The Effects of Reliable Social Feedback on Language Learning: Insights from Electroencephalography and Pupillometry

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Abstract

■ Language learning is often a social process, and social feedback may play a motivational role. We examined the neurophysiological correlates of word learning with feedback varying in reliability (accuracy) and social content. In a forced-choice task, participants learned to associate novel auditory words with known objects and received feedback. There were three types of feedback: Social Reliable (always providing accurate feedback regarding performance), Social Unreliable (providing random feedback: 50% correct and 50% incorrect feedback irrespectively of the performance), and Symbolic Reliable (always accurate feedback). Posttraining behavioral performance was better for words learned with social and symbolic reliable feedback. ERP amplitudes and pupil dilation showed differences as a function of feedback reliability and social content. In the reliable conditions, before feedback, stimulus-preceding negativity amplitude grew as learning progressed, likely due to the expectation of receiving positive feedback. During feedback, late positive complex amplitude for positive feedback diminished as learning progressed but not for negative feedback, which was likely consistently used for context updating. These effects were not observed for unreliable feedback, probably because its value was not used for updating information. Pupillometry results corroborated this showing greater dilation for negative versus positive feedback in reliable conditions. Finally, when feedback was social, processing was associated with more frontal activation and behavioral performance was closely correlated with both ERP and pupillometry results. Overall, our findings show differential processing of feedback depending on its informational and social content, advancing our understanding of how social and cognitive processes interact to shape word learning. ■

INTRODUCTION

Language learners frequently receive social feedback, informing them as to their success or failure in language performance (e.g., pronouncing a newly learned word), which they use to update linguistic knowledge and adapt future behavior (Mackey & Sachs, 2012). Evaluative social feedback, expressed through verbal or nonverbal reactions (e.g., praise, encouragement, disapproval), plays a key role in social learning (Sobczak & Bunzeck, 2023; Zonca, Vostroknutov, Coricelli, & Polonio, 2021; for a review, see Ho, MacGlashan, Littman, & Cushman, 2017). Beyond its informational value, social feedback has motivational and emotional significance, serving as a source of reward or disapproval (Tricomi & DePasque, 2016), which reinforces adaptive behavior. Despite the importance of social feedback in gating learning, its impact on language learning remains poorly understood. The current study investigated the neurocognitive mechanisms underlying the processing of social feedback during word learning in adults, as well as how different types of feedback affect word acquisition.

Learning to associate novel labels to existing semantic concepts, or word learning, is a fundamental aspect of language learning. Associative models of word learning (e.g., Smith, Smith, & Blythe, 2011; Smith & Yu, 2008) suggest that learners track co-occurrence probabilities between words and referents across exposures. Feedback, particularly when reliable, likely facilitates this process by reinforcing the association between an auditory word and the corresponding object (or image). Associative theories of predictive learning (e.g., Pearce & Hall, 1980) offer a compelling framework for explaining how feedback might guide language learning in these situations. These theories propose that learners continuously generate predictions about upcoming events and adjust their mental representations based on the discrepancy between expected and received outcomes, known as prediction errors. When the outcome violates a learner's current expectations, it generates a prediction error, which in turn might drive attentional shifts and learning by signaling the need to

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update existing associations (Luque, López, Marco-Pallares, Càmara, & Rodríguez-Fornells, 2012). Importantly, cues that generate prediction errors tend to attract more attention than those confirming correct predictions (Wills, Lavric, Croft, & Hodgson, 2007; Pearce & Hall, 1980). Over time, the reduction of such errors reflects successful learning. Thus, predictive learning theories provide a mechanistic explanation for how learners integrate both positive and negative feedback to refine lexical associations.

A key factor in feedback processing is reliability, which influences how learners monitor performance and evaluate feedback. Feedback is reliable when it is positive for a correct answer and negative for an incorrect answer. Reliable feedback has been shown to enhance both feedback anticipation and processing compared with unreliable feedback (Severo, Paul, Walentowska, Moors, & Pourtois, 2020; Ernst & Steinhauser, 2017; Schiffer, Siletti, Waszak, & Yeung, 2017; Walentowska, Moors, Paul, & Pourtois, 2016). Indeed, learners prioritize information from reliable sources, minimizing the costs associated with acquiring inaccurate or irrelevant feedback (Mangardich & Sabbagh, 2018; Begus, Gliga, & Southgate, 2016; Begus & Southgate, 2012; Scofield & Behrend, 2008; Koenig & Harris, 2005; Sabbagh & Baldwin, 2001). This preference for reliable sources is particularly evident during early language acquisition but likely extends to adult word learning. From an evolutionary perspective, selective social learning offers adaptive advantages, ensuring efficient acquisition of relevant knowledge (Henrich & McElreath, 2012; Sperber et al., 2010). For example, infants have been shown to seek more information and exhibit greater curiosity when interacting with reliable rather than unreliable speakers (Begus et al., 2026; Begus & Southgate, 2012, 2016). These findings suggest that sensitivity to the reliability of social cues emerges early and can guide attention and learning. However, to our knowledge, no studies have directly examined how the perceived reliability of evaluative social feedback, such as approval or disapproval from a communicative partner, influences language learning. In such contexts, reliable social feedback may support referential mapping by reinforcing attentional alignment and communicative intent. Orthogonal to reliability is the social nature of the feedback itself. Social feedback, or feedback delivered by an expressive, responsive human partner, is generally prioritized over nonsocial information (Williams, Cristino, & Cross, 2019; Wagner, Kelley, Haxby, & Heatherton, 2016; Chevallier, Kohls, Troiani, Brodkin, & Schultz, 2012). Its inherent emotional content provides an additional processing advantage, as emotional information is often processed more deeply and rapidly (Norris, Chen, Zhu, Small, & Cacioppo, 2004; Hariri, Tessitore, Mattay, Fera, & Weinberger, 2002). Positive or negative social feedback may serve as a powerful motivator for word learning by activating reward-motivational systems and enhancing both attention and memory processes (Martins et al., 2021; Mani & Ackermann, 2018). A major difficulty in observing the effect of social feedback on learning is providing participants with ecologically valid stimuli that mimic real-life human feedback. Most previous studies have used either static pictures of faces (Spreckelmeyer et al., 2009; for a review, see Risko, Laidlaw, Freeth, Foulsham, & Kingstone, 2012) or still images of thumbs up/down (Pfabigan, Gittenberger, & Lamm, 2017), which lack the inherent temporal dynamics of social feedback. In contrast, videos that show real humans in movement are thought to better reflect real-life interactions, leading to higher emotional arousal and motivational engagement (Kohls et al., 2013; Sato & Yoshikawa, 2007).

Feedback-related processes during learning are often examined using ERPs. The stimulus-preceding negativity (SPN) reflects a family of slow negative ERP shifts that progressively increases in amplitude before the presentation of informative feedback (see Brunia, Hackley, van Boxtel, Kotani, & Ohgami, 2011, for a review). Different topographies have been identified and probably reflect differential contribution to brain regions to the expected feedback (Brunia et al., 2011; van Boxtel & Böcker, 2004; Ohgami, Kotani, Hiraku, Aihara, & Ishii, 2004; Kotani, Hiraku, Suda, & Aihara, 2001). Functionally, the SPN is thought to reflect feedback expectation and anticipation, capturing motivational, affective, and preparatory processes tied to expected information (León-Cabrera, Hjortdal, Berthelsen, Rodríguez-Fornells, & Roll, 2024; Glazer, Kelley, Pornpattananangkul, Mittal, & Nusslock, 2018; Fuentemilla et al., 2014; Morís, Luque, & Rodríguez-Fornells, 2013; Poli, Sarlo, Bortoletto, Buodo, & Palomba, 2007; Masaki, Takeuchi, Gehring, Takasawa, & Yamazaki, 2006; Kotani et al., 2003; Böcker, Baas, Kenemans, & Verbaten, 2002). Recent research has shown that similar SPN-like slow negative ERP modulations are associated with the prediction of linguistic information in comprehension (León-Cabrera, Flores, Rodríguez-Fornells, & Morís, 2019; Grisoni, Miller, & Pulvermüller, 2017; León-Cabrera, Rodríguez-Fornells, & Morís, 2017; see León-Cabrera et al., 2024, for a review). The late positive complex (LPC or P3b) is a parietally distributed positive deflection occurring ~300–600 msec after feedback onset. It is associated with cognitive mechanisms such as working memory updating and attention allocation (Polich, 2007; Donchin & Coles, 1988). Enhanced LPC amplitudes have been linked to encoding processes that predict improved subsequent recall and retrieval performance (Lemhöfer, Lei, & Mickan, 2025; Turk et al., 2018; Batterink & Neville, 2011; Fabiani, Karis, & Donchin, 1986; Karis, Fabiani, & Donchin, 1984).

Another effective measure of feedback processing is pupil dilation (Mathôt, 2018). This psychophysiological response has been shown to index the anticipation of rewards (Schneider, Leuchs, Czisch, Sämann, & Spoormaker, 2018), interest (Hess & Polt, 1960), emotional arousal (Bradley, Miccoli, Escrig, & Lang, 2008), and curiosity for learning new information (Theobald, Galeano-Keiner, & Brod, 2022; Brod & Breitwieser, 2019; Kang et al., 2009). In line with this evidence, pupil dilation can be used as a marker of expectation and anticipation of upcoming feedback. Furthermore, pupil dilation has been widely examined in connection to mental effort (Schad, Nuthmann, Rösler, & Engbert, 2024), memory load (Kahneman & Beatty, 1966; Vilotijević & Mathôt, 2023), and recognition (Lapteva & Martarelli, 2024; Otero, Weekes, & Hutton, 2011). Crucially, pupil responses during encoding have been shown to predict subsequent learning or recollection success (Kuipers & Phillips, 2022; Pajkossy & Racsmány, 2019; Kafkas, 2021; for a review, see Kafkas, 2024), supporting its use as an indirect neural index of learning-related cognitive engagement.

Whereas ERPs offer fine-grained temporal resolution of rapid neural responses to feedback (Luck, 2014; Polich, 2007), pupil dilation reflects more sustained cognitive and affective states such as mental effort and arousal (Mathôt, 2018; Laeng, Sirois, & Gredebäck, 2012). When examining feedback anticipation and processing, these methods are complementary: ERPs capture fast, transient changes during feedback anticipation and evaluation, whereas pupillometry indexes slower, cumulative aspects of engagement. Prior studies have shown that combining them reveals distinct but converging insights (Kuipers & Phillips, 2022; Kostandyan et al., 2019; Kamp & Donchin, 2015). Here, we use this integrated approach to provide a more comprehensive view of feedback processing during second language learning, a novel application in this domain.

In the current study, we tracked the neurocognitive processes underlying word learning with feedback that differed in its reliability and social content. Using a within-subject design, we examined feedback expectation/anticipation and processing, as well as its impact on novel word acquisition. Positive and negative social feedback was presented via a series of short video clips, and symbolic feedback was presented as static images. Participants learned to associate novel auditory words with known objects through a forced-choice task, receiving feedback in three conditions: Social Reliable (accurate), Social Unreliable (randomly accurate or inaccurate), and Symbolic Reliable (accurate). A block design ensured participants were aware of the feedback type before its onset. Behavioral learning performance was evaluated during training and in a posttraining assessment.

Given the social nature of language learning, we hypothesized that reliable social feedback is a relevant and efficient "currency" for motivating word learning. We predicted that before feedback, reliable social feedback would result in greater SPN amplitude and pupil dilation, reflecting heightened feedback expectation and anticipation compared with symbolic and unreliable social feedback. During feedback, we predicted that reliable social feedback would evoke greater LPC amplitude and pupil dilation, indicative of enhanced feedback processing and better encoding, particularly for negative feedback. If supported, these findings would suggest that social feedback not only increases feedback expectation but also facilitates deeper processing and encoding, highlighting its role as a critical motivator in second language acquisition.

METHODS

Participants

Thirty-two right-handed Spanish–Catalan bilinguals with no previous knowledge of Hebrew or related languages participated in the study. Sample size was based on previous ERP studies focusing on the SPN and the LPC/P300 (Yang et al., 2019; Benning et al., 2016; Fuentemilla et al., 2014; Morís et al., 2013; Padrão, Mallorquí, Cucurell, Marco-Pallares, & Rodriguez-Fornells, 2013). Participants had normal or corrected-to-normal vision and reported no history of neurological deficits. Three participants were excluded from the EEG analyses due to excessive noise in the EEG signal and two due to technical sound difficulties during the experiment. Out of the remaining 27 participants (20 female participants, mean age: 22.5 ± 4 years), 5 were excluded from the pupillometry analyses due to recording issues (leaving 22 participants, 16 female participants, mean age: 23 ± 4 years). Before the experiment, participants gave written consent and were fully informed of the experimental procedure. They received €30 for their participation in the 2-hr session, 45-min preparation and 15-min online posttest. The study was approved by the local ethics committee.

