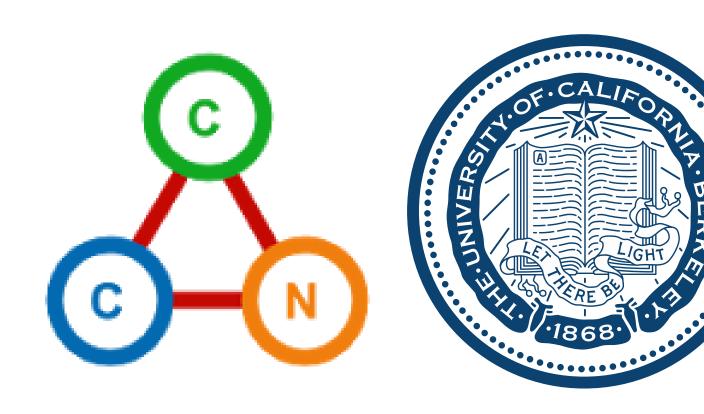


# Hierarchical Reinforcement Learning enables flexible transfer in humans



Liyu Xia, Anne G.E. Collins. University of California, Berkeley.

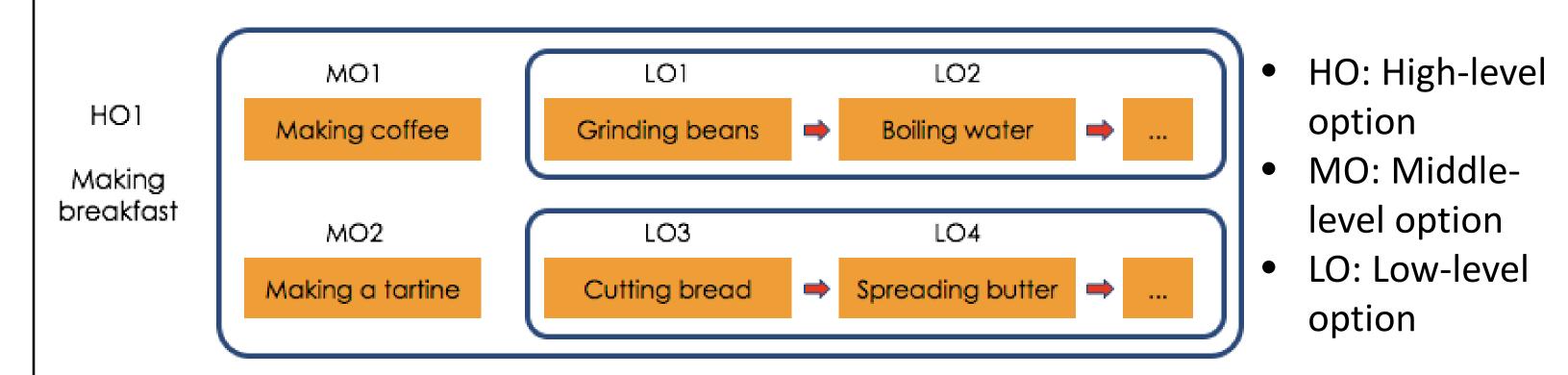
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# Introduction

Traditional reinforcement learning (RL) has 2 major limitations:

- 1. Cannot scale up to complex tasks that humans face.
- 2. **Cannot** explain how humans transfer previously learned skills to novel contexts.

