The Influence of Working Memory Load on Feedback Processing: Evidence from EEG Studies

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Abstract

The processing of feedback outcomes following actions is of significant importance for learning and environmental adaptation in individuals. How working memory load (WM load) influences this feedback processing remains unclear. Employing a dual-task paradigm with three conditions (baseline, low WM load, and high WM load), this issue was investigated using ERP technology. We found that RewP (reward positivity) was sensitive to valence but unaffected by WM load conditions; the difference wave between positive and negative feedback for Theta oscillations was smaller under high WM load compared to low WM load. These results support the HRL-ACC (hierarchical reinforcement learning theory of anterior cingulate cortex) perspective on RewP and theta oscillations: RewP reflects the function of feedback valence evaluation, theta oscillations reflect cognitive control function, and WM load selectively influences ACC’ s cognitive control function rather than its feedback valence evaluation function.

Full Text

The Effects of Working Memory Load on Feedback Processing: Evidence from an EEG Study

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Abstract

The processing of post-action feedback outcomes plays a crucial role in learning and environmental adaptation. However, how working memory load (WM load) influences this feedback processing remains unclear. Using a dual-task paradigm with baseline, low WM load, and high WM load conditions, combined with ERP technology, this study investigated this question. We found that RewP (reward positivity) was sensitive to feedback valence but was not affected by

WM load conditions. The difference wave of theta oscillation between positive and negative feedback was smaller under high WM load than under low WM load. These results support the hierarchical reinforcement learning theory of anterior cingulate cortex (HRL-ACC) regarding RewP and theta oscillations: RewP reflects feedback valence evaluation, theta oscillations reflect cognitive control functions, and WM load selectively affects ACC' s cognitive control function rather than its feedback valence evaluation function.

Keywords: Working memory load (WM load), feedback, reward positivity (RewP), theta oscillation, anterior cingulate cortex

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In daily life, feedback critically influences human learning and environmental adaptation. Individuals tend to maintain their existing behaviors after positive feedback and adjust their original behaviors after negative feedback, thereby acquiring knowledge and skills [?, ?]. The hierarchical reinforcement learning theory of anterior cingulate cortex function (HRL-ACC theory) [?, ?, ?] provides a detailed model of this process. Another obvious fact is that learning often involves not isolated actions but multiple simultaneous tasks—for example, students must listen to lectures while taking notes. Compared with single-task performance, multitasking increases cognitive resource demands and working memory load (WM load) [?, ?]. Previous studies have found that increased WM load during dual-task or multitask operations interferes with ongoing psychological processes [?, ?, ?, ?, ?], but how WM load affects feedback processing remains unclear. Although HRL-ACC theory [?, ?] mentions the influence of WM load on feedback processing and learning, direct evidence is lacking. This study uses EEG technology to investigate this issue.

Reward positivity (RewP), previously called feedback-related negativity (FRN), is the most important ERP component elicited during feedback processing. RewP is sensitive to feedback valence, with positive feedback evoking a more positive wave than negative feedback. This component appears 200–350 ms after feedback presentation, with maximum amplitude distributed over mid-frontal scalp regions. Dipole source localization and neuroimaging studies suggest that RewP originates from the anterior cingulate cortex (ACC) and nearby striatal regions [?, ?, ?, ?, ?, ?]. Understanding of RewP' s psychological function has undergone a transformation. Early research suggested RewP reflected negative feedback processing (e.g., monetary loss), with negative feedback evoking a more negative wave [?, ?, ?, ?, ?], hence the original name FRN. As research progressed, investigators shifted to the view that positive feedback (e.g., monetary gain) evokes a more positive wave [?, ?, ?, ?]. The amplitude difference between positive and negative feedback conditions reflects reward processing rather than negative feedback processing, leading Proudfit et al. (2015) to advocate renaming it RewP.