Stimuli

Ninety grayscale images were selected from the MultiPic standardized set of drawings (Duñabeitia et al., 2018), and 90 matching auditory nouns in Hebrew were recorded by a native speaker. Nouns belonged to six different categories: animals and insects, body parts, food, clothing, household items, and tools. Verbal labels were not transparent, meaning they bore no phonological resemblance to their equivalents in Spanish, Catalan, French, Italian, German, or English. The lexicon was separated into three separate lists controlled for word frequency and word length, which contained the same number of words from each category. Different lists were assigned to different feedback conditions for each participant, counterbalanced across participants. Feedback conditions during learning included the following: Symbolic Reliable feedback, Social Reliable feedback, and Social Unreliable feedback. For Symbolic Reliable feedback, participants saw an image of a check (positive) or cross (negative; Figure 1). We recorded 12 different videos with two professional actresses (herein referred to as Agents 1 and 2) who were physically distinctive from each other. To provide varied social feedback, social feedback consisted of the following: thumbs up/down, smile/frown, nod/head-shaking. Each of the six different videos per agent lasted 2 sec. All visual materials were controlled for isoluminance due to the use of pupillometry. Half of the participants saw Agent 1 in the Social Reliable condition and Agent 2 in the Social Unreliable condition; the other half had the opposite combination. In the Social Reliable and Symbolic Reliable conditions, participants always received 100% correct

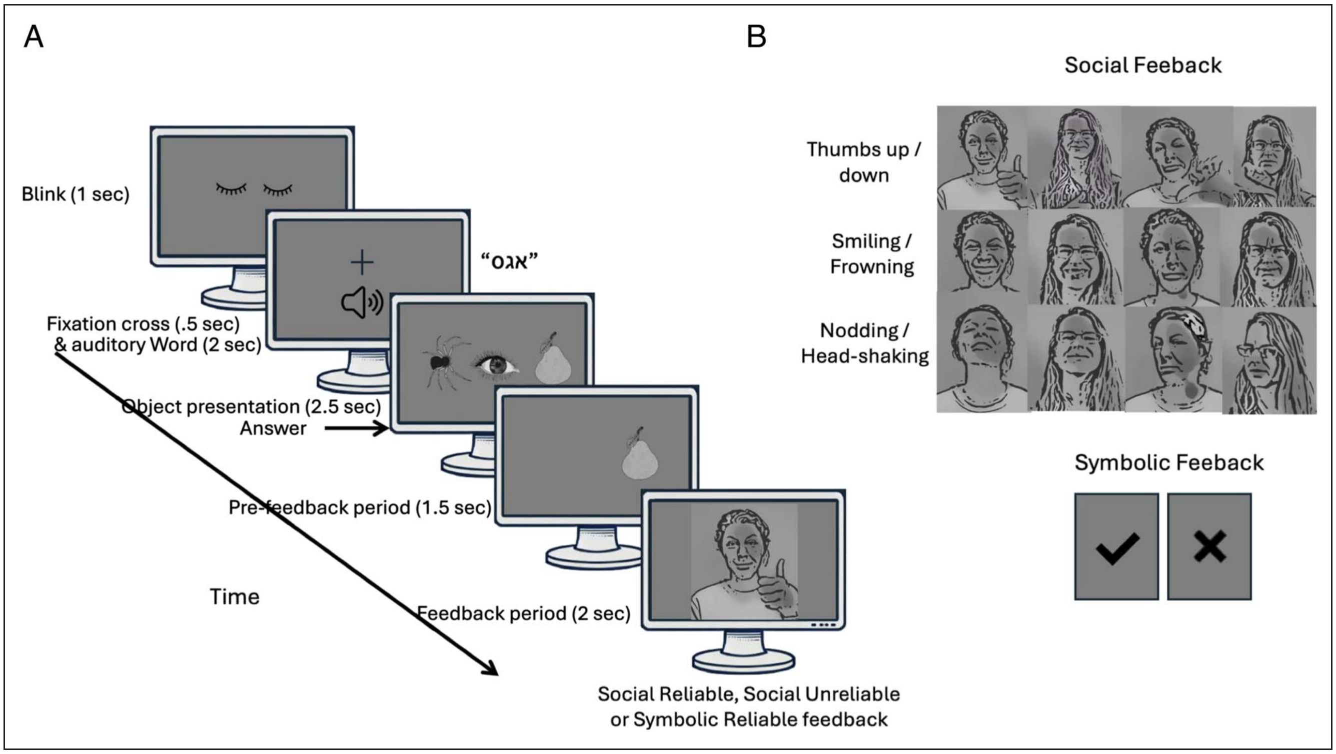


Figure 1. Trial design and feedback conditions. (A) Trial structure: Each trial began with a fixation cross, followed by an auditory word in Hebrew. Participants then viewed three images and selected the one they believed matched the word using keys 1–3 on a keyboard. The selected image remained on screen for 1.5 sec before feedback appeared. Feedback type depended on the block: Social Reliable, Social Unreliable, or Symbolic Reliable. In Social Reliable blocks, participants received video feedback from a social agent whose response (e.g., smile, nod) always matched response accuracy. In Social Unreliable blocks, the same type of social feedback was presented, but accuracy and feedback valence were uncorrelated (50% reliable). In Symbolic Reliable blocks, feedback consisted of static images (checkmark or cross) corresponding to correct or incorrect responses. Social feedback videos lasted 2 sec, and Symbolic feedback static images remained on the screen for 2 sec. (B) Feedback types: Social feedback included 12 short videos (6 per agent), comprising three positive expressions (thumbs up, smile, and nod) and three negative expressions (thumbs down, frown, and head shake). Symbolic feedback included two isoluminant static images: a checkmark (positive) and a cross (negative). Social agents were counterbalanced across participants.

feedback during training (after selecting the image they thought corresponded to each auditory noun). In the Social Unreliable condition, feedback was 50% correct and 50% incorrect, making it unreliable.

A separate experiment with 20 participants that were not involved in the current study was conducted to ensure that all feedback was equally perceived as positive or negative and to measure possible processing response timing differences between conditions. Participants were asked to rate how positive or negative the feedback was using a 5-point Likert scale. At least 90% of the participants rated 1 (fully negative) for negative feedback and 5 (fully positive) for positive feedback in all symbolic and social feedbacks. Social feedback was perceived as negative or positive 0.960 sec (*SD* = 0.130) after Symbolic feedback (Symbolic mean = 0.624 sec [*SD* = 0.072 sec], Social Agent 1, mean = 1.592 sec [*SD* = 0.126 sec], Social Agent 2, mean = 1.575 sec [*SD* = 0.134 sec]). No significant differences were found in RT between negative (mean = 1.612 sec [*SD* = 0.112 sec]) and positive (mean = 1.555 sec [*SD* = 0.140 sec]) social feedback videos, nor negative (mean = 0.644 sec [*SD* = 0.091 sec]) and positive (mean = 0.633 sec [*SD* = 0.062 sec]) symbolic videos.

Procedure and Tasks

Training

Participants were briefed on the procedure, capped with an elastic cap containing 32 electrodes and fitted with Pupil Labs glasses (Kassner, Patera, & Bulling, 2014). They were comfortably seated at a desk situated 60 cm away from a computer screen in a Faraday booth. Participants underwent a pretraining session with three auditory word and image pairs not included in the main training. During the pretraining, they were introduced to the two social agents and told that one of them had less teaching experience (Social Unreliable) than the other (Social Reliable) agent. Following this, participants underwent training. In each trial, participants heard a new word in Hebrew and saw three items (Figure 1A). Participants were asked to select the item they believed corresponded to the spoken word. Following the selection, they received feedback that came either in the form of a video or as a static image, depending on which condition was being presented in a given block. When feedback belonged to the Social Reliable condition, participants saw a video of a social agent giving positive feedback for a correct answer (e.g., thumbs up) or negative feedback for an incorrect answer (e.g., thumbs down). Videos lasted 2 sec. When the feedback was from the Social Unreliable condition, participants received either positive or negative feedback that was randomly related to their answer. Therefore, if a participant gave a correct answer, feedback could be either positive or negative, as was the case for an incorrect answer. Finally, in the Symbolic Reliable condition, participants saw a positive symbol for a correct answer and a negative symbol for an incorrect answer. The training session lasted roughly 2 hr, including short breaks after each block, during which they were invited to stretch and rest if necessary. After the first half of training (roughly 55 min), participants were given a 10-min break during which the screen was turned off and they could talk to the examinator and have a snack.

The 90 items were separated into three conditions (30 per condition) and eight blocks. Half of the items (15 in each condition) were learned during the first half of training and the other half during the second half of training (after the 10-min break). Conditions were separated by blocks, and each item was presented three times per block, six times total. Participants always began with a block of Symbolic Reliable or Social Reliable condition to ensure that they "trusted" the feedback in the beginning of training. The order of the first three blocks was then repeated to avoid different amounts of time between first three and second three item exposures in the different conditions. An illustration of a trial can be seen in Figure 1A and an example of block order in Figure 1B. A trial began with a blink prompt (1 sec), followed by the presentation of a centered fixation cross, which preceded the auditory verb by 500 msec and then remained on the screen during the subsequent presentation of an auditory word in Hebrew over speakers (2 sec). Participants then saw three items: the target, a distractor from the same list, and a distractor from another list (2.5 sec). After they selected an image using the 1, 2, and 3 key on the number pad of a keyboard, to indicate the item on the left side (1), middle (2), or right side (3) of the screen, the selected image remained on the screen for 1.5 sec. If participants took longer than 2.5 sec to answer, the objects disappeared and a message saying "You must answer more quickly" appeared on the screen. Target position was randomly assigned. Following the postanswer 1.5-sec period, participants saw either Social Reliable, Social Unreliable, or Symbolic Reliable feedback (2 sec), depending on the block.

Online Posttest

All participants performed an online posttest 10 days after training. They heard a noun, saw three objects, and were asked to select the object they thought corresponded to the auditory word. Words learned in all three conditions were mixed and presented three times throughout the list, in pseudorandom order. The four items presented consisted of the target, a distractor from the same list, and two distractors from the two other lists.

Data Acquisition

Behavioral Accuracy and RT

Accuracy and RT were recorded during training and during the online posttest.

EEG

Electroencephalographic (EEG) activity was recorded continuously from the scalp using a BrainAmp DC amplifier (BrainVision Recorder software, Brain Products). Electrodes were located at 29 standard positions (Fp1/2, Fz, F7/8, F3/4, FC1/2, FC5/6, FCz, Cz, C3/4, T7/8, CP1/2, CP5/6, Pz, P3/4, P7/P8, PO3/4, and Oz). Biosignals were referenced online to the right outer canthus eye electrode and rereferenced offline to the mean of the activity of two electrodes placed on the mastoids. Vertical eye movements were monitored with an electrode at the infraorbital ridge of the right eye. Electrode impedances were kept below 5 kΩ.

Pupillometry

To measure changes in pupil diameter, the participants wore an eye-tracking glasses (Pupil Labs, Kassner et al., 2014). This system monitored the pupil center, providing the absolute pupil diameter and a confidence index, which ranged from 0 (pupil not detected) to 1 (pupil detected with very high certainty; Faraji et al., 2023). The eye-tracker had a nonconstant sampling rate of 200 Hz, and it captured the pupil diameter of both eyes separately, using the dark pupil method in reference to a three-dimensional geometric model of the eyeball (Yeung, Lee, Han, & Chan, 2021).

Data Analyses

Behavioral Data Analysis

We performed a generalized linear mixed-effects model (GLMM) using the *glmer* function to examine accuracy during the last exposure of training and in the posttest. Accuracy (coded as correct or incorrect) was modeled using a binomial distribution with a logit link function. The fixed effect was Condition (Social Reliable, Social Unreliable, and Symbolic Reliable), and the random effects were Participant and Item.

ERP Analyses

Preprocessing

A noncausal Butterworth high-pass filter was applied to the continuous EEG (half-amplitude cutoff = 0.01 Hz, slope = 12 dB/octave). The electrophysiological signals were digitized at a rate of 500 Hz. Data were processed and filtered using ERPLAB (Lopez-Calderon & Luck 2014). Artifact rejection was performed offline and tailored to each participant. Independent component analysis (ICA) was carried out on the continuous data, for each participant, to exclude artifacts due to blinking. Before ICA, sections of the EEG signal that were highly contaminated with noise were removed. Following ICA rejection, the data were segmented and divided into the separate conditions. A time window 1500 msec time-locked to the response (and 100 msec before the answer, as a baseline) was used for the SPN analyses. A time window 2000 msec time-locked feedback onset (and 100 msec before feedback onset, as a baseline) was used for the LPC analyses. Epoch rejection criteria were individually determined using a simple voltage threshold ± 100 μV. None of the participants' rejection rate exceeded 20%. ERP figures were created using ERPLAB v2021.0.

Analysis

The ERP data were modeled using linear mixed-effects models for the mean voltage amplitudes in the prefeedback and feedback time windows. The prefeedback window was defined as the time-period preceding the onset of the still image Symbolic Reliable or the Social (Reliable or Unreliable) video feedback (Figure 3A). Epochs of 1.5 sec time-locked to the answer onset and conducted on the 200–1000 time-period (after the answer), on the following electrodes: CP1, CP2, P3, P4, Pz, PO3, PO4 (Brunia et al., 2011; Brunia & Damen, 1988). The feedback window was defined as the time-period following the onset of the still image Symbolic Reliable or the Social (Reliable or Unreliable) video feedback. Epochs of 2 sec were time-locked to the feedback onset (appearance of symbol for Reliable Symbolic feedback and onset of video for Reliable/Unreliable Social feedback). Windows for feedback-related analyses were selected using a comparison between negative and positive feedback, in each condition, using cluster-based permutation tests that performed 50,000 permutations (Maris & Oostenveld, 2007) over the full poststimulus time window (0–1998 msec), across all exposures, on the following electrodes: C3, C4, CP1, CP2, Cz, Oz, P3, P4, Pz, PO3, PO4 (Sun, Osth, & Feuerriegel, 2024; Yang et al., 2019; Figure 4A).

Pupillometry Analyses

All the pupillometry preprocessing was performed using MATLAB and considering guidelines from Kret and Sjak-Shie (2019). The preprocessing proceeded as follows: First, data with confidence values below 0.6 were removed (Yeung et al., 2021). Next, the data were filtered to identify and exclude three common types of invalid pupil size samples: dilation speed outliers and edge artifacts, trend-line deviation outliers, and temporally isolated samples. Valid samples were then interpolated using a high sampling rate (120 Hz) and processed to calculate the mean measure from both eyes. The resulting signal was smoothed using a zero-phase low-pass filter, with a cutoff frequency of 4 Hz (Kret & Sjak-Shie, 2019; Jackson & Sirois, 2009). Finally, external triggers indicating stimuli onsets were used to segment the pupillometry data. Similarly to ERP analyses, for the SPN analysis, epochs of 1.5 sec were time-locked to the answer onset, whereas for feedback analyses, epochs of 2 sec were time-locked to the feedback onset (the appearance of symbol for Symbolic Reliable feedback and onset of video for Reliable and Unreliable Social feedback). All epochs included a −500-msec prestimulus time window used for baseline correction.

Pupil dilation within the analyzed time windows was examined by analyzing the grand-averaged change in the pupil diameter. For both pre- and feedback periods, a linear mixed-effects model was fitted, considering the mean change in pupil diameter as the dependent variable, condition and exposure as fixed effects, and participant as a random factor. In the prefeedback period, we analyzed the time window from 250 msec onward. To determine the analyzed time window for the postfeedback, we performed a nonparametric cluster-based Monte Carlo simulation analysis with 10,000 permutations (Maris & Oostenveld, 2007). The cluster permutation test compared, with a significance level of $p < .05$, the change in pupil diameter between positive and negative feedback. For subsequent mixed models analyses, mean change in pupil diameter was averaged across all significant time windows for the statistical analysis. Finally, the differences in mean pupil diameter changes between positive and negative feedback were correlated with behavioral performance by means of a Pearson correlation.

