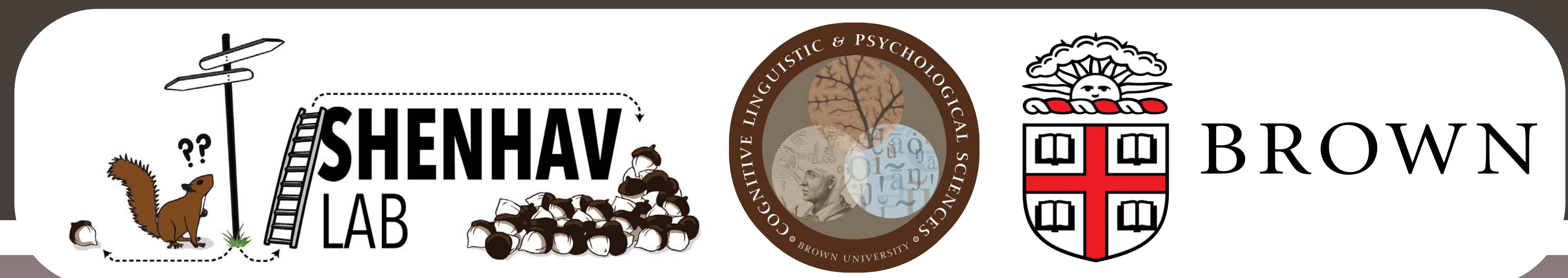


# Learning of Probabilistic Motivational Incentives and Their Effect on Effort Allocation

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## Introduction & Aims

Prior research has shown that individuals adjust cognitive control allocation based on given levels of positive (reward)<sup>1</sup> and negative (penalty)<sup>2</sup> incentives. However, few studies have looked into how these incentive levels are learned over time and if their influence changes over the course of the learning process.

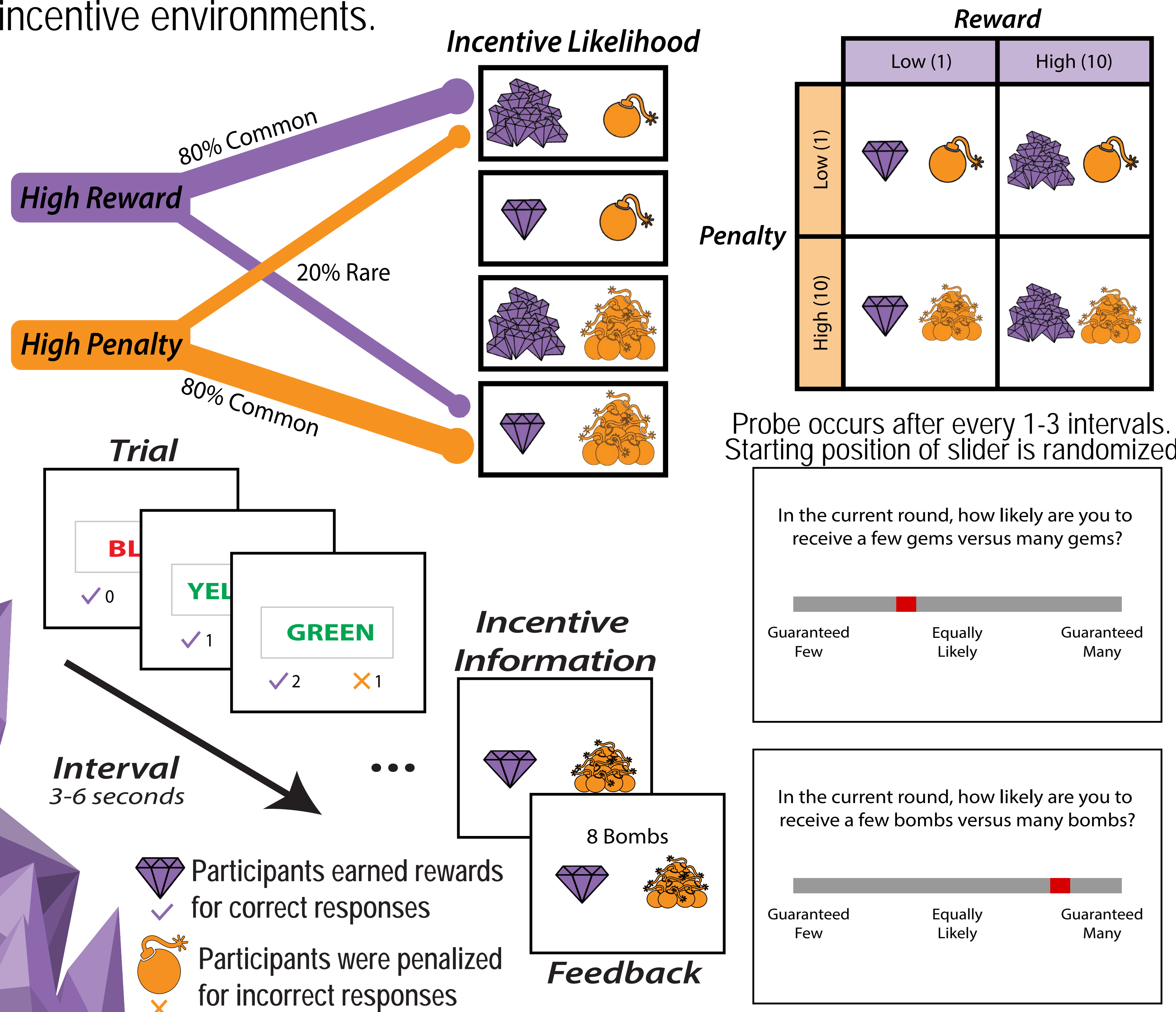
We conducted an online study to examine 1) how individuals learn and integrate incentive information over time and 2) how this learned incentive information influences cognitive control allocation in a self-paced incentivized Stroop Task.

