Reliability, Attenuation, and Order Effects of EEG Components Across Multiple Assessments

by

Patrick James Montgomery

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We acknowledge and respect the lək̓ʷəŋən peoples on whose traditional territory the university stands and the Songhees, Esquimalt and W̱SÁNEĆ peoples whose historical relationships with the land continue to this day.

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Supervisory Committee

Dr. Olave Krigolson, Supervisor

Division of Medical Sciences

Dr. Mauricio A. Garcia-Barrera, Outside Member

Department of Psychology

Dr. Bruce Wright, Member

Division of Medical Sciences

Abstract

How does one guarantee consistency in measurements of neural activity? Realistically, this cannot be done for any individual measure, but variation from the norm will not significantly impact a large enough sample. The task, then, is to account for non-targeted neural activity common across participants to control for influences on target measures. Often, this is easier said than done. The goal of the current research was to aid in uncovering potential sources of unexplained variability in established electroencephalography (EEG) phenomena using two common tasks. Specifically, the reward positivity and P300 event-related potentials (ERPs) were captured via the two-armed bandit task and the oddball task, and were analysed across three areas: Reliability, attenuation, and order effects. Importantly, these data were captured using a unique testing schedule involving five cognitive assessments across an approximately two-hour period. Reliability was tested for both the difference and the conditional waves for each component to see if these lined up with commonly reported values. Previous attenuation studies have established this effect across long durations, but this analysis sought to determine whether this pattern held across consecutive testing sessions. Order effects were expected to occur between the bandit and oddball tasks based on the interplay between neural regions and neurotransmitter activity. *Results:* Excellent reliability was found for all P300 measures and for the conditional reward positivity measures. These findings support the use of conditional waves instead of difference waves regarding the reward positivity specifically, as the difference wave appears to mask the high reliability present in each conditional wave. Attenuation results were unanticipated, showing no effect for the reward positivity and an opposite effect for the P300. The suggestion invoked is that something to do with the divergences between the current study's task and the long-duration tasks previously used to exhibit ERP attenuation altered participants' reactions to the oddball task. Further investigation into this unusual component behaviour is warranted. No order effects were discovered across two analyses focused on these results. Although effects were anticipated, the absence is encouraging for EEG research as this suggests that order effects need not be accounted for in tasks or experiments that elicit both the reward positivity and the P300 ERPs. Altogether, these findings reveal areas wherein reward positivity and P300 components are robust, and areas in which they require further investigation.

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List of Abbreviations

ACC	Anterior Cingulate Cortex
ACh	Acetylcholine
CA	Cognitive Assessment
DA	Dopamine
EEG	Electroencephalography
ERN	Error-Related Negativity
ERP	Event-Related Potentials
fERN	Feedback Error-Related Activity
FN	Feedback Negativity
FRN	Feedback Related Negativity
ICC	Intraclass Correlation Coefficient
LC	Locus Coeruleus
LC-NE	Locus Coeruleus-Norepinephrine
LHb	Lateral Habenula
LTP	Long-Term Potentiation
mPFC	Medial Prefrontal Cortex
NAcc	Nucleus Accumbens
NE	Norepinephrine
NET	Norepinephrine Transporter
PE	Prediction Error
rTPJ	Right Temporoparietal Junction
TPJ	Temporoparietal Junction
VS	Ventral Striatum

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I dedicate this thesis to my grandparents, which is only a grain of sand compared to their incredible dedication to their family. They supported every interest I ever had and are the foundation for who I am today. I know they would be proud.

Chapter 1: General Introduction

In scientific endeavors, as in much of daily life, the ordering of operations is fundamental. It makes no sense to tie running shoes before putting them on. Yet, sometimes knowing the proper order can be difficult, such as whether it is best to stretch before or after a run. This holds true when designing experiments with multiple tasks; it is often difficult to know what effect one task may impose on another. When studying neural components at a microvolt scale, even small changes in neural environments have the potential to change results radically. Additionally, both neural and non-neural alterations can occur with modified testing conditions, prompting the replication of previous research under unique conditions. Undertakings such as this not only act to test the robustness of effects but can illuminate underlying mechanisms via examination of any differences. Endeavoring to understand possible effects and interactions between conditions and tasks, as well as a consideration of possible mechanisms, is therefore essential to inform future experimental design in any relevant area.

Electroencephalography (EEG) is used in this thesis to investigate three discrete areas: Reliability, attenuation, and order effects. Reliability of EEG components is measured across multiple assessments with the dual purpose of validating component reliability within this study while also testing reliability across multiple sequential tasks – something rarely examined in previous studies. Attenuation of common EEG components is tested in the context of repeated assessments. This contrasts with continuous long-duration or individual-task assessments used traditionally in attenuation studies. Finally, possible unaccounted-for transactional influences between an attentional task and a reward-learning task are examined. An investigation into mechanisms of interaction between related neural systems is also provided. As this thesis focuses on these areas of investigation specifically as they pertain to EEG, an overview of EEG is first provided. A deeper investigation into the backgrounds of order effects, attenuation, and reliability follows.

For any runners still curious about the stretching question, static stretching has shown little benefit at best and a possible increased risk of injury in some cases (Baxter et al., 2017; Hulme et al., 2017). Foam rolling before running appears to be a promising alternative (Su et al., 2017).

1. 1. Electroencephalography

1. 1. 1. Overview

Electroencephalography (EEG) is a non-invasive method of measuring the electrical activity of the brain. It was first introduced in the 1920s by Hans Berger and gained significant prominence as a neuroimaging tool over the following two decades (Schirmann, 2014). Early on, EEG was used largely for studying epilepsy and localizing brain tumors (Schirmann, 2014), but has since expanded in utility to areas such as sleep studies (Zhao et al., 2021) and clinical disorder research (Iglesias-Tejedor et al., 2022; Proudfit, 2015; Umemoto et al., 2014). EEG works by measuring the electrical signals produced by postsynaptic potentials of large numbers of pyramidal neurons in parallel orientation (Cohen, 2017). These electrical signals are captured via electrodes embedded in a cap worn on the head.

A great advantage of EEG is its exceptional temporal accuracy with a concurrent disadvantage of having a low spatial accuracy (Cohen, 2017). This makes EEG an excellent tool for measuring the millisecond-activity of neural firing, allowing for a precise measure of orders of activation, but a less-than-optimal tool for localizing the measured activity (more on this later). The electrodes placed around the scalp capture summed electrical signals at their respective locations, meaning that the signal at each electrode is the product of all electrical currents that may accentuate or attenuate the measure. Non-neural sources also influence EEG measures, which is an issue of signal-to-noise ratio in the output. The goal in measuring EEG is to maximize the signal of interest while minimizing the signal-obscuring noise. The first way to improve the signal-to-noise ratio is to minimize noise in the initial recording (Luck, 2014). This can be achieved by properly setting up the experiment environment, testing the task for unintended systematic artifacts, and giving the participant clear instructions regarding ocular and muscular influences on the recording. Though methods exist for removing blinks and muscular activity, excessive amounts of either can lead to the loss of many trials, resulting in a weaker signal-to-noise ratio. Since the neural EEG signals are small relative to external sources, another method to increase signal involves amplification of the EEG signal to improve the signal-to-noise ratio. Amplification occurs in an amplifier connected to the electrodes, and sometimes also directly at each electrode. A final method of improving the signal-to-noise ratio involves filtering the recorded EEG data by removing frequencies that lie outside the range of interest. Generally, signals related to neural activity will sit between 0.1Hz and 100Hz. However, the filter range can be reduced at the slower end depending on the type of study and the range of relevant frequencies (Luck, 2014).

After filtering, the remaining signal should mostly reflect neural activity within the frequencies of interest. Recall, though, that the final output is a composite of signals from various areas of the brain. This leads to the issue of localizing the source, or sources, of the signal, known as the inverse problem. The gist of the inverse problem (as it pertains to EEG) is that the observed voltage can be created using an infinite number of source combinations, making it impossible to determine the source from the final product alone (Luck, 2014). There are efforts to solve this issue, including forward modeling, inverse modeling, and hybrid methods

(Awan et al., 2019), though there is still room for improvement. Previous knowledge of dipole locations improves source localization, emphasizing the need to collaborate with spatially focused neuroimaging techniques in establishing EEG component neural origins.

1. 1. 2. Event-Related Potentials

Event-Related Potentials (ERPs) are small electrical signals triggered by – and tied to – a stimulus or event (hereafter referred to only as stimulus). Sometimes known as ‘evoked potentials’ (Luck, 2014), ERPs are thought to be neural responses to the preceding stimulus, which gives insight into the nature of the response depending on the stimulus that triggered it. For example, suppose the stimulus is task performance feedback (e.g., correct/incorrect). In that case, if the person being measured is paying attention to the task, the subsequent neural activity can be linked to some aspect of feedback processing. This can be further validated by behavioural measures that correlate with ERP activity. Using the same example, if participants who show a large response to feedback improve on the task quickly and others who show small responses improve at a slower rate, this provides evidence that the neural signal has some important role in learning from feedback.

ERPs are identified by averaging across many trials to isolate the ERP from activity unrelated to the task (Luck, 2014). Individual trial measures may contain the signal-of-interest, but they invariably contain a great deal of other activity unrelated to the task as well. By averaging across many trials, the unrelated activity is mostly cancelled out while the activity related to the task is preserved. This happens because the related activity will appear at approximately the same time and in the same polarity (positive or negative deflection) in each time window. In contrast, the unrelated activity will be essentially random with both negative and positive deflections that average out to zero (Luck, 2014). What remains can be separated into ERP components, which are individually defined segments that generally differ in latency, polarity, and/or amplitude. For example, a change in stimulus during a discrimination task could elicit what is known as the N200 ERP component, a negative deflection approximately 200ms post stimulus tied to processing task-relevant changes in properties of a stimulus (Sur & Sinha, 2009), followed by the P300 ERP component, a positive deflection approximately 300ms post stimulus tied to context updating and memory functions (Polich, 2007). A more thorough overview of specific ERP components follows this section. Although ERPs have proven valuable for research, this approach is not without its faults.

Methods of identifying and processing ERPs are not uniform across laboratories. Williams et al. (2021) compared three common ERP measurement methods in a large-sample feedback processing study. After averaging the data across trials, these three methods disagree on how to identify ERP component amplitude best. The base-to-peak method measures the amplitude of a component as the difference between the peak of the component and the previous local maxima or minima. This method runs into the issue of being influenced by the previous component’s magnitude, leading to biased measures of the component of interest (Williams et al., 2021). Maximum peak methods of component identification find the largest amplitude within a specified window and count that as the amplitude of the component. According to Luck (2014), an issue is that peaks and components are not the same things. Using this measure for component amplitude is largely a historical technique from before computers were widely available and these measures were found using rulers. Luck (2014) goes on to point out that maximum peak measures are easily warped by high-frequency noise, meaning that a high-frequency blip unrelated to the task that occurs 50ms after the actual component peak will both move the latency up 50ms and falsely increase the component amplitude above the actual measure, distorting the findings. The method recommended by both Luck (2014) and Williams et al. (2021) is the mean amplitude method in which the amplitude of the component is calculated as an average of values within a specified window. Using this method, increased amplitudes caused by noise are averaged out, so the result is more representative of the actual component. While this method can still be negatively influenced if centred on a maximum, Williams et al. (2021) showed that it was far less biased by noise than the maximum peak method.

1. 1. 3. The Reward Positivity ERP

The reward positivity is an ERP with a convoluted past. This component was previously known as the feedback error-related negativity (fERN) or feedback-related negativity (FRN or FN), branching off from work with the error-related negativity (ERN; Miltner et al., 1997; Proudfit, 2015). The ERN is a negative deflection evoked during performance errors, shown often in speeded or conflict response studies (Hirsh & Inzlicht, 2010; Luu et al., 2004). The reward positivity, rather than appearing just after an error, occurs in response to feedback about performance (Proudfit, 2015). For example, in a speeded response task a person may choose incorrectly due to time constraints and know almost immediately that they made an error, thus eliciting an ERN. In a feedback learning task, correct or incorrect feedback is required to know whether a response was right, and only at this later point is the reward positivity elicited. The reason for the previous ‘fERN’ name for the reward positivity is clear since these components seem to differ largely in whether they respond to feedback or internal error-monitoring systems. Why the name change then?

While early accounts of the reward positivity (then FRN) by Miltner et al. (1997) sourced it as an attenuated signal in reaction to incorrect (negative) feedback, research by Holroyd and Krigolson (2007) and Holroyd et al. (2008) suggested that the difference was actually driven by correct (positive) feedback. This meant that instead of a negative polarity signal to negative feedback, positive feedback was driving a positive fluctuation in the measured signal. The second part of the reward positivity name change is derived from this reversed understanding of signal deflection. Functional theories regarding the reward positivity signal suggest that it reflects a prediction error – a difference between expected and actual outcomes (Schultz et al., 1997). Seminal work by Schultz et al. (1997) revealed that prediction errors (PE) are driven by reward feedback, as the decision-making process is largely directed towards gaining positive outcomes (AKA rewards). In line with this, PEs fall into one of two categories based on the direction of the difference in outcome: Positive or negative. A positive PE reflects outcomes better than expected rewards, whereas a negative PE reflects an outcome worse than expected rewards - both driven by reward or reward feedback. Thus, the new name 'reward positivity' was derived from the proposed inciting feedback type and the polarity of its deflection.

The connection between PEs and reward positivity suggest that an overview of PE dynamics will benefit an understanding of reward positivity functioning. Many reward-learning models have PEs as an integral part (Garrison et al., 2013; Krigolson et al., 2014; Shenhav et al., 2013). Early in a learning task, correct responses will yield relatively large positive PEs because there is no expectation of success or positive feedback, and an unanticipated reward is better than the expected no-reward. As the task is learned, the rewards become anticipated so that the expectation and outcome converge, leading to decreasing PE magnitudes. Indeed, this is what was found in an early review by Schultz et al. (1997). In the examined experiments, monkeys were trained to perform various tasks for rewards while the activity of single dopamine (DA) neurons were recorded. Initially, a phasic burst in DA neurons was seen in response to rewards, as they were unexpected. As the task was learned, DA phasic bursts decreased in size at reward presentation – behaviour that matches reward PE activity (Schultz et al., 1997). This research established DA as the neurotransmitter responsible for PE activity.

Mechanisms for PEs coincide superbly with reward positivity activity. Several reward-learning experiments have shown that reward positivity amplitude is largest early in a task and decreases with learning (Umemoto et al., 2019; Williams et al., 2020), even displaying a shallower component decrease concurrent with poorer learning of a task (Krigolson et al., 2009). Furthermore, the reward positivity has also been theorized to involve DA reward-learning systems (Proudfit, 2015), just as the PEs in the experiments by Shultz et al. (1997). As an additional connecting piece, these systems go a long way in explaining classical conditioning learning. In classical conditioning, unconditioned stimuli (US), such as positive feedback or rewards, automatically elicit positive responses. Stimuli that precede and predict US, such as prompts for decisions or actions, will initially be neutral stimuli. If a correct decision in the prompt phase leads to positive feedback a large portion of the time, this connection will be learned such that the prompt phase will become a conditioned stimulus (CS) and will begin to elicit the positive response that the US previously did. In the review by Shultz et al. (1997) and a study by Krigolson et al. (2009), the PE and the reward positivity response, respectively, shifted with learning to the stimuli that predicted the reward. This process mirrors the classical conditioning model. These strong associations go a long way in providing an overview of theorized reward positivity functions, but an understanding of the mechanisms of action require a deeper look into the underlying (non-motor) dopaminergic activity and its relationship to PEs and reward positivity.

1. 1. 4. Dopaminergic Activity and The Reward Positivity

As everything to do with the brain, the function of DA is complex. Early studies theorized DA as a hedonic neurotransmitter necessary for feelings of pleasure (Di Chiara & Tanda, 1997; Wise, 1982). Although DA was dissociated from hedonic pleasure as far back as 1998 (Berridge & Robinson), this remains a prevalent idea in popular science (*Psychology Today Canada*, 2023; Healthdirect, 2021; Watson, 2021). Currently, DA is most notably associated with PEs and motivational salience (Berke, 2018; Mohebi et al., 2019), with implications in a vast array of functions from addiction (Budygin et al., 2020; Grace, 2000) to immunological performance (Berke, 2018). As mentioned previously, PEs are learning signals indicating the magnitude of the difference between expected and actual outcomes. Motivational salience can be described as a bias in attention and motivated intention either towards (incentive salience) or away from (aversion salience) an object, event, or outcome (Puglisi-Allegra & Ventura, 2012). Though there are similarities between PEs and motivational salience, they are distinct functions that are not always in play at the same time (Berke, 2018). Both inform behaviours and often work in tandem, such as when a positive PE indicates a larger than expected reward and the source consequently develops incentive salience. Though this ordering makes logical sense, the question remains: How does DA encode both functions?

Studies looking at the PE/motivational salience question provide insight by looking at DA activity in specific neural regions. One such study suggests that dopaminergic functions in the nucleus accumbens (NAcc), a major component of the ventral striatum (VS), may hold the key to differentiating between prediction error and motivational salience DA activity. This research by Saddoris et al. (2015) showed differential DA firing activity between the core and shell of the NAcc that tracked prediction errors and motivational salience, respectively.

However, the authors do note that these systems exhibit a complexity that may not be reduceable to simple core and shell dynamics, and mention that there was some amount of overlap of activity. Other regions associated with PE and motivational salience include the anterior cingulate cortex (ACC) and lateral habenula (LHb). The ACC has been implicated in both positive and negative PEs (Holroyd & Coles, 2002; Kawai et al., 2015), while the LHb is more often linked with negative PEs (Bromberg-Martin & Hikosaka, 2011; Hennigan et al., 2015; Kawai et al., 2015). These regions appear to compute negative PEs in a slightly different manner, as the LHb has been shown to represent immediate negative value while the ACC signal carries information from previous experiences or trials and more accurately predicts shifts in behaviour (Kawai et al., 2015). Interestingly, some studies have supported a role for the LHb in salience attribution such that increased activity associated with a stimulus or event either reduces incentive salience or induces aversive salience (Danna et al., 2013; Lawson et al., 2014). These functional roles attributed to the NAcc, ACC, and LHb are not mutually exclusive. Not only do strong interconnections link these areas, but motivational salience is functionally split between the NAcc shell’s involvement in incentive salience and the LHb activity in the reduction of incentive salience and induction of aversive salience (Danna et al., 2013; Kawai et al., 2015; Lawson et al., 2014; Parkinson et al., 2000; Saddoris et al., 2015). The possibility remains that these systems work together in reward learning and motivational attribution functions.

