Neuroscience Letters 686 (2018) 145–149

Contents lists available at ScienceDirect

Neuroscience Letters

journal homepage: www.elsevier.com/locate/neulet

Research article

Feedback-related negativity reflects omission of monetary gains: Evidence from ERP gambling study

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ARTICLE INFO

Keywords:
Reward positivity hypothesis
Feedback-related negativity
FRN
ERP
EEG
Reward
Feedback learning
Gambling

ABSTRACT

Feedback processing is an important aspect of learning. In the human brain, feedback processing is often examined by measuring an event-related potential, the feedback-related negativity component. Typically, the feedback-related negativity component is investigated by directly comparing gain with loss feedback randomized across trials; however, this method does not control for confounds associated with unexpected feedback. For this study we used a blocked design gambling task to investigate the sensitivity of feedback-related negativity to positive and negative feedback separately for gains and losses. While there appeared to be no significant feedback-related negativity in the loss domain, results revealed an enlarged feedback-related negativity during the omission of gains compared to the reception of gains. These findings further support the reward positivity hypothesis which declares that the feedback-related negativity is associated with the processing of outcomes in the context of gains as opposed to losses, irrespective of unexpectedness.

1. Introduction

Many studies focus on the event-related potential (ERP) termed feedback-related negativity (FRN) to investigate neural mechanisms of feedback processing (see [1], for a review). The FRN is a mid-frontal negative deflection, which was initially discovered when comparing negative with positive feedback [2]. The difference in amplitude appears between 200 - 400 ms and peaks around 250 ms. Later, others utilized the FRN for investigating the neural mechanisms of feedback learning in association with monetary gains and losses [3–7]. Many studies have suggested that the FRN amplitude indicates a prediction error [8,9,49,50,52,53], measured by comparing the difference between expected and obtained rewards [10,11]. However, the precise role of the FRN with regards to valence and unexpectedness are still under debate.

One potential disadvantage to the measurement of the FRN is that gains and losses are typically compared directly, without considering the notion that gains and losses produce different neural networks [12]. Hence, it is difficult to discern whether the negativity associated with the FRN is merely due to suppression of the neural signal produced by loss negativity, or an enhanced signal generated by reward positivity ([13]; see [14] for review). A seminal electroencephalography (EEG) study found that the probability of gains modulated the FRN to wins, but not to losses [15], suggesting a specific role of reward expectation. This study also suggests different neural mechanisms underlying feedback processing for gains and losses. Some studies have demonstrated changes in the FRN amplitude for both gains and losses by manipulating probability of gains/losses [16] which also suggests that the FRN is related to unexpectedness of gains and losses [17]. Alternatively, others demonstrate a “contextual valence” effect of the FRN [18–23], illustrated by a shift in mean amplitude between positive and negative feedback in the gain domain, yet not for the loss domain. However, most of these studies randomized gains and losses for each trial such that gain and loss expectation were equivalently likely for each trial.

Since some have claimed that the FRN is both sensitive to expected and realized outcomes [16,24], this method may affect the way one perceives positive or negative feedback on a given trial and may affect the underlying biological mechanisms representing these processes. Thus, in our task design we attempted to control for reward/loss expectancy by portraying gains and losses across blocks using a block design. Furthermore, few studies had investigated the amplitude of the FRN using risky decision-making tasks [7,22,51], yet without comparing risky gambles with a certain (safe) gamble that would guarantee a monetary incentive. For this EEG study, we aim to compare event-related potential signals associated with the reception and omission of gains and losses in a risky decision-making task by separately blocking

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https://doi.org/10.1016/j.neulet.2018.09.007
Received 10 July 2018; Received in revised form 15 August 2018; Accepted 4 September 2018
Available online 06 September 2018
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gain and loss feedback from selected risky and safe gambles. The separation of gains and losses across blocks allows one to assess whether the negative deflection of the FRN is specifically associated with loss negativity via loss unexpectation or a reward-related positivity via reward unexpectation. In other words, our paradigm allows one to control for unexpectedness and valence within a single experiment.

