Title

Evidence for shared resources in visuospatial attention: Endogenous attention misleads the decoding of exogenous attention in alpha rhythms

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Contributions
M.L. and A.R. discussed and dreamed up the study. M.L. and J.D.C. designed experiments, collected data, and performed analyses. J.S., S.B. and A.R. provided feedback throughout the project. All authors wrote the manuscript. A.R secured funding and provided lab space and equipment to pursue this study.

Competing Interests
All authors declare no competing interest

Data and Codes availability
Data and codes will be available on OSF:
https://osf.io/z8wkp/?view_only=9cc6c28dc5504ec48bf933f002d6ee8c

Abstract

Prevailing accounts of visuospatial attention differentiate exogenous orienting, which corresponds to involuntary shifts of attention, from endogenous orienting, which reflects the voluntary control of attention. While these different forms of attention are functionally separable, evidence shows that they can nevertheless interact with each other. These dynamics have been at the center of ongoing debates for more than two decades. One hypothesis regarding these interactions is that, while both forms of attention orienting map onto independent functional systems, they are capable of mutual interference. This viewpoint implies that exogenous attention, a ballistic and stimulus-driven process, is not impervious to the influence of endogenous attention. Evidence in support of this view remains sparse and the mechanisms that underlie these interactions remain largely unknown. The present study tackles these questions by examining whether endogenous attention influences the neural processes of exogenous attention using multivariate pattern classification to electroencephalography (EEG). We contrasted the effects of exogenous attention across two experimental conditions: Single cueing where exogenous attention is engaged alone, and double cueing where exogenous attention is concurrently engaged with endogenous attention. Our results show that the simultaneous engagement of endogenous attention alters the emergence of exogenous attention across cue-related and target-related neural processes. Exogenous attention is therefore not impervious to the influence of endogenous attention. More importantly, we observed that classifiers trained to decode exogenous attention from the power and phase of alpha band activity during single cueing condition were systematically misled by endogenous attention when tested in the context of double cueing. Hence, both the power and phase of alpha rhythms are central to exogenous and endogenous attention. These findings not only highlight overlapping neural processes between both form of attention orienting, but further demonstrate that the dynamics of exogenous and endogenous attention are characterized by limited processing resources.

Significance Statement

Visuospatial attention is often dichotomized into top-down and bottom-up components: Top-down attention reflects slow voluntary shifts while bottom-up attention corresponds to fast involuntary demands. A large body of findings supports the view that these forms of attention orienting are functionally separable. Following longstanding debates about their interactions, the current study examines the relationship between top-down and bottom-up attention. Using electroencephalography (EEG) and multivariate pattern classification techniques, the researchers show that top-down attention modified the brain activity of bottom-up attention. Moreover, machine learning classifiers trained to decode bottom-up attention based on alpha band activity (8-12 Hz), a well-known marker of visuospatial attention, are systematically misled by top-down attention. The researchers conclude that both forms of visuospatial orienting are supported by several overlapping neural processes, which implies shared neural resources between them.

Introduction

Researchers often separate the control of visuospatial attention into exogenous and endogenous attention. According to this dichotomous account, exogenous orienting involves reflexive and involuntary shifts of attention triggered by salient events, while endogenous orienting corresponds to the voluntary control of attention based on the goals of individuals (Corbetta et al., 2008; Corbetta & Shulman, 2002; Jonides, 1981; Müller & Rabbitt, 1989; Posner, 1980; Wright & Ward, 2008). A towering body of work underlines critical differences between these two forms of attention orienting, which supports the idea that they map onto distinct independent systems (Chica et al., 2013). For example, exogenous orienting comes about through involuntary responses that quickly engages and disengages from attended locations. Endogenous orienting, on the other hand, corresponds to voluntary shifts of attention that occurs more gradually and enables individuals to attend to sensory events for an extended period of time (Carrasco, 2011). Visuospatial attention therefore involves separate systems that operate via distinct modes of control.

Most documented differences between exogenous and endogenous attention have been identified using the spatial cueing paradigm – an experimental approach for studying visuospatial attention (Chica et al., 2014). Here, researchers typically investigate exogenous orienting using task-irrelevant and peripheral stimuli (e.g., a visual flash occurring at the periphery) and endogenous attention based on task-relevant central cues instructing participants to voluntarily attend to a particular location (e.g., a symbolic cue). The perceptual benefits of visuospatial attention emerge by comparing trials where target events occur at the cued versus the uncued location (Posner et al., 1980). Some studies have examined the interplay between exogenous and endogenous attention using a double-cueing strategy where both forms of attention orienting are concurrently engaged. Following this approach, some findings support the dichotomous account by showing limited interactions between exogenous and endogenous attention during perceptual processing (Landry et al., 2021), while others have uncovered evidence for interferences in demanding context (Berger et al., 2005). Evidence shows that exogenous orienting can interfere with endogenous attention in certain contexts – an observation that emphasizes

the ballistic nature of exogenous attention (Theeuwes, 2019). Yet, the mechanisms that underlie these interactions remains unclear, as evidenced by ongoing debates about the dynamics between exogenous and endogenous attention for more than two decades (Luck et al., 2021).

An emerging hypothesis with regards to attention typologies proposes that these different forms of visuospatial orienting represent separate functional systems capable of mutual interference (Berger et al., 2005). Insofar that visuospatial attention operates by allocating processing resources (Luck et al., 1996), mutual interference entails that exogenous and endogenous attention compete for these resources. While exogenous attention emerges via stimulus-driven and ballistic processes, this viewpoint implies that it is not impervious to the influence of endogenous attention. Hence, exogenous attention does not solely reflect saliency and bottom-up processing (Folk et al., 1992). Evidence in support of this prediction, however, remains ambiguous. The current work tackles this point by exploring the dynamics of exogenous and endogenous attention using multivariate classification and machine learning – a collection of techniques that allow neuroscientists to test well-established psychological ontologies by decoding psychological states from neural data (Kragel et al., 2018). We leveraged these analytical advances to decode visuospatial attention and test whether endogenous attention influences cue-related and target-related components of exogenous attention.

Numerous findings show commonalities between exogenous and endogenous attention at the sensory level (Ahrens et al., 2019; Grubb et al., 2015; Hopfinger & West, 2006; MacLean et al., 2009) and across widespread brain networks (Bowling et al., 2020; Buschman & Miller, 2007; Nobre et al., 1997; Peelen et al., 2004). Recent electrophysiology work proposes that exogenous and endogenous orienting share a common neural marker of visuospatial attention: Alpha band dynamics (8-12 Hz; Keefe & Störmer, 2021). This work therefore provides a reliable neural marker for investigating trade-offs between exogenous and endogenous attention. In the context of visuospatial attention, modulations of alpha power are often construed as an index for neuronal inhibition relative to the selection of information at the sensory level (Klimesch, 2012). In

support of this hypothesis, a recent study showed that inducing changes in alpha power over the posterior cortex via neurofeedback yielded corresponding modulations of evoked responses for visual stimuli (Bagherzadeh et al., 2020). This outcome implies that changes in lateralized alpha rhythms cause shifts of spatial attention across the visual field. The present work therefore focusses on this marker to quantify how endogenous attention interacts with exogenous attention.

To evaluate whether exogenous attention is impervious to endogenous attention, our work compared the cue-related and target-related effects of exogenous attention across single cueing, where exogenous attention is engaged alone, and double cueing, where exogenous attention is concurrently engaged with endogenous attention. In our approach, the endogenous cue preceded the orientation of exogenous attention during double cueing, thus any modulations of endogenous attention over exogenous attention would therefore reflect the involvement of top-down resources rather than a perceptual confound (i.e., changes in the visual display). Moreover, we separated the double cueing condition into trials where both cues pointed to the same location and trials where they pointed to opposite locations. Our experimental strategy therefore allowed us to isolate situations where attention resources are split across the visual field. Lastly, we adjusted the difference in timing between cues and target events to the respective temporal profiles of both forms of attention orienting, wherein the perceptual benefits of exogenous attention are observed early following cue onset (i.e., around 300ms before a target), while those of endogenous occur later (i.e., around 700ms before a target) (Chica et al., 2014). We accordingly ensured that the target event would onset within the optimal window of processing for both endogenous and exogenous attention.

We employed two complementary analyses (i.e., two decoding challenges) to examine orienting-related and target-related responses of exogenous attention by applying multivariate statistical techniques over electroencephalography (EEG) data. In our first challenge, we verified how classifiers trained to decode cue-related and target-related effects of exogenous attention during the single cueing task would perform when tested in the context of double cueing. We accordingly hypothesized that interference

from endogenous attention would emerge as a decrease in classification performance. Classifiers trained to decode exogenous attention in single cueing and subsequently tested in double cueing should show a lower decoding performance if endogenous attention interferes with exogenous orienting. We performed these assessments across different features of the EEG, including the cue-related and target-related event related potentials (ERPs), and over the amplitude and the phase of alpha oscillations given the centrality of this neural marker in visuospatial attention. In our second challenge, we aimed to complement and corroborate our findings by training multivariate classifiers to decode the cueing condition directly (i.e., single versus double cueing). Our goal was to validate our findings for cue-related and targeted-related effects of exogenous attention across single and double cueing. For this analysis, above chance-level performance of the classifier would indicate differences in exogenous orienting between the single and double cueing. We further isolated the modulations of endogenous attention by applying principal component analysis (PCA) over the exogenous cue-related encoding model.

Results

Thirty-two participants completed spatial cueing conditions in a blocked design while we recorded their EEG. Participants were instructed to discriminate the orientation (clockwise versus counter-clockwise) of a Gabor target stimulus displayed either at the cued or uncued location (Figure 1). Participants completed an exogenous single-cueing task where we elicited exogenous orienting of attention alone, and in a double-cueing task that concurrently engaged both endogenous and exogenous orienting. Cue validity was determined following cue and target contingencies. The order of the experimental conditions was randomly counterbalanced between participants (see Methods).