Some research focuses on the efferent state of DA, suggesting that different mechanisms of DA efflux such as tonic and phasic activity allow for distinct signalling processes. Tonic DA activity is characterized as a relatively slow and steady release, while phasic DA activity involves large, high-frequency bursts of dopaminergic activity (Floresco et al., 2003). One explanatory model addressing the PE/motivational salience issue suggests that DA phasic activity promotes learning while tonic activity tracks motivational salience (Hamid et al., 2016; Wang et al., 2021). In an overview of DA dynamics, Berke (2018) adds to this model by describing how phasic bursts could communicate a learning signal via a specialized mechanism. First, Berke (2018) points to research showing that constant acetylcholine (ACh) activity suppresses DA-dependent plasticity mechanisms (Shen et al., 2015). Second, quantitative kinetic modeling by Nair et al. (2015) submits that local ACh activity could be momentarily interrupted during phasic DA activity, enabling synaptic changes. Thus, Berke (2018) suggests that PE phasic bursts enable updated learning models via synaptic changes, whereas ongoing DA activity signals motivational state.

While the separation of PEs and motivation to phasic and tonic activity is a satisfying division of functions, this model becomes complicated when combined with studies showing a modulatory relationship between DA tonic and phasic firing patterns (Badgaiyan et al., 2015; Bilder et al., 2004; Breitenstein et al., 2006; Budygin et al., 2020; Grace, 2000). These studies show that phasic release of DA leads to large amounts of synaptic DA that do not impact extrasynaptic levels due to rapid reuptake, whereas tonic release does have the capacity to influence extrasynaptic levels (Floresco et al., 2003). Furthermore, high levels of extrasynaptic DA leads to autoreceptor activation, inhibiting the presynaptic release of DA and contributing to an overall reduction of phasic activity. Thus, tonic DA release has the capacity to downregulate phasic activity (Badgaiyan et al., 2015; Bilder et al., 2004; Breitenstein et al., 2006; Budygin et al., 2020; Grace, 2000). If the tonic/phasic model of motivational salience/PE is accurate, this suggests that high levels of motivation would increase tonic activity and reduce phasic activity, thereby inhibiting the ability to learn from reward feedback in this state.

Initially, this tonic tracking of motivation seems highly unlikely, as it would ostensibly brand motivation as a maladaptive state in terms of Pavlovian learning. Yet, a consideration of the conditions for each of motivation and PEs suggests that this model may hold merit. Motivation is a state driven by the expectation of reward or positive outcome, often due to classical conditioning links between conditioned and unconditioned stimuli (Berridge, 2004). For PEs, a simple model suggests that the difference between received reward value (Rv) and a consistently updating estimate of reward (Re) accounts for PE magnitude (PE = Rv – Re; Watabe-Uchida et al., 2017). Though the PE has been linked to phasic DA activity, the neural components of the Rv and the Re are less clear. Linking the phasic and tonic activity together in this model suggests a possible neural mechanism underlying this process. If motivational tonic activity does indeed act to attenuate the response to a reward, the components of the equation can be filled in such that a PE is equal to the unfettered phasic response to a reward (Rv) attenuated by the magnitude of tonic motivational activity (Re). This interpretation suggests some interesting mechanisms within this system. Firstly, there would necessarily be a ceiling effect in extreme cases wherein a highly anticipated reward resulting in an even higher-value reward would not be capable of eliciting a positive PE. Tonic DA activity cannot increase indefinitely, indicating that there must be a maximal output. Support comes from research showing impaired habituation to environments in hypertonic DA mice (Zhuang et al., 2001), and from evidence showing that drug-enhanced tonic DA activity directly impairs associative learning in healthy adults (Breitenstein et al., 2006). The second mechanism suggested by the interplay of reward processing and motivation incorporates negative PEs and how they would be calculated within this system. If a received reward were worse than anticipated, the ensuing reduction or pause in DA activity would be accentuated by the heightened tonic activity preceding it in the motivated anticipation of reward. This might help explain how the much smaller negative PE signal manages to capture the same amount of information as the larger positive PE. Negative PEs could be calculated as the difference from tonic anticipatory activity to baseline or just below baseline. It seems reasonable that the pause in DA activity following negative PEs would elicit a similar learning signal to positive PEs. Indeed, Cragg (2006) suggests that both phasic and interrupted DA activity should lead to similar effects on ACh activity. In this case, the DA neuron synapses could then use information such as extrasynaptic DA levels to gauge the amount of tonic activity preceding the momentary cessation of DA activity and adjust accordingly.

As a signal thought to represent PE, the reward positivity ERP should fit into the discussed structures of PE dynamics. Previous accounts of the reward positivity have localized the source of this signal in the VS (Foti et al., 2011; Proudfit, 2015) or ACC (Doñamayor et al., 2011; Hauser et al., 2014). Although regional representations of motivation and PE activity were discussed for the NAcc in the VS and the LHb, the signals produced in these areas are not of the type that EEG excels at capturing. Individual neuron activity produces miniscule electrical dipoles, or electrical currents (Luck, 2014). For that signal to be measurable through the many layers between it and the electrode, large numbers of similarly oriented neurons need to activate together to form a large dipole (Luck, 2014). Neither the NAcc nor the LHb meet this profile, whereas the laminar surface of the ACC is precisely the organization required (Junaković et al., 2023). This means that the reward positivity is most likely a reflection of ACC activity. Fortunately, this does not mean that the reward positivity only captures a small aspect of the PE signal. In terms of positive PEs, the ACC has strong connections to the NAcc via the corticostriatal circuit (Haber, 2016). Further, lesions to either the ACC or NAcc lead to impairments in Pavlovian learning, suggesting that both are heavily involved in stimulus-reward learning (Parkinson et al., 2000). Recall that ACC phasic activity also signalled both positive and negative PEs (Holroyd & Coles, 2002; Kawai et al., 2015). While the LHb signalled negative outcome signals based on individual trials, the ACC signal represented information from previous trials and better predicted changes in behaviour (Kawai et al., 2015). Even though the ACC signal does a good job at approximating the PE, these findings suggest that the ACC may have a larger role in value attribution than PE alone. The PE represents a standalone value used to update a learning model that estimates expected value or reward. This description is much closer to what the LHb was found to signal, at least for negative PEs. The suggestion that the ACC incorporates information from previous trials intimates that it more closely resembles the learning model than the PE. While the ACC has been discussed in terms of phasic activity and its relationship to the reward positivity signal, indirect evidence also links the dorsal ACC to motivational functions. One line of evidence comes from dorsal ACC lesions leading to akinetic mutism - a disorder in which the will or motivation to act is obliterated (Németh et al., 1988). Conversely, stimulation of the ACC in one study caused a sense of upcoming challenge as well as strong feelings of motivation to overcome that challenge (Parvizi et al., 2013). Though the mechanisms behind these motivational aspects of ACC functioning are currently unclear, tonic ACC dopaminergic activity could play a leading part.

There are a few common tasks used to elicit the reward positivity. Previously mentioned was the time estimation task, in which a participant presses a button after they believe an elapsed time has passed (Umemoto et al., 2019). This task will often adjust the window of acceptable error to keep the correct and incorrect responses at a predetermined level. For example, if the task is to estimate a one-second interval, the acceptable window may begin at one second plus or minus 100ms. If the participant responds correctly, the window will decrease by ten milliseconds on each end so that the correct-response window is smaller. If, on the other hand, the participant responds outside of the window, it will increase on each end by ten milliseconds to facilitate correct responses (Umemoto et al., 2019). The adjusting window guarantees an adequate number of correct and incorrect responses for analysis. Another common task is a bandit task (AKA: gambling or doors task; Williams et al., 2021). In a bandit task, participants will be presented two or more options, each with hidden probabilities of eliciting a ‘win’ condition. In a simple version, two coloured squares are presented in each trial. One square will have a greater chance of eliciting a ‘win’, and the participant’s goal is to garner as many wins as possible by learning which of the options is better. In both the time-estimation and bandit task, the reward positivity is generally measured as the difference between positive (‘correct’ or ‘win’) and negative (‘incorrect’ or ‘lose’) feedback.

1. 1. 5. The P300 ERP

The discovery of the P300 ERP is attributed to Sutton et al. all the way back in 1965. In this seminal study, participants were presented with light or sound stimuli after a cue stimulus. Some cues were always followed by the light or the sound, making the second stimulus predictable whereas others were not. Sutton et al. (1965) found that there was a difference in the EEG recording between the predictable and unpredictable stimuli as a positive deflection around 300ms after stimulus presentation. This and other early studies underscored the role of stimulus probability and task relevance in the elicitation of the P300 component. An early review by Donchin (1981) sought to identify the functional role of the P300. Findings suggested that it may be involved in schema revision or context updating and may also play a role in memory functions. Donchin (1981) concluded his review with a general appeal to researchers to solidify an understanding of the functional significance of the P300. Though still not fully realized, significant progress has been made in this endeavor.

A more recent review by Polich (2007) highlights the same theories as Donchin (1981), but with an emphasis on attentional aspects and the addition of resource-allocation and/or inhibition theories tied to the P300. This review also highlights the division of the P300 into an early frontal P3a component and a later anterior P3b component, relating to DA-driven attentional processes and norepinephrine-driven context-updating/memory functions, respectively. Though both aspects certainly play important roles in cognitive functioning, the larger P3b signal often takes centre stage. Concordantly, the main task used to study the P300 (the oddball task) does a poor job of eliciting the P3a and requires an augmented oddball task or a no-go variation to keep the P3a substantial throughout. Due to the common focus on the P3b, the ongoing overview will reflect this emphasis in describing the P300 largely in terms of the P3b. Compelling research ties the P3b to locus-coeruleus norepinephrine (LC-NE) activity (Gurtubay et al., 2023; Murphy et al., 2011; Nieuwenhuis et al., 2005; Polich, 2007; Vazey et al., 2018), which appears promising in the search for Donchin's functional explanation of P300 activity. Considering this, an overview of LC-NE functioning seems appropriate before discussing the extensive overlap between the locus coeruleus (LC) and the P300.

1. 1. 6. The Locus Coeruleus-P300 Relationship

Located in the pons of the brainstem, the LC provides the majority of NE and has wide-reaching connections around the brain. The effect of NE release was initially thought to simply suppress or inhibit activity (Dillier et al., 1978; Segal & Bloom, 1974b, 1974a). Later research found that while activity was suppressed following NE release, spontaneous firing was attenuated to a larger degree than stimulus-evoked firing, resulting in a greater signal-to-noise ratio (Foote et al., 1975; Freedman et al., 1977; Segal & Bloom, 1976). Instead of suppressing signals, these results suggest that the role of NE may be to enhance signal transfer, whether excitatory or inhibitory. An important element of LC function involves differences in tonic and phasic activity. Tonic LC activity can be divided into three ranges: low (<2Hz), moderate (2-3Hz), and high (>3Hz) activity. Low-tonic LC activity occurs during drowsiness and low vigilance, moderate during external task performance, and high during states of distractibility and erratic performance (Aston-Jones et al., 2000; Aston-Jones & Bloom, 1981; Rajkowski et al., 1994). Phasic LC activity, on the other hand, is a brief high frequency (approx. 20Hz) discharge in response to task-relevant stimuli and salient unconditioned stimuli (Aston-Jones & Bloom, 1981; Nieuwenhuis et al., 2005). Importantly, the phasic response occurs only in periods of moderate-tonic LC activity and is absent in both low- and high-tonic states (Aston-Jones & Bloom, 1981). Potentially noteworthy is that these tonic states match the Yerkes-Dodson law in which performance increases with arousal to an optimal point, after which greater increases in arousal are accompanied by a decline in performance (Yerkes & Dodson, 1908). More relevant to the paper at hand is the relationship between the LC and the P300. Strong evidence suggests that phasic LC activity is the source of the P300 (Gurtubay et al., 2023; Murphy et al., 2011; Nieuwenhuis et al., 2005; Nieuwenhuis, 2011; Polich, 2007; Vazey et al., 2018), indicating that consideration of various LC projections could lend further insight into P300 functioning. Projections from the LC emanate to almost all areas of the brain, so only connections with potential relevance regarding the P300, and research regarding region-specific theories of activity, are presented.

The role of the temporoparietal junction (TPJ) in P300 activity is strongly supported by lesions studies that consistently show severely diminished P3a and P3b measures (Linden, 2005;

Polich, 2007). Theories regarding the role of the TPJ include attentional selection, reorientation, context updating, memory, and social processing (Carter & Huettel, 2013; Geng & Vossel, 2013). Many of these may sound familiar. The role of the right TPJ (rTPJ) accounts for a large portion of the attentional theories regarding this region. Firstly, spatial neglect – a severe deficit in the capacity to orient attention to a visual field (usually left) – is primarily associated with right parietal injury in regions including the rTPJ (Mort et al., 2003). Secondly, the rTPJ is a central hub of the ventral attention network, which is thought to be responsible for reorienting toward behaviourally relevant stimuli (Corbetta et al., 2000). In a review from Geng and Vossel, (2013), they argue against the reorienting interpretation of rTPJ activity due to its relatively late timing compared to dorsal network orienting signals, and they instead support a context updating framework partly because of TPJ sensitivity to violations of expectation.

An fMRI study by Kahnt and Tobler (2013) suggests that the rTPJ may play a major role in attentional aspects of LC activity, and gives insight into influencing elements of LC/rTPJ activity. In this study, participants learned a set of value-associated shapes and colours that were presented as combined gain and loss elements. Based on the relative value of the combination, the participant had to decide whether to accept or decline. For example, the participant may be presented with a high-value gain shape and a low-value loss colour, which would translate to a net gain in reward. On the other hand, a low-value gain shape matched with a high-value loss colour would result in a net loss and be a bad choice to accept. The researchers included three proposed choice-influencing variables to dissociate effects: Estimated value, global salience, and elemental salience. Estimated value was defined as the sum of the variable values. The result could be positive or negative depending on the magnitude of each variable. Global salience was defined as the absolute estimated value, emphasizing magnitude while ignoring polarity.

Elemental salience was defined as the sum of the absolute value of each element, making the value magnitude cumulative whether it was positive or negative. As a clarifying example, if a participant were presented with a +0.1/-1.0 trial resulting in a net loss of 0.9, the estimated value would be -0.9 $(-1.0 + 0.1)$, the global salience would be 0.9 $(|-1.0 + 0.1|)$, and the elemental salience would be 1.1 $(|-1.0| + |0.1|)$. Results of this study showed the predicted influence of expected value on choice, but also that elemental salience, and not global salience, was associated with faster reaction times. Elemental salience had no effect on choice behaviour, suggesting that its contribution was attentional. Further supporting this finding, elemental salience was positively correlated with rTPJ activity. As a final analysis, Kahnt and Tobler (2013) tested the functional connectivity between the LC and rTPJ and found stronger connectivity during high elemental salience trials and lower connectivity for lower elemental salience trials. In sum, this study demonstrated that rTPJ activity was sensitive to the sum of the absolute magnitude of each presented element, and that the connectivity between LC and rTPJ was strongest at higher absolute magnitudes. Tying this back with the P300 are studies that clearly show a P300 sensitivity to magnitude (Sato et al., 2005; Yeung & Sanfey, 2004).

Lesion studies provide insight into hippocampal involvement in P300 activity. Though P3a signals are reduced following lesion, P3b signals are unchanged (Linden, 2005; Polich, 2007). A study by Grella et al. (2019) shows that while the hippocampus may not contribute much to the P300 signal, LC effects on the hippocampus can still explain some of the associated functions. In this rat study, LC phasic activity was artificially stimulated or silenced in new or known environments. Grella et al. (2019) found that bilateral phasic stimulation caused hippocampal remapping to occur in known environments, and that silencing the LC prevented map reset in new environments, prompting areas of the hippocampus to retain old environment maps. This study supports an LC functional theory proposed in 2005 by Bouret and Sara suggesting that LC-NE phasic firing initiates a network reset that allows for cognitive shifts and behavioural adaptation.

A series of studies by Jefferies and Di Lollo (2019) specifically tested Bouret and Sara's (2005) network reset theory by using a speeded response task. For this study, a steady square was present on one side of a computer screen, but participants were to respond to a transient stimulus that could appear on either side. The experimental group were exposed to a phasic LC-NE triggering event (a noise or flash) preceding the appearance of the target stimulus. One finding was that the experimental group's overall reaction time was faster than the control group, suggesting superior context updating. On top of that, experimental group reaction time was quicker for stimuli that appeared inside the square than outside, while the control group showed no difference. These results imply that attention was drawn to the square as a new environmental stimulus after the transient event, supporting the network reset theory. Being thorough, Jefferies and Di Lollo (2019) tested this phenomenon in two illuminating variations. While both variations used the same intervention as the original, one had the phasic triggering event occur outside of the time range of the LC-NE phasic response – meaning that phasic effects returned to baseline before the stimulus appeared, while the other used participants with impaired LC-NE functioning. When the LC-NE triggering event occurred outside of the phasic response window, the experimental group lost both the increased reaction time effects. This indicates that both reaction time improvements were tied to the phasic LC response, but were they tied to each other? In the final variation using participants with impaired LC functioning, the phasic triggered group continued to show faster overall reaction time, but they lost the stimulus location effect from the original study (Jefferies & Di Lollo, 2019). This reveals dissociable functions of LC phasic activity because the improved context updating effects were present while the network reset was not. Overall, these additional results further support the network reset theory while suggesting concurrent context updating LC functions. The multifaceted roles of the LC may indicate why Donchin's (1981) prompt to discover the functional role of the P300 has yet to be fully realized.

A common method of eliciting the P300 uses the oddball task. In this task, a participant is presented with a series of frequent and infrequent (oddball) stimuli such as two different coloured circles for a visual oddball task, or two different tones for an auditory oddball task. The participant quickly becomes habituated to the frequent colour or tone, but the infrequent colour or tone represents a salient or task-relevant stimulus since it is both unexpected and is typically the stimulus to which the participant will respond. These circumstances reliably elicit the P300 response to infrequent stimuli (Polich, 2007; Squires et al., 1975).

1. 2. Order Effects

Order effects are important potential confound variables that must be considered for any well-designed multi-task experiment. When completing consecutive tasks, non-experimental influences will invariably impact a participant's performance to some degree. Common influences include fatigue, boredom, practice, and carryover effects, which can improve or worsen subsequent task performance (Zach, 2020). Counterbalancing task presentation can be used to control for bias in many situations by averaging out the influence of order effects across individuals tested. For example, if tasks A and B are both fatiguing then presenting an AB order to half and a BA order to the other half of the participants will average out the reduced performance on the second task and any found effects are more likely experimentally driven (*APA Dictionary of Psychology*, n.d.). In some situations, counterbalancing requires a more complicated experimental design, while in others it is simply impractical. For example, if one task requires testing a participant without certain knowledge and the other requires testing with this knowledge, it can only be performed in one direction. In any case, it is useful to know if order effects exist in order to plan the design and analysis properly.

