Neural alpha oscillations and pupil size differentially index cognitive demand under competing audio-visual task conditions

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Abstract

Cognitive demand is thought to modulate two often used, but rarely combined, measures: pupil size and neural alpha (8–12 Hz) oscillatory power. However, it is unclear whether these two measures capture cognitive demand in a similar way, and whether a measured 'cognitive demand' response in pupil size or brain activity is dependent on sensory modality by which the demand is induced. Here we recorded pupil size and neural alpha power (using electroencephalography), while human participants of both sexes concurrently performed a visual multiple object-tracking task and an auditory gap-detection task. Difficulties of the two tasks were manipulated independent of each other. Participants' performance decreased in accuracy and speed with increasing cognitive demand. Pupil size increased with increasing demand for both the auditory and the visual task. Alpha power emerging from two cortical sources showed counteracting neural dynamics: Alpha power in visual cortex decreased with increasing demand in the visual task, whereas alpha power in parietal cortex increased with increasing demand in the auditory task. Furthermore, demand-related changes in pupil size and alpha power were uncorrelated, suggesting that they index different aspects of cognitive demand. Overall, the current study demonstrates that the dynamics of the neurophysiological indices of cognitive demand and associated effort are multi-faceted and potentially modality-dependent under complex audio-visual task conditions.

Significance Statement

Pupil size and oscillatory alpha power are associated with cognitive demand and effort, but their sensitivity under complex audio-visual task conditions is unclear and so is the extent to which they share underlying mechanisms. Using an audio-visual dual-task paradigm, we show that pupil size increases with increasing cognitive demands for both audition and vision. In contrast, oscillatory alpha power changes depend on sensory modality: Power in auditory cortex increased with auditory demand, whereas alpha power in visual cortex decreased with visual demand. Hence, pupil size and alpha power show different sensitivity to cognitive demands, which is also indicated by the absence of a correlation between both measures, suggesting different underlying neural mechanisms.

Introduction

Many situations in everyday life require the integration of information from different sensory modalities. However, cognitive resources are limited (Kahneman, 1973; Lavie, 1995), and, depending on the induced cognitive demand, such situations may be experienced as effortful (Björn Herrmann & Johnsrude, 2020; Pichora-Fuller et al., 2016). This cognitive demand and related effort have practical relevance, because people who experience effort may avoid challenging situations and be at risk of social isolation (Mick et al., 2014; Shukla et al., 2020; Sung et al., 2016). A better understanding of how individuals manage cognitive resources under complex multi-sensory conditions, and of the underlying psychophysiology are critical to objectively measuring and identifying effort in people who struggle.

Dual-task paradigms are often used in behavioral research to investigate how perceptual or cognitive demands in one modality affect performance in another modality (Desjardins & Doherty, 2013; Gagné et al., 2017; Picou & Ricketts, 2014; Wu et al., 2016). A hallmark result of dual-task paradigms indicating cognitive constraint lies in the deterioration of behavioral performance for concurrent tasks that would be performed with high accuracy and speed if carried out separately (Desjardins & Doherty, 2013; Gosselin & Gagné, 2014; Picou & Ricketts, 2014; Wu et al., 2016). In addition, manipulating the difficulty of the individual tasks allows tapping into the dynamic allocation of cognitive resources to either task as a function of the respective task difficulty combinations. The current study aims to understand how physiological responses change with varying degrees of task difficulty and thus cognitive demand in single- and dual-task conditions combining the auditory and visual domain.

At least two neurophysiological measures have recently and repeatedly become associated with changes in cognitive demand: pupil size (Joshi & Gold, 2020; Koelewijn et al., 2012; Ohlenforst et al., 2018; Wendt et al., 2016) and neural oscillatory activity in the alpha-frequency band (8–12 Hz; Obleser et al., 2012; Paul et al., 2021; Wisniewski et al., 2017). Pupil size variations are mainly driven via noradrenergic pathways from Locus Coeruleus (Aston-Jones & Cohen, 2005; Joshi et al., 2016; Joshi & Gold, 2020) that is modulated by attention (Vazey et al., 2018) or arousal (Breton-Provencher & Sur, 2019; Murphy et al., 2011). Pupil size is long known to vary with the degree to which a person engages cognitively in a task (Kahneman & Beatty, 1966) and has recently gained substantial interest especially in the hearing sciences, as a potential indicator of listening effort: pupil size increases with increasing speech-comprehension difficulty induced by acoustic degradation (Miles et al., 2017; Winn et al., 2016), acoustic masking (Koelewijn et al., 2012; Zekveld et al., 2010), or linguistic complexity (Kadem et al.,

2020; Wendt et al., 2016). Apart from the sensitivity of pupil size to auditory-related demands, pupil size further increases with the degree of cognitive demand during visual stimulation (Martin et al., 2020; Porter et al., 2007; Stolte et al., 2020) and memory performance (Kahneman & Beatty, 1966; Miller et al., 2019). However, it is currently unknown how sensitive pupil size remains as an objective marker of cognitive effort under more realistically complex audio-visual conditions of varying demands.

The second neurophysiological measure that may enable segregating different contributions associated with cognitive demand is neural alpha power (8–12 Hz; Dimitrijevic et al., 2017; 2021; Petersen et al., 2015; Wöstmann et al., 2017). Alpha power in parietal cortex increases when auditory-induced cognitive demand increases (Henry et al., 2017; Björn Herrmann et al., 2022; Winneke et al., 2020), such as with acoustic degradation of speech (Obleser et al., 2012; Wöstmann et al., 2015). In contrast, increased cognitive demand in a visual task leads to a decrease in alpha power, often in visual rather than parietal areas (Erickson et al., 2019; Magosso et al., 2019; Roijendijk et al., 2013). A recently observed associated of the Locus Coeruleus activity with neural oscillatory activity (Dahl et al., 2020, 2022) raises the possibility that both pupil size and neural oscillatory activity are driven by a common underlying neural process, which might be noradrenergically mediated.

The present study investigates this hypothesis. We investigate how pupil size and source-localized alpha power in various sensory and executive brain areas covaries with varying levels of cognitive demand in an audio-visual, dual-task setting. If both measures are proxies for a common underlying neural process, they should co-vary with levels of cognitive demand.

Material and Methods

Participants

Twenty-four adults (age range: 19-30 years; mean = 23.7 years; SD = 3.09 years; 7 males, 17 females; all right-handed) were recruited for the current study via the participant database of the Department of Psychology at the University of Lübeck. They were native speakers of German and reported no history of neural disorders nor hearing problems.

Each participant took part in two sessions. In the first session, participants separately performed two single tasks. In the second session, participants performed the same tasks in a dual-task procedure.

Task procedures are described in detail below. The two sessions were conducted on different days, separated by at least one day (median: 7 days; range: 1-18 days).

Participants gave written informed consent prior to participation and were financially compensated with €10/hour or received course credits. The study was conducted in accordance with the Declaration of Helsinki and was approved by the local ethics committee of the University of Lübeck.

Experimental environment

Participants were seated in a comfortable chair in a sound-attenuated booth. Participants placed their head on a chinrest positioned at about 70 cm distance from a computer monitor (ViewSonic TD2421, refresh rate 60 Hz). The experimental stimulation was controlled by a desktop computer (Windows 7) running Psychtoolbox-3 in MATLAB and an external RME Fireface UC sound card. Visual stimulation was mirrored from the stimulation computer to the computer monitor in the sound booth. Sound was delivered binaurally via in-ear headphones (EARTONE 3A, 3M). Responses were given via a four-button response box (The Black Box Toolkit, Sheffield, UK).

