**How Does P300 Relate to Belief Updating in Different Learning Conditions and Inaccuracies?**

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**Abstract**

Individuals learn from changes, adjust their knowledge, and adapt to new situations. We studied the process of learning from surprise in different learning conditions. This study aims to investigate the underlying processes of learning and adaptation by looking into their brain signals using the P300 ERP. We combined EEG data with behavioral data to gain insights, as well as mixed-effects regression models to explain the association between learning and brain activity in our region of interest. The results indicate a higher P300 amplitude in oddball conditions. In addition, rare trials resulted in lower accuracy but significant learning in subsequent trials was observed. The findings suggest that P300 is a robust measure of sensitivity in different learning conditions and humans can implement their previously gained knowledge in future situations.

Keywords: P300, Prediction Error, Learning Adaptation

**Introduction**

Humans have the capacity to learn from changes in their environment and adjust their knowledge accordingly (Nassar et al., 2019). We test our knowledge intentionally or unintentionally in different situations and modify what we have learned based on the outcome. In the process of learning, several factors affect our gained knowledge, such as volatility (Behrens et al., 2007; Pulcu & Browning, 2017) and prediction errors. Prediction error is a crucial concept in reinforcement learning, but also in attention and motivation (Den Ouden et al., 2012). Schultz et al. (1997) showed the neural foundations of prediction error and its effect on future decisions in their fundamental study. Agents use prediction errors as a means to update their previous knowledge to perform better in future scenarios (Efron, 2004). More specifically, state prediction errors (SPE) act as a comparator between the current and previous states. SPE is a measure of surprise in new situations given the outcomes of previous states (Gläscher et al., 2010). In other words, SPEs evaluate the discrepancy between the potential outcome of the current situation and a previous event and anticipate the level of surprise based on this discrepancy. However, no two states are identical. P300, which has been previously shown to have a strong association with belief updating and learning adjustment, can be context-dependent, which means that it elicits differently in different states (Nassar et al., 2019). Therefore, in this study, we focus on the nuances of P300 in different learning conditions. In addition, we investigate behavior and its relation to the P300. We hypothesize that a higher P300 will be elicited in more surprising conditions, namely oddball rare conditions of the task. Moreover, we anticipate that the more surprising a condition, the less accurate the participants will be. Lastly, we hypothesize that participants will regain their level of accuracy in the next trial after the surprising trial.

**Methods & Procedure**

*Procedure*

Six healthy adults, including three males and three females (*m*age = 25.17, *SD* = 2.03 years), from an EEG course at the University of Hamburg volunteered to participate in this study and were compensated with course credits. The participants could choose their preferred appointment to come to the lab via an online registration form. After arrival, the participants’ heads were measured to find the suitable EEG cap. Then the cap was populated on a model’s head followed by applying the populated cap on the participant’s head. At last, they were presented with a learning task. The whole procedure of applying the EEG cap and performing the task was done in a 180-minute time window for each participant.