Brain research does not escape order effects, even though they may be substantially more challenging to anticipate. For example, a metanalysis by Shields et al. (2016) found that stress negatively influenced working memory to greater degrees at longer delays from stress onset. Though cortisol is one of the main ingredients of the stress response, cortisol administration alone led to the opposite effect; greater delays from administration led to greater enhancements of working memory (Shields et al., 2016). A possible explanation comes from Valentino and Van Bockstaele (2008) who argue that corticotropin releasing factor directly modulates LC activity and that a stress response increases tonic levels of NE release, initiating a high-arousal state. Recall that a moderate-tonic release is optimal for LC phasic activity and directed attention (Aston-Jones & Bloom, 1981). Valentino and Van Bockstaele (2008) go on to suggest that this high-arousal state may be evolutionarily adaptive during stress periods as it would promote environmental scanning and behaviour adjustments. However, you would see task-related deficits in areas such as working memory. Another factor to considered is the endocannabinoid system's modulatory influence on the LC-stress response (Wyrofsky et al., 2019). These studies emphasize that the interaction between neurotransmitters and neural systems is a complicated, yet vital, consideration.

1. 2. 1. *Order Effects and EEG*

Researchers have investigated possible relationships between the reward positivity and the P300 ERPs, but a literature review found no information on possible order effects. Recall that the reward positivity is associated with phasic DA activity in the ACC (Doñamayor et al., 2011; Hauser et al., 2014), while the P300 is associated with phasic LC-NE activity (Gurtubay et al., 2023; Murphy et al., 2011; Nieuwenhuis et al., 2005; Polich, 2007; Vazey et al., 2018). To fully address potential order effects, a study testing both would have to consider how these systems and neurotransmitters may influence each other and in which direction. Various studies have shown outputs connecting the LC-NE system to the ACC (Corona et al., 2022; Gompf et al., 2010; Joshi & Gold, 2022; Koga et al., 2020). This connection reveals the potential for a direct influence of LC firing on ACC activity. If LC activity produces sustained neuro-environmental changes in ACC regions, a repetitive LC phasic tasks, such as the oddball task, could influence the ACC-implicated reward positivity of a subsequent bandit task. Support for this possibility comes from three major factors. First, LC projections release not only NE, but also DA (Devoto et al., 2005; Ranjbar-Slamloo & Fazlali, 2020). Second, norepinephrine transporter (NET), responsible for reuptake of NE has been shown to additionally aid in DA reuptake. These two findings suggest that LC-NE phasic firing can slow DA reuptake in regions of high DA activity. Firstly, extra DA is released from LC terminals along with NE, increasing overall DA levels. Simultaneously, NET reuptake will be split between both neurotransmitters instead of focusing on DA, resulting slower DA reuptake and higher levels of extracellular DA. This is exactly what Devoto et al. (2005) found in a repeated LC stimulation rat study. A period of LC stimulation every 20 minutes led to increasing levels of extracellular DA in medial prefrontal and occipital cortical areas, highlighting the influence that the LC-NE system can exert on extracellular DA. The final factor to consider is that high levels of extracellular DA can reduce DA phasic activity via auto receptor activation, thus reducing DA-dependent phasic signals (Floresco et al., 2003). Furthermore, even at shorter time intervals LC-NE firing has been linked to reduced cerebral blood volume in the ACC, suggesting an inhibitory effect of NE on ACC function (Oyarzabal et al., 2022). These studies illustrate the precise influence LC-NE activity could exert over phasic DA activity such as the reward positivity. What remains to be seen is whether the LC activity in an oddball task reaches a threshold in effect size and duration to reveal similar influences on DA activity.

1. 3. Attenuation

Attenuation of ERP components can result from numerous stable or gradually changing conditions. Examples of states that influence component amplitude, but in a stable manner throughout the task, are attention-deficit hyperactivity disorder and age (Chen et al., 2023; Umemoto et al., 2014). On the other hand, learning and fatigue can influence component amplitudes differentially throughout a task (Umemoto et al., 2019; Williams et al., 2020). Only gradually changing conditions reflect task-independent physiological changes occurring during the task, which can be problematic. These influences are often related to order effects, as order effects can introduce changes in task performance within and between tasks. It can be difficult to identify the attenuating influence in ERP studies, but comparison to surveys or behavioural data can offer some insight. For example, if reduced ERP amplitude correlates with improved performance measures, it might be postulated that practice effects (AKA learning) caused the decrease.

A 2020 study by Williams et al. demonstrated attenuation of the reward positivity component during a learning task. In this experiment, participants matched symbols from other languages with English words. The results clearly exhibited gradual attenuation of the reward positivity that was predictive of performance, such that diminished reward positivity predicted better accuracy and reaction time (Williams et al., 2020). This interpretation fits with the theory of reward positivity as an index of prediction error. The prediction error would necessarily diminish as the task is learned, meaning that predicted outcomes more closely match actual outcomes. Further supporting reward positivity attenuation as a measure of learning is a shape discrimination study by Krigolson et al. (2009). Not only did the reward positivity (referred to as fERN in this study) decrease in amplitude with improved performance, but the researchers also found smaller reductions over time for participants with poorer discrimination, indicating that weak attenuation reflected weak or absent learning (Krigolson et al., 2009).

On top of reward positivity, a study by Umemoto et al. (2019) also provides an excellent representation of P300 and behavioural-measure attenuation in a sustained time-estimation task. Participants estimated a one-second duration for two hours while a shifting acceptable error window responding to performance kept success rates around 50 percent. The error window size was a behavioural marker of task performance, as smaller window size indicated more accurate time estimates. Throughout most of the task, both ERPs and the error window size showed steady attenuation. The proposed cause of attenuation shifted between early and later time-points for both the reward positivity and error window size. Early attenuation was suggested to reflect learning, while fatigue was considered a possible factor in later attenuation. For the P300, the steady attenuation throughout the experiment was suggested to reflect diminishing attentional control (Umemoto et al., 2019), which could still be interpreted as a reduced need for attentional control with early learning and a reduced capacity for attention with later fatigue. Though attenuation occurs across tasks for the reward positivity and the P300, how long this effect lasts is unknown. The short breaks afforded to participants during a task do not negate the attenuation effects, but would a longer break?

The suggestion by Umemoto et al. (2019) that early and late attenuation had different causes complicates this conjecture. Learning or practice effects that improve performance and the co-occurring reduction in reward positivity would not be expected to change unless the delay were long enough to undo the learning. On the other hand, attenuation caused by fatigue may be counteracted by a long enough rest in between tasks. On yet another hand, perhaps the longer breaks would increase boredom and disengagement from the task. A possible challenge is presented when considering that working memory impairments have been found over an hour after stress onset (Shields et al., 2016). This shows that cognitive effects can be long lasting, which would make it experimentally difficult to identify a required duration for a return to baseline. Still, if a longer break reversed the attenuation effect, this would indicate a rejuvenating influence of time away from the cognitive task, which would in turn support the advice to take breaks while working on a difficult project - such as a thesis.

1. 4. Reliability

Reliability, or test-retest reliability, is the ability of a test or device to capture equivalent measures at different times, all other things being equal (Aldridge et al., 2017). If reliability is lacking, then it becomes difficult to derive meaningful conclusions from a study because the magnitude of the introduced bias is unknown and inseparable from actual effects. Low reliability could originate from procedural effects, such as imprecise tools or unclear instructions, or from within-subject effects, such as changes in mood; experience; or energy. Procedural influences can be controlled simply by making sure the experiment is well designed with proper measurement tools and clear, tested experimental processes. Within-subject effects can be trickier. Testing within a short span of time can limit within-subject changes, but this method cannot always be applied. For example, depression scales need to be reliable across a longer period since changes in depression symptoms generally take weeks or months to alleviate with treatment (Machado-Vieira et al., 2010). In any case, it is important to verify the reliability of a test to ensure that measured changes are occurring largely because of known factors.

For EEG studies, reliability is just as important as anywhere else. Though ERPs may fluctuate from trial-to-trial, the averaged ERP is intended to be an accurate and stable representation of an individual's neural response. Consequently, numerous studies have examined reliability within EEG. For the intra-class correlation method of examining reliability, standard values of less than .50, .50 to .75, .75 to .90, and greater than .90, are used to interpret ICC scores as poor, moderate, good, and excellent reliability, respectively (Koo & Li, 2016). Reliability ERP results vary widely from poor-to-excellent in studies measuring infants (Munsters et al., 2019), children (Kompatsiari et al., 2016; Szenczy et al., 2021), adolescents (Segalowitz & Barnes, 1993), and older adults (Pollock & Schneider, 1992; Walhovd & Fjell, 2002); even those with cognitive decline (Devos et al., 2020). The most common delays between measures range from weeks (Cassidy et al., 2012; Huffmeijer et al., 2014; Ip et al., 2018; Larson et al., 2010) to months (Auerbach et al., 2016; Gaspar et al., 2011; Morand-Beaulieu et al., 2022), with some delays of over a year (Segalowitz & Barnes, 1993; Walhovd & Fjell, 2002; Weinberg & Hajcak, 2011). These findings generally support the reliability of ERP components across various delays. Few reliability studies have used time intervals of less than an hour. Of these, the P300 was found to have good reliability, but the reward positivity was not included (Kompatsiari et al., 2016; Segalowitz et al., 2010). A literature search failed to discover a test of reliability across multiple short delays (less than an hour), possibly because it is an unusual testing schedule. In general, reliability measures for the reward positivity are unfortunately sparse. The few studies that address the reward positivity found relatively large reliability for conditional measures, but poor reliability for the difference reward positivity (Levinson et al., 2017; Szenczy et al., 2021). Szenczy et al. (2021) suggest that the low difference values could stem from low individual measure reliability, unequal variance, or intercorrelations between conditional measures. Overall, evidence indicates that the P300 will show moderate to excellent reliability, while the reward positivity is suggested to be poor for the difference wave and larger for conditional waves.

1. 5. Current Study

Many factors can influence a study's viability, and an important task is to address these as much as possible. Order effects can bias measures from one task to the next if not addressed, but understanding this relationship allows for compensatory measures and greater control. The complexity of the neural environment can make predicting the influence of one task on another challenging in neural studies. Using EEG, one method of investigating possible order effects is to compare ERP amplitudes between the various task orders. If the second task consistently yields smaller ERPs, then the source could be anything from fatigue to boredom. On the other hand, if one task consistently reveals reduced ERPs following the other, and not vice-versa, then a direct influence of the first task on the second is strongly supported. Accordingly, addressing possible order effects is one goal of the current study. Reward positivity and P300 amplitudes will be compared between an oddball task first and a bandit task second, and a bandit task first with an oddball task second. A directional attenuating influence could suggest a mechanism of effect. For example, if reward positivity amplitude is reduced for bandit tasks performed second compared to bandit tasks first, this suggests a possible influence of repetitive LC-NE firing in the oddball task on the phasic DA activity of the reward positivity. This outcome is supported first by considering the connection between LC-NE firing and medial prefrontal cortical regions

(Gompf et al., 2010; Joshi & Gold, 2022; Koga et al., 2020), then by reflecting on the influence of increased NE and resultant increases in extracellular DA (Devoto et al., 2005; Pozzi et al., 1994), and finally by examining the attenuating effect that high levels of extracellular DA has on DA-phasic responses (Badgaiyan et al., 2015; Breitenstein et al., 2006; Grace, 1991, 2000). Due to the duration of increased extracellular DA suggested by relevant studies (Devoto et al., 2005; Lohani et al., 2018), the main hypothesis is that reward positivity amplitudes for bandit tasks performed second will be smaller than those for bandit tasks performed first. The suggestion that this effect is related to LC-NE activity will only hold up if it is also found that no difference exists between P300 measures for either task-order. A comparative decrease in the second measure P300 would suggest that both ERPs are simply under the influence of fatigue or boredom effects. A literature review found scant evidence of a directional relationship from ACC to LC, suggesting that the bandit task has less of an opportunity to influence the P300 in a subsequent oddball task (though see Gompf et al., 2010). Therefore, the hypothesis regarding the P300 is that it will not show a significant difference between task orders.

Unique datasets offer the opportunity to explore new relationships and to gain a deeper understanding of previously discovered effects. Though ERP component attenuation is a phenomenon already discussed in various studies (Krigolson et al., 2009; Umemoto et al., 2019; Williams et al., 2020), an extensive search revealed no articles addressing attenuation in repetitive task completion. Here, reward positivity and P300 ERPs are measured across five repetitive cognitive assessments to discover if attenuation is preserved in this model. Attenuation is suggested to occur due to boredom or fatigue effects, or to learning of the task (Krigolson et al., 2009; Umemoto et al., 2019; Williams et al., 2020). Since these factors should still be in effect across multiple assessments, it is hypothesized that attenuation will occur such that there will be a negatively sloped linear relationship between cognitive assessments and ERP amplitudes for both the reward positivity and the P300.

Though test-retest reliability has previously been assessed for the P300, it has not been assessed across five repeated measures, nor with such short delays between measures (fifteen minutes or less). Neither has the reward positivity, which also suffers from insufficient reliability measures in general even when searching all its previous monikers. This study seeks to identify the reliability of ERP components under these unique circumstances. The hypothesis for the P300 derived from previous reports is that it will exhibit moderate to excellent (.50 – 1.00) reliability using intra-class correlation (ICC) methods. The range of this hypothesis reflects the heterogeneous findings in the literature. In terms of the reward positivity, the few previous studies have found low reliability measures, driving the current study’s hypothesis that the reliability in the will be poor (0 - .50) for the difference wave. The previous literature regarding the reward positivity also suggests that conditional waves elicit much stronger reliability measures, which will be analysed here as well. The conditional waves are hypothesized to be much higher than the difference wave, ranging from good to excellent (.75 – 1.00). To keep the analysis balanced, conditional reliability will be assessed for the P300 as well. These are hypothesized to resemble the overall reliability, as there is no indication that they would not. These results will supplement the literature regarding ERP component reliability while adding the novelty of measures ranging across multiple sequential tests in a short time span. Cumulatively, these analyses will add to the body of EEG literature by examining established phenomena in a novel framework.

Chapter 2: The Study

2. 1. Introduction

Awareness of one event’s influence on another is essential to our ability to predict and optimize future outcomes. For example, knowing that you have a bad combination of perfectionism and attention deficit hyperactivity disorder can help prepare for the inevitable delays in writing a thesis, as a completely arbitrary and not personal example. Without knowledge of such influencing factors, this made-up individual could incorrectly interpret the task of writing a thesis as an insurmountable barrier, which could lead to disastrous long-term results. A more holistic and accurate understanding of the involved dynamics allows for greater prediction and control, thus increasing the chance of a meaningful outcome.

Knowledge of influencing factors becomes acutely important in the consideration of experimental procedures. In the same way that the definitely non-existent example individual could come to an improper conclusion, experimental results could be incorrectly interpreted when important influencing factors are overlooked. Experiments in the field of neuroscience often involve measuring minute changes in a complex neural environment. For electroencephalography (EEG), electrode sensors on the scalp capture changes in regional polarity at a microvolt scale. EEG measures can be sensitive to both external and internal influences, such as eye movements or blinks (Luck, 2014) and dopamine activity (Glazer et al., 2020; Hansch et al., 1982; Takeshita & Ogura, 1994; Umemoto et al., 2014), respectively. While the former can be controlled for with explicit instruction and data processing, the latter must be addressed less directly. Further prompting the need to consider internal alterations carefully, these changes can sometimes linger well past the inciting incident. As an example, a study by Devoto et al. (2005) showed that a single session of repeated Locus Coeruleus (LC) low-level burst stimulation (3Hz) led to significant increases in medial prefrontal cortex (mPFC) extracellular dopamine (DA) concentrations, which after repeated sessions would often remain above baseline levels even 20 minutes after stimulation ceased. Similar effects were found in a study eliciting high-level stimulation (100Hz) of ventral tegmental area neurons (Lohani et al., 2018). Importantly, extracellular DA levels have an inverse relationship with phasic (burst firing) DA responses such that higher levels of extracellular DA reduce phasic activity (Badgaiyan et al., 2015; Bilder et al., 2004; Breitenstein et al., 2006; Grace, 1991, 2000). Due to the import of phasic activity in event-related potential (ERP) studies and because they represent processes essential for learning and error-monitoring (Krigolson et al., 2009, 2014; Williams et al., 2020, 2021), consideration of this potential source of signal attenuation is warranted.

Two commonly studied ERPs in EEG research are the reward positivity and the P300. The reward positivity is associated with the anterior cingulate cortex (ACC) region of the mPFC and is thought to reflect a phasic DA signal indexing a prediction error in response to feedback (Proudfit, 2015). The P300 is associated with LC norepinephrine phasic activity and is commonly suggested to be involved in context updating and memory functions (Polich, 2007). Tasks that elicit these ERP components are designed to stimulate multiple phasic responses across the testing period. Component attenuation been documented with both ERPs, but the main explanations are learning in the case of the reward positivity (Krigolson et al., 2009; Williams et al., 2020) and task disengagement/mental fatigue to explain the P300 (Hopstaken et al., 2015; Umemoto et al., 2019). Although these explanations may be generally accurate, it is possible that some other important influencing factors are not being adequately investigated, such as task-related changes to neural environments.

The main goal of the current experiment was to test for possible order effects between classic reward positivity (bandit) and P300 (oddball) inducing tasks. First, test-retest reliability was measured for two reasons: To ensure ERPs met the expected reliability standards and to test reliability in a unique testing schedule. Participants in this study were tested five times sequentially on the same tasks with breaks from zero-15 minutes, whereas ERP reliability studies tend to measure across only two sessions and generally with delays of days to months (Ip et al., 2018; Kompatsiari et al., 2016; Morand-Beaulieu et al., 2022; Pollock & Schneider, 1992). Next, attenuation was assessed for each ERP component. This was done partly in order to determine whether the documented attenuation effects found in learning (Krigolson et al., 2009; Williams et al., 2020) and sustained-duration tasks (Hopstaken et al., 2015; Umemoto et al., 2019) would persist across multiple cognitive assessments with variable break periods, and partly to assess for differences in attenuation patterns between the reward positivity and the P300 under the current testing circumstances. Finally, order effects were analyzed to determine whether either task influenced the ERP measurements on the following task. Two analyses were run for order effects. First, an evaluation of effects across all five cognitive assessments for a general picture of whether task-order mattered. Next, the second and third assessments were grouped together since they were performed back-to-back without a break period. Each of the four possible task orders across the two assessments were analyzed to test for a specific hypothesis: That the oddball task would prompt attenuation in the subsequent bandit-task reward positivity measure while the bandit task would not influence subsequent P300 amplitude. This hypothesis is supported by the influence of LC firing on extracellular DA levels in mPFC areas (Devoto et al., 2005), by the influence of heightened extracellular DA on phasic responses (Badgaiyan et al., 2015; Breitenstein et al., 2006; Grace, 1991, 2000), and by an absence of evidence for a direct influence of reward positivity activity on P300 processes (exception: see Gompf et al., 2010). Specific interpretations of possible outcomes are outlined in methods (2.2.4)

2. 2. Methods

2. 2. 1. Participants and Materials

Twenty-six participants (15 female, 10 male, 1 non-binary; mean age 25.3 [95% CI: 21.7, 28.9]) were recruited from the University of Victoria and from online advertisements (usedvictoria.ca, craigslist.ca, timescolonist.com) in Victoria, BC. Recruitment from the University of Victoria used the university's online research participant pool and on-campus poster advertisements. To help increase the number of interested volunteers, all participants received monetary compensation. Participants provided informed consent in agreeance with the guidelines established by the University of Victoria Human Research Ethics Board (Ethics Protocol Number: 21-0179) and followed the ethical standards specified in the 1964 Declaration of Helsinki before commencing this experiment.