RESULTS

Behavioral Accuracy and RT

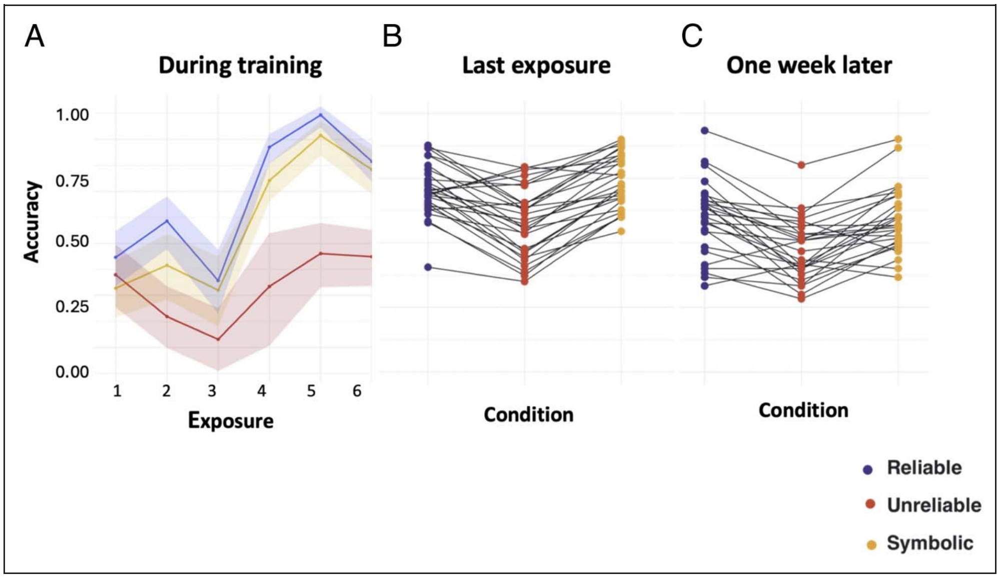
During Training

We first plotted participant performance during the whole training period. As expected, visual inspection of the learning curves showed faster and ultimately more successful learning for the Social Reliable and Symbolic Reliable conditions compared with the Social Unreliable condition (Figure 2). However, due to the blocked design and intermittent breaks between exposures, trial-by-trial learning trajectories are difficult to interpret and were not modeled statistically.

Behavioral Performance during Last Block of Learning: Mixed Model Results

Visual inspection of the immediate posttest plots revealed improved performance for the Social Reliable conditions compared with the Social Unreliable condition. To measure differences in performance as a function of condition during the last phase of learning (last

Figure 2. (A) Average accuracy over all participants across six exposures during training. Shaded areas represent 95% confidence intervals. (B) Average accuracy per participant at the last exposure of training. (C) Average accuracy per participant 1 week posttraining.



block of exposure for each item), we performed GLMM with a binomial distribution, which included the fixed factor Condition (Social Reliable, Social Unreliable, and Symbolic Reliable), and Participant and Item as random factors. We followed a forward model selection approach and retained the most complex model that converged, which included random intercepts for participant and item. The model [performance ~ condition + (1 | participant) + (1 | item), Akaike Information Criterion (AIC) = 2141687.2, log-likelihood (LL) = −1070840] revealed poorer performance for the Social Unreliable compared with the Symbolic Reliable ($\beta = -1.22$, $SE = 0.23$, $z = -5.36$, $p < .001$) condition and no differences between the Social Reliable and Symbolic Reliable conditions ($\beta = 0.04$, $SE = 0.27$, $z = -0.16$, $p = .87$; Table 1, Figure 2).

Table 1. Generalized Linear Mixed Model for Behavioral Performance during the Last Block of Training

Immediate Posttest				
	Estimate	*SE*	*z Value*	*p*
Intercept (Symbolic)	1.93415	0.24565	7.874	3.45e−15***
Reliable	0.04336	0.27354	0.159	.874
Unreliable	−1.22537	0.22865	−5.359	8.37e−08***

Random Effects		
	Variance	*SD*
Item (intercept)	0.3772	0.6141
Participant (intercept)	0.9207	0.9596

Model: Performance ~ Condition + (1 | Participant) + (1 | Target)	
Sampling units	Number of total observations = 2520
	Number of participants = 29; number of items = 90

AIC	*BIC*	*LL*
2141687	2141730	−1070840

***$p < .001$.

Table 2. Generalized Linear Mixed Model for Behavioral Performance 1 Week Posttraining

	1-Week Posttraining Test			
	Estimate	*SE*	*z Value*	*p*
Intercept (Symbolic)	0.46484	0.13311	3.492	.000479***
Reliable	−0.03100	0.08556	−0.362	.717102
Unreliable	−0.58887	0.08510 -	−6.920	4.51e−12***

	Random Effects	
	Variance	*SD*
Item (intercept)	0.3924	0.6264
Participant (intercept)	0.2677	0.5174

Model: Performance ~ Condition + (1 | Participant) + (1 | Item)		
Sampling units	Number of total observations = 4809	
	Number of participants = 27; number of items = 90	
AIC	*BIC*	*LL*
6185.2	6217.6	−3087.6

***$p < .001$.

Behavioral Performance 10 Days Posttraining

Visual inspection of the posttest 10 days later plots revealed improved performance for the Social Reliable conditions compared with the Social Unreliable condition. To measure differences in retention of auditory word–image association as a function of condition in which items were learned during training, 1 week post training, we performed a GLMM that included the fixed factor Condition, and Participant and Item as random factors. Once again, the model [performance ~ condition + (1|participant) + (1|item), AIC = 6185.2, LL = −3087.6] revealed poorer performance for the Social Unreliable compared with the Symbolic Reliable (β = −0.58887, *SE* = 0.08510, $z = -6.920$, $p < .001$) and Social Reliable (β = −0.03100, *SE* = 0.08556, $z = -0.362$, $p = .717102$) conditions. No differences emerged between the Symbolic Reliable and Social Reliable conditions (β = 0.03100, *SE* = 0.08556, $z = 0.362$, $p = .717$; Table 2, Figure 2).

EEG

Prefeedback

Visual inspection. We compared the ERP waveforms preceding feedback, per exposure, in the three conditions. Visual inspection of ERPs in the prefeedback window revealed a progressive development of a sustained negativity with exposure, in the Symbolic Reliable and Social Reliable conditions. However, no evidence of an exposure effect was observed in the Social Unreliable condition (Figure 3). The scalp distributions in Figure 3C represent the difference waveform between the sixth and first exposure, during the 200–1000 time-period (after the answer). In the Social Reliable and Symbolic Reliable conditions, the topography is centro-posterior (Figure 3A).

Linear mixed-effects models. We ran linear mixed-effects models, which included Condition and Exposure, and compared the mean voltage amplitudes in the 200- to 1500-msec post answer onset, at a subset of centro-parietal electrodes (CP1, CP2, P3, P4, Pz, PO3, PO4), averaged across this electrode subset. The forward selection strategy was used to select the model that best fitted the prefeedback data. Model 0 included only the random intercept. We then added the predictor Condition (Symbolic Reliable, Social Reliable, and Social Unreliable), then the predictor Exposure (Exposures 1, 2, 3, 4, 5, and 6), and finally their interaction (Table 3). The final lmer model [MV ~ condition × exposure + (1|participant), $p = .0002$, AIC = 2161.2, LL = −1060.6] revealed significant interactions, including that of Exposure by Condition (Table 4). Subsequent post hoc comparisons, corrected for multiple comparisons using the false discovery rate (FDR), further delineated these effects.

Pairwise comparisons showed that in the Social Reliable and Symbolic Reliable conditions, SPN amplitude was

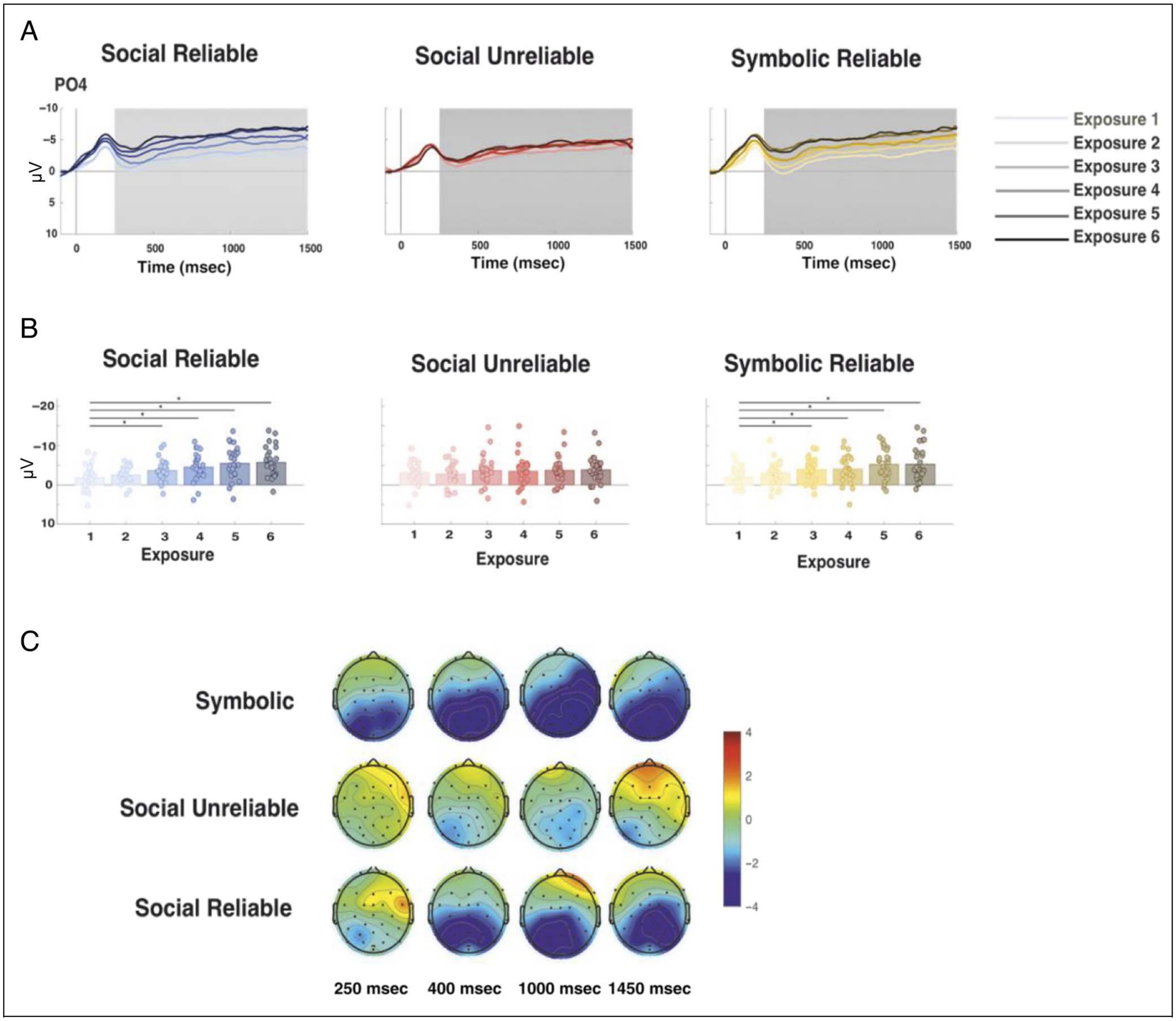


Figure 3. Prefeedback ERP analysis by exposure. (A) ERPs for different learning conditions at electrode PO4, time-locked to the participant's answer. For each plot, the lightest line of the given color scheme represents the first exposure and gets progressively darker for each exposure. The gray area shows the analyzed time window (200–1000 msec). (B) Barplots represent the grand average amplitude in the analyzed time window whereas dots represent each participant's mean amplitude, for the given exposure (1–6). Asterisks represent significant differences compared with the first exposure ($p < .05$). (C) Topographies represent the difference waveforms between the sixth and first exposure. The difference waveforms considered the grand average ERPs between 250 msec and 1500 msec before the answer with 150-msec intervals).

significantly greater at later exposures (2–6) compared with Exposure 1 in both the Social Reliable frontal (β = 3.849, SE = 0.535, z = 7.191, $p < .0001$) and Symbolic Reliable frontal (β = 3.247, SE = 0.535, z = 6.067, $p < .0001$) conditions (Table 4). In contrast, no differences were found across exposures in the Unreliable condition (β = 0.687, SE = 0.535, z = 1.284, p = .599).

To examine the progression of this effect over time, we performed additional comparisons between successive exposures (e.g., Exposure 1 vs. 2, 2 vs. 3, etc.; Table 5). These comparisons revealed a linear increase in SPN amplitude across exposures in the Social Reliable condition, with all estimates being positive. In the Symbolic Reliable condition, SPN increases were less consistent across exposure, showing a weaker and more variable pattern. In the Unreliable condition, no systematic progression was observed. As these repeated contrasts may be underpowered and augment the likelihood of Type I error, they are considered exploratory and to be interpreted with caution. Nevertheless, the overall pattern aligns with the significant Condition × Exposure interaction observed in the mixed-effects model.

During Feedback

Visual inspection. We compared the ERP waveforms after feedback presentation, separately for positive and

Table 3. Model Comparison for the Evaluation Prefeedback EEG

Prefeedback										
				Random Effects	*Model Fit*				*LRT Test Against Nested*	
7 Model Specification	*Model Name*	*Nested/Simpler Model*	*Fixed Effects Added*	*Participants*	*AIC*	*BIC*	*LL*	*df*	*df*	*p*
RE only	Null	—	—	Intercepts	2261.8	2274.4	−1127.9	3	—	—
FE main effect	Condition	Null	Condition	“ “	2261.3	2282.3	−1125.7	5	2	.108
FE main effect	Exposure	Condition	Exposure	“ “	2174.6	2208.1	−1079.3	5	2	<2.2e−16***
FE main effects	Exposure × Condition	Null	Exposure × Condition	“ “	2161.2	2244.9	−1060.6	20	17	.0001898***
Sampling units	Number of total observations = 486									
	Number of participants = 27									
	Number of electrodes =									

RE = random effects; FE = fixed effects. ***$p < .001$.

