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Intelligence mindset shapes neural learning signals and memory

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ABSTRACT

Intelligence mindset, which denotes individual beliefs about whether intelligence is fixed versus malleable, shapes academic success, but the neural mechanisms underlying mindset-related differences in learning are unknown. Here, we probe the effects of individual differences in mindset on neural responses to negative feedback after a competence threat manipulation. We hypothesized that when their competence was threatened, participants with fixed mindsets would interpret further negative feedback as punishing. After receiving either no score or a competence-threatening IQ score, participants performed a learning task with feedback that emphasized either the evaluative or informational weight of negative feedback. Participants who experienced the competence threat had the strongest predictive relationships between mindset, performance, and caudate activation. The competence threat may have compounded the subjective punishment of negative feedback for fixed mindsets relative to growth mindsets, causing poorer learning from negative feedback in the evaluative context and inflexible striatal responses to negative feedback across feedback contexts.

1. Introduction

Self-belief has been found to have a powerful effect on academic success. One influential line of research has focused on differences in academic achievement and motivation due to intelligence mindset, which refers to individual beliefs about whether intelligence is malleable or fixed (Dweck, Mangels, Good, Dai, & Sternberg, 2004; Dweck, 2006). Those who believe that intelligence is malleable have "growth mindsets" and are referred to as incremental theorists, while those who believe that intelligence is fixed have "fixed mindsets" and are referred to as entity theorists. Holding a fixed mindset can impede goal pursuit and impair test performance (Cury, Da Fonseca, Zahn, & Elliot, 2008), especially in the presence of a competence threat (e.g., an intelligence test). Such threats can strengthen the relationship between goal pursuit and intelligence mindset (Burnette, O'Boyle, VanEpps, Pollack, & Finkel, 2013). For entity theorists, who believe that their performance reflects their abilities in a fixed and unchangeable way, the threat induced by an intelligence test may enhance the threat carried by negative feedback and thus the subjective sense of punishment that it engenders. Whether this interaction between competence threat and intelligence mindset is reflected in neural learning signals remains unknown.

Several studies have examined the behavioral and neural correlates of intelligence mindset (Mangels, Butterfield, Lamb, Good, & Dweck, 2006; Moser, Schroder, Heeter, Moran, & Lee, 2011; Myers, Wang, Black, Bugescu, & Hoeft, 2016; Schroder, Moran, Donnellan, & Moser, 2014, 2017). Entity theorists, relative to incremental theorists, demonstrate a stronger alerting response to negative performance evaluative feedback (Mangels et al., 2006) and a reduced attentional allocation to post-error adjustments (Moser et al., 2011; Schroder et al., 2014, 2017). In contrast, incremental theorists have greater co-activation at rest between learning related regions (e.g., the striatum) and other executive function regions (Myers et al., 2016), presumably to support their flexible learning capacity. To date, however, no studies have examined task-based functional magnetic resonance imaging (fMRI) activation related to intelligence mindset or the interaction between intelligence mindset and competence threat. In educational settings, students are consistently presented with standardized tests that challenge their competence. It is thus important to understand the motivational factors that affect educational outcomes and elucidate the neural mechanisms that support differences in learning styles between the theorists.

A brain region implicated in learning, the striatum has been linked with reward and punishment contingencies (Delgado, Nystrom, Fissell, Noll, & Fiez, 2000; Delgado, Locke, Stenger, & Fiez, 2003). Feedback-based learning particularly relies on the caudate nucleus, which

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facilitates learning through neural signals reflecting the subjective value of response outcomes (Bartra, McGuire, & Kable, 2013; Clithero & Rangel, 2014; Daniel & Pollmann, 2014; Tricomi & Lempert, 2015). Striatal value signals are sensitive to individual differences in intrinsic motivation (DePasque & Tricomi, 2015) and achievement goals (DePasque Swanson & Tricomi, 2014) as well as contextual influences, such as the availability of other outcomes (Bischoff-Grethe, Hazeltine, Bergren, Ivry, & Grafton, 2009; Nieuwenhuis et al., 2005) and feedback timing (Dobryakova & Tricomi, 2013).

Previously we have found that manipulating the predictability of feedback receipt altered the informational value of negative feedback (Lempert & Tricomi, 2015). Whereas positive feedback is both intrinsically rewarding and informative, negative feedback is punishing but still informative. When feedback and no feedback trials were presented separately ("blocked feedback"), negative feedback evoked a dip in striatal activation, consistent with evidence that it typically elicits a punishment response (Marco-Pallarés, Müller, & Münte, 2007; Tricomi, Delgado, McCandliss, McClelland, & Fiez, 2006). In contrast, when feedback trials were intermixed with no feedback trials ("mixed feedback"), emphasizing the informational rather than evaluative weight of negative feedback, negative feedback elicited greater striatal activity than no feedback. Moreover, negative feedback was rated as more preferable in the mixed than in the blocked feedback condition, suggesting that participants experienced and valued negative feedback differently depending on the framing context (evaluative/informative). Whether this change in the subjective value of negative feedback in the mixed feedback context results from different types of curiosity (e.g., curiosity about feedback presence versus valence) is unknown. Satisfying curiosity through information receipt has been shown to activate the ventral striatum (Ligneul, Mermillod, & Morisseau, 2018). Valuation of negative feedback may also be further modulated by affective manipulations.

Recent evidence suggests that striatal responses may reflect the affective context of negative feedback. After a competence threat, individual differences in achievement goals modulated striatal responses to negative feedback (DePasque, Rivera, Laws Backstrom, & Tricomi, submitted) such that individuals whose learning goals were more oriented towards avoidance, rather than approach, had stronger decreases in striatal signal (i.e., a stronger "punishment" response). Goals to avoid failure under a competence threat may thus prevent individuals from recognizing the informational value of negative feedback. Because our mixed feedback paradigm manipulated the informational and evaluative weight of negative feedback, we employed it, in conjunction with a competence threat, to isolate the differences in learning from negative feedback that arise due to intelligence mindset.

In our neuroimaging study, we examined how a competence threat would change neural responses to feedback during learning for individuals varying in intelligence mindset. Because intelligence mindset is particularly likely to influence perceptions of negative feedback as threatening under emotionally salient contexts, we hypothesized that a competence threat manipulation would differentially affect individuals varying in mindset when they learned from negative feedback. After taking a purported IQ test, which resulted in either no score or a competence-threatening score, participants performed a word-association task during which feedback was "definitely" received or omitted (blocked condition) or "maybe" presented (mixed condition), thus biasing the subjective weight of negative feedback. We predicted that the competence threat would impact performance and striatal responses to negative feedback, and that striatal activation, particularly in the mixed feedback context, would depend on individual differences in intelligence mindset. Our study was designed to highlight the interplay between contextual and motivational factors influencing the ability to learn from negative feedback.

