Task complexity and experience dictate the use of online, versus offline, planning in humans

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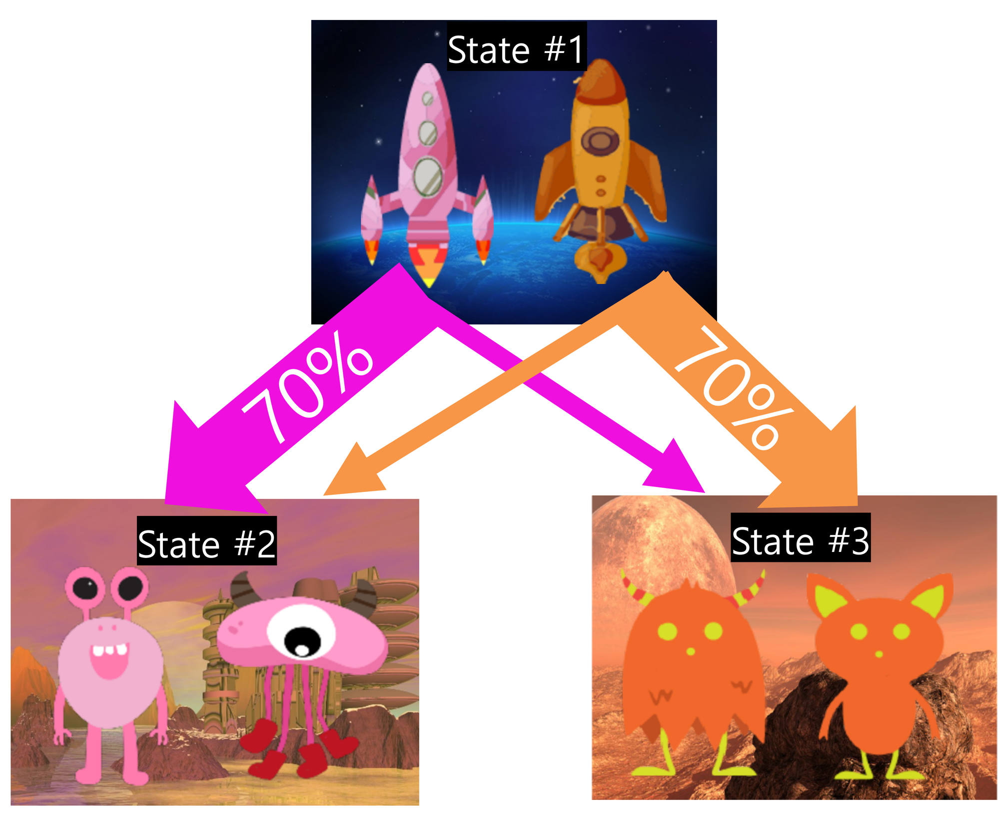
INTRODUCTION

- How much do our decisions depend on **deliberation in the moment**, as opposed to **reasoning performed ahead of time**?
  → **Online** and **offline planning** (Sutton & Barto, 2018)
- Understanding when each kind of planning is used can help predict how decisions may change in response to e.g., time pressures or context effects
- Artificial agents tend to use offline planning, after training on millions of examples (Hamrick et al 2020)
  - But online planning may be more effective when environments are not fully explored, as humans often face
- **Q) Do humans use online, versus offline, planning?**
- Previously, the parameter *w* in two-step tasks (TST) has been used to investigate planning

LIMITATIONS OF TST PARADIGM UPON INVESTIGATING ONLINE PLANNING

1. LACKS TASK COMPLEXITY



- State space complexity (SSC; number of different possible states within a task) is a way to define task complexity (Opheusden et al., 2019)
- In TST, SSC=3 for 100+ trials, and every trial has the same states
- Thus, participants can quickly learn to plan ahead of choices (offline planning), rather than deliberate at each decision time (online planning)

2. *W* CONFLATES ONLINE AND OFFLINE PLANNING

- *w* is a free parameter that captures a subject's tendency to plan:
  $Q = w^{*}Q_{MB} + (1-w)^{*}Q_{MF}$
- However, *w* provides a limited account on planning because it does not differentiate online from offline planning

OUR SOLUTIONS

1. **Increase complexity to increase demands on online planning**
➤ Prediction: Online planning will be more influential when the state spac e is large enough

2. **Measure planning's influence on first-stage response time (OPI: Online Planning Index), as a function of experience**
➤ Prediction: The influence of online planning within planning in general will increase as the agent learns the model