Behavior. We first confirmed that the exogenous cue facilitated discrimination performance by examining accurate response times (RTs) in the single-cueing condition via single-trial hierarchical linear regressions (Gelman & Hill, 2006). Note that discrimination performance was near ceiling across all cueing conditions (i.e., accuracy rate for single cueing, μ=94.4% (σ=3.6%) and double cueing, μ=93.6% (σ=3.9%). Our regression analysis included exogenous cue validity (i.e., valid vs. invalid) as a fixed

predictor and participants as a random factor for predicting accurate RTs. We found that exogenous cueing improved discrimination performances, with cue validity as a reliable predictor (β=-41.28, SE=2.83, 95% CI [-46.83, -35.74]; Figure 1A and Supplementary Tables 1 and 2). In the double-cueing condition we included the validity of the exogenous cue, the validity of the endogenous cue, and their interaction as fixed factors in the regression model, with participants as random predictors. We added these fixed factors in a stepwise fashion to determine the best-fitting model and assessed evidence for an interaction between exogenous and endogenous cue validity on RTs. This analysis shows that the main effects of exogenous cue validity (β=-39.27, SE=3.04, 95% CI [-45.22, -33.32]) and endogenous cue validity (β=-22.42, SE=3.22, 95% CI [-28.73, -16.11]; Figure 1B, and Supplementary Tables 3 and 4) were statistically reliable. Yet, we could not reject the null hypothesis for their interaction. This outcome confirms the engagement of both exogenous and endogenous attention in the double-cueing condition. Moreover, we observed that evidence weighted against their interaction, as indicated by a Bayes factor analysis: BF_{01}=105.59).

Next, we examined whether exogenous cue validity varied across single and double cueing conditions. Here, we performed two separate analyses. First, we evaluated exogenous cue validity across single cueing and double cueing when both cues indicate the same location (i.e., both exogenous and endogenous were engaged to the same location). We specified exogenous cue validity (valid vs. invalid cues), cueing task (single vs. double-cueing task) and their interaction as fixed predictors, and participants as random factors. We used a stepwise approach to assess the statistical reliability of our predictors. The best-fitting model included exogenous cue validity (β=-41.28, SE=2.93, 95% CI [-47.02, -35.55]), cueing task (β=39.98, SE=4.18, 95% CI [31.78, 48.18]), and their interaction (β=-19.91, SE=5.31, 95% CI [30.33, -9.49]) as predictors of RTs (Figure 1C, and Supplementary Tables 5 and 6). Second, we examined the cueing effect of exogenous attention across single cueing and double cueing when both cues indicated opposite locations (i.e., both exogenous and endogenous were engaged to different locations). The best-fitting model included exogenous cue validity (β=-41.31 SE=2.93, 95% CI [-47.02, -35.55]), cueing task (β=18.13, SE = 3.34, 95% CI [11.59, 24.69]), and

their interaction (β=24.48, SE = 5.37, 95% CI [13.98, 35.07]) as predictors of RTs (Figure 1D, and Supplementary Tables 7 and 8). Together, these results show that endogenous attention influences the cueing effect of exogenous attention. This effect remains regardless of the spatial location of endogenous attention i.e., when both cues are engaged towards the same location or when they are split.

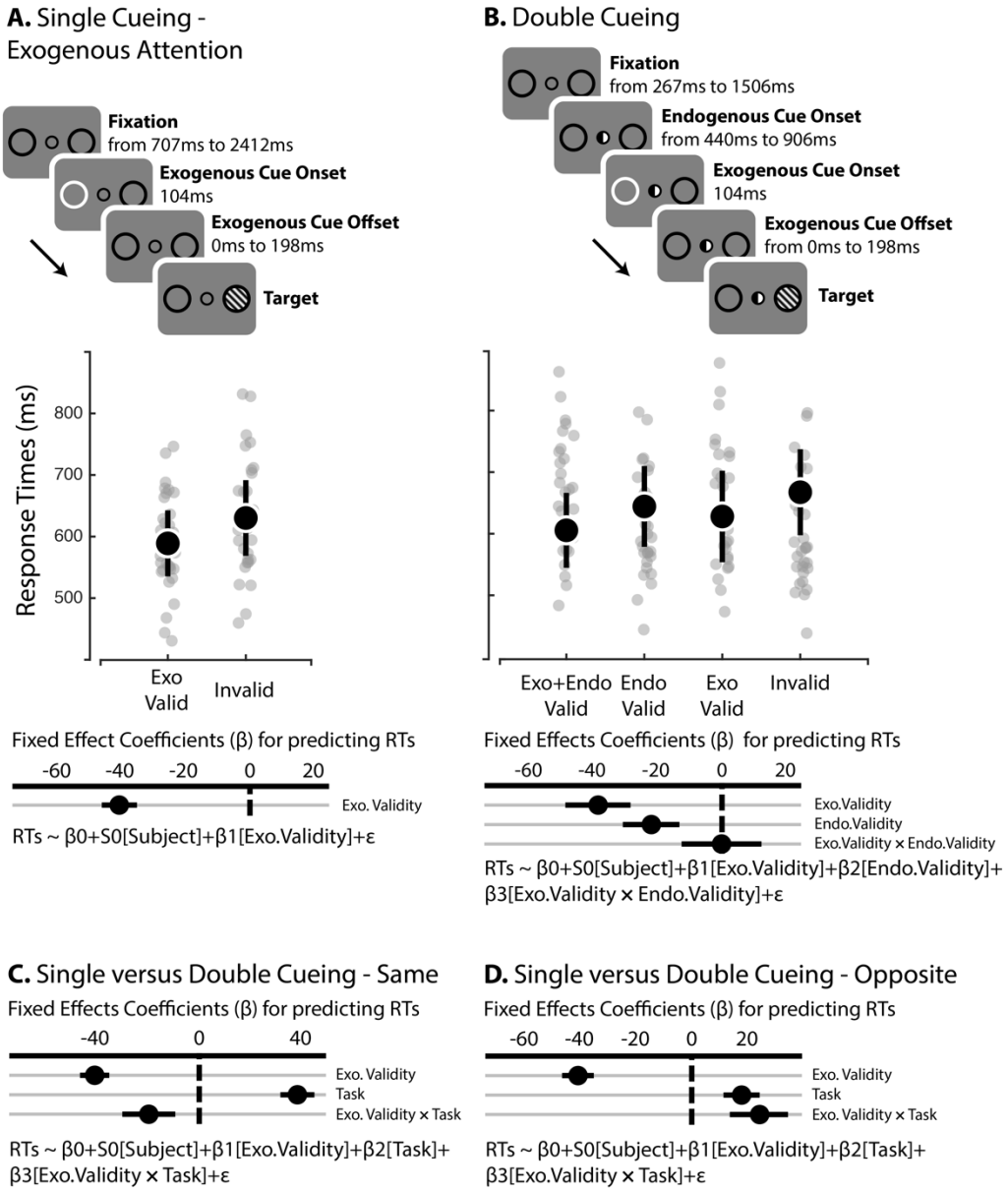

Figure 1. **A.** Top panel: in the single cue condition each trial began with a fixation screen, followed by the onset of the exogenous cue and lastly, the Gabor target at the valid or invalid location. The exogenous cue was task-irrelevant and predicted the upcoming target's location at chance-level. The scatter plot depicts group (black dots) and participant (grey dots) average RTs on the task. Error bars represent bootstrapped 95% C.I. Bottom panel: single-trial hierarchical regression model coefficients. Error bars represent 95% C.I.

B. Top panel: the double cueing condition comprised both exogenous and endogenous cueing where the exogenous cue did not predict the target's location and the endogenous cue predicted the target's location 66.66% of the time. The endogenous cue (i.e., fixation semicircles, where the white side indicated where the target was likely to occur; see Methods for details) appeared after a jittered interval, followed by the exogenous cue, and finally the target event. The scatter plot shows group (black dots) and subject (grey dots) average RTs. Error bars represent bootstrapped 95% C.I. Bottom panel: single-trial hierarchical regression model coefficients. Error bars represent 95% C.I. **C.** Single-trial hierarchical regression model coefficients where evaluated the effect of cueing condition on exogenous cue validity.

Electrophysiology. Challenge I – *Generalizing neural decoding of exogenous attention from single to double cueing.* We trained SVM classifiers to decode cue-related and target-related neural processes of exogenous attention based on EEG signals (Hong et al., 2020). Here, we aimed to decode (1) the direction of exogenous attention orienting (i.e., left versus right orienting of exogenous attention) from cue-related EEG; and (2) cue validity (i.e., valid versus invalid trials) from target-related EEG. Our approach follows from (Bae & Luck, 2018). Decoding was performed at the participant level using a three-fold cross-validation procedure where 2/3 of trials were randomly selected to train the classifier and validation was assessed on the remaining 1/3 of the trials. We decoded exogenous attention across each time-point separately through the time series (see supplementary Figure 1). For the first sets of analyses, we trained and validated classifiers in the single cueing and subsequently assessed their performance in the double cueing condition. We reasoned that poorer classification performance in the double cueing task would indicate that endogenous attention alters the neural features of exogenous attention. See methods for details.

We separated the double cueing condition into trials where both cues indicated the same location and those where both cues indicated opposite locations, which yielded three comparisons across these analyses: We contrasted the classifiers' performance for single cueing against that of the double cueing conditions when the exogenous and endogenous cues were directed to the same location in the double cueing task, we compared single cueing against double cueing when both cues indicated opposite locations in the double cueing task, and we compared classification performances from the double cueing condition when both cues indicated the same location versus when they both indicated opposite locations. We relied on cluster-corrected pairwise t-tests over decoding accuracy rates across the time series for these comparisons. We applied this

analytical approach to cue-related and target-related waveforms. Our goal was to examine the effects of double cueing across established neural markers of exogenous attention. We used cue-related lateralized alpha index (LAI) and intertrial phase clustering (ITPC) of alpha oscillations to decode exogenous attention orienting.

Decoding based on cue-related waveforms highlights the impact of the double cueing condition on single cueing. Here, we first validated our approach by showing that classification was above chance level for decoding the orientation of exogenous attention during single cueing and double cueing conditions (supplementary Figure 2A), thereby substantiating our approach. We observed that SVM classification could recover the direction of exogenous attention better than chance even when endogenous attention is concurrently engaged. We then compared classification performance across single cueing, double cueing for the same location, and double cueing for opposite locations. Critically, these contrasts show that classification performance worsens in the double cueing task compared to the single task for cue-related ERPs (Figure 2A). These effects occurred between 144ms and 496ms when both cues were directed towards the same location during double cueing. In turn, we found an early cluster (i.e., from 108ms to 180ms) and two late clusters (i.e., from ~448ms to ~596ms and from 636ms to 704ms) when the cues indicated opposite locations. Following our hypothesis, evidence shows that the concurrent engagement of endogenous attention modulates the neural dynamics of exogenous orienting, both when they align to the same location and when they are split across opposite locations. Furthermore, we observed a late significant cluster occurring from 628ms to 740ms when contrasting trials where both cues indicate the same direction versus when trials where both cues indicate opposite locations. This pattern denotes that classification returned to baseline more quickly when both cues were directed to opposite locations, which is consistent with the idea that endogenous orienting allows exogenous attention to be sustained at a particular location for an extended period when both forms of orienting are engaged towards the same location. Altogether, these results reveal that endogenous attention alters the neural dynamics of exogenous orienting.

