# Parallel contributions of distinct human memory systems during probabilistic learning

# Kathryn C. Dickerson<sup>a</sup>, Jian Li<sup>b</sup>, Mauricio R. Delgado<sup>a,\*</sup>

<sup>a</sup> Center for Molecular and Behavioral Neuroscience & Department of Psychology, Rutgers University, 101 Warren Street, Newark, NJ 07102, USA
<sup>b</sup> Department of Psychology, New York University, 6 Washington Place, New York, NY 10003, USA

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# ABSTRACT

Regions within the medial temporal lobe and basal ganglia are thought to subserve distinct memory systems underlying declarative and nondeclarative processes, respectively. One question of interest is how these multiple memory systems interact during learning to contribute to goal directed behavior. While some hypotheses suggest that regions such as the striatum and the hippocampus interact in a competitive manner, alternative views posit that these structures may operate in a parallel manner to facilitate learning. In the current experiment, we probed the functional connectivity between regions in the striatum and hippocampus in the striatum and hippocampus in the human brain during an event related probabilistic learning task that varied with respect to type of difficulty (easy or hard cues) and type of learning (via feedback or observation). We hypothesized that the hippocampus and striatum and hippocampus that showed an effect of cue difficulty during learning and found that such ROIs displayed a similar pattern of blood oxygen level dependent (BOLD) responses, irrespective of learning type, and were functionally correlated as assessed by a Granger causality analysis.

in the VTA fire in response to this novel information, releasing dopamine into the hippocampus where it enhances long term potentiation; thus forming a functional loop between the hippocampus, nucleus accumbens, and midbrain which specializes in novelty detection. However, this is not the sole anatomical connection between the striatum and the hippocampus. There is also a direct projection from the hippocampus to the ventral medial caudate nucleus in the rodent (Jung et al., 2003). Combining this information with the knowledge of the existence of multiple spiral loops between the striatum and the midbrain dopaminergic centers (Haber, 2003), it is plausible that there may be interactions between the hippocampus, midbrain DA areas, and more dorsal regions of the striatum, via a ventromedial to dorsolateral movement of information through these spiral loops.

To expand upon these interactions, it has been proposed that dopamine's role in reward related learning, which has been typically associated with striatal function (for review see Schultz, 2002), also facilitates long term memory formation in humans, which is more traditionally associated with hippocampal function (Adcock et al., 2006; Shohamy and Adcock, 2010; Shohamy and Wagner, 2008; Wittmann et al., 2005). While a role for dopamine facilitating hippocampal memory formation is well characterized in studies involving non human animals (Packard and White, 1991), only recently has this evidence been extended into human neuroimaging experiments (Adcock et al., 2006; Shohamy and Wagner, 2008; Wittmann et al., 2005). Considering the conflicting evidence regarding the nature of the interactions between these memory systems in well as an arrow which provides information regarding the cue's value. During the feedback phase, feedback is given to the participant following his or her response for the feedback version. In the observation version, participants receive a message indicating whether or not their response has been recorded. It is hypothesized that the feedback version is akin to trial and error learning, considered to be more similar to nondeclarative types of learning, as the participant must learn which cue is associated with what value via guessing (initially) and subsequently receiving feedback. The nondeclarative component of this version lies in the trial and error nature of the feedback trial structure, which has been known to recruit regions of the BG (Poldrack et al., 2001; Shohamy et al., 2008). Furthermore, it is thought that the observation version of the task is akin to paired-associate learning, considered to be more similar to declarative types of learning, as the participant views both the cue and its value simultaneously and may therefore overtly memorize the association. The declarative component of this version is the cue presentation phase, where participants may engage in memorization strategies, and has been linked with MTL function, particularly the hippocampus (Poldrack et al., 2001). However, these tasks may not be exclusively solved via one learning mechanism or another. This issue will be addressed further in Discussion.

The other independent variable manipulated was cue dif

motion correction), spatial smoothing (4 mm, FWHM), voxel wise linear detrending, high pass filtering of frequencies (3 cycles per time course), and normalizing the data to Talairach sterotaxic space (Talairach and Tournoux, 1988). A canonical two gamma hemodynamic response function was used to convolve the events of interest.

