

K.L. Ito¹, Laura Cao¹, Renee Reinberg¹, Brenton Keller¹, John Monterosso¹, Nicolas Schweighofer¹, & S.-L. Liew¹

¹University of Southern California, Los Angeles, CA

Introduction

- Healthy decision making is driven by a dual-system of control comprising habitual (fast, automatic) and goal-directed (slow, deliberate) strategies. Each are thought to be implemented in separate cortico-basal ganglia loops.¹
- Goal-directed control has been shown to decline with healthy aging, leading to an imbalance of the dual-system.²
- An imbalance of this dual-system has also been found in various basal ganglia-related neurological diseases, such as Parkinson’s Disease, Obsessive Compulsive Disorder, and Binge-eating Disorder.^{3,4}
- Given the presence of local and remote structural damage and neural dysfunction after stroke, it is possible that this dual-system balance may be impaired beyond healthy aging in individuals with stroke.
- Here, we examine (1) the behavioral effects of stroke on the balance between habitual and goal-directed decision-making compared to healthy young adults (YA) and healthy older adults (OA), and (2) examine cortico-striatal functional connectivity in a preliminary analysis of a subset of data.

Methods

- Forty-one participants (25 YA, 11 OA, 7 stroke) were trained on and completed a two-step Markov Decision Task, adapted from Daw et al. (2011)⁵ and Gillan et al. (2015⁶; Fig 1). Data from 6 participants were thrown out due to low learning rates on the task (2 YA, 3 OA, 1 stroke). MRI data collection was disrupted due to COVID-19; thus, we present fMRI data on 4 stroke participants and use data from 30 YA from the Human Connectome Project.

Task

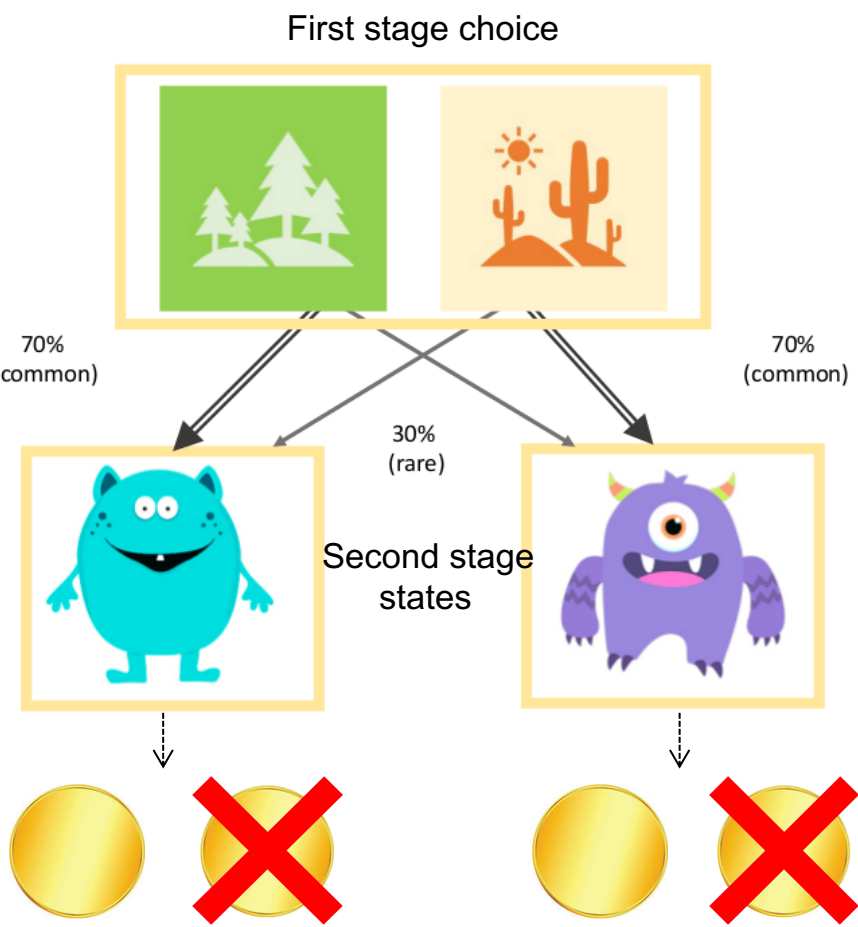


Figure 1. Two-stage Markov decision task (adapted from ref. X) On each trial, participants made a choice between two locations. One location more commonly (70%) led to one of the second-stage states, and rarely (30%) led to the other. Each second-stage state was associated with slowly changing reward probabilities.

Task Modeling and Group Behavioral Analysis

- Decision making behavior was fit at the subject-level, according to a hybrid algorithm from Daw et al. (2011)⁵
- Choices were assumed to be driven by a weighted combination, w , of learned action values via model-based reinforcement learning (Bellman’s equation) and model-free SARSA (lambda) TD learning. A weighting greater than 0.5 indicates goal-directed behavior, a weighting less than 0.5 indicates habitual behavior.
- R Stan’s Markov Chain Monte Carlo (MCMC) technique was used to perform Bayesian parameter estimation.
- A Kruskal-Wallis test was used to examine differences in mean w between groups.