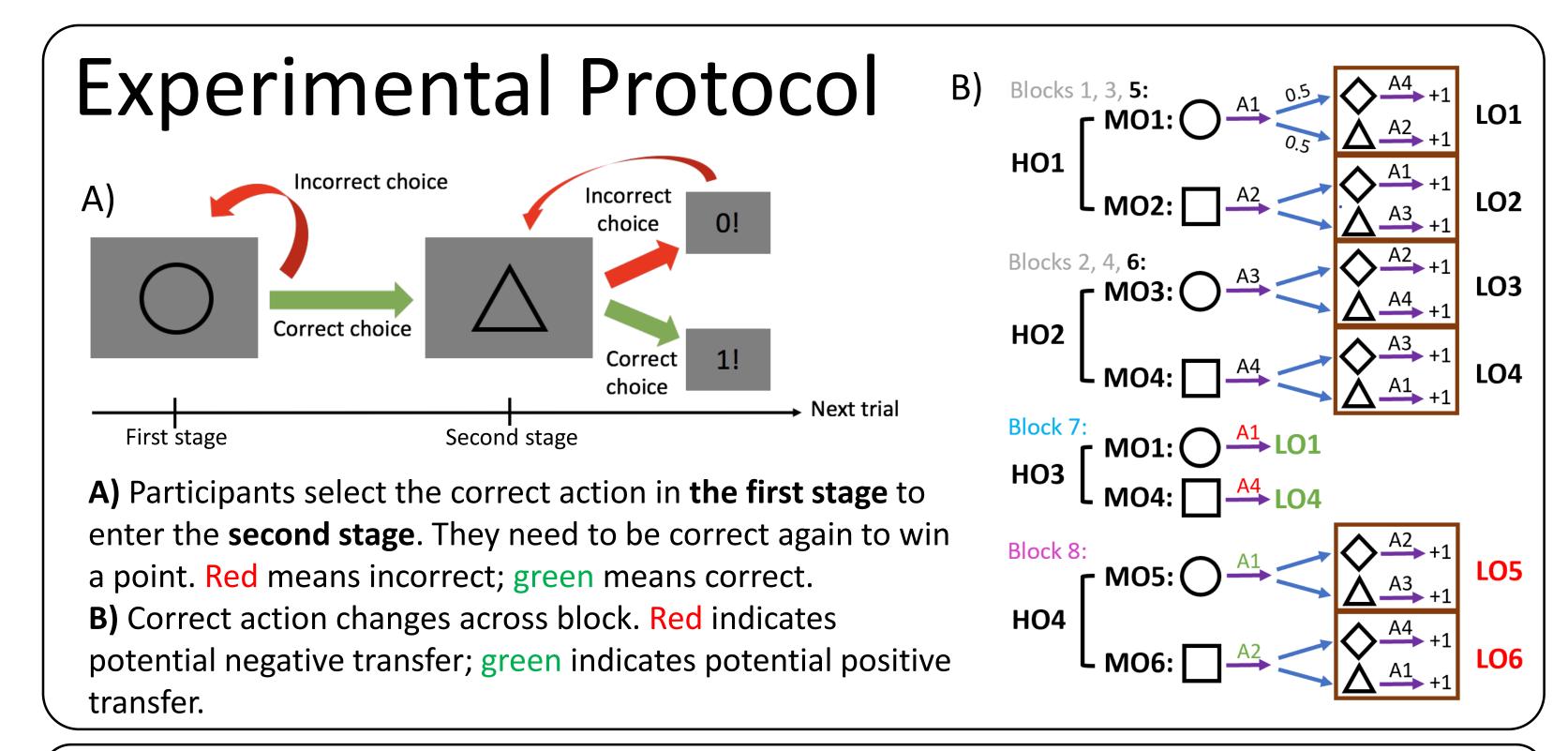
With the observation that human behavior is hierarchical [1], recent studies proposed **the options framework** [2] from Hierarchical Reinforcement Learning (HRL) which provides many theoretical benefits [3]. Options are temporally-extended policies composed of primitive actions and/or smaller options.



Prior work showed humans can learn 1-step policies (or task sets), and are able to transfer them to novel contexts [4].

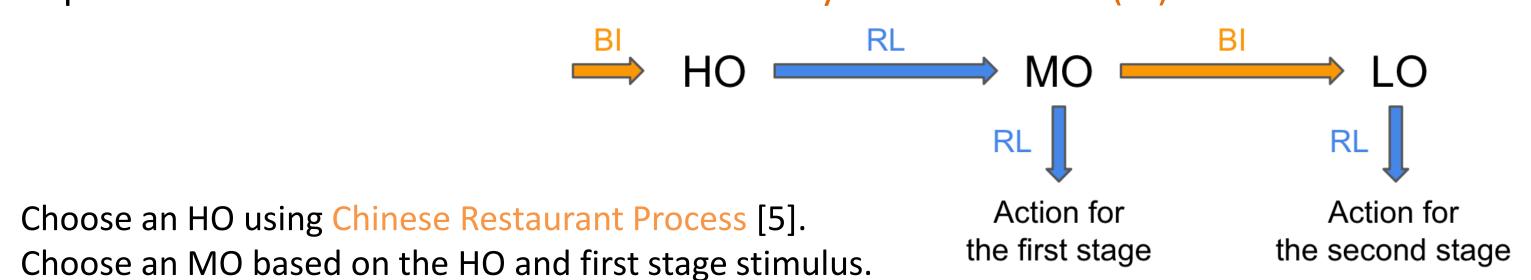
#### Questions:

- 1. Do humans learn options? At multiple levels?
- 2. If so, can humans transfer learned options?