During the learning phase, we examined neural activity across the 4 second period where learning occurred (2-s stimulus presentation/ participant response + 2-s feedback presentation). We chose to conduct the analysis in this manner due to the different nature of the feedback and observation trials. Relevant information in the feedback trials occurs during the feedback presentation (last 2 s of the trial) whereas relevant information in the observation trials occurs in the cue presentation phase (first 2 s of the trial). Thus, we examined the BOLD activity during the initial 4 second window of a trial to most accurately compare feedback and observation learning. We conducted a random effects general liner model (GLM) analysis using learning type (observation and feedback) and cue difficulty (easy and hard) as predictors. Additionally, 6 motion parameters were included as regressors of no interest to further control for motion related issues. From this GLM, we generated statistical parametric maps (SPM) thresholded at p < 0.005, using a cluster threshold with an extent of 5 contiguous voxels (equivalent to 135 mm<sup>3</sup> of tissue in  $1 \times 1 \times 1$  mm increments). Unless otherwise noted, for all SPMs generated during learning phase analyses, a correction for multiple comparisons was employed via the cluster level statistical threshold estimator plugin in the BrainVoyager analysis package (Forman et al., 1995; Goebel et al., 2006). This tool uses Monte Carlo simulations to determine the likelihood of observing clusters of various sizes. First, the map is thresholded at the desired level (e.g., p < 0.005) and then a whole brain correction is performed based on an estimate of the spatial smoothness of the map selected and Monte Carlo simulations which estimate the rate of cluster level false positives. Following 1000 iterations (the recommended number), the minimum cluster size threshold which produces the desired cluster level false positive alpha rate (5% was chosen) is automatically applied to the selected map. For each analysis, all active clusters in the resulting map are used to make a table which summarizes the number of clusters above the desired threshold for each size. When the analysis is complete, each cluster size is assigned an alpha value determined by the frequency of its occurrence in the SPM. Therefore, this method corrects for multiple cluster tests in the map and produces a cluster level false positive rate of 5%.

In order to investigate activity in the brain during learning, an Analysis of Variance (ANOVA) was conducted using learning type (feedback and observation) and cue difficulty (easy and hard) as within subjects factors. The first SPM of interest investigated a main effect of cue difficulty. This primary analysis allowed for a non biased examination of the relative engagement and pattern of activity in the BG, particularly the striatum, and the MTL, with focus on the hippocampus, during the learning phase of the task. Regions of interest (ROIs) were defined based on the results from the main effect of cue difficulty analysis and the BOLD signal (characterized by mean parameter estimates or beta weights) of these a posteriori ROIs (e.g., BG) was examined in order to explore differences between feedback and observation learning in a *post hoc* analysis. Additionally, a potential effect of time was examined during the learning phase. In order to model time, the learning phase was separated according to block/run. The BOLD signal was extracted from the a posterior regions of interest (e.g., hippocampus and caudate nucleus) for the first learning block/run of each learning type (e.g., observation trials 1 to 40; feedback trials 1 to 40) and again for the second learning block/ run of each learning type (e.g., observation trials 41 to 80; feedback trials 41 to 80). The mean BOLD signal from the "early" learning run was then compared to the mean BOLD signal from the "late" learning run in both ROIs for both learning types. The second SPM of interest investigated a main effect of learning type. The third SPM of interest examined potential interactions of learning type and cue difficulty.

During the test phase, we examined neural activity across the entire trial (stimulus onset and participant response). A random effects GLM was used with observation (easy and hard), feedback (easy and hard), and novel cues as predictors, along with 6 motion parameters as regressors of no interest. From this GLM, we generated SPMs thresholded at p < 0.005, that contrasted studied (observation and feedback cues collapsed across difficulty) vs. non studied (novel) cues. The cluster level statistical threshold estimator plugin was also used on the SPM generated for the test phase producing a cluster level false positive rate of 5%. Any ROIs which did not withstand correction are clearly labeled and should be interpreted with caution (Poldrack et al., 2008). Parameter estimates were extracted from the resulting ROI and used for further post hoc analyses. Post hoc analyses conducted on the learning phase behavior and neuroimaging data as well as the test phase behavior and neuroimaging data which consisted of more than two t tests within a family of comparisons were corrected for multiple comparisons with the sequential Bonferroni correction (Holm, 1979; Rice, 1989).