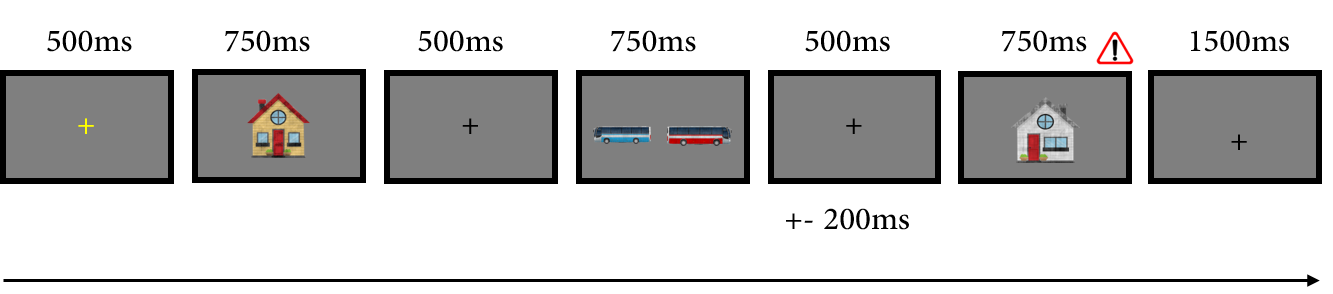
*Learning Task*

The participants were presented with a learning task - the bus task. The task began with a yellow fixation cross in the middle of the monitor for 500 ms. Then a house appeared to indicate the choice of interest for 750 ms followed by a fixation cross for 500 ms. After that, the buses appeared for 750 ms that the participants had to choose by pressing the corresponding buttons. Then a fixation cross appeared after 300 ms or 700 ms of the bus choice for 500 ms, and the house associated with the chosen bus was presented as feedback, accompanied by a warning sign solely in practice trials. At last, a 1500 ms long fixation cross was presented to end the trial. If a participant pressed a button before the onset of the buses, a prompt popped up with the text “too fast!”. In the opposite condition, if the participant did not choose any of the buses a prompt appeared with the text “too slow!”.

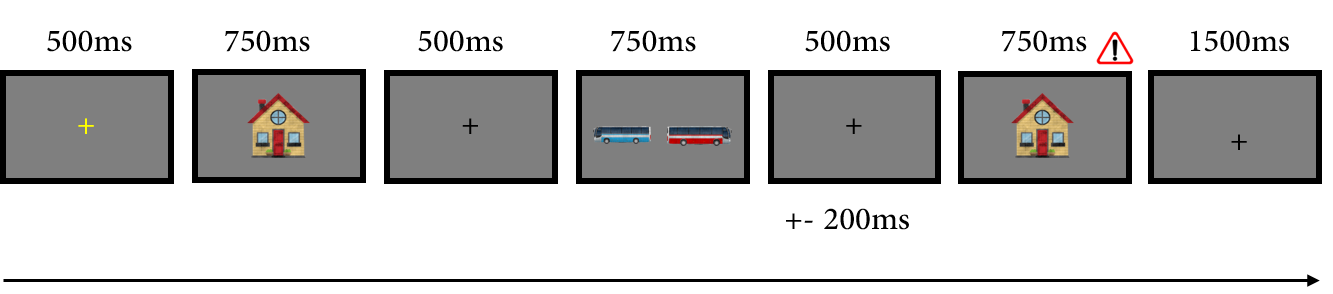
**Figure 1.**

*Depiction of Trials*

**a**



**b**



*Note*. The whole trial lasted from 3,550 ms to 3,950 ms. In figure (a) an expectancy violation is depicted, which indicates a surprising condition. The participant chose the bus associated with the yellow house, however, the white house appeared on the screen as feedback. In figure (b) no expectancy violation is illustrated because the house associated with the chosen bus appeared.

The task comprised two conditions namely oddball and reversal learning, which both had two associations. In the reversal learning condition, 80 percent of the trials are common trials, which follow the instructed and usual task structure. The remaining 20 percent of the trials are those in which an association is switched to another called rare trials. In the oddball condition, the same logic applies in terms of the number of associations. However, in this condition, 80 percent of the trials belong to one association forming the oddball common trials and the remainder shape the oddball rare trials, in which the task switches from one association to another similar to the rare trials in the reversal learning condition. To compare the associations in each condition, one block is required in the reversal learning condition, as opposed to two blocks of different associations in the oddball condition. Each participant completed 7 blocks of practice trials without any time pressure and 9 experimental blocks (3 reversal learning and 6 oddball conditions), with 60 trials in the reversal learning blocks and 30 trials in the oddball blocks. Half of the participants began the task with oddball blocks first and the other half started with reversal learning blocks. 20 percent of both blocks consisted of surprise events.

