I knew that! Response-based Outcome Predictions and Confidence Regulate Feedback Processing and Learning

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Abstract

Influential theories emphasize the importance of predictions in learning: we learn from feedback to the extent that it is surprising, and thus conveys new information. Here we explore the hypothesis that surprise depends not only on comparing current events to past experience, but also on online evaluation of performance via internal monitoring. Specifically, we propose that people leverage insights from response-based performance monitoring – outcome predictions and confidence – to control learning from feedback. In line with predictions from a Bayesian inference model, we find that people who are better at calibrating their confidence to the precision of their outcome predictions learn more quickly. Further in line with our proposal, EEG signatures of feedback processing were sensitive to the accuracy of, and confidence in, post-response outcome predictions. Taken together, our results suggest that online predictions and confidence serve to calibrate neural error signals to improve the efficiency of learning.

Keywords: confidence, reinforcement learning, graded feedback

Feedback is crucial to learning and adaptation. Across domains it is thought that feedback drives learning to the degree that it is unexpected and, hence, provides new information, e.g. in the form of prediction errors that express the discrepancy between actual and expected outcomes [1-9]. Yet, the same feedback can be caused by multiple sources: we may be wrong about what is the correct thing to do, or we may know what to do but accidentally still do the wrong thing [10]. When we know we did the latter, we should discount learning about the former [11,12] (cf. Fig. 1A). How do people assign credit to either of these potential causes of feedback when learning how to perform a new task? How do they regulate how much to learn from a given feedback depending on how much they know about its causes?

Performance monitoring, i.e., the internal evaluation of one's own actions, could reduce surprise about feedback and uncertainty about its causes by providing information about execution errors. In simple categorical choices, people are often robustly aware of their response errors [13-16] and this awareness is reflected in neural markers of error detection [17]. Although errors are often studied in simple categorization tasks in which responses are either correct or incorrect, in many tasks, errors occur on a graded scale (e.g., an arrow can miss the target narrowly or by a large margin), and both error detection, as well as feedback processing are sensitive to error magnitude [18-21]. People are even able to report gradual errors reasonably accurately [22,23].

This ability may be afforded by reliance on internal models to predict the outcome of movements [24], e.g. based on an efference copy of a motor command. These predictions could help discount execution errors in learning from feedback. In fact, if these predictions perfectly matched the execution error that occurred, the remaining mismatch between predicted and obtained feedback (sensory prediction error) could serve as a reliable basis for adaptation and render feedback maximally informative about the mapping from actions to outcomes.

Although participants are able to evaluate their own performance reasonably well, error detection is, however, far less certain than outlined in the ideal scenario above. People are critically sensitive to uncertainty, and learn more from feedback when they expect it to be more informative [1,25-28]. Uncertainty about what caused a given feedback inevitably renders it less informative, similar to decreases in reliability, and this uncertainty should be taken into account when learning from it. Confidence could support such adaptive learning from feedback by providing a read-out of the subjective precision of predicted outcomes [27,29-31], possibly relying on shared neural correlates of confidence with error detection[32,33]. Similar to its role in regulating learning of transition probabilities [30,34], information seeking/exploration in decision making [35,36], and hierarchical reasoning[37], people could leverage confidence to calibrate their use of online predictions.

In the present study, we tested the hypothesis that performance monitoring – error detection and confidence [38] – adaptively regulates learning from feedback (Figure 1A). This hypothesis predicts that error detection and confidence afford better learning and that learning is compromised when confidence is mis-calibrated. It further predicts that established neural correlates of feedback processing, such as the feedback-related negativity (FRN) and the P3a[40], should integrate information about post-response outcome predictions and confidence. That is to say, an error that could be predicted based on internal knowledge of how an action was executed should not yield a large surprise (P3a) or reward prediction error (FRN) signal in response to an external indicator of the error (feedback). We formalize our predictions using a Bayesian model of learning and test them using behavioral and EEG data in a modified time-estimation task.

Results

Rationale and Approach

Our hypothesis that performance monitoring regulates adaptive learning from feedback makes two behavioral predictions: 1) The precision of outcome predictions (i.e., the correlation between predicted and actual outcomes) should increase with confidence. 2) Learners with superior calibration of confidence to the precision of their outcome predictions should learn more quickly. Our hypothesis further predicts that feedback processing will be critically modulated by an agent's outcome prediction and confidence. We tested these predictions mechanistically using computational modeling and empirically based on behavioral and EEG data from 40 participants performing a modified time-estimation task (Figure 1B).

A Mechanism for Performance Monitoring-Augmented Learning

As a demonstration of proof of these learning principles, we implemented a computational model that uses performance monitoring to optimize learning from feedback (Figure 1C). The agent's goal is to learn the mapping between its actions and their outcomes (sensory consequences) in a time-estimation task wherein feedback on an initially unknown scale must be used to learn accurately-timed actions. Learning in this task is challenged in two ways: First, errors signaled by feedback include contributions of motor noise, that is, variability in the motor system. Second, the efference copy of the executed response varies in its precision. To overcome these challenges, the agent leverages performance monitoring: It infers the contribution of motor noise to a given outcome based on an outcome prediction derived from the efference copy, and the degree of confidence in its prediction based on an estimate of the current efference copy noise. The agent then weighs Prediction and Intended Response as a function of

Confidence and Motor Noise when updating beliefs about the Target and the Scale based on Feedback.

