

# Novelty drives human exploration even when it is suboptimal

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preprint

## 1. Introduction

- How do humans **explore** environments with **sparse** rewards?

**Intrinsically motivated RL algorithms** have been proposed in computational and behavioral neuroscience as models of human exploration [1].

However, **different choices of intrinsic reward** result in fundamentally **different exploration strategies**. [2]

- Which intrinsic reward** explains human exploration best?

**Our contribution:** Inspired by the “noisy TV” problem in machine learning [3], we design an experimental paradigm where **three representative intrinsic rewards** (novelty [4,5], surprise [6,7], and information-gain [8-10]) make **different behavioral predictions**. We test these predictions against **human behavior**.

[1] Gottlieb and Oudeyer, 2018;

[2] Aubret et al., 2022;

[3] Burda et al., 2019;

[4] Bellemare et al., 2016;

[5] Xu and Modirshanechi et al., 2021;

[6] Kobayashi et al., 2019;

[7] Pathak et al., 2017;

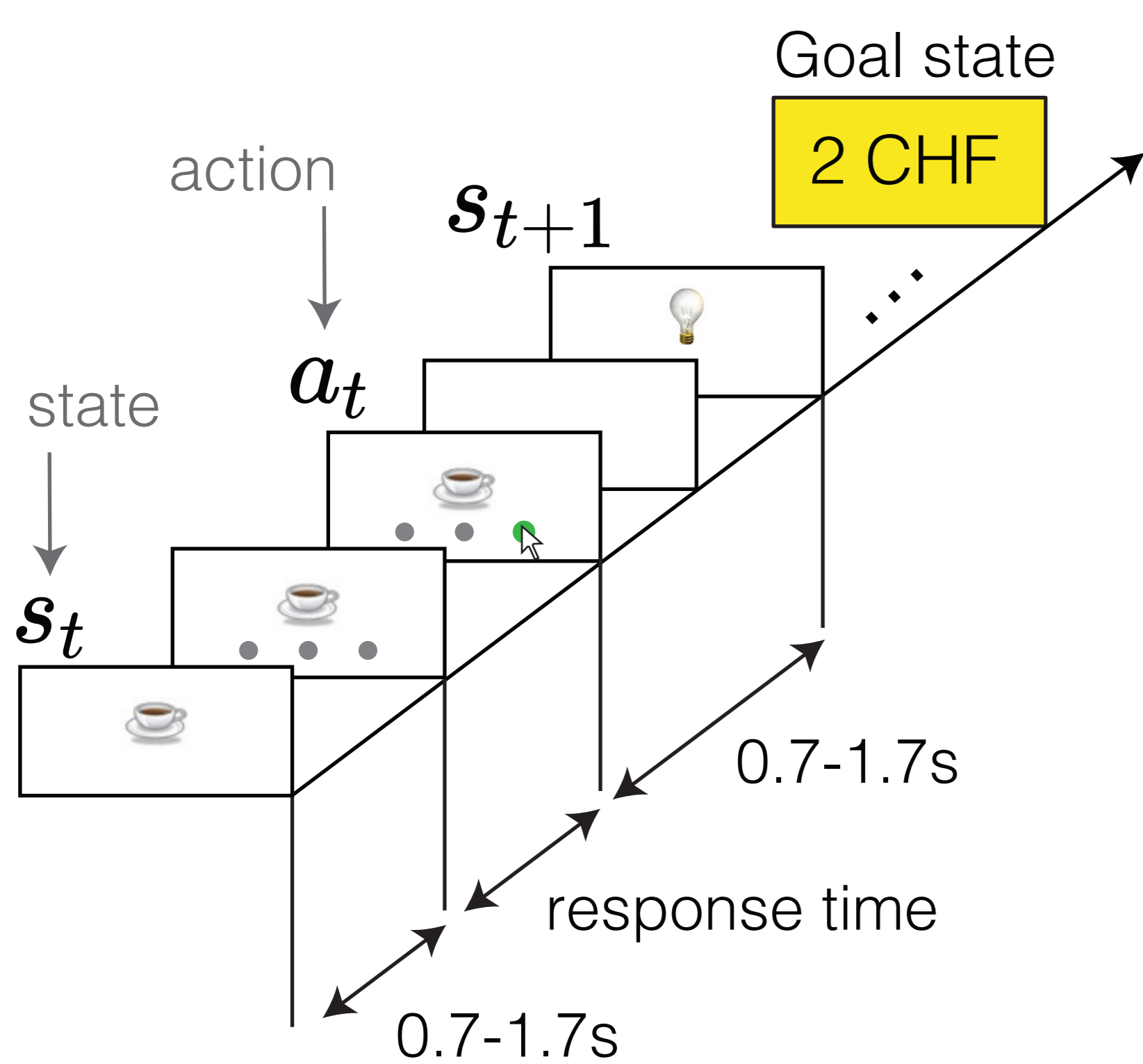
[8] Itti and Baldi, 2009;

