Local Context Dependency Effect in Feedback Evaluation: An ERP Study

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Date: 2019-07-29T00:00:00+00:00

Abstract

The human brain' s evaluation of feedback depends on its context. However, it remains unclear whether evaluation can only rely on global context (the outcome range of an entire block) or can also rely on local context (the outcome range of a single trial). The present study manipulated the feedback context of each trial through gain/loss cues to investigate whether feedback evaluation relies solely on global context or can extend to the local level. Twenty-five subjects participated in the experiment. The results revealed that when context varied between trials, in the gain context, ¥0 (negative feedback) elicited a more negative FRN (feedback-related negativity) than +¥4 (positive feedback); in the loss context, -¥4 (negative feedback) elicited a more negative FRN than ¥0 (positive feedback). This result demonstrates that feedback evaluation uses possible outcomes within a cue-defined context as a reference, and that the context-dependency of FRN can extend to the local level. In conjunction with previous research, we speculate that task type and feedback authenticity modulate the level of context dependency. In active tasks containing authentic feedback, the context-dependent effect of FRN can extend to the local level.

Full Text

Local Context Dependence in Feedback Evaluation: An ERP Study

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Abstract

Human feedback evaluation depends on its embedded context. However, it remains unclear whether the brain relies solely on global context (the range of outcomes across an entire block) or can also utilize local context (the range of outcomes within a single trial) when assessing feedback. The present study manipulated feedback context on a trial-by-trial basis using gain/loss cues to investigate whether feedback evaluation depends only on global context or can extend to the local level. Twenty-five participants completed the experiment. The results revealed that when context varied between trials, ¥0 (negative feedback) elicited a more negative FRN (feedback-related negativity) than +¥4 (positive feedback) in the gain context, while -¥4 (negative feedback) elicited a more negative FRN than ¥0 (positive feedback) in the loss context. These findings demonstrate that feedback evaluation references the range of possible outcomes within a specific cue-defined context, indicating that the context-dependent effect of FRN can extend to the local level. In conjunction with previous research, we speculate that task type and feedback authenticity modulate the level of context dependence. In active tasks with veridical feedback, the context-dependent effect of FRN can extend to the local level.

Keywords: feedback evaluation; feedback-related negativity; global context dependence; local context dependence
Classification: B842

Introduction

People frequently use external feedback to correct their errors. External feedback not only helps individuals detect mistakes and make timely adjustments in the short term but also aids in distinguishing rewards from punishments and reinforcing adaptive behaviors over longer periods. Consequently, researchers have long been interested in how the human brain evaluates external feedback. Feedback evaluation, also known as outcome evaluation, constitutes a component of performance monitoring that primarily involves comparing expected versus actual outcomes to determine their quality or valence (Ullsperger, Danielmeier, & Jocham, 2014). This process helps individuals optimize their behavioral strategies to better adapt to their environment (Holroyd & Coles, 2002). Behaviorally, feedback evaluation manifests as post-error slowing in simple choice reaction tasks (Wang et al., 2015) or increased adjustment magnitude following errors in time-estimation tasks (Xiang, Wang, & Zhang, 2012). ERP studies have identified the feedback-related negativity (FRN) as a neurophysiological marker for investigating the neural mechanisms underlying feedback evaluation (Li, Li, & Li, 2018; Sambrook & Goslin, 2015; Walsh & Anderson, 2012).

