



Full Length Article

Punishing temporal judgement boosts sense of agency and modulates its underlying neural correlates

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ABSTRACT

Feeling in control of one's actions is fundamental to the formation of action-outcome relationships. Reinforcement and its valence also change the action-outcome relationship, either through behavior promotion or diminishment. In this study we evaluated how reward and punishment reinforcement modulate sense of agency, as measured by intentional binding. Moreover, using electroencephalography (EEG) we evaluated how reward and punishment reinforcement changes outcome event related potentials associated with the accuracy of participants' judgement of the time interval between a key press and audio tone. We found that punishment reinforcement increased intentional binding between the action and outcome more than reward but not significantly more than control feedback. Punishment elicited greater outcome event-related potentials, P300s and Late Positive Potential, compared to reward and control. We also found increased N100s and diminished P300s and Late Positive Potentials when the participants did not actively participate in evoking the tone. Taken together, our findings showcase that punishment reinforcement boosts sense of agency and modulates associated neural activity more than reward and no reinforcement, as a function of increasing attention and arousal. These findings illuminate the greater effect punishment reinforcement has on behavior and brain activity by its modification of sense of agency, which is important for the development of treatments in psychiatric and neurological diseases.

1. Introduction

In this study, we evaluated the interaction of sense of agency and reinforcement feedback using a temporal estimation task with valence performance feedback. Moreover, we examine the underlying neural correlates of feedback processing during active and passive task engagements. When we perform voluntary actions, there is a sensation of ownership that corresponds with their execution, known as the "sense of agency". This subjective experience has been widely studied in cognitive science especially in the context of consciousness, and free will (Haggard, 2017; Moore, 2016). Changes in sense of agency have been noted in many psychiatric and neurological disorders (Haggard, 2017; Malik et al., 2022; Moore, 2016; Moore & Obhi, 2012). One widely used measure of sense of agency is the intentional binding effect (i.e. action-outcome binding), the temporal perception of two events (Moore & Obhi, 2012;

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Siebertz & Jansen, 2022; Wen, 2019), where voluntary actions and their consequences are perceived as being closer together and involuntary actions and their consequences are perceived more independently. Often action-outcome binding is assessed by comparing a person's temporal perception between self-initiated and passive actions (Haggard, 2017; Wen, 2019; Wen & Imamizu, 2022), where a person judges how much time passed between an action (i.e. button press) and an audio tone (Moore & Obhi, 2012; Siebertz & Jansen, 2022; Wen, 2019).

While temporal binding provides a robust measure of agency, a critical gap emerges when considering how different types of outcomes influence this binding effect. Previous behavioral investigations have examined the relationship between outcome valence and sense of agency. Modulating outcome valence is typically done by making the tone heard after the action, more appetitive or aversive, either by changing the tone frequency or pairing it with a visual stimulus. However, there have been mixed results regarding outcome valence and the action-outcome binding effect. For instance, studies show aversive outcome tones increase action-outcome binding (Majchrowicz et al., 2020a; Majchrowicz & Wierchoń, 2021), while others found decreases (Takahata et al., 2012; Yoshie & Haggard, 2013). Appetitive tones also decreases the action-outcome binding effect (Di Costa et al., 2018), but may be more effective than aversive tones by comparison (Takahata et al., 2012; Yoshie & Haggard, 2013). Moreover, some studies have found no differences in between appetitive and aversive outcomes (Barlas et al., 2017, 2018). Given the mixed nature of these findings, the effect of outcome valence on action-outcome binding is not clearly understood and needs further exploration (Kaiser et al., 2021a). These inconsistencies suggest that simple valence manipulations may be insufficient to understand how outcomes modulate agency experiences.

Reinforcement feedback is a powerful tool in shaping the relationship between our actions and their associated outcomes to promote behavioral change (Holroyd & Coles, 2002; Skinner, 1984; Sutton & Barto, 1981; Thorndike, 1898). Two common forms of reinforcement feedback are reward and punishment, which promote or diminish occurrences of certain behaviors, in turn strengthening action-outcome relationships (Holroyd & Coles, 2002; Skinner, 1984; Sutton & Barto, 1981; Thorndike, 1898). However, reinforcement feedback in the context of sense of agency has not been extensively studied and has largely remained separate, representing a critical theoretical and empirical gap (Seghezzi et al., 2023). One recent investigation evaluated how reinforcement feedback based on action timing accuracy, found that action-outcome binding decreased when accuracy increased, as a function of task learning and lowering cognitive load during action selection (Seghezzi et al., 2023). These findings suggest that performance-based feedback may fundamentally alter agency experiences through feedback and learning mechanisms.

Electroencephalography (EEG) has been used to evaluate brain activity during temporal perception tasks. Specifically, outcome event-related potentials (ERPs) have provided valuable insights into the cortical processing related to sense of agency. Distinct components of outcome ERPs peak between 50 and 600 ms after task relevant stimuli and reflect different aspects of outcome monitoring, including attention, stimuli significance, and saliency (Cohen et al., 2011; Kühn et al., 2011; Nieuwenhuis et al., 2002, 2004; Ullsperger, 2024). Previous studies demonstrate early components of outcome ERPs decrease in amplitude when a person voluntarily generates an outcome versus externally generated (Han et al., 2021, 2022; Kühn et al., 2013). Instances of coercion and manipulation (i.e. lower agency) decreases the amplitude of early outcome ERP components in comparison to free choice (Caspar et al., 2016, 2020). Conversely, amplitudes of later outcome ERP components increase in conditions where participants have higher control over their actions compared to low or no control (Han et al., 2021, 2022; Mühlberger et al., 2017).

Outcome ERPs have also been studied with reinforcement feedback across a wide variety of contexts (Anguera et al., 2009; Gehring & Willoughby, 2002; Hill et al., 2020; Holroyd & Coles, 2002; Krigolson, 2018; Nieuwenhuis et al., 2004; Palidis et al., 2019; Stürmer et al., 2011; Ullsperger, Danielmeier, et al., 2014; Walsh & Anderson, 2012; Yeung & Sanfey, 2004). Reward and punishment demonstrate differential effects on outcome ERPs thus reflecting different brain processing. Punishment elicits greater amplitude in early outcome ERP components (Potts, 2011). In part, early components represent activity in the anterior cingulate cortex, a portion of prefrontal cortex responsible for the detection of error and performance monitoring (Hill et al., 2020; Holroyd & Coles, 2002; Kirschner et al., 2021; Krigolson, 2018; Ullsperger, Danielmeier, et al., 2014). Later outcome ERP components have demonstrated increases with both reward and punishment feedback, reflecting greater attention and saliency (Potts, 2011; Wischniewski & Schutter, 2018, 2019). Taken together, these ERP studies reveal that agency and reinforcement feedback engage overlapping but distinct neural processes. However, no studies have examined how these two neural signatures interact.

A critical component of determining action-outcome binding is the temporal judgement made by the participant, where they report how much time they thought passed between the action and outcome (Haggard, 2017; Moore & Obhi, 2012; Reddy, 2021). However, there is a lack of studies evaluating how feedback related to temporal judgements can modulate action-outcome binding. Moreover, it is unclear how feedback related neural activity associated with temporal judgement changes in high and low agency conditions. Our goal is to provide clarity to these two areas of study. To this end, we employed a novel temporal estimation task with reward and punishment feedback based on temporal judgement accuracy. We utilized EEG to monitor outcome ERPs in response to the feedback provided after their temporal judgements. From the temporal estimation task, we compared our judgement error and action-outcome binding between three feedback groups (Reward, Punishment, Control). We compared early (N100) and late (P300, Late Positive Potential) outcome ERPs between feedback groups and active and passive task engagements. This integrated approach addresses critical gaps in both the agency and reinforcement learning.

2. Methodology

All procedures were approved by the University Institutional Review Board and were conducted according to the principles expressed in the Declaration of Helsinki. All participants provided written informed consent prior to participating. Thirty-three young healthy adults participated in this study [age range: 19–30 years, mean age $\pm$ standard deviation (SD): 21.84 ± 2.52 years, Edinburgh Handedness Inventory (EHI) (Oldfield, 1971) mean handedness score $\pm$ SD: 66.90 ± 55.99 [3 left-handed, 5 mixed handed, 25 right-

handed], males: 18, females: 15)]. Participants were free of major physiological (musculoskeletal, neurological, cardiovascular) and psychological (drug abuse, depression) disorders. Participants were recruited from the local population of the University and the surrounding communities using word of mouth, electronic announcements, and posted flyers. Each participant was randomly allocated to one of three feedback groups [Reward ($n = 11$, males = 8, females = 3), Punishment ($n = 11$, males = 3, females = 8), Control ($n = 11$, males = 7, females = 4)]. An a priori power calculation for 1 (group) $\times$ 3 (condition) ANOVA mixed repeated measures conducted in G*power 3.1.9.4 using a smallest effect size of interest (SESOI) (Lakens, 2022) of Cohen's $f = 0.25$, where $\alpha = 0.05$ and $\beta = 0.2$ (i.e., statistical power = 80 %). Based on these criteria, an adequate sample size of 36 was calculated. In alignment with other studies utilizing reinforcement feedback (Balconi & Crivelli, 2010; Carver & White, 1994; Del Popolo Cristaldi et al., 2024; Hill et al., 2020), we accounted for reinforcement sensitivity for each participant via the Behavioral Avoidance/Inhibition scales (BAS/BIS) which is divided into four subcomponents (BAS FUN, BAS DRIVE, BAS REWARD, BIS) (Aluja & Blanch, 2011). BAS FUN, BAS DRIVE, and BAS REWARD relate to pursuit and response to rewarding stimuli. While BIS denotes sensitivity to punishment and non-reward (Aluja & Blanch, 2011). These measurements were used to determine if the assigned group had equal sensitivity to reward and punishment.

3. Experimental procedures

3.1. Interval estimation paradigm

Participants were seated in a chair in front of a computer monitor, where they engaged in a modified version of Siebertz and Jansen (2022)'s interval estimation-paradigm via PsychoPy® software. The interval estimation-paradigm consisted of three blocks: one interval estimation-practice block (twelve practice trials total), followed by two counter-balanced active interval (90 active trials total) and passive interval (90 passive trials total) estimation blocks. During each practice trial, a fixation cross and the word 'ready' were displayed to prompt the participant to press the spacebar and trigger two sinusoidal tones (880 Hz), lasting 50 ms (ms) each. The tones were presented binaurally via insert earphones (Etymotic Research, Elk Grove Village, IL, model ER-3A). The first tone was presented 200 ms after the key press and a second tone was presented at one of three base intervals (200, 400, or 800 ms) with a modified random jitter ± 100 ms. Participants used the number row on a keyboard to enter their estimation of the interval between the tones and pressed enter. The actual interval in milliseconds was then displayed, followed by neutral feedback displaying the difference between the participant input and actual interval. Practice trials were not analyzed (Siebertz & Jansen, 2022).

After the practice block, participants engaged in active and passive interval estimation tasks, counter-balanced for each participant. In these blocks pressing the spacebar triggered only one tone, and participants were asked to estimate the interval between the key press and the tone which was presented at one of three base intervals (200, 400, or 800 ms) with a modified random jitter ± 100 ms. 500 ms after the tone, the participants were prompted to enter their estimation via a keyboard, followed by the feedback presentation 100 ms after their estimation input (Fig. 1). Each base interval was randomly presented for 30 trials (90 trials total per condition). In the active condition, participants pressed the button themselves. In the passive condition, participants were cued by the experimenter with a verbal "Ready" follow by the experimenter pressing the button. The participant had an unobstructed view of the keyboard and were free to observe the experimenter press the button throughout the passive condition. The experimenter sat in a chair beside the participants in both conditions but did not engage during the active condition (Siebertz & Jansen, 2022). This same experimenter performed all experiments. For both conditions, a participant's mean judgement error was calculated by subtracting the actual from the estimated intervals and presented on screen. A positive judgement error indicated overestimation, and a negative judgement error indicated underestimation of the temporal intervals (Siebertz & Jansen, 2022).