[9] Schmidhuber, 2010;

[10] Horvath et al., 2021

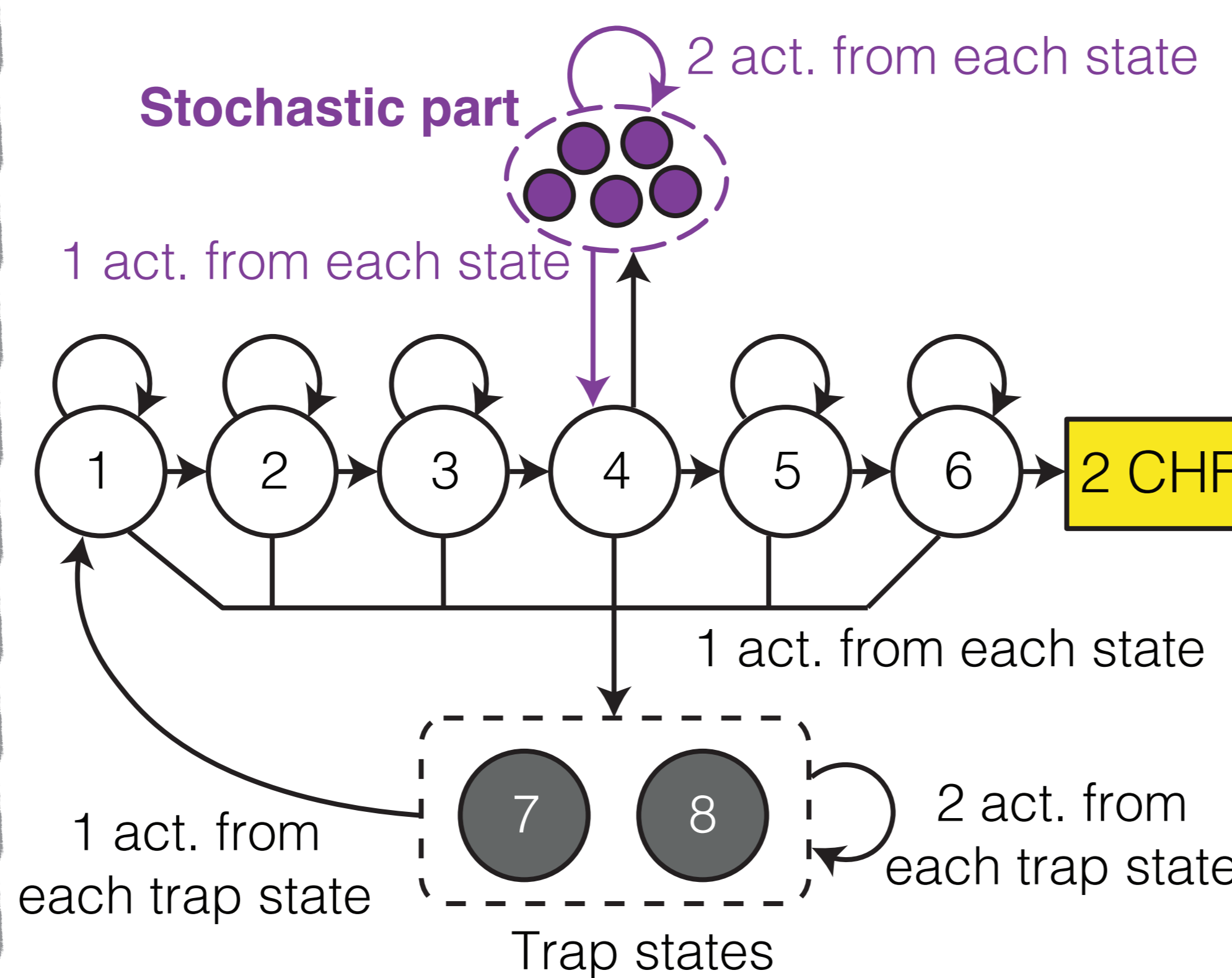
## 2. Experimental paradigm:

Multistep decision-making:

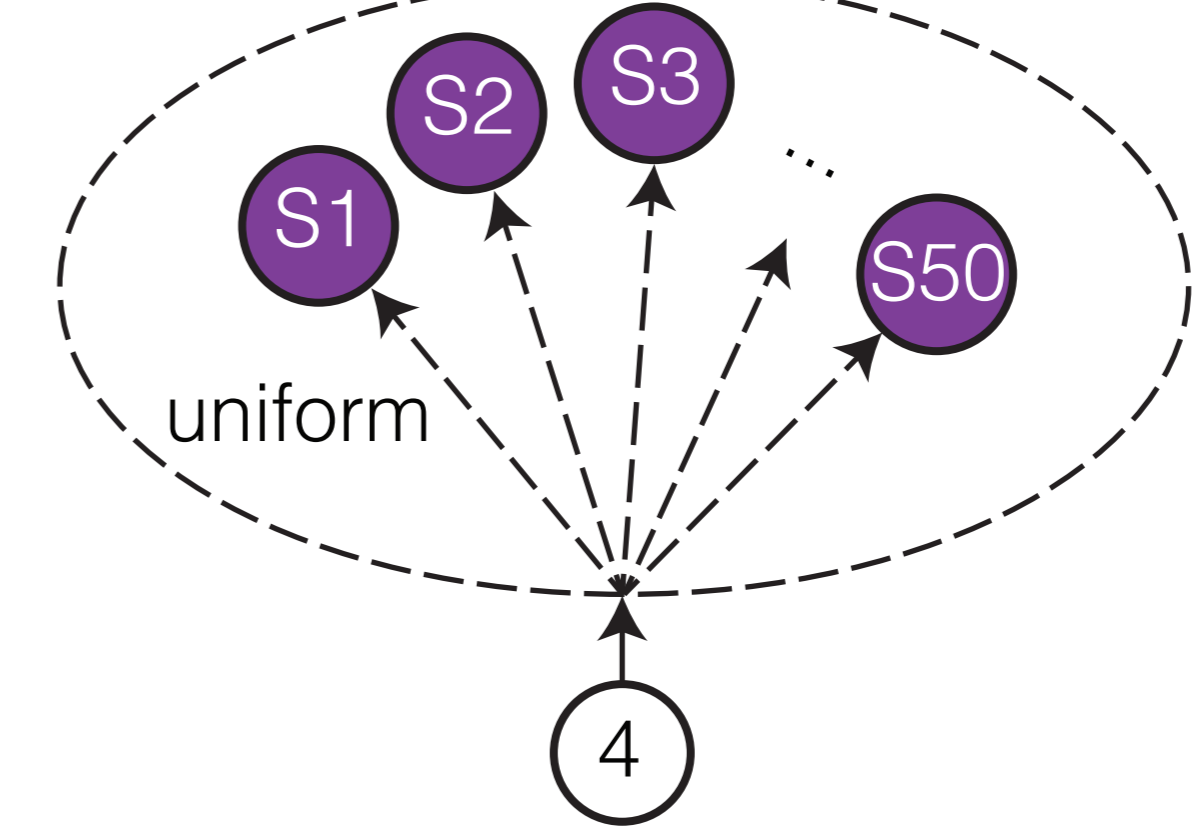


### 2.1. Underlying map (unknown