Attentional Engagement and Disengagement: Quantifying Attentional Shifts Utilizing the Steady State Visual Evoked Potentials

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Abstract

In the present study we aimed to measure and discern between attentional shift processes. We utilized the EEG frequency tagging technique in an experimental design that required participants to switch their attentional focus between four stimuli flickering at distinct frequencies. Through the analysis of steady-state visual-evoked potential (ssVEP) responses we were able to study the time course and temporal dynamics of different attentional shifts. Specifically, engagement with a to-be attended target, disengagement from a previously attended target and reengagement with a new target. Importantly, our experimental design and analysis allowed for measuring these processes not only on the group, but also on the individual subject level. On the group-level, both attentional disengagement and reengagement were evident, with the process of disengagement occurring prior to reengagement. Interestingly, on the individual subject level several distinct patterns of attentional shifts emerged: While a major portion of participants mirrored the group-level trend, in a subgroup of participants only attentional disengagement could be identified, in some only reengagement, and others showed no discernible shifts in ssVEP amplitude. Notably, the timing of these attentional shifts varied across individuals relative to target switch events. Echoing prior studies, our findings shed light on the independent and gradual nature of attentional shift processes and underscore the importance of examining these shifts at both the group and individual levels. Our study provides deeper insights into the neural mechanisms that drive attentional dynamics.

keywords: attentional shifts, attentional engagement, attentional disengagement, ssVEPs, EEG

Introduction

Moment by moment our senses are exposed to information from the external environment as well as our internal world, such as thoughts and bodily sensations. Attention processes allow us to deal with the limited capacity of perceptual and cognitive systems that use this information. One central hypothesis states that attentive selection is accomplished by biasing certain types of information and suppressing others (Desimone & Duncan, 1995). Consequently, attention modulates many essential cognitive processes such as perception, working memory and executive functions (Luck & Gold, 2008). A key attentional aspect allowing for adaptation in a continuously changing environment is selective attention - the ability to prioritize a certain location, stimulus feature, or sensory modality by shifting attention towards it (attentional engagement). This also includes the ability to shift attention away from a certain input (attentional disengagement) and to redirect it towards a new attended input (attentional reengagement; Petersen & Posner, 2012; Posner & Rothbart, 2007).

Understanding the time course and temporal dynamics of such attentional shifts is fundamental for elucidating the mechanisms underlying adaptive cognitive processing (Corbetta & Shulman, 2002). Attentional engagement, the allocation of attentional resources to a specific stimulus, is critical for perceptual accuracy, particularly in scenarios requiring rapid processing of environmental stimuli (Carrasco, 2011). Conversely, attentional disengagement, the withdrawal of attention from a stimulus, as well as the redirection or reengagement of attention to a new target is essential for cognitive flexibility, as it facilitates the reallocation of attentional resources in complex environments where the relevance of stimuli can change rapidly (Luck et al., 2021; Lutz et al., 2008; Theeuwes, 2010). The interplay and temporal relations between these components - engagement, disengagement, and reengagement - are central to the flexible allocation of cognitive resources, which is

fundamental for navigating in environments characterized by information flux and requiring continuous adaptation. Such adaptability not only underscores cognitive efficiency, but also hints at its significance in promoting resilience and well-being (Dahl et al., 2020).

One of the most prominent methods used in recent years to closely examine the time course and temporal dynamics of attentional shifts is steady-state visual evoked potentials (ssVEPs). SsVEPs are oscillatory cortical responses evoked by the periodic modulation of a sensory stimulus over a period of several seconds. These responses are characterized by rhythmic engagement of groups of neurons that are responsive to the stimulus. ssVEPs can be identified as oscillatory brain responses that match the frequency of the stimulus (Vialatte et al., 2010). This tool is especially useful in attentional research, with the time-varying amplitude of ssVEPs providing a continuous measure of attentional resource allocation. Specifically, increased ssVEP amplitudes are an indication of heightened attention directed towards locations, features and/or objects (Andersen et al., 2011a; Andersen & Müller, 2010; Hartjen & Müller, 2022; Müller et al., 1998; Norcia et al., 2015; Vialatte et al., 2010) while, decreased ssVEP amplitudes reflect decrease of attention towards such inputs (e.g., Kritzman et al., 2022).

SsVEPs provide several advantages when studying attention allocation related processes. These include high signal to noise ratio (SNR) due to the narrow band filtering of specific frequencies and the possibility of following attentional processes over longer periods of time without being constrained to time locked data. Moreover, ssVEPs enable the measurement of attentional allocation towards a specific stimulus even when it is embedded in a complex scene using the frequency tagging technique. In this technique the response to various stimuli can be isolated by periodically modulating the luminance of the stimuli (i.e., flickering) at different frequencies. This allows to quantify attention allocated towards different, simultaneously presented, stimuli and therefore to compare between attentional

conditions (Norcia et al., 2015; Wieser et al., 2016). For example when presenting two embedded random dot kinematograms (RDKs) of different colors flickering in different frequencies in the same spatial location, the mere direction of attention to one of the two RDKs (i.e., to a specific color) results in enhanced amplitude of the time-varying signal in the attended frequency (Adamian et al., 2019; Andersen et al., 2011a; Andersen & Müller, 2010; Forschack et al., 2017; Gundlach et al., 2022).

Studies utilizing this approach have also provided significant insights into the time-sensitive nature of such attentional shifts. For example, utilizing a design in which participants had to attend to either one of two superimposed RDKs, Andersen and Müller, (2010) found that, amplification of ssVEP amplitude in response to the attended stimulus occurred prior to the reduction in the amplitude associated with the stimulus that participants needed to ignore. This finding suggests that these two attentional processes are independent from one another. Later studies (Müller et al., 2016; Vieweg & Müller, 2021) have advanced our understanding of the temporal dynamics of attentional shifts, by examining switching of attentional targets, thus requiring the participants to disengage their attention from a previously attended target and to redirect it to a new target. Specifically, these studies employed a design in which participants had to switch their attention between overlapping, similar or different, features. Interestingly, the cortical response that represents reengaging attention to a new target occurred prior to disengagement from a previous one and did not occur simultaneously. Moreover, the latency of this switch was longer for attentional shifts that occur across different features (e.g., color to orientation) as compared with attentional shifts within the same features (e.g., one color to a different color). This points at the latency of disengagement and reengagement as an important indicator for attentional effort. While these studies offer significant insights, there is a further need to utilize additional approaches

that encompass the continuous and fluid nature of attention transitions between different stimuli throughout the entire experimental time course.

