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## Imaging the changing role of feedback during learning in decision-making

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Learning from the outcome of decisions can be expected not only to change future decisions, but also our reaction to future outcomes. Using functional magnetic resonance imaging we investigated the neural responses of healthy subjects to feedback about choice outcomes before and after learning a response strategy which led to correct choices only. The task was designed so that losses were unavoidable even when all the choices made were correct. Subjects showed a distinct pattern of learning starting with an initial exploratory phase in which hypotheses about the correct strategy were generated and tested, followed by a phase of rapid strategy acquisition before reaching a final phase of proficiency. Neural activation was more pronounced during feedback processing in the exploratory phase than in the proficiency phase in a distributed network encompassing prefrontal and parietal areas as well as the striatum. These areas are involved in working memory processes, the management of uncertainty and the establishment of stimulus-outcome contingencies. Reduced activation during feedback processing following learning was not only observed within subjects across learning phases, but also between subjects with different learning speeds. Thus, controlled and automatic processing are characterised by differing amounts of activation in identical task-relevant areas. Furthermore, whereas the same brain regions coded for gains and losses, the activation following gains changed to a larger extent with learning than following losses. This suggests that positive prediction errors are more sensitive to increased reward predictability than are negative prediction errors.

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### Introduction

Being able to learn from the consequences of previous decisions and to adapt behaviour accordingly is critical for maximising reward in a variety of situations. However, it seems

likely that learning to make correct choices will change the evaluation of the very outcomes upon which it is based. For example, in the course of acquiring a successful response strategy, outcomes become more and more predictable. Thus, as subjects can rely more on internal predictive information, external feedback becomes less informative and it might be expected that it is evaluated and processed differently. The goal of the present study was to investigate how the processing of outcome information, in particular the processing of gains and losses, changes with the acquisition of a correct response strategy.

Previous neuroimaging studies have consistently shown that practice leads to reduced activation during task processing in task-relevant areas (e.g., Chein and Schneider, 2005; Delgado et al., 2005; Jansma et al., 2001; Koch et al., 2006). Such local learning processes occurring in brain regions which handle task-specific information are assumed to be regulated by more general control processes that deploy working memory, attentional selection, and performance monitoring processes (Birnboim, 2003; Anderson, 1982; Fitts, 1964; Schneider and Shiffrin, 1977). It is assumed that these controlled processing resources determine behaviour to a lesser and lesser extent as learning progresses. Thus, learning causes a transition from a *controlled* to an *automatic* mode of processing, characterised by efficient and low-effort behaviour. Such a decreased reliance on controlled processes in the course of learning is reflected by reduced activation in certain distributed brain areas across a number of different perceptual, verbal and manual learning tasks (see Chein and Schneider, 2005 for a meta-analysis). These areas include the medial frontal (pre-SMA (BA 6), anterior cingulate (BA 32)), dorsolateral prefrontal (BA 9, 44, 46), posterior parietal (BA 7, 39, 40), and occipital (BA 18, 19) cortices. As the precise task requirements and therefore the areas relevant for achieving an optimal outcome differ across tasks, learning-related reduction in activation is to some extent task-dependent. For example, reward-based learning of probabilities has primarily been associated with reduced activation in the caudate nucleus (Delgado et al., 2005; Haruno et al., 2004). The caudate,

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together with the anterior cingulate cortex (ACC), has also been found to be activated during sequence and passive avoidance learning (e.g., Aizenstein et al., 2004 and Kosson et al., 2006, respectively).

Reward-related information is typically given in terms of monetary gains or losses or winning and losing game points. Responses to these types of outcomes have been observed in the prefrontal cortex (PFC), insula and caudate (Zalla et al., 2000; Elliott et al., 2000; Knutson et al., 2000; Krawczyk, 2002). However, results regarding brain activity during gains vs. losses have been inconsistent. For example, hippocampal regions have both been reported to be activated after gains but not losses (Zalla et al., 2000), and after losses but not gains (Elliott et al., 2000). Gains have been found to be associated with medial orbitofrontal cortex (OFC) activation (O'Doherty et al., 2001), particularly in the context of risk (Dickhaut et al., 2003), in some studies, but not in others (e.g., Knutson et al., 2000; Breiter et al., 2001; Seger and Cincotta, 2006). The differences in activation may stem from task-related or perhaps motivational disparities, but possibly also from differences in the analysis, since it is not always clear whether the observed activation occurred during feedback anticipation or during feedback processing. Although there is evidence that the areas activated during the anticipation and experience of feedback overlap (Breiter et al., 2001), the functional difference between these two stages leads to a different amount of activation in these areas (Ernst and Paulus, 2005).

In this investigation, we analysed how neuronal activation during the processing of feedback about the outcome of a choice differs *before* and *after* ascertaining and learning a correct response strategy. To this end, we adapted an existing EEG task from the literature that has previously been shown to engage the ACC (Gehring and Willoughby, 2002; Nieuwenhuis et al., 2004). In this task, subjects were asked to choose between one of two numbers, 5 and 25, which indicated points that could be won or lost. In addition, the choice could either be correct or wrong depending on whether the chosen outcome was better or worse than the alternative outcome. Nieuwenhuis et al. (2004) demonstrated that emphasising either the utilitarian aspect of the feedback in terms of gains and losses, or the performance aspect of the feedback in terms of correct and wrong responses, led to a similar medial frontal negative event-related potential component, the so-called error-related negativity (ERN). Thus, the ERN was sensitive to whichever aspect of the feedback was salient.

Accordingly, we expected that brain activation following either performance or utilitarian feedback should occur in similar areas, and should be larger for the more salient aspect. In our task, we made performance feedback more salient, because in the study of Nieuwenhuis et al., the responses of all subjects to this aspect were more consistent.

The original task was adapted so that the outcomes were no longer random, but determined according to a pattern that could be learned. This allowed us to investigate the effect of learning on the processing of outcome feedback.

We predicted that (i) feedback processing before learning the pattern would preferentially recruit limbic structures such as the striatum and orbitofrontal cortex relative to after learning, because these regions are involved in forming and updating associations between environmental stimuli and rewards (e.g., O'Doherty et al., 2003a, 2003b; Berns et al., 2001; Rolls, 2000; Thut et al., 1997), and (ii) activation in the ACC would be greater before learning than after because the ACC is involved in conflict processing (e.g.,

Botvinick et al., 1999; Bush et al., 1998; Carter et al., 2000; Gruber et al., 2002; MacDonald et al., 2000), and conflict about which of two response alternatives is – or was – correct should diminish during the course of learning. Since the original experiments with the paradigm on which our task is based concluded that activation in the ACC was larger for negative than for positive outcomes (Gehring and Willoughby, 2002; Nieuwenhuis et al., 2004), we also assumed that activation in the ACC would be associated with losses more than gains across the task. Furthermore, we predicted that (iii) activation in prefrontal structures engaged in working memory, particularly the dorsolateral prefrontal cortex (DLPFC), would be higher before learning than after because cognitive demands are reduced and/or processing is more efficient as performance becomes more automatic.

Furthermore, we explored how the processing of gains and losses changes with learning. Due to the striatum's role in reward, we expected the hypothesised decreased activation in the striatum with learning to be greater for gains than losses.