Table 4. Linear Fixed Effects Models for Prefeedback EEG

Fixed Effects					
	Estimate	*SE*	*df*	*t*	*p*
(Intercept)	−1.2682	0.6901	50.744	−1.838	.071967
ConditionSymbolic	−0.4117	0.5253	459	−0.784	.433545
ConditionUnreliable	−1.6919	0.5253	459	−3.221	.001368***
Exposure2	−1.1741	0.5253	459	−2.235	.025881*
Exposure3	−2.2553	0.5253	459	−4.294	2.15e−05***
Exposure4	−3.1483	0.5253	459	−5.994	4.15e−09***
Exposure5	−3.8405	0.5253	459	−7.311	1.18e−12***
Exposure6	−3.8491	0.5253	459	−7.328	1.06e−12***
ConditionSymbolic:Exposure2	−0.1523	0.7428	459	−0.205	.837678
ConditionUnreliable:Exposure2	1.6694	0.7428	459	2.247	.025096*
ConditionSymbolic:Exposure3	0.1607	0.7428	459	0.216	.828847
ConditionUnreliable:Exposure3	1.756	0.7428	459	2.364	.0185*
ConditionSymbolic:Exposure4	1.0637	0.7428	459	1.432	.152843
ConditionUnreliable:Exposure4	2.8111	0.7428	459	3.784	.000175***
ConditionSymbolic:Exposure5	0.51	0.7428	459	0.687	.492671
ConditionUnreliable:Exposure5	3.3136	0.7428	459	4.461	1.03e−05***
ConditionSymbolic:Exposure6	0.6013	0.7428	459	0.81	.418635
ConditionUnreliable:Exposure6	3.1619	0.7428	459	4.257	2.52e−05***

Random Effects		
	Variance	*SD*
Participant (intercept)	9.133	3.022

Model Fit		
R^2	*Marginal*	*Conditional*
	0.08546937	0.735081

p Values for fixed effects calculated using Satterthwaites approximations. Confidence intervals have been calculated using the Wald method. Model equation: MV ~ condition × correct before + (1 | participant) + (1 | electrode). $*p < .05$, $***p < .001$.

negative feedback in each condition. Visual inspection revealed a temporal difference in feedback processing such that the Symbolic Reliable condition showed greater positivity in an earlier time window (around 200–700 msec) whereas as the Social Reliable and Social Unreliable conditions showed greater positivity in a later time window (around 1200–2000 msec), likely due to the differential nature of the feedback (Figure 4). Although the symbolic feedback was immediately presented after participants answered, in the Social conditions, the videos took longer to fully reveal the valence of the feedback (see Stimuli section). We also saw greater positivity in the feedback window for negative compared with positive feedback for all conditions, but the difference appeared greater for the Symbolic Reliable and Social Reliable conditions compared with the Social Unreliable condition. Finally, visual inspection of the topo plots of the difference wave (negative minus positive feedback in the feedback window) revealed less positivity for the Social Unreliable condition (in line with ERP results). It also showed a wider, more

Table 5. Post Hoc Comparisons for Prefeedback EEG

		Social Reliable			
Contrast	*Estimate*	*SE*	*df*	*z.ratio*	*p Value*
Exposure1-Exposure2	1.1741	0.535	477	2.193	.0431*
Exposure2-Exposure3	1.08115	0.535	477	2.02	.0599
Exposure3-Exposure4	0.89306	0.535	477	1.668	.1199
Exposure4-Exposure5	0.69214	0.535	477	1.293	.2107
Exposure5-Exposure6	0.00867	0.535	477	0.016	.9871
		Social Unreliable			
Exposure1-Exposure2	−0.49526	0.535	477	−0.925	.6662
Exposure2-Exposure3	0.99453	0.535	477	1.858	.3189
Exposure3-Exposure4	−0.16209	0.535	477	−0.303	.8192
Exposure4-Exposure5	0.18965	0.535	477	0.354	.8192
Exposure5-Exposure6	0.16037	0.535	477	0.3	.8192
		Symbolic			
Exposure1-Exposure2	1.32637	0.535	477	2.478	.0291*
Exposure2-Exposure3	0.76821	0.535	477	1.435	.1815
Exposure3-Exposure4	−0.00995	0.535	477	−0.019	.9852
Exposure4-Exposure5	1.24579	0.535	477	2.327	.0356*
Exposure5-Exposure6	−0.08263	0.535	477	−0.154	.94

*$p < .05$.

frontal, distribution for the Social Reliable compared with the Symbolic Reliable condition (Figure 4).

Cluster-based permutation tests. Following visual inspection, we used cluster-based permutation tests to observe possible differences between negative and positive feedback and to determine the time windows to be used for subsequent mixed models analyses (which included the factor exposure). Significant clusters (shown in gray, Figure 4A) emerged in the Social Reliable condition between 314–746 msec ($t$mass: 902.22, $p < .001$) and 1210–1998 msec ($t$mass: 2263.90, $p < .001$) poststimulus. For the Unreliable Social condition, differences emerged between 1290 and 1540 msec ($t$mass: 390.48. $p = .004$) poststimulus. Considering the behavioral timing differences between Social and Symbolic stimuli processing (see Stimuli section), we used the second window for the late positivity analysis in the Social Reliable condition (which overlapped with that of the Social Unreliable condition). For the Symbolic Reliable condition, differences emerged between 338–888 msec ($t$mass: 1647.90, $p < .001$), 1246–1436 msec ($t$mass: 227.02, $p = .028$), and 1882–1998 msec ($t$mass:155.90, $p = .047$) poststimulus. Given that the effect was going in the same direction for all three windows, we collapsed them for mixed model statistical analysis (Figure 4A).

Topographical analysis. Given the visual differences between the Social Reliable and Symbolic Reliable difference wave (negative minus positive feedback) topo plots in this feedback window, we ran a linear mixed-effects models to explore topographical differences. We first ran the model [MV ~ condition × electrode + (1|participant)] in the mean voltage amplitudes in the 100-msec time window surrounding the peak amplitude in both conditions. Several interactions with electrode emerged, and we hence separated the electrodes into three separate ROIs: frontal (F3, F4, F7, F8, Fp1, Fp2, Fz, FC1, FC2, FC5, FC6, FCZ), central (C3, C4, CP1, CP2, CP5, CP6, Cz), and parietal (Pz, P3, P4, P7, P8, PO3, PO4, Oz) regions. We ran a second model that included ROI as a fixed factor [MV ~ condition × ROI + (1|participant)]. The model [MV ~ condition × ROI + (1|participant)] revealed significant interactions of Condition by ROI (Table 6).

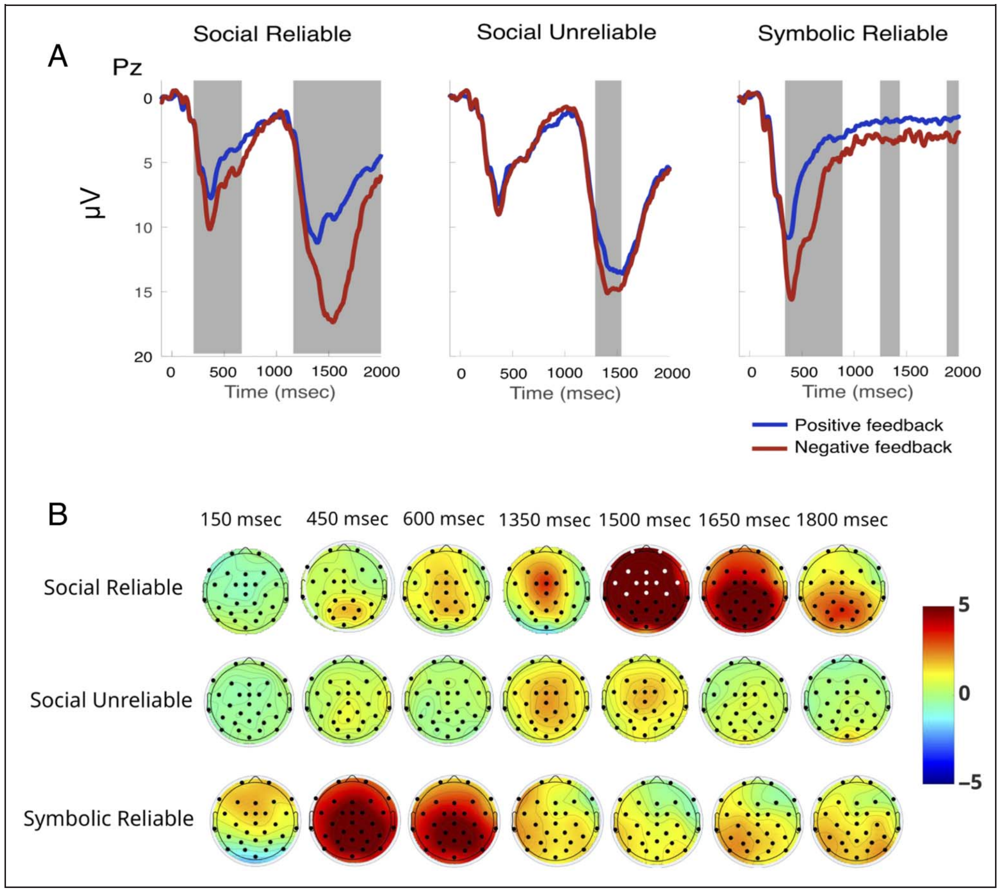


Figure 4. Positive versus negative feedback. (A) Feedback ERPs at electrode Pz for different learning conditions time-locked to feedback onset. The blue line corresponds to positive feedback, and the red line corresponds to negative feedback. The gray areas show the time periods during which cluster-based permutation tests revealed significant differences between amplitudes associated with positive and negative feedback ($p < .05$). (B) Topographies represent the difference waveforms between negative and positive feedback from 250 to 2000 msec with 50-msec intervals.

Subsequent post hoc comparisons, corrected for multiple comparisons using the FDR, further delineated these effects. Pairwise comparisons revealed a greater positivity in the difference wave (negative minus positive feedback in the feedback window) for the Social Reliable condition in the frontal ($\beta = 1.3994$, $SE = 0.202$, $z = 6.92$, $p < .0001$) and central ($\beta = 0.7101$, $SE = 0.335$, $z = 2.686$, $p < .0073$) ROIs, but not in the parietal ROI ($\beta = 0.0912$, $SE = 0.247$, $z = 0.369$, $p = .712$; Table 7). These results show a wider, more frontal, distribution for the Social Reliable compared with the Symbolic Reliable condition.

Linear mixed-effects models. We ran linear mixed-effects models, which included Condition, Exposure, and Valence (positive vs. negative feedback), and compared the mean voltage amplitudes in the time windows established by the permutation tests (Social Reliable: 1210–1998 msec, Social Unreliable: 1290–1540 msec, Symbolic Reliable: 338–1998 msec poststimulus), at a subset of centro-parietal electrodes (C3, C4, CP1, CP2, Cz, Oz, P3, P4, PO3, PO4, Pz). Once again, we used the forward selection strategy to select the model that best fitted the feedback data. Model 0 included only the random intercepts. We then added the predictor then the predictor Valence (positive feedback, negative feedback), then the predictor Exposure, and finally their interaction (Table 8). The final lmer model [MV ~ condition × valence × exposure + (1 | participant), $p < .001$, AIC = 58733, LL = −29327] revealed significant interactions (Table 9).

Subsequent post hoc comparisons, corrected for multiple comparisons using the FDR, further delineated these effects. Pairwise comparisons showed that when feedback was negative, no clear pattern emerged as a function of exposure in any of the conditions. When differences between exposures were significant, these changes went in different directions, sometimes becoming more positive and others more negative (Table 10). On the other hand, positive feedback resulted in clearer pattern of decreasing positivity as the learning session progressed. This pattern was most visible in the Social Reliable condition, where a decreased positivity could be seen in five out of the five exposure changes, between Exposures 1 and 2 ($\beta = 10.546$, $SE = 0.335$, $z = 3.152$, $p < .0019$), 2 and 3 ($\beta = 12.878$, $SE = 0.335$, $z = 3.850$, $p < .001$), 3 and 4 ($\beta = 0.7226$, $SE = 0.335$, $z = 2.160$, $p = .030$), 4 and 5 ($\beta = 0.9790$, $SE = 0.335$, $z = 2.927$, $p = .003$), and 5 and 6 ($\beta = 17.251$, $SE = 0.335$, $z = 5.157$, $p < .001$). The Symbolic Reliable condition also showed a similar pattern for three out of five of the exposure changes, between Exposures 1 and 2 ($\beta = 13.165$, $SE = 0.335$, $z = 3.936$, $p < .001$), 2 and 3 ($\beta = 12.390$, $SE = 0.335$, $z = 3.704$, $p < .001$), and 4 and 5 ($\beta = 12.038$, $SE = 0.335$, $z =$

Table 6. Linear Fixed Effects Model for Topographical Differences of Feedback Differences Waves

	Feedback					
	Fixed Effects					
	Estimate	*SE*	*df*	*t*	*p*	
(Intercept)	5.6823	0.5279	36.5038	10.764	7.05e−13	***
ConditionSymbolic	−0.7101	0.264	1537	−2.69	.00722	**
ROIFronto_central	−0.4697	0.2349	1537	−2	.04568	*
ROIParietal_and_Occipital	−1.5201	0.2556	1537	−5.947	3.37e−09	***
ConditionSymbolic:ROIFronto_central	−0.6892	0.3322	1537	−2.075	.03816	*
ConditionSymbolic:ROIParietal_and_Occipital	0.6189	0.3615	1537	1.712	.08705	

	Variance	*SD*
Participant (intercept)	7.100	2.665

Model Fit		
R^2	*Marginal*	*Conditional*
	0.1351363	0.6212379

p Values for fixed effects calculated using Satterthwaites approximations. Confidence intervals have been calculated using the Wald method. Model equation: (Pupil_size ~ Condition + Exposure +(1|Participant). $*p < .05$, $**p < .01$, $***p < .001$.

3.599, $p < .001$). Finally, in the Social Unreliable condition, changes were significant for two out of the five exposure changes, between Exposures 2 and 3 (β = 19.219, SE = 0.335, z = 5.745, $p < .001$) and 5 and 6 (β = 25.624, SE = 0.335, z = 7.660, $p < .001$). It should be noted that in the Symbolic Reliable condition, for positive feedback, changes between the other exposures, although not significant, showed a decreasing positivity as the learning session progressed, following the pattern of the significant changes. On the other hand, in the Social Unreliable condition, the nonsignificant changes showed an increasing positivity, and hence the lessening pattern was not observed in this condition (Figure 5A).

Correlation of different waveform during feedback (positive minus negative) and behavioral performance in posttest. A Pearson correlation was computed to determine the relationship between the amplitude of difference wave (difference in amplitude between positive and negative feedback electrode Pz) during the time windows established by cluster-based permutation tests (see Cluster-based permutation tests section) during feedback processing and average accuracy posttraining. The results indicate a significant, positive relationship between behavioral accuracy and difference wave amplitude in the Social Reliable condition (r = .51, p = .005), a null correlation in the Social Unreliable condition (r = .01, p = .959), and a nonsignificant, positive relationship in the Symbolic Reliable condition (r = .31, p = .097). The Fisher's z transformation test showed that the Social Reliable correlation was significantly different from that of the Social Unreliable condition (z = 1.97, p = .048). Symbolic Reliable and Social Unreliable correlations were not significantly different from each other (z = 1.14, p = .256; Figure 6).

