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# ASYMMETRIC MODULATION OF FRN BY THE PROBABILITY AND VALUE OF OUTCOMES IN AUDITORY MID TASK

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# ASYMMETRIC MODULATION OF FRN BY THE PROBABILITY AND VALUE OF OUTCOMES IN AUDITORY MID TASK [7]

Reward prediction error (RPE) reflects the discrepancy between received and predicted outcomes and therefore plays an important role in learning in a dynamic environment. Using electroencephalographic measures of response to obtained and expected outcomes, previous studies have suggested that feedback-related negativity (FRN) could code RPE. It has further been hypothesized that FRN should be sensitive to both the likelihood and magnitude of behavioral outcomes. Previous studies consistently demonstrated that FRN is sensitive to the probability of outcomes, while the evidence of its sensitivity to the magnitude of outcomes is less consistent. In neuroimaging studies, a monetary incentive delay (MID) task is often used to evaluate the dependence of feedback processing on the RPE's sign and size. In this article, for the first time, we studied FRN's sensitivity to the valence, likelihood, and magnitude of outcomes during a novel auditory version of an MID task. FRN demonstrated sensitivity to both the valence of an outcome (gain vs. omission of a gain) and its probability (high vs. low). However, we did not observe a modulation of FRN amplitude by the magnitude of the outcomes. We also found that subjects' behavior was more susceptible to changes in the probability than to the magnitude of the outcomes. Overall, FRN seems to be a promising tool to study the learning mechanisms of decision making.

Keywords: feedback-related negativity, monetary incentive delay task, expected value, electroencephalography

JEL Classification: Z

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# Introduction

Decision theory assumes that individuals' choices are driven by the values attached to prospective outcomes. In order to evaluate the expected values (EV) of options, individuals estimate the magnitude and probability of outcomes (Bandura, 1977; Von Neumann and Morgenstern, 1944). Neural correlates of EV (including the magnitude and probability of outcomes) have been widely investigated during the last two decades (see Glimcher et al., 2009 for a review). Decision theory is tightly interwoven with reinforcement learning (RL) theory (Bush and Mosteller, 1951). For example, the temporal difference model of RL (Rescorla and Wagner, 1972) indicates that an individual assigns high values to states that predict future rewards when encountered unexpectedly. Therefore, conceptually, reward prediction error (RPE) reflects any discrepancy between the obtained and expected outcomes: unexpected unfavorable outcomes (i.e., monetary loss) produce negative RPEs, whereas unexpected favorable outcomes (i.e., monetary gain) result in positive RPEs. Subsequently, with the seminal work of Wolfram Shultz (1997), RL theory has come to play an important bridging role between economics (e.g., Camerer and Ho, 1999; Erev and Roth, 1998), psychology (Rescorla and Wagner, 1972), and neuroscience (Schultz, 1997). It was proposed, that dopamine broadcasts a "prediction error" signal of precisely the form needed in reinforcement algorithms to drive convergence toward a standard dynamic programming value function (Barto and Sutton, 1982). Since then, the dopaminergic reward prediction error hypothesis has been tested using a variety of neuroimaging techniques (Caplin and Dean, 2008). Using electroencephalographic measures of reaction to the obtained and expected outcomes, Holroyd & Coles (2002) suggested that a feedback-related negativity (FRN) component of event-related potentials (ERPs) can code RPE.

FRN is a frontocentral negative deflection occurring 240–340 ms after feedback onset. FRN is believed to represent an alerting signal that follows unexpected and/or unfavorable outcomes and underlies RL and performance monitoring (Holroyd and Coles, 2002; Van Meel et al., 2005; Montague and Berns, 2002; Montague et al., 2004; Sambrook and Goslin, 2015a). FRN is known to be strongly affected by the valence of feedback — it is enhanced by unfavorable outcomes (Miltner et al., 1997; Sambrook and Goslin, 2015b). EEG and fMRI research has established a causal role for the dopaminergic system in FRN generation in the cingulate cortex (for review, see Walsh and Anderson, 2012).

An EEG study showed that FRN is a better index of negative RPE as compared to positive RPE (Gehring and Willoughby, 2002). This sensitivity to the valence of the outcome constitutes the core argument proving that FRN might be an encoder of the RPE's sign. It is critical that a negative RPE is generated when outcomes (a monetary loss or an omission of monetary gain) are worse than predicted (i.e, Holroyd and Coles, 2002; Luu et al., 2000). Overall, neuroimaging studies suggest that FRN is more sensitive to the probability of outcomes than to the magnitude of the outcomes (Walsh and Anderson, 2012), despite some evidence that the outcome magnitude exerts a modulatory effect on FRN (Sambrook and Goslin, 2015b).