Delta (<3 Hz) and theta (4–7 Hz) are two main oscillatory components elicited during feedback processing, each sensitive to monetary gain and loss respectively

[?, ?, ?]. To further understand the relationship between RewP, delta and theta oscillations, and positive/negative feedback processing, Foti et al. (2015) used time-frequency analysis to separate EEG components during feedback processing. They found theta oscillations significantly enhanced after negative feedback, while delta oscillations significantly enhanced after positive feedback. Brain source localization revealed the former in ACC and the latter in the striatum. Based on these findings, Foti et al. proposed a compromise view that RewP is a composite of theta activity sensitive to negative feedback and delta activity sensitive to positive feedback.

Regarding the relationship between RewP and feedback processing, reinforcement learning theory (RL theory) [?, ?] offers detailed hypotheses. Initially developed for FRN, this theory posits that FRN reflects reward prediction error (RPE) signals generated by the midbrain dopamine system during reinforcement learning. When actual feedback is better than expected, dopamine release increases; when worse than expected, dopamine decreases. This signal is projected to ACC for reinforcement learning and modulates FRN amplitude. Later, Holroyd et al. refined the theory, dividing ACC functions in goal-directed behavior into action selection and action driving, and incorporating both RewP (though renamed from FRN, its essence as a valence evaluation and RPE signal remains unchanged) and theta oscillations (called frontal midline theta, FMT) into what became HRL-ACC theory [?, ?, ?, ?].

HRL-ACC theory suggests that ACC receives feedback evaluation signals (RPE) from the midbrain dopamine system to learn the value of certain behaviors or tasks and select which actions to implement. Simultaneously, ACC drives task execution through control over other brain regions (dorsolateral prefrontal cortex, ventral striatum). HRL-ACC theory assigns important significance to RewP and theta oscillations, proposing that RewP is an EEG indicator of RPE signals acting on ACC' s input side, while theta oscillations represent EEG activity of control signals emitted by ACC, acting as output signals [?, ?, ?].

Current research and theory require further verification. First, regarding theta oscillations, HRL-ACC theory posits they reflect control signals from ACC. Important evidence for this view is that theta oscillations are affected by cognitive resources (e.g., WM load, attention) [?, ?, ?], especially in tasks requiring sustained cognitive control [?, ?]. However, direct evidence is lacking on whether theta oscillations during feedback processing are modulated by WM load levels. Second, unlike HRL-ACC theory, Foti et al. (2015) suggest theta oscillations reflect processing of negative outcomes without explicitly stating whether they are affected by cognitive resources. Therefore, this study examines how WM load affects theta oscillations elicited during feedback processing, testing HRL-ACC theory's view on theta oscillations and evaluating which perspective—HRL-ACC theory or Foti et al. (2015)—is more reasonable. Additionally, current research and theory have paid little attention to whether RewP and its reflected feedback valence evaluation process are affected by WM load. This study analyzes WM load' s influence on RewP to explore this question.

Beyond RewP and theta/delta oscillations, P3 and LPP (late positive potential) are also important EEG components elicited during feedback processing. P3 appears immediately after RewP, distributed over mid-posterior scalp regions. P3 is a multi-source EEG component related to attention resource allocation, contextual information integration, and working memory updating [?, ?, ?, ?]. According to the context-updating hypothesis [?, ?], when stimulus information is inconsistent with existing mental representations, internal representations are updated, and P3 reflects brain activity during mental representation revision. LPP is an ERP component following RewP and P3 during feedback processing, beginning 500–600 ms after feedback and lasting until approximately 1000 ms, with scalp distribution similar to P3. Compared with neutral stimuli, LPP amplitude increases after positive or negative stimuli, and research suggests it reflects sustained emotional-motivational processes during stimulus processing [?, ?, ?, ?, ?].

