Master Thesis

The Effect of Reward on Cognitive Control

Wouter Wissink

June 20, 2023

External Supervisor: Dr. rer. nat. Stefan Arnau
1st Supervisor: Prof. dr. ing. Willem B. Verwey
2nd Supervisor: Dr. Rob H.J. van der Lubbe

Human Factors and Engineering Psychology

Faculty of Behavioural, management and Social Sciences (BMS)

Section Cognition, Data & Education (CoDE) / Department of Learning, Data-Analytics and Technology

University of Twente, Enschede, The Netherlands

Abstract

Motivation is known to play an important role in moderating goal-directed behaviour, but the precise interaction between motivation and cognitive control remains unclear. The present study aimed to investigate how much increased motivation through reward incentives can shift cognitive control from a reactive to a more proactive mode. Using EEG in an incentive-based cued task-switching paradigm, we recorded 26 participants' brain activity while they completed high and low reward sequences. Our results revealed that the high reward sequences elicited shorter response times and larger EEG amplitudes for the cue-induced CNV and the task-induced P3b and N2 components, indicating a shift towards more proactive control. However, the cue-induced LPP, P3b and N2 did not respond to reward conditions, which might be due to how motivation was manipulated in sequences instead of on a trial-by-trial basis. Future studies should investigate the influence of different incentive manipulation strategies on these ERP components.

Table of Contents

Introduction

Imagine you are presented with a plate of your favourite food. However, summer is coming up and you want to lose a few pounds in order to impress your friends at the beach. Instead of eating the whole plate, you consider your goal and resist the temptation, restraining yourself to just eat a small portion of the dish instead. Now, imagine that it's winter. You still want to lose a few pounds, but you will not be going to the beach to show off your body anytime soon. This time, it is harder to resist the temptation to eat the whole plate, it is your favourite food after all. And would anyone really notice the difference? Before you realised it, you ended up eating the whole plate. As depicted in this example, humans do not always work towards their goals as well as they could. Goal-directed behaviour is motivated and depends on the personal wants, needs or desires of an individual (Satpute et al., 2012). It is the aim of the present study to investigate the influence of different motivation levels on goal-directed behaviour.

Research on the influence of motivation on performance shows that effects of reward are more prominent in tasks requiring cognitive control (Boehler et al., 2014; Kleinsorge & Rinkenauer, 2012; Padmala & Pessoa, 2011). Cognitive control refers to a set of top-down mental processes, that are needed for when an automatic processing mode does not suffice (Diamond, 2013). The functions of cognitive control include mental set shifting, information updating and monitoring, and inhibition of prepotent responses (Miyake et al. 2000; Diamond, 2013). These cognitive functions allow us to intentionally select thoughts, emotions and behaviour based on our current task demands and social contexts, while filtering and suppressing inappropriate habitual actions (Miller & Cohen, 2001, as cited in Dixon, 2015).

Although cognitive control has been studied extensively over the last decades, the interaction between cognitive control and motivation is not yet understood quite so well (Botvinick and Braver, 2015). In the Expected Value of Control framework, Shenhav et al. (2013) proposed how human decision-making is done. Their framework posits that the dorsal anterior cingulate cortex (dACC) integrates information pertaining to the anticipated payoff from a controlled process, the level of control investment needed to achieve that payoff, and the cognitive effort cost associated with it. This integrated information is then used to decide whether, where, and how much control is allocated to a task. A higher expected value of control for a task is associated with increased motivation for the individual to take action and strive

towards achieving the desired outcome. Incentives have often been utilised in order to motivate individuals to perform to the best of their abilities in experimental settings (e.g., Knutson et al., 2000). The findings from these experiments indicate that when motivated, human and animal performance can show improved speed and accuracy (Mir et al., 2011; Bijleveld et al., 2010), improved visual cognition (Small et al., 2005; Engelmann et al., 2009), better cognitive control (Locke & Braver, 2008), improved memory (Wittmann et al., 2005), improved task switching (Aarts et al., 2010, Umemoto & Holroyd, 2015) and even better performance in intelligence tests (Duckworth et al. 2011). In a classic Stroop task study conducted by Krebs et al. (2010) it was also found that larger rewards as opposed to smaller rewards led to better performance.

Cognitive control is not thought to be a single mechanism that can be used to a larger or lesser extent. Instead, Braver (2012) proposed the dual mechanisms of cognitive control (DMC) framework, in which cognitive control is described as having two distinct mechanisms: proactive and reactive control. Proactive control mechanisms are only engaged when a task is deemed important enough to actively anticipate future task demand, as the anticipatory activation requires more of the limited cognitive attentional resources than reactive control (Cowan, 2001). During proactive control, individuals will mentally prepare for an upcoming event so that they can quickly respond when the event presents itself. Imagine being in a street-race, waiting for the red traffic light to turn green. You anticipate for this moment, focusing intently on the exact moment the light changes so you can immediately accelerate without losing precious time. Reactive control on the other hand is engaged in other situations where a task is not deemed important enough to anticipate an upcoming event, or when it is not possible to prepare. Instead, the task is only engaged when it presents itself. Imagine waiting for the red traffic light to turn green again, but this time instead of racing, you're simply going grocery shopping and there is no need to hurry, concerning yourself only with the traffic light when the time comes. Compared to proactive control, which is thought to mostly involve the lateral prefrontal cortex (PFC), reactive control additionally originates from the ACC (Braver et al. 2009), the inferior frontal gyrus (IFG) and the anterior insula (AI; Kurzban et al., 2013). An increase in cognitive control to high reward conditions could be an indication of a shift in processing from a reactive to proactive control mode (Chiew & Braver, 2013, 2014; Fröber & Dreisbach, 2016). In the present study, the potential shift in processing strategy in relation to motivation will be investigated with EEG in order to study how far a potential shift from reactive to a proactive control mode is observable in

a high compared to a low reward condition.

Regarding the investigation of cognitive control processes, the EEG has specific advantages. The high temporal resolution of the EEG enables the distinct separation of preparatory processes from the task-processing itself. This is essential to distinguish proactive and reactive control modes as preparatory processes are associated with proactive cognitive control. An experimental paradigm that allows to do this is the cued task switching paradigm, as cue and target processing can be investigated separately. Cued task-switching paradigms differ from ordinary task-switching paradigms in that the upcoming task is indicated beforehand with a cue. Task-switching paradigms are generally used to investigate cognitive flexibility. Participants are usually slower and more error prone after switching to another task (Monsell, 2003; Vandierendonck et al., 2010). These decrements in behaviour are referred to as "switch cost". These switch costs are observable even if the participant has been warned of the upcoming task switch (Swainson et al., 2021; Hirch et al., 2021) as is the case with cued task-switching, where the participant is warned of an upcoming task-switch beforehand by providing them with a cue of what is expected of them. For example, Capa et al. (2013) conducted a study where participants had to perform either of three tasks for a varying monetary reward. Their cued task-switching paradigm contained three tasks that participants had to perform: judging whether a shown number was odd or even, whether the number was smaller or greater than 5, or whether the number was inside or outside the continuum of 1-9, with a task-switch likelihood of 50%. A task-cue was shown 1750 ms before stimulus onset to provide a warning for the upcoming task, displaying a variety of cues that inform about which task to perform in the subsequent stimulus. Combined with EEG, this cue allowed them to investigate whether incentives of varying monetary values impacted preparatory processes starting from task-cue onset in addition to investigating performance and accompanying task-related activity during task switches. They found shorter response times, associated with a larger contingent negative variation (CNV) at task-cue onset, and larger parietal P3 component under conditions of high conscious reward, which suggested a larger amount of working memory being invested during task performance (Capa et al., 2013). Although the switch cost can be reduced by such warning cues, a residual switch cost remains (Altmann, 2004; Mayr & Kliegl, 2000) The switch cost has been explained within Task set reconfiguration accounts (Mayr & Kliegl, 2000; Rogers & Monsell, 1995) and interference accounts (Goschke, 2000) as the result of needing to adapt to a new task set that is

needed to determine behaviour in a given (changed) context (Ye & Damian, 2022). Task switching performance has been shown to be affected by reward expectancy in particular (e.g. Kleinsorge & Rinkenauer, 2012), rendering this paradigm suited to investigate control mode shifts in different reward conditions.

In the present EEG study, an adaptation of the study conducted by Hubbard et al. (2019) was used. In their study, Hubbard et al. (2019) used a cued task-switching paradigm in which a stimulus array of eight circular gratings in a larger circular grating was shown. The circles contained gabor patches, two of which differed from the other patches by showing another colour (yellow/red) or tilt orientation (left/right) and an auditory cue indicating which aspect should be paid attention to. Our adaptation implemented monetary incentives in order to investigate the influence of high versus low reward conditions on cognitive control, and more specifically the influence on the engagement of proactive and reactive control modes, by observing the changes in after cue and target onset. With the EEG, the intention was to investigate event-related potentials (ERPs) in response to the cue and to the target stimulus. The ERP-components of interest that were studied were the frontal N2 in response to the cue and also the target, the frontal CNV during the cue-target interval, the posterior LPP during the cue-target interval and the posterior P3b-component, again in response to the cue and the target.

The frontal N2 is a negative deflection of the ERP that occurs around 200-350 ms after stimulus presentation and is associated with inhibition of incorrect response tendencies caused by the processing of irrelevant stimuli or by the choice process when given competing alternatives (Nieuwenhuis et al., 2003; Folstein & van Petten, 2004; Deng et al., 2015). Larger amplitudes can be observed in tasks where a stronger conflict detection is present, such as when switching tasks where behavioural rules need to be updated to the new requirements (Cudo et al., 2018). It is likely to originate from the ACC (Folstein & van Petten, 2007), which in terms of the DMC framework is related to reactive control (Cudo et al., 2018). The frontal N2 is also found to be larger whenever an individual is motivated to perform a task as opposed to when the task is of low importance (Jiang & Xu, 2014) which indicates that more attentional resources are allocated to the task.

The frontal CNV is a slow, surface-negative component that occurs in the interval between a warning stimulus and a probe stimulus to which a motor action is required, in a time window ranging from several hundred milliseconds to several seconds to the presentation of the

probe stimulus (Tecce, 1972; Kononowicz & Penney, 2016). It reflects the anticipation of the upcoming stimulus and has been related to response readiness, preparatory attention, motivation, and motor preparation (Schevernels et al., 2014). The CNV has been shown to be responsive to reward, with larger CNV amplitudes being measured in trials where rewards could be obtained (Capa et al., 2013), implicating a larger amount of cognitive resources spent on trials that are deemed more important. In terms of the DMC framework, a more negative amplitude in the CNV is associated with proactive control, as more anticipation and preparation is thought to occur (Li et al., 2018). A network of brain areas is thought to generate the CNV, among which the frontal sources in the supplementary motor area, the ACC, and the motor cortex (Gómez et al., 2003).

The posterior P3, or more specifically the P3b, is a positive-going component that occurs around 250-500 ms after a stimulus is presented and is associated with the allocation of attentional resources to task-relevant information and the updating of working memory (Donchin & Coles, 1988). The P3 amplitude is sensitive to the extent to which attentional resources are allocated during dual-task performance (Polich, 2007). Like the other components, it is larger for tasks that are deemed more important, or for which an individual is motivated to perform (Van den Berg et al., 2012). Larger parietal P3 amplitudes are being associated with better response times on tasks with a high reward, suggesting higher working memory investment (Capa et al., 2013). The P3 is thought to originate from the parietal lobes, which are involved in attentional processes, spatial processing and working memory (Polich, 2007). A more recent review by Verleger (2020) found it to be mostly associated with S-R link reactivation and memory storage. In terms of the DMC, a larger amplitude is associated with more proactive control (van Wouwe et al., 2011).

The late posterior positivity (LPP) is a positive-going component that emerges around 300-500 ms post stimulus, continuing for a sustained period and is associated with cue-based task selection, reflecting changes in mental effort, and sustaining attention to a stimulus (Kranz, 2015; Chevalier et al., 2015). The LPP shows larger amplitudes in task-switching trials than repetition trials (Chevalier et al., 2015; Manzi et al., 2011). The component is sensitive to arousal, showing larger amplitudes to more arousing emotional stimuli or monetary reward (Broyd et al., 2012; Kranz, 2015), the larger amplitudes being associated with more proactive control (Chevalier et al., 2015).

In this study, we expected to find that high reward trials should benefit behavioural performance compared to low reward trials: we expected higher accuracy and shorter response times, as these are common measures of behavioural effort investment that have been found in previous studies and might be associated with more cognitive resources being used for trials that are deemed more important. We also anticipated that for task switching trials response time would be longer, and accuracy would be lower than in repetition trials, as these trials are anticipated to be harder due to the need to adapt to new task sets. In addition, we expected to find an interaction of high reward trials on task switching interference, with high reward trials showing a decreased switch cost in switch vs repetition trials, as this has been observed in previous studies (Chiew & Braver, 2016; Kleinsorge & Rinkenauer, 2012). In regards to the electrophysiological data, we expected to find larger amplitudes for rewarded trials and switch trials, as these aspects are deemed to elicit more proactive behaviour than low reward or repetition trials. More specifically, during the cue-target interval we expected to find an enhanced CNV for high reward compared to low reward, and for switch trials compared to repetition trials, as the CNV is associated with proactive control, with larger amplitudes indicating an increase in motor preparation for the upcoming task. We anticipated that the P3b, which has been associated with resource engagement, context updating, working memory, and proactive control, would show larger positive amplitudes in both task-cue and target onset for switch and reward trials as reward induced motivation is anticipated to increase effort put into the task and task switching requires context updating. We anticipated that the LPP would be responsive to task switching, showing larger amplitudes than when repeating tasks. We also expected it to show larger amplitudes during high reward conditions. Regarding the N2, which is associated with conflict monitoring and incorrect response inhibition, we anticipated more negative amplitudes for high reward and for switch trials, in particular in response to the target stimuli.

Method

Participants

Participants were recruited via an announcement in a Facebook group of the Leibniz Research Centre for Working Environment and Human Factors Dortmund. Participants had to meet several criteria: an age between 18 and 30 years old, not to be diagnosed with any

psychiatric or neurological disorders, a normal or corrected-to-normal vision, and not being colourblind as tested with the Ishihara test (Ishihara, 1972). All participants were right-handed according to the Edinburgh Handedness Inventory. Furthermore, it was ensured that participants met the criteria for the acquisition of the structural MRI scan, which is not related to the present report. In total, the data of 27 participants were acquired for this study. Due to missing triggers in the EEG data, the data of one participant had to be excluded from the analysis. The resulting sample contains data of a total of 26 volunteers (3 men, 23 women) with a mean age of 21.7 (*SD* = 2.2). Participants received a monetary reward in exchange for their participation. The study received approval by the ethical committee of the Leibniz Research Centre for Working Environment and Human Factors Dortmund (Ifado) and was in accordance with the Declaration of Helsinki. Participants signed informed consent prior to the experiment. Data collection was done at the Leibniz Research Centre for Working Environment and Human Factors Dortmund.