We further investigated whether endogenous orienting impacts the cueing benefits of exogenous attention by decoding exogenous cue validity based on target-related waveforms. We validated that classification was above chance-level during single-cueing (supplementary Figure 2B). We similarly confirmed that SVM could decode exogenous cue validity in the context of double cueing (supplementary Figure 2B). Consistent with our behavioral findings showing that the concurrent engagement of endogenous attention interferes with the cueing effect of exogenous orienting, classification performance of exogenous cue validity was inferior during double cueing (Figure 2B). Comparing single and double cueing conditions yielded significant clusters between 196ms to 284ms whenever both cues were directed towards the same target event during double cueing, and between 288ms to 292ms when the cues directed exogenous and endogenous attention to opposite directions for double cueing.

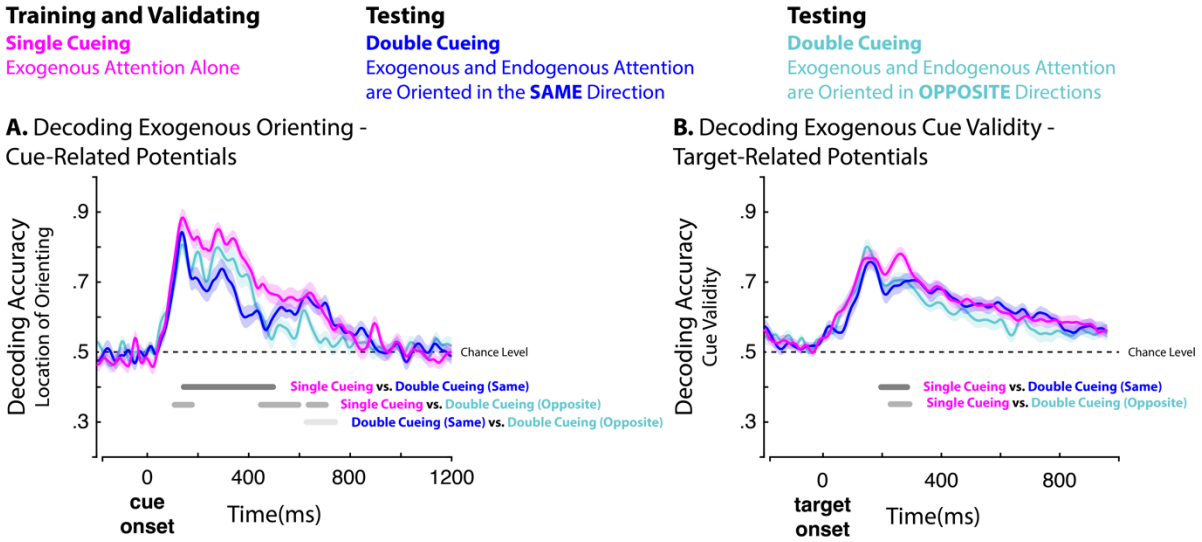

Figure 2. Multivariate classification of exogenous orienting and cue validity in both single and double cueing conditions. We examined trials in the double cueing condition where both cues indicated the same or opposite locations separately. We compared classification performances using cluster-corrected pairwise t-tests. Grey lines indicate significant clusters for each comparison. Shaded areas represent the SEM. **A.** Decoding the direction of exogenous orienting based on cue-related ERPs. **B.** Decoding exogenous attention cue-validity based on target-related ERPs.

Lastly, we used alpha band dynamics to decode the orienting of exogenous attention. We first validated that classification was above chance level for both the LAI and ITPC during single cueing, thereby confirming the reliability of our approach for uncovering the effects of exogenous attention (supplementary Figure 3A and 3B). Critically, our results show that classifiers trained to decode exogenous attention in the

context of single cueing are systematically misled by the direction of endogenous attention when tested in the context of double cueing condition. Classification performance was above chance level when both cues indicated the same spatial location in the double cueing task, and then below chance level when both cues indicated opposite locations (Figure 3; supplementary Figure 3A and 3B). This effect was apparent when we compared decoding accuracy between same and opposite cueing conditions during double cueing across power and phase of alpha rhythms: Significant clusters emerged between 72ms and 368ms for the LAI and from the onset of the cue until 496ms for the ITPC (Figure 3). This outcome provides compelling evidence regarding significant overlap between both systems across brain activity in the alpha band (8-12 Hz).

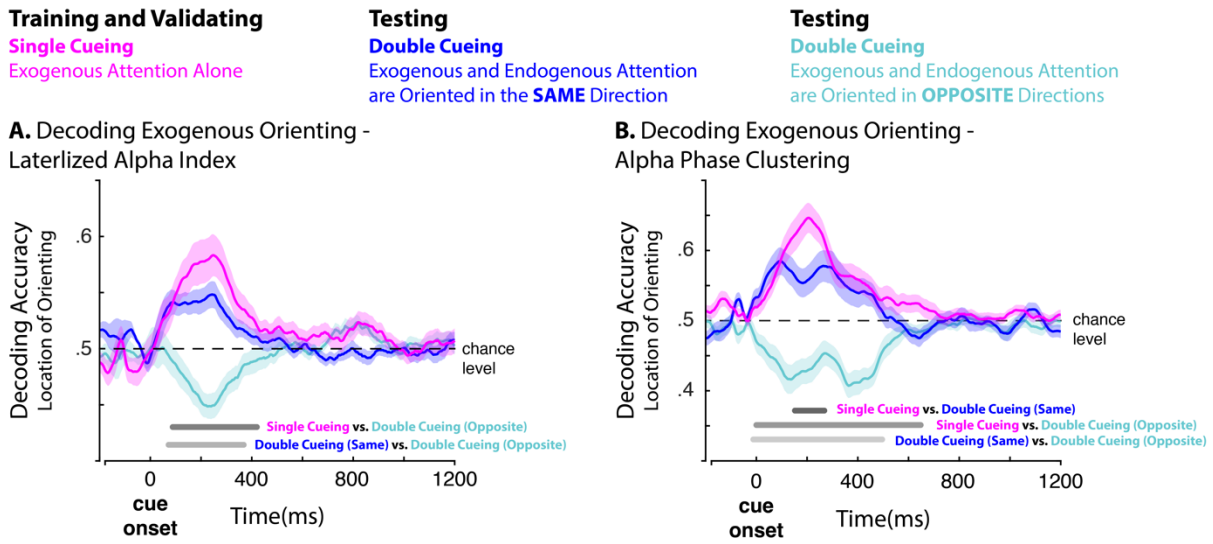

Figure 3. Multivariate classification of exogenous orienting and cue validity in both single and double cueing conditions. We examined trials in the double cueing condition where both cues indicated the same or opposite locations separately. We compared classification performances using cluster-corrected pairwise t-tests. Grey lines indicate significant clusters for each comparison. Shaded areas represent the SEM. **A.** Decoding of exogenous cue orienting based on cue-related LAI (see methods). **B.** Decoding of exogenous orienting based on cue-related alpha ITPC.

Electrophysiology. Challenge II – *Decoding cueing conditions.* We aimed to corroborate our primary findings by decoding the cueing condition: Single versus double cueing. We hypothesized that classification performance would be above chance if endogenous attention interferes with exogenous orienting given that this is the only difference between cueing conditions. Our decoding approach was similar to the one we previously described where we trained SVM classifiers based on a three-fold cross validation approach

(supplementary Figure 1). We separated trials where both cues indicated the same spatial location or opposite locations in the double cueing condition (see Methods for details). For cue-related brain activity, we trained SVM classifiers to distinguish the cueing conditions from lateralized ERPs (i.e., contralateral minus ipsilateral exogenous cue-related waveforms), LAI, and lateralized alpha band ITPC. For target-related processes, we examined exogenous cue validity (i.e., exogenous cue valid minus exogenous cue invalid) across ipsi- and contralateral sides relative to the target event.

Our results corroborated our previous findings. For cue-related waveforms, SVM classifiers differentiated cueing conditions (Figure 4A and 4D). Specifically, we observed significant clusters ranging from 140ms to 476ms when both cues indicated the same location for double cueing, and from 108ms to 614ms when both cues indicated opposite locations for double cueing. In the same vein, we observed significant clusters for LAI and phase clustering for alpha rhythms only when both cues were indicating opposite locations during double cueing, which is largely consistent with Challenge I (Figure 4B, 4C, 4E, 4F). Here, a large cluster emerged from 88ms to 432ms after cue onset for LAI (Figure 4E), and then from -24ms to 492ms after cue onset for the phase clustering of alpha oscillations (Figure 4F). These results complement our previous findings and suggest that the concurrent engagement of endogenous attention impacts exogenous cue-related EEG components.