Experimental Design

In all task conditions, participants were simultaneously presented with auditory and visual stimulation. The auditory stimulation consisted of a 7-s white noise sound in which a single gap occurred at one of 70 randomly selected and linearly spaced time points at 4–6 sec post noise onset (see Figure 1A). The task for participants was to press a button on a response box as soon as they detected the gap.

The auditory gap-detection task comprised two difficulty levels: In the hard condition, gap duration was titrated for each individual participant to about 75% gap-detection performance in training blocks prior to the main experimental blocks (4–6 training blocks, each about 2 min). In the easy condition, the estimated gap duration was doubled. Auditory stimuli were presented at 50 dB sensation level estimated using a methods of limits procedure (cf. Herrmann et al., 2018). All button responses occurring between 0.1–1s post gap onset were counted as hits. Response times were calculated as the time elapsed between gap onset and button press. Response speed was calculated as the inverse of response times (1/RT). Response speed was averaged across trials, separately for each condition and participant.

The visual stimulation consisted of a multiple object-tracking (MOT) display (Cavanagh & Alvarez, 2005; Björn Herrmann & Johnsrude, 2018; Pylyshyn & Storm, 1988; Scholl, 2009). The computer monitor

displayed a 14 × 14 cm white edged black rectangle on black background at a distance of 70 cm from participants' eyes (approximately 13° visual angle). A small, yellow fixation square was presented at the center of the rectangle. The critical stimuli were 16 dots presented within the borders of a rectangle (Figure 1A). At the beginning of each trial (prior to sound onset), a stationary display of the 16 dots was shown for 1 second. One or five of the 16 dots were colored red (target dots) whereas the rest of the dots were white (distractor dots). We refer to the one-dot condition as the 'easy' visual condition, whereas we refer to the five-dot condition as the 'hard' visual condition. After 1 second, the dots that were marked in red turned to white, and all 16 dots started to move for 7 seconds, simultaneously with the presentation of the white noise auditory stimulus. Participants were instructed to follow the target dot(s) (previously marked in red) over the 7-second period. After 7 seconds, all dots stopped moving, and one target dot and two distractor dots were colored green. The three colored dots were each also overlaid by the numbers 1, 2 and 3. Participants had to decide which of the three dots was a target dot by pressing the respective button on the response box with no explicit time limit. Response times for the visual task were calculated as the time elapsed between the onset of the answer screen and the occurrence of a button press. Again, response speed was calculated and averaged across trials for each participant and condition.

In the single-task session, participants were presented with a total of 70 trials for each of the four resulting task and difficulty combinations (Figure 1B, left panel). Trials were split across 8 blocks of 35 trials each. Task and difficulty levels were varied block-by-block resulting in two blocks per task and difficulty condition. The order of auditory-task blocks and visual-task blocks alternated. Starting block and difficulty condition were counterbalanced across participants. Difficulty levels of the to-be-ignored modality varied orthogonally to the difficulty of the target modality across the stimulation blocks. Each block started with written instructions, indicating the level of difficulty and target modality in the upcoming block. Prior to the main experimental blocks, participants performed the tasks separately to familiarize them with the tasks and procedures.

Similarly, in the dual-task session, participants were presented with 70 trials for each of the four difficulty combinations (Figure 1B, right panel), distributed across eight blocks. Participants performed two blocks per difficult combination which remained fixed throughout each block of 35 trials. Block order ensured that all four difficulty combinations were presented once before the presentation of the second block per difficulty combination. Condition order was counterbalanced across participants. Each block

started with instructions written on the screen, stating the difficulty combination of the trials in the upcoming block.

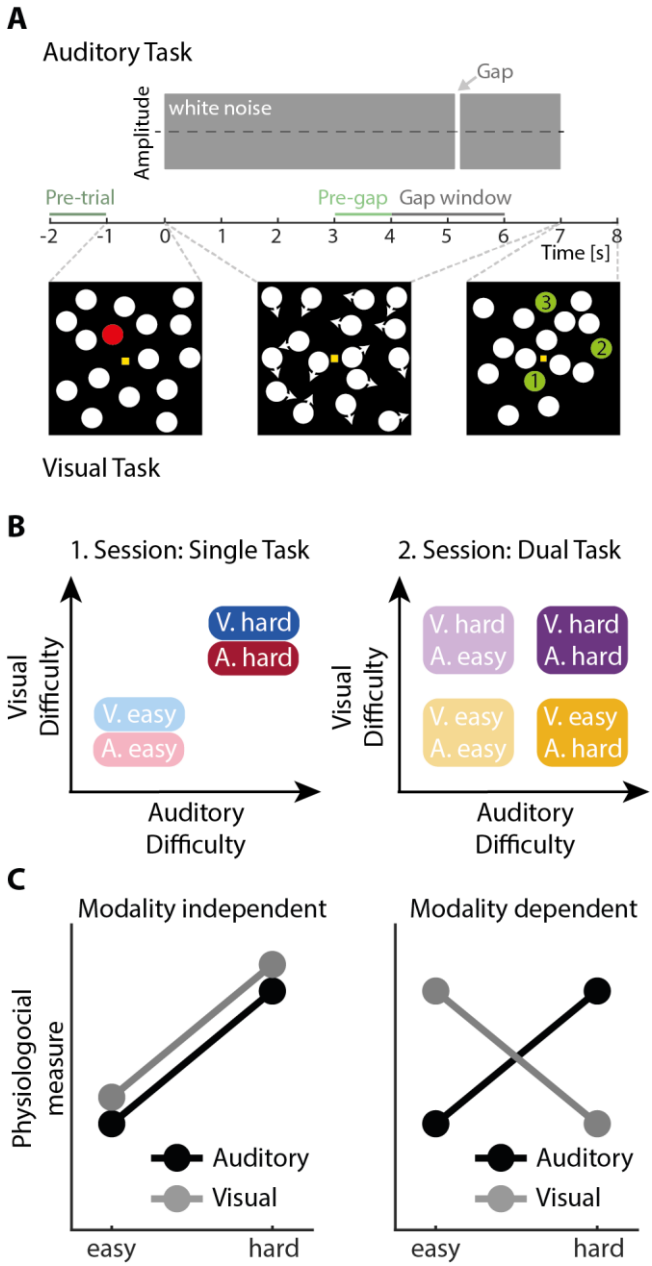

Figure 1. Experimental design. A: Trial design. Auditory and visual stimuli were presented concurrently. Auditory gap-detection task: Participant had to detect a gap within 7 s of white noise (the gap could occur within the 4–6-s time window). For the 'hard' condition, the gap duration was individually titrated to 75% correct. For the 'easy' condition, the gap duration was doubled. Multiple object-tracking task: Participants viewed 16 moving dots and were asked to follow the initially cued (red) dots in a moving-dot scene. After 7 s, dots stopped moving and three dots were marked green and labelled 1, 2, and 3. Participants had to decide which of the three dots was among the cued dots. Participants had to follow one (easy) or five (hard) dots. Analyses focused on the 3–4-s time window (pre-gap window; and additionally on the 5–6-s window for pupil size due to its slow response). **B:** Design for the single-task session (left) and the dual-task session (right). In the single-task session, participants performed the auditory and visual tasks separately (but were always presented with the audio-visual stimulation). In the dual-task condition, participants performed both tasks simultaneously. **C:** Schematic of hypotheses. If a physiological measure indexes cognitive demand independent of modality, the effect of increased difficulty should be the same across modalities (left panel). Alternatively, the effect of increased difficulty may differ between sensory modalities (right panel).