## Option Model:

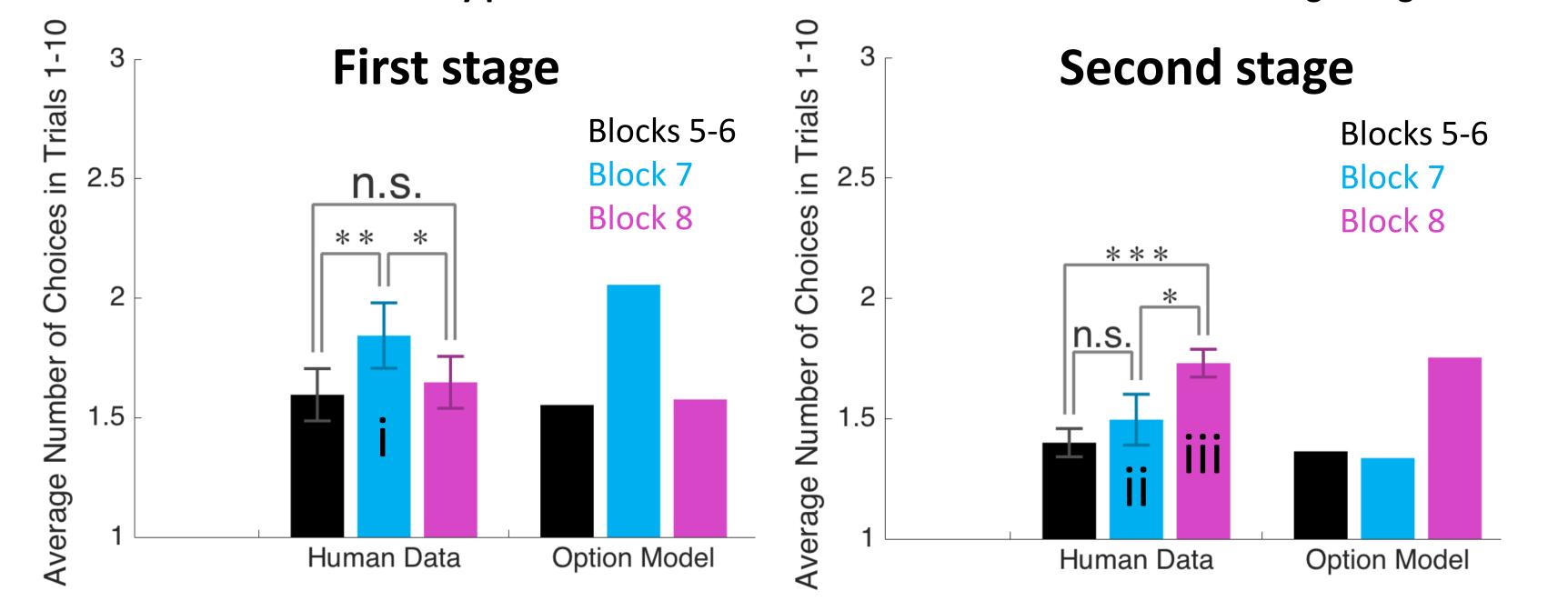
The option model is a combination of HRL and Bayesian inference (BI).



- 3. Choose an action for the first stage based on the policy dictated by the MO.
- 4. Choose an LO based on the MO's policy. This policy is learned by BI.
- 5. Choose an action for the second stage based on the policy dictated by the LO.