The FRN is a frontocentral negative deflection that was initially discovered as a difference wave between correct and incorrect feedback (Miltner, Braun, & Coles, 1997). This difference emerges 200–400 ms after feedback presentation, peaking around 250 ms (Gehring & Willoughby, 2002). Unfavorable outcomes, such as error feedback or monetary losses, elicit more negative FRN amplitudes compared to favorable outcomes (a valence effect). This phenomenon is termed good/bad binary evaluation (Gehring & Willoughby, 2002; Hajcak, Moser, Holroyd, & Simons, 2006; Holroyd, Hajcak, & Larsen, 2006; Yeung & Sanfey, 2004). The valence effect of FRN aligns with reinforcement learning theory (Holroyd

& Coles, 2002). Some researchers have recently argued that the difference between positive and negative feedback arises from a reward positivity (RewP) elicited by positive feedback rather than a negative component elicited by negative feedback (Proudfit, 2015). The reward positivity is typically derived from FRN difference waves (negative minus positive feedback) or through principal component analysis. However, since a negative deflection generally follows both positive and negative feedback, and based on intuitive observations and previous research (Sambrook & Goslin, 2015; Walsh & Anderson, 2012), the present study also refers to the ERP components elicited by positive and negative feedback as FRN.

A key question in feedback evaluation research concerns how the brain determines outcome valence and whether the same event is evaluated identically across different experimental contexts. Studies have shown that when evaluating feedback, the brain defines outcome quality based on relative value—comparing the outcome to other outcomes within the same context. Thus, the good/bad binary evaluation of FRN is fundamentally context-dependent (Holroyd, Larsen, & Cohen, 2004; Kujawa, Smith, Luhmann, & Hajcak, 2013; Osinsky, Walter, & Hewig, 2014).

Holroyd et al. (2004) first investigated whether feedback evaluation follows context-dependent or context-independent principles. If value judgments about a feedback stimulus remain constant across different experimental contexts, evaluation is context-independent. Conversely, if value assessments depend on the stimulus' s relative value within a specific context, evaluation is context-dependent (Holroyd et al., 2004). In their study, participants encountered two contexts: a "Win" context where they could gain a large amount (++), small amount (+), or zero (0); and a "Lose" context where they could lose a large amount (-), small amount (-), or zero (0). These contexts were presented block-by-block. Results showed that relatively worse outcomes elicited more negative FRN than relatively better outcomes in both contexts. Critically, the zero-amount outcome, which was the worst outcome in the Win context but the best outcome in the Lose context, elicited more negative FRN in the Win context than in the Lose context. These findings demonstrate context-dependent feedback evaluation. Holroyd et al. (2004) proposed that people judge performance quality based on expected levels rather than objective outcome values. Nieuwenhuis, Yeung, Holroyd, Schurger, and Cohen (2004) similarly suggested that context influences FRN amplitude by affecting the formation of subjective value. Nieuwenhuis et al. (2005) found context-dependent effects in reward-related brain regions such as the nucleus accumbens and amygdala. Xiang, Wang, Zhang, and Yuan (2008) demonstrated that FRN reflects relative value referenced to the bet amount, with no significant difference between slightly larger or smaller feedback outcomes, suggesting that the reference point is a range rather than a single point.

How do contextual factors influence outcome evaluation? Osinsky et al. (2014) found that the outcome of unchosen options serves as an important contextual reference for evaluating chosen options. When assessing a selected outcome, people reference it against the unchosen outcome to determine its relative value, with relatively worse outcomes eliciting more negative FRN. Osinsky et al. proposed that an internal reference system continuously integrates feedback and environmental information to form outcome expectations, with early evaluation judging quality based on these expectations. This system conceptually, functionally, and structurally overlaps with the reinforcement learning system proposed by Holroyd and Coles (2002), both being closely linked to outcome expectations.

Kujawa et al. (2013) further investigated whether FRN context dependence operates only at the global level or can also function at the local level. Global context dependence refers to referencing all possible outcomes within the same block, whereas local context dependence refers to referencing all possible outcomes within a single trial. Using a block-wide reference is relatively fixed and effortless, whereas using a trial-specific reference requires extracting the current trial' s context for each evaluation, making it more flexible but also more demanding.

