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14. ABSTRACT
The central aim of the project was to develop computational models of how individual decision-makers learn in real time to anticipate and take into account the risks and potential consequences of their actions. The main focus was on the medial prefrontal cortex (mPFC), an area of the brain known to signal mistakes as well as the level of difficulty or conflict facing the decision-maker. The research effort involved iteratively developing computational models and testing their predictions with fMRI, leading to further refinements of the model. The original goal of developing a model of risk prediction was achieved. Further effort yielded a more general model of how both good and bad potential consequences are learned and anticipated. The model predictions were validated by numerous behavioral and fMRI studies, and the effort also yielded an exact recursive model of hyperbolic temporal discounting. The results overall provide a new and relatively simple computational model of consequence prediction that accounts for and predicts a wide array of empirical data and is well-grounded in the known neurobiologically.

15. SUBJECT TERMS
Computational neural models, fMRI, cognitive control, risk, decision-making, hyperbolic discounting, intertemporal choice

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Computational Neural Models of Risk

FA9550-07-1-0454

Final Report

Feb. 24, 2010

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Executive summary

The central aim of the project was to develop computational models of how individual decision-makers learn in real time to anticipate and take into account the risks and potential consequences of their actions. The main focus was on the medial prefrontal cortex (mPFC), an area of the brain known to signal mistakes as well as the level of difficulty or conflict facing the decision-maker. The research effort involved iteratively developing computational models and testing their predictions with fMRI, leading to further refinements of the model. The original goal of developing a model of risk prediction was achieved. Further effort yielded a more general model of how both good and bad potential consequences are learned and anticipated. The model predictions were validated by numerous behavioral and fMRI studies, and the effort also yielded an exact recursive model of hyperbolic temporal discounting. The results overall provide a new and relatively simple computational model of consequence prediction that accounts for and predicts a wide array of empirical data and is well-grounded in the known neurobiologically.

Results

The effort began by using human fMRI to validate a prediction of the error likelihood computational model (Brown and Braver, 2005), finding that the medial prefrontal cortex (mPFC) signals the potential severity of adverse outcomes of an action, as well as the likelihood of adverse outcomes (Brown and Braver, 2007). This suggests an account of mPFC as signaling the risk associated with an action. A second fMRI study showed that these risk signals are specific to the particular context in which a decision is made (Krawitz et al., in preparation), and a modeling study further accounted for individual differences in risk-taking as reflecting the relative efficacy of learning signals due to mistakes (Brown and Braver, 2008). These studies fulfilled the original objectives of the project.

The PRO model. With the original objectives met, the project effort was expanded to include several additional goals. First, new fMRI evidence showed that mPFC signals the potential rewards as well as the potential risks of actions, and that these predictions compete at the neural level (Alexander and Brown, 2010a). This led to a generalization of the error likelihood model, namely that mPFC not only predicts the risks of an action but more generally predicts the probability of all potential outcomes of an action, both desirable and undesirable (Alexander and Brown, In Press). Subsequent project effort was devoted to developing a new computational neural model of mPFC to instantiate this hypothesis, and the model was able to capture a vast array of data from human behavior, fMRI, and ERP, as well as monkey single-unit neurophysiology (Alexander & Brown, In Prep). In essence, the model simulates how mPFC learns to predict the probable outcomes of planned actions, and these predictions are then compared against the actual outcomes. Any discrepancies between the predicted and actual outcomes provide an error signal that feeds back to refine the outcome predictions. This model is now called the predicted response outcome (PRO) model.

In its original form, the PRO model simulation was fairly complex. In the last year of the grant period, considerable effort was spent reworking the model to distill it down into its essence of a few equations that can still capture the vast range of data accounted for by the original simulation (Alexander and Brown, In Prep).

Testing the PRO model with fMRI. Armed with the PRO model, the effort expanded to simulate the model in new experimental paradigms and extract a series of *a priori* predictions.