Since it turned out that the variation in speed of learning between subjects was quite high, we additionally compared the brain activation in subjects who showed the expected learning course (termed “model-conform learners”) to the brain activation in subjects displaying comparatively fast and slow learning, respectively. We assumed that the brain activation of model-conform and fast learners would differ in the early stage of learning only, and that the brain activation of model-conform and slow learners would differ in the late stage of learning only.

## Methods

### Subjects

Thirty-eight right-handed female volunteers (mean age 26.4 years, ranging between 21.1 and 40.6 years) with normal or corrected-to-normal vision participated in the study after giving written informed consent. The reason for exclusively investigating females was that a subgroup of our subjects served as control group in a parallel study using the same task in patients with PTSD, all of which were female.

The study protocol was approved by the local ethics committee of the Medical University Vienna. Handedness was assessed by means of the Edinburgh Handedness Inventory (Oldfield, 1971). All the participants were free from psychological or personality disorders as assessed by a structured clinical interview for DSM-IV (SKID, Wittchen and Unland, 1991), administered by a clinical psychologist. In addition, the participants were screened to exclude those on medication or with conditions such as neurological illness or history of head injury. The participants received a fixed amount of €20 as financial compensation for participation in the study.

### Experimental design and task

Each participant underwent fMRI scanning whilst performing a total of 72 trials of the decision task illustrated in Fig. 1. The trials were arranged in 12 blocks of 6 trials. Tasks were projected onto a screen sited within the scanner bore, which the subjects viewed via a mirror mounted on the head coil, and responded to by pressing one of two buttons of a response box attached to the right thigh. The presentation of stimuli, recording of responses and external scanner trigger timing pulses were controlled by the software Presentation (Neurobehavioral Systems Inc., San Francisco, USA).

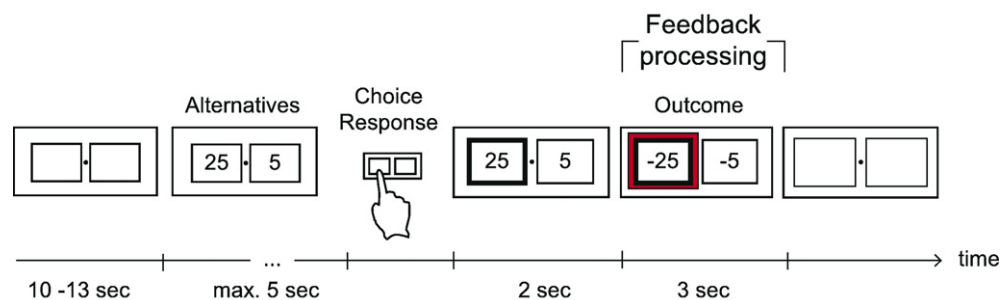


Fig. 1. Schematic example of experimental trial showing a "wrong" response resulting in a loss (for explanation see text). The analysis focused on the interval termed "feedback processing".

The task was adapted from Gehring and Willoughby (2002) and Nieuwenhuis et al. (2004, Experiment 2).

At the beginning of each trial, two rectangles were presented on the left and right of a central fixation spot. After a variable inter-stimulus interval of 10 to 13 s, the number 5 appeared in one of the rectangles and 25 in the other. These numbers represented points that the subjects could win or lose. Subjects were to select one of the alternatives by pressing the corresponding response button. The choice was marked by a thickening of the black outline of the respective rectangle. If a response was not made within 5 s, the trial was terminated and a warning was displayed, requesting the subject to answer more promptly on the next trial. 2 s after the button was pressed, the true values of both the option chosen and the alternative option were presented, by adding a sign (+ or -) before each value. A plus sign indicated a gain of the corresponding number, i.e. number of points, a minus sign indicated a loss. To emphasise whether the response was correct or wrong (to achieve the aim of maximising the total number of points), the thick black outline of the outcome selected turned green or red. A correct response meant that the subject had chosen the better of the two alternatives, i.e. a gain rather than a loss, the greater of two gains or the lesser of two losses. A wrong response meant that the subject had chosen the inferior of the two alternatives, i.e. a loss rather than a gain, the greater of two losses or the lesser of two gains. Thus, as in the original experiments, the gain/loss dimension could be evaluated independently of the correct/error dimension. The feedback remained on the screen for 3 s, after which the empty rectangles and fixation spot were presented again.

In contrast to the original experiments, the distribution of correct and wrong outcomes was not random, but followed a pattern that the subjects could learn. The correct sequence of responses was 5, 5, 25, 25, 5, 25 for every block of 6 trials. The positions at which the correct values were presented (left or right) differed in each block. In pilot studies with varying sequence lengths, the number of 6 elements per sequence had been proven to have the optimum level of difficulty, i.e. that for which the highest number of subjects learned the sequence at a useful time during the experiment's duration. Learning the correct sequence led to 100% correct responses, but losses were unavoidable.

After each sequence of 6 trials, there was a break of 15 s in which the subjects received feedback on the total amount of points won in that block, the maximum number of points they could have scored in that block, and the total score across all previous blocks. Following the original tasks of Gehring and Willoughby (2002) and Nieuwenhuis et al. (2004), if a block resulted in a net loss, the amount was not subtracted from the total score.

The instruction was an extended version of that used by Nieuwenhuis et al. (2004), translated into German which was

either the native language or spoken fluently by all participants. Subjects were told that their task was to accumulate the maximum number of points. They were informed about the nature of the + and - sign and the meaning of the coloured frame around the chosen outcome. They were also told that the sequence of correct responses would follow a system that they were supposed to deduce, learn and remember in order to maximise their total score.

#### Functional imaging

Imaging was performed with a 3 T Bruker Medspec S300 scanner (Bruker Biospin, Ettlingen, Germany) equipped with a birdcage head coil. T2\*-weighted single-shot echo-planar images were acquired, with 18 oblique slices of 4 mm thickness and 5 mm separation (aligned along the commissures), with TR=1000 ms, TE=28 ms, flip angle=90° and a matrix size of 64×64 and 21×25 cm<sup>2</sup> (LR and AP, respectively). The data were acquired in a single run of 1800 volumes (30 min), prefaced by 10 s of dummy scans to ensure a steady state of longitudinal magnetisation. Structural images were obtained using an MP-RAGE three-dimensional T1-weighted sequence.

#### fMRI data analysis

Image pre-processing and subsequent analyses were performed using statistical parametric mapping (SPM2) (<http://www.fil.ion.ucl.ac.uk/~spm/SPM2.html>). Images were realigned and normalised to the standard-space Montreal Neurological Institute (MNI) EPI template. Spatial smoothing was applied to the normalised images using a Gaussian kernel of 9 mm.

To allow a high flexibility in analysis (the classification of trials into multiple categories), each distinct section of each trial was modelled with a separate regressor. These sections were (1) problem presentation, (2) shaded box to indicate choice, (3) feedback (win or loss) and whether choice was correct or wrong; each section occurring 72 times. Additionally, six regressors for the presentation of block scores were added for each subject. Simple contrasts corresponding to the different feedback types, namely correct gains, correct losses, wrong gains, wrong losses, were created via combination of the relevant regressors. Group-level random effects analyses for these simple contrasts were calculated by entering whole-brain contrasts into one-sample *t*-tests. Phase contrasts were generated according to the learning phase of the individual as described in the following section. For a comparison of different learning phases, the data from phase 1 (exploratory phase) and 3 (proficiency phase) were compared separately for each individual.