Pupil data recording and preprocessing

Eye movements and pupil size of the right eye were continuously recorded using an Eyelink 1000 Plus eye tracker (SR Research) at a sampling rate of 500 Hz.

Data were preprocessed and analyzed using MATLAB (MathWorks, Inc.). Time points at which the pupil size was more than three standard deviations above or below the mean pupil size calculated

over the whole block were categorized as blinks and marked as invalid ('missing') data in the time window spanning 100 ms prior to and 100 ms following an identified blink. Subsequently, missing data in the pupil size time series were linearly interpolated. To control for the potential influence of eye movement-related changes, the x- and y-coordinates were regressed out of the pupil data (multiple linear regression; Fink et al., 2021) and the resultant residual pupil size time course was used for all further analyses. Data were then low-pass filtered at 4 Hz (Butterworth, 4th order) and segmented into trials ranging from –2 to 8 s relative to noise onset. Trials were excluded if more than 40% of data points within a trial had to be interpolated. The full dataset of a participant was excluded from analysis if more than 50% of trials were excluded in any of the conditions (N=1).

Pupil-size data were downsampled to 50 Hz. For each trial, the mean pupil size was calculated in the time window -2 to -1.1 s time window prior to noise onset and subtracted from the data at each time point (baseline correction). Pupil size was averaged across trials, separately for each condition. To account for the sluggishness of changes in pupil size, we averaged data both within the main time window of interest also used in EEG analysis (3–4 s) along with a later time window 5–6 s post noise onset (Montefusco-Siegmund et al., 2022).

EEG recording and preprocessing

We recorded participants' electroencephalogram (EEG) from 64 electrodes (ActiChamp, Brain Products, München) at a sampling rate of 1,000 Hz, referenced to electrode TP9 (280 Hz online low-pass filter). EEG data were analyzed with the FieldTrip toolbox (version 2019-09-20, (Oostenveld et al., 2011) for Matlab, MathWorks, Inc.). Data were re-referenced to the average across electrodes, high-pass filtered at 0.7 Hz (Hann window, 2391 points), and low-pass filtered at 100 Hz (Hann window, 89 points). Data were filtered with a 50-Hz elliptic band-stop filter to suppress line noise.

Independent components analysis (ICA) was calculated to remove artifacts due to blinks, lateral eye movements, and muscle activity. To this end, data were divided into 1-s segments, and segments with non-stereotypical artefacts were removed on the basis of visual inspection prior to ICA calculation. Noisy channels were removed prior to ICA. Artifact components were identified through visual inspection. The filtered, continuous data were projected to ICA space using the unmixing matrix (i.e., that was calculated using the 1-s segments for ICA). The components previously identified to contain artifacts were removed and the mixing matrix was used to project the data back to original 64 EEG-

channels. Noisy channels removed prior to ICA (for six participants, one channel each), were interpolated following ICA as the average across neighboring channels. Afterwards, data were low-pass filtered at 30 Hz (Hann window, 111 pts) and divided into trials of 12 seconds (-3 s to 9 s time-locked to the simultaneous onset of sound and dot movement). Finally, data were downsampled to 500 Hz and trials that exceeded a signal change of more than 200 µV across the entire epoch were excluded from analyses. Pooled across all participants, 0.8% of trials during the single task 0.7% of trials during the dual task were excluded.

Analysis of time-frequency power

In order to analyze oscillatory activity, single-trial time-domain EEG signals were convolved with Morlet wavelets. Complex wavelet coefficients were calculated for frequencies ranging from 1–20 Hz in steps of 0.5 Hz and time from –2 s to 8 s time-locked to noise onset, separately for each trial, electrode, and participant. Power was calculated by squaring the magnitude of the complex wavelet coefficients, separately for each trial, electrode, and time-frequency bin. Time-frequency power representations were then averaged across trials, separately for each condition. Power was baseline corrected to dB power change: Trial-averaged data at each time point were divided by the mean power in the baseline time window (–2 to –1.1 s), and subsequently log10 transformed.

Since we were primarily interested in changes in alpha power, we calculated alpha-power time courses by averaging across frequencies ranging from 8 to 12 Hz (Jensen & Mazaheri, 2010; Klimesch et al., 2007; Weisz et al., 2011). To avoid gap-related changes in parietal alpha power, we focused the analysis on the time window right before the gap. We thus averaged power across parietal electrodes (CPz, CP1, CP2, CP3, CP4, Pz, P1, P2, P3, P4, POz, PO3, PO4; Figure 4) and across the 3–4 s time window – that is the pre-gap window (Figure 1A).

Source localization

To localize the underlying sources related to alpha power, Fieldtrip's MRI template was used as source model (Holmes et al., 1998) along with a 3-layer boundary element model (BEM, Oostenveld et al., 2003) as volume conductor. This head-model was used to estimate individual leadfields (Nolte, 2003). A cross-spectral density matrix was calculated based on a fast Fourier transform using all trials per participants centered on 10 Hz (±2Hz spectral smoothing; multitaper) for the -2–8 s time window. The cross-spectral

density matrix was used to calculate spatial filters for each source location using dynamic imaging of coherent sources (DICS, Gross et al., 2001).

The spatial-filter coefficients resulting from the DICS calculation were multiplied with the single-trial wavelet coefficients that were calculated in the sensor-level time-frequency analysis. Similar to the sensor-level analysis, source localized single-trial time-frequency power was calculated by squaring the magnitude of the complex wavelet coefficients. Time-frequency power representations were averaged across trials, separately for each condition. Decibel (dB) power change was calculated relative to the baseline time window of −2 to −1.1 s.

Finally, we separately averaged individual source-projected power within three pre-defined regions of interest (ROI; auditory, visual, and parietal region; Figure 5) using functional parcels defined by the Human Connectome Project parcellation template (Glasser et al., 2017; Keitel & Gross, 2016). Similar to the analysis in sensor space, power was averaged in the time window of interest (3–4 s time-locked to noise onset).

Statistical analysis

For the analysis of behavioral performance in the single task, we tested for differences in performance accuracy and speed between the easy and the hard task difficulty using paired samples t-tests, separately for each sensory modality. For the analysis of behavioral data in the dual-task, we used a repeated-measures analysis of variance (rmANOVA) with the factors Auditory Difficulty (easy, hard) and Visual Difficulty (easy, hard), separately for the auditory and visual performance measures (accuracy and speed). Note that auditory and visual performance measures were treated separately for the behavioral analysis, because the scales and chance levels were different between modalities. Moreover, this allowed us to investigate the effect of visual difficulty on auditory performance and auditory difficulty on visual performance for the dual-task data.

For the analysis of pupil size in the single task, a rmANOVA with the factors Modality (auditory, visual) and Difficulty (easy, hard) was calculated. For the analysis of pupil size in the dual task, we calculated a rmANOVA with the two factors Auditory Difficulty (easy, hard) and Visual Difficulty (easy, hard). Analyses were conducted separately for the 3–4 s and the 5–6 s time window.

The details of the statistical analysis of alpha power data mirrored those for the analysis of pupil size. For the analysis of the single task, a rmANOVA with the factors Modality (auditory, visual) and

Difficulty (easy, hard) was calculated. For the analysis of alpha power in the dual task, we calculated a rmANOVA with the two factors Auditory Difficulty (easy, hard) and Visual Difficulty (easy, hard). For the analysis of alpha power in source space, the additional within-participants factor ROI (auditory, parietal, visual) was added to the rmANOVA.