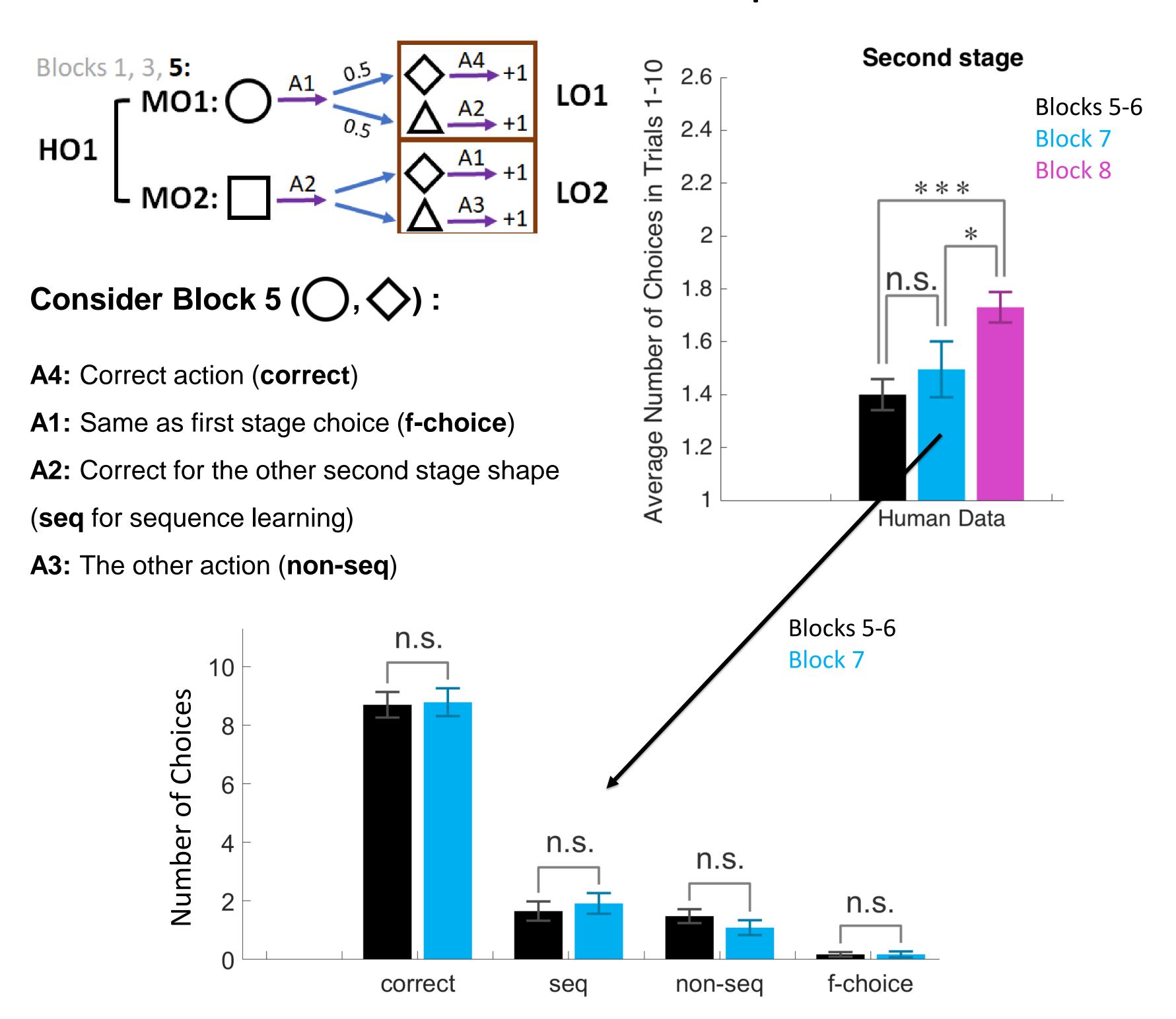
## Behavioral results support model predictions

We counted the number of key presses in the first 10 trials for transfer effects at the beginning of a block.



