Offline Storage of Negative Faces in Working Memory Does Not Affect Online Storage

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Abstract

Previous studies have shown that negative faces exhibit processing advantages in the online state storage of working memory; simultaneously, negative faces may also induce negative emotional states in individuals, thereby affecting subsequent working memory processing. However, no research has investigated whether negative face information stored in the offline state affects online state memory processing. This study employed a sequential memory retrieval task, combined with electroencephalography (EEG) recording and analysis techniques, to examine differences in behavioral performance and EEG responses of online state memory when offline state representations were angry/neutral faces. Behavioral results showed that offline memory performance for negative faces was superior to that for neutral faces, but there was no significant difference in online memory performance between the two conditions. EEG data analysis revealed that during online state memory processing, the Late Positive Potential (LPP) associated with attentional resource allocation during the encoding phase was not affected by offline state emotional face conditions. Furthermore, EEG decoding results during the maintenance phase also found no significant differences in neural activity between conditions. These results indicate that negative face information stored in the offline state does not influence online state memory encoding and maintenance processing. This finding provides new empirical evidence for understanding the processing mechanisms of emotional information in visual working memory.

Full Text

The Passive Storage of Negative Facial Expressions in Working Memory Does Not Affect Active State Storage

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Abstract

Previous studies have demonstrated that negative faces exhibit processing advantages in the active state of working memory and may also induce negative emotional states that influence subsequent working memory operations. However, it remains unknown whether negative faces stored in the passive state affect concurrent active memory processing. This study employed a sequential memory retrieval task combined with EEG recording and analysis techniques to examine differences in behavioral performance and neural responses during online memory processing when passive-state representations consisted of angry versus neutral faces. Behavioral results revealed superior offline memory performance for negative faces compared to neutral faces, yet no significant differences in active-state memory performance between conditions. EEG data analysis showed that the late positive potential (LPP), which reflects attentional resource allocation during the encoding phase, was unaffected by passive-state emotional face conditions during active-state memory processing. Furthermore, neural decoding results from the maintenance phase revealed no significant differences in neural activity between conditions. These findings indicate that negative face information stored in the passive state does not influence active-state memory encoding and maintenance processes, providing new empirical evidence for understanding the processing mechanisms of emotional information in visual working memory.

Keywords: Visual Working Memory, Emotional Faces, Multi-state Storage, ERP Decoding, LPP

1. Introduction

Visual Working Memory (VWM) is a capacity-limited system responsible for the temporary maintenance and manipulation of visual information. Traditional theories posit that working memory representations rely on sustained neuronal activation. However, recent research has revealed that neural activity during the maintenance phase is actually dominated by the relevance between memory items and current task demands (Lewis-Peacock et al., 2012; LaRocque et al., 2013). Information closely related to the current task is retained within the focus of attention and maintained through sustained neuronal activation, referred to as "active-state" memory. In contrast, information unrelated to the current task resides outside the focus of attention and is maintained through temporary changes in synaptic connection weights without observable neuronal activation, termed "passive-state" memory. Memory representations can flexibly transition between these two storage states according to task requirements (Chota et al., 2021; Muhle-Karbe et al., 2021; Rose, 2020). Previous studies have shown that although neural activation cannot be detected during passive-state representation storage, these representations remain effectively maintained and exhibit considerable stability against temporal decay and external interference (Zhang et al., 2022; Li et al., 2025). Additionally, the storage resources of active and passive states appear independent, as changes in load in one state do not affect memory performance in the other (Li et al., 2021; Oberauer, 2002). It should be noted that existing research has predominantly used simple visual stimuli (e.g., colors, shapes) to investigate passive-state storage mechanisms, which differs significantly from complex multimodal information processing in real-world contexts. As a social species, facial emotion processing holds special significance in human social cognition. Experimental studies have shown that human perception of faces is more acute than for other meaningful information or objects (Ye et al., 2018; Young & Burton, 2018). Therefore, investigating the passive-state storage mechanisms of emotional face information carries greater social value.