Materials and Apparatus

EEG data was recorded using 128 passive Ag/AGCl electrodes (Easycap GmbH, Herrsching, Germany) arranged according to the international 10-10 electrode placement system, connected to a NeurOne Tesla AC-amplifier (Bittium Biosignals Ltd, Kuopio, Finland) and using the BrainVision Recorder software. During recording, a 250 Hz low-pass filter was applied. The AFz electrode was used as the ground electrode, and the FCz electrode was used as the online reference. A sampling rate of 1000 Hz was used for data recording and electrode impedances were kept below 10 kΩ to ensure the signal was of acceptable quality for further analysis.

The experiment took place in an electrically shielded chamber, optimised for EEG experiments. The room contained a chair for the participant to sit on with each armrest containing one button for responding to the trial at hand. The experiment was shown on a 20” colour monitor (100 Hz, 1024 x 768px). To communicate with the participant, a microphone from outside could connect with speakers in the room for correcting instructions or answering questions. The participant could be observed from outside of the room with a camera.

Design and task

The focus of the study was to measure brain activity during varying states or levels of motivation and its influence on performance. For this, participants participated in an incentive based cued-task-switching paradigm, which was adopted from Hubbard and colleagues (2019).

Motivation was manipulated by implementing sequences where more points could be earned the better the performance, resulting in a higher financial reward. Participants were instructed to perform the task as quickly and accurately as possible in order to obtain these points, with a response threshold being determined based on the 60th percentile performance during the training blocks. A schematic presentation of the experiment is presented in Figure 1.

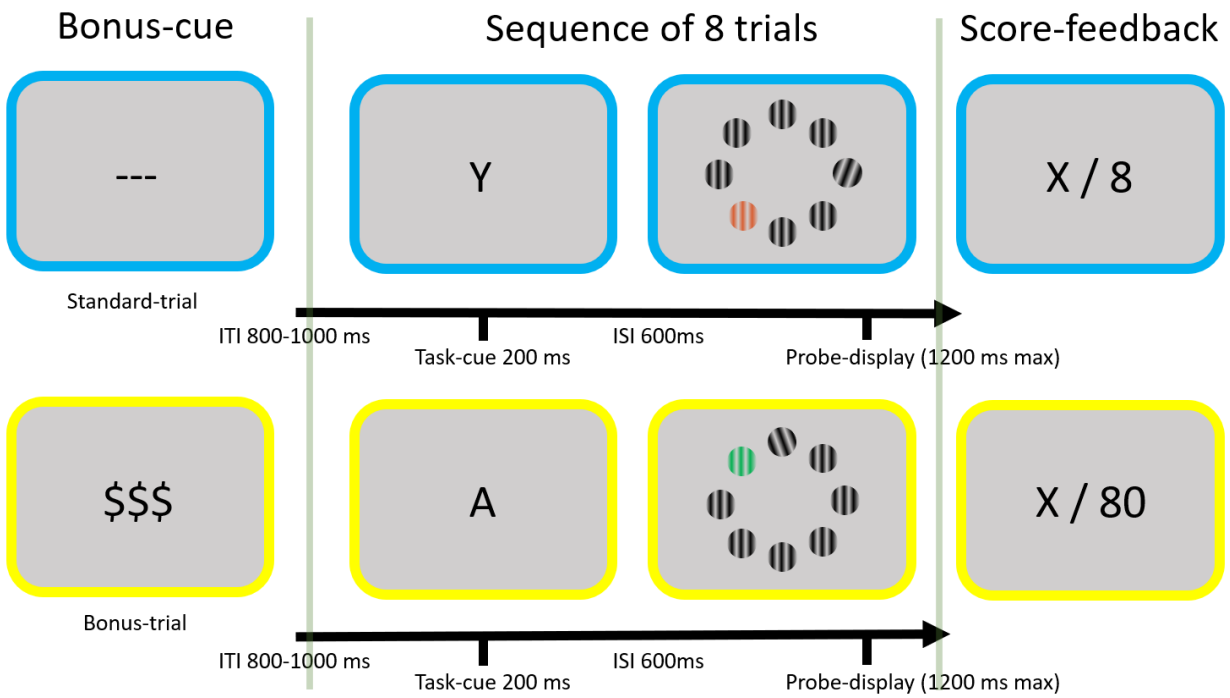

Figure 1. *Schematic overview of the sequence of events during each trial. An indication was given on whether the upcoming sequence of eight trials would be high reward ($$$) or low reward (---) at the beginning of each sequence, with an additional coloured border functioning as a reminder during the sequence. After an ITI of 800-1000 ms, the task-cue (A, Y) indicating the to-be performed task was presented for 200ms, indicating whether the participant should pay attention to the colour (green/red) or tilt orientation (left/right). The probe display containing a target and distractor variable at random positions in the tray was then presented for a maximum of 1200 ms, after an ISI of 600 ms. After a sequence had concluded a feedback screen was shown indicating the earned amount of points (X).*

The colours used in the experiment are reported in CIE 1931 XYZ colour-space values. Unless stated otherwise, all stimuli were presented in black (0.287 0.312 0.0) against a light grey

background (0.287 0.312 12.5). The presentation of the switching task occurred in alternating sequences of eight trials of low and high reward. On trials that were accurate and performed fast enough, 1 point could be earned for low reward trials, whereas on high reward trials 10 points could be earned with each correct fast response. Low reward trials were introduced with an 800 ms lasting "---" at the beginning of each sequence of 8 trials, high reward trial sequences were introduced with "$$$". Furthermore, the current reward condition was at any time framed at the edge of the screen with colour blue (0.222 0.282 50.0) or yellow (0.36 0.43 50.0) colours and corresponding sequences were counterbalanced across participants. At the end of each sequence, a feedback screen was shown at the centre of the screen for 800 ms, indicating the amount of earned points in comparison to the total amount that could be earned for the sequence, X out of 8 for low reward sequences or X out of 80 for high reward sequences.

Each trial within the sequences started with displaying the task cue consisting of the letter A, B, X or Y, with A/B indicating one task, and X/Y indicating the other task (1° viewing angle height). The cues indicating which task was to be performed were counterbalanced across participants and lasted for 200 ms, followed by a cue-target interval where a fixation mark was shown for 800 ms. Then, the probe-display was displayed, showing eight circles with a diameter of 1.5 degrees each, placed in a larger circle with a diameter of 6 degrees relative to the center of the main circle. These lasted until the participant had responded with a button on the modified chair or until a set amount of 1200 ms had passed. The probe-display circles were Gabor-patches, of which six were equal, the other two differing in colour, red (0.5 0.38 25.0) or green (0.264 0.456 25.0 at peak saturation) or orientation, with a patch being tilted by 20 degrees to the left or to the right. Depending on the task cue, participants had to pay attention to one of these aspects to perform the task: answering whether the deviating patch was either red or green in the colour task, or tilting to the left or to the right in the orientation task, whilst ignoring the distractor variable. Which colour belonged to which button was also counterbalanced across participants for the colour task, but not for the orientation task, with the purpose of preventing a S-R compatibility effect (Kornblum et al., 1990).

Before gathering data, participants were introduced to the tasks by performing four practice blocks. Participants learned the response mapping to the colour task in the first 16 trials, and then the mapping to the orientation task in the next 16 trials. The next block of 32 trials introduced the dual-task practice and the switching between them. The fourth block of 64 trials

introduced the low reward vs high reward trial practice and the 8-sequence structure of the low reward vs high reward trials. Here, it was also decided what the threshold for a successful trial was for a participant, with the 60th percentile of the response times observed in this block being an indication for a fast enough trial worth points. After these blocks, the experiment followed with eight experimental blocks of 256 trials each, leading up to 2048 trials per participant.

In total, there were eight different versions of the task to compensate for artefacts which might occur during each version, as versions differed in which button to press for the colour task (2), Cue indicators (AB/XY) and low vs high reward colour indicators (2). After completion of the tasks, participants were asked in a Likert scale questionnaire about the extent to which they put in effort amongst the different reward conditions, their level of motivation for an adequate performance on the experiment and the amount of experienced mind wandering.

Procedure

The experiment took place in one of the EEG experiment chambers of the Leibniz Research Centre for Working Environment and Human Factors. To control for circadian differences, all participants arrived at the institute at 8:30 am. After arrival, they conducted a COVID 19 rapid test. Participants were then led to the experiment chamber where they were seated on a chair to apply the EEG cap. Then, they performed the Ishihara test, the Edinburgh Handedness inventory, and a demographics questionnaire. Participants received a pre-experimental briefing regarding the monetary compensation consisting of a fixed amount of 35 Euro and a variable amount of up to 20 Euro, in addition, the fastest 50% of participants with the highest number of points would enter a lottery where one could win a voucher of 50 euro. They were instructed to respond as quickly and as accurately as possible to maximise the obtained score and the variable amount of the compensation. Participants signed informed consent. Then they were brought into the EEG room and sat in the modified chair. Participants had to perform one of the eight versions of the experiment. Task instructions were given on the screen in front of them. After going through the introduction blocks and the participant was certain they understood, the experiment began, which took roughly 2 hours to complete.

EEG Preprocessing and data analysis

EEG data was preprocessed and analysed in Matlab version R2022B (The Math Works Inc., Natick, Massachusetts), using the EEGLAB toolbox version v2022.1 (Delorme & Makeig,

2004) (see Appendix A). The first step was to re-reference the data to the CPz electrode to obtain the signal for the FCz electrode which had been used as the online reference during recording. The data was then downsampled to 250 Hz and larger noise artifacts were removed by cutting out one-second-long segments after boundary events and rejecting continuous portions of the data based on spectral thresholding in the frequency range from 20 to 40 Hz to address muscular artifacts. A band pass filter was applied from 0.1 Hz to 30 Hz and bad channels were detected and rejected based on kurtosis criteria. On average, M=8.23 (SD = 4.1) channels were rejected per participant. The remaining data was re-referenced to the average reference.

The continuous data was then segmented into epochs of 3600 milliseconds, from -1000 to 2600 from task-cue onset, after which noisy epochs with artefacts were rejected with an automated trial rejection function that removed trials above the fluctuation threshold of 1000 μV, a probability threshold of 5 SD, and a maximum percentage of rejected trials per iteration of 5%, removing on average 226.69 (SD = 85.5) epochs. After compressing the data to the dimensionality matching its rank using PCA, an independent component analysis (ICA) was performed with ICLabel (Pion-Tonachini et al., 2019) to identify and separate signals not originating from cortical activity. ICs with a probability of less than 0.3 likeliness to reflect brain activity, or a probability of more than 0.3 for the eyes category were rejected. This led to an average rejection rate of 70.04 ICs (SD = 10.97 ICs).

For the calculation of the ERPs a baseline was set from -200 ms to 0 ms relative to the task-cue onset. Only the EEG data of correctly answered trials were used and ERPs were calculated by averaging across trials within each condition combination (low reward-high reward and repeat-switch). Data were also averaged across electrodes, for a frontal electrode position cluster and a posterior electrode position cluster. The frontal electrode cluster contained the electrodes F1, Fz, F2, FFC1h, FFC2h, FC1, FCz, FC2, FCC1h, FCC2h, C1, Cz, C2, and the posterior electrode cluster contained the electrodes P1, Pz, P2, PPO1h, PPO2h, PO3, POz, PO4, POO1, and POO2. An overview of the electrode patches can be seen in Figure 2.

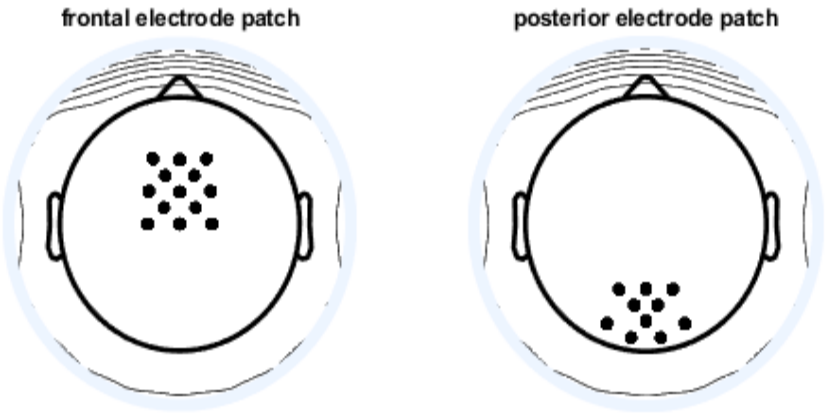

Figure 2. *Overview of the frontal and posterior electrode clusters*

Statistical analysis

The experiment involved a 2 x 2 factorial repeated measures design, as the focus of the study was to analyse the effects of the independent variables task switch conditions and reward conditions. The behavioural data which consisted of the dependent variables accuracy and response times of correct trials, and the EEG data of the frontal and posterior electrode patches, were both analysed using a within-subjects analysis of variance (ANOVA) with $\alpha \leq 0.05$ for all aspects (low/high reward, repeat/switch). For the EEG data, the dependent variables of interest were the frontal CNV and N2 components and the posterior P3b components, the time windows of these components being specified using a collapsed localizer approach.

Results

Behavioural data

The first hypothesis predicted that high reward trials would exhibit increased accuracy and reduced response times. The second hypothesis proposed that switch trials would show lower accuracy and increased response times. Visual inspection revealed that response times and accuracy were both influenced by reward and task switch conditions. With response times being shorter in high reward and repetition trials and longer in low reward and switch trials, and accuracy being most precise in high reward and repetition trials and least precise in low reward and switch trials (Figures 3 and 4).

