The adolescent brain : unraveling the neural mechanisms of cognitive and affective development

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Chapter 7

Predicting reading and mathematics from neural activity for feedback learning

This chapter is based on:

Peters, S., Van der Meulen, M., Zanolie, C.K.K. & Crone, E.A. Predicting reading and mathematics from neural activity for feedback learning: A longitudinal study (in revision, 2015).

Abstract

Although many studies use feedback learning paradigms to study the process of learning in laboratory settings, little is known about their relevance for real-world learning settings such as school. In a large developmental sample (*N* = 228, 8-27 years), we investigated whether performance and neural activity during a feedback learning task predicted reading and mathematics performance two years later. The results indicated that feedback learning performance predicted both reading and mathematics performance. Activity during feedback learning in left superior dorsolateral prefrontal cortex (DLPFC) and left superior parietal cortex (SPC) predicted reading performance, whereas activity in pre-supplementary motor area/anterior cingulate cortex (pre-SMA/ACC) predicted mathematical performance. Moreover, left superior DLPFC and pre-SMA/ACC activity predicted unique variance in reading and mathematics ability over behavioral testing of feedback learning performance alone. These results provide valuable insights into the relationship between laboratory-based learning tasks and learning in school settings, and the value of neural assessments for prediction of school performance over behavioral testing alone.

Introduction

Learning from performance feedback is an important skill allowing us to rapidly adjust behavior based on changes in environmental demands (Holroyd & Coles, 2002). Thus, it is an adaptive form of learning which allows individuals to flexibly and creatively adapt to a changing environment in a successful way. Feedback learning is often investigated in controlled laboratory settings to study the process of learning. However, it is unclear how feedback learning in these controlled experimental paradigms relates to real-world learning in settings such as school. In this study, we investigated this question in a large developmental sample of participants between 8-27 years, focusing on both neural and behavioral indices of feedback learning as predictors for school performance two years later.

School performance can be measured in different ways. The most important school performance skills taught in schools across the world are reading and mathematics, given that many courses in school rely on children's ability to read proficiently and perform mathematical calculations. Many children who are poor readers in school keep having difficulties with reading later in life (O'Shaughnessy, Lane, Gresham, & Beebe-Frankenberger, 2003) and research has demonstrated that performance on mathematical tests predicts employability, productivity and salaries in adulthood (Geary, 2000; Rivera-Batiz, 1992).

Although the link between laboratory-based feedback learning tasks and school performance (e.g., mathematics and reading performance) is not yet clear, several studies have provided evidence that both feedback learning and reading and mathematics are linked to executive functions. Executive functions are defined as the ability to behave in goal-directed actions in new situations and to overcome automatic thoughts and behaviors (Garon et al., 2008). Executive functions are thought to consist of three subprocesses, or basic executive functions: (1) working memory, (2) inhibition and (3) switching (Huizinga et al., 2006; Miyake et al., 2000). Prior research using structural equation modeling showed that complex executive function tasks, such as performance on the classic Wisconsin Card Sorting Task (WCST), requires several basic executive functions, such as working memory and task switching (Huizinga et al., 2006; Miyake et al., 2000). It has been argued that complex cognitive tasks which rely on multiple subprocesses of executive functions are the most reliable correlates of cognitive performance in daily life (Barcelo & Knight, 2002), possibly because these tasks are more similar to everyday challenges. Feedback learning can also be interpreted as a complex executive control process, which most likely relies on multiple subprocesses of executive functions (Peters & Crone, 2014), and may rely partly on working memory capacity, given that feedback learning shares commonalities with the classic WCST (Huizinga et al., 2006).

Evidence for the relationship between school performance and executive functioning comes from numerous studies that demonstrated a link between working memory, inhibition and switching on the one hand, and reading and mathematics performance on the other (Blair &

Razza, 2007; Bull & Scerif, 2001; Raghubar, Barnes, & Hecht, 2010; Van der Sluis, De Jong, & Van der Leij, 2004). The link between executive functioning and school performance is not surprising, given that to develop reading and mathematics understanding, children probably need additional cognitive skills. For example, children have to be able to understand grammatical and numerical structure, keep track of the sentences read or mathematical steps taken before, and integrate information from long-term memory with current information to form a coherent view (Cain, Oakhill, & Bryant, 2004; Landi, Frost, Mencl, Sandak, & Pugh, 2013), which are all processes intimately related to executive functioning. This led us to hypothesize that feedback learning in controlled laboratory settings is a valid predictor of real-world learning performance in schools.

A second reason why feedback learning and reading and mathematical ability are expected to be related, is because they rely on similar brain mechanisms. The main neural areas involved during feedback processing are the dorsolateral prefrontal cortex (DLPFC), superior parietal cortex (SPC) and pre-supplementary motor area/anterior cingulate cortex (pre-SMA/ACC) (Peters, Braams, et al., 2014; Zanolie et al., 2008). Meta-analyses of fMRI-activity during reading also show recruitment of the DLPFC (Ferstl, Neumann, Bogler, & Von Cramon, 2008) and pre-SMA/ACC (Ferstl et al., 2008; Houdé, Rossi, Lubin, & Joliot, 2010) amongst other areas (mostly lateralized to the left hemisphere). Meta-analyses on mathematics-related neural activity also showed involvement of the DLPFC (Arsalidou & Taylor, 2011; Houdé et al., 2010), parietal cortex and pre-SMA/ACC (Arsalidou & Taylor, 2011). Thus, it is to be expected that activity patterns in DLPFC and pre-SMA/ACC are linked to reading and mathematics.