#### Granger causality analysis

A Granger causality analysis was performed on the learning phase data to examine both functional and effective connectivity in the brain. The purpose of this analysis was to determine the relationship between a seed region (x) and activity within the rest of the brain. Geweke (1982) proposed a measure of linear dependence,  $F_{x,y}$  between two hypothetical times series of data, x[n] and y[n], using vector autoregressive models.  $F_{x,y}$  consists of the sum of three distinct components:

$$F_{\mathbf{x},\mathbf{y}} = F_{\mathbf{x}\to\mathbf{y}} + F_{\mathbf{y}\to\mathbf{x}} + F_{\mathbf{x}\cdot\mathbf{y}}$$

- $F_{x \to y}$  is a measure of the directed influence from x to y; examining if past values of x improve the current predicted value of y.
- $F_{y \rightarrow x}$  is a measure of the directed influence from y to x; examining if past values of y improve the current predicted value of x.
- $F_{x \cdot y}$  is a measure of the undirected instantaneous influence of x and y. This measure incorporates the current value of x or y into the model which already contains the past values of x and y.

Therefore, the Granger causality analysis measures both directed  $(F_{x \rightarrow y} \text{ and/or } F_{y \rightarrow x})$  as well as undirected instantaneous influence  $(F_{x \cdot y})$  between a specified seed region of the brain (x) and the rest of the brain (see Goebel et al., 2003; Roebroeck et al., 2005 for more details).

A Granger causality analysis was conducted to specifically probe interactions between the hippocampus and the striatum during probabilistic learning. The hippocampus ROI obtained from the main effect of cue difficulty analysis from the learning phase ANOVA was used as the principle seed region. As a caution for interpretation of the Granger causality results, it must be kept in mind that the seed region used for this analysis was obtained at a threshold of p < 0.005, uncorrected for multiple comparisons. We chose this ROI as the seed region given the direct anatomical projections from the hippocampus to the basal ganglia (Kelley and Domesick, 1982). Separate functional and effective connectivity maps for the feedback and observation data were calculated. For each participant's data, the two feedback runs were combined to form one feedback map while the two observation runs were combined to form one observation map. We then examined connectivity across the entire run (first to last time point, 240 volumes for each run). Next we combined all the feedback maps and all the observation maps from each participant to form one group map for the feedback data and one group map for the observation data (n = 16) at a threshold of p < 0.0001 and a cluster threshold with an

extent of 7 voxels for the observation maps and 8 voxels for the feedback maps (correcting to a cluster level false positive rate of 5%). Last, standard second level statistics were performed on the group maps; specifically we ran a *t* test on the group data. Reported results represent functional connectivity data (instantaneous influence without directionality information;  $F_{x\cdot y}$ ) as effective connectivity ( $F_{x\to y}$  and/or  $F_{y\to x}$ ) results were not observed between the *a posteriori* regions of interest. Finally, as a control analysis, a second Granger causality analysis was performed in an identical manner using the caudate nucleus ROI obtained from the main effect of cue difficulty analysis from the learning phase ANOVA. Maps were thresholded at p < 0.0005 and a cluster threshold of 12 (correcting to a cluster level false positive rate of 5%) unless otherwise stated.

# Prediction error analysis

We applied a reinforcement learning model to the behavioral accuracy data for the feedback trials only. The prediction error (PE) regressor was calculated based on a Qlearning model (Watkins, 1989). In this model, the expected values for actions (indicating whether the value of the cue was higher or lower than 5) were updated using the Bellman equation and subjects' actual choices were determined by a softmax function of action values. Three parameters were used in the model: (1) learning rate,  $\lambda$  (2) action values,  $w_{\uparrow}$  and  $w_{\downarrow}$  (3) softmax function temperature, *m*. Optimal values for these parameters were estimated using a maximum likelihood estimation algorithm (MLE). A single set of free parameters was used for all participants when modeling the PE regressor. The prediction error is represented by  $\delta$ ; *r* is equal to the amount of reward, which in the feedback trials was either 0 for incorrect trials or 1 for correct trials; *i* = trial number and, j represents action type: guessing a high or low value.