We also investigated the relation between pupil size and alpha power. To this end, we used the dual-task data for each participant and calculated the difference between the auditory & visual easy and the auditory & visual hard condition, separately for pupil size and alpha power. The relationship between the difference (hard minus easy) in pupil size and alpha power was analyzed using Pearson correlation.

Effect sizes for t-tests are reported as Cohen's d (Cohen, 1988). Effect sizes for ANOVAs are reported as generalized eta square (η_g^2) (Bakeman, 2005). For null results, Bayes Factors are reported. All statistical analyses were calculated in MATLAB (MathWorks, Inc).

Results

Behavioral performance declines with increasing task demand

For the analysis of behavioral performance (Figure 2) in the single task, we found that accuracy was lower for the hard compared to the easy difficulty level, as expected (auditory: $t_{23} = -8.60$, $p = 1.21 \times 10^{-8}$, $d = -1.76$; visual: $t_{23} = -13.5$, $p = 2.04 \times 10^{-12}$, $d = -2.76$). Response speed was also slower for the hard compared to the easy difficulty level (auditory: $t_{23} = -8.32$, $p = 2.19 \times 10^{-8}$, $d = -1.70$; visual: $t_{23} = -10.97$, $p = 1.24 \times 10^{-10}$, $d = -2.24$).

The analysis of performance in the dual task was carried out separately for the auditory and visual task. For the auditory-task performance, we observed lower accuracy and speed when the auditory task was hard compared to easy (main effect of Auditory Difficulty; accuracy: $F_{1,23} = 56.48$, $p = 1.23 \times 10^{-7}$, $\eta_g^2 = 0.46$; speed: $F_{1,23} = 36.51$, $p = 3.67 \times 10^{-6}$, $\eta_g^2 = 0.15$), whereas performance was not significantly affected by the concurrent visual-task difficulty (main effect of Visual Difficulty: for both accuracy and speed $p > 0.3$; Auditory Difficulty × Visual Difficulty interaction: for both accuracy and speed $p > 0.1$).

For the visual-task performance, we observed lower accuracy and speed when the visual task was hard compared to easy (main effect of Visual Difficulty; accuracy: $F_{1,23} = 113.99$, $p = 2.19 \times 10^{-10}$, η_g^2

= 0.65; speed: $F_{1,23} = 387.78$, $p = 6.66 \times 10^{-16}$, $\eta_g^2 = 0.43$). However, visual-task accuracy was also affected by the difficulty in the auditory task (main effect of Auditory Difficulty: $F_{1,23} = 9.8$, $p = 0.005$, $\eta_g^2 = 0.02$): accuracy in the visual task was lower when the concurrent auditory task was hard compared to easy (no main effect of Auditory Difficulty for speed: $p > 0.5$). The data perhaps suggest that participants prioritize the auditory task over the visual task (i.e., visual performance dropped when the auditory task was hard, whereas auditory performance was unaffected by visual-task difficulty). The Auditory Difficulty × Visual Difficulty interaction for visual performance was not significant (for both accuracy and speech $p > 0.1$).

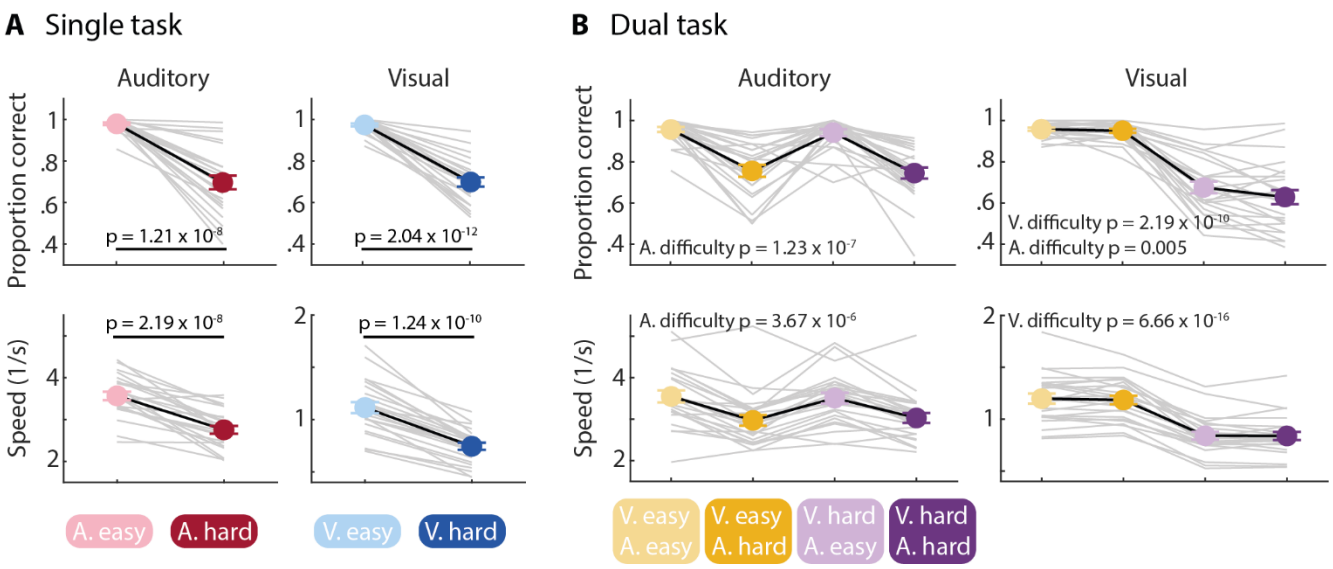

Figure 2. Effects of task difficulty on performance in the single and the dual task. A: Single task. Results for the auditory gap-detection task (left) and visual MOT task (right). Accuracy as proportion correct responses (top) and speed as inverse response time (bottom). For both modalities, performance was lower for the hard compared to the easy condition. P-values are obtained from paired samples t-tests. **B:** Dual task. Order is the same as in A. For both modalities, performance was lower for the hard than the easy condition. For accuracy in the visual task, a significant main effect of auditory difficulty was observed as well. Only significant effects of the rmANOVAs are presented. Error bars reflect the standard error of the mean. Gray lines show data from individual participants.

Pupil size reflects demand manipulation independent of sensory modality

Single task

Pupil-size time courses for each task and difficulty condition are shown in Figure 3A. Descriptively, difficulty-induced changes in pupil size followed modality-dependent trajectories: When participants performed the visual MOT task, pupil size increased relatively early during the trial for difficult compared to easy trials, whereas in the auditory gap-detection task, pupil size increased later for the hard relative to the easy condition. This is consistent with the nature of the different tasks. The visual MOT task

requires attention throughout, whereas the auditory gap-detection task requires participants to focus to a specific point in time.

More formally, in the 3-4 s time window, pupil size was larger for the hard compared to the easy condition (main effect Difficulty: $F_{1,22} = 9.98$, $p = 0.005$, $\eta_g^2 = 0.03$), but there was no difference in pupil size between modalities ($p > 0.07$) and no interaction ($p > 0.3$). In the 5-6 s time window, pupil size was also larger for the difficult relative to the easy condition (main effect of Difficulty: $F_{1,22} = 13.85$, $p = 0.001$, $\eta_g^2 = 0.04$) and for the auditory compared to the visual task (main effect of Modality: $F_{1,22} = 35.93$, $p = 4.94 \times 10^{-6}$, $\eta_g^2 = 0.21$). We did not find evidence for any interactive effects of task difficulty and modality ($p > 0.7$).