Recently, an increasing body of research has directed attention to predicting school performance from brain measures. A possible advantage of collecting neural measures in addition to behavioral measures is the hypothesis that brain measures can provide unique predictive information over behavioral measures alone (Dumontheil & Klingberg, 2012; Hoeft et al., 2007). In the current study, we investigated the link between learning in a controlled laboratory setting, and reading and mathematical ability as indices for real-world learning. We focused on fluency at reading single words, because this is one of the most crucial aspects of reading determining reading ability at a later stage (Jenkins, Fuchs, Van Den Broek, Espin, & Deno, 2003; Juel, 1988). To assess mathematics proficiency, we used a standardized arithmetic test that is part of the Wechsler Adult Intelligence Scale and the Wechsler Intelligence Scale for Children, which measures numerical reasoning and mathematical problem solving. In addition, we investigated whether individual differences in working memory capacity could explain a possible link between feedback learning and reading and mathematics performance. For instance, Huizinga et al. (2006) found that from the factors working memory, inhibition and switching, only working memory predicted WCST performance, a task that also relies on learning from feedback. We hypothesized that feedback learning performance would predict reading and mathematics performance two years later, and that neural measures would provide additional information over behavioral testing (feedback learning and working memory performance) alone.

Methods

Participants

The initial sample consisted of 299 participants (see also Peters, Braams, et al., 2014; Peters, Koolschijn, Crone, Van Duijvenvoorde, & Raijmakers, 2014), for whom data was collected on two time points (T1 and T2) which were approximately 2 years apart (M = 1.99, SD = 0.10, range: 1.66-2.47 years). The included sample with complete data at T1 for feedback learning and fMRI data consisted of 268 participants. At T1 participants were excluded from analyses for a variety of reasons, such as reported history of neurological or psychiatric disorders or use of psychotropic medication, movement in the MRI scanner exceeding 3.0 mm (N = 19), technical issues (N = 3) or because they were outliers at the lower end (more than three times the interquartile range) on feedback learning performance (N = 3).

At T2, there was complete data on reading and math performance for 228 participants (119 females) who were also included at T1 (aged 8.01 – 24.55 years at T1 (M = 14.35, SD = 3.57) and aged 9.92 – 26.62 at T2 (M = 16.34, SD = 3.58). All analyses were performed on these 228 participants. IQ scores at T1 were estimated using two subtests (Similarities and Block Design) of the WISC-III (participants 8-15 years old) or WAIS-III (participants 16-25 years old). Estimated IQ scores ranged from 85 to 143 (M = 110.78, SD = 9.80). The study was approved by the Institutional Review Board at the University Medical Center and all participants older than 12 (and participants' parents for children under 18) signed an informed consent form. Adults received payment (€60) for participation and children and their parents received brain-related presents and a payment for travel reimbursement (€30 for children 12-17 years, €25 for children 8-11 years).

Materials

Reading Fluency

Technical reading skills were measured with a reading fluency task at T2. We used one of the tests in the Dutch "Three-Minute-Test" (Krom, Jongen, Verhelst, Kamphuis, & Kleintjes, 2010). In this task, participants received a list of words and were instructed to read aloud as many words as possible in one minute. The total score is defined as the number of correct words minus the number of incorrect words. The Three-Minute-Test has good validity and reliability (Cronbach's alpha, dependent on age group > 0.92) (Krom et al., 2010).

Mathematics

Mathematical ability was measured with the subscale "Arithmetic" of the Wechsler Intelligence Scales (WISC-III for participants under 16, WAIS-III for participants of 16 years and older). A set of arithmetical problems of increasing difficulty was administered verbally. All arithmetic problems had a time limit of 30 to 75 seconds, depending on the difficulty of the problem. If the participants failed to correctly answer three consecutive problems the test was aborted. Both the WISC and the WAIS resulted in raw scores that were converted to norm scores relative to same-aged peers. We used norm scores in further analyses (see also Barnea-Goraly, Eliez, Menon, Bammer, & Reiss, 2005; Li, Hu, Wang, Weng, & Chen, 2013) to ensure comparability between the different ages (reflected in WISC and WAIS scores). In addition, we performed our main analyses with the mathematics subtest with raw scores for the WISC and WAIS group separately.

Working memory

We measured working memory performance at T1 to assess whether feedback learning and reading and mathematics performance were explained by individual differences in working memory. Working memory capacity was measured with the Mental Counters task (Huizinga et al., 2006), in which participants need to keep numerical information active. For this task, two independent counters were presented on a computer screen. The counters were horizontal bars for which the values changed depending on the position of a square. If a square was presented above a counter the participant was instructed to add 1 to the current value, if a square was presented below the counter the participant was instructed to subtract 1 from the current value of the counter. The squares appeared randomly above or below one of the two counters. Participant were instructed to keep track of both counters and to press a button as soon as one of the counters reached a given criterion value (e.g., when one of the counters reached the value 3). The squares were randomly presented in series (the number of trials before criterion was reached) of 5 or 7 trials with inter-trial intervals of 1000 to 1300 ms, with a total of 16 trials. The proportion of correct trials was used as a measure of performance.

