Reward influences simultaneous competition for feature-based attention: Insights from Steady-State Visually Evoked Potentials

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# Abstract

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# Introduction

Selective attention is crucial for adaptive behavior as it facilitates the processing of relevant stimuli in our environment, as well as the suppression of irrelevant stimuli (Chun, Golomb, & Turk-Browne, 2011; Desimone & Duncan, 1995). This selection depends on the physical salience of a stimulus (e.g., a loud noise) or on people’s current goals (e.g., searching for our keys; Corbetta & Shulman, 2002; Posner, 1980; Theeuwes, 2010). Another crucial factor determining the relevance of stimuli in the world around us is motivation. Goal-driven attentional control is enhanced when individuals are motivated with extrinsic rewards (Botvinick & Braver, 2015; Pessoa, 2015). Attentional can also be guided by previous reward history, independently from attentional control (Awh et al., 2012). Previous reward associations can worsen performance on attention tasks if they conflict with the current goals of the individual (Anderson, 2016; Failing & Theeuwes, 2018; Chelazzi et al., 2013).

Attentional control is enhanced when individuals are anticipating that they can earn rewards for good performance (Krebs & Woldorff, 2017). In fMRI studies reward-based improvements have been related to enhanced activity in frontoparietal regions crucial for attentional control (Pessoa & Engelman, 2010; Krebs et al., 2012). Electroencephalographic (EEG) studies have demonstrated similar preparatory attentional modulations following reward cues in the CNV component (Schevernels et al, 2014, van den Berg et al., 2014). While these studies implicate the frontoparietal activity in reward-based improvements in attentional control, it remains unclear how the activity in these regions is translated into the enhanced processing of relevant features in the visual cortex.

Another set of studies has focused on the influence of reward history on selective attention in situations in which such history is opposed to the current goals of an individual. These studies have provided some evidence for the reward-related changes in the early stages of visual processing (i.e., increase in the P1 component; Hickey, Chelazzi, & Theeuwes, 2010; Donohue et al., 2016; MacLean & Giesbrecht, 2015; Luque et al., 2017). However, other studies have failed to find evidence for such early modulations, and found changes in later stages of processing (increased N2pc component and improved decoding in later processing stages; Qi et al., 2013; Tankelevitch et al., 2019). Thus it remains unclear if the reward-history effects on attention are due to changes in plasticity at the very early stages of visual processing.

Theoretical frameworks propose that the allocation of attention toward stimuli which are (or used to be) predictive of rewards is facilitated, while the processing of other stimuli is suppressed (Anderson, 2016; Awh et al., 2012; Chelazzi et al., 2013; Failing & Theeuwes, 2017). Further, Roelfsema and colleagues proposed that this effect relies on the plasticity of the visual cortex induced by the join effect of top-down attentional control and dopamine (Roelfsema, van Ooyen, & Watanabe, 2010). However, we are aware of only one study to date which was able to directly test the facilitation and suppression of stimuli linked to different reward schedules. In an fMRI Hickey and Peelen (2015) demonstrated that representations of objects paired with high rewards are enhanced in object-selective visual cortex, while the representation of objects paired with low rewards are suppressed.

In this study we sought to directly test the mechanism through which rewards influence goal-directed. We investigated how stimulus features linked to different reward schedules simultaneously compete for attentional control when individuals are able to earn extra monetary rewards (training phase) and when such rewards were no longer available (test phase). We did so by probing the simultaneous deployment of attention to stimuli linked to high or low probability of earning a monetary reward. To this end, we used steady-state visual evoked potentials (SSVEPs) to track stimulus processing in early visual cortex. SSVEPs represent the oscillatory response of the visual cortex to flickering stimuli (Norcia, Appelbaum, Ales, Cottereau, & Rossion, 2015). They provide a continuous measure of feature-based attention deployed across multiple stimuli simultaneously, and are a reliably modulated by goals-driven attention (Andersen & Müller, 2010).

Here we investigated the simultaneous deployment of attention to two features (red and blue dots) across three phases of the experiment. On each trial participants were instructed to attend to one of the two colors and to press a key if the dots of the attended color moved coherently. They performed this task first without any reward (baseline) and then with each color associated with different probabilities of earning a rewards (training). In the last phase (test), participants were informed that they would not earn any more rewards.

This design enabled us to investigate two main questions. First, in the training phase individuals had a goal (e.g., track red dots) which could be congruent or incongruent with the reward manipulation. This meant that the feature linked to high rewards was the target on some trials and a distractor on others. This allowed us to investigate how value-based attention competes with goal-directed attention. Second, in the test phase individuals were no longer able to earn rewards. This allowed us to test how reward history competes with goal-directed attention. In both of these cases there are several mechanisms through which reward-based effects can emerge. Can they result from the improved processing of reward-related features (facilitation), reduced processing of stimuli not related to rewards (suppression), or both. Further, this mechanism can be either the same or not when rewards are introduced and when they are no longer present.

In this setting the theoretical accounts of reward-attention interactions predict that the amount of attention toward the high reward feature will increase (attentional facilitation), while the amount of attention allocated toward the low reward feature will decrease (attentional suppression) in the training phase compared to the baseline phase. Further, it is possible that this effect will persist when participants are aware that no more rewards can be earned (test phase). The use of the SSVEPs in the current paradigm allowed us to test the facilitation and suppression simultaneously on each trial as two features compete for attention.