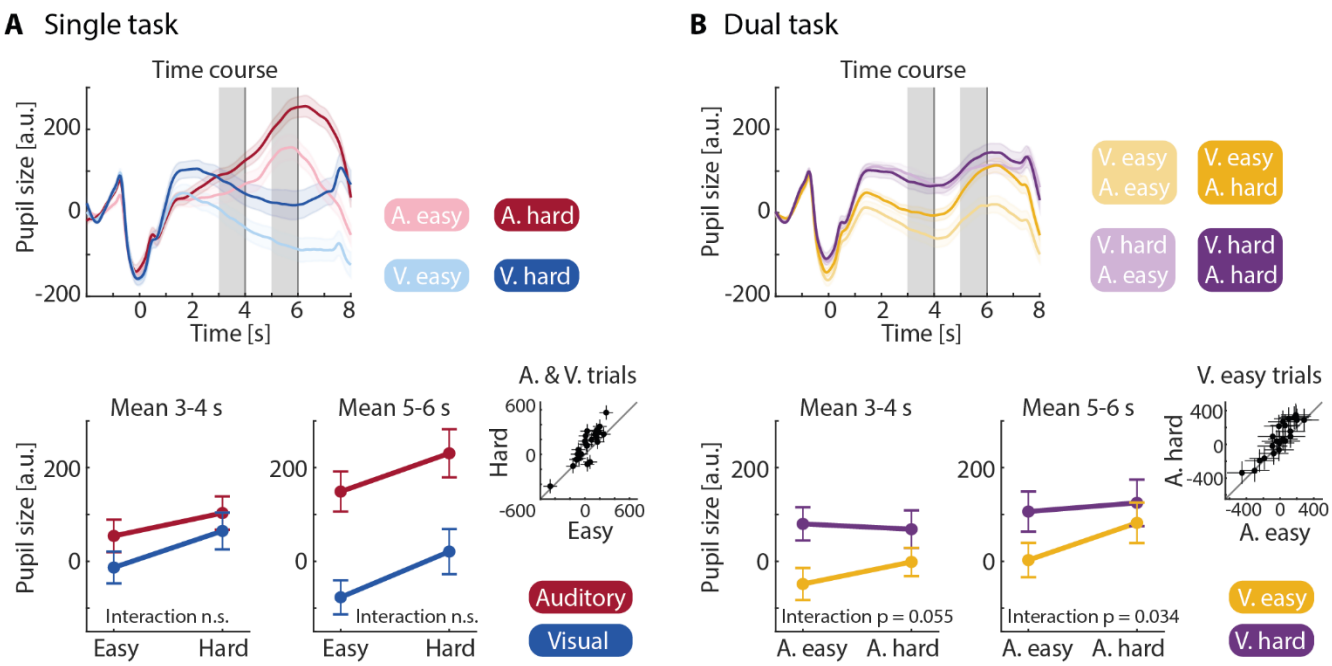

Figure 3. Pupil-size variation in the single and dual tasks. A: Single task. Top: Pupil-size time courses. Gray areas reflect the time windows of interest for statistical analysis, vertical gray lines indicate the time window during which a gap could occur. Bottom: Averaged pupil size for time windows of interest. Left: Time window 3-4 s. Pupil size increased with task difficulty independent of modality. Right: Time window 5-6 s. In addition to the difficulty effect, pupil size was larger for the auditory compared to the visual task. Inset: 45-degree plot for main effect difficulty. Black dots show individual averaged pupil size for each difficulty level averaged across modalities. The 45-degree line indicates no difference between conditions. **B:** Dual task. Order is the same as in panel A. Pupil size was larger when the visual task was hard compared to easy. The Interaction indicates that the auditory difficulty effect was greater when the visual task was easy. Inset: Black dots show individual data points for the visual easy condition, showing the driving effect of the interaction. Error bands reflect the within-subject error. Error bars indicate standard error of the mean. Crosshairs indicate 95% CI.

Dual task

Pupil-size time courses in the dual task are shown in Figure 3B. Time courses in the dual task visually appear to resemble the combination of the time courses in the auditory and visual single tasks.

In the 3-4 s time window, we observed a larger pupil size for the hard than the easy condition (main effect of Visual Difficulty: $F_{1,22} = 16.59$, $p = 0.001$, $\eta_g^2 = 0.08$), whereas there was no effect of Auditory Difficulty ($p > 0.07$). The Auditory Difficulty × Visual Difficulty interaction was marginally significant ($F_{1,22} = 4.12$, $p = 0.055$, $\eta_g^2 = 0.008$), showing that the increase in pupil size with auditory-task difficulty was greater when the visual task was easy compared to difficult.

Changes in pupil size in the 5-6 s time window were similar to those in the 3-4 s time window: pupil size was larger for the hard than the easy conditions, for both the visual and auditory task (main effect of Visual Difficulty: $F_{1,22} = 10.97$, $p = 0.003$, $\eta_g^2 = 0.03$; main effect of Auditory Difficulty: $F_{1,22} = 7.86$, $p = 0.01$, $\eta_g^2 = 0.01$). The Auditory Difficulty × Visual Difficulty interaction was significant ($F_{1,22} = 5.10$, $p = 0.034$, $\eta_g^2 = 0.006$), indicating again that the increase in pupil size with auditory-task difficulty was greater when the visual task was easy compared to difficult. Pupil size only differed between the auditory easy and hard conditions when the visual task was easy ($t_{22} = 4.28$, $p = 3.03 \times 10^{-4}$, $d = -0.89$), but not when the visual task was hard ($p > 0.4$).

Task difficulty affects alpha power differently for the auditory and visual modality

Single task

As shown in Figure 4A, alpha power was lower when participants performed the visual task compared to the auditory task (main effect of Modality: $F_{1,23} = 22.35$, $p = 9.19 \times 10^{-5}$, $\eta_g^2 = 0.28$), and when task difficulty was hard compared to easy (main effect of Difficulty: $F_{1,23} = 11.94$, $p = 0.002$, $\eta_g^2 = 0.03$). Critically, the decrease in alpha power with task difficulty was more pronounced for the visual compared to the auditory task (Modality × Difficulty interaction: $F_{1,23} = 11.89$, $p = 0.002$, $\eta_g^2 = 0.03$). Alpha power was only more suppressed for the hard compared to the easy conditions for the visual task ($t_{23} = -4.76$, p = 8.53 × 10-5, d = -0.97), whereas there was no task-difficulty effect for the auditory task ($p > 0.7$).

Dual task

Time courses for alpha power in the dual task are shown in Figure 4B. Alpha power was lower for the hard compared to the easy conditions in the visual task (main effect of Visual Difficulty: $F_{1,23} = 15.81$, $p = 0.001$, $\eta_g^2 = 0.05$) and lower for the easy compared to the hard condition in the auditory task (main effect of Auditory Difficulty: $F_{1,23} = 7.18$, $p = 0.013$, $\eta_g^2 = 0.008$). Critically, the Auditory Difficulty × Visual Difficulty interaction ($F_{1,23} = 8.82$, $p = 0.007$, $\eta_g^2 = 0.006$) shows that, when the visual task was hard and leading to an overall suppression of alpha power, this suppression was reduced when the concurrent

auditory task was hard relative to when it was easy (t_{23} = 3.87, p = 7.75 × 10^{-4}, d = 0.79; no auditory-difficulty effect when the visual task was easy: p > 0.7). Hence, the data demonstrate that, in a competing audio-visual situation, rising demands in the visual modality decrease alpha power (i.e., greater power suppression), whereas rising demands in the auditory modality increase alpha power.