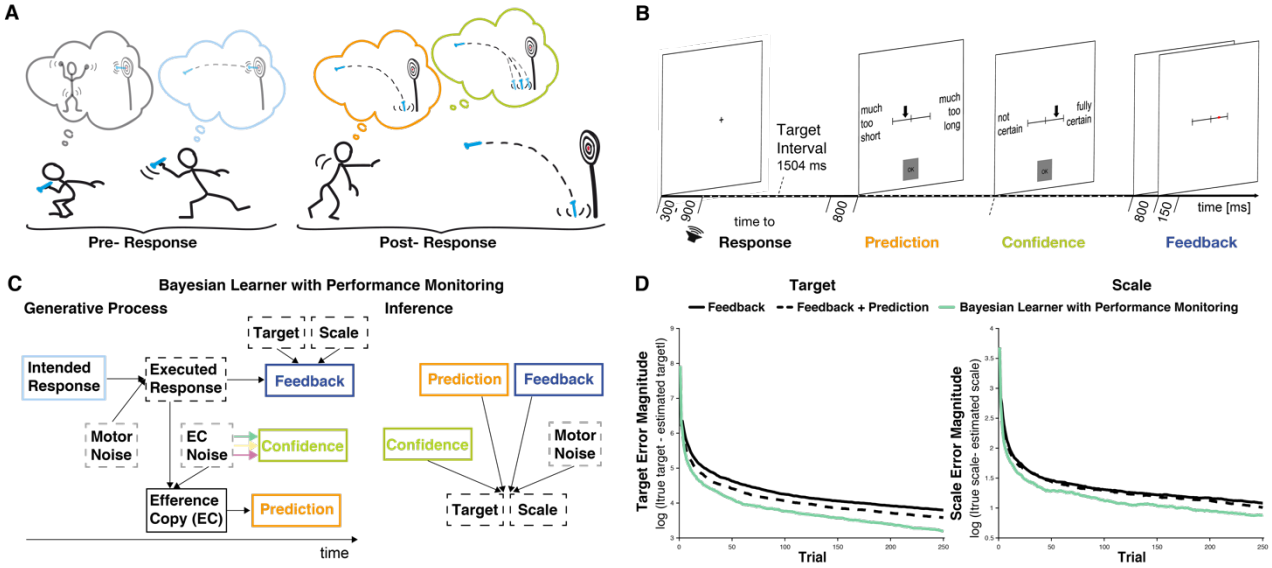


Figure 1. **Interactions between performance monitoring and feedback processing. A** Illustration of dynamic updating of predicted outcomes based on response information. Pre-response the agent aims to hit the bullseye and selects the action he believes achieves this goal. Post-response the agent realizes that he made a mistake and predicts to miss the target entirely, being reasonably confident in his prediction. In line with his prediction and thus unsurprisingly the darts hits the floor. **B** Trial schema. Participants estimated a time interval by pressing a button following a tone. Subsequently, they used an arrow slider to first estimate their accuracy (anchors: "much too short" = "viel zu kurz" to "much too long" = "viel zu lang") and then their confidence in that estimate (anchors: "not certain" = "nicht sicher" to "completely certain" = "völlig sicher"). Finally, feedback was provided. The current error was displayed as a red square on the feedback scale relative to the target interval at the center (Target) and scaled relative to the feedback anchors of -/+ 1s (Scale; cf. Fig. 3). Participants are told neither Target nor Scale and instead need to learn them. **C** Bayesian Learner with Performance Monitoring. The learner selects an intended response based on the current estimate of the Target. The Intended Response and independent Motor Noise produce the Executed Response. The Efference Copy of this response varies in its precision as a function of Efference Copy Noise. It is used to generate a Prediction as the deviation from the estimate of Target scaled by the estimate of Scale. The Efference Copy Noise is estimated and expressed as Confidence, approximating the precision of the Prediction. Learners vary in their Confidence Calibration, i.e. the precision of their predictions, and higher Confidence Calibration (arrows: green > yellow > magenta) leads to more reliable translation from Efference Copy precision to Confidence. Feedback is provided according to the Executed Response and depends on the Target and Scale, which are unknown to the learner. Target and Scale are inferred based on Feedback, Motor Noise, Prediction, and Confidence. Variables that are observable to the learner are displayed in solid boxes, whereas variables that are only partially observable are displayed in dashed boxes. **D** Target and scale error (absolute deviation of the current estimates from the true values) for the Bayesian learner with Performance monitoring (green, optimal calibration), a Feedback-only Bayesian Learner (solid black), and a Bayesian Learner with Outcome Prediction (dashed black).

We compare this model to one that has no insights into its trial-by-trial performance, but updates based on feedback and its fidelity due to motor noise alone (Feedback), and another

model that has insights into its trial-by-trial performance allowing it to generate predictions, and into the average precision of its predictions, but not the precision of its current prediction (Feedback + Prediction). We find that performance improves as the amount of insight into the agent's performance increases (Fig, 2 D): The optimally-calibrated Bayesian learner with performance monitoring outperforms both other models. Further, in line with our behavioral predictions, we find in this model that confidence varies with the precision of predictions (Fig.2A, Fig. S1) and, when varying the fidelity of confidence as a read-out of precision (Confidence Calibration), agents with superior Confidence Calibration learn better (Fig. 2B, Fig. S1). We next sought to test whether participants' behavior likewise displays these hallmarks of our hypothesis.

Confidence reflects precision of outcome predictions

To test the predictions of our model empirically, we examined behavior of human participants in a time-estimation task (Fig 1B). In addition to requiring participants to learn and produce a precisely-timed action on each trial, our task also included two key measurements that allowed us to better understand how performance monitoring affects feedback processing: 1) participants were required to predict the feedback they would receive on each trial (Figure 1B, Prediction) and 2) Participants indicated their degree of confidence in this prediction (Figure 1B, Confidence).

To test whether the precision of outcome predictions increases with confidence we regressed participants' *signed* timing production errors (signed error magnitude; scale: undershoot (negative) to overshoot (positive)) on their *signed* outcome predictions (Predicted Outcome; same scale as for signed error magnitude), Confidence, Block, as well as their interactions. Our results support our first behavioral prediction (Table 1): As expected, predicted

outcomes and actual outcomes were positively correlated, indicating that participants could broadly indicate the direction and magnitude of their errors. Crucially, this relationship between predicted and actual outcomes was stronger for predictions made with higher confidence (Fig. 2C).

In addition to this expected pattern, we found that both outcome predictions, as well as confidence calibration, improved across blocks, suggestive of learning at the level of performance monitoring (Fig. S2; cf. Supplemental results, Table S1).

Table 1. *Relations between actual performance outcome (signed error magnitude), predicted outcome, confidence in predictions and their modulations due to learning across blocks of trials*

	DV: Signed error magnitude			
Variable	*b*	*SE*	*t*	*p*
Intercept	4.13	10.38	0.40	.693
Predicted Outcome	522.27	28.93	18.05	<.001
Block	29.16	8.15	3.58	<.001
Confidence	-24.55	10.98	-2.24	.031
Predicted Outcome: Block	-143.69	22.10	-6.50	<.001
Predicted Outcome: Confidence	308.00	36.15	8.52	<.001
Block: Confidence	-23.84	9.18	-2.60	.009
Predicted Outcome: Block: Confidence	78.70	34.60	2.27	.023

Variance Components	*SD*	*Goodness of fit*	
Participants	62.12	Log likelihood	-68807
Confidence	52.42	REML deviance	137615
Predicted Outcome	141.87		
Block	44.33		
Confidence: Predicted Outcome	132.86		
Residuals	233.10		

Note: ":" indicates interactions between predictors

Superior calibration of confidence judgments relates to superior learning

To empirically test our second behavioral prediction, that people with better confidence calibration learn faster, we modeled log-transformed trial-wise error magnitude as a function of Trial (linear and quadratic effects to account for non-linearity in learning, i.e. stronger

improvements in the beginning), Confidence Calibration for each participant (correspondence of confidence to the accuracy of the prediction; see Method for quantification; Fig. 2D inset), and their interaction (Table 2). As expected, Confidence Calibration interacted significantly with the linear Trial component, i.e., with learning (Fig. 2D). Thus, participants with better confidence calibration showed greater performance improvements during the experiment. Importantly, Confidence Calibration did not significantly correlate with overall performance (cf. Fig 2D inset), supporting the assumption that confidence calibration relates to learning (performance change), rather than performance per se.

Table 2. *Confidence calibration modulation of learning effects on performance*

		log Error Magnitude		
Variable	*b*	*SE*	*t*	*p*
Intercept	5.17	0.06	80.74	<.001
Confidence Calibration	0.58	0.58	0.99	.329
Trial linear	-0.58	0.07	-8.81	<.001
Trial quadratic	0.16	0.02	6.80	<.001
Trial linear : Confidence Calibration	-0.86	0.31	-2.72	.009

Variance Components	*SD*	*Goodness of fit*	
Participants	0.35	Log likelihood	-15107
Trial linear	0.18	REML deviance	30213
Residuals	1.09		

Thus, taken together, our model simulations and behavioral results align with the behavioral predictions of our hypothesis: Participants' outcome predictions were better related to actual outcomes when those outcome predictions were made with higher confidence, and individuals with superior confidence calibration showed better learning. In addition to our model predictions, as learning progressed participants improved not only their time-estimation performance, but also their outcome predictions, and their confidence calibration. These results

indicate that learning took place not only at the level of task performance, but also at the level of performance monitoring.

