Correct! /

Incorrect!

#

+10/+1

750 ms

First calibration block

Second calibration block

Second calibration block

and pre-learning block

in Experiments 2 & 3

and pre-learning block

in Experiment 1

Learning blocks

## Jonas Simoens, Tom Verguts & Senne Braem

# SELECTIVELY REINFORCING THE SPEED-ACCURACY TRADE-OFF IN DECISION MAKING

## Introduction

- Recent theories suggest that cognitive control functions are subject to the same reinforcement learning principles as 'lower-level' behaviours (Abrahamse et al., 2016).
- In three experiments, we tested this notion on a well-studied cognitive control function: the regulation of one's speed-accuracy trade-off (SAT; i.e., caution) in decision making.
- Previous studies have demonstrated that the SAT can be modulated indirectly by differentially rewarding fast and slow correct and error responses (Heitz, 2014).
- However, we aimed to modulate the SAT more directly by quantifying the SAT by the drift diffusion model parameter 'boundary separation' and estimating and selectively reinforcing
  the boundary separation on a trial-by-trial basis.

## Methods

Random dot motion task

**Behavioural Results** 

- Experiment 1: 27 participants (± 14 in each group)
- Experiment 2: 54 participants (± 27 in each group)
  - Experiment 3: 77 participants (± 39 in each group) Total sample size: 158 participants (± 79 in each group)

Experimental procedure (only comparable experimental blocks):

- Calibration phase: task difficulty calibrated on individual level
- 2 x 120 trials (100 trials in Experiment 3)
- Pre-learning phase: pre-learning boundary separation estimations
   1 x 120 trials (100 trials in Experiment 3)
- Learning phase: boundary separations estimated twice after each response, using the (fast) EZ diffusion model (Wagenmakers et al., 2007): once based on previous 120 trials (100 trials in Experiment 3) and once based on previous 120 trials (100 trials in Experiment 3) + current trial

≤ 5000 ms

- Increase group: high reward each time boundary separations evolved towards value 25% higher than pre-learning value
  - Decrease group: high reward each time boundary separations decreased towards value 25% lower than pre-learning value
  - 4 x 120 trials (100 trials in experiment 3)

Data Analysis: boundary separations, as well as nondecision times and drift rates, re-estimated using the (robust) hierarchical drift diffusion model (HDDM; Wiecki et al, 2013)

500-1000 ms

#### Group x block interaction effect: F(1, 160) = 24.1, p < 0.0010.78 0.76 @ 0.74 uracies (in 0.72 0.70 ACC 0.68 0.66 Increase group - Decrease group 0.64 third learning block fourth learning block pre-learning block first learning block second learning block



## **Drift Diffusion Model Decomposition**







## Discussion

- The selective reinforcement procedure indeed modulated behaviour, however, not entirely as expected.
- Accuracies and drift rates were affected more than response times and boundary separation
- This could be due to the reinforcement procedure not being consciously experienced.
- Post-experiment questionnaires indeed indicate participants were unaware of the reinforcement procedure
- Future research should investigate whether boundary separations can be more selectively modulated by consciously experienced reinforcement procedures.

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