Surveys administered to participants included pre-screening for food allergy; Fatigue and Sleepiness Questionnaire; Personal History; Depression, Anxiety, and Stress Scale (DASS); Behavioural Inhibition System and Behavioural Activating System (BIS/BAS); and the Situational Motivation Scale (SIMS). Inclusion criteria required normal or corrected-to-normal vision, the ability to wear an EEG cap for an extended period, and no known food allergies. This last criterion was due to an aspect of the overall experiment in which some participants ingested a powdered supplement – a variable that was not included in the current analysis other than to ensure that no influence of the supplement confounded the current study (see Appendix A for results of analysis). The groups were then examined as one homogenous group for the remainder of the analysis.

2. 2. 2. Procedure

Arriving participants were first given privacy to read through the study consent form. Upon signing, participants received verbal information about the experimental procedures they would be running through, after which they completed the various surveys on a tablet while the EEG cap was fitted. Next, participants were seated in front of a 19-inch LCD computer monitor in a sound-dampened room to complete the cognitive assessments using a standard computer keyboard. The first cognitive assessment (CA_1) acted as a baseline, and timing began at zero following CA_1 completion. The time for the remaining cognitive assessments went as follows: CA_2 at 15 minutes, CA_3 at 30 minutes, CA_4 at 60 minutes, and CA_5 at 90 minutes. Participants were then debriefed, given the opportunity to ask questions, and given their compensation.

Cognitive assessments (originally written in MATLAB version R2016a using Psychophysics Toolbox extension version 3.0.12; Brainard, 1997) consisted of a visual oddball task and a two-armed bandit task presented in randomized order. During performance of the oddball task (figure 1), participants saw a series of blue (MATLAB RGB value = [0 0 255]) and green (MATLAB RGB value = [0 255 0]) colored circles that appeared for 800–1,200ms in the center of a dark gray screen (MATLAB RGB value = [108 108 108]). A black fixation cross was presented for 300 to 500ms (MATLAB RGB value = [0 0 0]) prior to the onset of the first circle and in between the presentation of subsequent circles. The green circles acted as the oddball, appearing less frequently (25%) than the more frequent blue circles (75%). The sequence of the coloured circles was random. Participants were instructed to press a key in response to the oddball circles within each block of trials and they completed three blocks of 40 trials during performance of the oddball task.

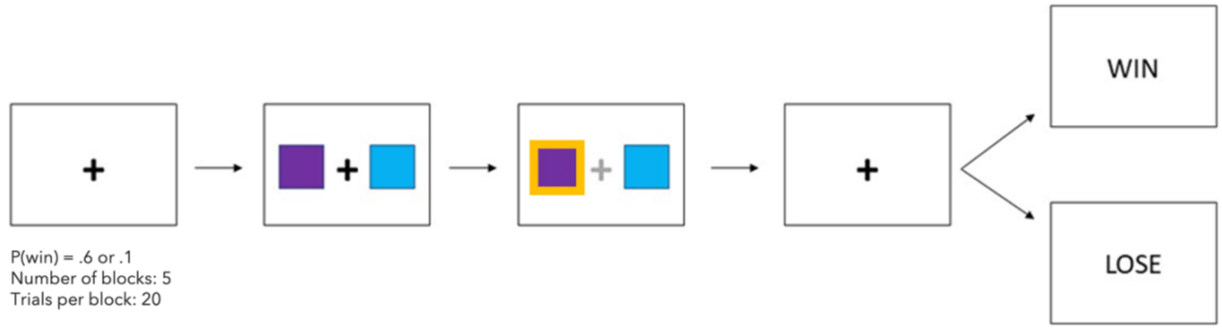
Figure 1

Oddball Task Example

The goal of the bandit task (figure 2) was for participants to accrue as many win trials as possible across five blocks of 20 trials. For each trial, participants viewed a black fixation cross (MATLAB RGB value = [0 0 0]) for 500ms that was followed by two coloured squares for 500 ms, followed by the fixation cross turning gray (go cue). Participants were asked on each trial to select one of the two squares within a 2,000ms time limit of the go cue. They were then presented with a black fixation cross for 300 to 500ms before simple feedback as to their performance ("WIN" for gain, "LOSE" for loss) was displayed for 1,000ms in black font. If the participants responded prior to the go cue, they received "TOO FAST" feedback instead. No response within the 2,000ms time limit was considered a loss. The participants were informed in the task instructions that one of the two squares would more often lead to gains (60% vs. 10%). These ratios allowed for the task to be learned from the provided feedback while also ensuring a suitable number of both win and loss trials. Each coloured square's position (left or right) was randomized in each trial and the colours used were randomized for each block.

Figure 2

Two-Armed Bandit Task Example



2. 2. 3. Data Acquisition and Processing

EEG data were recorded with a 64-electrode EEG system using the recording software Brain Vision Recorder (Version 1.21, Brain Products GmbH, Munich, Germany) with a 10-20 cap layout (ActiCAP, Brain Products GmbH, Munich, Germany). Electrodes were referenced to a common ground during recording with data sampled at 500Hz. EEG data were amplified using an AntiCHamp amplifier (ActiChamp, Revision 2, Brain Products GmbH, Munich, Germany) and an antialiasing low-pass filter of 245 Hz was applied. Stimuli and EEG markers were temporally synched using a DataPixx stimulus synchronization unit. All data were processed and analyzed using custom code in MATLAB (Version 9.6, Mathworks, Natick, USA)), using the EEGLAB open-source toolbox (Delorme & Makeig, 2004) and custom software developed in the Krigolson Laboratory, available at https://github.com/neuro-tools.

Data were processed twice – first, to identify noisy or damaged electrodes before processing the data for subsequent analysis. Channels identified as noisy were removed and then immediately re-interpolated using the spherical splines method. Data were re-referenced to average mastoid references (TP9, TP10) and filtered using a 0.1 to 30Hz passband (Butterworth, order 4) and 60Hz notch filter. Ocular artifacts were corrected using an independent component analysis (ICA) where components characteristic of blinks or saccades were automatically removed using EEGLAB and Krigolson Lab custom functions (*iclabel* & *doRemoveOcularICAComponents*). Afterwards, data were segmented (from -200 to 800ms relative to stimulus onset), baseline corrected (using a -200 to 0ms window) and run through artifact rejection with a difference threshold of 150 µV and a channel artifact tolerance of ten percent. The second pass was conducted only on those data in which electrodes were identified as noisy (artifacts > 10%) or damaged and consisted of the same procedures with the additional removal of the specified electrodes. Any data with more than four channels removed or any of the channels of interest (FCz, Pz, POz, Cz, Fp1, Fp2, TP9, TP10) removed were flagged for removal from the final analysis. Furthermore, in the interest of keeping full sets of data, only participants who had all five cognitive assessments pass these restrictions were kept for the final analysis leading to 23% being removed.

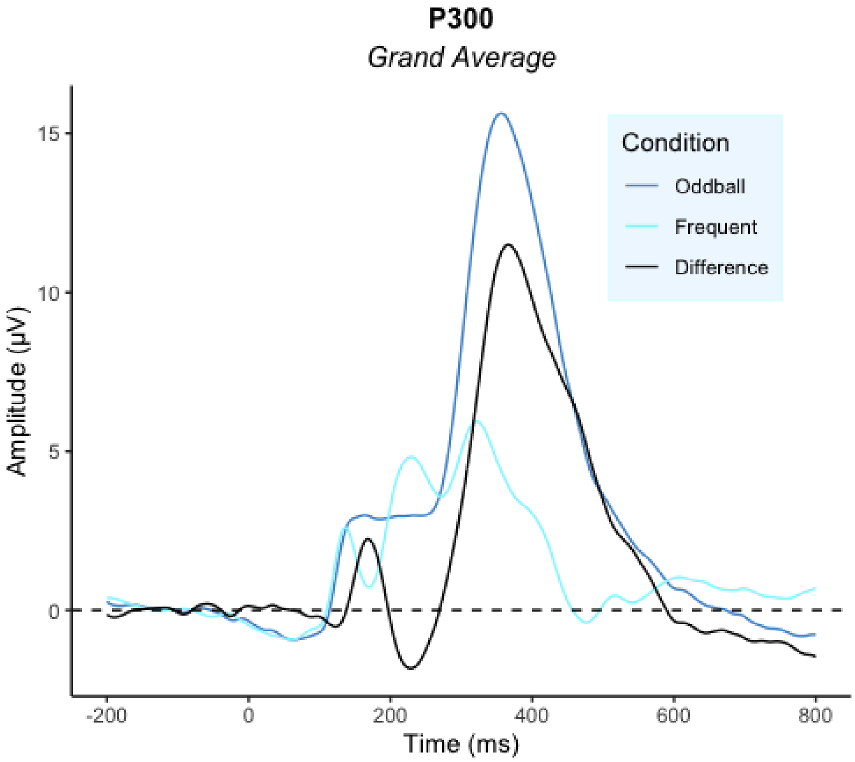
The processing of data resulted in ERP difference waveforms. For oddball ERPs, frequent and oddball condition trials were averaged at electrode Pz to create conditional waveforms for each participant. Grand average conditional waveforms were created as the average of participants' conditional waves, and a grand average P300 was the result of the grand average oddball wave minus the grand average frequent wave (Figure 3). Reward ERPs were derived in a similar manner at electrode FC2 as the location of greatest average component amplitude (Figure 4). As FCz is more commonly the site of maximal reward positivity, a parallel analysis was conducted using this electrode to ensure no major deviations existed between these electrodes. No differences were found in significance or reliability levels.

Gain and loss conditions were averaged across participants to create grand average conditional waveforms, and a grand average difference reward positivity was the result of the grand average gain condition minus the grand average loss condition. Note that although the P300 and the reward positivity can correctly refer to either conditional or difference waves, any mention of the P300 or reward positivity following this point will be in reference to the difference measure unless otherwise specified. Mean peak measures were used for the reward positivity and the P300 to attain final amplitudes, as per the recommendation of Williams et al. (2021) and Luck (2014). Window sizes of ±46ms for the reward positivity and ±54ms for the P300 were calculated as the inflection point in a series of averages derived from window sizes ranging from zero-100ms (see Williams et al., 2021). Grand average latencies were calculated as the latency at the peak of each grand average ERP. Individual latency measures were then calculated as the latency at the maximal peak of the individual difference wave within the predesignated window around each grand average latency.

Note: Due to an abnormally high percentage of negative values (24.62%), the mean peak values for the reward positivity were recalculated. The mean peak value was centered on a local peak latency, instead of at the initial site of the grand difference wave peak latency. The local peak latency was found at the max peak value within the window (±46ms) surrounding the grand difference wave peak latency (304ms). The window (±46ms) was then moved to center on the new peak, and the mean value was calculated at the new location. Cases in which there were no local peak, defined as the largest point within the window with decreasing values on both sides of the point (to avoid edge cases), were centered at the original latency of 304ms. This method was intended to close the gap between the current study and the expected amount of negative cases based on a large sample study that found negative reward positivity in 17.20 percent of cases (Williams et al., 2021). Following the new method, negative values were reduced by approximately three percent (to 21.54%). Thus, it was deemed beneficial towards a more representative reward positivity and used for this study. All reward positivity results reflect this second local-peak method of measuring the reward positivity.

Figure 3

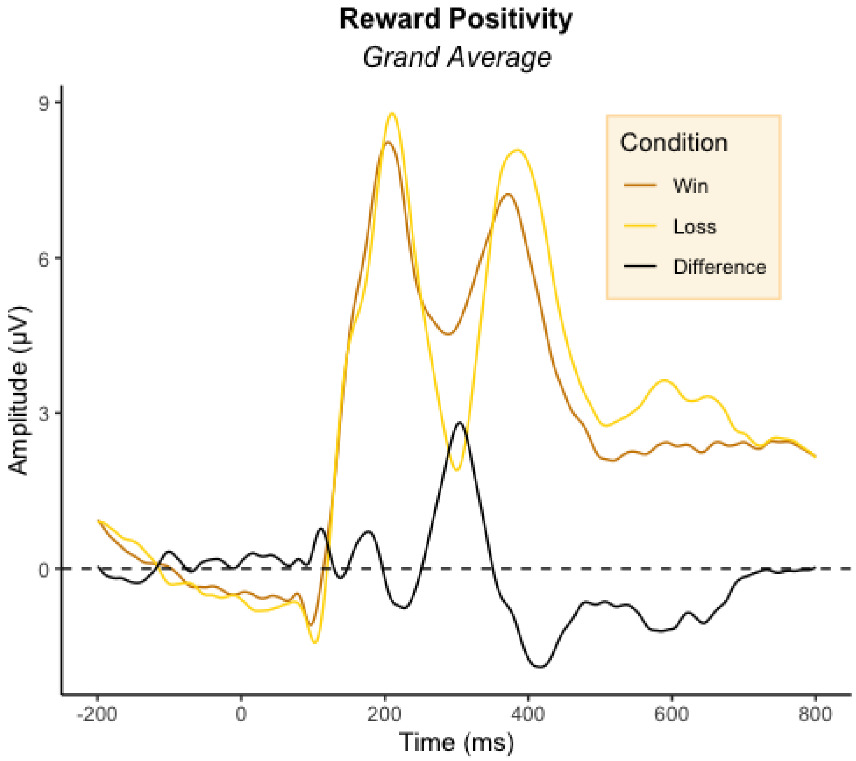
P300 Conditional and Difference ERPs



Note. P300 Difference ERP derived from Oddball minus Frequent conditions.

Figure 4

Reward Positivity Conditional and Difference ERPs



Note. Reward Positivity Difference ERP derived from Win minus Loss conditions.

2. 2. 4. Data Analysis and Figures

All statistics, Levene's tests, t-tests, linear mixed-effects models, correlations, and intra-class correlations (car package: Fox & Weisberg, 2019; Hmisc package: Harrell Jr. & Dupont, 2023; lmerTest package: Kuznetsova et al., 2017; lme4 package: Bates et al., 2015; nlme package: Pinheiro & Bates, 2023; psych package: Revelle, 2023; tidyverse package: Wickham et al., 2019), were computed using R (Version 4.2.1, The R Foundation, Vienna, Austria) and R Studio (Version 2022.7.2.576, RStudio Team, Boston, USA).

Figures 1 and 2 were created using Microsoft PowerPoint (Microsoft, 2023). All remaining figures, including supplemental figures, were created using R (Version 4.2.1, The R

Foundation, Vienna, Austria) and R Studio (Version 2022.7.2.576, RStudio Team, Boston, USA).

Win percentage and average reaction time were analysed for each participant. Win percentage was calculated as the number of 'win' trials divided by the total of 'win' and 'loss' trials. A one sample t-test was used to compare this to the average win percent expected from random choice (35%) to indicate whether the participants were able to learn the task. Average response time was then calculated for each CA for each task. The bandit task response time was defined as the average time between the 'go' cue and the response, whereas the oddball task used the average time between stimuli presentation and response. Average response times for each CA were analyzed using an ANOVA. Contingent on significance, planned comparisons using multiple Bonferroni corrected t-tests contrasted CA1 with CA2, CA2 with CA3, CA3 with CA4, and CA4 with CA5. Post-hoc tests were used to assess for any remaining difference between groups with multiple Bonferroni corrected t-tests.

Next, test-retest reliability was determined using intra-class correlations (ICC) for both components. A two-way random effects, absolute agreement, multiple raters [ICC(2, k)] form was determined to be the best fit for this test based on the guidelines presented by Koo and Li (2016). Standard values identified reliability as poor (< .50), moderate (.50 - .75), good (.75 - .90) and excellent (> .90), based on ICC scores (Koo & Li, 2016). Due to previous literature citing poor difference reward positivity ICCs and greatly improved ICCs for conditional reward positivity measures, conditional (win, loss) reward positivity ICCs were also calculated (Levinson et al., 2017; Szenczy et al., 2021). To keep things equal, conditional (oddball, frequent) ICCs were also calculated for the P300.

The attenuation of components across CAs was tested using linear mixed-effects models with fixed slope and random intercept parameters for each component of interest. The random intercept effect was set for each participant and CA number was set for fixed slope effects. The mixed-effects model was used to specifically measure linear changes across CAs without regard to the variability of component size between participants.

To analyze order effects, reward positivity and P300 measures were separated into groups of those derived from tasks that were first in the CA, and those derived from tasks that were second in the CA. Recall that task order was random, resulting in variable task orders for each participant across CAs. This separation resulted in four groups: reward positivities and P300s derived from bandit tasks followed by oddball tasks, and reward positivities and P300s derived from oddball tasks followed by bandit tasks. Order effects were then tested using two different methods. The first analysis took the average amplitudes of each of the four groups and used two-sample t-tests to compare the two reward positivity averages, and to compare the two P300 averages. This initial order effects analysis addressed overall effects of task order on component amplitudes. To investigate specific order-effects relationships, the second analysis focused on the second and third CAs as they were performed with minimal breaks in between. The resultant four possible task performance arrangements allow for a more sensitive order effects analysis, with associated predicted outcomes (Table 1). These outcomes directly test the main hypothesis - that the reward positivity will be attenuated when derived from bandit tasks that are performed after the oddball task. For this hypothesis to hold merit, we would also expect to see no difference in P300 measures in any order.

Table 1

Task Orders and Hypothesized Outcomes

BABA	1^{st} reward positivity > 2^{nd} reward positivity
ABAB	1^{st} reward positivity = 2^{nd} reward positivity
BAAB	1^{st} reward positivity > 2^{nd} reward positivity
ABBA	1^{st} reward positivity < 2^{nd} reward positivity

Note: 'B' represents the Bandit task, 'A' represents the Oddball task

2. 3. Results

2. 3. 1. Behavioural Results

Bandit Task Performance: Participants achieved 'win' trials an average of 52.1% [95%CI: 51.0, 53.2]. A one sample t-test comparing this to chance (35%) showed a significant difference, $t_{(129)} = 29.92$, $p < .001$, indicating that participants were successful in learning the task.

