Alpha oscillations and stimulus-evoked activity dissociate metacognitive reports of attention, visibility, and confidence in a rapid visual detection task

Matthew J. Davidson

Department of Experimental Psychology, University of Oxford, Oxford, UK
School of Psychology, University of Sydney, Sydney, Australia ✉

James S. P. Macdonald

School of Social Sciences, University of the West of England, Bristol, UK ✉

Nick Yeung

Department of Experimental Psychology, University of Oxford, Oxford, UK ✉

Variability in the detection and discrimination of weak visual stimuli has been linked to oscillatory neural activity. In particular, the amplitude of activity in the alpha-band (8–12 Hz) has been shown to impact the objective likelihood of stimulus detection, as well as measures of subjective visibility, attention, and decision confidence. Here we investigate how preparatory alpha in a cued pretarget interval influences performance and phenomenology, by recording simultaneous subjective measures of attention and confidence (experiment 1) or attention and visibility (experiment 2) on a trial-by-trial basis in a visual detection task. Across both experiments, alpha amplitude was negatively and linearly correlated with the intensity of subjective attention. In contrast with this linear relationship, we observed a quadratic relationship between the strength of alpha oscillations and subjective ratings of confidence and visibility. We find that this same quadratic relationship links alpha amplitude with the strength of stimulus-evoked responses. Visibility and confidence judgments also corresponded with the strength of evoked responses, but confidence, uniquely, incorporated information about attentional state. As such, our findings reveal distinct psychological and neural correlates of metacognitive judgments of attentional state, stimulus visibility, and decision confidence when these judgments are preceded by a cued target interval.

Introduction

This study explores the relationship between electroencephalogram (EEG) alpha oscillations, objective performance in a visual detection task, and subjective reports of visibility, attention, and confidence, with two aims. The first aim is to characterize the information that underpins subjective reports of attention, confidence, and visibility with a focus on the commonalities and dissociations that drive these overlapping psychological criteria.

There is a growing interest in the mechanisms and functional role of metacognitive processes that monitor and regulate ongoing processing (Fleming & Frith, 2014). Much of this work has focused on decision confidence—a subjective evaluation of the likelihood that a judgment reached is correct (Kepecs & Mainen, 2012; Yeung & Summerfield, 2012). According to influential theories, confidence reflects a readout of the strength of evidence in favor of the chosen option (Kepecs & Mainen, 2012; Pleskac & Busemeyer, 2010; Vickers & Packer, 1982). However, confidence is additionally sensitive to features such as the perceived reliability of evidence (Boldt, de Gardelle, & Yeung, 2017), speed of decision (Kiani, Corthell, & Shadlen, 2014), and even social context (Bang et al., 2017), suggesting that evidence strength is combined with relevant contextual information in generating confidence reports (Shekhar & Rahnev, 2018). In parallel with this work on confidence, a separate body of research has investigated people's introspective insight into their degree of attentional focus. Introspective reports of attentional state are also predictive of objective performance across a range of tasks (Smallwood & Schooler, 2015). Although some studies have begun to explore the relationship between

attention and confidence (Denison, Adler, Carrasco, & Ma, 2018; Kurtz, Shapcott, Kaiser, Schmiedt, & Schmid, 2017; Rahnev et al., 2011; Recht, de Gardelle, & Mamassian, 2021; Recht, Mamassian, & de Gardelle, 2019; Zizlsperger, Sauvigny, & Haarmeier, 2012), substantive questions remain, in particular regarding whether confidence reports incorporate contextual information about participants' attentional state, and the degree to which subjective reports of confidence and attention depend on similar versus distinct sources of information. We address these questions here.

The second aim is to investigate whether neural markers, as measured with EEG, may characterize the distinctions between objectively measured and subjectively experienced aspects of visual processing. Here, we focus on alpha oscillations measured in a cued pretarget interval, and the strength of stimulus-evoked responses.

Alpha (8–12 Hz) oscillations provide an exciting opportunity to investigate the relationships between attention, sensory processing, and introspective reports. Spontaneous alpha power, when measured before stimulus onset, is now recognized to account for a substantial portion of the behavioral variability that is recorded during psychophysical tasks (Ress, Backus, & Heeger, 2000). For example, recent magnetoencephalography/EEG studies have shown that the power (Babiloni, Vecchio, Bultrini, Luca Romani, & Rossini, 2006; Balestrieri & Busch, 2022; Benwell et al., 2017; Ergenoglu et al., 2004; Grabot & Kayser, 2020; Iemi & Busch, 2018; Iemi, Chaumon, Crouzet, & Busch, 2017; Limbach & Corballis, 2016; Samaha, Iemi, Haegens, & Busch, 2020; Samaha, LaRocque, & Postle, 2022) and phase (Busch, Dubois, & VanRullen, 2009; Coon et al., 2016; Mathewson, Gratton, Fabiani, Beck, & Ro, 2009; Sherman, Kanai, Seth, & VanRullen, 2016; VanRullen, Busch, Drewes, & Dubois, 2011) of spontaneous alpha activity can determine perceptual outcomes. A convergent theme within this literature is that alpha oscillations reflect a state of relative cortical excitation or inhibition (Samaha et al., 2020; Van Diepen, Foxe, & Mazaheri, 2019). In this context, weaker prestimulus alpha oscillations are indicative of a more highly excitable cortical state (Klimesch, Sauseng, & Hanslmayr, 2007; Romei et al., 2008), which supports the negative relationship that has been reported between alpha amplitude and detection performance (Ergenoglu et al., 2004; Hanslmayr et al., 2005; van Dijk, Schoffelen, Oostenveld, & Jensen, 2008). More recently, however, evidence has linked spontaneous alpha to the subjective aspects of visual decisions, which may bias behavioral performance in lieu of any change in sensory precision (Benwell et al., 2017; Limbach & Corballis, 2016; Samaha et al., 2022). In particular, low prestimulus alpha power has been shown to precede a higher incidence of target detection and false alarms (Iemi et al., 2017; Limbach & Corballis, 2016; Samaha

et al., 2020), suggesting that low alpha power may improve detection performance only indirectly, by biasing participants to report yes in a detection task, regardless of the veridical presence of a target stimulus. In support of this view, in two recent examples, the strength of alpha power preceding a two alternative forced choice discrimination task was shown to negatively correlate with decision confidence (Samaha, Iemi, & Postle, 2017), and perceptual awareness or target visibility (Benwell et al., 2017; Samaha et al., 2022) without any change in objective accuracy.

Consistent with this literature on spontaneous alpha dynamics, alpha power is also modulated under top–down control to facilitate sensory processing (Clayton, Yeung, & Cohen Kadosh, 2018; van Diepen, Cohen, Denys, & Mazaheri, 2015; van Diepen, Miller, Mazaheri, & Geng, 2016; Van Diepen et al., 2019). For example, alpha oscillations are sensitive to attention, decreasing over cortical sites when attending to task-relevant information (Gould, Rushworth, & Nobre, 2011; Peylo, Hilla, & Sauseng, 2021; Sauseng, Klimesch, & Doppelmayr, 2005; Thut, Nietzel, Brandt, & Pascual-Leone, 2006). We have previously shown that alpha oscillations during active task preparation vary with task engagement as it fluctuates over time (Macdonald, Mathan, & Yeung, 2011) and as a function of experimental manipulations, such as reward (Hughes, Mathan, & Yeung, 2013) Here, we again focus on preparatory alpha in a fixed cue to target interval, and investigate how the strength of preparatory alpha band activity influences performance, subjective reports, and the generation of sensory evoked potentials (Chaumon & Busch, 2014; Hanslmayr et al., 2007; Hughes et al., 2013; Iemi et al., 2019; Min et al., 2007).

We analyzed data from two EEG experiments involving a near-threshold target detection task, in which we collected simultaneous ratings of both decision confidence and attention (experiment 1) and target visibility and attention (experiment 2) on a trial-by-trial basis. For both experiments we used an identical rapid serial visual presentation (RSVP) task requiring reports about stimulus presence and absence—decisions that have distinct neural contributions (Mazor, Friston, & Fleming, 2020) and metacognitive correlates (Kanai, Walsh, & Tseng, 2010; Meuwese, van Loon, Lamme, & Fahrenfort, 2014) compared with their two alternative forced choice counterparts. When contrasted, the results of the two experiments provide insights into the contribution of attention and sensory evidence to judgments of confidence (experiment 1) and stimulus visibility (experiment 2). Combined, the results of the two experiments allow us to assess how preparatory alpha activity influences sensory processing and introspective reports.

To preview our results, we show that participants' confidence reports (but not their ratings of stimulus

visibility) correlate with their self-reported attentional state, suggesting a partial dependence of the two key forms of introspective report. This correlation notwithstanding, our EEG analyses indicate that evaluations of confidence and attention depend on partially distinct sources of information: We demonstrate that a quadratic, inverted U function links preparatory alpha amplitude to subjective visibility and confidence, whereas subjective attentional focus negatively and linearly correlated with alpha amplitude. We further show that both confidence and visibility increase with the strength of visually evoked potentials, which were also quadratically modulated by the strength of alpha amplitude in the preparatory period.

Materials and methods

Participants

A total of 21 participants participated in this research, 12 participants in experiment 1, and 9 in experiment 2. A portion of the data from experiment 1 has been published previously (Macdonald et al., 2011). That work showed that single trial ratings of subjective attention could be classified based on preparatory alpha power, and that this classification was optimal over a sliding window of several minutes (Macdonald et al., 2011). Here, we reanalyze this dataset, and focus instead on how preparatory alpha amplitude (and, in Supplemental analyses, the phase of this activity) affect the generation of target-evoked event related-potentials (ERPs), and the interaction of preparatory alpha and ERPs on subjective criteria. Experiment 2 is a new experiment. There were five males in experiment 1, and all participants' ages ranged from 18 to 29 years ($M = 22.3$; $SD = 4.4$). There were four males in experiment 2, and all participants' ages ranged from 19 to 23 years ($M = 20.6$; $SD = 1.8$). All participants were recruited for participation at the University of Oxford, were paid for their participation, and had normal or corrected to normal vision. This research was conducted in accordance with the University of Oxford's Institutional Review Board, and the American Psychological Association's standards for ethical treatment of participants.

Experimental procedures

The experimental procedure was very similar between the two experiments, and has previously been detailed in Macdonald et al. (2011). In each trial, participants were asked to monitor a RSVP of images for a difficult-to-detect target image. Each trial began with the words "Get Ready" presented on screen for

300 ms, before the 10 images comprising the RSVP stream were presented after a further 700 ms. Each image in the stream was presented for 50 ms, followed by a blank interval for 50 ms, resulting in a 10 Hz presentation rate. This presentation rate falls within the canonical frequency range of alpha EEG oscillations (8–12 Hz), but we have not found any clear evidence of interactions between intrinsic alpha activity and evoked responses from the alpha rate RSVP stream. The 10 Hz presentation rate was chosen because the experiments were conducted as part of an applied project on rapid satellite image triage (e.g., Hughes et al., 2013), in which the 10 Hz presentation was a standard rate used in the brain–computer interface device being studied. Each image in the RSVP stream was a grayscale pattern of white noise, and target images included a set of six superimposed concentric circles (each subtending 0.4° visual angle), arranged in a hexagonal pattern (subtending 3.3° visual angle) (Figure 1). There were 936 trials in total. Targets were presented on 50% of trials, with their position in the RSVP stream balanced across image positions 3 through 8. For each participant, the contrast of the hexagonal target pattern was determined in a pre-experimental session to titrate detection rates to approximately 75% (QUEST, Psychophysics Toolbox 3, Brainard, 1997).

After the RSVP stream, participants indicated their subjective attention and confidence (experiment 1), or attention and visibility (experiment 2) ratings by providing a single mouse-click within the response screen (Figure 1). In experiment 1, the response screen was subdivided into four quadrants by faint gray lines, with the prompts "Did you see the target?", "How confident are you of that?", and "How focused were you?" Displayed at the top of the screen. The words "Sure Absent" and "Sure Present" were presented on the left and right extrema of the *x*-axis, and "More Focused" and "Less Focused" placed on the top and bottom of the *y*-axis. In experiment 2, the prompt at the top of the screen replaced the question about confidence with one targeting stimulus visibility: "How much of the target did you see?", with extremes of the *x*-axis labelled as "None" and "All". In both experiments, the response screen was 201 × 201 pixels. Attention was measured on a 201-point scale according to the *y*-axis click location. In experiment 1, confidence in presence or absence was measured on a 100-point scale (decreasing or increasing distance from the vertical midline), and in experiment 2 visibility was measured on a 201-point scale according to the *x*-axis click location.