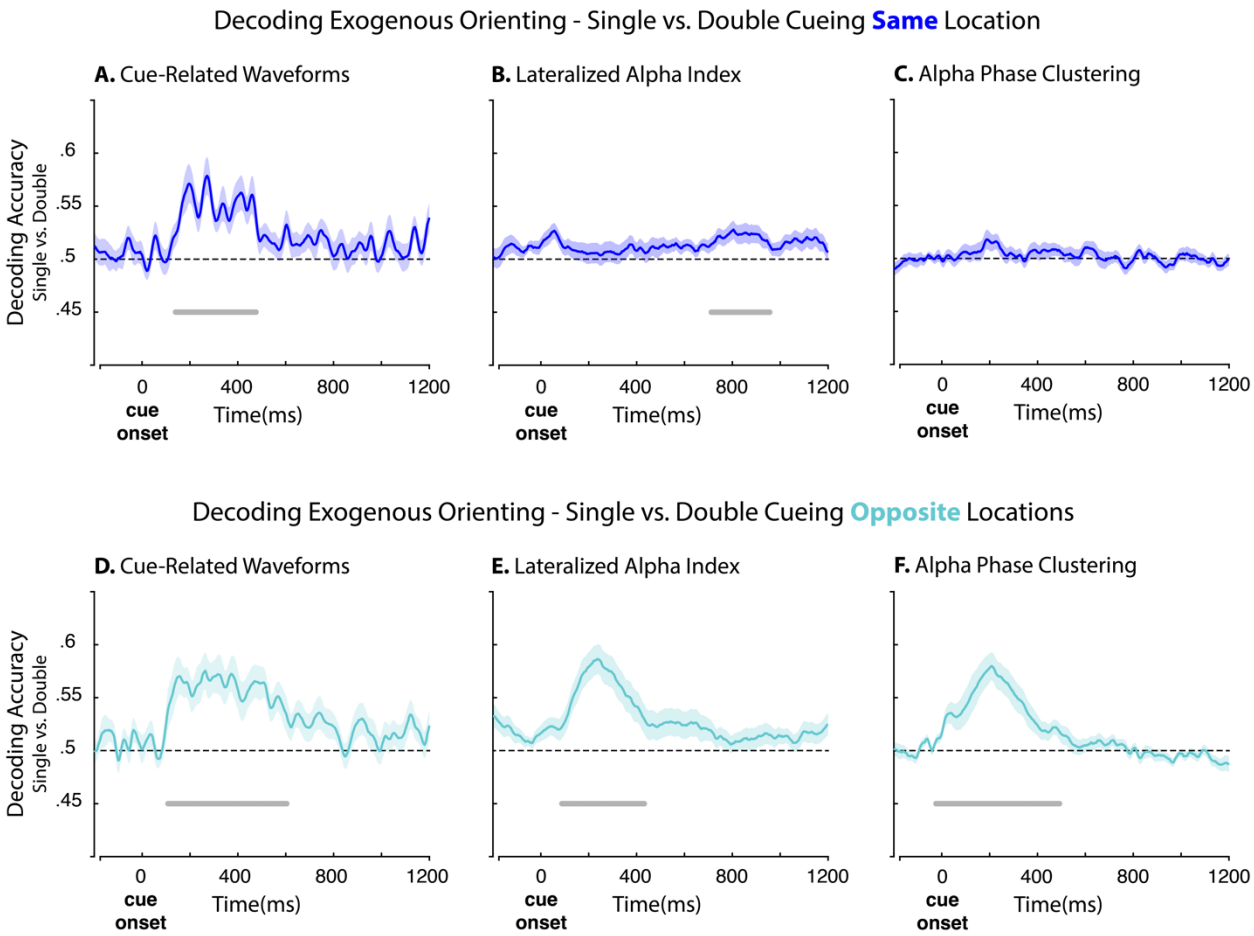

Figure 4. Multivariate classification of cueing conditions based on cue-related ERPs, LAI, and phase clustering. We assessed classification performance separately for trials in the double cueing condition where both cues indicated the same location (**A,B,C)** and opposite location (**D,E,F)**. Grey lines indicate above chance-level classification based on cluster-corrected t-tests. Bold lines represent the averaged time series and shaded areas the SEM.

Similarly, we observe evidence for interference between both systems when decoding cueing conditions based on target-related waveforms (Figure 5). Here, we found that classification was better than chance across both contra- and ipsilateral trials when both cues were directed toward the same location. We observed a significant cluster from 236ms to 304ms for the contralateral side (Figure 5A), and a much larger one from 72ms to 372ms for the ipsilateral side (Figure 5B). In turn, for trials where both cues indicated opposite locations during double cueing, we observed a significant cluster on the ipsilateral side only, between 168ms and 280ms (Figure 5C, 5D). These results confirm our hypotheses, showing that endogenous attention influences exogenous cue validity–even when both forms of orienting are engaged towards the same target event.

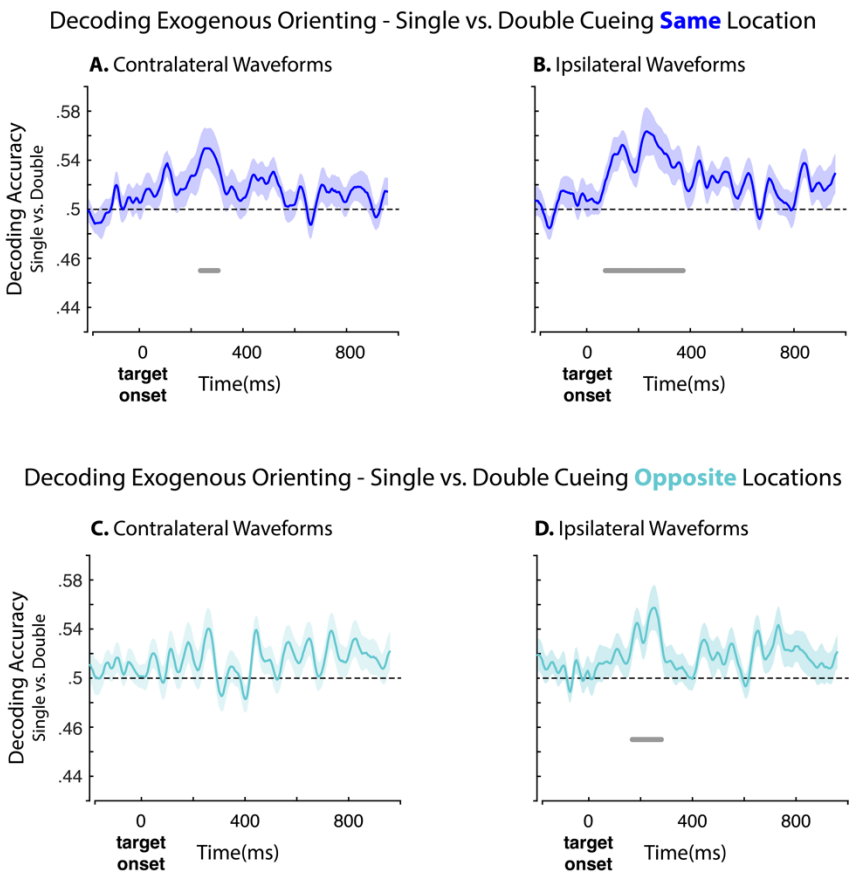

Figure 5. Multivariate classification of cueing conditions based on target-related ERPs for contra- and ipsilateral channels (i.e., cue valid minus cue invali. We assessed classification performance for contralateral trials to the target when both cues indicated the same location (**A**) and the opposite location (**C**). We repeated this analysis for ipsilateral trials (**C**) and (**D**). Grey lines indicate significant clusters against chance-level based on cluster-corrected t-tests. Bold lines represent the averaged time series and shaded areas of the SEM.

Electrophysiology. Encoding model of exogenous orienting. We examined encoding models for the classification of exogenous orienting based on cue-related ERPs to better isolate the influence of endogenous attention during double cueing. Based on previous work, we expected that double cueing would modulate exogenous attention at the sensory level (Fernández & Carrasco, 2020; Hopfinger & West, 2006). To test this hypothesis, we first trained classifiers in the single and double cueing conditions separately, and then computed interpretable SVM weights of these models using an established procedure (Haufe et al., 2014). See supplementary Figure 4 for the averaged decoding accuracy of these models across single and double cueing. Next, we applied principal component analysis (PCA) to these weights to identify the underlying components pertaining to exogenous orienting of attention based on cue-related

waveforms. We performed this procedure separately for trials when both cues indicated the same location, and when both cues indicated opposite locations in the double cueing condition. See methods for more details. This procedure yielded two significant components of the exogenous cue-related encoding model. The first component explained 57% of the variance and was marked by a posterior and lateralized topography. This component showed early variation of the SVM weights after cue onset, trailed by slower variations (see supplementary Figure 2). These patterns suggest that this component reflects sensory processes. We compared single and double cueing conditions, which revealed two clusters involving trials when both cues indicate opposite locations – a first one ranging from 204ms to 268ms post-cue, and a second one from 360ms to 456ms (Figure 6A). Likewise, we report significant differences in the endocding models of exogenous orienting between trials when the cue indicated the same vs the opposite location in the double cueing condition. A first one from 156ms to 472ms and a second one from 560ms to 668ms (Figure 6A). Conversely, we did not observe any differences for the second component, which explained 28.5% of the variance and was marked by a more anterior pattern and slowed deflection of SVM weights from 200ms to 500ms post-cue (Figure 6B).

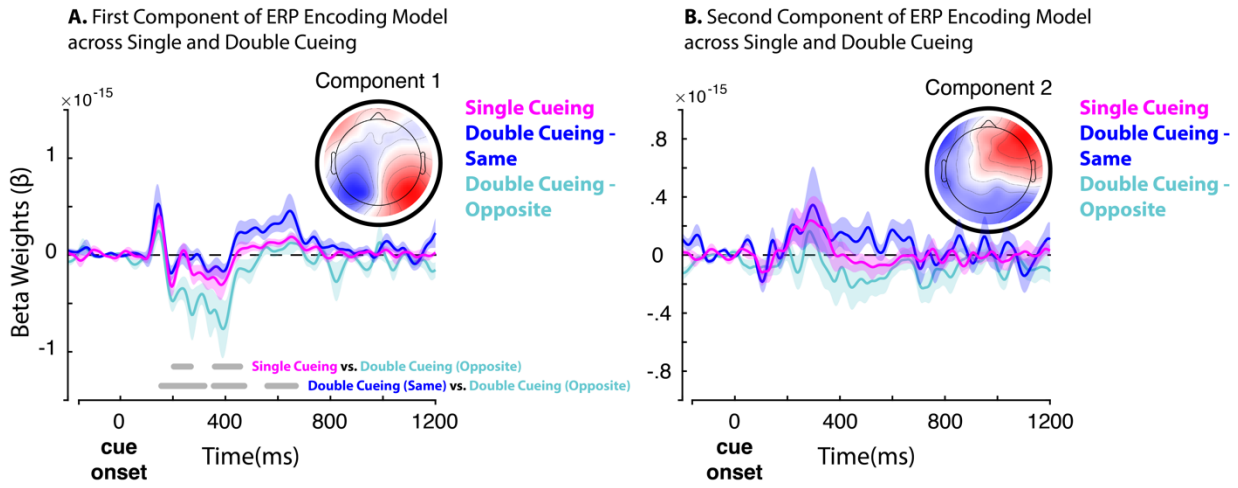

Figure 6. Comparison of single (pink), double cueing for same cueing location (blue), and double cueing for opposite cueing locations across first (**A**) and second (**B**) PCA components for the exogenous cue-related encoding model. Grey lines indicate significant clusters based on cluster-corrected pairwise t-tests. Bold lines represent the averaged time series and shaded areas of the SEM.

Discussion

Exogenous and endogenous orienting correspond to distinct control systems of visuospatial attention (Chica et al., 2013). Some reports highlight experimental contexts where we observe interactions between them, thereby challenging the idea that they operate completely independently from one another (Ahrens et al., 2019; Grubb et al., 2015; Hopfinger & West, 2006; MacLean et al., 2009). Yet, these dynamics remain unclear (Berger et al., 2005; Luck et al., 2021). In the present work, we combined multivariate statistics with single and double spatial cueing procedures to examine the influence of endogenous attention over exogenous attention. Contrary to the idea that exogenous orienting is impervious to top-down factors (Landry et al., 2021; Pinto et al., 2013), our behavioral and neurophysiological results highlight that endogenous attention impacts exogenous attention across both cue-related and target-related processing. Critically, our findings not only show that classifiers trained to decode the effects of exogenous attention during single cueing perform worst when tested in the context of double cueing, but also highlight that classifiers trained to decode the direction of exogenous attention can be misled by the parallel engagement of endogenous attention. Our findings therefore provide evidence of overlap and shared neural resources between exogenous and endogenous attention at the sensory level of processing.