Numerous studies have observed different deflections and amplitude changes in P3 and LPP after positive and negative feedback. Some studies found larger P3 amplitudes after positive than negative feedback [?, ?, ?], interpreting this as representing attention resource investment or affective value changes during feedback processing. Some studies found LPP sensitive to feedback valence, with increased LPP amplitude after positive compared to negative feedback [?, ?, ?], while others found increased LPP amplitude after negative feedback [?, ?]. One important reason for these discrepancies is differences in experimental tasks, which involve varying WM load. For example, in Webb et al. (2017), participants had to guess which of three options concealed a reward (a green ball) while simultaneously performing a memory task for the number of green balls, whereas in Donaldson et al. (2016), participants simply guessed reward location between two options. Clearly, the former posed a greater WM load challenge. This study also analyzes how WM load levels affect P3 and LPP stages during feedback processing.

This study employed a dual-task design combining a simple gambling task with a working memory task to create baseline, low WM load, and high WM load conditions, examining WM load' s influence on feedback processing. Specifically, we analyzed WM load' s effects on RewP, P3, LPP components, and delta and theta oscillations. First, based on HRL-ACC theory, we expected WM load to modulate theta activity, particularly the feedback valence effect of theta activity, with differences across WM load conditions. Second, since P3 reflects response mode updating and behavioral adjustment following feedback processing, we expected WM load to affect P3' s processing of feedback valence. Additionally, current theory and research lack clear hypotheses about whether WM load affects RewP, delta oscillations, and LPP, which this experiment also explored.

2.1 Participants

Twenty-five adult participants took part in the experiment, all right-handed with normal or corrected-to-normal vision and no history of psychiatric disorders or head trauma. One participant had incorrect filter bandpass settings during the experiment, resulting in no valid EEG data. Another participant verbally reported sleepiness and fatigue and failed to perform the task seriously. After excluding these two participants, valid data were obtained from 23 participants (13 female), aged 18–25 years (M = 20 ± 1.4). Participants received corresponding remuneration after the experiment. This study was approved by the Shandong Normal University Ethics Committee.

2.2 Experimental Design and Procedure

Sample size was calculated using G*Power 3.1. The maximum effect size was set to f = 0.4, $\alpha = 0.05$, and the correlation between repeated measures was r = 0.5. This study used a 2 × 3 within-subjects design, so the number of groups was 1 with 6 factor levels. The final calculated sample size was 15 participants. This study obtained valid data from 23 participants, meeting the sample size requirement.

We used a dual-task paradigm to manipulate WM load levels through a working memory task combined with feedback processing. A 2 × 3 within-subjects design was employed, with two factors: WM load level (baseline, low WM load, high WM load) and feedback valence (reward, no reward).

The working memory task was adapted from Han et al. (2017). As shown in Figure 1a [Figure 1: see original paper], memory materials consisted of a 4$×$4 grid (visual angle: 2.9° × 2.9°) and black squares serving as memory items. The working memory task included two conditions: in the low WM load condition, one small square appeared randomly in any position of the grid; in the high WM load condition, three small squares appeared randomly in the grid, with the constraint that the three squares were clustered together. As shown in Figure 1b, the working memory task included a memory phase and a probe phase, with the simple gambling task embedded between these two phases.

Figure 1. Examples of memory materials for high and low WM load conditions (1a), and experimental flowchart (1b). As shown in 1b, the experiment used a dual-task paradigm with the simple gambling task embedded within the working memory task.

Participants sat in a soundproof, dimly lit shielded room, 100 cm from the display screen. The experimental procedure is shown in Figure 1b. First, a fixation point appeared for 500 ms, followed by a grid lasting 1000 ms. Participants were required to remember the positions of black squares in the grid picture. Then an 800 ms blank screen appeared, followed by two blank cards. Participants were informed that pressing the "F" key selected the left card and pressing the "J" key selected the right card, and they had to make a choice within 3 s. If no choice was made within 3 s, a "Too slow" message appeared. After the choice, a blank screen with random duration of 600-1000 ms appeared, followed by a 1000 ms feedback stimulus (visual angle: 2.3° × 2.3°), where "√" indicated winning 0.1 yuan in that trial and "×" indicated no monetary gain or loss. Subsequently, an 800 ms blank screen appeared, followed by the grid picture again. Participants had to judge whether the square positions in this grid were the same as the previous grid, pressing "F" for same and "J" for different, within 1000 ms. Finally, an 800 ms blank screen served as the inter-trial interval.