Feedback Learning Task

Participants performed a feedback learning task in the MRI scanner (Peters, Braams, et al., 2014; Peters, Koolschijn, et al., 2014). On every trial, three empty boxes were presented in the top half of the screen in the stimulus and feedback display. During presentation of the stimulus display one of three different stimuli was presented in the centre of the bottom half of the screen (see Figure 1). Participants were instructed that each stimulus belonged in one of three boxes for an entire sequence and they had to find the correct location for all three stimuli by using performance feedback. Each trial started with a 500 ms fixation cross, presented in the center of the screen. After fixation the stimulus display was presented for 2500 ms, during which participants were required to sort the stimulus in one of three squares. Participants responded by pressing one of three buttons strapped to their right leg. If participants failed to respond within 2500 ms "Too Late" was presented in the centre of the screen, after which the sequence continued. After the response, performance feedback was presented for 1000 ms. When a participant sorted a stimulus in the correct square a plus-sign (positive feedback) was shown, when a participant sorted a stimulus in the incorrect square a minus-sign (negative feedback) was shown. Inter-trial interval (blank screen) was jittered to optimize the timing for fMRI based on OptSeq (Dale, 1999) with intervals between 0 and 6 seconds. A sequence was aborted when the participant sorted each stimulus twice in the correct location, or after 12 trials in total. When a sequence ended a new sequence with three new unique stimuli was presented. There were 15 sequences in total, resulting in a maximum of 180 trials. Stimuli were presented in a pseudorandom order, with a maximum of two identical stimuli in a row. Before the MRI session, all participants practiced three sequences. During the MRI session the task was divided into two runs of eight and seven sequences, respectively.

To calculate a performance measure for feedback learning we calculated the percentage of trials in the learning phase where feedback was successfully used on the next trial. For this purpose we divided the number of trials during the learning phase which were succesfully applied in the next trial, by the total number of trials during the learning phase.

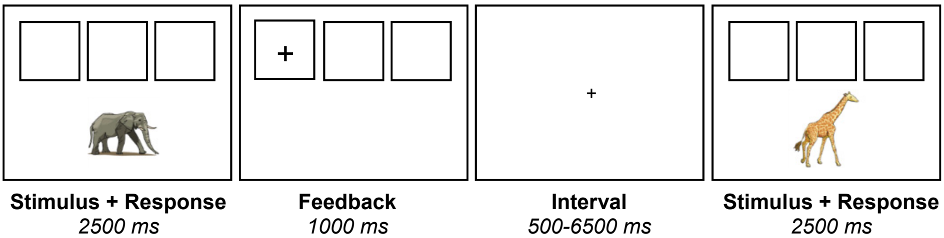

Figure 1: Display of task sequence for the feedback learning task. A trial started with a 2500 ms stimulus display during which the participant responded by sorting the stimulus in one of the three boxes. In this example, the participant (correctly) chose the left box. Next, feedback was presented for 1000 ms by either a '+' for correct feedback or a '–' for incorrect feedback. After an inter-trial interval (varying from 0-6 s) and a 500 ms fixation cross, the next stimulus was presented.

FMRI data acquisition

MRI scans were obtained with a Philips 3.0 Tesla MRI scanner. Functional scans for the feedback learning tasks were acquired during two runs with T2*-weighted echo-planar imaging (EPI). The first two volumes were discarded to allow for equilibration of T1 saturation effects. The following settings were used: TR = 2.20 s, TE = 30 ms, sequential acquisition, 38 slices, slice thickness = 2.75 mm, Field of View (FOV) = 220 x 220 x 114.68 mm. For the structural scan, a high-resolution 3D T1-FFE was obtained after the experimental tasks (TR = 9.76 ms, TE = 4.59 ms, 140 slices, voxel size = 0.875 mm, FOV = 224 × 177 × 168 mm). The experimental task was projected on a screen, which was visible to participants through a mirror. Participants were accustomed to the MRI environment and sounds with a mock scanner before the actual MRI scan.