Previous research on negative emotional faces in working memory has demonstrated stable processing advantages for negative emotional information. For example, Jackson et al. (2009) found that participants showed better working memory performance for angry faces compared to neutral and happy faces. Subsequent studies have suggested that this advantage stems from greater allocation of attentional resources during encoding and maintenance phases, thereby improving representation quality (Sessa, 2011; Lee & Cho, 2019; Schindler & Bublatzky, 2020), independent of arousal (Jackson et al., 2014; Lee & Cho, 2019). This advantage can be explained by neural activity during negative emotion processing, with researchers finding that negative emotions enhance amygdala and fusiform gyrus activity, brain regions closely related to threat detection and attentional control (Li et al., 2023). It is important to note that previous working memory tasks involving emotional faces have been limited to active-state storage and have not addressed passive-state storage. When negative emotional faces are stored using the passive-state system, does the storage process itself still automatically allocate more cognitive processing resources, thereby creating resource competition with active-state representation storage? This question requires further experimental verification.

Moreover, previous studies have found that emotional information from faces can induce changes in participants' own emotional states during facial emotion classification tasks (Falkenberg et al., 2012; Schneider et al., 1994; Srivastava et al., 2003). Individuals' working memory processing patterns differ across emotional states; for instance, negative emotional states reduce working memory capacity (Figueira et al., 2017) and affect working memory processing (Lin & Liang, 2023; Long et al., 2020; Xie et al., 2023; Ye et al., 2024). These findings suggest another potential mechanism: passive-state storage of negative face information may exert top-down modulation on concurrent active-state storage by inducing changes in emotional state. Therefore, when observing significant effects of negative face passive-state storage on active-state storage, it is necessary to distinguish between potential mechanisms: does this influence stem from direct competition for cognitive resources or from indirect modulation through emotional state changes?

Research has shown that a sustained positive wave appears in parietal and occipital regions during the encoding phase around 500 ms post-stimulus, known as the Late Positive Potential (LPP), which effectively reflects attentional resource allocation during encoding and sustained attention to task goals (Gable & Adams, 2013; Hajcak et al., 2013; Ribes-Guardiola et al., 2023; Schindler et al., 2022). Studies have demonstrated that angry faces elicit larger LPP amplitudes than neutral faces, indicating significant advantages in attentional resource allocation (Schindler et al., 2020; Lin & Liang, 2023). Furthermore, if prior materials interfere with attentional processes for the current task during face encoding, LPP amplitude is also affected (Lin & Liang, 2023). Additionally, neural activity during working memory maintenance is typically indexed by Contralateral Delay Activity (CDA), a sustained negative slow wave elicited by lateralized stimuli in contralateral parieto-occipital regions, whose amplitude positively correlates with active-state storage load. Numerous studies have shown that CDA reflects online maintenance of working memory items; when memory items transition to passive-state storage, CDA returns to baseline levels (Kreither et al., 2022; Zhang et al., 2022). Based on this, CDA can serve as an important indicator for monitoring state transitions of memory items.

In summary, this study employed a sequential memory retrieval paradigm combined with EEG technology to investigate whether negative face information in the passive state affects encoding and maintenance of face information in the active state. The experiment controlled the sequential presentation of two memory arrays (M1/M2) with reversed probing to achieve state separation (Li et al., 2024; Zhang et al., 2022). Simultaneously, EEG event-related potentials (ERPs) were used to select and analyze LPP and CDA components, combined with Multivariate Pattern Analysis (MVPA) for neural decoding of EEG signals. For stimulus manipulation, only the facial emotion in M1 was manipulated (angry/neutral), with lateralized presentation of M1 items to elicit specific CDA components, while M2 always contained neutral faces presented at the midline to eliminate spatial interference. We hypothesized that significant CDA components would be observed after M1 presentation but would disappear after M2 presentation, indicating complete transition of M1 storage to the passive state. If passive-state storage of negative faces affects active-state face storage, then LPP amplitude observed during M2 encoding should be significantly larger in the angry condition than in the neutral condition. Additionally, effective decoding based on emotional conditions should be observed during both M1 and M2 processing phases. Since decoding curves cannot reveal the specific neural activity changes induced by condition manipulation—namely, whether neural activity differences between conditions result from emotional states evoked by angry faces or from differences in resource allocation—we introduced temporal generalization analysis as a supplement. If neural activity differences stem from negative emotional states induced by angry faces, the decoding model should demonstrate strong generalization ability throughout the task, allowing classification models from M1 and M2 maintenance phases to decode each other. If differences result from resource allocation differences for emotional faces, the decoding model should change dynamically over time and lack generalization ability across distant time points, meaning the decoding model from M1 maintenance phase could not decode EEG data from M2 maintenance phase.