Participants were instructed to rate their subjective state only with respect to the current trial and to incorporate their attention, confidence, and visibility in this single response. Thus, in experiment 1, the horizontal distance from the vertical midline represents confidence in the presence or absence of a target, and
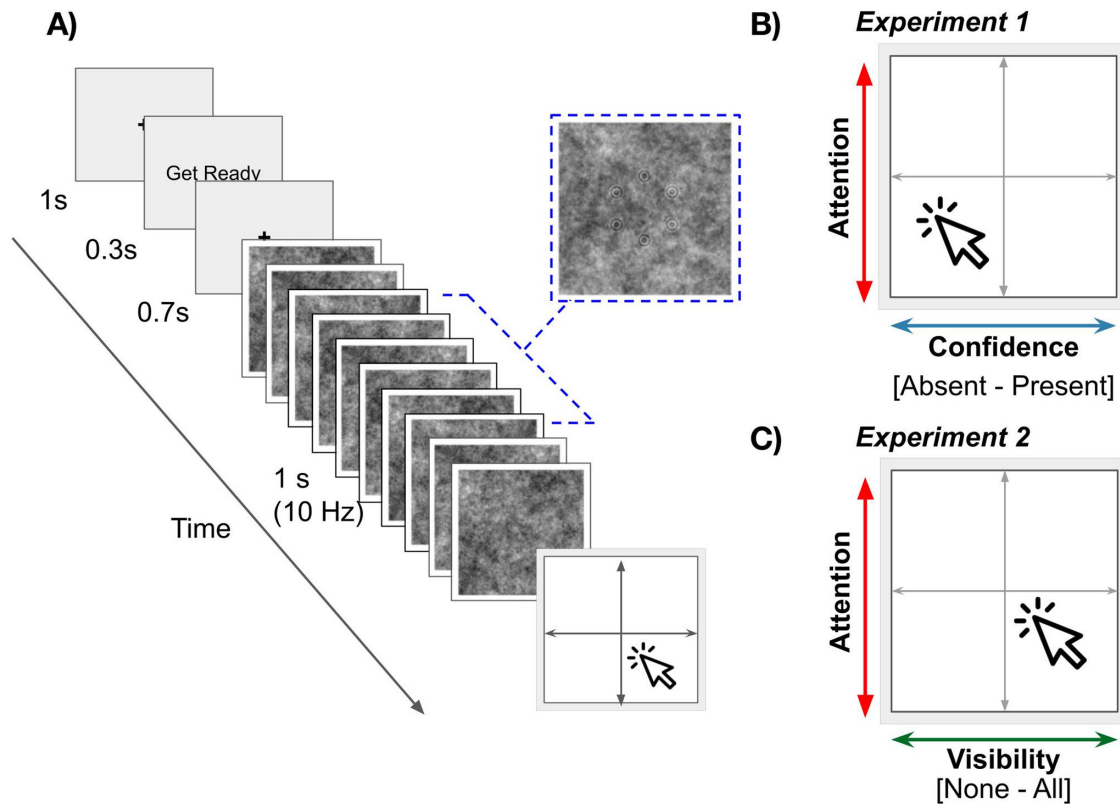
Figure 1. Trial procedure and response options. (A) Each trial began with the words "Get Ready" presented on screen. After a fixed interval of 1 second, the RSVP sequence began, and a target image was presented once, on 50% of trials. Targets (shown outlined in blue) were presented in one of positions 3 to 8 in the RSVP stream. (B) After each trial, participants rated either their subjective confidence and attention (experiment 1), or (C) the perceived visibility of the target and their attention (experiment 2).

in experiment 2 click distance from the left extrema represents target visibility. In both experiments, the click position on the vertical axis represents trial-specific attention to the detection task.

Behavioral analysis

For our behavioral analysis, we calculated overall target accuracy (% correct), as well as the hit rate (i.e., yes responses in target-present trials), false alarm rate (i.e., yes responses in target-absent trials), and standard metrics from signal detection theory (Green & Swets, 1966). Hits and false alarms (i.e., trials on which participants' responses were taken to indicate a target was present rather than absent) were defined in experiment 1 as clicks in the right half of the response screen, and in experiment 2 as any click away from the left extrema of this screen. We calculated d', which measures the sensitivity between signal and noise distributions in the signal detection framework, as well as decision criterion (c), which measures the likelihood of yes responses, regardless of the veridical presence of a stimulus. When c is positive, the decision criterion is

said to be conservative, and negative c values indicate a more liberal criterion, or a tendency to respond yes in detection tasks, relative to the true unbiased response probability given by the intersection between signal and noise distributions.

We also calculated metacognitive sensitivity (type 2 performance), which captures the fidelity of introspective judgments with relevance to objective performance. A high type 2 performance indicates that introspective judgments are well-calibrated, and positively correlated with the objective likelihood of a correct response. A low type 2 performance indicates that introspective judgments are a poor indicator of objective accuracy. We quantified type 2 performance as the area under the receiver operating characteristic curve (Fleming & Lau, 2014), constructed from each participant's subjective confidence, visibility, or attention ratings. Specifically, for every rating value used by a particular participant, we calculated the proportion of all correct response trials and the proportion of all incorrect response trials with ratings that exceeded this value, and then calculated the area under the curve created by plotting these proportions (on the y-axis and x-axis, respectively) for all rating values. A value of 1

indicates perfect sensitivity; a value of 0.5 indicates chance performance.

EEG recording and preprocessing

EEGs were recorded from 32 Ag/AgCl electrodes using a Neuroscan Synamps 2 system. Electrode positions were FP1, FPz, FP1, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, POz, Oz, Oz, and O2. During recording, all electrode impedances were kept at less than 50 kΩ. Four additional electrodes were placed over the outer canthi of the left and right eyes, and above and below the right eye to measure eye movements. Two additional electrodes were attached to the left and right mastoids, of which the left acted as a reference. All EEG data were recorded at a sampling rate of 1,000 Hz, before being downsampled off-line to 250 Hz, and low pass-filtered at 48 Hz. EEG data were epoched from 0.5 s before, to 3 s after the onset of the words "Get Ready" on screen and demeaned using the whole-epoch average. Noisy channels were identified by visual inspection and replaced with the average of nearest neighbors. In experiment 1, an average of 0.25 channels were removed (three over all participants), and no channels were removed in experiment 2. An independent component analysis was performed to identify and remove artefacts using the SASICA toolbox (Chaumon et al., 2015), and all epochs were visually inspected for rejection. On average, less than 4% of trials were discarded per participant.

Preparatory alpha analysis

Analysis was performed within MATLAB (R2019a) using custom scripts, and functions from the EEGlab (Delorme & Makeig, 2004), FieldTrip (Oostenveld et al., 2011), and Chronux (Bokil et al., 2010) toolboxes. Our analysis focused on alpha activity in the preparatory window, covering 1 s between the presentation of the words "Get Ready" and onset of the RSVP stream, as well as the amplitude of ERPs evoked by the RSVP stream. Alpha oscillations, measured over 1 s between the words "Get Ready" and the onset of the RSVP stream, were strongest over parieto-occipital electrodes (POz, O1, Oz, and O2). We averaged over these electrodes for all our alpha analyses, described elsewhere in this article.

To avoid the possibility of post-stimulus activity (i.e., the RSVP response) contaminating our measure of alpha band activity within the preparatory window, we avoided the use of a sliding window spectrogram (e.g., Davidson et al., 2020). Instead, single-trial alpha amplitude was calculated by applying the fast Fourier transform (FFT) to the Hanning tapered

preparatory period in each epoch. We used a single taper per frequency (zero padded; resolution, 0.24 Hz) and retained the complex values of the FFT. We quantified the strength of alpha band activity by taking the magnitude of these complex values, and estimated preparatory alpha amplitude by averaging these values over 8 to 12 Hz at each channel. Across both experiments, all participants' peak alpha frequency fell within this canonical band (experiment 1: $M = 10.53$ Hz, $SD = 1.06$; experiment 2: $M = 10.06$ Hz, $SD = 0.76$), and corresponding results with those presented below were observed when we reran analyses based on each participant's individual alpha peak. To facilitate comparisons across participants, we first applied the z-transform to all single-trial estimates of alpha amplitude per participant. We sorted single-trial values of alpha amplitude into quintiles, by binning according to the 0% to 20%, 21% to 40%, 41% to 60%, 61% to 80%, and greater than 80% values of the cumulative probability distribution of z-transformed data. When sorting by a subclass of outcome (e.g., hits only), we applied the quintile split after first restricting to the range of relevant trials, to ensure approximately equal trial numbers in each quintile bin. We performed the same quintile separation and binning procedure when also analyzing behavioral and ERP responses by subjective criteria. When visualizing the power spectrum across frequencies (Figure 4), we additionally squared the complex values of our FFT and applied the log transform.

ERP analysis

After sorting trials according to quintiles of alpha amplitude per participant, we next characterized how preparatory alpha modulates the event-related potentials evoked by the RSVP stream. Based on previous research, we focused on two measures: the early sensory-evoked P1 component elicited by the first image of each RSVP stream (which never contained a target stimulus) and the centroparietal positivity (CPP or P300) elicited by detected targets. We use the P1 as a measure of the overall excitability of sensory cortex and evaluate the CPP to detected targets as a measure of the strength of evidence associated with those targets (Murphy et al., 2015; O'Connell et al., 2012; Twomey, Murphy, Kelly, & O'Connell, 2015).

We closely followed the analysis procedures detailed by Rajagovindan and Ding (2011), to investigate whether alpha affected early stimulus processing. To quantify the amplitude of the P1 component, each whole-trial preprocessed epoch was additionally filtered between 1 and 25 Hz (one-pass zero phase, hamming-windowed FIR filters), and a pre-RSVP baseline correction was applied using the period from –50 to 0 ms relative to RSVP onset (950–1,000 ms

relative to the start of each trial). The P1 amplitude was calculated by first averaging all trials within each alpha quintile, and then retaining the maximum positive peak within the window of 80 to 160 ms after RSVP onset. We observed a reliable P1 component (i.e., positivity in 80–160 ms, across all five quintiles), only at the most occipital electrode sites (O1, Oz, and O2) and report the P1 amplitude averaged across these electrodes.

We also averaged the ERP response to targets that were embedded within the RSVP stream on target-present trials, focusing on the CPP that is thought to reflect the accumulating evidence for a decision. Target-locked ERPs were calculated after filtering preprocessed epochs between 0.1 and 8.0 Hz to remove the influence of the 10 Hz RSVP component (one-pass, zero phase, hamming-windowed FIR filters). We then subselected the period of –200 ms to 1.5 s relative to target onset, and baseline corrected using the –100-ms to the target onset window. When targets were presented within the RSVP stream ("hits" and "misses"), we quantified the CPP strength by averaging over a cluster of centroparietal electrodes (C3, Cz, C4, CP3, CPz, and CP4), over the period of 250 to 550 ms relative to the target onset. This period was selected to contain the majority of the peak observed in the CPP (cf. Figure 7D) (for similar see Kelly & O'Connell, 2013; Twomey et al., 2015).

Mixed-effects analyses

One of our key motivations was to assess the effect that the strength of preparatory alpha band activity, split into quintiles, had on subjective measures. Because we observed a mixture of both linear and quadratic trends, we used mixed effects models to formally test the nature of these trends, in preference to other analysis options such as a repeated-measures analysis of variance. Our justification for this choice is two-fold. First, mixed effects models allow us to account for variance, which is attributable to either individual participants (random effects) or a relevant category (e.g., fixed effects of alpha). Second, and most important, mixed effect models are more appropriate to our research question, as by specifically testing either a linear or quadratic model, we can explicitly compare which may be a better fit to the data.

We formally tested the nature of linear and quadratic coefficients by performing a series of stepwise mixed effects analyses to model either linear or quadratic fixed effects of alpha amplitude, which included random effects (intercepts) per participant. We performed likelihood ratio tests between the full model, which combined random, linear, and quadratic effects, with restricted models of increasing simplicity (removing first the quadratic and then linear term). We compared the goodness of fit for each model using likelihood ratio tests, and in our results report when either the linear or quadratic model was a better fit to the data than the basic model, which included only random effects per participant. When a significant linear or quadratic effect is reported, the fixed effect coefficient (β) and 95% confidence intervals are also included.

Results

We recorded continuous measures of both confidence and attention (experiment 1), and visibility and attention (experiment 2) on a trial-by-trial basis in a visual detection task. We first present the behavioral results from these tasks, showing an asymmetry in the behavioral correlations between subjective measures and objective performance. We then report how differences in these performance measures are influenced by preparatory alpha amplitude. Finally, we show that alpha amplitude quadratically modulates the generation of sensory-evoked potentials, which in turn correlates with confidence and visibility judgments.

Behavioral results

Confidence and visibility correlate differently with attention ratings

The use of subjective responses and introspective accuracy varied between experiments 1 and 2. After each trial, participants were asked to indicate either their trial-specific confidence and attention ratings (experiment 1) or visibility and attention ratings (experiment 2) by providing a single mouse-click within a response square. Figure 2A displays the cumulative total click responses in both experiments. Trials in which targets were presented within the RSVP stream are shown in orange and trials without a target are shown in purple. Figure 2 plots data pooled across all participants, but key trends apparent here are mirrored in single-participant data (see Supplementary Figures S1 and S2), despite typically observed idiosyncratic differences across participants in their use of subjective rating scales (cf. Ais et al., 2016).