FMRI data Analysis

We used SPM8 (Wellcome Department of Cognitive Neurology, London) to analyze fMRI. The following pre-processing steps were used: correction for slice timing acquisition and rigid body motion, spatial normalization to T1 templates (MNI305 stereotaxic space (Cocosco et al., 1997)) using a 12-parameter affine transform together with a nonlinear transformation involving cosine basis functions and resampling of the volumes to 3 mm voxels. Functional scans were smoothed with an 8mm FWHM isotropic Gaussian kernel. For further fMRI analyses, we used a contrast that reveals brain areas with sensitivity to informative feedback for learning (Eliassen et al., 2012; van den Bos et al., 2009), that is, areas responding more to feedback providing new information (i.e., more informative) compared to feedback providing known information. To compare neural activity for 'informative' and 'uninformative' feedback, we distinguished between a learning phase and an application phase for each stimulus. For the learning phase, we included trials where participants had not correctly sorted this particular stimulus yet, and were thus still using feedback to determine the correct location. Only trials for which feedback was used appropriately on the next trial for that stimulus were included. Thus, feedback was categorized as learning, when positive feedback resulted in choosing the same location on a next trial and when negative feedback resulted in sorting in a different location. These trials during the learning phase were compared to the application phase: trials in which a stimulus was sorted correctly on a preceding trial, and continued to be sorted correctly. All further analyses were based on a comparison between the learning phase and the application phase, i.e. the contrast Learning > Application. In order to calculate this contrast for all participants, we first modeled the fMRI time series with events corresponding to the events "Positive Learning", "Negative Learning", and "Application", time-locked with 0-duration to the moment of feedback, which were convolved with a canonical hemodynamic response function. Other trials (e.g., trials during the learning phase that did not result in learning or trials where participants responded too late) were modeled as events of no interest. The events were used in a general linear model; along with a set of cosine functions which high-pass filtered the data. The least-squares parameter estimates of height of the best-fitting canonical HRF for each condition were used for the calculation of the contrast Learning (Positive Learning + Negative Learning) > Application for each subject. The resulting contrast images were submitted to higher-level analyses.

FMRI Region-of-interest analysis

In order to examine neural effects of feedback learning and its relation to reading and mathematics performance, region-of-interest (ROI) analyses were performed with the Marsbar toolbox in SPM8 (Brett et al., 2002). The contrast used to generate functional ROIs was Learning > Application (FWE corrected, $p < .05$, > 10 contiguous voxels). The resulting ROIs spanned several brain regions. Therefore, the ROIs were subdivided by masking the functional ROI with the following anatomical Marsbar ROIs (based on Automated Anatomical Labeling (AAL)): left and right DLPFC (Middle Frontal Gyrus in AAL), pre-SMA/ACC (Supplementary Motor Area in AAL; left and right combined), left and right SPC (Superior Parietal Lobule in AAL). These ROIs were selected based on earlier studies demonstrating that these areas show developmental changes for feedback learning (Crone et al., 2008; Peters, Braams, et al., 2014; van Duijvenvoorde et al., 2008) and were also used in a prior study with the same experimental task (Peters, Braams, et al., 2014).

The DLPFC ROIs, even after masking, were still very large (right: 28488 mm; left: 28240 mm), therefore, we created 6 mm radius spheres based on four local maxima within the DLPFC regions (two per hemisphere). These areas are referred to as 'superior DLPFC (sup-DLPFC)' and 'mid-DLPFC'. Centre-of-mass MNI (x y z) coordinates for the ROIs were: pre-SMA/ACC: 0 9 58; right sup-DLPFC: 21 9 57; left sup-DLPFC: -24 3 57, right mid-DLPFC: 42 18 39; left mid-DLPFC: -42 24 39; right SPC: 27 -62 55; left SPC: -23 -64 50 (See Figure 2).

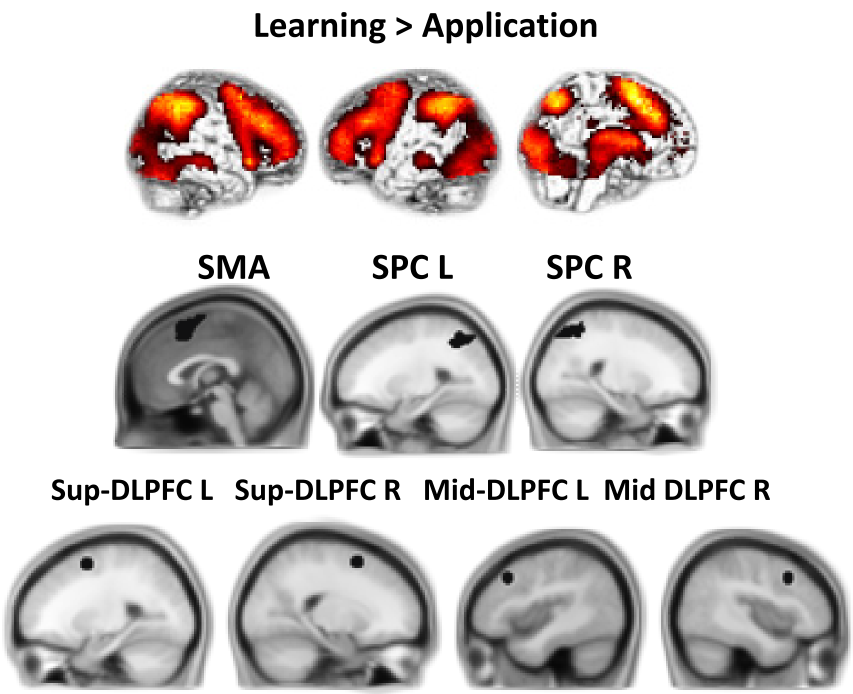

Figure 2: Wholebrain results for the contrast Learning > Application (FWE-corrected at p < .05, > 10 contiguous voxels) and the regions-of-interest based on this contrast.

Results

Data checks

We performed several data quality checks by investigating relationships between the main variables of interest (neural activity and behavioral performance for feedback learning, and reading and mathematics) and age, IQ, working memory and sex (See Table 1 for an overview of the values for age, IQ, working memory, feedback learning, reading and mathematics).