# Methods

## Participants

We tested 48 participants with normal or corrected-to-normal vision and no history of psychiatric or neurological disorders. Four participants were excluded due to technical problems during recording. Four additional participants were discarded due to excessive artifacts in the EEG signal (i.e., the percentage of rejected epochs in one or more conditions exceeded 35%). Thus, the final data set consisted of 40 participants (27 females, 13 males; median age = 22). Participants received a fixed payoff of 20 €, plus up to 6 € extra as performance-contingent monetary rewards (on average 25.5 €). The study was approved by the ethics committee of Ghent University.

## Stimuli and task

We used the Random Dot Kinematogram (RDK) task (Andersen & Müller, 2010), in which participants were presented with two overlapping circular RDKs of isoluminant colors (red and blue) on a grey background. Viewing distance was fixed with a chinrest at 55 cm from the 21-inch CRT screen (resolution of 1024 x 768 pixels, 120 Hz refresh rate). At the beginning of each trial, participants were instructed which of the two RDKs to attend by a verbal audio cue: “red” (241 ms) or “blue” (266 ms). The two RDKs had a diameter corresponding to 20.61 degrees of visual angle and consisted of 125 randomly and independently moving dots each (0.52 degrees of visual angle per dot). The two RDKs flickered at a different frequencies (10 or 12 Hz). One-third of trials contained one, two, or three coherent motion intervals, occurring with equal probability in the attended (targets) or unattended (distractors) color RDK. During these intervals, dots in one of the RDKs moved with 75% coherence in one of four cardinal directions (up, down, left, or right) for 300 ms. Participants had to detect the coherent movement as fast as possible by pressing the space key on a standard AZERTY USB keyboard. Response time was limited to 1,500 ms post-RDK onset and no response was recorded before 200 ms. Correct responses were followed by a tone (200 ms sine wave of either 800 or 1,200 Hz, counterbalanced across participants). Responses that were too late or incorrect were followed by a 200 ms square wave tone of 400 Hz.

The experiment started with 4 practice blocks of 60 trials. After each block, participants received feedback on their performance. After finishing the practice phase, participants completed 12 blocks of 50 trials divided into 3 phases (*baseline*, *training*, and *test*). Each phase contained 100 trials on which participants were instructed to attend to the red color and 100 trials in which they were instructed to attend to the blue color. Out of those 100 trials, 40 trials contained no dot motion, and 60 trials contained one, two, or three dot motions (120 motions in total). During baseline, participants were simply doing the described task. In the training phase, the task was identical but participants could earn additional monetary rewards (up to 6 €) based on their performance. They were instructed that one of the colors would be paired with high probability (80%) and the other color with low probability (20%) of earning 10 extra cents for each correct detection. The mapping between color and reward probability was counterbalanced across participants. The receipt of the reward was signaled by a new tone that replaced the usual correct tone. If the correct tone was a sine wave of 800 Hz, the reward tone was a sine wave of 1,200 Hz and vice versa. At the end of each of the 4 blocks of the training phase, participants got feedback on both their performance and the amount of extra money earned within the block. The third phase, test, was identical to baseline (i.e., no monetary rewards assigned). The whole task lasted for approximately 50 minutes, plus a few minutes of break in between blocks. After completing the task, participants filled in two questionnaires aimed at assessing their reward sensitivity (BIS-BAS; Franken et al., 2005) and depression levels (BDI-II; Van der Does, 2002).

This experiment was realized using Cogent 2000 developed by the Cogent 2000 team at the FIL and the ICN and Cogent Graphics developed by John Romaya at the LON at the Wellcome Department of Imaging Neuroscience.



**Figure 1. Depiction of a signle trial and the phases of the experiment. A)** Each trial started with an audio cue (”Blue” or ”Red”) which instructed participants which color to attend to in that trial. The trial lasted for 3.25 seconds during which dots of either of the colors could move from 0 to 3 times. If the participants were instructed to attend to the blue dots and the blue dots moved coherently participants should have pressed the response button. In that case they would hear the auditory feedback signaling the correct detection of the movements. **B)** The experiment started with a practice and a baseline block in which the participants heard an audio cue at the begginning of the trial and two types of feedback sound (incorrect or correct). In the training block a third sound was introduced to signal that the participants were both correct and received a reward for that response. They would still at times hear the the old correct feedback which would signal that they were correct, but not rewarded. The test phase was the same as the baseline phase.

## Behavior

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## EEG recording and pre-processing

Electroencephalographic activity (EEG) was recorded with an ActiveTwo amplifier (BioSemi, Inc., The Netherlands) at a sampling rate of 512 Hz. Sixty-four Ag/AgCl electrodes were fitted into an elastic cap, following the international 10/10 system (Chatrian, Lettich, & Nelson, 1985). The common mode sense (CMS) active electrode and the driven right leg (DRL) passive electrode were used as reference and ground electrodes, respectively. Additional external electrodes were applied to the left and right mastoids, as well as on the outer canthi of each eye and in the inferior and superior areas of the left orbit (to record horizontal and vertical electrooculogram, EOG).