The monetary incentive delay task (MID) is an elegant tool to study the different stages of RL, from reward anticipation to its delivery (Knutson et al., 2000, 2005). It can be used to delineate the neural mechanisms of performance monitoring during behavioral acts with different EVs and RPEs. By introducing incentive cues signaling both the magnitude and probability of prospective outcomes, it is possible to study the effects of magnitude and probability on neural activity that are associated with feedback evaluation (Knutson et al., 2005). Initially, an MID task was used in fMRI studies of reward processing (Knutson et al., 2000). Subsequent EEG and MEG studies have employed MID to study the neural dynamics of reward processing (Broyd et al., 2012; Doñamayor et al., 2012; Thomas et al., 2013). To our knowledge, none of the previous studies investigated the simultaneous effects on FRN of the valence, magnitude, and probability of outcomes.

In a classic MID task, visual stimuli such as circles, squares, and triangles were utilized as an incentive cues that coded the probabilities and magnitudes of outcomes. We developed an auditory version of an MID task that relied on sounds of different physical characteristics as incentive cues, which can also be used in studies of auditory perceptual learning.

Using the auditory MID task, we studied the effect of the outcome's valence, magnitude, and likelihood on FRN as index of performance monitoring for the first time. Crucially, the current study allowed us to develop a new paradigm investigating the mechanism of auditory perceptual learning during a neuroeconomic task using FRN as a neural signature of performance monitoring.

# Methods

### Subjects

Seven subjects (4 women, 22±2 y.o.) participated in the behavioral pilot experiment. Forty-two subjects (20 women, 23±4 y.o.) participated in the EEG experiment, in which both behavioral and electrophysiological data were collected. Data from five additional subjects were excluded due to excessive EEG artifacts. All subjects were right-handed, with normal or corrected-to-normal vision and with no history of psychiatric or neurological disorders. The study was approved by the local ethics committee, and all participants gave written informed consent prior to their participation.

## Auditory stimuli

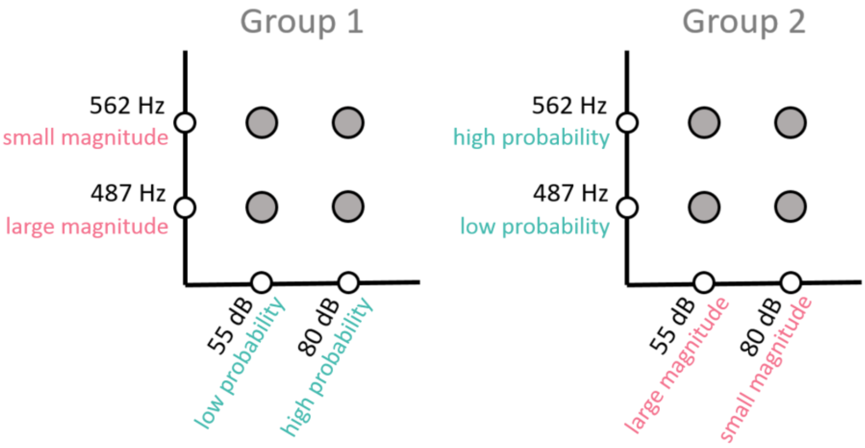


**Figure 1. Physical parameters of acoustic stimuli used as incentive cues in an MID task.** This illustrates how the gain magnitude and the gain probability were encoded in the frequency and intensity of the acoustic cues. Gray dots represent four acoustic cues. In group 1, the frequency of the acoustic cue encoded the gain magnitude, while the intensity of the acoustic cue indicated the gain probability. In group 2, the encoding of the gain magnitude and the gain probability was reversed.

Acoustic cues signaled a high or low prospective reward probability (0.80 and 0.20, respectively) and a high or low prospective reward magnitude (4 or 20 rubles, respectively), as illustrated by Fig. 1. We used two levels of frequency (fundamental frequencies of 562 Hz for the higher and 487 Hz for the lower tones) and two levels of intensity (55 and 80 dB) to encode the prospective reward probability and magnitude. All tones had a duration of 200 ms (including 5 ms of rising and falling times). Stimuli were generated with the PRAAT software. The probability and magnitude of reward were encoded differently in the two experimental groups. In group 1 (n = 24), the outcome magnitude was encoded by the intensity of the acoustic cue, while the gain probability was encoded by the frequency of the acoustic cue. In group 2 (n = 25), the encoding of the gain magnitude and gain probability was reversed.