The high SNR of ssVEP is an advantage not only for studying attentional allocation related processes on the group level, but also on the individual subject-based level (e.g., Gundlach et al., 2020; Nunez et al., 2015). Studying these processes on the individual level is of significant importance considering the high inter-individual variability in attentional processes (Petersen & Posner, 2012). The latter is often masked by group-level analyses which can potentially miss inter-individual differences and therefore reach conclusions that do not represent the entire sample/population. By analyzing data at the individual level, researchers can identify a richer set of patterns that might not be evident in group averages. Moreover, such analysis is essential for understanding the neural mechanisms underlying attentional shifts more fully. For instance, Gundlach et al., 2022 demonstrated that participants with the greatest ssVEP amplitude facilitation towards an attended stimulus did not necessarily show the highest magnitude of ssVEP amplitude suppression to the unattended stimulus, supporting the idea that attentional engagement and disengagement are two separate processes and suggesting that individuals may exhibit various combinations of abilities in these processes. Furthermore, individual differences in attentional shifts have also been repeatedly linked to individual differences in several psychological conditions such as anxiety and depression (Eysenck et al., 2022; Koster et al., 2017). For instance, an individual's unique attentional biases might lead them to overly focus on negative stimuli, potentially exacerbating anxiety, or depressive symptoms. Conversely, those with a natural propensity to disengage quickly from distressing stimuli might exhibit resilience against these conditions (Abado et al., 2020; Bar-Haim et al., 2007; Derakhshan, 2020; Dolcos et al., 2020; Okon-Singer, 2018). Therefore, examining attentional shifts on the individual level is crucial for capturing the complexity and diversity of attentional processes and allows for a more

nuanced understanding of the neural mechanisms underlying attention and their role in psychopathology and healthy functioning.

The main goal of the present study was to measure and discern between attentional shift related processes, namely engagement, disengagement, and reengagement of attention on both the group and individual subject level. To this end, we have utilized the frequency tagging technique in an experimental design that required the participants to switch their attentional focus between stimuli presented simultaneously in the same visual space. A second goal of this study was to quantify individual differences in the latency of disengagement, and reengagement processes. We hypothesized that ssVEP responses will reflect distinct patterns of neural activity corresponding to attentional engagement, disengagement, and reengagement. Specifically, we expected to observe an increase in ssVEP amplitude during engagement, a decrease during disengagement, and a subsequent increase during reengagement. In addition, we anticipated that there will be significant individual variability in patterns of attentional shifts as measured by the latencies of attentional disengagement and reengagement.

Method

Participants

Forty-one participants with normal color perception in ages between 18 - 35 were recruited from the Reichman university's psychology department for course credits. Exclusion criteria included current or past neurological or psychiatric disorders. Twelve participants were excluded from analysis: Six due to equipment malfunction, one due to low task performance (for details see “Behavioral accuracy” in the Results section), and five due to excessive lateral eye movements (for details see “Data preprocessing” in the Methods section). Thus,

the final experimental sample included 29 participants (18 females; 24 right-handed, mean age = 24.48 (SD = 3.26). The study was approved by the university's ethics committee.

Experimental stimuli

In line with previous designs (e.g., Andersen et al., 2011a), two overlapping random dot kinematograms (RDKs) of different colors (red, RGB = 1, 0, 0, and green, RGB = 0, 0.8, 0) were presented on both the left and the right side of a central fixation arrow (see Figure 1). Each of the total four RDKs consisted of a population of 700 dots flickering at either 8, 10, 12 or 15 Hz. For each participant, the flickering frequencies were pseudo-randomly assigned to each of the four RDKs. The outer edges of each circle shaped RDK had a visual angle of 13.92° and the circles' inner edges were located 0.92° from a fixation point. Each dot occupied 0.15° and was moving randomly to one of four cardinal directions. Coherent motion events in the RDK were created for the behavioral task (see section Experimental task) by including short periods (333 ms) during which 80 percent of the dots in the attended RDK moved in the same direction. Stimuli were presented against a black background on a 24-inch monitor display (AOC G2460PF), with resolution of 1920 X 1080, and a refresh rate of 60 frames per second.

Experimental task

Each trial started with the presentation of a red or green cue arrow, pointed either to the left direction, the right direction or a bidirectional arrow pointing to both directions, as shown in Figure1. Thus, there were overall 6 possible attentional targets which occurred with equal probability: red-right, red-left, red-bidirectional, green-right, green-left, and green-bidirectional. A white fixation dot appeared at the center of each arrow during the entire task. Following a random interval of 1 to 2 s (average of 1.5 s across trials ± 0.5 s jitter), all four RDKs appeared on the screen. To obtain measures of attentional disengagement and

reengagement (as defined in the introduction), a target shift occurred in the middle of the trial: after a random interval of 2.5 to 3.5 s (average of 3 s across trials ± 0.5 s jitter, to avoid temporal expectancy effects) the cue arrow changed either its color, its direction or both ("target switch"), and all flickering dots remained on the screen until a 6 s interval elapsed. In each trial, the participants were given the task of attending to a specific RDK (attended target) specified by the first cue arrow, and to switch their attention to a new target after the arrow has changed. In addition, to assure that participants were engaged with the task they were asked to detect short intervals of coherent motions in the attended stimulus, which occurred in 30 % of the trials. Coherent motion events could appear in the first attended target (before the condition switch), in the second attended target (after the switch) or in both, and their onset did not occur earlier than 0.4 s following the onset of the RDKs or the target switch and not later than 0.25 s before the switch or the end of the trial. At the end of each trial, participants were asked to report the number of coherent motions they detected using a button press (possible answers were 0, 1 or 2 coherent motions). The experiment included a total of 180 trials, presented in 6 blocks of 30 trials with one break between the blocks (total of 5 breaks). Participants were instructed to maintain their gaze on the white fixation dot located at the center of the cue arrow during the entire task.

