Feedback timing modulates interactions between feedback processing and memory encoding: Evidence from event-related potentials



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Abstract

Feedback-based learning relies on a procedural learning system driven by reward prediction errors (RPEs). The processing of temporally delayed feedback is supported by brain structures associated with declarative memory processes, but it is still unknown how delayed feedback processing and memory encoding interact. In this study, a subsequent memory paradigm was employed to investigate how the incidental encoding of feedback pictures presented with a short (SD, 500 ms) or long (LD, 6500 ms) delay in a probabilistic learning task affects the event-related potential (ERP) correlate of RPEs (i.e., the feedback-related negativity; FRN). In an ensuing test phase, a surprise recognition memory test for the feedback pictures was conducted. FRN amplitudes measured in the feedback-locked ERPs recorded during the learning phase (FRN_{peak}) and in the negative minus positive feedback difference wave (FRN_{diff}) were compared for subsequently remembered and forgotten feedback pictures. Feedback processing and memory encoding competed for similar neural processing resources. As evidenced by large FRN_{diff} amplitudes in the SD condition, the evaluation of shortly delayed feedback strongly relied on the procedural learning system. A complementary model-based single trial analysis was conducted to validate models of the functional significance of the FRN. Consistent with previous studies, feedback-locked N170 and P300 amplitudes were sensitive to feedback delay. In the test phase, memory for LD feedback pictures was better than for SD pictures and accompanied by a late old–new effect, presumably reflecting extended recollective processing.

Keywords Event-related potentials · Reinforcement learning · Reward prediction error · Feedback timing · Declarative memory

Feedback-based learning relies on the evaluation of outcomes associated with an action and is driven by reward prediction errors (RPEs) indicating the deviation between the expected and received outcome of an action. At the neurobiological level, this procedural type of learning is mediated by the phasic activity of midbrain dopamine neurons and their projections to the striatum (Pessiglione, Seymour, Flandin, Dolan, & Frith, 2006; Schultz, 1998). Recent neuroimaging research suggests that, depending on the learning situation, feedback-

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based learning can also be supported by medial temporal lobe (MTL) structures associated with declarative memory processes (Delgado & Dickerson, 2012; Shohamy & Daw, 2014). For instance, it has been found that temporally delayed feedback processing is associated with a strong involvement of the hippocampus and a high proportion of correct highconfidence memory decisions for feedback pictures (Foerde & Shohamy, 2011; Lighthall, Pearson, Huettel, & Cabeza, 2018). The latter results suggest that declarative memory for delayed feedback events benefits from the hippocampal involvement during the initial processing of these events.

Other studies have found that memory encoding and retrieval interfere with feedback processing and reward learning (Dickerson & Delgado, 2015; Wimmer, Braun, Daw, & Shohamy, 2014). In the study conducted by Wimmer and colleagues, participants chose between two options that were each associated with a fluctuating reward probability. Taskunrelated pictures were presented together with the choice options. Successful memory encoding was associated with

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diminished reward learning, higher hippocampal-striatal connectivity, and decreased striatal RPE signals, suggesting that incidental memory encoding interfered with reward learning due to a competition for striatal processing resources.

In studies examining event-related brain potentials (ERPs), the feedback-related negativity (FRN) is associated with the processing of RPE signals elicited by feedback during learning (Sambrook & Goslin, 2015; Walsh & Anderson, 2012). Recent studies have emphasized that the FRN signal results from an overlap between the N200 and a later positivity elicited by positive feedback (reward positivity; Holroyd, Pakzad-Vaezi, & Krigolson, 2008; Proudfit, 2015). Studies showing that larger reward positivity amplitudes are predictive of later successful recognition of to-be-learned associations (Arbel, Goforth, & Donchin, 2013), and pictures presented together with positive feedback (Höltje & Mecklinger, 2018) suggest that reward signals elicited by positive feedback can support memory encoding.

Even though the brain systems associated with feedbackbased learning and declarative memory have been disclosed (Eichenbaum & Cohen, 2001; Shohamy & Daw, 2014), it is less clear under which circumstances these learning systems interact, and how this is reflected in electrophysiological measures of feedback processing. To shed further light on these questions, the present study investigated how feedback processing as reflected in the FRN interacts with concurrent incidental memory encoding under two different conditionsnamely, when feedback processing strongly relies on the procedural learning system (shortly delayed feedback) or engages the declarative learning system (long delayed feedback). Participants performed a probabilistic learning task in which they used feedback to learn associations between Chinese characters and responses. Feedback was given in the form of scene pictures that signaled the valence of the feedback (outdoor = positive, indoor = negative) and arrived with a short (500 ms) or long (6,500 ms) temporal delay. Recognition memory for the feedback pictures was tested in a surprise memory test. To explore whether successful memory encoding modulates the FRN, a subsequent memory paradigm was used: EEG activity recorded during feedback picture presentation in the learning task was sorted according to whether a picture was subsequently remembered or forgotten (for reviews, see Cohen et al., 2015; Paller & Wagner, 2002).

As stated above, the FRN signal results from an overlap between the N200 and the later reward positivity. The N200 is generally elicited by unexpected, task-relevant events (including unexpected feedback; Folstein & Van Petten, 2008; Holroyd, 2004). When measured as the difference between the N200 and the preceding positive peak (i.e., the P200), the FRN is sensitive to the salience (unexpectedness) of feedback, irrespective of valence (Ferdinand, Mecklinger, Kray, & Gehring, 2012). Delayed feedback processing is associated with larger amplitudes of this FRN_{peak} measure than shortly delayed feedback (Höltie & Mecklinger, 2018; Peterburs, Kobza, & Bellebaum, 2016). It is thus conceivable that the FRN_{peak} is more sensitive to the processing of expectancy violations in the declarative learning system and is less specific for the processing of positive or negative action outcomes. In contrast, the reward positivity is often measured as the peak amplitude in the negative minus positive feedback difference wave (i.e., the amplitude at the time point of the maximal difference between the waveforms elicited by positive and negative feedback). In keeping with previous studies (Höltje & Mecklinger, 2018; Peterburs et al., 2016), we denote this measure as FRN_{diff} in the following. Consistent with the view that the FRN_{diff} reflects the involvement of the procedural learning system, which is more engaged by the processing of immediate than delayed feedback outcomes (Foerde & Shohamy, 2011), the FRN_{diff} is more pronounced for shortly delayed than for long delayed feedback (e.g., Höltje & Mecklinger, 2018; Peterburs et al., 2016; Weismüller & Bellebaum, 2016). In the present study, both FRN measures (FRN_{peak} and FRN_{diff}) were used to explore two distinct feedback-related processes-namely, general expectancy violations as reflected in the FRN_{peak} and the processing of unexpected positive outcomes as indexed by the FRNdiff.