In experiment 1, participants rated their confidence in the presence or absence of a target on the *x*-axis, and attentional state rating on the *y*-axis. Single-clicks on the left half of the response screen represent confidence values ranging from sure absent to unsure, and the right half represent unsure to sure present. As such, purple dots on the left half represent increasing confidence in the absence of a physically absent target (correct rejection), and orange dots on the left half represent confidence in the absence of a target that was physically present (miss). Orange and purple dots on the right-hand side represent, respectively, the confidence in present targets (hits) and confidence in target
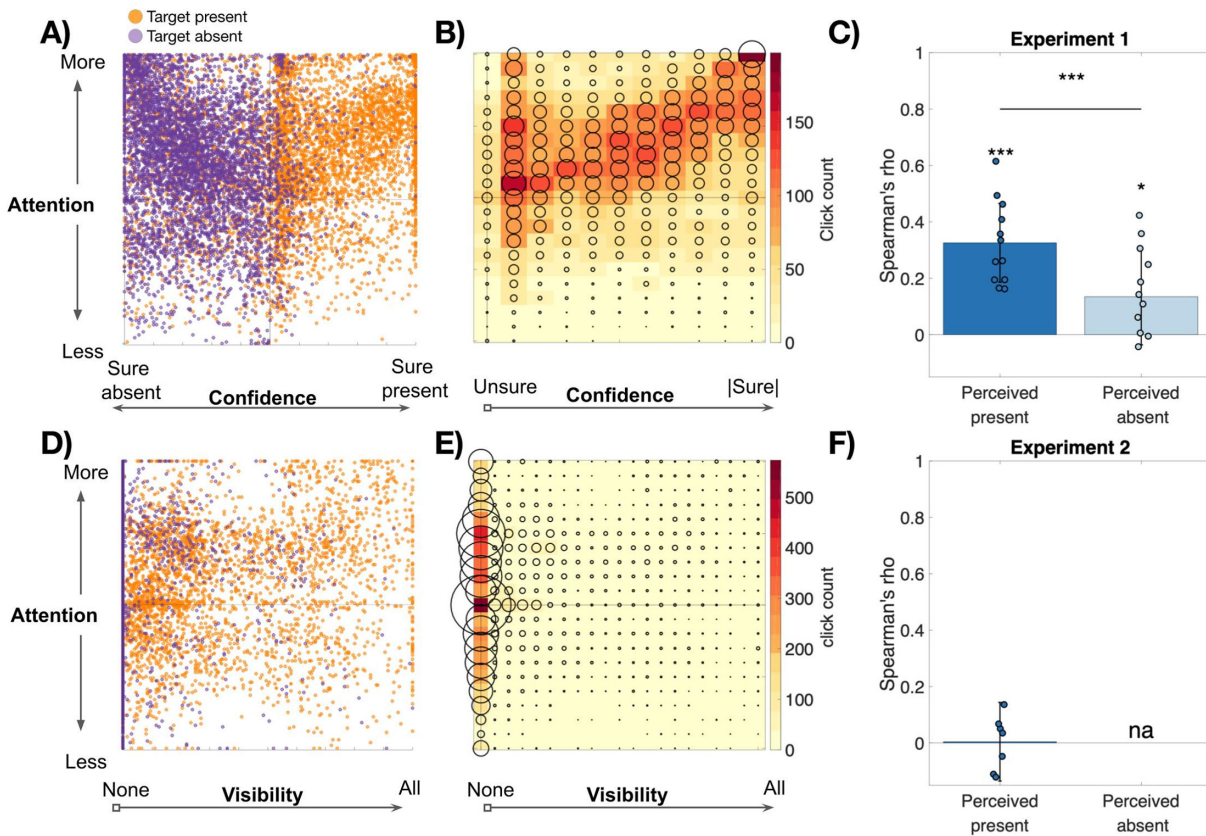
Figure 2. Subjective responses to the same visual detection task. (A) In experiment 1, participants rated their decision confidence that a target was either absent or present, simultaneously with their subjective attention, with a single click in the response square. Orange dots indicate target present trials, purple dots represent target absent trials. (B) Increases in subjective confidence positively correlated with an increase in attention. Larger circle sizes correspond with higher click counts. (C) Average linear correlation coefficients were significantly positive for attention and perceived-presence (orange), as well as attention and perceived absence (purple). Error bars display 1 SD. (D) In experiment 2, participants rated the subjective visibility of targets on the *x*-axis. Color conventions are the same as in (A–C). (E, F) Subjective visibility did not positively correlate with attention ratings. Note: no correlation is calculated for "perceived absent" trials in experiment 2 because these trials were defined as having the same (zero) visibility rating on all trials.

presence when, objectively, no target was presented (false alarm). A qualitative inspection reveals a dense diagonal cloud of responses, indicating that confidence in the presence and absence of targets correlated with attentional state ratings. This diagonal density of responses can be appreciated in Figure 2B, where the absolute value of confidence from unsure to sure is plotted against attentional state ratings, pooling both sure present and sure absent responses on the *x*-axis. To assess the strength of these correlations quantitatively, we calculated the nonparametric linear correlation coefficient between attention and confidence ratings, separately for each participant for target-present and target-absent trials. This analysis revealed a consistently positive correlation between trial-wise attentional state ratings and confidence, both in the presence of a target (one-sample *t*-tests against zero), $t(11) = 7.74$, $p < 0.001$, $d = 2.23$, as well as the absence of a

target, $t(11) = 2.61$, $p = .025$, $d = 0.78$. The strength of these correlations differed significantly, revealing an asymmetry between subjective measures of attention and decision confidence in the presence or absence of a target (paired samples *t* test), $t(11) = 5.23$, $p < 0.001$, $d = 1.51$ (Figure 2C).

In experiment 2, participants rated the visibility of the target, responding to the prompt "How much of the target did you see?", by clicking on the *x*-axis between the ranges of none to all. As such, purple dots at the far-left value (zero) of the visibility scale represent correct rejections (trials without a target, rated as such) and orange dots at this value represent missed targets, whereas purple and orange dots with nonzero values represent false alarms and hits, respectively. In contrast with experiment 1, no consistent correlation was observed between visibility judgments and attention ratings, $t(8) = .09$, $p = 0.93$ (Figure 2F).
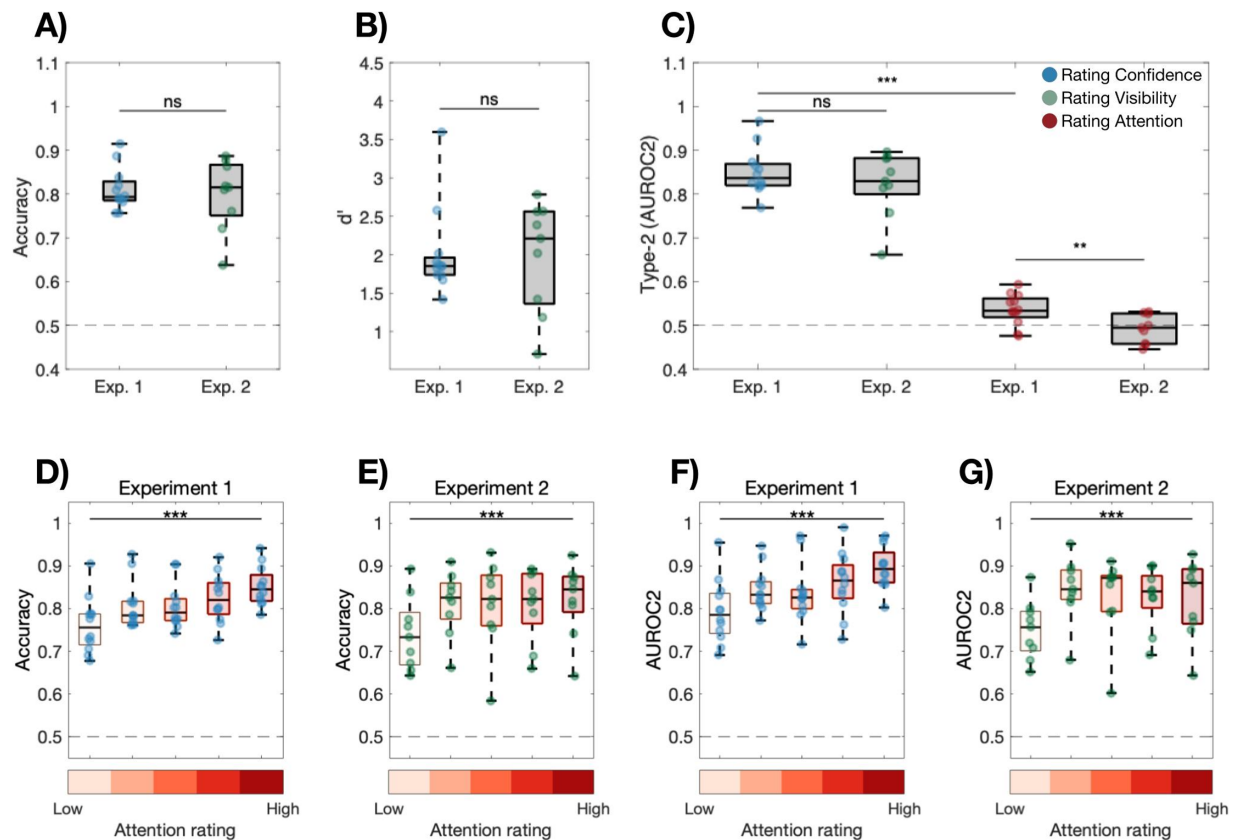
Figure 3. Objective and metacognitive accuracy in both experiments. (A) No significant difference was observed in objective accuracy across experiments. (B) Signal-detection theory measures of sensitivity (d') were also similar across experiments. (C) Metacognitive sensitivity was greatest for confidence and visibility judgments and did not differ significantly between experiments. Metacognitive sensitivity based on attention was significantly stronger in experiment 1, although significantly weaker than metacognitive sensitivity based on confidence or visibility judgments in both experiments. (D, E) In both experiments, accuracy increased with the intensity of subjective attention. (F, G) In both experiments, metacognitive sensitivity also increased with subjective attention. In each box, the bottom, central, and top lines indicate the 25th, 50th, and 75th, percentiles respectively. Whiskers extend to the furthest data points. AUROC2, type 2 performance as the area under the receiver operating characteristic curve; ns, not significant.

We return to this asymmetric pattern of responses in our Discussion. For now, we note two aspects of these data that provide important context for the detailed EEG analyses to follow. First, the results indicate that participants did not base their attentional state ratings solely on their sensory experience of seeing versus not seeing a target stimulus ("I saw a target clearly so I must've been paying attention"; cf. Head & Helton, 2018): Confidence that a target was absent increased rather than decreased with attention ratings in experiment 1, and no hint of a correlation was apparent between visibility and attention ratings in experiment 2. Second, the contrast between experiments 1 and 2 suggests that different information is conveyed in confidence and visibility ratings, with confidence being markedly more sensitive to variations in (rated) attentional state.

Matched objective performance and metacognitive sensitivity

In contrast with this varied pattern of subjective responses, objective task performance was very similar across both experiments (Figure 3). Before each experiment, target contrast was adapted using a staircase procedure to approximate 75% detection accuracy for each participant. Mean contrast values were 0.15 ($SD = 0.02$) for experiment 1, and 0.16 ($SD = .02$) for experiment 2. The overall accuracy, incorporating target-absent trials, was 81% ($SD = 4\%$) for experiment 1, and 80% ($SD = 8\%$) for experiment 2, with no significant difference in performance between experiments ($t < 1$) (Figure 3A). The mean detection rates in both experiments (experiment 1 = 71%, $SD = 8\%$; experiment 2 = 73%, $SD = 8\%$) were not significantly different ($t < 1$). False alarm rates

(experiment 1 = 9%, *SD* = 5%; experiment 2 = 13%, *SD* = 13 %) were also not significantly different, $t(19) = -1.02$, $p = 0.32$. We observed similar results for perceptual sensitivity (d′; experiment 1 = 2.01, *SD* = 0.57; experiment 2 = 1.98, *SD* = 0.72) (Figure 3B) and criterion (*c*; experiment 1 = 0.43, *SD* = 0.22; experiment 2 = 0.36, *SD* = 0.38), which did not significantly differ between experiments (both $p > 0.59$).

We also calculated the metacognitive (type 2) sensitivity based on confidence and visibility ratings. Type 2 sensitivity captures the degree to which subjective ratings correlate with the objective likelihood of successful task performance—that is, the degree to which the true positive rate exceeds the false positive rate at each rated value of confidence/visibility. The mean type 2 performance in experiment 1 ($M = 0.85$, *SD* = .07) was not significantly different from experiment 2, $M = 0.82$, *SD* = .07; $t(19) = 1.05$, $p = 0.31$ (Figure 3C), and both differed significantly from chance (both $t > 13$, $p < 0.001$), despite the large differences observed in the pattern of subjective responses.

We also took the opportunity to calculate metacognitive sensitivity based on attention state ratings—that is, the degree to which participants' attentional state ratings were calibrated with the likelihood of a correct response. Although a nascent literature, metacognitive sensitivity based on attention ratings has recently been shown to approximate type 2 sensitivity based on confidence in a somatosensory detection task (e.g., Whitmarsh, Barendregt, Schoffelen, & Jensen, 2014; Whitmarsh, Gitton, Jousmäki, Sackur, & Tallon-Baudry, 2021, Whitmarsh, Oostenveld, Almeida, & Lundqvist, 2017). In the current visual detection tasks, type 2 sensitivity based on attentional state ratings in experiment 1 ($M = 0.54$, *SD* = 0.05) was significantly lower than when based on confidence, $t(11) = 18.74$, $p = 1.07 \times 10^{-9}$, $d = 5.41$. Similarly, type 2 sensitivity based on attentional state ratings in experiment 2 was significantly lower than visibility-based type 2 sensitivity, $M = .49$, *SD* = .03; $t(8) = 11.60$, $p = 2.77 \times 10^{-6}$, $d = 3.87$. Only the attention-based type 2 sensitivity in experiment 1 was significantly above chance, $t(11) = 3.51$, $p = 0.005$, $d = 1.01$, and the strength of this type 2 sensitivity differed significantly between experiments, $t(19) = 2.88$, $p < 0.01$, $d = 1.03$. This latter result extends the asymmetric patterns shown in Figure 2, in which attention ratings correlated with confidence (in experiment 1) but not visibility ratings (in experiment 2), to show that attention ratings captured metacognitive sensitivity only in experiment 1, when paired with confidence ratings.

Next, we investigated whether objective accuracy and metacognitive sensitivity varied with participants' evaluations of their attentional states (Figure 3D–G). Replicating previous findings, performance varied significantly as a function of rated attention, with objective accuracy differing significantly across attention quintiles in experiment 1, $F(4,44) = 15.71$, p

< 0.001, $\eta_p^2 = .59$, and experiment 2, $F(4,44) = 7.83$, $p < 0.001$, $\eta_p^2 = .50$. Perceptual sensitivity (d′) increased with attention ratings in experiment 1, $F(2.14, 23.54) = 6.75$, $p < 0.001$, $\eta_p^2 = .38$, (Greenhouse–Geisser corrected), but not significantly in experiment 2 ($p = 0.06$). This criterion was not affected by attention in either study ($ps > 0.2$). A more novel finding was that metacognitive sensitivity also significantly increased alongside higher attention ratings in both experiment 1, $F(4,44) = 12.09$, $p < 0.001$, $\eta_p^2 = .52$, and experiment 2, $F(4,44) = 6.67$, $p < 0.001$, $\eta_p^2 = 0.46$. Thus, when more attentive, participants were not only better at the task, but also more accurately evaluated their perceptions and decisions.

Overall, therefore, in our behavioral data we observed quantitatively distinct patterns of responses when participants were asked to report either their decision confidence and attention, or visibility and attention, despite matched objective performance. In both experiments, performance increased with self-rated attention, yet only confidence, but not visibility, also positively correlated with attention ratings. To unpack this discrepancy, we turn to the strength of alpha band activity, which has been linked to the subjective intensity of visibility (Benwell et al., 2017), confidence (Samaha et al., 2017), and attention (Macdonald et al., 2011) in visual tasks.