*EEG Data Preprocessing*

The preprocessing steps were mainly inspired by the instructions of Luck (2014) in MATLAB (Mathworks, Natick MA) through the EEGLAB package (Delorme & Makeig, 2004). The EEG data were recorded using 64 electrodes in a 10-20 system with a BrainVision recorder (Brainvision Recorder vers. V. 1.25.0202 Brain Products GmbH, Gliching, Germany) at a 500 Hz sampling rate, while the ground electrode was located at Fpz and the reference electrode at FCz. Data were re-referenced to the average of left and right mastoids. During the initial visual inspection, no bad channels were identified in any participant, therefore no channels were interpolated. The raw data was filtered with a 0.5 Hz to 30 Hz band-pass and segmented into 1500 ms epochs, starting at 500 ms before the stimulus onset until 1000 ms after it in each trial. On average, 10 epochs per participant - less than 3 percent of the epochs - were removed in the secondary visual inspection.

The data were baseline corrected at 500 ms before the stimuli until its onset. To remove the artifacts an independent component analysis (ICA) was utilized in two steps. ICA was first run without removing any components followed by manually rejecting the artifacts. Artifacts such as eye blinks, heartbeat, head movements, and impedances were removed in this stage, however, no additional components were excluded due to the potential risk of mistaking genuine neural activity for artifacts.

*Behavioral Data Preprocessing*

All of the behavioral data preprocessing was done in RStudio using MuMIn (Bartoń, 2010), broom (Robinson et al., 2014), tidyr (Wickham et al., 2014), ggplot2 (Wickham, 2016), lme4 (Bates et al., 2015), lmerTest (Kuznetsova et al., 2017), broom.mixed (Bolker & Robinson, 2018), and dplyr (Wickham et al., 2023).

**Results**

*EEG Analysis*

Participants showed higher P300 ERPs in reversal learning trials (*m* = 5.74, *SD* = 4.06) than oddball trial types (*m* = 5.01, *SD* = 2.84). As is evident in Figure 4 and 5, the common trials elicited lower amplitudes, especially in the oddball common trials (*m* = 4.07, *SD* = 2.05).

To investigate how P300’s amplitude is related to the expectancy violation and learning in different conditions, we conducted a mixed-effects regression analysis for each condition and their corresponding trial types. The results indicate a significant effect of P300 in all conditions and trial types, especially where the associations switched.

For the sake of robustness, initially we selected random time points within the 300 to 400 ms timeframe from the grand-averaged EEG data and gathered three different datasets from these time points. We centered the data towards the conditions. In this method, we allocated numerical values to conditions resulting in oddball conditions possessing -1 and reversal learning trials possessing +1. This enabled us not only to avoid dummy data but also facilitated the identification of the relationships’ directions.

Then we fitted a mixed-effects regression model in RStudio using the lme4 package (Bates et al., 2015) to each dataset separately. To identify the value of amplitude, the coefficients, standard errors, and other parameters for each trial type and condition and their interactions (see Appendix 1) were calculated through this equation:

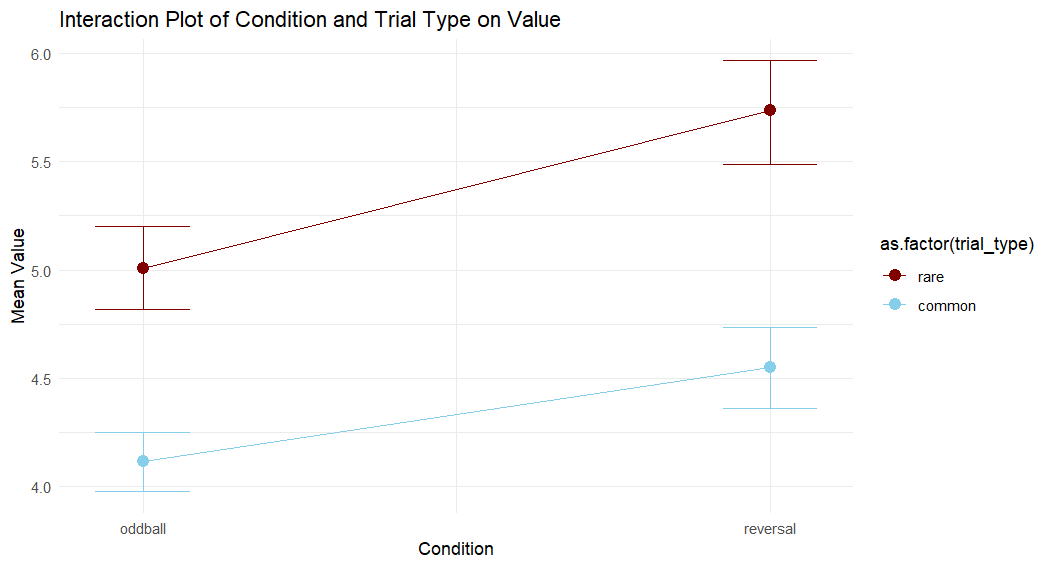
In this equation, is the intercept, is the coefficient for the trial type, is the coefficient for the conditions, coefficient accounts for the interaction between conditions and trial types, is the random intercept for subject , and shows the residual error.