To compare the effect of utilitarian (gains/losses) to performance (correct/wrong) feedback in phase 1, voxelwise and clusterwise differences in BOLD signal change were examined using a  $2 \times 2$  repeated-measures analysis of variance (ANOVA). Such an analysis allows for the examination of any main effect or interaction between the two types of feedback, using whole-brain statistical maps. This analysis was only possible for phase 1, since phase 3 was defined by the absence of wrong responses.

To evaluate the effect of learning on the reaction to gain and loss feedback, a further repeated-measures ANOVA was computed which comprised the factors feedback (gain/loss) and learning phase (exploratory/proficiency).

Significant main effects and interactions were further explored based on the parameter estimates for each of the conditions entered in the analysis which were extracted for any cluster uncovered by the whole-brain ANOVA. A significance threshold of  $p < 0.005$  (uncorrected) and a spatial extent of  $\geq 20$  voxels were applied to all effects of interest.

Since it turned out that a number of subjects learned the task, according to our definition, too slowly or too fast (see Results), we compared the brain activation for subjects with distinct learning phases to that of subjects who learned too slowly or too fast, respectively, by means of between-subjects  $t$ -tests. According to a classification described in the following section, the subjects were grouped into “model-conform learners”, “fast learners” and “slow learners”. We assumed that the slow learners’ brain activation during the entire experiment would be similar to that of model-conform learners in the exploratory phase, but different to that of model-conform learners in the proficiency phase. Furthermore, we also assumed that the fast learners’ brain activation during the entire experiment would be similar to that of model-conform

learners in the proficiency phase, but different to that of model-conform learners in the exploratory phase.

Therefore, we used the contrasts of all feedback types (comprising gains, losses, correct or wrong feedback) during the entire experiment for slow learners and compared them to the contrast of feedback in the exploratory phase and to feedback in the proficiency phase of model-conform learners. A separate, analogous analysis was performed for fast learners. Statistical maps were created using a threshold of  $p < 0.001$  (uncorrected) with a cluster threshold of  $\geq 20$  voxels.

After converting MNI coordinates to Talairach coordinates using the algorithm of Brett et al. (2002; <http://imaging.mrc-cbu.cam.ac.uk/imaging/MniTalairach>), Brodmann areas (BA) were identified using the Talairach Daemon software (Lancaster et al., 2000).

#### Behavioural data analysis

The percentage of correct answers in each of the 12 blocks was calculated and plotted against block number (Fig. 2). These data were fitted with a simplified version of the generalised logistic or Richards’ Curve (Richards, 1959);  $f(x) = A_0 + \frac{A_1}{1 + \exp(A_2 - x)}$ , where  $f(x)$  is the percentage of correct answers in block  $x$ . The constant  $A_0$  determines the lower asymptote and  $A_0 + A_1$  the upper.  $A_2$  determines the block number about which the learning curve is centred.

The function and fit routine were programmed in the Interactive Data Language (Research Systems Inc., Boulder, USA) and the parameters  $A_0$ ,  $A_1$  and  $A_2$  determined using the Curvefit gradient-expansion algorithm with the initial estimates  $A_0 = 50$ ,  $A_1 = 4$  and  $A_2 = 50$ ; that is, expecting that 50% of answers would be correct in

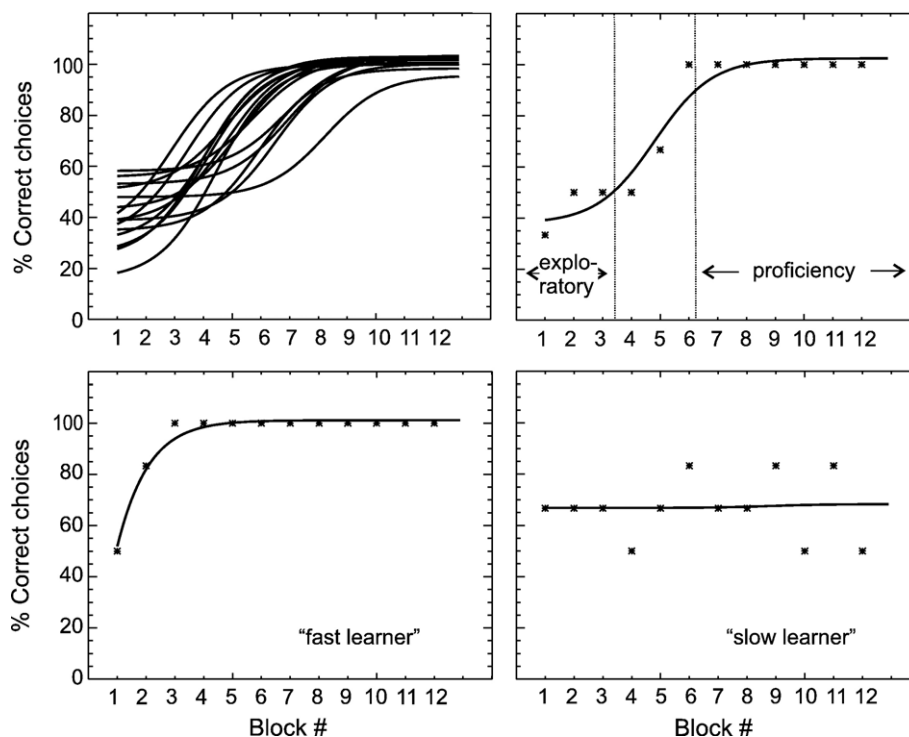


Fig. 2. Percentage of correct choices across blocks for 15 model-conform learners fitted to sigmoid curve (upper left). Exemplary learning curve of single model-conform learner with start and end of the exploratory and proficiency phases (upper right); exemplary learning curves of single fast learner (lower left) and slow learner (lower right).

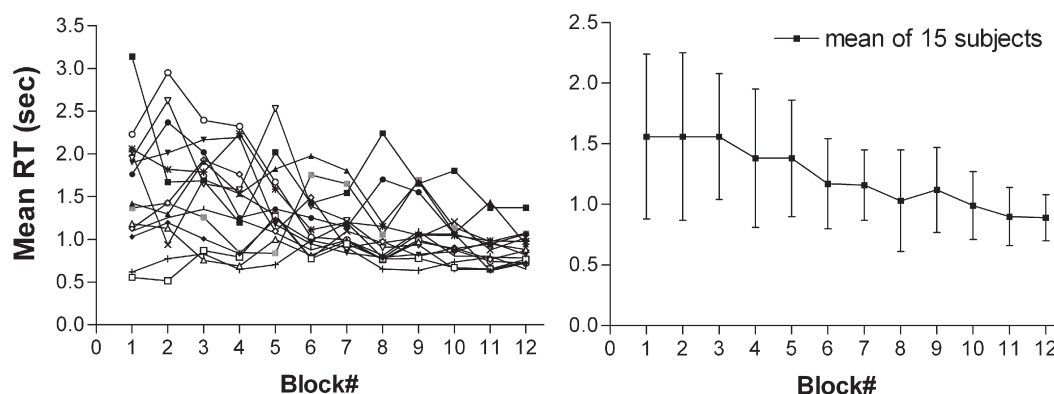


Fig. 3. Mean reaction time across blocks of 6 trials as mean for each of 15 different individuals (left), and mean and standard deviation across all 15 subjects (right). Note the different ranges on the ordinate.

the exploratory (not learned) phase (by chance), that subjects would learn the system close to the 4th block and that their score in the final blocks would rise (by 50%) to 100%.