Past EEG studies relate the cueing of exogenous attention to an early posterior component emerging at the sensory level (Hopfinger & West, 2006; Störmer et al., 2019). Following this pattern, classifiers trained to decode exogenous orienting in the single cueing context, based on cue-related waveforms, achieved a lower performance when tested in the double cueing context 150ms after cue onset. Furthermore, our results indicate that the concurrent engagement of endogenous attention alters early visual processes, as evidenced by our encoding model of exogenous orienting. These results align with brain imaging assays indicating that exogenous and endogenous attention modulate neurons in the sensory areas (Dugué et al., 2020; Müller & Ebeling, 2008) . The present study therefore extends this body of work by showing that top-down attention alters the subsequent emergence of exogenous attention over posterior brain areas. We markedly observed this influence by comparing classification performances of exogenous attention within the double cueing condition. When both cues indicated the same target

location, decoding performance remained above chance-levels for a longer period than when they indicated opposite spatial locations. Combining both forms of attention orienting therefore entails functional consequences for exogenous attention. The current work also shows that the interference of endogenous attention over exogenous orienting yields sensory consequences for exogenous attention – an effect we observed across behavioral and neurophysiological data. This outcome follows earlier work showing that both exogenous and endogenous processing interact during sensory processing of target events (Hopfinger & West, 2006).

Importantly, we further tested the modulations of endogenous attention over exogenous attention across alpha rhythms – a well-established marker of visuospatial attention (Klimesch, 2012). This analysis revealed that SVM classifiers trained to decode exogenous attention in the single cueing condition were systematically misled by the direction of endogenous attention in the double cueing condition. Specifically, classification performance was above chance level when the direction of endogenous attention matched that of exogenous attention, and below when endogenous and exogenous indicated opposite spatial locations. This result implies that endogenous attention interferes with the neural processes of exogenous attention through alpha band activity. Accordingly, the present study not only corroborates the centrality of alpha waves across both forms of visuospatial attention (D'Andrea et al., 2019; e.g., Keefe & Störmer, 2021; Störmer et al., 2016; Thut et al., 2006), but also reveals significant overlap between them for this neural marker. This is consistent with the idea that both attention systems tap into a common neural resource indexed by alpha rhythms. One prevailing hypothesis posits that alpha oscillations reflect inhibitory and selection processes – two key elements in the emergence of selective attention (Klimesch, 2012). This viewpoint postulates that alpha waves capture spatiotemporal aspects of attention through modulations of neuronal excitability at the sensory level such that attending to a particular location in our visual field reduces local inhibition and increases feedforward processing at the contralateral visual site (Jensen & Mazaheri, 2010). Moreover, the timing of these effects are indexed by the periodicity of oscillatory patterns, which yields rhythmic sampling of sensory inputs (Haegens et al., 2011). Following this overarching view, our findings suggest that both

exogenous and endogenous attention tap onto these neural processes to facilitate perceptual processing, as indexed alpha oscillations.

In their pursuit to elucidate the dynamics of exogenous and endogenous attention, Berger et al. (2005) submit that their relationship is marked by competition for limited resources. This viewpoint implies that they are capable of mutual interference, whereby exogenous attention is not impervious to the influence of endogenous attention. Relying on neural markers of visuospatial attention and multivariate pattern classification, our findings support this hypothesis by showing that endogenous attention overlaps with exogenous attention across alpha rhythms. The selection of information emerges by allocating resources that prioritize perceptual processing (Luck et al., 1996; Theeuwes, 2019). Our study shows that the capacities of bottom-up and top-down attention to recruit these resources are shared and limited.

Methods

Participants. We recruited 42 participants (29 women, mean age = 22.2(sd = 3.09)) based on convenience sampling. Each individual received monetary compensation of $10/hour for completing 4 different tasks in one testing session lasting approximately 2 hours. All participants had normal or corrected-to-normal vision, had no prior history of neurological disease, and provided consent. The experiments were approved by the McGill Ethics Board Office (Certificate #511-0516).

We excluded data from ten participants: Seven participants were excluded due to the overwhelming presence of EEG recording artifacts. One participant did not complete all tasks. We excluded one participant because they performed below chance-level (~40% averaged across all conditions). Lastly, one participant was excluded due to a high volume of timeout errors (response times > 1500ms on ~11% of trials overall). Data analysis therefore proceeded from the data of 32 individuals (24 women, Mean age = 21.9 (SD = 2.6)). We determined our sample size based on previous work using the double cueing experimental approach (Landry et al., 2021). In this work, simulations following effect size estimates of performance revealed that 6 participants were required

to achieve a power of .8 for the within-individual cueing effects of exogenous and endogenous orienting in a target discrimination task when alpha is set .05. The sample size for the present work was therefore more than adequate to detect the desired attention effect at the behavioral level, and almost twice that of previous EEG experiments investigating combined effects of exogenous and endogenous orienting (Hopfinger & West, 2006; Keefe & Störmer, 2021).

Stimuli, Apparatus & Design. Participants viewed tasks on a 24-in BenQ G2420HD monitor sitting approximately 60 cm away, where stimuli presentation was controlled via MATLAB R2015b (Mathworks Inc., Natick, MA, USA) using the third version of the Psychophysics toolbox (Brainard & Vision, 1997; Kleiner et al., 2007; Pelli, 1997). The screen was set to 75hz. All stimuli were black (i.e., RGB values of 0, 0, 0; 1.11 cd/m^2) and white (i.e., RGB values of 255, 255, 255; 218.8 cd/m^2) drawings on a grey background (i.e., RGB values of 128, 128, 128; 70.88 cd/m^2). The fixation marker was an empty circle made from a black line drawing subtending a radius of 1.2° located in the center of the screen. Two target placeholders were located at 8.7° away from the fixation marker on the left and right side of the screen. These placeholders consisted of black line drawings of empty circles with a 2.4° radius. We cued exogenous attention by briefly changing the line drawing from one of the placeholders to white. To ensure that this cue solely engaged exogenous orienting, the cue-target spatial contingency was set to 50%, such that the cue was task-irrelevant and not predictive of the target's location per the standard in the field (Chica et al., 2014). We cued endogenous attention by coloring the inside of the fixation marker, wherein the right or left half of the circle was shaded in black and the other half in white. The side of the fixation marker that turned white indicated where the target was likely to occur. For example, if the right side turned white, the target was 66.6% likely to appear in the right placeholder. In this way, we avoided using overlearned directional cues, like an arrow, to engage endogenous attention (Ristic & Kingstone, 2012; Ristic & Landry, 2015). The targets were sinusoidal black and white gratings enveloped by a Gaussian with a spatial frequency of 3 cpd and tilted 5° degrees clockwise or counter-clockwise from vertical.

Procedure. Participants completed four tasks: A non-cueing task, a single exogenous cueing task, a single endogenous cueing task, and a double cueing task where both exogenous and endogenous orienting occured. Participants performed 10 practice trials prior to each task which consisted of 384 trials each. Task order was randomized across participants. In the current manuscript, we analyzed data for the non-cueing, the exogenous cueing, and the double cueing tasks in this manuscript.

Participants were asked to stare at the center of the screen throughout the experiment, while we assessed their eye movements using electro-oculogram. We jittered the latencies between the fixation point and the cues, between the endogenous and the exogenous cues, and between the cues and the target event based on a uniform distribution to minimize the effects of temporal prediction following spatial cueing. In this regard, cue-target latencies were adjusted following the temporal profiles of exogenous and endogenous so that attention facilitation would be maximized for each (Chica et al., 2014).

In the non-cueing task, participants viewed the fixation stimulus between 1276ms and 1782ms, which was immediately followed by the onset of the target event that stayed on the screen until participants' responses. Note the non-cueing task was used as a baseline against which we regressed the sensory effects of cue stimuli for the target-related analysis (see the *Electroencephalography* section below).

In the exogenous orienting task, participants were first presented the fixation marker followed by the exogenous cue between 707ms and 2412ms, which stayed on the screen for 104ms, and then the target would onset at one of the target's locations following a jitter between 0ms and 198ms post-cue. The target remained on the screen until participants' response.

In the double cueing task, participants were first presented with the fixation marker followed by the endogenous cue after 267ms to 1506ms. The endogenous cue stayed on the screen until the end of the trial. The stimulus onset asynchrony between the

endogenous cue and the target event varied between 440ms and 906ms. The exogenous cue would then onset before the target stimulus between 106ms and 307ms, and stayed on the screen for 107ms (see Figure 1). As we mentioned previously, the exogenous cue was uninformative about the target's location, whereas the endogenous cue was made task-relevant by indicating the correct target location for 66.6% of trials. Participants were aware of these contingencies. Participants were instructed to discriminate the orientation of the Gabor target as quickly and accurately as possible on a QWERTY keyboard by pressing the F key to input counter-clockwise orientation and the J key to input clockwise orientation. Inter-trial period was set to 1s.