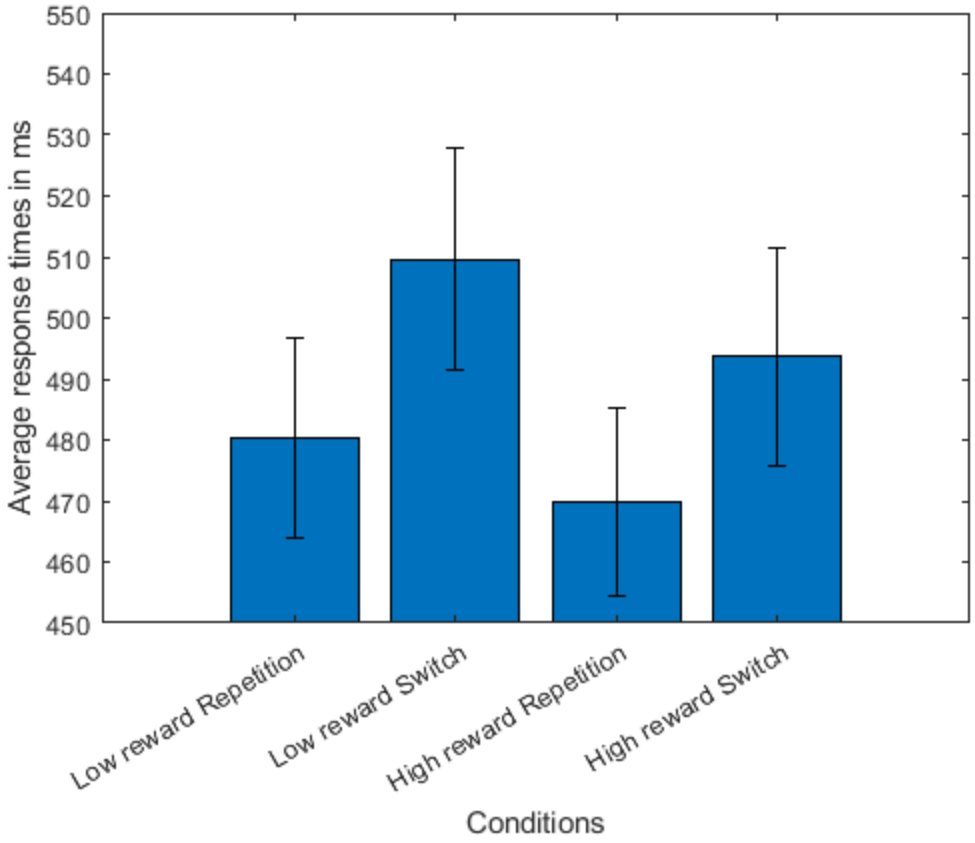

Figure 3. *Mean response times in ms across all conditions. Error bars show standard error of the mean.*

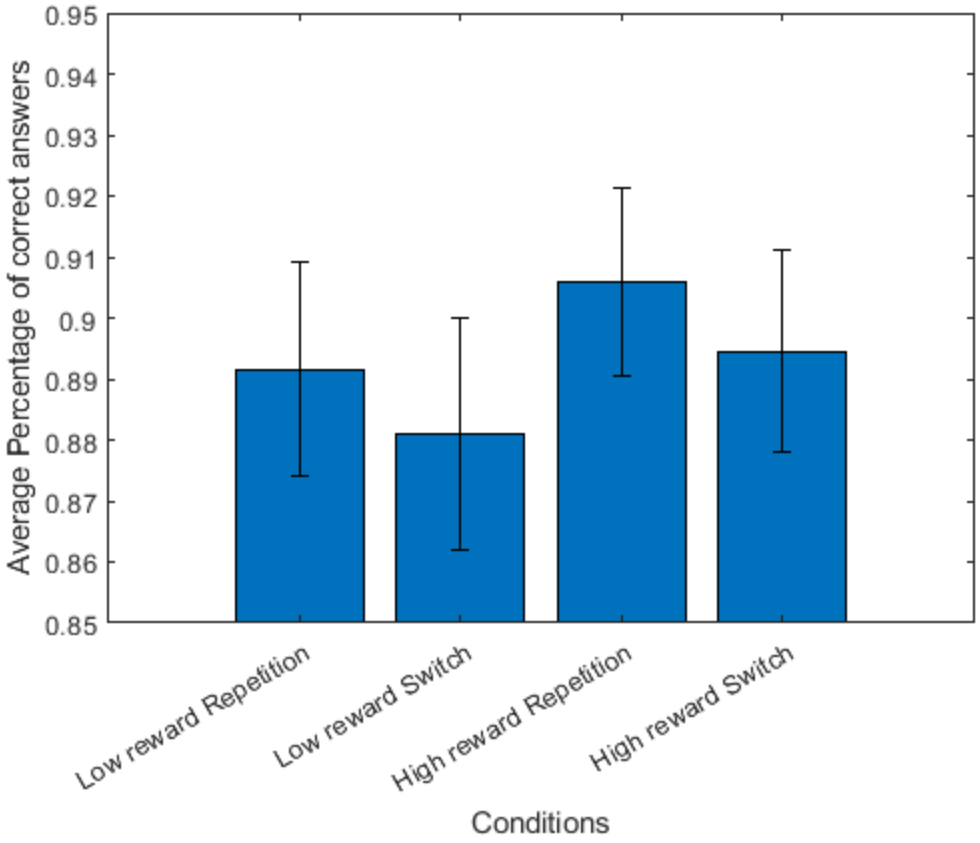

Figure 4. *Mean score for accuracy in percentage across all conditions. Error bars show standard error of the mean.*

Response time

The mean response times across all conditions are presented in Figure 3. The within-subjects ANOVA was conducted to analyse the effects of reward conditions and task switch conditions on response times. The results revealed significant main effects for reward conditions $F(1, 25) = 21.509$, $p < .001$, $\eta_p^2 = .462$, and task switch conditions $F(1, 25) = 51.498$, $p < .001$, $\eta_p^2 = .674$. Specifically, response times were shorter for high reward trials compared to low reward trials in both task switch conditions, and switch trials took longer to respond compared to repetition trials in both reward conditions. However, no significant interaction was found between reward conditions and task switch conditions $F(1, 25) = 1.625$, $p = 0.214$, $\eta_p^2 = .061$.

Accuracy

The accuracy rates across all conditions are displayed in Figure 4. The within-subjects ANOVA showed a significant main effect for task switch conditions $F(1, 25) = 6.578, p < .001$, $\eta_p^2 = .208$, with switch trials showing lower accuracy compared to repetition trials in both reward conditions. However, there were no significant differences in accuracy between high reward and low reward trials $F(1, 25) = 3.783$, $p = 0.063$, $\eta_p^2 = .131$. Additionally, no interaction for accuracy was found between reward conditions and task switch conditions, $F(1, 25) = 0.008$, $p = 0.930$, $\eta_p^2 = .001$.

ERP analysis

The remaining hypotheses all focus on ERP components. ERPs were calculated for frontal and posterior electrode clusters from -200 to 1600 from task-cue onset (Figures 5 and 6).

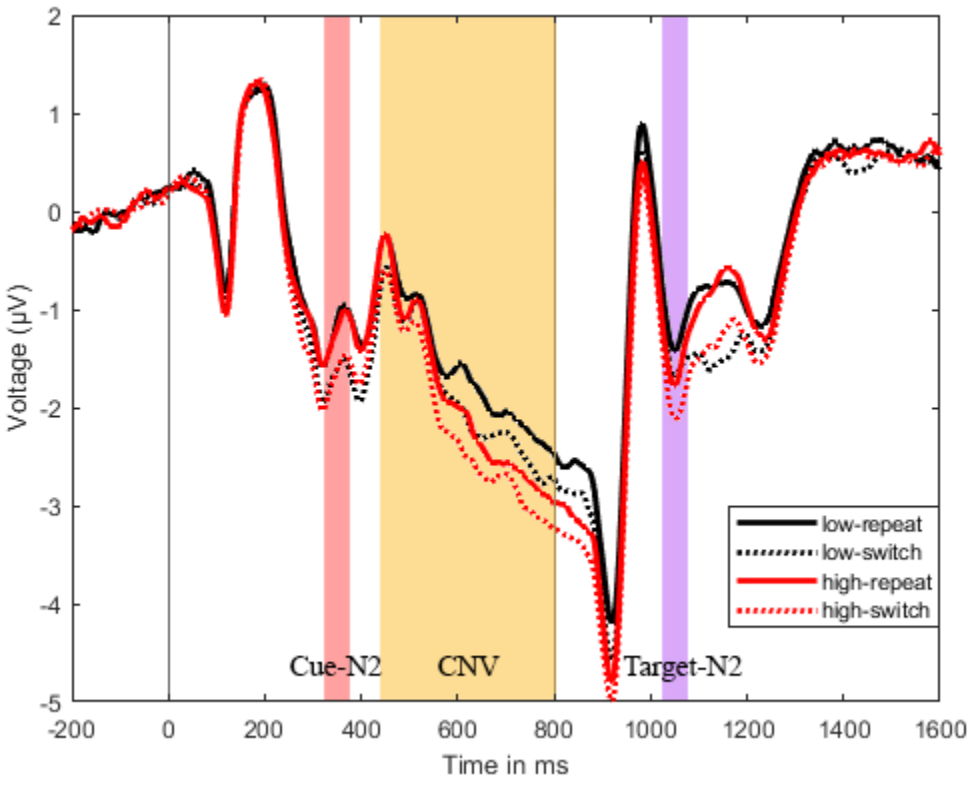

Figure 5. *ERPs of the frontal electrode cluster containing electrodes F1, Fz, F2, FFC1h, FFC2h, FC1, FCz, FC2, FCC1h, FCC2h, C1, Cz, and C2*

Note. The components of interest and their time windows have been specified with a collapsed localizer approach. For the CNV, the frontal electrodes within 440 to 800 ms of task-cue onset

were analysed (yellow). For N2, frontal electrodes within 325-375 ms from task-cue onset (red), and 1025-1075 ms from task-cue onset were analysed for the target-related N2 (purple).

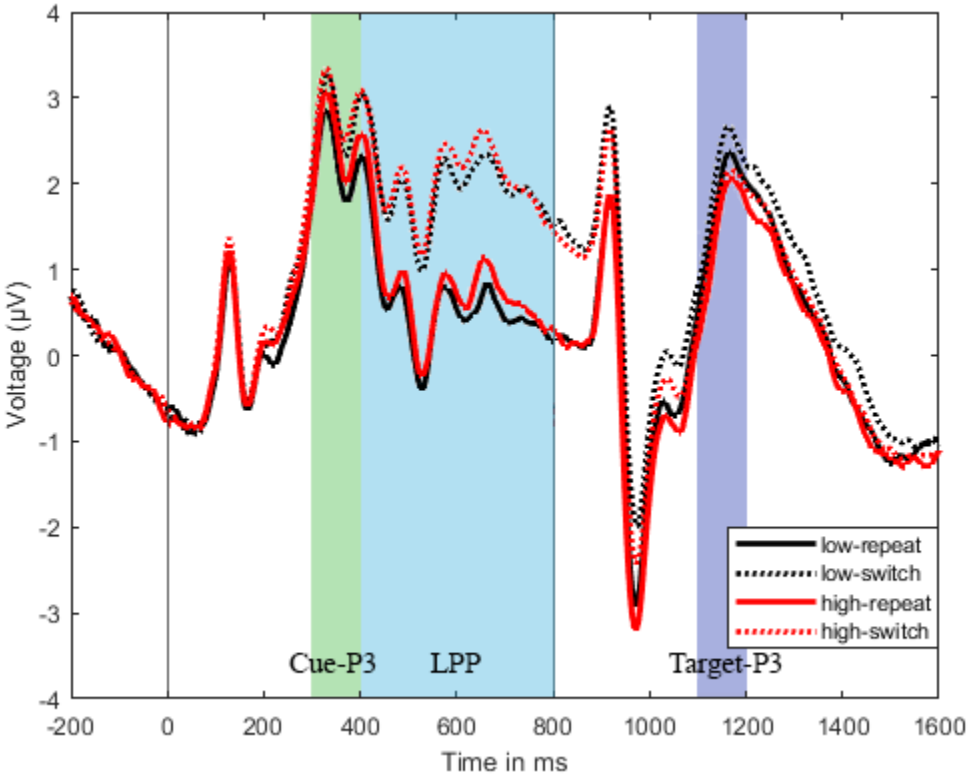

Figure 6. *ERPs of the posterior electrode cluster containing electrodes P1, Pz, P2, PPO1h, PPO2h, PO3, POz, PO4, POO1, and POO2.*

Note. The time windows for analysing the P3b components were also determined using a collapsed localizer approach. For the task-cue onset P3b, the time window of 300-400 ms from task-cue onset (green), for the LPP, the time window of 400-800 ms from cue-onset (light blue) and for the target-related P3, the time window of 1100-1200 ms from cue-onset was analysed (dark blue).

Frontal N2 component

Our expectations were that the frontal N2 component would be larger for tasks where conflict detection is deemed more important. A topography was made for the frontal N2 with the time frame of 325 – 375 ms from task-cue onset to visualise brain activity (see Figure 7).

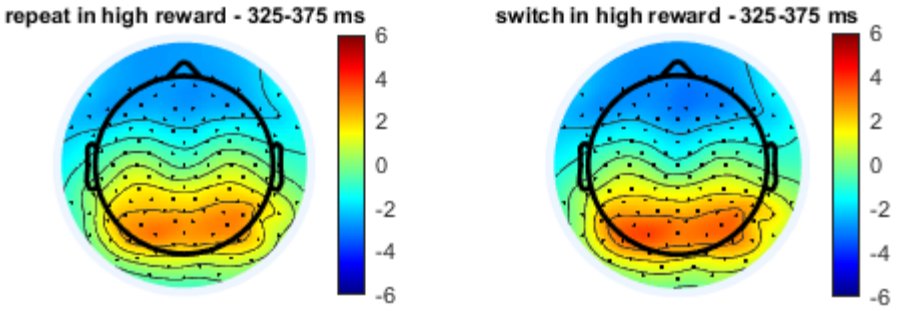

Figure 7. *Topography of the expected task-cue onset N2 time window of 325-375 ms*

The within-subjects ANOVA revealed a significant main effect of task switch conditions $F(1, 25) = 22.7$, $p < .001$, $\eta_p^2 = .475$, indicating that switch trials elicit a larger negative amplitude than repetition trials. No significant differences were found in the reward conditions $F(1, 25) = 0.058$, $p = 0.812$, $\eta_p^2 = .002$ for the task-cue onset N2. Additionally, no interaction was found between reward conditions and task switch conditions $F(1, 25) = 0.054$, $p = 0.818$, $\eta_p^2 = .002$.

For the target onset N2 the ERP of the frontal electrodes observed the component in the time window of 1025-1075 ms. A topography was created to visualise brain activity during this time window, as presented in Figure 8.

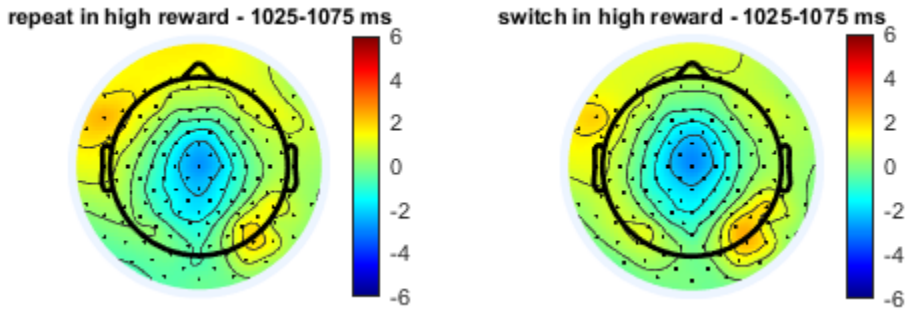

Figure 8. *Topography of the expected target onset N2 time window of 1025-1075 ms*

The within-subjects ANOVA showed that there were significant differences for both reward conditions $F(1, 25) = 11.189$, $p < .05$, $\eta_p^2 = .308$ and task switch conditions $F(1, 25) = 5.478$, $p < .05$, $\eta_p^2 = .180$ in the target onset N2, with high reward trials and switch trials both showing a larger negative amplitude in both conditions. Additionally, no interaction was found between reward conditions and task switch conditions $F(1, 25) = 0.150$, $p = 0.702$, $\eta_p^2 = .006$.