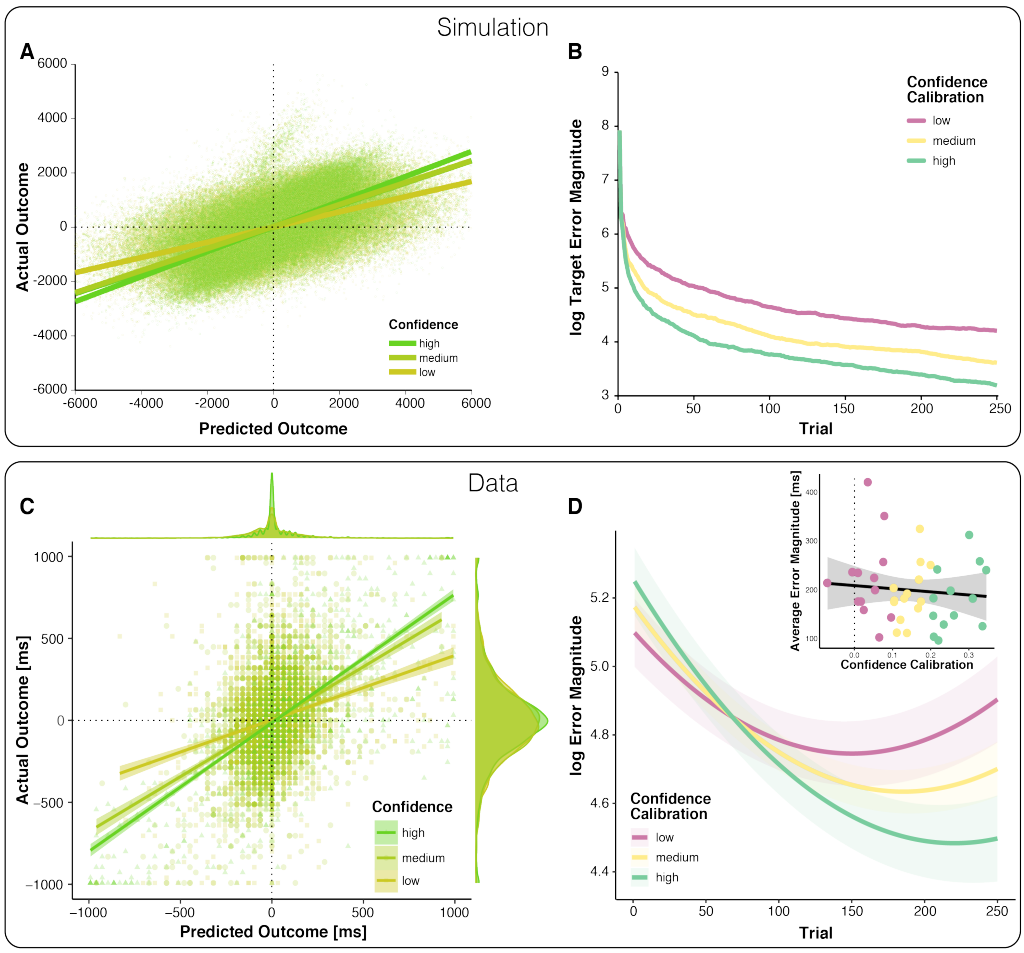


Figure 2. **Relationships between outcome predictions and actual outcomes in the model and observed data (top vs. bottom)**. **A**. Model prediction for the relationship between Prediction and actual outcome (Feedback) as a function of Confidence. The relationship between predicted and actual outcomes is stronger for higher confidence. **B** The model-predicted effect of Confidence Calibration on learning. Better Confidence Calibration leads to better learning. **C**. Observed relationship between predicted and actual outcomes. Each data point corresponds to one trial of one participant; all trials of all participants are plotted together. Regression lines are local linear models visualizing the relationship between predicted and actual error separately for high, medium and low confidence. At the edges of the plot, the marginal distributions of actual and predicted errors are depicted by confidence levels. **D**. Change in error magnitude across trials as a function of confidence calibration. Lines represent LMM-predicted error magnitude for low, medium and high confidence calibrations, respectively. Shaded error bars represent corresponding SEMs. Inset: Average Error Magnitude for every participant plotted as a function of Confidence Calibration level. The vast majority of participants show positive confidence calibration. The regression line represents a local linear model fit and the error bar represents the standard error of the mean.

Outcome Predictions and Confidence modulate feedback processing

At the core of our hypothesis and model lies the change in feedback processing as a function of outcome predictions and confidence. People's response-based outcome predictions and the confidence in those outcome predictions should thus be reflected in canonical prediction error correlates in scalp-recorded EEG signals. To test this prediction, we contrasted participants' outcome predictions with objective feedback to compute estimates of two distinct types of prediction errors (Fig. 3A). The first, reward prediction error (RPE), indexing whether the outcome of a particular response was better or worse than expected, is thought to drive reinforcement learning. The second, sensory prediction error (SPE), indexing whether the outcome of a particular response was close to or far off the predicted one, is thought to underlie forward model-based and direct policy learning in the motor domain [41]. To illustrate the difference, one might expect to miss a target 20 cm to the left but find the arrow misses it 20 cm to the right instead. There is no RPE, as the actual outcome is exactly as good or bad as the predicted one, however, there is a large SPE, because the actual outcome is very different from the predicted one.

We predicted that participants' internal evaluations would modulate feedback processing as indexed by distinct feedback-related potentials in the EEG: the feedback-related negativity (FRN), P3a and P3b. Thus, the amplitude of a canonical index of signed RPE [39], the FRN, should increase to the extent that outcomes were worse than predicted, that is, with more negative-going RPE. P3a amplitude, a neural signature of surprise[42], should increase with the absolute difference between participants' outcome predictions and actual outcomes (i.e., with SPE) and be enhanced in trials in which participants indicated higher confidence in their outcome predictions. To

further explore the possible role of performance monitoring in learning, we also tested the joint effects of our experimental variables on the P3b as a likely index of learning[43].

If participants did not take their predictions into account, ERP amplitudes should scale with the actual error magnitude reflected in the feedback (Error Magnitude). Note that both RPE and SPE are equivalent to Error Magnitude in the special case where predicted errors are zero (Fig. 3A), and thus Error Magnitude can be thought of as the default RPE and SPE that would arise if an individual predicted perfect execution on each trial. Thus, if participants did not take knowledge of their own execution errors into account, their FRN and P3a should both simply reflect Error Magnitude. A key advantage of our experimental design is that RPE, SPE and Error Magnitude vary differentially as a function of actual and predicted outcomes (Fig. 3A), which allowed us to test our predictions by examining whether ERP amplitudes are modulated by prediction errors (SPE and RPE) and Confidence, while controlling for other factors including Error Magnitude.

Reward Prediction Error modulates the Feedback-Related Negativity. The feedback-related negativity (FRN) is an error-sensitive ERP component with a fronto-central scalp distribution that peaks between 230 to 330 ms following feedback onset [44](Fig. 3B). It is commonly thought to index neural encoding of RPE [39]: Its amplitude increases with the degree to which an outcome is worse than expected and, conversely, decreases to the extent that outcomes are better than expected [45-49]. Its amplitude thus decreases with increasing reward magnitude [20] and reward expectancy [50]. However, it is unknown whether reward prediction errors signaled by the FRN rely on predictions based only on previous feedback, or whether they might incorporate ongoing performance monitoring. Based on our overarching hypothesis, we predicted that FRN amplitude would scale with our estimate of RPE, which quantifies the degree to which actual

feedback was "better" than the feedback predicted after action execution (Fig. 3A), causing more negative RPEs to produce larger FRN amplitudes (cf. Fig. 3C). A key alternative option is that the FRN indexes the magnitude of an error irrespective of the participant's post-response outcome prediction (e.g., with large FRN to feedback indicating a large error, even when the participant knows to have committed this error) [51-53]. Note that the prediction errors experienced by most error-driven learning models would fall into this alternative category, as they would reflect the error magnitude minus some long term expectation of that magnitude, but not update these expectations after action execution. Thus, to test whether RPE explains variation in FRN above and beyond Error Magnitude, and to control for other factors, we included Error Magnitude, SPE, Confidence, and Block in the model (Table 3).

