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Confidence Regulates Feedback Processing During Human Probabilistic Learning

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Uncertainty presents a key challenge when learning how best to act to attain a desired outcome. People can report uncertainty in the form of confidence judgments, but how such judgments contribute to learning and subsequent decisions remains unclear. In a series of three experiments employing an operant learning task, we tested the hypothesis that confidence plays a central role in learning by regulating resource allocation to the seeking and processing of feedback. We predicted that, as participants' confidence in their task knowledge grew, they would discount feedback when it was provided and be correspondingly less willing to pay for it when it was costly. Consistent with these predictions, we found that higher confidence was associated with reduced electrophysiological markers of feedback processing and decreased updating of beliefs following feedback receipt. Bayesian modeling suggests that this decrease in processing was due to a drop in the expected informative value of novel information when participants were highly confident. Thus, when choosing whether to pay a fee to receive further feedback, participants' subjective confidence, rather than the objective accuracy of their decisions, guided their choices. Overall, our results suggest that confidence regulates learning and subsequent decision making.

Public Significance Statement

As we learn, we experience a growing sense of confidence in our abilities. This study tests the hypothesis that this sense of confidence plays an important role in the learning process. Specifically, our experiments test the hypothesis that confidence affects the way people seek and use feedback during learning. We measure these effects in three ways in a simple learning task: how much people learn from the feedback provided, the size of their brain response when feedback is presented, and how willing people are to pay for feedback. We find that as learners become more confident, they pay less attention to feedback and are less likely to pay a price for it. We suggest that this variation in attention to feedback is a "feature" rather than a "bug" in human learning: It allows a learner to judge when feedback is useful versus when it is likely to be a distraction (particularly if feedback is not always reliable) or a waste of effort (if it just tells the learner something they already know).

Keywords: metacognition, confidence, learning, electroencephalographic, decision making

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A critical challenge for any learner is dealing with underlying uncertainty in the environment, as contingencies between events are typically stochastic, rather than deterministic, and can change dynamically across time. Moreover, the evidence available when deciding is often noisy, making it difficult to accurately evaluate a situation and to choose how to act. Theories of learning incorporate this uncertainty, for example, in terms of graded variation in the associative strength between events, actions, and outcomes, capturing variation in the strength of observed relationships (Rescorla & Wagner, 1972; Sutton & Barto, 2018). Furthermore, in some theories, uncertainty is represented and used explicitly as the estimated volatility of the learning environment, modulating the rate at which learning occurs (Behrens et al., 2007; Esber & Haselgrove, 2011; Mackintosh, 1975).

Evidence suggests that people can consciously access and report their uncertainty. For instance, in a task with varying transition probabilities between successive stimuli, people's reported confidence in their predictions of the next stimulus accurately tracked the true transitional probability in a manner that closely paralleled the inferences made by a normative Bayesian model (Meyniel & Dehaene, 2017; Meyniel, Schlunegger, & Dehaene, 2015; Meyniel, Sigman, & Mainen, 2015). These representations may serve to regulate the learning rate (Meyniel & Dehaene, 2017), so that as confidence increases, the weight of new information decreases, and more emphasis is placed on prior learning than current experience.

These ideas converge with a growing body of evidence indicating that humans (Boldt & Yeung, 2015; Meyniel, Sigman, & Mainen, 2015; Navajas et al., 2017; Yeung & Summerfield, 2012) and other animals (Kepecs et al., 2008; Kepecs & Mainen, 2012) represent the uncertainty involved in decision making in the form of subjective confidence and that they use these representations adaptively to guide their behavior. For instance, people's ability to quantify uncertainty explains differences in learning across age groups (Nassar et al., 2016), and confidence in one's knowledge predicts study strategies (Bjork et al., 2013; Metcalfe & Finn, 2008; Mihalca et al., 2017; Nelson & Dunlosky, 1991; Thiede, 1999), individual differences in learning speed (Frömer et al., 2021), information-seeking (Desender et al., 2018; Fernbach et al., 2019; Wood & Lynch, 2002), and task selection (Carlebach & Yeung, 2020). Meanwhile, on a social level, confidence can be used to communicate uncertainty when sharing information (Bahrami et al., 2010; Bonaccio & Dalal, 2006; Pescetelli et al., 2016, 2021).

A crucial challenge in understanding the functional role of metacognitive representations, such as confidence, lies in distinguishing the impact of these processes from the direct effect of the lower level processes they are hypothesized to monitor (Nelson & Narens, 1990): Confidence in learning will inevitably tend to correlate with the strength of underlying learned associations, which raises both a methodological question—of how to tease apart their separate contributions to behavior—as well as the conceptual question of why the metacognitive representations are functionally necessary (Le Pelley, 2012). An influential answer to the latter question holds that explicit, conscious representations serve to make information globally available within the cognitive system, allowing flexible and intentional control of behavior (Dehaene & Changeux, 2011; Nelson & Narens, 1990). According to this perspective, the core function of confidence in learning would be to guide mechanisms outside of the direct learning process itself (e.g., attention, decision making), exceeding simple modulation of learning parameters like the learning rate. The present research explores this idea.

In three experiments, we test the hypothesis that confidence regulates the way performance feedback is accessed and assessed during learning. Our proposal goes beyond established Bayesian models (Meyniel, Sigman, & Mainen, 2015), which posit that new evidence carries lower informational value for a learner who is already confident in their prior knowledge and, hence, should lead to small updates of prior beliefs. Whereas this idea does address how confidence affects the way a learner updates their beliefs based on observed evidence, here we address how confidence guides the way learners seek and process that evidence in the first place. Specifically, we hypothesize that, anticipating reduced information gain from feedback compared to when low in confidence, a highly confident learner will also invest less effort into seeking and processing this new evidence, echoing theoretical ideas of "optimal data selection" in reasoning and hypothesis testing (Oaksford & Chater, 1994) and "rational inattention" in economic decision making (Maćkowiak et al., 2023; Sims, 2003). According to this hypothesis, the effects of confidence about learning can extend beyond the learning process itself and can lead to adaptive changes in other cognitive systems, such as those involved in attention (to feedback, when it is presented) and action selection (i.e., whether to seek feedback, when it is available).

We tested these predictions using an operant learning task comprising short blocks of learning trials in which participants had to learn the appropriate responses to two new stimuli. In each trial, participants received probabilistic feedback on the accuracy of their responses to the stimuli presented and rated their confidence in their chosen response. We found that subjective confidence tracks objective accuracy overall, increasing as learning progresses, but does so imperfectly, enabling us to assess the impact of confidence separately from the underlying learning. We show that increased confidence is associated with reduced feedback processing, as reflected in updated beliefs after surprising negative feedback (Experiments 1 and 2) and diminished neural responses to feedback, as evident in electroencephalographic (EEG) recordings (Experiment 2), even when assessed after performance accuracy largely stabilizes at a high level. Finally, we show that confidence ratings predict whether people are willing to pay a cost to obtain feedback when it is not freely provided (Experiment 3).

Experiments 1 and 2

The main aim of Experiments 1 and 2 was to test our hypothesis that confidence regulates the extent to which subsequent feedback is attended to and incorporated throughout learning. Both experiments employed the same task, with the difference that in Experiment 2, EEG data were collected to measure the impact of confidence on event-related potentials (ERP) time-locked to feedback delivery. Importantly, in addition to providing a neurophysiological measure of feedback processing, Experiment 2 also allowed us to carry out a preregistered replication of the behavioral task from Experiment 1 (see below for details of preregistration).

Method

Participants

A total of 25 participants took part in Experiment 1 and 30 in Experiment 2. Five participants were excluded from analysis in

Experiment 2 because they did not fulfill preregistered inclusion criteria: Two participants failed to reach a predetermined accuracy criterion (their mean accuracy fell over 2 standard deviations [*SD*] below the mean sample accuracy). Noisy EEG data led to the exclusion of three further participants who did not have the predetermined minimum of 20 artifact-free trials per condition (first vs. second half of trials post accuracy breakpoint; see below for more details) from which to obtain an average feedback-related negativity (FRN; cf. Marco-Pallares et al., 2011).

Thus, in both experiments, the final sample comprised 25 participants (Experiment 1: 18 self-identified as cisgender women and seven as cisgender men, aged 18–34; Experiment 2: 13 self-identified as cisgender women and 12 as cisgender men, aged 19–35; no further demographics were collected aside from gender and age). For both experiments, we selected this sample size since previous research has shown reliable effects of confidence on decision making with 20 or more participants (Carlebach & Yeung, 2020; Desender et al., 2018). Participants were recruited from an online database and received either course credit or payment for their time in addition to a monetary bonus relating to task performance, as described below. All experiments reported here were approved by the Central University Research Ethics Committee at the University of Oxford, and all participants gave written informed consent.