$$w_{j,i+1} \leftarrow w_{j,i} + \lambda \delta \tag{1}$$

$$\delta = r - w_{j,i} \tag{2}$$

The prediction errors generated from the above equations using the optimal parameters were used as a regressor in the GLM neuroimaging analysis. We also included two additional predictors, trial event and missed responses, as well as the six motion parameters as regressors of no interest in the analysis. The PE was coded during the 2-s feedback presentation phase for the feedback learning trials only. The resulting SPM was generated at a threshold of p < 0.005 with a voxel contiguity threshold of 5 continuous voxels (correcting to a cluster level false positive rate of 5%) and probed regions of the brain that correlated with PE during probabilistic learning in the feedback session.

# Results

# Behavioral results

#### *Learning phase: accuracy*

In order to examine accuracy differences between the learning types and levels of cue difficulty, a 2 (learning type: feedback vs. observation)×2 (cue difficulty: easy vs. hard) repeated measures ANOVA was performed. A main effect of cue difficulty,  $(F_{(1,15)} = 16.04; p < 0.01)$ , no main effect of learning type  $(F_{(1,15)} = 1.47; p > 0.05)$ , and no significant interaction  $(F_{(1,15)} = 0.85; p > 0.05)$  were observed (Fig. 2A). Post hoc *t* tests were performed to further examine the main effect of cue difficulty within and across conditions. The results revealed that within both the observation  $(t_{(15)} = 2.54; p < 0.025)$  and feedback  $(t_{(15)} = 2.45; p < 0.05)$  trials participants performed significantly better on easy compared to hard cues. Performance was nearly significantly better for easy cues during observation compared to In13.7(a)0() (55.cm 13.09(p) 18(r) i 7.7(7) 8.6(t) 19.77(7) (10.07))

In13.7(e)0()-655(cq-13(90(p)-18(r)-i-7.7(7)-8.6(t)-1earni7D(gsnal.569using)onf[(Thn)3.5(miof)-435ntinuous)onN)Tj-26.56(that)43nses(and4829050.6

Bonferroni correction), but no differences were observed for observation performance ( $t_{(15)} = 1.04$ ; p > 0.05). As expected, participants' performance in the novel condition did not differ over time ( $t_{(15)} = 1.01$ ; p > 0.05).

During the individual test phases, no differences between feedback and observation trials or between easy and hard cues were observed. In the immediate test phase, for example, a 2 (learning type: observation vs. feedback) × 2 (cue difficulty: easy vs. hard) repeated measures ANOVA was performed to examine differences in accuracy between learning types and the level of cue difficulty (excluding the novel information and examining only the previously studied material during the immediate test session). This analysis revealed no significant main effect of learning type ( $F_{(1,15)} = 0.06$ ; p > 0.05), no significant main effect of cue difficulty ( $F_{(1,15)} = 0.23$ ; p > 0.05), nor a significant interaction ( $F_{(1,15)} = 1.92$ ; p > 0.05), suggesting that participants successfully learned contingencies independent of learning type and cue difficulty. A similar  $2 \times 2$  repeated measures ANOVA was performed for the follow up test phase examining potential differences between learning type and level of cue difficulty. No significant main effect of learning type ( $F_{(1,15)} = 0.51$ ; p > 0.05), no significant main effect of cue difficulty ( $F_{(1,15)} = 0.37$ ; p > 0.05), nor a significant interaction ( $F_{(1,15)} = 0.00, p > 0.05$ ) were observed.

# Neuroimaging results

# *Learning phase: main effect of cue difficulty*

From the learning type × cue difficulty ANOVA, a main effect of cue difficulty was examined (Supplementary Table 1). A region of the left caudate nucleus was involved in processing a main effect of cue difficulty (Fig. 3), along with a cluster in the left hippocampus which