2. Methods

2.1. Participants

Forty participants (20 male, 20 female; mean age = 23.48, SD = 6.06), were recruited via posted advertisements. Participants were diverse in ethnicity and race (13 White/Caucasian, 12 Asian, 6 Black/African American, 5 Hispanic or Latino, and 4 self-reported Other (2 Biracial, 1 African, 1 Indian)). All gave written informed consent. The experiment was approved by the institutional review board of Rutgers University.

2.2. Stimuli information

All words were matched for word length (4–8 letters and 1–2 syllables) and frequency (Kučera–Francis frequencies of 20–650 words per million) at the trial level, and had imageability ratings of over 400 according to the MRC database (Coltheart, 1981). Words presented on the same trial had low semantic relation (i.e., had a score of less than 0.2 on the latent semantic analysis similarity matrix (Landauer, Foltz, & Laham, 1998)). Likewise, none rhymed or began with the same letter.

2.3. Experimental procedure

This experiment followed the procedures outlined in previous work (Fig. 1) (DePasque, Rivera, Laws Backstrom, & Tricomi, submitted; Lempert & Tricomi, 2015). All participants had a twenty-minute time limit to complete a fake, but believable, computerized intelligence test, comprised of 15 items ostensibly related to verbal and reasoning abilities (cf. Laws & Rivera, 2012). The researcher introduced the test as a separate study on "cognitive factors" being conducted in collaboration with a colleague (see Supplementary Text for manipulation checks). Participants were pseudorandomly assigned into two gender-matched groups: those who were not evaluated and received no score upon completion of the IQ test (non-threat) and those who received a low score of the 47th percentile, meant as a threat to their perceived competence (threat).

Next participants performed a paired-associate word learning task, similar to those in our other feedback-based learning work (Dobryakova & Tricomi, 2013; Lempert & Tricomi, 2015; Tricomi & Fiez, 2008, 2012). Participants first completed the "study phase," in which 220 distinct target words were presented for six seconds above their two possible word matches, with the correct match highlighted in green. Participants were told to remember the correct match for each target word, since their memory would be tested later.

Inside the scanner, participants then completed the "learning phase" (Fig. 1). Prior to each set of 8 trials, participants were informed of the block condition (mixed feedback, labeled, "maybe feedback" or blocked feedback, labeled, "definite feedback" and "no feedback"). This was followed by a jittered inter-trial interval of 1–8 seconds. One hundred and sixty of the target words from the study phase were then randomly presented; however, their correct matches were no longer highlighted. Sixty words from the study phase were not included here so that we could quantify the effect of receiving feedback on later memory relative to mere memorization of the paired-associates. Within a four-second period, participants registered their responses by pressing the button associated with the word that they believed correctly matched the target word. Feedback lasted one second.

In "maybe feedback" blocks (i.e., the mixed feedback condition), half of the trials yielded veridical feedback (an image of a green check mark for a correct response; a red X for a wrong response), while the other half yielded no feedback (a gray pound sign). Participants understood that whether feedback was presented on "maybe feedback" trials was random, but veridical when it was presented. In "definite feedback" blocks, feedback was always delivered contingent on participants' actual response accuracy, while in "no feedback" blocks, the

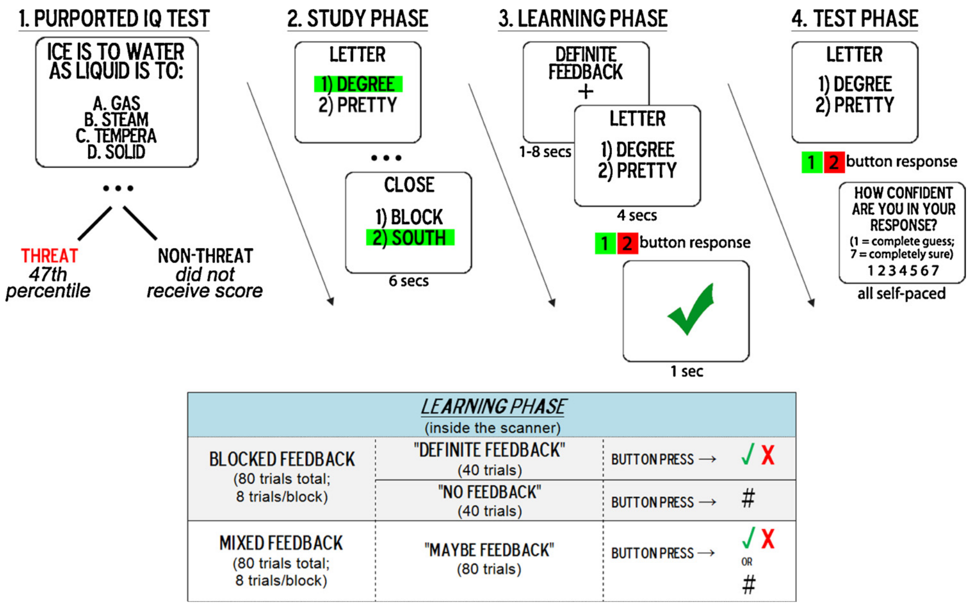

Fig. 1. Summary of Task Procedure. Participants took a fake, but believable, intelligence test ostensibly related to verbal reasoning abilities. Upon completion, participants either received no test score (non-threat) or a score of the 47th percentile as a challenge to their competence (threat). Next participants performed a paired-associate learning task. In the study phase, participants learned the associations between a target word and its correct match highlighted in green. During the learning phase, participants used feedback, when available, and encoded the correct word-associations. Each trial began with a label indicating the trial condition (mixed feedback i.e., "maybe feedback," or blocked feedback i.e., "no feedback" and "definite feedback"). Following a jittered interval of 1–8 seconds, participants had four seconds to choose via button press which response option matched the presented target word. Veridical or no feedback was then delivered contingent upon response accuracy as well as trial condition, and lasted for one second. There were an equal number of blocked and mixed feedback trials, ensuring that feedback was expected on half of the trials and intermittent on the other half. Participants indicated their knowledge of the word-associations in the test phase. The experiment ended after participants answered a post-test questionnaire (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

pound sign was always presented irrespective of accuracy. The blocked feedback condition consisted of "definite feedback" and "no feedback" blocks so that the receipt or omission of feedback was always predictable. Mixed and blocked feedback runs alternated within participants, and block order was counterbalanced across participants, so that participants either performed blocked/mixed/blocked/mixed or mixed/blocked/mixed/block runs.