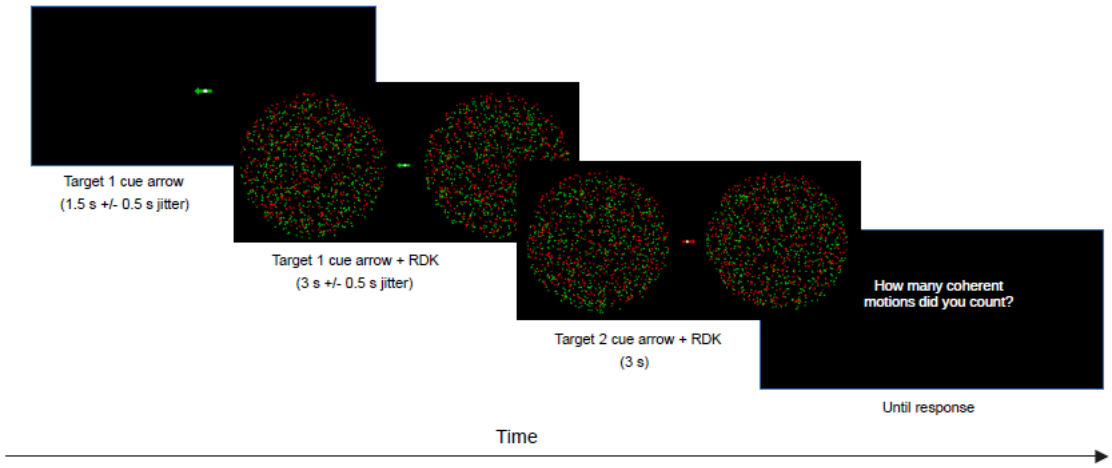

Figure 1. The experimental trial design and configuration (not to scale). Each trial started with 1.5 s ± 0.5 s presentation of a red or green cue arrow, pointing either to the left direction, the right direction or to both directions, followed by the appearance of four random dot kinematograms (RDKs; four clouds of dots, each flickering in one of the stimulation frequencies). After a random interval of 2.5 to 3.5 s the cue arrow changed its color, or its direction or both ("target switch"), and all flickering dots remained on the screen until a 6 s interval elapsed. Participants had to direct their attention to the target according to the cue arrow. At the end of each trial participants were asked to report the number of coherent motions they counted (0,1 or 2).

Procedure

Upon arrival at the lab, participants were given an overview of the experiment, and after signing a consent form, they were connected to the EEG set up. The experiment took place in a dimly lit room. Participants were seated approximately 0.65 meters from the screen. Following a 6-min baseline recording (3 minutes resting state with eyes open and 3 minutes with eyes closed) they were provided with instructions for the main task and performed a training session of 18 trials or more, until the experimenter confirmed that participants understood the task (via conversation and observation of their performance during the practice trials). They then performed the main task followed by an additional resting state recording performed as described above.

Data acquisition

Continuous electroencephalographic (EEG) activity was recorded using the ActiveTwo BioSemi system (BioSemi, Amsterdam, The Netherlands). Recordings were obtained from 64 scalp electrodes based on the ten-twenty system, as well as from two electrodes placed on the left and right mastoids. The electrooculogram (EOG) generated from blinks and eye movements was recorded from four facial electrodes: two approximately 1 cm above and below the participant's right eye, one approximately 1 cm to the left of the left eye, and one approximately 1 cm to the right of the right eye. As per BioSemi's design, the ground electrode during acquisition was formed by the Common Mode Sense active electrode and

the Driven Right Leg passive electrode. All bioelectric signals were digitized on a laboratory computer using ActiView software (BioSemi). Data was digitized at a sampling rate of 2048 Hz, utilizing a high pass filter set at 0.16 Hz and a low-pass online filter set at 100 Hz. The electrode offset was kept within ± 25 mV according to the user manual. In order to achieve greater synchronization between visual stimuli presentation and EEG recordings, we used a set of photodiodes that sent the stimulus triggers with high precision as they appeared on the screen (Peterson et al., 2014).

Behavioral accuracy

Behavioral accuracy scores in the coherent motion detection task were calculated using the following formula which was based on Pollatos & Schandry, (2004).

$$Accuracyscore = \frac{1}{N}\sum_{i=1}^{N} 1 - \left(\frac{ncoherentmotion_i - ncoherentmotion\ reported_i}{ncoherentmotion_i}\right)$$

Where N is the total number of trials in which coherent motions were presented and n is the number of coherent motions in a specific trial (i).

Data pre-processing

Offline pre-processing was performed in Matlab (The MathWorks; R2020a), using in-house built scripts, based on functions from EEGLAB (Delorme & Makeig, 2004) and Fieldtrip (Oostenveld et al., 2010). The continuous data were bandpass filtered offline in the 1- 60 Hz range (Hamming windowed sinc FIR filter) and were then down-sampled to 512 Hz. Subsequently, the data was segmented into 8 s epochs from 1 s before the onset of the RDKs to 1s after the offset of the RDKs. The data was then re-referenced to the average of both mastoids. Blinks and eye movement artifacts were identified and corrected utilizing the Second Order Blind Identification method (Belouchrani et al., 1997) and the IClabel (Pion-Tonachini et al., 2019). In order to assure that amplification/attenuation of response to the

different attentional targets can be attributed to the allocation of attention and is not the result of directing gaze towards and away from the attended targets, participants with excessive lateral eye movements were excluded from the analysis (five participants). Further rejection of artifactual trials and interpolation of noisy electrodes were performed using a Statistical Control of Artifacts in Dense Arrays Studies (SCADS) method, fully described in (Junghöfer et al., 2000).

SsVEP analysis

To assure that selective attention was solely based on the stimulus color and direction, with no interference from coherent motion events, trials containing coherent motions were excluded from the analysis. The current analysis was focused on attentional allocation towards unidirectional stimuli only (i.e., attending to RDKs on either the left or the right side of the fixation arrows), such that trials containing bidirectional stimuli (i.e., trials in which subjects needed to attend simultaneously to RDKs flickering on both sides of the fixation arrows) were not included. These conditions were included in the experiment to assess attentional processes related to the narrowing and widening of attention, which is beyond the scope of the current paper.

SsVEP signal quality evaluation

To visualize and evaluate the quality of the ssVEP signal, the pre-processed time-domain EEG data was averaged across trials, posterior electrodes (‘OZ’, ‘POZ’, ‘O1’, ‘O2’), conditions and subjects. In addition, the frequency content of the data was estimated by subjecting the trial-averaged time domain data to a fast Fourier transform (FFT) analysis to verify that the flickering dots reliably evoked steady-state responses in the expected stimulation frequencies. This analysis was conducted on the data within a time window extending from one second post RDK onset to one second pre RDK offset.

