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 process 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 how stimuli will be processed is motivation. Goal-driven attentional control is enhanced when individuals are motivated with extrinsic rewards (Botvinick & Braver, 2015; Pessoa, 2015). Attention can also be guided by previous reward history, independently from top-down attentional control (Awh, Belopolsky, & Theeuwes, 2012). Previous reward associations can worsen performance on attention tasks if they conflict with the current goals of the individual (Anderson, 2016; Chelazzi, Perlato, Santandrea, & Della Libera, 2013; Failing & Theeuwes, 2017).

Attentional control is enhanced when individuals are anticipating that they can earn rewards for good task-performance (Krebs & Woldorff, 2017). In fMRI studies reward-based improvements have been linked to enhanced activity in frontoparietal regions crucial for attentional control (Krebs, Boehler, Roberts, Song, & Woldorff, 2012; Pessoa & Engelmann, 2010). Electroencephalographic (EEG) studies have demonstrated similar preparatory attentional modulations following reward cues in the CNV event-related potential (ERP) component (Schevernels, Krebs, Santens, Woldorff, & Boehler, 2014; Van Den Berg, Krebs, Lorist, & Woldorff, 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 our current goals. These studies have provided some evidence for the reward-related changes in the early stages of visual cortical processing (i.e., increase in the P1 component; Donohue et al., 2016; Hickey, Chelazzi, & Theeuwes, 2010; Luque et al., 2017; MacLean & Giesbrecht, 2015). 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, Zeng, Ding, & Li, 2013; Tankelevitch, Spaak, Rushworth, & Stokes, 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 (Hickey & Peelen, 2015) demonstrated that representations of objects paired with high rewards were enhanced in object-selective visual cortex, while the representation of objects paired with low rewards were suppressed.

In this study we sought to directly test the mechanism through which rewards influence attentional control. We investigated how stimulus features linked to different reward schedules simultaneously competed for attentional control when individuals were able to earn extra monetary rewards and when such rewards were no longer available. We recorded steady-state visual evoked potentials (SSVEPs) to track stimulus processing in the 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 attentional control (Andersen & Müller, 2010). Crucially, different stimuli can be tagged with different frequencies allowing for the simultaneous measurement of the amount of attention allocated to each of the stimuli.

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 high or low probability of earning a reward (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 stimulus value influences goal-directed attention. Second, in the test phase individuals were no longer able to earn rewards. This allowed us to test how previous, but no longer relevant, stimulus value interacts with goal-directed attention. In both cases there are several mechanisms through which reward-based effects can emerge. They can result from the improved processing of the targets (facilitation), reduced processing of the distractors (suppression), or both. Further, the processing of targets and distractors can be modulated by their value.

# 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

In this study we investigated how rewards influence goal-directed attention. Specifically, we compared the amount of attention allocated toward targets and distractors when they are linked to different reward probabilities. Compared to baseline, the introduction of rewards improved the sensitivity (d prime) and reaction times in the random dot kinematogram task. Further, dots linked to higher reward probability were detected faster, which was accompanied by an increased amount of attention allocated toward these stimuli, as measured by the amplitude of the corresponding SSVEP. This was true both when the high reward feature was a target and a distractor. When rewards were no longer available the amount of attention, went back to baseline level, while the behavioral effect of reward probability did not change. These findings have several important implications for the understanding of the relationship between rewards and goal-directed attention.

We have directly replicated the finding that the SSVEP amplitudes are strongly influenced by goal-directed attention (Andersen & Müller, 2010; Andersen, Müller, & Hillyard, 2012). Across all of the phases of the experiment, the SSVEP amplitudes in the frequency of the target stimuli were robustly higher than the amplitudes in the frequency of the distractors. This robust 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 goal-directed attention. This result is in line with the previous findings using fMRI and ERPs. These findings also corroborate the theoretical models which posit motivation as being crucial in the control of attention (Brown & Alexander, 2017; Holroyd & McClure, 2015; Shenhav, Botvinick, & Cohen, 2013; Verguts, Vassena, & Silvetti, 2015).

Crucially, our experiment allowed us to better understand the mechanisms through which rewards influence goal-directed attention. Our results indicate that the enhancement in goal-directed attention comes from the facilitated processing of stimuli linked to high reward probability. It is likely that the enhanced anticipatory frontoparietal activity reported in fMRI studies of reward attention (Krebs & Woldorff, 2017) leads to the increase in the processing of reward-related targets in the visual cortex which we observe. Our finding is in line with the results by Hickey and Peelen (2015) who reported evidence for stronger representations of objects linked to high rewards in object-selective visual cortex.