Bandit Task Response Time: A repeated measures ANOVA was used to assess differences in response time between CAs. First, outliers were identified. Since the outliers followed the trend of the rest of the data set, they were not expected to impact the outcome. Even so, the ANOVA was run with and without the outliers to check for major differences. A visual inspection of a q-q plot suggested that the assumption of normality was likely not met for this data, and Mauchly's test for sphericity confirmed this, $W = 0.12$, $p < .001$. Thus, Greenhouse-Geisser corrected tests were used ($\epsilon = .47$) and an effect of CA on response time was found, $F_{(1.88,\ 46.90)} = 11.65$, $p < .001$, $\eta_g^2 = 0.04$. An examination of the same analysis on the dataset with outliers removed showed minimal difference ($F_{(2.05,\ 49.19)} = 10.33$, $p < .001$, $\eta_g^2 = 0.07$), so they were retained for the remaining analyses.

Planned comparisons of average response time in milliseconds were assessed for CA_1 ($M = 188$, $SD = 86.50$) to CA_2 ($M = 159$, $SD = 72.10$), CA_2 to CA_3 ($M = 152$, $SD = 65.60$), CA_3 to CA_4 ($M = 148$, $SD = 64.90$), and CA_4 to CA_5 ($M = 147$, $SD = 72.30$). These comparisons revealed a significant difference between CA_1 and CA_2, $M_D = 29$ms, $t_{(25)} = 4.30$, $p_{adj} < .001$, but no other significant effects, $M_D = 7$ms, $t_{(25)} = 1.48$, $p_{adj} = .60$; $M_D = 4$ms, $t_{(25)} = 0.93$, $p_{adj} = 1.00$; $M_D = 1$ms, $t_{(25)} = 0.38$, $p_{adj} = 1.00$.

Post-hoc pairwise Bonferroni corrected paired sample t-tests revealed significant differences between CA_1 and CA_3, $M_D = 36$ms, $t_{(25)} = 4.37$, $p_{adj} = .002$, CA_1 and CA_4, $M_D = 40$ms, $t_{(25)} = 4.26$, $p_{adj} = .003$, and CA_1 and CA_5, $M_D = 41$ms, $t_{(25)} = 3.78$, $p_{adj} = .009$, but no other differences.

2. 3. 2. Test-Retest Reliability

Test-retest reliability was assessed using ICC(2, k) for the amplitude of the P300 and reward positivity ERP components. As a reminder, standard values for ICCs are < .50, .50 - .75, .75 - .90, and > .90, representing poor, moderate, good, and excellent reliability, respectively (Koo & Li, 2016).

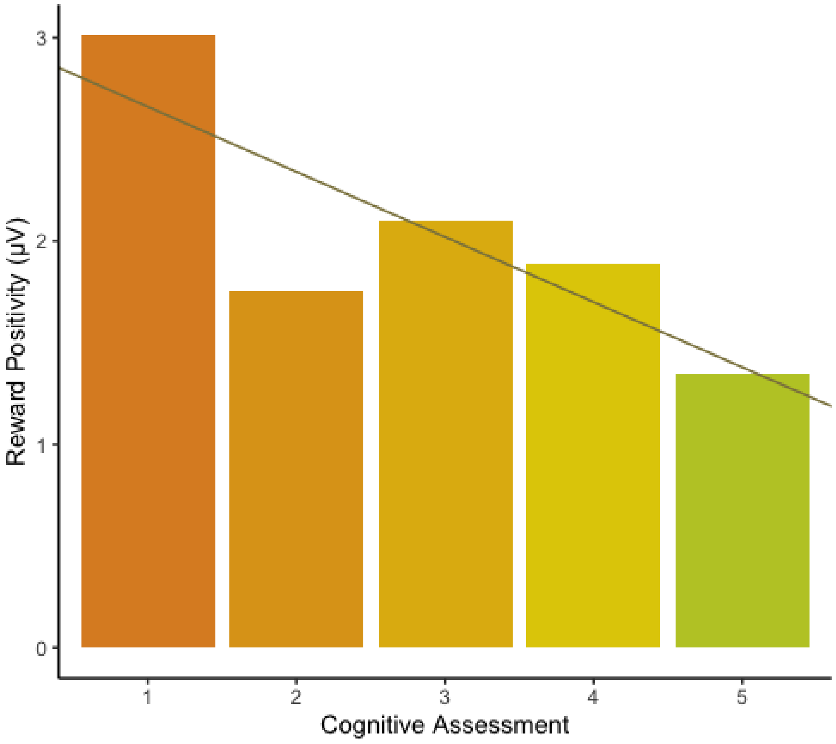
P300 reliability was excellent, ICC = .91, $p < .001$, which was reflected in the conditional analysis for both oddball, ICC = .94, $p < .001$, and frequent, ICC = .92, $p < .001$, conditions. Reliability for the reward positivity was on the low end of moderate, ICC = .52, $p = .005$. Conditional reward positivity reliability was excellent for the win condition, ICC = .91, $p < .001$, as well as the loss condition, ICC = .94, $p < .001$.

2. 3. 3. Attenuation

The attenuation of components across CAs were tested using linear mixed-effects models. Fixed effects were set as CA number (1-5) and random effects for intercept were set for individual participants. Likelihood ratio tests were performed on each model to support parameter inclusion. For the reward positivity model (Figure 5), CA did not affect component amplitude ($\chi^2_{(1)} = 3.69$, $p = .055$), though it was trending in a negative slope estimated at -0.32 µV ± 0.17, [95%CI: -0.65, 0.01], (*random effects:* participant number, *SD* = 1.27, residual = 2.68). The P300 (Figure 6) model displayed a CA influence on component amplitude ($\chi^2_{(1)} = 18.50$, $p < .001$), though the relationship showed a positive slope of 0.65 µV ± 0.15, [95%CI: 0.36, 0.94], (*random effects*: participant number, *SD* = 3.67, residual = 2.34).

Figure 5

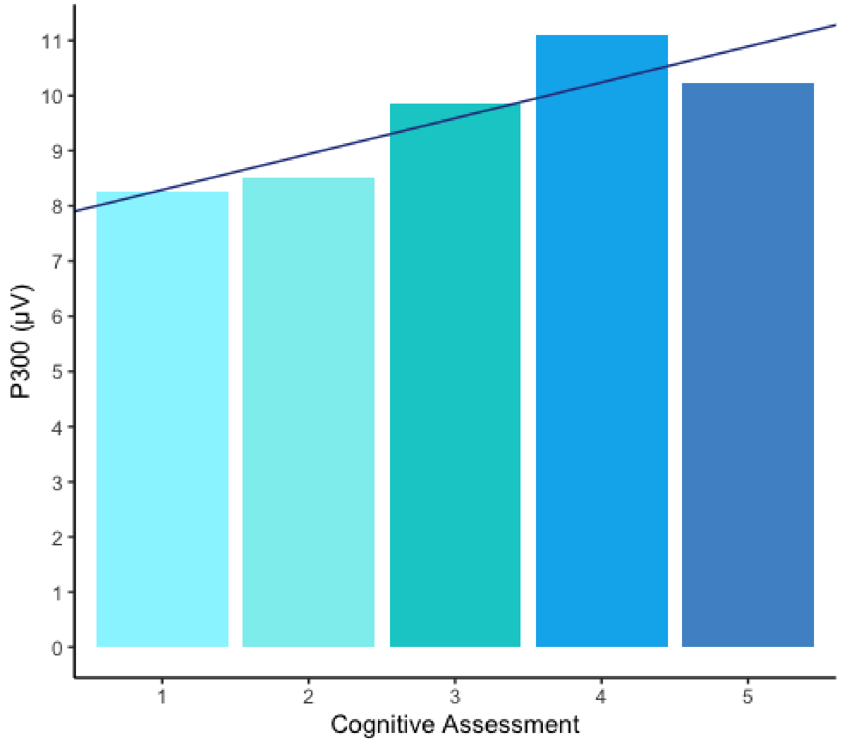
Reward Positivity Average Amplitudes Across Cognitive Assessments with Slope



Note. Slope line is derived from the mixed effects model. Not significant.

Figure 6

P300 Average Amplitudes Across Cognitive Assessments with Slope



Note. Slope line is derived from the mixed effects model.

2. 3. 4. Order Effects

Levene’s tests for the reward positivity, $F_{(1,128)}$, p = .53, and the P300, $F_{(1, 128)}$ = 1.32, p = .25, between first and second testing orders met the assumption of homogeneity of variance. Order effects were first tested using two sample t-tests for overall measures of component amplitude when presented first versus second in each CA. Neither the reward positivity, M_D = -0.27 µV, $t_{(128)}$ = -0.51, p = .61, nor the P300, M_D = -1.05 µV, $t_{(128)}$ = -1.37, p = .17, showed a difference between groups.

The second test for order effects combined the second and third CAs and compared the first and second presentation reward positivity amplitudes and P300 amplitudes using two sample t-tests. The combination led to the following possible task orders: BABA, ABAB, BAAB, ABBA (A = oddball, B = bandit). A summary of the observed reward positivity results along with the hypothesized results can be seen below in Table 2. In terms of the reward positivity, BABA: $M_D = -0.68$ µV, $t_{(3)} = -0.31$, $p = .77$, ABAB: $M_D = 0.82$ µV, $t_{(9)} = 0.73$, $p = .48$, BAAB: $M_D = -1.16$ µV, $t_{(8)} = -0.54$, $p = .60$, and ABBA: $M_D = -1.4$ µV, $t_{(2)} = -0.99$, $p = .43$, all revealed no order effects. This was much the same for the P300, BABA: $M_D = -3.32$ µV, $t_{(3)} = -1.08$, $p = .36$, ABAB: $M_D = -1.36$ µV, $t_{(9)} = -1.79$, $p = .11$, BAAB: $M_D = 0.58$ µV, $t_{(8)} = 0.53$, $p = .61$, and ABBA: $M_D = -4.35$ µV, $t_{(2)} = -1.41$, $p = .29$.

Table 2

Observed Order Effects and Hypothesized Order Effects for the Reward Positivity

	BABA	**ABAB**	**BAAB**	**ABBA**
OBSERVED	$B_1 = B_2$	$B_1 = B_2$	$B_1 = B_2$	$B_1 = B_2$
HYPOTHESIZED	$B_1 > B_2$	$B_1 = B_2$	$B_1 > B_2$	$B_1 < B_2$

Note: B = Reward positivity derived from the Bandit task, A = Oddball task.

2. 4. Discussion

The current study endeavored to evaluate ERP component activity across multiple assessments consisting of two tasks. Specifically, the bandit task was assessed for performance and response timing, while the reward positivity and the P300 were analyzed for reliability, attenuation, and order effects. This experiment required participants to perform the same cognitive assessment five times consecutively with minimal breaks. Multiple analyses were performed, in part, due to the current study's unique design, which created the opportunity to examine ERP phenomena under a new and informative framework.

Participants demonstrated understanding of the bandit task and a continued effort throughout the experiment. This was exhibited by 'win' trials well above chance, and by an improved response time for all CAs compared to the first. Reliability assessments revealed excellent P300 reliability and a moderate reliability for the difference reward positivity ERP. Conditional reward positivity waves both achieved excellent reliability, far outperforming the difference wave assessment. All reliability scores all fell within hypothesized values, except for the difference wave reliability which was better than predicted. Reward positivity reliability measures overall still followed expected patterns of low difference score and much larger conditional scores. Hypothesized attenuation of both ERPs were disaffirmed with a failure to show linear change for the reward positivity, and an actual increase in P300 amplitude across CAs. The hypothesized task-related order effects were similarly unsupported, as order showed no influence either ERP's amplitude. These results suggest that across five consecutive testing sessions, 1) ERP attenuation does not occur, 2) P300 amplitudes tend to increase, and 3) there are no order effects influencing the components in either task.

The indication that participants in the bandit task were able to identify the square with a higher probability of ‘win’ feedback is a necessary element of this analysis. A failure to show this would affect the interpretive value of other analyses involving the bandit task. For example, a win percentage closer to chance would suggest that participants did not learn the task or were not trying to accomplish the task. In this situation, normal attenuation of the reward positivity would be unlikely to occur, as suggested by Krigolson et al, (2009) and Williams et al. (2020). Faster response times for all CAs following the first in the bandit task suggests practice effects for the initial decrease and sustained effort for the continued decrease.

All reliability measures were found either in the higher levels of expected values, or above expected value in one case. The short delays between assessments may initially be considered as a driving influence of these ICC scores. Discounting this notion, good to excellent P300 reliability has been found with delays of four months to three years, suggesting that delay does not significantly affect reliability (Brunner et al., 2013; Huffmeijer et al., 2014; Sandman & Patterson, 2000). Similarly, increased reliability due to multiple measures is unlikely. A four assessment reliability study by Ip et al. (2018) showed similar P300 ICC scores for each between-assessment comparison and for overall reliability. Trial count does appear to have a strong influence on reliability. Numerous studies have reported ICC scores for various portions of total trial counts, revealing increasing trends in reliability at increasing trial counts (Huffmeijer et al., 2014; Ip et al., 2018; Levinson et al., 2017). This suggests that the current study used appropriate trial counts in the assessments of reliability.

The P300 reliability was excellent, indicating that participants had a similar pattern of amplitudes across CAs. Not unexpectedly, conditional P300 reliability was similarly excellent, suggesting that the difference P300 accurately represents overall reliability. The difference reward positivity reliability scored on the low end of moderate, signifying increased variability across CAs but at an acceptable level of coherence. Conditional reward positivity waves consisting of neural responses to win or loss feedback both had excellent reliability, mimicking the trend established by Levinson et al. (2017) and Szenczy et al. (2021). Numerous studies cite unequal variance between conditional waves as a likely candidate for this effect (Bress et al., 2015; Levinson et al., 2017; Szenczy et al., 2021). Evidently, reliability can be high for the reward positivity conditional waves even though it is obscured for the difference wave. Due to the clear trend showing reduced difference reward positivity reliability scores and the possibility of obscuring actual reliability, it is recommended that reliability be established using conditional reward positivity waves instead of the difference wave.

The anticipated attenuation effects were not found in the current study. Indeed, the P300 showed opposite-to-expected effects with an increasing amplitude trend across CAs. This finding contrasts those of Umemoto et al. (2019) and Hopstaken et al. (2015) who both found a general decrease in P300 amplitude across long duration cognitively fatiguing tasks. They suggested that fatigue and/or degraded effort for outcome trade-off evaluation led to task disengagement and consequential attenuated P300 amplitudes. This explanation might point to an important difference between these and the current study – breaks. Firstly, the inclusion of breaks between CAs help to alleviate some cognitive fatigue. Secondly, cognitive control is more costly in a fatigued state, so decreased cognitive fatigue would necessarily lead to a more favourable effort to outcome evaluation (Kok, 2022). This might explain the lack of attenuation, but not the increase in amplitude size. A possible explanation is elucidated in a study by Carrillo-de-la-Peña and Cadaveira (2000) in which increased motivation was revealed to increase the P300. If early cognitive assessments only required low levels of motivation but maintained performance in later sessions required greater motivation, this could appear as an increasing P300 amplitude.

Another possible cause of the amplitude increase could involve mechanisms of long-term potentiation (LTP). EEG research by Clapp et al. (2005) inducing auditory tetanus revealed an increase in amplitude in an early perceptual ERP. This process mirrored LTP mechanisms supporting a role for EEG in measuring these plastic neural changes. Although this connection remains speculative due to the non-invasive nature of EEG recording, the authors suggest that the overlap between their findings and cellular studies are promising in terms of interpreting this process as LTP. In the current study, participants completed the oddball task five times within a two-hour period. Though there was no intention to induce LTP, the increases in P300 amplitude suggests that some kind of facilitation process took place. Across the P300 literature, differences in P300 size can be explained inter-individually. Influencing factors include age (Chen et al., 2023) and depression (Santopetro et al., 2021, 2022), for example. As far as the current author can determine, intra-individual increases in P300 activity within a task is a rare occurrence.

The lack of attenuation for the reward positivity appears to be more straightforward of an explanation. The word ‘appears’ is key here, as a bar graph of the results shows the greatest change in amplitude between CA_1 and CA_2, and only small fluctuations following. This suggests a floor effect following the first CA, meaning that the reward positivity was maximally attenuated within the win/loss probabilities of this task from CA_2 to CA_5. Supporting this are the many reports of reward positivity attenuation with learning or fatigue, establishing reward positivity attenuation as a reliable phenomenon that would be expected to occur throughout a bandit task (Krigolson et al., 2009; Umemoto et al., 2019; Williams et al., 2020). Further support comes from the trend of the linear mixed effects model that was near significance with an upper

95 percent confidence interval that was just 0.01 over zero. Even without sustained amplitude reduction in the final four CAs, there was an insinuated attenuation effect. If a floor effect is the cause of the null result here, then a slower learning task would better capture attenuation across consecutive assessments. For example, Williams et al. (2020) found that participants in a language-learning task showed increasing attenuation in reward positivity amplitudes even on the fifth correct response of a particular word. Using a similar task but with adjustments to the similarity of the symbols and the amount of symbols to match could maintain the learnability of the task while increasing the amount of time it took to learn, allowing for testing across multiple sessions with increased learning throughout.

Another interpretation of the reward positivity attenuation results is that there was more capacity for attenuation, but it was not captured in this data. Though adjusted measures lowered the percentage of negative reward positivity amplitudes, there remained an above average ratio compared to those found in a large sample study using the same task (Williams et al., 2021). One possibility is that the negative values had a proportionally larger impact on middle CA sessions, which could mask the underlying attenuation effect. Although this may be the case, the interpretation of this effect depends on what negative reward positivity values indicate. If they are a natural occurrence, then the first interpretation stands. On the other hand, if negative values indicate some form of error, then they could be obscuring real effects. Due to the sheer number of people exhibiting this effect in the aforementioned large-sample study by Williams et al. (2021), more probable is that there are a subset of people who do indeed have a larger response to negative than positive feedback. Ultimately, the driving force of this effect is still unknown. It could be anything from alternate learning tactics to heightened negative feedback sensitivity, or even distraction-caused increased latency that pushes the reward positivity out of the detection window.

Two analyses for order effects both showed null results. The first analysis compared averaged reward positivities from first- and second-order bandit tasks, as well as the equivalent P300 measures. The second analysis compared reward positivity and P300 amplitudes using the four arrangements of task order available from CA_2 and CA_3 combined. These results indicate that order effects do not influence either component measure. Firstly, this suggests that fatigue or boredom effects have no influence on these component's amplitudes across an approximately 15-minute cognitive assessment. Secondly, these results support the use of both P300 and reward positivity eliciting tasks in EEG studies - without the need to account for the influence of one ERP's activity on the other. Research by Devoto et al. (2005) has shown that LC-NE activity can influence extracellular DA levels, while other's research establishes that increases in extracellular DA can downregulate phasic DA activity (Badgaiyan et al., 2015; Breitenstein et al., 2006; Grace, 1991, 2000). In the study showing the influence of LC firing on extracellular DA, Devoto et al. (2005) delivered stimulation in bursts four times per second at 700 µV for 20 minutes. These laboratory conditions are unlikely to reflect natural rates of neural activity, and greatly outdoes the oddball task in terms of rate and overall length of phasic activity. Highly probable is that conditions in the current experiment did not activate LC-NE phasic firing at a rate or magnitude necessary to alter midbrain DA activity in any meaningful way. Another possible factor that could hide order effects is the same one that could have reduced attenuation effects: Floor effects of reward positivity attenuation. If the reward positivity were maximally attenuated early on in each bandit task, that could effectively eliminate or obviate further reduction.