Rhythmic entrainment source separation (RESS) analysis

SsVEP responses were extracted via rhythmic entrainment source separation (RESS; Cohen & Gulbinaite, 2017). In this analysis, a map of spatial weights across all electrodes is created in order to extract ssVEP signal, without relying on a priori or post-hoc electrode selection. Specifically, in RESS analysis linear spatial filters are created to maximally differentiate the covariance between signal in the flicker frequency and neighboring frequencies, thereby the SNR at a particular frequency is optimized, for each participant. After obtaining signal and neighboring covariance matrices, a generalized eigen decomposition is computed, and the eigenvector with the largest eigenvalue is used as channel weights to obtain a single component time course, which reduces multiple comparisons across channels in statistical testing. RESS was performed on the entire pool of artifact-clean trials, including trials that contain bidirectional targets that were otherwise not analyzed (see section SsVEP analysis). Interpolated electrodes (see section Data pre-processing) were not included in the analysis (Cohen & Gulbinaite, 2017). A single RESS filter was created for the four distinct stimulation frequencies by computing separately four covariance matrices and then averaging them together, to yield a single signal covariance matrix (Cohen & Gulbinaite, 2017). A single reference ("noise") covariance matrix was constructed similarly. A generalized eigen decomposition was then computed on the signal and reference covariance matrices as described above. The spatial filter (i.e., weights) was then applied, by multiplying it by the EEG electrode time series.

The Time-varying ssVEP Amplitude

For each stimulation frequency, we extracted the full length of all trials in which this frequency was the attended target before the switch (i.e., target 1). Similarly, for each stimulation frequency, trials in which this frequency was the attended target after the switch

(i.e., target 2) were extracted (see Figure 2). Thus, two attentional conditions were formed: 1) “engage target 1 - disengage target 1” and 2) “ignore target 2 - reengage target 2”.

For each stimulation frequency the time-varying amplitude envelopes in each of these attentional conditions were extracted by subjecting the RESS time series to Hilbert transform, as described in FreqTag toolbox (Figueira et al., 2022; using the function freqtag HILB). In the first step, trials for each frequency and each attentional condition were averaged separately. Next, each averaged signal was baseline corrected by subtracting the mean amplitude of a 0.5 s pre-stimulus period (i.e., prior to RDK onset), from each time point along the trial. The data from each frequency was then narrow band filtered (in the stimulation frequency range ± 0.5; 9th order Butterworth). The amplitude was extracted as the absolute value of the Hilbert transformed analytic signal (see Figure 2 for the full procedure).

To be able to average trials within the same attentional condition across different stimulation frequencies, the data was normalized to account for the typical ‘1/*f*’ distribution of power spectrum data, (i.e., the decrease of amplitude (A) with increasing frequency), (Andersen et al., 2011b; Gyurkovics et al., 2021). As dictated by the experimental design, all four stimulation frequencies were presented in each trial, and trials differed from each other by the frequency at which the attended target was flickered. Therefore, the normalization was performed, as follows (as described in the equation below): For each participant (i), for each attentional condition (k: “engage target 1 - disengage target 1”, “ignore target 2 - reengage target 2”) and each of the stimulation frequencies (j: 8 Hz, 10 Hz, 12 Hz, 15 Hz), the amplitude of the attended frequency was divided by the weighted mean of that same frequency's amplitude when derived from all possible stimulation conditions (nT = number of trials in the specified frequency condition). For example, the normalized amplitude of 8 Hz target frequency was calculated by dividing its amplitude in the attend 8 Hz conditions, by

the weighted mean of the 8 Hz amplitude measured in all possible target frequency conditions (i.e., when the attended target was either 8 Hz, 10 Hz, 12 Hz, 15 Hz).

$$normalizedA_{ikj} = \frac{A_{ikj}}{\frac{1}{nT_{total}} * (A_{ikj(8\,Hz)} * nT_{ikj(8\,Hz)} + A_{ikj(10\,Hz)} * nT_{ikj(10\,Hz)} + A_{ikj(12\,Hz)} * nT_{ikj(12\,Hz)} + A_{ikj(15\,Hz)} * nT_{ikj(15\,Hz)}}$$

Thus, a normalized amplitude value > 1 signifies a greater response to the attended target (e.g., red-left) over the response to all possible flickering stimuli (e.g., red-left, green-left, red-right, green-right), whereas a normalized amplitude value < 1 signifies a decreased response to the attended target (e.g., red-left) over the response to all possible flickering stimuli (e.g., red-left, green-left, red-right, green-right; Figure 2). Following normalization, the signals were averaged across target frequencies in each attentional condition for each participant, to yield a single time series per attentional condition, which were submitted to statistical analysis. The main steps of the analysis are summarized in Figure 2.