Each person was allocated to one of three groups: Reward, Punishment, and Control. The color of the presentation of the judgement error determined the group assignment. The Reward feedback group was presented with green judgement error when the judgement error was within 100 ms of the actual interval (Target Feedback) and white judgement error when not within 100 ms of the actual interval (Neutral Feedback). The Punishment feedback group was presented with red judgement error when the judgement error was not within 100 ms of the actual interval (Target Feedback) and white judgement error when within 100 ms of the actual interval (Neutral Feedback). The Control feedback group was presented with white judgement error regardless of the magnitude of the

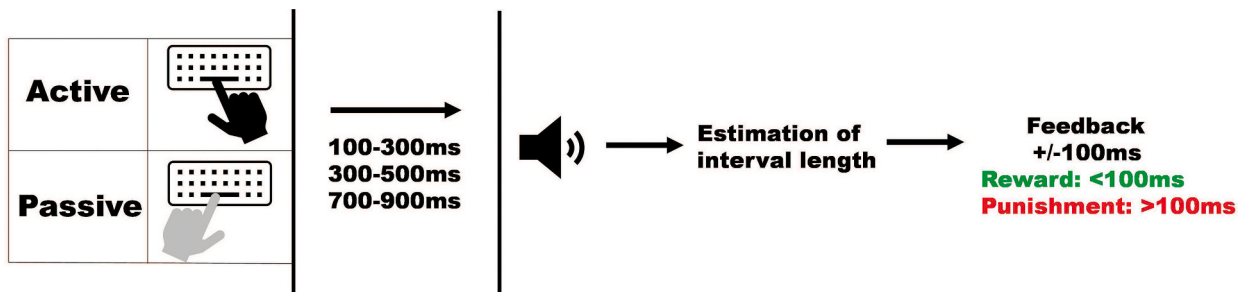


Fig. 1. A schematic of experimental procedures. The participant (Active) or the experimenter (Passive) pressed the button. This generated a tone after one of the three base time intervals. Participants then input their time estimation between the button press and the tone. Feedback was provided based on the difference between participants estimation and the actual tone latency.

difference between the estimated and actual intervals.

Participants in the Reward feedback group were told that they would start at \$0.00 and earn money for each trial where they were accurate up to \$10.00. Participants in the Punishment feedback group were told that they would start at \$10.00 and would lose money for each trial they were inaccurate, down to \$0.00. The Control feedback group was provided with either the instructions of the Reward or Punishment groups to control the effects of the script (Galea et al., 2015; Hill et al., 2020; Song & Smiley-Oyen, 2017). A Mann-Whitney *U* test was used to determine differences in Active and Passive error between the Control instruction subgroups. We found no differences between the instruction sub-group for Active Error ($U = 25.00$, $p = 0.082$, $d = 0.667$) and Passive Error ($U = 26.00$, $p = 0.052$, $d = 0.667$). At the end of the experiment, all groups were paid \$10.00 independent of their performance (Hill et al., 2020, 2021).

Action-outcome binding was calculated for each participant by subtracting the mean active judgement error from mean passive judgement error, in each time interval (200, 400, 800) (Siebertz & Jansen, 2022). This value is positive if the key press and tone are perceived as closer in time when participants press the button (i.e. stronger temporal binding). A negative value suggests stronger binding when the experimenter presses the button.

3.2. EEG recording and processing

Surface EEG data was recorded at 2048 Hz with a 34 channel Quik-Cap electrode system and a Compumedics Neuroscan Grael EEG amplifier (Charlotte, NC, USA). Electrodes were placed according to the 10–20 system at sites FZ, CZ, PZ, OZ, FP1, FP2, F3, F4, F7, F8, FT7, FT8, FC3, FC4, C3, C4, CP3, CP4, P3, P4, T3, T4, T7, T8, P7, P8, TP7, TP8, O1, O2, VEOL, VEOU, A1, and A2. A saline solution was applied with a blunt tip syringe into the individual electrodes to lower electrical signal noise. Electrical impedance for each electrode was kept below 10k Ω throughout the data collection.

All raw EEG data was exported and processed in Matlab R2020b software (Mathworks, Inc.), using the EEGLAB version 2024.0 and ERPLab version 12.0 toolboxes (Delorme & Makeig, 2004; Lopez-Calderon & Luck, 2014). Continuous data were down sampled to 500 Hz, rereferenced to linked mastoids (A1 + A2), had EOG and trigger channel(s) removed, and segmented into time-locked data 900 ms epochs around the feedback presentation, with a 100 ms pre-stimulus baseline and an 800 ms post-stimulus period. During epoching, baseline correction was applied using amplitudes averaged across the prestimulus period. An initial visual inspection of the epochs was performed to remove trials containing artifacts. Then signal decomposition was performed using independent components analysis on each participant's data utilizing the 'runica' procedure in EEGLAB. Additional trials containing artifacts were identified using the resultant components of the signal decomposition and were removed from the analysis. Components reflecting eye blinks and electromyography activity were removed by visual inspection.

Grand average outcome ERP waveforms were computed for each participant in each action condition (Active, Passive) and feedback type (Target, Neutral). We utilized both existing literature and visual inspection to identify waveform components (Luck, 2022; Luck & Gaspelin, 2017). Upon identifying components, we then referenced previous research studies corresponding with previous action-outcome binding (Caspar et al., 2020; Kühn et al., 2013; Mühlberger et al., 2017) and reinforcement feedback (Foti et al., 2011; Hajcak et al., 2009; Hajcak & Foti, 2020; Hill et al., 2020; Maclean et al., 2015; Meadows et al., 2016; Palidis et al., 2019; Polich, 2007, 2011; Proudfit, 2015) to add nomenclature and identify proper time windows for analysis. We identified waveform components N100, P300, and Late Positive Potential and analyzed peak amplitude and latency for all groups and conditions by looking in the following latency ranges: N100 (50–170 msec) (Han et al., 2021, 2022), P300 (300–500 msec) (Maclean et al., 2015; Polich, 2007, 2011), Late Positive Potential (515–650 msec) (Hajcak et al., 2009; Hajcak & Foti, 2020; Speed et al., 2015). Amplitude and latency analyses were performed in electrodes where specific waveform components are most prominent. N100 amplitude and latency was extracted from the Fz electrode (Ullsperger, Danielmeier, et al., 2014; Ullsperger, Fischer et al., 2014). Whereas, P300 and Late Positive Potential amplitudes and latencies were obtained from the Pz electrode (Hajcak et al., 2005; Hajcak & Foti, 2020; Maclean et al., 2015; Polich, 2007, 2011).

3.3. Statistical analysis

Participant descriptive data, BAS/BIS subscales, and N100 amplitudes were evaluated with separate One-way analysis of variances (ANOVAs) to determine differences between the three feedback groups (Control, Reward, Punishment).

Mixed repeated measures ANOVAs were used to determine differences in judgement error and action-outcome binding across Feedback Groups (Reward, Punishment, Control) and Time Intervals (200, 400, 800). Violations of sphericity were corrected using the Greenhouse-Geisser correction factor.

Separate linear mixed models for repeated measures were used to determine differences for ERP amplitudes and latencies across feedback groups, feedback type, and action conditions. ERP amplitudes and latencies were held as the dependent variables. Feedback Group (Reward, Punishment, Control), Feedback Type (Target, Neutral), and Action Condition (Active, Passive) were held as fixed effects and individual subjects' intercept were held as random effects (Boisgontier & Cheval, 2016; Giboin et al., 2020; Hill et al., 2024; Kumari et al., 2020). Individual slopes were not included due our small sample size and avoid convergence issues with an overly complex model (Burnham & Anderson, 2004; Matuschek et al., 2017; Meteyard & Davies, 2020). The model selection approach in which variables of interest were entered into the model and were retained based on the Akaike information criterion (AIC). Effect size d was calculated using previously recognized methods (Brysbaert & Stevens, 2018; Westfall et al., 2014). All follow-up analysis for multiple comparisons, main effects and interactions were performed with a Sidak correction. All frequentist statistical analysis was conducted in SPSS v26 (IBM Corp., Armonk, NY, United States).

Alongside the frequentist statistics, Bayesian versions of each analysis were performed comparing against the null model (Keysers

et al., 2020a; Palidis et al., 2021; Rouder et al., 2012; Wagenmakers et al., 2018). Bayes factors (BF_{10}) was used to provide evidence for or against the null hypothesis. Bayes factors > 3 and > 10 were taken as moderate and strong evidence in favor of the alternative hypothesis, respectively. Bayes factors $< 1/3$ and $< 1/10$ were taken as moderate and strong evidence in favor of the null hypothesis, respectively. Bayes factors between $1/3$ and 3 were taken as inconclusive evidence (Dienes, 2014; Keyesers et al., 2020b). Bayesian ANOVAs and RMANOVAs were conducted with prior of 0.5 for the fixed effects (r scale Cauchy prior width = 0.5) (Wagenmakers et al., 2018) in JASP 0.19.3.0 (van Doorn et al., 2021). Bayesian ANOVAs and RMANOVAs were performed with the same between and within-subjects factors and as their frequentist counterparts. Bayesian linear mixed models were performed using R (R Core Team, 2024) using the lmerTest (Kuznetsova et al., 2017) and BayesFactor (Morey & Rouder, 2018) packages. As with the frequentist analysis, Feedback Group (Reward, Punishment, Control), Feedback Type (Target, Neutral), and Action Condition (Active, Passive) were held as fixed effects and individual subjects' intercept were held as random effects with Jeffreys-Zellner-Siow priors with default r scale = 0.5 for fixed effects and r scale = 1.0 for random effects.

4. Results

The experimental paradigm PsychoPy code and data are available at https://osf.io/an6fh/?view_only=06f516fcec1548e880f111bebd0b4cbe.

4.1. Participant characteristics

To ensure similarity between groups and to confirm successful randomization we analyzed the demographic and reinforcement sensitivity variables. All groups demonstrated similar descriptive characteristics (Table 1). A One-way ANOVA revealed there were no significant differences among the three testing groups for EHI ($F(2,30) = 0.392, p = 0.679, \eta_p^2 = 0.025, BF_{10} = 0.259$) and Age ($F(2,30) = 0.587, p = 0.562, \eta_p^2 = 0.038, BF_{10} = 0.294$). All groups demonstrated similar sensitivity to reinforcement feedback. A One-way ANOVA revealed there was no significant difference among the three testing groups on the four subscales within the BAS/BIS scale [BAS Drive ($F(2,30) = 0.070, p = 0.932, \eta_p^2 = 0.005, BF_{10} = 0.210$), BAS FUN ($F(2,30) = 0.599, p = 0.556, \eta_p^2 = 0.038, BF_{10} = 0.297$), BAS Reward Responsiveness ($F(2,30) = 0.471, p = 0.629, \eta_p^2 = 0.030, BF_{10} = 0.273$), BIS ($F(2,30) = 0.260, p = 0.772, \eta_p^2 = 0.017, BF_{10} = 0.238$)]. In summation, all groups were similar across descriptive and psychological factors.