## Study design

The main goal of this study was to investigate the effect of the valence, magnitude, and probability of gain on FRN. The experiment consisted of two MID task sessions performed on two consecutive days.

*Day 1.* At the beginning of each experiment, the ability of participants to identify auditory stimuli was tested during a recognition test. Prior to the MID task, the probe structure and meaning of each acoustic cue were explained to participants. Next, participants performed the first session of the MID task. *Day 2.* At approximately the same time of the day, participants performed the second MID task session.

The design of our paradigm aimed to investigate the effect of RPE on FRN over the course of learning in the MID task in two consecutive days.

*Recognition test*

The recognition test was designed to ensure that participants were able to discriminate acoustic cues coding EV. The participants were instructed to press a button corresponding to the delivered sound. The sound descriptions and target buttons were displayed on the screen (i.e., high loud sound, button 1, etc.) during the task. Participants received positive and negative visual feedback to facilitate learning. The EEG session started when the subject successfully identified 8 out of 10 consecutive sounds. On average, participants made more mistakes in frequency identification (5.14±1.26; S±SEM) as compared to intensity identification (2.00±0.51) and mistakes in the simultaneous identification of frequency and intensity of sounds (1.90±0.64).

*Auditory MID task*

During the auditory MID task (Fig. 2), participants were exposed to acoustic cues encoding the prospective gain magnitude (4 or 20 rubles) and probability of a win (0.80 and 0.20). After a variable anticipatory delay period (2000–2500 ms), participants responded with a single button press immediately after the presentation of a visual target (white square) (Fig. 2). After a short delay, subsequent feedback (2000 ms) notified subjects as to whether they had won money and of their cumulative total outcome. The probability of a win was manipulated by altering the average target duration through an adaptive timing algorithm that followed subjects' performance, such that they would succeed in 80% of the high-probability trials and 20% of the low-probability trials. Overall, the outcomes were positive (gain 4 or 20 rubles) or negative (miss 4 or 20 rubles).

At the beginning of the task, the initial duration of the target was based on reaction times collected during the training session. It is important to note that, prior to the MID task, participants were instructed as to which acoustic cues corresponded to which probabilities and magnitudes of outcomes.

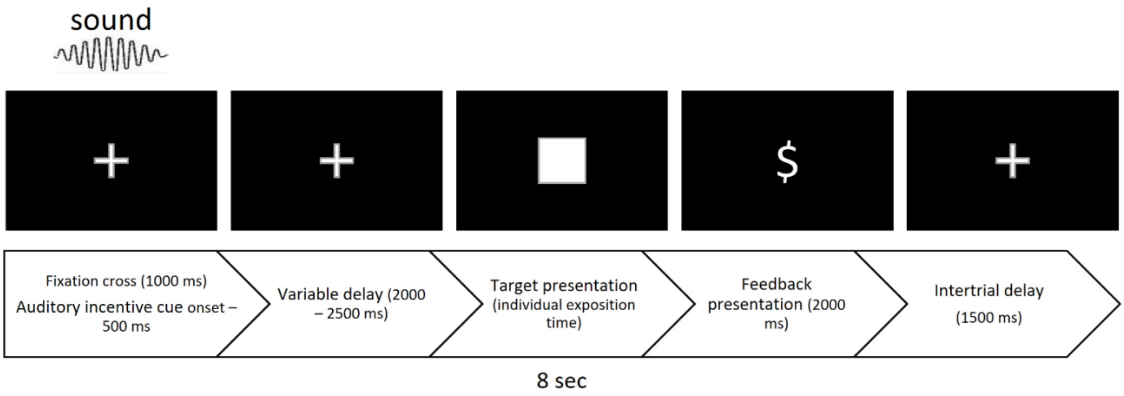


**Figure 2. Trial scheme of auditory MID task.**

On average, the duration of the target presentation was set to 276±29 ms for trials with a high gain probability and 189±26 ms for those with a low gain probability. The reward feedback was presented in an average of 58±4 trials out of 76 in the case of 80% gain probability and an average of 13±3 trials out of 76 for the 20% gain probability. On average, subjects earned 854(±76) rubles by the end of the game.