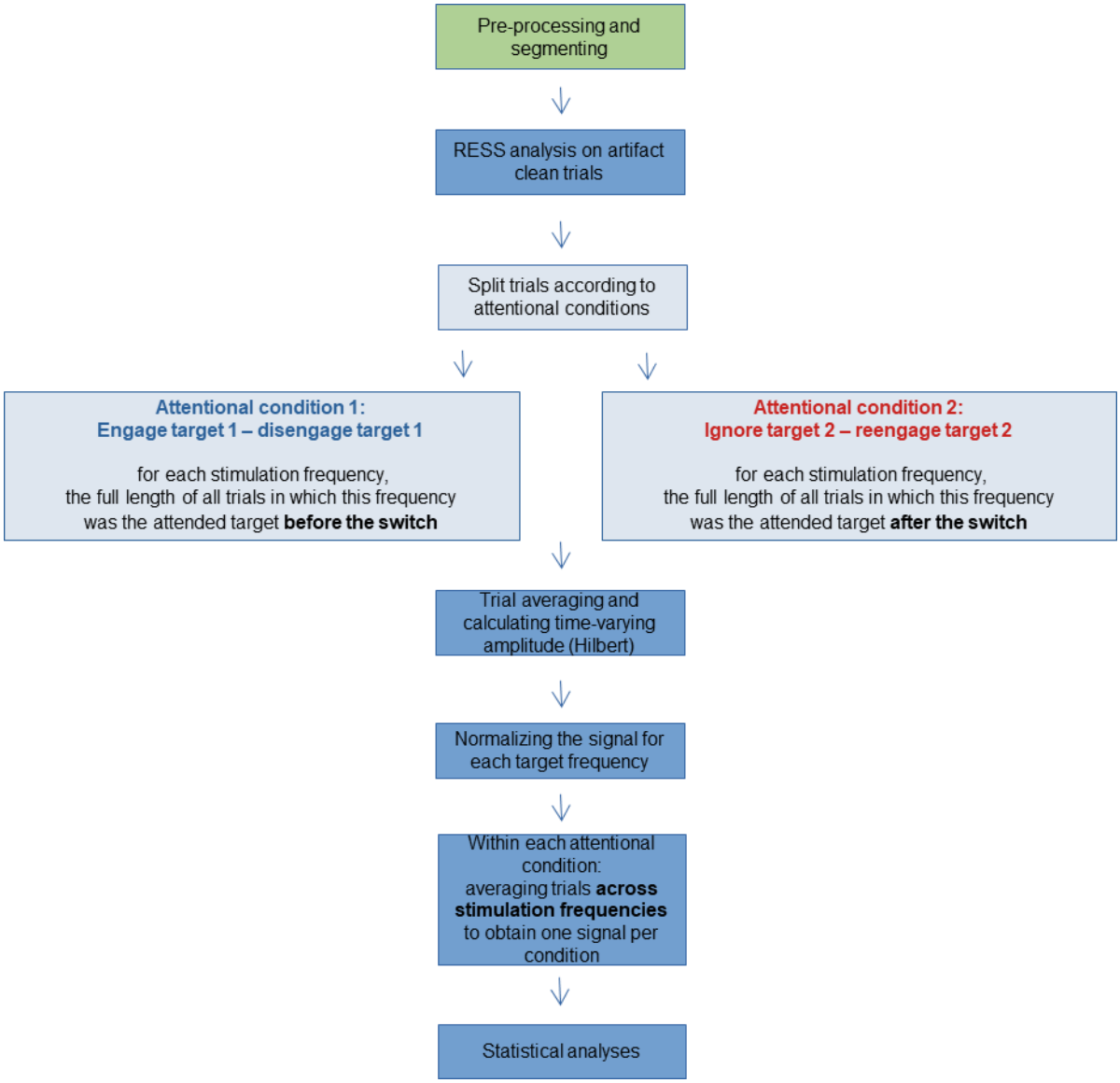

Figure 2. Main steps in data analysis. Following the initial steps of data preprocessing and segmentation, the entire pool of artifact-clean trials was subjected to RESS analysis, which allows for the extraction of ssVEP signals without relying on a priori or post-hoc electrode selection. The RESS procedure resulted in a single time series per trial, for each participant. The trials were then split according to the two attentional conditions defined: 1) "engage target 1 - disengage target 1" and 2) "ignore target 2 - reengage target 2". Next, for each attentional condition, the trials of each stimulation frequency were averaged separately and subjected to Hilbert transform, to calculate the time-varying ssVEP amplitudes. The data was then normalized, which enabled the averaging of trials across the different stimulation frequencies. The normalized data were averaged within each attentional condition, resulting in a single signal per attentional condition, which was then used for statistical analysis.

Statistical analysis

For statistical analysis, two time windows were defined per each attentional condition: an early time window of 2.5 s before the target switch starting 0.5 s after the onset of the RDKs, and a later 2.5 s window starting 0.5 s after the target switch. These intervals were chosen in order to avoid contaminating responses related to RDK onset and to the target switch cue. This resulted in a 2x2 within-subject design of two time windows (before switch, after switch) by two attentional conditions ("engage target 1 - disengage target 1", "ignore target 2 - reengage target 2"). Specifically, for each participant and for each attentional condition, the amplitude of the time-varying signal was averaged across data points within each time window to yield four distinct values per participant (i.e., engage target 1 before switch, disengage target 1 after switch, ignore target 2 before switch, reengage target 2 after switch). These values were compared using a 2x2 repeated measures ANOVA with Bonferroni correction for multiple comparisons.

Change point analysis

To identify attentional shifts and calculate their latency (relative to the target switch) on the group and on the individual subject level, we utilized the cumulative sum approach based on Taylor (2000). Using this approach, it is possible to determine whether and if so, when, a change in the data occurred. To this end, the trial-averaged time varying signal of each participant (for the individual level analysis) and the group averaged signal (for the group level analysis) in each attentional condition was first down sampled to include a total of 31 points (out of the original 3074 points), in line with previous work (e.g., Tebbe et al., 2021). The signal was then averaged across these data points and the difference between each point and this averaged signal was calculated. Next, a cumulative sum was calculated such that

these differences were added consecutively. Finally, a magnitude of change estimator was established by calculating the difference between the highest and lowest values along the cumulative sum curve. The significance of change was determined by means of bootstrap analysis such that the 31 data points were randomly reordered to create 1,000 possible datasets. The same cumulative sum procedure was performed for each randomized data and a magnitude of change estimator was calculated. To determine whether a significant change has occurred, the number of estimators in the randomized data smaller than the magnitude of change estimator in the original data was divided by the number of bootstraps (1,000) and multiplied by 100 to produce a percentage of estimators smaller than the real estimator. This reflects the confidence interval that a real change has occurred. If a significant change was indeed observed, the extreme point in the cumulative sum curve was extracted and used as an estimate of when this change has occurred. Since this procedure was applied separately for each attentional condition, it allowed us to determine whether attentional disengagement (i.e., shifting attention away from target attended before the switch), reengagement (i.e., shifting attention towards a target that was unattended before the switch), or both occurred and if so, when they occurred along the experimental trial timeline.

Signal-to-Noise ratio analysis

To ensure that inter individual differences in attentional patterns were not attributable to individual variations in Signal-to-Noise Ratio (SNR), we calculated SNR values for each participant by extracting the power in the stimulation frequency (8, 10, 12, 15 Hz; i.e., the signal) and dividing it by the average power of neighboring frequencies (±1 Hz; i.e., the noise). The power values were extracted as described in section SsVEP signal quality evaluation. The SNR values obtained for each stimulation frequency were then averaged to obtain a single SNR score per participant. Subsequently, a repeated measures ANOVA was

employed to examine the SNR scores in relation to the four distinct patterns of attentional disengagement and reengagement identified (see section Change point analysis).

Results

Behavioral accuracy

Participants were successful at performing the visual task, as indicated by their high behavioral accuracy scores (M = 0.85, SD = 0.13, range: 0.44 – 0.98). The data from one participant who performed poorly on the task (accuracy score = 0.44) was excluded from further analysis leading to mean accuracy scores of M = 0.86, SD = 0.11, range: 0.64 – 0.98.

SSVEP signal quality analysis

The steady-state visual evoked signal is illustrated in Figure 3a. Reliable peaks at the four stimulation frequencies (8, 10 12 and 15 Hz) are clearly seen in the FFT power spectrum (Figure 3b). Figure 3c shows the topography of activity in each stimulation frequency.