Table 1: Descriptive values for age, IQ, working memory, feedback learning, reading and mathematics scores for male and female participants separately. In the right-most column, we indicated the p-value for sex differences.

	Female				**Male**				
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***p* sex**
Age T1	14.10	3.39	8.01	22.79	14.63	3.75	8.01	24.55	.27
Age T2	16.10	3.40	10.02	24.83	16.60	3.77	9.92	26.62	.30
IQ T1	109.83	10.09	85.00	143.00	111.81	9.40	93.00	138.00	.13
Working Memory T1	0.79	0.17	0.13	1.00	0.86	0.12	0.38	1.00	p<.001
Feedback Learning T1	93.62	5.36	71.29	100.00	93.78	4.40	81.11	100.00	.81
Reading Fluency T2	98.02	14.51	64.00	120.00	97.72	15.46	58.00	120.00	.88
Mathematics T2	11.75	2.88	6.00	19.00	12.44	2.69	4.00	18.00	.06

Age at T1 correlated positively with reading fluency (r = .31, p < .001), working memory (r = .34, p < .001), and feedback learning performance (r = .47, p < .001). Age was also positively related to neural activity for the difference score Learning > Application in all 7 ROIs. Therefore, we corrected for age in further analyses. Even though mathematics scores were norm scores, i.e., scores relative to same-aged peers, there was still a small but significant correlation with age (r = .16, p = .018). We therefore also corrected for age in all further analyses with mathematics scores. Figure 3 shows the relations with age separated in categories for illustrative purposes.

Working memory at T1 correlated positively (corrected for age) with feedback learning performance (r = .33, p < .001), reading fluency (r = .15, p = .026) and mathematics (r = .25, p < .001) but not with neural activity at T1. IQ estimates correlated with mathematics norm scores (r = .32, p < .001, age-corrected) but not with the other measures. Note that the mathematics test (measured at T2) was part of the WISC/WAIS IQ test, although the estimated IQ scores (measured at T1) were measured two years earlier and based on only the subtests Similarities and Picture Completion. Finally, there was an age-corrected correlation between reading and mathematics scores (r = .20, p = .003).

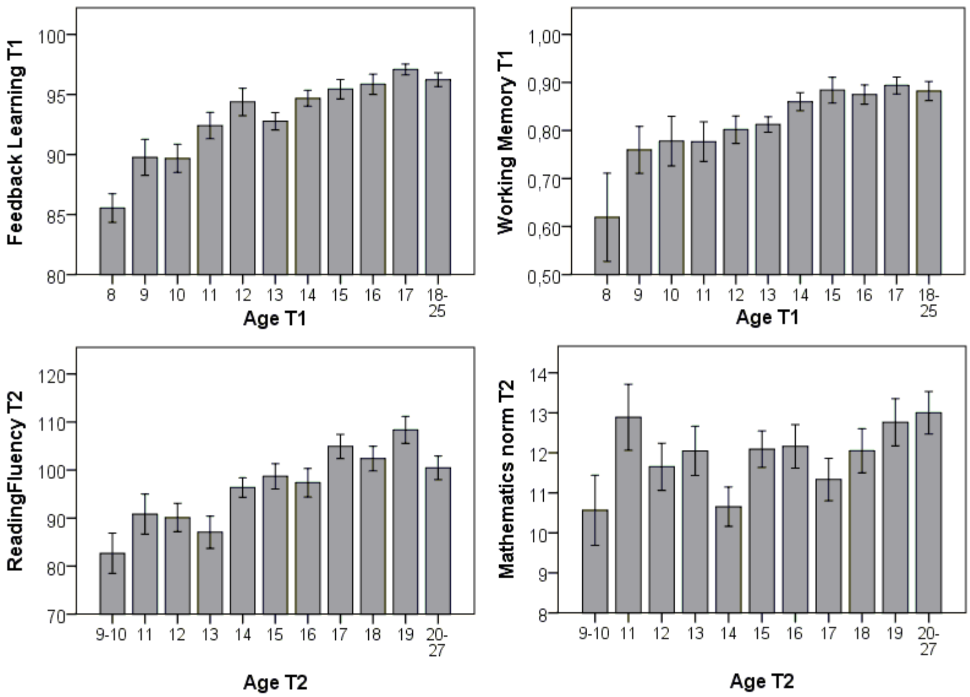

Figure 3: Display of age effects for feedback learning, working memory, reading and mathematics. Note that for T2 one participant was 9.92 years old, therefore the youngest age group at T2 was 9 and 10 years combined.

Predicting reading and mathematics performance at T2 from T1 feedback learning

We first investigated whether reading and mathematics performance at T2 could be predicted from behavioral performance on the feedback learning task at T1. A hierarchical regression with age at T1 entered as a first step and feedback learning performance at T1 as a second step, showed that in addition to age, feedback learning performance significantly predicted reading fluency and mathematics performance two years later (positive relation), see Table 2.

Table 2: Hierarchical linear regression models with age and feedback learning performance as significant predictors for reading and mathematics performance.