Table 7. Post Hoc Comparisons for Topographical Distribution of Feedback Difference Waves

Contrast		*Estimate*	*SE*	*df*	*z.ratio*	*p Value*
Social Rel − Symbolic Rel	Frontal	1.3994	0.202	Inf	6.929	<.0001*
Social Rel − Symbolic Rel	Central	0.7101	0.335	Inf	2.686	<.0073
Social Rel − Symbolic Rel	Parietal	0.0912	0.247	Inf	0.369	.7124

$*p < .05$.

Table 8. Model Comparison for Feedback EEG

Model Specification	Model Name	Nested/Simpler Model	Fixed Effects Added	*Random Effects*		*Model Fit*				*LRT Test Against Nested*	
				Participants	*Electrodes*	*AIC*	*BIC*	*LL*	*df*	*df*	χ^2
RE only	Null	—	—	Intercepts	Intercepts	63710	63739	−31851	4	—	—
FE main effect	Condition	Null	Condition	"	"	59906	59950	−29947	6	2	<2.2e−16***
FE main effects	Condition + Valence	Condition	+Valence	"	"	59238	59289	−29612	7		<2.2e−16***
Two-way interaction	Condition * Valence	Condition + Valence	*Valence	"	"	59220	59286	−29601	9	2	1.619e−05***
Two-way interaction	Condition * Valence + Exposure	Condition * Valence	+Exposure	"	"	58503	58604	−29237	14	5	<2.2e−16***
Two-way interaction	Condition * Valence * Exposure	Condition * Valence + Exposure	*Exposure	"	"	58221	58503	−29071	39	25	<2.2e−16***
Sampling units	Number of total observations = 10,263										
	Number of participants = 27, number of items = 90, number of electrodes = 11										

*$p < .05$, ***$p < .001$.

Table 9. Linear Fixed Effects Models for Feedback EEG

	Fixed effects					
	Estimate	*SE*	*df*	*t*	*p*	
(Intercept)	8.51E+03	6.13E+02	4.81E 04	13.871	<2e−16	***
ConditionSymbolic	−2.80E+03	3.35E+02	1.02E+07	−8.363	<2e−16	***
ConditionUnreliable	4.61E+03	3.35E+02	1.02E+07	13.779	<2e−16	***
ValencePositive feedback	5.22E+02	3.35E+02	1.02E+07	1.560	.118843	
Exposure2	5.01E+02	3.35E+02	1.02E+07	1.498	.134090	
Exposure3	1.07E+03	3.38E+02	1.02E+07	3.154	.001615	**
Exposure4	3.43E+02	3.35E+02	1.02E+07	1.025	.305349	
Exposure5	1.65E+03	3.58E+02	1.02E+07	4.591	4.45e−06	***
Exposure6	−1.82E+03	3.82E+02	1.02E+07	−4.773	1.84e−06	***
ConditionSymbolic:ValencePositive feedback	−1.15E+02	4.73E+02	1.02E+07	−0.244	.807265	
ConditionUnreliable:ValencePositive feedback	−1.55E+03	4.73E+02	1.02E+07	−3.285	.001023	**
ConditionSymbolic:Exposure2	5.68E+02	4.73E+02	1.02E+07	1.201	.229820	
ConditionUnreliable:Exposure2	4.90E+01	4.73E+02	1.02E+07	0.104	.917559	
ConditionSymbolic:Exposure3	2.63E+02	4.78E+02	1.02E+07	0.550	.582348	
ConditionUnreliable:Exposure3	−1.65E+02	4.75E+02	1.02E+07	−0.348	.727898	
ConditionSymbolic:Exposure4	−4.93E+02	4.75E+02	1.02E+07	−1.036	.300278	
ConditionUnreliable:Exposure4	−1.28E+03	4.73E+02	1.02E+07	−2.696	.007024	**
ConditionSymbolic:Exposure5	−1.67E+03	5.00E+02	1.02E+07	−3.330	.000872	***
ConditionUnreliable:Exposure5	−2.83E+03	4.90E+02	1.02E+07	−5.780	7.67e−09	***
ConditionSymbolic:Exposure6	5.00E+01	5.64E+02	1.02E+07	0.089	.929307	
ConditionUnreliable:Exposure6	−9.08E+01	5.12E+02	1.02E+07	−0.177	.859329	
ValencePositive feedback:Exposure2	−1.56E+03	4.73E+02	1.02E+07	−3.289	.001010	**
ValencePositive feedback:Exposure3	−3.41E+03	4.75E+02	1.02E+07	−7.168	8.14e−13	***
ValencePositive feedback:Exposure4	−3.41E+03	4.73E+02	1.02E+07	−7.204	6.28e−13	***
ValencePositive feedback:Exposure5	−5.69E+03	4.90E+02	1.02E+07	−11.606	<2e−16	***
ValencePositive feedback:Exposure6	−3.95E+03	5.08E+02	1.02E+07	−7.774	8.31e−15	***
ConditionSymbolic:ValencePositive feedback:Exposure2	−8.30E+02	6.69E+02	1.02E+07	−1.241	.214738	
ConditionUnreliable:ValencePositive feedback:Exposure2	1.65E+03	6.69E+02	1.02E+07	2.461	.013852	*
ConditionSymbolic:ValencePositive feedback:Exposure3	−4.76E+02	6.72E+02	1.02E+07	−0.708	.479031	
ConditionUnreliable:ValencePositive feedback:Exposure3	1.23E+03	6.71E+02	1.02E+07	1.830	.067338	.
ConditionSymbolic:ValencePositive feedback:Exposure4	5.21E+02	6.71E+02	1.02E+07	0.777	.437188	
ConditionUnreliable:ValencePositive feedback:Exposure4	3.32E+03	6.69E+02	1.02E+07	4.956	7.30e−07	***

Table 9. (*continued*)

	Fixed effects					
	Estimate	*SE*	*df*	*t*	*p*	
ConditionSymbolic:ValencePositive feedback:Exposure5	1.47E+03	6.88E+02	1.02E+07	2.134	0.032899	*
ConditionUnreliable:ValencePositive feedback:Exposure5	5.78E+03	6.81E+02	1.02E+07	8.482	<2e−16	***
ConditionSymbolic:ValencePositive feedback:Exposure6	1.06E+03	7.36E+02	1.02E+07	1.445	0.148470	
ConditionUnreliable:ValencePositive feedback:Exposure6	2.20E+03	6.97E+02	1.02E+07	3.153	0.001620	**

	Variance	*SD*
Participant (intercept)	5.443	2.333
Electrode (intercept)	1.304	1.142

Model Fit		
R^2	*Marginal*	*Conditional*
	0.3386539	0.5296346

p Values for fixed effects calculated using Satterthwaites approximations. Confidence intervals have been calculated using the Wald method. Model equation: MV ~ condition × valence × exposure + (1 | participant) + (1 | electrode). $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Pupillometry

Prefeedback

Visual comparison. We compared the pupil dilation/constriction preceding feedback, per exposure, in the three conditions. Visual inspection of the prefeedback window revealed increasing constriction with each exposure, in the Symbolic reliable and Social Reliable conditions, and no visible differences in the Social Unreliable condition.

Mixed models. We applied linear mixed-effects models to the prefeedback pupillometry data. The forward selection strategy was used to select the model that best fitted the prefeedback data. Model 0 included only the random intercept. We then added the predictor Condition, then Exposure, and finally their interaction (Table 11). The final lmer model [pupil dilation ~ condition + exposure + (1| participant), $p = .037$, AIC = −1483.0 LL = 751.50] revealed a main effect of Condition such that the Symbolic Reliable condition showed greater dilation compared with Social Reliable condition (β = 1.29, $SE = 8.49$, $t = 2.370$, $p = .023$). No differences emerged between the Social Reliable and Social Unreliable conditions (β = −7.89, $SE = 3.74$, $t = -0.211$, $p = .833$; Table 12). There was also a main effect of Exposure such that Exposures 5 and 6 showed greater constriction compared with Exposure 1 (β = 1.37, $SE = 5.27$, $t = -2.596$, $p = .009$, for Exposure 5 and β = −1.07E, $SE = 5.28$, $t = -2.025$, $p = .043$, for Exposure 6; Figure 7).

During Feedback

Visual inspection and cluster-based permutation tests. As with the ERP analyses, we plotted negative and positive feedback separately for each condition. Visual inspection revealed greater dilation in the feedback window for negative compared with positive feedback in the Social Reliable and Symbolic Reliable conditions, but not in the Social Unreliable condition. Notice also the earlier effect on pupil dilatation for the symbolic compared with the social condition, due to the nature of the feedback.

Following visual inspection, we used cluster-based permutation tests to determine the time windows to be used for subsequent mixed models' analyses. Significant clusters (shown in gray, Figure 8) emerged in the Social Reliable condition between 52 and 2000 msec (*t*-mass: −6286.2, $p = .001$) poststimulus, and in the Symbolic Reliable condition between 199 and 501 msec (*t*-mass: −2338.6, $p = .030$) poststimulus. No significant clusters emerged in the Social Unreliable condition (Figure 8).

Linear mixed-effects models. We ran linear mixed-effects models to compare pupil dilation using the time

Table 10. Post Hoc Comparisons for Feedback EEG

Contrast	*Estimate*	*SE*	*df*	*z.ratio*	*p Value*
Social Reliable Negative					
Exposure1-Exposure2	−0.5012	0.335	Inf	−1.498	.1547
Exposure2-Exposure3	−0.5643	0.338	Inf	−1.670	.1294
Exposure3-Exposure4	0.7226	0.338	Inf	2.139	.0487
Exposure4-Exposure5	−13.022	0.358	Inf	−3.634	.0006
Exposure5-Exposure6	34.675	0.402	Inf	8.627	<.0001*
Social Unreliable Negative					
Exposure1-Exposure2	−0.5502	0.335	Inf	−1.645	.1154
Exposure2-Exposure3	−0.3499	0.335	Inf	−1.046	.3167
Exposure3-Exposure4	18.327	0.335	Inf	5.479	<.0001*
Exposure4-Exposure5	0.2557	0.335	Inf	0.764	.4446
Exposure5-Exposure6	0.7248	0.341	Inf	2.123	.0422
Symbolic Negative					
Exposure1-Exposure2	−10.693	0.335	Inf	−3.197	.0021*
Exposure2-Exposure3	−0.2589	0.338	Inf	−0.766	.5543
Exposure3-Exposure4	14.778	0.341	Inf	4.333	.0001*
Exposure4-Exposure5	−0.1300	0.352	Inf	−0.369	.7630
Exposure5-Exposure6	17.528	0.428	Inf	4.093	.0001*
Social Unreliable Positive					
Exposure1-Exposure2	−0.6412	0.335	Inf	−1.917	.0691
Exposure2-Exposure3	19.219	0.335	Inf	5.745	<.0001*
Exposure3-Exposure4	−0.2562	0.335	Inf	−0.766	.5121
Exposure4-Exposure5	0.0747	0.335	Inf	0.223	.8234
Exposure5-Exposure6	25.624	0.335	Inf	7.660	<.0001*
Symbolic Positive					
Exposure1-Exposure2	13.165	0.335	Inf	3.936	.0001*
Exposure2-Exposure3	12.390	0.335	Inf	3.704	.0003*
Exposure3-Exposure4	0.4808	0.335	Inf	1.437	.1614
Exposure4-Exposure5	12.038	0.335	Inf	3.599	.0004*
Exposure5-Exposure6	0.4150	0.335	Inf	1.241	.2147

*p < .05.

windows where significant positive versus negative feedback differences came out in the permutation tests, for the Social Reliable and Symbolic Reliable conditions (but not for the Social Unreliable condition as it showed no significant differences in the permutation tests). The models included Condition, Exposure and Valence. We used the forward selection strategy to select the model that best fitted the feedback data. Model 0 included only

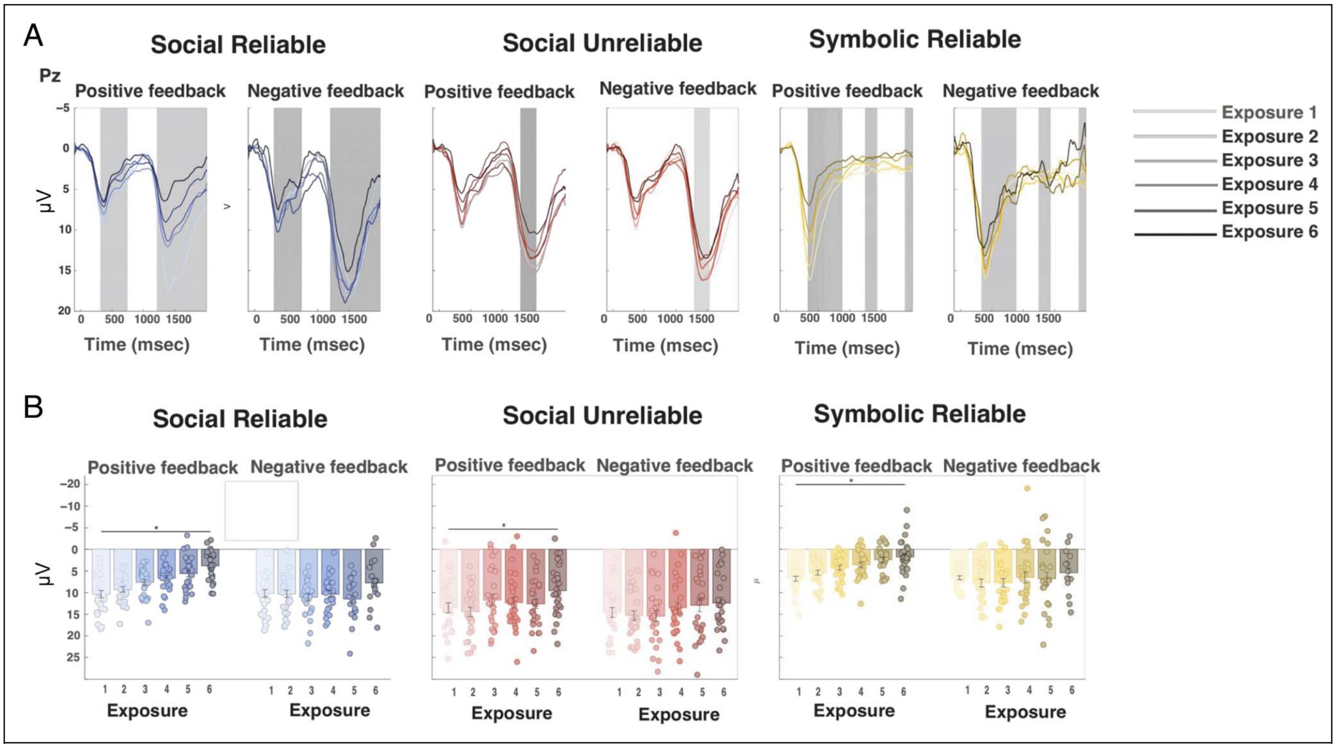


Figure 5. During feedback by exposure. (A) Feedback ERPs for different learning conditions at electrode Pz and time-locked to feedback onset. For each plot, the lightest line of the given color scheme represents the first exposure and gets progressively darker for each exposure. The gray areas show the time periods during which cluster-based permutation tests revealed significant differences between amplitudes associated with positive and negative feedback. (B) Barplots represent the grand average amplitude in the analyzed time window whereas dots represent each participant's mean amplitude, for the given exposure (1–6). Asterisks represent significant differences compared with the first exposure ($p < .05$).