A series of fMRI and behavioral studies were then designed to test the model predictions, and all fMRI results were consistent with the model predictions. It was found that error-related activation in mPFC can be reversed when error likelihood is high (Jessup et al., In Press), following the model prediction that mPFC signals a discrepancy of actual vs. *expected* outcomes, as distinct from a comparison of actual vs. *intended* outcomes. It was found that apparent response conflict-related activation in mPFC persists even when the task conditions are changed so that multiple responses are no longer in conflict with each other (Brown, 2009), consistent with the model account of greater activity due to predicting a greater number of impending action outcomes. Another study now shows that mPFC is sensitive to the timing as well as the valence of predicted outcomes (Forster and Brown, In Prep). Yet another study shows that mPFC has distinct functional subregions corresponding with specific model components (Nee, Kastner, and Brown, In Prep). In the course of testing model predictions, it was necessary to further develop methods of quantitatively fitting and testing model predictions directly with fMRI data. This led to another methods-based paper on hierarchical Bayesian methods of model selection criteria with respect to fMRI data (Ahn et al., revised).

Recursive hyperbolic discounting model. In the course of developing models of outcome prediction, the effort ran into a persistent issue in reinforcement learning theory. On the one hand, human and animal studies of intertemporal choice consistently show hyperbolic temporal discounting. On the other hand, existing recursive models and temporal difference learning models generally show exponential discounting. The effort was therefore further expanded to develop the first exact recursive model of hyperbolic temporal discounting, which now allows simple and accurate online simulations of animal and human choice behavior (Alexander and Brown, 2010b).

Overall, the effort achieved and went well beyond the original objectives. Some of the newer results are still in various stages of preparation and review, but the results lay a foundation of a neurobiologically grounded mathematical and computational theory of how individuals predict and take into account the potential outcomes of their decisions.

Personnel supported

Joshua W. Brown, Ph.D. – PI
William Alexander, Ph.D. – Post-Doc
Adam Krawitz, Ph.D. – Post-Doc
Derek Nee, Ph.D. – Post-Doc
Woo-Young Ahn – Graduate student
Rena Fukunaga – Graduate student
Elizabeth Dinh – Research Assistant
Sarah Forster – Graduate student
Rich Lewis – Research Assistant

Publications resulting from the grant:

1. Forster SE, **Brown JW** (in preparation) Medial prefrontal cortex learns to predict the timing of action outcomes.
2. Alexander WH, **Brown JW** (in preparation) Think before you act: medial prefrontal cortex as a predictor of action consequences

3. Krawitz A, Braver TS, Barch DM, **Brown JW** (in preparation) Impaired Error-Likelihood Prediction and Evaluation in Anterior Cingulate Cortex in Schizophrenia.

4. Nec DE, Kastner S, **Brown JW** (submitted) Functional heterogeneity of conflict, error, and task switching effects within medial prefrontal cortex.

5. Ahn WY, Krawitz A, Busemeyer JR, Kim W, **Brown JW** (revised) Neural Correlates of Subjective Outcome Evaluation in an Experience-Based Decision-Making Task. *J. Neurosci. Psychol. Econ.*

6. Alexander WH, **Brown JW** (revised) Computational neuroscience models: Error monitoring, conflict resolution, and decision making. In V. *Cutsuridis, D. Polani, A. Hussain, T. Tishby, and J. Taylor* (eds.) Perception-reason-action cycle: Models, algorithms and systems. New York: Springer

7. Krawitz A, Fukunaga R, **Brown JW** (revised) Anterior insula activity predicts the influence of gain framed messages on risky decision-making. *Cogn. Aff. Behav. Neurosci.*

8. Alexander WH, **Brown JW** (In Press) Computational models of performance monitoring and cognitive control. *TopiCS*

9. Jessup RK, Busemeyer JR, **Brown JW** (In Press) Error effects in anterior cingulate cortex reverse when error likelihood is high. *J. Neurosci.*