Importantly, the facilitated processing of the feature linked to high reward is present both when that feature is a target and a distractor. When the high reward feature is a distractor, the facilitated processing of the feature is in collision with the goal to attend to the other feature. This finding is in line with the theories proposing that reward associations can counteract top-down attentional control (Chelazzi et al., 2013; Anderson, 2016; Failing & Theeuwes, 2018). However, the faciliciated processing of the distractor in this case did not lead to worse or slower detection of the targets compared to baseline. However, participants were slower in detecting the movement of the targets on these trials compared to the trials on which the targets were the high rewarded feature.

Our paradigm allowed us to simultaneously measure the processing of stimuli linked to both high and low reward probability. We have not found evidence for the suppression of the stimulus feature linked to low rewards, neither when it was presented as a target nor when it was presented as a distractor. The amount of attention allocated toward this feature remained unchanged throughout the experiment. This finding is different from the results of Hickey and Peelen (2015) who have reported decreased decodability to the suppression of the objects representations related to low rewards. An important difference between our task and that of Hickey and Peelen is that the attended feature changed trial-by-trial in our experiment, while they employed small blocks of 16 trials in which the attended feature was always the same (e.g., search for a car in the picture). This difference could explain why they found evidence for suppression while we did not. When individuals are aware that they will be searching for one object or feature across a number of future trials, it is possible that the optimal solution for the cognitive system is to suppress the processing of the other features or objects (i.e., distractors). However, if individuals are aware that the attended feature is likely to change on each trial, as in our experiment, the suppression of the low rewarded feature could be maladaptive as it would increase the switch cost on the next trial, when that feature has to be attended. This idea could be tested in our experimental paradigm by introducing mini-blocks of trials in which the attended feature is always the same. Further, in our experiment both of the stimuli features were related to rewards, but they differed in reward probability, while in the experiment of Hickey and Peelen one stimulus category was related to rewards, while others were not. Thus in our paradigm it could be adaptive for participants to not suppress the low rewarded feature because correct responses to the movements of this feature would still earn them a reward on 20% of trials.

In the test phase the behavior displayed the same patterns as in the training phase. Individuals were faster to detect movements of the dots in color related to high reward probability. This finding follows the reward-history effects reported in several paradigms (REFs). However, our results show that the amount of attention allocated toward the high reward feature was the same as in the baseline. This result indicates that the longer lasting effect of reward history was not mediated by goal-driven attention. There are several ways to explain this finding. First, it is possible that the longer lasting effects of reward history rely on changes in the early visual processing which might not be captured by the SSVEPs. There is some evidence to support this idea based on the ERP studies which have found reward-history modulations of the early ERP components such as the P1 (REFs). However in the study of Tanklevitch (2019) it was demonstrated that the improved decoding of the high rewarded feature is possible after XXX ms. This effect is within the time range which could be captured by SSVEPs as the enhancement of the processing of the attended feature in our paradigm happens after 220ms, followed by the suppression of the unattended feature 130ms later (Andersen & Hillyard, 2010). Another explanation for this finding is that the reward-based improvements in goal-directed attention rely on attention initially, but they are later transferred into more simple stimulus-response associations. This would imply that the reward-history effects rely more on simpler motor mappings to certain features and are not involving attention. Finally, our study was not primarily designed to assess the reward-history effects. Although the number of trials in the training phase is approximately the same as the number in studies demonstrating reward history effects (REFs), we used the same task in the training and test phase, which is not common for such studies. Further research using SSVEPs in tasks designed to explicitly address the reward-history effects could help disentangle between the possible explanations of our findings.

Results of this study reveal a mechanism through which reward can improve goal-directed attention. We were able to directly measure the amount of attention allocated toward processing of targets and distractors of different values. We show that monetary rewards can influence goal-directed attention. Further, we demonstrate that the feature linked to high rewards receives more attention both when it acts as a target and a distractor. Further, this biased competition disappears once the rewards are no longer available. This result corroborates the importance of motivation in guiding attention (Botvinick & Braver, 2015; Chelazzi et al., 2013; Failing & Theeuwes, 2017; Pessoa, 2015). These findings provide a clear mechanisms through which motivation can influence attention in the visual cortex which is in line with the existing models (Roelfsema et al., 2010). Finally, this study demonstrates the value of using the SSVEPs to investigate the simultaneous competition for attentional resources of stimuli of different values. This technique can be used to further test the existing theoretical models which relate attention and motivation. Crucially, this technique allows for measuring the processing of both targets and distractors, while dissociating between the effects of goal-driven attention and reward.

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. 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.

# 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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