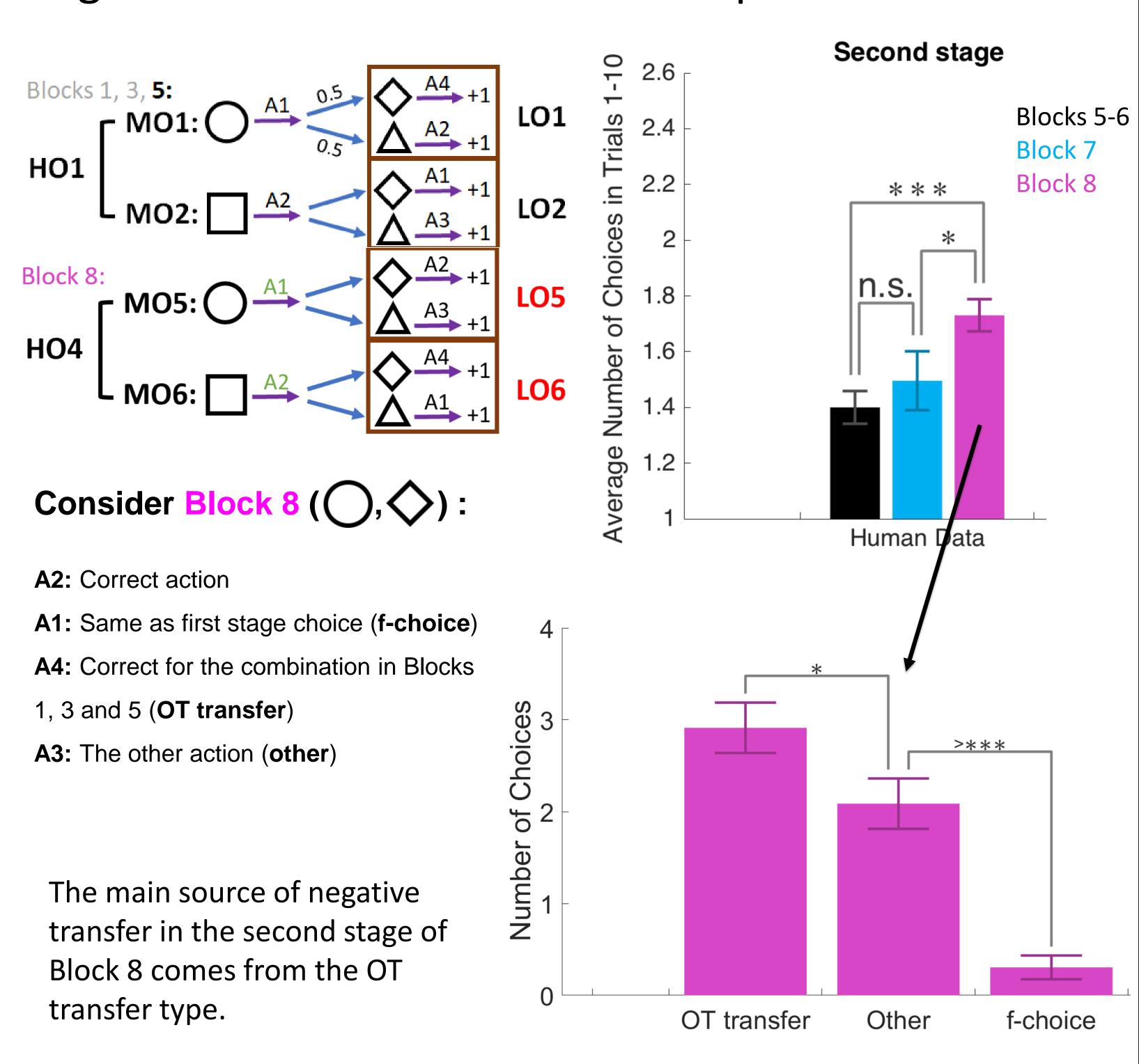
- 1. Behavioral data provides initial evidence for different transfer effect at both stages: (i) Negative transfer in Block 7 First stage
- (ii) No negative transfer in Block 7 Second stage(iii) Negative transfer in Block 8 Second stage
- 2. Option model simulations reproduce qualitative effects in behavioral data. No traditional flat RL can reproduce these transfer effects.

#### Positive transfer of middle-level options in Block 7



- 1. There is **no** significant difference between the second stage of Blocks 5-6 and Block 7 across all choice types, indicating that participants were able to flexibly transfer middle-level options as a whole even in the presence of interference from negative transfer in the first stage of Block 7.
- 2. We also compare the RT between **seq** and **non-seq** types and find no significant difference, indicating that the transfer effects cannot be explained by sequence learning alone.

## Negative transfer of middle-level options in Block 8



## Conclusions

#### Summary

- Humans learn temporally-extended policies called options, confirmed by both positive and negative transfer effects.
- Humans are able to flexibly transfer options at different levels.
- The Option Model captures transfers in human behavior qualitatively.
- Sequence learning alone cannot account for the transfer effects.

#### Future directions

- What is the neural underpinning of option learning? Is there any difference in the neural representation of 1-step policies and options?
- In novel contexts, do humans learn a new option, or rewrite an old one that is similar enough?

#### Bibliography

[1] Botvinick, M. M. (2008). Hierarchical models of behavior and prefrontal function. *Trends in cognitive sciences*, 12(5), 201-

[2] Sutton, R. S., Precup, D., & Singh, S. (1999). Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning. *Artificial intelligence*, 112(1-2), 181-211.

[3] Botvinick, M. M., Niv, Y., & Barto, A. C. (2009). Hierarchically organized behavior and its neural foundations: a reinforcement learning perspective. *Cognition*, 113(3), 262-280.

[4] Collins, A. G., & Frank, M. J. (2013). Cognitive control over learning: Creating, clustering, and generalizing task-set structure. *Psychological review*, 120(1), 190.

[5] Aldous, D. J. (1985). Exchangeability and related topics. In *École d'Été de Probabilités de Saint-Flour XIII—1983* (pp. 1-198). Springer, Berlin, Heidelberg.