10. Alexander WH, **Brown JW** (In Press) Hyperbolically discounted temporal difference learning. *Neural Computation*

11. Alexander WH, **Brown JW** (2010) Competition between learned reward and error outcome predictions in anterior cingulate cortex. *NeuroImage* 49:3210-3218. doi:10.1016/j.neuroimage.2009.11.065

12. **Brown JW** (2009) Conflict effects without conflict in medial prefrontal cortex: multiple response effects and context specific representations. *NeuroImage* 47:334-341

13. **Brown JW**, Braver TS (2009) Executive function and higher-order cognition: Computational models. In L. Squire (ed.) *Encyclopedia of Neuroscience* 4:93-98. Oxford: Academic Press.

14. **Brown JW** (2009) Multiple cognitive control effects of error likelihood and conflict. *Psychological Research.* 73:744-750. DOI *10.1007/s00426-008-0198-7*

15. **Brown JW**, Braver TS (2008) A computational model of risk, conflict, and individual difference effects in the anterior cingulate cortex. *Brain Research.* 1202:99-108. doi:10.1016/j.brainres.2007.06.080

16. **Brown JW**, Braver TS (2007) Risk Prediction and Aversion by Anterior Cingulate Cortex. *Cogn. Aff. Behav. Neurosci.* 7(4):266-277

Technology assists:

Feb-Mar 2009: On request, the PI shared some raw countermanding task data from Brown & Braver (2005) with Glenn Gunzelmann and Rick Moore at AFRL, who are extending it to studies and models of sleep deprivation effects on cognitive control functions.

Other interactions and presentations during the grant period:

1. **Brown JW**, Nee DE, Kastner S (2009) Medial prefrontal cortex shows a regional gradient of monitoring and control functions consistent with a role in outcome prediction. Program No. 93.2. 2009 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
2. Forster S, **Brown JW** (2009) Violations of temporal expectancy activate discrete regions of medial prefrontal cortex in risk-averse and risk-seeking individuals. Program No. 93.1. 2009 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
3. Fukunaga R, **Brown JW** (2009) Informative messages against risky behavior show differential risk-aversion related activity in substance-dependent compared to healthy individuals. Program No. 93.3. 2009 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
4. **Brown JW** (2009) Computational neural models of risk. Invited talk. *AFOSR Joint Program Review – Cognition and Decision Program and Human-System Interface Program.* Jan 28-30, 2009, Arlington, VA
5. Alexander WH, **Brown JW** (2008) A computational neural model of learned response-outcome predictions by anterior cingulate cortex. Program No. 682.21. 2008 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
6. **Brown JW**, Finn PR (2008) Error likelihood and error consequence prediction effects are inverted in the anterior cingulate cortex of substance abusers. Program No. 682.19. 2008 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
7. Ahn WY, Krawitz A, Kim W, Busemeyer JR, **Brown JW** (2008) Disentangling neural processing of the Iowa gambling task: a model-based fMRI study. Program No. 681.7. 2008 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
8. Krawitz A, Braver TS, Barch DM, **Brown JW** (2008) The influence of working memory on error-likelihood prediction in the anterior cingulate cortex and its disturbance in schizophrenia. Program No. 288.3. 2008 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
9. Ashourvan A, **Brown JW**, Port NL (2008) A dynamical systems neural network model of predictive remapping of the tilt aftereffect preceding saccadic eye movements. Program No. 167.6. 2008 Neuroscience Meeting Planner. Washington, DC: Society for Neuroscience. Online.
10. **Brown JW** (2008) The basic science behind neuromarketing. Invited talk to Shoppability conference, Kelley Executive Partners, Kelley School of Business, Indiana University. October 2008.