In addition to high and low WM load conditions, the experiment included a baseline condition with only the simple gambling task. Following White and Grant (2017), to avoid contamination of the baseline condition by working memory conditions, participants always performed the baseline condition first. The baseline condition comprised one block of 100 trials. The low and high WM load conditions each included two blocks, with 50 trials per block. The order of the four blocks for high and low WM load conditions was counterbalanced across participants.

Before each condition, participants completed a practice phase of at least 15 trials to ensure they understood the procedure. Since feedback ratio affects feedback-related EEG components, and to ensure positive and negative feedback probabilities were approximately 50% with no significant difference, the experiment used a pseudo-random design following previous research [**?**, **?**, **?**, **?**, **?**, **?**]. Positive and negative feedback appeared pseudo-randomly, independent of participants' card choices. To maintain task motivation, participants were told that a pattern existed between the cards and were encouraged to discover it to maximize gains in the gambling task. After the experiment, participants were informed about the pseudo-random design and the experimental purpose.

2.3 EEG Recording and Processing

The experimental program was written using E-Prime 2.0 (Psychology Software Tools, Inc., Sharpsburg, PA). EEG was recorded using a 64-channel Brain Products system (Brain Products GmbH, Munich, Germany) with electrodes placed according to the 10-20 system. Vertical electrooculogram (VEOG) was recorded from an electrode 1.5 cm below the right eye, horizontal electrooculogram (HEOG) from an electrode 1.5 cm lateral to the left eye, and bilateral mastoid data (M1, M2) were also recorded. The filter bandpass was 0.016–70 Hz, A/D sampling rate was 1000 Hz/channel. All electrodes were online-referenced to FCz, with AFz as ground. Electrode impedance was maintained below 10 KΩ.

Offline analysis was performed using BrainVision Analyzer 2.1 software. First, the sampling rate was reduced to 500 Hz, and average mastoid reference was applied. A 0.1–30 Hz bandpass filter was used, and independent component analysis was applied to correct ocular artifacts while excluding other artifacts with amplitudes exceeding $±$80 μV. ERP components were obtained by averaging EEG in a time window from 200 ms before to 800 ms after feedback presentation, with a 200 ms pre-feedback baseline.

This study analyzed three ERP components: RewP, P3, and LPP. Electrode sites and time windows were determined through visual inspection of EEG results and reference to previous literature. For RewP, the average amplitude from 210–290 ms after feedback was extracted from Fz, FCz, and Cz, and the mean of these three values was used as the RewP amplitude [?, ?, ?, ?]. For P3, the average amplitude from 310–400 ms was extracted from Pz and POz, and the mean of these two values served as the P3 amplitude [?, ?, ?]. For LPP, the average amplitude from 500–750 ms was extracted from Cz, CPz, Pz, and POz, and the mean of these four values served as the LPP amplitude [?, ?, ?].

Time-frequency analysis followed Webb et al. (2017). In BrainVision Analyzer 2.1, continuous wavelet transformation (CWT) was selected. Similar to time-domain analysis, EEG data were segmented first. To avoid edge effects, the time window was extended, using EEG from 1000 ms before to 1500 ms after feedback presentation for complex Morlet wavelet transformation (Morlet parameter: c = 3.5). Frequencies from 0.5–20 Hz were divided into 30 steps based on a logarithmic scale, with EEG from -500 ms to -300 ms before feedback serving as baseline for correction. Data from different conditions were then averaged, and the time window was re-segmented to 200 ms before and 800 ms after feedback for analysis. To obtain delta and theta activity power, wavelets with center frequencies of 2.3 Hz (spectral bandwidth: 1.32 Hz) and 5.6 Hz (spectral bandwidth: 3.2 Hz) were extracted. Based on results and previous research [?, ?, ?], the delta analysis time window was 220–430 ms after feedback, with values extracted from Cz and CPz and averaged. The theta analysis time window was 250–400 ms after feedback, with values extracted from Fz and FCz and averaged.