Resting-State Analysis

- We used the CONN toolbox for preprocessing and first-and second-level analyses.
- We examined intrahemispheric connectivity of the caudate and putamen (defined individually with Freesurfer) to the lateral prefrontal cortices (LPFC) and lateral sensorimotor regions (SM) respectively, defined with CONN’s network atlases.

Results

1. Healthy OA and individuals with stroke were least goal-directed.

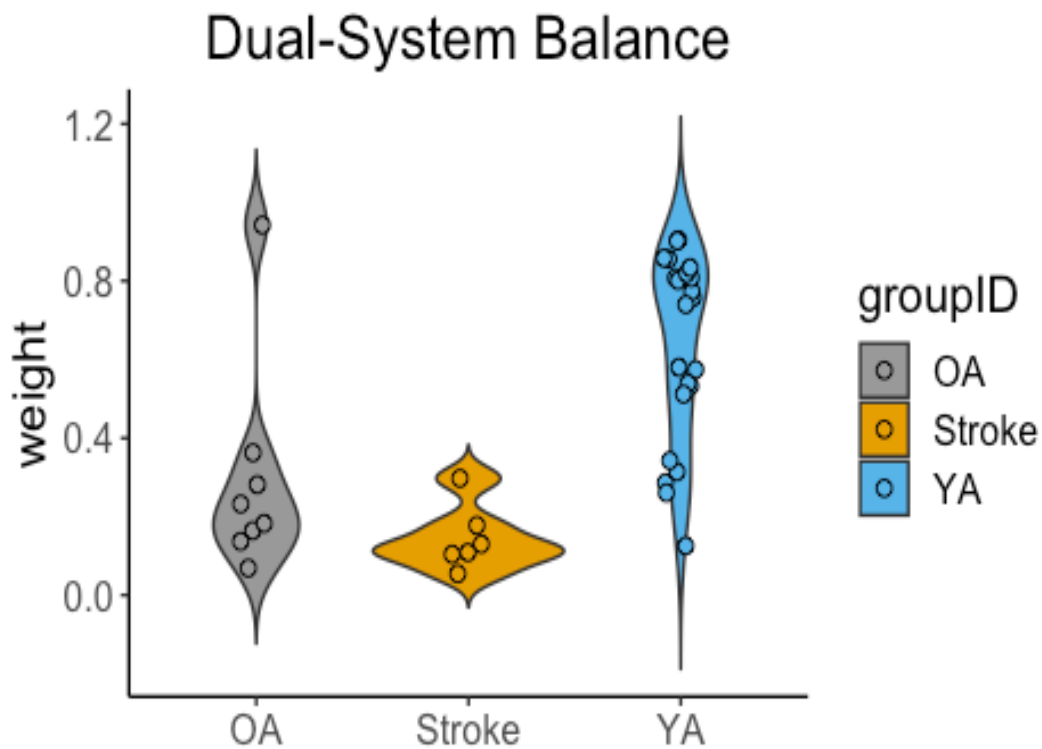


Figure 2. Behavioral Results. Overall the YA group was most goal-directed (mean $w=0.64$), followed by the OA group (mean $w=0.29$), then the stroke group (mean $w=0.15$). w was significantly different between groups ($\chi^2=15.99$, $p<0.001$), where the YA group was significantly more goal-directed than both the OA and stroke groups ($p<0.05$). No significant difference was found between the stroke and OA groups.