Data pre-processing was performed offline with custom MATLAB scripts and functions included in EEGLAB v14.1.1b (Delorme & Makeig, 2004). After subtracting the mean value of the signal (DC offset), the continuous EEG data were epoched between 0 and 3,250 ms, corresponding to the beginning and end of the RDK trial, respectively. After referencing to *Cz*, FASTER v1.2.3b (Nolan, Whelan, & Reilly, 2010) was used for artifact identification and rejection using the following settings: (i) over the whole normalized EEG signal, channels with variance, mean correlation, and Hurst exponent exceeding *z* = ±3 were interpolated via a spherical spline procedure (Perrin, Pernier, Bertrand, & Echallier, 1989); (ii) the mean across channels was computed for each epoch and, if amplitude range, variance, and channel deviation exceeded *z* = ±3, the whole epoch was removed; (iii) within each epoch, channels with variance, median gradient, amplitude range, and channel deviation exceeding *z* = ±3 were interpolated; (iv) grand-averages with amplitude range, variance, channel deviation, and maximum EOG value exceeding *z* = ±3 were removed; (v) epochs containing more than 12 interpolated channels were discarded. All remaining epochs were scanned with SCADS (Junghöfer, Elbert, Tucker, & Rockstroh, 2000) and rejected when flagged as containing residual artifacts. For details, see our commented code at https://osf.io/5hryf/. After pre-processing, the average number of interpolated channels was 4.08 (*SD* = 1.75, range 0 – 7) and the mean percentage of rejected epochs was 9.74% (*SD* = 6.77, range 0 – 32.50; similar rejection rate across conditions). After re-referencing to averaged mastoids, trials in each condition were averaged separately for each participant, resulting in the following grand-averages: (i) baseline, red attended; (ii) baseline, blue attended; (iii) training, red attended; (iv) training, blue attended; (v) test, red attended; (vi) test, blue attended.

Electrodes with maximum SSVEP amplitudes were identified by calculating isocontour voltage maps based on grand-averaged data collapsed across all conditions. After removing linear trends, Fast Fourier Transforms on the EEG signal in a time window from 500 ms (to exclude the typically strong phasic visual evoked response to picture onset) to 3,250 ms after stimulus onset was applied, and amplitudes were obtained by extracting the absolute values of the resulting complex Fourier coefficients. We extracted SSVEP amplitude at 10 and 12 Hz from each individual electrode cluster, separately for each condition (averaged across trials). The amplitudes were normalized for each participant and frequency separately by dividing amplitudes by the average amplitude across all six conditions. To account for inter-individual variations in topographical SSVEP amplitude distributions, we identified and averaged activity from the four electrodes displaying, for each participant, the largest frequency-specific amplitude.

## Statistical analyses

Behavioral and EEG data were analyzed using Bayesian multilevel regressions. We fitted and compared multiple models of varying complexity to predict hit rates, reaction times for correct responses, and SSVEP amplitudes. Each of the fitted models included both constant and varying effects (also known as fixed and random). Participant-specific characteristics are known to affect both behavioral performance (e.g., response speed) and EEG signal (e.g., skull thickness, skin conductance, hair); therefore, we decided to model this variability by adding varying intercepts in our models. Additionally, the studied effects (e.g., reward sensitivity and selective attention) are known to vary in magnitude over participants, so we opted for including varying slopes in our models. It should be noted that, because of the simultaneous estimation of group-level and participant-level parameters, multilevel models display a property called *shrinkage*. In brief, estimates that strongly deviate from the mean (e.g., a participant performing the task much worse than the average of the total sample) will be pulled toward the group mean (McElreath, 2016). This advantageous property prevents extreme values from having large effects on the results.

Models were fitted in R using the package *brms* (Bürkner, 2016) that employs the probabilistic programming language *Stan* (Carpenter et al., 2016)to implement Markov Chain Monte Carlo (MCMC) algorithms in order to estimate posterior distributions of the parameters of interest. Each of the models were fitted using weakly regularizing prior distributions (default priors in *brms*) and Gaussian likelihood. Four MCMC simulations (“chains”) with 10,000 iterations (2,000 warmup) and a thinning interval of 1 were run to estimate parameters in each of the fitted models. Further analyses were done following the recommendations for Bayesian multilevel modeling using *brms* (Bürkner, 2016, 2017; Nalborczyk & Bürkner, 2019). We confirmed that all models converged by examining trace plots, autocorrelation, and variance between chains (Gelman-Rubin statistic; Gelman & Rubin, 1992). We compared models based on their fit to the actual data using the Bayesian *R*2 (Gelman, Goodrich, Gabry, & Ali, 2017), and their out-of-sample predictive performance using the Widely Applicable Information Criterion (WAIC; Watanabe, 2010). The best model was selected and the posterior distributions of conditions of interest were examined. Differences between conditions were assessed by computing the mean and the 95% highest density interval (HDI) of the difference between posterior distributions of the respective conditions (Kruschke, 2014). Additionally, we calculated the evidence ratios (ERs) for our hypotheses as the ratios between the percentage of posterior samples on each side of the zero of a difference distribution between two conditions. ERs can be interpreted as the probability of a hypothesis (e.g. “Condition A is larger than condition B”) against its alternative (“Condition B is larger than condition A”).