EEG results

We analyzed the amplitude of alpha oscillations (8–12 Hz) over a 1-s preparatory period, from the onset of the words "Get Ready" to the first presentation of an image in the RSVP stream (hereafter alpha amplitude). Consistent with previous reports (Macdonald et al., 2011; Samaha et al., 2017), we observed alpha amplitude to be strongest over a cluster of parieto-occipital electrodes (POz, Oz, O1, and O2) and focus our remaining analysis on this subset (Figure 4). To preview our results, in both experiments, we observed that subjective attention ratings decreased with increased alpha amplitudes. In contrast with these linear effects, we observed a quadratic, inverted U function linked preparatory alpha to subjective confidence and visibility.

Alpha amplitude is negatively correlated with subjective attention

For the effect of alpha on subjective attention ratings, when rating attention on all trials, the linear model differed significantly from the basic model, confirming a significant linear effect of alpha amplitude on subjective attention in experiment 1, $\chi^2(1) = 16.14$, $p = 5.90 \times 10^{-5}$, $\beta = -0.04$ (-0.06, -0.02). We further subdivided our analysis into target-present, and target-absent cases.
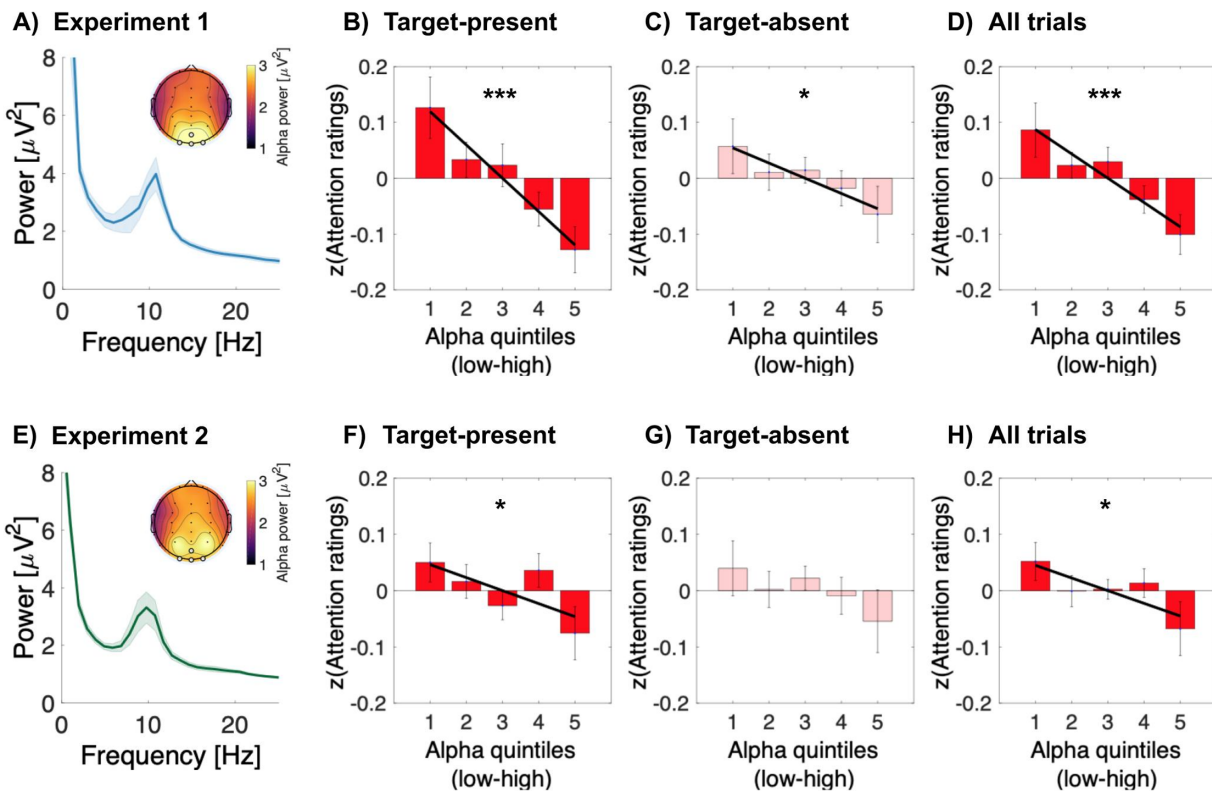
Figure 4. Preparatory alpha amplitude is negatively correlated with attention ratings. In experiment 1, strong preparatory alpha over occipital electrode sites correlated negatively and linearly with attention ratings on both target-present (B) and target-absent (C) trials, as well as in the pooled data (D). In experiment 2, a similar topography of alpha band activity (E) negatively correlated with attention ratings on target-present trials (F) and in a pooled analysis (H), but not reliably in target-absent trials (G). Error bars represent 1 SEM, corrected for within-participant comparisons (Cousineau, 2005). Black lines display linear lines of best fit. Asterisks denote significant linear effects. ***p < 0.001, *p < 0.05.

Our motivation was to inspect whether the intervening presence (or absence) of a target within the RSVP stream would impact the observed relationship between preparatory alpha amplitude and attention. A key point is that this distinction allows us to investigate whether the influence of alpha exclusively biases the strength of evidence in favor of target detection.

When restricted to target-present trials, a linear effect of alpha was again the best fitting model in experiment 1, $\chi^2(1) = 19.94$, $p = 7.99 \times 10^{-6}$, $\beta = -0.06$ (–0.08, –0.03). When analyzing the matched subset of target-absent trials, a weaker effect of preparatory alpha on attention was observed, $\chi^2(1) = 5.13$, $p = .024$, $\beta = -0.03$ (–0.05, –0.004). We formally tested for the equivalence of regression coefficients (cf. Equation 4, Paternoster et al., 1998) and found the regression slopes to significantly differ between target-present and target-absent trial types ($Z = -1.91$; $p = 0.028$). This result indicates that, although preparatory alpha was consistently negatively related to subjective attention, the effect of this relationship was strongest when reflecting on target-present compared with target-absent trials.

The same pattern of results was present in experiment 2. When considering all targets together, the linear model differed significantly from the basic model, $\chi^2(1) = 4.97$, $p = 0.025$, $\beta = -0.02$ (–0.04, –0.003). This effect was again strongest when considering target-present trials, $\chi^2(1) = 4.41$, $p = 0.036$, $\beta = -0.02$ (–0.04, –0.001), as the linear model did not differ significantly from the basic model in target-absent trials ($p = 0.6$). However, the difference between the linear regression coefficients for target-present and target-absent classes was not significant ($p = 0.42$), reflecting the similar negative trend apparent in both trial types.

Alpha amplitude quadratically modulates confidence and visibility

In contrast with the monotonic and approximately linear relationship between alpha and attention ratings, alpha amplitude showed a quadratic relationship with the two other introspective ratings (confidence and visibility) that were recorded simultaneously with self-reported attention. In experiment 1, a consistent quadratic trend was found, linking intermediate alpha
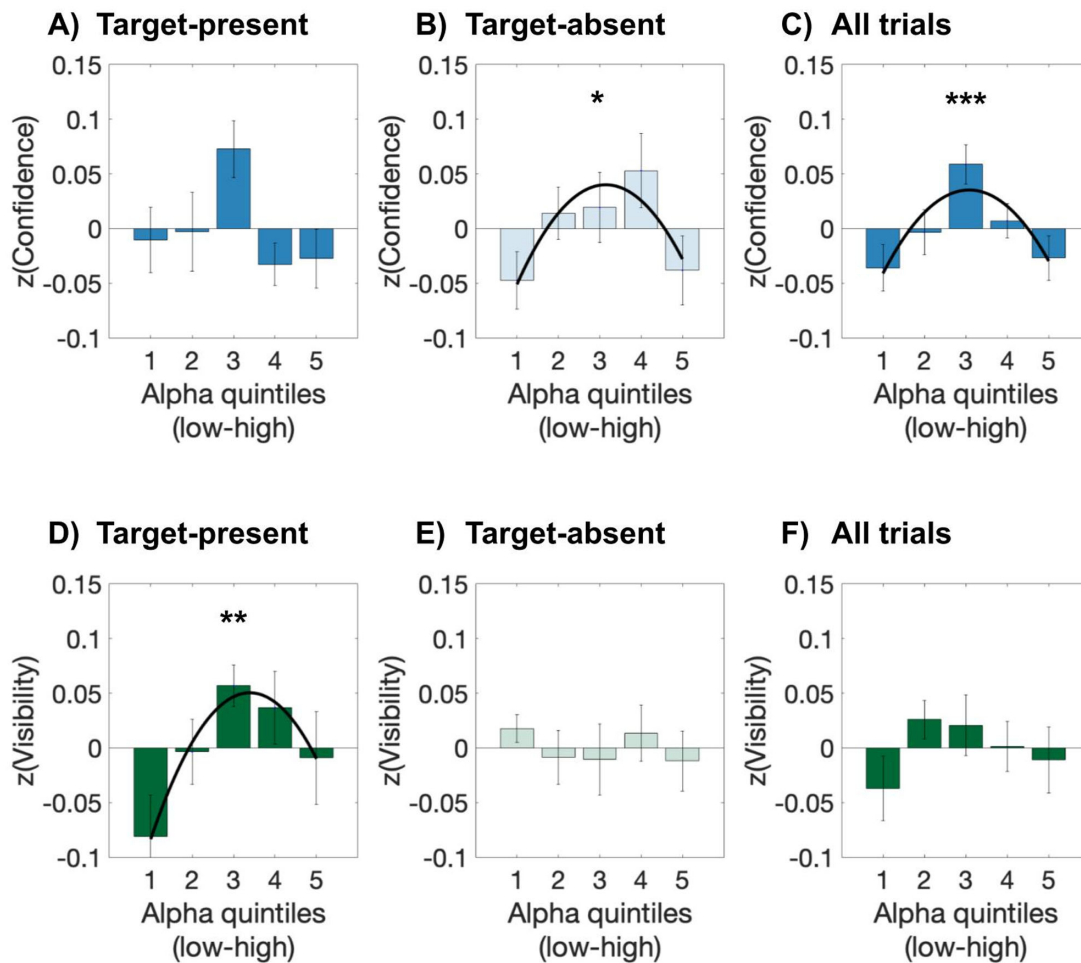
Figure 5. Preparatory alpha amplitude is quadratically related to subjective visibility and confidence. (A–C) Decision confidence in the presence of a target is maximal at intermediate values of alpha amplitude on target-absent trials and when pooling all trial types. (D) Subjective target visibility is maximal at intermediate values of alpha amplitude on target-present trials. (E) No significant effect of preparatory alpha on visibility when targets are absent, or (F) when pooling across all target types. Error bars represent 1 SEM, corrected for within-participant comparisons (Cousineau, 2005). Quadratic lines of best fit are shown in black. Asterisks mark significant quadratic fits. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

strength to enhanced confidence that a target was present in the RSVP stream. This effect was strongest when considering decision confidence across all trials, as the quadratic model differed significantly from the basic model, $\chi^2(1) = 11.15, p = 0.004$, and was a better fit than the linear model, $\chi^2(1) = 10.97, p = 0.0009, \beta = -0.02$ (−0.03, −0.007). The same quadratic trend was found when subdividing into the subset of only target-present trials but was not significant, $\chi^2(1) = 2.99, p = 0.08$. On target-absent trials, alpha amplitude significantly and quadratically modulated confidence, that is, (misplaced) confidence that a target was presented, and was a better fit than the basic model, $\chi^2(1) = 6.58, p = 0.037$, and linear model, $\chi^2(1) = 6.22, p = 0.013, \beta = -0.02$ (−0.04, −0.004) (Figures 5A–C). In experiment 2, when rating target visibility, the same quadratic trend occurred. The quadratic effect was significant only on target-present trials, and a better fit than the basic model, $\chi^2(1) =$

11.17, $p = 0.004$, and linear models, $\chi^2(1) = 8.16, p = 0.004, \beta = -0.02$ (− 0.04, −0.007). For target-absent trials, or when all trials were pooled together, neither linear nor quadratic models were a better fit to the data than the basic model, with only random effects per subject (all $p > 0.2$), reflecting very low variability in participants' visibility ratings on target-absent trials (in which most trials were given the same [zero] visibility rating).