In Holroyd et al. (2004), the Win and Lose contexts varied between blocks, so the observed context dependence could be considered global. Kujawa et al. (2013) used a simple gambling task with trial-by-trial cues: a half-green, half-white circle indicated a gain trial (50% chance of gain, 50% chance of zero), while a half-red, half-white circle indicated a loss trial (50% chance of loss, 50% chance of zero). Results showed that in the gain context, zero-gain feedback elicited more negative FRN than gain feedback; however, in the loss context, zero-loss and loss feedback did not differ significantly. Cross-context comparisons revealed no significant differences between zero-gain, zero-loss, and loss feedback, though both zero-loss and loss feedback elicited more negative FRN than gain feedback. These results suggest that cues did not influence evaluation, and that outcome assessment referenced all possible outcomes across the entire block rather than the current trial' s possible outcomes. Thus, these findings support global rather than local context dependence. However, Angus et al. (2017) used a similar trial-by-trial cuing paradigm and found that relatively worse feedback elicited more negative FRN than relatively better feedback in both gain and loss contexts. This indicates that cues were effective, with each cue establishing a corresponding context for that trial, and that evaluation referenced only the current trial' s possible outcomes—supporting local context dependence. Consequently, conclusions remain inconsistent regarding whether local context can influence outcome evaluation. The present study addresses this question: when evaluating outcomes, does context dependence operate only at the global level, or can it extend to the local level?

To investigate this issue, we improved upon Kujawa et al. (2013) by employing a cued time-estimation task (estimating a 1-second interval) (Mars, De Bruijn, Hulstijn, Miltner, & Coles, 2004; Miltner et al., 1997; Xiang et al., 2012). At the beginning of each trial, a cue determined whether the trial was a gain or loss context. Participants then received correct or incorrect feedback based on their time-estimation accuracy. We analyzed FRN following feedback presentation to determine whether context-dependent effects occurred at the global or local level. Data processing followed Kujawa et al. (2013). Our study featured two improvements over Kujawa et al. (2013): First, we used an active task with veridical feedback, whereas Kujawa et al. used a simple gambling task with pseudorandom feedback. Active tasks with real feedback enhance participant motivation and promote detailed processing of each trial. Second, we increased the number of trials to 80 per experimental condition, compared to 20 trials per condition in Kujawa et al. (2013). Too few trials may prevent participants from fully grasping cue meanings; increasing trial numbers should promote cue processing and improve use of local context.

As shown in Figure 1 [Figure 1: see original paper], if local context dependence operates, relatively worse outcomes should elicit more negative FRN than relatively better outcomes within each trial. Specifically, zero feedback should elicit more negative FRN than gain feedback in gain contexts, while loss feedback should elicit more negative FRN than zero feedback in loss contexts. Additionally, gain-zero feedback should elicit more negative FRN than loss-zero feedback (Angus et al., 2017). If global context dependence operates, results should resemble those of Kujawa et al. (2013): relatively worse outcomes (loss feedback and zero feedback) should elicit more negative FRN than relatively better outcomes (gain feedback) across all possible outcomes, regardless of trial-specific cues (Kujawa et al., 2013).

Figure 1 illustrates the two patterns of context dependence. Under global dependence (left panel), participants reference all possible outcomes, with relatively worse outcomes eliciting more negative FRN irrespective of trial cues. Under local dependence (right panel), participants reference only the current trial' s possible outcomes, with relatively worse outcomes eliciting more negative FRN within that specific context.

2.1 Participants

Twenty-five healthy adults (17 females; mean age = 21.96 years) participated in the time-estimation task. All participants were right-handed as determined by the Oldfield (1971) method, had normal or corrected-to-normal vision, and reported no history of neurological or psychological disorders. Participants provided informed consent after reading the consent form. The study was approved by the Ethics Committee of Shandong Normal University.