Frontal CNV component

We hypothesised that the CNV component should show more negative amplitudes in tasks that are perceived more intense and important, as more effort is put into preparing for the task. In the ERP for frontal electrodes, the CNV can be observed from 440-800 ms. A topography has been created to visualise the brain activity in this time window (see Figure 9).

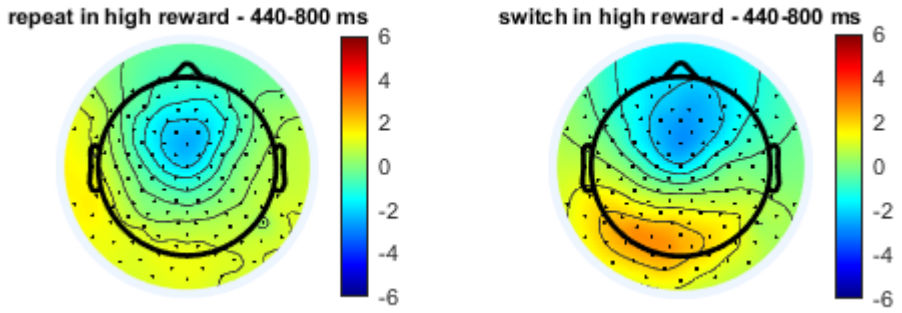

Figure 9. *Topography of the CNV component time window of 440-800 ms*

The results of the within-subjects ANOVA showed that there were significant main effects for both reward conditions, $F(1, 25) = 30.652$, $p < .001$, $\eta_p^2 = .551$, and task switch conditions $F(1, 25) = 8.266$, $p < 0.05$, $\eta_p^2 = .249$ in the CNV amplitude, with high reward trials and switch trials showing larger negative amplitudes in both conditions. No interaction was found between reward conditions and task switch conditions $F(1, 25) = 0.007$, $p = 0.935$, $\eta_p^2 = .001$.

Posterior P3b component

We anticipated that there would be a significant difference in cue and target onset for the P3b component in the posterior electrode cluster. For the task-cue onset P3b, a timeframe of 300-400 ms had been selected. A topography was made to visualise brain activity in this time window (see Figure 10).

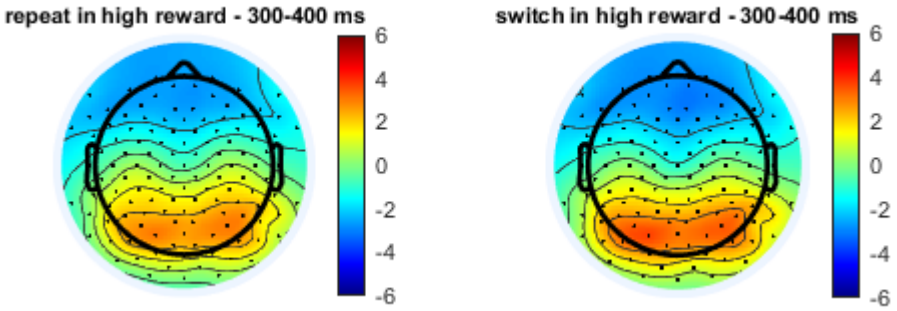

Figure 10. *Topography of the expected task-cue onset P3 time window of 300-400 ms*

The within-subjects ANOVA showed that there were only significant differences in task switch conditions $F(1, 25) = 24.274$, $p < .001$, $\eta_p^2 = .493$, with switch trials showing a larger positive amplitude than repetition trials in the task-cue onset P3b. No significant differences were found in the reward conditions $F(1, 25) = 3.061$, $p = 0.092$, $\eta_p^2 = .110$. Furthermore, no interaction was found between reward conditions and task switch conditions $F(1, 25) = 0.378$, $p = 0.544$, $\eta_p^2 = .015$.

For the target onset P3b, a topography has been created at the same 300-400 time interval after target onset, resulting in a topography of 1100-1200 ms from task-cue onset (see Figure 11).

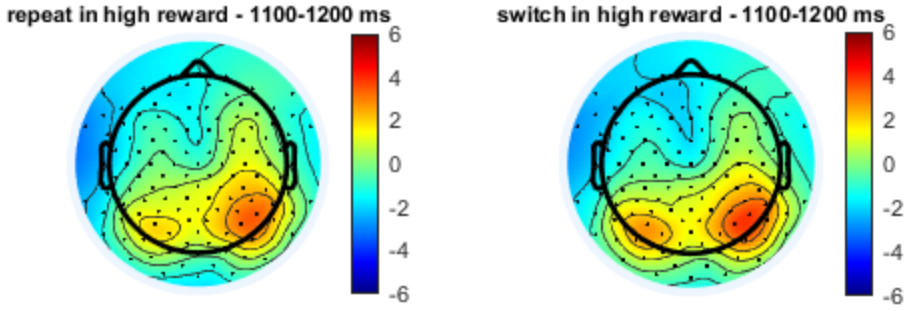

Figure 11. *Topography of the expected target onset P3 time window of 1100-1200 ms*

The within-subjects ANOVA revealed significant main effects for both reward conditions $F(1, 25) = 5.8135$, $p < 0.05$, $\eta_p^2 = .189$, and task switch conditions $F(1, 25) = 6.285$, $p < 0.05$, $\eta_p^2 = .202$ in the target onset P3b, with switch trials and low reward trials showing larger positive

amplitudes in both conditions than repetition and high reward trials. No interaction was found between reward conditions and task switch conditions $F(1, 25) = 0.487$, $p = 0.492$, $\eta_p^2 = .019$.

Posterior LPP component

We anticipated that the LPP component should show more positive amplitudes in tasks that are deemed more important as more attention is drawn to the stimulus. In the ERP for posterior electrodes, the LPP can be observed from 400-800 ms. A topography has been created to visualise the brain activity in this time window (see Figure 12).

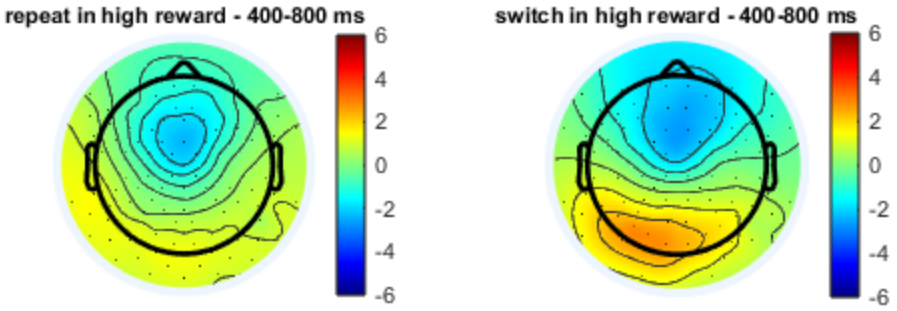

Figure 12. *Topography of the LPP component time window of 400-800 ms*

The results of the within-subjects ANOVA showed that there was a significant main effect for task switch conditions $F(1, 25) = 89.093$, $p < 0.05$, $\eta_p^2 = .782$ in the LPP amplitude, with switch trials showing a larger positive amplitude than repetition trials. No significant differences were found in the reward conditions $F(1, 25) = 2.215$, $p = 0.149$, $\eta_p^2 = .082$, and no interaction was found between reward conditions and task switch conditions $F(1, 25) = 0.284$, $p = 0.599$, $\eta_p^2 = .011$.

Discussion

The aim of the current study was to investigate the influence of different motivation levels on goal-directed behaviour. More specifically, we investigated whether monetary incentives could provoke a shift from reactive to more proactive cognitive control as described by the DMC (Braver, 2012). For this purpose, we used a cued task-switching paradigm where participants were rewarded based on their performance in switch and repetition trials in low and high reward conditions. To assess whether the experimental manipulations affected the invested cognitive effort during the experiment, we looked at the behavioural measures response time and accuracy. Additionally, we recorded the brain activity with the EEG and analysed ERP

components occurring during task preparation and execution, the frontal N2 and CNV, and the posterior LPP and P3b. In line with our hypothesis, the data suggest that proactive control can indeed be provoked with monetary incentives. However, not all predictions were met, as the reward component did not affect the behavioural accuracy or the task-cue N2, LPP and task-cue P3b ERPs. First, the behavioural expectations and findings will be discussed, then, we will describe the EEG findings.

The behavioural data showed that response times and accuracy were both affected by reward and switch conditions. Response times were shown to be shorter for rewarded trials and longer for switch trials, which was in line with the literature and our expectations (Bijleveld et al., 2010; Botvinick & Braver, 2015; Capa et al., 2013; Mir et al.; 2011). Accuracy was lower in switch trials, which can be attributed to task-switching leading to higher cognitive demand due to the need to update behavioural rules and adjusting to different control mappings (Cudo et al., 2018). However, a higher reward did not result in a better accuracy, which has been observed in recent studies too (Krebs et al., 2011; Padmala & Pessoa, 2011; Umemoto & Holroyd, 2014). One explanation for this observation is the presence of a speed-accuracy trade-off, which can occur in paradigms where participants know a reward can be earned (Wickelgren, 1977; Bijleveld et al., 2010). We instructed participants to respond as fast and accurately as possible, but perhaps participants prioritised responding faster rather than more accurate. Regardless, there is no clear evidence of a speed-accuracy trade off in our results either, as although it was not a significant result in either direction, the mean accuracy score for high reward trials was still higher than low reward trials. Although the behavioural measurements indicated that our paradigm succeeded in eliciting changes in performance depending on task-demand, there was no interaction between reward trials and task switching, indicating that reward did not decrease interference cost in incentivized switch trials, which had been observed in earlier studies (Chiew & Braver, 2016; Kleinsorge & Rinkenauer, 2012).

The high temporal resolution of the EEG allowed us to observe changes in brain activity in ERP components that are associated with goal-driven behaviour and cognitive control, specifically, the CNV, N2 and P3b. As we were interested in the dynamics of proactive control, we investigated task preparation during the cue-target interval in addition to the target response interval. This allows us to disentangle task-preparation, and task-processing and -execution. The CNV in particular has been associated with task-preparation and proactive control and is

observed leading up to an event (Tecce, 1972; Schevernels et al., 2014; Li et al., 2018). The literature associates the negative amplitude of the CNV with changes in activity of the ACC, the supplementary motor area, and the motor cortex (Gómez et al., 2003). Larger amplitudes have been observed during preparation of more important or demanding trials (Schevernels et al., 2014). The N2 component is of interest as it is a correlate of conflict processing in cognitive control, also originating from the ACC (Folstein & van Petten, 2004). Here, we investigated the modulation of the N2 after the cue as well as during the target-response interval amplitude related to the factors task switch and reward and the interaction. Last, we investigated the P3b originating from the parietal lobes (Polich, 2007) which is associated with the expenditure of cognitive resources during task processing.

During the cue-target interval, we observed an increase in CNV activity for both switch trials and rewarded trials, which was in line with our expectations and the literature, where increased CNV amplitudes during task-preparation are often found for trials that are regarded as more important or demanding (Capa et al., 2013; Falkenstein et al., 2003; Li et al., 2018). This suggests that both experimental factors, reward conditions and switch conditions, modulated the need for proactive cognitive control in order to perform well on the upcoming task, as larger CNV amplitudes have been associated with shorter RTs (van den Berg et al., 2014). Regarding the N2 during the cue-target interval, we observed larger amplitudes for the switch condition compared to repetition trials. This probably reflects a conflict detection related to the need to update the task rule after cue onset. Our finding was in line with our expectation that larger N2 amplitudes would be observed in trials introducing a cognitive conflict (Cudo et al., 2018). However, we did not observe systematic modulations of the frontal N2 amplitudes in response to the task-cue related to the reward condition. This is in contrast to Van den Berg et al. (2014), whose research did find an enhanced cue-N2 for reward conditions, attributing it to the salience of their reward prospect. In contrast to our design, however, they manipulated reward on a trial-by-trial basis, whereas in the design of the present study reward contingencies were manipulated in alternating sequences of eight trials. Our results therefore suggest that the previously observed reward-related modulation of the N2 in response to the task-cue is not related to high versus low reward per se, but possibly reflected reward cue processing. For the cue-target LPP we observed an increase in amplitude for switch tasks after cue onset, which was in line with the literature and our expectations (Chevalier et al., 2015; Manzi et al., 2011). However, we did not observe an

increase in amplitude for reward conditions, which contrasts the literature where the component had been found to be responsive to reward stimuli, however in these reports reward was manipulated on a trial by trial basis (Broyd et al., 2012; Zhan et al., 2016). For the cue-target interval P3b, we observed the same result pattern as for the N2 and LPP: The P3b responded to the switch-condition but not to manipulations of reward. As the P3b is associated with the updating of task-relevant stimulus information and investment of attentional resources we expected it to increase for both conditions. This finding is in contrast to Schmitt et al. (2015), who did observe larger P3b amplitudes for motivationally salient cues. Like in the study of Van den Berg and colleagues (2014), reward conditions were manipulated on a trial-by-trial basis. Again, these results suggest that previous findings regarding cue-related ERP components from studies using trial-to-trial modulations of reward conditions possibly reflect reward cue processing. Summarising our findings, the N2, LPP and P3 results indicate that task-cue processing was affected by the task-switching, but not by reward. Previous studies with different results used a trial-by-trial manipulation of reward. The CNV, however, is sensitive to both manipulations.

During the target-response interval, the N2-amplitudes were modulated by both experimental factors, that is by switching tasks and reward conditions. This was in line with our expectations as the N2 is associated with inhibition of incorrect response tendencies (Nieuwenhuis et al., 2003; Folstein & van Petten, 2004; Deng et al., 2015) and would need the participant to pick the correct variable in the presence of competing alternatives. Our result suggests that when the target was presented, additional resources were invested into the conflict processing within the task whenever it was deemed more important and demanding, which corresponds with the literature (Gajewski et al., 2010; Capa et al., 2013;). For the target-related P3b, we observed significant differences for both experimental factors, reward condition and task-switching. The observation of increased P3b amplitudes for switch trials is in line with the literature (Nicholson et al., 2005) and is generally associated with updating processes, organization, and implementation of the new task-set (Capa et al., 2013). The finding that high reward trials showed a smaller P3b amplitude compared to low reward trials is interesting, as we would have expected more cognitive resources to be invested in trials of larger importance. It might be the case that the increased reliance on proactive control in high reward trials, an increase of preparatory processes that are possibly reflected by the increased CNV amplitudes,

allowed for less resources to be invested after target presentation. The larger P3b amplitudes in low compared to high reward trials in response to the target could therefore be a correlate of re-active control. It should be noted that for the EEG results no interaction of reward on switch was observed. This is in accordance with Capa et al (2013) who found that both unconscious and conscious reward did not affect the switch cost either.

