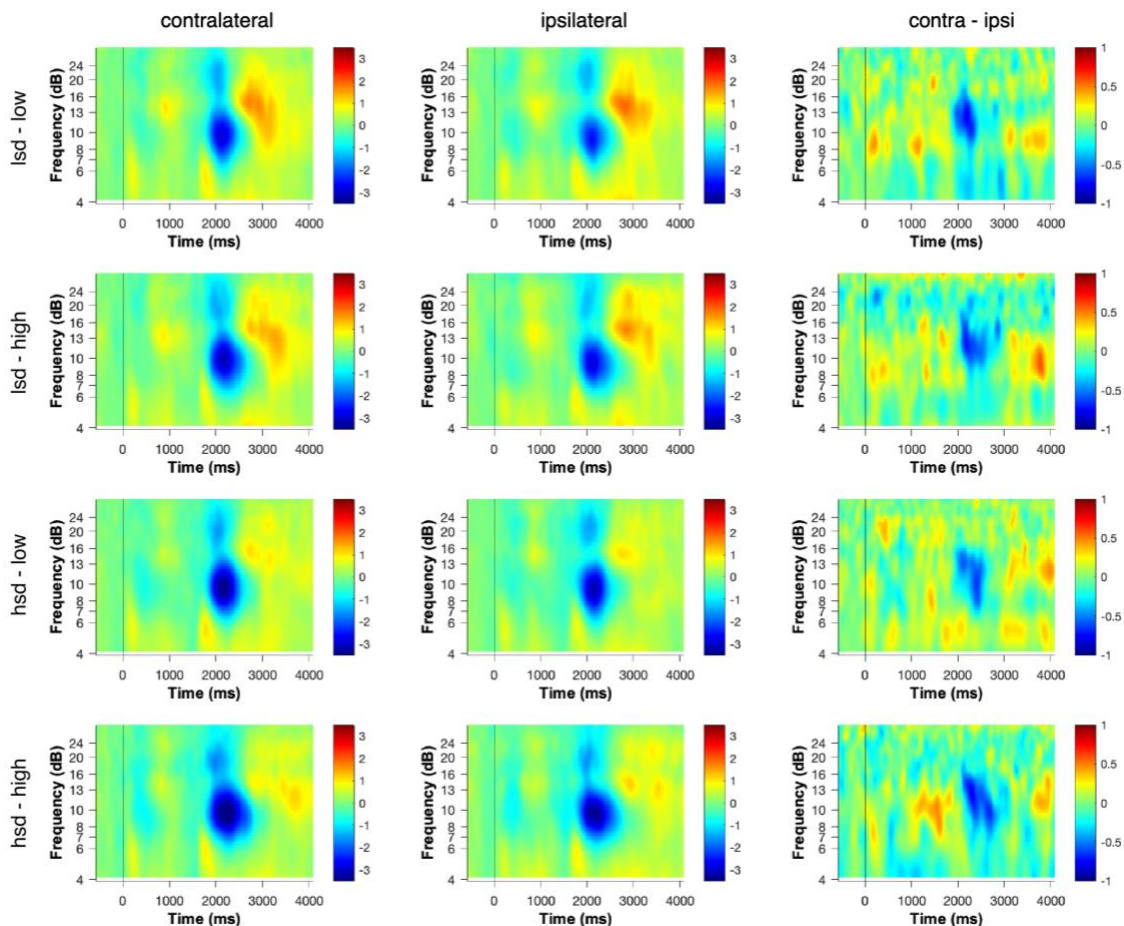
Attentional Modulations of Alpha Power Are Sensitive to the Task-relevance of Auditory Spatial Information

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1 S1. Time-Frequency Plots

2 Supplementary figure 1 illustrates contralateral, ipsilateral, as well as contralateral minus
3 ipsilateral power at a cluster of posterior electrodes (PO7/8, P7/8, P3/4, or PO3/4) for a
4 frequency range of 4 to 30 Hz separately for each condition. The figure confirms that
5 lateralization effects are mostly limited to the alpha frequency range.