Procedure

Experiment 1. Participants were instructed to learn the mapping between two stimuli appearing onscreen and two responses—the right and the left mouse click—over a series of 16-trial blocks in which responses for a new pair of stimuli had to be learned in each block as illustrated in Figure 1. In each trial, one of two images of everyday objects appeared onscreen for 150 ms. Participants had 1,750 ms during which the screen remained empty to make a response by clicking either the right or the left mouse button: the correct response to one object was the right-click and the correct response to the other object was the left-click. Following an 800-ms interval, feedback was displayed onscreen for 400 ms.

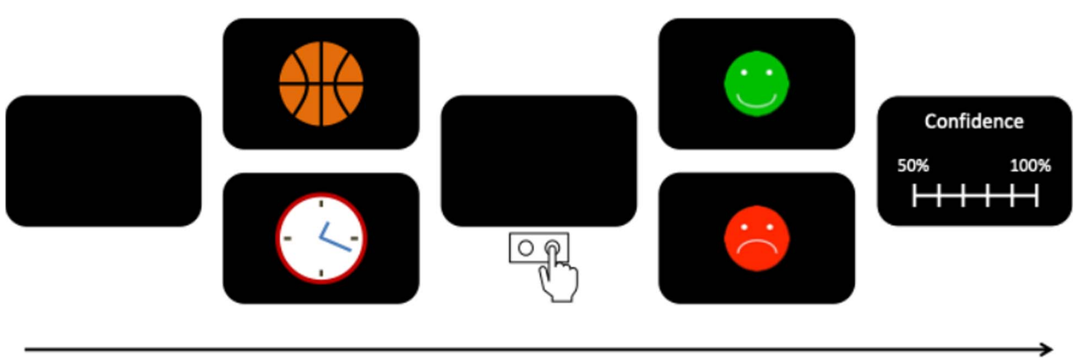
Correct responses elicited a green, smiley face on 75% of trials and a red, displeased face on 25% of trials; the reverse probabilities held when an incorrect response was made. If participants failed to respond within the 1,750 ms time limit, a white, neutral, crossed-out face appeared, and the subsequent trial began. These trials (<2% of all trials per participant) were excluded from analyses. After viewing feedback, participants were asked to rate their confidence in having responded correctly on a 51-point visual analog scale. The scale ranged from 50% confidence—equivalent to guessing—to 100% confidence—indicating absolute certainty that the correct response had been made. Participants moved the mouse vertically to increase (up) or decrease (down) their confidence estimate and pressed the right mouse button to confirm their rating. Following a 500-ms intertrial interval, the next trial began.

Participants were informed of the 75% contingency between response accuracy and feedback type (positive or negative) and were told that, for example, on some trials, they might receive negative feedback after a correct response and vice versa. They were told that their goal should be to make correct responses, rather than to obtain smiley faces. The instructions specified that each correct response earned them points that would be converted into a monetary reward at the end of the experiment. Points were never displayed during learning, and participants were shown a tally of the points earned only at the end of each block; therefore, response feedback was the only information provided throughout the block. Correct responses were rewarded with £0.01 (regardless of whether followed by positive or negative feedback).

Participants completed one practice block followed by 30 experimental blocks; novel stimulus pairs were used in each new block. All experiments were coded in MATLAB (MathWorks, Natick, Massachusetts, United States) using the Psychophysics toolbox (Brainard, 1997; Pelli, 1997).

Experiment 2. The behavioral procedure in Experiment 2 was the same as in Experiment 1 with some timing adjustments to allow

Figure 1
Experiment 1 Task Design



Note. One of two stimuli appeared on each trial at the centre of the screen for 150 ms. Participants then had 1750 ms to make a response using the right or left mouse buttons. Responses were followed by an 800 ms interval before feedback appeared at the centre of the screen. Correct responses were followed by positive feedback (a green smiley face) 75% of the time and negative feedback (a red displeased face) 25% of the time. The reverse occurred following incorrect responses. Feedback stayed onscreen for 400 ms, after which participants rated their confidence on a scale from 50% to 100% confidence. The task in Experiment 2 was the same as in Experiment 1, with adjustments to stimuli presentation times to account for EEG data collection. See the online article for the color version of this figure.

for ERPs of interest to be measured without interference from subsequent events. Specifically, the interval between response and feedback was lengthened to 1,000 ms, during which the screen remained empty, and feedback remained onscreen for 800 ms.

EEG Procedure. EEG data in Experiment 2 were recorded using a Neuroscan Synamps2 system (10 GΩ input impedance, 29.8 nV resolution; Neuroscan, El Paso, Texas) from 32 Ag/AgCl electrodes mounted on a fabric cap according to the international 10–20 system of electrode positioning. Six additional electrodes were attached externally above and below the left eye and to the outer canthi of each eye to measure electrooculogram data, as well as to both mastoids. Electrode recordings were referenced to the right mastoid. Impedance levels were kept below 10 kΩ on all electrodes, and data were sampled at a rate of 1000 Hz. An online high-pass filter at 0.1 Hz was applied to the data.

Analysis Plan

Behavioral Data Analysis. Participants' accuracy and confidence over the 30 blocks were averaged separately for each of the 16 trials per block, generating individual accuracy and confidence curves. In pilot work with this task, we observed that these curves were consistently characterized by an initial phase of roughly linear increase until a *breakpoint* was reached, after which performance remained relatively stable, with differing breakpoints apparent for accuracy and confidence. As a simple quantification of this pattern, we characterized each participant's averaged accuracy and confidence curves using a piecewise linear function, in which each curve was fitted with two separate lines, one positively sloped (fitted via regression) and the other flat (with a value set to the mean of the trial data points being fitted). Fits to empirically observed curves are shown for Experiment 1 in the Supplemental Figures S1 and S2, which illustrate that this simple method captures key trends in the data. No theoretical model of learning or confidence is implied by this method of quantifying the data, and it is likely that other, more complex learning-curve functions would provide an incrementally better quantitative fit to the data. Nevertheless, the piecewise linear approach provides an attractively simple method that quantifies relevant features of the data while also clearly specifying the point at which learning reached a relatively stable plateau (i.e., at the identified breakpoint).

The algorithm for deriving the piecewise linear fit was designed to identify the combination of lines that generated the least mean squared error compared to the empirical data. Best fit was determined by a simple grid search across all possible lengths of the two lines, separately for accuracy and confidence curves, individually for each participant. If the best fit for any given curve was a single positively sloped line, the breakpoint was set to the maximum number of trials in the block (i.e., 16, reflecting that the curve had not peaked and reached a stable plateau by the end of the block). This condition never applied to participants' accuracy curves but applied in several cases to participants' confidence curves (such that the later breakpoint for confidence than accuracy reported below is, if anything, an underestimate of the true effect). The breakpoint trial number was then used to quantify the point at which accuracy and confidence separately plateaued for that participant within a 16-trial block.

Some of our analyses focused specifically on the period after the accuracy curve breakpoint, during which objective performance was relatively stable but in which we hypothesized (in part based on ongoing changes in confidence ratings, see below) that aspects of learning continued. In some of these analyses, the trials in this period were divided into an early and a late section according to whether they fell, respectively, in the first or second half of the post breakpoint period, as computed separately for each participant. Where there were an odd number of trials in this period, the middle trial in the set was discarded from analysis (e.g., if there were seven trials post breakpoint, the early bin was defined as Trials 1–3 and the late bin as Trials 5–7).

EEG Preprocessing. Ocular artifacts were removed from the continuous EEG data using a regression approach (Semlitsch et al., 1986) implemented in Scan 4.5 (Neuroscan, El Paso, Texas). All further preprocessing and analysis of the EEG data used the EEGLab toolbox for MATLAB (Delorme & Makeig, 2004). First, the data were low-pass filtered offline at 24 Hz with a Hamming window synchronized finite impulse response function (Widmann & Schröger, 2012). Then, they were down sampled to 250 Hz for processing efficiency. Electrodes that, after having extracted epochs (see details below), led to the rejection of more than 10% of trials were removed and replaced by spherical interpolation. Trials were discarded if voltage differences at the relevant electrodes for the components of interest exceeded 100 μV. For both the FRN and the P300, epochs were extracted starting from 500 ms prior to feedback onset until 1,500 ms post feedback onset. Epochs were baseline corrected to a time window between −200 and −100 ms from feedback onset.

EEG Data Analysis. Consistent with our preregistered analysis plan, we quantified ERP components (the FRN and P300) following the methods of Schiffer et al. (2017). Our preregistered analyses focused on the FRN and, to a lesser extent, on the P300 and the stimulus-preceding negativity. In the event, we did not run analyses of the stimulus-preceding negativity, in part because our predictions for this component were less clear and in part because our design was not optimized to study this component (with a relatively short interval separating participants' task response and the presentation of feedback). We therefore focus below on the FRN and P300 as neural indices of feedback processing, in common with previous research. The FRN is often characterized as a rapid evaluation of feedback valence, being larger (more negative) in amplitude for negative outcomes, particularly when they are unexpected, whereas the P300 indexes feedback processing as it relates to immediate updating of action plans (Chase et al., 2011; Kirschner et al., 2022; Schiffer et al., 2017; Yeung & Sanfey, 2004).