Data analyses for behavioral performance. Participants' discrimination performance was near ceiling - averaged accuracy rate was ~93%. We therefore only examined accurate response times (RTs). We removed trials where participants made anticipation (i.e., RTs < 150ms) or timeout (i.e., RTs > 1500ms) errors, which accounted for less than 2% of trials overall, as well as wrong key presses, less than 1% of trials. We used hierarchical linear regression models (Gelman & Hill, 2006) to test the effects of cueing (i.e., valid versus invalid) and task (i.e., single versus double cueing), wherein predictors were added in stepwise fashion. We applied a chi-square goodness-of-fit test over the deviance to determine whether predictors significantly improved the fit and assessed Bayesian information criterion (BIC) to confirm which model best fit the data. We also estimated Bayes factor weighting evidence for the null against the alternative hypothesis (Wagenmakers, 2007) :

$$BF_{10} = e^{\Delta BIC_{01}/2}$$

We ran four statistical analyses on the behavioural performance of participants. First, we ran a regression on the single exogenous cueing condition where we included cue validity as a fixed factor. Second, for the double cueing task, we ran a regression where we included exogenous cue validity, endogenous cue validity, and their interaction as fixed predictors. Given that our approach focused on comparing the single and double cueing conditions, we examined if the cueing effect of exogenous attention varied as a

533 function of task (i.e., single and double cueing). Here, we ran a regression where we
534 included exogenous cue validity and cueing condition (i.e., single versus double cueing
535 condition) as fixed factors. We performed two such analyses: Once where double cueing
536 involved trials where both cues indicated the same location, and then again when both
537 cues indicated opposite locations. We included participants as a random factor for all
538 regression models.
539
540 *Electroencephalography*. We recorded neurophysiology using 64 Ag/AgCl active
541 electrodes EEG at a sampling rate of 1000 Hz (ActiCap System; Brain Products GmbH;
542 Gilching, Germany) positioned following the 10-20 system. We additionally monitored eye
543 blinks and eye movements through bipolar electrodes placed at the outer canthi, as well
544 as the superior and inferior orbits of the left eye. Impedances of all electrodes were kept
545 below 10 kΩ. All electrophysiological signals were amplified (ActiChamp System; Brain
546 Products GmbH; Gilching, Germany). Electrodes were referenced online to C4, and re-
547 referenced offline to an average reference. Preprocessing and analysis were conducted
548 in BrainVision Analyzer (ActiChamp System; Brain Products GmbH Inc.; Gilching,
549 Germany) and MATLAB (R2020a; Mathworks Inc., Natick, MA) using Brainstorm (Tadel
550 et al., 2011) and custom scripts. We downsampled the data to 250 Hz and applied two
551 IIR Butterworth filters: a first High-pass 0.1 Hz filter of 8th order and a 60Hz notch filter.
552 We then topographically interpolated bad channels (1.12% of channels). Next, we
553 performed an independent component analysis to identify artifacts relating to eye
554 movements and blinks using the BrainVision Analyzer Ocular correction ICA tool. We
555 corroborated these analyses with the electro-oculogram. We corrected the EEG signal
556 following these artifacts. We visually inspected EEG signals to manually remove atypical
557 noise patterns, as well as activity exceeding ± 200 μV across all electrodes. All triggers
558 were realigned according to our photodiode stimulations linked to the onset of the
559 exogenous cue, the endogenous cue, and the target event.
560
561 For target-related events, in lieu of the adjacent response filter method (Woldorff,
562 1993), we removed event-related responses from exogenous and endogenous cueing by
563 taking the residuals of the linear regression model using the non-cueing condition as

baseline. A hierarchical linear regression was run with condition as a dummy coded fixed factor, and subjects as a random factor. 'Raw' Residuals were obtained from the MATLAB function *residuals()* for all channels and subjects.

Event-related potentials. We analyzed cue-related and target-related event-related potentials. To compute the waveforms, we first applied a FIR bandpass-pass filter between 0.5 and 15 Hz and then divided the EEG into epochs spanning -200 and 1000ms. We baseline corrected ERPs from -100 to 0ms.

Lateralized alpha index. We computed the alpha lateralized index (LAI) based on time-resolved modulations of alpha power. These neural rhythms were computed for cue-related epochs across all channels between -200 and 1000ms. We first estimated the instantaneous amplitude of alpha waves (i.e., 8 to 12hz) related to the exogenous cue using the real part of the complex filter Hilbert transformation, and then computed the LAI following the direction of the cue at each time point according to the following equation:

$$\frac{\alpha\ power\ contralateral - \alpha\ power\ ipsilateral}{\alpha\ power\ contralateral + \alpha\ power\ ipsilateral}$$

Contra- and ipsilateral sides were defined according to the direction of exogenous attention. Note that we computed LAI for lateral channels only, which excluded central channels, while we paired every lateral channel with its corresponding match on the opposite side (e.g., O1 and O2). Lastly, we z-score normalized the LAI from baseline activity between -100 and 0ms.

Intertrial phase clustering. To examine the phase component of alpha oscillations, we computed intertrial phase clustering (ITPC) for exogenous cue-related EEG activity across all channels between -200 and 1000ms centered around the cue. This analysis rests on the imagery part of the complex filter Hilbert transformation, which tracks the phase angle of the oscillation (Cohen, 2014). We obtained ITPC time-resolved phase alignment across trials based on the following equation:

$$ITPC_{tf} = |\, n^{-1} \sum_{r=1}^{n} \quad e^{ik_{tfr}} \,|$$

Where, n corresponds to the number of trials and $e^{ik_{tfr}}$ provides the complex polar representation of the phase angle k on trial r for the index for time and frequency tf. Lastly, we transformed ITPC indices into z-scores from baseline ranging from -100 to 0ms.

Multivariate decoding analyses. Our goal was to evaluate whether endogenous attention modulates cue-related and target-related exogenous attention using multivariate statistical approach (Hong et al., 2020). We tackled this objective using complementary analyses. First, we trained SVM classifiers to decode the effects of exogenous attention during single cueing and then evaluated the performance of these classifiers in the context of both single and double cueing conditions. Comparing classification accuracy from the single and double cueing conditions based on models that were only trained in the single cueing condition allowed us to assess the generalization of decoding performance going from single cueing to double cueing. We hypothesized that a decrease in decoding performance from single to double cueing would reflect interference from endogenous attention on exogenous attention – i.e., that exogenous attention is not impervious to the concurrent engagement of endogenous attention. In our secondary complementary approach, we trained linear SVM classifiers to decode cueing conditions -- i.e., single versus double cueing. We therefore aimed to directly explore the interference of endogenous attention over exogenous attention.

Our decoding analyses followed from Bae and Luck (2018). We trained linear support vector machines (SVM) based on exogenous cue-related and target-related EEG. In our first series of analyses, we accordingly trained the classifiers to determine the direction of exogenous attention orienting – left versus right orienting based on cue-related components, and to determine exogenous cue validity – cue valid against cue invalid based on target-related EEG components. Separate trials were used for the training and testing of our classifiers following a three-fold cross-validation plan. Classifiers were trained separately for each participant and time-points across the cue-related and target-related time series.

We performed multivariate decoding analyses using linear support vector machine (SVM) implemented in MATLAB's (i.e., *fitcsvm*). Following our three-fold cross-validation procedure, 2/3 of trials were randomly selected to train the classifier, and the remaining 1/3 of the trials were used to test the performance of the SVM. Specifically, we organized the data of each participant into three equally sized bins of trials and averaged these trials together to produce three separate time-series. Two of the three averaged time-series served as the training dataset, and the remaining average served as the testing set. Decoding accuracy was determined on the correct identification of the data we left-out. We iterated through all possible combinations of training such that each averaged time-series served as the testing set once. For each participant, we performed 50 iterations of the above binning, averaging, and decoding procedure. As we mentioned previously, we applied our decoding strategy across two decoding challenges.

Challenge I: Generalization of decoding going from single to double cueing. We wanted to assess how classifiers trained in the single cueing condition generalize to the double cueing condition. Here, we trained and tested the SVM classifiers following the approach we described previously on the data from the exogenous single cueing condition. Next, we tested the ability of these SVM classifiers to decode exogenous attention in the context of double cueing. Critically, for the double cueing condition, we assessed trials where both attention cues pointed to the same and opposite directions separately. We applied this approach to cue-related ERPs, LAI patterns, and phase clustering to assess both cue-related and target-related effects (see Methods *Electroencephalography*).

First, we evaluated cue-related exogenous orienting responses based on ERPs, LAI patterns, and phase clustering. We trained SVM classifiers to decode cue direction – i.e., left orienting versus right orienting (Hong et al., 2020). Each bin used to produce averaged time series for decoding comprised 25 trials.

Second, we evaluated target-related ERPs as a function of exogenous cueing. Here, we decoded cueing effects – i.e., exogenous cue valid versus exogenous cue invalid. To ensure that the classifier did not rely on the target's location, we performed our

decoding analysis separately for target events occurring on the left- and right-hand side of the screen, and averaged the classification performance across both locations thereafter. Each bin used to generate the averaged time series for decoding included 21 trials.

Decoding was performed for each participant, cueing condition, and neurophysiological features (i.e., ERPs, LAI and phase clustering). We averaged decoding accuracy for each participant, cueing condition, and neurophysiological features. We used a five-sample sliding window -- i.e., a 20ms window to smooth the average decoding accuracy time series. We then computed pairwise t-statistics at each time point to ssstest decoding performance against chance-level (i.e., 50% decoding accuracy). We additionally used t-statistics to compare: i) single cueing against double cueing--when both cues indicate the same direction; ii) single cueing against double cueing--when both cues indicate opposite directions, and iii) double cueing--same direction against double cueing--opposite direction. We applied cluster-corrected permutation tests to control for family-wise type-II error. We performed 1000 permutations where we randomly varied the data and then contrasted observed cluster sizes against surrogate distributions for the null hypothesis. The cluster forming threshold was set to $p < .05$. We applied this statistical approach for all decoding analyses.

Challenge II: Decoding cueing conditions. Our secondary and complementary analysis focused on decoding the cueing conditions (i.e., exogenous single cueing versus double cueing). We followed a similar three-fold procedure as described previously, except for the following changes described below.

For exogenous orienting cue-related EEG, we examined the cue-related lateralized ERP, LAI and the lateralized alpha phase clustering. To get at this, we averaged trials from bins separately for ipsilateral and contralateral channels and then subtracted the resulting time series from one another (i.e., contralateral minus ipsilateral). This process resulted in three averaged time series that we used for decoding, akin to the procedure above. Each bin contained 32 trials. Again, we separated trials in the double

cueing condition into trials where both cues pointed to the same direction and trials where cues pointed in opposite directions

For target-related EEG, we decoded cueing conditions (i.e., single versus double cueing) based on exogenous cue-validity ERPs. We performed this analysis across contralateral and ipsilateral channels separately and split trials in the double cueing condition into trials where the cues pointed to the same or opposite direction. We averaged trial bins separately for cue valid and invalid trials and subtracted these waveforms (i.e., exogenous cue valid minus exogenous cue invalid) before training and testing the data. This analysis yielded three averaged time series for our decoding analysis per condition akin to the approach described above. Each bin used to compute the average time series contained 14 trials.

Applying principal component analysis to the cue-related exogenous orienting of attention. We aimed to isolate the effects of endogenous attention over the exogenous cue-related processes based on the encoding model. For this analysis, we trained SVM classifiers to decode the exogenous orientation of attention (i.e., left versus right) using the three-fold cross-validation approach we described previously over cue-related ERPs. Decoding of exogenous orienting was trained and tested separately for single exogenous cueing, double cueing when both cues indicate the same location, and lastly double cueing when both cues indicate opposite locations. We therefore divided trials into separate bins for all three conditions – 16 trials per bin. For all three conditions, we evaluated decoding performance against chance-level using cluster-corrected one-sample t-tests. Next, we examined the encoding model using an established procedure, whereby we extracted the beta weights from each classifier at each time point and then we multiplied them by the covariance of the corresponding ERP data (Haufe et al., 2014). For each participant, we then averaged the encoding model from all the iterations, which resulted into variations of the SVM beta weights across the time series. Next, we averaged these time series of SVM beta weights across all participants for each condition separately. We applied principal component analysis (PCA) to the averaged SVM beta weights from single cueing, double cueing when cues indicate the same location and

double cueing when cues indicate opposite locations. Next, we rotated the loadings using varimax rotation and kept the first two components, which explained 84.5% of the total variance. We plotted the topography from both components. We then projected the averaged SVM weights from each participant and cueing conditions onto both dimensions. Lastly, we compared all three cueing conditions using cluster-corrected one-sample t-tests across the time series of SVM weights and PCA components separately.