## Methods

Participants (N = 38, 15 Female, Ages 20-40) were recruited via Prolific to perform on online incentivized cognitive control task.

They were given small or large rewards (gems) for correct responses and penalized with small or large losses (bombs) for incorrect responses.

Participants performed 4 blocks of this task. Each block had 48 intervals. There were two possible magnitudes of incentive: high (+/- 10) and low (+/- 1). For each block, both reward and penalty possessed a common magnitude (80%) and a rare magnitude (20%), resulting in a four different incentive environments.



## Predictions

1. We predicted that participants would report increasingly accurate predictions of incentive likelihood over the course of a given block.

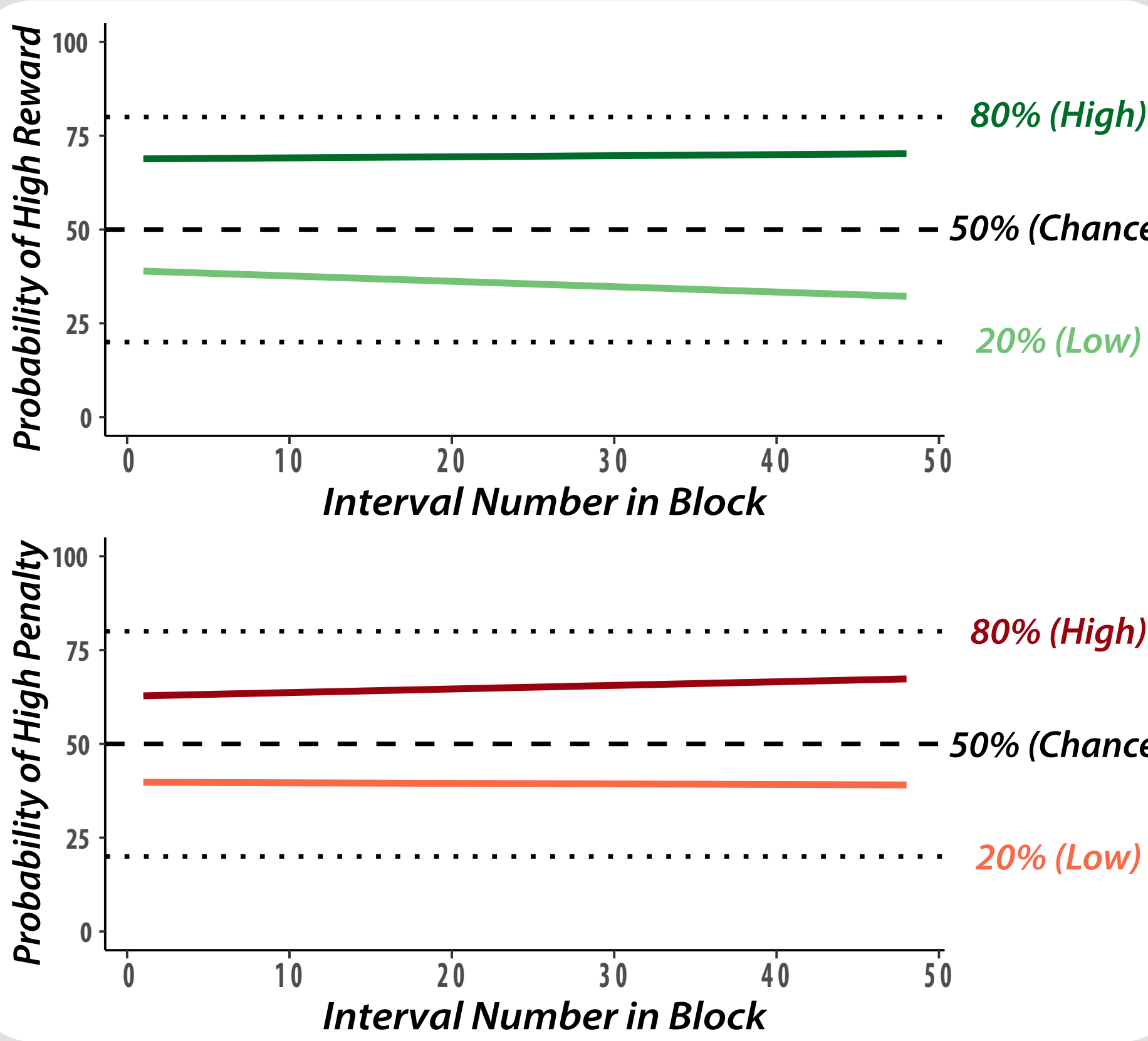
2. We predicted that people would adjust their effort to reflect their updated expectations about reward and penalty.