We expected to replicate previous findings—namely, that shortly delayed feedback is associated with larger FRN_{diff} amplitudes than long delayed feedback, and the reverse pattern (larger amplitudes for long delayed than for shortly delayed feedback) applies to the FRN_{peak}. Finding that the amplitude of the FRN_{peak} or FRN_{diff} differs between subsequently remembered and forgotten pictures would suggest that feedback processing and memory encoding interact electrophysiologically.

In recent years, there has been considerable debate about the question whether the FRN reflects the processing of reward prediction errors, a parameter that codes the reward value (positive or negative) and expectedness of an outcome. An alternative account states that the FRN is more sensitive to general expectancy violations irrespective of valence (e.g., Ferdinand et al., 2012; Oliveira, McDonald, & Goodman, 2007). Computational modeling is a promising method to decide between these accounts because it enables to compute trial-by-trial estimates of prediction errors. In functional neuroimaging studies, computational models are widely used to identify brain regions in which BOLD signals correlate with model-derived learning signals (for reviews, see Daw & Doya, 2006; O'Doherty, Hampton, & Kim, 2007). In a similar vein, correlations between model-derived prediction errors and single trial EEG data were used to validate models of the functional significance of the FRN_{peak} and FRN_{diff} in the present study. A computational reinforcement learning model was used to estimate trial-by-trial reward prediction errors (RPEs). Best fits between RPEs and EEG activity in the time periods in which FRN effects are present would confirm that the FRN reflects the processing of RPEs. We also computed unsigned RPEs that code the expectedness of an outcome without taking into account its valence (better or worse than expected). These unsigned RPEs thereby constitute salience prediction errors (SPEs) that are largest when outcomes are highly unexpected irrespective of their valence. As we assumed that the FRN_{peak} is more sensitive to more general expectancy violations, we expected best fits between SPEs and EEG activity in the FRN_{peak} time interval.

The main goal of the present research was to investigate interactions between feedback-based learning and memory encoding by focusing on the FRN as the electrophysiological correlate of reward prediction error signals in feedback processing. In addition, we also explored other ERP components elicited by feedback stimuli that have been shown to be sensitive to feedback delay manipulations (i.e., the N170 and the P300).

Arbel, Hong, Baker, and Holroyd (2017) found that delayed feedback elicited larger (more negative) N170 amplitudes than immediate feedback and proposed that the N170 constitutes a marker of the involvement of the MTL in delayed feedback processing. We therefore expected delayed feedback to be associated with larger N170 amplitudes and also explored whether this component predicts subsequent memory for feedback pictures.

The P300 is thought to reflect the updating of the stimulus context in memory (Donchin, 1981; Polich, 2007). Based on the results obtained in two recent studies (Wang, Chen, Lei, & Li, 2014; Weismüller & Bellebaum, 2016), we expected immediate feedback to elicit stronger P300 amplitudes than delayed feedback.

Another aim of the present study was to explore the effects of feedback delay on the retrieval of feedback events. Dual process models of recognition memory assume that two distinct processes, familiarity and recollection, contribute to recognition memory (Yonelinas, 2002). Whereas familiarity refers to a fast and context-free memory strength signal, recollection is a slower threshold process that includes the retrieval of contextual details. Familiarity and recollection are associated with qualitatively different patterns of ERP old-new effects (for reviews, see Friedman & Johnson, 2000; Rugg & Curran, 2007). Whereas familiarity elicits an early midfrontal old-new effect (also denoted as FN400), recollection manifests in a late parietal old-new effect. Even though previous studies have shown that reward or positive feedback selectively boosts fast and contextfree familiarity-based remembering and selectively modulates the midfrontal old-new effect (Eppinger, Herbert, & Kray, 2010; Höltje & Mecklinger, 2018), it is less clear how feedback timing affects memory retrieval. As stated above, previous studies have found that delayed feedback processing is associated with an involvement of the hippocampus. Because recollection relies on the hippocampus (Eichenbaum, Yonelinas, & Ranganath, 2007), we expected long delayed feedback pictures to be associated with a stronger late parietal old-new effect than shortly delayed feedback pictures.

Method

Participants

Fifty-eight healthy young adults participated in the experiment. All participants were German native speakers, had normal or corrected-to-normal vision and no self-reported neurological or psychiatric conditions. The experimental procedures were carried out in accordance with the Declaration of Helsinki and approved by the ethics board of the Faculty of Human and Business Sciences at Saarland University. Participants gave their informed consent before the experiment and received money (8€ per hour) or course credit as a compensation for their participation. Fourteen participants had to be excluded from all analyses-five participants were excluded because they did not learn the associations in the learning phase, as determined by their performance in the final block of the probabilistic learning task (see Procedure), and nine were excluded because they performed at chance level in the test phase. The incidental nature of memory encoding in the probabilistic learning task may have increased task difficulty and thereby contributed to the relatively high number of participants excluded because of poor recognition performance. One further participant had to be excluded because of a technical error. Thus, the behavioral analyses are based on data from 43 participants (36 female, 36 right-handed). Their age ranged between 19 and 30 years, with a median age of 23 years. Because of the exclusion criteria for ERP data, these analyses are based on a lesser number of data sets (see EEG Recording and Processing). Behavioral results for the full sample (except for the participant excluded because of a technical error, N = 57) are provided in the supplementary online material.

Stimuli

A total of 560 scene pictures, consisting of 280 indoor and 280 outdoor scenes, were used in this experiment. Four hundred of these pictures were the same as in the Höltje and Mecklinger (2018) study. One hundred and sixty additional scene pictures were collected from various free Internet sources. The size of the pictures was scaled to a width of maximal 600 pixels and a height of maximal 450 pixels.

Procedure

The preparations for the EEG recording took about 45 minutes. Thereafter, participants were seated in front of a 19-inch computer screen with a resolution of $1,280 \times 1,024$ pixels in an electrically shielded and sound-attenuated booth. The experimental tasks were presented using E-Prime 2 software (Psychology Software Tools, Inc.), and participants used a keyboard for their responses.