In accordance with a learning phase classification in motor learning (Sailer et al., 2005), we assumed that subjects would start with an exploratory phase in which they generated and tested hypotheses about successful strategies, followed by a phase of strategy acquisition in which performance improved rapidly, and finally, a proficiency phase in which they refined the learned strategy. In the present experiment, Phase 1, the “exploratory phase”, was defined as that in which performance was in the range  $A_0$  to  $A_0 + 0.2 * A_1$ , Phase 2, the “strategy acquisition phase”, where performance was in the range  $A_0 + 0.2 * A_1$  to  $A_0 + 0.8 * A_1$  and Phase 3, the “proficiency phase” where performance was above  $A_0 + 0.8 * A_1$ , all based on the fit values and rounded to the nearest block number. Task blocks were categorised according to these learning phase definitions.

Subjects were considered to have shown these separate learning phases and termed “model-conform learners” if their final performance ( $A_0 + A_1$ ) was greater than 95% (allowing leeway for occasional lapses in attention once the system was learned) and the “strategy acquisition” phase began after block 2 and ended before block 10. “Fast learners” were defined as those subjects in which the strategy acquisition phase began before block 2 and 100% performance were reached in or before block 5. “Slow learners” were defined as those subjects who were not classified as either fast or model-conform learners and who did not reach the proficiency phase.

## Results

### Behavioural data

Of the 38 subjects, 15 were model-conform learners showing three learning phases as defined above (see Fig. 2). In these 15 subjects, the strategy acquisition phase started around the fourth block. The fMRI data of the model-conform subjects were the basis for the analysis of brain activation in different learning phases. Of the remaining subjects, 12 learned the strategy too fast, i.e. were fast learners who failed to show a distinct exploratory phase. The remaining 11 subjects were slow learners who learned too slowly or not at all.

Behavioural reaction time was calculated for each model-conform subject as the time from the onset of the choice

alternatives to the button press. Trials in which subjects had exceeded the maximal response time of 5 s were excluded from this analysis.

Fig. 3 shows that there was a decrease in reaction time and particularly, variance of reaction time, with increasing practice across all subjects.

The percentage of correct responses was significantly smaller in the exploratory than in the proficiency phase (2-tailed Wilcoxon matched pairs test,  $Z=3.41$ ,  $p<.001$ ). At the same time, reaction time was significantly higher in the exploratory than in the proficiency phase (paired  $t$ -test,  $t=4.47$ ,  $df=14$ ,  $p<.001$ ). Thus, the two learning phases were clearly different in terms of performance.

### Imaging data

#### Utilitarian vs. performance feedback in the exploratory phase

In general, higher brain activation was observed after gains than losses in the orbitofrontal cortex (OFC; BA 45, BA 11), the caudate nucleus and the frontopolar area (BA 10), as revealed by a main effect of utilitarian feedback ( $df=1.39$ ; see Table 1 and Fig. 4A).

Brain activation was also higher following correct than wrong performance feedback in the OFC, precuneus and dorsolateral prefrontal cortex (DLPFC), as shown by a main effect for performance feedback ( $df=1.39$ ; see Table 2 and Fig. 4B).

There was also an interaction between performance and utilitarian feedback in a number of areas (see Table 3 and Fig. 5).

Table 1

MNI coordinates (mm) of activation maxima within a cluster during processing of gains versus losses in the exploratory phase with a cluster extent of  $k$

Region	Brodmann area (BA)	Side	F-value	Z-value	k	x	y	z
OFC	45	L	27.40	4.38	336	-54	+34	+2
OFC	11	L	13.28	3.16	73	-12	+68	-10
Caudate nucleus	-	L	16.54	3.51	441	-6	+12	+6
Frontopolar area	10	L	15.21	3.38	192	-14	+44	-12
Frontopolar area	10	R	13.39	3.18	108	+4	+68	0

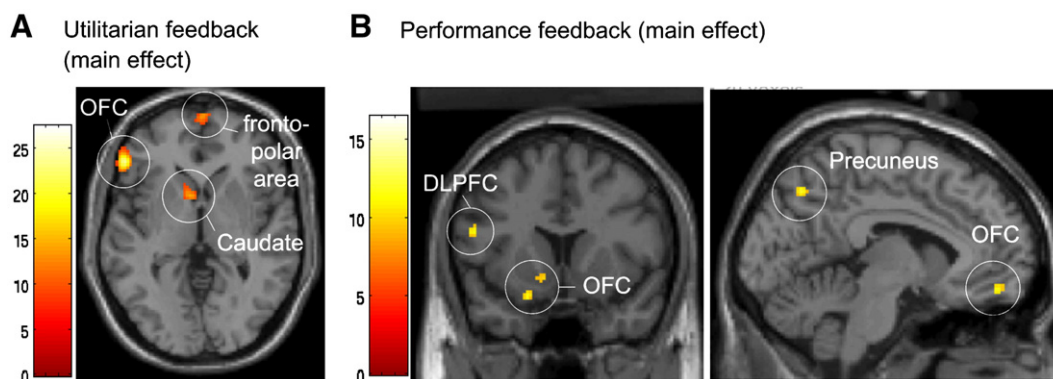


Fig. 4. Subset of areas activated during processing of gains versus losses (A) and correct versus wrong performance feedback (B) in the exploratory phase.

This interaction indicated that the different feedback types could be grouped into ambiguous, i.e., correct loss and wrong win, versus unambiguous, i.e. correct gain and wrong loss, feedback. Except for one area, the inferior temporal area, activation in all areas was either larger or smaller following both types of ambiguous feedback versus both types of unambiguous feedback (see Fig. 6).

In the pre-supplementary motor area (pre-SMA) and prefrontal regions (the frontopolar area and DLPFC) as well as parietally in the precuneus and supramarginal area activation was larger following unambiguous than ambiguous feedback. In the remaining areas such as the ACC, the middle temporal area, caudate, insula and the OFC, activation was larger following ambiguous than unambiguous feedback. Only activation in the inferior temporal area (BA 20) showed a different pattern with lower activation following correct gains compared to the other three types of feedback.

In general, unambiguous feedback led to more pronounced neural responses than ambiguous feedback. This implies that the observed main effects are mainly due to the effects of the unambiguous factor levels. For example, the main effect for utilitarian feedback in the caudate is primarily due to the larger activation after correct gains compared to after wrong losses.