FRN. The FRN was estimated as an average base-to-peak measure over the mean voltage across a fronto-central cluster of electrodes comprising F3, FZ, F4, FC3, FCZ, FC4, C3, CZ, and C4. Measuring the FRN as the average base to peak ensured that the resulting amplitude was independent of the magnitude of the P300 within which the FRN occurs. For analyses of single-trial FRN amplitude, the timings of the three peaks derived from each subject's average FRN waveform across all trials in the condition of interest were used on the single-trial waveforms to derive the size of the component (Chase et al., 2011).

P300. The P300 was measured as the peak positive voltage in a cluster of centro-parietal electrodes comprising CP3, CPZ, CP4, P3, PZ, P4, and POZ in a time window spanning from 300 to 420 ms post feedback onset.

Computational Modeling. The task we employed lends itself well to Bayesian computational modeling to further probe the mechanisms underlying the relationship between learning and confidence. We used a model testing the probability that each of the two possible stimulus–response mappings—that is, either (a) stimulus A maps to a left-click and stimulus B to a right-click or (b) stimulus A maps to a right-click and stimulus B to a left-click—was the correct one, updating each value through Bayes' equation:

$$P(M_C|F) \propto \frac{P(F|M_C)P(M_C)}{P(F)}, \quad (1)$$

where M_C is the chosen mapping and F is the incoming feedback. Therefore, the equation states that the probability of M_C being the correct rule given F is proportional to the likelihood of F occurring given M_C being the correct rule, multiplied by the learner's prior belief in M_C being the correct rule. The resulting value is scaled by the overall probability of observing the feedback.

In this way, we can generate an updated estimate of the model's confidence in M_C being correct, specifically as the prior, $P(M_C)$, at the start of the trial and the posterior, $P(M_C|F)$, after receiving feedback. The latter value is then carried over to the next trial where it becomes the new prior. As described above, the confidence scale used by participants ranged from 50% to 100%. Therefore, to match those task parameters more closely in our modeling analyses, we separately computed the confidence value for the model as its posterior with a lower bound of 0.5.

Because there were only two possible mappings, we assumed that feedback supporting one option also provided proportionally strong evidence against the other option. Therefore, the objective likelihood of positive feedback given M_C being the correct rule, $P(F_+|M_C)$, was 0.75 (i.e., the true level of feedback reliability), while the objective likelihood of negative feedback given M_C being the correct rule, $P(F_-|M_C)$, was $1 - P(F_+|M_C)$, that is, 0.25. The reverse weights applied to the unchosen mapping on any given trial. In our initial run of the model, we used the objective levels of feedback likelihood, as described above.

In later simulations, as described below, we allowed the values of $P(F_+|M_C)$ and $P(F_-|M_C)$ to vary from the task-defined values, while being mutually constrained, so that $P(F_-|M_C) = 1 - P(F_+|M_C)$. Via these fits, we used the model to infer how participants interpreted the reliability of the feedback they received (assuming that their learning is approximately Bayesian). As such, the model has one key free parameter, $P(F_+|M_C)$, which enables it to fit patterns in the empirical data, specifically where those patterns deviate from the Bayesian norm.

The model has a second parameter, which relates to the SoftMax function that we used to generate probabilities of selecting each response based on the derived belief values:

$$P_t(R_a) = \frac{e^{\frac{P(M_c)}{\tau}}}{\sum_{i=1}^{n} e^{\frac{P(M_i)}{\tau}}}, \quad (2)$$

in which $P_t(R_a)$ is the probability that the model would select response R_a on trial t, $P(M_i)$ is the model's confidence (as derived from Bayes' equation above) at the start of trial t that the mapping M_i is correct, where i takes two values corresponding to the two possible mappings. τ is a temperature parameter, where values approaching zero make the model respond more deterministically. In the experimental task, participants were informed of the feedback contingency level, and that negative feedback did not necessarily imply incorrect performance. Furthermore, selecting the correct mapping rather than receiving positive feedback earned participants points. These features should have encouraged participants to select their responses deterministically. For this reason, we set a low-temperature parameter of 0.1, which remained constant throughout the block and across all simulations. With this low value, the model has a strong tendency to respond according to whichever mapping it currently estimates as having the higher likelihood of being correct (rather than being more exploratory in its behavior). On each simulated trial, the model chooses one of the two responses probabilistically according to the values derived from the formula above.

As well as applying Bayesian analysis to overall learning curves, we ran a second type of analysis in which we used Bayes' rule to estimate participants' changing use of feedback across trials. Specifically, to infer the value of the feedback likelihood parameter, $P(F|M_C)$, from participants' confidence ratings during learning, confidence on trial $t - 1$ was used as the model's prior belief in the correct stimulus–response mapping, and the model was provided the same feedback as participants had on trial t. By rearranging the terms of Bayes' rule, we can obtain the value of $P(F|M_C)$ that participants would have employed to generate the observed confidence change from trial $t - 1$ (prior belief) to trial t (posterior belief) given the feedback received, assuming that participants' reported confidence reflects their internal probabilistic estimate that their representation of the current rule is correct. A Bayesian learner never achieves 100% certainty based on probabilistic feedback. Therefore, to account for this fact and deal with trials in which participants rated their confidence level as 100%, confidence ratings were scaled so that values were constrained to be <0.99, by dividing individual values by 101.

Transparency and Openness

We preregistered key aspects of the design (e.g., sample size) and analyses in Experiment 2 (full details available at https://osf.io/se2bw). In particular, we preregistered the prediction that the breakpoint for the confidence curve would occur later on average than the breakpoint for the accuracy curve, as determined via the piecewise linear fit method. Other key analyses focused on the impact of feedback on behavioral and EEG indices at different points during learning, with specific focus on misleading negative feedback—that is, negative feedback following objectively correct responses. These trials provide a critical insight into the progress of learning: To the extent that participants know the correct rule, they should be surprised by negative feedback following correct responses; however, to the extent that they are confident in their knowledge of the rule, they should discount this feedback and not update their beliefs (cf. Schiffer et al., 2017). Misleading positive feedback (i.e., positive feedback following an objectively incorrect response) can in principle provide similar insights, but these trials were significantly rarer given participants' high overall accuracy (>90% on average in the critical post breakpoint period), and there were therefore too few such trials to analyze meaningfully. Specifically, we predicted that misleading negative feedback would result in greater reductions in confidence in the early versus late period post accuracy breakpoint and that the amplitude of the FRN following misleading negative feedback and of the P300 following all feedback would be larger in early versus late trials. Finally, we predicted that confidence on trial $t - 1$ would significantly predict the magnitude of the FRN on trial t in the period following the accuracy breakpoint. Experimental data for both experiments and code for our computational models are available in an open online repository (https://osf.io/z463e).

Results

Participants' learning patterns showed that they followed the instructions, prioritizing responding correctly rather than receiving smiley faces, as accuracy peaked at above 75% toward the end of the blocks (Figure 2A).

Accuracy Versus Confidence

As expected, confidence increased throughout learning but did so at a slower rate than objective accuracy, reaching breakpoint significantly later, Experiment 1: $t(24) = 5.54$, $p < .001$, $d = 1.11$, 95% CI [0.60, 1.60]; Experiment 2: $t(24) = 7.36$, $p < .001$, $d = 1.48$, 95% CI [0.90, 2.04]. On average, the confidence breakpoint occurred approximately four trials after the objective accuracy breakpoint (though some participants did not reach a stable plateau of confidence within the 16-trial block, as reflected in the monotonically increasing function apparent in Figure 2A). Because we fit each participant's accuracy and confidence curves separately, the across-participant averages in Figure 2A appear to show some change in accuracy even after the mean breakpoint for accuracy is reached, but this smearing is notably reduced when the data are replotted relative to the breakpoint itself (Figure 2B).