# Results

## Behavioral results

We fitted three models to predict both hit rates (proportion of hits) and reaction times (in milliseconds) separately (*Figure 2* and *Table 1*). First, we fitted the *Null model* with one constant and multiple varying intercepts across participants. This model was fitted in order to explore the possibility that the data would be best explained by simple random variation between participants. To investigate the effect of reward phase (baseline, training, test), we fitted the *Reward phase model* that included only reward phase as the constant predictor and varying intercepts and slopes across participants for this effect. To investigate the possible interaction between reward phase and reward probability, we fitted the *Interaction model* including these two effects and their interaction as constant effects. The intercepts and slopes of main effects and their interaction were allowed to vary across participants. Please note that there are two additional models that, although possible to fit, are not plausible in the context of our experiment. Specifically, the model with only the effect of reward probability overlooks the fact that this effect would necessarily be most pronounced in the training phase, thus interacting with the effect of reward phase. The same logic applies to the model with additive effects of reward phase and probability (i.e., these effects cannot act independently in our experimental design).

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| Table 1  *Means and 95% HDIs (in square brackets) of hit rates and reaction times.* | | | |
| Reward phase | Reward probability | Hit rates (proportion) | Reaction times (milliseconds) |
| Baseline | High | 0.60 [0.32, 0.70] | 547.18 [460.90, 612.74] |
| Baseline | Low | 0.59 [0.32, 0.70] | 552.93 [470.68, 631.36] |
| Training | High | 0.62 [0.37, 0.80] | 526.00 [457.23, 599.49] |
| Training | Low | 0.63 [0.47, 0.77] | 538.41 [465.32, 605.14] |
| Test | High | 0.61 [0.32, 0.74] | 528.21 [448.50, 599.83] |
| Test | Low | 0.61 [0.39, 0.79] | 538.21 [464.21, 642.55] |



**Figure 2.** Distributions and means of raw hit rates and reaction times per condition.

## Hit rates

As can be seen in *Table 1*, this task was quite challenging as participants were able to detect only about 60% of the movements across different experimental conditions. Nonetheless, it should be noted that this is a signal detection task, so the performance of 50% is not chance level. Of all the tested models, the interaction model best predicted hit rates (*Table 2*). This result points to the importance of the interaction between reward phase and reward probability in predicting hit rates. The posterior distributions of the interaction model (*Figure 3*) revealed that hit rates improved in the training phase compared to the baseline for both low (*M =* 0.04; 95% HDI [0.02, 0.06]; ER = 999.00) and high rewarded color (*M =* 0.02; 95% HDI [0.00, 0.04]; ER = 33.48). This improvement was more pronounced for low compared to high reward probability (*M =* 0.02; 95% HDI [-0.01, 0.05]; ER = 8.43). Conversely, evidence for the difference between training and test phases was much weaker. Participants were slightly less accurate in test compared to training in the low rewarded condition (*M =* -0.01; 95% HDI [-0.04, 0.01]; ER = 8.43), while there was very little difference in the high rewarded condition (*M =* -0.01; 95% HDI [-0.03, 0.02]; ER = 2.42).

These results suggest that participants were reliably more accurate in the training phase compared to baseline, and more so for the low rewarded color. There was also evidence for a drop in their accuracy in the test phase for the low rewarded, but not high rewarded color.

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| Table 2  *Mean and standard errors (in parenthesis) of WAIC and Bayesian R2 for each model predicting hit rates and reaction times.* | | | | |
| Model | | *WAIC (SE)* | | *Bayesian R2 (SE)* |
| *Hit rates* | | | | |
| Null | | -475.41 (32.92) |  | 0.34 (0.05) |
| Reward phase | | -471.65 (33.43) |  | 0.36 (0.05) |
| Reward phase x Reward probability | | -709.13 (23.99) |  | 0.82 (0.03) |
| *Reaction times* |
| Null | | 2,346.29 (32.74) |  | 0.49 (0.04) |
| Reward phase | | 2,329.70 (35.38) |  | 0.56 (0.04) |
| Reward phase x Reward probability | | 2,154.64 (25.19) |  | 0.84 (0.03) |

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| Table 3  *Means and 95% HDIs of the posterior distributions of reaction times and hit rates in each condition.* | | | |
| Reward phase | Reward probability | Hit rates (proportion) | Reaction times (milliseconds) |
| Baseline | High | 0.60 [0.57, 0.63] | 547.19 [534.84, 559.56] |
| Baseline | Low | 0.59 [0.55, 0.62] | 552.97 [539.22, 567.24] |
| Training | High | 0.62 [0.59, 0.65] | 526.03 [513.90, 538.04] |
| Training | Low | 0.63 [0.59, 0.66] | 538.50 [525.69, 550.34] |
| Test | High | 0.61 [0.58, 0.65] | 528.29 [515.32, 541.69] |
| Test | Low | 0.61 [0.57, 0.65] | 538.35 [522.97, 554.23] |



**Figure 3.** Posterior distributions of the interaction models for hit rates and reaction times across conditions.

## Reaction times

The interaction model (Reward phase x Reward probability) also best predicted reaction times (*Table 2*). Participants were reliably faster in the training compared to the baseline phase in both the high rewarded (*M =* -21.16; 95% HDI [-29.79, -12.27]; ER = *Inf.*, i.e. whole posterior distribution above zero) and the low rewarded conditions (*M =* -14.47; 95% HDI [-24.71, -4.63]; ER = 332.33). Moreover, this difference was larger in the high compared to low rewarded condition (*M =* -6.69; 95% HDI [-18.01, 4.77]; ER = 7.20). We found little evidence for any changes in reaction times between the training and the test phase. Participants were approximately equally fast in training and test for both the high (*M =* 2.26; 95% HDI [-6.80, 11.00]; ER = 2.26), and the low reward condition (*M =* -0.15; 95% HDI [-10.86, 10.26]; ER = 1.05).