6 **Figure 1. Time-frequency plots.** Power is depicted for a frequency range of 4 to 30 Hz at electrodes contralateral
7 (left column) and ipsilateral (middle column) to the target location as well as for the contralateral minus ipsilateral
8 (right column) differences. The conditions are abbreviated as follows: lsd-low = low spatial demand / low
9 perceptual load, lsd-high = low spatial demand / high perceptual load, hsd-low = high spatial demand / low
10 perceptual load, hsd-high = high spatial demand / high perceptual load.

11

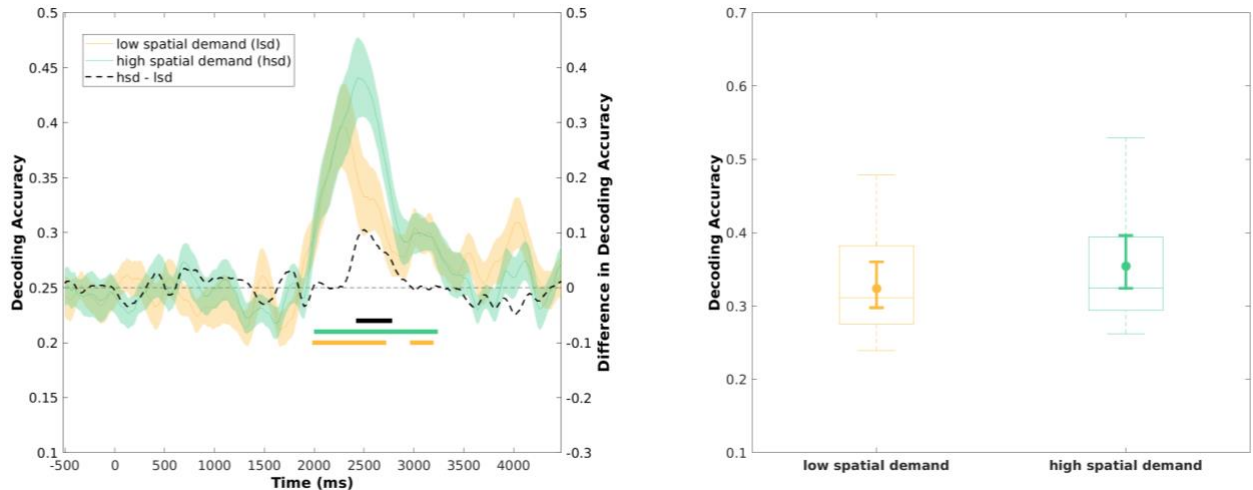
12 **S2. Alpha lateralization magnitude and target eccentricity**

13 Deng, Choi, and Shinn-Cunningham (2020) have previously reported that alpha lateralization
14 is greater when attention was directed to locations further away from the central position. In
15 the present study, targets could be likewise presented in rather close proximity to central
16 fixation ($\pm 30^\circ$) or at a greater distance ($\pm 90^\circ$). We computed alpha lateralization magnitude
17 separately for inner ($\pm 30^\circ$) and outer ($\pm 90^\circ$) targets. Then, we performed post-hoc paired-
18 sample *t*-tests to contrast the difference in alpha lateralization magnitude between inner
19 minus outer targets for the LSD versus HSD condition (separately for the low and high
20 perceptual load condition). Neither in the low perceptual load condition $t(16) = 0.64, p =$
21 $.531, p_{\text{adj}} = .797$, nor in the high perceptual load condition, $t(16) = -1.05, p = .310, p_{\text{adj}} = .797$,
22 did we find that the difference in alpha lateralization magnitude between inner vs. outer
23 targets differed between the low and the high spatial demand condition.

24

25 **S3. Decoding based on alpha power at parieto-occipital scalp sites**

26 In previous studies that applied alpha-band decoding, results have been shown to be virtually
27 identically for analyses including all vs. only posterior electrodes (e.g., van Moorselaar et al.,
28 2018), suggesting that most (or even all) relevant information that contributes to decoding
29 performance is represented in posterior electrode sites. Hence, we performed an additional,
30 exploratory decoding analysis, using only parieto-occipital scalp sites as input to the
31 classifier. Otherwise, all parameters in the decoding analysis were used, as described in the
32 main analysis. Specifically, alpha power at electrodes P7, P3, P1, Pz, P2, P4, P8, PO7, PO3, POz,
33 PO4, PO8, O1, Oz, O2, PO9, and PO10 was used as input to the classifier. Figure S3A shows
34 the resulting time-course of decoding accuracy as well as the difference between the low and
35 high spatial demand condition. In addition, panel B illustrates the average decoding accuracy
36 per condition.