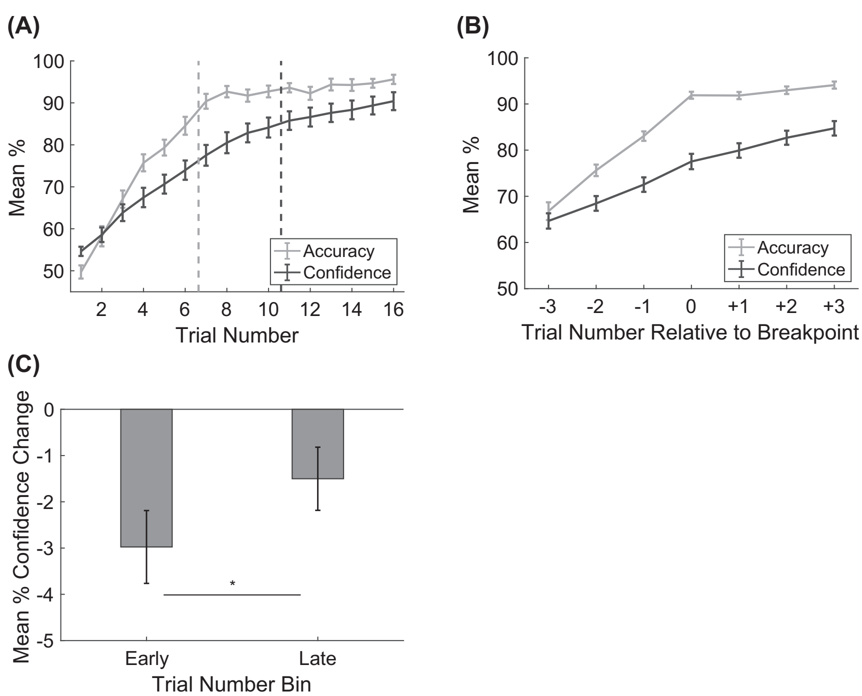
Average accuracy did show a small increase from the early to late post breakpoint periods, from 92.2% to 94.5% in Experiment 1, $t(24) = 3.08$, $p = .005$, $d = 0.62$, 95% CI [0.18, 1.04], and from 93.7% to 95.4% in Experiment 2, $t(24) = 3.41$, $p = .002$, $d = 0.68$, 95% CI [0.24, 1.11], but these ~2% differences are very small relative to the >40% increase leading up to the breakpoint (cf. Figure 2B). Moreover, average reaction times did not differ significantly between early and late periods (Experiment 1: $M_{\text{early}} = 480$ ms vs. $M_{\text{late}} = 476$ ms, $t < 1$; Experiment 2: $M_{\text{early}} = 526$ ms vs. $M_{\text{late}} = 520$ ms), $t(24) = 1.79$, $p = .09$, $d = 0.36$, 95% CI [−0.05, 0.76]. Thus, the period following the accuracy breakpoint is one in which participants stably settled on a stimulus–response mapping but during which confidence continued changing in reaction to feedback. Subsequent analyses therefore centered on how feedback was processed during this period with relatively stable accuracy but changing confidence. Aspects of the accuracy data already hint at feedback processing differences: In an analysis of variance comparing the impact of misleading negative feedback (against a baseline of true positive feedback) after correct responses, we observed a larger drop in accuracy (i.e., a greater tendency to switch to the alternative response mapping) in the early compared to late period in Experiment 1, as reflected in the interaction between period and feedback valence: $F(1, 24) = 13.20$, $p = .001$, $\eta_p^2 = 0.36$, but not in Experiment 2 ($F < 1$).

Confidence Updates After Negative Feedback

To provide preliminary evidence for our hypothesis that confidence regulates learning by modulating feedback processing, we quantified

Figure 2

Accuracy Versus Confidence During Learning



Note. (A) Mean accuracy and confidence curves throughout learning in Experiment 1. Dashed vertical lines show the mean breakpoint of each curve. Error bars show SEM. (B) Mean accuracy and confidence curves in the three trials preceding and the four trials following the accuracy breakpoint in Experiments 1 and 2 (data from one participant were omitted in this figure due to the breakpoint in their curve occurring at Trial 2). Error bars show SEM. (C) Mean confidence change after misleading negative feedback in trials following the accuracy breakpoint in Experiment 1. Error bars show SEM. SEM = standard error of the mean.

* $p < .05$.

the extent to which confidence itself shifted in response to feedback as learning progressed. We focused analysis on trials in which participants received negative feedback after a correct response—that is, misleading negative feedback—and predicted that higher initial confidence would be associated with smaller confidence drops after such feedback.

This is a strong prediction: Numerically, any floor effect in confidence ratings would tend to produce the opposite pattern; further, theoretically, many accounts of learning emphasize the critical role of surprise (typically formalized as a prediction error) in learning (Rescorla & Wagner, 1972; Sutton & Barto, 2018). Therefore, prediction errors should be particularly high when negative feedback is received after a high-confidence response, promoting further learning. However, we predicted that people would attend to feedback less when they were more confident in their choices, as they would rely more heavily on their internal knowledge than on external information to determine whether they had made a correct or incorrect choice.

As detailed above, for each participant, we divided trials in the period following the accuracy breakpoint into early versus late bins. Average confidence in the late bin was significantly higher than that in the early bin, Experiment 1: $t(24) = 7.72$, $p < .001$, $d = 1.54$, 95% CI [0.95, 2.12]; Experiment 2: $t(24) = 10.10$, $p < .001$, $d = 2.02$, 95% CI [1.32, 2.70]. However, as predicted, confidence dropped significantly more after participants received misleading negative feedback in the early bin—when absolute confidence levels were generally lower—than in the late bin—when confidence levels were generally higher (Figure 2B), Experiment 1: $t(24) = 2.34$, $p = .03$, $d = 0.47$, 95% CI [0.05, 0.88]; Experiment 2: $t(24) = 2.91$, $p = .008$, $d = 0.58$, 95% CI [0.15, 1.00]. This result suggests that prediction error alone could not have been driving participants' behavior and that confidence might have played a role in regulating the extent to which feedback was evaluated.

Confidence in an Associative Learning Model

To formalize these intuitions that our findings are not easily captured in terms of prediction error learning, and to provide a contrast with our Bayesian model, we implemented a simple model of associative learning in our task. The model chooses responses based on the strength of associations between the presented stimulus and possible response mapping, increasing the strength of the chosen mapping following positive feedback and weakening the association in the case of negative feedback. Trial-by-trial changes in associative strength, or value (V), were implemented according to the Rescorla–Wagner (Rescorla & Wagner, 1972) learning rule as:

$$\Delta V_A = \alpha_A \beta(\lambda - V_A), \tag{3}$$

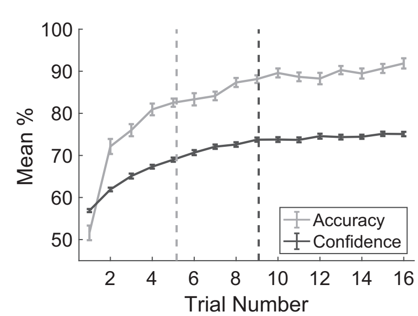
where ΔV_A is the change in the associative strength between the presented stimulus, A, and the chosen response mapping at the end of the trial after feedback delivery; α_A is the associability of stimulus A determined by its salience; β is a learning rate parameter; λ is the reward accrued on the trial (set to 1 on trials with positive feedback and 0 on trials with negative feedback); and V_A is the strength of the stimulus–response association at the start of the trial. α_A and β are free parameters, set to 0.5 here but with qualitatively similar results evident for a range of parameter values. V_A was initialized to 0.5 at the start of each block, reflecting that each response mapping has an equal likelihood at this point. On each trial, a response is chosen according to the same SoftMax rule as in our Bayesian model above, but with a mapping's associative strength, V_A substituting instead of $P(M_i)$. Within this model, confidence is conceptualized as the associative strength of the chosen mapping, and responses are chosen probabilistically according to the relative strengths of the two possible mappings.

Figure 3 plots the simulated accuracy and confidence of this associative learning model of our task, which captures some features of the empirical data but fails to capture others (cf. Figure 2A). Specifically, the model successfully simulates the empirical finding of an accuracy breakpoint that precedes the confidence breakpoint by a few trials. This effect is observed despite the model's choices and confidence both reflecting the learned associative strength (V) between stimuli and responses. The difference in breakpoints arises from the low-temperature parameter in the SoftMax function, which means that even when V is close to 0.5 (i.e., confidence is low in the chosen mapping), the model can achieve high accuracy by applying the mapping consistently in choosing how to respond. In this way, the model captures the intuition that, based on the first few trials of feedback, participants can begin to identify the most likely mapping and choose accordingly, but their confidence that they are choosing correctly may continue to grow as they receive positive feedback on subsequent trials. However, whereas our participants eventually become highly confident that they are choosing the correct mapping, with average confidence approaching 90% by the end of learning blocks and some individual participants reporting 100% confidence (Figure 2A, Supplemental Figure S2), the model's confidence (V) plateaus at 75%. This asymptote is not parameter-dependent in the model but rather is a consequence that V is limited to the maximum likelihood of positive feedback even when responding perfectly accurately in the task.

These successes and failures of the model notwithstanding, the critical discrepancy between the model and the empirical data relates to the effect of misleading negative feedback on confidence (V). As described above, our empirical data confirmed our original prediction that misleading negative feedback would have a greater impact on participants' confidence in the early versus late period after the initial accuracy breakpoint. The opposite pattern is observed in the associative learning model, with a smaller reduction in confidence

Figure 3

Accuracy and Associative Strength in a Rescorla–Wagner Learning Model



Note. Mean response accuracy and associative strength curves averaged across the 16 trials of learning. Dashed vertical lines show the breakpoint of each curve. Error bars show SEM. SEM = standard error of the mean.

in early versus late post breakpoint trials, $t(24) = 6.37$, $p < .001$, $d = 1.28$, 95% CI [0.74, 1.80].