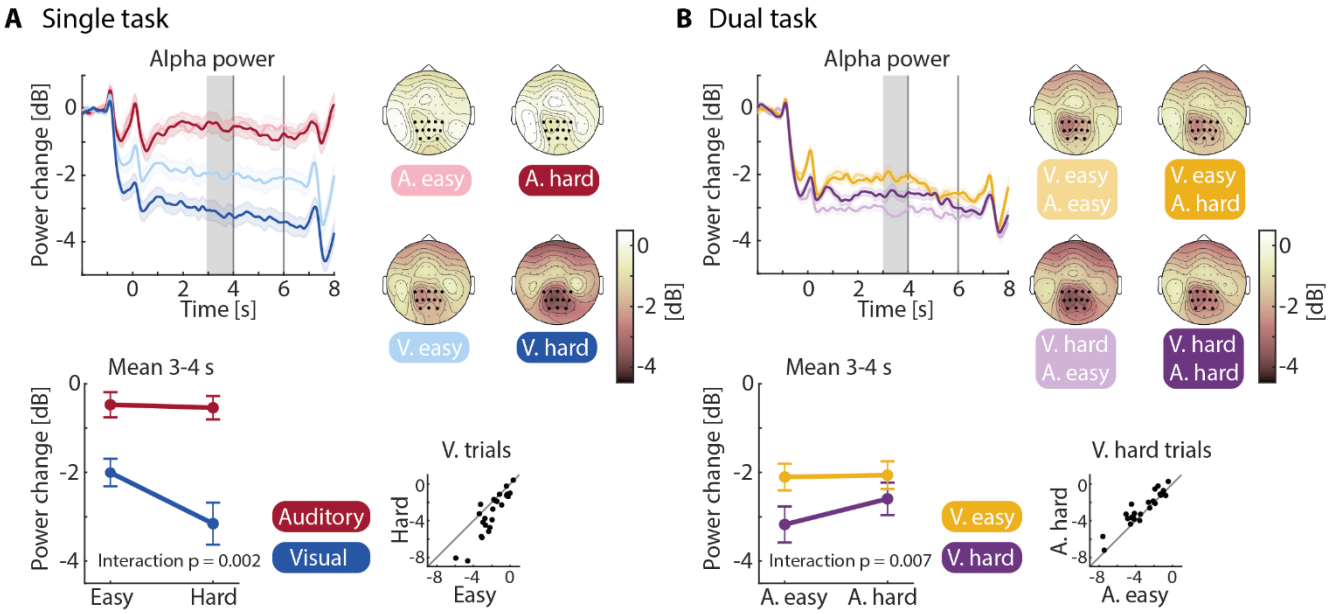

Figure 4. Alpha-power results in the single and the dual task. A: Single task. Top row: Alpha power time courses. Gray areas reflect the time window of interest for statistical analysis. Right: Topographies for the time window of interest. Bottom row: Averaged data across participants for the time window of interest. The difficulty effect was only present for visual but not for auditory task. Inset: Difficulty effect of the visual task shown in a 45-degree plot. Black dots show averaged alpha power per difficulty level for visual task, separately for each participant. The 45-degree line indicates no difference between conditions. **B:** Dual task. Order is the same as in A. Increasing the visual demand led to greater alpha-power suppression. This suppression was reduced when the auditory demands were high. Inset: Black dots show averaged alpha power for each participant in this hard visual condition, showing the driving effect for the interaction. Error bands reflect the within-subject error. Error bars indicate standard error of the mean.

Cortical regions differentially reflect modality specific demand

We were interested in characterizing the region specificity of the alpha oscillatory dynamics. To this end, we projected alpha-power data to source space to differentiate between alpha oscillatory activity in auditory, parietal, and visual cortices (Figure 5; see Methods for details).

Single Task

Source-localized alpha power was overall more suppressed during the visual compared to the auditory task (main effect of Modality: $F_{1,23}$ = 13.45, p = 0.001, η_g^2 = 0.15). Critically, the Modality × Difficulty interaction was significant ($F_{1,23}$ = 6.51, p = 0.018, η_g^2 = 0.009), showing that alpha power was larger for

the hard compared to the easy auditory task, whereas alpha power was smaller (i.e., more suppressed) for the hard compared to the easy visual task (Figure 5C).

There was also a main effect of ROI ($F_{2,46}$ = 6.06, p = 0.005, η_g^2 = 0.03), showing that the suppression of alpha power in auditory cortex was lower compared to the suppression in visual cortex (t_{23} = 2.5, p = 0.02, d = 0.51) and parietal cortex (t_{23} = 2.5, p = 9.74×10^{-6}, d = 1.15). No other interaction was significant.

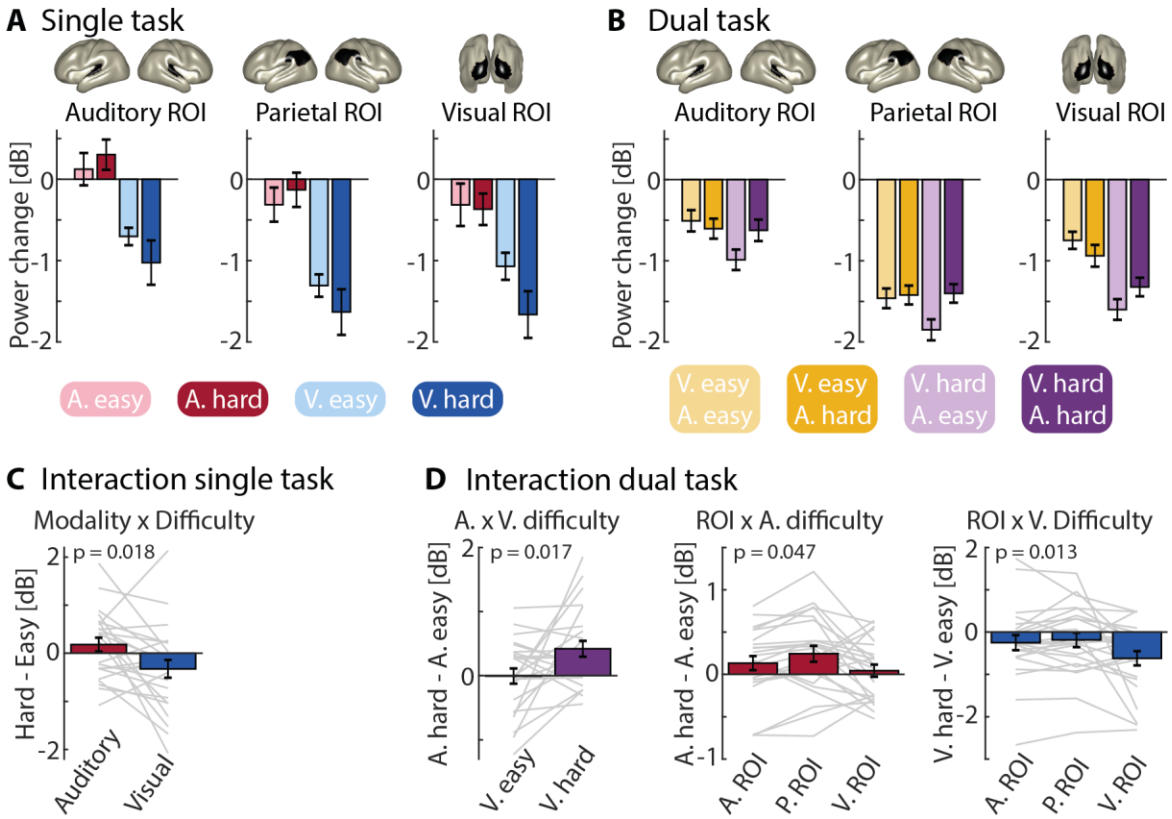

Figure 5. Source-localized alpha power in three brain regions of interest. A: Single-task data for the auditory, parietal and visual regions of interest (ROIs). Data are averaged in the pre-gap time window (3-4 s). Areas on the brain surfaces show the ROIs. The same ROIs were used for the single- and the dual-task analyses. **B:** Dual-task data. **C:** Mean difference between the hard and easy conditions for the auditory and the visual single task (Modality × Difficulty interaction). Alpha power was larger for the hard compared to the easy condition during the auditory task, whereas the reverse effect was present for the visual task. **D:** Condition differences to visualize significant interactions for dual-task data. Left: The difference between the hard and easy conditions in the auditory task was larger when the visual task was difficult compared to easy. Middle: The auditory difficulty effect (i.e., hard minus easy) was greatest in the parietal cortex. Right: Alpha-power suppression for the hard compared to the easy visual task was greatest in visual cortex.