37

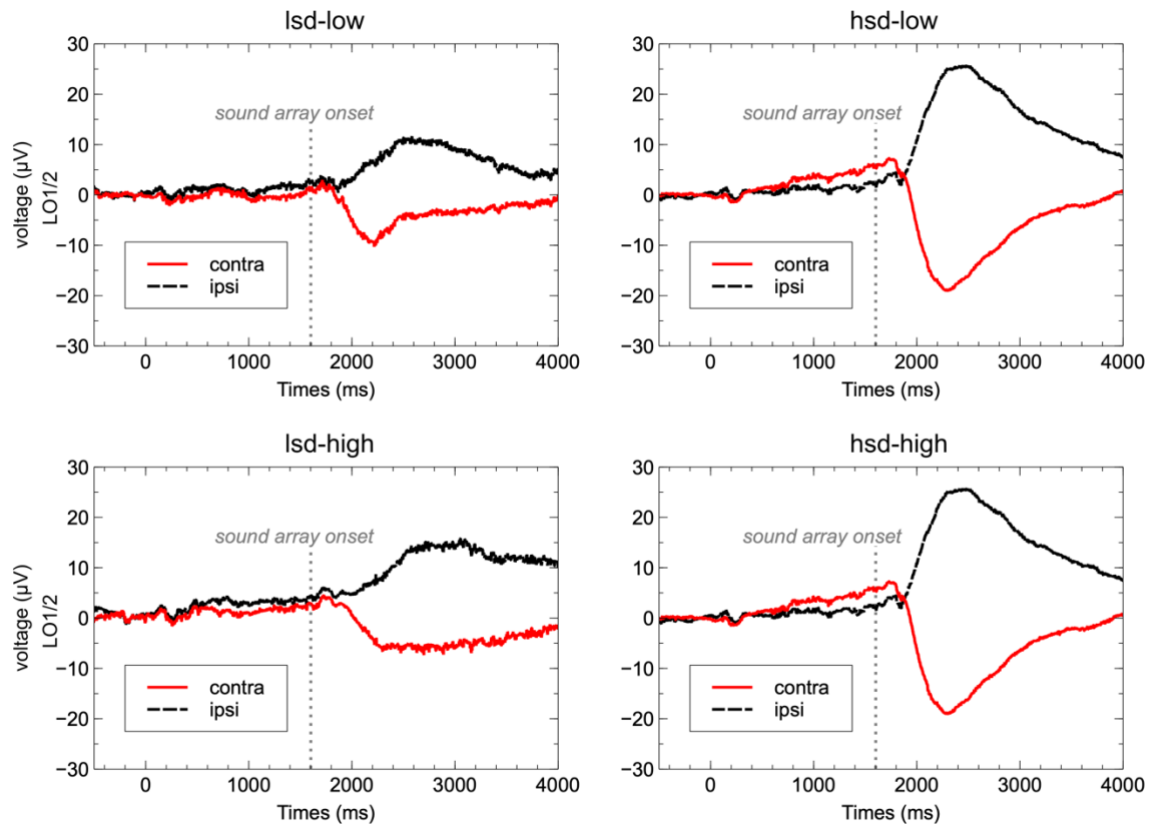
38 **Figure 2. Location decoding based on the scalp distribution of alpha power at posterior electrode sites.** (A)
39 Time-course of the average decoding accuracy results in the low (yellow) and high (green) spatial demand
40 condition, respectively. The colored shading indicates ± 1 SEM. Chance-level performance (i.e., 25%) is indicated by
41 the grey dashed horizontal line. The yellow and green solid bars indicate significant cluster of decoding accuracy
42 in the low and high spatial demand condition, respectively (cluster-based permutation, all $p < .017$). The black
43 solid bar denotes significant differences (cluster-corrected sign-permutation test, one-sided, $p = .002$) in decoding
44 ability between the low and the high spatial demand condition. Note that only time-points in-between 1600 –
45 3800 ms were considered in the statistical analysis. (B) Boxplots refer to the average decoding accuracy in-
46 between 2000 - 3240 ms relative to cue-onset (i.e., 400 – 1640 ms following sound array onset). The latter time
47 window includes the approximate time interval that resulted in significant within-condition decoding for both
48 conditions. As per convention, boxplots illustrate the interquartile range and the median. Whiskers extent to the
49 1.5 times the interquartile range. The superimposed circles show the average decoding accuracy, while the
50 corresponding error bars denote the 95% bootstrap confidence interval of the mean (number of bootstrap
51 samples = 10000). A one-sided permutation test revealed a significant difference in the overall decoding ability
52 between the low and high spatial demand condition, $p = .012$.