Alpha amplitude quadratically modulates behavioral performance

Recent work has shown that the prestimulus alpha power may uniquely mediate subjective criteria, while leaving objective accuracy unchanged (for review, see Samaha et al., 2020). In our data, we have seen a strong
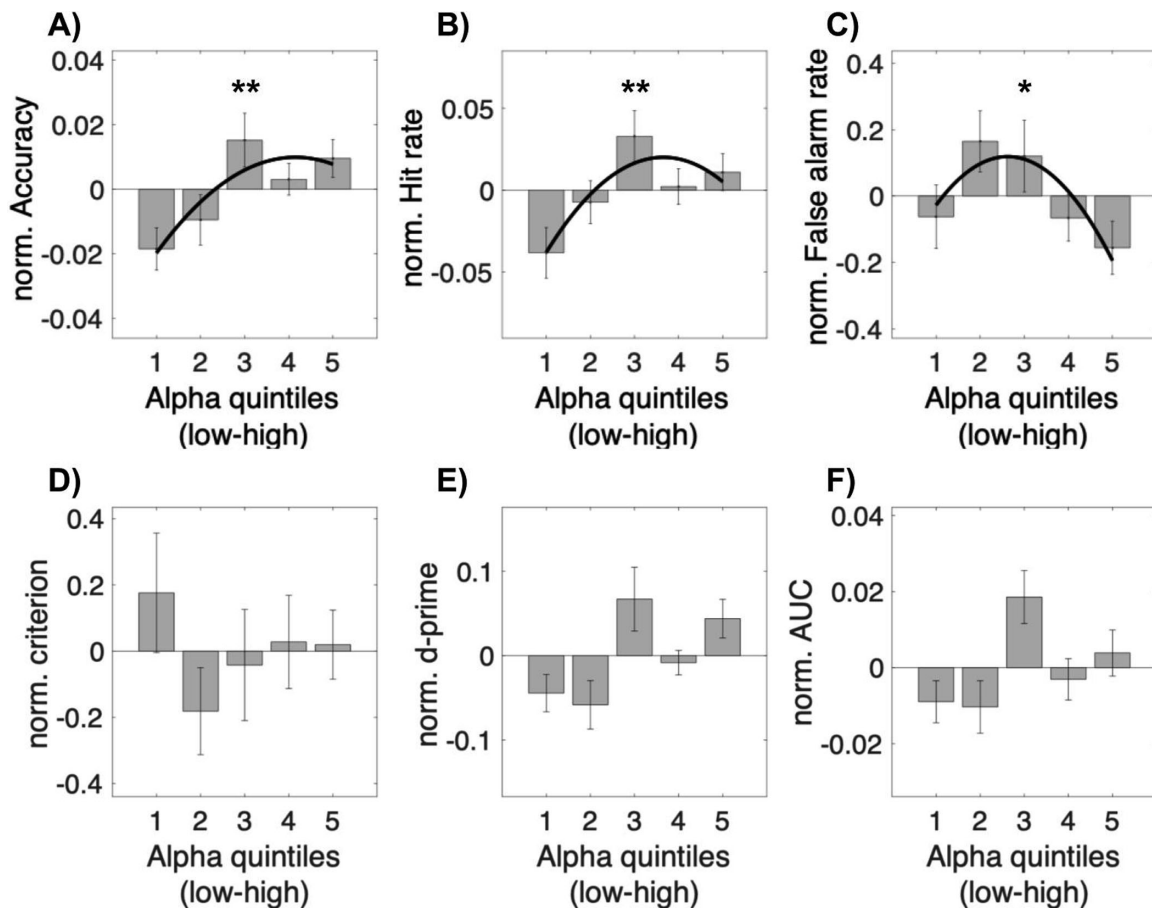
Figure 6. Preparatory alpha amplitude and behavioral performance. Alpha amplitude quadratically modulates (a) accuracy, (b) hit rate, and (c) false alarm rate, but not (d) criterion, (e) d′, or (f) area under the curve (AUC) in combined experimental data ($N = 21$). Responses are normalized per subject, by dividing by the mean across alpha bins, and zero centered by subtracting by 1. *$p < 0.05$, **$p < 0.01$. For separate experiments, see Supplementary Figure S3.

and consistent relationship between the strength of alpha oscillations and subjective ratings of attentional state, as well as a significant relationship between rated attention and behavioral accuracy (Figure 3). We next examined whether alpha amplitude would also affect objective measures of performance, and focused our analyses on accuracy, hit and false alarm rates, as well as signal detection metrics of sensitivity (d′) and criterion (c). Finally, we also investigated whether metacognitive sensitivity, which was enhanced by subjective attention, would also vary with the strength of preparatory alpha amplitude. Following previous research (Busch et al., 2009; Iemi & Busch, 2018), we first normalized these responses per subject, by dividing by the mean response (accuracy, hit rate, criterion, etc.) across all alpha quintiles.

Because both experiments had a very similar task structure, and the objective accuracy was very similar between experiments 1 and 2, we continued by pooling the data across all 21 participants to increase statistical power. The pattern of results we present (Figure 6) is

consistent, although statistically weaker when keeping each cohort separate, as shown in the Supplementary materials.

Alpha amplitude in the preparatory window significantly affected overall accuracy. Both the linear model, $\chi^2(1) = 8.40$, $p = 0.004$, $\beta = 0.006$ (0.002, 0.01), and quadratic models, $\chi^2(1) = 10.87$, $p = 0.005$, $\beta = -0.002$, $(-0.006, -0.0007)$, were superior fits than the basic model. When comparing the linear and quadratic fits, neither were a better fit to the data ($p = 0.12$). Post hoc comparisons, adjusting for a family-wise error rate of 10, revealed that only the lowest and intermediate alpha bins differed significantly, bin 1 versus bin 3: $t(20) = -2.91$; $p_{\text{bonf}} = 0.047$; $d = -0.57$. Therefore, like subjective visibility and confidence ratings, the effect was an enhancement of objective accuracy at intermediate alpha amplitudes.

In stimulus detection tasks, accuracy measures can be influenced by both the likelihood of detecting a present target, as well as withholding responses on target-absent trials. To parse these effects, we also analyzed signal

detection theory (SDT) stimulus–response categories of performance. Alpha amplitude significantly affected the normalized hit rate during all trials, and a quadratic model was again the best fit to the data, $\chi^2(1) = 12.39$; $p = 0.002$; $\beta = -0.008$ (–0.015, –0.001). When comparing linear and quadratic models, likelihood ratio tests revealed the quadratic model was a significantly better fit, $\chi^2(1) = 5.54$; $p = 0.02$, with post hoc comparisons again revealing that this effect was driven by a significant difference between the lowest and intermediate alpha bins, bin 1 versus bin 3: $t(20) = -3.39$, $p_{bonf} = 0.011$, $d = -0.61$. A quadratic model was the best fit to the data for the FA rate, $\chi^2(1) = 7.43$, $p = 0.024$, $\beta = -0.06$ (– 0.1, –0.008), which significantly improved upon the linear model, $\chi^2(1) = 6.37$, $p = 0.012$. Given this parallel increase in hits and false alarms at intermediate levels of preparatory alpha, it is not surprising that we do not find a significant effect of preparatory alpha amplitude on sensitivity (d′), somewhat in contrast with the quadratic effects apparent in the simpler measure of overall accuracy (which in our data is primarily driven by hit rate because of the low incidence of false alarms). More surprisingly, given the increase we observed in both hits and false alarms at intermediate levels of alpha, and given recent evidence that a low prestimulus alpha power is associated with a more liberal detection criterion (Samaha et al., 2020), we found no significant effect of preparatory alpha amplitude on criterion (*p*s > 0.5). Similarly, alpha amplitude did not significantly affect type-2 sensitivity (*p*s > 0.09) (Figure 6).

Alpha amplitude quadratically modulates event-related potentials

Across the two experiments, we have observed an interaction between preparatory alpha amplitude and subjective ratings of attention, confidence, and visibility. Moreover, a dependence on the trial type, whether targets were physically present or absent from the intervening trial window, also modulates these effects. For example, in experiment 1, the relationship between alpha and attention was significantly greater in target-present trials. Similarly in experiment 2, intermediate alpha amplitudes quadratically modulated subjective target visibility, yet only when targets were physically present. Given these interactions, we hypothesized that alpha would affect the underlying neural response to target stimuli, particularly at intermediate levels of alpha amplitude. We directly tested for this relationship by focusing on two ERP measures, namely, the P1, which reflected the initial sensory response to the RSVP stream onset, and the CPP to target stimuli embedded in one-half of the RSVP streams. Again, to increase statistical power, and given the identical structure of the tasks in terms of stimulus presentation, we pooled the data across all participants for these analyses.

Quadratic modulation of early sensory-evoked response (P1): How the generation of sensory evoked potentials are influenced by prestimulus neural activity is the focus of ongoing research (Gruber et al., 2014; Iemi et al., 2019; Min et al., 2007). Notably, a quadratic, inverted U function such as the type we report elsewhere in this article, linking preparatory alpha amplitude with confidence and visibility reports, has also been reported to link prestimulus alpha power and the amplitude of the early P1 component of the ERP (Rajagovindan & Ding, 2011). Accordingly, we tested whether the amplitude of the P1 component evoked 80 to 160 ms after RSVP onset was also modulated by preparatory alpha. The quadratic model was a significant improvement upon the basic model, $\chi^2(1) = 9.47$, $p = 0.009$, $\beta = -0.08$ (– 0.15, –0.02), and the linear model, $\chi^2(1) = 7.26$, $p = 0.007$, demonstrating that the alpha amplitude quadratically modulates the amplitude of the early P1 component (Figure 7B). The same pattern, although statistically weaker, was observed in the data for experiment 1 when analyzed separately, quadratic: $\chi^2(1) = 12.49$, $p = 0.002$, $\beta = -0.12$ (–0.20, –0.03); comparison: $\chi^2(1) = 7.36$, $p = 0.006$, although did not reach significance in experiment 2 (*p*s > 0.3).

Quadratic modulation of the CPP: Next, as an index of decision-related processes, we investigated whether the amplitude of target-locked activity evoked on hit trials (successful detection of present targets) was also modulated by preparatory alpha. In the scalp EEG, we observed a typical broad CPP after target onset that was strongest over central electrodes (C3, Cz, C4, CP3, CPz, and CP4). We computed the average CPP amplitude across these electrodes, over the period 250 to 550 ms relative to target onset, based on quintiles of preparatory alpha amplitude. We observed that a quadratic fit was the best fit to the data, and a significant improvement on the basic model, $\chi^2(1) = 6.78$, $p = 0.034$, $\beta = -0.15$ (–0.33 –0.03), but not the linear model ($p = 0.1$). When examining each experiment in isolation, the same pattern was only significant in experiment 1, quadratic: $\chi^2(1) = 7.64$, $p = 0.02$, $\beta = -0.24$, (– 0.52, –0.03), with neither the linear nor quadratic models reaching significance in experiment 2 (*p*s > 0.7).

The CPP positively correlates with subjective confidence and visibility

We have shown that alpha amplitude quadratically modulated subjective confidence and visibility, as well as the strength of early (P1) and late (CPP) event-related potentials. Previous research has also shown that the amplitude of the CPP captures the strength of a perceptual experience (Tagliabue et al., 2019), consistent with the notion that it indexes the strength of accumulated evidence in favor of a particular
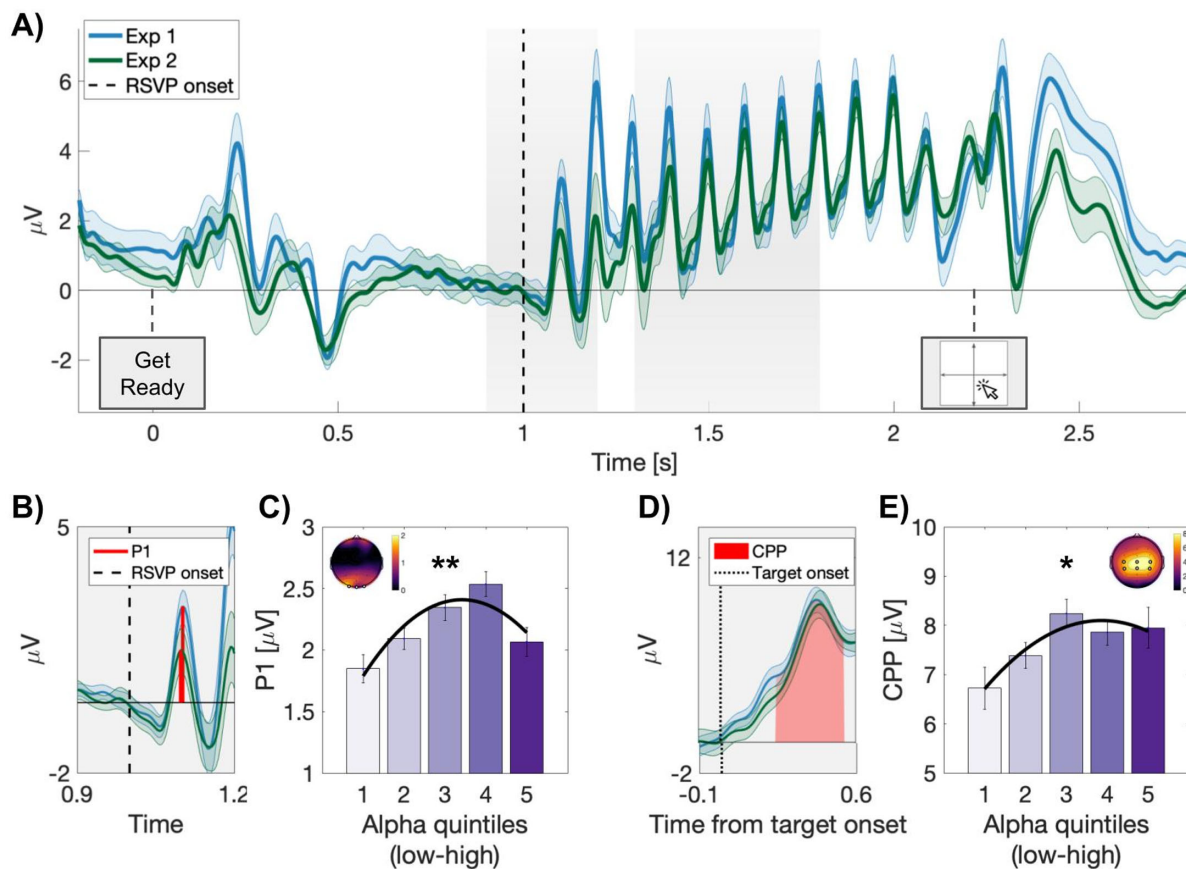
Figure 7. Preparatory alpha amplitude quadratically modulates event-related potentials. (A) Grand average whole-trial epochs for experiments 1 and 2. Gray-shaded regions note the time windows used to calculate the P1, and target-locked CPP (see Methods). (B) Grand average P1 from experiments 1 and 2. (C) Preparatory alpha quadratically modulates the amplitude of the early P1 component, evoked by the first image in our RSVP stream in experiment 1. (D) Grand average target locked CPP. Red shading indicates 250 to 550 ms relative to target onset. (E) Average CPP amplitude over a period 250 to 550 ms relative to target onset in experiment 1. In all plots error bars and shading indicate 1 SEM, corrected for within-participant comparisons (Cousineau, 2005). *$p < 0.05$, **$p < 0.01$.

perceptual decision (Murphy et al., 2015; O'Connell et al., 2012; Twomey et al., 2015). We, therefore, next tested whether CPP amplitude in our paradigm varied with subjective ratings of confidence, visibility, or attention. Consistent with our expectations, we observed that the amplitude of the CPP varied strongly and consistently with both confidence and visibility ratings. In experiment 1, CPP strength increased with subjective confidence, linear model versus basic model: $\chi^2(1) = 24.25, p = 8.5 \times 10^{-7}, \beta = 0.96\ (0.62, 1.30)$; linear versus quadratic: $p = 0.35$. In experiment 2, CPP strength also increased with subjective visibility, linear model versus basic model: $\chi^2(1) = 55.95, p = 7.4 \times 10^{-14}, \beta = 1.30\ (1.08, 1.53)$; linear versus quadratic: $p = 0.54$.