**Analysis of behavioral results**

Reaction time (RT) on each trial type was averaged for each individual, grand averaged and subjected to mixed four – way repeated measures analyses of variance (ANOVA) with *Group* as a between-subject variable (group 1 vs. group 2) and *Session* (MID – session 1 vs. MID – session 2), *Magnitude* (low magnitude vs. high magnitude) and *Probability* (0,20 vs. 0,80) as within-subject variables.

**EEG data acquisition**

EEG data were recorded using 28 active electrodes (Brain Products GmbH) at a sampling rate of 500 Hz, according to the extended version of the 10–20 system: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T7, T8, P7, P8, Fz, Cz, Pz, Oz, FC1, FC2, CP1, CP2, FC5, FC6, CP5, and CP6. Active channels were referenced against the mean of two mastoid electrodes in order to display the maximal FRN response at the frontal electrode sites. The electrooculogram (EOG) was recorded with electrodes placed at the outer canthi and below the right eye. Data was acquired with a BrainVision actiCHamp amplifier (Brain Products GmbH) and sampled at 500 Hz. Impedance was confirmed to be less than 5 kΩ in all electrodes prior to recording.

**Auditory MID task EEG data analysis**

EEG signals were pre-processed with the BrainVision Analyzer 2.1 (Brain Products GmbH). The EEG was filtered offline (passband 1–30 Hz, notch filter 50 Hz), and then an ICA-based ocular artifacts correction was performed. After manual inspection of the raw data for remaining artifacts, the data were segmented into epochs of 600 ms, including a 100 ms pre-stimulus. Each trial was baseline corrected to an average activity between -100 and 0 ms before stimulus onset. Epochs including voltage changes exceeding 75 mV at any channel were omitted from the averaging. Epochs were separately averaged for different trial types. Averaged ERP waveforms were computed within each subject and condition with a minimum number of 15 trials per condition.

We processed feedback-locked visual ERP in two different ways: pooling ERPs for expected (highly likely) and unexpected (highly unlikely) outcomes, irrespective of magnitude, and pooling ERPs for the high (20 rub) and low (4 rub) magnitudes, irrespective of probability. ERPs obtained during the first and the second sessions were pooled together. As a result, we obtained 4×2 different types of waveforms. This procedure also helped to increase the number of trials averaged for each type of feedback because of a large difference in the number of trials for expected and unexpected outcomes. FRN peak amplitudes were quantified as the average amplitude (±20 ms) around the local minimum occurring within the timeframe of interest (270-350 ms at electrode Fz) post–stimulus onset. A time window chosen for statistical analysis of FRN was based on visual inspection of the grand-average waveforms and the results of previous studies. Timeframes of interest were the same for all eight types of feedback. For probability-pooled ERPs, we calculated ERPs (27±6 trials) to unlikely positive outcomes (gain, p=0.20), ERPs (110±14 trials) to likely positive outcomes (gain, p=0.80), ERPs (28±7 trials) to unlikely negative outcomes (miss, p=0.80), and ERPs (110±19 trials) to likely negative outcomes (miss, p=0.20). For magnitude-pooled ERPs, we calculated ERPs (67±5 trials) to small positive outcomes (4 rub), ERPs (84±10 trials) to large positive outcomes (20 rub), ERPs (71±8 trials) to small negative outcomes (misses of 4 rub), and ERPs (68±7 trials) to large negative outcomes (misses of 20 rub). ERPs obtained during the first and the second sessions were pooled together. Mixed four-way repeated measures ANOVAs with *Group* as a between-subject variable (group 1 vs. group 2) and *Valence* (gain vs. miss), *Probability* (unlikely vs. likely), and *Electrode* (Fz vs. Cz vs. Pz) as within-subject variables were conducted for FRN amplitudes derived from probability-pooled ERPs. Mixed four-way repeated measures ANOVAs with *Group* as a between-subject variable (group 1 vs. group 2) and *Valence* (gain vs. miss), *Magnitude* (low magnitude vs. high magnitude), and *Electrode* (Fz vs. Cz vs. Pz) as within-subject variables were conducted for FRN amplitudes derived from magnitude-pooled ERPs.