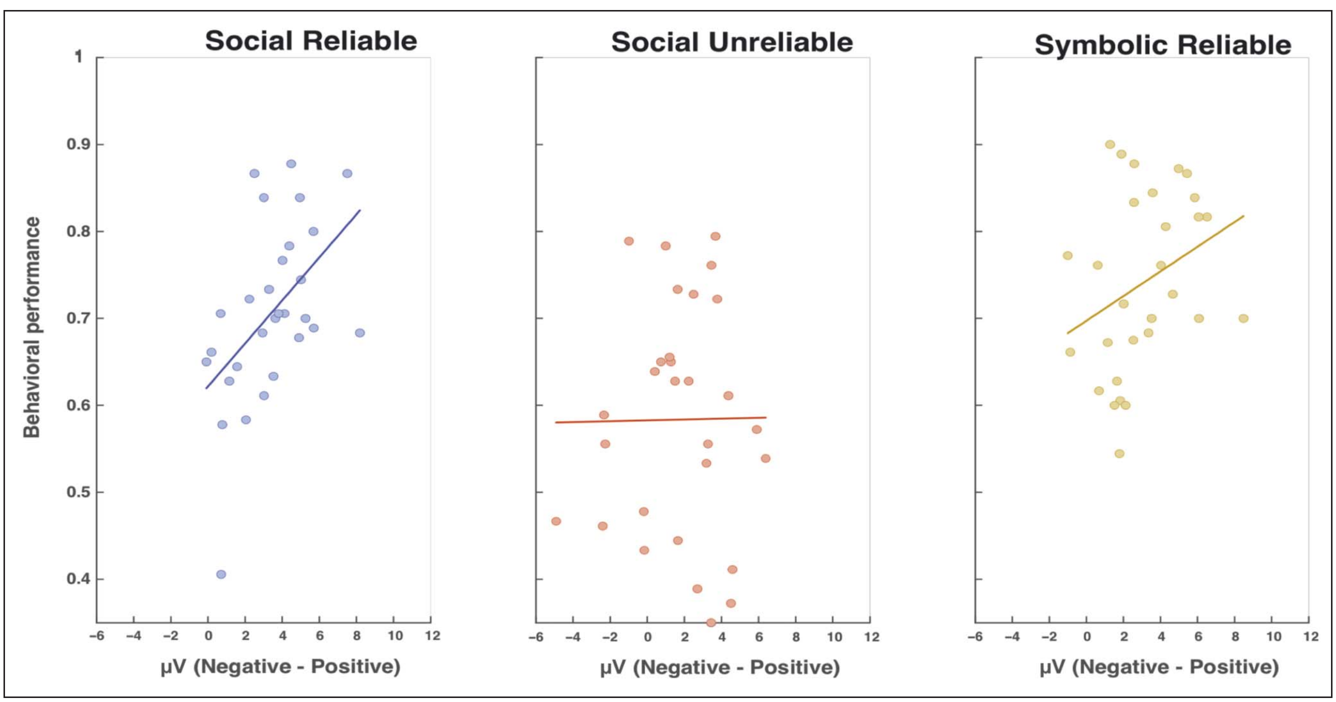


Figure 6. Correlation between performance posttraining and negative minus positive difference wave for ERPs at electrode Pz during feedback. The x axis represents the average amplitude of the difference waveform (negative minus positive feedback), and the y axis represents the behavioral performance score. Each point represents a participant.

Table 11. Model Comparison for Prefeedback Pupillometry

				Prefeedback						
				Random Effects	*Model Fit*				*LRT Test Against Nested*	
Model Specification	*Model Name*	*Nested/ Simpler Model*	*Fixed Effects Added*	*Participants*	*AIC*	*BIC*	*LL*	*df*	*df*	*p*
RE only	Null	—	—	Intercepts	−1469.1	−1457.3	737.56	3	—	—
FE main effect	Condition	Null	Condition	“ “	−1481.2	−1461.6	745.58	5	2	.0003263***
FE main effects	**Condition + Exposure**	**Condition**	**+Exposure**	**“ “**	**−1483.0**	**−1443.8**	**751.50**	**10**	**5**	**.03715********
FE main effects	Condition * Exposure	Condition + Exposure	*Exposure	“ “	−1472.6	−1394.2	751.50	20	10	.4758
Sampling units	Number of total observations = 372									
	Number of participants = 21									

RE = random effects; FE = fixed effects. ***p < .001, ****p < 1e−5.

Table 12. Linear Fixed Effects Model for Prefeedback Pupillometry

	Fixed Effects					
	Estimate	*SE*	*df*	*t*	*p*	
(Intercept)	2.01E+01	8.49E+00	3.44E+04	2.370	.023538	*
Conditionsym	1.29E+01	3.72E+00	3.51E+05	3.471	.000584	***
Conditionunrel	−7.89E−01	3.74E+00	3.51E+05	−0.211	.833058	
Exposure2	−1.19E+00	5.23E+00	3.51E+05	−0.228	.819907	
Exposure3	−1.95E+00	5.25E+00	3.51E+05	−0.371	.711035	
Exposure4	−9.36E+00	5.25E+00	3.51E+05	−1.784	.075293	
Exposure5	−1.37E+01	5.27E+00	3.51E+05	−2.596	.009839	**
Exposure6	−1.07E+01	5.28E+00	3.51E+05	−2.025	.043589	*

	Variance	*SD*
Participant (intercept)	0.0011295	0.03361

	Model Fit	
R^2	*Marginal*	*Conditional*
	0.03276862	0.5817841

p Values for fixed effects calculated using Satterthwaites approximations. Confidence intervals have been calculated using the Wald method. Model equation: (Pupil_size ~ Condition + Exposure + (1|Participant). *$p < .05$, **$p < .01$, ***$p < .001$.

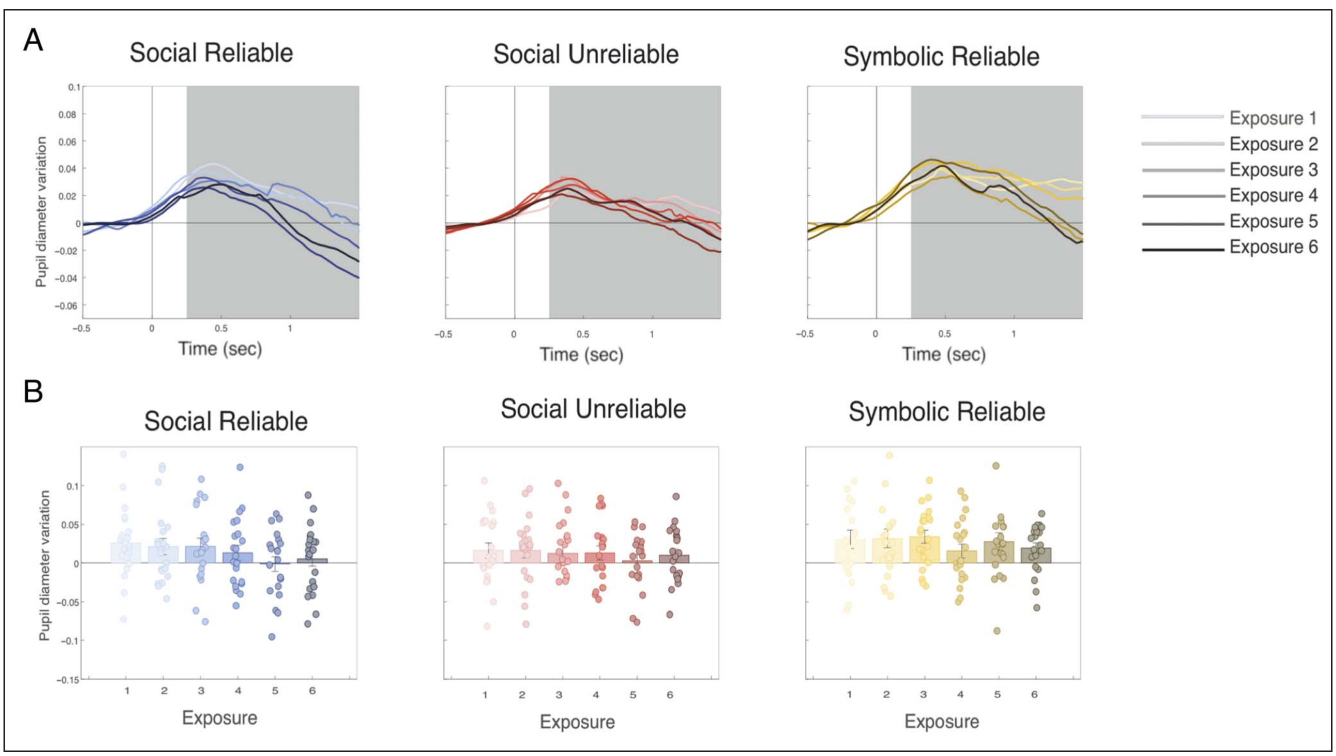


Figure 7. Prefeedback by exposure. (A) Prefeedback pupil diameter variation (negative values represent constriction and positive values represent dilation) for different learning conditions, time-locked to the participant's answer. Like the ERP results, for each plot, the lightest line of the given color scheme represents the first exposure and gets progressively darker for each exposure. The gray area shows the analyzed time window (200–1000 msec). (B) Barplots represent the grand average in the analyzed time window whereas dots represent each participant's mean pupil change, for the given exposure (1–6).

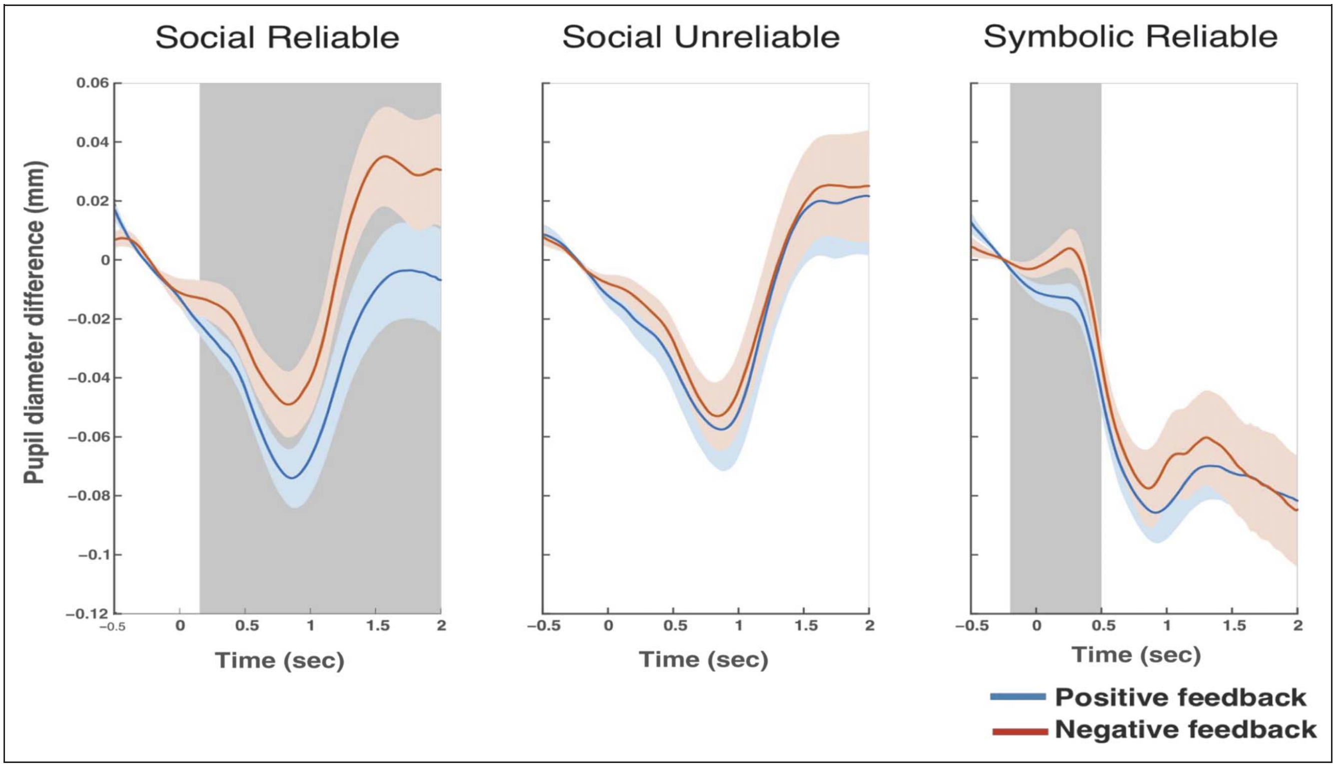


Figure 8. Postfeedback pupil diameter variation across learning conditions, time-locked to the feedback onset. The blue line corresponds to positive feedback, and the red line corresponds to negative feedback. The gray areas show the time periods during which cluster-based permutation tests revealed significant differences between pupil variation associated with positive and negative feedback ($p < .05$).

the random intercepts. We then added the predictor Condition, then the predictor Valence, then the predictor Exposure, and finally their interaction (Table 13). The final lmer model [pupil dilation ~ condition + valence + exposure + (1|participant), $p < .001$, AIC = −15114, LL = 765.70] revealed a main effect Valence, indicating negative feedback was associated with greater pupil dilation for both the Social Reliable and Symbolic Reliable conditions. There was also a main effect of Condition, showing greater dilation for the Symbolic condition overall but no interaction with Valence. Finally, the model revealed a main effect of Exposure, showing a significant difference between the first and third, fourth, fifth, and sixth exposures, in both the Social Reliable and Symbolic Reliable conditions ($p < .05$), indicating that pupil constriction increased as learning progressed (Table 14, Figure 9).