4.2. Judgement error

An objective of this study was to examine how different types of feedback influences temporal judgment performance across different time intervals (200, 400, 800) and task conditions (Active, Passive). To this end, we tested the average judgement error within each interval and average across intervals. Equality of variance was tested across time intervals using Levene's Test [Active ($F(2,96) = 2.064, p = 0.133, BF_{10} = 0.482$), Passive ($F(2,96) = 1.980, p = 0.144, BF_{10} = 0.245$)]. Judgement error increased as the time interval increased in both the Active and Passive conditions (Fig. 2A). A significant main effect was found for Interval ($F(2,60) = 18.921, p < 0.001, \eta_p^2 = 0.387, BF_{10} = 57836.039$) in the Active condition. Post-hoc comparisons revealed lower judgement error in interval 200 compared 400 [MD: 28.013, $p = 0.015$, 95 % CIs = 0.471–55.555, $d = 0.493, BF_{10} = 1.765$] and 800 [MD: 68.417, $p < 0.001$, 95 % CIs = 40.875–95.959, $d = 1.203, BF_{10} = 2225213.962$]. Moreover, a lower judgement error was found in interval 400 compared to 800 [MD: 40.404, $p = 0.002$, 95 % CIs = 12.862–67.946, $d = 0.711, BF_{10} = 14.508$]. No significant differences were found between Groups ($F(2,30) = 1.131, p = 0.336, \eta_p^2 = 0.070, BF_{10} = 0.318$).

A significant main effect for Interval ($F(2,60) = 18.321, p < 0.001, \eta_p^2 = 0.379, BF_{10} = 22467.963$) for the Passive condition. Post-hoc comparisons revealed lower judgement error in interval 200 compared to 400 [MD: 56.957, $p = 0.001$, 95 % CIs = 28.891–85.022, $d = 0.994, BF_{10} = 950.106$] and 800 [MD: 62.171, $p < 0.001$, 95 % CIs = 34.106–90.236, $d = 1.085, BF_{10} = 1029.340$]. No significant differences were found between intervals 400 and 800 [MD: 5.214, $p = 0.649$, 95 % CIs = -33.279–22.85, $d = 0.091, BF_{10} = 0.205$]. No significant differences were found between Groups ($F(2,30) = 1.131, p = 0.336, \eta_p^2 = 0.070, BF_{10} = 0.309$).

Average judgement error was different when the participant pressed the space bar than when the experimenter pressed it. A significant main effect for Condition ($F(1,30) = 8.988, p = 0.005, \eta_p^2 = 0.231, BF_{10} = 5.369$) was found where average judgement error during the Passive condition was higher compared to the Active condition [MD: 18.213, $p = 0.005$, 95 % CIs = 5.806–30.620, $d = 0.462, BF_{10} = 5.259$]. No significant differences were found between Groups ($F(2,30) = 1.131, p = 0.336, \eta_p^2 = 0.017, BF_{10} = 0.289$) (Fig. 2B). These results show a linear relationship between time interval length and judgement error, without an effect of reinforcement feedback. Moreover, the task role of the participant (Active v. Passive) is more influential on judgement error than feedback valence alone.

Table 1
Participant Descriptive Data. Presented as mean $\pm$ standard deviation.

Group	Age (Years)	EHI	BAS DRIVE	BAS FUN	BAS REWARD	BIS
REWARD	21.27 $\pm$ 0.13	54.45 $\pm$ 6.18	11.00 $\pm$ 0.19	11.63 $\pm$ 0.22	17.72 $\pm$ 0.14	21.09 $\pm$ 0.35
PUNISHMENT	22.45 $\pm$ 0.33	73.23 $\pm$ 4.94	11.18 $\pm$ 0.18	12.00 $\pm$ 0.15	18.45 $\pm$ 0.19	22.18 $\pm$ 0.19
CONTROL	21.81 $\pm$ 0.26	73.00 $\pm$ 5.92	10.81 $\pm$ 0.28	12.55 $\pm$ 0.21	18.18 $\pm$ 0.18	21.18 $\pm$ 0.41

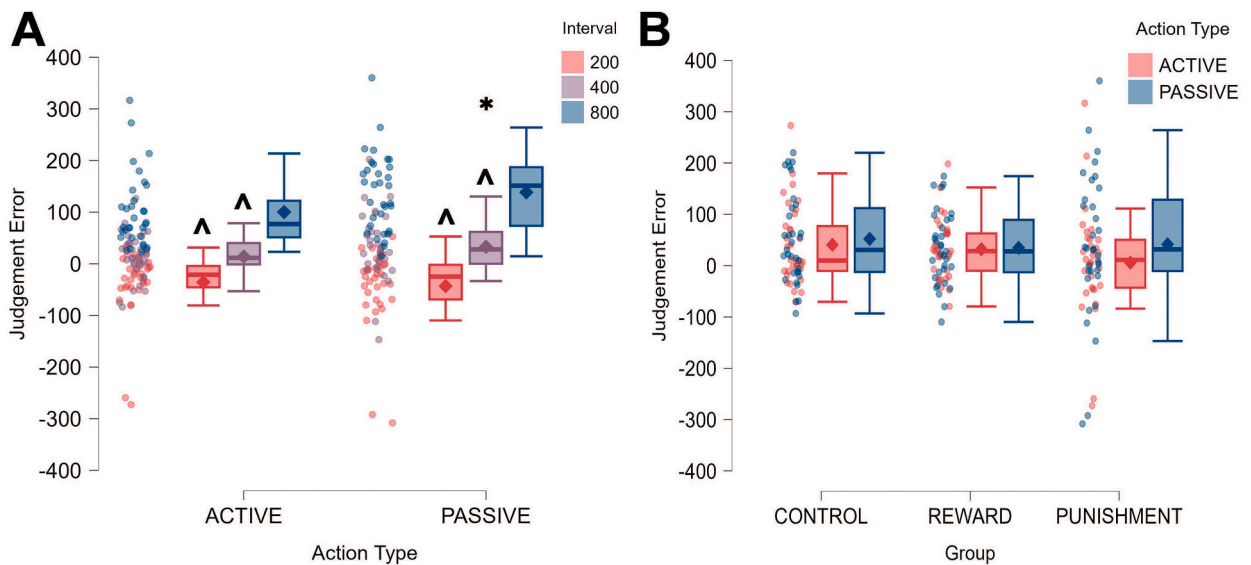


Fig. 2. A. Boxplots for Judgement Error for each time interval [200 ms (red), 400 ms (purple), 800 ms (blue)] in the Active and Passive conditions. Box ends represent the interquartile range (IQR) [25th percentile (Q1) – 75th percentile (Q3)]. Whiskers represent minimum (Q1–1.5*IQR) and maximum (Q3 + 1.5*IQR). Median is represented by horizontal line inside of the box. Diamonds represent means and dots represent individual data. * = significantly different from Active. ^ = significantly different from 800 ms. B. Boxplots for Reward, Punishment, and Control groups' Judgement Error in the Active (red) and Passive (blue) conditions. Diamonds represent means and dots represent individual data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.3. Action-outcome binding

To best assess how sense of agency is modified by different kinds of feedback, we evaluated action-outcome binding, a widely used measure for sense of agency, across different interval lengths. Action-outcome binding was dependent on the time interval and the assigned group. A significant main effect for Interval ($F(1.229, 36.863) = 21.550, p < 0.001, \eta_p^2 = 0.418, BF_{10} = 298528.867$) was found (Fig. 3). Post-hoc comparisons revealed lower action-outcome binding in interval 800 compared 200 [MD: 61.860, $p = 0.005$, 95 % CIs = 0.084–1.702, $d = 0.893, BF_{10} = 6.249$] and 400 [MD: 100.172, $p < 0.001$, 95 % CIs = 0.789–2.104, $d = 1.447, BF_{10} = 3592$]. Similarly, there was lower action-outcome binding in interval 200 compared to 400 [MD: 38.312, $p = 0.007$, 95 % CIs =

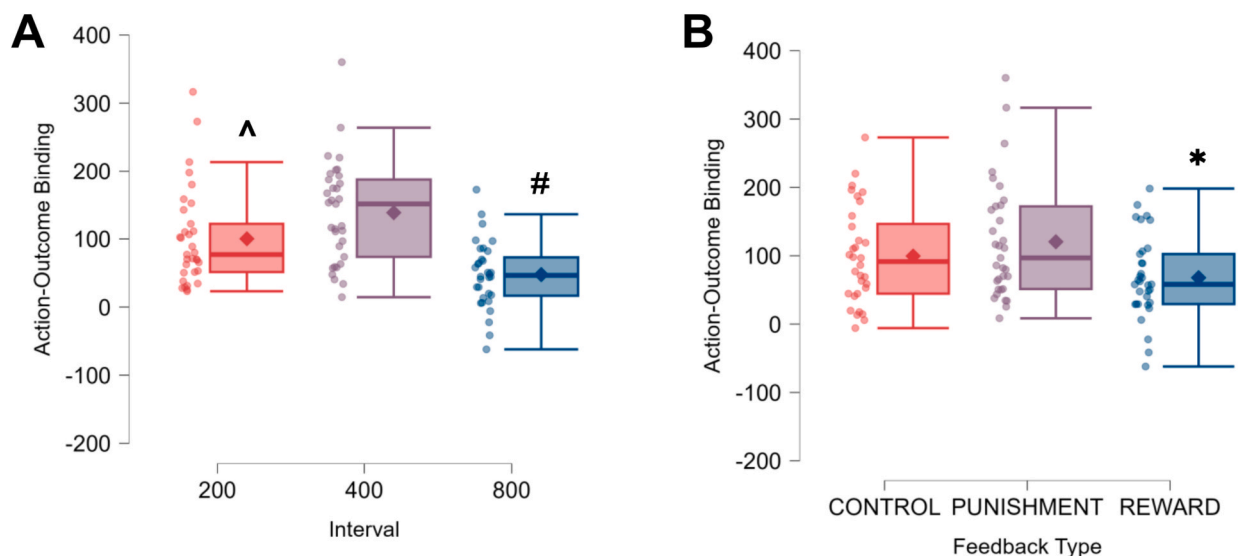


Fig. 3. A. Boxplots for Action-outcome Binding across the three time intervals [200 ms (pink), 400 ms (purple), 800 ms (blue)]. # = significantly different from 200 ms and 400 ms. ^ = significant different from 400 ms. B. Boxplots for Reward, Punishment, and Control groups' Action-outcome Binding. Diamonds represent means and dots represent individual data. * = significantly different from Punishment. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

0.095–1.011, $d = 0.553$, $BF_{10} = 8.508$]. A significant main effect for Group ($F(2,30) = 3.526$, $p = 0.042$, $\eta_p^2 = 0.190$, $BF_{10} = 0.773$) was found. Punishment elicited greater action-outcome binding across all intervals compared to Reward [MD: 52.588, $p = 0.039$, 95 % CIs = 2.017–103.159, $d = 0.759$, $BF_{10} = 7.627$] but not Control [MD: 31.747, $p = 0.244$, 95 % CIs = 18.823–82.318, $d = 0.458$, $BF_{10} = 0.601$]. No differences were found between Control and Reward [MD: 20.840, $p = 0.304$, 95 % CIs = –29.730–71.411, $d = 0.091$, $BF_{10} = 0.410$]. Taken together, we found that punishment increases action-outcome binding more than reward but not control feedback. Moreover, the length of interval modulated the magnitude of action-outcome binding regardless of group assignment.