Steps	Predictor	B	SE B	β	*p*	*F*	R^2
Dependent: Reading Fluency T2							
1	Overall model					23.10***	.09
	Age T1	1.28	.27	.30	<.001***		
2	Overall model					16.96***	.13
	Age T1	.84	.30	.20	.005**		
	Feedback Learning T1	.67	.21	.22	.002**		
Dependent: Mathematics T2							
1	Overall model					5.47*	.02
	Age T1	.12	.05	.15	.020*		
2	Overall model					10.53***	.09
	Age T1	.02	.06	.02	.760		
	Feedback Learning T1	.16	.04	.28	<.001***		

* $p < .05$ ** $p < .01$ *** $p < .001$

Predicting reading and mathematics performance at T2 from T1 neural activity during feedback learning

Next, we assessed whether brain activity during feedback learning in 7 ROIs at T1 predicted reading and mathematics performance at T2. We performed hierarchical regressions with age at T1 as first step and neural activity in one of the 7 ROIs as second step. These analyses showed that in addition to age, reading fluency was predicted by left SPC and left sup-DLPFC (see Table 3). For mathematics performance at T2, activity in pre-SMA/ACC and right sup-DLPFC were significant predictors above age (see Table 4). For a visual representation of the relationship between right sup-DLPFC activity and mathematics performance, and left sup-DLPFC and reading fluency, see Figure 4.

We also tested whether neural activity for feedback learning explained additional variance in reading and mathematics above age and behavioral performance for feedback learning. We analyzed this with hierarchical regressions with age at T1 as first step, feedback learning performance at T1 as second step, and neural activity (per ROI) as third step. Neural activity explained additional variance for reading fluency (left sup-DLPFC remained significant ($\beta = .20$, $p = .004$), left SPC did not remain significant ($\beta = .12$, $p = .096$) and mathematics (pre-SMA/ACC remained significant ($\beta = .15$, $p = .029$), right sup-DLPFC did not remain significant ($\beta = .11$, $p = .113$)). This indicates that neural activity in left sup-DLPFC and pre-SMA/ACC explained unique variance in reading and mathematics over and beyond age and behavioral feedback learning performance.

Table 3: Hierarchical linear regression models for neural activity in left SPC and left sup-DLPFC as significant predictors above age for reading fluency.

Steps	Predictor	B	SE B	β	p	F	R^2
Dependent: Reading Fluency T2							
1	Overall model					23.10***	.09
	Age T1	1.28	.27	.31	<.001***		
2	Overall model					13.96***	.11
	Age T1	.97	.30	.23	.002**		
	SPC L	1.897	.90	.15	.036*		
1	Overall model					23.10***	.09
	Age T1	1.28	.27	.31	<.001***		
2	Overall model					17.56***	.14
	Age T1	.90	.28	.21	.002**		
	Sup-DLPFC L	2.78	.84	.23	.001**		

* $p < .05$ ** $p < .01$ *** $p < .001$

Table 4: Hierarchical linear regression models for neural activity in pre-SMA/ACC and right sup-DLPFC as significant predictors above age for mathematics performance.

Steps	Predictor	B	SE B	β	p	F	R^2
Dependent: Mathematics							
1	Overall model					5.47*	.02
	Age T1	.12	.05	.15	.020*		
2	Overall model					6.31**	.05
	Age T1	.08	.05	.10	.159		
	Pre-SMA/ACC	.54	.21	.18	.009**		
1	Overall model					5.47*	.02
	Age T1	.12	.05	.15	.020*		
2	Overall model					4.73*	.03
	Age T1	.09	.05	.11	.120		
	Sup-DLPFC R	.38	.19	.14	.049*		

* $p < .05$ ** $p < .01$ *** $p < .001$

Adding working memory and IQ as control variables

To assess whether the relationship between feedback learning and reading and mathematics performance could be explained by individual differences in working memory, we tested whether the above effects remained significant when analyzing a hierarchical regression with age as a first step, working memory and IQ at T1 as a second step, and feedback learning performance or neural activity as a third step. Most analyses remained significant: For reading fluency, feedback learning performance was still a significant predictor ($\beta = .20$, $p = .011$) over age ($\beta = .31$, $p < .001$), working memory ($\beta = .16$, $p = .025$) and IQ ($\beta = -.19$, $p = .763$). Reading fluency was also still predicted by left sup-DLPFC ($\beta = .21$, $p = .002$), over age, IQ and working memory. Left SPC, however, was not a significant predictor anymore (β = .13, p = .065) after adding working memory and IQ. In this model, working memory was a significant predictor (β = .16, p = .025) but IQ was not (β = -.19, p = .763), indicating the lack of significance for left SPC is due to the addition of working memory to the model. For mathematics, feedback learning performance remained a significant predictor (β = .18, p = .015) over age (β = .16, p = .018), working memory (β = .22, p = .001) and IQ (β = .30, p < .001). Pre-SMA/ACC (β = .15, p = .023) was also still significant over age, IQ and working memory, but right sup-DLPFC (β = .12, p = .065) was only marginally significant after adding age, IQ and working memory. Both working memory (β = .22, p = .001) and IQ (β = .30, p < .001) were significant predictors in this model. Together, these results indicate that some of the effects of feedback learning activity are explained by working memory and IQ, but for others feedback learning performance and neural activity explained unique variance that was not explained by working memory or IQ.