*Utilitarian (gain/loss) feedback in exploratory vs. proficiency phase*

No areas were found in which activation across learning phases was selective for either gains or losses, as indicated by the lack of a main effect for feedback. A main effect for learning phase

indicated that a number of areas were activated to a larger extent during the exploratory than the proficiency phase ( $df=1.42$ ; see Table 4).

This main effect was further qualified by an interaction between feedback (gain/loss) and learning phase (exploratory/proficiency) that occurred in the OFC, putamen, and the frontopolar area ( $df=1.42$ ; see Table 5 and Fig. 7A).

The parameter estimates revealed that in all these areas, activation was larger for gains in the exploratory phase than for all the other conditions (see Fig. 7B). Importantly, the response to gains changed to a larger extent with learning than did the response to losses. Activation following gains was larger in the exploratory phase than in the proficiency phase in the left lateral OFC, the right OFC, the putamen and the frontopolar area. In contrast, activation following losses was somewhat lower in the exploratory phase than in the proficiency phase both in the lateral OFC and the putamen. Learning-related activation changes in the right OFC and the frontopolar area only occurred during the processing of gain, not loss feedback.

*Comparison of model-conform learners with slow learners*

There were no areas in which model-conform learners showed larger activation than slow learners, neither in the exploratory nor in the proficiency phase. In contrast, slow learners showed more activation in the precuneus (BA 7;  $k=62$ ,  $T=4.16$  at  $x=-26$ ,  $y=-74$ ,  $z=+58$ ) than model-conform learners did in the exploratory phase. Slow learners also showed more activation in the precuneus ( $k=368$ ,  $T=4.55$  at  $x=-24$ ,  $y=-76$ ,  $z=58$ ), and in the inferior parietal cortex (supramarginal area, BA 40;  $k=70$ ,  $T=4.07$  at  $x=+42$ ,  $y=-54$ ,  $z=+60$  and BA 39;  $k=34$ ,  $T=3.86$  at  $x=+36$ ,  $y=-68$ ,  $z=+40$ ) than model-conform learners did in the proficiency phase. Thus, the larger parietal activation throughout the experiment distinguished slow from model-conform learners.

*Comparison of model-conform learners with fast learners*

There were no areas which were activated to a larger extent in fast learners than in model-conform learners. Moreover, there was no difference in brain activation for model-conform and fast learners in the proficiency phase; that phase in which both groups already had acquired the correct response strategy. However, fast learners showed less brain activation in the supramarginal area (BA 40,  $k=55$ ,  $T=4.13$  at  $x=-58$ ,  $y=-36$ ,  $z=+38$ ), the caudate ( $k=33$ ,  $T=4.12$  at  $x=-8$ ,  $y=+2$ ,  $z=+4$ ) and the superior temporal

Table 2  
MNI coordinates (mm) of activation maxima within a cluster during processing of correct vs. wrong performance feedback in the exploratory phase with a cluster extent of  $k$

Region	Brodmann area (BA)	Side	F-value	Z-value	k	x	y	z
Lateral OFC	47	R	16.43	3.50	81	+18	+32	-16
OFC	11	R	15.96	3.45	125	+2	+54	-14
Lateral OFC	47	L	12.13	3.03	34	-20	+10	-20
Lateral OFC	47	L	11.70	2.97	90	-16	+20	-10
Primary motor cortex	4	L	15.72	3.43	88	-48	-6	+48
Precuneus	7	L	11.83	2.99	24	-6	-68	+46
DLPFC	44	L	11.07	2.89	21	-52	+12	+20

Table 3

MNI coordinates (mm) of activation maxima within a cluster for the interaction of utilitarian and performance feedback with a cluster extent of  $k$ 

Region	Brodmann area (BA)	Side	F-value	Z-value	$k$	$x$	$y$	$z$
Pre-SMA	6	L	20.33	3.85	306	-32	+12	+68
Frontopolar area	10	L	17.53	3.61	72	-50	+54	+4
Primary motor cortex	4	L	16.66	3.52	129	-38	-16	+42
ACC	24	R	14.82	3.33	250	+2	-24	+38
ACC	24	-	12.51	3.07	44	0	+6	+28
Inferior temporal area	20	R	14.22	3.27	174	+60	-56	-20
Middle temporal area	21	L	13.62	3.20	50	-56	-6	-12
Supramarginal area	40	R	14.16	3.26	51	+54	-46	+58
Caudate	-	R	13.36	3.17	43	+12	-16	+30
Insula	13	L	13.07	3.14	206	-48	-24	+22
DLPFC	46	L	13.02	3.13	219	-42	+30	+24
Superior parietal area	5	L	11.95	3.00	107	-8	-46	+64
Precuneus	7	R	11.94	3.00	204	+28	-58	+46
Precuneus	7	R	11.64	2.97	81	+30	-68	+62
OFC	25	L	11.26	2.92	57	-12	+16	-22

area bilaterally ( $k=275$ ,  $T=4.41$ , at  $x=-40$ ,  $y=-52$ ,  $z=+20$ ; and  $k=29$ ,  $T=3.97$  at  $x=+44$ ,  $y=-52$ ,  $z=+16$ ) than model-conform learners did in the exploratory phase.

## Discussion

We investigated how the processing of feedback about choice outcomes changes before and after learning a response strategy that led to correct choices only. Learning this strategy did not prevent the subjects from experiencing losses, however, allowing differential changes in activation associated with experiencing gains and losses to be analysed.

The subjects showed a distinct pattern of learning that started with an initial exploratory phase which was characterised by chance-level performance. Subjects in this phase generate and test hypotheses about the correct task strategy. This exploratory phase was soon – around the fourth block – followed by a phase of rapid performance improvement, the so-called strategy acquisition phase. In the proficiency phase subjects had learned the correct response strategy and were applying it successfully so they made correct choices only. This improvement in performance was associated with decreasing and more homogeneous reaction times across subjects.

The imaging results show that the processing of feedback was generally associated with increased neuronal activation in the exploratory phase over the proficiency phase. We hypothesised that a decrease in activation would occur with learning, particularly in

the striatum, orbitofrontal cortex, ACC, and prefrontal structures engaged in working memory functions, especially the DLPFC. We further expected ACC activation to be particularly pronounced for losses and the decrease in striatal activation to be particularly pronounced for gains. With the exception of a decrease in ACC activation following losses, our hypotheses were confirmed. Additionally, lower activation following learning occurred not only within subjects across learning phases, but also between subjects with different learning speed.