Correlation of difference waveform during feedback (positive minus negative) and behavioral performance in posttest. A Pearson correlation was computed to determine the relationship between the size of the difference in pupil dilation between positive and negative feedback and average accuracy posttraining for the Social Reliable and Symbolic Reliable conditions (during the time windows established by the cluster-based permutation tests). The results indicate a strong trend and positive relationship between behavioral accuracy and negative/positive difference in the Social Reliable condition (r = .43, p = .050), and a nonsignificant positive relationship in the Symbolic Reliable condition (r = .33, p = .150). The Fisher's z transformation test showed that the Symbolic and Social Reliable correlations were not significantly different from each other (z = 0.37, p = .709).

DISCUSSION

In the present study, we evaluated learners' responses to feedback with differing informational and social content during early word learning in adults. Employing a novel approach with dynamic social videos, we captured nuanced feedback expectation and processing shifts as learning progressed, via changes in ERPs and pupil dilation. Overall, our results highlight several pre- and postfeedback ERP components (i.e., stimulus-preceding negativity, SPN, and an LPC) as key markers of feedback expectation/anticipation and processing during word learning (Table 15). Using these components, we showed that participants processed social feedback differently from nonsocial feedback. ERPs exhibited temporal modulations that directly reflected differences in types of feedback: an LPC effect emerged approximately at 300 msec for symbolic feedback (static still images) but was greatly delayed (approximately at 1300 msec) for both social feedback conditions due to their dynamic nature (piloting data showed that it took about 1 sec to interpret social feedback videos; see Figure 4). These temporal distinctions

Table 13. Model Comparison for Feedback Pupillometry

Feedback										
				Random Effects	*Model Fit*				*LRT Test Against Nested*	
Model Specification	*Model Name*	*Nested/ Simpler Model*	*Fixed Effects Added*	*Participants*	*AIC*	*BIC*	*LL*	*df*	*df*	*p*
RE only	Null	—	—	Intercepts	−1477.4	−1464.9	741.68	3	—	—
FE main effect	Condition	Null	Condition	“ “	−1483.9	−1467.2	745.93	4	1	.003537**
FE main effects	Condition + Valence	Condition	+Valence	“ “	−1488.0	−1467.2	749.02	5	1	.01301*
FE main effects	Condition * Valence	Condition + Valence	*Valence	“ “	1488.5	−1463.6	750.26	6	1	.1145
FE main effect	Condition	Null	Condition	“ “	−1483.9	−1467.2	745.93	4	1	
FE main effects	Condition + Exposure	Condition	+Exposure	“ “	−1511.4	−1469.8	765.70	10	4	5.622e−07***
FE main effects	Condition * Exposure	Condition + Exposure	*Exposure	“ “	−1502.9	−1440.5	766.47	15	5	.9093
FE main effects	Condition + Valence	Condition	+Valence	“ “	−1488.0	−1467.2	749.02	5	1	
FE main effects	Condition + Valence + Exposure	Condition + Valence	+Exposure	“ “	−1511.4	−1469.8	765.70	10	6	3.182e−06***
FE main effects	Condition + Valence + Exposure	Condition + Valence	+Exposure	“ “	−1511.4	−1469.8	765.70	10		
FE main effects	Condition + Valence + Condition * Exposure	Condition + Valence + Exposure	+Condition * Exposure	“ “	−1506.2	−1443.8	768.08	15	5	.4462
FE main effects	**Condition + Valence + Exposure**	**Condition + Valence**	**+Exposure**	**“ “**	**−1511.4**	**−1469.8**	**765.70**	**10**		
FE main effects	Condition + Exposure + Condition * Valence	Condition + Valence + Exposure	+ Condition * Valence	“ “	−1512.1	−1466.3	767.04	11	1	.102
Sampling units	Number of total observations = 473									
	Number of participants = 21									

RE = random effects; FE = fixed effects. *p < .05, **p < .01, ***p < .001.

Table 14. Linear Fixed Effects Model for Feedback Pupillometry

	Fixed Effects					
	Estimate	*SE*	*df*	*t*	*p*	
(Intercept)	−0.007446	0.008132	66.166941	−0.916	.363167	
Conditionsym	0.012969	0.004212	452.209496	3.079	.002201	**
Valenceincorr	0.009668	0.004235	452.886876	2.283	.022897	*
Exposure2	−0.011937	0.007059	452.026006	−1.691	.091509	.
Exposure3	−0.025092	0.007152	452.22681	−3.508	.000496	***
Exposure4	−0.029016	0.007104	452.091009	−4.085	5.22E-05	***
Exposure5	−0.03534	0.00737	452.596013	−4.795	2.21E-06	***
Exposure6	−0.031398	0.007402	452.715071	−4.242	2.69E-05	***

	Variance	*SD*
Participant (intercept)	0.0006777	0.02603

	Model Fit	
R^2	*Marginal*	*Conditional*
	0.07508394	0.3013511

p Values for fixed effects calculated using Satterthwaites approximations. Confidence intervals have been calculated using the Wald method. Model equation: (Pupil_size ~ Condition + Exposure + (1|Participant). $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

highlight the precision with which the LPC captured feedback processing throughout word learning, offering a foundational result that guided further analyses. In addition, this study showed effects of reliable versus nonreliable feedback in pre- and postfeedback ERP components, underscoring the importance of reliable feedback for word learning, whether social or not.

Sensitivity to Reliable versus Unreliable Feedback during Word Leaning

A comparison between how learners processed reliable versus unreliable social feedback provides valuable evidence concerning the importance of feedback informativeness during word learning. Behaviorally, learners showed improved accuracy at the end of training and in a subsequent posttest in the reliable social condition. This is in line with our hypothesis, as unreliable (i.e., randomly accurate or inaccurate) feedback does not allow learners to use feedback to learn; instead, they need to rely on cross-situational learning mechanisms (using statistical co-occurrences across time to infer the accuracy of the potential label–object association; Dautriche & Chemla, 2014; Smith & Smith, 2012; Smith et al., 2011). As outlined in the Introduction section, we select information sources very carefully, prioritizing knowledgeable over inexperienced teachers (Mangardich & Sabbagh, 2018; Turner, Giraldeau, & Flynn, 2017; Scofield & Behrend, 2008: Sabbagh & Baldwin, 2001). For instance, Mangaridch and Sabbagh (2018) showed that children disrupt semantic consolidation processes when learning from ignorant speakers as opposed to knowledgeable ones. Similarly, previous studies on adults have shown that uninformative feedback is associated with diminished SPN amplitudes compared with informative feedback (Walentowska et al., 2018; Chwilla & Brunia, 1991). We posit that this extends to adult word learning. Unlike in the effects observed in the SPN amplitude for both reliable conditions, unreliable feedback did not show an increase in the amplitude of the SPN component between early and later exposures (see Figure 3), suggesting that unreliable feedback did not elicit increased expectations of positive feedback. Thus, these results corroborate the fact that learners are sensitive to the accuracy of information provided by feedback from potential "teachers."

As further proof of learners' disregard of unreliable feedback, important ERP differences emerged between reliable and unreliable feedback processing. Whereas we observed a progressive decrease in the LPC for positive feedback in the two other conditions (see Figure 5), most likely due to learners using this feedback less and less in comparison with the negative feedback, this was not the

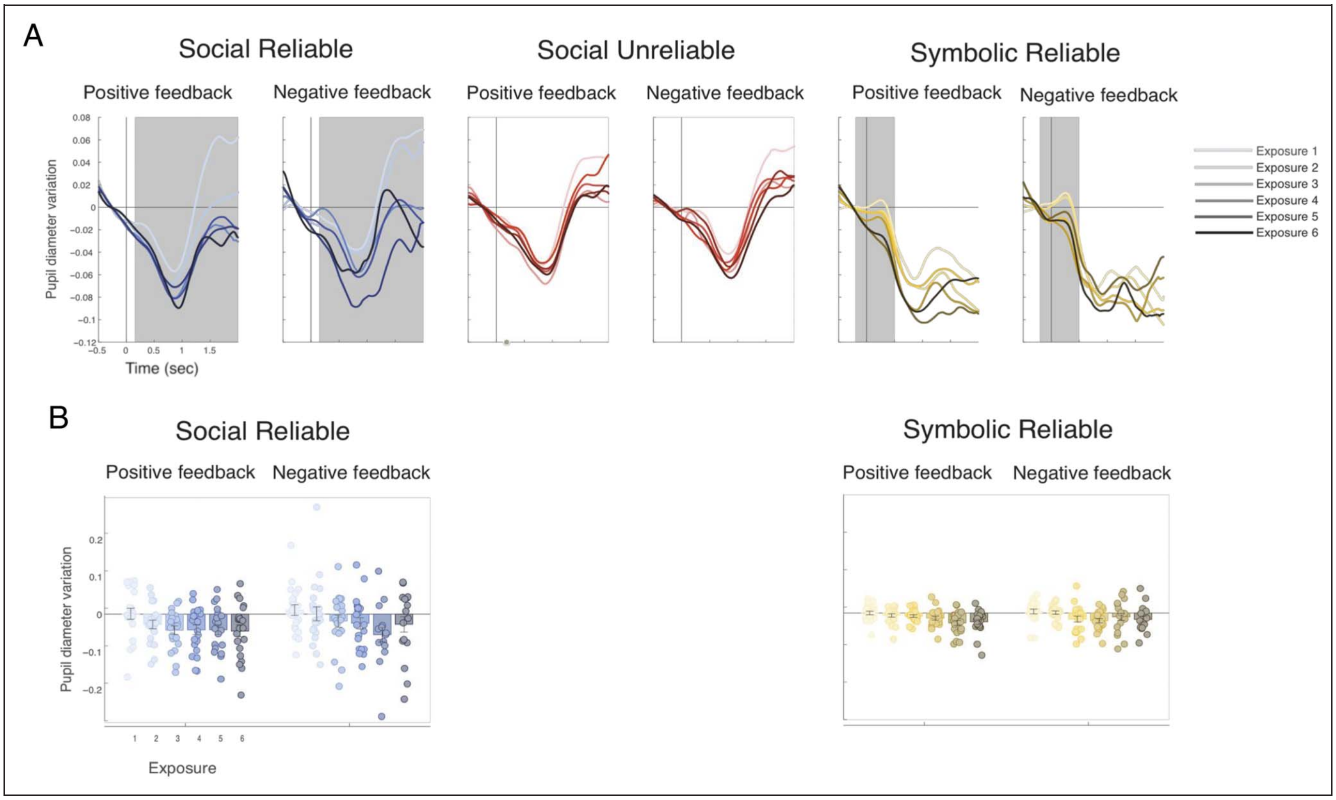


Figure 9. During feedback by exposure. (A) Feedback pupil diameter variation (negative values represent constriction and positive values represent dilation) for different learning conditions, time-locked to the participant's answer. Like the ERP results, for each plot, the lightest line of the given color scheme represents the first exposure and gets progressively darker for each exposure. The gray area corresponds to the cluster-based permutation analyses (differences between pupil variation associated with positive and negative feedback). (B) Barplots represent the grand average in the analyzed time window whereas dots represent each participant's mean pupil change, for the given exposure (1–6). There is no barplot for the Social Unreliable condition as cluster-based permutation analyses did not reveal any differences between positive and negative feedback.

case for unreliable feedback. In addition, the two reliable conditions showed significantly greater negativity in the LPC for negative versus positive feedback overall, whereas this effect was greatly reduced in the unreliable condition. This difference likely results from learners not trusting that this feedback was indicative of their performance and not using it for context updating. Although the LPC component showed slightly more negative amplitude for negative versus positive feedback in the unreliable condition, this difference was much smaller, briefer, and less widespread than that shown for the reliable conditions. Importantly, no correlation emerged between the LPC difference waveform and behavioral performance in the unreliable condition. It is therefore likely the LPC differences here are a result of an automatic recognition of negative versus positive facial expressions and that this information was not used for context updating. Indeed, emotional information is known to elicit attention (Öhman, Flykt, & Lundqvist, 2000), often described as *motivated attention*, or attention that is automatically allocated to emotional Stimuli (Ferrari, Codispoti, Cardinale, & Bradley, 2008).

Interestingly, posttraining performance for words learned with unreliable feedback was above chance. It thus seems that uninformative social feedback can be overridden and that learners can use different strategies to acquire image–word associations. Learners may have partially used implicit learning mechanisms, often employed in environments where explicit feedback is unavailable or untrusted, enabling the formation of associations through repeated exposure and statistical regularities (Morgan-Short, Steinhauer, Sanz, & Ullman, 2012). Hence, our results showing successful learning with unreliable feedback align with evidence that cross-situational statistical learning can serve as an alternative strategy in word acquisition (Angwin, Armstrong, Fisher, & Escudero, 2022; Dautriche, Rabagliati, & Smith, 2021; Smith & Smith, 2012). In this sense, this study also provides new evidence on how different ERP components are involved in associative and cross-situational learning (Benitez & Li, 2024; Smith et al., 2011), suggesting the implication of different cognitive processes contingent on the type of learning.