was uncorrected. Mean parameter estimates from these two a posteriori ROIs were then extracted for further analyses. In the left caudate nucleus (x, y, z = -15, 20, 7; Fig. 3A and B), the pattern of BOLD responses was similar for both feedback and observation learning sessions, with no differences between learning type when collapsed across cue difficulty ( $t_{(15)} = 1.00$ ; p > 0.05). Post hoc *t* tests reveal a greater BOLD response for easy than hard cues in both learning types [feedback:  $(t_{(15)} = 5.02; p < 0.025)$ ; observation:  $(t_{(15)} = 3.99;$ p < 0.05]. In the left hippocampus ROI (x, y, z = -36, -28, -8; Fig. 3C and D) a marginally significant effect was observed when comparing mean parameter estimates from the feedback and observation sessions  $(t_{(15)} = 2.01; p = 0.06)$ , with a trend towards greater BOLD responses during the observation session. This difference was primarily driven by performance during the hard trials ( $t_{(15)} = 2.40$ ; p = 0.03; trend after sequential Bonferroni correction). Post hoc t tests indicate a greater BOLD response for easy than hard cues in the feedback trials ( $t_{(15)} =$ 3.73; p < 0.025) and a trend towards a greater response for easy compared to hard cues in the observation trials:  $(t_{(15)} = 1.79; p = 0.09)$ .

Finally, we examined changes in the mean BOLD signal for feedback and observation trials over time by comparing the BOLD signal early (first block) and late (second block) during the learning phase. A 2 (learning type: feedback vs. observation)×2 (cue difficulty: easy vs. hard)×2 (time: early vs. late) repeated measures ANOVA conducted on the mean BOLD signal from the caudate nucleus revealed no main effect of learning type ( $F_{(1,15)} = 0.82$ ; ; p > 0.05), a main effect of cue difficulty ( $F_{(1,15)} = 95.47$ ; p < 0.01), no main effect of time ( $F_{(1,15)} = 1.97$ ; ; p > 0.05), and no significant interactions. Mean parameter estimates approached a significant increase as learning progressed for the observation hard cues in the caudate nucleus ( $t_{(15)} = 2.25$ ; p = 0.04; trend after sequential Bonferroni correction; Supplementary Fig. 1A).



**Fig. 3.** Main effect of cue difficulty analysis during the learning phase identified regions of interest in the (A) left caudate nucleus (x, y, z = -15, 20, 7) and (C) left hippocampus (x, y, z = -36, -28, -8). Graphs depict mean parameter estimates for both the (B) left caudate nucleus and (D) left hippocampus across learning type and cue difficulty. Error bars represent s.e.m.

The same  $2 \times 2 \times 2$  repeated measures ANOVA was conducted on the mean BOLD signal from the hippocampus ROI and revealed a trend towards a main effect of learning type ( $F_{(1,15)} = 3.36$ ; ; p = 0.09), a main effect of cue difficulty ( $F_{(1,15)} = 20.69$ ; p < 0.01), a main effect of time ( $F_{(1,15)} = 5.35$ ; ; p < 0.05), and a trend towards a significant interaction between learning type and time ( $F_{(1,15)} = 3.76$ ; ; p < 0.07). Post hoc comparisons revealed a nearly significant increase for the feedback hard cues in the hippocampus as learning progressed ( $t_{(15)} = 2.38$ ; p = 0.03; trend after sequential Bonferroni correction; Supplementary Fig. 1B).

# Learning phase: Main effect of learning type

From the same learning type × cue difficulty ANOVA, a main effect of learning type was examined (Supplementary Table 2). This analysis revealed activation in different regions of the basal ganglia, specifically the right ventral portion of the head of the caudate nucleus (x, y, z = 6, 3, 4) and the left ventral caudate nucleus extending into the globus pallidus (x, y, z = −12, 2, 4; Supplementary Fig. 2). No differences with respect to cue difficulty were observed in these ROIs. At the threshold of p < 0.005, no voxels within the hippocampus were observed.

Learning phase: interaction of cue difficulty and learning type

An investigation of the interaction between learning type and cue difficulty from the ANOVA revealed activation in an area of the left medial prefrontal cortex. Post hoc *t* tests conducted on the mean parameter estimates extracted from this region indicated greater activity for observation easy compared to hard trials ( $t_{(15)} = 4.63$ ;

p<0.025); but no differences in difficulty for the TE560a6767xttoE.p(fat+)B(TD)(-p.62F).5008.55157.93D/(4007b).(Fe27badks/E296b5g482323.11(-d)22957.12(d)628662866396