The random effects of the fitted linear mixed-effects model showed a standard deviation of 3.090697 for the intercept and 1.207117 for the residual. The fixed effects estimates analysis yielded intercept (β = 4.853, SE = 1.262, t(3663) = 3.846, p < .001), condition (β = 0.290, SE = 0.020, t(3663) = 14.572, p < .001), trial type (β = -0.519, SE = 0.020, t(3663) = -26.059, p < .001), and the interaction between condition and trial type (β = -0.073, SE = 0.020, t(3663) = -3.667, p < .001). Overall, the analysis indicates significant and strong effects for conditions and trial types. Their interaction effect is weaker but significant.

**Figure 2.**

*Interaction Plot of Condition and Trial Type Predicting the Amplitude Value*

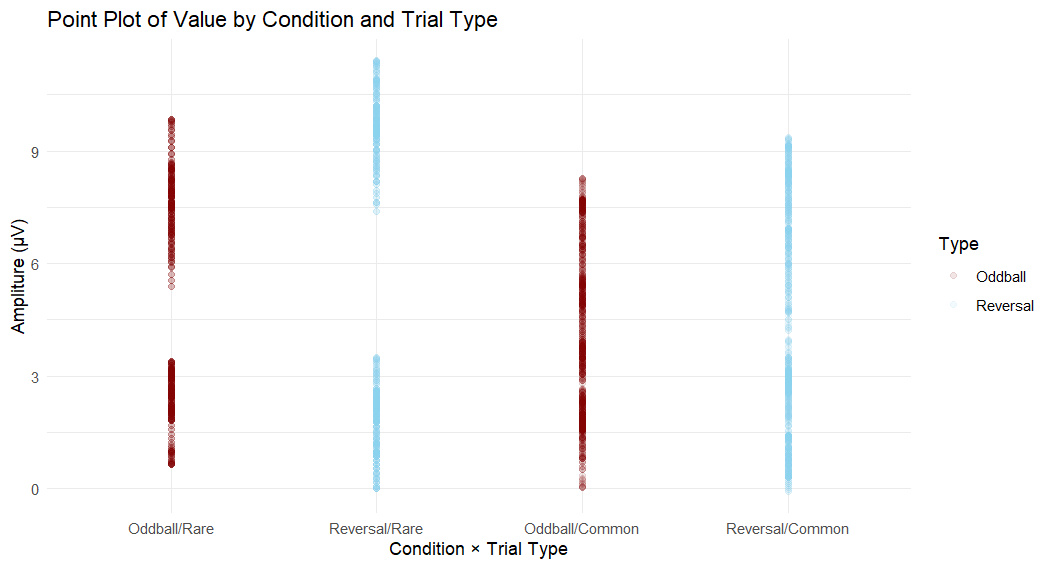
*Note*. The plot shows a higher mean amplitude value in reversal learning conditions for both trial types. In addition, rare trials elicit a higher amplitude in both conditions compared to common trials.