These results indicate that participants were faster in the condition in which they could earn rewards, and more so in the condition with higher probability of earning a reward. Also, there was no evidence for any changes in reaction times when rewards were no longer available.

Supplementary analyses carried out to assess possible training effects indicated some evidence for the presence of training effects in hit rates and scant evidence for such effects in reaction times. These results can be found in *Appendix 1*.

## SSVEP amplitudes

As shown in *Figure 4*, activity averaged over conditions was mainly localized at central occipital channels (i.e., *Oz*, *POz*, *O2*, *PO3*). Also, the FFT-amplitude spectra showed the expected peaks at the frequencies of 10 and 12 Hz.



**Figure 4.** Grand average FFT-amplitude spectra derived from EEG signals at each participant's best four-electrode cluster for the 10 and 12 Hz signal. Data in the figure are filtered with 1Hz high-pass filter for visualization purposes.

We fitted seven models to predict the trial-averaged SSVEP amplitudes (in a.u. due to the normalization) across conditions (*Figure 5* and *Table 4*). The *Null model* included one constant and multiple varying intercepts across participants. The *Attention model* included the constant effect of attention; the *Reward phase model* included the constant effect of reward phase; the *Reward phase + attention* model included the additive effects of reward phase and attention; and the *Reward phase x attention* model also included the interaction between reward phase and attention. The *Reward probability x reward phase + attention* model consisted of the constant effects of reward probability and phase, their interaction, and the independent effect of attention. The last model was the *Interaction* model which included all constant effects and their interaction (*Reward probability x reward phase x attention*). All models, except for the *Null* *model*, included varying slopes and intercepts across participants for all constant effects. As was the case for the behavioral data, several models were not fitted because they were not plausible in the context of our experiment (e.g., the models that include both reward phase and probability, but not their interaction).

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| Table 4  *Means and 95% HDIs of recorded SSVEP amplitudes in each condition.* | | | |
| Attention | Reward phase | Reward probability | Amplitudes (a.u.) |
| Attended | Baseline | High | 1.11 [0.77, 1.42] |
| Attended | Baseline | Low | 1.09 [0.41, 1.44] |
| Attended | Training | High | 1.10 [0.77, 1.50] |
| Attended | Training | Low | 1.04 [0.55, 1.40] |
| Attended | Test | High | 1.07 [0.72, 1.47] |
| Attended | Test | Low | 1.09 [0.76, 1.59] |
| Unattended | Baseline | High | 0.95 [0.65, 1.43] |
| Unattended | Baseline | Low | 0.89 [0.58, 1.32] |
| Unattended | Training | High | 0.91 [0.57, 1.30] |
| Unattended | Training | Low | 0.90 [0.62, 1.21] |
| Unattended | Test | High | 0.93 [0.51, 1.37] |
| Unattended | Test | Low | 0.92 [0.60, 1.34] |



**Figure 5.** Distributions, means, and credible intervals of SSVEP amplitudes per condition.

The interaction model best predicted SSVEP amplitudes across conditions (*Table 5*). The analysis of the posterior distributions of the interaction model (*Figure 6*) revealed a strong effect of attention: in all conditions, SSVEP amplitudes were higher for the attended compared to the unattended stimuli. At baseline, the posterior distribution of the difference between attended and unattended stimuli did not include zero, thus resulting in infinite probability that the attended stimuli would elicit higher SSVEP amplitudes compared to the unattended ones (for high reward probability: *M =* 0.17; 95% HDI [0.09, 0.24]; ER = *Inf.*; for low reward probability: *M =* 0.19; 95% HDI [0.11, 0.27]; ER = *Inf.*). In the training phase, amplitudes were higher in the attended condition for both high rewarded (*M =* 0.19; 95% HDI [0.11, 0.27]; ER = *Inf.*) and low rewarded stimuli (*M =* 0.11; 95% HDI [-0.02, 0.23]; ER = 22.81). Similarly, in the test phase amplitudes were higher in the attended condition for highly rewarded stimuli (*M =* 0.14; 95% HDI [0.05, 0.23]; ER = 999) and for low rewarded stimuli (*M =* 0.14; 95% HDI [0.00, 0.26]; ER = 51.63). These results reveal a very robust effect of attention across all experimental conditions.