This difference is not parameter-dependent but rather arises as a direct consequence of the prediction error learning rule: Prediction error is greatest late in the block where (based on the recent history of high accuracy and correspondingly positive feedback) there is the strongest prediction of positive feedback. Thus, the empirical pattern of reduced impact of misleading negative feedback late in learning is not an inherent consequence of any learning system since a paradigmatic model of learning in our operant task fails to simulate this effect.

Confidence as Bayesian Updating

By contrast with the associative learning model, general patterns of learning and confidence are captured well by our Bayesian learning model that estimates the probability of (i.e., confidence in) each of the two possible stimulus–response mappings being correct, according to the feedback received and the estimated reliability of that feedback (see the Method section for details). Setting the estimated feedback reliability as the objectively true value of 0.75, and generating responses based on the model's beliefs using a simple SoftMax function, allowed the model to replicate three key characteristics of participants' behavior (Figure 4A).

First, accuracy and confidence peaked at levels well above 75%, despite never receiving positive feedback above this rate. Thus, in contrast to the simple associative learning model, confidence in the Bayesian model (i.e., the model's strength of belief in the correct mapping) can exceed the maximum rate of positive feedback (75%). Second, the accuracy of the model's response decisions reached a plateau earlier than its confidence, $t(24) = 4.13$, $p < .001$, $d = 0.83$, 95% CI [0.36, 1.27]. As with the prediction error learning model, the Bayesian model can choose consistently according to its current estimate of the correct rule, even before it gains high confidence that this rule is in fact correct. Last, and crucially in contrast to a simple prediction-error model, the change in the model's confidence after receiving misleading negative feedback was significantly greater in the first half than in the second half of trials after the response accuracy curve breakpoint, $t(24) = 10.71$, $p < .001$, $d = 2.14$, 95% CI [1.42, 2.85], consistent with our empirical data.

Decreased updating of one's belief with stronger priors is an intrinsic feature of Bayesian learning (Meyniel & Dehaene, 2017; Meyniel, Sigman, & Mainen, 2015). Thus, our finding that confidence was more affected by misleading feedback earlier versus later in learning is not a unique prediction of our key hypothesis that confidence regulates feedback processing. However, additional modeling suggests that discounting of feedback later in learning in the current task goes beyond the simple Bayesian prescription. Instead of updating beliefs according to the true feedback reliability of 0.75, we allowed this parameter to vary, capturing the idea that participants might represent the informational value of feedback as labile and differing from its objective reliability. When fit to the across-participant averaged learning and confidence curves (pooled across Experiments 1 and 2), the version of this model that generated the least squared errors compared to the empirical data used an estimated feedback reliability of 0.60 (Figure 4B), suggesting that, overall, participants treated feedback as less reliable than it really was.

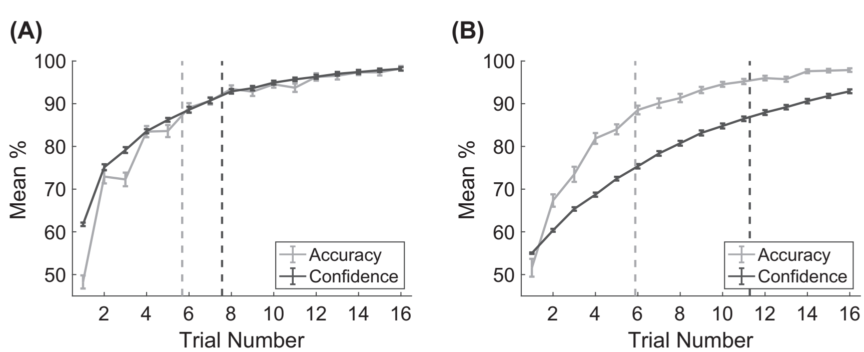
Taking this analysis a step further, we used Bayes' rule to derive feedback reliability values from each participant's observed changes in confidence from one trial to the next throughout learning. We found that these values were significantly higher in early than late trials after the accuracy breakpoint, $t(49) = 4.95$, $p < .001$, $d = 0.70$, 95% CI [0.39, 1.01]; Supplemental Figure S3. That is, participants overdiscounted feedback compared to the normative learning trajectory of the Bayesian model, and they did so in a manner that varied dynamically during learning, with greater deviations from simple Bayesian updating as learning progressed (and confidence increased). Our interpretation of this difference is that it reflects a decrease in the informative value that participants attribute to feedback as confidence in their knowledge increases, even though feedback reliability was fixed at 0.75 throughout each block. For this reason, we will refer to it henceforth as *perceived feedback informativeness*.

Confidence Modulates Neural Correlates of Feedback Processing

If greater confidence leads to a decrease in the extent to which people process feedback, we would expect to see this reflected in neural responses to feedback presentation. In Experiment 2, we

Figure 4

Accuracy and Confidence in a Bayesian Learning Model



Note. Mean response accuracy and confidence curves throughout 16 trials of learning for the Bayesian model using the objective feedback likelihood value of 0.75 (A) and the best-fitting value to participants' responses in Experiments 1 and 2 of 0.60 (B). Dashed vertical lines show the breakpoint of each curve, determined via the same piecewise linear function as was applied to the empirical data. Error bars show SEM. SEM = standard error of the mean.

therefore collected EEG data as participants performed the task. The analysis focused on two ERPs that are known to index distinct aspects of feedback processing during learning—the FRN and the P300 (Chase et al., 2011; Rose et al., 2001; Strayer & Kramer, 1990; Walsh & Anderson, 2012; Yeung et al., 2005; Yeung & Sanfey, 2004).

The FRN reflects a rapid evaluation of feedback valence (occurring approximately 250 ms after feedback delivery) and has been characterized as varying with negative reward prediction error—that is, increasing in amplitude to the degree that outcomes are worse than expected (Holroyd & Coles, 2002; Sambrook & Goslin, 2015). On this view, we would expect FRN amplitude to be larger late in learning—when confidence is high and negative feedback should generate a large prediction error—than earlier in learning when confidence is low and negative feedback is more likely and therefore expected. However, comparing FRN amplitude following misleading negative feedback early versus late in learning (again in the period after accuracy breakpoint, where accuracy was relatively stable) revealed numerically larger FRN amplitude in the early period (early FRN: $M = 12.4$ µV, $SD = 5.7$ µV vs. late FRN: $M = 11.6$ µV, $SD = 5.0$ µV), although the difference was not statistically reliable, $t(24) = 1.61$, $p = .12$, $d = 0.32$, 95% CI [−0.08, 0.72].

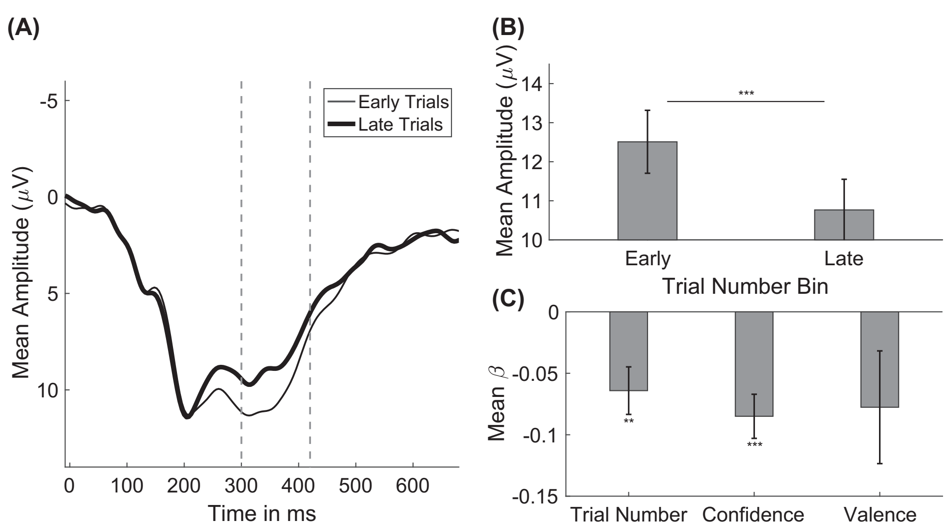
This analysis confounds the conflicting effects of prediction error (Holroyd & Coles, 2002) and feedback informativeness (Schiffer et al., 2017) in our task. To tease apart these factors, we therefore ran a separate linear regression on each participant's trials in the post accuracy breakpoint period with trial number, feedback valence, and confidence as predictors of FRN amplitude. Specifically, we used confidence on trial $t - 1$ to predict component amplitude on trial t: As confidence was rated at the end of each trial after feedback was provided, rated confidence on the previous trial was the key predictor of the informativeness of feedback on the current trial. We then averaged the resulting β values for each predictor (denoted β_M, with SD β_{SD}) across the individual participants' regressions and compared them to zero.