The experiment consisted of a learning phase (25 min), a test phase (35 min), and two quiet rest phases of 15 minutes each that took place before and after the learning phase. In the learning phase, participants learned associations between four different Chinese characters and two response keys in a probabilistic learning task with probabilistic feedback. Scene pictures were presented as feedback, and the picture category designated the valence of the feedback with a fixed mapping for all participants (outdoor = correct, indoor = incorrect; cf. Foerde & Shohamy, 2011). The learning phase was followed by one block in which participants continued performing the task without feedback. The performance in this block served as a criterion for learning success, and participants who performed at chance level in this block were excluded from all analyses (see Participants). In the test phase that followed approximately 20 minutes after the learning phase, recognition memory for the scene pictures was tested in a surprise memory test.

Learning phase Four different Chinese characters (汉, 礼, 归, 仗) were used in the probabilistic learning task, with two characters assigned to each of the two feedback delay conditions (short: 500 ms, long: 6,500 ms). The assignment of characters and conditions was balanced across subjects. Every character was associated with one of two responses (the c and n keys of the keyboard). Participants were instructed to learn the associations by trial and error and to use the feedback for this purpose. Feedback was always presented with 70% validity, meaning that when participants responded with the correct (incorrect) button, they received positive (negative) feedback in seven out of 10 times. Participants were informed that the feedback would not always be valid, but the instructions emphasized that the feedback would be valid most of the time, and that it was possible to use the feedback for learning. Overall, there were 200 trials, which were divided into five blocks of 40 trials each. Each character was presented 10 times per block, in pseudorandomized order, so that no character was repeated on the next trial, and not more than three characters from the same delay condition were presented in direct succession. Participants were given eight practice trials before they started working on the task. The scene pictures were divided into two lists of 280 pictures each (140 outdoor and 140 indoor scenes). The pictures from one of these lists were used as feedback pictures in the learning phase, and the pictures from the other list served as lures in the ensuing memory test. The assignment of the two lists to the feedback or lure function was balanced across subjects. Each picture was presented only once during learning, but not every picture from the list was necessarily used as a feedback picture. The reason for this is that the number of pictures presented from one category (indoor or outdoor scene) ultimately depended on the number of correct responses given by the participant. Importantly, even if a participant's responses were 100% correct (incorrect), no more than 140 outdoor (indoor) scene pictures were presented. The reason for this is that feedback was presented with 70% validity, as stated above.

A schematic of the trial procedure is depicted in Fig. 1a. Each trial of the probabilistic learning task started with a central fixation cross (500 ms), followed by a Chinese character that was presented in the center of the screen. In the bottom left and right corners of the screen, a blue and a vellow button were presented. The buttons represented the left and right response keys. As soon as the participant responded with one of the keys, the chosen button remained on the screen, and the other button disappeared. At the same time, the character was surrounded by a frame of the same color as the chosen button. This screen served to make the choice salient and was shown for a duration defined by the delay condition (short: 500 ms, long: 6,500 ms). If the participants did not respond within 1,500 ms after onset of the Chinese character, they were informed that their response was too slow and the trial was repeated. The delay period was followed by a central fixation cross (500 ms) and a feedback picture (1,500 ms). After the feedback, a blank screen was presented for 1,000 ms before the next trial started.

Performance in the learning phase was assessed as the proportion of correct responses in the probabilistic learning task and in the final block of the task without feedback. A variancestabilizing transformation (arcsine transformation; Winer, Brown, & Michels, 1991) was applied to the proportions of correct responses before submitting them to statistical analyses.

Test phase The 200 feedback pictures from the learning phase were presented together with 200 new scene pictures in pseudorandomized order, so that not more than three adjacent target or lure items were presented in direct succession. Moreover, the same number of target pictures from each category (outdoor and indoor) was presented as lure pictures. Participants were admitted a short break after every 80 trials. In the beginning of each trial, a fixation cross was presented with a duration jittered between 1,000 and 1,500 ms, followed by a picture presented for 1,500 ms. Participants were instructed to decide for every picture whether it was old or new using a six-step confidence scale (sure old, probably old, maybe old, maybe new, probably new, sure new). After the presentation of the picture, a blank screen appeared for 1,000 ms. Then, the question "Old or New?" appeared, together with a depiction of the rating scale. The old-new decision could be given as soon as the picture was presented. As soon as participants made a response, a blank screen was shown for 1,000 ms before the next trial started.

To assess memory performance, Pr scores (Snodgrass & Corwin, 1988) were calculated as the difference between the proportions of correct and incorrect *old* decisions (hits and false alarms). For this purpose, the corresponding three steps of the confidence scale were collapsed into *old* and *new*









Fig. 1. Trial procedure in the probabilistic learning task (**a**): At the beginning of each trial, one of four Chinese characters was presented. As soon as the participant made a choice, it was displayed for a duration defined by the delay condition (short: 500 ms, long: 6,500

ms). Outdoor (indoor) scene pictures were presented as positive (negative) feedback. Behavioral results in the learning phase (**b**) and in the test phase (**c**). Beeswarm plots show individual data points in addition to means and confidence intervals. (Color figure online)

decisions. In addition, high-confidence Pr scores were calculated based on *sure* and *probably* decisions only.

Computational modeling

A standard reinforcement learning model with two free parameters was fitted to each participant's observed choices in the learning phase (Daw, 2011). On each trial t of the probabilistic learning task, participants chose either the left or the right response button (choice $c_t = L$ or R). According to a *Q*-learning model (Watkins, 1989), subjects assign an expected value *Q* to each of the choice options. This expected value was initialized at a value of 0.5 on the first trial and subsequently updated on each trial according to the formula $Q_{t+1}(c_t) = Q_t(c_t) + \alpha \cdot \delta_t$, where α is a free learning rate parameter that indicates how readily choice behavior is changed as a reaction to reinforcement, with higher values signifying faster updating, and the prediction error $\delta_t = r_t - Q_t(c_t)$ is defined as the difference

between the actually received (r_t) and the expected value of the outcome. The observation model that links the theoretically expected choice values with the probabilities of the observed choices was assumed to follow a softmax distribution:

$$P(c_t = L|Q_t(L), Q_t(R)) = \frac{\exp\left(\beta \cdot Q_t(L)\right)}{\exp\left(\beta \cdot Q_t(R)\right) + \exp\left(\beta \cdot Q_t(L)\right)}.$$