**Fig. 4.** Granger causality analysis using the hippocampus ROI obtained from the main effect of cue difficulty analysis as a reference region. (A) Two regions of the right caudate nucleus (x, y, z = 14, 18, 13) and (x, y, z = 14, 12, 19; not shown) correlated with the hippocampus during the feedback trials, while (B) nearly the same ROIs (x, y, z = 14, 12, 19; not shown) correlated with the hippocampus during the feedback trials, while (B) nearly the same ROIs (x, y, z = 14, 12, 19; not shown) correlated with the hippocampus during the feedback trials, while (B) nearly the same ROIs (x, y, z = 14, 12, 19; not shown) and a region of the right ventral putamen (x, y, z = 22, 3, -4; not shown) correlated with the hippocampus during the observation trials.

interaction may potentially be explained by dopaminergic modulation during reward related learning (Lisman and Grace, 2005; Shohamy et al., 2008) as both BG and MTL ROIs were found to correlate with a prediction error signal, further corroborating the hypothesis that these distinct memory systems interact in a parallel manner while processing probabilistic information to facilitate goal directed behavior.

These results complement the visuomotor learning and simple association learning literature, which suggests that the medial temporal lobe and basal ganglia may be online simultaneously and are involved in learning arbitrary visuomotor associations (Amso et al., 2005; Haruno and Kawato, 2006; Law et al., 2005; Toni et al., 2001). In particular, our results are consistent with a recent study by Mattfeld and Stark (2010) which investigated the interaction of the MTL and the BG during an arbitrary visuomotor association task. The authors reported that several regions of the MTL and BG demonstrated an increase in BOLD signal as the strength of memory increased during a trial and error task, suggesting that regions of the MTL and BG are involved in learning arbitrary associations. Our observation of the hippocampus and caudate nucleus exhibiting larger BOLD responses to easy compared to hard cues complements Mattfeld and Stark's result. The authors also employed a functional connectivity analysis which revealed connectivity between both the ventral (nucleus accumbens) and dorsal (caudate nucleus) striatum with the hippocampus during learning, further supporting the interactive nature of these systems during learning and memory processes. One important distinction between our current task design and more traditional visuomotor tasks is the inclusion and investigation of different types of learning (observation and feedback).

Our results enhance recent neuroimaging findings demonstrating noncompetitive interactions between the BG and MTL during category learning (Cincotta and Seger, 2007; Voermans et al., 2004). For instance, a recent blocked design fMRI study which used an information integration category learning task observed similar patterns of activation to feedback and observation information in the hippocampus and regions of the striatum (Cincotta and Seger, 2007). The focus of this paper was on categorizing the BOLD response of different sub regions of the striatum to feedback and observation information. Interestingly, bilateral hippocampal activity to both types of information was also reported, leading to the interpretation that the striatum and hippocampus interact noncompetitively during information integration category learning. In the current experiment, an event related design allowed for the decoupling of factors such as difficulty and examining changes across learning to further lend support to the hypothesis that parallel processing in the BG and MTL contributes to overall learning during probabilistic paradigms (irrespective of the type of learning). Furthermore, we observed a significant positive correlation between the BG (caudate nucleus) and MTL (hippocampus) during the observation learning session and a trend towards a positive correlation during the feedback learning session. Whereas negative correlations may imply competition between memory systems (Poldrack et al., 2001), positive correlations may suggest noncompetitive, perhaps even synergistic interactions, leading to the interpretation that one system may inform the other in specific contexts to facilitate probabilistic learning. This functional connectivity is illustrated by Granger causality maps using both the hippocampus and the caudate nucleus as seed regions, which highlighted that areas within the striatum and the hippocampus were correlated at simultaneous time points during the learning phase.

It should be noted that our hippocampus region of activation from the main effect of cue difficulty analysis is reported at p<0.005, uncorrected for multiple comparisons. Additionally, two regions from the test phase analysis, the caudate nucleus and a region adjacent to the hippocampus, are also reported at p<0.005 uncorrected. Although this information could be useful for future studies, regions reported at



**Fig. 5.** Activation in both (A) left putamen (*x*, *y*, *z* = −30, 2, 4) and (B) right hippocampus (*x*, *y*, *z* = 27, −28, −14) were found to positively correlate with a prediction error signal during probabilistic feedback learning.

an uncorrected level should be regarded with caution when interpreting the results due to the increased likelihood of producing a Type I error (Poldrack et al., 2008).