2. Methods

2.1 Participants

Twenty-two college students from Liaoning Normal University participated in this experiment (mean age = 21 ± 2.01 years, 13 females). All participants had normal or corrected-to-normal vision. Based on Cohen (2013), we defined a large effect size of 0.80. Using G*Power 3.19 software, we calculated that with Cohen’ s d = 0.80, $\alpha = 0.05$, and N = 22, the statistical power 1 - β 0.95. This study followed the Declaration of Helsinki and was approved by the Ethics Committee of Liaoning Normal University.

2.2 Apparatus

Participants were tested in a dim, quiet room, seated 60 cm from the screen. The screen resolution was 1920 × 1080 with a refresh rate of 60 Hz. The experimental computer used Windows 7, and the experimental program was written in Matlab R2017a and PsychToolBox 3.0.

2.3 Materials

Experimental materials were selected from the Chinese Affective Picture System (CAPS). Previous research has shown that male faces facilitate better recognition than female faces (Becker et al., 2007; Ye et al., 2018). Meanwhile, angry faces are more effective than other negative faces at capturing attention and facilitating recognition (Fox et al., 2000). Therefore, this experiment only used male neutral and angry facial expression pictures as materials. In the angry condition, 2 angry faces were randomly selected from 8 angry faces as M1 memory items; in the neutral condition, 2 neutral faces were selected from 8 neutral faces as M1 memory items. To avoid repetition with M1 neutral faces, the 2 memory items in M2 were selected from another set of 16 neutral faces. The number of pictures was set to ensure equal probability of each face appearing as a memory item. Additionally, 8 neutral face pictures outside the experimental materials were randomly selected, each divided into 5$×5fragments.The8×5×5fragmentswererandomlycombinedinto8newpictures, whichservedasplaceholders The horizontal distance between M1 and the fixation cross was 2.9°, and the vertical distance was 1.6°; the vertical distance between M2 and the fixation cross was 1.6°.

2.4 Procedure

This study used a sequential memory retrieval task, with the experimental procedure shown in Figure 1 [Figure 1: see original paper]. Previous research has found that face memory capacity is 2 (Jackson & Raymond, 2004). To fully occupy working memory resources, both memory arrays contained 2 face pictures. The specific procedure was as follows: each trial began with an 800 ms fixation cross, followed by the memory phase. In M1, participants needed to remember emotional face pictures presented on the left or right side of the screen. These two pictures were either angry faces (angry condition) or neutral faces (neutral condition), with placeholders on the opposite side. In M2, two neutral face pictures were presented above or below the fixation point. To ensure complete consolidation of each face picture, each memory array was presented for 1 s, with a maintenance duration of 1 s (Jackson et al., 2009; Mallett et al., 2020). During the probe phase, participants judged whether the face in the red frame in Probe Array 1 matched the face in the corresponding position in M2, pressing the "f" key if matched and the "j" key otherwise. They then judged whether the face in the red frame in Probe Array 2 matched the face in the corresponding position in M1, using the same key responses. In Probe Arrays 1 and 2, changed and unchanged trials each accounted for 50%. In changed trials, face pictures with the same emotion but different identity were used as probe stimuli; in unchanged trials, the original pictures were used as probe stimuli, requiring participants to remember both emotional and identity information about the faces. The experiment was conducted in four blocks, each containing 64 trials. Angry and neutral conditions appeared randomly in each block, each accounting for 50% of total trials.