2. Healthy YA had greater caudate-LPFC connectivity; stroke had greater putamen-SM connectivity.

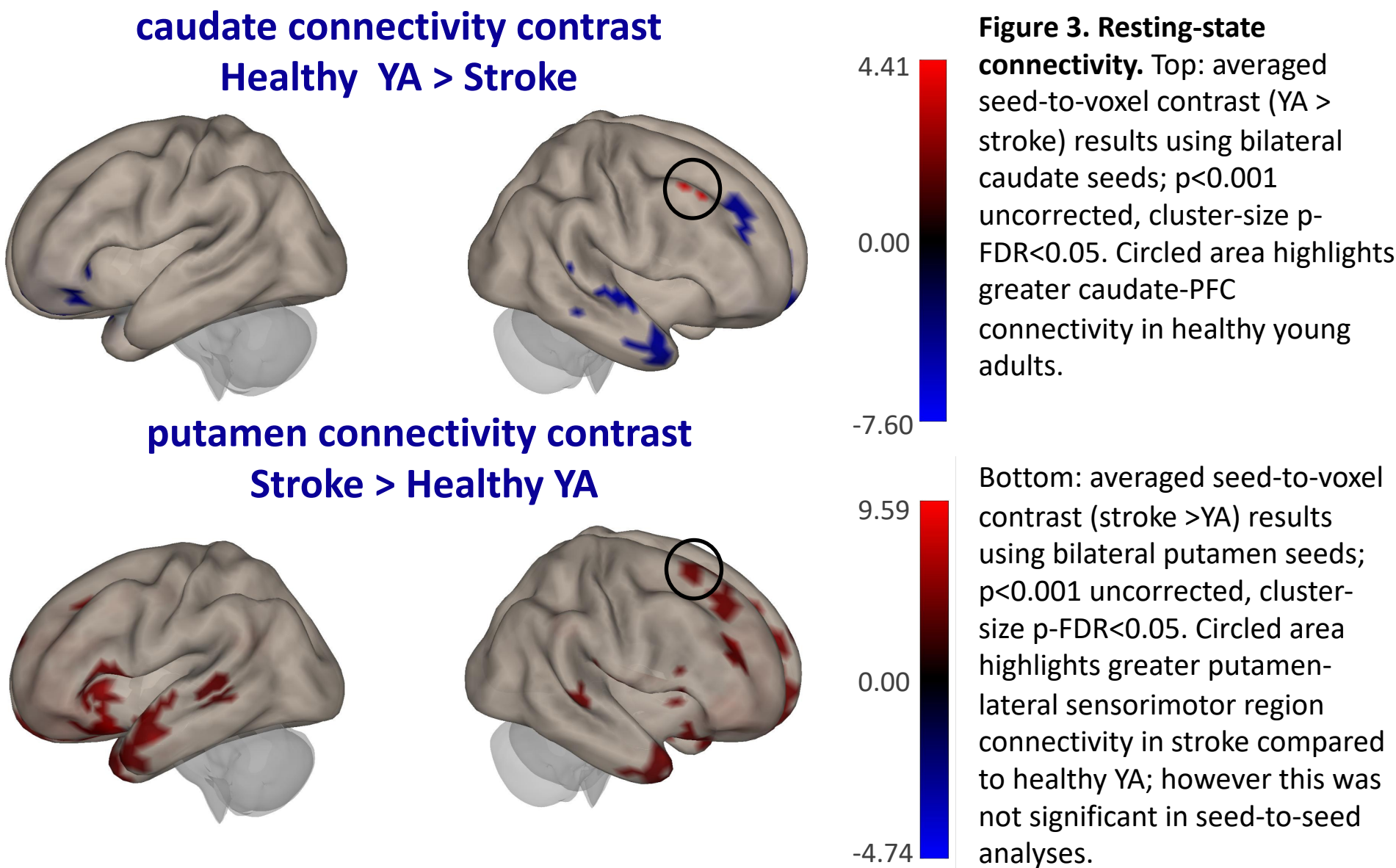


Figure 3. Resting-state connectivity. Top: averaged seed-to-voxel contrast (YA > stroke) results using bilateral caudate seeds; $p<0.001$ uncorrected, cluster-size $p\text{-FDR}<0.05$. Circled area highlights greater caudate-PFC connectivity in healthy young adults.

Bottom: averaged seed-to-voxel contrast (stroke >YA) results using bilateral putamen seeds; $p<0.001$ uncorrected, cluster-size $p\text{-FDR}<0.05$. Circled area highlights greater putamen-lateral sensorimotor region connectivity in stroke compared to healthy YA; however this was not significant in seed-to-seed analyses.

Discussion

- These preliminary results suggest that stroke may not alter decision-making behavior beyond healthy aging.
- However, more data, particularly from stroke and healthy OA, is needed to determine the strength of these effects and draw more conclusive results.
- Moreover, lesion location will likely play a role in altering cortico-striatal connectivity; however, we had insufficient data to examine for effects of lesion load.
- Data collection is now continuing online, and we are also collecting measures of working memory, as previous research⁷ has shown that working memory protects against habitual decision making.

Acknowledgments

Research was supported by USC Chan Division of Occupational Science & Occupational Therapy.

For further information: Contact Kaori Ito at kaoriito@usc.edu

References

- ¹Sutton, R. S. and Barto, A. G. (2018) Reinforcement learning: An introduction. MIT press.
- ²de Wit, S., van de Vijver, I. and Ridderinkhof, K. R. (2014) ‘Impaired acquisition of goal-directed action in healthy aging’, *Cognitive, Affective, & Behavioral Neuroscience*, 14(2), pp. 647–658.
- ³Ferrazzoli, D., et al.. (2016). Dopamine Replacement Therapy , Learning and Reward Prediction in Parkinson ’ s Disease : Implications for Rehabilitation, 10(June), 1–8.
- ⁴Gillan, C. M., & Robbins, T. W. (2014). Goal-directed learning and obsessive–compulsive disorder. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 369(1655), 20130475.
- ⁵Daw, N. D. et al. (2011) ‘Model-based inuences on humans’ choices and striatal prediction errors’, *Neuron*. Elsevier, 69(6), pp. 1204–1215.
- ⁶Gillan, C. M. et al. (2015) ‘Model-based learning protects against forming habits’, *Cognitive, Affective, & Behavioral Neuroscience*. Springer, 15(3), pp. 523–536.
- ⁷Otto, A. R., Raio, C. M., Chiang, A., Phelps, E. A., & Daw, N. D. (2013). Working-memory capacity protects model-based learning from stress. *Proceedings of the National Academy of Sciences*, 110(52), 20941-20946.