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| Table 6  *Means and 95% HDIs of the posterior distributions of the SSVEP amplitudes for each condition.* | | | |
| Attention | Reward phase | Reward probability | Amplitudes (a.u.) |
| Attended | Baseline | High | 1.11 [1.06, 1.16] |
| Attended | Baseline | Low | 1.09 [1.02, 1.15] |
| Attended | Training | High | 1.10 [1.04, 1.15] |
| Attended | Training | Low | 1.04 [0.97, 1.11] |
| Attended | Test | High | 1.07 [1.01, 1.13] |
| Attended | Test | Low | 0.95 [0.84, 1.06] |
| Unattended | Baseline | High | 0.95 [0.89, 1.01] |
| Unattended | Baseline | Low | 0.89 [0.83, 0.96] |
| Unattended | Training | High | 0.91 [0.84, 0.97] |
| Unattended | Training | Low | 0.93 [0.82, 1.04] |
| Unattended | Test | High | 0.93 [0.85, 1.00] |
| Unattended | Test | Low | 0.95 [0.84, 1.06] |

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| Table 5  *Model comparison indices for EEG results* | | | |
| Model | *WAIC (SE)* |  | *Bayesian R2 (SE)* |
| Null | -122.16 (38.14) |  | 0.00 (0.00) |
| Reward phase | -115.47 (38.14) |  | 0.02 (0.01) |
| Attention | -211.10 (41.72) |  | 0.21 (0.04) |
| Reward phase + attention | -200.35 (41.10) |  | 0.22 (0.04) |
| Reward phase x attention | -193.05 (40.69) |  | 0.23 (0.04) |
| Reward probability x reward phase + attention | -272.18 (42.75) |  | 0.43 (0.04) |
| Reward phase x reward probability x attention | -300.60 (40.58) |  | 0.53 (0.05) |
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**Figure 6.** Posterior distributions of the interaction models for SSVEP amplitudes across conditions.

The posterior distributions also indicated that reward phase and probability interacted differently across attended and unattended stimuli. Focusing on the attended stimuli first, there was no evidence for a difference between training and baseline when stimuli were highly rewarded (*M =* 0.02; 95% HDI [-0.06, 0.09]; ER = 2.06), but there was weak evidence for lower amplitudes in training when the stimuli were lowly rewarded (*M =* 0.04; 95% HDI [-0.04, 0.12]; ER = 6.69). There was little evidence that amplitudes were lower in training compared to test for the high reward condition (*M =* 0.03; 95% HDI [-0.05, 0.11]; ER = 3.02). For the low reward condition, there was weak evidence that amplitudes were higher in test compared to training (*M =* 0.05; 95% HDI [-0.04, 0.14]; ER = 5.80). For the unattended stimuli, the amplitudes slightly lowered from baseline to training in the high rewarded condition (*M =* 0.04; 95% HDI [-0.03, 0.11]; ER = 5.76), but not in the low rewarded condition (*M =* 0.04; 95% HDI [-0.10, 0.18]; ER = 2.48). Amplitudes did not reliably change from training to test for neither the high reward (*M =* 0.02; 95% HDI [-0.07, 0.11]; ER = 1.78) nor the low reward condition (*M =* 0.02; 95% HDI [-0.07, 0.11]; ER = 1.88).

To summarize, in the attended condition SSVEP amplitudes did not change across reward phases for high rewarded stimuli. However, for low rewarded stimuli, there was some evidence that they lowered from baseline to training and increased from training to test. For the unattended condition, amplitudes elicited by the low rewarded color did not change across reward phases. For the high rewarded color, there was some evidence that amplitudes decreased from baseline to training and increased from training to test.

We also observed an unexpected (albeit weak) baseline difference between the two reward probability conditions, both in the unattended (*M =* 0.05; 95% HDI [-0.03, 0.14]; ER = 8.90) and attended conditions (*M =* 0.03; 95% HDI [-0.06, 0.11]; ER = 2.73). This was surprising because participants had no way of knowing which color would be rewarded in the training phase; in addition, they were informed about the possibility of earning rewards only when they completed the baseline phase. However, this baseline difference does not affect our results given that our comparisons of interest are between reward phases for the same reward probability.

# Discussion

Our results show that rewards influence the deployment of voluntary attention at both behavioral and neural levels. The introduction of rewards improved behavioral performance in the task, and the stimuli linked to higher probability of obtaining a reward were detected faster. The absence of rewards in the test phase did not influence behavior. This result provides a conceptual replication of the value-driven effects found in studies using visual search and cueing tasks (Anderson et al., 2011; Failing & Theeuwes, 2014). This replication is significant given the large differences between our task and the previously used tasks. In our paradigm, participants were instructed which features to pay attention to, and they were doing so over the much longer periods of time than in previously used paradigms. This result thus provides additional support to the robustness of the value-driven attentional effects (Anderson, 2016; Chelazzi et al., 2013; Failing & Theeuwes, 2017).

At the neural level we have directly replicated the finding that the SSVEP amplitudes are strongly influenced by voluntary attention (Andersen & Müller, 2010; Andersen, Müller, & Hillyard, 2012). Across all of the phases of the experiment, the SSVEP amplitudes in the frequency of the attended stimuli were robustly higher than the amplitudes in the frequency of the unattended stimuli. This strong gating effect was modulated by reward. Model comparisons have provided evidence that the models which take into account the reward manipulation account better for the data compared to the model that includes only the effect of voluntary attention. This result further corroborates models of cognitive control which posit motivation as the crucial component in the voluntary allocation of attention (Brown & Alexander, 2017; Holroyd & McClure, 2015; Shenhav, Botvinick, & Cohen, 2013; Verguts, Vassena, & Silvetti, 2015).

