**Habitual control of goal selection**

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**The distinction between habitual and goal-directed action is fundamental to behavioral research1-3. Habits form as stimulus-response pairings are “stamped in” following reward. They enable computationally efficient decision making, but at the cost of behavioral flexibility. In contrast, goal-directed behavior requires planning over a causal model. This enables more flexible decision-making, but at a potentially severe computational cost. Exhaustive search over candidate plans becomes prohibitive as the space of possible goals grows. Thus, a key requirement for goal-directed action is to efficiently select candidate goals with a high likelihood of reward. Here, we provide evidence for a potential solution: Habitual control over the process of goal selection. Although many existing treatments of the distinction between habitual and goal-directed action emphasize their competition over behavioral control4, our results illustrate a codependence between the systems. The role of habitual control in goal-directed action captures diverse phenomena such as the automatic selection of goals under contextual cuing5,6 and the basis of practice effects in cognitive skills**7-9**.**

Our approach depends on a formalization of habitual and goal-directed behavior derived from the reinforcement learning (RL) framework10. Model-based RL maintains an explicit causal model of the world and uses it to choose actions by assessing their likely consequences. In contrast, model-free algorithms do not maintain an explicit causal model, and thus do not allow planning. Rather, they assign value to candidate actions based on their context-dependent history of reward. Like Thorndike’s law of effect3, model-free RL increases the probability of rewarded actions and decrease the probability of punished actions. The resulting stimulus-response habits are often globally adaptive, but may exhibit locally irrationality11,12.

RL models capture several core features of learning and choice in humans1,11,13. In particular, the midbrain dopamine reward system appears to implement several key features of model-free RL including prediction-error updating and temporal difference learning14-16. While early research on model-free control emphasized the role of subcortical circuits in selecting motor actions in response to sensory stimuli, recent research emphasizes their pervasive role in higher-level cognition17,18, including the gating of working memory19 and the construction of hierarchical task representations20. These models offer an appealing functional explanation for the neuronal connections between striatum and frontal cortex21.

Inspired by formal models of hierarchical RL22, we posit a similar role for model-free control in implementing goal selection. Pure model-based control over goal selection requires an organism to derive the expected value of pursuing candidate goals from a causal model of the rewards obtained during goal pursuit. In order to avoid the computational cost of exhaustive search, however, an organism could select candidate goals according to the reward history associated with past instances of their selection; i.e., based on model-free value update. Subsequent planning to achieve the selected goal would then proceed in a model-based fashion. In essence, our proposal captures the commonsense notion of a “habit of thought”, as well as the broad contours of prior models of hierarchically organized action2,23. The constituent cognitive operations that comprise controlled cognition—and which allow us to transcend purely habitual stimulus-response behavior—may themselves be habitized17.

In order to test for the influence of model-free value representations in goal selection we adapted a multistep choice paradigm from prior research11. The original paradigm behaviorally dissociates the influence of habitual (model-free) and goal-directed (model-based) control on choice, and is well-validated4,24-26. Our modification allows us to index not only model-free value assignment to actions (as in the original task) but also model-free value assignment to goals that may be subsequently pursued via model-based planning (Figure 1a). At Stage 1 of each trial participants make a choice between two options drawn from the set (1, 2, 3, 4). These choices stochastically transition to a second set of three states (blue, red, green). Finally, Stage 2 states deterministically transition to three unique reward distributions. The rewards drift over time. Thus, participants are motivated to choose Stage 1 options that maximize the likelihood of transitioning to the current reward-maximizing final state. For task details, see Supplementary Materials.







**Figure 1: Task structure. a**, In Experiment 1 participants performed a two-stage Markov decision task. **b**, Experiment 2 was identical except that participants were pre-trained on a set of transitions from Stage 0 to Stage 1, and then presented with Stage 0 choices during the main task only on critical “congruent goal” test trials. **c**, In Experiment 3, Stage 2 options varied along two orthogonal dimensions: shape and color. On each trial the participant was cued whether rewards would be determined by shape or color for that trial.

Our analysis depends on a critical subset of trials. For example, a participant is presented with the choice set (1, 3) at Stage 1 and chooses 1. Because 1 typically leads to the blue state, we assume that this participant’s goal was to transition to blue. On our critical trails, however, they experience a low-probability transition to the green state, and then experience a very large reward. A model-based system would discard this information because transitions to the green state are equally likely from all Stage 1 options. This renders forward planning toward green irrelevant. In contrast, model-free assignment of value to an action would increase the likelihood of selecting 1 on subsequent trials due to the positive reward history11. Our interest, however, is in the model-free assignment of value to a goal; in this case, the goal of transitioning to blue. If the experience of reward increases the likelihood of selecting blue as a goal, then participants should exhibit a greater likelihood of choosing 2 on the subsequent trial (when paired with either 3 or 4). Conversely, the experience of punishment should decrease the likelihood of choosing 2. This influence of the reinforcement history of choosing 1 on the subsequent choice of 2 cannot be explained by model-free update of an value to the specific action (choosing 1); rather, it depends on the assignment of value to their shared goal (getting to blue).