### Learning-related activation changes

The OFC is thought to code for the incentive value of both sensory (e.g., taste or touch) and abstract (money or game points) rewarding stimuli (Krawczyk, 2002; Breiter et al., 2001; O'Doherty et al., 2001; Elliott et al., 2000; O'Doherty, 2004), particularly when the contingencies between reward and behaviour change (Kringelbach and Rolls, 2003; O'Doherty et al., 2003a,b; Schoenbaum et al., 2006; Remijne et al., 2005). The incentive value encoded in the OFC is linked to specific cues particularly when this information is relevant to the rules that guide task performance (for a review, see Schoenbaum and Setlow, 2001). The OFC and the dorsal striatum are prominent target areas of dopamine neurons. They are connected via the mesolimbic dopamine system which is postulated to function as a reward system. It arises in the substantia nigra and ventral tegmental area of the midbrain and terminates in the ventral striatum, dorsal

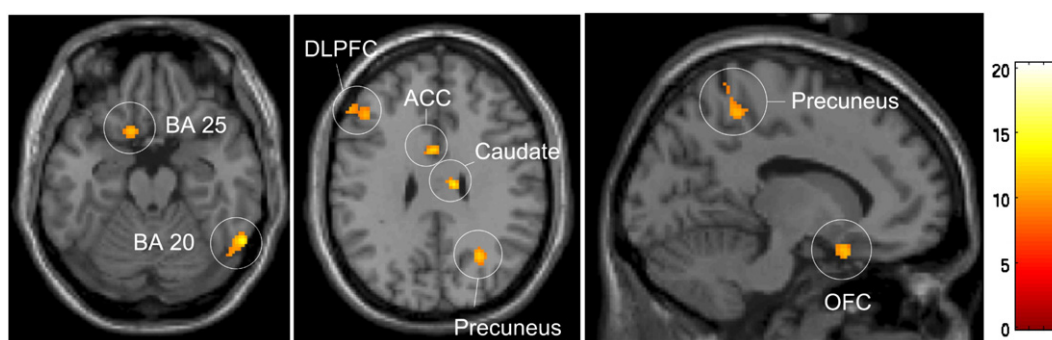
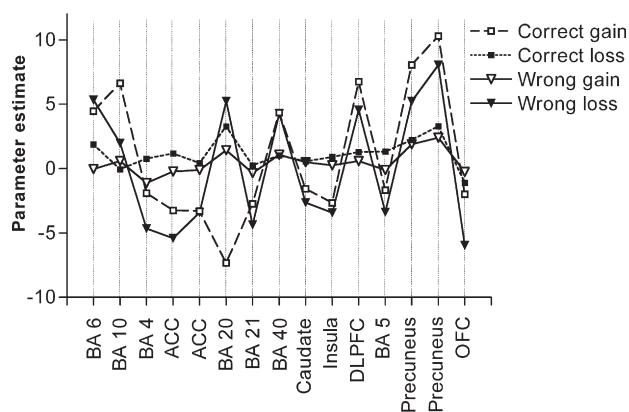


Fig. 5. Subset of areas activated in interaction with performance and utilitarian feedback in the exploratory phase.



Areas with interaction of performance and utilitarian feedback

Fig. 6. Parameter estimates ( $\beta$ ) of the different levels of the factors utilitarian vs. performance feedback in areas with significant interaction (exploratory phase). The areas are in the order of Table 3.

striatum (caudate and putamen) and the prefrontal cortex (Schultz, 2002; Wise, 2002). The crucial role that both the OFC and the putamen play in reward-related behaviour is stressed by human neuroimaging studies that identified prediction error signals (O'Doherty et al., 2003a, 2003b; McClure et al., 2003; Knutson et al., 2000; Berns et al., 2001) in these regions. Such signals

Table 5

MNI coordinates (mm) of activation maxima within a cluster for the interaction of feedback and learning phase with a cluster extent of  $k$

Region	Brodman area (BA)	Side	F-value	Z-value	k	x	y	z
Lateral OFC	47	L	14.74	3.35	79	-54	+32	+2
OFC	11	R	11.30	2.94	20	+22	+38	-12
Putamen	-	L	13.04	3.15	55	-14	+16	-10
Frontopolar area	10	L	11.15	2.92	51	-14	+40	-10

indicate that an event is better or worse than expected (Montague et al., 2004; Schultz et al., 1997). In the present task, reward expectations are built up in the exploratory phase and are fully established in the proficiency phase. Consequently, no reward prediction errors should occur after learning. Additionally, prediction error signals should be effective during a longer time for subjects who show an exploratory learning phase than for subjects who start off with the correct strategy right away. Indeed, the fast learning subjects displayed lower activation in the caudate.

The putamen and OFC are thus both involved in evaluating or establishing contingencies between stimuli, rewards and behaviours as is required in the exploratory phase. It seems that what is tracked are rather rewards than punishments, since activation of the OFC and putamen was larger for gains than for any of the other

Table 4

MNI coordinates (mm) of activation maxima within a cluster during processing of gains and losses in the exploratory vs. proficiency phase with a cluster extent of  $k$

Region	Brodman area (BA)	Side	F-value	Z-value	k	x	y	z
Superior temporal area	22	L	25.70	4.30	924	-48	-52	+18
Middle temporal area	21	L	16.54	3.53	177	-60	-50	0
Middle temporal area	21	R	15.10	3.39	180	+66	-26	-8
Middle temporal area	21	R	12.53	3.09	193	+66	-48	-2
Middle temporal area	21	R	11.74	2.99	63	+66	-8	-6
Inferior temporal area	20	L	13.09	3.16	42	-64	-42	-18
Temporopolar area	38	R	16.41	3.52	152	+46	+24	-20
pCC	29	L	16.17	3.50	142	-12	-48	+18
Thalamus	-	L	15.89	3.47	130	-10	-2	+12
Pre-SMA	6	L	20.06	3.86	119	-32	+12	+68
Pre-SMA	6	R	14.79	3.35	147	+38	+14	+64
DLPFC	9	L	13.72	3.23	126	-54	+16	+40
DLPFC	8	L	12.59	3.10	33	-26	+40	+48
DLPFC	9	L	12.18	3.05	31	-24	+24	+34
Parastriate area	19	L	13.16	3.17	118	-40	-62	-14
Parastriate area	19	L	17.10	3.59	317	-52	-72	8
Parastriate area	19	L	12.97	3.15	42	-14	-52	-8
Parastriate area	19	R	12.38	3.07	91	+42	-78	0
Parastriate area	19	R	10.21	2.79	23	+28	-96	+14
Parastriate area	19	R	10.91	2.88	67	+36	-78	+20
Parastriate area	18	L	10.70	2.86	29	-2	-88	-12
Postcentral gyrus	2	R	12.84	3.13	26	+38	-24	+34
Precuneus	7	L	12.15	3.05	62	-26	-68	+60
Precuneus	7	R	11.87	3.01	40	+38	-62	+58
Precuneus	7	L	11.03	2.90	86	-12	-70	+56
Precuneus	7	R	9.99	2.76	49	+4	-80	+52
Insula	13	R	12.07	3.03	37	+44	-44	+14
Parahippocampal gyrus	36	L	15.67	3.45	118	-36	-30	-12
Parahippocampal gyrus	37	L	12.05	3.03	65	-22	-46	-16
Parahippocampal gyrus	35	R	10.04	2.76	20	+18	-26	-12
OFC	45	L	10.57	2.84	56	-48	+28	+10