Conclusion

Our findings confirmed that incentive based manipulation of motivation influences goal-directed behaviour in the sense that more proactive control is induced when participants perceive that more reward can be earned, as evidenced by the improved response times and increased EEG amplitudes of the preparatory CNV, associated with task preparation, and task-related posterior P3b and frontal N2, respectively associated with expenditure of cognitive resources during task processing and conflict processing. The lack of responsiveness of the preparatory posterior LPP and P3b and frontal N2 or interaction between reward condition and task switch might be due to how motivation was manipulated in sequences rather than trial-by-trial, as it can be theorised that this resulted in a more general state of proactive readiness instead of being primed as a result from the cue as is the case with other studies that manipulated motivation this way.

Limitations and future studies

This study has some potential limitations that might have an influence on the results. First, due to the baseline preceding the cue-target interval, all interpretations of the ERP results in the target-response time window have to be taken with caution due to the presence of the slow wave effect of the CNV. As the CNV does not abruptly cease upon target onset, placing a baseline directly before target onset could have overlooked the ongoing influence of the CNV, which cannot be ruled out. Second, the sample size could be larger, adding more power to the analysis. Another aspect is the way reward was manipulated in this study. We made it clear that more points could be earned on reward sequences, with more points resulting in a larger monetary reward, but we did not translate these points to monetary value within the experiment itself. Perhaps that being more clear by using stronger reward associations, such as explicitly stating a sequence could either reward 1 cent per trial vs 10 cents per trial would create a

stronger reward effect. That being said, our paradigm did show responsiveness to the way reward has been handled and can be used for this purpose.

For future research it would be interesting to directly compare sequence-based manipulation of reward versus trial-by-trial manipulation of reward and its influence on these behavioural and EEG measurements, which to our knowledge has not been extensively researched before. This could increase understanding of how different temporal handling of motivational cues affect the dynamics of performance over time. Investigating whether or not this influences the occurrence of an interaction would provide insights in regards to how various levels of proactive control interacts with the cost of task-switching.

References

Aarts, E., Roelofs, A., Franke, B., Rijpkema, M., Fernández, G., Helmich, R. C., & Cools, R. (2010). Striatal Dopamine Mediates the Interface between Motivational and Cognitive Control in Humans: Evidence from Genetic Imaging. *Neuropsychopharmacology*, *35*(9), 1943–1951. https://doi.org/10.1038/npp.2010.68

Altmann, E. M. (2004). Advance Preparation in Task Switching: What Work Is Being Done? *Psychological Science*, *15*(9), 616–622. https://doi.org/10.1111/j.0956-7976.2004.00729.x

Bijleveld, E., Custers, R., & Aarts, H. (2010). Unconscious reward cues increase invested effort, but do not change speed–accuracy tradeoffs. *Cognition*, *115*(2), 330–335. https://doi.org/10.1016/j.cognition.2009.12.012

Boehler, C. N., Schevernels, H., Hopf, J.-M., Stoppel, C. M., & Krebs, R. M. (2014). Reward prospect rapidly speeds up response inhibition via reactive control. *Cognitive, Affective, & Behavioral Neuroscience*, *14*(2), 593–609. https://doi.org/10.3758/s13415-014-0251-5

Botvinick, M., & Braver, T. (2015). Motivation and Cognitive Control: From Behavior to Neural Mechanism. *Annual Review of Psychology*, *66*(1), 83–113. https://doi.org/10.1146/annurev-psych-010814-015044

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Braver, T. S., Paxton, J. L., Locke, H. S., & Barch, D. M. (2009). Flexible neural mechanisms of cognitive control within human prefrontal cortex. *Proceedings of the National Academy of Sciences*, *106*(18), 7351–7356. https://doi.org/10.1073/pnas.0808187106

Broyd, S. J., Richards, H. J., Helps, S. K., Chronaki, G., Bamford, S., & Sonuga-Barke, E. J. S. (2012). An electrophysiological monetary incentive delay (e-MID) task: A way to decompose the different components of neural response to positive and negative monetary reinforcement. *Journal of Neuroscience Methods*, *209*(1), 40–49. https://doi.org/10.1016/j.jneumeth.2012.05.015

Capa, R. L., Bouquet, C. A., Dreher, J.-C., & Dufour, A. (2013). Long-lasting effects of performance-contingent unconscious and conscious reward incentives during cued task-switching. *Cortex*, *49*(7), 1943–1954. https://doi.org/10.1016/j.cortex.2012.05.018

Chevalier, N., Martis, S. B., Curran, T., & Munakata, Y. (2015). Metacognitive Processes in Executive Control Development: The Case of Reactive and Proactive Control. *Journal of Cognitive Neuroscience, 27*(6), 1125–1136. https://doi.org/10.1162/jocn_a_00782

Chiew, K. S., & Braver, T. S. (2013). Temporal Dynamics of Motivation-Cognitive Control Interactions Revealed by High-Resolution Pupillometry. *Frontiers in Psychology*, *4*. https://doi.org/10.3389/fpsyg.2013.00015

Chiew, K. S., & Braver, T. S. (2014). Dissociable influences of reward motivation and positive emotion on cognitive control. *Cognitive, Affective, & Behavioral Neuroscience*, *14*(2), 509–529. https://doi.org/10.3758/s13415-014-0280-0

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, *24*(1), 87–114. https://doi.org/10.1017/S0140525X01003922

Cudo, A., Francuz, P., Augustynowicz, P., & Stróżak, P. (2018). The Effects of Arousal and Approach Motivated Positive Affect on Cognitive Control. An ERP Study. *Frontiers in Human Neuroscience*, *12*, 320. https://doi.org/10.3389/fnhum.2018.00320

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Deng, Y. , Wang, Y. , Ding, X. & Tang, Y. (2015). Conflict monitoring and adjustment in the task-switching paradigm under different memory load conditions. *NeuroReport, 26* (3), 124-130. https://doi.org/10.1097/WNR.0000000000000310

Diamond, A. (2013). Executive Functions. *Annual Review of Psychology*, *64*(1), 135–168. https://doi.org/10.1146/annurev-psych-113011-143750

Dixon, M. L. (2015). Cognitive control, emotional value, and the lateral prefrontal cortex. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00758

Donchin, E., & Coles, M. G. H. (1988). Is the P300 component a manifestation of context updating? *Behavioral and Brain Sciences*, *11*(03), 357. https://doi.org/10.1017/S0140525X00058027

Duckworth, A. L., Quinn, P. D., Lynam, D. R., Loeber, R., & Stouthamer-Loeber, M. (2011). Role of test motivation in intelligence testing. *Proceedings of the National Academy of Sciences*, *108*(19), 7716–7720. https://doi.org/10.1073/pnas.1018601108

Engelmann, J. B. (2009). Combined effects of attention and motivation on visual task performance: Transient and sustained motivational effects. *Frontiers in Human Neuroscience*, *3*. https://doi.org/10.3389/neuro.09.004.2009

Falkenstein, M., Hoormann, J., Hohnsbein, J., & Kleinsorge, T. (2003). Short-term mobilization of processing resources is revealed in the event-related potential. *Psychophysiology*, *40*(6), 914–923. https://doi.org/10.1111/1469-8986.00109

Folstein, J. R., & Van Petten, C. (2004). Multidimensional Rule, Unidimensional Rule, and Similarity Strategies in Categorization: Event-Related Brain Potential Correlates. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*(5), 1026–1044. https://doi.org/10.1037/0278-7393.30.5.1026

Folstein, J. R., & Van Petten, C. (2007). Influence of cognitive control and mismatch on the N2 component of the ERP: A review. *Psychophysiology*, *0*(0), 070915195953001-??? https://doi.org/10.1111/j.1469-8986.2007.00602.x

Fröber, K., & Dreisbach, G. (2016). How performance (non-)contingent reward modulates cognitive control. *Acta Psychologica*, *168*, 65–77. https://doi.org/10.1016/j.actpsy.2016.04.008

Gajewski, P. D., Wild-Wall, N., Schapkin, S. A., Erdmann, U., Freude, G., & Falkenstein, M. (2010). Effects of aging and job demands on cognitive flexibility assessed by task

switching. *Biological Psychology*, *85*(2), 187–199. https://doi.org/10.1016/j.biopsycho.2010.06.009

Gómez, C. M., Marco, J., & Grau, C. (2003). Preparatory visuo-motor cortical network of the contingent negative variation estimated by current density. *NeuroImage*, *20*(1), 216–224. https://doi.org/10.1016/S1053-8119(03)00295-7

Goschke, T. (2000). 14 Intentional Reconfiguration and. *Control of cognitive processes: Attention and performance XVIII*, *18*, 331.

Hirsch, P., Roesch, C., & Koch, I. (2021). Evidence for a multicomponent hierarchical representation of dual tasks. *Memory & Cognition*, *49*(2), 350–363. https://doi.org/10.3758/s13421-020-01097-3

Hubbard, J., Kikumoto, A., & Mayr, U. (2019). EEG Decoding Reveals the Strength and Temporal Dynamics of Goal-Relevant Representations. *Scientific Reports*, *9*(1), 9051. https://doi.org/10.1038/s41598-019-45333-6

Ishihara, S. (1972). *Tests for colour-blindness*. Kanehara Shuppan Co.

Jiang, H., & Xu, B. (2014). Reward enhances backward inhibition in task switching. *Journal of Cognitive Psychology*, *26*(2), 178–186. https://doi.org/10.1080/20445911.2013.878717

Kleinsorge, T., & Rinkenauer, G. (2012). Effects of Monetary Incentives on Task Switching. *Experimental Psychology*, *59*(4), 216–226. https://doi.org/10.1027/1618-3169/a000146

Knutson, B., Westdorp, A., Kaiser, E., & Hommer, D. (2000). FMRI Visualization of Brain Activity during a Monetary Incentive Delay Task. *NeuroImage*, *12*(1), 20–27. https://doi.org/10.1006/nimg.2000.0593

Kononowicz, T. W., & Penney, T. B. (2016). The contingent negative variation (CNV): Timing isn't everything. *Current Opinion in Behavioral Sciences*, *8*, 231–237. https://doi.org/10.1016/j.cobeha.2016.02.022

Kornblum, S., Hasbroucq, T., & Osman, A. (1990). Dimensional overlap: Cognitive basis for stimulus-response compatibility--A model and taxonomy. *Psychological Review, 97*(2), 253–270. https://doi.org/10.1037/0033-295X.97.2.253

Kranz, L. S. (2015). *Proactive control of emotional distraction: An ERP investigation* [Msc]. Victoria University of Wellington.

Krebs, R. M., Boehler, C. N., & Woldorff, M. G. (2010). The influence of reward associations on conflict processing in the Stroop task. *Cognition*, *117*(3), 341–347. https://doi.org/10.1016/j.cognition.2010.08.018

Kurzban, R., Duckworth, A., Kable, J. W., & Myers, J. (2013). An opportunity cost model of subjective effort and task performance. *Behavioral and Brain Sciences*, *36*(6), 661–679. https://doi.org/10.1017/S0140525X12003196

Li, Y., Zhang, Q., Liu, F., & Cui, L. (2018). The effect of the high-approach versus low-approach motivational positive affect on the processing stage of cognitive control: An event-related potential study. *NeuroReport*, *29*(1), 41–47. https://doi.org/10.1097/WNR.0000000000000925

Locke, H. S., & Braver, T. S. (2008). Motivational influences on cognitive control: Behavior, brain activation, and individual differences. *Cognitive, Affective, & Behavioral Neuroscience*, *8*(1), 99–112. https://doi.org/10.3758/CABN.8.1.99

Manzi, A., Nessler, D., Czernochowski, D., & Friedman, D. (2011). The development of anticipatory cognitive control processes in task-switching: An ERP study in children, adolescents, and young adults: Development of cognitive control in task-switching. *Psychophysiology*, *48*(9), 1258–1275. https://doi.org/10.1111/j.1469-8986.2011.01192.x

Mayr, U., & Kliegl, R. (2000). Task-set switching and long-term memory retrieval. *Journal of experimental psychology. Learning, memory, and cognition*, *26*(5), 1124–1140. https://doi.org/10.1037//0278-7393.26.5.1124

Mir, P., Trender-Gerhard, I., Edwards, M. J., Schneider, S. A., Bhatia, K. P., & Jahanshahi, M. (2011). Motivation and movement: The effect of monetary incentive on performance speed. *Experimental Brain Research*, *209*(4), 551–559. https://doi.org/10.1007/s00221-011-2583-5

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and Diversity of Executive Functions and Their Contributions to Complex "Frontal Lobe" Tasks: A Latent Variable Analysis. *Cognitive Psychology*, *41*(1), 49–100. https://doi.org/10.1006/cogp.1999.0734

Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences*, *7*(3), 134–140. https://doi.org/10.1016/S1364-6613(03)00028-7

Nicholson, R., Karayanidis, F., Poboka, D., Heathcote, A., & Michie, P. T. (2005). Electrophysiological correlates of anticipatory task-switching processes. *Psychophysiology*, *0*(0), 050826083856001-??? https://doi.org/10.1111/j.1469-8986.2005.00350.x

Nieuwenhuis, S., Yeung, N., van den Wildenberg, W., & Ridderinkhof, K. R. (2003). Electrophysiological correlates of anterior cingulate function in a go/no-go task: Effects of response conflict and trial type frequency. *Cognitive, Affective, & Behavioral Neuroscience*, *3*(1), 17–26. https://doi.org/10.3758/CABN.3.1.17

Padmala, S., & Pessoa, L. (2011). Reward Reduces Conflict by Enhancing Attentional Control and Biasing Visual Cortical Processing. *Journal of Cognitive Neuroscience*, *23*(11), 3419–3432. https://doi.org/10.1162/jocn_a_00011

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, *198*, 181–197. https://doi.org/10.1016/j.neuroimage.2019.05.026

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019

Rogers, R. D., & Monsell, S. (1995). Costs of a predictible switch between simple cognitive tasks. *Journal of Experimental Psychology: General, 124*(2), 207–231. https://doi.org/10.1037/0096-3445.124.2.207

Satpute A. B., Badre D., Ochsner K. N. (2012). The neuroscience of goal-directed behavior. In Aarts H., Elliot A. (Eds.), *Goal-directed behavior (Frontiers of social psychology)* (pp. 49-84). London, England: Psychology Press.