As expected, there was a significant effect of valence, $\beta_M = 0.29$, $\beta_{SD} = 0.43$, $t(24) = 3.37$, $p = .003$, $d = 0.67$, 95% CI [0.23, 1.10], indicating larger FRN amplitude to negative than positive feedback (see Supplemental Figure S6). The effect of confidence did not differ significantly from zero, $\beta_M = 0.01$, $\beta_{SD} = 0.08$, $t < 1$. However, a significant effect of trial number, $\beta_M = -0.04$, $\beta_{SD} = 0.08$, $t(24) = 2.66$, $p = .01$, $d = 0.53$, 95% CI [0.11, 0.95], indicated that feedback received later in a block elicited smaller FRNs than feedback received earlier in a block, suggesting increased discounting of feedback as learning progressed. The interaction between confidence and feedback valence was not significant, $\beta_M = 0.03$, $\beta_{SD} = 0.14$, $t(24) = 1.08$, $p = .29$, $d = 0.22$, 95% CI [−0.18, 0.61].

Overall, analysis of the FRN does not allow us to determine conclusively whether and how confidence affected learning. The average β value for confidence, was not significantly different from zero. Conversely, the negative average β value for trial number is consistent with our proposal that feedback is discounted as learning progresses. However, the latter effect could also reflect a natural decline in FRN amplitude throughout a block irrespective of processes related to confidence or learning (Sailer et al., 2010).

The impact of confidence was clearer in analyses of the P300 (Figure 5), a component that is not subject to the confounding influence of prediction error (Chase et al., 2011; Yeung & Sanfey, 2004). Instead, it is held to reflect attention related to the evaluation of feedback (Datta et al., 2007; Polich, 2007; Rose et al., 2001;

Figure 5
Feedback Processing as a Function of Confidence



Note. (A) Grand averaged event-related potentials in early and late trials post accuracy breakpoint for a cluster of centro-parietal electrodes comprising CP3, CPZ, CP4, P3, PZ, P4, and POZ, with a prominent P300 peak in the period from 200 to 400 ms post feedback onset. The 0 ms mark represents feedback onset. Dashed vertical lines indicate the time window within which the P300 was quantified. (B) Binned P300 amplitude in early and late trials post accuracy breakpoint. Error bars show SEM. (C) Regression coefficients for trial number, confidence on the previous trial, and feedback valence as predictors of P300 amplitude. Error bars show SEM. SEM = standard error of the mean.
** $p < .01$. *** $p < .001$.

Strayer & Kramer, 1990; Wu & Zhou, 2009) and the likelihood of behavioral adaptations resulting from incoming information (Chase et al., 2011; Schiffer et al., 2017).

Analysis of trials in the period following the accuracy breakpoint revealed significantly larger P300 amplitude to feedback early versus late in learning (Figure 5A and 5B; early P3: $M = 12.5$ μV, $SD = 4.0$ μV vs. late P3: $M = 10.8$ μV, $SD = 3.9$ μV), $t(24) = 3.89$, $p < .001$, $d = 0.78$, 95% CI [0.32, 1.22]. A more detailed regression analysis on trials in the post accuracy breakpoint period, with confidence, feedback valence, and trial number as predictors (Figure 5C), revealed that trial number was a significant negative predictor of P300 amplitude, $\beta_M = -0.06$, $\beta_{SD} = 0.10$, $t(24) = 3.32$, $p = .003$, $d = 0.66$, 95% CI [0.22, 1.09], as for the FRN. Crucially, P300 amplitude was also significantly predicted by confidence, $\beta_M = -0.09$, $\beta_{SD} = 0.09$, $t(24) = 4.74$, $p < .001$, $d = 0.95$, 95% CI [0.47, 1.41], such that greater confidence was associated with reduced P300 amplitude. Thus, this analysis converges with the FRN results in suggesting reduced processing of feedback as learning continues and shows further that confidence predicts unique variance in feedback processing. β values for feedback valence ($\beta_M = -0.08$, $\beta_{SD} = 0.23$), $t(24) = 1.69$, $p = .10$, $d = 0.34$, 95% CI [−0.07, 0.74], and for the interaction between confidence and feedback valence ($t < 1$) were not significantly different from zero.

Given this relationship between confidence and feedback processing, we assessed whether the amplitude of the feedback P300 would also be predicted by model-derived estimates of perceived feedback informativeness. As described above, this parameter provides an estimate of participants' down-weighting of feedback as their confidence in learning increased, over and above simple Bayesian belief updating. A regression with trial number and perceived feedback informativeness as predictors of P300 amplitude replicated the effect of trial number described above ($\beta_M = -0.09$, $\beta_{SD} = 0.09$), $t(24) = 4.73$, $p < .001$, $d = 0.95$, 95% CI [0.47, 1.41], but crucially also revealed that perceived feedback informativeness positively predicted P300 amplitude ($\beta_M = 0.07$, $\beta_{SD} = 0.09$), $t(24) = 3.82$, $p < .001$, $d = 0.76$, 95% CI [0.31, 1.20]. This effect suggests that P300 amplitude at feedback delivery increased as a function of the perceived informativeness of feedback or, in other words, that participants processed the feedback to a greater degree as they tended to perceive it as more informative.

Discussion

Experiments 1 and 2 provide a novel exploration of confidence and its relation to objective accuracy in a probabilistic learning task. We find that confidence tracks objective accuracy but critically lags it during the learning process such that confidence continues to increase even after participants' objective performance stabilizes and settles on a choice rule that is, on average, highly accurate. Thus, in common with metacognitive judgments of confidence in other domains, such as memory and decision making, people's self-evaluations are a correlated but imperfect gauge of their objective performance.

Methodologically, the observed dissociation between objective accuracy and subjective confidence provides an opportunity to study the influence of confidence on the learning process, enabling us to assess how confidence affects behavioral and neural indices of feedback processing during a phase of learning where objective performance is relatively stable. Our results indicate that confidence negatively modulates feedback processing in this task—reflected in reduced impact of misleading negative feedback on learning and reduced amplitude of EEG indices of feedback processing.

These findings are not inherent features of learning in our task, as demonstrated by the fact that standard prediction-error learning models fail to capture the empirically observed effects. Instead, we find that these effects can be characterized by a Bayesian model that overdiscounts incoming information as prior beliefs become stronger and the perceived gain in information from feedback decreases. Critically, our findings go beyond previous accounts of the effect of confidence on learning: Within a standard Bayesian account, a confident learner will tend to discount negative feedback as reflecting the unreliability of the feedback, whereas an unconfident learner will tend to interpret the same feedback as an indication that their response was incorrect (Meyniel, Sigman, & Mainen, 2015). Our findings suggest further that the confident learner, anticipating the reduced informativeness of feedback given the security of their existing knowledge, will pay less attention to processing that feedback, above and beyond discounting its impact on current beliefs. This reduced attention to feedback is apparent in both our behavioral data—where Bayesian analysis suggests that participants reduce their estimate of the informativeness of feedback as learning progresses—as well as in our EEG data—where we find that confidence predicts a reduced P300 to feedback.

A prediction that follows from our account is that, if the perceived informative value of feedback drops when confidence is high, people should be less willing to incur a cost to obtain feedback when it comes at a price. Experiment 3 tested this prediction directly, using an extension of the same learning task as above: In half of the blocks, participants were provided with feedback on all trials (as in Experiments 1 and 2) but, critically, in the other half, they had to choose on each trial whether to pay a fee to view feedback or to avoid the fee and skip to the next trial. Confidence was sampled immediately after a response was made (i.e., before feedback choice and delivery), enabling us to evaluate the relationship between confidence and feedback seeking.

Experiment 3

This experiment tested directly whether participants' decision to seek feedback depends on subjective confidence. In blocks where participants could choose to skip feedback and its associated cost, we expected that they would do so once they perceived that they had learned the rule for the new pair of stimuli in the block. Our key preregistered prediction was that across-participant variation in the point at which participants stopped asking for feedback would be predicted by variation in confidence—specifically the point at which each participant's confidence reached its breakpoint—and more so than by variation in objective accuracy.

Method

Participants

A total of 27 participants took part in Experiment 3 to obtain 25 participants as in the previous experiments (14 self-identified as cisgender women and 11 as cisgender men, aged 18–35). Two participants' data were excluded from analysis for failing to reach a preregistered accuracy criterion (their accuracy fell over 2 *SD*s below the mean sample accuracy). Recruitment was as for Experiments 1 and 2.

Procedure

The task was similar to that of Experiments 1 and 2. However, in this experiment, participants first rated their confidence in each trial before viewing feedback. Further, feedback came at a cost, and in half the blocks (experimental blocks) participants could choose on each trial whether to view the feedback or to decline it, whereas in the other half (control blocks), they viewed feedback on every trial (Figure 6).