The free inverse temperature parameter β indicates the extent to which the observed choices follow the learned values of the choice options. The learning rate α and inverse temperature β were estimated using a maximum likelihood estimation procedure. The MATLAB function fmincon was used to identify parameter values that minimized the inverse data likelihood (which is equal to maximizing the data likelihood). The estimation of the free parameters was iterated twenty times with random starting points and, as recommended by Daw (2011), constrained by prior distributions that penalized the data likelihood for extreme parameter values. The prior distribution used for the learning rate α was a beta distribution with the shape parameters $\alpha = 1.1$ and $\beta = 1.1$. This distribution puts a strong penalty on learning rate values smaller than 0 and larger than 1. The inverse temperature β was constrained by a gamma distribution with the shape parameter $\alpha = 1.2$ and the scale parameter θ = 5. This distribution puts a strong penalty on temperature values that are either smaller than or much larger than zero. For every participant, the parameter pair that yielded the highest likelihood was selected. These optimal parameters were averaged across subjects and used as model parameters. Initially, two separate models were fit to the short and long delay conditions, the parameters of which are given in Table 1. Because the estimated parameters and likelihoods did not differ between the delay conditions, learning rate α : t(42) = 0.24, p = .81, d = 0.05; inverse temperature β : t(42) =0.46, p = .65, d = 0.09; likelihood: t(42) = 0.26, p = .79, d =0.04, a combined model, collapsed across delay conditions, was fit to the data (cf. Foerde & Shohamy, 2011). Likelihood ratio tests (Daw, 2011) showed that all models provided a better fit to the data than a chance model. Individual datapoints for estimated parameters and model fits are provided in the supplementary online material. The combined model parameters were then used to calculate trial-by-trial estimates of

Table 1. Reinforcement learning model parameters

reward prediction errors (RPEs) for every subject. Salience prediction errors (SPEs) were computed by calculating the absolute values of each RPE estimate.

EEG recording and processing

The EEG was recorded during the learning phase and the recognition memory test from 28 Ag/AgCl scalp electrodes embedded in an elastic cap with positions according to the 10-20 electrode system (Fp1, Fp2, F7, F3, Fz, F4, F8, FC5, FC3, FCz, FC4, FC6, T7, C3, Cz, C4, T8, CP3, CPz, CP4, P7, P3, Pz, P4, P8, O1, O2, and A2). The vertical and horizontal EOG was recorded from four electrodes placed above and below the right eye and at the canthi of the left and right eyes. The electrodes were on-line referenced to a left mastoid electrode (A1), and AFz was used as a ground electrode. The EEG was amplified with a BrainAmp DC amplifier (Brain Products GmbH) from 0.016 to 250 Hz and digitized at 500 Hz. For off-line processing of the EEG data, the EEGLAB (Delorme & Makeig, 2004) and ERPLAB (Lopez-Calderon & Luck, 2014) toolboxes for MATLAB (MathWorks, Inc.) were used. Electrodes were rereferenced to the average of the left and right mastoid electrodes. The data from the learning phase and from the recognition memory test were bandpass-filtered at 0.1-30 Hz using a second order Butterworth filter. Segments were extracted from the learning phase data from 200 ms before feedback onset to 800 ms thereafter, and segments from 200 ms before picture onset to 1,500 ms thereafter were extracted from the test phase data. The segments were baseline corrected based on activity during the 200 ms before feedback or picture onset. Independent component analysis (ICA) was applied to the segmented data to correct for ocular artifacts. Components associated with ocular artifacts were identified and rejected manually based on their activations and topographies. Segments containing artifacts were rejected using the following criteria: A minimal and maximal allowed total amplitude of $\pm 100 \mu$ V, a maximal difference of values of 150 µV during intervals of 200 ms (window steps of 100 ms), a maximal allowed voltage step of 30 µV/ms, and maximal

	Short delay		Long delay		Combined	
	Mean	SEM	Mean	SEM	Mean	SEM
Learning rate (α)	0.22	0.04	0.21	0.03	0.16	0.03
Inverse temperatures (β)	10.37	1.25	9.72	1.10	11.13	1.18
Pseudo R^2	0.32	0.05	0.30	0.05	0.29	0.05
Model fit (log likelihood)	-47.30	3.75	-48.35	3.72	-98.79	7.58
Chance model fit	-69.31		-69.31		-138.63	
Liklihood ratio test	p < .001		p < .001		p < .001	

100 ms activity with a deviation of less than 0.4 μ V from the maximum or minimum voltage in the segment. On average, 1.25% and 1.6% of all segments were rejected in the learning phase and the test phase, respectively. One data set was excluded from the learning phase ERP analysis because of more than 25% rejected segments. For the same reason, two data sets were excluded from the test phase ERP analysis. Grand average waveforms were low-pass filtered at 10 Hz for illustration purposes.

ERPs in the learning phase ERPs were averaged for every combination of the factors delay (short, long), valence (positive, negative), and memory (hits, misses). Feedback pictures judged as being "old" or "new" in the test phase were counted as hits and misses, respectively. For this purpose, the three corresponding steps of the confidence scale were collapsed into *old* and *new* decisions. Six data sets had to be excluded from this analysis because there were not enough artifact-free trials (<7) to calculate reliable ERPs in one of the conditions. For the purpose of peak detection, the subject average waveforms were low-pass filtered at 10 Hz.

Because FRN effects are typically largest at frontocentral sites (Holroyd & Coles, 2002; Miltner, Braun, & Coles, 1997), FRN measures were analyzed at electrode FCz. The FRN was quantified in two ways: The FRN_{peak} was measured according to an algorithm described in Holroyd, Nieuwenhuis, Yeung, and Cohen (Holroyd, Nieuwenhuis, Yeung, & Cohen, 2003; see Ferdinand et al., 2012; Holroyd, Hajcak, & Larsen, 2006; Peterburs et al., 2016, for studies that used a similar approach) as the difference between the N200 peak (180-300 ms) and the preceding P200 peak (140-200 ms). The FRN_{diff} was measured as the peak amplitude between 300 and 450 ms in the negative minus positive feedback difference wave (cf. Becker, Nitsch, Miltner, & Straube, 2014; Peterburs et al., 2016; Weismüller & Bellebaum, 2016).

For the N170 quantification, electrodes were rereferenced to the average of all electrodes (cf. Arbel et al., 2017). This was done because the mastoid electrodes are located in close proximity to the occipitotemporal electrode sites at which the N170 is usually largest, which complicates the measurement of the N170 (Luck, 2014). N170 amplitudes were quantified as the difference between the N170 peak (140–200 ms) and the preceding P100 peak (90–150 ms) at electrodes P7 and P8.

As determined by an inspection of the waveforms, the feedback-locked P300 peaked around 500 ms at electrode Pz. P300 mean amplitudes between 450 and 600 ms were analyzed at electrodes Fz and Pz.