Based on previous studies<sup>3</sup>, we expect effort adjustments to show higher accuracy with low rewards and high penalties and faster response times with high rewards and low penalties.

## Results

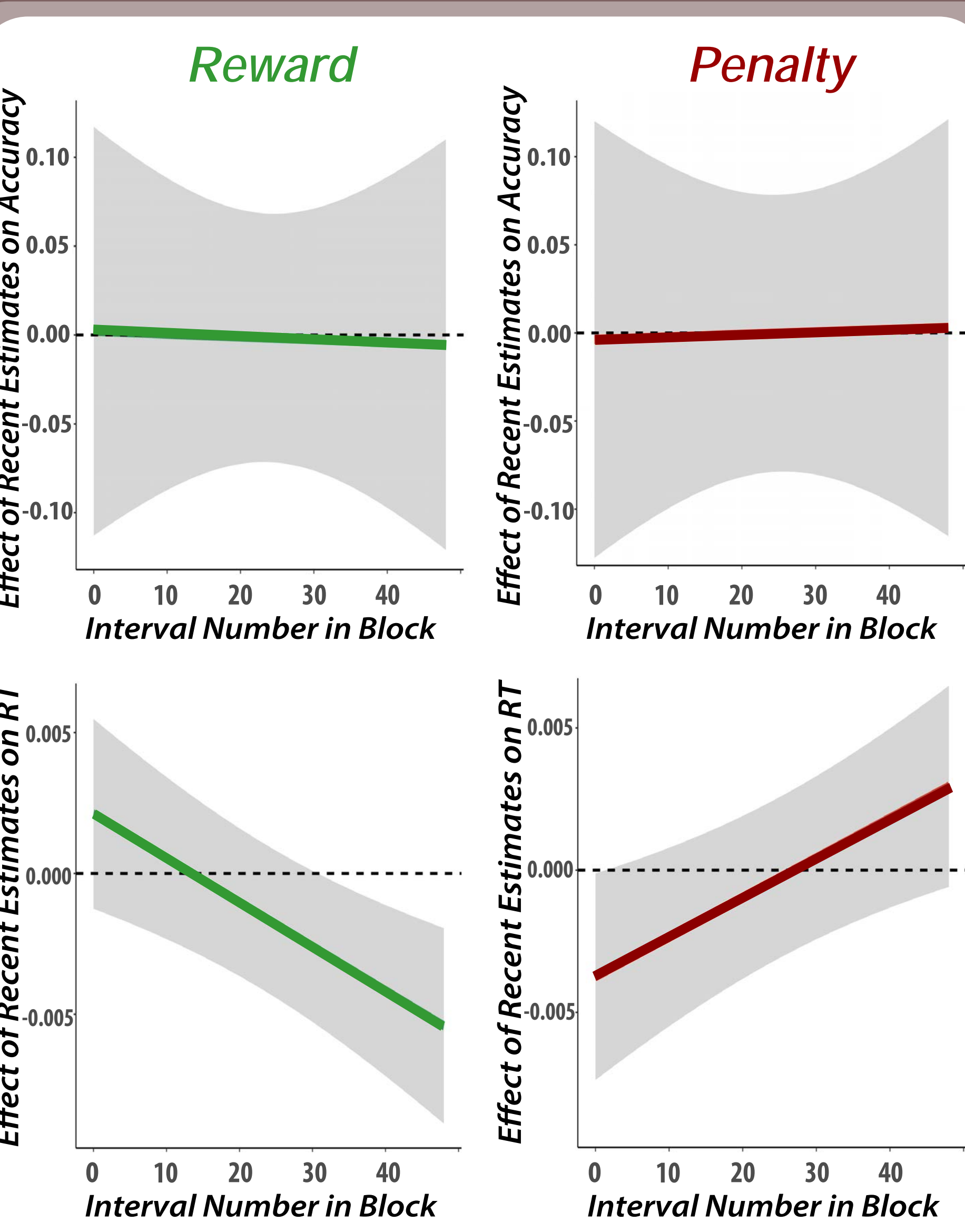
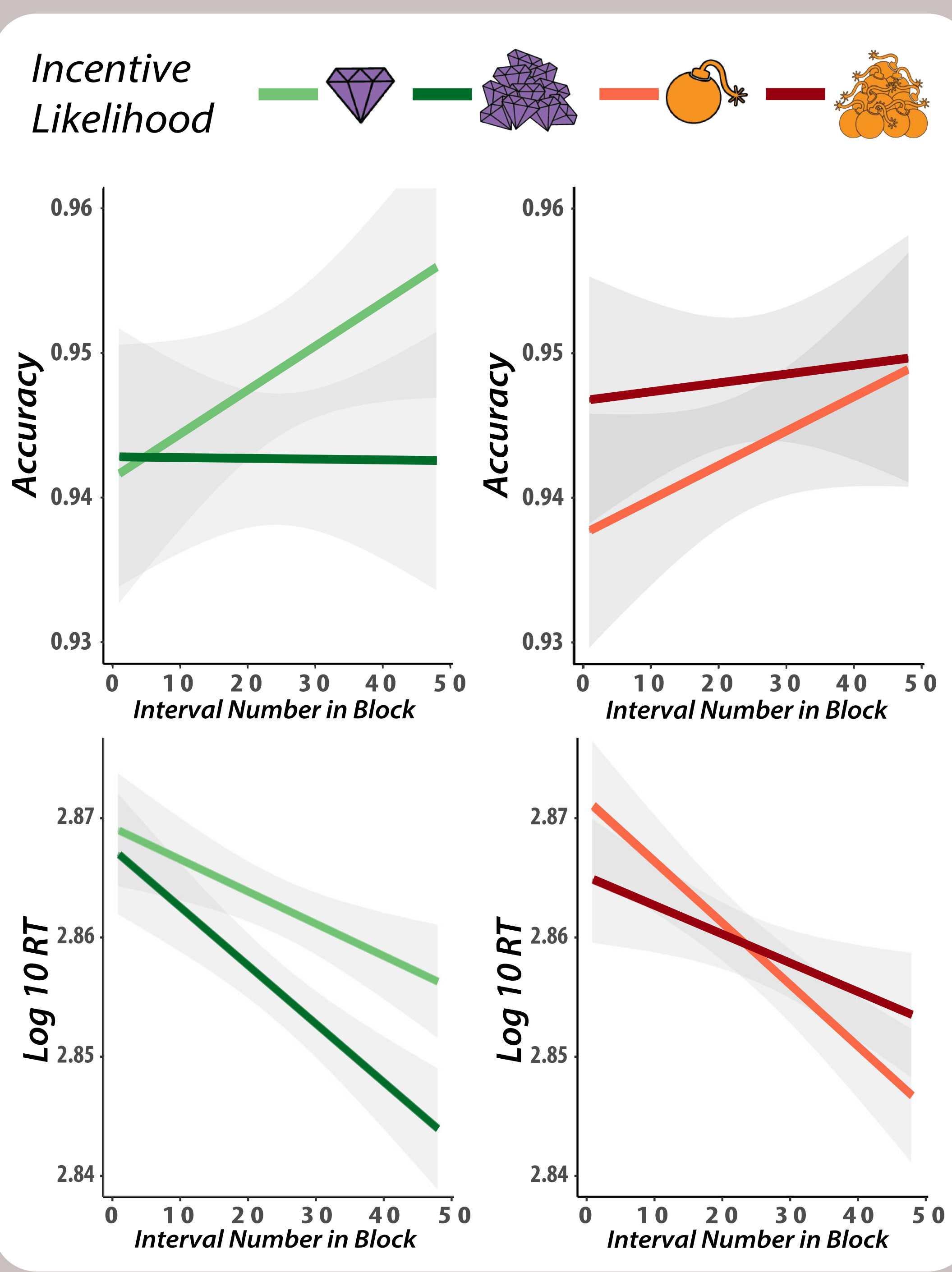
### Participants differentiated between incentive likelihoods, but likelihood was continually underestimated