2.5 EEG Recording and Analysis

Throughout the experiment, a 32-channel electrode cap (according to the international 10/20 system: FP1/2, F7/8, F3/4, Fz, FC5/6, FC1/2, C3/4, Cz, M1/M2, CP5/6, P7/8, P3/4, PO7/8, PO3/4, Pz, O1/2, POz, VEOG, HEOG) was used to record participants' EEG activity. Vertical electrooculogram (VEOG) was recorded 1 cm below the left eye, and horizontal electrooculogram (HEOG) was recorded 1 cm lateral to the outer canthus of the right eye. Impedance for each electrode was reduced below 5 kΩ. Online reference was CPz, and the sampling rate was 500 Hz.

Experimental data were offline referenced to the average of bilateral mastoids (M1 and M2), bandpass filtered from 0.01 Hz to 30 Hz with a slope of 12 dB/octave, and segmented from 800 ms before memory array presentation to the end of Maintenance Period 2 (4000 ms). Independent Component Analysis (ICA) was used to remove horizontal and vertical eye movements, and trials with voltages exceeding $±$100 V were removed. The mean number of retained trials was 113.89 ± 13.07 for the angry condition and 113.63 ± 13.51 for the neutral condition. Finally, data were baseline-corrected using the mean of the 400 ms pre-stimulus period.

CDA analysis time windows were Maintenance Period 1 (1000 ~ 2000 ms) and Maintenance Period 2 (3000 ~ 4000 ms). Four pairs of electrodes (P7/8, P3/4, PO7/8, and PO3/4) were used for CDA component analysis (Ankaoua & Luria, 2023; Balaban & Luria, 2015; Wang et al., 2019). Difference waves were obtained by subtracting the average voltage ipsilateral to the stimulus presentation location (left or right) from the contralateral average voltage. LPP component time windows were the encoding phases of M1 and M2 (M1: 500 ~ 1000 ms, M2: 2500 ~ 3000 ms), with midline electrodes Fz, Cz, Pz, and POz as analysis electrodes (Jia et al., 2022). Decoding analysis used all active electrodes except reference and EOG electrodes, totaling 28 channels.

2.6 ERP Decoding

This study utilized the ERPLAB (10.02) toolbox to decode M1 array emotional conditions based on ERP waveforms. The time window was set from 400 ms before M1 array presentation to 4000 ms after presentation, with the temporal sampling rate reduced to 100 Hz. All trials were divided into 2 categories based on M1 emotional condition, generating a 4-dimensional data matrix for each participant with dimensions including M1 emotional condition (2), time points (440), EEG channels (28), and trials. Since the preprocessing excluded an undetermined number of trials, the number of trials per condition might vary.

Taking one participant as an example, we describe the decoding process for a single time point. Suppose a participant had 112 and 103 remaining trials for the two emotional conditions, with the minimum being 103 trials. At each time point, 96 trials were randomly selected from each condition (a multiple of 8). These 96 trials were then randomly divided into 8 groups, and the average ERP amplitude for each EEG channel was calculated for each group. For each emotional condition, we iteratively used one group' s ERP average as test data and the remaining 7 groups' averages as training data for 8-fold cross-validation. In each training session, based on the ECOC method (error-correcting output codes, Thomas & Ghulum, 1994), we first trained an SVM classifier (a 28-dimensional hyperplane) for the 2 emotions using data from 7 groups × 2 emotions, then input the 2 groups of test data into the classifier to obtain an optimal decision (one classified as angry, the other as neutral) as the decoding result. After all 8 groups had served as training and test data, 16 decoding results were obtained for the 2 emotional conditions. This entire process was iterated 30 times, with all trials being randomly resampled and regrouped each time, yielding 480 decoding results total. These 480 decoding results were compared with the true emotional conditions of the test data each time, and the accuracy rate was taken as the decoding accuracy value for that participant at that time point.