Single trial EEG analysis From all artifact-free EEG segments recorded in the learning phase, single trial mean amplitudes at

electrode FCz were extracted in 32 time bins of 25-ms duration each, ranging from zero to 800 ms after stimulus onset. To ensure that the results of the single trial EEG analysis were based on the same data as the ERP results in the learning phase, we restricted this analysis to the same 36 subjects that were included in the ERP analysis. For every subject, standardized trial-by-trial RPE and SPE estimates derived from the reinforcement learning model (see Computational Modeling) were used to predict standardized single-trial mean amplitudes across the experimental conditions in separate linear regression models for every time bin. The correlations (beta weights) between model-derived RPEs/SPEs and single trial EEG amplitudes were then submitted to a statistical analysis.

ERPs in the test phase ERPs were averaged for every combination of the factors valence (positive, negative) and item status (short delay hits, long delay hits, correct rejections). One data set had to be excluded from this analysis because there were not enough artifact-free trials (<7) to calculate reliable ERPs in one of the conditions. Mean amplitudes were analyzed in two adjacent time windows, ranging from 300-500 ms and 500-1,100 ms. The early time window is typically used for the analysis of FN400 effects in ERP studies of recognition memory (see Rugg & Curran, 2007, for a review). The later 500-1,100 ms time window was chosen because, as evident from Fig. 3c, an inspection of the waveforms suggested that the late old-new effect continued until approximately 1,100 ms at anterior electrodes. In order to cover frontal electrode sites, where FN400 effects are largest, as well as parietal electrode sites at which late old-new effects are typically most pronounced, mean amplitudes were analyzed at 15 electrodes broadly distributed across the scalp (F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4).

Statistical analyses

All statistical analyses were conducted using IBM SPSS software. Behavioral and electrophysiological measures were analyzed using repeated-measures ANOVAs and dependent *t* tests. Greenhouse–Geisser-corrected degrees of freedom and *p* values are reported whenever the assumption of sphericity was violated. Significant effects were decomposed using lower level ANOVAs and dependent *t* tests. As measures of effect sizes, partial eta squared (η_p^2) are reported for ANOVA results. For independent *t* tests, Cohen's *d* was calculated. For dependent *t* tests, *d* was calculated according to Dunlap, Cortina, Vaslow, and Burke (1996), taking into account the correlations between measurements. Error margins in graphs represent 95% confidence intervals based on the mean square error of the depicted effect (Jarmasz & Hollands, 2009).

Results

Performance in the learning phase

Correct responses in the probabilistic learning task are depicted as a function of delay and block in Fig. 1b and were analyzed in a 2 (delay: short, long) \times 5 (block) ANOVA. A main effect of block was found, F(3.04, 127.56) = 70.08, p_{corr} < .001, $\eta_p^2 = .63$, indicating that the frequency of correct responses changed during the course of the learning task. Subsidiary t tests revealed that correct responses increased from the first to the second block, t(42) = 7.37, p < .001, d =0.91, from the second to the third block, t(42) = 4.22, p < .001, d = 0.52, from the third block to the fourth, t(42) = 2.61, p < 100.05, d = 0.33, and from the fourth block to the fifth, t(42) =2.03, p < .05, d = 0.24. No main effect of delay, F(1,42) < 1, p = .63, η_p^2 = .01, and no Delay × Block interaction, F(4, 168) < $1, p = .96, \eta_p^2 = .00$, were found. Correct responses in the final block of the probabilistic learning task (without feedback) are shown in Fig. 1b and did not differ between the two delay conditions, t(42) = 0.98, p = .33, d = 0.20.

Recognition memory in the test phase

Pr scores and high-confidence Pr scores are given as a function of delay and valence in Fig. 1c. Pr scores were analyzed in a 2 (delay: short, long) × 2 (valence: positive, negative) ANOVA. There was a significant main effect of delay, F(1, 42) = 5.08, p < .05, $\eta_p^2 = .11$, driven by higher Pr scores for long delayed feedback pictures. The main effect of valence was also significant, F(1, 42) = 40.72, p < .001, $\eta_p^2 = .49$, reflecting higher Pr scores for negative (indoor) than for positive (outdoor) feedback pictures. The Delay × Valence interaction was not significant, F(1, 42) < 1, p = .56, $\eta_p^2 = .01$.

The analysis of the high-confidence Pr scores did not yield a significant main effect of delay, F(1, 42) = 3.49, p = .07, $\eta_p^2 = .08$, but only a strong main effect of valence, F(1, 42) = 40.23, p < .001, $\eta_p^2 = .49$, reflecting higher scores for negative (indoor) than for positive (outdoor) feedback pictures. The Delay × Valence interaction was not significant, F(1, 42) < 1, p = .41, $\eta_p^2 = .02$.

ERPs in the learning phase

FRN_{peak} and **FRN**_{diff} Feedback-locked ERPs in the learning phase are shown at electrode FCz as a function of delay, valence, and memory in Fig. 2a. The corresponding FRN_{peak} amplitudes were analyzed in a 2 (delay: short, long) × 2 (valence: positive, negative) × 2 (memory: hit, miss) ANOVA. This analysis yielded a significant main effect of valence, F(1, 35) = 9.93, p < .01, $\eta_p^2 = .22$, driven by more negative amplitudes for negative feedback pictures than for positive feedback pictures. Notably, a significant Delay × Memory

interaction was obtained, F(1, 35) = 4.40, p < .05, $\eta_p^2 = .11$. Long delayed feedback pictures that were subsequently forgotten elicited more negative FRN_{peak} amplitudes than those that were subsequently remembered, t(35) = 2.16, p < .05, d =0.14. In contrast, no difference was found between subsequently remembered and forgotten feedback pictures that were presented with a short delay, t(35) = -1.28, p = .21, d = -0.10. No further ANOVA effects reached significance, all p values > .40.

Negative minus positive feedback difference waves are shown as a function of delay and memory in Fig. 2b. FRN_{diff} peak amplitudes were analyzed in a 2 (delay: short, long) × 2 (memory: hit, miss) ANOVA that yielded a significant main effect of delay, F(1, 35) = 8.53, p < .01, $\eta_p^2 = .20$, driven by more negative amplitudes for shortly delayed feedback pictures than for long delayed feedback pictures. No significant main effect of memory, F(1, 35) < 1, p = .50, $\eta_p^2 = .01$, and no Delay × Memory interaction, F(1, 35) < 1, p = .41, $\eta_p^2 = .02$, were obtained.

N170 Feedback-locked waveforms at electrodes P7 and P8 are depicted in Fig. 3a. N170 amplitudes were analyzed in a 2 (delay: short, long) × 2 (memory: hit, miss) × 2 (electrode: P7, P8) ANOVA that yielded a significant main effect of delay, F(1, 35) = 9.13, p < .01, $\eta_p^2 = .21$, reflecting larger N170 amplitudes elicited by long delayed than by shortly delayed feedback pictures. No further effects reached significance, all p values > .16.