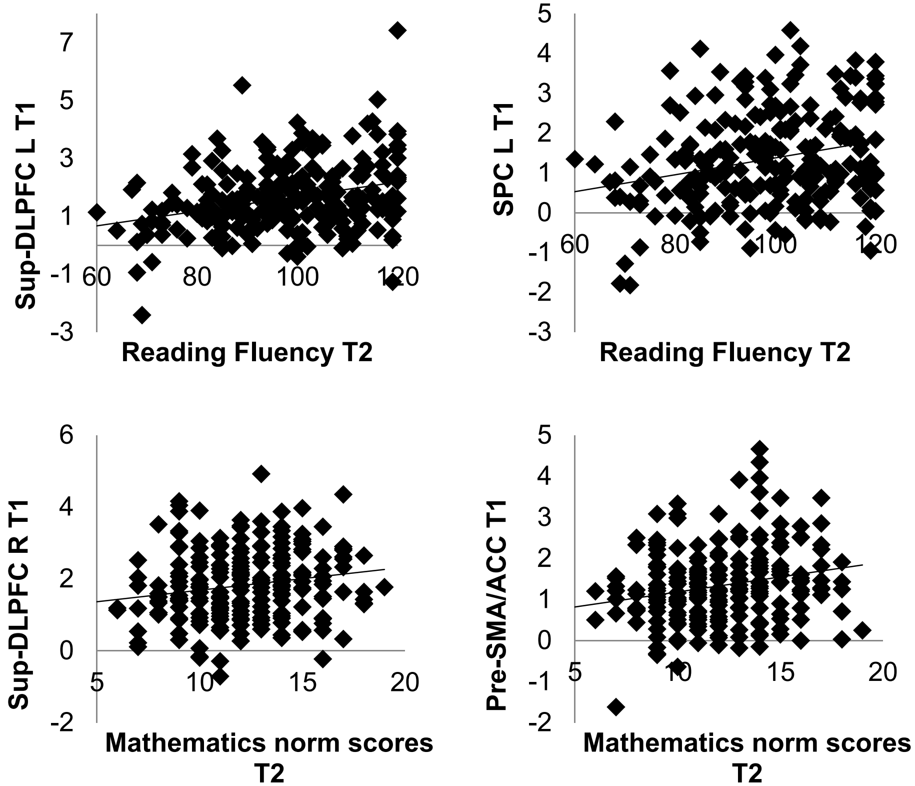

Figure 4: Scatterplot of the significant relationships between reading and mathematics performance at T2 and neural activity at T1 for the contrast Learning > Application.

Mathematics raw scores

All prior analyses used mathematics norm scores. To investigate whether results were also present when using raw scores, we also performed the analyses with feedback learning performance and neural activity as predictors for raw mathematics scores. Because the younger age group (10-15, n = 116) performed the mathematics test from the WISC-III and the older group (16-27, n = 112) the WAIS-III, these age groups were analyzed separately. The results showed that effects were only present in the younger adolescents but not the in the older adolescent/adult group. That is, for the youngest group, mathematics performance was predicted above age by feedback learning performance (β = .14, p = .027) and by pre-SMA/ACC activity (β = .20, p = .033) and there was only a trend for right sup-DLPFC activity (β = .15, p = .094). None of the effects were significant for the participants who were 16 years and older.

Discussion

In this study we investigated whether performance and neural activity during a feedback learning paradigm, used to study learning processes in a controlled laboratory setting, could predict indices of real-world learning performance in school two years later (reading and mathematics performance). The results of this study showed that 1) Feedback learning performance predicted both reading and mathematics performance two years later, 2) Neural activity during feedback learning in left sup-DLPFC and left SPC predicted reading fluency, and neural activity in right sup-DLPFC and pre-SMA/ACC predicted mathematics performance two years later, 3) Left sup-DLPFC and pre-SMA/ACC predicted unique variation in school performance over behavioral testing alone, and 4) Relations between feedback learning performance and neural activity and school performance remained significant when controlling for individual differences in working memory capacity and IQ.

Relation between feedback learning performance and school performance

For both reading and mathematical ability, we found that performance could be predicted by feedback learning performance two years earlier. Possibly, this relation can be explained by underlying individual differences in executive functions. It is well conceptualized that both feedback learning and school performance are related to executive functions (Diamond, 2013). Especially working memory was expected to be an important underlying factor, given that WCST performance (a complex feedback learning task) in a previous study was predicted by working memory in children (Huizinga et al., 2006) and adults (Miyake et al., 2000). Miyake et al. (2000) additionally found that switching was predictive for WCST performance, but this was not replicated in the child-aged sample of Huizinga et al. (2006). Consistent with these prior findings, we found a positive correlation with working memory performance and feedback learning, as well as with reading and mathematics performance, also when controlling for age differences. However, even when adding working memory as a predictor to the model, feedback learning performance predicted unique variance for both reading and mathematics, suggesting that working memory may explain a part of, but not all variance. We investigated whether differences in general intelligence might explain the relation between feedback learning and school performance, but there was still a significant prediction of reading and mathematics scores by feedback learning when controlling for IQ.