We completed the above decoding analysis for each participant at all time points, obtaining a 22$×$440 matrix of decoding accuracies.

2.7 Statistical Analysis of Decoding Results

First, for each time point, we performed a one-sample t-test comparing all participants' actual decoding accuracy values against chance level (1/2) to obtain t-values and p-values for each time point. We then identified continuous temporal clusters where decoding accuracy was significantly greater than chance level (at least 3 consecutive time points with $p < 0.05$) and calculated each cluster' s t-mass (the sum of t-values within the temporal cluster).

Next, to determine whether decoding accuracy in these temporal clusters was truly above chance expectation, we used cluster-based permutation testing to construct a null distribution of cluster t-mass, similar to previous decoding studies (Bae & Luck, 2019). We downloaded scripts from osf.io/2h6w9. In each iteration of permutation testing, to preserve temporal consistency, we selected the same random label (“angry” or “neutral”) for all time points of each test to replace the true condition. We then compared the decoding results obtained from the actual decoding process with these random labels, marking matches as correct and mismatches as incorrect, and took the accuracy rate as the virtual decoding accuracy. Similarly, virtual decoding accuracy at each time point was compared with chance level (1/2) via one-sample t-test, continuous temporal clusters where virtual decoding accuracy was significantly above chance were identified, and cluster-level t-mass was calculated. In each iteration, if multiple significant clusters existed, the largest t-mass was recorded; if no significant clusters existed, the t-mass for that iteration was recorded as zero. Permutation testing was repeated for 1000 iterations to form a null distribution of 1000 invalid cluster t-masses.

After establishing the null distribution, the t-mass of each significant cluster obtained from actual decoding was compared with the t-masses in the null distribution. If a temporal cluster' s t-mass was greater than 95% of values in the null distribution, decoding accuracy in that time period was considered significantly above chance level.

2.8 Temporal Generalization Analysis

Finally, due to limitations of decoding curves in revealing specific neural activity changes induced by condition manipulation, this study conducted temporal generalization analysis as a supplement. In temporal generalization analysis, to reduce computational difficulty, the sampling rate was reduced to 50 Hz, with other steps being essentially the same as the decoding process. The difference was that we trained a classifier at each time point separately, then used data from all other time points as test data to calculate the classifier' s decoding accuracy for other time points, thereby obtaining the generalization ability of the classification model across the temporal dimension.

3. Results

3.1 Behavioral Results

This study analyzed memory accuracy and discriminability (d’) for M1 and M2, with results shown in Figure 2 [Figure 2: see original paper]. For M1, accuracy was 0.67 (SE = 0.017) and d’ = 0.95 (SE = 0.11) in the angry condition, and accuracy was 0.60 (SE = 0.015) and d’ = 0.54 (SE = 0.08) in the neutral condition. For M2, accuracy was 0.76 (SE = 0.014) and d’ = 1.49 (SE = 0.08) in the angry condition, and accuracy was 0.76 (SE = 0.012) and d’ = 1.52 (SE = 0.08) in the neutral condition.

To control for Family-Wise Error Rate (FWER), we applied Bonferroni correction to all comparison p-values, dividing the significance level of 0.05 by the number of comparisons (4), yielding a corrected significance level of $\alpha = 0.0125$. Paired t-test results showed that M1 recall accuracy in the angry condition was significantly higher than in the neutral condition, t(21) = 4.49, $p < 0.001$, Bonferroni-corrected, 95% CI [0.037, 0.10], Cohen’ s d = 0.97. Discriminability d’ was also significantly higher in the angry condition, t(21) = 4.04, p = 0.001, Bonferroni-corrected, 95% CI [0.20, 0.62], Cohen’ s d = 0.86. However, for M2, neither accuracy (t(21) = -0.32, p = 0.752, Bonferroni-corrected, 95% CI [-0.24, 0.16], Cohen’ s d = 0.0088) nor discriminability d’ (t(21) = 0.551, p = 0.588, Bonferroni-corrected, 95% CI [-0.17, 0.10], Cohen’ s d = 0.117) differed significantly between conditions. These results indicate that emotional valence changes in passive-state faces only affect memory performance in that storage state, without affecting behavioral performance for active-state face information.