4.4. Outcome event-related potentials

Outcome ERPs for the Reward, Punishment, and Control groups in Active and Passive conditions in Fz, Cz, and Pz electrodes can be found in Fig. 4. The average number of rejected trials across conditions (out of 180 total per participant) for each group was: Control (Mean = 5.56; SD = 5.88; 96.91 % trials retained), Reward (Mean = 1.91; SD = 2.84; 98.93 % trials retained), Punishment (Mean = 4.25; SD = 6.56; 97.63 % trials retained). The number of ICA components removed for each group ranged from 1 to 9 with the average, across conditions, for each group: Controls (Mean = 2.78; SD = 0.81), Reward (Mean = 3.32; SD = 1.34), Punishment (Mean = 4.05; SD = 1.84).

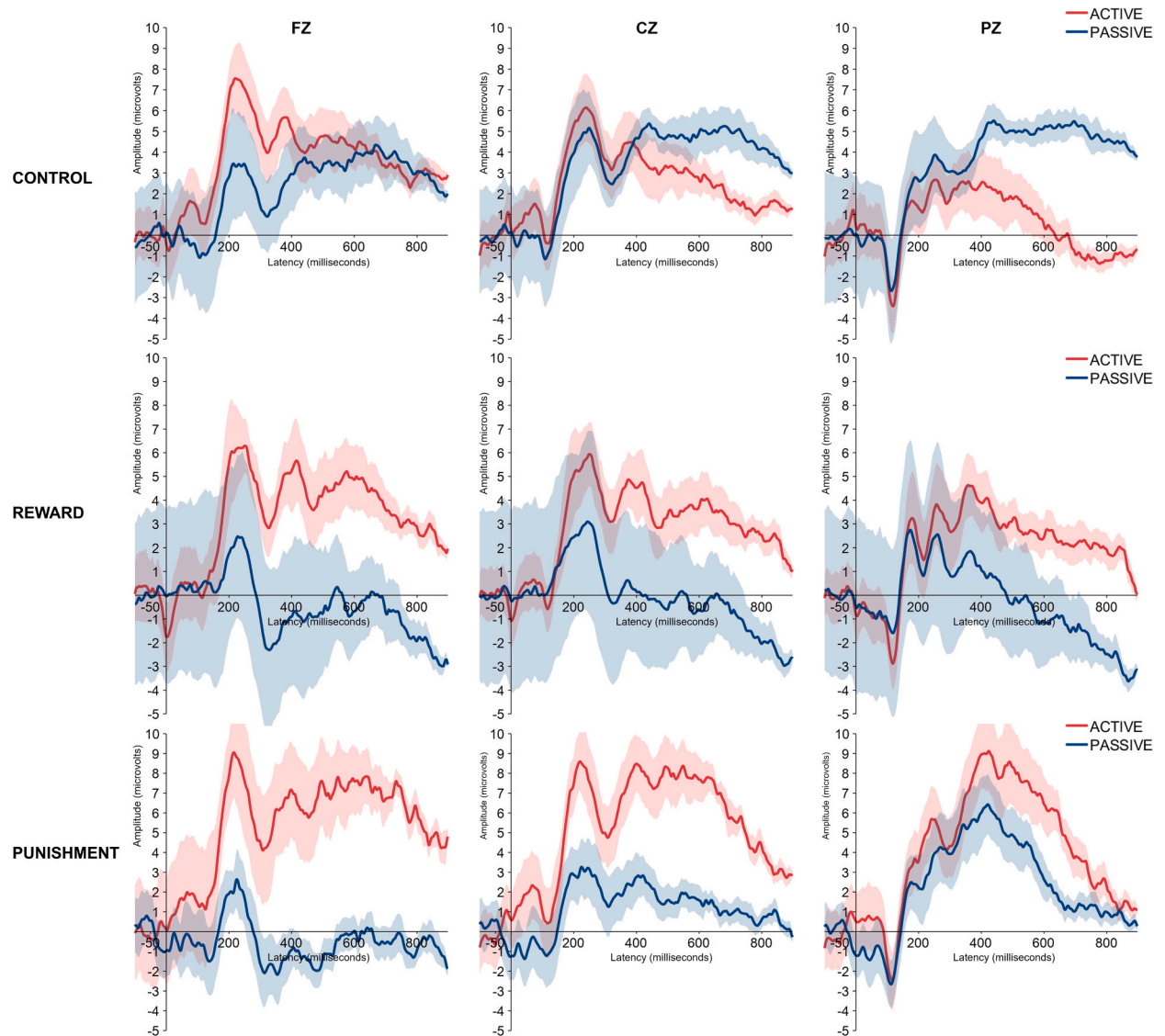


Fig. 4. Outcome event-related potentials after judgement feedback presentation for the Reward, Punishment, and Control groups in the Active (red) and Passive (blue) conditions in the Fz, Cz, and Pz electrodes. Shaded error-bars indicate standard error. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.5. N100 amplitude and latency

A goal of this study was to use N100, a frontal-central ERP that has been widely studied in the domain of agency (Gentsch et al., 2012; Gentsch & Schütz-Bosbach, 2011; Kaiser et al., 2021b; Majchrowicz & Wierchoń, 2021; Ren et al., 2023; Wen & Imamizu, 2022), as marker of interaction between agency and reinforcement. N100 changed between Active and Passive conditions in the Fz electrode (Fig. 5). A significant main effect for Condition was found for N100 amplitude ($F(2,84.192) = 7.431, p < 0.001, \eta_p^2 = 0.150, BF_{10} = 226.929$). The Active condition demonstrated a more positive N100 amplitude compared to the Passive condition [MD: 1.771, $p < 0.001, 95\% \text{ CIs} = 0.851\text{--}2.681, d = 1.320$]. N100 amplitude was similar between groups ($F(2,28.042) = 0.616, p = 0.547, \eta_p^2 = 0.041, BF_{10} = 0.205$) and feedback type ($F(2,84.047) = 0.033, p = 0.857, \eta_p^2 = 0.002, BF_{10} = 0.190$). N100 latency was similar feedback types ($F(1,83.934) = 0.002, p = 0.961, \eta_p^2 = 0.004, BF_{10} = 0.471$), and conditions ($F(1,84.424) = 0.633, p = 0.428, \eta_p^2 = 0.014, BF_{10} = 0.222$). Our one-way ANOVA between groups ($F(2,121) = 0.913, p = 0.480, \eta_p^2 = 0.015, BF_{10} = 0.165$) revealed no significant differences between groups. In short, we saw the participants' role (Active v Passive) changed N100 amplitude regardless of the feedback provided.

4.6. P300 amplitude and latency

To better understand how different feedback types influence cognitive processing in different agency conditions, we investigated P300 amplitude and latency in the Pz electrode. Punishment demonstrated higher P300 amplitude regardless of the condition (Fig. 6). A significant Group $\times$ Condition interaction was found for P300 amplitude ($F(2,84.220) = 4.067, p = 0.021, \eta_p^2 = 0.088, BF_{10} = 9.053$). Punishment elicited a higher P300 compared to Reward [MD: 5.554, $p = 0.04, 95\% \text{ CIs} = 0.192\text{--}10.915, d = 1.105$] and Control [MD: 7.131, $p = 0.006, 95\% \text{ CIs} = 1.781\text{--}12.480, d = 1.418$] feedback during the Active condition. Reward feedback elicited a higher P300 amplitude during the Active condition compared to Passive [MD: 2.421, $p = 0.038, 95\% \text{ CIs} = 0.140\text{--}4.702, d = 0.47$]. Punishment feedback also elicited a higher P300 amplitude during the Active condition compared to Passive [MD: 2.535, $p = 0.023, 95\% \text{ CIs} = 0.360\text{--}4.709, d = 0.471$]. No significant differences between Active and Passive conditions were found Control [MD: 1.161, $p = 0.192, 95\% \text{ CIs} = -3.836\text{--}0.783, d = 0.297$]. No significant differences between feedback types ($F(1,84.220) = 2.0976, p = 0.151, \eta_p^2 = 0.021, BF_{10} = 0.0506$). These findings indicate that agency (Active v Passive) specifically modulates the processing of reinforcement feedback.

Control feedback elicited a quicker P300 in comparison to reinforcement feedback. A significant main effect for Group was found for P300 latency ($F(2,27.901) = 5.077, p = 0.013, \eta_p^2 = 0.266, BF_{10} = 5.244$). Control demonstrated a faster P300 latency compared to Punishment [MD: 71.022, $p = 0.004, 95\% \text{ CIs} = 25.250\text{--}116.794, d = 1.324$] but not Reward [MD: 41.577, $p = 0.080, 95\% \text{ CIs} = 5.272\text{--}88.425, d = 0.775$]. No significant difference found between Reward and Punishment [MD: 29.445, $p = 0.198, 95\% \text{ CIs} = 16.310\text{--}75.202, d = 0.549$]. P300 latency was similar between feedback types ($F(1,83.934) = 1.711, p = 0.194, \eta_p^2 = 0.004, BF_{10} = 0.392$), and conditions ($F(1,84.424) = 0.774, p = 0.381, \eta_p^2 = 0.014, BF_{10} = 0.247$). These latency differences suggest that reinforcement feedback requires additional processing resources compared to neutral stimuli.



Fig. 5. Boxplots for N100 amplitude in microvolts for the Reward, Punishment, and Control groups in the Active (red) and Passive (blue) conditions in the Fz electrode. Diamonds represent means and dots represent individual data. * = significantly different from Passive condition. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

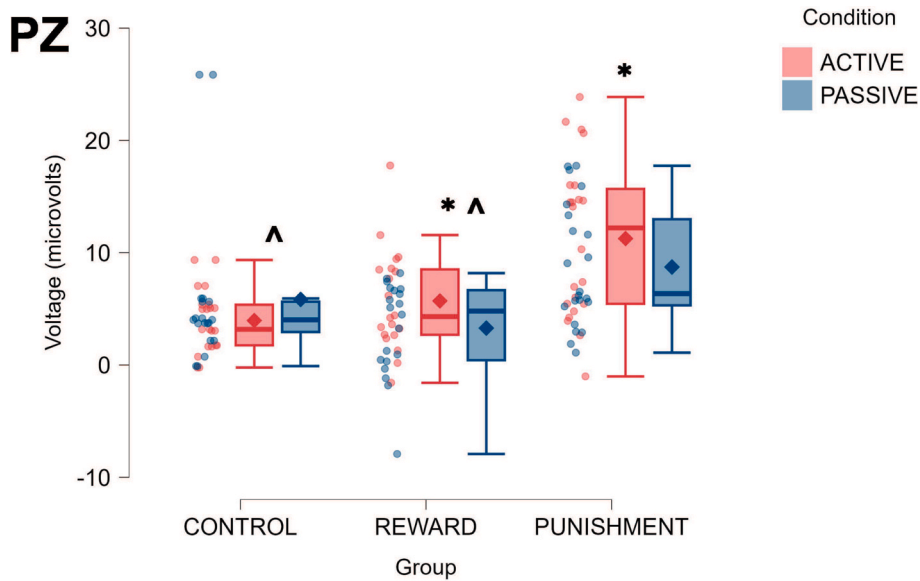


Fig. 6. Boxplots for P300 amplitude in microvolts for the Reward, Punishment, and Control groups in the Active (red) and Passive (blue) conditions in the Pz electrode. Diamonds represent mean and dots represent individual data. * = significantly different from Passive. ^ = significantly different from Punishment. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.7. Late positive potential amplitude and latency

The Late Positive Potential provides insight into affective processing associated with stimuli, making it a powerful tool for studying how agency and reinforcement interact. Punishment feedback changed brain activity more than Control and Reward feedbacks during the Active condition and compared to its Passive condition (Fig. 7). A significant Group $\times$ Condition interaction was found for late positive potential amplitude ($F(2,82.994) = 5.076$, $p = 0.008$, Westfall's $d = 1.411$, $BF_{10} = 5.777$). Post-hoc pairwise comparisons revealed the Punishment group had a higher late positive potential amplitude during the Active conditions compared to Control [MD: 6.955, $p = 0.010$, 95 % CIs = 1.397–12.494, $d = 1.334$] and Reward [MD: 6.243, $p = 0.024$, 95 % CIs = 0.680–11.805, $d = 1.119$].