Relation between neural activity for feedback learning and school performance

An important question tested in this study was whether neural activity could predict reading and mathematics performance two years later, and whether neural activity could provide additional information over behavioral testing alone. This was based on prior studies showing that neural measures can predict reading (Hoeft et al., 2007; Maurer et al., 2009) and mathematics performance (Dumontheil & Klingberg, 2012). Consistent with these studies, we found evidence for a relation between neural activity for feedback learning and reading and mathematics ability. First, we found that left sup-DLPFC and left SPC activity predicted reading ability. These findings fit with earlier research showing that a mostly left-lateralized network including DLPFC is involved during reading tasks (Ferstl et al., 2008). Second, right sup-DLPFC and pre-SMA/ACC predicted mathematics ability two years later. This fits with meta-analyses showing involvement of pre-SMA/ACC and DLPFC during arithmetical tasks (Arsalidou & Taylor, 2011; Houdé et al., 2010). Notably, for all areas we found a positive relation, indicating that increased activity predicts better performance on reading or mathematics tests. With the current design, it is not possible to determine whether higher activity might indicate better functioning or perhaps earlier maturation of these regions. Future research could build on this study by analyzing longitudinal fMRI measures and data on structural brain development.

In addition, we performed analyses to assess whether neural measures provided unique information that cannot be captured by behavioral testing alone. The regions that remained significant predictors when controlling for behavioral feedback learning were left sup-DLPFC for reading and right sup-DLPFC and pre-SMA/ACC for mathematics. This indicated that assessing feedback learning ability is useful for predicting reading and mathematics, but adding neural measures in addition to behavioral assessment further enhanced predictive ability. The finding that neural activity measures have added value over behavioral testing alone fits with earlier studies for the prediction of reading (Hoeft et al., 2007) and mathematics (Dumontheil & Klingberg, 2012; Hoeft et al., 2007).

Prior research suggested that working memory is an important component of both feedback learning (Miyake et al., 2000) and reading and mathematics (Alloway & Alloway, 2010), therefore it was possible that working memory is the underlying factor explaining these relations. Indeed, the prediction of reading performance from left SPC activity was no longer significant when controlling for working memory, indicating that working memory might underlie this relation. However, even when we controlled for working memory and IQ, there was still a significant prediction of reading fluency from feedback learning performance and activity in left sup-DLPFC, and for prediction of mathematics from feedback learning performance and activity in pre-SMA/ACC. This indicates that although working memory plays a role in the relation between feedback learning and reading and mathematics, there is still unique variation in reading and mathematics that is explained by neural activity during feedback learning. Other aspects of feedback learning performance that might be relevant for learning in school settings, are for instance the capacity to monitor one's actions and keep track of performance feedback, ignoring irrelevant aspects of the task, perceived competence and motivation (Fortier, Vallerand, & Guay, 1995; St Clair-Thompson & Gathercole, 2006). Future research is needed to examine this in more detail.

An interesting laterality difference was observed for predicting reading and mathematics in superior DLPFC. That is to say, we found that activity in left superior DLPFC during feedback learning predicted reading ability, whereas activity in right superior DLPFC predicted mathematical ability. The left-right distinction fits nicely with the well-established finding that the neural network for learning is left-lateralized (Frost et al., 1999). There is no conclusive evidence for a possible right-lateralized network for mathematics. The current findings suggest that left-right hemispheric differences may be an important factor explaining differences between reading and mathematics related school processes.

Limitations and future directions

There are several limitations to this study. First, school performance can be measured in many ways. In this study, we measured only two short, well-validated measures for reading and mathematics. Future research could build on this study by relying on a more extensive assessment of school performance involving multiple measures. Second, we only collected reading fluency and mathematics data at the second time point but not at the first time point. An interesting question would be to investigate whether feedback learning and brain measures can predict reading and mathematics even better than tests for reading and mathematics themselves. On the other hand, an advantage of measuring feedback learning or other executive functioning tasks is that it captures abilities that are essential to both reading and mathematics. Third, IQ was assessed with only two subtests of the WISC/WAIS. A more comprehensive assessment of IQ might give a more definite answer to the question whether the relation between feedback learning and school performance is driven by underlying differences in general intelligence. Fourth, mathematics was assessed with the WISC for younger participants (10-15 years at T2) and with the WAIS for older participants (16-27 years at T2). When we performed the analyses with mathematics raw scores rather than norm scores (scores relative to same-aged peers), we needed to perform the analyses in separate age groups. These analyses showed that the prediction of mathematics scores from behavioral performance and neural activity for feedback learning was only present in the youngest age group (10-15 years). One tentative interpretation is that prediction is stronger in the younger age groups, when brain maturation is still undergoing major changes (Giedd & Rapoport, 2010). Alternatively, it is possible that the WISC scores are more sensitive for picking up change than the WAIS scores. Future studies should use a wider battery of tests to test these competing hypotheses in more detail.

Conclusion

In conclusion, this study found contributions of feedback learning performance and neural activity in predicting school outcomes two years later. This provides evidence that studying learning processes through simplified laboratory tasks provides at least some relevance for real-world learning. In addition, we showed that neural measures explain unique variance in school outcomes two years later that is not captured by behavioral testing of executive functions alone.