11. **Brown JW** (2008) Risk predictions and cognitive control of decision-making. Invited talk at Johns Hopkins. October 2008.
12. Potter RF, Lang A, **Brown JW**, Fukunaga R, Krawitz A (2008) Brain activation during risk: The influence of trait motivation on ACC activation during choice and consequence. Contributed paper at *International Communication Association* annual meeting, Montreal, Canada, May 23, 2008
13. Alexander W, **Brown JW** (2008) Error likelihood effects in anterior cingulate cortex modulated by average reward and reinforcement learning. Contributed poster at Indiana Neuroimaging Symposium, IUPUI, April 2008
14. Ahn WY, Krawitz A, Busemeyer JR, **Brown JW** (2008) Neural correlates of decision-making processes in the Iowa gambling task: a model-based fMRI study. Contributed poster at Indiana Neuroimaging Symposium, IUPUI, April 2008
15. **Brown JW** (2008) fMRI methods – a brief overview. Invited talk. *Indiana Neuroimaging Symposium*. IUPUI campus, April 2008.
16. Fukunaga R, Krawitz A, **Brown JW** (2008) Persuasive messages against risky behavior increase risk aversion-related activity in the anterior cingulate cortex and insula. Poster presentation, *Cognitive Neuroscience Society*. San Francisco, CA
17. **Brown JW** (2008) Conflict effects without conflict in medial prefrontal cortex. Poster presentation, *Cognitive Neuroscience Society*. San Francisco, CA
18. Alexander W, **Brown JW** (2008) Error likelihood effects in anterior cingulate cortex modulated by average reward and reinforcement learning. Poster presentation, *Cognitive Neuroscience Society*. San Francisco, CA
19. Krawitz A, Braver TS, **Brown JW** (2008) The influence of working memory on error-likelihood prediction in the anterior cingulate cortex. Poster presentation, *Cognitive Neuroscience Society*. San Francisco, CA
20. **Brown JW** (2008) Individual differences in medial prefrontal cortex, conflict, error likelihood prediction, and risk aversion. *Invited Symposium, International Congress of Psychology*. Berlin, Germany
21. **Brown JW** (2008) Computational neural models of risk. Invited talk. *AFOSR Joint Program Review – Cognition and Decision Program and Human-System Interface Program* Jan 22-24, 2008, Arlington, VA
22. **Brown JW, Braver TS** (2007) Individual differences in medial prefrontal cortex, conflict, error likelihood prediction, and risk aversion. Program No. 232.9. 2007 Abstract Viewer/Itinerary Planner. Washington DC: Society for Neuroscience.
23. **Brown JW** (2007) Error and conflict, prediction, and the adaptive regulation of control. Invited talk at Conflicts as Signals workshop, Berlin, Germany
24. **Brown JW** (2007) The Role of Medial Prefrontal Cortex in Learned Risk Prediction and Aversion. Invited talk at Max-Planck Institute for Adaptive Behavior and Cognition, Berlin, Germany

References

Alexander W, Brown J (In Press) Computational models of performance monitoring and cognitive control. Topics in Cognitive Science.

Alexander WH, Brown JW (2010a) Competition between learned reward and error outcome predictions in anterior cingulate cortex. Neuroimage 49:3210-3218.

Alexander WH, Brown JW (2010b) Hyperbolically Discounted Temporal Difference Learning. Neural Comput.

Brown J, Braver TS (2007) Risk prediction and aversion by anterior cingulate cortex. Cog Aff Behav Neurosci 7:266-277.

Brown JW (2009) Multiple cognitive control effects of error likelihood and conflict. Psychol Res 73:744-750.

Brown JW, Braver TS (2005) Learned Predictions of Error Likelihood in the Anterior Cingulate Cortex. Science 307:1118-1121.

Brown JW, Braver TS (2008) A computational model of risk, conflict, and individual difference effects in the anterior cingulate cortex Brain Res 1202:99-108.

Jessup RK, Busemeyer JR, Brown JW (In Press) Error effects in anterior cingulate cortex reverse when error likelihood is high. J Neurosci.