In contrast with the consistent monotonic, linear relationship between CPP amplitude and confidence/visibility ratings, a more complex relationship was observed between CPP amplitude and attention ratings

(Figure 8). In experiment 1, although we observed that CPP amplitude was maximal at highest ratings of attention, the best fit to the data was a quadratic model rather than a linear one, quadratic model versus basic model: $\chi^2(1) = 9.23, p = 0.0097, \beta = 0.40\ (0.07, 0.74)$; quadratic versus linear, $\chi^2(1) = 5.49, p = 0.019$. By comparison, in experiment 2, attention did not significantly predict CPP amplitude ($ps > 0.49$). A straightforward implication of these findings is that they provide further evidence that participants' attention ratings do not simply reflect the strength of their perceptual experience—if they did, we would expect a simple monotonic relationship. The specific, detailed pattern is more complex to explain, and we return to this point in the Discussion. For now, we note only that the contrast across experiments suggests that the nature of the decision made by participants influenced the CPP, which would be consistent with this component indexing a high-level, decision-related process.
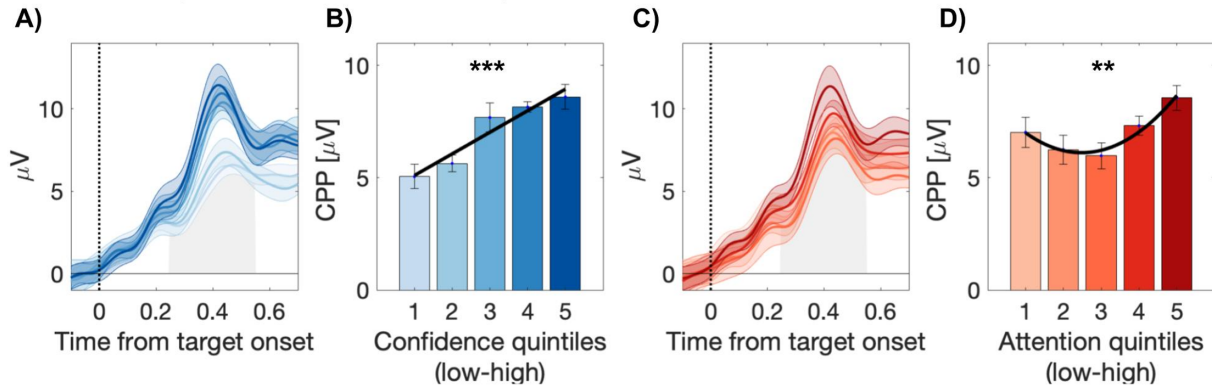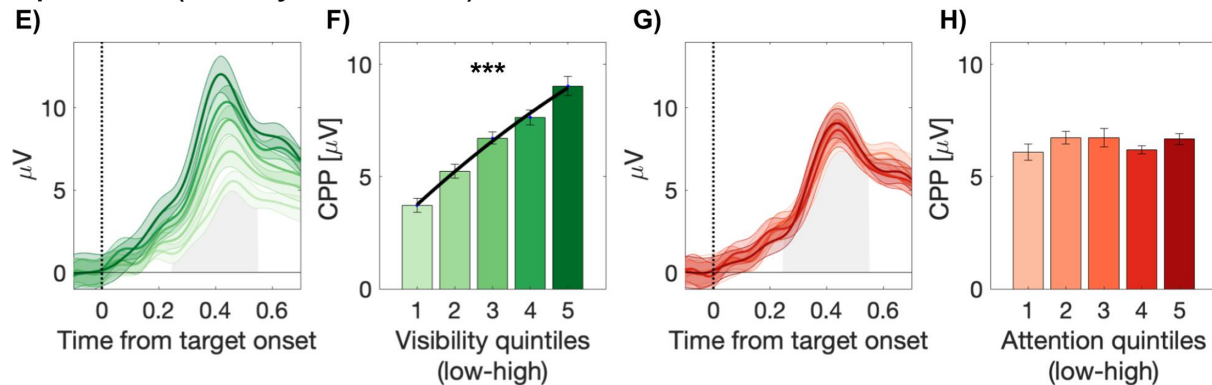
Figure 8. The subjective correlates of the CPP. CPP amplitude increases with reported confidence (A, B), and visibility (E, F), in experiments 1 and 2, respectively. CPP amplitude also varied as a function of subjectively rated attention in experiment 1 (C, D), but not in experiment 2 (G, H). Gray-shaded regions note 250 to 550 ms relative to target onset, used to calculate the CPP.

Discussion

This study aimed to characterize the relationship between preparatory alpha amplitude and subjective ratings of attention, confidence, and stimulus visibility, and thereby provide insight into the basis of these introspective judgments. Previous work, focusing mainly on visual discrimination tasks, has demonstrated a negative linear relationship linking prestimulus and spontaneous alpha power to all three of these subjective criteria. Here we demonstrate that, in a visual detection task, alpha amplitude during a period of active task preparation likewise negatively correlates with subjectively rated attention, but that it quadratically modulates decision confidence and visibility. In support of this quadratic relationship, we also found that alpha amplitude quadratically modulates objective performance, as well as the amplitude of event-related potentials elicited by task stimuli. Importantly, we outline the neural commonalities and dissociations of these overlapping subjective criteria.

The relationship between attention, confidence, and visibility ratings

Our findings provide new insight into the relationship between introspective reports of attention and sensory experience. Although attention and confidence have traditionally been studied in isolation, recent research has begun to expand our understanding of their relationship. Predominantly, this goal has been achieved by contrasting confidence between attended and unattended conditions. For example, when spatial attention is validly cued toward a target location, subjective confidence increases in discrimination tasks compared with confidence at unattended, or invalidly cued locations (Kurtz et al., 2017; Zizlsperger et al., 2012, 2014; yet see Wilimzig et al., 2008), for the opposite effect). As a complement to these effects of cued attention, here we show that increased subjective attentional engagement in a task is also associated with increases in confidence in a graded manner. The intensity of attention also increased both objective performance accuracy and metacognitive sensitivity in

our paradigm. Consequently, our results speak to the value of monitoring subjective attentional demand in perceptual research, because even matched conditions, if differing in perceived attentional effort, will result in significant differences to both subjective and objective performance.

The incorporation of attention-related information may improve perceptual decisions by decreasing uncertainty (Denison et al., 2018), or alternatively by boosting confidence owing to an apparent increase in stimulus contrast (Carrasco et al., 2004). Indeed, perceptual confidence has been tightly yoked to the amount of sensory information that is available in favor of a decision (for a review, see Mamassian, 2016). In this regard, the effects of attention are reminiscent of the near-ubiquitous effect of objective task difficulty on confidence, whereby easier tasks are associated with greater confidence in correct responses and reduced confidence in errors, and therefore an overall increase in metacognitive sensitivity (Kepecs & Mainen, 2012; Maniscalco & Lau, 2012). However, our results suggest that attention does not only affect confidence indirectly via changes in signal quality. If so, we might not expect significant effects of attention on decision confidence in the absence of a target (which were clearly apparent in experiment 1), and we would expect similarly strong effects of attention on visibility judgments (which were not observed in experiment 2).

Instead, confidence reports seem to integrate information about attentional state more directly such that, above and beyond any effects of attention on signal quality, people experience or express higher confidence in decisions they make when focused on (vs. distracted from) the task at hand. Thus, confidence correlates strongly with attention, more so than visibility ratings, and in a manner that can be normatively justified. Intuitively, one should place less trust in a given perceptual impression (whether of presence or absence of a target) when it is derived from an inattentive glimpse than from careful, focused viewing. This interpretation is consistent with other recent suggestions that confidence is not a direct readout of accumulated evidence strength, but instead integrates relevant contextual information (Bang et al., 2017; Boldt et al., 2017; Kiani et al., 2014). Such a two-stage model of confidence formation (cf. Shekhar & Rahnev, 2018) contrasts with earlier proposals that confidence directly reflects the strength of accumulated evidence (for reviews, see Pleskac & Busemeyer, 2010; Yeung & Summerfield, 2012), but aligns with other evidence that confidence can be manipulated without a change in sensory evidence (e.g., Cortese et al., 2016, 2017). This higher-order influence on decisions (see Denison et al., 2018; Mazor & Fleming, 2020, for related discussions) may have been exacerbated in our task paradigm, because responses were not speeded, allowing sufficient time for reflection and adjustment

of subjective ratings between the RSVP stream and response options. Future work will be necessary to test whether decreased stimulus–response intervals mediate the correlation between target-absent confidence and attention ratings.

This correlation between attention and confidence notwithstanding, the two ratings showed some dissociations. Confidence showed a linear relationship with the strength of sensory evidence as reflected in sensory evoked potentials, but varied quadratically when measured across all trials as a function of preparatory alpha amplitude. Attention ratings, in contrast, were negatively and linearly related to alpha amplitude. More broadly, we found little evidence that attention ratings are inferred indirectly from the strength of perceptual evidence accumulated for a decision ("I saw a target clearly so I must've been paying attention"; cf. Head & Helton, 2018), and instead they seem to depend on more direct insight into the true underlying attentional state (as it is reflected in alpha amplitude, for example). This insight might come from monitoring the state of sensory systems themselves, but perhaps more plausibly derives from access to one's current level of motivation and effort expended on the task (i.e., information about the strength of exerted attention and control). That said, a nuance of the present results was that participants' attention ratings differed subtly across experiments, for example, showing a stronger relationship with CPP amplitude in experiment 1 than experiment 2. Although it remains possible that comparisons between these groups are hampered by differences in statistical power, another possibility is that the specific wording used for the visibility question in experiment 2 ("How much of the target did you see?") may have primed a quantitative, as opposed to a qualitative, use of the visibility scale and encouraged participants to distinguish their sensory experience from the subjective level of engagement in the task. In contrast, the experiential focus of the confidence question in experiment 1 ("How confident are you?") may have led participants to base their attention ratings more on experiential cues, such as the strength of their perceptions (e.g., it would be counterintuitive to indicate you were sure a target was present or absent, even though you had been paying little attention to the task). Although speculative, this possibility can easily be tested in future research by adapting the visibility prompt to instead include a qualitative estimate of perceptual awareness that is a standard in consciousness research (e.g., "How clear was your visual experience?"; see Overgaard & Sandberg, 2012; Ramsøy & Overgaard, 2004; Sandberg et al., 2010). An additional possibility is that attention ratings also varied depending on whether they were paired with confidence or visibility, as is evident in the differences between the distribution of attention responses in Figures 2B and E. For example, attention responses were predominantly above zero in

experiment 1, yet clustered around zero in experiment 2. Whether such differences are attributable to the response criteria used or the between-subjects nature of our design could be explored in future research with a within-participant comparison between single and simultaneous subjective criteria.

Preparatory alpha amplitude and subjective reports

Given the natural correlation between cortical excitability, attention, and subjective judgments of visibility and confidence, in many situations their inter-relationships are difficult to disentangle. The present dataset is interesting in this regard because we observe that alpha amplitude showed a different relationship with attention ratings versus ratings of confidence and visibility. Specifically, after splitting alpha amplitude into quintiles, we observed the expected negative and monotonic relationship between alpha and subjectively rated attention, but found that the highest subjective ratings of decision confidence and visibility were associated with intermediate levels of alpha. Intermediate alpha amplitude was also associated with increased accuracy, as well as increased amplitude of early (P1) and late (CPP) sensory evoked potentials.

This inverted U function contrasts with recent examples of a negative and linear relationship between spontaneous alpha power measured just before stimulus onset and various performance measures in discrimination tasks (Benwell et al., 2017; Iemi et al., 2017; Samaha et al., 2017). Our aim here was not to explore the mechanisms underpinning the quadratic relationship we observed; rather, observing this effect gave us the opportunity to dissociate measures—of attentional state, evoked responses, task performance, and performance evaluations—that are typically mutually correlated. Nevertheless, it is interesting to ask what may drive such a quadratic association. A quadratic link between prestimulus oscillatory power and performance has previously been reported in somatosensory detection tasks (Linkenkaer-Hansen et al., 2004; Zhang & Ding, 2010), and between alpha power and the amplitude of early visually evoked potentials when, like here, alpha was measured during a cue-to-target interval (Rajagovindan & Ding, 2011). In their model, Rajagovindan and Ding (2011) proposed that the total output of a neural ensemble can be characterized by its position on a sigmoidal curve, with each point on the curve being jointly determined by background synaptic activity and the addition of a sensory evoked response (see Rajagovindan & Ding, 2011, for details). Their model predicts maximal sensory-evoked output at intermediate levels of alpha power, where the sigmoidal curve is steepest, and

was supported by measuring the amplitude of the P1 response at attended, compared with unattended locations. Our visual detection tasks differ in many important ways, yet we also find that early visual evoked responses in the P1 window are quadratically modulated by the strength of alpha oscillations. As an extension of these results, here we can add that subjective visibility and confidence are also greatest at intermediate levels of preparatory alpha amplitude. Interestingly, increased confidence and visibility that a target was present was associated with intermediate alpha, even on exclusively target-absent trials (Figures 5A–C). Thus, the relationship between preparatory alpha amplitude and decision confidence seems to be directional: Intermediate alpha amplitude does not enhance confidence in any decision, but enhances confidence in perceiving the presence of a target, even on exclusively target-absent trials.