After the scan, participants completed the self-paced "test phase" in which a target word and its two possible matches were presented in a randomized order; this included all study phase trials. Participants again selected the word they believed correctly matched the target word and rated their confidence for their choice along a 1–7 scale (1 = complete guess, 7 = completely sure). Finally, participants filled out a battery of post-test questionnaires, including the six-item Theory of Intelligence scale (TOI; Dweck, 2006; Blackwell, Trzesniewski, & Dweck, 2007), which measures the extent to which individuals believe that intelligence is malleable (incremental) versus fixed (entity) on a scale from one (strongly disagree) to six (strongly agree). TOI questions were scored such that lower scores (e.g., 1–3) indicate incremental beliefs that intelligence is fluid and malleable, while higher scores (e.g., 4–6) indicate entity beliefs that intelligence is fixed and nonmalleable. Both pre-screen (taken outside of lab as part of a survey ensuring MRI eligibility) and post-test TOI scores had high reliability (Cronbach's alpha = 0.92 and 0.96, respectively), and removing any one item resulted in worse α. Participants also answered questions about their preferences for the feedback conditions as well as their subjective feelings after receiving or having not received their IQ test score. Because previous literature has indicated that intelligence mindset groups differ in achievement goals (e.g., Dweck, 2006), we had participants fill out the Achievement Goal Questionnaire (Elliot & Church, 1997), which measures individual differences in goal orientations. For exploratory purposes, we had participants fill out the Cognitive Interference Scale (Sarason, 1978), which measures mind-wandering and the frequency of off-task thoughts, and the Cognitive Appraisal Index (Lazarus & Folkman, 1984), which measures individual differences in coping with cognitive demands.

All questionnaires were presented in a randomized order. Experimental scripts can be found at: https://github.com/christinabejjani/mindset_fMRI.

2.4. fMRI data acquisition

A 3 T Siemens Trio scanner was used for data acquisition at the Rutgers University Brain Imaging Center. Anatomical images were collected using a T-1 weighted protocol (a 256 × 256 matrix, 176 1-mm sagittal slices). Using a single-shot EPI sequence (TR = 2500 ms, TE = 30 ms, flip angle = 90°, FOV = 192 x 192 mm, slice gap = 0 mm), forty-one contiguous slices of 3 mm isotropic voxels were acquired parallel to the AC-PC line in an interleaved order.

Each scanning session consisted of four functional runs comprised of 172 2.5 s TRs. The trial conditions were presented in their own runs and alternated. The two possible orders were counterbalanced across participants.

2.5. Data analysis

Accuracy (proportion correct) was analyzed for the learning and test phase data. For the learning phase, we ran paired t-tests to compare the number of positive and negative feedback events from the learning phase between the mixed and blocked conditions as confirmation that their fMRI power was roughly matched. We also ran a repeated-measures ANOVA on learning phase accuracy data, using feedback condition (mixed/blocked) and feedback availability (received/omitted) as within-subjects factors, IQ test group (threat/non-threat) as a between-subjects factor, and Theory of Intelligence (TOI) scores as a covariate (see Supplementary text for learning phase analysis). Test phase accuracy was similarly analyzed with a repeated-measures ANOVA, using feedback condition (mixed/blocked), feedback availability in the learning phase (received/omitted), and learning phase accuracy (correct/incorrect) as within-subject factors, IQ test group (threat/non-threat) as a between-subjects factor and TOI scores as a covariate (see Supplementary text for comparisons between threat and non-threat on test phase accuracy). All results were Greenhouse-Geisser corrected where appropriate.

Imaging data was analyzed with Brain Voyager QX, version 2.4.2 (Brain Innovation, Maastricht, The Netherlands). Six parameters corrected for three-dimensional motion, while cubic spline interpolation corrected for slice scan time. Spatial smoothing using a three-dimensional Gaussian filter (6 mm FWHM), as well as a high-pass filtering of frequencies (three cycles per time course), were performed. All structural and functional data were transformed to standard Talairach stereotaxic space (Talairach and Tournoux, 1988).

After image preprocessing, the functional data was analyzed with a random-effects general linear model (GLM). The onsets of each feedback event were modeled as stick functions and then convolved with a canonical hemodynamic response function to create regressors of interest for the different conditions (i.e. positive, negative, and no feedback events for both mixed and blocked feedback). To ensure that our model covered the entire experiment, regressors of no interest included the motion parameters generated during preprocessing, trials for which no response was recorded, and stimulus presentation events.

Because the striatum has been implicated in feedback-based learning, we selected *a priori* regions-of-interest (ROIs) in the caudate and ventral striatum based on previous work (Lempert & Tricomi, 2015). In the caudate, cubic regions of 125 mm^3 were centered at x = +/- 12, y = 8, and z = 12, while ventral striatum ROIs were the same size and centered at x = +/- 10, y = 8, z = −4 (see Supplementary text for ventral striatum results). Previous studies on performance feedback and reward processing have used or found peak activation at these coordinates (Bischoff-Grethe et al., 2009; Delgado et al., 2000; Lempert & Tricomi, 2015; Tricomi & Fiez, 2012). From these regions, we extracted parameter estimates of activity for our six event types (i.e., positive, negative, and no feedback events for both mixed and blocked feedback) and ran correlations with our individual difference measures. Paired and independent samples t-tests were run when further clarification was needed.

We performed an ANCOVA on positive, negative, and no feedback events within both the mixed and blocked feedback runs (see Supplementary text for whole-brain pairwise activation analysis). Using TOI scores as our covariate, we contrasted feedback types between conditions (positive/negative/no feedback blocked > positive/negative/no feedback mixed). Whole-brain statistical maps were generated based on correlations between TOI scores and pairwise activity, and cluster threshold corrected to a whole brain p-value of 0.05 from an uncorrected voxel-wise p-value of $p < 0.001$.

3. Results

3.1. Test phase accuracy

On average, participants performed above chance on the test phase, regardless of IQ test group (Fig. 2; mean accuracy = 0.67, 95% CI [0.64, 0.71], $t(39) = 9.89$, $p < 0.001$, Cohen's $d = 1.56$; threat accuracy = 0.64, 95% CI [0.59, 0.69], $t(19) = 6.39$, $p < 0.001$, Cohen's $d = 1.43$; control accuracy = 0.70, 95% CI [0.65, 0.76], $t(19) = 7.92$, $p < 0.001$, Cohen's $d = 1.77$).

Consistent with motivational differences due to achievement goals (see Supplementary text), intelligence mindset also influenced test phase accuracy in the omnibus ANOVA. There was a significant interaction between feedback availability, condition, and TOI ($F(1,36) = 9.80$, $p = 0.003$, $\eta_p^2 = 0.21$) and an interaction that approached significance between learning phase accuracy, condition, IQ test group, and TOI ($F(1,36) = 2.86$, $p = 0.100$, $\eta_p^2 = 0.08$). Because we were primarily interested in how participants would process and learn from negative feedback across the mixed and blocked feedback contexts (cf. Lempert & Tricomi, 2015), we decompose these interactions from the omnibus ANOVA by focusing on how participants learn from negative feedback.