In addition to analysis of FRN amplitudes, we calculated the differential FRN (dFRN). *Valence dFRN* was defined as FRN to all positive outcomes (gain) and *minus* FRN to all negative outcomes (omission of a gain). *Probability dFRN* and *Magnitude dFRN* were calculated similar to Sambrook and Goslin, 2015a. By subtracting the waveforms for gains and misses with the same size of RPE, we obtained difference waveforms reflecting differences in processing feedback valence in the cases of small RPE and large RPE. Then, we subtracted the obtained difference waveforms for small RPE from the waveforms for large RPE. Thus, the overall scheme of *Probability dFRN* calculation was as follows: (unexpected misses — unexpected gains) — (expected misses — expected gains), irrespective of the magnitude of outcome. For *Magnitude dFRN*, the calculation scheme was similar: (large misses — large gains) — (small misses — small gains). Amplitudes of *Valence dFRN*, *Probability dFRN*, and *Magnitude dFRN* were detected with the same procedure used for amplitudes of FRN. We conducted a two-way mixed model ANOVA with dFRN amplitudes as the dependent variable, *Group* as a between-subject variable (group 1 vs. group 2), and *FRN type* (valence vs. probability vs. magnitude) as a within-subject variable. Timeframes of interest for the three difference FRN waveforms (dFRN were the same as for FRN. This procedure allowed us to compare the sensitivity of FRN and dFRN to valence and to components of EV.

In all repeated measures ANOVAs, significant interactions were further decomposed with simple effect tests (Howell and Lacroix, 2012; Stevens, 1991). The level of significance was set to $p < 0.05$. P-values reported for the ANOVAs were adjusted with the use of the Greenhouse–Geisser correction. All statistical analyses were performed using the Matlab 2015a and SPSS software package (22.0).

# Results

## Behavioral results

Mean RT was 232±25 ms. RT in each trial type was averaged individually for MID — session 1 and MID — session 2 (Fig. 3). A repeated measures ANOVA revealed significant main effects of *Group* [$F(1, 48) = 5.708$, $p = 0.021$, $\eta^2p = 0.275$]: we observed a longer average RT in Group 1 (221±5) as compared to Group 2 (204±5). The probability and valence of the expected outcome significantly modulated the RTs (factors *Probability* [$F(1, 48) = 135.632$, $p < 0.001$, $\eta^2p = 0.739$] and *Magnitude* [$F(1, 48) = 18.209$, $p < 0.001$, $\eta^2p = 0.275$]). On average, participants were faster in trials with a low probability of positive outcomes (202±4) as compared to those with a high probability (222±3). The RT was faster in trials with a large magnitude of expected gains (210±3) as compared to trials with a small magnitude (215±4). No significant interactions between factors were observed.

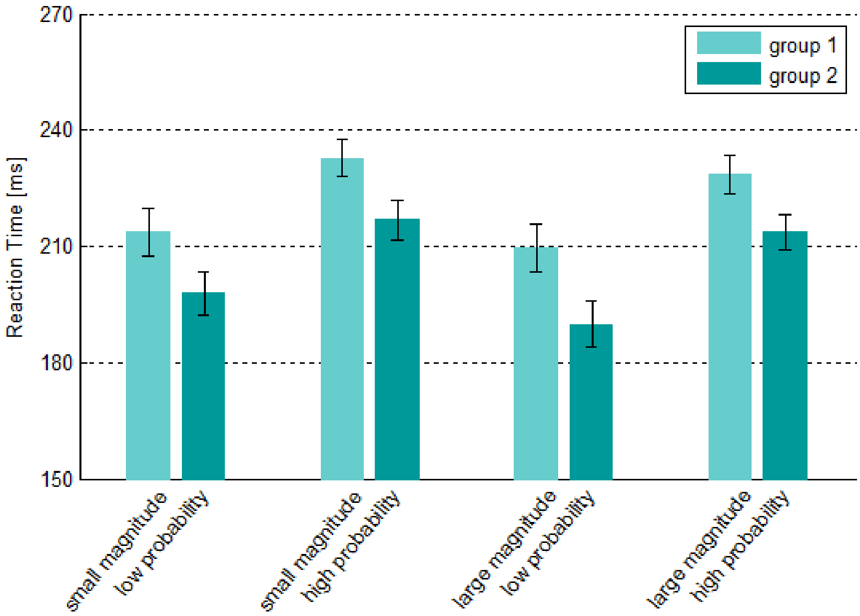


**Figure 3.** RTs for different types of trials in two experimental groups (light blue — group 1, green — group 2)**.**

**Electrophysiological results**

Fig. 4 presents eight different types of feedback-locked visual ERP waveforms recorded in the MID at Fz. In all conditions, feedback is followed by FRN as a negative deflection around 300 ms. For both experimental groups, FRN was stronger for negative outcomes than for positive outcomes: the smallest FRN was evoked by unexpected gains, while the largest FRN was evoked by small negative outcomes (Fig. 4).