2.2 Experimental Procedure

Participants sat in a quiet laboratory 1 m from the computer screen. The experimental procedure is illustrated in Figure 2 [Figure 2: see original paper]. Each trial began with a fixation point (800 ms). Before the time-estimation phase, a cue indicated the specific context for that trial, presented for 1000 ms. Cues consisted of a circle containing either a "+" (gain context) or "−" (loss context) (visual angle: 2.3° × 2.3°) (Angus et al., 2017; Pfabigan et al., 2015). During the 1000–1500 ms interval following cue onset (randomly jittered), participants were instructed to remember the cue while preparing their response. When a gold star appeared (target stimulus, visual angle: 2.3° × 2.3°), participants estimated a 1-second interval while the computer recorded time. When participants believed 1 second had elapsed (i.e., that the target had been presented for 1 second), they pressed the spacebar with their right index finger, which stopped the timer and made the target disappear. After a random interval of 400–600 ms, the computer provided feedback based on the participant' s actual time-estimation accuracy, presented for 1000 ms. Following another random interval of 400–600 ms, the next trial began.

Participants began with an initial bonus of ¥30. In the gain context, accurate estimation yielded +¥4, while inaccurate estimation yielded ¥0. In the loss context, accurate estimation yielded ¥0, while inaccurate estimation yielded -¥4. The experimenter explained the rules during the instruction phase, and participants practiced to ensure they understood the cue and feedback meanings. If local context dependence operated, participants would use the cues to evaluate outcomes, yielding four conditions: gain-positive (+¥4), gain-negative (¥0), loss-positive (¥0), and loss-negative (-¥4). If global context dependence operated (i.e., trial cues were ineffective), participants would evaluate feedback as three types: positive (+¥4), neutral (¥0), and negative (-¥4). Following Kujawa et al. (2013), we used this design to test whether context dependence could operate at the local level.

To maintain time-estimation accuracy at approximately 50% across all contexts, we employed a sliding time window (Mars et al., 2004; Miltner et al., 1997). The initial window was 1000 ± 120 ms, meaning participants' estimates had to fall within 880–1120 ms to be considered accurate (positive feedback); otherwise, they received negative feedback. An adaptive mechanism dynamically adjusted the window based on performance: after accurate estimates, the window narrowed by 10 ms at each boundary to increase difficulty and reduce accuracy; after inaccurate estimates, the window widened by 10 ms at each boundary to decrease difficulty and increase accuracy.

During the practice phase, participants completed practice trials until they were familiar with the procedure. The formal experiment comprised 320 trials, with 160 gain-context trials and 160 loss-context trials presented in random order. Participants took short breaks every 40 trials (approximately 5 minutes) and longer breaks every 80 trials (10–15 minutes).

2.3 EEG Recording and Analysis

The experimental program was written in E-Prime 2.0 (Psychology Software Tools, Inc., Sharpsburg, PA). EEG data were collected using a Brain Products system (Brain Products GmbH, Munich, Germany) with a standard 10–20 electrode cap (bandpass filter: 0.0531–80 Hz; sampling rate: 500 Hz). Data were recorded online with FCz as the reference and AFz as the ground. Electrode-scalp impedance was maintained below 10 kΩ. Horizontal electrooculogram (HEOG) was recorded from an electrode placed below the right eye, and vertical electrooculogram (VEOG) from an electrode placed 1 cm lateral to the left eye.

Offline analysis was performed using Brain Vision Analyzer 2.0. First, the reference was re-set to the average of the bilateral mastoids, and FCz was restored as an active electrode. Data were filtered with a 0.1–20 Hz bandpass filter (24 dB/octave). Epochs ranged from -200 to 800 ms relative to feedback onset, with the -200 to 0 ms interval serving as baseline. Ocular artifacts were corrected using ICA-based algorithms. Trials with amplitudes exceeding ±80 μV were automatically rejected as artifacts. Finally, EEG data were averaged for each condition. The number of valid trials per condition is provided in Supplementary Table 1 .