Table *3.* *LMM statistics of learning effects on FRN*

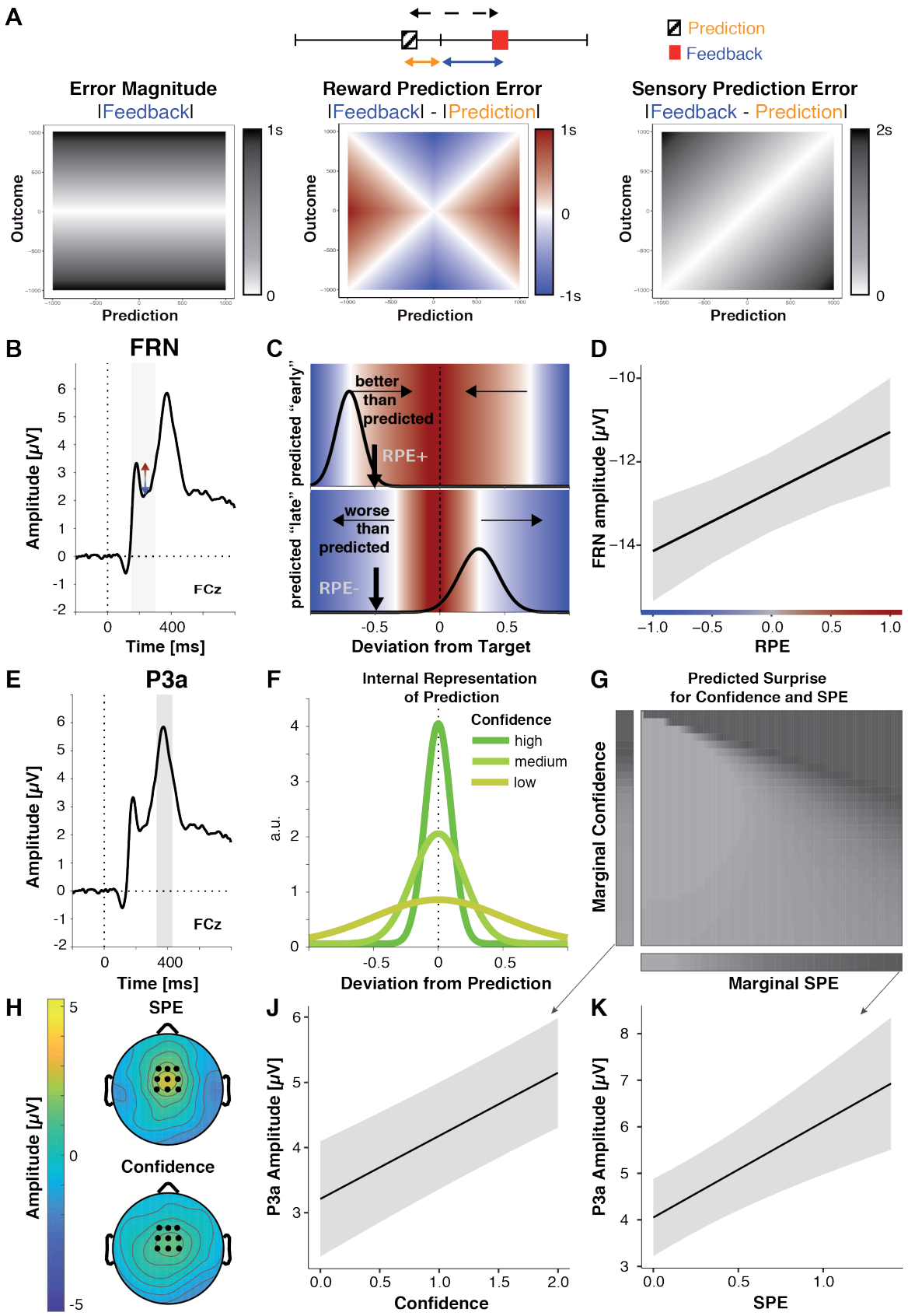
	Peak-to-Peak FRN amplitude			
Variable	*b*	*SE*	*t*	*p*
Intercept	-12.67	0.49	-26.03	<.001
Confidence	-0.19	0.15	-1.25	.212
Reward Prediction Error	1.43	0.41	3.47	<.001
Sensory Prediction Error	-0.67	0.42	-1.61	.108
Error Magnitude	0.51	0.55	0.92	.357
Block	-0.15	0.11	-1.43	.159
Variance Components	*SD*	*Goodness of fit*		
Participants	3.03	Log likelihood		-29909
Block	0.47	REML deviance		59818
Error Magnitude	1.49			
Residuals	5.26			

As predicted, FRN amplitude decreased with more positive-going RPEs ($b = 1.43$, $p < .001$, Fig. 3D), extending previous work that investigated prediction errors as a function of reward magnitude and frequency [39,49]. In contrast, error magnitude and SPE did not significantly affect FRN amplitude, suggesting in the case of the error magnitude that when errors can be

accounted for by faulty execution, they do not drive internal reward prediction error signals. We found no other reliable effects and when including interaction terms, they were neither significant, nor supported by model selection ($\Delta X^2(10) = 10.98$, $p = .359$, $AIC_{reduced\text{-}full} = -9$, $BIC_{reduced\text{-}full} = -81$). We conclude that FRN amplitude reflects the degree to which feedback is better than predicted, and critically, that the outcome predictions incorporate information about likely execution errors.

Sensory Prediction Error and Confidence modulate P3a. The frontocentral P3a is a surprise-sensitive positive-going deflection between 250 and 500 ms following stimulus onset (Figure 3E)[42]. Its functional significance can be summarized as signaling the recruitment of attention for action to surprising and motivationally relevant stimuli [42,54]. P3a has been shown to increase with larger prediction errors in probabilistic learning tasks [43], higher goal-relevance in a go/no-go task [55], with increasing processing demands [56], and with meta-memory mismatch (feedback about incorrect responses given with high confidence [57]).

Surprise can be quantified using Shannon information, which reflects the amount of information provided by an outcome given a probability distribution over outcomes[58]. As seen in Figure 3G, this measure scales with increasing confidence, as well as SPE, i.e., increasing deviations between predicted and actual outcome (margins). To generate these predictions, we computed the Shannon Information for a range of outcomes given a range of predictive distributions with varying precision, assuming that confidence reflects the precision of a distribution of predicted outcomes (Fig. 3F). Thus, P3a amplitude should scale with both SPE and Confidence. We tested our predictions by examining whether P3a was modulated by SPE, and Confidence, in a model that also included Error Magnitude, RPE and Block as control variables.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Amplitude [μV]
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Time [ms]
C
better than predicted
RPE+
worse than predicted
RPE-
predicted "early"
predicted "late"
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Internal Representation of Prediction
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Figure 3. **Multiple Prediction Errors in Feedback Processing. A. Dissociable information provided by feedback.** An example for a prediction (hatched box) and a subsequent feedback (red box) are shown overlaid on a rating/feedback scale. We derived three error signals that make dissociable predictions across combinations of predicted and actual outcomes. The solid blue line indicates Error Magnitude (distance from outcome to goal). As smaller errors reflect greater rewards we computed Reward Prediction Error (RPE) as the signed difference between negative Error Magnitude and the negative predicted error magnitude (solid orange line, distance from prediction to goal). Sensory Prediction Error (SPE, dashed line) was quantified as the absolute discrepancy between feedback and prediction. Values of Error Magnitude (left), RPE (middle), and SPE (right) are plotted for all combinations of prediction (x-axis) and outcome (y-axis) location. **B.- D. FRN amplitude is sensitive to predicted error magnitude. B**. FRN, grand mean, the shaded area marks the time interval for peak-to-peak detection of FRN. Negative peaks between 200 and 300 ms post feedback were quantified relative to positive peaks in the preceding 100 ms time window. **C**. Expected change in FRN amplitude as a function of RPE (color) for two predictions (black curves represent schematized predictive distributions around the reported prediction for a given confidence), one too early (top: high confidence in a low reward prediction) and one too late (bottom: low confidence in a higher reward prediction). Vertical black arrows mark a sample outcome (deviation from the target; abscissa) resulting in different RPE/expected changes in FRN amplitude for the two predictions, indicated by shades. Blue shades indicate negative RPEs/larger FRN, red shades indicate positive RPEs/smaller FRN and grey denotes zero. Note that these are mirrored at the goal for any predictions, and that the likelihood of the actual outcome given the prediction (y-axis) does not affect RPE. In the absence of a prediction or a predicted error of zero, FRN amplitude should increase with the deviation from the target (abscissa). **D**. LMM- estimated effects of RPE on peak-to-peak FRN amplitude visualized with the effects package; shaded error bars represent 95% confidence intervals. **E. – K. P3a amplitude is sensitive to SPE and Confidence. E**. Grand mean ERP with the time-window for quantification of P3a highlighted. **F**. Hypothetical internal representation of predictions. Curves represent schematized predictive distributions around the reported prediction (zero on abscissa). Confidence is represented by the width of the distributions. **G**. Predictions for SPE (x-axis) and Confidence (y-axis) effects on surprise as estimated with Shannon information (darker shades signify larger surprise) for varying Confidence and SPE (center). The margins visualize the predicted main effects for Confidence (left) and SPE (bottom). **H**. LMM fixed effect topographies for SPE, and Confidence. **J. – K**. LMM-estimated effects on P3a amplitude visualized with the effects package; shaded areas in **J.** (SPE) and **K.** (confidence) represent 95% confidence intervals.