The main effect of *Valence* [$F_{(1,40)}$ = 25.892, $p$ < 0.001, $\eta^2_p$ = 0.393] resulted from more negative amplitudes of FRN for misses (4.133±0.372) as compared to gains (6.337±0.611). A main effect of *Probability* [$F_{(1,40)}$ = 42.099, $p$ < 0.001, $\eta^2_p$ = 0.513] reflected larger FRN for expected outcomes (4.423±0.471) as compared to unexpected outcomes (6.047±0.477) (Fig. 4). It was of note that there was a significant two-way interaction of *Valence* x *Probability* [$F_{(1, 40)}$ = 10.540, $p$ = 0.002, $\eta^2_p$ = 0.209]: the effect of probability for misses was smaller [$F_{(1, 40)}$ = 5.294, $p$ = 0.027, $\eta^2_p$ = 0.117] than for gains [$F_{(1, 40)}$ = 38.101, $p$ < 0.001, $\eta^2_p$ = 0.494].

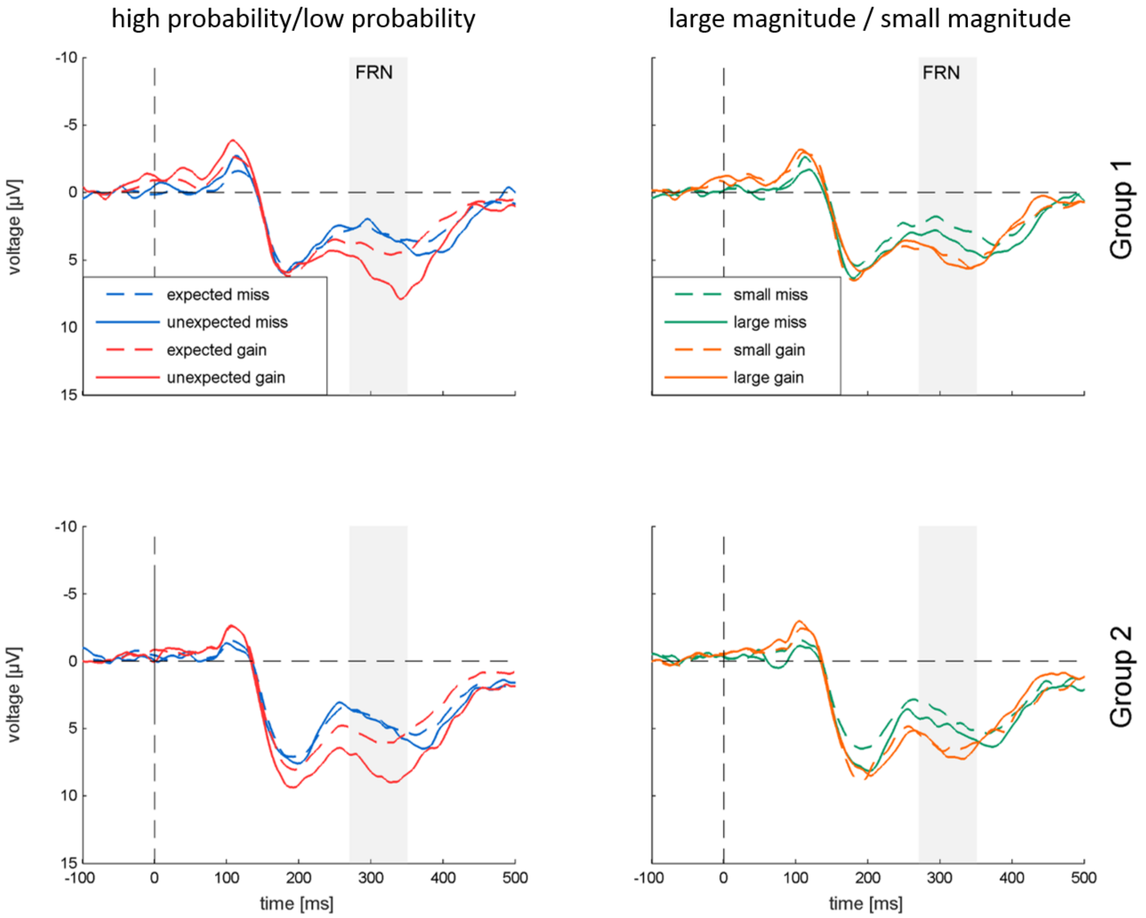


**Figure 4.** Grand-averaged visual ERP waveforms superimposed for eight types of feedback (averaged across two MID task sessions), as a function of probability (left part) or magnitude (right part). The FRN component (270 – 350 ms) is highlighted by gray shading).