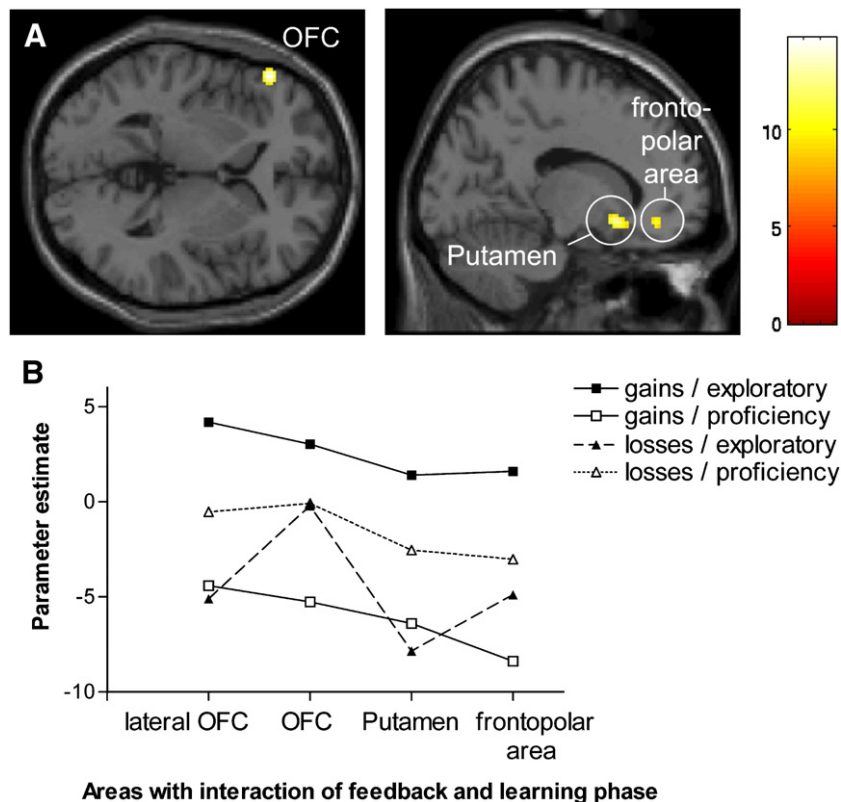


Fig. 7. (A) Subset of areas activated in interaction with feedback and learning phase. (B) Parameter estimates ( $\beta$ ) of the different levels of the factors feedback and learning phase in these areas.

outcomes in the exploratory phase. Along these lines, it has been reported previously that the putamen is activated primarily in response to unexpected primary rewards (McClure et al., 2003; O'Doherty et al., 2003a,b) and following positive than negative feedback (Seger and Cincotta, 2006; Delgado et al., 2005; van Veen et al., 2004; Preuschoff et al., 2006; Nieuwenhuis et al., 2005). Since the putamen has traditionally been associated with motor-related activities (e.g., Alexander et al., 1986) it could be tentatively assumed that the putamen activation observed in our task is more related to aspects of the behavioural adjustments to be made, whereas OFC activation may rather reflect the affective aspect of rewards.

There is also significant functional connectivity between the putamen and the DLPFC (Postuma and Dagher, 2006). Consistent with our hypothesis, activation in the DLPFC after both gains and losses decreased with learning. Thus, the automatization of task performance, and therefore, the decrease in cognitive requirements on working memory was reflected in a decrease in prefrontal activation. It has been suggested that working memory for novel stimuli requires the additional recruitment of parahippocampal regions (Hasselmo and Stern, 2006). The increased parahippocampal activation observed in the exploratory phase of our task may be explained in this way, because in this phase, a sequence of novel stimuli had to be maintained, whereas the stimuli were already familiar in the proficiency phase.

Additional structures not covered by our hypotheses that showed reduced activation after learning following both gains and losses were the middle and inferior temporal area, the peristriate area, the precuneus and the pre-SMA (BA 6). The middle temporal

area is involved in language and semantic memory processing (e.g., Chao et al., 1999; Cabeza and Nyberg, 2000). Activation in this region may be larger in the exploratory phase because subjects try to verbalise and/or extract semantic knowledge about the correct response sequence. Similarly, the middle temporal area has been reported to be activated during uncertain vs. certain decisions when the task employed words (Blackwood et al., 2004). At the same time, the middle temporal area seems to be involved in the processing of losses, for example, following losses as compared to gains in risky decision-making (Dickhaut et al., 2003), following streaks of losses (Akitsuki et al., 2003) and following an outcome that was more negative than the alternative outcome (Coricelli et al., 2005). A similar pattern was observed in our task where activation in the middle temporal area was smaller for correct gains than for any of the other outcomes. An interesting question arising from the different roles of this structure described in the literature is whether the increased activation in this area following both losses, ambiguous feedback and during the exploratory phase is associated with disappointment, as understood by Coricelli et al. (2005), or with a kind of sense-making of the provided feedback.

The learning-related activation decreases observed in the peristriate area may be due to sensory adaptation following repeated presentation of always the same stimuli. The inferior temporal gyrus is involved in processing and representing visual information (e.g., Ranganath, 2006; Herath et al., 2001), the need for which presumably also decreases as subjects learn the correct response sequence. One may speculate that the larger activation in this area following ambiguous than unambiguous feedback is also due to an increased processing demand arising from conflicting

visual information, for example, a “good” plus sign in combination with the “bad” red colour.

Learning-related decreases in the precuneus have been described previously using working memory (modified Sternberg task; Koch et al., 2006) and decision-making tasks (Ernst et al., 2002). Interestingly, precuneus activation was also what distinguished slow learners from model-conform learners both during the exploratory and the proficiency phase. The precuneus is closely connected to the DLPFC and has – among others – been ascribed a role in shifting attention between different targets and object features (Cavanna and Trimble, 2006). For example, in a set-shifting task that required to change the sorting criterion in response to incorrect feedback, a transient increase of activation occurred in the precuneus and the pre-SMA which was time locked with attention shifts (Nagahama et al., 1999). The precuneus is also activated during risky decision-making (Dickhaut et al., 2003; Paulus et al., 2003; Krain et al., 2006; Ernst et al., 2004) which may also be explained by the attentional requirements involved in tracking contingencies and supplying alternative response strategies in the presence of uncertainty (Paulus et al., 2001).

Similarly, differing set- and attention-shifting requirements can explain why precuneus activation was larger in the exploratory phase than in the proficiency phase, why it was noticeably larger following ambiguous than unambiguous feedback in the exploratory phase, and finally, why it was also larger in slow learners than in model-conform learners. As slow learners fail to grasp and automatise the correct response strategy, they may feel a greater need to adjust their response strategy and to pay more attention to the task than model-conform learners from the beginning of the task up to its end. This difference in attentional involvement is particularly pronounced during the proficiency phase, when slow learners also activated other attention-related areas such as the supramarginal area to a larger extent than model-conform learners. In fact, activation in the supramarginal area also distinguished fast learners from model-conform learners. This probably reflects the fact that attentional and working memory demands are reduced for fast learners who lack the initial exploratory phase and – as they start off with the correct sequence at once – do not have to work and try out different response strategies.

A further structure that plays a role in working memory (Naghavi and Nyberg, 2005; Derrfuss et al., 2004) and shows reduced activation after learning is the pre-SMA. The pre-SMA has also been implicated in decision-making under conditions of uncertainty (Blackwood et al., 2004). This applies to our task, in which correct responses and outcomes are uncertain in the exploratory, but not in the proficiency phase. Moreover, pre-SMA activation was larger with unambiguous than ambiguous feedback which also supports a role of the pre-SMA in uncertainty management. As our analysis was focused on the feedback period, uncertainty cannot be related to the question of which alternative to choose, but rather to the way to interpret the feedback given or to evaluate the consequences of an uncertain choice. Consistent with this view, activation in the pre-SMA has been previously found to decrease during the learning of arbitrary stimulus–response associations (Boettiger and D’Esposito, 2005).