P300 Feedback-locked waveforms at electrode Pz are shown in Fig. 3b. Mean amplitudes in the 450-600-ms time window were analyzed in a 2 (delay: short, long) × 2 (valence: positive, negative) \times 2 (memory: hit, miss) \times 2 (electrode: Fz, Pz) ANOVA that yielded significant main effects of delay, F(1, $35 = 5.25, p < .05, \eta_p^2 = .13$, and valence, F(1, 35) = 5.41, p < .05.05, η_p^2 = .13, qualified by a Delay × Valence × Electrode interaction, F(1, 35) = 8.28, p < .01, $\eta_p^2 = .19$. No further effects involving the experimental factors reached significance, all p values > .09. To disentangle the significant triple interaction, mean amplitudes at electrodes Fz and Pz were analyzed in separate ANOVAs including the factors delay, valence, and memory. At electrode Fz, a significant main effect of valence was obtained, F(1, 35) = 9.76, p < .01, $\eta_p^2 =$.22, reflecting more positive amplitudes elicited by positive than by negative feedback pictures. No further effects reached significance, all p values > .08. At electrode Pz, more positive amplitudes were elicited by shortly delayed than by long delayed feedback pictures, F(1, 35) = 4.46, p < .05, $\eta_p^2 = .11$. No further effects reached significance, all p values > .10.

Correlations between prediction error estimates and EEG activity in the learning phase The analysis of FRN amplitudes in the learning phase were complemented by a model-based



Fig. 2. FRN and single trial EEG results in the learning phase. Feedbacklocked ERP waveforms (**a**) and negative minus positive feedback difference waves (**b**) at electrode FCz. Shaded areas indicate the time windows used for the detection of P200/N200 peak amplitudes (140–300 ms) and FRN_{diff} peak amplitudes (300–450 ms). Mean correlations between reward and salience prediction errors (RPE/SPE) and single trial EEG mean

amplitudes at electrode FCz (c). Shaded areas indicate the time windows in which significant correlations between single trial EEG mean amplitudes and RPE (150–300 ms, 350–425 ms, 550–625 ms) and SPE (150–275 ms) estimates were obtained. Beeswarm plots show individual datapoints in addition to means and confidence intervals. (Color figure online)

single trial EEG analysis that was aimed at validating models of the functional significance of the FRN_{peak} and FRN_{diff} measures used in the present study. High correlations between EEG amplitudes and trial-by-trial estimates of reward prediction errors (RPEs) in time windows in which FRN_{peak} and FRN_{diff} effects were present would confirm that EEG activity in these time windows reflects the processing of RPEs. High correlations between EEG amplitudes and salience prediction errors (SPEs) in the FRN_{peak} and FRN_{diff} time windows would indicate that EEG activity in these time windows is sensitive to general expectancy violations irrespective of valence.

Mean correlations between model-derived trial-by-trial RPE and SPE estimates and feedback-locked single trial EEG amplitudes at electrode FCz are depicted as a function of time in Fig. 2c. Correlations between RPEs and EEG activity were marked by two distinctive positive peaks around 200 and 400 ms, indicating that large negative RPEs (as elicited by unexpected negative feedback) were associated with more negative EEG amplitudes around these time points. Correlations between SPEs and EEG activity showed a pronounced negative peak around 200 ms, suggesting that unexpected feedback, irrespective of valence, was associated with more negative EEG amplitudes around this time point. These observations were confirmed by a series of t tests testing the significance of the mean correlations between RPEs/SPEs and

EEG activity in each of the 32 time bins. When correcting for multiple comparisons ($\alpha = 0.0016$), significant correlations between EEG amplitudes and RPE estimates were obtained in the 150–300-ms and the 350–425-ms time intervals in which FRN_{peak} and FRN_{diff} effects were present, and in a later (550–625 ms) time interval. Significant correlations between EEG amplitudes and SPEs were only present in the 150–275-ms time window in which the FRN_{peak} was measured.

Taken together, EEG activity in the FRN_{peak} and FRN_{diff} time windows reflected the processing of RPEs, as evidenced by high correlations between EEG amplitudes and RPE estimates. In contrast, significant correlations between EEG amplitudes and SPEs were confined to the early FRN_{peak} time window, which suggests that EEG activity in this time window was sensitive to general expectancy violations irrespective of whether the feedback was better (positive) or worse (negative) than expected.

ERPs in the test phase

ERPs waveforms associated with correct memory decisions in the recognition memory test are depicted in Fig. 3c. Mean amplitudes in the 300–500-ms and 500–1,100-ms time windows were analyzed in two separate four-way ANOVAs including the factors valence (positive, negative), item status



Fig. 3. Feedback-locked waveforms in the learning phase at electrodes P7 and P8 (a). Shaded areas indicate the time window used for the detection of P100/N170 peak amplitudes (90–200 ms). Feedback-locked waveforms in the learning phase at electrode Pz (b). Shaded areas indicate the 450–600-ms time window in which P300 mean amplitudes were analyzed. ERP waveforms associated with correct memory

decisions in the test phase are shown for three representative frontal, central, and parietal electrodes (c). Shaded areas indicate the 300-500-ms and 500-1,100-ms time windows used to analyze old-new effects. Beeswarm plots show individual datapoints in addition to means and confidence intervals. (Color figure online)

(short delay hits, long delay hits, correct rejections), antpos (F = frontal, FC = frontocentral, C = central, CP = centroparietal, P = parietal), and side (left, midline, right).

In the 300–500-ms time window, a significant main effect of valence was obtained, F(1, 41) = 29.60, p < .001, $\eta_p^2 = .42$, reflecting more positive amplitudes elicited by positive feedback pictures than by negative ones. The Valence × Side interaction was only marginally significant, F(1.58, 64.73) =3.36, $p_{corr} = .05$, $\eta_p^2 = .08$. No further effects involving the experimental factors reached significance, all p values > .25.