Note that we index whether a participant learned from negative feedback by comparing test phase accuracy on trials for which participants had previously received negative feedback in the learning phase relative to trials for which participants had been likewise incorrect in the learning phase but had received no learning-related feedback. In such cases, we infer that participants used the feedback to encode the correct paired-associates. For illustration and analytic purposes, a median split separated participants into incremental (low TOI scores ($M = 1.48$, SD = 0.41); growth mindsets, beliefs that intelligence is malleable) and entity (high TOI scores ($M = 3.95$, SD = 0.86); fixed mindsets, beliefs that intelligence is fixed) groups. To better understand the significant three-way and trending four-way interactions in the omnibus ANOVA as a function of learning from negative feedback and intelligence mindset, we therefore dropped the within-subjects learning phase accuracy factor and included TOI as a between-subjects factor.

Consistent with the omnibus ANOVA, we still find a three-way interaction between feedback availability, condition, and TOI ($F(1,36) = 6.97$, $p = 0.012$, $\eta_p^2 = 0.16$). We first addressed the extent to which incremental theorists were able to learn from negative feedback across the feedback contexts. As shown in Fig. 2a, incremental theorists learned from blocked negative feedback ($M = 0.60$, 95% CI [0.53, 0.67] vs. blocked no feedback (incorrect trials): $M = 0.42$, 95% CI [0.35, 0.48]) but did not learn from mixed negative feedback ($M = 0.51$, 95% CI [0.44, 0.59] vs. mixed no feedback (incorrect trials): $M = 0.49$, 95% CI [0.43, 0.56]). Indeed, incremental theorists learned more from blocked negative feedback ($M = 0.60$, 95% CI [0.53, 0.67]) than from mixed negative feedback ($M = 0.51$, 95% CI [0.44, 0.59]), suggesting that they learn from the informational content of negative feedback in the context that emphasizes its evaluative sting but may become distracted in the intermittent feedback context.

In contrast, entity theorists did not learn from blocked negative feedback ($M = 0.51$, 95% CI [0.44, 0.58] vs. blocked no feedback (incorrect trials): $M = 0.43$, 95% CI [0.35, 0.52]) but learned from mixed negative feedback ($M = 0.58$, 95% CI [0.50, 0.67] vs. mixed no feedback (incorrect trials) $M = 0.47$, 95% CI [0.41, 0.54]). Indeed, entity theorists learned more from mixed negative feedback ($M = 0.58$, 95% CI [0.50, 0.67]) than from blocked negative feedback ($M = 0.51$, 95% CI [0.44, 0.58]), suggesting that entity theorists learn from negative feedback when its value is biased to be more informational than evaluative.

We then compared the theorists across feedback contexts. Based on the three-way interaction between feedback availability, condition, and TOI, we found that incremental theorists learned significantly more from blocked negative feedback than entity theorists (incremental: $M = 0.60$, 95% CI [0.53, 0.67]; entity: $M = 0.51$, 95% CI [0.44, 0.58], $t(38) = 2.05$, $p = 0.048$, Cohen's $d = 0.65$) but that entity theorists did not learn significantly more from mixed negative feedback than incremental theorists (incremental: $M = 0.51$, 95% CI [0.44, 0.59]; entity: $M = 0.58$, 95% CI [0.50,0.67]; $t(38) = 1.36$, $p = 0.181$, Cohen's $d = 0.43$). This suggests two main points: first, when the feedback context biased the evaluative value of negative feedback, entity theorists did poorer compared to incremental theorists. Second, when the feedback context emphasized the informational weight of negative feedback, entity theorists actually learned from negative feedback in the mixed feedback context but did not outperform their incremental peers, likely due to their maladaptive strategy in coping with negative feedback.

Finally, there was also a significant interaction between TOI and IQ test group on test phase accuracy (Fig. 2b; $F(1,36) = 4.38$, $p = 0.044$, $\eta_p^2 = 0.11$). Incremental theorists had relatively similar test phase accuracy, regardless of IQ test group (threat: M = 0.66, 95% CI [0.59, 0.74]; non-threat: M = 0.68, 95% CI [0.59, 0.77]). However, entity theorists who received the competence threat performed significantly worse overall than those in the non-threat condition (threat: $M = 0.62$, 95% CI [0.56, 0.68]; non-threat: $M = 0.72$, 95% CI [0.66, 0.79]), indicating that they may have fixated more on their IQ test performance and subsequent low score to the decrement of later learning. For participants who believe that their intelligence is a fixed trait, receiving and then ruminating on their low IQ test score might have exacerbated the performance threat induced by negative feedback.