**Figure 3.**

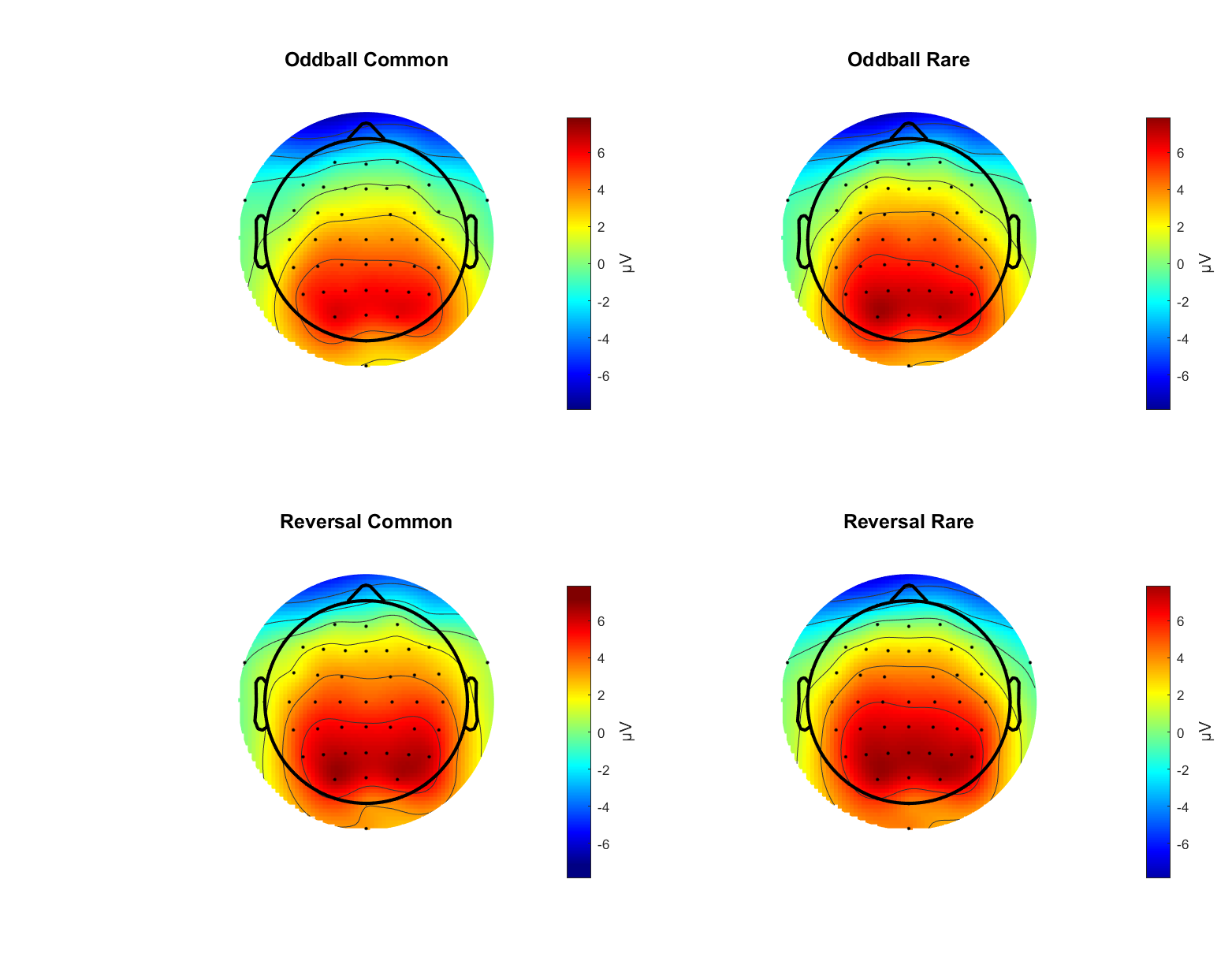
*Point Plot of the Amplitude Value by Condition and Trial Type*

*Note*. Pointplot was used instead of a boxplot due to a its higher capability depiction of variabilities.