3.2 CDA

CDA waveforms are shown in Figure 3 [Figure 3: see original paper]. A 2 (condition: angry vs. neutral) × 2 (laterality: contralateral vs. ipsilateral) repeated-measures ANOVA was conducted on CDA components during Maintenance Period 1. Results showed a significant main effect of laterality (F(1,21) = 51.371, $p < 0.001$, 95% CI [-1.67, -0.92], $p^2 = 0.710$), indicating significant CDA during the maintenance period after M1, meaning M1 memory items entered and were effectively maintained in the working memory system. The main effect of condition was not significant (F(1,21) = 0.274, p = 0.606, $p^2 = 0.013$), nor was the interaction between laterality and condition (F(1,21) = 0.161, p = 0.693, $p^2 = 0.008$). During Maintenance Period 2, the same repeated-measures ANOVA showed neither main effects of laterality (F(1,21) = 0.458, p = 0.506, $p^2 = 0.021$) nor condition (F(1,21) = 0.407, p = 0.530, $p^2 = 0.019$) were significant, and the interaction was also not significant (F(1,21) = 0.726, p = 0.404, $p^2 = 0.033$). CDA activity in both angry (t(21) = -0.16, p = 0.877, 95% CI [-0.51, 0.44]) and neutral (t(21) = -1.02, p = 0.319, 95% CI [-0.70, 0.24]) conditions did not differ significantly from baseline. These results indicate that CDA returned to baseline levels during Maintenance Period 2.

3.3 LPP

During the M1 encoding phase (500 ~ 1000 ms), a two-way repeated-measures ANOVA on electrodes (Fz, Cz, Pz, and POz) and emotion (angry vs. neutral) revealed a significant main effect of emotion (F(1,21) = 9.47, p = 0.006, p^2 = 0.310) and a significant interaction between electrode and emotion (F(1,21) = 3.45, p = 0.037, p^2 = 0.353). Further simple effects analysis found significant differences in LPP components between emotional conditions at POz electrode (t(21) = 3.63, p = 0.002, 95% CI [0.47, 1.72], Cohen' s d = 0.77), at Pz electrode (t(21) = 3.80, p = 0.001, 95% CI [0.62, 2.13], Cohen' s d = 0.80), and at Cz electrode (t(21) = 2.436, p = 0.024, 95% CI [0.20, 2.55], Cohen' s d = 0.51). However, the LPP component at frontal electrode Fz did not differ significantly between conditions (t(21) = 1.31, p = 0.205, 95% CI [-3.1, 1.34], Cohen' s d = 0.27). In summary, angry faces elicited stronger LPP components in parieto-occipital regions during M1 encoding.

During the M2 encoding phase (2500 ~ 3000 ms), a two-way repeated-measures ANOVA on electrodes (Fz, Cz, Pz, POz) and emotion (angry vs. neutral) showed a significant main effect of electrode (F(1,21) = 4.55, p = 0.015, p^2 = 0.418) and a significant interaction between electrode and emotion (F(1,21) = 4.87, p = 0.011, p^2 = 0.435). Further simple effects analysis revealed that LPP amplitude at frontal electrode Fz in the angry condition was significantly lower than in the neutral condition (t(21) = -3.56, p = 0.002, 95% CI [-2.41, -0.63], Cohen's d = 0.67). Additionally, LPP amplitude at Fz in the angry condition was significantly lower than at Cz (p = 0.047), Pz (p = 0.009), and POz (p = 0.006). No significant differences between conditions were found at other electrodes. Therefore, during M2 encoding, the neutral condition elicited significantly larger LPP components at frontal Fz than the angry condition.