Schevernels, H., Krebs, R. M., Santens, P., Woldorff, M. G., & Boehler, C. N. (2014). Task preparation processes related to reward prediction precede those related to task-difficulty expectation. *NeuroImage*, *84*, 639–647. https://doi.org/10.1016/j.neuroimage.2013.09.039

Schmitt, H., Ferdinand, N. K., & Kray, J. (2015). The influence of monetary incentives on context processing in younger and older adults: An event-related potential study. *Cognitive, Affective, & Behavioral Neuroscience*, *15*(2), 416–434. https://doi.org/10.3758/s13415-015-0335-x

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The Expected Value of Control: An Integrative Theory of Anterior Cingulate Cortex Function. *Neuron*, *79*(2), 217–240. https://doi.org/10.1016/j.neuron.2013.07.007

Small, D. M., Gitelman, D., Simmons, K., Bloise, S. M., Parrish, T., & Mesulam, M.-M. (2005). Monetary Incentives Enhance Processing in Brain Regions Mediating Top-down Control of Attention. *Cerebral Cortex*, *15*(12), 1855–1865. https://doi.org/10.1093/cercor/bhi063

Swainson, R., Prosser, L., Karavasilev, K., & Romanczuk, A. (2021). The effect of performing versus preparing a task on the subsequent switch cost. *Psychological Research*, *85*(1), 364–383. https://doi.org/10.1007/s00426-019-01254-7

Tecce, J. J. (1972). Contingent negative variation (CNV) and psychological processes in man. *Psychological Bulletin*, *77*(2), 73–108. https://doi.org/10.1037/h0032177

Umemoto, A., & Holroyd, C. B. (2015). Task-specific effects of reward on task switching. *Psychological Research*, *79*(4), 698–707. https://doi.org/10.1007/s00426-014-0595-z

van den Berg, B., Krebs, R. M., Lorist, M. M., & Woldorff, M. G. (2014). Utilization of reward-prospect enhances preparatory attention and reduces stimulus conflict. *Cognitive, Affective, & Behavioral Neuroscience*, *14*(2), 561–577. https://doi.org/10.3758/s13415-014-0281-z

Van den Berg, I., Shaul, L., Van der Veen, F. M., & Franken, I. H. A. (2012). The role of monetary incentives in feedback processing: Why we should pay our participants. *NeuroReport*, *23*(6), 347–353. https://doi.org/10.1097/WNR.0b013e328351db2f

van Wouwe, N. C., Band, G. P. H., & Ridderinkhof, K. R. (2011). Positive Affect Modulates Flexibility and Evaluative Control. *Journal of Cognitive Neuroscience*, *23*(3), 524–539. https://doi.org/10.1162/jocn.2009.21380

Vandierendonck, A., Liefooghe, B., & Verbruggen, F. (2010). Task switching: Interplay of reconfiguration and interference control. *Psychological Bulletin*, *136*(4), 601–626. https://doi.org/10.1037/a0019791

Verleger, R. (2020). Effects of relevance and response frequency on P3b amplitudes: Review of findings and comparison of hypotheses about the process reflected by P3b. *Psychophysiology*, *57*(7). https://doi.org/10.1111/psyp.13542

Wickelgren, W. A. (1977). Speed-accuracy tradeoff and information processing dynamics. *Acta Psychologica*, *41*(1), 67–85. https://doi.org/10.1016/0001-6918(77)90012-9

Wittmann, B. C., Schott, B. H., Guderian, S., Frey, J. U., Heinze, H.-J., & Düzel, E. (2005). Reward-Related fMRI Activation of Dopaminergic Midbrain Is Associated with Enhanced Hippocampus- Dependent Long-Term Memory Formation. *Neuron*, *45*(3), 459–467. https://doi.org/10.1016/j.neuron.2005.01.010

Ye, W., & Damian, M. F. (2022). Exploring task switch costs in a color-shape decision task via a mouse tracking paradigm. *Journal of Experimental Psychology: Human Perception and Performance*, *48*(1), 8–20. https://doi.org/10.1037/xhp0000975

Zhan, Y., Chen, J., Xiao, X., Li, J., Yang, Z., Fan, W., & Zhong, Y. (2016). Reward Promotes Self-Face Processing: An Event-Related Potential Study. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.00735

Appendix A
Matlab preprocessing script

```
% PATH VARS

PATH_EEGLAB       = '/home/plkn/eeglab2021.1/';

PATH_LOGFILES     = '/mnt/data_dump/bocotilt/0_logfiles/';

PATH_RAW          = '/mnt/data_dump/bocotilt/0_eeg_raw/';

PATH_ICSET        = '/mnt/data_dump/bocotilt/1_icset/';

PATH_AUTOCLEANED  = '/mnt/data_dump/bocotilt/2_autocleaned/';

% Subjects

subject_list = {'VP08', 'VP09', 'VP17', 'VP25'};

% Test switch

if false

  subject_list = {'VP25'};

end

% Init eeglab

addpath(PATH_EEGLAB);

eeglab;

channel_location_file = which('dipplot.m');

channel_location_file = channel_location_file(1 : end - length('dipplot.m'));

channel_location_file = [channel_location_file, 'standard_BESA/standard-10-5-cap385.elp'];

% Iterate subjects

for s = 1 : length(subject_list)

  % participant identifiers
```

```
subject = subject_list{s};
id = str2num(subject(3 : 4));
% Load
EEG = pop_loadbv(PATH_RAW, [subject, '.vhdr'], [], []);
% Fork response button channels
RESPS = pop_select(EEG, 'channel', [65, 66]);
EEG = pop_select(EEG, 'nochannel', [65, 66]);
% Open log file
fid = fopen([PATH_LOGFILES, subject, '_degreeLog.txt'], 'r');
% Extract lines as strings
logcell = {};
tline = fgetl(fid);
while ischar(tline)
    logcell{end + 1} = tline;
    tline = fgetl(fid);
end
% Delete header
logcell(1 : 3) = [];
% Get colour and tilt positions in probe display (numbers 1-8)
positions = [];
for l = 1 : length(logcell)
    line_values = split(logcell{l}, ' ');
    positions(l, 1) = str2num(line_values{8});
```

```
    positions(l, 2) = str2num(line_values{10});
end
% Open trial log file
fid = fopen([PATH_LOGFILES, subject, '_trials.txt'], 'r');
% Extract lines as strings
logcell = {};
tline = fgetl(fid);
while ischar(tline)
    logcell{end + 1} = tline;
    tline = fgetl(fid);
end
% Delete header
logcell(1 : 3) = [];
% Get response side, accuracy and rt from log file
trial_log = [];
for l = 1 : length(logcell)
    line_values = split(logcell{l}, '|');
    trial_log(l, 1) = str2num(line_values{5});
    trial_log(l, 2) = str2num(line_values{6});
    trial_log(l, 3) = str2num(line_values{7});
end
% Get version of task
if id < 8
```

```
    error("Preprocessing invalid for id < 8.");
elseif id == 8
    EEG.task_version = 1;
else
    EEG.task_version = mod(id, 8);
    if EEG.task_version == 0
        EEG.task_version = 8;
    end
end
% Event coding
EEG = bocotilt_event_coding(EEG, RESPS, positions, trial_log);
% Add FCz as empty channel
EEG.data(end + 1, :) = 0;
EEG.nbchan = size(EEG.data, 1);
EEG.chanlocs(end + 1).labels = 'FCz';
% Add channel locations
EEG = pop_chanedit(EEG, 'lookup', channel_location_file);
% Save original channel locations (for later interpolation)
EEG.chanlocs_original = EEG.chanlocs;
% Remove FCz again
EEG = pop_select(EEG, 'nochannel', [127]);
% Remove data at boundaries
EEG = pop_rmdat(EEG, {'boundary'}, [0, 1], 1);
```

```
% Resample data
ERP = pop_resample(EEG, 250);
EEG = pop_resample(EEG, 200);
% Filter
ERP = pop_basicfilter(ERP, [1 : ERP.nbchan], 'Cutoff', [0.01, 30], 'Design', 'butter', 'Filter', 'bandpass', 'Order', 4, 'RemoveDC', 'on', 'Boundary', 'boundary');
EEG = pop_basicfilter(EEG, [1 : EEG.nbchan], 'Cutoff', [1, 30], 'Design', 'butter', 'Filter', 'bandpass', 'Order', 4, 'RemoveDC', 'on', 'Boundary', 'boundary');

% Bad channel detection
[ERP, i1] = pop_rejchan(ERP, 'elec', [1 : ERP.nbchan], 'threshold', 10, 'norm', 'on', 'measure', 'kurt');
[ERP, i2] = pop_rejchan(ERP, 'elec', [1 : ERP.nbchan], 'threshold', 5, 'norm', 'on', 'measure', 'prob');
ERP.chans_rejected = [i1, i2];
[EEG, i1] = pop_rejchan(EEG, 'elec', [1 : EEG.nbchan], 'threshold', 10, 'norm', 'on', 'measure', 'kurt');
[EEG, i2] = pop_rejchan(EEG, 'elec', [1 : EEG.nbchan], 'threshold', 5, 'norm', 'on', 'measure', 'prob');
EEG.chans_rejected = [i1, i2];
% Reref common average
ERP = pop_reref(ERP, []);
EEG = pop_reref(EEG, []);
% Determine rank of data
```

```
dataRank = sum(eig(cov(double(EEG.data'))) > 1e-6);
% Interpolate channels
ERP = pop_interp(ERP, ERP.chanlocs_original, 'spherical');
EEG = pop_interp(EEG, EEG.chanlocs_original, 'spherical');
% Epoch data
ERP = pop_epoch(ERP, {'trial'}, [-0.8, 2.6], 'newname', [subject '_epoched'], 'epochinfo', 'yes');
ERP = pop_rmbase(ERP, [-200, 0]);
EEG = pop_epoch(EEG, {'trial'}, [-0.8, 2.6], 'newname', [subject '_epoched'], 'epochinfo',
'yes');
EEG = pop_rmbase(EEG, [-200, 0]);
% Autoreject trials
[ERP, rejsegs] = pop_autorej(ERP, 'nogui', 'on', 'threshold', 1000, 'startprob', 5, 'maxrej', 5);
ERP.n_segs_rejected = length(rejsegs);
[EEG, rejsegs] = pop_autorej(EEG, 'nogui', 'on', 'threshold', 1000, 'startprob', 5, 'maxrej', 5);
EEG.n_segs_rejected = length(rejsegs);
% Find standard latency of event in epoch
lats = [];
for e = 1 : length(ERP.event)
    lats(end+1) = mod(ERP.event(e).latency, ERP.pnts);
end
lat_mode = mode(lats);

% Compile a trialinfo matrix
```

```
trialinfo = [];
counter = 0;
for e = 1 : length(ERP.event)
   if strcmpi(ERP.event(e).type, 'trial') & (mod(ERP.event(e).latency, ERP.pnts) == lat_mode)
      counter = counter + 1;
      % Compile table
      trialinfo(counter, :) = [id,...
                              ERP.event(e).block_nr,...
                              ERP.event(e).trial_nr,...
                              ERP.event(e).bonustrial,...
                              ERP.event(e).tilt_task,...
                              ERP.event(e).cue_ax,...
                              ERP.event(e).target_red_left,...
                              ERP.event(e).distractor_red_left,...
                              ERP.event(e).response_interference,...
                              ERP.event(e).task_switch,...
                              ERP.event(e).correct_response,...
                              ERP.event(e).response_side,...
                              ERP.event(e).rt,...
                              ERP.event(e).accuracy,...
                              ERP.event(e).log_response_side,...
                              ERP.event(e).log_rt,...
                              ERP.event(e).log_accuracy,...
```

```
                    ERP.event(e).position_color,...
                    ERP.event(e).position_tilt,...
                    ERP.event(e).position_target,...
                    ERP.event(e).position_distractor,...
                    ERP.event(e).sequence_position,...
                    ERP.event(e).sequence_length,...
                    ];
    end
end
% Save trialinfo
ERP.trialinfo = trialinfo;
writematrix(trialinfo, [PATH_AUTOCLEANED, subject, '_trialinfo_erp.csv']);
% Find standard latency of event in epoch
lats = [];
for e = 1 : length(EEG.event)
    lats(end+1) = mod(EEG.event(e).latency, EEG.pnts);
end
lat_mode = mode(lats);



% Compile a trialinfo matrix
trialinfo = [];
counter = 0;
```

```
for e = 1 : length(EEG.event)
   if strcmpi(EEG.event(e).type, 'trial') & (mod(EEG.event(e).latency, EEG.pnts) == lat_mode)
      counter = counter + 1;
      % Compile table
      trialinfo(counter, :) = [id,...
                               EEG.event(e).block_nr,...
                               EEG.event(e).trial_nr,...
                               EEG.event(e).bonustrial,...
                               EEG.event(e).tilt_task,...
                               EEG.event(e).cue_ax,...
                               EEG.event(e).target_red_left,...
                               EEG.event(e).distractor_red_left,...
                               EEG.event(e).response_interference,...
                               EEG.event(e).task_switch,...
                               EEG.event(e).correct_response,...
                               EEG.event(e).response_side,...
                               EEG.event(e).rt,...
                               EEG.event(e).accuracy,...
                               EEG.event(e).log_response_side,...
                               EEG.event(e).log_rt,...
                               EEG.event(e).log_accuracy,...
                               EEG.event(e).position_color,...
                               EEG.event(e).position_tilt,...
```

```
                    EEG.event(e).position_target,...
                    EEG.event(e).position_distractor,...
                    EEG.event(e).sequence_position,...
                    EEG.event(e).sequence_length,...
                    ];
    end
end
% Save trialinfo
EEG.trialinfo = trialinfo;
writematrix(trialinfo, [PATH_AUTOCLEANED, subject, '_trialinfo.csv']);
% Runica & ICLabel
EEG = pop_runica(EEG, 'extended', 1, 'interrupt', 'on', 'PCA', dataRank);
EEG = iclabel(EEG);
% Find nobrainer
EEG.nobrainer = find(EEG.etc.ic_classification.ICLabel.classifications(:, 1) < 0.3 |
EEG.etc.ic_classification.ICLabel.classifications(:, 3) > 0.3);
% Copy ICs to erpset
ERP = pop_editset(ERP, 'icachansind', 'EEG.icachansind', 'icaweights', 'EEG.icaweights',
'icasphere', 'EEG.icasphere');
ERP.etc = EEG.etc;
ERP.nobrainer = EEG.nobrainer;
% Save IC set
pop_saveset(ERP, 'filename', [subject, '_icset_erp.set'], 'filepath', PATH_ICSET, 'check', 'on');
```

```
  pop_saveset(EEG, 'filename', [subject, '_icset.set'], 'filepath', PATH_ICSET, 'check', 'on');

  % Remove components

  ERP = pop_subcomp(ERP, ERP.nobrainer, 0);

  EEG = pop_subcomp(EEG, EEG.nobrainer, 0);

  % Save clean data

  pop_saveset(ERP, 'filename', [subject, '_cleaned_erp.set'], 'filepath', PATH_AUTOCLEANED,
'check', 'on');

  pop_saveset(EEG, 'filename', [subject, '_cleaned.set'], 'filepath', PATH_AUTOCLEANED,
'check', 'on');


end
```