3.2. Caudate nucleus region-of-interest analysis

Fig. 3 displays parameter estimates for each feedback event type in

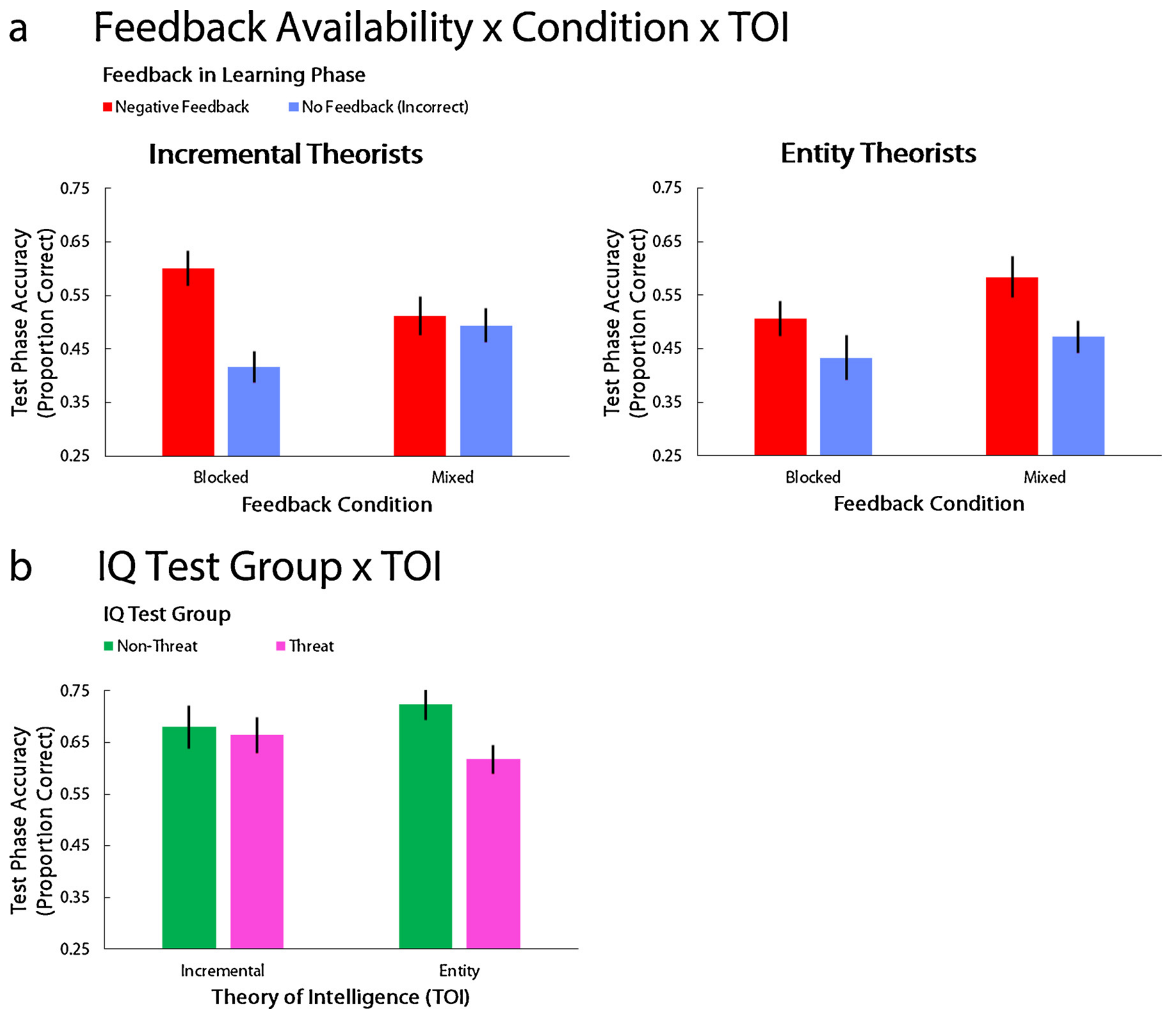

Fig. 2. Behavioral results. Test phase accuracy (proportion correct) (± SEM) data are shown as a function of (**A**) feedback condition in the learning phase (blocked (left), mixed (right)), feedback availability in the learning phase (received/negative feedback (left), omitted/no feedback (right)), and intelligence mindset theorist (incremental (left), entity (right)) and (**B**) intelligence mindset theorist (incremental (left), entity (right)) and IQ test group (non-threat (left), threat (right)).

the caudate head, defined a priori by the coordinates +/- 12,812 (Lempert & Tricomi, 2015). To investigate potential associations between mindset and learning-related activation, correlations were run between our individual difference measures and parameter estimates. TOI scores were significantly correlated with left caudate activation for positive compared to negative mixed feedback ($r(38) = 0.39$, $p =$ 0.013, 95% CI [0.09, 0.63]) as well as that of negative compared to no mixed feedback ($r(38) = -0.36$, $p =$ 0.022, 95% CI [-0.60, -0.06]). Compared to entity theorists, incremental theorists may have seen negative mixed feedback as informative, causing less striatal activation for positive than negative mixed feedback and greater for negative than no mixed feedback. Indeed, unlike entity theorists, incremental theorists showed a negative mixed feedback signal with magnitude comparable to that of positive feedback and an intrinsic reward.

Although incremental and entity theorists both showed a typical punishment response in the blocked condition to negative feedback (Fig. 4), they substantially diverged in response to mixed negative feedback, an effect driven by the competence threat. For participants who received the competence threat, higher incremental beliefs about intelligence led to a smaller difference in activity for positive compared to negative mixed feedback and greater difference in activity for negative compared to no mixed feedback, though the latter difference was not significant ($r(18) = 0.55$, $p =$ 0.013, 95% CI p0.14, 0.80]; $r(18) =$ -0.44, $p =$ 0.052, 95% CI [-0.74, 0.00]). Whereas the entity threat theorists performed more poorly on the test phase relative to entity non-threat theorists, incremental theorists who had received the competence threat may have continued to see negative mixed feedback as informative, leading to this difference in striatal signal but not resulting in a performance benefit relative to incremental non-threat theorists. Neither relationship between caudate activation and TOI was significant for the non-threat condition ($r(18) = 0.26$, $p =$ 0.277, 95% CI [-0.21, 0.63]; $r(18) =$ -0.28, $p =$ 0.236, 95% CI [-0.64, 0.19]), suggesting that TOI is especially important when competence is threatened.

Next we analyzed whether differences in caudate activation affected test phase performance for trials on which participants had previously received negative feedback. We first confirmed that TOI was related to the difference in test phase accuracy for trials on which participants had previously received negative blocked vs. negative mixed feedback (b = -0.051, 95% CI [-0.089, -0.013], $t(38) = -2.71$, $p =$ 0.010, r-squared = 0.16). After controlling for IQ test group and the difference in test phase confidence ratings for trials on which participants had received negative blocked vs. negative mixed feedback, the relationship between TOI and test phase accuracy remained significant (b = −0.052, 95% CI [−0.091, −0.013], $t(36) =$ -2.70, $p =$ 0.011, r-squared = 0.17, total r-squared = 0.17). However, bilateral caudate activation for negative blocked vs. mixed feedback was not related to the difference in test phase confidence ratings or accuracy for trials on which participants had received negative blocked vs. negative mixed feedback (all $ts < 0.91$). This is evident when we control for bilateral caudate