Trials began with a fixation screen for 500 ms, followed by the flashing of a stimulus at the center of the screen for 200 ms. Participants had 1,750 ms to respond using the right or the left mouse button. Following a 500-ms interval, participants rated their confidence on the same scale as in Experiments 1 and 2. After having registered their confidence, a 500-ms interval preceded the appearance of the feedback question: In the key experimental blocks, two boxes appeared, one labeled "Pay 2 points for feedback" and the other labeled "Skip feedback for free." Participants were instructed to click on the appropriate box. In control blocks with compulsory feedback, instead, participants saw a single option after rating their confidence, "Pay 1 point to view feedback," which they had to click before continuing.

Participants were informed that, in both block types, correct responses would earn 3 points, whereas incorrect responses lost 3 points. Therefore, in experimental blocks, they could lose up to a maximum of 5 points per trial if they chose to view feedback following an incorrect response, and they could earn up to a maximum of 3 points per trial if they chose to forgo feedback following a correct response. Total points were converted to a monetary bonus at the end of the experiment, with 3 points worth £0.01.

If participants chose to view the feedback, a green smiley face or a red displeased face appeared at the center of the selected box (as in Experiments 1 and 2) for 400 ms. If they chose to forgo feedback, the screen remained empty for the same interval duration. Following the 500-ms intertrial interval, the subsequent trial began. Participants completed two practice blocks—one of each type—followed by 20 experimental and 20 control blocks of 16 trials each. The order of presentation of the two block types was randomized, and instructions about which block type was about to begin were displayed onscreen prior to the start of a block.

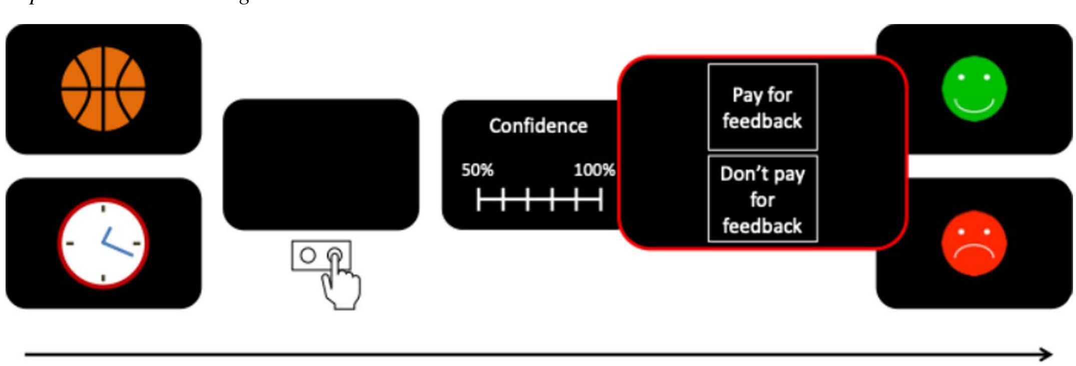
Analysis Plan

As with Experiments 1 and 2, participants' confidence and accuracy curves throughout learning were fitted with a piecewise linear function that generated individual breakpoints for each variable. In this experiment, separate breakpoints were calculated for control and experimental blocks.

To test the main prediction that people used subjective confidence rather than objective accuracy to guide their feedback-seeking choices, we performed hierarchical regressions with accuracy and confidence as predictors of when participants would stop paying for feedback. We defined this point as the first time that participants declined viewing feedback twice consecutively in an experimental block, irrespective of whether they subsequently returned to viewing feedback within that block. We used each participant's breakpoints for confidence and accuracy in the control blocks—as participants received feedback on every trial in this condition—as the predictors and ran two separate regressions: in one, the accuracy breakpoint was entered into the model first and the confidence breakpoint second; in the other regression, the order in which the two variables were entered was reversed.

To assess each participant's consistency in feedback-seeking as a function of confidence, we calculated the area under the receiver operating characteristic curve generated by plotting hit rate against false alarm rate: Hit rate was defined as the proportion of all trials in which feedback was declined that exceeded a threshold level of confidence, while false alarm rate was defined as the proportion of all trials in which feedback was accepted that exceeded this threshold. These values were calculated separately for each possible level of confidence to construct the receiver operating characteristic curves.

Figure 6
Experiment 3 Task Design



Note. One of two stimuli appeared on each trial at the centre of the screen for 150 ms. Participants had 1750 ms to respond using either the right or the left mouse button, after which they rated their confidence in having selected the correct response on a scale from 50–100%. After rating their confidence, participants could choose whether to pay two points to view feedback or to forgo it for free. Paying for feedback revealed feedback, which was 75% reliable; not paying for feedback led to the subsequent trial. See the online article for the color version of this figure.

Transparency and Openness

We preregistered the experimental design, including sample size, and main analyses at https://osf.io/6yxjv. Experimental data are also available in an online repository (https://osf.io/96dwn). Our key preregistered analyses were the two hierarchical regressions described above. We predicted that when participants' confidence breakpoints were introduced as a predictor after the accuracy breakpoints, they would significantly predict when participants stopped paying for feedback. Conversely, when the accuracy breakpoint was introduced as a predictor after the confidence breakpoint, it would not significantly predict when participants stopped paying for feedback.

Results

As in Experiments 1 and 2, on average, participants' accuracy curve reached breakpoint significantly earlier than the confidence curve in both control blocks, $t(24) = 4.31$, $p < .001$, $d = 0.86$, 95% CI [0.40, 1.32], and in experimental blocks, $t(24) = 5.05$, $p < .001$, $d = 1.01$, 95% CI [0.52, 1.49]; see Supplemental Figure S4.

Confidence Predicts Feedback Seeking

Overall, participants sought feedback adaptively, reducing their rate of feedback seeking as learning progressed (Figure 7A). Crucially, consistent with our prediction, participants' reported confidence predicted their choice of when to stop seeking feedback, whereas their objective accuracy correlated very weakly with feedback-seeking choices (Figure 7B). The preregistered hierarchical regressions confirmed these visual impressions: Specifically, a first hierarchical regression showed that the timing of participants' confidence breakpoint significantly predicted when they would stop paying for feedback, $\beta = 0.52$, $t(24) = 2.82$, $p = .01$, even after adjusting for their individual accuracy breakpoints. Conversely, after adjusting for the timing of participants' confidence breakpoints in a second regression, the timing of their accuracy breakpoint did not significantly predict their feedback-seeking behavior ($\beta = 0.02$, $t < 1$). As a follow-up to these preregistered regression analyses, based on a reviewer's suggestion, we also compared the correlation coefficients for confidence and accuracy breakpoints as predictors of declining feedback (taking into account that these correlations share a variable in common; Lee & Preacher, 2013). This analysis revealed a significant difference (Steiger's $Z = 1.73$, $p = .042$, one-tailed given our directional prediction), suggesting, again, that subjective confidence predicts feedback-seeking behavior more strongly than objective performance.

Exploratory analyses revealed that feedback-seeking choices were also predicted by confidence at a within-participant level. In a receiver operating characteristic curve analysis of participants' trial-wise choice of whether or not to seek feedback as a function of trial-reported confidence (see the Method section), confidence very consistently predicted information seeking and did so almost perfectly in many participants, median area under the curve = 0.93, range = 0.56–0.98, significantly greater than chance (0.5), $t(24) = 19.77$, $p < .001$, $d = 3.95$, 95% CI [2.77, 5.13]; see Supplemental Figure S5.

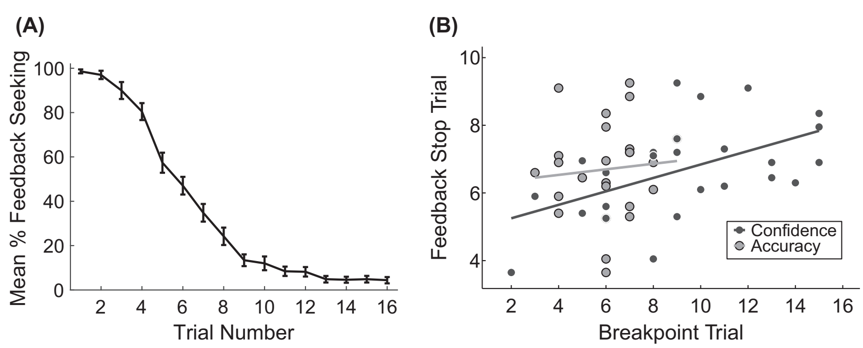
Moreover, although participants rarely returned to asking for feedback after having initially stopped paying for it in a given block (on 3% of trials following the first successive pair of trials in which feedback was declined), for those participants who did so ($N = 21$), confidence was significantly lower on such trials ($M = 79$, $SD = 12$) than when they continued declining it ($M = 87$, $SD = 12$), $t(20) = 4.20$, $p < .001$, $d = 0.92$, 95% CI [0.40, 1.42]. This comparison of confidence between declined versus viewed feedback remained significant even when the analysis was limited to those participants ($N = 9$) who had more than 10 trials across all blocks in which they returned to requesting feedback after two or more successive trials of declining it.