Because feedback-related ERP components (e.g., P2, FRN, P300) are susceptible to component overlap, we employed a peak-to-peak algorithm based on previous research (Holroyd, Nieuwenhuis, Yeung, & Cohen, 2003; Osinsky, Mussel, & Hewig, 2012; Osinsky et al., 2014; Pfabigan, Alexopoulos, Bauer, & Sailer, 2011; Xiang et al., 2012). FRN peak-to-peak amplitude (FRN–P2) was calculated as the difference between the most negative peak within 200–300 ms post-feedback (FRN amplitude) and the most positive peak within 150–250 ms post-feedback (P2 amplitude). If the peak-to-peak value was non-negative, FRN amplitude was recorded as 0 μV (Holroyd et al., 2003; Xiang et al., 2012). Following this rule, 23 data points (7.67%) were recorded as 0 μV. FRN amplitudes were extracted from electrodes Fz, FCz, and Cz.

The ERP analysis comprised two parts. First, a three-way repeated-measures ANOVA was conducted with cue (gain, loss), feedback valence (positive, negative), and electrode (Fz, FCz, Cz) as factors to test for local context dependence. Second, to test for global context dependence, ERP data from the electrode showing maximal FRN amplitude were analyzed using paired-samples t-tests to compare: gain-positive versus gain-negative, loss-positive versus loss-negative, and the two zero-value feedback conditions (gain-negative vs. loss-positive). This latter comparison specifically tested whether the brain evaluates outcomes based on relative value within context or absolute value.

2.4 Behavioral Data Analysis

To verify the effectiveness of the sliding time window, we used t-tests to compare the number of accurate versus inaccurate trials across conditions. To examine how cues and feedback valence influenced behavioral adaptation, we conducted a 2 (cue: gain, loss) × 2 (feedback valence: positive, negative) repeated-measures ANOVA on the absolute difference between consecutive time estimates (|trial − trial |) (Xiang et al., 2012), with the previous trial' s cue and feedback valence as independent variables. All analyses were performed using SPSS 17.0, with Greenhouse-Geisser correction applied when necessary.

3.1 Behavioral Results

Comparisons of accurate versus inaccurate trial counts revealed no significant differences across conditions: gain context (positive: 79.84 ± 6.58, 95% CI = 77.12–82.56; negative: 80.20 ± 6.58, 95% CI = 77.48–82.92), $t(19) = -0.14$, $p = 0.892$, $d = 0.03$; loss context (positive: 79.76 ± 5.79, 95% CI = 77.37–82.15; negative: 79.92 ± 5.79, 95% CI = 77.53–82.31), $t(19) = -0.07$, $p = 0.945$, $d = 0.01$. Overall accuracy was 49.98%. These results confirm that the sliding time window effectively controlled the ratio of positive to negative feedback.

Figure 3 [Figure 3: see original paper] shows the trial-to-trial adjustment magnitude in time estimation. ANOVA revealed a significant main effect of feedback valence, $F(1,24) = 37.47$, $p < 0.001$, $^2 = 0.61$, with negative feedback (M = 135.46 ms, 95% CI = 123.92–145.00 ms) producing significantly larger adjustments than positive feedback (M = 168.47 ms, 95% CI = 155.21–183.74 ms). The main effect of cue was not significant (gain: M = 151.95 ms, 95% CI = 139.77–164.12 ms; loss: M = 152.99 ms, 95% CI = 139.06–166.91 ms), $F(1,24) = 0.13$, $p = 0.719$, $^2 = 0.006$. The interaction between cue and feedback valence was marginally significant, $F(1,24) = 4.03$, $p = 0.056$, $^2 = 0.14$. These behavioral results indicate that participants utilized cue information to discriminate relative outcome valence within specific contexts and adjusted their behavior accordingly.