As predicted, our analyses showed that P3a amplitude significantly increased with increasing SPEs, in line with the idea of stronger violations of expectations by less accurately predicted outcomes (Fig. 3H, 3J, Table 4), and with increasing Confidence (Fig. 3H, 3K). Our Shannon Information simulation also predicts a small interaction between SPE and Confidence (see slight diagonal component in Figure 3G). However, when including the interaction term it was not significant and did not improve model fit , $\Delta X^2(10) = 10.36$, $p = .410$ ($AIC_{reduced\text{-}full} = -10$, $BIC_{reduced\text{-}full} = -81$), suggesting that any such effect was minimal.

In addition, P3a amplitude decreased across blocks, perhaps reflecting decreased motivational relevance of feedback as participants improved their performance and

predictions[55,59]. We also observed a significant decrease of P3a with increasing Error Magnitude and larger P3a amplitudes for more negative reward prediction errors. However, these effects showed more posterior scalp distributions than those of SPE and confidence. As P3a temporally overlaps with the more posteriorly distributed P3b, these effects are likely a spillover of the P3b. Hence, we discuss them below. Taken together our results support our hypothesis that predictions and confidence shape feedback processing at the level of the P3a.

Table 4. *LMM statistics of learning effects on P3a*

	P3a amplitude			
Variable	*b*	*SE*	*t*	*p*
Intercept	4.10	0.42	9.79	<.001
Confidence	0.97	0.13	6.96	<.001
Sensory Prediction Error	2.05	0.48	4.27	<.001
Error Magnitude	-1.95	0.44	-4.43	<.001
Block	-0.91	0.07	-12.93	<.001
Reward Prediction Error	-0.74	0.38	-1.98	.048
Variance Components	*SD*	*Goodness of fit*		
Participants	2.61	Log likelihood		-28998
SPE	1.74	REML deviance		57996
Residuals	4.79			

Prediction Errors, Objective Errors and Confidence converge in the P3b. Our overarching hypothesis and model predict that outcome predictions and confidence should affect the degree to which feedback is used for future behavioral adaptation. The parietally distributed P3b scales with learning from feedback [40,43,60-62] and predicts subsequent behavioral adaptation [43,62]. P3b amplitude has been found to increase with feedback salience (reward magnitude irrespective of valence; [60]), behavioral relevance (choice vs. no choice; [63]), with more negative-going RPE [40,64], but also with better outcomes in more complex tasks [65].

Consistent with their necessity for governing behavioral adaptation, P3b was sensitive to participants' outcome predictions (cf. Table 5). P3b amplitude increased with increasing SPE (Fig. 4B, E), indicating that participants extracted more information from the feedback stimulus when outcomes were less expected. As for P3a, this SPE effect decreased across blocks, and so did overall P3b amplitude, suggesting that participants made less use of the feedback as they improved on the task [43].

P3b amplitude also increased with negative-going RPE (Fig. 4B, C), hence, for worse-than-expected outcomes, replicating previous work [40,64]. This RPE effect was significantly modulated by Confidence and Block, indicating that the main effect needs to be interpreted with caution, and the relationship between P3b and RPE is more nuanced than previous literature suggested. In the first block, P3b amplitude was highest for large negative RPE and *high* Confidence, whereas in the last block it was highest for large negative RPE and *low* Confidence (Fig. 4D, cf. Supplementary Results, Table S2). Hence, early on in learning when little is known about the task, participants make less accurate predictions and confidence is less related to the precision of these predictions (high and low confidence predictions are equally likely to be accurate), negative RPEs appear to have a stronger impact under *high* Confidence. This might indicate that participants learned more in earlier blocks when they were inappropriately confident in their predictions, possibly to calibrate their confidence. In later trials, when lower confidence is indeed indicative of less accurate predictions, it may trigger information seeking [35] and hence amplify RPE effects. In line with previous findings [65,66], we further observed significant increases of P3b amplitude with decreasing Error Magnitude, thus, with better outcomes (Fig. 4B, F, Table 5). We found no further significant interactions, and excluding the non-significant

interaction terms from the full model did not significantly diminish goodness of fit, $\Delta X^2(5) = 10.443$, $p = .064$ ($AIC_{reduced\text{-}full} = 0$; $BIC_{reduced\text{-}full} = -35$).

Taken together, our ERP findings support our main hypothesis that individuals take their internal evaluations into account when processing feedback, such that distinct ERP components reflect different aspects of internal evaluations rather than just signaling objective error.

Table 5. *LMM statistics of learning effects on P3b*

	P3b amplitude			
Variable	*b*	*SE*	*t*	*p*
Intercept	4.12	0.29	14.12	<.001
Confidence	0.08	0.20	0.42	.677
Sensory Prediction Error	1.75	0.46	3.76	<.001
Error Magnitude	-2.35	0.46	-5.14	<.001
Reward Prediction Error	-1.12	0.46	-2.43	.018
Block	-0.48	0.09	-5.20	<.001
Confidence: Reward Prediction Error	-0.51	0.55	-0.92	.356
Confidence: Block	0.07	0.18	0.41	.682
Reward Prediction Error: Block	-0.52	0.44	-1.18	.236
Sensory Prediction Error: Block	-0.98	0.46	-2.12	.034
Confidence: Reward Prediction Error: Block	2.22	0.72	3.08	.002

Variance Components	*SD*	*Goodness of fit*	
Participants	1.78	Log likelihood	-29198
Sensory Prediction Error	1.47	REML deviance	58396
Reward Prediction Error	1.29		
Confidence	0.79		
Residuals	4.89		