3.4 Correlation Analysis Between Behavioral and EEG Results

To investigate the relationship between EEG results and behavioral performance —specifically, whether enhanced LPP amplitude induced by angry faces positively correlated with improved discriminability for M1—we calculated the average difference in LPP amplitude between conditions at parieto-occipital regions (Cz, Pz, and POz) during M1 encoding and conducted a one-tailed correlation test with the difference in M1 discriminability. Results showed a positive correlation between the difference in centro-parieto-occipital LPP amplitude and the difference in discriminability d' for M1 (r = 0.369, p = 0.045, 95% CI [-0.017, 0.22]), indicating that the advantage in passive-state working memory performance for angry faces was related to attentional resource allocation during encoding. However, the difference in LPP amplitude at frontal electrode Fz during M2 encoding was not significantly correlated with the difference in discriminability d' for M2 (r = -0.048, p = 0.416), meaning M2 working memory performance was not influenced by frontal LPP components.

3.5 Decoding and Temporal Generalization Analysis

Decoding analysis revealed that decoding accuracy for M1 emotional information was above chance level during two time periods after M1 presentation: 330 ~ 1710 ms and 1760 ~ 3250 ms, as shown in Figure 6 [Figure 6: see original paper]. Since 3000 ms post-stimulus corresponds to the active maintenance phase of M2, this result indicates that passive emotional faces could not be effectively decoded during M2 maintenance. Additionally, temporal generalization analysis found no generalization ability of decoding models at corresponding time points to other test time points. This suggests that in ERP decoding, the two significant time periods may reflect different brain activities.

4. Discussion

This study employed a sequential memory task paradigm to investigate for the first time the mechanisms by which negative emotional faces stored in working memory’ s passive state affect active-state information processing. Behavioral data showed that emotional characteristics of angry faces stored in the passive state had no significant impact on active-state face memory accuracy, a finding highly consistent with the resource independence hypothesis of multi-state representations. Event-related potential analysis revealed the neural mechanisms underlying this phenomenon: during M2 encoding, no significant differences were found in parieto-occipital LPP amplitudes, indicating that passive-state negative representations did not trigger attentional resource competition during active-state encoding. Decoding results showed that offline-stored facial emotional features could not be effectively decoded during M2 maintenance, further confirming the neural resource independence between the two representation states.

Unlike previous studies that manipulated cognitive load to explore resource allocation mechanisms, this study systematically manipulated the emotional characteristics of passive-state representations, extending the resource independence mechanism of working memory’ s multi-state representations from simple visual features to complex socially relevant stimuli for the first time. This finding has important implications for understanding human social information processing mechanisms: when processing sequentially presented social information, the parallel storage characteristics of multi-state representations can ensure that the cognitive system efficiently encodes newly input social cues while maintaining existing emotional information representations. This characteristic may constitute the neural basis for social animals to adapt to complex interpersonal interactions.

This study found that negative faces still exhibit memory advantages when stored in working memory’ s passive state, consistent with previous research on active-state processing (Jackson et al., 2014; Jackson & Raymond, 2004; Jackson et al., 2009). ERP analysis showed that angry faces elicited stronger LPP activity in parieto-occipital regions during M1 encoding, which was closely related to improved working memory performance. This result supports the view that negative faces receive more attentional resources during encoding. Specifically, angry faces trigger stronger approach motivation during processing (Carver & Harmon-Jones, 2009), and this motivational attention may confer advantages in attentional resource allocation (Ferreira de Sá et al., 2019; Jackson et al., 2014). The dual functions of the amygdala provide a neural explanation—research shows that the amygdala not only participates in emotional processing but also plays a key role in attentional control and working memory encoding (Li et al., 2023; Most et al., 2006; Richter-Levin & Akirav, 2000). During M1 maintenance, although no differences in CDA components were found between conditions, ERP decoding results showed significant differences in neural activity between different emotional conditions. Temporal generalization analysis indicated that these differences were phase-specific, with decoding models lacking generalization ability across distant time points and instead changing continuously over time. This means that the processing advantage for negative faces is not achieved by inducing negative emotional states but rather results from independent neural activities in encoding and maintenance phases. Sessa et al. (2011) suggested that negative faces might have higher processing advantages during maintenance, but CDA measures cannot effectively reflect this. On one hand, CDA components can only effectively reflect the quantity of representations maintained in visual cortex, not other information such as representation quality. Compared to neutral faces, the advantage in attentional resource allocation during encoding for negative faces leads to higher representation quality during maintenance. On the other hand, unlike simple color patches, face stimuli are more complex, and broader brain regions may be involved during maintenance. The decoding results of this study seem to confirm that negative faces indeed exhibit different neural activity during maintenance compared to neutral faces, partially supporting Sessa et al.’ s (2011) speculation about maintenance-phase advantages for negative faces. In summary, the results support processing advantages for negative faces in both encoding and maintenance phases of working memory and extend these findings from single-state representations to passive-state storage in working memory.