3.2 ERP Results

ANOVA revealed a significant main effect of feedback valence, $F(1,24) = 61.14$, $p < 0.001$, $^2 = 0.72$, with negative feedback (M = -6.97 μV, 95% CI = -8.34 to -5.60 μV) eliciting significantly more negative FRN than positive feedback (M = -3.77 μV, 95% CI = -5.12 to -2.42 μV). The main effect of electrode was also significant, $F(2,48) = 13.31$, $p = 0.001$, $^2 = 0.36$. Amplitudes at Fz (M = -5.98 μV, 95% CI = -7.41 to -4.54 μV) and FCz (M = -5.59 μV, 95% CI = -6.94 to -4.24 μV) were significantly larger than at Cz (M = -4.55 μV, 95% CI = -5.75 to -3.35 μV; $p = 0.001$ and $p < 0.001$, respectively), while Fz and FCz did not differ significantly ($p = 0.089$). The main effect of cue (gain: M = -5.68 μV, 95% CI = -6.98 to -4.37 μV; loss: M = -5.06 μV, 95% CI = -6.42 to -3.71 μV) was not significant, $F(1,24) = 3.84$, $p = 0.062$, $^2 = 0.14$. As our primary focus was on the interaction between cue and feedback valence, we report only this interaction.

The analysis revealed no significant cue × feedback valence interaction, $F(1,24) = 0.02$, $p = 0.899$, $^2 = 0.001$. Further paired-samples t-tests on ERP data from electrode Fz examined different trial types. Results showed that negative feedback elicited significantly more negative FRN than positive feedback in both gain ($t(24) = 4.19$, $p < 0.001$, $d = 0.84$) and loss contexts ($t(24) = 3.31$, $p = 0.003$, $d = 0.66$). Comparisons between relatively favorable feedback across contexts (gain-positive vs. loss-positive) and relatively unfavorable feedback across contexts (gain-negative vs. loss-negative) revealed no significant differences ($t(24) = 0.48$, $p = 0.634$, $d = 0.09$; $t(24) = -1.10$, $p = 0.284$, $d = 0.22$, respectively). Critically, the two zero-value feedback conditions differed significantly: gain-negative feedback (relatively unfavorable) elicited more negative FRN than loss-positive feedback ($t(24) = -6.86$, $p < 0.001$, $d = 1.37$).

Figure 4 [Figure 4: see original paper] displays mean FRN amplitudes and standard deviations across the four experimental conditions at Fz, FCz, and Cz. Figure 5 [Figure 5: see original paper] shows the grand-averaged ERP waveforms for the four conditions at Fz, FCz, and Cz. Figure 6 [Figure 6: see original paper] presents FRN waveforms for positive and negative feedback at Fz and the topographic map of the difference wave.

In summary, when context varied between trials, relatively worse feedback elicited more negative FRN than relatively better feedback in both gain and loss contexts, demonstrating that FRN exhibits context-dependent effects at the local level. These results align with Angus et al. (2017) but contradict Kujawa et al. (2013).

Because Kujawa et al. (2013) included only 20 trials per condition whereas our study included 80, we hypothesized that insufficient trial numbers might impair cue-outcome association learning and affect whether the brain uses cues to evaluate trial-specific outcomes. To rule this out, we re-analyzed only the first 20 trials of each condition. The number of valid trials for this analysis is provided in Supplementary Table 2 .

The results from the first 20 trials (see Appendix 1) were identical to those from the full dataset, with similar amplitude patterns following feedback onset. This indicates that trial number did not significantly affect FRN amplitude across conditions, ruling out trial count as a confounding factor. Moreover, the first-20-trials analysis still differed from Kujawa et al. (2013), further supporting that FRN context dependence can extend to the local level.

To explore how the brain evaluates outcome quality, Holroyd et al. (2004) proposed and validated the context-dependent effect of FRN. Subsequent research has examined various forms of context dependence, including outcome frequency (Holroyd et al., 2003), outcome sequence (Osinsky et al., 2012), and possible outcomes within a given context (Angus et al., 2017; Holroyd et al., 2004; Kujawa et al., 2013; Osinsky et al., 2014; Pfabigan et al., 2015). Using a time-estimation task with trial-by-trial contextual cues and veridical feedback based on whether estimates fell within a sliding time window, the present study investigated whether outcome evaluation references all possible outcomes globally or possible outcomes within the local context.