A limitation with the second order effects analysis resulted from both uneven numbers of order combinations, and less-than-ideal counts for two of the orders. The randomized ordering of bandit and oddball tasks would likely yield near equivalent numbers at high enough measures. In the current study, there were insufficient numbers for the orders ABBA (n = 3) and BABA (n = 4), as well as less than ideal numbers for the remaining two orders [ABAB (n = 10) and BAAB (n = 9)] to properly analyze the statistical differences. Even so, the lack of any meaningful differences found in the two orders with more acceptable measures suggests that there is no effect. To be sure, future studies would do better to pseudo-randomize task order to ensure near-equivalent counts for each of the orders. To address possible floor effects, a slower learning task is also recommended.

A major limitation in this study also involves the circumstances of the testing. As mentioned, these participants were tested for a study unrelated to the current project. Although this is a rich dataset with a unique testing schedule, it was not optimised for the analyses performed. Examples of this include the unequal breaks between testing periods and the randomized task orders that supplied uneven combinations of orders. Although there is a non-zero chance that this could have influenced the results in unexpected ways, the analyses took everything possible into consideration and so it is not thought that the elements that were not intentional were detrimental in any way to the current project.

2. 5. Conclusions

Using an oddball task and a bandit task, this study measured reliability, attenuation, and order effects for the P300 and reward positivity ERPs. Reliability was found to be excellent for the difference P300, and for both conditional P300 measures. The reward positivity difference wave had a moderate reliability, while both conditional reliability measures rocketed up to excellent. Based on this and previous findings, it is recommended that reward positivity reliability measures focus on conditional waves, as the difference measure masks the reliability effects (see Appendix B). Attenuation was not seen in either ERP across CAs. Fascinatingly, the P300 tended to increase across CAs. The mechanism behind this activity is not known but were speculated to be related to either motivational increase or LTP actions. Order effects were predicted to occur due to an interplay of neurotransmitters involved in P300 and reward positivity phasic activity. This was not found in the current study, suggesting that EEG studies measuring these two ERPs do not have to account for any interference effects. It was conjectured that phasic activity in these tasks is elicited too infrequently to meaningfully affect neural regions involved in these tasks.

References

Aldridge, V. K., Dovey, T. M., & Wade, A. (2017). Assessing test-retest reliability of psychological measures: Persistent methodological problems. *European Psychologist*, *22*(4), 207–218. https://doi.org/10.1027/1016-9040/a000298

APA Dictionary of Psychology. (n.d.). Retrieved February 13, 2023, from https://dictionary.apa.org/

Aston-Jones, G., & Bloom, F. E. (1981). Activity of norepinephrine-containing locus coeruleus neurons in behaving rats anticipates fluctuations in the sleep-waking cycle. *Journal of Neuroscience*, *1*(8), 876–886. https://doi.org/10.1523/JNEUROSCI.01-08-00876.1981

Aston-Jones, G., Rajkowski, J., & Cohen, J. (2000). Locus coeruleus and regulation of behavioral flexibility and attention. *Progress in Brain Research*, *126*, 165–182. https://doi.org/10.1016/S0079-6123(00)26013-5

Auerbach, R. P., Bondy, E., Stanton, C. H., Webb, C. A., Shankman, S. A., & Pizzagalli, D. A. (2016). Self-referential processing in adolescents: Stability of behavioral and ERP markers. *Psychophysiology*, *53*(9), 1398–1406. https://doi.org/10.1111/psyp.12686

Awan, F., Saleem, O., & Kiran, A. (2019) Recent trends and advances in solving the inverse problem for EEG source localization. *Inverse Problems in Science and Engineering*, *27*(11), 1521-1536. 10.1080/17415977.2018.1490279

Badgaiyan, R. D., Sinha, S., Sajjad, M., & Wack, D. S. (2015). Attenuated Tonic and Enhanced Phasic Release of Dopamine in Attention Deficit Hyperactivity Disorder. *PLOS ONE*, *10*(9), e0137326. https://doi.org/10.1371/journal.pone.0137326

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). "Fitting Linear Mixed-Effects Models Using lme4." *Journal of Statistical Software*, *67*(1), 1–48. doi:10.18637/jss.v067.i01.

Baxter, C., Mc Naughton, L. R., Sparks, A., Norton, L., & Bentley, D. (2017). Impact of stretching on the performance and injury risk of long-distance runners. *Research in Sports Medicine, 25*(1), 78–90. https://doi.org/10.1080/15438627.2016.1258640

Beldzik, E., Ullsperger, M., Domagalik, A., & Marek, T. (2022). Conflict- and error-related theta activities are coupled to BOLD signals in different brain regions. *NeuroImage, 256*, 119264. https://doi.org/10.1016/j.neuroimage.2022.119264

Berke, J. D. (2018). What does dopamine mean? *Nature Neuroscience*, *21*(6), 787–793. https://doi.org/10.1038/s41593-018-0152-y

Berridge, K. C. (2004). Motivation concepts in behavioral neuroscience. *Physiology & Behavior, 81*(2), 179–209. https://doi.org/10.1016/j.physbeh.2004.02.004

Berridge, K. C., & Robinson, T. E. (1998). What is the role of dopamine in reward: Hedonic impact, reward learning, or incentive salience? *Brain Research Reviews*, *28*(3), 309–369. https://doi.org/10.1016/S0165-0173(98)00019-8

Bilder, R. M., Volavka, J., Lachman, H. M., & Grace, A. A. (2004). The catechol-o-methyltransferase polymorphism: Relations to the tonic–phasic dopamine hypothesis and neuropsychiatric phenotypes. *Neuropsychopharmacology, 29*(11), 1943-1961. https://doi.org/10.1038/sj.npp.1300542

Bouret, S., & Sara, S. J. (2005). Network reset: A simplified overarching theory of locus coeruleus noradrenaline function. *Trends in Neurosciences*, *28*(11), 574–582. https://doi.org/10.1016/j.tins.2005.09.002

Breitenstein, C., Korsukewitz, C., Flöel, A., Kretzschmar, T., Diederich, K., & Knecht, S. (2006). Tonic dopaminergic stimulation impairs associative learning in healthy subjects. *Neuropsychopharmacology, 31*(11), 2552-2564. https://doi.org/10.1038/sj.npp.1301167

Bress, J. N., Meyer, A., & Proudfit, G. H. (2015). The stability of the feedback negativity and its relationship with depression during childhood and adolescence. *Development and Psychopathology*, *27*(4pt1), 1285–1294. https://doi.org/10.1017/S0954579414001400

Bromberg-Martin, E. S., & Hikosaka, O. (2011). Lateral habenula neurons signal errors in the prediction of reward information. *Nature Neuroscience, 14*(9), 1209-1216. https://doi.org/10.1038/nn.2902

Brunner, J. F., Hansen, T. I., Olsen, A., Skandsen, T., Håberg, A., & Kropotov, J. (2013). Long-term test-retest reliability of the P3 NoGo wave and two independent components decomposed from the P3 NoGo wave in a visual Go/NoGo task. *International Journal of Psychophysiology*, *89*(1), 106–114. https://doi.org/10.1016/j.ijpsycho.2013.06.005

Budygin, E. A., Bass, C. E., Grinevich, V. P., Deal, A. L., Bonin, K. D., & Weiner, J. L. (2020). Opposite Consequences of Tonic and Phasic Increases in Accumbal Dopamine on Alcohol-Seeking Behavior. *IScience*, *23*(3), 100877. https://doi.org/10.1016/j.isci.2020.100877

Carrillo-de-la-Peña, M. T., & Cadaveira, F. (2000). The effect of motivational instructions on P300 amplitude. *Neurophysiologie Clinique/Clinical Neurophysiology*, *30*(4), 232–239. https://doi.org/10.1016/S0987-7053(00)00220-3

Carter, R. M., & Huettel, S. A. (2013). A nexus model of the temporal–parietal junction. *Trends in Cognitive Sciences*, *17*(7), 328–336. https://doi.org/10.1016/j.tics.2013.05.007

Cassidy, S. M., Robertson, I. H., & O'Connell, R. G. (2012). Retest reliability of event-related potentials: Evidence from a variety of paradigms. *Psychophysiology*, *49*(5), 659–664. https://doi.org/10.1111/j.1469-8986.2011.01349.x

Chen, P., Hung, H.-Y., & Goh, J. O. S. (2023). Age-related differences in ERP correlates of value-based decision making. *Neurobiology of Aging*, *123*, 10–22. https://doi.org/10.1016/j.neurobiolaging.2022.11.008

Clapp, W. C., Kirk, I. J., Hamm, J. P., Shepherd, D., & Teyler, T. J. (2005). Induction of LTP in the human auditory cortex by sensory stimulation. *European Journal of Neuroscience, 22*(5), 1135–1140. https://doi.org/10.1111/j.1460-9568.2005.04293.x

Cohen, M. X. (2017). Where does EEG come from and what does it mean? *Trends in Neurosciences*, *40*(4), 208–218. https://doi.org/10.1016/j.tins.2017.02.004

Corbetta, M., Kincade, J. M., Ollinger, J. M., McAvoy, M. P., & Shulman, G. L. (2000). Voluntary orienting is dissociated from target detection in human posterior parietal cortex. *Nature Neuroscience*, *3*(3), 292-297. https://doi.org/10.1038/73009

Corona, A., Choe, J., Muñoz-Castañeda, R., Osten, P., & Shea, S. D. (2022). A circuit from the locus coeruleus to the anterior cingulate cortex modulates offspring interactions in mice. *bioRxiv*, n.p. https://doi.org/10.1101/2022.12.04.519053

Cragg, S. J. (2006). Meaningful silences: How dopamine listens to the ACh pause. *Trends in Neurosciences*, *29*(3), 125–131. https://doi.org/10.1016/j.tins.2006.01.003

Danna, C., Shepard, P., & Elmer, G. (2013). The habenula governs the attribution of incentive salience to reward predictive cues. *Frontiers in Human Neuroscience*, *7,* n.p. https://www.frontiersin.org/articles/10.3389/fnhum.2013.00781

Devos, H., Burns, J. M., Liao, K., Ahmadnezhad, P., Mahnken, J. D., Brooks, W. M., & Gustafson, K. (2020). Reliability of P3 event-related potential during working memory across the spectrum of cognitive aging. *Frontiers in Aging Neuroscience*, *12,* n.p. https://doi.org/10.3389/fnagi.2020.566391

Devoto, P., Flore, G., Saba, P., Fà, M., & Gessa, G. L. (2005). Co-release of noradrenaline and dopamine in the cerebral cortex elicited by single train and repeated train stimulation of the locus coeruleus. *BMC Neuroscience*, *6*(1), 31. https://doi.org/10.1186/1471-2202-6-31

Di Chiara, G., & Tanda, G. (1997). Blunting of reactivity of dopamine transmission to palatable food: A biochemical marker of anhedonia in the CMS model? *Psychopharmacology*, *134*, 351–353. https://doi.org/10.1007/s002130050465

Dillier, N., Laszlo, J., Müller, B., Koella, W. P., & Olpe, H.-R. (1978). Activation of an inhibitory noradrenergic pathway projecting from the locus coeruleus to the cingulate cortex of the rat. *Brain Research, 154*(1), 61–68. https://doi.org/10.1016/0006-8993(78)91051-X

Doñamayor, N., Marco-Pallarés, J., Heldmann, M., Schoenfeld, M. A., & Münte, T. F. (2011). Temporal dynamics of reward processing revealed by magnetoencephalography. *Human Brain Mapping*, *32*(12), 2228–2240. https://doi.org/10.1002/hbm.21184

Donchin, E. (1981). Surprise!… Surprise? *Psychophysiology*, *8*(5), 493-513. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1469-8986.1981.tb01815.x

Dopamine | Psychology Today Canada. (2023). https://www.psychologytoday.com/ca/basics/dopamine

Floresco, S. B., West, A. R., Ash, B., Moore, H., & Grace, A. A. (2003). Afferent modulation of dopamine neuron firing differentially regulates tonic and phasic dopamine transmission. *Nature Neuroscience*, *6*(9), 968-973. https://doi.org/10.1038/nn1103

Foote, S. L., Freedman, R., & Oliver, A. P. (1975). Effects of putative neurotransmitters on neuronal activity in monkey auditory cortex. *Brain Research*, *86*(2), 229–242. https://doi.org/10.1016/0006-8993(75)90699-X

Foti, D., Weinberg, A., Dien, J., & Hajcak, G. (2011). Event-related potential activity in the basal ganglia differentiates rewards from nonrewards: Temporospatial principal components analysis and source localization of the feedback negativity. *Human Brain Mapping*, *32*(12), 2207–2216. https://doi.org/10.1002/hbm.21182

Fox J, Weisberg S (2019). An R Companion to Applied Regression, Third edition. *Sage*, Thousand Oaks CA. https://socialsciences.mcmaster.ca/jfox/Books/Companion/.

Freedman, R., Hoffer, B. J., Woodward, D. J., & Puro, D. (1977). Interaction of norepinephrine with cerebellar activity evoked by mossy and climbing fibers. *Experimental Neurology*, *55*(1), 269–288. https://doi.org/10.1016/0014-4886(77)90175-3

Garrison, J., Erdeniz, B., & Done, J. (2013). Prediction error in reinforcement learning: A meta-analysis of neuroimaging studies. *Neuroscience & Biobehavioral Reviews*, *37*(7), 1297–1310. https://doi.org/10.1016/j.neubiorev.2013.03.023

Gaspar, C. M., Rousselet, G. A., & Pernet, C. R. (2011). Reliability of ERP and single-trial analyses. *NeuroImage*, *58*(2), 620–629. https://doi.org/10.1016/j.neuroimage.2011.06.052

Geng, J. J., & Vossel, S. (2013). Re-evaluating the role of TPJ in attentional control: Contextual updating? *Neuroscience & Biobehavioral Reviews*, *37*(10, Part 2), 2608–2620. https://doi.org/10.1016/j.neubiorev.2013.08.010

Glazer, J., King, A., Yoon, C., Liberzon, I., & Kitayama, S. (2020). DRD4 polymorphisms modulate reward positivity and P3a in a gambling task: Exploring a genetic basis for cultural learning. *Psychophysiology*, *57*(10), e13623. https://doi.org/10.1111/psyp.13623

Gompf, H. S., Mathai, C., Fuller, P. M., Wood, D. A., Pedersen, N. P., Saper, C. B., & Lu, J. (2010). Locus ceruleus and anterior cingulate cortex sustain wakefulness in a novel environment. *The Journal of Neuroscience, 30*(43), 14543. https://doi.org/10.1523/JNEUROSCI.3037-10.2010

Grace, A. A. (1991). Phasic versus tonic dopamine release and the modulation of dopamine system responsivity: A hypothesis for the etiology of schizophrenia. *Neuroscience*, *41*(1), 1–24. https://doi.org/10.1016/0306-4522(91)90196-U

Grace, A. A. (2000). The tonic/phasic model of dopamine system regulation and its implications for understanding alcohol and psychostimulant craving. *Addiction, 95*(8s2), 119–128. https://doi.org/10.1046/j.1360-0443.95.8s2.1.x

Grella, S. L., Neil, J. M., Edison, H. T., Strong, V. D., Odintsova, I. V., Walling, S. G., Martin, G. M., Marrone, D. F., & Harley, C. W. (2019). Locus coeruleus phasic, but not tonic, activation initiates global remapping in a familiar environment. *Journal of Neuroscience*, *39*(3), 445–455. https://doi.org/10.1523/JNEUROSCI.1956-18.2018

Gurtubay, I. G., Perez-Rodriguez, D. R., Fernandez, E., Librero-Lopez, J., Calvo, D., Bermejo, P., Pinin-Osorio, C., & Lopez, M. (2023). Immediate effects and duration of a short and single application of transcutaneous auricular vagus nerve stimulation on P300 event related potential. *Frontiers in Neuroscience, 17,* n.p. https://www.frontiersin.org/articles/10.3389/fnins.2023.1096865

Haber, S. N. (2016). Corticostriatal circuitry. *Dialogues in Clinical Neuroscience, 18*(1), 7–21. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4826773/

Hamid, A. A., Pettibone, J. R., Mabrouk, O. S., Hetrick, V. L., Schmidt, R., Vander Weele, C. M., Kennedy, R. T., Aragona, B. J., & Berke, J. D. (2016). Mesolimbic dopamine signals the value of work. *Nature Neuroscience, 19*(1), 117-126. https://doi.org/10.1038/nn.4173

Hansch, E. C., Syndulko, K., Cohen, S. N., Goldberg, Z. I., Potvin, A. R., & Tourtellotte, W. W. (1982). Cognition in Parkinson disease: An event-related potential perspective. *Annals of Neurology*, *11*(6), 599–607. https://doi.org/10.1002/ana.410110608

Harrell Jr., F. E. & Dupont, C. (2023, April). *Hmisc: Harrell miscellaneous.* CRAN. https://cran.r-project.org/package=Hmisc

Hauser, T. U., Iannaccone, R., Stämpfli, P., Drechsler, R., Brandeis, D., Walitza, S., & Brem, S. (2014). The feedback-related negativity (FRN) revisited: New insights into the localization, meaning and network organization. *NeuroImage*, *84*, 159–168. https://doi.org/10.1016/j.neuroimage.2013.08.028

Healthdirect. (2021, November 1). *Dopamine*. Healthdirect Australia. https://www.healthdirect.gov.au/dopamine

Hennigan, K., D'Ardenne, K., & McClure, S. M. (2015). Distinct midbrain and habenula pathways are involved in processing aversive events in humans. *Journal of Neuroscience, 35*(1), 198–208. https://doi.org/10.1523/JNEUROSCI.0927-14.2015

Hirsh, J. B., & Inzlicht, M. (2010). Error-related negativity predicts academic performance. *Psychophysiology*, *47*(1), 192–196. https://doi.org/10.1111/j.1469-8986.2009.00877.x

Holroyd, C. B., & Coles, M. G. H. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review, 109*(4), 679-709. 10.1037/0033-295X.109.4.679

Holroyd, C. B., & Krigolson, O. E. (2007). Reward prediction error signals associated with a modified time estimation task. *Psychophysiology, 44*(6), 913–917. https://doi.org/10.1111/j.1469-8986.2007.00561.x

Holroyd, C. B., Pakzad-Vaezi, K. L., & Krigolson, O. E. (2008). The feedback correct-related positivity: Sensitivity of the event-related brain potential to unexpected positive feedback. *Psychophysiology*, *45*(5), 688–697. http://ezproxy.library.uvic.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=byh&AN=33625261&site=ehost-live&scope=site