We assessed trials of this type by comparing instances when the participant experienced reward vs. punishment following low-probability transition to the green state. The mean proportion of trials on which participants selected the congruent-goal option following positive reward (89%) was significantly greater than following negative reward (69%) *t*(134)=-12.5, *p*<.0001 (Figure 2a). Additional supporting analyses for all experiments are presented in supplementary materials.



**Figure 2: Results.** Bars represent that proportion of trials on which participants chose the goal-congruent action, averaged across participants. Whiskers indicate the standard error of the mean of these proportions across participants. **a-c** show results from Experiments 1-3, respectively. **c**, congruent trials analyze the effect of reward experienced on a trials of the same type (shape vs. color) while incongruent trials analyze the effect of reward experienced on trials of the opposite type.

This result is consistent with model-free control over goal selection in which the habitually selected goal then participates in a process of forward planning over a causal model of the transition structure of the task. It is also consistent, however, with some hierarchical reinforcement learning models that do not invoke true model-based planning, such as the options framework22,27. These models assume that “goal states” merely establish internally represented contexts that bias model-free stimulus response associations. We designed Experiment 2 to test whether the goals selected in our paradigm could be flexibly integrated with knowledge of independent state transitions, a hallmark of true planning.

Participants were first trained on a deterministic set of transitions between four Stage 0 options (A, B, C, D) and the same four Stage 1 options used in Experiment 1 (Figure 1b). During this training phase the Stage 1 comprised the terminal states. Then, participants trained on and performed the same task used in Experiment 1, without any involvement of Stage 0 choices. Finally, we tested each participant in a set of critical trials—those involving a low-probability transition followed by a goal-congruent choice—but presented participants with a pair of Stage 0 choices in place of the ordinary Stage 1 choices. In order to integrate information about a desired goal with the set of Stage 0 choices, participants were therefore required to engage in forward planning over the learned transition structure between Stage 0 and Stage 1. Here, again, we found that participants were significantly more likely to choose the congruent-goal option following positive reward (85%) than following negative reward (69%) *t*(172)=-9.17, *p*<.0001 (Figure 2b).

The statistical dependencies present in our task could support associative pairings between Stage 1 options28. For instance, participants might associate options 1 and 2 because they share a common high-probability transition to the blue state in Stage 2. Do such associative pairings account for the transfer of reward history between goal-congruent options in our task?

To investigate this possibility we conducted a third experiment (Figure 1c). Stage 2 states were arranged in a 2×2 design crossing color (red versus blue) and shape (circle versus square), with a fifth state that differed on both dimensions (a green triangle). Each trial was defined as a “color trial” or “shape trial”, with the trial type dictating the deterministic transitions to drifting rewards. Thus, three reward distributions were accessible on color trials, while three independent reward distributions were accessible on shape trials. Across trial types, each Stage 1 option was equally statistically associated to two other Stage 1 options: One by virtue of a shared Stage 2 color, and another by virtue of a Stage 2 shape. A model invoking associative pairings would predict equal transfer of reward history from any Stage 1 choice (e.g., 1) to two other Stage 1 choices (e.g., 2 and 3). Conditioned on trial type, however, only a single Stage 2 dimension is goal relevant. A model-free influence on goal selection therefore predicts that reward history will influence the choice only for trials of the congruent type (shape vs. color). That is, the reinforcement of a color goal will only influence color trials, and likewise for shape goals and shape trials. Our findings confirm this prediction. Following trials on which participants experienced a low probability transition to the green triangle state, they were more likely to choose the congruent goal Stage 1 option on the subsequent trial following reward (83%) compared with punishment (76%) *t*(302)=-4.82, *p*<.001. On incongruent goal trials, however, there was no significant difference (positive: 50%; negative: 47%) *t*(282)=-.94, *p=.35* (Figure 2c).

In sum, we find that goal selection is partially determined by model-free value representations derived from reward history. These goals are subsequently used during model-based planning according to an internally represented causal model of the task structure. Thus, while our proposal relies upon the conceptual distinction between habitual (model-free) and goal-directed (model-based) behavioral control, it also demonstrations an area of mutual dependence between them.

This proposed integration captures several phenomena that blend canonical features of habits and goals. Many studies find that contextual cues can trigger goal pursuit outside of conscious awareness5, consistent with the operation of stimulus-response habits in the process of goal selection. In cases of “utilization behavior” among individuals with insult to prefrontal cortex, goal-directed behavior may be intrusive or inappropriately invoked based on contextual cues6. Among neurotypical individuals, “functional fixedness” describes the tendency to consider a limited set of candidate means-end relationships based on past experience with a tool9. Finally, it is commonly observed in educational settings that the execution of controlled cognitive processes improves with practice—in other words, that learning complex tasks requires the incremental acquisition of appropriate habits of thought7,8. It is widely recognized that human performance on complex tasks involves hierarchically organized sets of goals and subgoals2,22,29. Thus, proficiency may require the gradual acquisition of habitual subgoal selection given the contextual state of a superordinate goal.