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SUPPLEMENTARY MATERIAL

We present the tables from all hierarchical linear regression models for predicting correct response times. We performed the comparison and selection of models using chi-square goodness-of-fit tests and Bayesian Information Criterion (BIC). The best fitting model is highlighted in bold.

Table 1. Single cueing task. Hierarchical linear regression models for predicting RTs as a function of exogenous cue validity.

Models	X^2	p-value	BIC
RTs ~ β0 + S0 [*Subject*] + ε			148220
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + ε	**210.91**	**p < .001**	**147990**

Table 2. Single cueing task. Hierarchical linear regression parameters of the best model for predicting RTs as a function exogenous cue validity.

Model: RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + ε

Variables	Coefficient	Std. Error	95% C.I.
Intercept	630.19	14.62	[601.53, 658.85]
Exo Cue Validity	-41.28	2.82	[-46.83, -35.74]

Table 3. Double cueing task. Hierarchical linear regression models for predicting RTs as a function of exogenous and endogenous cue validity.

Models	X^2	p-value	BIC
RTs ~ β0 + S0 [*Subject*] + ε			14530
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + ε	166.27	p < .001	145150
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Endo.CueValidity*] + ε	**48.37**	**p < .001**	**145110**
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Endo.CueValidity*] + β3[*Exo.CueValidity* × *Endo.CueValidity*] + ε	< .1	p = .98	145120

Table 4. Double cueing task. Hierarchical linear regression parameters of the best fitting model for predicting RTs as a function exogenous and endogenous cue validity.

Model: RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Endo.CueValidity*] + ε

Variables	Coefficient	Std. Error	95% C.I.
Intercept	670.72	16.36	[638.66, 702.78]
Exo Cue Validity	-39.27	3.04	[-45.22, -33.32]
Endo Cue Validity	-22.41	3.21	[-28.73, -16.11]

Table 5. Comparing single to double cueing – same cueing location. Hierarchical linear regression models for predicting RTs as a function of exogenous cue validity and task.

Models	X^2	p-value	BIC
RTs ~ β0 + S0 [*Subject*] + ε			221920
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + ε	315.65	p < .001	221610
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Task*] + ε	114.18	p < .001	221540
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Task*] + β3[*Exo.CueValidity × Task*] + ε	**14.01**	**p < .001**	**221490**

Table 6. Exogenous cueing effect across single and double cueing – same cueing location. Hierarchical linear regression parameters of the best fitting model for predicting RTs as a function exogenous cue validity and task.

Model: RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Task*] + β3[*Exo.CueValidity × Task*] + ε

Variables	Coefficient	Std. Error	95% C.I.
Intercept	630.3	14.83	[602.7, 657.91]
Exo Cue Validity	-41.28	2.93	[-47.02, -35.55]
Task	39.98	4.18	[31.78, 48.18]

Exo.CueValidity × Task	-19.91	5.31	[-30.33, -9.49]

Table 7. Exogenous cueing effect across single and double cueing – opposite cueing locations. Hierarchical linear regression models for predicting RTs as a function of exogenous cue validity and task.

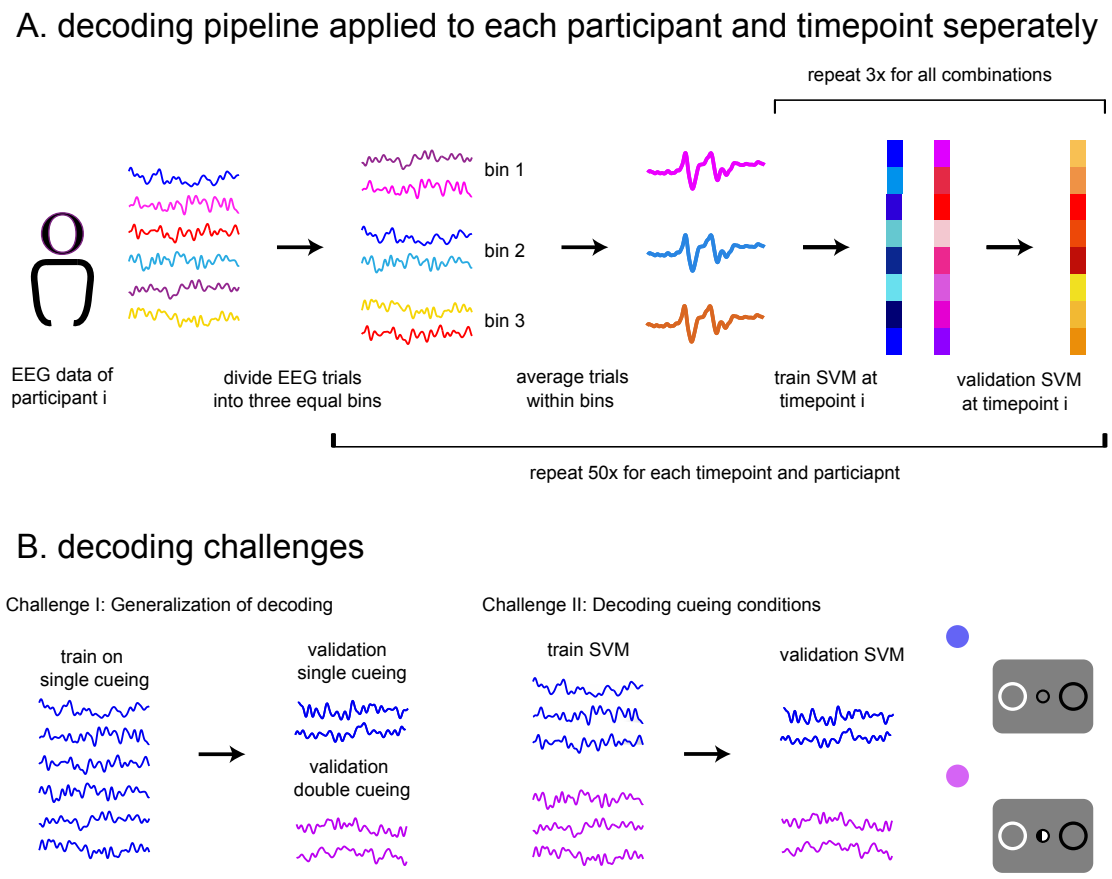
Models	X^2	p-value	BIC
RTs ~ β0 + S0 [*Subject*] + ε			221030
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + ε	241.58	p < .001	220820
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Task*] + ε	110.89	p < .001	220680
RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Task*] + β3[*Exo.CueValidity × Task*] + ε	**20.82**	**p < .001**	**220660**

Table 8. Exogenous cueing effect across single and double cueing – opposite cueing locations. Hierarchical linear regression parameters of the best fitting model for predicting RTs as a function exogenous cue validity and task.

Model: RTs ~ β0 + S0[*Subject*] + β1[*Exo.CueValidity*] + β2[*Task*] + β3[*Exo.CueValidity × Task*] + ε

Variables	Coefficient	Std. Error	95% C.I.
Intercept	630.32	14.44	[602.01, 658.62]
Exo Cue Validity	-41.31	2.94	[-47.08, -35.54]
Task	18.13	3.34	[11.59, 24.69]
Exo.CueValidity × Task	24.48	5.37	[13.98, 35.07]

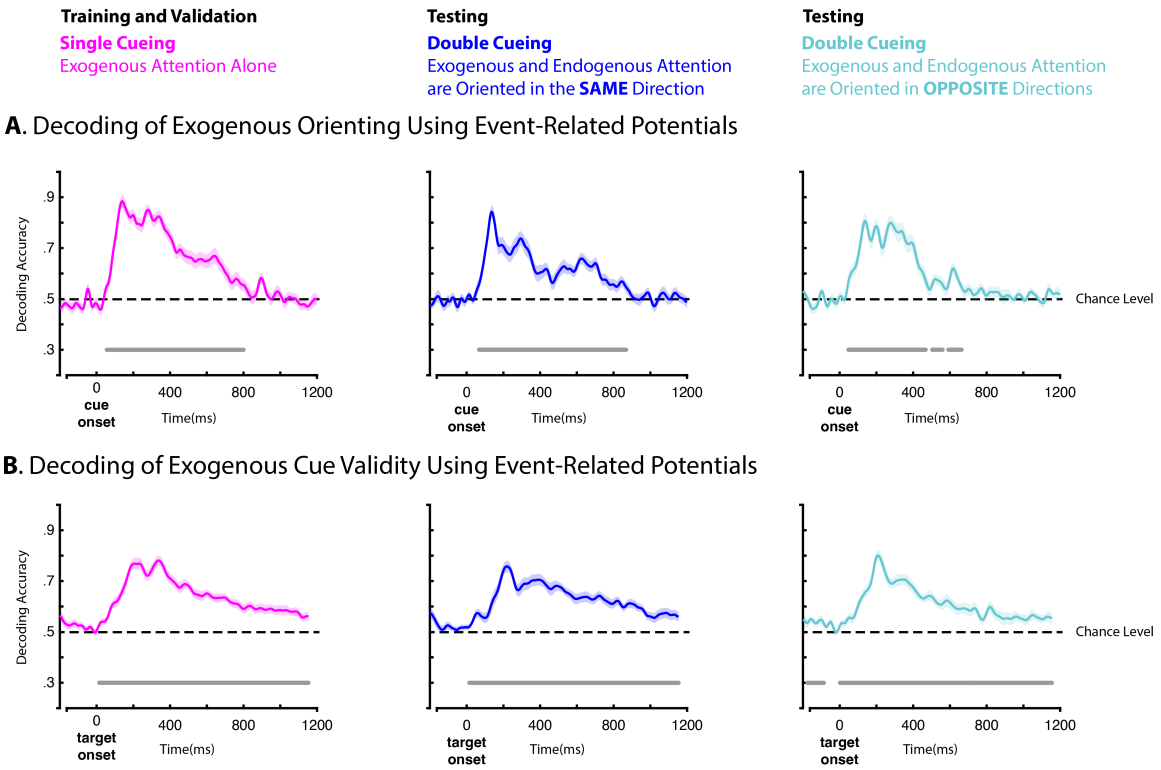
Next, we used multivariate pattern classification to examine the effects of exogenous orienting on cue-related and target-related neural dynamics across single and double cueing. We used a three-fold cross-validation approach described in the method section across two separate decoding challenges. Supplementary Figure 1 provides a description of the pipeline we used.