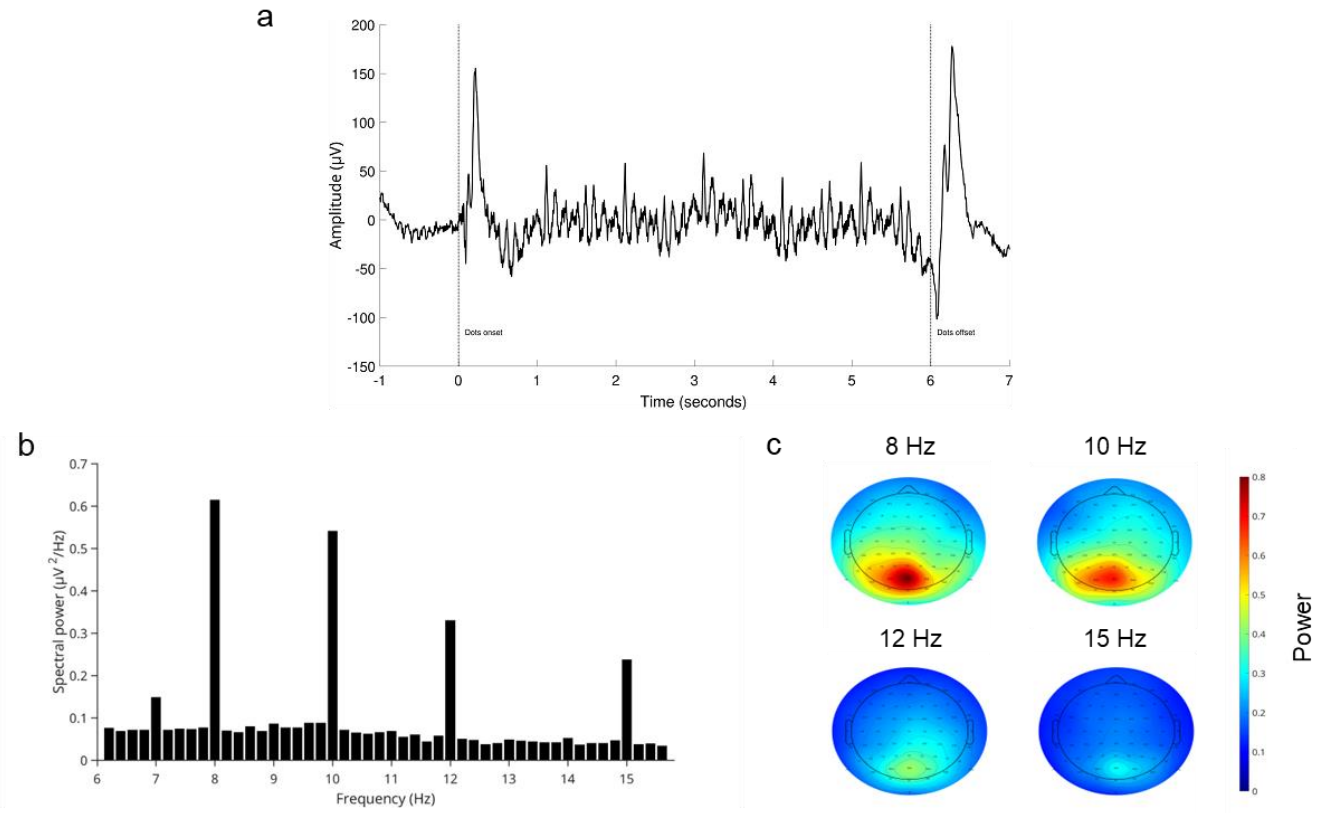

Figure 3. Illustration of the steady-state visual evoked signal. (a) Time domain data from posterior electrodes ('O1', 'Oz', 'POz', 'O2') averaged across trials, attention conditions and across subjects and the FFT power spectrum (b). Reliable peaks in the power spectrum are evident at the stimulation frequencies (8, 10 12 and 15 Hz) (c) Topographic plots of the averaged power (across trials, conditions and subjects) in each stimulation frequency.

Time Course and Temporal Dynamics of Attentional Shifts

The final number of trials did not differ significantly between attentional conditions ("engage target 1 - disengage target 1"; "ignore target 2 - reengage target 2"); mean number of first target trials = 79.62, SD = 6; mean number of second target trials = 80.41, SD = 6.17, $p > .05$, paired t-test)**.**

The time courses of the group averaged signal along the experimental trial in each attentional condition are presented in Figure 4a. As hypothesized, the averaged group activity in trials that corresponded to attentional condition 1 (blue line) was increased after the onset of the RDKs followed by a later decrease, after the switch to attentional condition 2. The averaged group activity in trials that corresponded to attentional condition 2 (red line) showed the opposite pattern, where activity was decreased after the onset of the RDKs (and before the switch) and increased later, after the switch to attentional condition 2.

For statistical analysis, the activity from each attentional condition was averaged across time points within the two time windows: 2.5 s before the target switch and 2.5 s after the target switch (see section Statistical Analysis), resulting in a 2x2 within-subject repeated measures design, of two time windows (before switch, after switch) by two attentional conditions (Figure 4b). A significant interaction effect was found between time window and attentional condition $F(1, 28) = 28.537$, $p < .001$, partial $\eta^2 = .505$. Pairwise comparisons

using Bonferroni corrections revealed significant differences for the first attentional condition ("engage target 1 - disengage target 1") between time windows, such that the magnitude of response while attending target 1 before the switch (Figure 4b, blue full bar) was significantly higher than the magnitude of response when disengaging target 1 after the switch ($p <. 001$; Figure 4b, blue empty bar). The opposite pattern was found for the second attentional condition ("ignore target 2 - reengage target 2") with lower magnitude of response while ignoring target 2 before the switch (Figure 4b, red empty bar) compared with the magnitude of response to target 2 when attending target 2 after the switch ($p < .001$; Figure 4b, red full bar). Significant differences were also found between conditions in both time windows ($p < .001$ in the first-time window and $p = 0.002$ in the second time window).