to the participants)

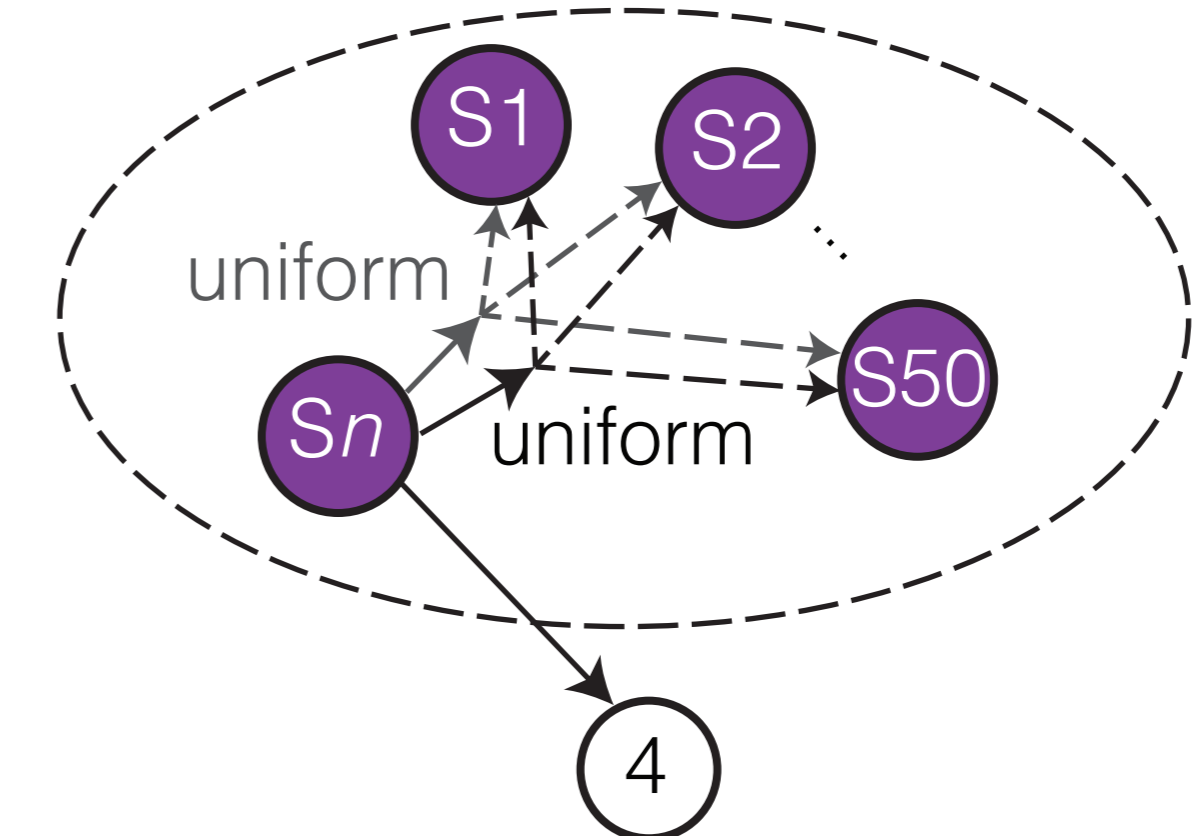
58 states + 3 actions per state:



### 2.1.1. Transitions to stoch. states

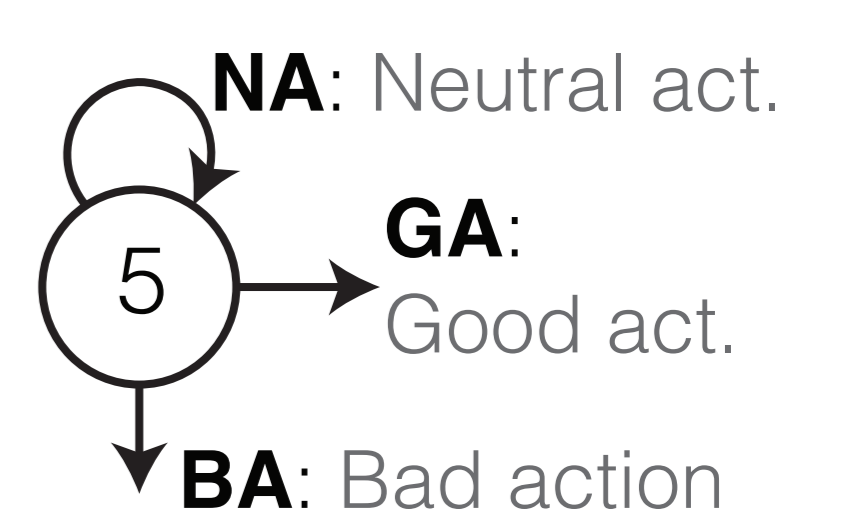


### 2.1.2. Transitions from stoch. states

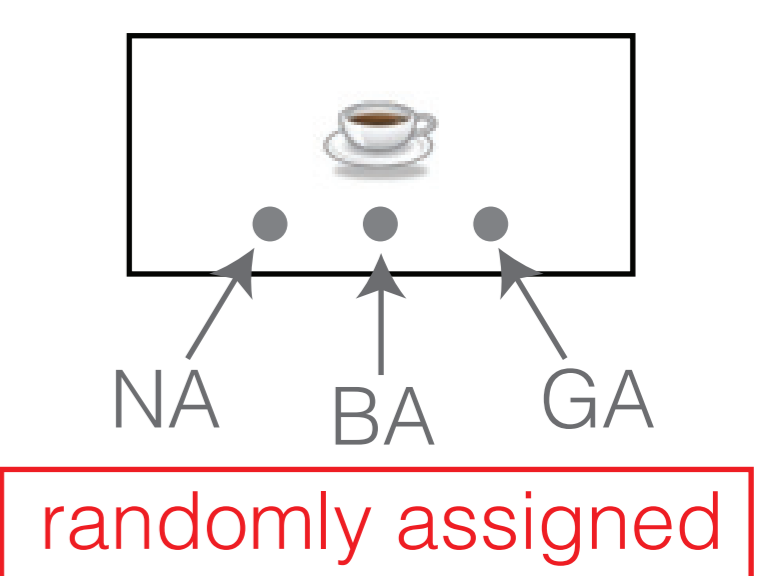


### 2.1.3. State representation

An exemplar state:



Representation in the experiment:



### 2.2. Instruction given to participants:

- Participants were instructed to move to **any** of the three goal states **5 times** (= 5 episodes).



CHF: Swiss Franc

### 2.3. Reward manipulation:

- We focus on the group of participants with **lowest** reward: (see our **preprint** for the other groups)



Highly motivated to explore in episodes 2-5 to find the larger rewards!