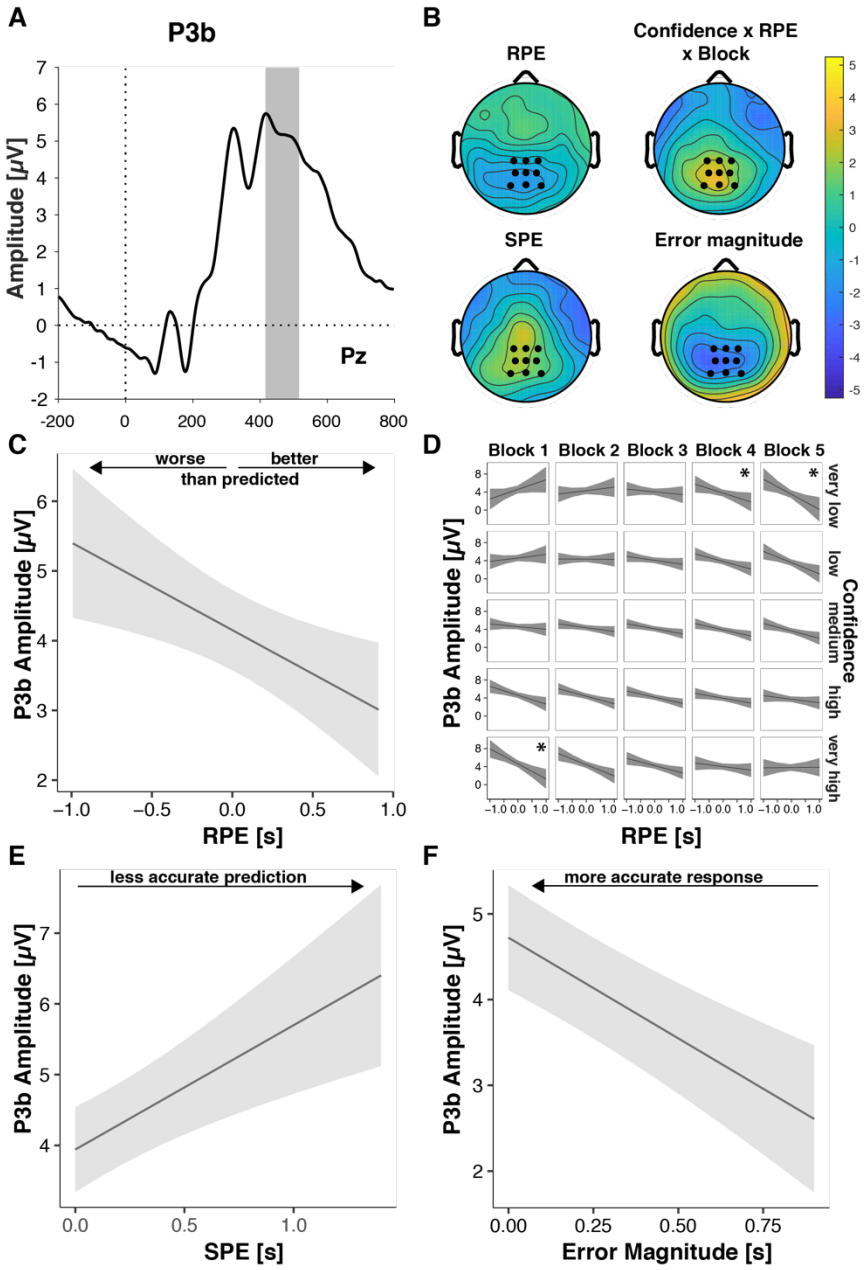

Figure 4. **Performance-relevant information converges in the P3b**. **A**. Grand average ERP waveform at Pz with the time window for quantification highlighted. **B**. Effect topographies as predicted by LMMs for RPE, error magnitude, SPE and the RPE by Confidence by Block interaction. **C. - F**. LMM-estimated effects on P3b amplitude visualized with the effects package in R; shaded areas represent 95% confidence intervals. **C**. RPE. Note the interaction effects with Block and Confidence (D), that modulate the main effect **D**. Three-way interaction of RPE, Confidence and Block. Asterisks denote significant RPE slopes within cells. **E**. P3b amplitude as a function of SPE. **F**. P3b amplitude as a function of Error Magnitude.

Discussion

The present study explored the hypothesis that learning from feedback depends on internal performance evaluations as reflected in outcome predictions and confidence. Comparing different Bayesian agents with varying insights into their trial-by-trial performance, we show that performance monitoring provides an advantage in learning, as long as agents' confidence is accurately calibrated. To test our hypothesis empirically, we collected participants' trial-wise outcome predictions and confidence judgments in a time-estimation task prior to receiving feedback, while recording EEG. Like the simulations from the Bayesian learner with performance monitoring, our empirical results show that trial-by-trial confidence tracks the precision of outcome predictions, and individuals with better coupling between predictions and confidence (confidence calibration) showed greater improvements in performance over the course of the experiment. Moreover, participants' subjective predictions, as well as their confidence in those predictions, influenced feedback processing as revealed by feedback-related potentials.

Our study builds on an extensive body of work on performance monitoring, proposing that deviations from performance goals are continuously monitored, and expectations are updated as soon as novel information becomes available [39,67]. Hence, performance monitoring at later stages should depend on performance monitoring at earlier stages [39]. Specifically, learning from feedback should critically depend on internal performance monitoring. Our results extend previous work demonstrating a shift from feedback-based to response-based evaluations as learning progresses [68,69]: They show that performance monitoring and learning from feedback are not mutually exclusive modes of performance evaluation; instead, they operate in concert, with

confidence in response-based outcome predictions determining the degree to which this information is relied on.

Participants' behavior displayed hallmarks of error monitoring [22,23], such that outcome predictions tracked factual errors in both direction and magnitude. Crucially, extending those previous findings, our empirical results align with unique predictions based on our hypothesis: Confidence reflected the precision of participants' outcome predictions, and participants with superior calibration of their confidence judgments to the accuracy of their predictions learned better than those with poorer calibration. This latter finding is notable given that overall confidence calibration was similar for participants with different performance quality (error magnitude). Therefore, the empirical confidence calibration effect on learning is unlikely to be a consequence of better overall ability as described in the "unskilled and unaware effect" [70] or of the dependence of confidence calibration (or metacognitive sensitivity) on performance [71]. Instead, the finding supports our hypothesis that confidence supports learning via optimized feedback processing.

Our simulations and ERP data reveal two critical mechanisms through which performance monitoring may impact learning from feedback: modulation of surprise and reduction of uncertainty via credit assignment. The main impact of error monitoring is to *reduce* the surprise about outcomes. All else being equal, a given outcome is less surprising the better it matches the predicted outcome. Consistent with discounting of predicted deviations from the goal, we found that participants' trial-by-trial subjective outcome predictions consistently modulated feedback-based evaluation reflected in ERPs. Participants' response-based outcome predictions were reflected in the amplitudes of FRN reward prediction error signals [39,47,49], of P3a surprise signals, as well as of the P3b signals combining information about reward

prediction error and surprise. In our computational models, reducing surprise by taking response-based outcome predictions into account led to more accurate updating of internal representations supporting action selection and thus superior learning.

Learning was further supported by the adaptive regulation of uncertainty-driven updating via confidence. Specifically, as deviations from the goal were predicted with higher confidence, these more precise outcome predictions *enhanced* the surprise elicited by a given prediction error. Thus, a notable finding revealed by our simulations and empirical data is that, counterintuitively, agents and participants learned *more* from feedback when confidence in their predictions had been high. While FRN amplitude was not modulated by confidence, we found that P3a increased with confidence, as predicted by uncertainty driven changes in surprise. Our results align with previous findings of larger P3a amplitude for metacognitive mismatch [57] and offer a computational mechanism underlying previous theorizing that feedback about errors committed with high confidence attracts more attention, and therefore leads to hypercorrection [72,73]. We also found that confidence modulated RPE effects on P3b amplitude, such that in initial blocks, where most learning took place, RPE effects were amplified for higher confidence, whereas this effect reversed in later blocks, where RPE effects were present for low, but not high confidence. This shift is intriguing and may indicate a functional change in feedback use as certainty in the response-outcome mapping increases and less about this mapping is learned from feedback, but the effect was not directly predicted and therefore warrants further research and replication.

Confidence has typically been studied in two-alternative choice tasks, and only rarely in relation to continuous outcomes [30,34,36,74-76]. By reconceptualizing error detection as outcome prediction, our results shed new light on the well-supported claim that error monitoring and

confidence are tightly intertwined [32,38,77-79] and forge valuable links between research on performance monitoring[39,40,67] and on learning under uncertainty[1,3,58,80]. In doing so, our results provide further evidence to the growing literature on the role of confidence in learning and behavioral adaptation [34-36].

While we captured the main effects of interest with our Bayesian model and our key behavioral results are in line with our overarching hypothesis, our behavioral findings also reveal other aspects of learning that remain to be followed up on. Unlike our Bayesian agents, participants exhibited signatures of learning not only at the level of first order performance, but also at the level of performance monitoring. The precision of the outcome predictions increased as learning progressed, as did the calibration of confidence to this precision. Identifying the mechanisms that drive this metacognitive learning, i.e., whether changes in confidence follow the uncertainty in the internal model or reflect refinement of the confidence calibration to the efference copy noise, is an exciting question for future work.

Anyone who tried to learn a sport can relate to the intuition that just because you find out what you did was wrong doesn't mean you know how to do it right. Our task also evokes this so-called distal problem, which refers to the difficulty of translating distal sensory outcomes of responses to required proximal movement parameter changes. Indeed, when practicing complex motor tasks, individuals prefer and learn better from feedback following successful trials compared to error trials [81-83]. In line with the notion that positive feedback is more informative than error feedback in motor learning, we, like others in the time estimation task [65,66], observed increasing P3b amplitude after more positive feedback, in addition to prediction error effects.

In our study the P3b component, previously shown to scale with the amount of information provided by a stimulus[84] and the amount of learning from a stimulus[43], was sensitive

to both RPE and SPE, indicating that multiple learning mechanisms may act in parallel, supported by different aspects of feedback. Our findings resonate with recent work in rodents showing that prediction error signals encode multiple features of outcomes[85], and are based on distributed representations of predictions [86]. This encoding of multiple features of outcomes, like the uncertainty in predictions, may help credit assignment and support learning at multiple levels. It is still unclear to what degree different learning mechanisms – error based, model based, reinforcement learning – contribute to motor learning[87]. Further research is needed to identify whether the same or different learning mechanisms operate across levels, e.g., via hierarchical reinforcement learning[88,89], and how learning interacts between levels.