53

54 **S4. Control analyses: eye movements**

55 We evaluated the epoched data at horizontal EOG (hEOG) electrodes. To obtain ERPs, the
56 continuous EEG data was segmented into epochs, ranging from -1000 to 4500 ms relative to
57 sound cue onset. For baseline correction, the 200 ms time interval prior to sound cue onset
58 was used (i.e., -200 to 0 ms). Trials classified as premature responses (i.e., with response times
59 < 200 ms) were removed. Otherwise, no preprocessing was performed.

60 Supplementary figure 3 depicts the contralateral versus ipsilateral voltages at hEOG
61 electrodes LO1/LO2 relative to the target position. The ERP at horizontal EOG electrodes
62 clearly indicates typical lateralized voltage differences, depending on the target position.
63 Thus, despite the instruction to fixate the central LED, on at least a subset of trials, saccades
64 toward the target sounds were present. Figure 3 also shows that saccades were more
65 pronounced in the high spatial demand condition.



66

67 **Figure 3. Contralateral versus ipsilateral voltages at lateral EOG electrodes LO1 and LO2 relative to the**
68 **target position for each of the four conditions.**

69

70 To assess the potential impact of horizontal eye movements on alpha lateralization
71 magnitude, we conducted an analysis of covariance, including spatial demand (high vs. low),
72 perceptual load (high vs. low), and asymmetry (contra vs. ipsi) as within-subject factors and
73 the average lateralized hEOG as a covariate. Specifically, to obtain the average lateralized
74 hEOG voltages, the contralateral minus ipsilateral waveforms for each subject were averaged
75 across all conditions. In the resulting average waveforms, mean amplitude was measured in-
76 between 2000 – 3000 ms post cue onset (i.e., 400 – 1600 ms post-sound array). Alpha
77 lateralization magnitude (using the same time window as reported in the main manuscript)
78 served as the dependent variable. We found that the covariate (i.e., saccades) was not
79 significantly related to the magnitude of alpha-band lateralization, as indicated a non-
80 significant interaction of the factor saccades and asymmetry, $F(1,15) = 0.67, p = .425$.
81 Importantly, the main effect of asymmetry remained significant, $F(1,15) = 12.39, p = .003$,
82 after controlling for the effect of saccades. This suggests that the overall presence of alpha

83 lateralization is not affected by the occurrence of horizontal eye movements. Further, none of
84 the interactions, involving the factor saccades turned out to be significant, all $p > .19$.