Supplementary Figure 1. Decoding pipeline that we applied at the subject-level (**A**). For each participant, across all channels, we randomly separated epoched EEG time series from each trial in three separate bins. We then averaged the time series from each bin separately. We used SVM to decode the effects of exogenous attention. For each time point, we trained the classifier using two data points and then validated it on the remaining one. We iterated this process three times so that each averaged epoched was used twice for training and once for validation. We applied this strategy across two decoding challenges (**B**). In the first challenge, we focused on classifiers trained and validated during single cueing and examined how well they performed in the context of double cueing. For the second challenge, we validated whether SVM classifiers could decode the cueing condition: Single versus double cueing.

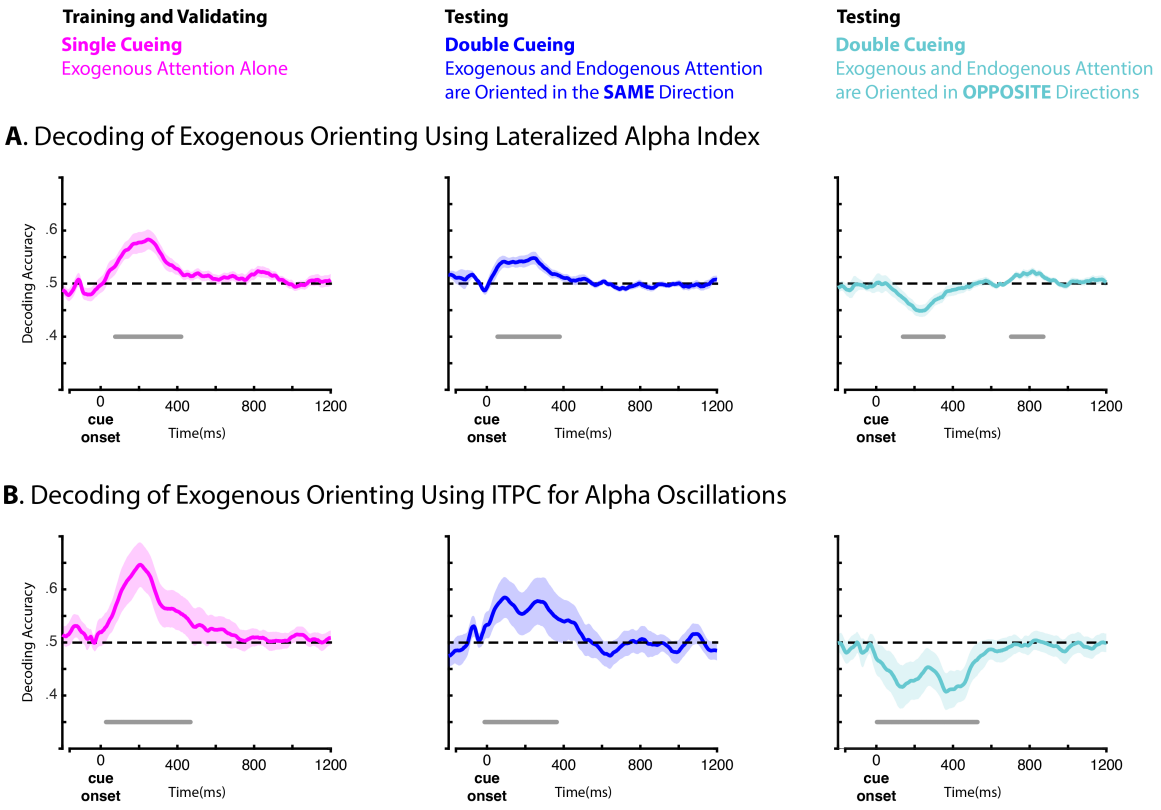
Challenge I: Generalization of decoding

We first applied this decoding approach to cue-related and target-related waveforms. We evaluated classification performances using cluster-corrected one sample t-tests against chance-level (i.e., 50%). Here, the validation procedure shows that the classifiers were able to perform above chance level (i.e., 50%) in all conditions for single cueing (supplementary Figure 2A and 2B). Next, we examined how well these classifiers performed when they were tested in the context of double cueing. Again, the classifiers performed better than chance-level (supplementary Figure 2A and 2B).



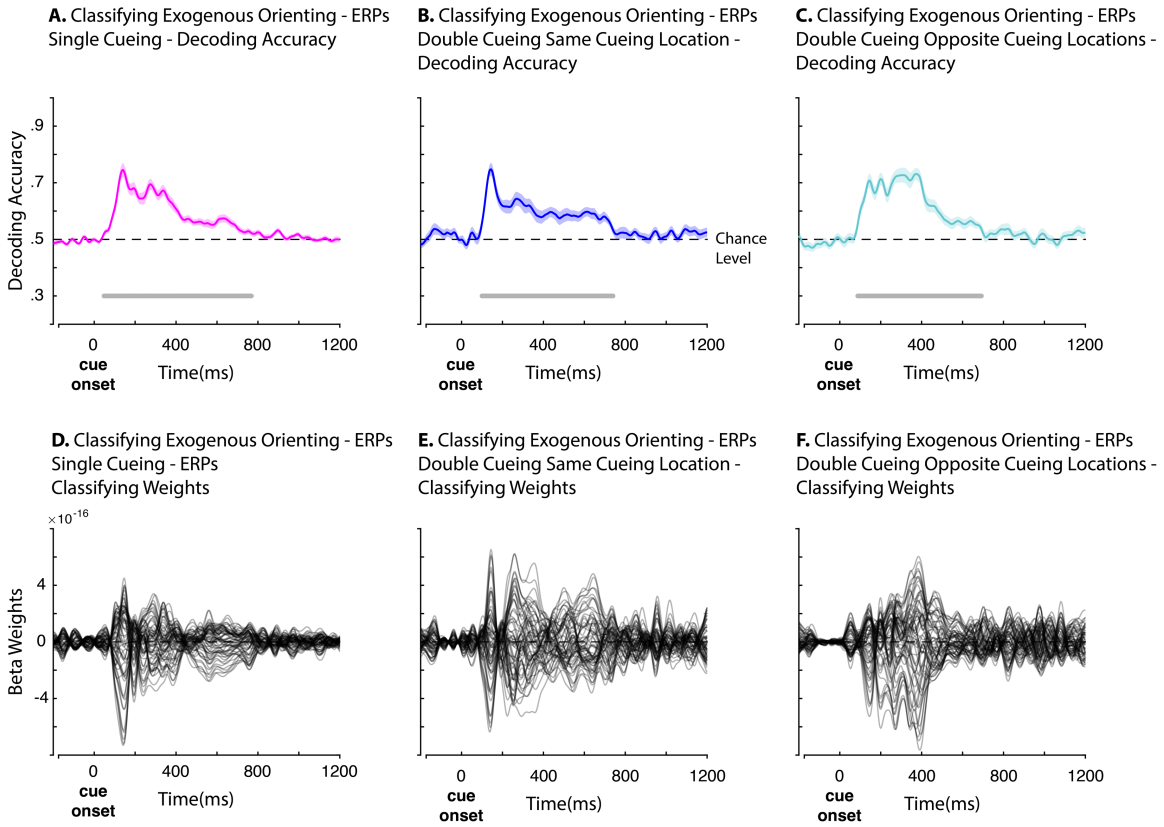
Supplementary Figure 2. Multivariate classification of exogenous orienting and cue validity where we trained and validated SVM linear classifiers in the context of single cueing and validated it in contexts of single and double cueing. We separated double cueing into trials where both cues were indicating the same location and trials where they indicated opposite locations. Classification was done at subject-level. We evaluated classification performances using cluster-corrected one sample t-tests against chance-level (i.e., 50%). Grey lines indicate significant clusters. Error bars indicate the SEM for each condition. **A.** Decoding the direction of exogenous orienting based on cue-locked ERPs. **B.** Decoding exogenous attention cue-validity based on target-locked ERPs.

We similarly examined the generalization of classifiers trained in the single cueing condition to the double cueing condition using the power and phase of alpha rhythms. First, we confirmed that validation was better than chance-level using cluster-corrected one sample t-tests against chance-level (i.e., 50%; supplementary Figure 3A and 3B). We then examined how well these classifiers would perform in the double cueing condition. Classification performance was above chance level when both cues indicated the same location. However, when both cues indicated opposite locations, classification performance dropped below chance level (supplementary Figure 3A and 3B).



Supplementary Figure 3. Multivariate classification of exogenous orienting and cue validity where we trained and validated SVM linear classifiers in the context of single cueing and validated it in contexts of single and double cueing. We separated double cueing into trials where both cues were indicating the same location and trials where they indicated opposite locations. Classification was done at subject-level. We evaluated classification performances using cluster-corrected one sample t-tests against chance-level (i.e., 50%). Grey lines indicate significant clusters. Error bars indicate the SEM for each condition. **A.** Decoding the direction of exogenous orienting based on cue-locked lateralized alpha oscillations **B.** Decoding the direction of exogenous orienting based on cue-locked intertrial phase clustering of alpha oscillations.

Lastly, we aimed to explore the encoding model of cue-related processes of exogenous attention. We applied principal component analysis (PCA) to the classifiers' weights to uncover the underlying components to exogenous orienting. In this effort, we decoded the direction of exogenous attention across single cueing alone, double cueing when both cues indicate the same location and double cueing when both cues indicate opposite locations based on cue-related waveform. We validated these classifiers against chance level across all conditions (supplementary Figure 4A, 4B, 4C). We then extracted the beta weights from these conditions (supplementary Figure 4D, 4B, 4C). PCA was applied to these weights. See Method section for more details.



Supplementary Figure 4. Multivariate classification of exogenous orienting based on cue-related waveform across single cueing, double cueing when both cues indicate opposite locations, double cueing when both cues indicate the same location. We trained and validated SVM classifier based on our three-fold cross-validation across all conditions. Classification was done at subject-level. We evaluated classification performances using cluster-corrected one sample t-tests against chance-level (i.e., 50%) across single cueing (**A**), double cueing when both cues indicate the same location (**B**), and double cueing when both cues indicate opposite locations (**C**). Grey lines indicate significant clusters. Error bars indicate the SEM for each condition. Then, we extracted the beta weights of the SVM classifiers across the time series for single cueing (**D**), double cueing when both cues indicate the same location (**E**), and double cueing when both cues indicate opposite locations (**F**).