The SSVEP results further indicate that when participants were attending to the stimuli paired with high reward probability, the amplitudes did not change during the phases of the experiment. This result is somewhat surprising given that previous neuroimaging studies demonstrated enhanced processing of targets paired with high rewards (Hickey et al., 2010; Hickey, Peelen, Hickey, & Peelen, 2015). One of the possible explanations for this result is that it is due to the high difficulty of our task. As can be seen from the behavioral data, on average participants had 60% correct responses. Having this in mind, it is possible that our participants were already at the ceiling in terms of the allocation of attentional resources. This would suggest that there was no room for the further increase in the SSVEP amplitudes. However, it was possible to adaptively allocate less resources to certain features.

When the participants were attending to the low rewarded stimuli, the SSVEP amplitudes decreased in the reward phase and went back to the baseline level in the test phase. The opposite was true when looking at the unattended stimuli. While the low rewarded stimuli did not change over the experiment, the amount of attention being allocated toward the high rewarded stimuli dropped in the reward phase, and stayed at that level in the test. The finding of suppression in processing of the stimuli related with low rewards is comparable to the results found in the fMRI study focusing on the visual cortex (Hickey et al., 2015). Our result suggests that the voluntary allocation of attention was flexibly adapted depending on the possibility of earning extra monetary rewards in the experiment. This is the first electrophysiological study that has looked into the simultaneous deployment of attention to stimuli linked both to high and low reward probability. As such it provides a novel insight into the flexible dynamics of attentional deployment based on value of different stimuli. Also, this result is contrary to the prediction made by the value-based attention account, but in line with the prediction made by cognitive control models. Namely, the value-driven attentional account posits that linking stimuli to high reward probability induces a long lasting attentional bias toward such stimuli. However, our data suggests the opposite. Attention is flexibly deployed in order to maximize the probability of obtaining a reward, but then goes back to the baseline levels once the possibility of earning rewards is gone.

These results point to the importance of several factors in the allocation of attention based on goals and reward history. First, our electrophysiological measure displayed an interesting decoupling from the behavior. While the behavioral data seems to be in line with the persistent effect of reward history, the neural data suggests that this effect does not arise from the long-lasting change in the amount of attention being allocated based on previous rewards. This is contrast to some of the existing electrophysiological studies (MacLean & Giesbrecht, 2015), but it is important to point out that there are very few such studies to date. Future studies could explore further why such a decoupling occurs. Tentatively, there is a possibility that the persistent behavioral effect is driven by a more motor effect, rather than a one mediated by attention. Interestingly, the value-driven attentional bias has mostly been demonstrated by the speeded responses to the previously rewarded stimuli compared to neutral stimuli. It is possible that such an effect is driven by the motor pairing of a stimulus and a fast response.

Another important factor in the allocation of reward-guided attention is the type of the task used. Our results demonstrate the importance of more rigorous tests of the idea that reward history can counteract goal-driven allocation of attention. The tasks used in most studies only infer that the goals of participants have changed in the test phase, or that they are induced in the instruction prior to the experiment (Anderson et al., 2011; Anderson, 2013; Failing & Theeuwes, 2014). We have demonstrated that, in the task in which participants have a goal on every trial, we did not observe the value-driven attentional bias in our measure of sustained attention. We believe that such an experimental setup provides a more rigorous way of looking at the competition between the goal-driven and value-driven attention. However, it is important to stress that our paradigm could favor the goal-directed effects on attention, while the previous paradigm could have favored the value-driven effects.

# Conclusion

# Appendix 1

In order to assess potential training effects on behavioral performance, we split each reward phase into two halves (*Supplementary Figure 1* and *Supplementary Table 1*). If training effects were influencing the behavioral outcome, we could expect performance improvement through baseline and training. To investigate this possibility, we fitted the *Interaction model* that was identical as the one described in the results section. We then compared behavioral performance between the first and the second part of the baseline phase, and between the second part of baseline and the first part of training phase.

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| --- | --- | --- | --- |
| Supplementary Table 1  *Means and 95% HDIs of hit rates and reaction times across six phases of the experiment* | | | |
| Reward phase | Reward probability | Hit rates (proportion) | Reaction times (milliseconds) |
| Baseline1 | High | 0.59 [0.28, 0.76] | 548.80 [471.00, 613.76] |
| Baseline1 | Low | 0.57 [0.25, 0.85] | 551.68 [458.26, 629.69] |
| Baseline2 | High | 0.62 [0.37, 0.81] | 546.07 [443.45, 620.36] |
| Baseline2 | Low | 0.61 [0.41, 0.78] | 554.75 [479.48, 650.73] |
| Training1 | High | 0.61 [0.33, 0.80] | 522.80 [437.90, 604.61] |
| Training1 | Low | 0.64 [0.47, 0.86] | 541.89 [457.58, 593.47] |
| Training2 | High | 0.64 [0.31, 0.76] | 529.67 [462.00, 598.58] |
| Training2 | Low | 0.63 [0.45, 0.79] | 536.08 [471.00, 618.25] |
| Test1 | High | 0.62 [0.33, 0.77] | 529.58 [457.88, 596.17] |
| Test1 | Low | 0.61 [0.43, 0.85] | 535.20 [444.89, 629.69] |
| Test2 | High | 0.62 [0.28, 0.78] | 526.88 [456.00, 639.89] |
| Test2 | Low | 0.62 [0.35, 0.78] | 541.75 [450.11, 633.28] |