85

86 Further, to assess the potential impact of eye movements on our decoding results, we
87 performed an exploratory decoding analysis, using the horizontal (LO1/LO2) and vertical
88 (IO1/IO2) EOG channels as input. The decoding analysis was performed as described in the
89 main manuscript, with the following exception: Given that all trials (except for individual
90 premature responses, target-absent trials and incorrectly answered trials) served as input to
91 the decoding analysis, a five-fold (rather than a three-fold) cross validation was performed.
92 Supplementary figure 4 illustrates the time-course of decoding accuracy for the low and high
93 spatial demand condition, respectively. In both conditions, it was possible to decode target
94 location based on hEOG input (all $p < .011$). However, in contrast to the main decoding
95 analysis based on the whole-scalp topography of alpha power, we did not find a significant
96 difference in decoding accuracy between the high vs. low spatial demand condition (cluster-
97 corrected sign-permutation test, $p = 1$). In addition, overall, decoding accuracy was lower for
98 hEOG based decoding compared to alpha power decoding, which matches an observation
99 also made by Popov, Gips, Weisz, & Jensen (2021). Thus, even though it appears that
100 saccades are more pronounced in the high spatial demand condition, this does not account
101 for the higher decoding accuracy in the high spatial demand condition that becomes
102 apparent in the alpha-based decoding.

103

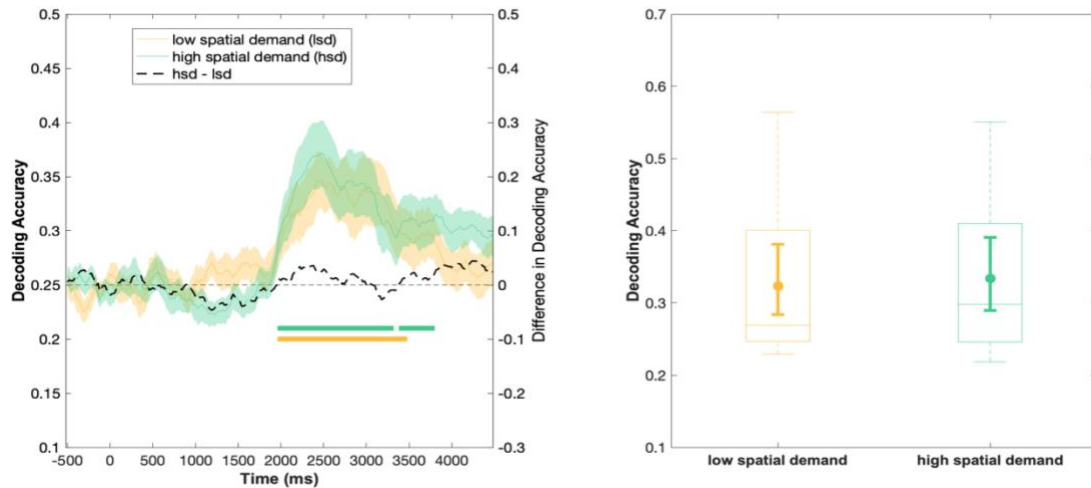


Figure 4. Location decoding based on the ERP signal at horizontal and vertical EOG electrodes. (A) Time-course of the average decoding accuracy results in the low (yellow) and high (green) spatial demand condition, respectively. The colored shading indicates ± 1 SEM. Chance-level performance (i.e., 25%) is indicated by the grey dashed horizontal line. The yellow and green solid bars indicate significant decoding of the target location in the low and high spatial demand condition, respectively. The black solid bar denotes significant differences in decoding ability between the low and the high spatial demand condition. Note that only time-points in-between 1600 – 3800 ms were considered in the statistical analysis. (B) Boxplots refer to the average decoding accuracy in-between 1960 – 3500 ms relative to cue-onset (i.e., 300 – 1900 ms following sound array onset). As per convention, boxplots illustrate the interquartile range and the median. Whiskers extent to the 1.5 times the interquartile range. The superimposed circles show the average decoding accuracy, while the corresponding error bars denote the 95% bootstrap confidence interval of the mean (number of bootstrap samples = 10000).

104

105 Finally, to follow up more closely on whether the apparent differences in hEOG asymmetry
106 between conditions (and between subjects) systematically covary with the effect of spatial
107 demand on alpha-based decoding accuracy, we performed a post-hoc ANCOVA: The average
108 decoding accuracy in-between 1940 – 3340 ms (i.e., approximate time window that resulted
109 in significant within-condition decoding) served as a dependent variable, spatial demand (low
110 vs. high) served as a within-subject factor, and the difference in hEOG lateralization (2000 –
111 3000 ms post cue onset) between the spatial demand conditions (hsd – lsd) was included as a
112 covariate (referred to as factor 'saccades'). The covariate was not significantly related to
113 decoding accuracy, $F(1,15) = 0.52$ $p = .481$. Critically, the main effect of spatial demand was
114 still significant after controlling for effect of saccades, $F(1,15) = 7.14$, $p = .017$. The interaction
115 between saccades and spatial demand was not significant, $F(1,15) = 0.03$, $p = 0.855$.