- People rated high rewards more likely in high reward likelihood conditions ( $p < .001$ ) and high penalties more likely in high penalty likelihood conditions ( $p < .001$ )
- Participants slightly improved estimates over the course of the block but continued to underestimate the incentive likelihood (Rew x IntervalNum:  $p = .078$ ; Pen x IntervalNum:  $p = .090$ )



### The influence of incentives on performance increased over course of the block

- Low reward likelihood led to increased accuracy ( $p = .06$ ), with the influence of reward level increasing over time ( $p = .088$ )
- High penalty likelihood conditions showed slightly increased accuracy ( $p = .109$ ), though differences based on penalty level seemed to decrease over the course of the block ( $p = .985$ )
- Response time in high reward likelihood conditions was increasingly faster than response time in low reward likelihood conditions ( $p = 0.055$ )
- The rate at which participants got faster over the block was greater in low penalty likelihood conditions relative to high penalty likelihood conditions ( $p = 0.038$ )



### Participant performance is predicted by the average value of the last 5 probe estimates

- Higher recent estimates of reward and penalty likelihood did not significantly predict accuracy over the block (Rew x IntervalNum:  $p = .801$ ; Pen x IntervalNum:  $p = .703$ )
- Higher recent estimates of reward likelihood led to response time decreasing faster over the block ( $p = .001$ )
- Higher recent estimates of penalty likelihood led to response time decreasing more slowly over the block ( $p = .003$ )

## Discussion & Conclusions

We found that participants were able to differentiate between incentive likelihoods. However, contrary to our prediction, the accuracy of their predictions did not increase drastically over the block and likelihood was consistently underestimated.

Despite this, the influence of incentives increased over the course of the block as shown in both task performance and the effect size of recent estimates.

As predicted, participants were increasingly accurate in low reward likelihood conditions and increasingly fast at responding in high reward likelihood conditions.

Also as expected, high penalty likelihood conditions led to slower responses over the block. Penalty effects on accuracy were less clear, but overall participants were slightly more accurate in high penalty likelihood conditions.

Altogether, we see that task performance is predicted by subjective estimates of both reward and penalty likelihood, which differ from the actual values of the experimentally manipulated incentive likelihoods.

## References

1. Krebs, R. M., Boehler, C. N., & Woldorff, M. G. (2010). The influence of reward associations on conflict processing in the Stroop task. *Cognition*, 117(3), 341-347.
2. Yee, D. M., Leng, X., Shenhav, A., & Braver, T. S. (2022). Aversive motivation and cognitive control. *Neuroscience & Biobehavioral Reviews*, 133, 104493.
3. Leng, X., Yee, D., Ritz, H., & Shenhav, A. (2021). Dissociable influences of reward and punishment on adaptive cognitive control. *PLoS computational biology*, 17(12), e1009737.

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