We employed a risky decision-making task as used in a previous experiment [25]. The advantage of this task paradigm is that it allows one to measure the reception and omission of gains and losses separately across blocks (rather than between trials) thus allowing one to control for differences in valence expectation. To empirically test the traditional view that the FRN represents a negative going deflection produced by negative feedback, we expect to find differences in mean amplitude between 200 and 400 ms for negative compared to positive feedback for either gains or losses. Specifically, the reward positivity hypothesis would predict a reduced amplitude in the FRN by comparing negative (+0 monetary units [MU]; i.e. 'non-reward' – zero-value outcomes) with respect to positive feedback (+50 MU) within the gain domain, yet no differences within the loss domain.

2. Methods

2.1. Participants

Twenty-five healthy participants (23 right-handed; 18 females; mean age 21.61; age range 18–34 years; SD = 4.49) with normal or corrected to normal vision and with no neurological disorders participated in the study. All participants provided a written consent approved by a local ethics committee in accordance with the Declaration of Helsinki. All participants were screened for psychological/psychiatric disorders and none of them reported use of drugs or alcohol in the days preceding the experiment.

2.2. Stimuli and procedure

We used a novel risky decision-making task – 'rewarded voluntary switch task' (see [25] for original design). It combines the voluntary task switching paradigm [26–33] with a two-choice financial decision-making task (e.g [34–36].) such that a selection of either risky or safe decisions depended on voluntarily switching or repeating task-sets. Fig. 1 illustrates two consecutive trials of the paradigm.

Each trial began with a centered fixation cross displayed between 500 and 1000 ms followed by a stimuli screen, containing a single digit (1, 2, 3, 4, 6, 7, 8, or 9). To select between *risky* and *safe* decisions participants had to select one out of two task-sets represented as an *Odd/Even game* or a *Higher/Lower than 5 game* by pressing one of the corresponding buttons (odd, even, high, low). For half of the blocks, *repeating* the same game in successive trials yielded the *safe decision* while *switching* between game types yielded a *risky decision*. In the other half of the experiment, instructions were counterbalanced such that switching led to a safe decision.

Importantly, the task was also divided into *gain* and *loss blocks*. In gain blocks, safe decisions were defined and instructed as "100% probability that you would receive 25 MU", while risky decisions were instructed as "50% probability that you would receive 50 MU" (or alternatively 0 MU – zero-value outcomes). In loss blocks, the safe decision indicated that "100% probability that you would lose 25 MU" while risky decisions indicated "50% probability that you would lose 50 MU" (alternatively -0 MU – zero-value outcomes). For each response a feedback screen displayed for 2000 ms indicated the amount of MUs rewarded or lost for that particular trial. Positive feedback in gain blocks was 50 MU and 0 MU for loss blocks. Negative feedback in gain blocks was 0 MU and -50 for loss blocks. Neutral feedback was 25 MU and -25 MU for gain and loss blocks, respectively. If response time exceeded 4000 ms or participants responded erroneously participants viewed negative feedback (e.g. 0 MU for gain block, -50 MU for loss blocks). Stimuli and procedure were identical to the previous study [25], with exception to the number of trials and the duration/appearance of the feedback screen. During the presentation of feedback a letter and a number positioned in the center of the screen was displayed for 2000 ms. 'R' or 'S' indicating the choice selected (i.e. Risk/ Safe) and the gain/ loss amount for positive, neutral and negative feedback (i.e. + 50 MU, +25 MU, +0 MU for gains; -0 MU, -25 MU, -50 MU for losses). All other features of the task were identical to the previous task paradigm. Importantly, contrary to some previous studies of the FRN [22,23] participants were able to choose between risky and safe (non-risky) decisions.