116

117 Taken together, the above presented control analyses reassure that the most critical finding –
118 namely, the greater decoding accuracy for the high spatial demand condition – is not based
119 on systematic difference in eye movements. Although we cannot be perfectly sure that the

120 within-condition decoding of target location has somewhat picked up on saccade-related
121 contributions in the signal, we don't think such a contribution should be regarded as merely
122 artefactual. Rather, it highlights the multimodal functional relevance of auditory alpha
123 oscillatory activity and the naturally occurring interaction between audition and vision. In line
124 with that, using a forward encoding procedure, Popov et al., (2021) nicely illustrate that in a
125 purely auditory task, spatial tuning based on the hEOG signal is positively related to alpha
126 tuning responses. Specifically, they argue that "auditory attention is linked to the visual
127 system, at least in part, through pro-active orientation towards the relevant sound origin via
128 saccades in the direction consistent with the sound origin" (Popov et al 2021, p.18).

129 **S5. Decoding analysis based on minimally preprocessed data**

130 Artifact correction has been proposed to be less critical in decoding analysis, given that
131 classifiers can – in principle – learn to ignore bad channels or suppress noise during training
132 (Grootswagers, Wardle, & Carlson, 2017). Moreover, minimal preprocessing prevents
133 unwanted artefacts and spurious decoding due to high-pass (van Driel, Olivers, & Fahrenfort,
134 2021) or low-pass (Grootswagers et al., 2017) filtering. Hence, the original decoding analysis
135 was performed using only minimally preprocessed data. Following reviewer concerns, that
136 artefacts might influence decoding performance, we modified the preprocessing pipeline for
137 decoding to include artefact correction. The latter is now presented in the main manuscript.
138 For reasons of transparency, here, we report the decoding results based on minimally
139 preprocessed data. The latter yielded very comparable results.

140 The continuous data was epoched to create single-trial segments, ranging from -1000
141 to 4500 ms relative to cue onset, and baseline corrected (i.e., using the 200 ms time-period
142 prior to cue onset as a baseline). Further, target-absent trials, incorrectly answered trials as
143 well as trials with a response time < 200 (i.e., premature responses) were excluded. No
144 filtering, trial rejection or ICA-based artefact correction was applied. The decoding analysis
145 was performed as described in the main manuscript, except that five rather than three cross-
146 validations were performed (accounting for the higher number of trials because no further
147 trial rejection procedure was applied).

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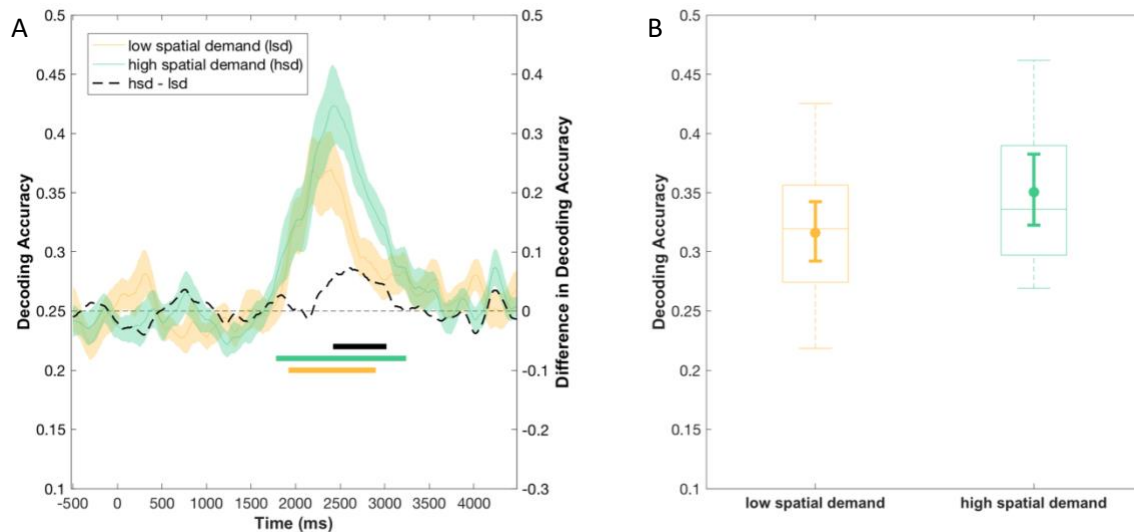