**Supplementary Figure 1.** Distributions and means of raw hit rates and reaction times per condition.

The posterior distributions for hit rates (*Supplementary Figure 2* and *Supplementary Table 2*) revealed performance improvement from the first to the second part of the baseline for both high (*M =* 0.02; 95% HDI [-0.01, 0.05]; ER = 7.77) and low (*M =* 0.04; 95% HDI [0.01, 0.08]; ER = 141.86) reward probability conditions. When comparing the second part of baseline to the first part of training, there was no difference in the high reward probability condition (*M =* 0.01; 95% HDI [-0.03, 0.04]; ER = 1.82). However, in the low probability condition, hit rates were higher in the first part of training (*M =* 0.03; 95% HDI [-0.01, 0.06]; ER = 9.31). These results indicate that participants improved not only throughout the baseline phase, but also from the end of baseline to the first part of the training (albeit for low rewarded color only). This might indicate some presence of training effects on the hit rate data.

The posterior distributions of reaction times (*Supplementary Figure 2* and *Supplementary Table 2*) revealed no differences between the first and the second part of baseline for neither high (*M =* 2.74; 95% HDI [-8.78, 13.75]; ER = 2.17) nor low (*M =* 3.08; 95% HDI [-8.53, 14.75]; ER = 2.37) reward probability condition. The comparison between the second part of baseline and the first part of training revealed a very reliable improvement in both high (*M =* 23.34; 95% HDI [12.06, 35.22]; ER = *Inf.*) and low (*M =* 12.86; 95% HDI [1.09, 25.28]; ER = 54.55) reward probability conditions. These results clearly point to the absence of training effects in reaction time data.

Taken together, these results indicate that our effects were not driven by the improved performance over the course of the task. Although there is some evidence that hit rates were improving during the baseline phase, reaction times clearly indicate that the main shift in performance happens in the beginning of training, when rewards are introduced. Importantly, the strongest behavioral effects in our study were found on reaction time data, as indicated in the results section.

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| Supplementary Table 2  *Means and 95% HDIs of hit rates and reaction times across six phases of the experiment* | | | |
| Reward phase | Reward probability | Hit rates (proportion) | Reaction times (milliseconds) |
| Baseline 1 | High | 0.59 [0.56, 0.63] | 548.95 [535.99, 561.51] |
| Baseline 1 | Low | 0.62 [0.58, 0.65] | 546.20 [531.50, 560.00] |
| Baseline 2 | High | 0.57 [0.53, 0.61] | 551.83 [537.82, 566.18] |
| Baseline 2 | Low | 0.61 [0.57, 0.65] | 554.91 [539.42, 571.04] |
| Training 1 | High | 0.61 [0.57, 0.64] | 522.87 [509.89, 535.59] |
| Training 1 | Low | 0.64 [0.60, 0.67] | 529.79 [516.87, 542.59] |
| Training 2 | High | 0.64 [0.60, 0.68] | 542.05 [528.28, 556.21] |
| Training 2 | Low | 0.63 [0.59, 0.67] | 536.26 [521.92, 549.75] |
| Test 1 | High | 0.62 [0.58, 0.65] | 529.68 [515.80, 543.76] |
| Test 1 | Low | 0.62 [0.58, 0.66] | 526.96 [512.84, 540.61] |
| Test 2 | High | 0.61 [0.56, 0.65] | 535.39 [518.62, 552.17] |
| Test 2 | Low | 0.62 [0.58, 0.67] | 541.87 [525.02, 557.85] |



**Figure 2.** Posterior distributions of the interaction models for hit rates and reaction times across six reward phase conditions.

Similar analyses could not be performed for the EEG data, because splitting the number of trials in each phase would significantly affect the signal-to-noise ratio. However, our EEG results point to changes in SSVEP amplitudes in only one of the reward probability conditions. If amplitude changes were mainly driven by training effects, the differences across reward phases would be expected for both reward probability conditions. This observation, combined with the lack of strong training effects in behavior, suggests that our EEG results are not driven by training effects.

## Software for data visualization and analysis

Visualization and statistical analyses were performed using R v3.4.4 (R Core Team, 2017) via RStudio v1.1.453 (RStudio Team, 2015). We used the following packages (and their respective dependencies):

• data manipulation: tidyverse v1.2.1 (Wickham, 2017);

• statistical analyses: Rmisc v1.5 (Hope, 2013), brms v2.3.1 (Bürkner, 2016);

• visualization: cowplot v0.9.2 (Wilke, 2016), yarrr v0.1.5 (Phillips, 2016), viridis v0.5.1 (Garnier, 2018), eegUtils v0.2.0 (Craddock, 2018), BEST (J. K. Kruschke & Meredith, 2017);

• report generation: pacman v0.4.6 (Rinker & Kurkiewicz, n.d.), knitr v1.20 (Xie, 2018).

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# Author contributions

IG, AS, and SKA conceived the study. SKA and IG programmed the experimental paradigm. SKA, GP, and EHWK contributed reagents/materials/tools. IG collected the data, supervised by AS. IG and AS analyzed the data. IG and AS wrote the main manuscript text. IG, AS, GP, EHWK, and SKA reviewed and critically revised the manuscript.

# Data availability

Raw and pre-processed data, materials, and analysis scripts are available at: https://osf.io/kjds3/.

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