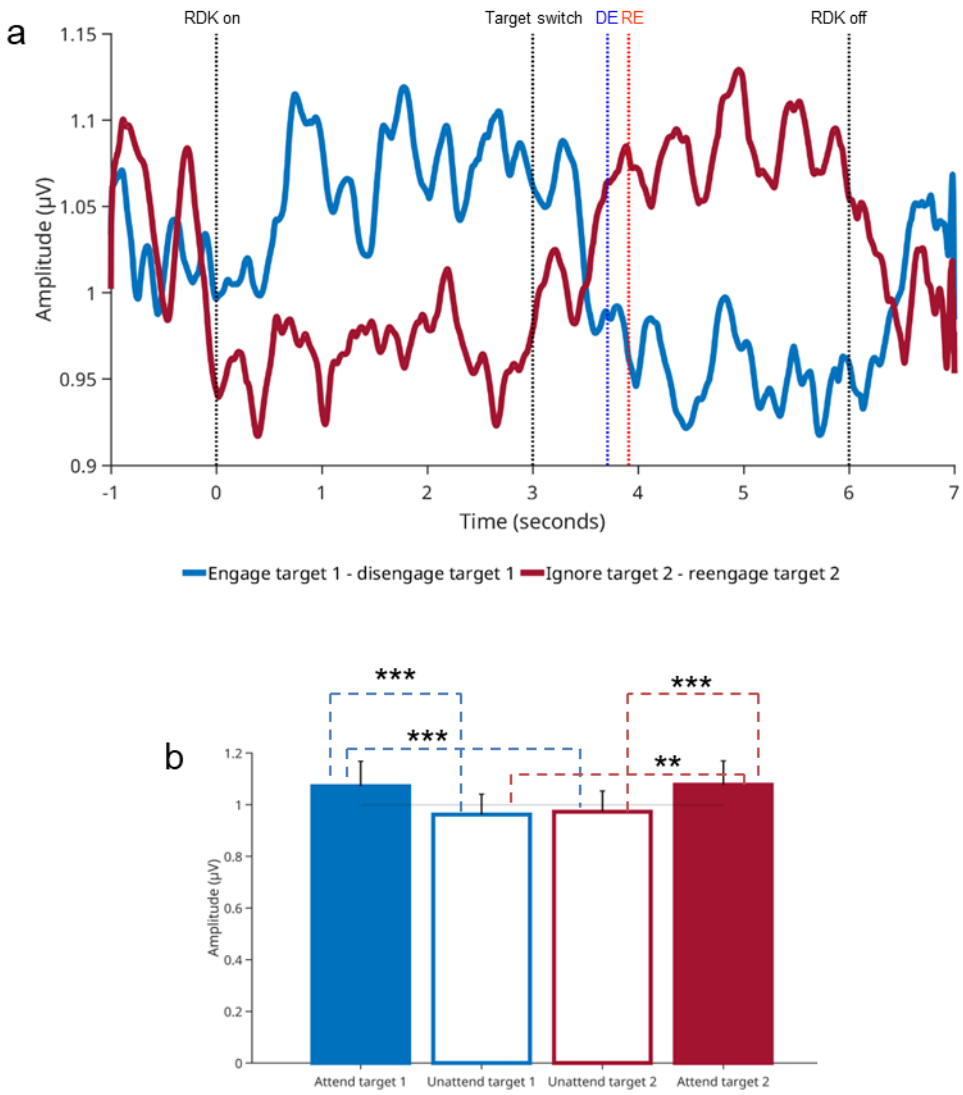

Figure 4. Time course of attentional engagement, disengagement and reengagement (a) Temporal dynamics of the ssVEP response (hilbert envelope) in the two attentional conditions. Significant change points representing the time points in which attentional disengagement (DE) and attentional reengagement (RE) occurred are marked in blue and red vertical lines, respectively (b) Group averaged activity in each attentional conditions in 2.5 s time windows before condition switch (“Engage target 1” and “Ignore target 2” bars) and after condition switch ("Disengage target 1” and “Reengage target 2” bars); **p<.01. ***p<.001.

To test the occurrence and temporal dynamics of attentional shifts on the group and the individual level, each attentional condition was subjected to the cumulative sum change point analysis (as detailed in section Change point analysis). For each participant and for each

attentional condition, points of significant shifts of attention were identified using bootstrap analysis. This approach allowed us to determine whether an attentional shift towards the target, away from the target, or both have occurred, indicating attentional disengagement and reengagement respectively. On the group level, both attentional shifts were found significant ($p < .001$) with disengagement occurring prior to reengagement (time point 3.71 and 3.91 seconds respectively, as depicted in figure 4a, blue and red vertical lines).

On the individual subject level, our analysis revealed four possible patterns of attentional shifts among participants: 1) Both disengagement and reengagement occurred 2) Only disengagement occurred 3) Only reengagement occurred 4) Both disengagement and reengagement did not occur (see Table 1 and supplementary Figure 1). These results indicate that attentional disengagement and reengagement are separate processes, and their latency varies across individuals. Thus, using this analysis we were able not only to determine if a significant shift occurred, but also *when* it occurred along the continuous time varying signal (see Figure 5).

No significant differences in SNR (section Signal-to-Noise ratio analysis) were observed among the four emerging attentional shifts patterns described above $F(3,25) = 1.500$, $p = .239$, with the group means in SNR as follows: no discernable shifts (engagement or disengagement; M = 6.65, SD = 2.16), disengagement only (M = 3.87, SD = 2.15), reengagement only (M = 4.47, SD = 1.93), and both engagement and disengagement (M = 5.99, SD = 2.61). These results suggest that individual differences in attentional shifts patterns cannot be attributed to differences in SNR.

Table 1 proportion of subjects successful in attentional disengagement and attentional reengagement

Proportion of Success in Each Condition (%)		
	Success in Disengagement	Failure in Disengagement
Success in Reengagement	44.83	6.90
Failure in Reengagement	24.14	24.14

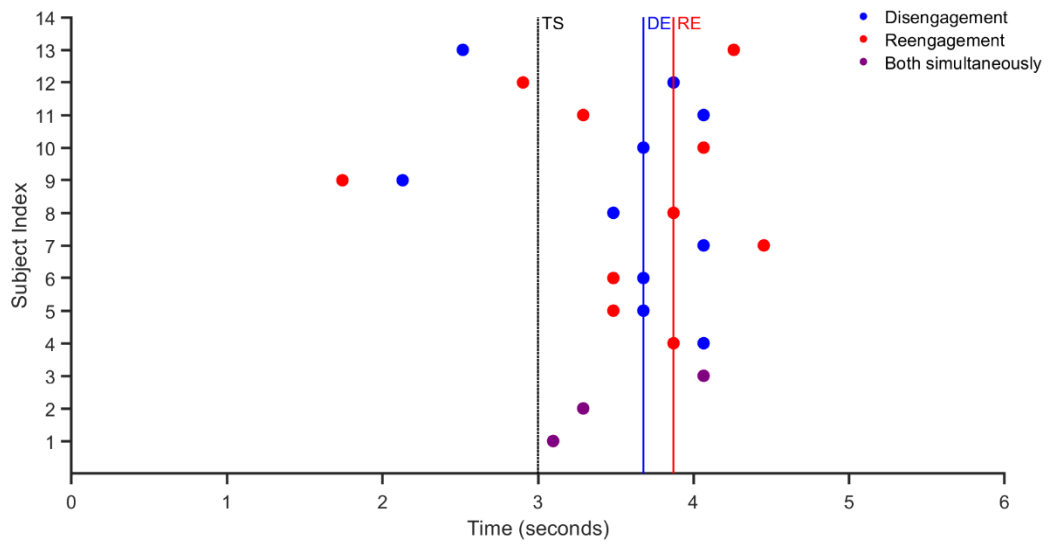

Figure 5: **Significant change points for subjects successful in both attentional disengagement and reengagement**. Each circle represents an individual change point of attentional disengagement (blue), reengagement (red) or both (purple). Blue and red vertical lines represent the change point of the group averaged data for attentional disengagement (DE) and attentional reengagement (RE), respectively. Averaged time point for target switch (TS) in the task is marked in black vertical line.