Matlab ERP processing

```
% Path variables

PATH_EEGLAB      = '/home/plkn/eeglab2021.1/';

PATH_AUTOCLEANED = '/mnt/data_dump/bocotilt/2_autocleaned/';

% Subject list

subject_list = {'VP08', 'VP09', 'VP17', 'VP25'};

% Init eeglab

addpath(PATH_EEGLAB);

eeglab;

% This is where we collect the ERPs as a subject x condition x times matrix

erp_matrix = [];

% Loop subjects
```

```
for s = 1 : length(subject_list)
  % Load data
  EEG = pop_loadset('filename', [subject_list{s} '_cleaned_erp.set'], 'filepath',
PATH_AUTOCLEANED, 'loadmode', 'all');
  % Trial data
  % Columns:
  %  1: id
  %  2: block_nr
  %  3: trial_nr
  %  4: bonustrial
  %  5: tilt_task
  %  6: cue_ax
  %  7: target_red_left
  %  8: distractor_red_left
  %  9: response_interference
  % 10: task_switch
  % 11: correct_response
  % 12: response_side
  % 13: rt
  % 14: accuracy
  % 15: log_response_side
  % 16: log_rt
  % 17: log_accuracy
```

```
% 18: position_color

% 19: position_tilt

% 20: position_target

% 21: position_distractor

% 22: sequence_position

% 23: sequence_length

trialinfo = EEG.trialinfo;

% Time vector

erp_times = EEG.times;


% The data matrix: channels x times x trials

eeg_data = EEG.data;

% Get index of channel

channel_idx = [];

%channels = {'Fz', 'F1', 'F2', 'FC1', 'FC2', 'FFC1h', 'FFC2h'};

%channels = {'Pz', 'POz', 'PPO1h', 'PPO2h'};

channels = {'POz'};

for ch = 1 : length(channels)

   channel_idx(end + 1) = find(strcmp({EEG.chanlocs.labels}, channels{ch}));

end

% Average data across selected channels (result is 2d matrix, times x trials)

chan_data = squeeze(mean(eeg_data(channel_idx, :, :), 1));

% Define baseline
```

```
bl_win = [-200, 0];

bl_idx = erp_times >= bl_win(1) & erp_times <= bl_win(2);

chan_data = chan_data - mean(chan_data(bl_idx, :));

% Get indices of correct standard and bonus trials for repetition and switch trials

idx_std_rep = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 0 & trialinfo(:, 10)
== 0;

idx_std_swi = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 0 & trialinfo(:, 10)
== 1;

idx_bon_rep = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 1 & trialinfo(:, 10)
== 0;

idx_bon_swi = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 1 & trialinfo(:, 10)
== 1;

% Calculate ERPs by averaging across trials within each condition combination

erp_std_rep = mean(chan_data(:, idx_std_rep), 2);

erp_std_swi = mean(chan_data(:, idx_std_swi), 2);

erp_bon_rep = mean(chan_data(:, idx_bon_rep), 2);

erp_bon_swi = mean(chan_data(:, idx_bon_swi), 2);

% Get indices of correct standard and bonus trials for start- versus end-of-sequence trials

idx_std_start = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 0 & trialinfo(:, 22)
<= 4;

idx_std_end   = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 0 & trialinfo(:, 22)
> 4;

idx_bon_start = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 1 & trialinfo(:, 22)
<= 4;
```

```
  idx_bon_end   = trialinfo(:, 17) == 1 & trialinfo(:, 2) > 4 & trialinfo(:, 4) == 1 & trialinfo(:, 22)
> 4;
  % Calculate ERPs by averaging across trials within each condition combination
  erp_std_start = mean(chan_data(:, idx_std_start), 2);
  erp_std_end   = mean(chan_data(:, idx_std_end  ), 2);
  erp_bon_start = mean(chan_data(:, idx_bon_start), 2);
  erp_bon_end   = mean(chan_data(:, idx_bon_end  ), 2);
  % Copy ERPs to ERP-result matrix
  erp_matrix(s, 1, :) = erp_std_rep;
  erp_matrix(s, 2, :) = erp_std_swi;
  erp_matrix(s, 3, :) = erp_bon_rep;
  erp_matrix(s, 4, :) = erp_bon_swi;
  erp_matrix(s, 5, :) = erp_std_start;
  erp_matrix(s, 6, :) = erp_std_end;
  erp_matrix(s, 7, :) = erp_bon_start;
  erp_matrix(s, 8, :) = erp_bon_end;
end % End subject loop
% Average ERPs across subjects -> grand averages as condition x time matrix
grand_averages = squeeze(mean(erp_matrix, 1));
% Create a plot of ERPs, averaged across subjects
figure;
plot(erp_times, grand_averages(1, :), '-', 'LineWidth', 2, 'Color', 'k');
hold on;
```

```
plot(erp_times, grand_averages(2, :), ':', 'LineWidth', 2, 'Color', 'k');
plot(erp_times, grand_averages(3, :), '-', 'LineWidth', 2, 'Color', 'r');
plot(erp_times, grand_averages(4, :), ':', 'LineWidth', 2, 'Color', 'r');
legend({'standard-repeat', 'standard-switch', 'bonus-repeat', 'bonus-switch'});
xline(0);
xline(800);
xlim([-500, 2000]);
% Create a plot of ERPs, averaged across subjects
figure;
plot(erp_times, grand_averages(5, :), '-', 'LineWidth', 2, 'Color', 'k');
hold on;
plot(erp_times, grand_averages(6, :), ':', 'LineWidth', 2, 'Color', 'k');
plot(erp_times, grand_averages(7, :), '-', 'LineWidth', 2, 'Color', 'r');
plot(erp_times, grand_averages(8, :), ':', 'LineWidth', 2, 'Color', 'r');
legend({'standard-start', 'standard-end', 'bonus-start', 'bonus-end'});
xline(0);
xline(800);
xlim([-500, 2000]);
```

Matlab behavioural analysis

```
% Path to behavioral data
```

```
path_behavioral_data = 'C:\Users\woute\Desktop\BoCoTilt Datafiles/';

% Load data

load([path_behavioral_data, 'behavioral_data.mat']);

% Determine number of participants

n_subjects = size(behavior_rt, 1);

% Perform rmANOVA for rt

varnames = {'id', 'b1', 'b2', 'b3', 'b4'};

t = table([1 : n_subjects]', behavior_rt(:, 1), behavior_rt(:, 2), behavior_rt(:, 3), behavior_rt(:, 4), 'VariableNames', varnames);

within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus', 'switch'});

rm = fitrm(t, 'b1-b4~1', 'WithinDesign', within);

anova_rt = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');

anova_rt

% Perform rmANOVA for accuracy

varnames = {'id', 'b1', 'b2', 'b3', 'b4'};

t = table([1 : n_subjects]', behavior_ac(:, 1), behavior_ac(:, 2), behavior_ac(:, 3), behavior_ac(:, 4), 'VariableNames', varnames);

within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus', 'switch'});

rm = fitrm(t, 'b1-b4~1', 'WithinDesign', within);

anova_ac = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');

anova_ac

%1 st rep, 2 st switch, 3 bonus rep, 4 bonus switch
```

```
%means, st.dev and st.error for response times across participants

mean_rt = mean(behavior_rt)

std_rt = std(behavior_rt)

stderror_rt= std(behavior_rt) / sqrt( length(behavior_rt))

%means, st.dev and st.error for accuracy across participants

mean_ac = mean(behavior_ac)

std_ac = std(behavior_ac)

stderror_ac= std(behavior_ac) / sqrt( length(behavior_ac))

%Response barchart, labels + standard error of the mean

figure

bar(mean(behavior_rt))

%title('Mean response times in ms across conditions')

xlabel ('Conditions')

ylabel ('Average response times in ms')

set(gca,'xticklabel',{'Low reward Repetition','Low reward Switch','High reward Repetition', 'High
reward Switch'});

ylim([450, 550])

%errorbar rt

hold on

er = errorbar(mean_rt,stderror_rt);

er.Color = [0 0 0];

er.LineStyle = 'none';

hold off
```

```
saveas(gcf,'RT+SEM.png')

%Accuracy barchart, labels + standard error of the mean

figure

bar(mean(behavior_ac))

%title('Mean accuracy rates in percentage across conditions')

xlabel ('Conditions')

ylabel ('Average Percentage of correct answers')

set(gca,'xticklabel',{'Low reward Repetition','Low reward Switch','High reward Repetition', 'High reward Switch'});

ylim([.85, .95])

%errorbar ac

hold on

er = errorbar(mean_ac,stderror_ac);

er.Color = [0 0 0];

er.LineStyle = 'none';

hold off

saveas(gcf,'AC+SEM.png')
```