2.4 Data Statistics and Analysis

At the behavioral level, paired-sample t-tests were conducted on response times and accuracy rates for the working memory task across different WM load levels. For ERP data, RewP, P3, and LPP amplitudes were analyzed using a 3 (WM load condition: baseline, low, high) × 2 (feedback valence: reward, no reward) two-way repeated measures ANOVA.

For theta and delta components, a 3 (WM load condition: baseline, low, high) × 2 (feedback valence: reward, no reward) two-way repeated measures ANOVA was conducted. Additionally, since the ANOVA for theta revealed an interaction between WM load condition and feedback valence, to further analyze the valence effect under different WM load conditions, theta activity after negative feedback was subtracted from that after positive feedback to obtain theta difference values between positive and negative feedback. These difference values were then analyzed using a one-way (WM load condition: baseline, low, high) repeated measures ANOVA.

Data analysis was performed using SPSS 19.0. P-values violating sphericity assumptions were corrected using the Greenhouse-Geisser correction. Effect sizes were reported: for t-tests, Cohen' s d was reported ($d = 0.2$ indicates small effect, $d = 0.5$ medium, $d = 0.8$ large); for F-tests, ^{2}p was reported ($^{2}p < 0.06$ indicates weak relationship, $0.06 \leq$ $^{2}p < 0.14$ medium, $^{2}p > 0.14$ strong).

3.1 Behavioral Results

Participants' response times in the recognition phase of the working memory task did not differ significantly across WM load conditions, $t(22) = -0.13$, $p = 0.902$. However, accuracy rates differed significantly, $t(22) = 3.03$, $p = 0.006$, Cohen' s $d = 0.73$, 95% CI = [1.01%, 5.39%], with higher accuracy in the low WM load condition (93.69 ± 3.62%) than in the high WM load condition (90.48 ± 4.94%).

3.2 ERP Results

RewP results are shown in Figure 2 [Figure 2: see original paper]. The main effect of valence was significant, $F(1, 22) = 46.31$, $p < 0.001$, $^{2}p = 0.68$, with RewP amplitude after positive feedback (11.12 ± 1.15 μV) more positive than after negative feedback (6.76 ± 0.93 μV). No other main effects or interactions were significant, ps ≥ 0.100. Figure 2 also presents RewP difference waves and topographical maps. RewP difference waves were obtained by subtracting negative feedback from positive feedback in each WM load condition, showing a positive component around 210–290 ms, with topographical distribution primarily over mid-frontal scalp regions.

Figure 2. Raw and difference waveforms of RewP across conditions (at Fz, FCz, and Cz), and topographical maps of RewP difference waves.

As shown in Figure 3 [Figure 3: see original paper], P3 showed a significant main effect of valence, $F(1, 22) = 21.65$, $p < 0.001$, $^{2}p = 0.50$, with P3 amplitude after positive feedback (14.10 ± 1.10 μV) more positive than after negative feedback (11.46 ± 1.06 μV). No other main effects or interactions were significant, ps ≥ 0.397.

Figure 3. P3 waveforms across conditions (at Pz and POz), and P3 topographical maps.

As shown in Figure 4 [Figure 4: see original paper], LPP results showed a marginally significant WM load × valence interaction, $F(1, 22) = 2.58$, $p = 0.088$, $^{2}p = 0.11$. Given the medium effect size, simple effects tests were conducted, revealing significant differences between positive and negative valence only in the high WM load condition, with LPP after positive feedback (7.13 ± 0.86 μV) larger than after negative feedback (5.94 ± 0.73 μV). No other main effects or interactions were significant, ps ≥ 0.101.

Figure 4. LPP waveforms across conditions (at Cz, CPz, Pz, and POz), and LPP topographical maps.