The major differences between the feedback and observation versions of our task were outlined the Materials and methods section. Despite their differences, however, the two learning sessions share the common goal of learning the value of probabilistic cues. Thus, participants may engage in a variety of cognitive strategies in order to facilitate successful performance. As learning progresses over time in the feedback session, for instance, it is possible that participants employ a more declarative based cued recall strategy during the cue phase. Participants may also use verbal rehearsal strategies during the learning phase, irrespective of the task version. Research examining how participants solve another probabilistic learning task, the Weather Prediction Task (WPT), may shed some insight into possible declarative and nondeclarative components of category learning tasks as well as the knowledge that participants may have during these types of learning tasks (Gluck et al., 2002; Meeter et al., 2006). A relatively recent study by Newell et al. (2007)

differences were also apparent. First, only regions within the basal ganglia were modified by a main effect of learning type, while no voxels were identified in the MTL showing such differentiation. Several neuroimaging papers have shown that feedback and reward processing recruit ventromedial regions of the striatum (for review see Delgado, 2007), thus, it is not surprising that this region was recruited more strongly during the feedback learning trials. It may have been expected that the MTL would be selectively modulated by the observation version given previous results (Poldrack et al., 2001); however we did not observe this. While a null result in neuroimaging is not indicative of any particular finding per se and the context and details of our paradigm differ from previous probabilistic learning studies, it is possible that MTL BOLD signals within our paradigm are recruited during both feedback and observation learning-as suggested by the main effect of difficulty analysis-to contribute to overall learning. A second difference which emerged between the hippocampus and caudate nucleus was that the hippocampus showed a main effect of time (early × late learning) during the learning session, whereas caudate nucleus responses were not significant. This effect was driven primarily by activity during feedback learning (primarily for the hard cues), which was greater during late compared to early stages of learning in the hippocampus. This result may suggest that the involvement of the hippocampus in feedback learning happens later on during the learning process.

One finding to note is that the active voxels comprising regions of interest within the BG varied according to the type of analysis. It is perhaps not surprising, given the multifunctionality and connectivity of the striatum (Middleton and Strick, 2000a,b; Pennartz et al., 2009) that different voxels would be sensitive to the type of learning or level of difficulty. In the current experiment, dorsomedial regions of the striatum (caudate nucleus) were involved in initial learning and testing, whereas the dorsolateral regions (putamen) were involved in subsequent analyses with activity during learning positively correlating with prediction error signals. A functional connectivity analysis also revealed correlations between both caudate nucleus and putamen regions and the hippocampus. Interestingly, a ventromedial striatum region was found to be more responsive to feedback compared to observation learning, suggesting that some striatal subcomponents may distinguish between learning type (Poldrack et al., 2001) as supported by neuropsychological studies (Shohamy et al., 2004). In our design, however, this analysis is affected by the presence of affective feedback known to engage regions of the ventromedial striatum (for review see Delgado, 2007). Yet, this result is in accordance with previous probabilistic learning studies which report engagement of posterior parts of the caudate nucleus and putamen during learning, and more anterior parts of the caudate nucleus and ventral striatum linked with feedback processing (Cincotta and Seger, 2007; Seger and Cincotta, 2006).

In contrast to the striatum results, activity in the hippocampus was fairly consistent across analyses. There has also been recent research parsing out the distinct functional role of the subregions of the hippocampus. However, these studies have focused more on other issues such as anatomical distinctions between regions involved in memory encoding versus retrieval as well as pattern completion versus pattern separation (Bakker et al., 2008; Eldridge et al., 2005; Greicius et al., 2003). Future studies using high resolution fMRI may investigate how distinct subregions of MTL and BG interact during learning, to contribute to decision making processes underlying goal directed behaviors. To conclude, an investigation of the interactions between the MTL and BG during probabilistic learning suggests that these distinct memory regions may interact in a parallel manner to facilitate goal directed learning, acting synergistically during prediction error like learning scenarios.

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# Appendix A. Supplementary data

Supplementary data to this article can be found online at doi:10.1016/j.neuroimage.2010.10.080.

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