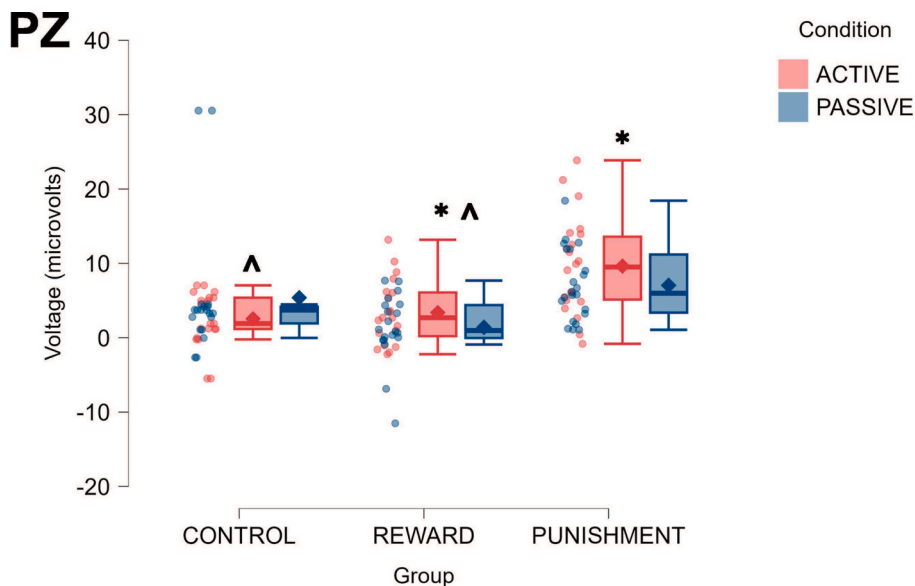


Fig. 7. Boxplots for Late Positive Potential amplitude in microvolts for the Reward, Punishment, and Control groups in the Active (red) and Passive (blue) conditions in the Pz electrode. Diamonds represent means and dots represent individual data. * = significantly different from Passive. ^ = significantly different from Punishment. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Punishment feedback also elicited a higher late positive potential amplitude during the Active condition compared to Passive [MD: 2.578, $p = 0.034$, 95 % CIs = 0.206–4.951, $d = 0.505$]. No significant differences were found for Control [MD: 2.434, $p = 0.055$, 95 % CIs = 0.056–4.924, $d = 0.454$] and Reward [MD: 1.988, $p = 0.116$, 95 % CIs = –0.502–4.478, $d = 0.371$] between task conditions. Late Positive Potential amplitude was similar between feedback types ($F(1,84.954) = 1.278$, $p = 0.264$, Westfall's $d = 0.138$, $BF_{10} = 0.345$). Overall, punishment feedback increases brain activity associated with affective processing, especially when participants were actively performing the task.

Control feedback elicited a quicker late positive potential in comparison to reinforcement feedback. A significant Group $\times$ Condition interaction was found for late positive potential latency ($F(2,84.602) = 6.159$, $p = 0.003$, $\eta_p^2 = 0.127$, $BF_{10} = 666.661$). Control feedback elicited a faster late positive potential in the Active condition compared to Punishment [MD: 60.166, $p = 0.015$, 95 % CIs = 9.442–110.890, $d = 1.243$] and Reward [MD: 68.220, $p = 0.006$, 95 % CIs = 16.288–120.152, $d = 1.243$]. No significant difference found between Reward and Punishment [MD: 8.055, $p = 0.973$, 95 % CIs = –42.976–59.085, $d = 0.165$]. Passive condition elicited a slower late positive potential latency compared to the Active condition [MD: 75.690, $p < 0.001$, 95 % CIs = 41.690–109.690, $d = 1.541$] for the Control group. No significant differences were found for Reward [MD: 5.700, $p = 0.738$, 95 % CIs = –28.016–39.416, $d = 0.114$] and Punishment [MD: 0.727, $p = 0.964$, 95 % CIs = –31.420–32.875, $d = 0.015$]. Late Positive Potential latency was similar between feedback types ($F(1,84.934) = 0.643$, $p = 0.424$, $\eta_p^2 = 0.007$, $BF_{10} = 0.230$). Taken together, the latency differences highlight the value and informational differences between reinforcement (Reward and Punishment) and neutral feedbacks.

5. Discussion

The purpose of this study was to evaluate how action-outcome binding was changed by modulating the valence of reinforcement feedback associated with temporal judgement accuracy and to examine the neural correlates underlying this feedback processing. We took the novel approach of changing the valence of feedback associated with task performance, rather than the outcome (i.e. tone) and found modulation of both agency and its underlying neural activity. Behaviorally, we found that punishment feedback elicited greater action-outcome binding than reward feedback, but not more than control feedback. Moreover, we found that judgement errors increased when participants took a passive role in the temporal estimation task. In line with our behavioral findings, punishment elicited greater late ERP amplitudes in comparison to reward and control feedback. However, the late ERP amplitudes for both reward and punishment decreased in the Passive condition compared to Active, showcasing the role of agency in processing reinforcement feedback.

5.1. Interval length and action type changed temporal judgement error

We found that judgement error was higher in longer intervals (~800 ms) than shorter ones (~200 ms, ~400 ms). These findings also align with Weber's Law, which describes the relationship between stimulus threshold for perception and stimulus intensity. This principle has been widely applied in time perception research (Erdoğan & Balci, 2024; Haigh et al., 2021). More specifically, research shows the ability to tell two time periods apart is still based on their ratio, not their absolute difference. The increase in error during the longer 800 ms interval may arise out of lower discriminability. Moreover, judgement error was higher in the Passive condition compared to Active. These results are in line with other previous studies in this domain (Asai & Tanno, 2008; Haggard et al., 2002; Imaizumi & Tanno, 2019; Ruess et al., 2017; Sato & Yasuda, 2005). Longer intervals and actions performed by others limit the integration of embodied sensory cues (i.e. proprioception) to be entangled with external consequences. As a result, the brain's forward models that generate a sense of agency are not adequately formed, leading to more error during longer intervals (Imaizumi & Tanno, 2019).

However, we did not find modulation of judgement error due to the type of feedback received. All groups had a similar amount of judgment error across the intervals. Previous studies in the context of skill learning, have found error is corrected more quickly when punished or rewarded (Abe et al., 2011; Galea et al., 2015; Steel et al., 2016). This lack of an effect could be attributed to the randomized presentation of the intervals. By randomizing the tone intervals, the task became more challenging, thus harder to correct errors from one trial to the next.

5.2. Punishment increased action-outcome binding

Previous studies have investigated outcome valence as a potential moderator of action-outcome binding. Aversive auditory tones associated with monetary loss decreased international binding compared to positive and neutral tones (Takahata et al., 2012; Yoshie & Haggard, 2013). However, another study found no modulation of temporal binding with appetitive and aversive faces (Moreton et al., 2017). Di Costa et al., (2018) evaluated the effect of feedback valence after outcome judgements were made (Di Costa et al., 2018). Importantly, this feedback was the same valence as the tone presented after their action and not in response to their judgement performance. They found greater international binding with negative feedback than reward feedback (Di Costa et al., 2018). Our results align with this finding in that punishment feedback after the participants made interval estimations, increased action-outcome binding compared to reward, but was not significantly different from control feedback. We suggest that providing punishment via monetary loss, increases the binding of the action and outcome via greater attention and arousal (Braem et al., 2013; Stürmer et al., 2011). Punishment feedback elicits more top-down control to avoid future punishments (Braem et al., 2013; Jean-Richard-Dit-Bressel et al., 2018; Stürmer et al., 2011), in turn leading to greater action and outcome binding.

Action-outcome binding was not different between control and reward feedback, which aligns with Yoshie & Haggard, (2013). This

indicates reward and control feedbacks create similar binding, despite the different feedback valence. It should be noted that our feedback presentation was different compared to these previous studies (Takahata et al., 2012; Yoshie & Haggard, 2013). Instead of modulating the valence of the tone, our novel approach modulated feedback associated with the participant's judgements (i.e. estimating the time between the button press and tone). This distinction in methodology could explain our divergent results and requires further testing.

5.3. Punishment after self-initiated actions attenuated early outcome event related potentials

N100, in part, represents immediate error and sensory processing (Kirschner et al., 2021; Ullsperger, Fischer et al., 2014). Previous studies have evaluated the effect of self- vs externally generated actions on outcome processing, using N100 (Gentsch et al., 2012; Gentsch & Schütz-Bosbach, 2011; Kaiser et al., 2021b; Majchrowicz & Wierzchoń, 2021; Ren et al., 2023; Wen & Imamizu, 2022). These studies show N100 amplitude decreases during self-generated outcomes, reflecting sensory attenuation. Other studies have compared the effect of different outcome valences on N100 amplitude when comparing self and externally generated actions. One study observed no effect of outcome valence (positive or negative) on N100 amplitude during self-generated outcomes (Gentsch et al., 2015). Our findings agree in part with these previous studies. Punishment feedback elicited a greater, N100 amplitude during the Passive condition compared to the Active condition, suggesting a sensory attenuation in error processing when pushing the button themselves. The amplitude attenuation during the Active condition can be attributed to the predictability of the outcome. A previous study noted N100 amplitude was not modulated by level of agency when outcomes were equally predictable (Kaiser & Schütz-Bosbach, 2018). During the Passive condition, participants were unable to form an adequate model of the task, as they did not actively press the button generating the tone. As a result, they are missing out on critical sensory information to form a complete model of the task. When feedback is then delivered in the Passive condition, the outcome is not as predictable, leading to a larger N100. Moreover, this effect is heightened with punishment feedback creating, a greater N100 when feedback is less predictable. This is similar to another study where N100 amplitude increased when punishment was delivered by a third-party (Ao et al., 2023). However, it should be noted that other studies have shown decreases in N100 amplitude when actions were caused under coercion (i.e. low agency) (Caspar et al., 2016) and no differences between active and passive actions (Han et al., 2021, 2022). Thus, more research is needed to understand how N100 is modulated by self- and externally generated actions.

5.4. Reinforcement feedback increased late outcome event related potentials amplitude and latency

P300 represents various aspects of human perception, including attention, significance, and valence (Hajcak & Foti, 2020; Polich, 2011; Wen & Haggard, 2018). In the context of agency, P300 increases with high agency compared to low agency conditions (Bellebaum et al., 2010; Fang et al., 2020; Hassall et al., 2019; Kaiser et al., 2021c; Mühlberger et al., 2017; Potts et al., 2011; Yi et al., 2018). Our findings align with this assertion, but as a function of feedback type. Reward and punishment feedback modulated P300 amplitude more in the Active condition compared to Passive and elicited a greater P300 compared to control feedback. Other studies have noted similar outcomes where P300 increased in response to a reward presented during an active task compared to a passive one (Hassall et al., 2019; Potts et al., 2011). Previous work suggests P300 reflects goal directed behavior and activity of the locus coeruleus (Bradley, 2009; Hajcak & Foti, 2020; Nieuwenhuis et al., 2005, 2011). We suggest reinforcement feedback activates the motivational circuits of locus coeruleus more during the Active condition than the Passive condition. However, it should be noted that, Majchrowicz et al., (2020) found no modulation of P300 with positive or negative outcomes during an interval estimation task (Majchrowicz et al., 2020b). This study evaluated the feedback valence associated with the outcome rather than feedback related to the participants interval judgement, as in this study.