The experiment was programmed by E-Prime 2.0 software. Stimuli were centered on the screen and remained on the screen until a response has been made. The text was displayed in black font on a gray scale background and all participants were instructed to use both hands. Participants received two rounds of training, which consisted of eight blocks of 10 trials, resulting in 80 trials in total. If accuracy was below 95% additional training sessions were provided. This learning phase was reflected in the actual experiment; accuracy for all except one participant (86%) was above 92%. Initially, nine participants received 16 blocks of 30 trials (480 trials total); however, to ensure enough trials for each feedback condition the number of trials per block was increased to 40 trials (640 trials total) for the remaining sixteen participants. After performing the task, participants were shown the total cumulative feedback on the computer screen. Participants received 500 MU for participation (500 MU ≈ 7 USD) and an additional bonus, between -300 and + 300 MU, based on the feedback outcomes of six randomly selected trials to maintain an equal motivation for risky decision making across blocks (see [37]).

2.3. EEG recording

The EEG data were recorded with BrainAmp amplifiers and BrainVision Recorder software (Brain Products GmbH, Munich, Germany) using silver ActiCap active scalp electrodes mounted in an elastic cap located at 60 standard positions according to the international 10–20 system. Impedances were kept < 10 kΩ. EEG signals were referenced to the mean of the activity at the two mastoid processes. Electrooculogram were recorded with electrodes placed at both lateral canthi and below the left eye. The electrophysiological signals were filtered online using a sampling rate of 500 Hz in the frequency range 0.2–100 kHz.

Data preprocessing of the EEG data was performed using BrainVision Analyzer 2.0. First, signals in bad channels were replaced by signals averaged over surrounding channels. Second, a bandpass filter (1–40 Hz) was applied to the data, after which eye-blink- and eye-movement-related activity was removed in the data using independent component analysis. Finally, intervals containing non-systematic artifacts produced by electromyographic activity, skin potentials and other sources were manually rejected from the data. Across subjects, 10.1% (σ = 0.090) of trials were excluded from the analysis. ERP's for each condition were segmented between -200 – 1000 ms and averaged across each condition. Baseline correction was performed using the time window of -200 – 0 ms. FRN difference waves were calculated by contrasting negative with positive feedback conditions, separately for gains and losses.

2.4. Statistical analysis

Accuracy was tested using a one sample *t*-test to determine whether accuracy was above chance level. Response times of risky and safe decisions were analyzed across gains and losses using repeated measures analysis of variance (ANOVA) with a Bonferroni correction procedure. To determine whether the percentage of selected risky gambles was above or below chance level, a one sample *t*-test across all conditions was computed. Incorrect trials and trials in which participants