3.3 Time-Frequency Analysis Results

As shown in Figure 5 [Figure 5: see original paper], theta oscillations showed a significant main effect of WM load, $F(1, 22) = 3.45$, $p = 0.040$, $^2p = 0.14$. Post-hoc comparisons using Bonferroni method revealed a marginally significant difference between theta activity in the high WM load condition (38.53 ± 6.73 μV^2) and baseline condition (47.86 ± 7.57 μV^2), $p = 0.084$. Since Bonferroni is conservative, LSD post-hoc comparisons were also conducted, showing significantly smaller theta activity in the high WM load than baseline condition, $p = 0.028$.

The main effect of valence was significant, $F(1, 22) = 17.88$, $p < 0.001$, $^2p = 0.45$, with theta activity after negative feedback (60.46 ± 10.12 μV^2) significantly stronger than after positive feedback (22.81 ± 3.66 μV^2).

The WM load condition $\times$ valence interaction was significant, $F(1, 22) = 4.33$, $p = 0.019$, $^2p = 0.16$. Simple effects tests showed significant valence differences across all WM load conditions ($ps < 0.004$). Analysis of theta difference values between positive and negative feedback revealed a significant main effect of WM load, $F(1, 22) = 4.33$, $p = 0.019$, $^2p = 0.16$. Theta difference values were larger in the low WM load condition (43.10 ± 8.74 μV^2) than in the high WM load condition (29.49 ± 9.20 μV^2), $p = 0.032$.

Figure 5. Time-frequency analysis of theta activity across conditions (at Fz and FCz).

As shown in Figure 6 [Figure 6: see original paper], delta results showed a significant main effect of valence, $F(1, 22) = 14.97$, $p = 0.001$, $^2p = 0.39$, with delta activity after positive feedback (32.45 ± 4.27 μV^2) significantly stronger than after negative feedback (22.23 ± 2.94 μV^2). No other main effects or interactions were significant, $ps \geq 0.172$.

Figure 6. Time-frequency analysis of delta activity across conditions (at Cz and CPz).

Discussion

This study combined a simple gambling task with a working memory task to investigate how WM load conditions affect feedback processing. At the behavioral level, accuracy in the recognition phase of the working memory task differed significantly across WM load conditions, with lower accuracy when more squares needed to be remembered, indicating effective manipulation of WM load conditions.

At the electrophysiological level, first, RewP replicated the valence effect [**?**, **?**, **?**, **?**], showing larger positive deflection after positive (reward) than negative (no reward) feedback. No effect of WM load on RewP was found. Second, time-frequency analysis revealed feedback-related theta and delta oscillations, which also showed valence effects consistent with previous research [**?**, **?**, **?**, **?**]: theta power increased more after negative than positive feedback, while delta power increased more after positive than negative feedback. Importantly, WM load changes modulated the valence effect of theta oscillations, with the difference between positive and negative feedback theta oscillations reduced under high compared to low WM load. Additionally, we examined P3 and LPP components in later stages of feedback processing. P3 showed a valence effect, with positive feedback evoking more positive P3 than negative feedback, but was unaffected by WM load changes. The interaction between valence and WM load for LPP was marginally significant, with significant differences between positive and negative feedback LPP amplitudes observed only under high WM load.

RewP was sensitive to feedback valence, with positive feedback evoking more positive RewP, consistent with mainstream research findings [**?**, **?**, **?**, **?**, **?**, **?**] and with HRL-ACC theory' s view that RewP is a valence evaluation signal from the midbrain dopamine system. Additionally, this study found RewP insensitive to WM load. According to HRL-ACC theory, RewP acts as a valence evaluation signal at ACC' s input side, and our results suggest WM load does not affect this valence evaluation process in ACC.

This study found delta and theta oscillations sensitive to positive and negative feedback respectively, which superficially supports Foti et al.' s (2015) view that delta and theta oscillations are separate EEG indicators for processing positive and negative feedback. Moreover, only theta results showed an interaction between WM load and valence, with higher WM load reducing the difference between positive and negative feedback-evoked theta activity. This might suggest that during evaluation of positive and negative feedback, negative feedback processing is impaired as WM load increases, while positive feedback processing remains unaffected. However, this interpretation cannot explain why WM load had no effect on RewP in this study. RewP is an effective indicator of feedback valence processing [**?**, **?**, **?**, **?**, **?**]. If negative feedback processing were impaired by increased WM load, RewP' s ability to distinguish between positive and negative feedback would decrease, resulting in a WM load × valence interaction in RewP ANOVA. The absence of this interaction does not support the view that theta oscillations reflect negative feedback processing.