The present work complements recent evidence linking the amplitude of prestimulus and spontaneous oscillations to the intensity of subjective reports (Samaha, Iemi, et al., 2020), by examining alpha activity observed during explicitly cued task preparation, and the role of intervening event-related potentials on measures of confidence, visibility, and attention. Previous links between spontaneous alpha power and subjective reports studied each in isolation, or omitted ERP analyses (Benwell et al., 2017; Samaha et al., 2017; Whitmarsh et al., 2021), which in the present work have revealed novel dissociations between these overlapping subjective criteria. Specifically, we find that alpha amplitude during active task preparation negatively correlated with the intensity of subjective attention on both target-present and target-absent trials, and when rating either visibility or confidence in the intervening trial window. Participants could distinguish these fluctuations in attention from the strength of sensory evidence when rating perceived target visibility, which positively correlated with the amplitude of sensory evoked responses, whereas ratings of attention did not (CPP; cf. Figure 8). In contrast, confidence ratings incorporated both the context of attentional state and the strength of sensory evidence, as these subjective reports were positively correlated, and increased concomitantly with CPP amplitude.

We also observed a quadratic relationship linking the strength of alpha oscillations to both the amplitude of event-related potentials and the strength of visibility and confidence judgments. We can now characterize the information that underpins subjective reports of attention and confidence in this way: after a preparatory cue, alpha amplitude is negatively correlated with the intensity of subjective attention, and quadratically modulates the strength of sensory-evoked potentials. The strength of these sensory-evoked potentials, in turn, partially determine the intensity of subjective visibility and confidence—with the latter also incorporating, and

correlating, with the intensity of subjective attention. These observations add to a growing literature that the CPP represents the accumulation of decision likelihood based on internal states, which include the subjective certainty of a decision (Gherman & Philiastides, 2015; Rangelov & Mattingley, 2020; Tagliabue et al., 2019), as well as an index of physical sensory evidence (O'Connell et al., 2012).

Our previous work (Macdonald et al., 2011), also showed that alpha oscillations covary with subjective attention over longer time scales, suggesting the effects reported here may be a mixture of both short time scale within-trial dependencies, and slower fluctuations of alpha with time-on-task. In support of the short-scale temporal dependency, we found that alpha (at trial t) did not predict confidence or visibility on subsequent ($t + 1$) trials, in contrast to the quadratic effects observed at the single-trial level. However, alpha did negatively correlate with attention on subsequent trials ($t + 1$). Thus, both short and longer time scale dependencies may modulate the relationship between alpha amplitude and subjective measures, with the former mainly affecting visibility and confidence judgments, and the latter, ratings of subjective attention.

Another caveat, however, is that interpreting the relationship between alpha and evoked responses is complicated by recent work showing that alpha oscillations have a nonzero mean (Iemi et al., 2019). It is possible, therefore, that the ERP differences we observe across alpha quintiles might reflect contamination from baseline period activity, rather than true modulation of the evoked response. To control for this possibility, in analyses not reported in detail here we confirmed that the patterns corresponding to those reported above were still apparent when we quantified ERP responses using a shared, and not quintile-specific, baseline.

The inverted U function we observed contrasts with recent examples of a negative and linear relationship between prestimulus alpha power and detection performance (e.g., (Iemi et al., 2017) as well as confidence and visibility in two alternative forced choice visual discrimination tasks (e.g., Benwell et al., 2017; Samaha et al., 2017). As such, it is important to consider the differences between our present and previous works that may contribute to these discrepancies. Most notably, discrimination and detection judgments may be supported by fundamentally distinct processes, and previous work has described independent behavioral (Kanai et al., 2010; Meuwese et al., 2014), as well as neural. correlates (e.g., Mazor & Fleming, 2020) that distinguish these judgment types. More practically, detection in the present work required identification of a single image within an RSVP stream, and alpha oscillations were measured in a preparatory window after the instruction to "Get Ready" was displayed on screen. As a result, alpha oscillations were not spontaneous, but evoked, in a manner similar to prior work on the spatial (Kelly, Lalor, Reilly, & Foxe, 2006; Rihs, Michel, & Thut, 2007; Thut et al., 2006) and temporal (Kizuk & Mathewson, 2017; Rohenkohl & Nobre, 2011; van Diepen et al., 2015) reorientation of attention after a cue. In our task, alpha measured during the preparatory window was also time-locked to the cue, but could vary in distance from the actual target onset, which occurred anywhere on images three through eight in our RSVP stream. Making decisions based on this RSVP stream also involved processing target signals embedded in noise, thus integrating evidence over an extended period. Collectively, these features change the anticipatory and predictive demands of our paradigm compared with previous work focused primarily on spontaneous alpha, and it is presently unclear how these differences may combine to interact with alpha oscillations and target detection (Clayton et al., 2015, 2018; Van Diepen et al., 2019).

In addition to the proposed link between alpha amplitude and perceptual performance, another nonexclusive possibility is that the phase of alpha oscillations rhythmically modulate inhibition–excitation cycles, which also determine perceptual outcomes (Chapeton et al., 2019; Jensen et al., 2012; Klimesch, 2012; Klimesch et al., 2007; Mathewson et al., 2012; Jensen & Mazaheri, 2010). For example, it has previously been reported that the phase of prestimulus alpha oscillations can determine whether near-threshold targets are detected (Busch et al., 2009; Mathewson et al., 2009). Moreover, the phase of spontaneous alpha can be adjusted under top-down control, in anticipation of stimulus onset Samaha et al., 2015; yet see van Diepen et al., 2015). To our knowledge, however, whether subjective estimates, such as confidence, visibility, or attention, are also modulated by anticipatory phase has not been reported. Although it is beyond the scope of the present article, it was clear in our dataset that subjective confidence and the visibility of a target were systematically biased by the phase of alpha during task preparation, although attention was not (Supplementary Figure S4). Future work will be necessary to untangle these complex relationships and further determine how the phase of alpha may similarly mediate sensory-evoked potentials.

Conclusion

Our study sheds new light on the interaction between preparatory alpha amplitude and subjective phenomena in an RSVP target detection task. Alpha amplitude negatively and linearly correlated with the intensity of subjective attention, yet quadratically modulated the strength of decision confidence and visibility. This partial independence speaks to the importance of choosing appropriate subjective response options

in experimental tasks, and for future studies of metacognition, suggesting that confidence reports (but not visibility) may conflate attentional state ratings. Importantly, understanding the influence of alpha on subjective criteria can be enriched by considering the intervening effect of alpha on stimulus-evoked responses. We show that people can distinguish and separately report their sensory experience (here, stimulus visibility) and their attentional state, with the former reflected in sensory-evoked potentials and the latter in alpha oscillations. But they seem to combine these signals when they report the reliability of their perceptions as reflected in the confidence they express in their decisions. Collectively, these findings provide insight into the commonalities and dissociations among different subjective reports in their psychological properties and neural underpinnings.

Keywords: alpha oscillations, attention, confidence, visibility, metacognition, EEG

Acknowledgments

Commercial relationships: none.
Corresponding author: Matthew J. Davidson.
Email: matthew.davidson@sydney.edu.au.
Address: Room 210A, Griffith Taylor Building (A19), University of Sydney, NSW 2006, Australia.

References

Ais, J., Zylberberg, A., Barttfeld, P., & Sigman, M. (2016). Individual consistency in the accuracy and distribution of confidence judgments. *Cognition, 146,* 377–386.

Babiloni, C., Vecchio, F., Bultrini, A., Luca Romani, G., & Rossini, P. M. (2006). Pre- and poststimulus alpha rhythms are related to conscious visual perception: A high-resolution EEG study. *Cerebral Cortex, 16*(12), 1690–1700.

Balestrieri, E., & Busch, N. A. (2022). Spontaneous alpha-band oscillations bias subjective contrast perception. *Journal of Neuroscience, 18*(25), 5058–5069, https://doi.org/10.1523/JNEUROSCI.1972-21.2022.

Bang, D., Aitchison, L., Moran, R., Herce Castanon, S., Rafiee, B., & Mahmoodi, A., . . .Summerfield, C. (2017). Confidence matching in group decision-making. *Nature Human Behaviour, 1*(6), 1–7.

Benwell, C. S. Y., Tagliabue, C. F., Veniero, D., Cecere, R., Savazzi, S., & Thut, G. (2017). Prestimulus EEG power predicts conscious awareness but not objective visual performance. *ENeuro, 4*(6), ENEURO.0182–17.2017, https://doi.org/10.1523/ENEURO.0182-17.2017.

Bokil, H., Andrews, P., Kulkarni, J. E., Mehta, S., & Mitra, P. P. (2010). Chronux: A platform for analyzing neural signals. *Journal of Neuroscience Methods, 192*(1), 146–151.

Boldt, A., de Gardelle, V., & Yeung, N. (2017). The impact of evidence reliability on sensitivity and bias in decision confidence. *Journal of Experimental Psychology. Human Perception and Performance, 43*(8), 1520–1531.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision, 10*(4), 433–436.

Busch, N. A., Dubois, J., & VanRullen, R. (2009). The phase of ongoing EEG oscillations predicts visual perception. *Journal of Neuroscience, 29*(24), 7869–7876.

Carrasco, M., Ling, S., & Read, S. (2004). Attention alters appearance. *Nature Neuroscience, 7*(3), 308–313.

Chapeton, J. I., Haque, R., Wittig, J. H., Jr, Inati, S. K., & Zaghloul, K. A. (2019). Large-scale communication in the human brain is rhythmically modulated through alpha coherence. *Current Biology, 29*(17), 2801–2811.

Chaumon, M., Bishop, D. V., & Busch, N. A. (2015). A practical guide to the selection of independent components of the electroencephalogram for artifact correction. *Journal of Neuroscience Methods, 250,* 47–63.

Chaumon, M., & Busch, N. A. (2014). Prestimulus neural oscillations inhibit visual perception via modulation of response gain. *Journal of Cognitive Neuroscience, 26*(11), 2514–2529.

Clayton, M. S., Yeung, N., & Cohen Kadosh, R. (2018). The many characters of visual alpha oscillations. *European Journal of Neuroscience, 48*(7), 2498–2508.

Coon, W. G., Gunduz, A., Brunner, P., Ritaccio, A. L., Pesaran, B., & Schalk, G. (2016). Oscillatory phase modulates the timing of neuronal activations and resulting behavior. *NeuroImage, 133,* 294–301.

Cortese, A., Amano, K., Koizumi, A., Lau, H., & Kawato, M. (2017). Decoded fMRI neurofeedback can induce bidirectional confidence changes within single participants. *NeuroImage, 149,* 323–337.

Cortese, A., Amano, K., Koizumi, A., Kawato, M., & Lau, H. (2016). Multivoxel neurofeedback selectively modulates confidence without changing perceptual performance. *Nature Communications, 7*(1), 1–18.

Cousineau, D. (2005). Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson's method. *Tutorials in Quantitative Methods for Psychology, 1*(1), 42–45.

Davidson, M. J., Mithen, W., Hogendoorn, H., Van Boxtel, J. J., & Tsuchiya, N. (2020). The SSVEP tracks attention, not consciousness, during perceptual filling-in. *Elife, 9*, e60031.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods, 134*(1), 9–21.

Denison, R. N., Adler, W. T., Carrasco, M., & Ma, W. J. (2018). Humans incorporate attention-dependent uncertainty into perceptual decisions and confidence. *Proceedings of the National Academy of Sciences of the United States of America, 115*(43), 11090–11095.

Ergenoglu, T., Demiralp, T., Bayraktaroglu, Z., Ergen, M., Beydagi, H., & Uresin, Y. (2004). Alpha rhythm of the EEG modulates visual detection performance in humans. *Brain Research. Cognitive Brain Research, 20*(3), 376–383.

Fleming, S. M., & Lau, H. C. (2014). How to measure metacognition. *Frontiers in Human Neuroscience, 8*, 443.

Fleming, S. M., & Frith, C. D. (2014). In S. M. Fleming, & C. D. Frith, (Eds). *The cognitive neuroscience of metacognition*. Berlin Heidelberg: Springer.

Gherman, S., & Philiastides, M. G. (2015). Neural representations of confidence emerge from the process of decision formation during perceptual choices. *Neuroimage, 106*, 134–143.

Gould, I. C., Rushworth, M. F., & Nobre, A. C. (2011). Indexing the graded allocation of visuospatial attention using anticipatory alpha oscillations. *Journal of Neurophysiology, 105*(3), 1318–1326.

Grabot, L., & Kayser, C. (2020). Alpha activity reflects the magnitude of an individual bias in human perception. *Journal of Neuroscience, 40*(17), 3443–3454, https://doi.org/10.1523/JNEUROSCI. 2359-19.2020.

Green, D. M., & Swets, J. A. (1966). *Signal Detection Theory and Psychophysics* (Vol. *1*, pp. 1969–2012). New York: Wiley.

Gruber, W. R., Zauner, A., Lechinger, J., Schabus, M., Kutil, R., & Klimesch, W. (2014). Alpha phase,

temporal attention, and the generation of early event related potentials. *Neuroimage, 103*, 119–129.

Hanslmayr, S., Klimesch, W., Sauseng, P., Gruber, W., Doppelmayr, M., Freunberger, R., . . . Pecherstorfer, T. (2005). Visual discrimination performance is related to decreased alpha amplitude but increased phase locking. *Neuroscience Letters, 375*(1), 64–68.

Hanslmayr, S., Klimesch, W., Sauseng, P., Gruber, W., Doppelmayr, M., & Freunberger, R., . . .Birbaumer, N. (2007). Alpha phase reset contributes to the generation of ERPs. *Cerebral Cortex, 17*(1), 1–8.

Head, J., & Helton, W. S. (2018). The troubling science of neurophenomenology. *Experimental Brain Research, 236*(9), 2463–2467.

Hughes, G., Mathan, S., & Yeung, N. (2013). EEG indices of reward motivation and target detectability in a rapid visual detection task. *NeuroImage, 64*, 590–600.