P300 peak latency differed between groups. Control feedback elicited faster P300s compared to reinforcement feedback. Faster P300 latencies represent quicker stimuli classification (Polich, 2007, 2011) and lower cognitive load (Kok, 2001; Polich, 1987). Reinforcement feedback includes information regarding valence and direction of performance, which inherently increases the processing time and cognitive load placed on the brain. This amount of information and context is not present in control feedback, resulting in slower processing of reinforcement feedback.

The late positive potential has been linked to affective processing and the activation extent of appetitive or aversive motivational systems (Bradley, 2009; Hajcak & Foti, 2020; Hajcak & Olvet, 2008). Previous studies found increased late positive potential amplitude when viewing unpleasant images compared to pleasant or neutral (Beauchaine & Crowell, 2018; Hajcak et al., 2009; Hajcak & Olvet, 2008; Speed et al., 2015). Moreover, the late positive potential in response to aversive and appetitive images have divergent neural substrates. For instance, aversive stimuli recruit ventrolateral prefrontal, insula and cingulate cortex. Whereas appetitive stimuli recruit prefrontal cortex, amygdala and precuneus (Liu et al., 2012). Punishment feedback increased the amplitude of the late positive potential in comparison to reward and control feedbacks, which can be indicative of punishment feedback engaging different brain pathways, thus increasing late positive potential amplitude. Moreover, these effects were attenuated during the Passive condition, with punishment feedback demonstrating similar late positive potential amplitude as control feedback. Stimulus significance is a driver of late positive potential amplitude (Beauchaine & Crowell, 2018; Hajcak et al., 2009; Hajcak & Olvet, 2008; Speed et al., 2015). Our findings signify that punishment feedback when delivered after actions not executed by the person themselves, loses significance and value compared to when they actively engage in the task. This mirrors our behavioral findings; a greater action-outcome binding was found for the punishment group (i.e. less judgment error in the active condition compared to passive).

Like our P300 results, latencies for peak late positive potentials were faster for the control feedback compared to reward and punishment groups. In part, late positive potential represents emotional processing of stimuli. Given that control feedback has non-

valanced information, it does not recruit areas of the brain associated with emotional processing. Thus, resulting in quicker processing compared to reinforcement.

5.5. Limitations

Although this work provides valuable insight into the relationship between reinforcement and action-outcome binding, it is not without limitations. A single experimenter was used for all data collections. Though this ensured consistency across all the conditions and participants collected, it may introduce bias in the operating procedures which may influence the results. Future studies should provide counterbalanced experimenters to mitigate potential experimenter bias. Additionally, this study fell short of the needed sample size of 36, thus rendering our study under powered and reduces the stability of observed effects.

6. Conclusion

In conclusion, reinforcement feedback based on temporal judgement accuracy changes our sense of agency and cortical processes associated with outcome monitoring. Specifically, we found that when we perform actions ourselves, feedback associated with our judgements are perceived as being more salient and significant, opposed to actions generated by others. Moreover, aversive feedback (i.e. punishment) enhances this effect compared to more appetitive or neutral feedback. These findings could be important for understanding changes to human sense of control and agency in psychiatric disorders, such as schizophrenia and obsessive-compulsive disorder.

Ethics statement

The studies involving humans were approved by Northern Illinois University Institutional Review Board. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

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CRediT authorship contribution statement

Christopher M. Hill: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Numa Samnani:** Project administration, Methodology, Investigation, Data curation. **Leo Barzi:** Methodology, Investigation, Data curation. **Matt Wilson:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

References

- Abe, M., Schambra, H., Wassermann, E. M., Luckenbaugh, D., Schweighofer, N., & Cohen, L. G. (2011). Reward improves long-term retention of a motor memory through induction of offline memory gains. *Current Biology*, 21(7), 557–562. <https://doi.org/10.1016/j.cub.2011.02.030>
- Aluja, A., & Blanch, A. (2011). Neuropsychological behavioral inhibition system (BIS) and behavioral approach system (BAS) assessment: A shortened sensitivity to punishment and sensitivity to reward questionnaire version (SPSRQ-20). *Journal of Personality Assessment*, 93(6), 628–636. <https://doi.org/10.1080/00223891.2011.608760>
- Anguera, J. A., Seidler, R. D., & Gehring, W. J. (2009). Changes in performance monitoring during sensorimotor adaptation. *Journal of Neurophysiology*, 102(3), 1868–1879. <https://doi.org/10.1152/JN.00063.2009>
- Ao, L., Gao, Y., Yang, L., Du, X. Y., Wang, H., & Liu, Y. (2023). Group environment modulates how third parties assess unfairly shared losses and unfairly shared gains: Neural signatures from ERPs and EEG oscillations. *Journal of Clinical and Experimental Neuropsychology*, 45(9), 840–854. <https://doi.org/10.1080/13803395.2024.2313258>
- Asai, T., & Tanno, Y. (2008). Highly schizotypal students have a weaker sense of self-agency. *Psychiatry and Clinical Neurosciences*, 62(1), 115–119. <https://doi.org/10.1111/J.1440-1819.2007.01768.X>
- Balconi, M., & Crivelli, D. (2010). Veridical and false feedback sensitivity and punishment-reward system (BIS/BAS): ERP amplitude and theta frequency band analysis. *Clinical Neurophysiology*, 121(9), 1502–1510. <https://doi.org/10.1016/J.CLINPH.2010.03.015>
- Barlas, Z., Hockley, W. E., & Obhi, S. S. (2017). The effects of freedom of choice in action selection on perceived mental effort and the sense of agency. *Acta Psychologica*, 180, 122–129. <https://doi.org/10.1016/j.actpsy.2017.09.004>
- Barlas, Z., Hockley, W. E., & Obhi, S. S. (2018). Effects of free choice and outcome valence on the sense of agency: Evidence from measures of intentional binding and feelings of control. *Experimental Brain Research*, 236(1), 129–139. <https://doi.org/10.1007/S00221-017-5112-3/FIGURES/3>
- Beauchaine, T. P., & Crowell, S. E. (2018). *The oxford handbook of emotion dysregulation. The Oxford Handbook of Emotion Dysregulation*, 1–502. <https://doi.org/10.1093/OXFORDHB/9780190689285.001.0001>
- Bellebaum, C., Kobza, S., Thiele, S., & Daum, I. (2010). It was not MY Fault: Event-related brain potentials in active and observational learning from feedback. *Cerebral Cortex*, 20(12), 2874–2883. <https://doi.org/10.1093/CERCOR/BHQ038>