**Figure 4.**

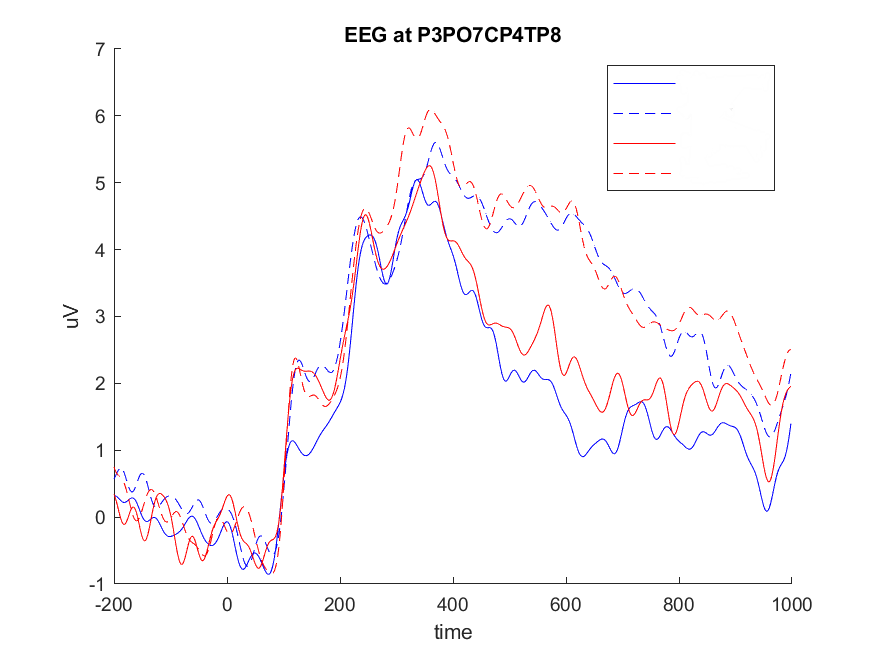
*Topographies for conditions and trials types*



*Note.* These plots indicate brain activation in the ROI during a 300ms-400ms timeframe. Parallel to the previous analysis a higher activation in the parietal region can be seen during reversal learning conditions and rare trials.

**Figure 5.**

*Grand Averaged P300 components at ROI*



**Oddball/Common**

**Oddball/Rare**

**RL/Common**

**RL/Rare**

*Note*. The ROI of Pz, CPz, P1 and P2 the electrodes.

*Behavioral Analysis*

Participants performed somewhat similar in oddball condition (m = 0.70, SD = .46, min = 0.56 , max = 0.76) and reversal learning condition (m = 0.70, SD = 0.46, min = 0.66 , max = 0.74). The same applied for reaction times in these conditions (oddball: min = 329.21 ms, max = 433.193 ms, m = 364.56ms, SD = 8.26 ms; reversal learning: min = 305.77 ms , max = 410.96, m = 356.43 ms, SD = 7.54ms).

However, unsurprisingly, in rare trial types participants performed with lower accuracy (*m*rare = 0.07, *SD*rare = 0.25) than in common trials (*m*common = 0.83, *SD*common = 0.37). Similar to conditions, in trial types participants seem to perform similarly in different trial types in terms of reaction times (oddball: *m*rare = 0.36, *SD*rare = 0.12; *m*common = 0.35, *SD*common = 0.12; reversal learning: *m*surprise = 0.37, *SD*surprise = 0.10; *m*common = 0.37, *SD*common = 0.19).

Participants learned how to perform better in rare trials as t-test shows a significant difference in terms of accuracy in rare trials and their following trials in both oddball (*t*(351.04) = 17.15, *p* < 0.001, *CI* = [0.56, 0.71]) and reversal learning conditions (*t*(318.84) = 17.81 , *p* < 0.001, *CI* = [0.57, 0.71]).