Notably, this study observed significant differences in frontal LPP components between conditions during M2 encoding. The M2 time window involves two parallel processing streams: (1) online encoding of the current M2 memory array, and (2) passive-state storage of M1 memory content. Since M2 only used neutral faces as memory materials and behavioral performance and parieto-occipital LPP components were unaffected by emotional information, the above differences may stem from non-emotional neural regulation during passive-state storage rather than M2 encoding processes. Temporal generalization analysis further supports this inference: decoding models from M1 and M2 encoding phases lacked cross-phase generalization ability, indicating significant heterogeneity in neural representation patterns between the two phases. Therefore, decoding results also reflect differences in neural activity during passive-state storage for different emotional faces.

Previous research indicates that frontal LPP is closely related to top-down cognitive control (Ferrari et al., 2008; Moratti et al., 2011). The condition differences in frontal LPP found in this study may result from two mechanisms: (1) Reduced frontal LPP in the angry condition may reflect emotion regulation effects. Previous studies show that emotion regulation is an automatic process that benefits subsequent memory processing (Flores Jr & Berenbaum, 2017; Lin & Liang, 2023; Mauss et al., 2007). Specifically, the frontal cortex suppresses negative emotional reactions to optimize memory performance (Li et al., 2022), and this regulatory process may lead to reduced LPP amplitude. Therefore, we speculate that the emotion regulation process prevented the emotional state induced by angry faces from affecting M2 memory processing, and regulation of negative emotions caused the decrease in frontal LPP components. (2) In the neutral condition, frontal LPP amplitude was significantly elevated. This may stem from feature limitations of neutral stimuli: compared to angry faces with rich emotional cues, neutral faces have less feature information (e.g., lack of salient emotional features), requiring stronger cognitive control resources for passive-state storage (Li et al., 2024). Specifically, passive-state storage requires suppression of redundant neural activity to maintain representation stability (Li et al., 2024). Since both M1 and M2 were neutral faces in the neutral condition, stronger frontal inhibition mechanisms may be needed to counteract memory interference. Additionally, according to the activity-silent state theory (Kuo et al., 2016), passive-state transition involves dynamic balance between internal attention (maintaining M1) and external attention (encoding M2). The low feature salience of neutral faces may force the frontal cortex to allocate more resources to internal attention processes to stably maintain neutral face representations stored in the passive state (Kuo et al., 2016; Liang, 2023). Notably, the regulatory effect of frontal LPP did not extend to M2 behavioral performance, revealing that the cognitive control mechanism of the frontal cortex may be independent of traditional attentional resource allocation processes. This finding supports the complexity of multi-state storage for emotional faces: compared to simple stimuli, their processing may involve broader distributed brain networks (e.g., frontal-parietal-amygdala circuits). Future studies could use dynamic brain network analysis or dual-task paradigms to further clarify the specific role of the frontal cortex in emotional working memory multi-state representations.

5. Conclusion

This study reveals that resource independence in visual working memory multi-state storage is not affected by emotional information. Meanwhile, negative faces stored in the passive state still maintain advantages in working memory performance. Additionally, different emotional information may affect executive control processes during passive-state storage, implying that broader brain region coordination is involved in emotional face passive-state storage in working memory. These results provide a new perspective for understanding how emotional faces influence multi-state storage in working memory.

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