In contrast to our expectation, activation in the ACC did not change with learning. A number of studies have confirmed the ACCs role in error detection (Carter et al., 1998; Holroyd and Coles, 2002; Nieuwenhuis et al., 2004), conflict detection (van Veen et al., 2004; Botvinick et al., 1999) and the evaluation of emotion-related aspects of the choice or outcome (Bush et al.,

2000; Krawczyk, 2002; Gehring and Willoughby, 2002). The fact that the ACC was activated more strongly after ambiguous than unambiguous feedback supports its role in resolving conflict. Since both errors and conflict about which response is or was correct are reduced in the proficiency phase, it seems at first sight surprising that ACC activation remained constant. One explanation could be that conflicts may still have been present in the proficiency phase, because subjects still incurred losses despite 100% correct responses. This might be perceived as a somewhat paradoxical situation leading to the experience of conflict. Indeed, in the exploratory phase, correct losses evoked larger ACC activation than correct gains. It seems plausible that this difference continued throughout the proficiency phase. A different explanation for the lacking decrease in ACC activation with learning could be that the ACC serves a more general role than conflict detection alone, namely updating control states in tasks that require following a course of mental activity that comprises several steps (Anderson, 2005). Recently, Fincham and Anderson (2006) showed that activity in the ACC increased in the course of learning when additional decision steps were introduced. Similarly, one could argue that the control demand in the present experiment is constant, as the length of the sequence was always the same. Even if the subjects began testing the wrong strategy – e.g., a sequence of right and left button presses – they had only 6 items to remember before they could try a new strategy. Thus, the number of mental operations did not change in the course of the experiment, which could explain why ACC activity did not change either.

Finally, it has to be noted that the supposed ACC activation underlying the ERN observed in the original version of the task (Gehring and Willoughby, 2002) was deduced from dipole localisation modeling, which – in addition to some questionable basic assumptions (see, for example, Luck, 2005) such as assuming a single dipole – is limited by a lower localisation accuracy compared to fMRI. Moreover, in a study applying the same task both during EEG and fMRI, a distinct ERN following negative feedback was not paralleled by activation in the ACC (Nieuwenhuis et al., 2005).

#### *Learning-related activation changes specific to gains and losses*

There were no areas which were specific for processing either gains or losses across learning phases. This suggests that losses and gains are coded by the same brain regions. Within these regions, however, the activation following gains and losses changed differentially with learning. Whereas the activation following losses increased with learning in the left lateral OFC and the putamen, the activation following gains decreased in those same areas and additionally in the right OFC (BA 11) and the frontopolar area. In general, the effect of learning on brain activation was larger for gains than for losses.

Since both the OFC and the dorsal striatum are associated with reward prediction error, our data suggest that positive and negative reward prediction errors are not processed in the same way as learning progresses and rewards become more probable. A similar asymmetry in responses to gains and losses was recently reported in an EEG study in which gain-related, but not loss-related ERPs were modulated by learning (Cohen et al., 2007). Since loss-related ERPs constitute the ERN which is believed to be associated with reward prediction error, these data may also be interpreted in terms of positive reward prediction errors being more sensitive to increased reward probability than negative reward prediction errors.

Activations in the frontopolar cortex, a further area that showed learning-related changes following gains in our study, are commonly observed in tasks that involve the executive control of cognitive functions, many of which require the application of a strategy to information held on-line such as the Wisconsin Card Sorting Task (Nagahama et al., 1996; Berman et al., 1995; Rogers et al., 2000). Activation in the frontopolar area has also been found to be associated with stimulus-driven attention shifts, particularly when subjects had already paid attention to a certain visual dimension (such as size or location) and then had to reallocate attention to a different dimension (Pollmann, 2001). Correspondingly, the frontopolar area seems to be engaged during rule induction, but no longer during rule application once a rule has been learnt (Strange et al., 2001). In the present experiment, frontopolar activation was larger after gains than losses, particularly after correct gains, and only the gain-related activation decreased with learning. This suggests that frontopolar activation is not so much related to a change in strategy, but more to the establishment of a strategy. Possibly, only the positive reinforcement through gains stabilises such a strategy held in working memory. Along these lines, activation in the frontal pole has also been observed during evaluation of the valence of pleasant, but not unpleasant words, compared to neutral words (Maddock et al., 2003), as well as during viewing pleasant, but not unpleasant pictures, compared to neutral pictures (Lane et al., 1999). This region may thus play a more general role in positively valenced emotional processes.

#### *Utilitarian vs. performance feedback*

The results show that the distinction between utilitarian and performance feedback is not reflected in brain activation. The distinction that most clearly affects brain activation is between ambiguous and unambiguous feedback. In general, unambiguous feedback, that is correct gains and wrong losses, yielded the strongest responses. The reason for this result may be that unambiguous feedback represents the clearest indication for a good or a bad outcome. The results may also indicate that our subjects were not quite aware of the difference between utilitarian and performance feedback during the exploratory phase, although they were able to use this information later on for learning. In contrast, the results of Nieuwenhuis et al. (2004) using a similar emphasis on performance feedback point to a clear grouping of ERPs with regard to performance vs. utilitarian feedback, with a larger error-related negativity for the two wrong outcomes, i.e., wrong gains and wrong losses, than for the two correct outcomes. One reason for this difference may be that the subjects in the Nieuwenhuis study underwent a much greater number of trials and therefore had more opportunity to grasp the distinction between the two types of feedback. A different explanation may be that in our study, the two feedback types did not differ as much from each other in terms of their physical appearance. Finally, ERPs might capture a different aspect than the feedback-related activation measured in our fMRI study. In addition to differences in the physiological mechanisms underlying BOLD and EEG signals, ERN amplitude is also related to the frequency of negative feedback. Negative feedback occurring at lower frequencies generates a larger ERN (Nieuwenhuis et al., 2002; Holroyd et al., 2003). In fact, both in our study as well as in the one of Nieuwenhuis et al. (2004) ambiguous feedback occurred less often than unambiguous feedback. For example, choosing “+25” would

be deemed a correct gain with both the alternatives “–5” and “+5”, whereas a correct loss could only occur in the form of choosing “–5” when the alternative was “–25”. The lower frequency of ambiguous feedback may explain the larger amplitude of the ERN found by Nieuwenhuis and colleagues while leaving the BOLD signal unaffected.

To summarise, we have presented evidence that learning to make correct decisions is associated with a decrease in brain activation in areas related to the establishment of stimulus–outcome contingencies, uncertainty management and working memory. Moreover, the effect of learning on brain activation was particularly pronounced for gains. This finding suggests that positive prediction errors are more sensitive to changes in reward predictability than negative prediction errors. Finally, there was no difference in the processing of utilitarian vs. performance feedback. Instead, unambiguous as compared to ambiguous feedback evoked the largest neural response. Thus, the feedback’s intelligibility is more important than the emphasis on its utilitarian or performance character.

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