Current RewP literature also does not support Foti et al.' s (2015) perspective. As mentioned in the introduction, a fundamental conclusion in feedback processing ERP research is that RewP reflects reward processing and is a reward sensitivity indicator [**?**, **?**, **?**, **?**], without discovering any ERP indicator sensitive to negative feedback, suggesting the human brain may not process negative outcomes. Oliveira et al. (2007) proposed that people have an optimistic bias, tending to expect positive outcomes after responses. When feedback is presented, processing involves matching reward expectations with actual feedback rather than processing reward or loss per se, which may explain why no ERP component sensitive to negative feedback has been found. The conclusion that the human brain does not process negative feedback also suggests theta should not be a component related to negative feedback processing. The view that delta oscillations are sensitive to positive feedback is relatively consistent across studies.

If theta oscillations are not a signal for negative feedback processing, what psychological function do they reflect? Insight can be drawn from expectation violation theories related to RewP (or FRN). Early RewP was considered a negative component FRN [?, ?, ?, ?], and besides reinforcement learning theory [?, ?], expectation violation theories also explained this component. For example, the predicted response-outcome model (PRO) [?, ?, ?] suggests people use feedback to gradually learn the relationship between responses and outcomes, forming outcome expectations after responses that, when violated, elicit FRN. The expectation violation hypothesis [?, ?] holds a similar view. According to expectation violation theories, cognitive activity evoked by negative feedback is not negative feedback processing itself but expectation violation processing. These theories emphasize the significance of negative feedback, suggesting no control is needed after positive feedback, while after negative feedback the brain allocates attention and implements control to improve behavior [?, ?, ?].

Although current research suggests RewP is only sensitive to positive feedback, making expectation violation theories unable to use FRN as a validation index, theta oscillations sensitive to negative feedback could serve as an alternative. In other words, theta oscillations may reflect attention allocation and cognitive control implemented by the brain after expectation violation. This could both solve the problem of finding a test index for expectation violation theories and support HRL-ACC theory' s hypothesis about theta oscillations [?, ?].

HRL-ACC theory posits that theta oscillations are cognitive control signals projected from ACC to brain regions such as ventrolateral prefrontal cortex to drive behavior [?, ?, ?, ?]. An important basis for this view is that theta oscillations are sensitive to cognitive resource levels (e.g., WM load) [?, ?, ?]. However, evidence is lacking on whether theta oscillations during feedback processing are modulated by WM load levels. This study found that WM load affects theta oscillations' encoding of feedback valence, with the difference wave between positive and negative feedback theta oscillations reduced under high compared to low WM load. Combined with HRL-ACC theory, this can be interpreted as higher WM load reducing theta oscillations' sensitivity to encoding positive and negative feedback, thereby decreasing ACC' s ability to send control signals to dorsolateral prefrontal cortex and other regions based on different feedback.

Regarding P3, the experiment only observed a valence effect, with positive feedback evoking larger P3 than negative feedback, consistent with previous research [?, ?, ?], but no changes in P3 across different WM load conditions were observed. Many previous studies suggest P3 represents cognitive or attention resource allocation, with P3 amplitude related to invested cognitive resources [?, ?, ?]. Other researchers have discussed P3' s psychological significance from the perspective of interaction between reinforcement learning and working memory systems [?, ?, ?]. Rodriguez et al. (2018) suggested that during feedback learning, individuals need to update reward expectations in real-time based on actual feedback, a capacity that partly depends on the working memory system. However, this study found no effect of WM load on P3, which seems inconsistent with these theories. A possible explanation is that this study used a simple gambling task without learning significance. Although participants processed feedback valence and cognitive control output, they could not perform working memory updating or form effective rule criteria, so no WM load effect on P3 was observed.