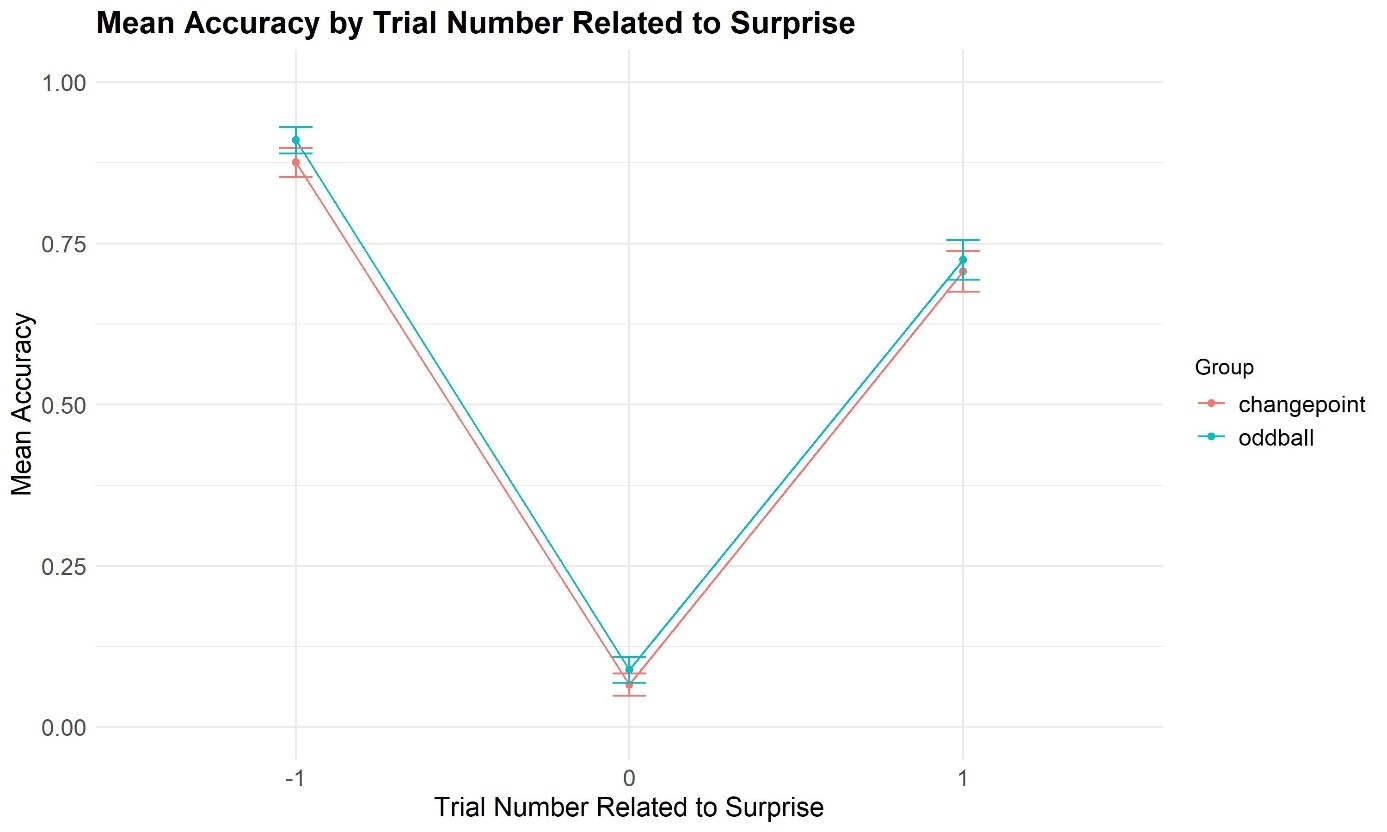
As depicted in Figure 6, participants performed significantly worse in the subsequent trial after rare trials in both conditions (oddball: *t*(352.39) = 4.99, *p* < 0.001, *CI* = [0.11, 0.26]; reversal learning:

*t*(376.51)= 4.35, *p* < 0.001, *CI* = [0.09, 0.25]).

Potentially due to a limited sample size, correlational analysis of subsequent accuracy did not yield significant results in either conditions when EEG P300 amplitude was accounted for (oddball: *r* = 0.27, *p* = 0.61; reversal learning: *r* = 0.66, *p* = 0.16)

**Figure 6.**

*Mean Accuracy in Trials, Preceding and Proceedeing Rare Trials*



reversal learning

oddball

Trial Type

*Note*. Participants performed less accuratly in rare trials in both conditions. They also could not regain their previous accuracy in trials immediately after rare trials (+1) and performed at a lower level than before (-1).