Dual Task

The analysis of source-localized alpha power in the dual task revealed that all three two-way interactions were significant, whereas the three-way interaction was not significant (p > 0.89). Specifically, the Auditory Difficulty × Visual Difficulty interaction ($F_{1,23}$ = 6.63, p = 0.017, η_g^2 = 0.007) demonstrates that

the power increase for the hard relative to the easy condition associated with the auditory task was more pronounced when the concurrent visual task was hard compared to easy (Figure 5D, left). The ROI × Auditory Difficulty interaction ($F_{2,46}$ = 3.27, p = 0.047, η_g^2 = 0.001) shows that the difficulty effect (i.e., hard minus easy) associated with the auditory task was greatest in parietal cortex (Figure 5D, middle), and significantly larger than the difficulty effect in visual cortex (t_{23} = 2.21, p = 0.04, d = 0.45). Finally, alpha-power suppression for the hard compared to the easy condition in the visual task was greatest in visual cortex (ROI × Visual Difficulty interaction $F_{2,46}$ = 4.76, p = 0.013, η_g^2 = 0.005; Figure 5D, right), and significantly smaller than in parietal cortex (t_{23} = -2.46, p = 0.02, d = -0.50).

Overall, the results of the source-localized alpha power in the dual task suggest that the greater alpha-power suppression associated with visual-task difficulty originates primarily from visual cortex. In contrast, the relative diminishment of this alpha-power suppression associated auditory-task difficulty originates primarily from parietal cortex (Figure 5D).

Task difficulty influences pupil size and alpha power largely independently

In the previous sections, we have reported the effects of task difficulty and sensory modality separately for pupil size and alpha power. One key question in the field is whether these two neurophysiological measures of cognitive demand (or effort) are driven by a common underlying mechanism (Ala et al., 2020; Alhanbali et al., 2019; Miles et al., 2017). If the same mechanism were to underlie changes in pupil size and alpha power, we would expect these measures to correlate.

In order to investigate the relationship between pupil size and alpha power, we calculated individual difficulty effects (auditory–visual hard vs. auditory–visual easy conditions in the dual-task data) and did so separately for pupil size and alpha power. This allowed us to calculate a simple Pearson correlation between the pupil-size difficulty effect and the alpha-power difficulty effect. Note that we did so separately for each of the three regions of interest: auditory, parietal, and visual cortex (Figure 6). There was no significant correlation between pupil size and alpha power in any of the three brain regions ($p > 0.05$). Visual cortex exhibits an indecisive r = –.41 correlation (Bayes Factor BF_{10} ~1.5), in the auditory and parietal cortices, however, Bayes factors (BF_{10} ~ 1/3) provide tentative evidence for the absence of a true correlation. The overriding picture emerging is one of no unitary, underlying process driving the effect in these two neurophysiological measures of cognitive demand.

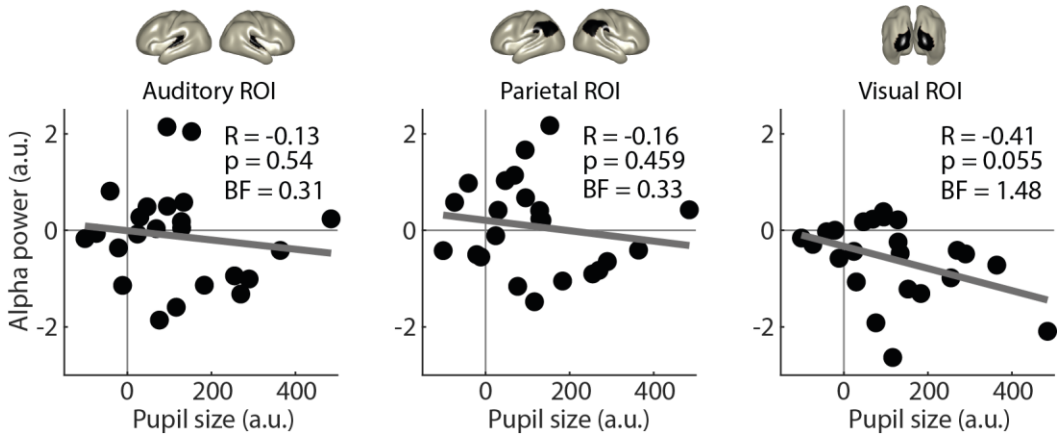

Figure 6. No correlation between pupil size and alpha power for three regions of interest. Data points reflect the difference between the auditory & visual hard and auditory & visual easy condition for dual-task data, for pupil size and alpha power. The gray line reflects the best fitting line (correlation). Left: Auditory region of interest (ROI). Middle: Parietal ROI. Right: Visual ROI.

Discussion

In the current study, we investigated how two key and often used neurophysiological measures, pupil size and neural alpha oscillatory power, change depending on different degrees of cognitive demand under complex audio-visual dual-task conditions. First, our behavioral data suggest that individuals prioritized auditory over visual task performance. Second, we observed that changes in cognitive demand affected pupil size and alpha power differently. Pupil size increased with increasing demands in both the auditory and the visual modality, and the temporal dynamics of the pupil size indicated the specific temporal evolution of the required cognitive task demands in each modality. In contrast, changes in alpha power with increasing cognitive demand, on the other hand, differed as a function of task modality and appeared to originate from two different neural sources: Alpha power in parietal cortex increased with auditory cognitive demand, whereas alpha power in occipital cortex decreased with visual cognitive demand. Lastly, our data suggest that pupil size and alpha power index different facets of cognitive demand under complex audio-visual conditions.

Behavioral performance suggests prioritization of the auditory over the visual task

As expected, based on previous work (Björn Herrmann et al., 2022; Björn Herrmann & Johnsrude, 2018; Ritz et al., 2020; Wutz et al., 2020), behavioral performance decreased with increasing cognitive demand in the auditory and the visual task, as well as under single- and dual-task conditions. In previous uses of

dual tasks, participants were explicitly instructed to prioritize one task over the other (Gagné et al., 2017; Picou & Ricketts, 2014; Wu et al., 2016). We avoided such prioritization instruction to investigate how different degrees of cognitive demand in either task affect performance. Our behavioral results suggest that participants prioritized the auditory task over the visual task, as indicated by the performance decline in the visual task with increasing difficulty in the auditory task (Figure 1B). The data suggest that the available cognitive resources were insufficient to perform both tasks well concurrently. This is broadly in line with the dual-task literature showing performance decline in a secondary task with increasing demand in a primary task (Desjardins & Doherty, 2013; Gagné et al., 2017; Gosselin & Gagné, 2014; Picou & Ricketts, 2014).