Taken together, our findings provide evidence that feedback evaluation is an active constructive process that is fundamentally affected by an individual's internal representations of their own performance at the time of feedback. These internal representations in turn influence how people learn and thus which beliefs they will have and which actions they will take, driving what internal and external states they will encounter in the future. The present study is a first step towards elucidating this recursive process of performance optimization via internal performance monitoring and monitoring of external task outcomes.

Method

Task variables

- t denotes the target interval, which was set to $t := 19$,
- s denotes the feedback scale, which was set to $s := 90$,
- r denotes the model's or participant's response,
- f denotes the feedback in the task, which was defined as

$$f := (r - t)s \tag{1}$$

Computational model

The Bayesian learner with performance monitoring attempted to sequentially infer the target interval t and feedback scale s over multiple trials, based on its intended response i, an efference copy c of its executed response and feedback f indicating the magnitude and direction of its timing errors. On each trial the model computed its intended response based on the inferred target interval. During learning, the model faced several obstacles including 1) the initially unknown scale of the feedback, making it difficult to judge whether feedback indicates small or large timing errors, 2) motor noise, which offsets executed responses from intended ones, and 3) efference copy noise, which makes the efference copy unreliable to a degree that varies from trial to trial. Formally, the Bayesian learner with performance monitoring is represented by the following variables:

- $p(t) \coloneqq U(t; [0,100])$ denotes the model's prior distribution over the target interval t,
- $p(s) \coloneqq U(s; [0.1, 100])$ denotes the model's prior distribution over the feedback scale s
- $p^{\sigma_r^2}(r|i) \coloneqq N(r; i, \sigma_r^2)$ denotes the model's response distribution, where i denotes the model's intended response, which corresponds to the expected target interval

$i := E_{p(t)} = \sum_t p(t)t$, and σ_r^2 denotes the response noise, which was set to $\sigma_r := 10$ in terms of the standard deviation

- $p^{\sigma_c^2}(c|r) \coloneqq N(c; r, \sigma_c^2)$ denotes the model's efference-copy distribution with efference-copy noise expressed as standard deviation $\sigma_c \in \{5, 10, 20\}$, where $p(\sigma_c) \coloneqq Cat(\sigma_c, 1/3)$. Here we assumed that the model was aware of its trial-by-trial efference copy noise. That is, from the perspective of the Bayesian learner with performance monitoring, efference-copy noise was not a random variable.

Intended response

During the response phase in the task, the model first computed its intended response i and then sampled its actual response r from the Gaussian response distribution. We assumed that the model's internal response monitoring system subsequently generated the noisy efference copy c.

Learning

Based on the definition of the task and the Bayesian learner with performance monitoring, the joint distribution over the variables of interest during a trial of the task is given by

$$p^{i,\sigma_c^2,\sigma_r^2}(t, s, f, r, c) := p(f|r, t, s)p^{\sigma_c^2}(c|r)p^{i,\sigma_r^2}(r)p(t, s) \quad (2)$$

To infer the target interval t and the feedback scale s, we can evaluate the posterior distribution conditional on the efference copy c and feedback f and given the intended response i, response noise σ_r^2 and efference copy noise σ_c^2 according to Bayes' rule:

$$p^{i,\sigma_c^2,\sigma_r^2}(t,s|\,c,f) \tag{3}$$

$$\propto \int p^{i,\sigma_c^2,\sigma_r^2}(t,s|c,f,r)\,dr$$

$$\propto \int p(f|r,t,s)p^{\sigma_c^2}(c|r)p^{i,\sigma_r^2}(r)p(t,s)\,dr$$

Note that we assumed that the Bayesian learner with performance monitoring was aware how feedback f was generated in the task (cf. eq. 1), that is, conditional on the response r, target interval t and feedback scale s, the model was able to exactly compute the probability of the feedback according to

$$p(f|r,t,s) = \begin{cases} 1, & if\ f = (r-t)s \\ 0, & else \end{cases} \tag{4}$$

We approximated inference using a grid over the target interval $t \in [0,100]$ and feedback scale $s \in [0.1,100]$. The model first computed the probability of the currently received feedback. Although it was aware how feedback was generated in the task, it suffered from uncertainty over its response due to noise in the efference copy. For each *s* and *t* on the grid, the model evaluated the Gaussian distribution

$$p^{i,\sigma_c^2,\sigma_r^2}(f|c,t,s) := N(f;(m-t)^T s, vA) \tag{5}$$

where A was a 100×50 matrix containing the grid values of *t* and *s*.

$$v = \frac{1}{\frac{1}{{\sigma_c}^2} + \frac{1}{{\sigma_r}^2}} \tag{6}$$

denotes the expected variance in feedback under consideration of both efference-copy noise ${\sigma_c}^2$ and response noise ${\sigma_r}^2$ and

$$m = v\frac{1}{{\sigma_c}^2}c + v\frac{1}{{\sigma_r}^2}i \tag{7}$$

denotes the expected feedback under the additional consideration of efference copy *c* and intended response *i.* When computing the probability of the feedback, our model thus took into account the efference copy *c* and the response it intended to produce *i*, which were weighted according to their respective reliabilities.

Second, the model multiplied the computed probability of the observed feedback with the prior over the scale and target response, i.e.,

$$p^{i,\sigma_c^2,\sigma_r^2}(t,s|c,f) \propto N(f;(m-t)^T s, vA)p(s,t) \tag{8}$$

In the grid approximation, the model started with a uniform prior on the joint distribution over t and s and was applied recursively, such that the posterior joint distribution on t and s for each trial served as the prior distribution for the subsequent one.

Outcome prediction

On each trial, the model reports an outcome prediction po and the confidence in this prediction, which we refer to as co. The outcome prediction maps the discrepancy between the intended response and the efference copy onto the feedback scale given the best guess of the current *t* and *s*.

$$po = (c - i)\sum_s p(s)s \tag{9}$$

Note that this outcome prediction is different from the mean of the uncertainty-weighted expectancy distribution defined in eq. 7, in that it does not take uncertainty into account, but

reflects the expectation given the efference copy alone. The inverse uncertainty σ_c^2 of the efference copy, as described below, is translated into the agent's confidence report.

Confidence Calibration

Confidence calibration $cc \in \{0, 0.75, 1\}$ denotes the probability that the agent assumes the correct efference copy variance σ_c^2 for learning (c.f. eqs. 6-7). $cc = 1$ indicates that the subjectively assumed efference-copy precision is equal to the true precision and $cc = 0$, in contrast, indicates that the assumed precision of the efference copy is different from the true one. That is, in the case of $cc = 0.75$, the agent more likely assumes the true precision of the efference copy but sometimes fails to take it accurately into account during learning. As shown in Figure 1, we simulated behavior of three agents that differed in their confidence calibration according to this idea.

Confidence report

In our model, the confidence report $\mathrm{co} \in \{3, 2, 1\}$ reflects how certain the agent thinks its efference copy is, where 3 refers to "completely certain", and 1 to "not certain". In particular,

$$co = \begin{cases} 3, & if\ \sigma_c = 5 \\ 2, & if\ \sigma_c = 10 \\ 1, & if\ \sigma_c = 20 \end{cases}$$

That is, the confidence report is directly related to the subjective precision of the efference copy, which, as shown above, depends to the agent's level of confidence calibration.

Model with incomplete performance monitoring

We also applied a model that had no insight into the precision of its current predictions. The agent was thus unaware of its trial-by-trial efference-copy noise σ_c and therefore relied on the average value of σ_c, i.e., $\sum \sigma_c p(\sigma_c) = 12$. As the model does not differentiate between precise and imprecise predictions but treats each prediction as average precise, it relies too much on imprecise predictions and too little on precise ones.

Model without performance monitoring

Finally, we applied a model that was aware about its motor noise but, because it completely failed to consider its efference copy, it lacked insight into its trial-by-trial performance. In this version, we had

$$v = \frac{1}{\frac{1}{{\sigma_r}^2}} \tag{11}$$

and $m = i$.

