P1-H-67 Neuro-computational Mechanism of Reliability-based Arbitration between Observational and Experiential Learning

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Introduction

"What would you like to have?"

Question: What is the underlying behavioral and neural computations supporting the dynamic integration of information from observational and experiential learning?

Hypotheses:

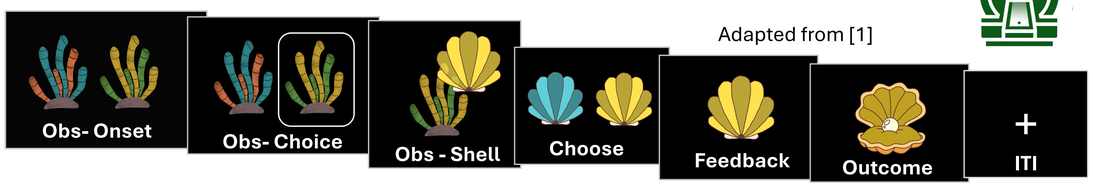
- Our brain integrates observational & experiential information by a reliability-based arbitration process
- Reliability is a function of the degree of uncertainty in the two systems, which determines relative weights assigned to the two information sources upon the integration

Social Pearl Hunting Task

Participants: N = 32, male : female = 17:15, age = 33.4 ± 9.0

Data collection: 4 blocks * 50 trials/block inside a Siemens 3T scanner.

Adapted from [1]



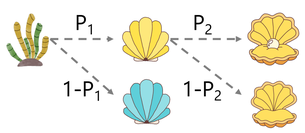
Observational Learning (OL)

Partner knows is better, but explore

Experiential Learning (EL)

You choose , and see

State Transitions



OL/EL Uncertainty

(P_1,P_2)		OL (P1)	
		High	Low
EL(P2)	High	(0.6,0.65)	(0.8,0.65)
	Low	(0.6,0.85)	(0.8,0.85)

Environment Volatility

Goal token changes every 6-10 trials

OL uncertainty changes ~ every 15 trials

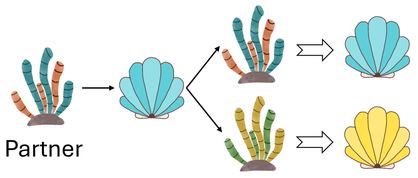
EL uncertainty changes ~ every 15 trials

Data Analysis & Modeling

Definition of behavioral signatures

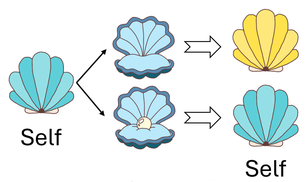
OL-consistent choice

Partner's goal



EL-consistent choice

Self outcome



Distinguishable trial:
a choice can be either OL-consistent, or EL-consistent, but not both/neither

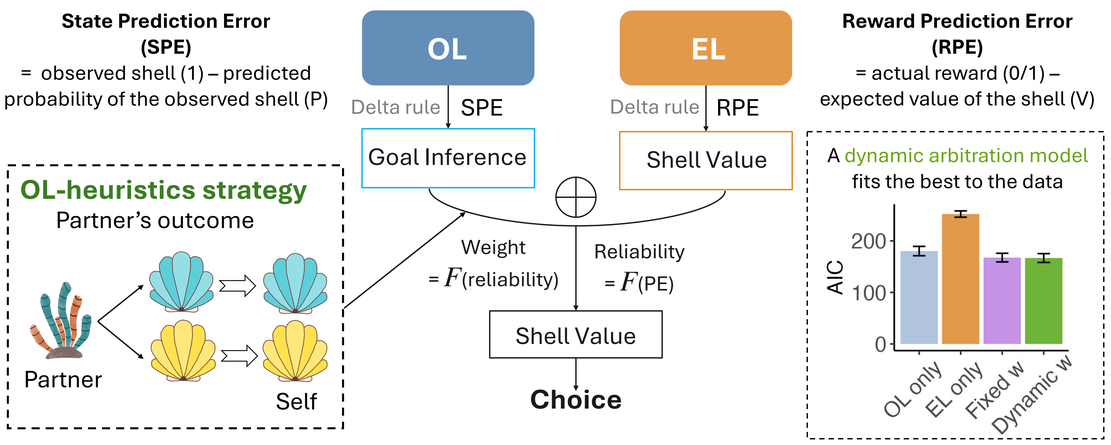
OL propensity

$$= \frac{\#\text{ OL consistent choices}}{\#\text{ distinguishable trials}}$$

Computational Model

State Prediction Error (SPE)
= observed shell (1) – predicted probability of the observed shell (P)

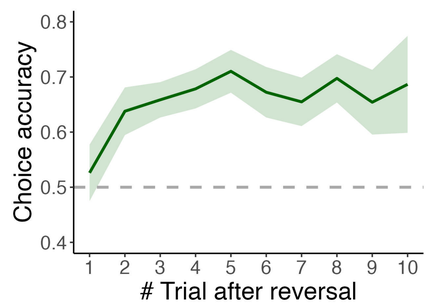
Reward Prediction Error (RPE)
= actual reward (0/1) – expected value of the shell (V)