One potential reason for why participants may have prioritized the auditory over the visual task in the current study may be related to the different timing of when cognitive investment was required in the auditory and in the visual task. For the auditory task, participants were required to detect a single event in time with some degree of temporal predictability (Björn Herrmann et al., 2022) as it always occurred within 4-6 s after sound onset, whereas the visual MOT task required participants to attentively focus throughout a trial (Cavanagh & Alvarez, 2005; Björn Herrmann & Johnsrude, 2018; Pylyshyn & Storm, 1988; Scholl, 2009; Wutz et al., 2020). Participants may have lost the dots they were asked to track during the moments they fully focused on and responded to the auditory gap-detection task.

Pupil size tracks cognitive demand in the auditory and visual tasks

Pupil size increased with the degree of cognitive demand for both the auditory and the visual task (Figure 3). This increase in pupil size with cognitive demand is generally consistent with previous work (Kadem et al., 2020; Kahneman & Beatty, 1966; Koelewijn et al., 2012; Martin et al., 2020; Ohlenforst et al., 2018; Porter et al., 2007; Stolte et al., 2020; Wendt et al., 2016; Winn et al., 2018; Zekveld et al., 2010; Zekveld & Kramer, 2014; Zhao et al., 2019).

The time course of the pupil size mirrored the temporal evolution of the cognitive demand manipulation in each task. The pupil-size time courses for the auditory task diverged late between task-difficulty conditions and peaked late during a trial, mirroring the temporal occurrence of the gap. For the visual task, pupil-size time courses diverged between task-difficulty conditions right from the beginning of a trial and remained different throughout, potentially reflecting the need to track the relevant dots from the beginning to the end of a trial (Cavanagh & Alvarez, 2005; Bjorn Herrmann &

Johnsrude, 2018; Björn Herrmann & Johnsrude, 2018; Pylyshyn & Storm, 1988; Scholl, 2009; Wutz et al., 2020). Our data thus suggest high sensitivity of pupil-size changes to when in time and to what degree participants invest cognitively during an auditory or visual task.

Under dual-task conditions, we further observed that auditory difficulty effects were only present when the concurrent visual task was easy but not hard. This may suggest that the respective highly demanding task is driving the pupil response. Therefore, the pupil-size time courses under dual-task setting are more similar to single-task time courses of the auditory task when the concurrent visual task was easy, but more similar to the visual single-task time courses when the visual task was hard.

Cognitive demand modulated alpha power differently under auditory and visual task conditions

In contrast to variations in pupil size, most likely linked to changes in global arousal or vigilance state, alpha-oscillatory responses should offer more nuanced insights into the cognitive-demand sensitivity of different neural systems. Indeed, alpha power in parietal cortex increased with auditory cognitive demand, whereas alpha power in occipital cortex decreased with visual cognitive demand (Figure 5).

These findings shed light on the differential cognition-related changes in alpha power in vision and audition. An increase in alpha power has been observed when auditory demands increase (Obleser et al., 2012; Winneke et al., 2020; Wisniewski et al., 2017; Wöstmann et al., 2015), and this effect may originate from an oscillator in parietal cortex (Björn Herrmann et al., 2022). In contrast, a decrease in alpha power – that is, alpha-power suppression – has been observed when demands in a visual task increase (Erickson et al., 2019; Magosso et al., 2019), and this effect may originate from an oscillator in occipital cortex (Bonnefond & Jensen, 2012).

Although we observed a distinction based on sensory modality, others have suggested that demand-dependent changes in alpha power may differ with the degree of internal (e.g., audition) or external processing (e.g., vision) requirements (Palva & Palva, 2011). Regardless of this functional distinction, our data emphasize the presence of multiple alpha oscillators in the brain (see also Başar et al., 1997; Bollimunta et al., 2008; Herrmann et al., 2022; Mo et al., 2011; Wisniewski et al., 2021) that are modulated differently by cognitive demand, depending on task modality.

A dominant line of thinking assumes alpha oscillatory activity to reflect functional inhibition, such that brain regions in which alpha power increases are inhibited (Foxe & Snyder, 2011; Jensen & Mazaheri, 2010; Klimesch et al., 2007; Weisz et al., 2011). Our observations that alpha power decreases

with increasing difficulty in the visual task is consistent with this function inhibition view, potentially reducing inhibition in visual cortices.

In contrast, the increase in alpha power in parietal cortex with increased cognitive demand in the auditory task may be less consistent with function inhibition, except if we were to assume that parietal cortex is selectively inhibited when individuals invest cognitively in the auditory task. Nonetheless, this increase in alpha power under auditory attention is consistent with other previous work (Obleser et al., 2012; Winneke et al., 2020; Wisniewski et al., 2017; Wöstmann et al., 2015), and more generally aligns with recent suggestions that the functional inhibition hypothesis may not generalize across sensory modalities (Ai & Ro, 2014; Björn Herrmann et al., 2016; Linkenkaer-Hansen et al., 2004).

Pupil size and alpha power may reflect different facets of cognitive investment

Pupil size and alpha power were both modulated by cognitive demand, although in somewhat different ways. Perhaps not surprisingly, given the different sensitivity to cognitive demand of the two measures, the degree to which cognitive demand affected pupil size was not significantly correlated with the degree to which cognitive demand affected alpha power (Figure 6). The absence of a correlation between pupil size and alpha power is consistent with previous work that also did not find a relationship (Ala et al., 2020; Alhanbali et al., 2019; Miles et al., 2017). One potential reason for the missing relationship might be that the two measures largely reflect separable neural pathways associated with cognitive resource recruitment (Alhanbali et al., 2019; Strand et al., 2018). The present study shows that the pupil size tracked the cognitive demand induced by the different tasks more closely. Pupil size may thus be taken as the more intuitive index for cognitive demand, also in terms of sign and magnitude of the pupil signal: A greater pupil size means higher cognitive demand (Kahneman & Beatty, 1966; Pichora-Fuller et al., 2016). As discussed above, assigning an equally parsimonious interpretation to alpha-power changes is not an accurate representation of the extant empirical data.

In order to interpret alpha-power changes, the different alpha oscillators and their spatial mixing in EEG recordings (perhaps less in magnetoencephalography recordings) need to be considered and could explain the lack of the relation between pupil size and alpha power. Alpha power may perhaps index more clearly the cognitive demands in auditory tasks when stimulation is devoid of visual input (Henry et al., 2017; Björn Herrmann et al., 2022; Paul et al., 2021; Wöstmann et al., 2015), and vice versa

in visual tasks (Bonnefond & Jensen, 2012; Erickson et al., 2019; Magosso et al., 2019; Roijendijk et al., 2013). The current data provide a detailed picture of the multi-faceted, modality-dependent changes in alpha power under complex audio-visual task conditions.

Conclusions

Our results show that pupil size and parietal alpha power are not two interchangeable neurophysiological measures of cognitive investment or effort, but reflect different neurophysiological facets of task-induced cognitive demands. Specifically, we demonstrate that pupil size tracks increase in cognitive demand independently of the sensory modality that induces the demand. However, the changes in magnitude of neural alpha power associated with task demands depend greatly on the sensory modality from which the demands originate. Alpha power in parietal cortex increases with auditory cognitive demand, whereas alpha power in occipital cortex decreases with visual cognitive demand. Finally, our data add on the amounting evidence that pupil size and alpha power variations are not driven by a unitary and putatively noradrenergically governed pathway. Overall, the current study demonstrates that the dynamics of the neurophysiological indices of cognitive effort are multi-faceted and potentially modality-dependent under complex audio-visual task conditions.

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