References

1 Dolan, R. J. & Dayan, P. Goals and habits in the brain. *Neuron* **80**, 312-325 (2013).

2 Norman, D. A. & Shallice, T. *Attention to action*. (Springer, 1986).

3 Thorndike, E. L. Animal intelligence: An experimental study of the associative processes in animals. *Psychological Monographs: General and Applied* **2**, i-109 (1898).

4 Otto, A. R., Gershman, S. J., Markman, A. B. & Daw, N. D. The curse of planning: dissecting multiple reinforcement-learning systems by taxing the central executive. *Psychol Sci* **24**, 751-761, doi:10.1177/0956797612463080 (2013).

5 Huang, J. Y. & Bargh, J. A. The Selfish Goal: Autonomously operating motivational structures as the proximate cause of human judgment and behavior. *Behavioral and Brain Sciences* **37**, 121-135 (2014).

6 Lhermitte, F. ‘Utilization behaviour’and its relation to lesions of the frontal lobes. *Brain* **106**, 237-255 (1983).

7 Perkins, D. N. & Salomon, G. Are cognitive skills context-bound? *Educational researcher* **18**, 16-25 (1989).

8 Sfard, A. On the dual nature of mathematical conceptions: Reflections on processes and objects as different sides of the same coin. *Educational studies in mathematics* **22**, 1-36 (1991).

9 Adamson, R. E. Functional fixedness as related to problem solving: A repetition of three experiments. *Journal of experimental psychology* **44**, 288 (1952).

10 Sutton, R. S. & Barto, A. G. Reinforcement learning. *Journal of Cognitive Neuroscience* **11**, 126-134 (1999).

11 Daw, N. D., Gershman, S. J., Seymour, B., Dayan, P. & Dolan, R. J. Model-based influences on humans' choices and striatal prediction errors. *Neuron* **69**, 1204-1215 (2011).

12 Dickinson, A., Balleine, B., Watt, A., Gonzalez, F. & Boakes, R. A. Motivational control after extended instrumental training. *Learning & behavior* **23**, 197-206 (1995).

13 Simon, D. A. & Daw, N. D. Neural correlates of forward planning in a spatial decision task in humans. *The Journal of neuroscience* **31**, 5526-5539 (2011).

14 McClure, S. M., Berns, G. S. & Montague, P. R. Temporal prediction errors in a passive learning task activate human striatum. *Neuron* **38**, 339-346 (2003).

15 O'Doherty, J. P., Dayan, P., Friston, K., Critchley, H. & Dolan, R. J. Temporal difference models and reward-related learning in the human brain. *Neuron* **38**, 329-337 (2003).

16 Bayer, H. M. & Glimcher, P. W. Midbrain dopamine neurons encode a quantitative reward prediction error signal. *Neuron* **47**, 129-141 (2005).

17 Dayan, P. How to set the switches on this thing. *Current Opinion in Neurobiology* (2012).

18 Graybiel, A. M. Habits, rituals, and the evaluative brain. *Annu. Rev. Neurosci.* **31**, 359-387 (2008).

19 O'Reilly, R. C. & Frank, M. J. Making working memory work: a computational model of learning in the prefrontal cortex and basal ganglia. *Neural Computation* **18**, 283-328 (2006).

20 Badre, D. & Frank, M. J. Mechanisms of Hierarchical Reinforcement Learning in Cortico–Striatal Circuits 2: Evidence from fMRI. *Cerebral Cortex* **22**, 527-536 (2012).

21 Miller, E. K. The prefrontal cortex and cognitive control. *Nature Reviews* **1**, 59-65 (2000).

22 Botvinick, M. M., Niv, Y. & Barto, A. C. Hierarchically organized behavior and its neural foundations: A reinforcement learning perspective. *Cognition* **113**, 262-280 (2009).

23 Cooper, R. & Shallice, T. Contention scheduling and the control of routine activities. *Cognitive Neuropsychology* **17**, 297-338 (2000).

24 Otto, A. R., Skatova, A., Madlon-Kay, S. & Daw, N. D. Cognitive Control Predicts Use of Model-based Reinforcement Learning. (2014).

25 Otto, A. R., Raio, C. M., Chiang, A., Phelps, E. A. & Daw, N. D. Working-memory capacity protects model-based learning from stress. *Proceedings of the National Academy of Sciences* **110**, 20941-20946 (2013).

26 Smittenaar, P., FitzGerald, T. H., Romei, V., Wright, N. D. & Dolan, R. J. Disruption of dorsolateral prefrontal cortex decreases model-based in favor of model-free control in humans. *Neuron* **80**, 914-919 (2013).

27 Ribas-Fernandes, J. Ú. J. F. *et al.* A neural signature of hierarchical reinforcement learning. *Neuron* **71**, 370-379 (2011).

28 Daw, N. D. & Shohamy, D. The cognitive neuroscience of motivation and learning. *Social Cognition* **26**, 593-620 (2008).

29 Lashley, K. S. *The problem of serial order in behavior*. 112-131 (Wiley, 1951).