In the 500–1,100-ms time window, significant main effects of valence, F(1, 41) = 45.76, p < .001, $\eta_p^2 = .53$, and item status, F(2, 82) = 10.72, p < .001, $\eta_p^2 = .21$, were obtained, qualified by significant interactions between valence and antpos, F(1.27, 51.90) = 4.38, $p_{corr} < .05$, $\eta_p^2 = .10$; item status and antpos, F(2.67, 109.37) = 6.80, $p_{corr} < .01$, $\eta_p^2 = .14$; valence and side, F(1.64, 67.24) = 6.67, $p_{corr} < .01$, $\eta_p^2 = .14$; and valence, antpos, and side, F(4.97, 203.80) = 2.69, $p_{corr} < .05$, $\eta_p^2 = .06$. No further effects involving the experimental factors reached significance, all p values > .26. Because we were chiefly interested in the effect of item status, which did not interact with valence, we further explored the significant Item Status × Antpos interaction and conducted separate one-way ANOVAs including the factor item status for each level of the antpos factor. The main effect of item status was significant at each level of the antpos factor. Effect sizes were largest over frontocentral ($\eta_p^2 = .21$) and smallest over parietal electrode sites ($\eta_p^2 = .18$). Subsidiary *t* tests revealed that short delay hits did not differ significantly from correct rejections, all p values > .07. In contrast, long delay hits were associated with more positive mean amplitudes than correct rejections at each level of the antpos factor. Effect sizes

were largest at frontal (d = 0.32) and smallest at parietal electrodes (d = 0.15). Notably, long delay hits were also associated with more positive mean amplitudes than short delay hits. These effects were obtained at each level of the antpos factor, but here, effect sizes were largest at parietal electrodes (d = 0.24) and smallest at frontal electrodes (d = 0.18).

Discussion

In the present study, ERPs were used to investigate interactions between feedback-based learning and concurrent incidental memory encoding of feedback pictures in a probabilistic learning task. In the learning phase, participants used feedback pictures that were provided with either a short (500 ms) or long (6,500 ms) temporal delay to learn associations between Chinese characters and motor responses. Based on evidence from neuroimaging studies suggesting that the processing of temporally delayed feedback engages the MTL-based declarative learning system, we used a feedback delay manipulation to establish a short delay condition in which feedback processing should strongly rely on the procedural learning system, and a long delay condition in which the declarative learning system should be more involved in feedback processing. As evidenced by the performance in the probabilistic learning task, participants were able to use the feedback for learning the stimulus-response associations and, consistent with previous studies (e.g., Foerde & Shohamy, 2011; Weismüller & Bellebaum, 2016), learned equally well in the short and long feedback delay conditions.

The major goal of the present study was to explore how feedback-based learning with long (and short) feedback delay interacts with memory encoding. In previous studies investigating the effects of feedback delay on memory for feedback pictures, delayed feedback pictures were associated with a higher proportion of correct high-confidence memory responses (Foerde & Shohamy, 2011; Lighthall et al., 2018). Consistent with these studies, and in support of the view that the involvement of the declarative memory system boosts memory for feedback events, we found that long delayed feedback pictures were remembered better than shortly delayed feedback pictures.

Of note, it has been argued that studies investigating interactions between reward learning and memory encoding need to control for motivational and attentional confounds that could affect memory encoding (Murayama & Kitagami, 2014). In the present study, these confounds were avoided by the use of an incidental learning paradigm. Furthermore, the fixed assignment of picture and feedback categories (outdoor = positive, indoor = negative) ensured that participants needed to process the picture content in order to use the feedback for learning. As these important boundary conditions were met in the present study as well in previous studies investigating the effects of feedback timing on memory (Foerde & Shohamy, 2011; Lighthall et al., 2018), we feel safe to conclude that they reflect the involvement of different neural systems for immediate and delayed feedback processing.

Consistent with previous ERP studies, we analyzed FRN amplitudes in the feedback-locked ERP waveforms (FRNpeak) and in the negative minus positive feedback difference waves (FRN_{diff}). Whereas the FRN_{peak} primarily captures variance related to the N200 and has been functionally related to the general violation of action-outcome relationships irrespective of their valence (Ferdinand et al., 2012), the FRN_{diff} carries valence-related variance as reflected by the reward positivity (Holroyd et al., 2008; Proudfit, 2015). Prior studies investigating the effects of feedback timing on the FRN have found that whereas shortly delayed feedback is associated with larger FRN_{diff} amplitudes than long delayed feedback (e.g., Höltje & Mecklinger, 2018; Peterburs et al., 2016; Weismüller & Bellebaum, 2016), the reverse applies for the FRN_{peak} (Höltje & Mecklinger, 2018; Peterburs et al., 2016). Consistent with these studies, shortly delayed feedback elicited larger FRN_{diff} amplitudes than long delayed feedback. This finding confirms the view that the procedural learning system was strongly involved in the processing of shortly delayed feedback. Interestingly, in the present study, FRN_{peak} amplitudes did not differ between shortly delayed and long delayed feedback. Different from previous studies that have found increased FRN_{peak} amplitudes for long delayed feedback (Höltje & Mecklinger, 2018; Peterburs et al., 2016), the cue (the Chinese character) and the choice (the colored button representing the response key) remained on the screen during the delay period of the feedback learning task, thereby lowering the working memory demands in the present study as compared to the aforementioned studies. It is conceivable that in the Peterburs et al. (2016) and Höltje and Mecklinger (2018) studies, higher working memory demands in the delayed feedback condition were associated with a stronger working memory-guided build-up of action-outcome expectations, the violation of which resulted in higher FRN_{peak} amplitudes.

Comparing FRN measures for subsequently remembered or forgotten feedback pictures, we found that the FRN_{peak} was attenuated for subsequent hit responses relative to subsequent misses in the long feedback delay condition. This finding indicates that feedback processing and incidental memory encoding competed for neural processing resources, which is in principle consistent with a similar interaction reported by Wimmer et al. (2014). As the subsequent memory effect (SME) was only found for long delayed feedback, the processing of which has been shown to engage the hippocampus (Foerde & Shohamy, 2011; Lighthall et al., 2018), it is tempting to speculate that the SME reflects a competition for hippocampal processing resources. This conjecture is supported by the finding that no SME was found in the short delay condition. In contrast, Wimmer et al. (2014) found that successful memory encoding was associated with diminished reward processing as reflected in striatal RPE signals, which could reflect a competition between memory encoding and reward learning for striatal processing resources. Importantly, Wimmer and colleagues used a reward learning task with a short reward delay (1.5 seconds) in which presumably reward learning strongly relied on the striatum. Thus, the interaction between memory encoding and delayed feedback processing in the present study most likely reflects competition for different (hippocampal) processing resources than the one reported by Wimmer et al. (2014).