Behavioral results showed that accuracy rates were approximately 50% overall and within each context, confirming the effectiveness of the sliding time window (Mars et al., 2004; Miltner et al., 1997; Xiang et al., 2012). For trial-to-trial adjustment magnitude, negative feedback produced significantly larger adjustments than positive feedback in both gain and loss contexts, indicating that participants learned from errors and modified inappropriate behaviors to improve performance (Luft, 2014). These behavioral results demonstrate that participants used cue information to discriminate relative outcome valence within specific contexts and adjusted their behavior accordingly.

ERP results from both the full dataset and the first-20-trials analysis were consistent. First, feedback valence significantly affected FRN, with relatively worse feedback eliciting more negative FRN than relatively better feedback. This aligns with numerous previous studies (Angus et al., 2017; Gehring & Willoughby, 2002; Hajcak, Holroyd, Moser, & Simons, 2005; Holroyd et al., 2004; Kujawa et al., 2013) and supports the good/bad binary evaluation prediction of reinforcement learning theory (Holroyd & Coles, 2002). More importantly, participants utilized cue information, evaluating event quality relative to the specific context. In gain contexts, relatively worse feedback (zero gain) elicited more negative FRN than relatively better feedback (gain). In loss contexts, relatively worse feedback (loss) elicited more negative FRN than relatively better feedback (zero loss). Critically, the two zero-value feedback conditions differed: gain-zero (relatively worse) elicited more negative FRN than loss-zero (relatively better). These results align with Angus et al. (2017) and support our hypothesis that during feedback processing, participants referenced possible outcomes within a local context, indicating that FRN context dependence can extend to the local level. However, these findings contradict Kujawa et al. (2013), who found that outcome evaluation referenced all possible outcomes rather than context-specific outcomes, resulting in no significant FRN difference between gain-zero and loss-zero feedback, and both eliciting more negative FRN than gain feedback.

Why do outcome evaluations sometimes reference global outcomes (Kujawa et al., 2013) and sometimes local outcomes (Angus et al., 2017) in similar trial-by-trial cuing paradigms? Based on previous research (Heydari & Holroyd, 2016; Mulligan & Hajcak, 2018; Soder & Potts, 2018) and comparisons between our study and Kujawa et al. (2013), we speculate that task type and feedback authenticity are key factors.

ERP studies of feedback evaluation typically employ three task types: passive tasks (no response required, feedback is neither false nor true) (Talmi, Atkinson, & Elderedy, 2013; Soder & Potts, 2018), active tasks with false feedback (response required but feedback is pseudorandom, not based on actual performance) (Heydari & Holroyd, 2016; Kujawa et al., 2013; Mulligan & Hajcak, 2018), and active tasks with veridical feedback (response required and feedback reflects actual performance) (Angus et al., 2017).

Talmi et al. (2013) and Soder and Potts (2018) used passive tasks requiring no response and found no FRN sensitivity to valence (no significant difference between positive and negative feedback). Heydari and Holroyd (2016) addressed this by using an active T-maze task where participants chose directions and received false reward/non-reward feedback, finding that outcome evaluation followed a binary classification rule with negative feedback eliciting more negative FRN. Mulligan and Hajcak (2018) used a simple gambling task requiring active choice and obtained similar results. Kujawa et al. (2013) also found binary classification and global context dependence. Our study and Angus et al. (2017) used active tasks with veridical feedback based on performance accuracy and found that context dependence extended to the local level.