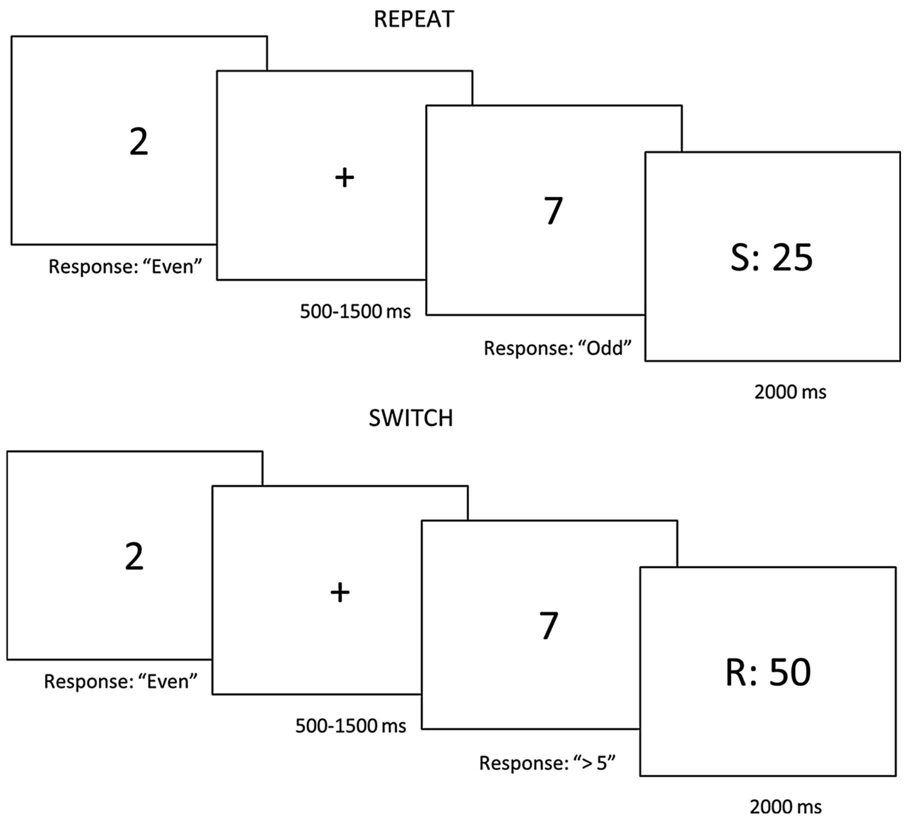

Fig. 1. Switch-risk task. Risky decision making depends on voluntary switching and repeating task-sets. Safe decisions yield 25 MU with a probability of 100% whereas risky decisions yield 50 MU or 0 MU with a probability of 50%. Figure represents trial in the “Switch = Risk” reward block.

responded longer than 4000 ms were excluded from the analysis.

For the FRN analysis, the mean amplitude between 200 and 400 ms after the feedback onset was computed, corresponding with prior studies [2,17]. Mean amplitude across condition for each subject were tested for statistical significance using a repeated measures ANOVA test with three factors (*feedback* [positive vs. negative feedback], *valence* [gain vs. loss blocks], and *electrode* [FCz and Fz]). Bonferroni correction procedure was used to correct for post-hoc comparisons.

3. Results

3.1. Behavioral analysis: descriptive statistics

Mean accuracy was very high: 96.7% ($\sigma = 0.029$), which was above chance level ($p < 0.001$; one sample *t*-test). Subjects preferred risky decisions (58.2%, $\sigma = 0.121$) compared to safe decisions ($p < 0.001$; one sample *t*-test). Behavioral analysis also revealed a significant preference for risky decisions compared to safe decisions for both gains (60.34% risk) and losses (56.29% risk). The proportion of risky decisions was nearly significantly greater in loss blocks compared to gain blocks ($p = 0.058$; paired sample *t*-test), perhaps indicating a reflection effect, a decision-making bias favoring gambles when the choices are prospective losses, as compared to when mathematically equivalent choices are prospective gains ([38,39]; also see [40]). Moreover, participants responded more slowly when they selected safe decisions compared to risky decisions ($F_{1,24} = 9.566$, $p = 0.005$, partial $\eta^2 = 0.285$) and more slowly in the loss condition compared to the gain condition ($F_{1,24} = 17.867$, $p < 0.001$, partial $\eta^2 = 0.427$). The interaction between valence and decision on reaction times was not significant ($p = 0.690$).

3.2. Event-related potential analysis

Visual ERPs, scalp topographies, and mean amplitude for each feedback condition across gains and losses are displayed in Fig. 2a and b. Analysis of ERPs within the 200–400 ms time-window revealed a significant main effect of *feedback* ($F_{2,48} = 5.118$, $p = 0.010$, partial $\eta^2 = 0.176$). Post-hoc analysis demonstrated a significant decrease in ERP’s amplitude ($p = 0.001$) for negative feedbacks (2.67 μV) compared to positive feedback (3.52 μV) following risky decisions, yet no differences were found between ERPs to negative feedbacks following risky decisions and neutral feedbacks following safe decisions ($p = 0.850$), and between ERPs to positive feedbacks following risky decisions and neutral feedbacks following safe decisions ($p = 0.276$). Hence, the main effect of feedback supports the traditional view that the FRN reflects the difference between negative and positive feedback. The analysis also revealed a significant two-way interaction effect between factors *feedback* and *valence* ($F_{2,48} = 12.521$, $p = 0.004$, partial $\eta^2 = 0.202$). Post-hoc analysis demonstrated a reduced ERP’s amplitude during negative feedback in gain blocks (2.190 μV) as compared to loss blocks (3.153 μV; $p = 0.003$).