Iemi, L., & Busch, N. A. (2018). Moment-to-moment fluctuations in neuronal excitability bias subjective perception rather than strategic decision-making. *ENeuro, ENEURO, 043*(3), ENURO.0430–17.2018, https://doi.org/10.1523/ENEURO.0430-17.2018.

Iemi, L., Busch, N. A., Laudini, A., Haegens, S., Samaha, J., Villringer, A., . . . Nikulin, V. V. (2019). Multiple mechanisms link prestimulus neural oscillations to sensory responses. *ELife, 8*, e46320, https://doi.org/10.7554/eLife.43620.

Iemi, L., Chaumon, M., Crouzet, S. M., & Busch, N. A. (2017). Spontaneous neural oscillations bias perception by modulating baseline excitability. *Journal of Neuroscience, 37*(4), 807–819.

Jensen, O., Bonnefond, M., & VanRullen, R. (2012). An oscillatory mechanism for prioritizing salient unattended stimuli. *Trends in Cognitive Sciences, 16*(4), 200–206.

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Frontiers in Human Neuroscience, 4*, 186.

Kanai, R., Walsh, V., & Tseng, C.-H. (2010). Subjective discriminability of invisibility: a framework for distinguishing perceptual and attentional failures of awareness. *Consciousness and Cognition, 19*(4), 1045–1057.

Kelly, S. P., Lalor, E. C., Reilly, R. B., & Foxe, J. J. (2006). Increases in alpha oscillatory power reflect an active retinotopic mechanism for distracter suppression during sustained visuospatial attention. *Journal of Neurophysiology, 95*(6), 3844–3851.

Kelly, S. P., & O'Connell, R. G. (2013). Internal and external influences on the rate of sensory evidence accumulation in the human brain. *Journal of Neuroscience, 33*(50), 19434–19441.

Kepecs, A., & Mainen, Z. F. (2012). A computational framework for the study of confidence in humans and animals. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 367*(1594), 1322–1337.

Kiani, R., Corthell, L., & Shadlen, M. N. (2014). Choice certainty is informed by both evidence and decision time. *Neuron, 84*(6), 1329–1342.

Kizuk, S. A. D., & Mathewson, K. E. (2017). Power and phase of alpha oscillations reveal an interaction between spatial and temporal visual attention. *Journal of Cognitive Neuroscience, 29*(3), 480–494.

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences, 16*(12), 606–617.

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: The inhibition–timing hypothesis. *Brain Research Reviews, 53*(1), 63–88.

Kurtz, P., Shapcott, K. A., Kaiser, J., Schmiedt, J. T., & Schmid, M. C. (2017). The influence of endogenous and exogenous spatial attention on decision confidence. *Scientific Reports, 7*(1), 6431.

Limbach, K., & Corballis, P. M. (2016). Prestimulus alpha power influences response criterion in a detection task. *Psychophysiology, 53*(8), 1154–1164.

Linkenkaer-Hansen, K., Nikulin, V. V., Palva, S., Ilmoniemi, R. J., & Palva, J. M. (2004). Prestimulus oscillations enhance psychophysical performance in humans. *Journal of Neuroscience, 24*(45), 10186–10190.

Macdonald, J. S. P., Mathan, S., & Yeung, N. (2011). Trial-by-trial variations in subjective attentional state are reflected in ongoing prestimulus EEG alpha oscillations. *Frontiers in Psychology, 2*(MAY), 1–16.

Mamassian, P. (2016). Visual confidence. *Annual Review of Vision Science, 2*(1), 459–481.

Mathewson, K. E., Prudhomme, C., Fabiani, M., Beck, D. M., Lleras, A., & Gratton, G. (2012). Making waves in the stream of consciousness: entraining oscillations in EEG alpha and fluctuations in visual awareness with rhythmic visual stimulation. *Journal of Cognitive Neuroscience, 24*(12), 2321–2333.

Mathewson, K. E., Gratton, G., Fabiani, M., Beck, D. M., & Ro, T. (2009). To see or not to see: prestimulus alpha phase predicts visual awareness. *Journal of Neuroscience, 29*(9), 2725–2732.

Mazor, M., & Fleming, S. M. (2020). Distinguishing absence of awareness from awareness of absence. *Philosophy and the Mind Sciences, 1*(II), https://doi.org/10.33735/phimisci.2020.II.69.

Mazor, M., Friston, K. J., & Fleming, S. M. (2020). Distinct neural contributions to metacognition for detecting, but not discriminating visual stimuli. *ELife, 9*, e53900.

Meuwese, J. D. I., van Loon, A. M., Lamme, V. A. F., & Fahrenfort, J. J. (2014). The subjective experience of object recognition: comparing metacognition for object detection and object categorization. *Attention, Perception & Psychophysics, 76*(4), 1057–1068.

Min, B.-K., Busch, N. A., Debener, S., Kranczioch, C., Hanslmayr, S., Engel, A. K., . . . Herrmann, C. S. (2007). The best of both worlds: Phase-reset of human EEG alpha activity and additive power contribute to ERP generation. *International Journal of Psychophysiology, 65*(1), 58–68.

Murphy, P. R., Robertson, I. H., Harty, S., & O'Connell, R. G. (2015). Neural evidence accumulation persists after choice to inform metacognitive judgments. *Elife, 4*, e11946.

O'Connell, R. G., Dockree, P. M., & Kelly, S. P. (2012). A supramodal accumulation-to-bound signal that determines perceptual decisions in humans. *Nature Neuroscience, 15*(12), 1729–1735.

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience, 2011*.

Overgaard, M., & Sandberg, K. (2012). Kinds of access: Different methods for report reveal different kinds of metacognitive access. *Philosophical Transactions of the Royal Society B: Biological Sciences, 367*(1594), 1287–1296.

Paternoster, R., Brame, R., Mazerolle, P., & Piquero, A. (1998). Using the correct statistical test for the equality of regression coefficients. *Criminology, 36*(4), 859–866.

Peylo, C., Hilla, Y., & Sauseng, P. (2021). Cause or consequence? Alpha oscillations in visuospatial attention. *Trends in Neurosciences, 44*(9), 705–713.

Pleskac, T. J., & Busemeyer, J. R. (2010). Two-stage dynamic signal detection: A theory of choice, decision time, and confidence. *Psychological Review, 117*(3), 864–901.

Rahnev, D., Maniscalco, B., Graves, T., Huang, E., de Lange, F. P., & Lau, H. (2011). Attention induces conservative subjective biases in visual perception. *Nature Neuroscience, 14*(12), 1513–1515.

Rajagovindan, R., & Ding, M. (2011). From prestimulus alpha oscillation to visual-evoked response: an inverted-U function and its attentional modulation. *Journal of Cognitive Neuroscience, 23*(6), 1379–1394.

Ramsøy, T. Z., & Overgaard, M. (2004). Introspection and subliminal perception. *Phenomenology and the Cognitive Sciences, 3*(1), 1–23.

Rangelov, D., & Mattingley, J. B. (2020). Evidence accumulation during perceptual decision-making is sensitive to the dynamics of attentional selection. *NeuroImage, 220*, 117093.

Recht, S., de Gardelle, V., & Mamassian, P. (2021). Metacognitive blindness in temporal selection during the deployment of spatial attention. *Cognition, 216*, 104864.

Recht, S., Mamassian, P., & de Gardelle, V. (2019). Temporal attention causes systematic biases in visual confidence. *Scientific Reports, 9*(1), 11622.

Ress, D., Backus, B. T., & Heeger, D. J. (2000). Activity in primary visual cortex predicts performance in a visual detection task. *Nature Neuroscience, 3*(9), 940–945.

Rihs, T. A., Michel, C. M., & Thut, G. (2007). Mechanisms of selective inhibition in visual spatial attention are indexed by alpha-band EEG synchronization. *European Journal of Neuroscience, 25*(2), 603–610.

Rohenkohl, G., & Nobre, A. C. (2011). α oscillations related to anticipatory attention follow temporal expectations. *Journal of Neuroscience, 31*(40), 14076–14084.

Romei, V., Brodbeck, V., Michel, C., Amedi, A., Pascual-Leone, A., & Thut, G. (2008). Spontaneous fluctuations in posterior alpha-band EEG activity reflect variability in excitability of human visual areas. *Cerebral Cortex, 18*(9), 2010–2018.

Samaha, J., Bauer, P., Cimaroli, S., & Postle, B. R. (2015). Top-down control of the phase of alpha-band oscillations as a mechanism for temporal prediction. *Proceedings of the National Academy of Sciences, 112*(27), 8439–8444.

Samaha, J., Iemi, L., Haegens, S., & Busch, N. A. (2020). Spontaneous brain oscillations and perceptual decision-making. *Trends in Cognitive Sciences, 24*(8), 693–653, https://doi.org/10.1016/j.tics.2020.05.004.

Samaha, J., Iemi, L., & Postle, B. R. (2017). Prestimulus alpha-band power biases visual discrimination confidence, but not accuracy. *Consciousness and Cognition, 54*, 47–55.

Samaha, J., LaRocque, J. J., & Postle, B. R. (2022). Spontaneous alpha-band amplitude predicts subjective visibility but not discrimination accuracy during high-level perception. *Consciousness and Cognition, 102*, 103337.

Sandberg, K., Timmermans, B., Overgaard, M., & Cleeremans, A. (2010). Measuring consciousness: Is one measure better than the other? *Consciousness and Cognition, 19*(4), 1069–1078.

Sauseng, P., Klimesch, W., & Doppelmayr, M. (2005). EEG alpha synchronization and functional coupling during top-down processing in a working memory task. *Human Brain Mapping, 26*(2), 148–155, https://onlinelibrary.wiley.com/doi/abs/10.1002/hbm.20150.

Shekhar, M., & Rahnev, D. (2018). Distinguishing the roles of dorsolateral and anterior PFC in visual metacognition. *Journal of Neuroscience, 38*(22), 5078–5087.

Sherman, M. T., Kanai, R., Seth, A. K., & VanRullen, R. (2016). Rhythmic influence of top–down perceptual priors in the phase of prestimulus occipital alpha oscillations. *Journal of Cognitive Neuroscience, 28*(9), 1318–1330.

Smallwood, J., & Schooler, J. W. (2015). The science of mind wandering: Empirically navigating the stream of consciousness. *Annual Review of Psychology, 66*, 487–518.

Tagliabue, C. F., Veniero, D., Benwell, C. S., Cecere, R., Savazzi, S., & Thut, G. (2019). The EEG signature of sensory evidence accumulation during decision formation closely tracks subjective perceptual experience. *Scientific reports, 9*(1), 1–12.

Thut, G., Nietzel, A., Brandt, S. A., & Pascual-Leone, A. (2006). Alpha-band electroencephalographic activity over occipital cortex indexes visuospatial attention bias and predicts visual target detection. *Journal of Neuroscience, 26*(37), 9494–9502.

Twomey, D. M., Murphy, P. R., Kelly, S. P., & O'Connell, R. G. (2015). The classic P300 encodes a build-to-threshold decision variable. *European Journal of Neuroscience, 42*(1), 1636–1643.

van Diepen, R. M., Cohen, M. X., Denys, D., & Mazaheri, A. (2015). Attention and temporal expectations modulate power, not phase, of ongoing alpha oscillations. *Journal of Cognitive Neuroscience, 27*(8), 1573–1586.

van Diepen, R. M., Foxe, J. J., & Mazaheri, A. (2019). The functional role of alpha-band activity in attentional processing: The current zeitgeist and future outlook. *Current Opinion in Psychology, 29*, 229–238.

van Diepen, R. M., Miller, L. M., Mazaheri, A., & Geng, J. J. (2016). The role of alpha activity in spatial and feature-based attention. *ENeuro, 3*(5), ENEURO.0204–16.2016, https://doi.org/10.1523/ENEURO.0204-16.2016.

van Dijk, H., Schoffelen, J.-M., Oostenveld, R., & Jensen, O. (2008). Prestimulus oscillatory activity in the alpha band predicts visual discrimination ability. *Journal of Neuroscience, 28*(8), 1816–1823.

VanRullen, R., Busch, N. A., Drewes, J., & Dubois, J. (2011). Ongoing EEG phase as a trial-by-trial

predictor of perceptual and attentional variability. *Frontiers in Psychology, 2*(APR), 1–9.

Vickers, D., & Packer, J. (1982). Effects of alternating set for speed or accuracy on response time, accuracy and confidence in a unidimensional discrimination task. *Acta Psychologica, 50*(2), 179–197.

Whitmarsh, S., Barendregt, H., Schoffelen, J.-M., & Jensen, O. (2014). Metacognitive awareness of covert somatosensory attention corresponds to contralateral alpha power. *NeuroImage, 85*(Pt 2), 803–809.

Whitmarsh, S., Gitton, C., Jousmäki, V., Sackur, J., & Tallon-Baudry, C. (2021). Neuronal correlates of the subjective experience of attention. *European Journal of Neuroscience, 55*(11–12), 3465–3482, https://doi.org/10.1111/ejn.15395.

Whitmarsh, S., Oostenveld, R., Almeida, R., & Lundqvist, D. (2017). Metacognition of attention during tactile discrimination. *NeuroImage, 147*, 121–129.

Wilimzig, C., Tsuchiya, N., Fahle, M., Einhäuser, W., & Koch, C. (2008). Spatial attention increases performance but not subjective confidence in a discrimination task. *Journal of Vision, 8*(5), 7–7.

Yeung, N., & Summerfield, C. (2012). Metacognition in human decision-making: confidence and error monitoring. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 367*(1594), 1310–1321.

Zhang, Y., & Ding, M. (2010). Detection of a weak somatosensory stimulus: Role of the prestimulus mu rhythm and its top–down modulation. *Journal of Cognitive Neuroscience, 22*(2), 307–322.

Zizlsperger, L., Sauvigny, T., Händel, B., & Haarmeier, T. (2014). Cortical representations of confidence in a visual perceptual decision. *Nature Communications, 5*(1), 1–13.

Zizlsperger, L., Sauvigny, T., & Haarmeier, T. (2012). Selective attention increases choice certainty in human decision making. *PloS One, 7*(7), e41136.