Hopstaken, J. F., van der Linden, D., Bakker, A. B., & Kompier, M. A. J. (2015). A multifaceted investigation of the link between mental fatigue and task disengagement. *Psychophysiology*, *52*(3), 305–315. https://doi.org/10.1111/psyp.12339

Huffmeijer, R., Bakermans-Kranenburg, M. J., Alink, L. R. A., & van IJzendoorn, M. H. (2014). Reliability of event-related potentials: The influence of number of trials and electrodes. *Physiology & Behavior*, *130*, 13–22. https://doi.org/10.1016/j.physbeh.2014.03.008

Hulme, A., Nielsen, R. O., Timpka, T., Verhagen, E., & Finch, C. (2017). Risk and protective factors for middle- andlong-distance running-related injury. *Sports Medicine*, *47*(5), 869–886. https://doi.org/10.1007/s40279-016-0636-4

Iglesias-Tejedor, M., Díez, Á., Llorca-Bofí, V., Núñez, P., Castaño-Díaz, C., Bote, B., Segarra, R., Sanz-Fuentenebro, J., & Molina, V. (2022). Relation between EEG resting-state power and modulation of P300 task-related activity in theta band in schizophrenia. *Progress in Neuro-Psychopharmacology & Biological Psychiatry*, *116*, 1–8. https://doi.org/10.1016/j.pnpbp.2022.110541

Ip, C.-T., Ganz, M., Ozenne, B., Sluth, L. B., Gram, M., Viardot, G., l'Hostis, P., Danjou, P., Knudsen, G. M., & Christensen, S. R. (2018). Pre-intervention test-retest reliability of EEG and ERP over four recording intervals. *International Journal of Psychophysiology, 134*, 30–43. https://doi.org/10.1016/j.ijpsycho.2018.09.007

Jefferies, L. N., & Di Lollo, V. (2019). Sudden events change old visual objects into new ones: A possible role for phasic activation of locus coeruleus. *Psychological Science, 30*(1), 55–64. https://doi.org/10.1177/0956797618807190

Joshi, S., & Gold, J. I. (2022). Context-dependent relationships between locus coeruleus firing patterns and coordinated neural activity in the anterior cingulate cortex. *ELife, 11*, e63490. https://doi.org/10.7554/eLife.63490

Junaković, A., Kopić, J., Duque, A., Rakic, P., Krsnik, Ž., & Kostović, I. (2023). Laminar dynamics of deep projection neurons and mode of subplate formation are hallmarks of histogenetic subdivisions of the human cingulate cortex before onset of arealization. *Brain Structure & Function*, *228*(2), 613–633. https://doi.org/10.1007/s00429-022-02606-7

Kahnt, T., & Tobler, P. N. (2013). Salience signals in the right temporoparietal junction facilitate value-based decisions. *The Journal of Neuroscience, 33*(3), 863. https://doi.org/10.1523/JNEUROSCI.3531-12.2013

Kawai, T., Yamada, H., Sato, N., Takada, M., & Matsumoto, M. (2015). Roles of the lateral habenula and anterior cingulate cortex in negative outcome monitoring and behavioral adjustment in nonhuman primates. *Neuron, 88*(4), 792–804. https://doi.org/10.1016/j.neuron.2015.09.030

Koga, K., Yamada, A., Song, Q., Li, X.-H., Chen, Q.-Y., Liu, R.-H., Ge, J., Zhan, C., Furue, H., Zhuo, M., & Chen, T. (2020). Ascending noradrenergic excitation from the locus coeruleus to the anterior cingulate cortex. *Molecular Brain*, *13*(1), 49. https://doi.org/10.1186/s13041-020-00586-5

Kok, A. (2022). Cognitive control, motivation and fatigue: A cognitive neuroscience perspective. *Brain and Cognition*, *160*, 105880. https://doi.org/10.1016/j.bandc.2022.105880

Kompatsiari, K., Candrian, G., & Mueller, A. (2016). Test-retest reliability of ERP components: A short-term replication of a visual Go/NoGo task in ADHD subjects. *Neuroscience Letters*, *617*, 166–172. https://doi.org/10.1016/j.neulet.2016.02.012

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of Chiropractic Medicine*, *15*(2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012

Krigolson, O. E., Hassall, C. D., & Handy, T. C. (2014). How we learn to make decisions: rapid propagation of reinforcement learning prediction errors in humans. *Journal of Cognitive Neuroscience*, *26*(3), 635–644. https://doi.org/10.1162/jocn_a_00509

Krigolson, O. E., Pierce, L. J., Holroyd, C. B., & Tanaka, J. W. (2009). Learning to become an expert: reinforcement learning and the acquisition of perceptual expertise. *Journal of Cognitive Neuroscience*, *21*(9), 1833–1840. https://doi.org/10.1162/jocn.2009.21128

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, 82(13), 1–26. doi:10.18637/jss.v082.i13.

Larson, M. J., Baldwin, S. A., Good, D. A., & Fair, J. E. (2010). Temporal stability of the error-related negativity (ERN) and post-error positivity (Pe): The role of number of trials. *Psychophysiology*, *47*(6), 1167–1171. https://doi.org/10.1111/j.1469-8986.2010.01022.x

Lawson, R. P., Seymour, B., Loh, E., Lutti, A., Dolan, R. J., Dayan, P., Weiskopf, N., & Roiser, J. P. (2014). The habenula encodes negative motivational value associated with primary punishment in humans. *Proceedings of the National Academy of Sciences*, *111*(32), 11858–11863. https://doi.org/10.1073/pnas.1323586111

Levinson, A. R., Speed, B. C., Infantolino, Z. P., & Hajcak, G. (2017). Reliability of the electrocortical response to gains and losses in the doors task. *Psychophysiology*, *54*(4), 601–607. https://doi.org/10.1111/psyp.12813

Linden, D. E. J. (2005). The P300: Where in the brain is it produced and what does it tell us? *The Neuroscientist*, *11*(6), 563–576. https://doi.org/10.1177/1073858405280524

Lohani, S., Martig, A. K., Underhill, S. M., DeFrancesco, A., Roberts, M. J., Rinaman, L., Amara, S., & Moghaddam, B. (2018). Burst activation of dopamine neurons produces prolonged post-burst availability of actively released dopamine. *Neuropsychopharmacology*, *43*(10), 2083–2092. https://doi.org/10.1038/s41386-018-0088-7

Luck, S. J. (2014). *An Introduction to the Event-Related Potential Technique, second edition*. MIT Press Journals. https://books.google.ca/books?hl=en&lr=&id=y4-uAwAAQBAJ&oi=fnd&pg=PR5&dq=luck+2014&ots=jC00z6LNFH&sig=MK0BCjR9iu1A1mk_RANcoyrkh0Y#v=onepage&q=luck 2014&f=false

Luu, P., Tucker, D. M., & Makeig, S. (2004). Frontal midline theta and the error-related negativity: Neurophysiological mechanisms of action regulation. *Clinical Neurophysiology*, *115*(8), 1821–1835. https://doi.org/10.1016/j.clinph.2004.03.031

Machado-Vieira, R., Baumann, J., Wheeler-Castillo, C., Latov, D., Henter, I. D., Salvadore, G., & Zarate, C. A. (2010). The timing of antidepressant effects: A comparison of diverse pharmacological and somatic treatments. *Pharmaceuticals*, *3*(1), 19–41. https://doi.org/10.3390/ph3010019

Microsoft. (2023, September 8). *Microsoft PowerPoint.* https://owl.purdue.edu/owl/research_and_citation/apa_style/apa_formatting_and_style_guide/reference_list_electronic_sources.html

Miltner, W. H. R., Braun, C. H., & Coles, M. G. H. (1997). Event-related brain potentials following incorrect feedback in a time-estimation task: Evidence for a “generic” neural system for error detection. *Journal of Cognitive Neuroscience*, *9*(6), 788–798. https://doi.org/10.1162/jocn.1997.9.6.788

Mohebi, A., Pettibone, J. R., Hamid, A. A., Wong, J.-M. T., Vinson, L. T., Patriarchi, T., Tian, L., Kennedy, R. T., & Berke, J. D. (2019). Dissociable dopamine dynamics for learning and motivation. *Nature*, *570*(7759), 65-70. https://doi.org/10.1038/s41586-019-1235-y

Morand-Beaulieu, S., Perrault, M.-A., & Lavoie, M. E. (2022). Test-retest reliability of event-related potentials across three tasks. *Journal of Psychophysiology*, *36*(2), 100–117. https://doi.org/10.1027/0269-8803/a000286

Mort, D. J., Malhotra, P., Mannan, S. K., Rorden, C., Pambakian, A., Kennard, C., & Husain, M. (2003). The anatomy of visual neglect. *Brain*, *126*(9), 1986–1997. https://doi.org/10.1093/brain/awg200

Munsters, N. M., van Ravenswaaij, H., van den Boomen, C., & Kemner, C. (2019). Test-retest reliability of infant event related potentials evoked by faces. *Neuropsychologia*, *126*, 20–26. https://doi.org/10.1016/j.neuropsychologia.2017.03.030

Murphy, P. R., Robertson, I. H., Balsters, J. H., & O'connell, R. G. (2011). Pupillometry and P3 index the locus coeruleus–noradrenergic arousal function in humans. *Psychophysiology*,*48*(11), 1532-1543. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1469-8986.2011.01226.x?casa_token=C6JjiFbpWvMAAAAA:scG2y8uyIiPMivhs4K9JsQGtGn0cd-HaOQIwKt6tBhFF4ml40jTCtxdBYwIHeTokXJMkoL_CexEwUoq_pg

Nair, A. G., Gutierrez-Arenas, O., Eriksson, O., Vincent, P., & Kotaleski, J. H. (2015). Sensing positive versus negative reward signals through adenylyl cyclase-coupled GPCRs in direct and indirect pathway striatal medium spiny neurons. *Journal of Neuroscience*, *35*(41), 14017–14030. https://doi.org/10.1523/JNEUROSCI.0730-15.2015

Németh, G., Hegedüs, K., & Molnâr, L. (1988). Akinetic mutism associated with bicingular lesions: Clinicopathological and functional anatomical correlates. *European Archives of Psychiatry and Neurological Sciences*, *237*(4), 218–222. https://doi.org/10.1007/BF00449910

Nieuwenhuis, S., Aston-Jones, G., & Cohen, J. D. (2005). Decision making, the P3, and the locus coeruleus—norepinephrine system. *Psychological Bulletin*, *131*(4), 510–532. https://doi.org/10.1037/0033-2909.131.4.510

Nieuwenhuis, S. (2011). Learning, the P3, and the locus coeruleus-norepinephrine system. In R. B. Mars, J. Sallet, M. F. S. Rushworth, & N. Yeung (Eds.), *Neural basis of motivational and cognitive control* (pp. 209-222). The MIT Press.

Oyarzabal, E. A., Hsu, L.-M., Das, M., Chao, T.-H. H., Zhou, J., Song, S., Zhang, W., Smith, K. G., Sciolino, N. R., Evsyukova, I. Y., Yuan, H., Lee, S.-H., Cui, G., Jensen, P., & Shih, Y.-Y. I. (2022). Chemogenetic stimulation of tonic locus coeruleus activity strengthens the default mode network. *Science Advances, 8*(17), eabm9898. https://doi.org/10.1126/sciadv.abm9898

Parkinson, J. A., Willoughby, P. J., Robbins, T. W., & Everitt, B. J. (2000). Disconnection of the anterior cingulate cortex and nucleus accumbens core impairs Pavlovian approach behavior: Further evidence for limbic cortical–ventral striatopallidal systems. *Behavioral Neuroscience*, *114*(1), 42–63. https://doi.org/10.1037/0735-7044.114.1.42

Parvizi, J., Rangarajan, V., Shirer, W. R., Desai, N., & Greicius, M. D. (2013). The will to persevere induced by electrical stimulation of the human cingulate gyrus. *Neuron, 80*(6), 1359–1367. https://doi.org/10.1016/j.neuron.2013.10.057

Pinheiro, J., & Bates, D. (2023). *nlme: Linear and Nonlinear Mixed Effects Models*. R package version 3.1-163, https://CRAN.R-project.org/package=nlme.

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology, 118*(10), 2128-2148. https://www-sciencedirect-com.ezproxy.library.uvic.ca/science/article/pii/S1388245707001897?via%3Dihub

Pollock, V. E., & Schneider, L. S. (1992). Reliability of late positive component activity (P3) in healthy elderly adults. *Journal of Gerontology, 47*(3), M88–M92. https://doi.org/10.1093/geronj/47.3.M88

Pozzi, L., Invernizzi, R., Cervo, L., Vallebuona, F., & Samanin, R. (1994). Evidence that extracellular concentrations of dopamine are regulated by noradrenergic neurons in the frontal cortex of rats. *Journal of Neurochemistry*, *63*(1), 195–200. https://doi.org/10.1046/j.1471-4159.1994.63010195.x

Proudfit, G. H. (2015). The reward positivity: From basic research on reward to a biomarker for depression. *Psychophysiology, 52*(4), 449–459. https://doi.org/10.1111/PSYP.12370

Puglisi-Allegra, S., & Ventura, R. (2012). Prefrontal/accumbal catecholamine system processes high motivational salience. *Frontiers in Behavioral Neuroscience*, *6*, n.p. https://www.frontiersin.org/articles/10.3389/fnbeh.2012.00031

Rajkowski, J., Kubiak, P., & Aston-Jones, G. (1994). Locus coeruleus activity in monkey: Phasic and tonic changes are associated with altered vigilance. *Brain Research Bulletin*, *35*(5), 607–616. https://doi.org/10.1016/0361-9230(94)90175-9

Ranjbar-Slamloo, Y., & Fazlali, Z. (2020). Dopamine and noradrenaline in the brain; Overlapping or dissociate functions? *Frontiers in Molecular Neuroscience*, *12*, 334. https://doi.org/10.3389/fnmol.2019.00334

R Core Team (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/

Revelle, W. (2023). *psych: Procedures for Psychological, Psychometric, and Personality Research*. Northwestern University, Evanston, Illinois. R package version 2.3.3, https://CRAN.R-project.org/package=psych.

RStudio Team (2022). RStudio: Integrated Development Environment for R. RStudio, PBC, Boston, MA URL: http://www.rstudio.com/.

Saddoris, M. P., Cacciapaglia, F., Wightman, R. M., & Carelli, R. M. (2015). Differential dopamine release dynamics in the nucleus accumbens core and shell reveal complementary signals for error prediction and incentive motivation. *Journal of Neuroscience*, *35*(33), 11572–11582. https://doi.org/10.1523/JNEUROSCI.2344-15.2015

Sandman, C. A., & Patterson, J. V. (2000). The auditory event-related potential is a stable and reliable measure in elderly subjects over a 3 year period. *Clinical Neurophysiology*, *111*(8), 1427–1437. https://doi.org/10.1016/S1388-2457(00)00320-5

Santopetro, N. J., Brush, C. J., Bruchnak, A., Klawohn, J., & Hajcak, G. (2021). A reduced P300 prospectively predicts increased depressive severity in adults with clinical depression. *Psychophysiology*, *58*(4), e13767. https://doi.org/10.1111/psyp.13767

Santopetro, N. J., Mulligan, E. M., Brush, C. J., & Hajcak, G. (2022). Reduced P300 amplitude is consistently associated with trait anhedonia across repeated assessments. *Psychophysiology*, *59*(12). https://doi.org/10.1111/psyp.14127

Sato, A., Yasuda, A., Ohira, H., Miyawaki, K., Nishikawa, M., Kumano, H., & Kuboki, T. (2005). Effects of value and reward magnitude on feedback negativity and P300. *NeuroReport*, *16*(4), 407. https://journals.lww.com/neuroreport/fulltext/2005/03150/effects_of_value_and_reward_magnitude_on_feedback.20.aspx?casa_token=kvikVfGT4IYAAAAA:HPUtZPBuCYIDzP6uBf6TgQtFnIhMI0lmJW8c41fX5q_ATnjXNtiQdsb7ctUWxFwvtrO2olP10Si7G9J6D9-hUE4ONmbh

Scheeringa, R., Petersson, K. M., Oostenveld, R., Norris, D. G., Hagoort, P., & Bastiaansen, M. C. M. (2009). Trial-by-trial coupling between EEG and BOLD identifies networks related to alpha and theta EEG power increases during working memory maintenance. *NeuroImage*, *44*(3), 1224–1238. https://doi.org/10.1016/j.neuroimage.2008.08.041

Schultz, W., Dayan, P., & Montague, P. R. (1997). A neural substrate of prediction and reward. *Science*, *275*(5306), 1593–1599. https://doi.org/10.1126/science.275.5306.1593

Segal, M., & Bloom, F. E. (1974a). The action of norepinephrine in the rat hippocampus. I. Iontophoretic studies. *Brain Research*, *72*(1), 79–97. https://doi.org/10.1016/0006-8993(74)90652-0

Segal, M., & Bloom, F. E. (1974b). The action of norepinephrine in the rat hippocampus. II. Activation of the input pathway. *Brain Research*, *72*(1), 99–114. https://doi.org/10.1016/0006-8993(74)90653-2

Segal, M., & Bloom, F. E. (1976). The action of norepinephrine in the rat hippocampus. IV. The effects of locus coeruleus stimulation on evoked hippocampal unit activity. *Brain Research*, *107*(3), 513–525. https://doi.org/10.1016/0006-8993(76)90141-4

Segalowitz, S. J., & Barnes, K. L. (1993). The reliability of ERP components in the auditory oddball paradigm. *Psychophysiology*, *30*(5), 451–459. https://doi.org/10.1111/j.1469-8986.1993.tb02068.x

Segalowitz, S. J., Santesso, D. L., Murphy, T. I., Homan, D., Chantziantoniou, D. K., & Khan, S. (2010). Retest reliability of medial frontal negativities during performance monitoring. *Psychophysiology*, *47*(2), 260–270. https://doi.org/10.1111/j.1469-8986.2009.00942.x

Shen, W., Plotkin, J. L., Francardo, V., Ko, W. K. D., Xie, Z., Li, Q., Fieblinger, T., Wess, J., Neubig, R. R., Lindsley, C. W., Conn, P. J., Greengard, P., Bezard, E., Cenci, M. A., & Surmeier, D. J. (2015). M4 muscarinic receptor signaling ameliorates striatal plasticity deficits in models of L-DOPA-induced dyskinesia. *Neuron*, *88*(4), 762–773. https://doi.org/10.1016/j.neuron.2015.10.039

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

Shields, G. S., Sazma, M. A., & Yonelinas, A. P. (2016). The effects of acute stress on core executive functions: A meta-analysis and comparison with cortisol. *Neuroscience & Biobehavioral Reviews*, *68*, 651–668. https://doi.org/10.1016/j.neubiorev.2016.06.038