Reliable Social and Nonsocial (Symbolic) Feedback: Similarities and Differences

SPN amplitude increased after the first exposure block (Exposures 2–6 vs. Exposure 1) in both Reliable conditions, suggesting emerging feedback expectation,

Table 15. Summary of Behavioral, ERP, and Pupillometry Main Statistical Effects Observed

Section	*Measure/Analysis*	*Main Findings*
3.1 Behavioral	GLMM: Accuracy ~ Condition (Last Block)	Social Unreliable < Symbolic Reliable (p < .001); no difference between Social Reliable and Symbolic Reliable (p = .874; Figure 2, Table 1)
	GLMM: Accuracy ~ Condition (Posttest)	Social Unreliable < Symbolic Reliable (p < .001); no difference between Social Reliable & Symbolic Reliable (p = .717; Figure 2, Table 2)
3.2.1 ERPs Prefeedback	SPN (200–1500 msec prefeedback onset)	SPN increased with exposure in Social Reliable & Symbolic Reliable; no increase in Social Unreliable (Figure 3, Tables 3–5)
	GLMM: SPN ~ Condition × Exposure	Significant Exposure × Condition interaction; SPN increased between Exposure 1 and later exposures (2–6) in Social Reliable & Symbolic Reliable, not in Social Unreliable (Figure 3, Tables 3–5)
3.2.2 ERPs During Feedback	LPC (time-locked to feedback onset)	Symbolic Reliable: positivity in earlier time window (200–700 msec); Social conditions: positivity in later time widow (~1200–2000 msec).
	Cluster Permutation Tests	Significant negative vs. positive clusters in Social Reliable & Symbolic Reliable; smaller effect in Social Unreliable (Figure 4).
	Topography of pos vs. neg difference: LPC ~ Condition × ROI	Social Reliable > Symbolic Reliable in frontal & central regions, not parietal (Figure 4B, Table 7)
	GLMM: LPC ~ Condition × Valence × Exposure	Positive feedback: decreasing positivity over time, especially in Social Reliable; no clear patterns for negative feedback (Figure 5, Tables 8–10)
3.2.3 ERP - Behavior Correlation	Pearson correlation (Pz)	Significant in Social Reliable (r = .51, p = .005), not in Social Unreliable & a trend in Symbolic Reliable; z test: SocRel > SocUnrel (p = .048; Figure 6)
3.3.1 Pupillometry Prefeedback	GLMM: Dilation ~ Condition + Exposure	Greater dilation in Symbolic Reliable than Social Reliable; significant constriction over time in Social and Symbolic Reliable (Figure 7, Table 12)
3.3.2 Pupillometry During Feedback	Cluster Permutation Tests	Greater dilation for negative vs. positive feedback in Social Reliable and Symbolic Reliable only (not Social Unreliable; Figure 8)
	GLMM: Dilation ~ Condition + Valence + Exposure	Greater dilation for negative feedback; Symbolic Reliable > Social Reliable; constriction over time in both (Figure 9, Tables 13 &14)
Pupil - Behavior Correlation	Pearson correlation	Strong trend in Social Reliable (r = .43, p = .050); not significant in Symbolic Reliable (r = .33, p = .150; Figure 10)

particularly in the Social Reliable condition (see Figure 3). Given that behavioral performance improved consistently, we propose that this pattern reflects an increasing expectation of positive feedback. This aligns with prior research demonstrating a clear association between the SPN and learning (Fuentemilla et al., 2014; Moris et al., 2013; Mangels, Butterfield, Lamb, Good, & Dweck, 2006; Perfetti, Wlotko, & Hart, 2005) and the SPN and reward expectation (Fryer et al., 2021; Hackley, Valle-Inclán, Masaki, & Hebert, 2014; Ohgami et al., 2004). These results provide novel evidence linking the growth of the SPN during learning to positive feedback anticipation, establishing it as an important neural correlate of word learning. Concurrently, larger pupil dilation was observed for symbolic compared with social feedback conditions in the prefeedback phase (see Figure 7). We interpret this finding as possibly reflecting the more immediate interpretability of symbolic feedback (still images), whereas social feedback (videos) required additional processing time to infer valence. Increased pupil dilation might, therefore, reflect the anticipation of more immediate feedback, though further studies are necessary to clarify how pupil responses signal feedback anticipation during learning.

During feedback processing, we showed an increase in the LPC component for negative compared with positive feedback, an effect that was observed across both reliable conditions (Fields, 2023; Polich & Kok, 1995; Donchin & Coles, 1988; see Figure 4). This increased amplitude for negative valanced feedback is associated information-updating mechanisms and suggests a need to reevaluate the information acquired. Interestingly, the amplitude of the LPC in response to positive feedback decreased with repeated exposure (see also Luque et al., 2012; see Figure 5). This likely reflects the diminishing utility of positive feedback as it became expected and less impactful for guiding learning. In contrast, the amplitude of the LPC for negative feedback remained steady across exposures, underscoring its ongoing relevance for information updating and learning (Fields, 2023; Bultena, Danielmeier, Bekkering, & Lemhöfer, 2017; Polich & Kok, 1995; Donchin & Coles, 1988; see Polich, 2007). Positivity in this window is also associated with more infrequent Stimuli, which could explain why the LPC decreased for positive feedback, which became more and more frequent with learning. Indeed, Luque and colleagues (2012) found a very similar pattern in the same time window for positive and negative feedback during associative learning, as learning progressed.

This LPC pattern aligns with our hypotheses based on predictive learning theories, which propose that learners update associations to reduce prediction errors (Luque et al., 2012) and allocate more attention to cues signaling these errors (Wills et al., 2007; Pearce & Hall, 1980). Similarly, larger LPC effects have been observed when negative feedback is provided for high-confidence errors (Metcalfe, Casal-Roscum, Radin, & Friedman, 2015; Butterfield & Mangels, 2003), that is, when learners were highly certain about their incorrect responses. This negative increase in LPC amplitude following negative feedback likely reflects the level of surprise experienced (larger prediction error) and heightened attention to correct the previously learned association. Supporting this interpretation, Pashler, Cepeda, Wixted, and Rohrer (2005) found that negative feedback significantly improved word learning and posttraining retention.

Our findings underscore the critical role of negative feedback in updating knowledge during word learning and highlight the LPC component as a valuable neural marker for tracking this process. Moreover, a significant correlation emerged between LPC differential amplitude (negative vs. positive feedback) and subsequent learning outcomes in both reliable feedback conditions, suggesting that participants who prioritized negative over positive feedback achieved better learning outcomes. In addition, consistent with studies linking pupil dilation to mental effort (Laeng et al., 2012), pupillometry revealed greater dilation for negative feedback (see Figure 8), further indicating that this feedback was more effectively used to update information during learning. Overall, these results align with prior findings showing that larger positivity responses during learning are associated with improved information retrieval (Lemhöfer et al., 2025; Turk et al., 2018; Azizian & Polich, 2007; Dolcos & Cabeza, 2002; Fabiani et al., 1986; Karis et al., 1984). For the first time in word learning, they demonstrate that LPC amplitude within the feedback window can serve as an indicator of context updating (Fields, 2023).

Regarding the differences between the reliable conditions (social and symbolic), we observed robust differences in the scalp distribution. Social feedback showed more widespread frontal central activity when compared with the symbolic condition (see Figure 4). Understanding social cues involves interpreting others' mental states or intentions, frequently termed mentalizing or theory of mind (Fehlbaum, Borbás, Paul, Eickhoff, & Raschle, 2021; Frith & Frith, 2005). This cognitive ability is associated with the activation of a broad network, often referred to as the default mode network, including the medial prefrontal, TPJ, and posteromedial cortex (Kliemann & Adolphs, 2018). More specifically, Tan and colleagues (2022) recently pointed to dorsomedial pFC as being specialized for metalizing. Indeed, evolutionarily, the development of social cognition has been linked to the expansion of frontoparietal networks (Allen, Hallquist, & Dombrovski, 2023; Tan et al., 2022). In this context, the more widespread scalp distribution observed for our reliable social feedback, especially in more frontal regions, might suggest the engagement of mentalizing processes for interpreting social feedback. This aligns with two studies by Schindler and Kissler (2016) and Schindler, Kruse, Stark, and Kissler (2019) showing the involvement of mentalizing and "socially motivated" attention during supposed human-generated feedback processing. Like theirs, our results suggest that sender identity (i.e., social vs. nonsocial) may modulate how feedback is processed, although further work is needed to isolate these effects.

Correlations further emphasized the importance of social feedback. The strongest correlation between LPC differential amplitude (negative vs. positive feedback) and behavioral performance was observed in the reliable social condition (see Figure 6). Although this correlation was stronger in magnitude compared with the same correlation in the reliable symbolic condition, no significant differences were found between the two, limiting the interpretability of this result. Nevertheless, this observation might suggest a potential social advantage, aligning with findings by Schindler, Vormbrock, and Kissler (2022), who demonstrated that memorizing adjectives in a social condition was associated with greater LPC amplitude during encoding and improved subsequent recognition compared with control conditions. In addition, correlation analyses revealed a positive relationship between pupil dilation and posttraining accuracy (see Figure 10), but only in the reliable social condition. This finding is consistent with previous studies showing that pupil dilation during encoding predicts subsequent recognition accuracy (Papesh, Goldinger, & Hout, 2012) and retrieval (Pajkossy & Racsmány, 2019; Kucewicz et al., 2018; Naber, Frässle, Rutishauser, & Einhäuser, 2013). Overall, the correlations observed between both LPC amplitude and pupil dilation with behavioral accuracy in the reliable social condition suggest a stronger relationship between encoding processes and word retention in social learning. This effect may reflect an optimized use of social information, consistent with prior evidence highlighting the prioritization of social cues (Williams et al., 2019; Wagner et al., 2016; Chevallier et al., 2012).

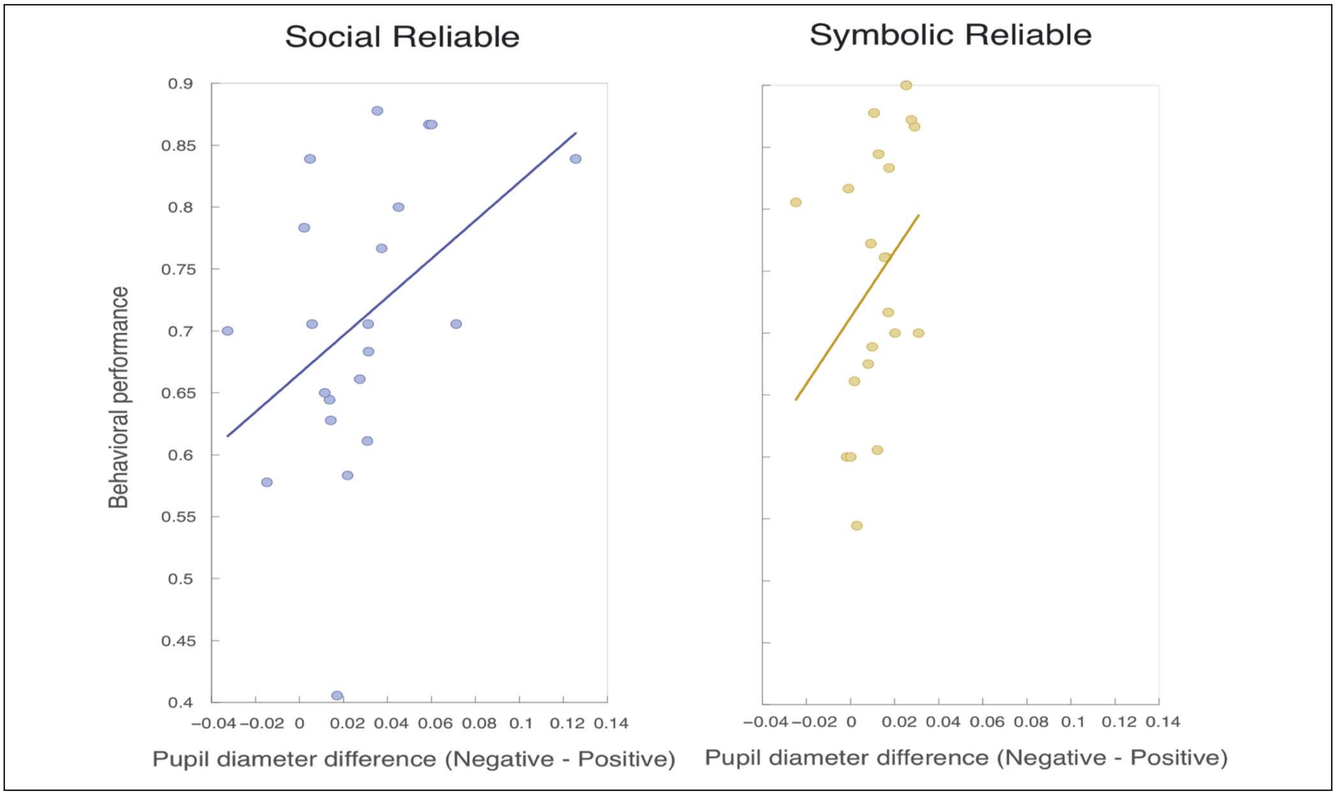


Figure 10. Correlation between performance posttraining and pupillometry negative minus positive difference during feedback. The x axis represents the average pupil variation of the difference waveform (negative minus positive feedback), and the y axis represents the behavioral performance score. Each point represents a participant.

Reliable Social Feedback in the Context of Word Learning

Studies investigating how social feedback affects performance and learning have provided mixed results showing either processing advantages (Pfabigan & Han, 2019; Pfabigan et al., 2018; Colombo, Stankevicius, & Seriès, 2014, though contingent on culture; Schindler et al., 2022; Vernetti, Smith, & Senju, 2017), disadvantages (Beston, Barbet, Heerey, & Thierry, 2018; Hu et al., 2015), or no differences (Sailer, Wurm, & Pfabigan, 2024). This variability is not surprising given the diverse types of social feedback (i.e., a still image of a thumbs up, pictures of faces, dynamic videos) and the populations studied (i.e., social anxiety disorder patients, young children and adults). Furthermore, most prior studies engaged participants in tasks that were not inherently social, such as incentive delay or social incentive delay tasks (Sobczak & Bunzeck, 2023; Sobczak et al., 2021; Williams, Bilbao-Broch, Downing, & Cross, 2020; Kohls et al., 2013), the probabilistic reward task (Sailer et al., 2024), cue–reward association (Vernetti et al., 2017), or time estimation tasks (Pfabigan et al., 2017).

In contrast, language use—and, by extension, language learning—is inherently social, making it a uniquely suitable context for investigating social feedback. Our study suggests that social feedback during word learning can be as effective as symbolic feedback in supporting behavioral performance, and that it may engage somewhat distinct neural and physiological dynamics. Importantly, our results highlight the critical role of feedback reliability in word learning. Unreliable feedback led to inferior behavioral outcomes and showed diminished expectation of positive feedback along with limited differentiation between positive and negative feedback during learning. It forced learners to use a different type of strategy, most probably tracking regularities across time to infer correct associations. Overall, EEG and pupillometry results, which captured feedback processing both before and during feedback, as well their relationship with performance, demonstrate that reliable feedback—both social and symbolic—engages learning-related processes, with some evidence suggesting different processing dynamics in the social condition. Ours is the first study to examine the neural correlates of word learning as a function of feedback reliability and the social nature of feedback, offering new insight into how these factors influence learning-related processes.

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Data Availability Statement

The anonymized data necessary to reproduce the analyses presented here are available on the Open Science Framework platform (https://osf.io/czhve). The materials necessary to attempt to replicate the findings presented here are not publicly accessible but are available from the corresponding author upon request.

Author Contributions

A. Z., D. C., and A. R. F. planned the study. P. O., M. M., and A. Z. performed the EEG measurements. X. C., D. C., M. M., P. O., and A. Z. analyzed the data and performed the statistical analyses. A. Z., D. C., X. C., and A. R. F. contributed to the interpretation of the data. A. Z. and A. R. F. wrote the manuscript.

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Diversity in Citation Practices

Retrospective analysis of the citations in every article published in this journal from 2010 to 2021 reveals a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience* (*JoCN*) during this period were M(an)/M = .407, W(oman)/M = .32, M/W = .115, and W/W = .159, the comparable proportions for the articles that these authorship teams cited were M/M = .549, W/M = .257, M/W = .109, and W/W = .085 (Postle and Fulvio, *JoCN*, 34:1, pp. 1–3). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance. The authors of this paper report its proportions of citations by gender category to be: M/M = .416; W/M = .267; M/W = .149; W/W = .168.

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