**Discussion**

These results show how subtle the role of P300 amplitude is in different learning conditions. The significant rise of P300 in reversal learning trials relative to oddball trials shows an intensified neural response to unanticipated changepoints in associations. This suggests that belief updating is more sensitive to contextually framed surprises, as indicated by unique P300 amplitude changes. Moreover, rarer trials within both conditions exhibited stronger P300 responses that also underscored neural sensitivity towards unexpected events, supporting the idea that prediction error and surprise can be reliably measured by P300 amplitude.

There were lower accuracies in rare trials, indicative of difficulty with unexpectedness as revealed by behavioral data aligned with EEG results. Participants showed a clear learning effect; their accuracy increased during subsequent trials after rare events. This finding supports our hypothesis about the initial disruption of performance under surprising conditions, while participants are able to adjust and improve accuracy in subsequent trials. Therefore, human learning mechanisms demonstrate resilience due to adaptability towards prediction errors. However, the insignificant correlations between later accuracy and P300 amplitude imply that while P300 represents initial surprise, it does not affect immediate response.

According to our mixed-effects regression model, interaction effects between condition and trial type show that the context in which surprises occur (i.e., oddball or reversal learning conditions) has a significant impact on neural as well as behavioral reactions. A weaker but still significant interaction effect shows that even if both conditions elicit strong P300 responses, the nature of the surprise is crucial in moderating this response. These findings enhance understanding around the intricacies of learning and prediction error processing by highlighting the contextual influence on brain activities and subsequent behavior. Future research may want to validate and extend these findings by using larger and more varied samples.

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Appendix 1: *Mixed-effects Regression Analysis for the 3 Extracted Datasets*

**Table 3.1**

*Mixed-effects Regression Analysis: Dataset 1*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Effect | Amplitude Estimate (β) | *SE* | *p* | *t* | *SD* |
| Fixed effects |  |  |  |  |  |
| Intercept | 4.81 | 1.24 | .0001 | 3.85 |  |
| Condition a | .26 | .028 | .0000 | 7.70 |  |
| Trial typeb | −.56 | .018 | .0000 | -16.03 |  |
| Condition × Trial type c | −.10 | .001 | .0007 | -2.67 |  |
| Random effects |  |  |  |  |  |
| Intercept |  |  |  |  | 3.05 |
| Residuals |  |  |  |  | 1.22 |

**Table 3.2**

*Mixed-effects Regression Analysis: Dataset 2*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Effect | Amplitude Estimate (β) | *SE* | *p* | *t* | *SD* |
| Fixed effects |  |  |  |  |  |
| Intercept | 4.81 | 1.24 | .0001 | 3.85 |  |
| Condition a | .26 | .028 | .0000 | 7.70 |  |
| Trial typeb | −.56 | .018 | .0000 | -16.03 |  |
| Condition × Trial type c | −.10 | .001 | .0007 | -2.67 |  |
| Random effects |  |  |  |  |  |
| Intercept |  |  |  |  | 3.05 |
| Residuals |  |  |  |  | 1.22 |

**Table 3.3**

*Mixed-effects Regression Analysis: Dataset 3*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Effect | Amplitude Estimate (β) | *SE* | *p* | *t* | *SD* |
| Fixed effects |  |  |  |  |  |
| Intercept | 4.93 | 1.29 | .0001 | 3.85 |  |
| Condition a | .33 | .03 | .0000 | 10.11 |  |
| Trial typeb | −.43 | .03 | .0000 | −13.24 |  |
| Condition × Trial type c | −.03 | .03 | .32 | −.97 |  |
| Random effects |  |  |  |  |  |
| Intercept |  |  |  |  | 3.17 |
| Residuals |  |  |  |  | 1.14 |

*Note*. (a) oddball or reversal learning, (a) common or rare,  (c) interaction of trial types and conditions