Matlab EEG analysis

```
% path variables

path_erp_data = 'C:\Users\woute\Desktop\BoCoTilt Datafiles\';

path_eeglab   = 'C:\Users\woute\AppData\Roaming\MathWorks\MATLAB Add-Ons\Collections\EEGLAB';
```

```
path_results  = 'C:\Users\woute\Desktop\BoCoTilt Datafiles\';
% Initialize eeglab
addpath(path_eeglab);
eeglab;
% Load the erp data:
load([path_erp_data, 'erp_bocotilt.mat']);
% defining frontal and posterior electrode patches that we want to use for analyses
frontal_idx = [33, 17, 34, 65, 66, 21, 127, 22, 97, 98, 35, 18, 36];
posterior_idx = [37, 19, 38, 71, 72, 45, 63, 46, 107, 108];
% Plot these electrode patches to show which electrodes are included
figure()
subplot(1, 2, 1)
topoplot(ones(1, 127), chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'off', 'emarker2', {frontal_idx, '.', 'k', 14, 1});
colormap('white')
title('frontal electrode patch')
subplot(1, 2, 2)
topoplot(ones(1, 127), chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'off', 'emarker2', {posterior_idx, '.', 'k', 14, 1});
colormap('white')
title('posterior electrode patch')
% Plotting the posterior electrode ERPS
erp_posterior_low_reward_repeat  = squeeze(mean(erp_matrix(:, 1, 1, posterior_idx, :), [1, 4]));
```

```
erp_posterior_low_reward_switch  = squeeze(mean(erp_matrix(:, 1, 2, posterior_idx, :), [1, 4]));
erp_posterior_high_reward_repeat = squeeze(mean(erp_matrix(:, 2, 1, posterior_idx, :), [1, 4]));
erp_posterior_high_reward_switch = squeeze(mean(erp_matrix(:, 2, 2, posterior_idx, :), [1, 4]));
% plotting all posterior conditions in a single plot
figure()
plot(eeg_times, erp_posterior_low_reward_repeat, 'k-', 'LineWidth', 2)
hold on;
plot(eeg_times, erp_posterior_low_reward_switch, 'k:', 'LineWidth', 2)
plot(eeg_times, erp_posterior_high_reward_repeat, 'r-', 'LineWidth', 2)
plot(eeg_times, erp_posterior_high_reward_switch, 'r:', 'LineWidth', 2)
title('Posterior electrodes ERP')
legend({'low-repeat', 'low-switch', 'high-repeat', 'high-switch', 'target-onset'})
%xline([0, 800, 300, 400, 1100, 1200])
xlabel ('Time in ms')
ylabel ('Voltage (μV)')
% Plotting the frontal electrode ERPs
erp_frontal_low_reward_repeat  = squeeze(mean(erp_matrix(:, 1, 1, frontal_idx, :), [1, 4]));
erp_frontal_low_reward_switch  = squeeze(mean(erp_matrix(:, 1, 2, frontal_idx, :), [1, 4]));
erp_frontal_high_reward_repeat = squeeze(mean(erp_matrix(:, 2, 1, frontal_idx, :), [1, 4]));
erp_frontal_high_reward_switch = squeeze(mean(erp_matrix(:, 2, 2, frontal_idx, :), [1, 4]));
% Plotting all frontal conditions in a single plot
figure()
plot(eeg_times, erp_frontal_low_reward_repeat, 'k-', 'LineWidth', 2)
```

```
hold on;
plot(eeg_times, erp_frontal_low_reward_switch, 'k:', 'LineWidth', 2)
plot(eeg_times, erp_frontal_high_reward_repeat, 'r-', 'LineWidth', 2)
plot(eeg_times, erp_frontal_high_reward_switch, 'r:', 'LineWidth', 2)
title('Frontal electrodes ERP')
legend({'low-repeat', 'low-switch', 'high-repeat', 'high-switch', 'target-onset'})
%xline([0, 800, 325, 375, 440, 1025, 1075])
xlabel ('Time in ms')
ylabel ('Voltage (μV)')
%Inspecting the posterior P3 on cue anova
% Reset out time indices
time_idx = eeg_times >= 300 & eeg_times <= 400;
% We use loops to iterate participants and conditions
% We want to store our results here (initialize as an empty matrix)
anova_table_cueP3 = [];
% Loop participants
for s = 1 : size(erp_matrix, 1) % First dimension has length of number of participants...
  % A counter
  counter = 0;
  % Loop high versus low reward
  for rew = 1 : 2
    % Loop repeat / switch
    for sw = 1 : 2
```

```
            % Since we have a specific subject-condition combination here, we
            % can index the matrix accordingly.
            erp_value = squeeze(mean(erp_matrix(s, rew, sw, posterior_idx, time_idx), [4, 5]));
            % Increase counter
            counter = counter + 1;
            % Now we store this value in the 'anova_table'. We need the counter for this to
            % find the correct column.
            anova_table_cueP3(s, counter) = erp_value;
        end
    end
end
% You can now save this table as a csv file
writematrix(anova_table_cueP3, [path_results, 'anova_table_cueP3.csv']);
% Performing an ANOVA in Matlab:
varnames = {'id', 'cond1', 'cond2', 'cond3', 'cond4'};
t = table([1 : size(erp_matrix, 1)]', anova_table_cueP3(:, 1), anova_table_cueP3(:, 2),
anova_table_cueP3(:, 3), anova_table_cueP3(:, 4), 'VariableNames', varnames);
within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus',
'switch'});
rm = fitrm(t, 'cond1-cond4~1', 'WithinDesign', within);
anova_posterior_p3cue = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');
% Print anova results to matlab console
anova_posterior_p3cue
```

```
%creating a P3 cue onset topography

time_idx = eeg_times >= 300 & eeg_times <= 400;

% 'squeeze()' gets rid of the now useless temporal dimension:

erp_matrix_timewin = squeeze(mean(erp_matrix(:, :, :, :, time_idx), 5));

% Again, select repeat and switch in the high reward condition and average across participants.

% The resulting data is a vector of length 127. One value for each electrode.

topo_values_repeat = squeeze(mean(erp_matrix_timewin(:, 2, 1, :), 1));

topo_values_switch = squeeze(mean(erp_matrix_timewin(:, 2, 2, :), 1));

% Lets use eeglabs topoplot function to plot the mV values of this timewindow for both
conditions:

figure()

subplot(1, 2, 1)

topoplot(topo_values_repeat, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');

title('repeat in high reward - 300-400 ms')

colorbar()

clim([-6, 6])

subplot(1, 2, 2)

topoplot(topo_values_switch, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');

title('switch in high reward - 300-400 ms')

colorbar()

clim([-6, 6])
```

```
%Inspecting Posterior P3 on Task-Onset ANOVA
%reset the time windows.
time_idx = eeg_times >= 1100 & eeg_times <= 1200;
% We use loops to iterate participants and conditions
% We want to store our results here (initialize as an empty matrix)
anova_table_taskP3 = [];
% Loop participants
for s = 1 : size(erp_matrix, 1)
  % A counter
  counter = 0;
  % Loop high versus low reward
  for rew = 1 : 2
    % Loop repeat / switch
    for sw = 1 : 2
      % Since we have a specific subject-condition combination here, we
      % can index the matrix accordingly.
      erp_value = squeeze(mean(erp_matrix(s, rew, sw, posterior_idx, time_idx), [4, 5]));
      % Increase counter
      counter = counter + 1;
      % Now we store this value in the 'anova_table'. We need the counter for this to
      % find the correct column.
      anova_table_taskP3(s, counter) = erp_value;
    end
```

```
  end
end
% You can now save this table as a csv file
writematrix(anova_table_taskP3, [path_results, 'anova_table_taskP3.csv']);
% Matlab ANOVA
varnames = {'id', 'cond1', 'cond2', 'cond3', 'cond4'};
t = table([1 : size(erp_matrix, 1)]', anova_table_taskP3(:, 1), anova_table_taskP3(:, 2),
anova_table_taskP3(:, 3), anova_table_taskP3(:, 4), 'VariableNames', varnames);
within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus',
'switch'});
rm = fitrm(t, 'cond1-cond4~1', 'WithinDesign', within);
anova_posterior_p3task = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');
% Print anova results to matlab console
anova_posterior_p3task
% Creating a p3 target onset topography
time_idx = eeg_times >= 1100 & eeg_times <= 1200;
% 'squeeze()' gets rid of the now useless temporal dimension:
erp_matrix_timewin = squeeze(mean(erp_matrix(:, :, :, :, time_idx), 5));
%  Select repeat and switch in the high reward condition and average across participants.
% The resulting data is avector of length 127. One value for each electrode.
topo_values_repeat = squeeze(mean(erp_matrix_timewin(:, 2, 1, :), 1));
topo_values_switch = squeeze(mean(erp_matrix_timewin(:, 2, 2, :), 1));
```

```
% Lets use eeglabs topoplot function to plot the mV values of this timewindow for both conditions:

figure()

subplot(1, 2, 1)

topoplot(topo_values_repeat, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off', 'electrodes', 'on');

title('repeat in high reward - 1100-1200 ms')

colorbar()

clim([-6, 6])

subplot(1, 2, 2)

topoplot(topo_values_switch, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off', 'electrodes', 'on');

title('switch in high reward - 1100-1200 ms')

colorbar()

clim([-6, 6])

%Inspecting the posterior LPP on cue anova
% Reset out time indices
time_idx = eeg_times >= 400 & eeg_times <= 800;
% We use loops to iterate participants and conditions
% We want to store our results here (initialize as an empty matrix)
anova_table_cueLPP = [];


% Loop participants
for s = 1 : size(erp_matrix, 1) % First dimension has length of number of participants...

    % A counter
    counter = 0;
```

```
    % Loop high versus low reward
    for rew = 1 : 2

        % Loop repeat / switch
        for sw = 1 : 2

            % Since we have a specific subject-condition combination here, we
            % can index the matrix accordingly. In time and space we are not specific
            % yet, as we have a patch of electrodes and multiple timepoints constitute
            % The time window. So we average across these dimensions.
            erp_value = squeeze(mean(erp_matrix(s, rew, sw, posterior_idx, time_idx), [4, 5]));

            % Increase counter
            counter = counter + 1;

            % Now we store this value in the 'anova_table'. We need the counter for this to
            % find the correct column.
            anova_table_cueLPP(s, counter) = erp_value;

        end
    end
end

% You can now save this table as a csv file to use in R or SPSS or whatever...
writematrix(anova_table_cueLPP, [path_results, 'anova_table_cueLPP.csv']);

% As an alternative, Matlab has also an ANOVA function. It is a bit clunky, but
% if you know how to set it up it works just fine.
% An example:
varnames = {'id', 'cond1', 'cond2', 'cond3', 'cond4'};
```

```
t = table([1 : size(erp_matrix, 1)]', anova_table_cueLPP(:, 1), anova_table_cueLPP(:, 2),
anova_table_cueLPP(:, 3), anova_table_cueLPP(:, 4), 'VariableNames', varnames);
within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus',
'switch'});
rm = fitrm(t, 'cond1-cond4~1', 'WithinDesign', within);
anova_posterior_LPPcue = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');

% Print anova results to matlab console
anova_posterior_LPPcue

%Now for a nice LPP cue onset topography
time_idx = eeg_times >= 400 & eeg_times <= 800;
% 'squeeze()' the again gets rid of the now useless temporal dimension:
erp_matrix_timewin = squeeze(mean(erp_matrix(:, :, :, :, time_idx), 5));
% Again, select repeat and switch in the high reward condition and average scross participants.
% The resulting data is avector of length 127. One value for each electrode.
topo_values_repeat = squeeze(mean(erp_matrix_timewin(:, 2, 1, :), 1));
topo_values_switch = squeeze(mean(erp_matrix_timewin(:, 2, 2, :), 1));
% Lets use eeglabs topoplot function to plot the mV values of this timewindow for both
conditions:
figure()
subplot(1, 2, 1)
topoplot(topo_values_repeat, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');
title('repeat in high reward - 600-800 ms')
colorbar()
clim([-6, 6])
subplot(1, 2, 2)
topoplot(topo_values_switch, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');
title('switch in high reward - 600-800 ms')
```

```
colorbar()
clim([-6, 6])

% Frontal cue-onset N2.
%reset the time windows.
time_idx = eeg_times >= 325 & eeg_times <= 375;
% We use loops to iterate participants and conditions
% We want to store our results here (initialize as an empty matrix)
anova_table_cueN2 = [];
% Loop participants
for s = 1 : size(erp_matrix, 1) % First dimension has length of number of participants...
  % A counter
  counter = 0;
  % Loop high versus low reward
  for rew = 1 : 2
    % Loop repeat / switch
    for sw = 1 : 2
      % Since we have a specific subject-condition combination here, we
      % can index the matrix accordingly.
      erp_value = squeeze(mean(erp_matrix(s, rew, sw, frontal_idx, time_idx), [4, 5]));
      % Increase counter
      counter = counter + 1;
      % Now we store this value in the 'anova_table'. We need the counter for this to
```

```
        % find the correct column.
        anova_table_cueN2(s, counter) = erp_value;
    end
  end
end
% You can now save this table as a csv file
writematrix(anova_table_cueN2, [path_results, 'anova_table_cueN2.csv']);
% Matlab ANOVA
varnames = {'id', 'cond1', 'cond2', 'cond3', 'cond4'};
t = table([1 : size(erp_matrix, 1)]', anova_table_cueN2(:, 1), anova_table_cueN2(:, 2),
anova_table_cueN2(:, 3), anova_table_cueN2(:, 4), 'VariableNames', varnames);
within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus',
'switch'});
rm = fitrm(t, 'cond1-cond4~1', 'WithinDesign', within);
anova_frontal_cueN2 = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');
% Print anova results to matlab console
anova_frontal_cueN2
%n2 cue onset topography
time_idx = eeg_times >= 325 & eeg_times <= 375;
% 'squeeze()' gets rid of the now useless temporal dimension:
erp_matrix_timewin = squeeze(mean(erp_matrix(:, :, :, :, time_idx), 5));
% Again, select repeat and switch in the high reward condition and average across participants.
% The resulting data is avector of length 127. One value for each electrode.
```

```
topo_values_repeat = squeeze(mean(erp_matrix_timewin(:, 2, 1, :), 1));

topo_values_switch = squeeze(mean(erp_matrix_timewin(:, 2, 2, :), 1));

% Lets use eeglabs topoplot function to plot the mV values of this timewindow for both
conditions:

figure()

subplot(1, 2, 1)

topoplot(topo_values_repeat, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');

title('repeat in high reward - 325-375 ms')

colorbar()

clim([-6, 6])

subplot(1, 2, 2)

topoplot(topo_values_switch, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');

title('switch in high reward - 325-375 ms')

colorbar()

clim([-6, 6])

%Now for the frontal N2 task onset.

%reset the time windows.

time_idx = eeg_times >= 1025 & eeg_times <= 1075;

% We use loops to iterate participants and conditions

% We want to store our results here (initialize as an empty matrix)

anova_table_taskN2 = [];
```

```
% Loop participants
for s = 1 : size(erp_matrix, 1) % First dimension has length of number of participants...
  % A counter
  counter = 0;
  % Loop high versus low reward
  for rew = 1 : 2
    % Loop repeat / switch
    for sw = 1 : 2
      % Since we have a specific subject-condition combination here, we
      % can index the matrix accordingly.
      erp_value = squeeze(mean(erp_matrix(s, rew, sw, frontal_idx, time_idx), [4, 5]));
      % Increase counter
      counter = counter + 1;
      % Now we store this value in the 'anova_table'. We need the counter for this to
      % find the correct column.
      anova_table_taskN2(s, counter) = erp_value;
    end
  end
end
% You can now save this table as a csv file to use in R or SPSS or whatever...
writematrix(anova_table_taskN2, [path_results, 'anova_table_cueN2.csv']);
% Matlab ANOVA
varnames = {'id', 'cond1', 'cond2', 'cond3', 'cond4'};
```

```
t = table([1 : size(erp_matrix, 1)]', anova_table_taskN2(:, 1), anova_table_taskN2(:, 2), anova_table_taskN2(:, 3), anova_table_taskN2(:, 4), 'VariableNames', varnames);

within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus', 'switch'});

rm = fitrm(t, 'cond1-cond4~1', 'WithinDesign', within);

anova_frontal_taskN2 = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');

% Print anova results to matlab console

anova_frontal_taskN2

%n2 target onset topography

time_idx = eeg_times >= 1025 & eeg_times <= 1075;

% 'squeeze()' gets rid of the now useless temporal dimension:

erp_matrix_timewin = squeeze(mean(erp_matrix(:, :, :, :, time_idx), 5));

% Again, select repeat and switch in the high reward condition and average across participants.

% The resulting data is a vector of length 127. One value for each electrode.

topo_values_repeat = squeeze(mean(erp_matrix_timewin(:, 2, 1, :), 1));

topo_values_switch = squeeze(mean(erp_matrix_timewin(:, 2, 2, :), 1));

% Lets use eeglabs topoplot function to plot the mV values of this timewindow for both conditions:

figure()

subplot(1, 2, 1)

topoplot(topo_values_repeat, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off', 'electrodes', 'on');

title('repeat in high reward - 1025-1075 ms')

colorbar()
```

```
clim([-6, 6])

subplot(1, 2, 2)

topoplot(topo_values_switch, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');

title('switch in high reward - 1025-1075 ms')

colorbar()

clim([-6, 6])

%Now for the CNV.

%reset the time windows.

time_idx = eeg_times >= 440 & eeg_times <= 800;

% We use loops to iterate participants and conditions

% We want to store our results here (initialize as an empty matrix)

anova_table_CNV = [];

% Loop participants

for s = 1 : size(erp_matrix, 1) % First dimension has length of number of participants...

  % A counter

  counter = 0;

  % Loop high versus low reward

  for rew = 1 : 2

    % Loop repeat / switch

    for sw = 1 : 2

      % Since we have a specific subject-condition combination here, we

      % can index the matrix accordingly.
```

```
            erp_value = squeeze(mean(erp_matrix(s, rew, sw, frontal_idx, time_idx), [4, 5]));
            % Increase counter
            counter = counter + 1;
            % Now we store this value in the 'anova_table'. We need the counter for this to
            % find the correct column.
            anova_table_CNV(s, counter) = erp_value;
        end
    end
end
% You can now save this table as a csv file
writematrix(anova_table_CNV, [path_results, 'anova_table_CNV.csv']);
% Matlab ANOVA
varnames = {'id', 'cond1', 'cond2', 'cond3', 'cond4'};
t = table([1 : size(erp_matrix, 1)]', anova_table_CNV(:, 1), anova_table_CNV(:, 2),
anova_table_CNV(:, 3), anova_table_CNV(:, 4), 'VariableNames', varnames);
within = table({'std'; 'std'; 'bon'; 'bon'}, {'rep'; 'swi'; 'rep'; 'swi'}, 'VariableNames', {'bonus',
'switch'});
rm = fitrm(t, 'cond1-cond4~1', 'WithinDesign', within);
anova_frontal_CNV = ranova(rm, 'WithinModel', 'bonus + switch + bonus*switch');
% Print anova results to matlab console
anova_frontal_CNV
%cnv timewindow topography
time_idx = eeg_times >= 440 & eeg_times <= 800;
```

```
% 'squeeze()' the again gets rid of the now useless temporal dimension:
erp_matrix_timewin = squeeze(mean(erp_matrix(:, :, :, :, time_idx), 5));
% Again, select repeat and switch in the high reward condition and average scross participants.
% The resulting data is avector of length 127. One value for each electrode.
topo_values_repeat = squeeze(mean(erp_matrix_timewin(:, 2, 1, :), 1));
topo_values_switch = squeeze(mean(erp_matrix_timewin(:, 2, 2, :), 1));
% Lets use eeglabs topoplot function to plot the mV values of this timewindow for both
conditions:
figure()
subplot(1, 2, 1)
topoplot(topo_values_repeat, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');
title('repeat in high reward - 440-800 ms')
colorbar()
clim([-6, 6])
subplot(1, 2, 2)
topoplot(topo_values_switch, chanlocs, 'plotrad', 0.7, 'intrad', 0.7, 'intsquare', 'on', 'conv', 'off',
'electrodes', 'on');
title('switch in high reward - 440-800 ms')
colorbar()
clim([-6, 6])
```