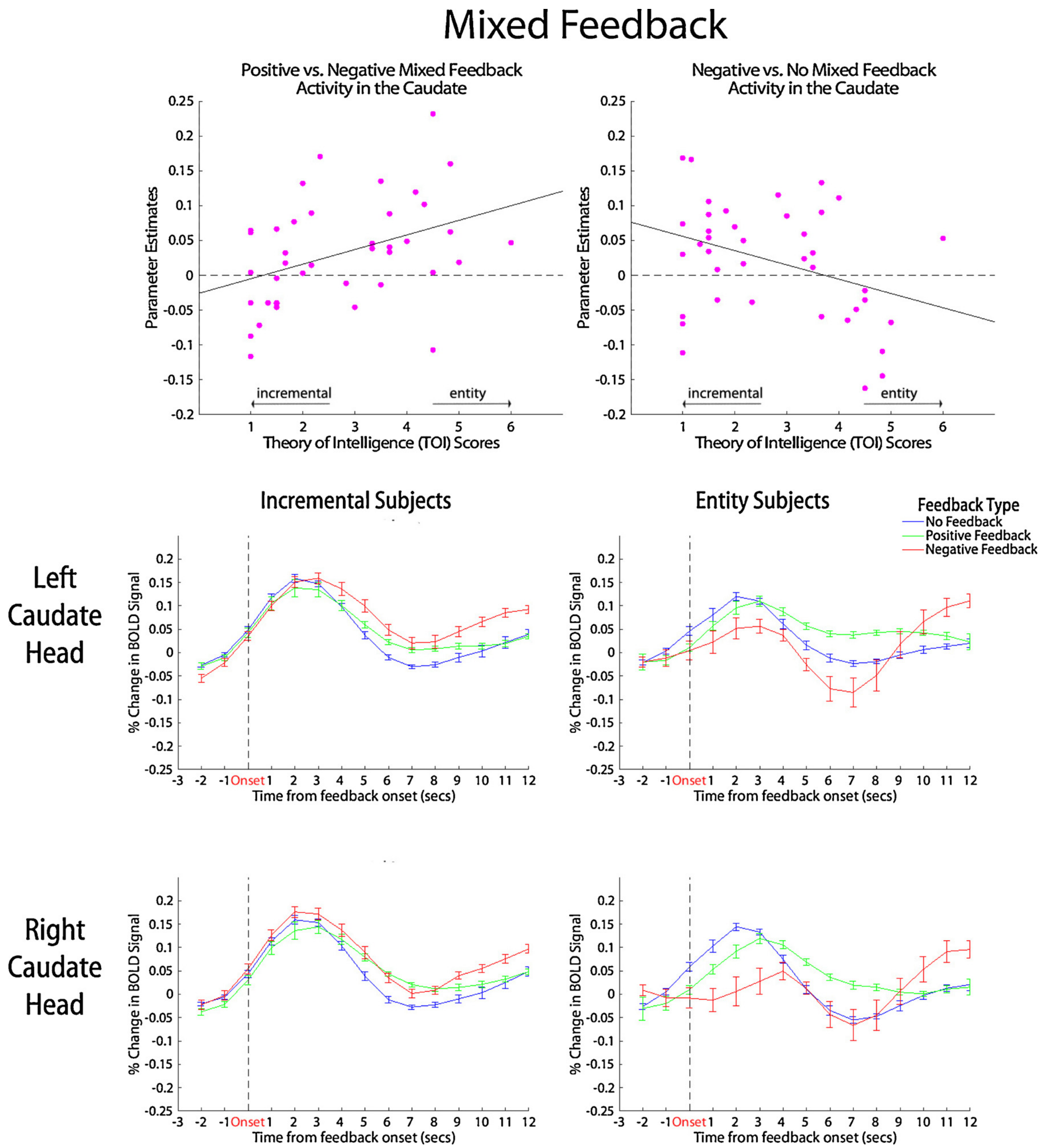

Fig. 3. Relationship between caudate activation and theory of intelligence (TOI) scores. The scatter plots (with best-fitting regression lines) in the top row show the relationship between TOI score and BOLD caudate head activation for negative mixed feedback compared to positive and no mixed feedback. TOI was scored such that higher scores indicated entity beliefs about intelligence/fixed mindsets, while lower scores indicated incremental beliefs about intelligence/growth mindsets. The bottom row shows the hemodynamic response from the *a priori* caudate head coordinates ± 12,812 by feedback event type for the mixed feedback condition. Feedback onset is indicated by the dotted vertical line. The incremental (left) and entity (right) groups were formed from a median split for illustrative purposes only.

activation to negative blocked vs. mixed feedback: accounting for bilateral striatal activation, confidence, and IQ test group, TOI was still significantly related to test phase accuracy (b = -0.049, 95% CI [-0.090, -0.01], $t(34) = -2.40$, $p = 0.022$, r-squared = 0.15, total R-squared = 0.23) such that a one point increase in intelligence mindset (towards entity beliefs) resulted in a 4.9% decrease in test phase accuracy for learning from negative blocked vs. mixed feedback. Notably, this model only explained 23% of the total variance in TOI and test phase accuracy on trials for which participants had previously received negative feedback.

Consistent with Lempert and Tricomi (2015), although we observed a change in striatal activation for negative feedback, subjective valuation did not appear to moderate test phase performance. Thus, while TOI and the competence threat affected striatal feedback signals, no subsequent effects on performance were observed.

4. Discussion

In this experiment, we tested how a competence threat impacts the ability to learn from negative feedback as a function of intelligence mindset. Participants first took a believable, but fake, intelligence test and upon completion, received a low, competence-threating score of the 47th percentile or received no score. Participants then completed a paired associates task consisting of a study phase, learning phase (in the scanner), and test phase. During the learning phase, feedback was manipulated to always be predictable (blocked feedback) or

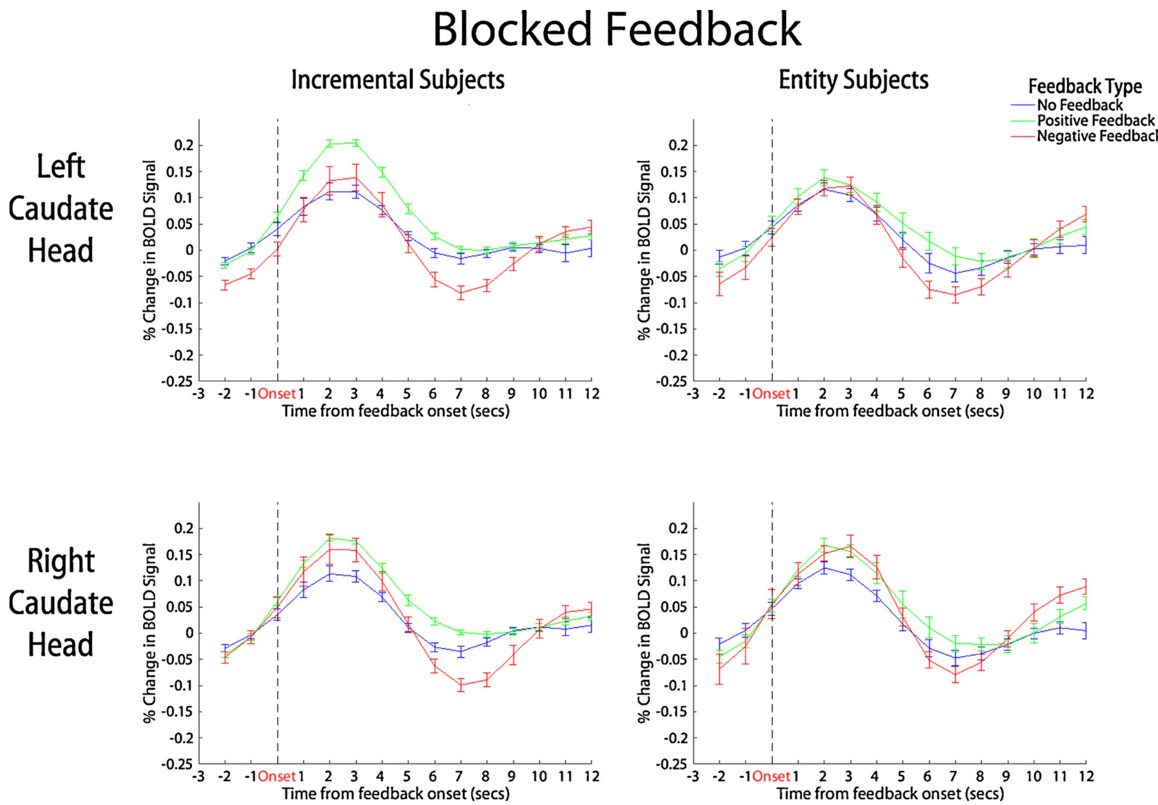

Fig. 4. Time courses extracted from the bilateral caudate head ROI (± 12, 8, 12) in the blocked feedback condition across intelligence mindset groups. Feedback onset is indicated by the dotted vertical line. The incremental (left) and entity (right) groups were formed from a median split for illustrative purposes.