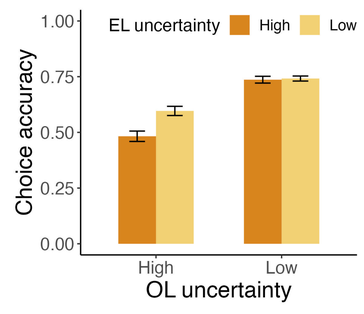
Results

❖Choices are Driven by Both OL & EL Uncertainty

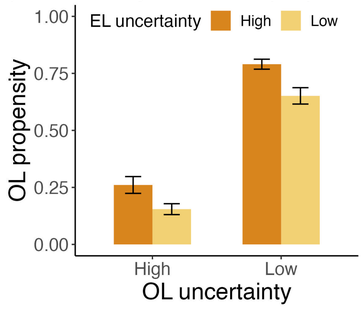
a) Participants learned the goal over time



b) Uncertainty affects accuracy

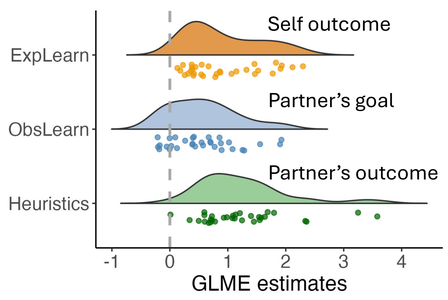


c) Uncertainty affects OL propensity

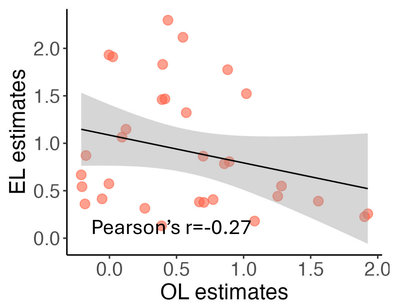


❖General Linear Mixed-Effects Model (GLME) Predicts Choices Using 3 Strategies

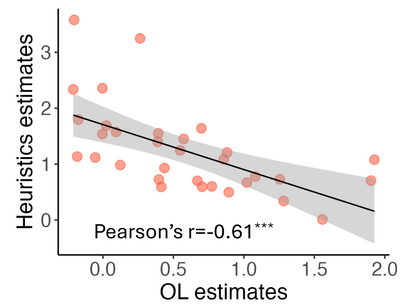
a) Fixed effects found in all 3 strategies



b) OL and EL strength not correlated



c) More heuristics, less OL

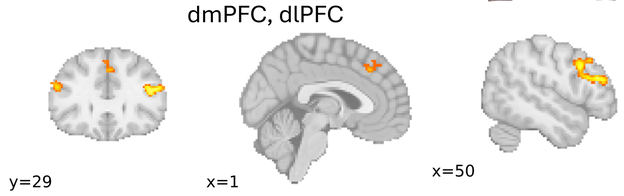


❖Neural Correlates of The OL & EL Learning Signals

Voxel threshold p<0.001, uncorrected
FWE cluster-level correction p<0.05

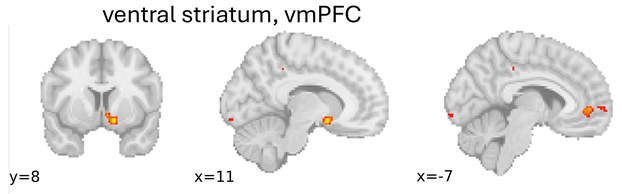
Observational State Prediction Error

dmPFC, dlPFC



Experiential Reward Prediction Error

ventral striatum, vmPFC



❖Different Brain Areas Compute Different Decision Signals

Observational Goal Inference

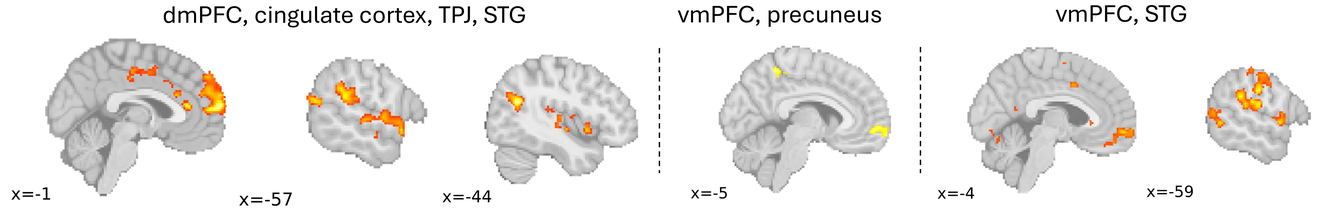
dmPFC, cingulate cortex, TPJ, STG

Experiential Value Signal

vmPFC, precuneus

OL+EL Decision Signal

vmPFC, STG



Conclusion

- Using a social pearl hunting task, we quantified the integration of observational and personal info during decision-making
- We identified behavioral signatures of how individuals flexibly adapt to uncertain environments through arbitration
- Evidence from the fMRI activations supported a computational model of reliability-based arbitration mechanism
- Next step is to find the neural correlates corresponding to the computations of reliability during arbitration

Acknowledgement & Reference

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Reference: [1] Charpentier, C. J., Wu, Q., Min, S., Ding, W., Cockburn, J., & O'Doherty, J. (2023, April 10). Heterogeneity in strategy use during arbitration between experiential and observational learning. https://doi.org/10.31234/osf.io/pcjg7