We also observed a significant interaction of *Electrode* x *Probability* [$F_{(2,\ 68)}$ = 5.275, $p$ = 0.011, $\eta^2_p$ = 0.117], indicating the frontocentral maximum of the effect. The main effect of *Group* was not significant, and no significant interactions with other factors were observed.

We further tested the effect of magnitude on FRN amplitudes. We observed a significant main effect of *Electrode* [$F_{(1,56)}$ = 6.089, $p$ = 0.009, $\eta^2_p$ = 0.132], supporting a frontocentral maximum of FRN. The main effect of *Valence* [$F_{(1,40)}$ = 11.248, $p$ = 0.002, $\eta^2_p$ = 0.219] resulted from the more negative amplitude of FRN to misses (4.292±0.381) as compared to gains (5.772±0.579). We did not observe any significant main effects of *Magnitude* and *Group* or the interaction thereof.

An analysis of dFRN (Fig. 5) showed a significant main effect of *dFRN type* [$F_{(2,\ 76)}$ = 12.515, $p$ < 0.001, $\eta^2_p$ = 0.238], indicating a larger *Probability dFRN* (-2.454±0.528) when compared to the *Valence dFRN* (-1.847±0.440) and the nearly absent *Magnitude dFRN* (0.691±0.518). The main effect of *Group* and the *dFRN type* × *Group* interaction on dFRN was not significant. Topographies clearly showed frontocentral dFRN distribution for *Valence dFRN* and *Probability dFRN* but not for *Magnitude dFRN*.