Discussion

The main goal of the present study was to measure and discern between shifts in attentional focus, specifically engagement, disengagement, and reengagement with an attentional target, on both the group and individual level. To this end, we utilized the frequency tagging technique in an experimental framework that enabled us to characterize and quantify the time course of attentional shifts. Specifically, on the group level, we initially observed increased amplitude in response to an attended stimulus, which subsequently declined when the focus was shifted away from it. In a similar vein, when a second stimulus

became the new target of attentional focus (following a target switch), we observed an increase in amplitude compared to the amplitude measured before it became the attended target. These patterns are aligned with previous work showing that attentional processes such as attention facilitation and suppression occur independently and gradually (Andersen & Müller, 2010; Gabay & Behrmann, 2014; Müller et al., 2016; Vieweg & Müller, 2021).

Indeed, we demonstrated the ability to capture the temporal dynamics of these attentional processes. This was done by quantifying the point in time along the experimental timeline in which a significant attentional shift away from previous target (disengagement) and towards a new target (reengagement) has occurred. Interestingly, we were able to show that while on the group level both shifts were evident, with disengagement occurring slightly prior to reengagement, analysis on the individual subject level revealed different patterns, with some individuals exhibiting only disengagement, some only reengagement, and others exhibiting either both or none. Moreover, our data suggests that for different individuals, attentional shifts occur in different time points relative to the target switch. Furthermore, even when both attentional shifts were evident, they did not necessarily occur concurrently or in the same order relative to one another. These disparities in latencies are consistent with earlier observations, wherein attentional shifts across different features demanded longer latencies than shifts within the same features (Müller et al., 2016; Vieweg & Müller, 2021). Such latency differences might serve as markers of attentional effort reflecting the cognitive exertion required during these attentional processes.

It should be noted that while the above-mentioned studies assessing temporal shifts using ssVEPs found that attentional facilitation of the new target occurred earlier relative to a time-delayed attentional suppression of the previous target, our results suggest that the process of attentional disengagement (away from a previous target) started before the process of attentional reengagement (towards a new target). These findings can be related to the

different analysis used in our study, namely change point analysis (Taylor, 2000). This method particularly identifies when a significant change in trend occurred, rather than detects a significant deviation from a baseline. The divergence in our results vis-à-vis past studies can be attributed to our individual-level analysis, which underscores the variable nature of these processes across subjects. This supports a growing body of literature (e.g., Antonov et al., 2020; Gundlach et al., 2020, 2022; Vieweg & Müller, 2021) emphasizing that attentional shifts are not a uniform process, but instead can be influenced by several factors including task conditions, individual's cognitive capacity, and other personal attributes which highlight the importance of examining these inter-individual variations.

Examining the variability in temporal dynamics and latencies of attentional processes across individuals holds substantial importance, as it may also indicate specific psychological conditions. For instance, increased antisaccade latency found in eye-tracking tasks is a consistent finding among highly anxious individuals indicating a less efficient deployment of attention (Berggren & Derakshan, 2013; Derakshan et al., 2009). Moreover, differences in latencies in ERP components have been associated with several different conditions such as attention deficit/hyperactivity disorder (ADHD) (Kaiser et al., 2020), anxiety (Hsieh et al., 2021) and aging (Kropotov et al., 2016). Therefore, unraveling the processes of engagement, disengagement, and reengagement of attention over continuous periods of time, with the ability to examine the latency of these processes may be valuable for both diagnosis and treatment of psychopathologies (Richter et al., 2020) as well as for recognizing adaptive psychological states such as those developed during meditation practice (Lutz et al., 2015). Moreover, as suggested by MacLeod et al., 2019, gathering information on the individual basis could be especially helpful when assessing attentional related interventions targeted at training more adaptive attentional shifts such as attention bias modification (Hakamata et al., 2010) or mindfulness based interventions (Goldberg et al., 2022). Thus, an experimental

design such as the one used in the current study, which allows to quantify attentional processes objectively and directly, may provide important insights into attentional dynamics associated with both adaptive and maladaptive psychological conditions. Furthermore, this approach may be useful for evaluating the efficacy of interventions, such as attention bias modification or mindfulness-based practices, in modifying attentional patterns. Such insights are particularly important when examining individual differences, for tailoring interventions and understanding the spectrum of attentional behaviors across diverse populations.

Several limitations should be taken into considerations when interpreting the results of our study. First, our experimental design may have introduced a bias in favor of the first attentional target, since the first cue arrow presented before the RDK onset was always identical to the one denoting the first target. While our analysis shows that the overall responses to target 1 and target 2 did not differ significantly (Figure 4b), future designs should account for such a potential bias. Second, in the current experimental design, attentional shifts were possible between different features (two colors – red and green) in the same and / or in different location (left or right side of a central fixation point). Except the constraint that a target cannot remain the same before and after the attentional switch, all shifts were possible. While this design enabled us to quantify the processes we intended to examine (namely attentional engagement, disengagement, and reengagement), there are nuances regarding specific patterns of attentional shifts in the different attention allocation options introduced by our design, that require higher statistical power (i.e., more trials of each type of shift) in order to be profoundly examined. For example, in Adamian et al., 2019, dividing attention between features did not result in a similar outcome as dividing attention between locations. Therefore, it is possible, for example, that in our study participants displaying a pattern of reengagement alone (i.e., no disengagement) may have actually divided their attention without cost, i.e., they widened their attention focus to include the new

target, rather than switched it between the previous and the new target. Thus, further studies with a larger number of trials for each type of shift, whether feature-based or spatial, are needed in order to characterize attentional processes more fully.

In conclusion, the current experimental design allows for the understanding of the time course of attentional engagement, disengagement and reengagement and represents a step forward in understanding the temporal dynamics of attentional shifts. Our findings highlight the independent and gradual nature of these processes and underscore the importance of examining attentional shifts on both the group and individual levels.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgments

This study was supported by the Joy Academic Grant Program and the Sagol family foundation. We extend our gratitude to Amotz Taub-Tabib for his invaluable insights and dedication. Special thanks to our research assistants Adi Gnapp, Eden Tzadik and Galit Pesyachov, for their exceptional contributions and commitment to this study.

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