Squires, K. C., Squires, N. K., & Hillyard, S. A. (1975). Decision-related cortical potentials during an auditory signal detection task with cued observation intervals. *Journal of Experimental Psychology: Human Perception and Performance*, *1*(3), 268–279. https://doi.org/10.1037/0096-1523.1.3.268

Su, H., Chang, N.-J., Wu, W.-L., Guo, L.-Y., & Chu, I.-H. (2017). Acute effects of foam rolling, static stretching, and dynamic stretching during warm-ups on muscular flexibility and strength in young adults. *Journal of Sport Rehabilitation*, *26*(6), 469–477. https://doi.org/10.1123/jsr.2016-0102

Sur, S., & Sinha, V. K. (2009). Event-related potential: An overview. *Industrial Psychiatry Journal*, *18*(1), 70–73. https://doi.org/10.4103/0972-6748.57865

Sutton, S., Braren, M., Zubin, J., & John, E. R. (1965). Evoked-potential correlates of stimulus uncertainty. *Science*, *150*(3700), 1187–1188. https://doi.org/10.1126/science.150.3700.1187

Szenczy, A. K., Levinson, A. R., Hajcak, G., Bernard, K., & Nelson, B. D. (2021). Reliability of reward- and error-related brain activity in early childhood. *Developmental Psychobiology*, *63*(6), e22175. https://doi.org/10.1002/dev.22175

Takeshita, S., & Ogura, C. (1994). Effect of the dopamine D2 antagonist sulpiride on event-related potentials and its relation to the law of initial value. *International Journal of Psychophysiology*, *16*(1), 99–106. https://doi.org/10.1016/0167-8760(94)90046-9

Thomas Broome, S., Louangaphay, K., Keay, K. A., Leggio, G. M., Musumeci, G., & Castorina, A. (2020). Dopamine: An immune transmitter. *Neural Regeneration Research*, *15*(12), 2173–2185. https://doi.org/10.4103/1673-5374.284976

Umemoto, A., Inzlicht, M., & Holroyd, C. B. (2019). Electrophysiological indices of anterior cingulate cortex function reveal changing levels of cognitive effort and reward valuation that sustain task performance. *Neuropsychologia*, *123*, 67–76. https://doi.org/10.1016/j.neuropsychologia.2018.06.010

Umemoto, A., Lukie, C. N., Kerns, K. A., Müller, U., & Holroyd, C. B. (2014). Impaired reward processing by anterior cingulate cortex in children with attention deficit hyperactivity disorder. *Cognitive, Affective, & Behavioral Neuroscience*, *14*(2), 698–714. https://doi.org/10.3758/s13415-014-0298-3

Valentino, R. J., & Van Bockstaele, E. (2008). Convergent regulation of locus coeruleus activity as an adaptive response to stress. *Stress Hormone Actions in Brain, in Health and Disease*, *583*(2), 194–203. https://doi.org/10.1016/j.ejphar.2007.11.062

Vazey, E. M., Moorman, D. E., & Aston-Jones, G. (2018). Phasic locus coeruleus activity regulates cortical encoding of salience information. *Proceedings of the National Academy of Sciences*, *115*(40), E9439–E9448. https://doi.org/10.1073/pnas.1803716115

Walhovd, K. B., & Fjell, A. M. (2002). One-year test-retest reliability of auditory ERPs in young and old adults. *International Journal of Psychophysiology*, *46*(1), 29–40. https://doi.org/10.1016/S0167-8760(02)00039-9

Wang, Y., Toyoshima, O., Kunimatsu, J., Yamada, H., & Matsumoto, M. (2021). Tonic firing mode of midbrain dopamine neurons continuously tracks reward values changing moment-by-moment. *ELife*, *10*, e63166. https://doi.org/10.7554/eLife.63166

Watabe-Uchida, M., Eshel, N., & Uchida, N. (2017). Neural circuitry of reward prediction error. *Annual Review of Neuroscience*, *40*, 373–394. https://doi.org/10.1146/annurev-neuro-072116-031109

Watson, S. (2021, July 20). *Dopamine: The pathway to pleasure*. Harvard Health. https://www.health.harvard.edu/mind-and-mood/dopamine-the-pathway-to-pleasure

Weinberg, A., & Hajcak, G. (2011). Longer term test–retest reliability of error-related brain activity. *Psychophysiology*, *48*(10), 1420–1425. https://doi.org/10.1111/j.1469-8986.2011.01206.x

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., Françoism R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., & Yutani, H. (2019). "Welcome to the tidyverse." *Journal of Open Source Software*, *4*(43), 1686. doi:10.21105/joss.01686.

Williams, C. C., Ferguson, T. D., Hassall, C. D., Abimbola, W., & Krigolson, O. E. (2021). The ERP, frequency, and time–frequency correlates of feedback processing: Insights from a large sample study. *Psychophysiology*, *58*(2), e13722. https://doi.org/10.1111/psyp.13722

Williams, C. C., Hassall, C. D., Lindenbach, T., & Krigolson, O. E. (2020). Reward prediction errors reflect an underlying learning process that parallels behavioural adaptations: A trial-to-trial analysis. *Computational Brain & Behavior*, *3*(2), 189–199. https://doi.org/10.1007/s42113-019-00069-4

Wise, R. A. (1982). Neuroleptics and operant behavior: The anhedonia hypothesis. *Behavioral and Brain Sciences*, *5*(1), 39–53. https://doi.org/10.1017/S0140525X00010372

Wyrofsky, R. R., Reyes, B. A. S., Zhang, X.-Y., Bhatnagar, S., Kirby, L. G., & Van Bockstaele, E. J. (2019). Endocannabinoids, stress signaling, and the locus coeruleus-norepinephrine system. *Neurobiology of Stress*, *11*, 100176. https://doi.org/10.1016/j.ynstr.2019.100176

Yamamoto, B. K., & Novotney, S. (1998). Regulation of extracellular dopamine by the norepinephrine transporter. *Journal of Neurochemistry*, *71*(1), 274–280. https://doi.org/10.1046/j.1471-4159.1998.71010274.x

Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology*, *18*(5), 459–482. https://doi.org/10.1002/cne.920180503

Yeung, N., & Sanfey, A. G. (2004). Independent coding of reward magnitude and valence in the human brain. *Journal of Neuroscience*, *24*(28), 6258–6264. https://doi.org/10.1523/JNEUROSCI.4537-03.2004

Zach. (2020, September 24). What are order effects? (Explanation & Examples). *Statology*. https://www.statology.org/order-effects/

Zhuang, X., Oosting, R. S., Jones, S. R., Gainetdinov, R. R., Miller, G. W., Caron, M. G., & Hen, R. (2001). Hyperactivity and impaired response habituation in hyperdopaminergic mice. *Proceedings of the National Academy of Sciences*, *98*(4), 1982–1987. https://doi.org/10.1073/pnas.98.4.1982

Appendix A

Supplemental Analysis Results

Supplement Group versus Control Group

Levene's tests for reward positivity amplitude, $F_{(1,\ 128)} = 1.01$, $p = .32$, and latency, $F_{(1,\ 128)} = 2.16$, $p = .14$, as well as P300 amplitude, $F_{(1,\ 128)} = 3.72$, $p = .06$ and latency, $F_{(1,\ 128)} = 2.30$, $p = .13$, all met the assumption of homogeneity of variance.

Two-sample *t*-tests were used to check for differences between amplitudes and latencies of each component between the supplement group and control group. The reward positivity amplitude, $M_D = -0.25$ µV, $t_{(128)} = -0.48$, $p = .64$, and latency, $M_D = -4.09$ µV, $t_{(128)} = -1.06$, $p = .29$, showed no difference between groups. The P300 amplitude, $M_D = 0.86$ µV, $t_{(128)} = 1.12$, $p = .27$, and latency, $M_D = -2.95$ µV, $t_{(128)} = -0.77$, $p = .44$, similarly showed no differences in effects. Thus, these groups were treated as one homogenous group throughout the analysis.

Demographic Results

Differences in the reward positivity and P300 were tested for both gender and age variables. Since there were not enough non-binary participants (n =1) for a representative sample, only female and male genders were included in this analysis. Levene's tests indicated equal variance for both reward positivity, $F_{(2,\ 23)} = 3.03$, $p = .07$, and P300, $F_{(2,\ 23)} = 0.61$, $p = .55$. Subsequent two-sample *t*-tests revealed no amplitude differences between female and male groups for either the reward positivity, $M_D = -0.11$ µV, $t_{(23)} = -0.16$, $p = .88$, or the P300, $M_D = 0.70$ µV, $t_{(23)} = 0.48$, $p = .64$. A correlation analysis revealed no relationship between age and reward positivity, $r_{(24)} = .22$, $p = .29$, but a strong negative correlation between age and P300, $r_{(24)} = -.63$, $p < .001$.

Appendix B

Supplemental Figures

Figure B 1

Boxplots of water and supplement groups for overall component measures.

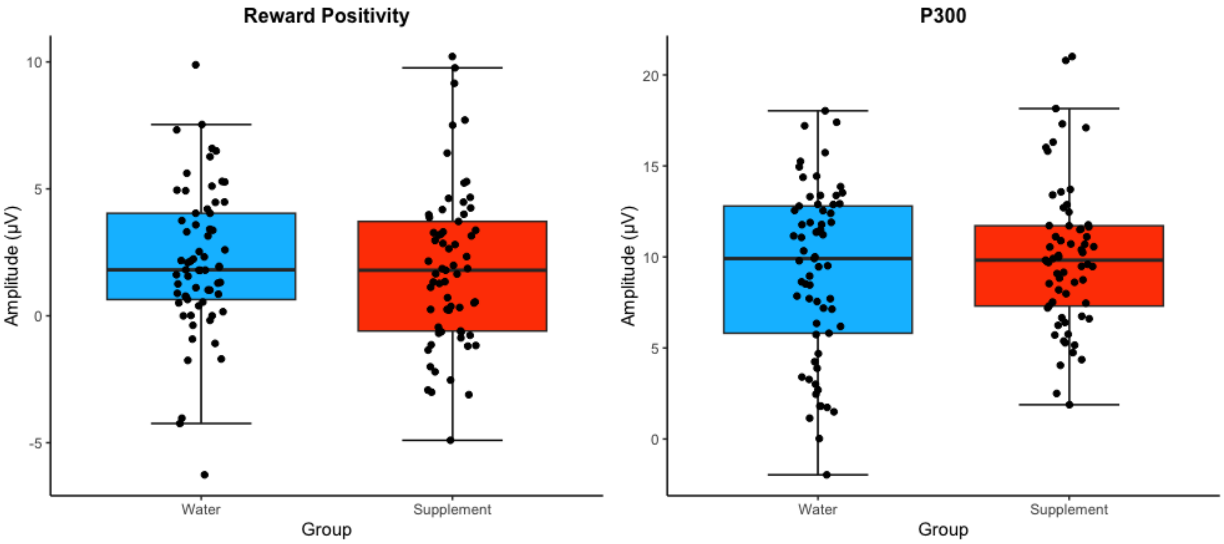
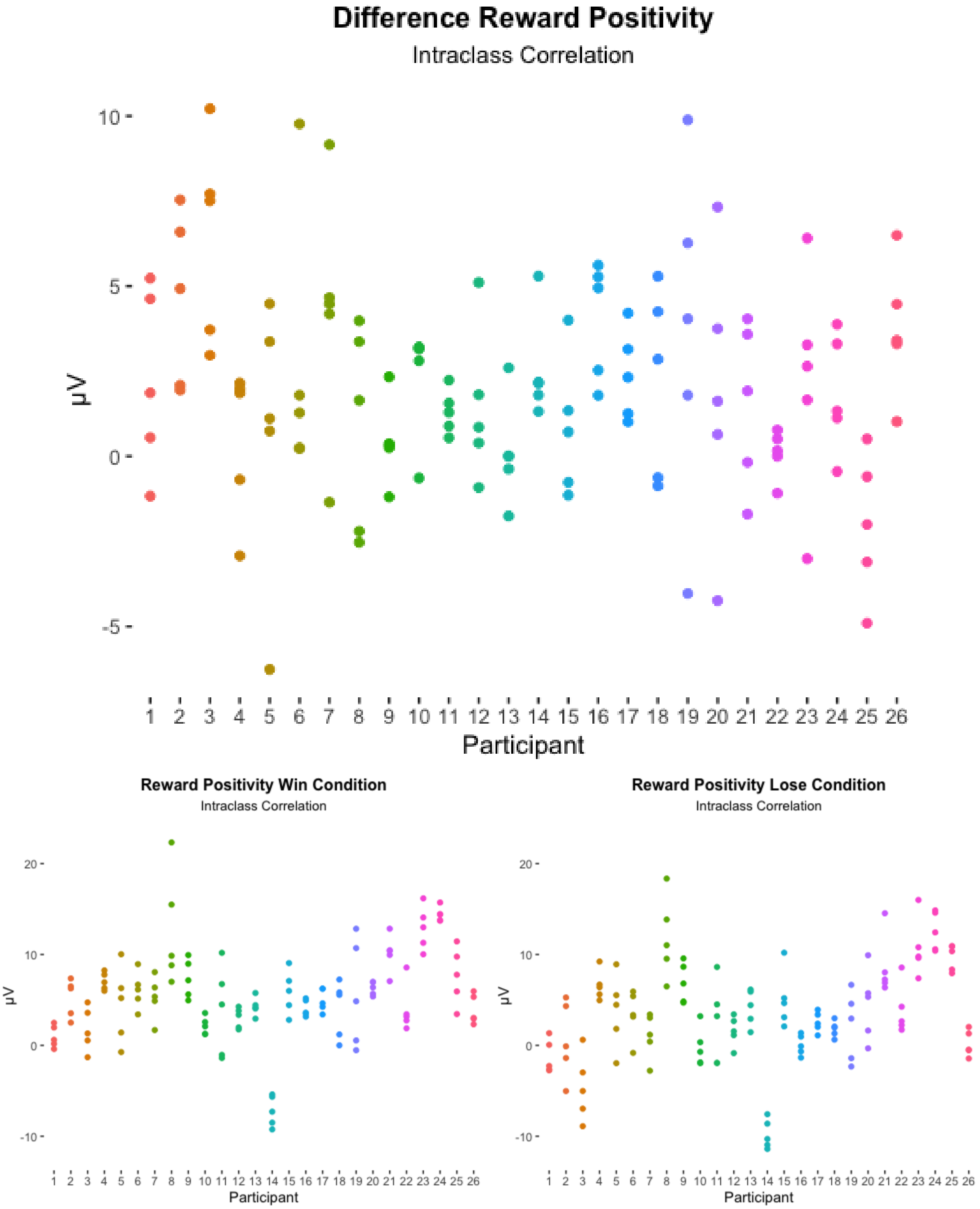


Figure B 2

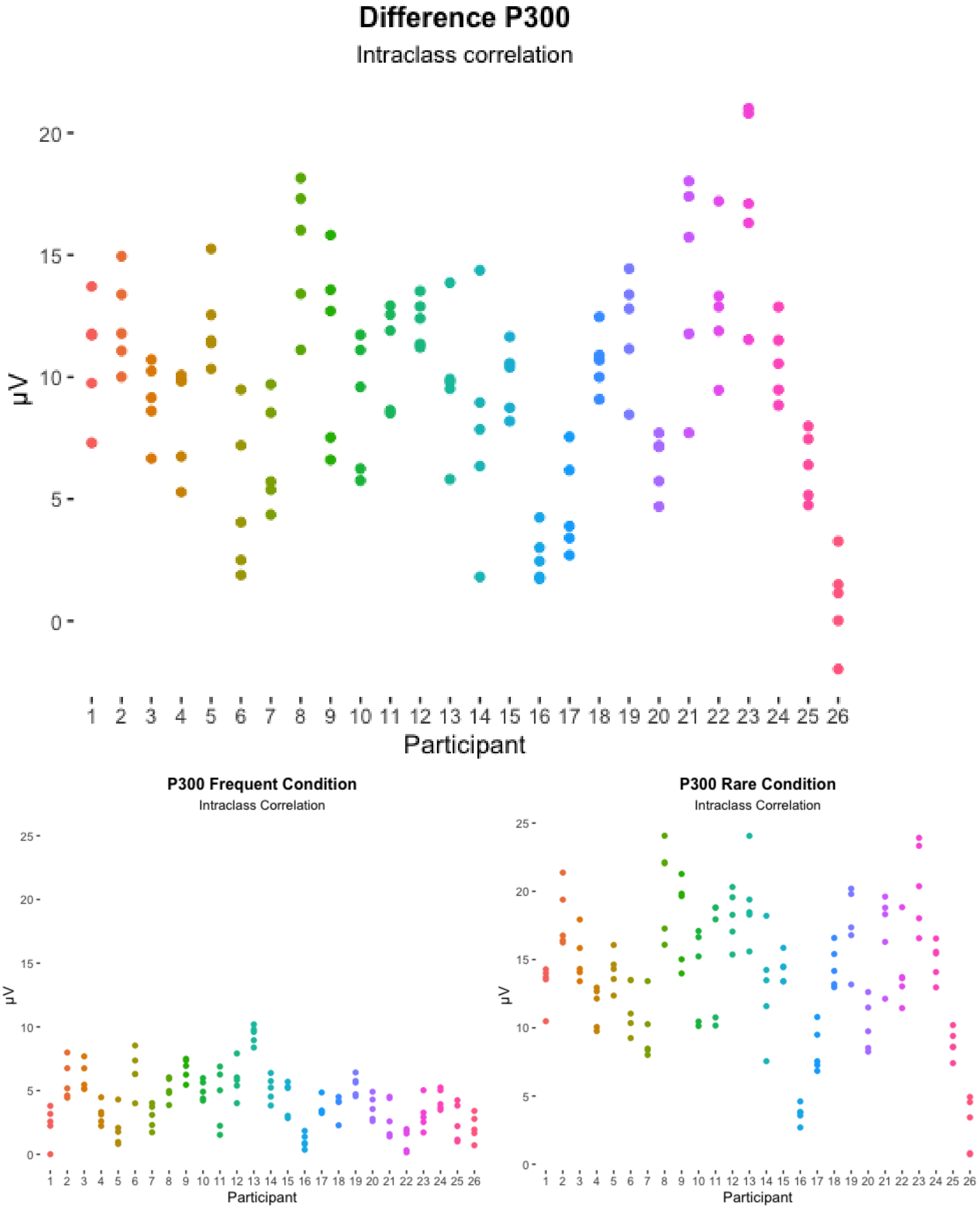
ICCs for the Reward Positivity.



Note. Difference reward positivity (top) derived from Win condition minus Loss condition. Amplitude measures bundled closer together for each participant indicates a stronger ICC score.

Figure B 3

ICCs for the P300



Note. Difference P300 (top) derived from Rare minus Frequent conditions. Amplitude measures bundled closer together for each participant indicates a stronger ICC score.