This model accounts for the expected variance in the feedback, but cannot differentiate between trials in which the feedback is driven more by incorrect beliefs about the target versus incorrect execution. Therefore, it adjusts its beliefs too much following feedback primarily driven by execution errors and too little following feedback primarily driven by incorrect beliefs.

Participants

The experimental study included 40 participants (13 males) whose average age was 25.8 years (*SD* = 4.3) and whose mean handedness score [90] was 63.96 (*SD* = 52.09; i.e., most participants were right-handed). Participants gave informed consent to the experiment and were remunerated with course credits or 8 € per hour.

Task and procedure

Participants performed an adapted time-estimation task [18,44] that included subjective accuracy and confidence ratings. The time-estimation task is well established for ERP analyses e.g. [18,44], and has the advantages that it limits the degrees of freedom of the response, and precludes concurrent visual feedback that might affect performance evaluation. The task consisted of four parts on each trial, illustrated in Figure 1B. After a fixation cross lasting for a random interval of 300-900 ms, a tone (600 Hz, 200 ms duration) was presented. Participants' task was to terminate an initially unknown target interval of 1504 ms from tone onset, by pressing a response key with their left hand. We chose a supra-second duration to make the task sufficiently difficult [18]. Following the response, a fixation cross was presented for 800 ms. Participants then estimated the accuracy of the interval they had just produced by moving an arrow on a visual analogue scale (*too short – too long*; ± 125 pixel, 3.15 ° visual angle) using a mouse cursor with their right hand. Then, on a scale of the same size, participants rated their confidence in this estimate (*very unconfident – very confident*). The confidence rating was followed by a blank screen for 800 ms. Finally, participants received feedback about their performance with a red square (0.25° visual angle) placed on a scale identical to the accuracy estimation scale but without any labels. The placement of the square on the scale visualized error magnitude in the interval produced, with undershoots shown to the left and overshoots on the

right side of the center mark, indicating the correct estimate. Feedback was presented for only 150 ms to preclude eye movements. The interval until the start of the next trial was 1500 ms.

The experiment comprised five blocks of 50 trials each, with self-paced rests between blocks. We used Presentation software (Neurobs.) for stimulus presentation, event and response logging. Visual stimuli were presented on a 4/3 17'' BenQ Monitor (resolution: 1280x1024, refresh rate: 60Hz) placed at 60 cm distance from the participant. A standard computer mouse and a customized response button (accuracy 2 ms, response latency 9 ms) were used for response registration.

Prior to the experiment, participants filled in demographic and personality questionnaires: Neuroticism and Conscientiousness Scales of NEO PI-R [91] and the BIS/BAS scale [92], as well as a subset of the Raven's progressive matrices as an index for figural-spatial intelligence [93]. These measures were registered as potential control variables and for other purposes not addressed here. Participants were then seated in a shielded EEG cabin, where the experiment including EEG recording was conducted. Prior to the experiment proper, participants performed three practice trials.

Psychophysiological recording and processing

Using BrainVision recorder software (Brain Products, München, Germany) we recorded EEG data from 64 Ag/AgCl electrodes mounted in an electrode cap (ECI Inc.), referenced against Cz at a sampling rate of 500 Hz. Electrodes below the eyes (IO1, IO2) and at the outer canthi (LO1, LO2) recorded vertical and horizontal ocular activity. We kept electrode impedance below 5 kΩ and applied a 100 Hz low pass filter, a time constant of 10 s, and a 50 Hz notch filter. At the beginning of the session we recorded 20 trials each of prototypical eye movements (up, down, left, right) for offline ocular artifact correction.

EEG data were processed using custom Matlab (The MathWorks Inc.) scripts [94] and EEGlab toolbox functions [95]. We re-calculated to average reference and retrieved the Cz channel. The data were band pass filtered between 0.5 and 40 Hz. Ocular artifacts were corrected using BESA [96]. We segmented the ongoing EEG from -200 to 800 ms relative to feedback onset. Segments containing artifacts were excluded from analyses, based on values exceeding ± 150 µV and gradients larger than 50 µV between two adjacent sampling points. Baselines were corrected to the 200 ms pre-stimulus interval (feedback onset).

The FRN was quantified in single-trial ERP waveforms as peak-to-peak amplitude at electrode FCz, specifically as the difference between the minimum voltage in a window from 200 to 300 ms post-feedback onset and the preceding positive maximum in a window from -100 to 0 ms relative to the detected negative peak. To define the time windows for single-trial analyses of P3a and P3b amplitudes, we first determined the average subject-wise peak latencies at FCz and Pz, respectively, and exported 100 ms time windows centered on the respective latencies. Accordingly, the P3a was quantified on single trials as the average voltage within an interval from 330 – 430 ms after feedback onset across all electrodes within a fronto-central region of interest (ROI: F1, Fz, F2, FC1, FCz, FC2, C1, Cz, C2). P3b amplitude was quantified in single trials as the average voltage within a 416 – 516 ms interval post-feedback across all electrodes within a parietally-focused region of interest (ROI: CP1, CPz, CP2, P1, Pz, P2, PO3, POz, PO4).

Analyses

Outlier inspection of the behavioral data identified one suspicious participant (average RT > 10 s) and single trials in four additional participants (RTs > 6 s). These data were excluded from further analyses. We computed two kinds of prediction errors (cf. Fig 3A): SPE was

determined as the absolute difference between predicted and actual interval length: |Prediction – Feedback|. RPE was computed as the difference between the absolute predicted error and the absolute actual error as revealed by feedback: |Prediction| – |Feedback|. We quantified confidence calibration as each participant's correlation of confidence and SPE (absolute deviation of the prediction from the actual outcome) across all trials, controlling for average error magnitude per block to account for shared changes in our confidence calibration measure with performance. To ease interpretation, we sign-reversed the correlations, such that higher values correspond to higher confidence calibration.

Statistical analyses were performed by means of linear mixed models (LMMs) using R [97] and the lme4 package [98]. We chose LMMs, similar to linear multiple regression models, as they allow for parametric analyses of single-trial measures. Further, LMMs are robust to unequally distributed numbers of observations across participants, and simultaneously estimate fixed effects and random variance between participants in both intercepts and slopes. For all dependent variables, full models, including all predictors, were reduced step-wise until model comparisons indicated significantly decreased fit.

We report model comparisons and fit indices: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which decrease with improving model fit. Random effect structures were determined using singular value decomposition. Variables explaining zero variance were removed from the random effects structure [99,100].

Prior to the analyses, error magnitude, RPE and SPE were scaled from ms to seconds and confidence and block were also scaled to a range of ± 1 for similar scaling of all predictors. Furthermore, block, error magnitude, confidence, and SPE were centered on their medians for accurate intercept computation. RPE was not centered, as zero represents a meaningful value on

the scale (predicted and actual error magnitude are the same), and positive and negative values are qualitatively different (negative and positive values represent outcomes that are, respectively, worse or better than expected). To test the assumption that outcome prediction meaningfully tracks actual performance, and that the relationship is moderated by confidence, we analyzed signed objective error magnitude (negative = undershoot, positive = overshoot) with the following predictors: signed predicted error magnitude (negative = undershoot, positive = overshoot), block, and confidence. To investigate the relevance of accurate confidence judgments, we computed individual correlations between SPE and confidence, controlling for covariance with performance across blocks (confidence calibration). We analyzed error magnitude – log-transformed in order to achieve normal distribution – as a function of Confidence Calibration, and trial as a continuous predictor with separate linear and quadratic components, as well as the interaction of Confidence Calibration and Trial. To test our predictions regarding the impact of confidence and prediction errors on ERP markers of feedback processing, we analyzed the amplitudes of the FRN, P3a, and P3b components, using RPE, SPE, confidence, block, and error magnitude as predictors.

Data Availability

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Code Availability

Scripts for all analyses are available under https://github.com/froemero/Outcome-Predictions-and-Confidence-Regulate-Learning.

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Author Contributions

RF, NY, WS and BS conceived the study. RF collected the data. RF analyzed the data. MRN, RF, and RB conducted the computational modeling. The manuscript was written by RF, with contributions of MRN and RB. All authors discussed results and edited the manuscript.

Competing Interests

The authors declare no competing interests.

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