Figure 5. Location decoding based on the multivariate scalp distribution of alpha power (minimally preprocessed data). (A) Time-course of the average decoding accuracy results in the low (yellow) and high (green) spatial demand condition, respectively. The colored shading indicates ± 1 SEM. Chance-level performance (i.e., 25%) is indicated by the grey dashed horizontal line. The yellow and green solid bars indicate significant decoding of the target location in the low and high spatial demand condition, respectively. The black solid bar denotes significant differences in decoding ability between the low and the high spatial demand condition. Note that only time-points in-between 1600 – 3800 ms were considered in the statistical analysis. (B) Boxplots refer to the average decoding accuracy in-between 1800 – 3200 ms relative to cue-onset (i.e., 200 – 1600 ms following sound array onset). As per convention, boxplots illustrate the interquartile range and the median. Whiskers extent to the 1.5 times the interquartile range. The superimposed circles show the average decoding accuracy, while the corresponding error bars denote the 95% bootstrap confidence interval of the mean (number of bootstrap samples = 10000).

150

151 Figure 5A shows the time-course of decoding accuracy for the low vs. high spatial demand
152 condition, when decoding the exact target sound location based on the topography of alpha-
153 band activity, as well as the difference in decoding accuracy between conditions. Decoding
154 accuracy starts to rise above chance level (i.e., 25%) at around 1800 ms (i.e., 200 ms following
155 sound array onset) and at first, increases continuously in both spatial demand conditions. In
156 the high spatial demand condition, decoding accuracy reaches a peak at around 2180 ms (i.e.,
157 580 ms post-sound onset), remains at this level for a couple hundred milliseconds and then
158 gradually decreases throughout the remainder of the response interval; in the low spatial
159 demand condition, decoding accuracy continues to rise beyond the peak in the high spatial
160 demand condition until around ~2440 ms (i.e., 840 ms post-sound onset), and declines quite
161 immediately thereafter, although it remains on a higher level compared to the low spatial
162 demand condition. Toward the end of the response interval (i.e., around 3800 ms), decoding
163 accuracy returns to chance level in both conditions. The cluster mass test revealed that
164 decoding was significantly greater than chance in both spatial demand conditions. We
165 identified a significant cluster following sound array onset in each of the two conditions ($p <$

166 10^{-4} , see Figure 5A, solid green and yellow lines). In the high spatial demand condition, the
167 cluster extends from around 1800 ms to ~3200 ms; in the low spatial demand condition, the
168 cluster spans a time period in-between ~1900 ms and 2880 ms relative to sound array onset.
169 Note, however, that cluster-based permutation test results should not be used to derive
170 conclusions about the specific onset or offset of a certain effect (Sassenhagen & Draschkow,
171 2019).

172 The black, dashed line in Figure 5A illustrates the difference in decoding accuracy
173 between the two spatial demand conditions. A cluster-corrected sign-permutation test
174 indicated significant differences in decoding ability ($p < .01$, one-sided test, cluster extending
175 from ~2440 – 3000 ms), with higher decoding accuracy in the high spatial demand condition
176 compared to the low spatial demand condition.

177 Finally, we assessed the overall difference in decoding ability within the post-stimulus
178 period (specifically, within the approximate time-window that resulted in above-chance
179 decoding accuracy within both spatial demand conditions). A one-sided permutation test of
180 the average decoding accuracy between 1800 – 3200 ms consistently revealed a significant
181 difference in decoding accuracy between the spatial demand conditions ($p = .001$).

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