Additionally, LPP results showed a marginally significant interaction between valence and WM load, with significant differences between positive and negative feedback LPP amplitudes observed only under high WM load. Previous research suggests LPP reflects late-stage motivational-affective processes in feedback processing [**?**, **?**]. The valence effect on LPP under high WM load may indicate increased affective value. Research has shown that cognitive effort during task performance increases the value of subsequent rewards [**?**, **?**]. Similarly, under high WM load conditions, participants' effort was higher, assigning additional emotional-motivational significance to feedback outcomes, resulting in larger LPP. This also partially explains why some studies observed differences between positive and negative feedback LPP while others did not [**?**, **?**, **?**, **?**], as WM load imposed by experimental tasks is undoubtedly an important factor.

In summary, this study validates and enriches HRL-ACC theory, supporting the view that RewP reflects feedback valence processing while theta oscillations reflect cognitive control functions, and demonstrates that WM load changes selectively affect the latter. However, this study used a simple gambling task without learning significance. Future research should employ tasks with learning significance to examine feedback evaluation and cognitive control processes in HRL-ACC theory and the role of WM load. Additionally, the baseline condition design had limitations. Following White et al. (2017), the baseline condition was presented separately to reduce contamination, with high and low WM load blocks presented randomly. This arrangement may have caused unstable differences between baseline and WM load conditions. Future studies should design better baseline conditions within WM load conditions.

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English Abstract

Feedback processing plays an important role in behavior modification and knowledge acquisition. Previous research has explored the neurophysiological basis and psychological functions of feedback processing and proposed corresponding theoretical models, but little is known about how working memory (WM) load affects feedback processing. Studies have reported electrophysiological indicators, such as the reward positivity (RewP) and the related theta and delta oscillations, the P3 and the late positive potential (LPP), during brain processing feedback. This study will further examine how WM load modulates these electrophysiological components and their corresponding cognitive functions.

In the present study, we used a dual-task paradigm to investigate feedback processing under different WM load conditions. This study included 25 healthy college students and used a 3 (WM load: baseline vs. low WM load vs. high WM load) by 2 (feedback valence: positive vs. negative) within-participant factorial design. During the experiment, participants were asked to perform a simple gambling task and a spatial memory task simultaneously, and the magnitude of the WM load included three conditions: baseline, low WM load and high WM load. The RewP generated in the early stage of feedback processing and the LPP generated in the late stage of feedback processing, as well as the delta and theta oscillations related to feedback evaluation, were analyzed.

The behavioral results showed that the accuracy of the low WM load condition was significantly higher than that of the high WM load condition. The electrophysiological results showed that the amplitudes of the RewP were sensitive to feedback valence, with positive feedback evoking larger RewP than negative feedback, but the RewP was not affected by the WM load. There was no difference in the P3 amplitude under the different WM load conditions. For the LPP, there was a significant interaction between the WM load and feedback valence. Further analysis revealed that, in the high WM load condition, the LPP amplitude was larger for positive feedback than for negative feedback. The theta power differences between negative feedback and positive feedback were larger in the low WM load condition than in the high WM load condition. For delta oscillations, the power was increased after positive feedback compared to after negative feedback, but there was no difference at different WM load levels.

The RewP results indicate that the participants process feedback valence information well under all three WM load conditions in the experiment. The LPP results suggest that the participants assigned additional emotional motivation to the feedback outcome as a result of their cognitive efforts under high WM load conditions. The ERP results for the time domain dimensions showed that the effect of the WM load on feedback processing was most noticeable in the later stages of feedback processing. Moreover, these observations support the argument that the RewP and theta power reflect distinct cognitive phenomena; namely, the RewP reflects the processing of feedback valence in the anterior cingulate cortex (ACC), whereas theta oscillations reflect the role of the ACC in cognitive control. The WM load selectively modulates the cognitive control process in the ACC.

Keywords: WM load, feedback, reward positivity (RewP), theta oscillation, anterior cingulate cortex

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