Difference waves were calculated by subtracting ERPs of positive feedback from ERPs of negative feedback yielding a fronto-central FRN waveform. ERPs to negative feedback (+0 MU: 2.190 μV) were significantly lower than ERPs to positive feedback (+50 MU: 3.671 μV; $p = 0.001$) within gain blocks. No statistically significant difference was found between ERPs to positive (-0 MU) and negative feedback (-50 MU) in loss blocks (all $p > 0.05$). Overall, our findings revealed that the FRN was most prominent in gain blocks as compared to loss blocks.

4. Discussion

Prior studies measuring the FRN component commonly compared gains and losses occurring in randomized trials, without considering

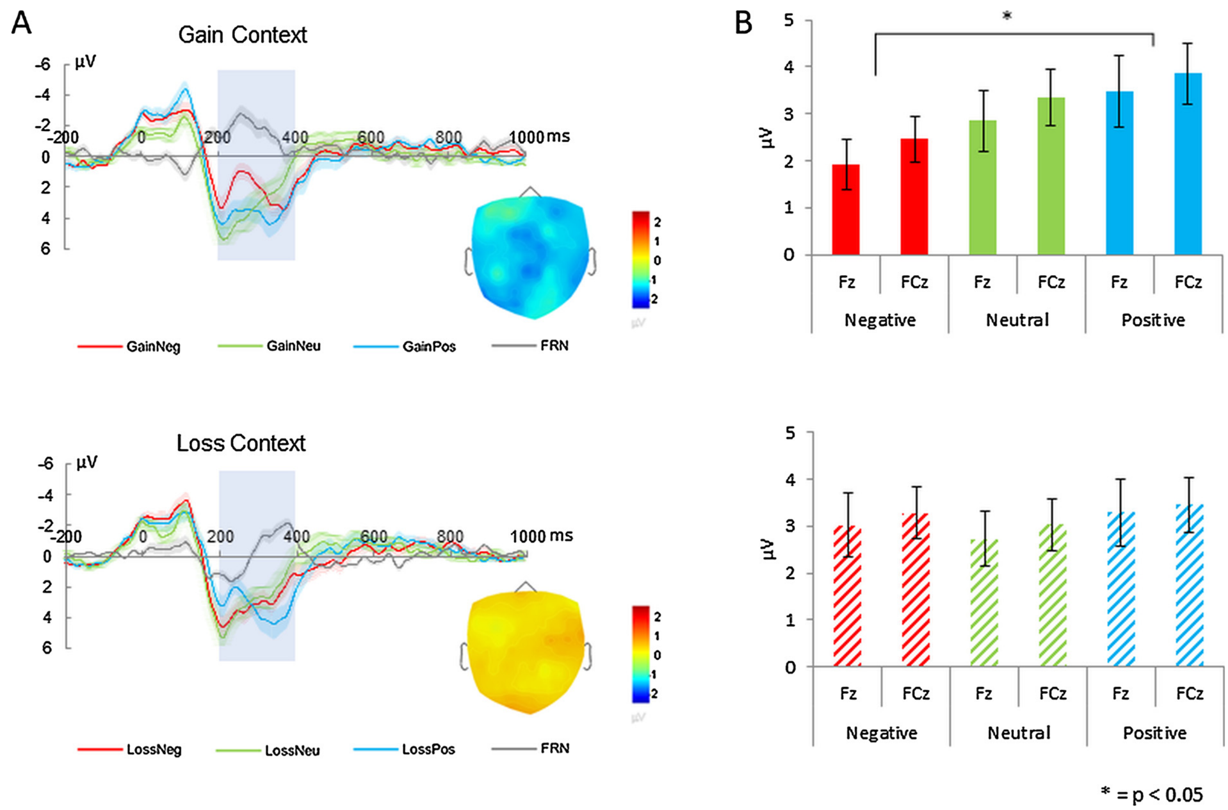

Fig. 2. (a) ERPs and scalp topographies to positive (+50 MU; blue line), neutral (+25 MU; green line), and negative (+0 MU; red line) feedbacks during gain blocks (up) and losses blocks (down) at electrode FCz. FRN is displayed as a difference wave between ERPs to negative (+0 MU) and ERPs to positive feedback (+50 MU). Scalp topographies plotted for 200–400 ms time-windows. (b) Mean amplitude between 200–400 ms for each feedback condition at electrode FCz for gains (up) and losses (down). Error bars represent standard error of the mean (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

omission of gains and losses separately across blocks [18,20,21]. Although a typical experimental procedure for investigating context valence effect of the FRN, no studies considered potential confounds associated with valence expectation. For this experiment we tested the reward positivity hypothesis; which states that the FRN may not reflect the difference between losses and gains per se, but rather the difference between the omission of gains and receiving gains [14]. Specifically, we attempted to assess whether the FRN was sensitive to gain omission [14], by controlling unexpectedness, i.e. reflecting a general signal of expectation violation despite valence [41]. Expectancy in our task was controlled by separating gain/loss reception and omission across blocks using a block design. Our results revealed a negative FRN-like deflection during the omission of gains compared to the reception of gains between 200 - 400 ms. Importantly, we found no statistically significant FRN response in loss blocks during the same time interval. Based on the notion that the FRN signifies negative feedback, after controlling for valence expectation, our results indicate that the FRN may be specific to the gain domain. Therefore, our results provide further empirical support for the reward positivity hypothesis, which were not confounded by differences in unexpectedness between trials for gains or losses.