CHF: Swiss Franc

## 3. Results

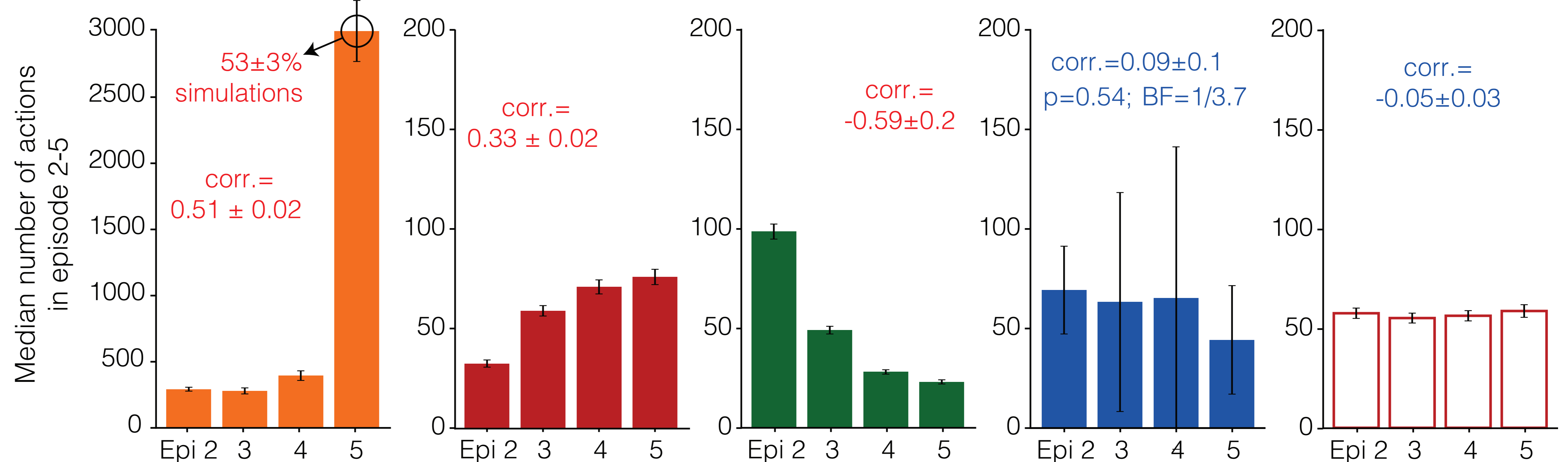
### 3.1. Humans and novelty-seeking agents exhibit a persistent attraction to stochasticity during episodes 2-5.

Predictions before data:

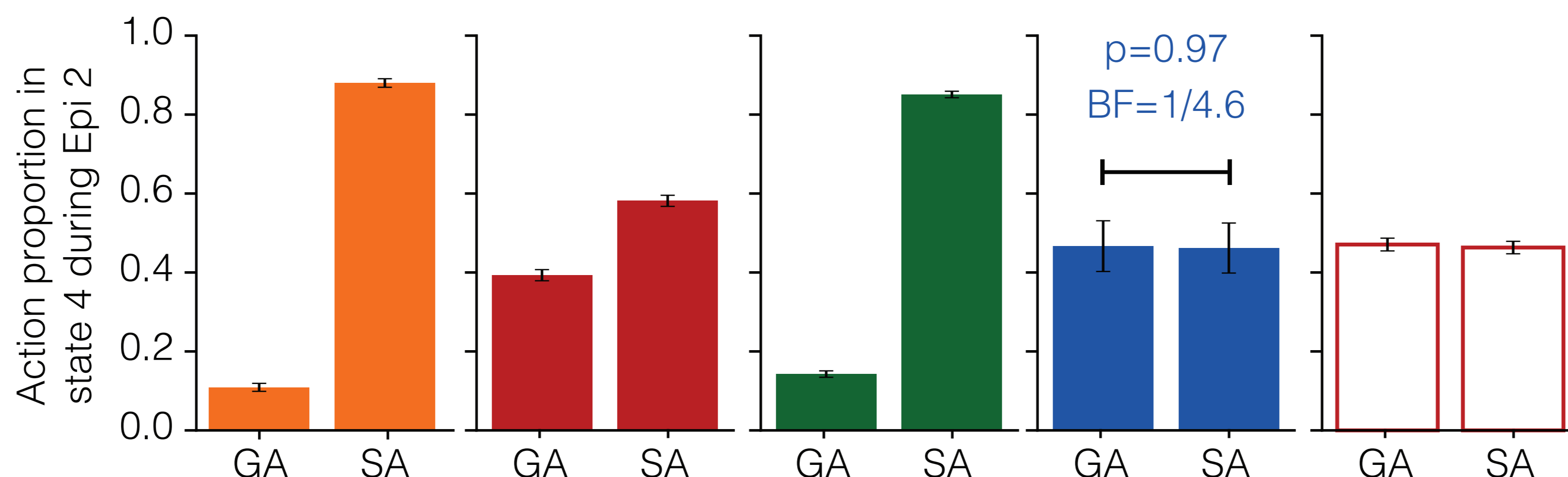
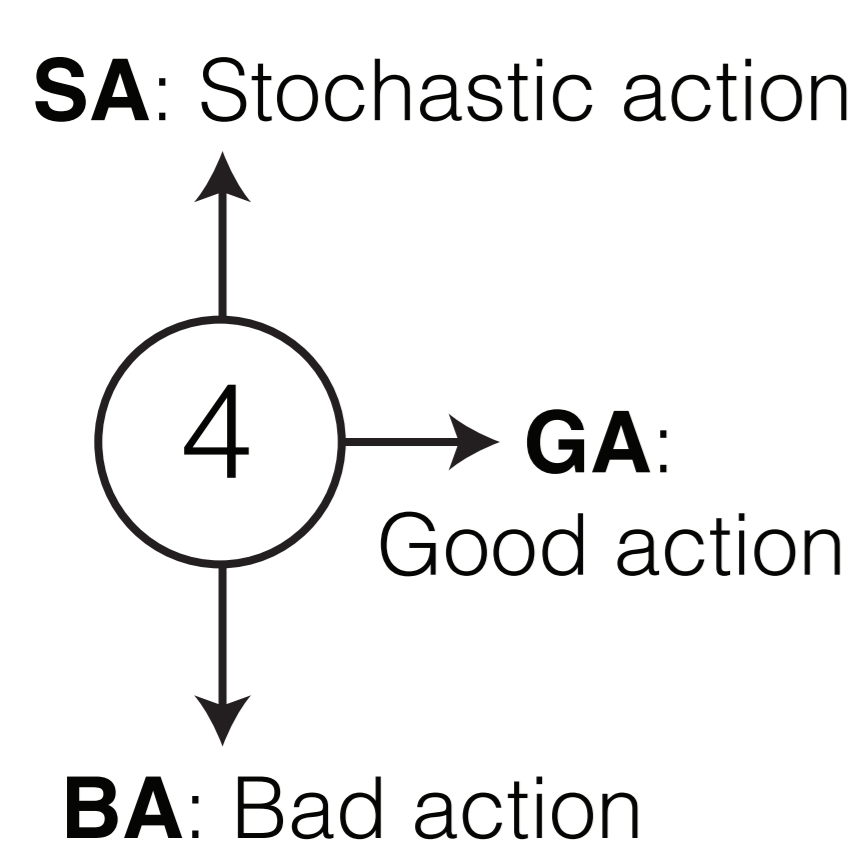
- purely surprise-seeking (N=500)
- purely novelty-seeking (N=500)
- purely inf.-gain-seeking (N=500)

Analyses with data:

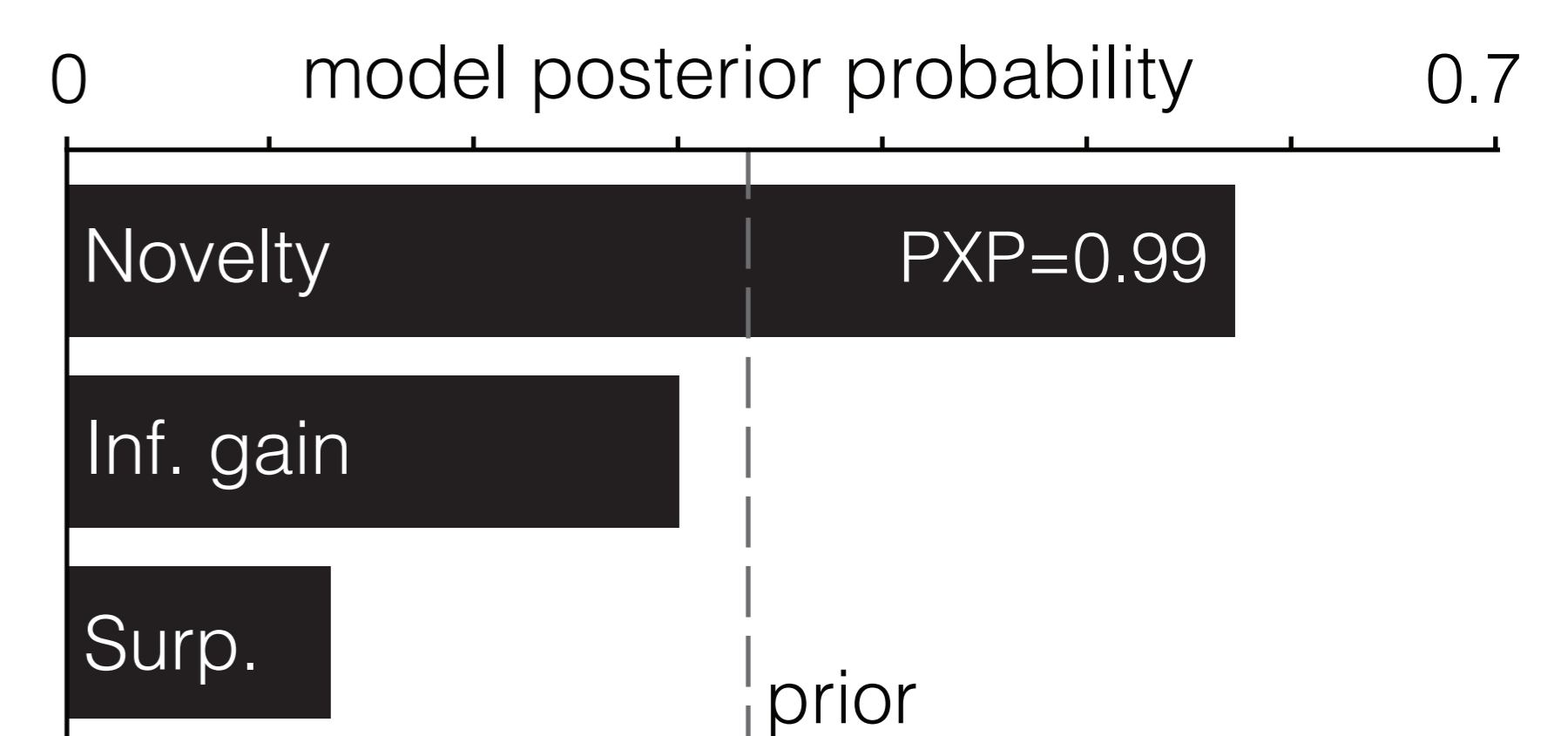
- human behavior (N=21)
- fitted novelty-seeking (N=500) (posterior pred. checks)



### 3.2. Humans and novelty-seeking agents show a similar preference for GA and SA during Epi 2



### 3.3. Bayesian model-selection:



## 4. Conclusions

- Human participants who are **optimistic** about the availability of goal states of higher value than those already known exhibit **a persistent attraction** to stochasticity.
- This behavior is **consistent with** that of **novelty-driven** agents but **NOT** with those driven by **information-gain** (≈ optimal behavior) or **surprise**.
- Our work suggests that humans use **suboptimal** but **computationally cheap** policies (such as novelty-seeking) for exploration in **complex environments**.