intermittent (mixed feedback). We have previously used this feedback manipulation to bias participants towards viewing negative feedback in an evaluative context (blocked feedback) or an informative context (intermittent) (Lempert & Tricomi, 2015). We hypothesized that when their competence was threatened, participants who believe that their intelligence is fixed and cannot be developed through effort (entity theorists, fixed mindsets) would interpret further negative feedback as punishing.

Consistent with our hypothesis, the results demonstrate that when competence was threatened, participants who view intelligence as fixed showed stronger “punishment” responses to negative feedback, even when the feedback context de-emphasized the evaluative weight of negative feedback (mixed feedback). Receiving a competence threat may thus have exacerbated the threat of failure inherent in receiving negative feedback, causing poorer learning from negative feedback in the evaluative, blocked feedback context and a punishment response to negative feedback in both feedback contexts. This suggests that when competence is threatened, entity theorists may interpret further negative appraisals as punishing, which may prevent them from benefiting from the information provided by negative feedback. Indeed a significant relationship between mastery-oriented goals and intelligence mindset was observed such that entity theorists reported caring less about mastering the learning task (see Supplementary text), in line with previous literature on the relationship between goal pursuit and intelligence mindset (Burnette et al., 2013). After a competence threat, entity theorists are thus less likely than their peers who view intelligence as malleable (incremental theorists, growth mindsets) to orient their learning towards mastery strategies.

Entity theorists also did not adaptively use negative feedback to improve, consistent with previous research on how they correct their mistakes to achieve their goals (Burnette et al., 2013; Dweck, 2006; Mangels et al., 2006; Moser et al., 2011; Schroder et al., 2014, 2017). Entity versus incremental theorists differ in their immediate neural attentional orientation to feedback: incremental theorists encode learning-relevant feedback and index on-line corrective information to improve accuracy and rebound from mistakes, while entity theorists focus more on ability-relevant feedback and do not process errors adaptively, to the detriment of performance (Mangels et al., 2006; Moser et al., 2011; Schroder et al., 2014, 2017). We further extend the literature in examining not only how the intelligence mindset theorists allocate attentional resources to process feedback but also how they individually process feedback using the reward system. We show that a cognitive manipulation can activate a relationship with the social self to have downstream effects on learning and memory as supported by task-based fMRI and localize these effects to show that feedback context can differentially influence performance and the learning styles of the theorists.

Neural differences between entity versus incremental theorists were most evident across feedback contexts. In the mixed feedback context, trials with and without feedback were intermixed to bias learners towards viewing the informational rather than evaluative weight of negative feedback, which otherwise elicits a punishment response (Lempert & Tricomi, 2015). Thus, the sting of negative feedback should be reduced, yet entity theorists showed a punishment response across feedback contexts. However, although incremental theorists showed a more dynamic striatal response to negative mixed feedback, their attenuated punishment response did not lead to a subsequent increase in test phase accuracy. This calls into question the purpose of increased striatal activation to negative mixed feedback for incremental theorists, if not to increase the subjective value of negative feedback and improve learning. Their change in signal may actually have reinforced incorrect information. Incremental theorists have been shown to have greater coactivation at rest between reinforcement learning related regions, such as the striatum, and executive function related regions, such as the dorsal anterior cingulate cortex (dACC) and dorsolateral prefrontal cortex (dlPFC) (Myers et al., 2016). A possible mechanistic explanation is that the increased attentional demand of the mixed feedback condition distracted entity theorists from worrying about their IQ test performance (Cury et al., 2008). This may have buffered their performance relative to incremental theorists, whose mastery-oriented strategy meant engaging regions such as the dACC and dlPFC to then correct their striatal reinforcement signals. Indeed, as revealed by a whole-brain analysis (see Supplementary text), many regions showed differential activity based on feedback receipt and TOI scores, suggesting that neural learning signals across the brain are differentially affected by intelligence mindset.

These learning differences may arise as a result of negative mixed feedback subsequently attaining more subjective value or due to recruitment of other learning-related brain regions. For instance, in this task, the performance feedback is presented after all choices have been removed from the screen, suggesting that participants would only learn the correct paired-associates if they correctly updated the association in working memory. Future work should address the extent to which other regions mediate these differences in performance and striatal signals. How entity and incremental theorists process positive feedback may also prove enlightening, since entity theorists here perform best in the mixed feedback context when the difference between their neural signals for positive and negative feedback is largest, suggesting that sensitivity to feedback as a marker of attention and salience could be important.

Our results emphasize the importance of intelligence mindset in learning from negative feedback, particularly after threatening self-appraisals such as IQ tests. In educational domains, students are frequently evaluated with stressful standardized tests, and at universities in low-income cities like Rutgers-Newark, many students are also battling socioeconomic and social mobility barriers. Much intervention work has been done to improve educational agency and intrinsic motivation through the promotion of incremental beliefs about intelligence (cf. Claro, Paunesku, & Dweck, 2016; also see Baird, Scott, Dearing, & Hamill, 2009; Blackwell et al., 2007; Dweck, 2006; Schroder et al., 2014). Understanding the neural mechanisms that drive mindset-related differences in learning may further help improve engagement in classroom settings and educational outcomes.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.biopsycho.2019.06.003.

References

Baird, G. L., Scott, W. D., Dearing, E., & Hamill, S. K. (2009). Cognitive self-regulation in youth with and without learning disabilities: Academic self-efficacy, theories of intelligence, learning vs. performance goal preferences, and effort attributions. *Journal of Social and Clinical Psychology, 28*(7), 881–908.

Bartra, O., McGuire, J. T., & Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *Neuroimage, 76*, 412–427.

Bischoff-Grethe, A., Hazeltine, E., Bergren, L., Ivry, R. B., & Grafton, S. T. (2009). The influence of feedback valence in associative learning. *Neuroimage, 44*(1), 243–251.