Because the functional significance of the FRN is still a matter of debate, the analysis of FRNpeak and FRNdiff amplitudes in the learning phase was complemented by a modelbased single trial EEG analysis in which we explored how the processing of reward prediction errors (RPEs) and general expectancy violations irrespective of valence was reflected in the EEG signal. Using a computational reinforcement learning model, we computed trial-by-trial estimates of RPEs and fitted them to the EEG data. Our assumption was that if the FRN reflects the processing of RPEs, best fits between RPEs and EEG amplitudes should be obtained in the time windows in which FRN effects are present in the ERP waveform. This is exactly what we found: Reliable RPE correlations were selectively observed in the FRN_{peak} (140-300-ms) and FRN_{diff} (300–450-ms) time windows. This finding confirms the view that the FRN reflects the processing of RPE signals on the single trial level. Notably, an exception to this pattern of results was the cluster of significant RPE correlations in the 550-625-ms time period. Even though this result was not predicted, it is conceivable that correlations in this late time interval were related to the P300, which peaked around 500 ms at parietal electrodes in the present study. Further research is needed to clarify the functional significance of this finding.

Different from signed RPEs, unsigned prediction errors or salience prediction errors (SPEs) distinguish between expected and unexpected outcomes without taking into account the valence of the prediction error. Based on the assumption that the FRN_{peak} is sensitive to this more general type of violation of action-outcome expectations, we hypothesized that best fits between model-derived SPEs and single trial EEG amplitudes should occur in the FRN_{peak} window. We found significant SPE correlations between 150 and 275 ms, where FRN_{peak} effects occurred, but not in the later time windows in which correlations with the RPE dominated in the ERP waveforms. This finding confirms the view that the $\ensuremath{\mathsf{FRN}}_{\ensuremath{\mathsf{peak}}}$ primarily reflects variance related to the N200 and by this indicates the salience (unexpectedness) of an outcome irrespective of feedback valence. More generally, the results of the single trial EEG analysis provide further evidence in support of the view that the FRN_{peak} and the FRN_{diff} constitute functionally

distinct ERP components reflecting different aspects of feedback processing (i.e., the processing of general expectancy violations and unexpected rewards, respectively).

We also analyzed two ERP components that have recently been found to be sensitive to feedback delay manipulations (i.e., the N170 and the P300). We expected that delayed feedback should elicit larger N170 amplitudes than immediate feedback. Furthermore, if the N170 reflects the involvement of declarative memory processes it is conceivable that these processes interact with memory encoding. In the present study, delayed feedback pictures elicited larger N170 amplitudes, but no effects of successful memory encoding were obtained. Based on the extant data, it is difficult to make inferences about which precise declarative memory processes the N170 delay effect reflects. It is conceivable that the N170 elicited by delayed feedback is linked to an MTL-based process that binds together the reaction given by the participants and the temporally delayed feedback stimulus (Arbel et al., 2017; Foerde & Shohamy, 2011).

Consistent with the studies by Wang et al. (2014) and Weismüller and Bellebaum (2016), we found that shortly delayed feedback pictures elicited larger P300 amplitudes than those presented with long feedback delay. Notably, in the two aforementioned studies the P300 delay effect was significant at frontal electrodes, whereas we found a significant P300 delay effect at parietal, but not at frontal electrodes. The frontal P300 effects obtained in the studies by Wang et al. (2014) and Weismüller and Bellebaum (2016) resemble frontal slow wave activity associated with the maintenance of information in working memory (Ranganath & Paller, 1999, 2000; Werkle-Bergner, Mecklinger, Kray, Meyer, & Düzel, 2005). Consistent with the recent proposal that the feedback-locked parietal P300 reflects the updating of the value assigned to an action (Fischer & Ullsperger, 2013; Ullsperger, Fischer, Nigbur, & Endrass, 2014), the P300 delay effect obtained in the present study could reflect stronger action value updating under short feedback delay conditions for the reaction given by the participant, potentially as a downstream consequence of the more pronounced feedback evaluation process reflected in the FRN_{diff} in this condition.

Even though P300 amplitudes are often predictive of subsequent memory and reflect the encoding of item-specific details (Fabiani, Karis, & Donchin, 1986; Kamp, Bader, & Mecklinger, 2017; Karis, Fabiani, & Donchin, 1984), surprisingly no parietal subsequent memory effect (SME) was obtained in the present study. Interestingly however, as evidenced by the FRN_{peak}, an SME was obtained in the delayed feedback condition. ERPs elicited by delayed feedback pictures showed effects of successful memory encoding, albeit in an earlier time period than the P300 SME usually found during incidental encoding. Thus, it is possible that the presence of feedback stimuli and the ensuing expectancy violations speeded up memory formation in particular in the long delay condition, hereby provoking interference between feedback evaluation and memory encoding processes that relied on similar neural processing resources.

We also hypothesized that delayed feedback processing with hippocampal involvement should primarily boost the recollection of feedback pictures and give rise to a parietal old–new effects, the putative ERP correlate of recollective processing. In partial confirmation of this prediction, long delayed feedback pictures elicited a strong old–new effect between 500 and 1,100 ms poststimulus. In contrast, feedback pictures that had been presented with a short feedback delay in the learning phase were not associated with an old–new effect in this late time interval. This pattern of results is consistent with the behavioral finding that feedback pictures presented with a long delay were associated with better recognition memory than those presented with a short delay.

Notably, the late old-new effect associated with long delayed feedback was more broadly distributed than typically observed in ERP studies of recognition memory. This finding is reminiscent of studies that have found more anterior topographical distributions of N400 effects for pictures as compared with words (Ganis, Kutas, & Sereno, 1996), which has been taken as evidence for partially different sets of neural generators for the N400 to verbal and pictorial stimuli (for a review, see Kutas & Federmeier, 2000). Similarly, the broad topographical distribution of the late old-new effect observed in the present study could reflect overlapping, but nonidentical sets of neural generators underlying the late old-new effect for pictorial and verbal stimuli. Consistent with this view, in a recognition memory study in which scene pictures similar to those in the present study were used, young adults elicited a broadly distributed old-new effect between 300 and 900 ms that was largest over central electrode sites (Gutchess, Ieuji, & Federmeier, 2007).

In the present study, a significant early frontal old–new effect was obtained in neither condition, indicating that there was no substantial contribution of familiarity to recognition memory. This finding contrasts with our previous study in which superior memory for pictures presented with positive feedback was associated with an early frontal old–new effect (Höltje & Mecklinger, 2018), and indicates that positive feedback valence and feedback delay benefit memory by distinct mechanisms: Whereas reward signals elicited by positive feedback strengthen a context-free and familiarity-based form of recognition, delayed feedback fosters the recollection of feedback pictures, presumably mediated by the hippocampal involvement in feedback processing.

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