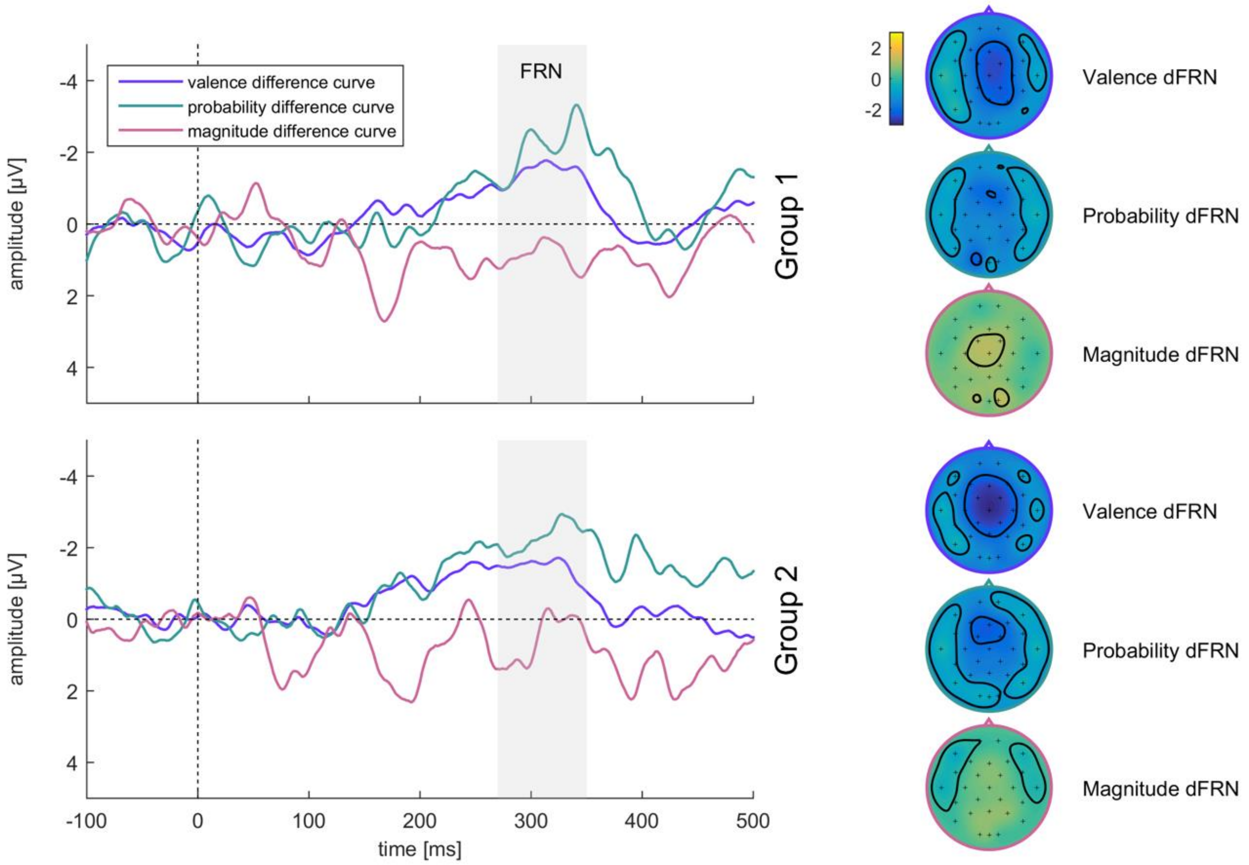


**Figure 5.** Grand-averaged visual ERP difference waveforms superimposed for three types of FRN (dFRN), calculated separately for valence (misses — gains), for probability ((unexpected misses — unexpected gains) — (expected misses — expected gains)) and for magnitude ((big misses — big gains) — (small misses — small gains)). Difference waveforms were calculated separately for two experimental groups: group 1 — top left picture, group 2 — bottom left picture. Time windows (270 – 350 ms), indicated by gray shading, were used for individual peak amplitude measurement and for topographies calculation. Scalp topographies (right row) show the dFRN distribution for valence, probability, and magnitude.

# Discussion

Here we investigated the effect of the expected value (magnitude and probability of an outcome) on FRN recorded during an auditory MID task.

We found that both the magnitude and probability of the expected outcome strongly influenced RT, similar to previous studies (Helfinstein et al., 2013; Knutson et al., 2003, 2005; Rademacher et al., 2014).

An analysis of FRN strongly supports previous findings, showing an FRN sensitivity to outcome valence (Hajcak et al., 2006; Nieuwenhuis et al., 2004; Yeung and Sanfey, 2004). In our study, the FRN amplitude was higher overall for misses compared to gains, in waveforms pooled by both probability and magnitude. It has previously been proposed that FRN reflects an evaluation of positive vs. negative outcomes and that this binary evaluation is more pronounced in processing utilitarian (gain vs. miss) than in performance (correct vs. incorrect) feedback information (Nieuwenhuis et al., 2005).

The probability of the outcome more strongly influenced FRN amplitude than the magnitude of the outcome. Previous studies demonstrated gain/loss asymmetry of the effect of probability on FRN: the likelihood of an outcome affects waveforms for gains more strongly than for losses or omissions of a gain (for review, see Walsh and Anderson, 2012). This preferential sensitivity of FRN to the changes in size of negative RPE might indicate different neural mechanisms underlying feedback processing for wins and losses (Cohen et al., 2007). The design of the current study could affect the strong influence of probability on FRN magnitude. Results of RT analysis suggest that the probability of a gain was more salient for participants than the gain magnitude, as it more strongly affected RTs. This behavioral saliency could affect reward expectations.

We did not find a significant modulation of FRN by magnitude: *Magnitude dFRN* was nearly absent during the time window of interest. The modulation of FRN by the magnitude of the expected outcome is still controversial. Some studies have suggested that FRN is not influenced by reward magnitude (Cui et al., 2013; Hajcak et al., 2003, 2006; Holroyd et al., 2006; Marco-Pallares et al., 2008; Nieuwenhuis et al., 2004; De Pascalis et al., 2010; Yeung and Sanfey, 2004). However, there is also mounting evidence that FRN encodes magnitude in addition to probability and valence (Bellebaum et al., 2010; Kreussel et al., 2012; Toyomaki and Murohashi, 2005). Our results support those previous findings showing no FRN modulation by reward magnitude, but these results might be affected by a relatively low difference in the magnitude of gains — the difference could be insufficiently salient to result in significantly distinct FRN amplitudes. Bellebaum et al. (2010) proposed that the effect of the outcome magnitude on FRN can be clearly observed using a contrast between large gains vs. an omission of large gains and small gains vs. an omission of small gains, rather than by contrasting large gains and small gains. Further studies using a larger variety of rewards are clearly needed to determine the role of reward magnitude in FRN generation.

## Conclusion

Overall, our results indicate that only the probability of rewards affects FRN amplitudes. Our study supports the hypothesis that separate neural networks underlie the processing of reward probability and reward magnitude during performance monitoring. Thus, FRN is more sensitive to the probability but not to the reward component of RPE. Our results indicate that FRN can be used as a neural signature of RL to study auditory perceptual learning using an MID task.

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