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child Development, 78*(1), 246–263.

Burnette, J. L., O'Boyle, E. H., VanEpps, E. M., Pollack, J. M., & Finkel, E. J. (2013). Mindsets matter: A meta-analytic review of implicit theories and self-regulation. *Psychological Bulletin, 139*(3), 655–701.

Claro, S., Paunesku, D., & Dweck, C. S. (2016). Growth mindset tempers the effects of poverty on academic achievement. *Proceedings of the National Academy of Sciences, 113*(31), 8664–8668.

Clithero, J. A., & Rangel, A. (2014). Informatic parcellation of the network involved in the computation of subjective value. *Social Cognitive and Affective Neuroscience, 9*(9), 1289–1302.

Coltheart, M. (1981). The MRC psycholinguistic database. *The Quarterly Journal of Experimental Psychology, 33*(4), 497–505.

Cury, F., Da Fonseca, D., Zahn, I., & Elliot, A. (2008). Implicit theories and IQ test performance: A sequential mediational analysis. *Journal of Experimental Social Psychology, 44*(3), 783–791.

Daniel, R., & Pollmann, S. (2014). A universal role of the ventral striatum in reward-based learning: Evidence from human studies. *Neurobiology of Learning and Memory, 114*, 90–100.

Delgado, M., Locke, H., Stenger, V., & Fiez, J. (2003). Dorsal striatum responses to reward and punishment: Effects of valence and magnitude manipulations. *Cognitive, Affective & Behavioral Neuroscience, 3*(1), 27–38.

Delgado, M. R., Nystrom, L. E., Fissell, C., Noll, D., & Fiez, J. A. (2000). Tracking the hemodynamic responses to reward and punishment in the striatum. *Journal of Neurophysiology, 84*(6), 3072–3077.

DePasque, S., & Tricomi, E. (2015). Effects of intrinsic motivation on feedback processing during learning. *Neuroimage, 119*, 175–186.

DePasque Swanson, S., & Tricomi, E. (2014). Goals and task difficulty expectations modulate striatal responses to feedback. *Cognitive, Affective & Behavioral Neuroscience, 14*(2), 610–620.

Dobryakova, E., & Tricomi, E. (2013). Basal ganglia engagement during feedback processing after a substantial delay. *Cognitive, Affective & Behavioral Neuroscience, 13*(4), 725–736.

Dweck, C. (2006). *Mindset: The new psychology of.* Success: Random House.

Dweck, C. S., Mangels, J. A., Good, C., Dai, D., & Sternberg, R. (2004). Motivational effects on attention, cognition, and performance. In D. Y. Dai, & R. J. Stenberg (Eds.). *Motivation, emotion, and cognition: Integrative perspectives on intellectual functioning and development* (pp. 41–55). Mahwah, New Jersey: Lawrence Erlbaum Associates.

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 72*(1), 218–232.

Landauer, T. K., Foltz, P. W., & Laham, D. (1998). An introduction to latent semantic analysis. *Discourse Processes, 25*(2-3), 259–284.

Laws, V. L., & Rivera, L. M. (2012). The role of self-image concerns in discrepancies between implicit and explicit self-esteem. *Personality & Social Psychology Bulletin, 38*(11), 1453–1466.

Lazarus, R. S., & Folkman, S. (1984). Coping and adaptation. In W. D. Gentry (Ed.). *The handbook of behavioral medicine* (pp. 282–325). New York: Guilford.

Lempert, K. M., & Tricomi, E. (2015). The value of being wrong: Intermittent feedback delivery alters the striatal response to negative feedback. *Journal of Cognitive Neuroscience, 28*(2), 261–274.

Ligneul, R., Mermillod, M., & Morisseau, T. (2018). From relief to surprise: Dual control of epistemic curiosity in the human brain. *NeuroImage, 181*, 490–500.

Mangels, J. A., Butterfield, B., Lamb, J., Good, C., & Dweck, C. S. (2006). Why do beliefs about intelligence influence learning success? A social cognitive neuroscience model. *Social Cognitive and Affective Neuroscience, 1*(2), 75–86.

Marco-Pallarés, J., Müller, S. V., & Münte, T. F. (2007). Learning by doing: An fMRI study of feedback-related brain activations. *Neuroreport, 18*(14), 1423–1426.

Moser, J. S., Schroder, H. S., Heeter, C., Moran, T. P., & Lee, Y.-H. (2011). Mind your errors evidence for a neural mechanism linking growth mind-set to adaptive posterror adjustments. *Psychological Science, 22*(12), 1484–1489.

Myers, C. A., Wang, C., Black, J. M., Bugescu, N., & Hoeft, F. (2016). The matter of motivation: Striatal resting-state connectivity is dissociable between grit and growth mindset. *Social Cognitive and Affective Neuroscience, 11*(10), 1521–1527.

Nieuwenhuis, S., Heslenfeld, D. J., von Geusau, N. J. A., Mars, R. B., Holroyd, C. B., & Yeung, N. (2005). Activity in human reward-sensitive brain areas is strongly context dependent. *Neuroimage, 25*(4), 1302–1309.

Sarason, I. G. (1978). The test anxiety scale: Concept and research. In C. D. Spielberger, & I. G. Sarason (Eds.). *Stress and anxiety*. Washington D.C: Hemisphere Publishing Corporation.

Schroder, H. S., Fisher, M. E., Lin, Y., Lo, S. L., Danovitch, J. H., & Moser, J. S. (2017). Neural evidence for enhanced attention to mistakes among school-aged children with a growth mindset. *Developmental Cognitive Neuroscience, 24*, 42–50.

Schroder, H. S., Moran, T. P., Donnellan, M. B., & Moser, J. S. (2014). Mindset induction effects on cognitive control: A neurobehavioral investigation. *Biological Psychology, 103*, 27–37.

Talairach, J., & Tournoux, P. (1988). *Co-planar stereotaxic atlas of the human brain.* Stuttgart, New York: Thieme Medical Publishers.

Tricomi, E., Delgado, M. R., McCandliss, B. D., McClelland, J. L., & Fiez, J. A. (2006). Performance feedback drives caudate activation in a phonological learning task. *Journal of Cognitive Neuroscience, 18*(6), 1029–1043.

Tricomi, E., & Fiez, J. A. (2008). Feedback signals in the caudate reflect goal achievement on a declarative memory task. *Neuroimage, 41*(3), 1154–1167.

Tricomi, E., & Fiez, J. A. (2012). Information content and reward processing in the human striatum during performance of a declarative memory task. *Cognitive, Affective & Behavioral Neuroscience, 12*(2), 361–372.

Tricomi, E., & Lempert, K. M. (2015). Value and probability coding in a feedback-based learning task utilizing food rewards. *Journal of Neurophysiology, 113*(1), 4–13.