We propose that task type and feedback authenticity critically influence whether FRN exhibits binary classification and whether context dependence operates globally or locally. The underlying mechanism may involve how these factors affect subjective agency and motivation during outcome evaluation (Sambrook & Goslin, 2015). Passive designs may reduce perceived control and subjective engagement, whereas active choice maximizes FRN amplitude (Walsh & Anderson, 2012; Yeung & Sanfey, 2004). Consequently, negative feedback in passive tasks produces smaller FRN (Heydari & Holroyd, 2016; Sambrook & Goslin, 2015), while active tasks produce larger FRN. Compared to pseudorandom false feedback, veridical feedback reflecting actual performance may enhance subjective agency and motivation, allocating more attentional resources to trial-initial cues and enabling construction of trial-specific contexts. This leads outcome evaluation to reference local context-specific outcomes rather than global cross-trial outcomes.

In summary, we hypothesize that task type (active vs. passive) and feedback authenticity (veridical vs. false) influence FRN valence sensitivity and the level of context dependence by affecting subjective agency, motivation, and attentional resource allocation. In active tasks with false feedback, outcome evaluation references all possible outcomes globally; in active tasks with veridical feedback, evaluation references possible outcomes within the local context.

Our study has limitations in data analysis depth. More sophisticated methods such as principal component analysis and time-frequency analysis could provide additional perspectives on FRN context dependence. Furthermore, single-trial EEG analysis could better explore the neural mechanisms of behavioral adaptation in time-estimation tasks.

Appendix 1: FRN Results from the First 20 Trials

A three-way ANOVA (2 [cue: gain, loss] × 2 [feedback valence: positive, negative] × 3 [electrode: Fz, FCz, Cz]) revealed a significant main effect of feedback valence, $F(1,24) = 28.91$, $p < 0.001$, $^2 = 0.55$, with negative feedback (M = -6.39 µV, 95% CI = -8.74 to -5.80 µV) eliciting significantly larger FRN than positive feedback (M = -4.38 µV, 95% CI = -5.70 to -3.05 µV). The main effect of electrode was significant, $F(2,48) = 12.04$, $p = 0.001$, $^2 = 0.33$, with the largest FRN amplitude at Fz. Amplitudes at Fz (M = -6.39 µV, 95% CI = -7.74 to -5.03 µV) and FCz (M = -5.98 µV, 95% CI = -7.35 to -4.61 µV) were significantly larger than at Cz (M = -5.10 µV, 95% CI = -6.34 to -3.86 µV; $p = 0.001$ and $p < 0.001$, respectively), while Fz and FCz did not differ significantly ($p = 0.061$). The main effect of cue (gain: M = -5.79 µV, 95% CI = -7.17 to -4.41 µV; loss: M = -5.86 µV, 95% CI = -7.25 to -4.45 µV) was not significant, F(1,24) = 0.01, p = 0.905, ^{2} = 0.001. The cue × feedback valence interaction was also not significant, F(1,24) = 1.77, p = 0.196, ^{2} = 0.07.

Paired-samples t-tests on Fz data examined different trial types. Negative feedback elicited significantly more negative FRN than positive feedback in both gain (t(24) = 4.72, p < 0.001, d = 0.94) and loss contexts (t(24) = 2.15, p = 0.042, d = 0.43). No significant differences emerged between gain-positive and loss-positive feedback (t(24) = 1.31, p = 0.201, d = 0.26) or between gain-negative and loss-negative feedback (t(24) = -0.85, p = 0.407, d = 0.17). Importantly, gain-negative feedback elicited significantly more negative FRN than loss-positive feedback (t(24) = -3.32, p = 0.003, d = 0.66).

Figure 7 [Figure 7: see original paper] shows mean FRN amplitudes and standard deviations for the four experimental conditions from the first 20 trials. Figure 8 [Figure 8: see original paper] presents the grand-averaged ERP waveforms for these conditions.

Supplementary Table 1
Valid trial counts per participant and condition (full dataset)

Supplementary Table 2
Valid trial counts per participant and condition (first 20 trials)

Note: Figure translations are in progress. See original paper for figures.

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