Discussion

The results of Experiment 3 replicated the relationship observed in Experiments 1 and 2 between subjective confidence and objective accuracy in a learning task: Increases in confidence during learning

Figure 7

Feedback Seeking in Experiment 3



Note. (A) Mean percentage of trials on which participants paid to view feedback, as a function of trial number in each block. Error bars show SEM. (B) Relationships between accuracy and confidence breakpoint and mean trial number on which participants stopped paying for feedback in a block. Lines are the least squared error line for each variable with 95% confidence intervals (shaded gray areas). Separate pairwise correlations revealed a significant correlation with feedback stop trial for the confidence breakpoint, $r(23) = 0.52$, $p < .01$, but not for the accuracy breakpoint, $r(23) = 0.09$, $p = .68$. SEM = standard error of the mean.

lagged behind improvements in objective accuracy, such that confidence continued to increase for a few trials after participants adopted a relatively stable, accurate response strategy. Critically, in blocks where participants could choose to skip otherwise costly feedback, we found that confidence predicted feedback-seeking choices: Across participants, individual differences in the choice over when to stop receiving feedback were predicted by individual differences in confidence even after accounting for individual differences in objective accuracy; the opposite was not true. Within participants, trial-wise choices of whether to seek or skip feedback were likewise well predicted by subjective confidence ratings.

General Discussion

Since being proposed as an area of inquiry (Flavell, 1979), research on metacognition has identified several ways in which the ability to represent one's cognitive processes contributes to decision making, from guiding the selection of study strategies (Bjork et al., 2013; Metcalfe & Finn, 2008; Nelson & Dunlosky, 1991) to weighting the reliability of advice (Bahrami et al., 2010; Pescetelli et al., 2016). One area that has recently received attention is associative learning, where evidence suggests that people accurately represent uncertainty in a learning environment and use their confidence in their knowledge to modulate the rate of learning (Meyniel & Dehaene, 2017; Meyniel, Schlunegger, & Dehaene, 2015).

Our findings extend these ideas to show that, anticipating a reduction in the value of new information relative to prior knowledge as confidence increases, learners will correspondingly reduce the resources they devote to seeking and processing feedback (cf. Oaksford & Chater, 1994; Sims, 2003). Thus, analysis of participants' confidence reports using our Bayesian model suggests that participants reduce the weight they assign to feedback as their learning progresses and do so beyond a simple Bayesian prescription. More directly, we find that confidence predicts participants' EEG response to feedback and their willingness to pay for feedback when it is optional and costly. In this way, information about the state of learning influences decisions about whether to seek feedback and, if feedback is available, how to allocate attention to it. These results are consistent with the crucial role of explicit metacognitive representations in making information globally available to the wider cognitive system (Dehaene & Changeux, 2011; Nelson & Narens, 1990).

Our findings provide converging evidence that confidence modulates the weight of incoming feedback during learning, hence predicting variations in feedback processing and in participants' feedback-seeking choices. Confidence judgments made late in a block—when average confidence was high—dropped less in response to negative feedback than did earlier judgments—when average confidence was lower—even when objective response accuracy was relatively stable across the two phases. This pattern cannot be explained in terms of simple prediction error, which should be larger later in learning, and instead can be explained by the idea that feedback is weighted by its estimated informativeness (Schiffer et al., 2017). Consistent with this interpretation, in our ERP data, we found that the amplitude of the P300 following feedback delivery was larger early than late in a block and was predicted negatively by participants' rated confidence and positively by a model-derived estimate of feedback informativeness.

Confidence may have influenced feedback processing in various ways. For instance, it may have modulated how much attention was paid to feedback, how the feedback was weighted in the calculation of the prediction error, or how prediction errors impacted the strength of the learned associations. The EEG results shed some light in this respect, as confidence negatively predicted the amplitude of the P300 but not that of the FRN. These components track distinct aspects of feedback processing: Whereas the FRN is thought to reflect prediction error (Chase et al., 2011; Holroyd & Coles, 2002; Oliveira et al., 2007), the P300 has been linked to upcoming behavioral adaptations (Chase et al., 2011; Schiffer et al., 2017) and allocation of attention to feedback (Polich, 2007; Wu & Zhou, 2009). As such, the present results are more congruent with confidence playing a role in regulating attentional mechanisms of feedback evaluation or behavioral changes in response to feedback.

Our modeling results show that a simple Bayesian model generates beliefs that are qualitatively similar to our participants' confidence ratings. However, when we allowed variation in a parameter that represented the perceived informativeness of feedback, we found that the best-fitting model took a parameter value that fell well below the objectively correct (and instructed) value of feedback reliability in our task (0.60 best fit vs. 0.75 objective reliability). Correspondingly, when we derived a trial-varying estimate of perceived feedback informativeness—based on inverting Bayes' rule applied to confidence ratings on successive trials—we replicated this finding and observed, additionally, that the fitted values varied across learning and did so in a manner that was predictive of observed neural responses to feedback. As such, our findings indicate that participants deviated from optimal Bayesian learning in a systematic way, overdiscounting feedback as learning progressed.

Importantly, discounting feedback can have obvious downsides, especially when it is available for free as in Experiments 1 and 2. The overdiscounting we found in our results occurred in the context of a stable learning environment in which participants knew that stimulus–response mappings remained stable throughout learning. However, in a volatile environment in which contingency rules may vary, and perhaps even reverse, ignoring evidence when highly confident could lead to missing crucial, new information, producing inflexible and inadequate behaviors. Especially in high-stakes situations like the operating theater or the political arena, thus, overconfidence could have substantial effects, as decisions could be made suboptimally, in disregard of up-to-date evidence. Further research will be needed to evaluate whether people discount feedback in a similar way also in more unstable situations, where relationships within the environment may change.

The way that confidence influenced feedback-seeking choices in Experiment 3, when feedback came at a cost, hints at a potential reason for the discounting we found in the first two experiments. Specifically, it could be that feedback processing is associated with implicit costs in the same way as other aspects of cognitive control are (Cools, 2016; Froböse et al., 2018; Manohar et al., 2015). For instance, attending to feedback may be expensive in terms of resources like attentional or working memory capacity (Tumber et al., 2014). Feedback processing could also incur opportunity costs (Boureau et al., 2015), such that allocating resources to it reduces one's ability to focus on competing goals. In our task, the opportunity costs could result from the engagement of attentional and/or working memory resources involved in associative learning (Collins et al., 2014; Collins & Frank, 2012). Therefore, when confidence is high and there is little left to learn from further feedback, a decision is made to disengage from its evaluation.

In this way, representations of local uncertainty (here regarding associative learning) can contribute to the broader optimization of a person's behavior. This optimization parallels that seen in other forms of metacognition, such as evaluations of decision confidence governing whether to seek more information before committing to a choice (Desender et al., 2018), or metamemory evaluations in educational settings, where confidence in knowledge of material ahead of a test determines which items people choose to revise and how much time they spend revising (e.g., Bjork et al., 2013; Metcalfe & Finn, 2008; Thiede, 1999). Our findings show that similar metacognitive regulation operates even in basic learning processes. Methodologically, these results show that participants' explicit confidence reports can provide a useful window into the associative learning process: We found significant variation in confidence during a period in which objective performance was largely stable, and that variations in confidence were predictive of subtle features of the learning process. Sensitivity to our own uncertainty is a determiner of our learning and may provide a more general metacognitive influence on cognition and behavior. Conceptually, our findings add to the growing body of evidence showing a pervasive influence of metacognitive regulation in cognitive processes.

Constraints on Generality

The studies reported in this article target healthy, working-age adults with no known cognitive impairments. The sample tested consisted of a mixture of university students and people from the local, general population. We would expect the results to generalize to all cognitively healthy adults, as we did not target a specific, limited participant sample, and we view our experimental task as probing cognitive functions—learning from feedback and judging confidence in that learning—that are core and general, rather than specific to particular individuals. However, as a frontal function closely related to other executive functions (Kraft et al., 2017; Roebers, 2017), metacognitive abilities too might decline in later life, and as such, the pattern of results observed in this study might vary in older adults.

The stimuli used consisted of images of everyday objects, and the responses were mouse clicks. Given the simplicity of the design, the pattern of results found is expected to replicate in any instrumental learning situation without reversals and with probabilistic feedback. We would further expect the results to generalize to other learning tasks characterized by feedback that is imperfect (or perceived as such by learners), such as in education settings.

One factor that might impact the results, however, is the level of cognitive load placed on participants during the task, as metacognitive sensitivity has been shown to rely on cognitive resources shared with other mechanisms (e.g., perceptual vigilance; Maniscalco et al., 2017). Therefore, if a different task-related function was taxed more heavily by modifying the design (e.g., adding complexity to the stimuli or to the stimulus–response associations) or adding a separate task onto the paradigm, it is possible that confidence judgments would be affected and differ from those observed in our study.

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