- Boisgontier, M. P., & Cheval, B. (2016). The anova to mixed model transition. *Neuroscience & Biobehavioral Reviews*, 68, 1004–1005. <https://doi.org/10.1016/J.NEUBIOREV.2016.05.034>
- Bradley, M. M. (2009). Natural selective attention: Orienting and emotion. *Psychophysiology*, 46(1), 1–11. <https://doi.org/10.1111/J.1469-8986.2008.00702.X>
- Braem, S., Duthoo, W., & Notebaert, W. (2013). Punishment sensitivity predicts the impact of punishment on cognitive control. *PLoS One*, 8(9), Article e74106. <https://doi.org/10.1371/JOURNAL.PONE.0074106>
- Brysbaert, M., & Stevens, M. (2018). Power analysis and effect size in mixed effects models: A tutorial. *Journal of Cognition*, 1(1), 9. <https://doi.org/10.5334/JOC.10/GALLEY/20/DOWNLOAD/>
- Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. In *Sociological Methods and Research* (Vol. 33, Issue 2, pp. 261–304). Sage Publications/Sage CA: Thousand Oaks, CA. doi: [10.1177/0049124104268644](https://doi.org/10.1177/0049124104268644).
- Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS scales. *Journal of Personality and Social Psychology*, 67(2), 319–333. <https://doi.org/10.1037/0022-3514.67.2.319>
- Caspar, E. A., Christensen, J. F., Cleeremans, A., & Haggard, P. (2016). Coercion changes the sense of agency in the human brain. *Current Biology*, 26(5), 585. <https://doi.org/10.1016/J.CUB.2015.12.067>
- Caspar, E. A., Lo Bue, S., De Saldanha, M., da Gama, P. A., Haggard, P., & Cleeremans, A. (2020). The effect of military training on the sense of agency and outcome processing. *Nature Communications*, 11(1), 1–10. <https://doi.org/10.1038/s41467-020-18152-x>
- Cohen, M. X., Wilmes, K., & van de Vijver, I. (2011). Cortical electrophysiological network dynamics of feedback learning. *Trends in Cognitive Sciences*, 15(12), 558–566. <https://doi.org/10.1016/J.TICS.2011.10.004>
- Del Popolo Cristaldi, F., Palmiotti, G. P., Cellini, N., & Sarlo, M. (2024). Pulling the lever in a hurry: The influence of impulsivity and sensitivity to reward on moral decision-making under time pressure. *BMC Psychology*, 12(1), 1–11. <https://doi.org/10.1186/s40359-024-01773-Y/FIGURES/4>
- Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1), 9–21. <https://doi.org/10.1016/J.JNEUMETH.2003.10.009>
- Di Costa, S., Théro, H., Chambon, V., & Haggard, P. (2018). Try and try again: Post-error boost of an implicit measure of agency. *The Quarterly Journal of Experimental Psychology*, 71(7), 1584–1595. https://doi.org/10.1080/17470218.2017.1350871/ASSET/IMAGES/LARGE/10.1080_17470218.2017.1350871-FIG4.JPEG
- Dienes, Z. (2014). Using Bayes to get the most out of non-significant results. *Frontiers in Psychology*, 5, 85883. <https://doi.org/10.3389/FPSYG.2014.00781/BIBTEX>
- Erdogan, M., & Balci, F. (2024). Absolute, not perceived, delay modulates agency judgement: Evidence for cognitive impenetrability of sense of agency. *The Quarterly Journal of Experimental Psychology*. <https://doi.org/10.1177/17470218241306433>
- Fang, H., Wan, X., Zheng, S., & Meng, L. (2020). The Spillover effect of autonomy frustration on human motivation and its electrophysiological representation. *Frontiers in Human Neuroscience*, 14. <https://doi.org/10.3389/FNHUM.2020.00134/PDF>
- 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. <https://doi.org/10.1002/HBM.21182>
- Galea, J. M., Mallia, E., Rothwell, J., & Diedrichsen, J. (2015). The dissociable effects of punishment and reward on motor learning. *Nature Neuroscience*, 18(4), 597–602. <https://doi.org/10.1038/nn.3956>
- Gehring, W. J., & Willoughby, A. R. (2002). The medial frontal cortex and the rapid processing of monetary gains and losses. *Science*, 295(5563), 2279–2282. <https://doi.org/10.1126/science.1066893>
- Gentsch, A., Schütz-Bosbach, S., Endrass, T., & Kathmann, N. (2012). Dysfunctional forward model mechanisms and aberrant sense of agency in obsessive-compulsive disorder. *Biological Psychiatry*, 71(7), 652–659. <https://doi.org/10.1016/J.BIOPSYCH.2011.12.022>
- Gentsch, A., & Schütz-Bosbach, S. (2011). I did it: Unconscious expectation of sensory consequences modulates the experience of self-agency and its functional signature. *Journal of Cognitive Neuroscience*, 23(12), 3817–3828. <https://doi.org/10.1162/JOCN.A.00012>
- Gentsch, A., Weiss, C., Spengler, S., Synofzik, M., & Schütz-Bosbach, S. (2015). Doing good or bad: How interactions between action and emotion expectations shape the sense of agency. *Social Neuroscience*, 10(4), 418–430. <https://doi.org/10.1080/17470919.2015.1006374>
- Giboin, L. S., Tokuno, C., Kramer, A., Henry, M., & Gruber, M. (2020). Motor learning induces time-dependent plasticity that is observable at the spinal cord level. *The Journal of Physiology*, 598(10), 1943–1963. <https://doi.org/10.1113/JP278890>
- Haggard, P. (2017). Sense of agency in the human brain. *Nature Reviews Neuroscience*, 18(4), 196–207. <https://doi.org/10.1038/nrn.2017.14>
- Haggard, P., Clark, S., & Kalogeras, J. (2002). Voluntary action and conscious awareness. *Nature Neuroscience*, 5(4), 382–385. <https://doi.org/10.1038/NN827>
- Haigh, A., Aphorop, D., & Bizo, L. A. (2021). The role of Weber's law in human time perception. *Attention, Perception, and Psychophysics*, 83(1), 435–447. <https://doi.org/10.3758/S13414-020-02128-6/FIGURES/8>
- Hajcak, G., Dunning, J. P., & Foti, D. (2009). Motivated and controlled attention to emotion: Time-course of the late positive potential. *Clinical Neurophysiology*, 120(3), 505–510. <https://doi.org/10.1016/J.CLINPH.2008.11.028>
- Hajcak, G., & Foti, D. (2020). Significance?... Significance! Empirical, methodological, and theoretical connections between the late positive potential and P300 as neural responses to stimulus significance: An integrative review. *Psychophysiology*, 57(7), Article e13570. <https://doi.org/10.1111/PSYP.13570>
- Hajcak, G., Holroyd, C. B., Moser, J. S., & Simons, R. F. (2005). Brain potentials associated with expected and unexpected good and bad outcomes. *Psychophysiology*, 42(2), 161–170. <https://doi.org/10.1111/J.1469-8986.2005.00278.X>
- Hajcak, G., & Olvet, D. M. (2008). The persistence of attention to emotion: Brain potentials during and after picture presentation. *Emotion (Washington, D.C.)*, 8(2), 250–255. <https://doi.org/10.1037/1528-3542.8.2.250>
- Han, N., Jack, B. N., Hughes, G., Elijah, R. B., & Whitford, T. J. (2021). Sensory attenuation in the absence of movement: Differentiating motor action from sense of agency. *Cortex*, 141, 436–448. <https://doi.org/10.1016/J.CORTEX.2021.04.010>
- Han, N., Jack, B. N., Hughes, G., & Whitford, T. J. (2022). The role of action–Effect contingency on sensory attenuation in the absence of movement. *Journal of Cognitive Neuroscience*, 34(8), 1488–1499. <https://doi.org/10.1162/JOCN.A.01867>
- Hassall, C. D., Hajcak, G., & Krigolson, O. E. (2019). The importance of agency in human reward processing. *Cognitive, Affective and Behavioral Neuroscience*, 19(6), 1458–1466. <https://doi.org/10.3758/S13415-019-00730-2/FIGURES/4>
- Hill, C. M., Sebastião, E., Barzi, L., Wilson, M., & Wood, T. (2024). Reinforcement feedback impairs locomotor adaptation and retention. *Frontiers in Behavioral Neuroscience*, 18, Article 1388495. <https://doi.org/10.3389/FNBEH.2024.1388495>
- Hill, C. M., Stringer, M., Waddell, D. E., & Del Arco, A. (2020). Punishment feedback impairs memory and changes cortical feedback-related potentials during motor learning. *Frontiers in Human Neuroscience*, 14. <https://doi.org/10.3389/fnhum.2020.00294>
- Hill, C. M., Waddell, D. E., & Del Arco, A. (2021). Cortical preparatory activity during motor learning reflects visuomotor retention deficits after punishment feedback. *Experimental Brain Research*, 239(11), 3243–3254. <https://doi.org/10.1007/s00221-021-06200-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. <https://doi.org/10.1037/0033-295X.109.4.679>
- Imazumi, S., & Tanno, Y. (2019). Intentional binding coincides with explicit sense of agency. *Consciousness and Cognition*, 67, 1–15. <https://doi.org/10.1016/J.CONCOG.2018.11.005>
- Jean-Richard-Dit-Bressel, P., Killcross, S., & McNally, G. P. (2018). Behavioral and neurobiological mechanisms of punishment: implications for psychiatric disorders. *Neuropsychopharmacology*, 43(8), 1639–1650. <https://doi.org/10.1038/s41386-018-0047-3>
- Kaiser, J., Buciuman, M., Gigl, S., Gentsch, A., & Schütz-Bosbach, S. (2021). The interplay between affective processing and sense of agency during action regulation: A review. *Frontiers in Psychology*, 12, Article 716220. <https://doi.org/10.3389/FPSYG.2021.716220/BIBTEX>
- Kaiser, J., Buciuman, M., Gigl, S., Gentsch, A., & Schütz-Bosbach, S. (2021b). The Interplay Between Affective Processing and Sense of Agency During Action Regulation: A Review. In *Frontiers in Psychology* (Vol. 12, p. 716220). Frontiers Media S.A. doi: 10.3389/fpsyg.2021.716220.
- Kaiser, J., & Schütz-Bosbach, S. (2018). Sensory attenuation of self-produced signals does not rely on self-specific motor predictions. *The European Journal of Neuroscience*, 47(11), 1303–1310. <https://doi.org/10.1111/EJN.13931>

- Keyesers, C., Gazzola, V., & Wagenmakers, E. J. (2020). Using Bayes factor hypothesis testing in neuroscience to establish evidence of absence. *Nature Neuroscience*, 23(7), 788–799. <https://doi.org/10.1038/s41593-020-0660-4>
- Kirschner, H., Humann, J., Derrfuss, J., Danielmeier, C., & Ullsperger, M. (2021). Neural and behavioral traces of error awareness. *Cognitive, Affective and Behavioral Neuroscience*, 21(3), 573–591. <https://doi.org/10.3758/S13415-020-00838-W/FIGURES/8>
- Kok, A. (2001). On the utility of P3 amplitude as a measure of processing capacity. *Psychophysiology*, 38(3), 557–577. <https://doi.org/10.1017/S0048577201990559>
- Krigolson, O. E. (2018). Event-related brain potentials and the study of reward processing: Methodological considerations. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, 132(Pt B), 175–183. <https://doi.org/10.1016/J.IJPSYCHO.2017.11.007>
- Kühn, S., Brass, M., & Haggard, P. (2013). Feeling in control: Neural correlates of experience of agency. *Cortex*, 49(7), 1935–1942. <https://doi.org/10.1016/J.CORTEX.2012.09.002>
- Kühn, S., Nenchev, I., Haggard, P., Brass, M., Gallinat, J., & Voss, M. (2011). Whodunnit? Electrophysiological Correlates of Agency Judgements. *PLoS One*, 6(12), Article e28657. <https://doi.org/10.1371/JOURNAL.PONE.0028657>
- Kumari, N., Taylor, D., Rashid, U., Vandal, A. C., Smith, P. F., & Signal, N. (2020). Cerebellar transcranial direct current stimulation for learning a novel split-belt treadmill task: a randomised controlled trial. *Scientific Reports* 2020 10:1, 10(1), 1–14. doi: 10.1038/s41598-020-68825-2.
- 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. <https://doi.org/10.18637/JSS.V082.I13>
- Lakens, D. (2022). Sample size justification. *Collabra Psychology*, 8(1). <https://doi.org/10.1525/COLLABRA.33267/120491>
- Liu, Y., Huang, H., McGinnis-Deweese, M., Keil, A., & Ding, M. (2012). neural substrate of the late positive potential in emotional processing. *Journal of Neuroscience*, 32(42), 14563–14572. <https://doi.org/10.1523/JNEUROSCI.3109-12.2012>
- Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: An open-source toolbox for the analysis of event-related potentials. *Frontiers in Human Neuroscience*, 8(1 APR), 213. <https://doi.org/10.3389/FNHUM.2014.00213/BIBTEX>
- Luck, S. J. (2022). *Applied Event-Related Potential Data Analysis*. LibreTexts. <https://doi.org/10.18115/D5QG92>
- Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn't). *Psychophysiology*, 54(1), 146–157. <https://doi.org/10.1111/PSYP.12639>
- Maclean, S. J., Hassall, C. D., Ishigami, Y., Krigolson, O. E., & Eskes, G. A. (2015). Using brain potentials to understand prism adaptation: The error-related negativity and the p300. *Frontiers in Human Neuroscience*, 9(June), 1–14. <https://doi.org/10.3389/fnhum.2015.00335>
- Majchrowicz, B., Kulakova, E., Di Costa, S., & Haggard, P. (2020). Learning from informative losses boosts the sense of agency. *The Quarterly Journal of Experimental Psychology*, 73(12), 2272–2289. https://doi.org/10.1177/1747021820958258/ASSET/IMAGES/LARGE/10.1177_1747021820958258-FIG8.JPEG
- Majchrowicz, B., & Wierzbicki, M. (2021). Sensory attenuation of action outcomes of varying amplitude and valence. *Consciousness and Cognition*, 87, Article 103058. <https://doi.org/10.1016/J.CONCOG.2020.103058>
- Malik, R. A., Galang, C. M., & Finger, E. (2022). The sense of agency for brain disorders: A comprehensive review and proposed framework. *Neuroscience & Biobehavioral Reviews*, 139, Article 104759. <https://doi.org/10.1016/J.NEUBIOREV.2022.104759>
- Matuschek, H., Kliegl, R., Vasishth, S., Baayen, H., & Bates, D. (2017). Balancing Type I error and power in linear mixed models. *Journal of Memory and Language*, 94, 305–315. <https://doi.org/10.1016/J.JML.2017.01.001>
- Meadows, C. C., Gable, P. A., Lohse, K. R., & Miller, M. W. (2016). The effects of reward magnitude on reward processing: An averaged and single trial event-related potential study. *Biological Psychology*, 118, 154–160. <https://doi.org/10.1016/j.biopsycho.2016.06.002>
- Meteyard, L., & Davies, R. A. I. (2020). Best practice guidance for linear mixed-effects models in psychological science. *Journal of Memory and Language*, 112, Article 104092. <https://doi.org/10.1016/J.JML.2020.104092>
- Moore, J. W. (2016). What is the sense of agency and why does it matter? *Frontiers in Psychology*, 7(AUG), Article 209433. <https://doi.org/10.3389/FPSYG.2016.01272/BIBTEX>
- Moore, J. W., & Obhi, S. S. (2012). Intentional binding and the sense of agency: A review. In *Consciousness and Cognition* (Vol. 21, Issue 1, pp. 546–561). Academic Press. doi: 10.1016/j.concog.2011.12.002.
- Moreton, J., Callan, M. J., & Hughes, G. (2017). How much does emotional valence of action outcomes affect temporal binding? *Consciousness and Cognition*, 49, 25–34. <https://doi.org/10.1016/J.CONCOG.2016.12.008>
- Morey, R. D., & Rouder, J. N. (2018). *Bayesfactor: Computation of Bayes Factors for Common Designs*. <https://philpapers.org/rec/MORBCO-2>.
- Mühlberger, C., Angus, D. J., Jonas, E., Harmon-Jones, C., & Harmon-Jones, E. (2017). Perceived control increases the reward positivity and stimulus preceding negativity. *Psychophysiology*, 54(2), 310–322. <https://doi.org/10.1111/psyp.12786>
- Nieuwenhuis, S., De Geus, E. J., & Aston-Jones, G. (2011). The anatomical and functional relationship between the P3 and autonomic components of the orienting response. *Psychophysiology*, 48(2), 162–175. <https://doi.org/10.1111/J.1469-8986.2010.01057.X>
- Nieuwenhuis, S., Holroyd, C. B., Mol, N., & Coles, M. G. H. (2004). Reinforcement-related brain potentials from medial frontal cortex: Origins and functional significance. *Neuroscience & Biobehavioral Reviews*, 28(4), 441–448. <https://doi.org/10.1016/J.NEUBIOREV.2004.05.003>
- Nieuwenhuis, S., Ridderinkhof, K. R., Talsma, D., Coles, M. G. H., Holroyd, C. B., Kok, A., & Van Der Molen, M. W. (2002). A computational account of altered error processing in older age: Dopamine and the error-related negativity. *Cognitive, Affective and Behavioral Neuroscience*, 2(1), 19–36. <https://doi.org/10.3758/CABN.2.1.19>
- Nieuwenhuis, S., Slagter, H. A., Von Altting Geusau, N. J., Heslenfeld, D. J., & Holroyd, C. B. (2005). Knowing good from bad: Differential activation of human cortical areas by positive and negative outcomes. *The European Journal of Neuroscience*, 21(11), 3161–3168. <https://doi.org/10.1111/J.1460-9568.2005.04152.X>
- Oldfield, R. C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychologia*, 9(1), 97–113. [https://doi.org/10.1016/0028-3932\(71\)90067-4](https://doi.org/10.1016/0028-3932(71)90067-4)
- Palidis, D. J., Cashaback, J. G. A., & Gribble, P. L. (2019). Neural signatures of reward and sensory error feedback processing in motor learning. *Journal of Neurophysiology*, 121(4), 1561–1574. <https://doi.org/10.1152/jn.00792.2018>
- Palidis, D. J., McGregor, H. R., Vo, A., MacDonald, P. A., & Gribble, P. L. (2021). Null effects of levodopa on reward- and error-based motor adaptation, savings, and anterograde interference. *Journal of Neurophysiology*, 126(1), 47–67. <https://doi.org/10.1152/jn.00696.2020>
- Polich, J. (1987). Task difficulty, probability, and inter-stimulus interval as determinants of P300 from auditory stimuli. *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, 68(4), 311–320. [https://doi.org/10.1016/0168-5597\(87\)90052-9](https://doi.org/10.1016/0168-5597(87)90052-9)
- Polich, J. (2007). Updating P300: An Integrative Theory of P3a and P3b. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, 118(10), 2128. <https://doi.org/10.1016/J.CLINPH.2007.04.019>
- Polich, J. (2011). Neuropsychology of P300. *The Oxford Handbook of Event-Related Potential Components*. <https://doi.org/10.1093/OXFORDHB/9780195374148.013.0089>
- Potts, G. F. (2011). Impact of Reward and punishment Motivation on Behavior monitoring as indexed by the Error Related Negativity. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, 81(3), 324. <https://doi.org/10.1016/J.IJPSYCHO.2011.07.020>
- Potts, G. F., Martin, L. E., Kamp, S. M., & Donchin, E. (2011). Neural response to action and reward prediction errors: Comparing the error-related negativity to behavioral errors and the feedback-related negativity to reward prediction violations. *Psychophysiology*, 48(2), 218–228. <https://doi.org/10.1111/J.1469-8986.2010.01049.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>
- R Core Team (2024). *R: A Language and Environment for Statistical Computing* (2024.04.2). <https://www.r-project.org/>.
- Reddy, N. N. (2021). The implicit sense of agency is not a perceptual effect but is a judgment effect. *Cognitive Processing*, 23(1), 1–13. <https://doi.org/10.1007/S10339-021-01066-X>
- Ren, Q., Gentsch, A., Kaiser, J., & Schütz-Bosbach, S. (2023). Ready to go: Higher sense of agency enhances action readiness and reduces response inhibition. *Cognition*, 237, Article 105456. <https://doi.org/10.1016/J.COGNITION.2023.105456>

- Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, 56(5), 356–374. <https://doi.org/10.1016/j.jmp.2012.08.001>
- Ruess, M., Thomaschke, R., & Kiesel, A. (2017). The time course of intentional binding. *Attention, Perception, and Psychophysics*, 79(4), 1123–1131. <https://doi.org/10.3758/S13414-017-1292-Y/FIGURES/4>
- Sato, A., & Yasuda, A. (2005). Illusion of sense of self-agency: Discrepancy between the predicted and actual sensory consequences of actions modulates the sense of self-agency, but not the sense of self-ownership. *Cognition*, 94(3), 241–255. <https://doi.org/10.1016/j.cognition.2004.04.003>
- Seghezzi, S., Parés-Pujolràs, E., & Haggard, P. (2023). Sense of agency decreases during learning when to. *OSF*. <https://doi.org/10.31234/OSF.IO/X9FST>
- Siebertz, M., & Jansen, P. (2022). Diverging implicit measurement of sense of agency using interval estimation and Libet clock. *Consciousness and Cognition*, 99, Article 103287. <https://doi.org/10.1016/j.concog.2022.103287>
- Skinner, B. F. (1984). An operant analysis of problem solving. *Behavioral and Brain Sciences*, 7(4), 583–591. <https://doi.org/10.1017/S0140525X00027412>
- Song, Y., & Smiley-Oyen, A. L. (2017). Probability differently modulating the effects of reward and punishment on visuomotor adaptation. *Experimental Brain Research*, 235(12), 3605–3618. <https://doi.org/10.1007/s00221-017-5082-5>
- Speed, B. C., Nelson, B. D., Perlman, G., Klein, D. N., Kotov, R., & Hajcak, G. (2015). Personality and emotional processing: A relationship between extraversion and the late positive potential in adolescence. *Psychophysiology*, 52(8), 1039–1047. <https://doi.org/10.1111/PSYP.12436>
- Steel, A., Silson, E. H., Stagg, C. J., & Baker, C. I. (2016). The impact of reward and punishment on skill learning depends on task demands. *Scientific Reports*, 6. <https://doi.org/10.1038/SREP36056>
- Stürmer, B., Nigbur, R., Schacht, A., & Sommer, W. (2011). Reward and punishment effects on error processing and conflict control. *Frontiers in Psychology*, 2(NOV), 13941. <https://doi.org/10.3389/FPSYG.2011.00335/BIBTEX>
- Sutton, R. S., & Barto, A. G. (1981). Toward a modern theory of adaptive networks: Expectation and prediction. *Psychological Review*, 88(2), 135–170. <https://doi.org/10.1037/0033-295X.88.2.135>
- Takahata, K., Takahashi, H., Maeda, T., Umeda, S., Suhara, T., Mimura, M., & Kato, M. (2012). It's not my fault: Postdictive modulation of intentional binding by monetary gains and losses. *PLoS One*, 7(12), Article e53421. <https://doi.org/10.1371/JOURNAL.PONE.0053421>
- Thorndike, E. L. (1898). Animal intelligence: An experimental study of the associative processes in animals. *The Psychological Review: Monograph Supplements*, 2(4), i–109. <https://doi.org/10.1037/H0092987>
- Ullsperger, M. (2024). Beyond peaks and troughs: Multiplexed performance monitoring signals in the EEG. *PSYCHOPHYSIOLOGY*, 61(7), Article e14553. <https://doi.org/10.1111/PSYP.14553>
- Ullsperger, M., Danielmeier, C., & Jocham, G. (2014). Neurophysiology of performance monitoring and adaptive behavior. *Physiological Reviews*, 94(1), 35–79. <https://doi.org/10.1152/physrev.00041.2012>
- Ullsperger, M., Fischer, A. G., Nigbur, R., & Endrass, T. (2014). Neural mechanisms and temporal dynamics of performance monitoring. *Trends in Cognitive Sciences*, 18(5), 259–267. <https://doi.org/10.1016/j.tics.2014.02.009>
- van Doorn, J., van den Bergh, D., Böhm, U., Dablander, F., Derks, K., Draws, T., Etz, A., Evans, N. J., Gronau, Q. F., Haaf, J. M., Hinne, M., Kucharský, Š., Ly, A., Marsman, M., Matzke, D., Gupta, A. R. K. N., Sarafoglou, A., Stefan, A., Voelkel, J. G., & Wagenmakers, E. J. (2021). The JASP guidelines for conducting and reporting a Bayesian analysis. *Psychonomic Bulletin and Review*, 28(3), 813–826. <https://doi.org/10.3758/S13423-020-01798-5>
- Wagenmakers, E. J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Selker, R., Gronau, Q. F., Dropmann, D., Boutin, B., Meerhoff, F., Knight, P., Raj, A., van Kesteren, E. J., van Doorn, J., Šmíra, M., Epskamp, S., Etz, A., Matzke, D., & Morey, R. D. (2018). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin and Review*, 25(1), 58–76. <https://doi.org/10.3758/S13423-017-1323-7/FIGURES/16>
- Walsh, M. M., & Anderson, J. R. (2012). Learning from experience: Event-related potential correlates of reward processing, neural adaptation, and behavioral choice. *Neuroscience and Biobehavioral Reviews*, 36(8), 1870–1884. <https://doi.org/10.1016/j.neubiorev.2012.05.008>
- Wen, W. (2019). Does delay in feedback diminish sense of agency? A review. *Consciousness and Cognition*, 73, Article 102759. <https://doi.org/10.1016/J.CONCOG.2019.05.007>
- Wen, W., & Haggard, P. (2018). Control changes the way we look at the World. *Journal of Cognitive Neuroscience*, 30(4), 603–619. https://doi.org/10.1162/JOCN_A.01226
- Wen, W., & Imamizu, H. (2022). The sense of agency in perception, behaviour and human-machine interactions. In *Nature Reviews Psychology* (Vol. 1, Issue 4, pp. 211–222). Nature Publishing Group. doi: 10.1038/s44159-022-00030-6.
- Westfall, J., Kenny, D. A., & Judd, C. M. (2014). Statistical power and optimal design in experiments in which samples of participants respond to samples of stimuli. *Journal of Experimental Psychology: General*, 143(5), 2020–2045. <https://doi.org/10.1037/XGE0000014>
- Wischniewski, M., & Schutter, D. J. L. G. (2018). Dissociating absolute and relative reward- and punishment-related electrocortical processing: An event-related potential study. *International Journal of Psychophysiology*, 126, 13–19. <https://doi.org/10.1016/J.IJPSYCHO.2018.02.010>
- Wischniewski, M., & Schutter, D. J. L. G. (2019). Electrophysiological correlates of prediction formation in anticipation of reward- and punishment-related feedback signals. *Psychophysiology*, 56(8). <https://doi.org/10.1111/PSYP.13379>
- 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>
- Yi, W., Mei, S., Li, Q., Liu, X., & Zheng, Y. (2018). How choice influences risk processing: An ERP study. *Biological Psychology*, 138, 223–230. <https://doi.org/10.1016/J.BIOPSYCHO.2018.08.011>
- Yoshie, M., & Haggard, P. (2013). Negative emotional outcomes attenuate sense of agency over voluntary actions. *Current Biology*, 23(20), 2028–2032. <https://doi.org/10.1016/J.CUB.2013.08.034>