Few articles have compared the reception of gains with gain omission [18,19,23,42–45]. For example, EEG studies isolating this contrast [18,44] suggest that while reward omission/ loss reception compared to reward reception/ loss omission reflects a “worse than expected” prediction error, loss omission/ reward reception compared to loss reception/ reward omission has been interpreted as a “better than expected” prediction error (see [44]). Similar to our results, the recent EEG study also demonstrated that the FRN in response to the omission of outcome was larger in the gain blocks than in the loss blocks, reflecting the context dependence of the FRN [23].

By parcellating the FRN waveform into subcomponents using principal component analysis it was shown that the P2, P300 and slow wave ERPs displayed similar waveforms between reward and non-reward events, while the reward-related positivity ERP generated a sharp decrease in amplitude during the occurrence of a non-reward [14]. Overall, our results support the hypothesis suggesting that the negativity of the FRN actually reflects a reward-omission positivity. It has been proposed that the generation of the FRN is linked to phasic dopamine signals produce the mesencephalic dopamine system and projects to the dorsal anterior cingulate cortex which accounts for reinforcement learning theory [8,17,46]. Evidence for this theory is supported by neural activity of the dopaminergic system which responds to situations that are better or worse than expected [54,55]. According to this theory, worse than expected events co-occur with decreases in phasic dopaminergic activity between the midbrain and dorsal anterior cingulate cortex eliciting an enlarged FRN component [8]. Hence, while phasic decreases in dopamine activity elicited by worse than expected feedback increase the negativity of the FRN. Our results further suggest that neural response to the reception of rewards but the reception of losses generates the FRN.

5. Conclusion

For this article, we aimed to empirically test the reward positivity hypothesis which suggests that the FRN reflects the difference in amplitude between omission and reception of gains rather than the difference in amplitude between gains and losses. More specifically, we tested whether the effect of valence on the FRN is still present when the unexpectedness of feedback is controlled by separating gains and losses across blocks. Using this experimental approach, we demonstrated that the FRN was specific to the gain domain – it was observed to negative outcomes during gain blocks, but not during loss blocks.

Acknowledgements

The study was supported by Grant 16-18-00065 of the Russian Science Foundation.

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