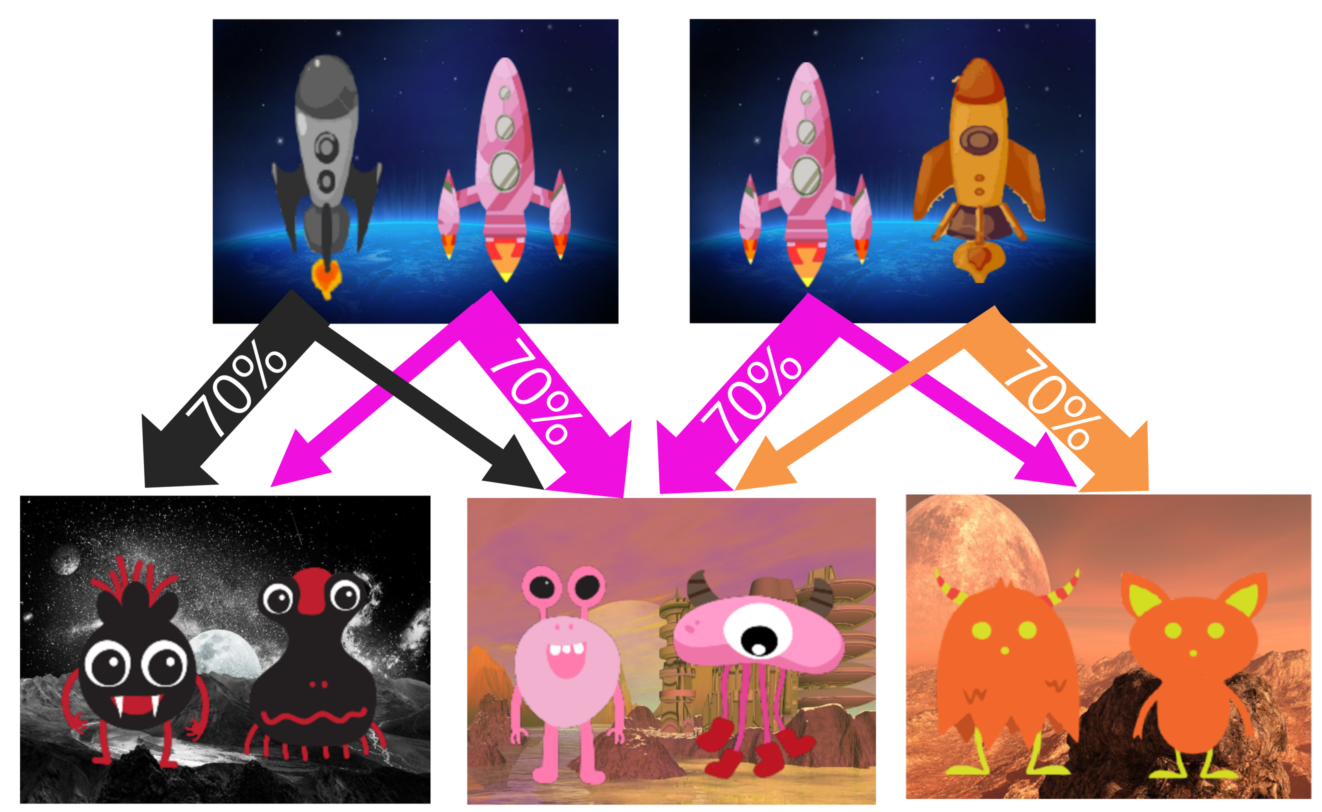
METHODS

1. MULTINOMIAL TST

Trial *n* Trial *n+1*

1[st] stage

2[nd] stage



▪ We varied the possible number of 1[st]-stage options (i.e., spaceships) from **2** (=original TST) to **3, 4,** and **5**
▪ The transition structure varied dynamically according to the combination of the two spaceships presented
▪ Thus, *n* spaceships yield a total of ${}_{n}C_{2}$ (**1[st] stage) + *n* (2[nd] stage)** SSC: **3, 6, 10, and 15 SSC** for 2-, 3-, 4-, and 5-spaceship TST
▪ We conducted the four TST variants on N=110 participants each

2. ONLINE PLANNING INDEX

▪ OPI: an operational measure of decision-time deliberation
- The degree to which model-based values (Q_{MB}) explain response times in first stage choices (RT_1)

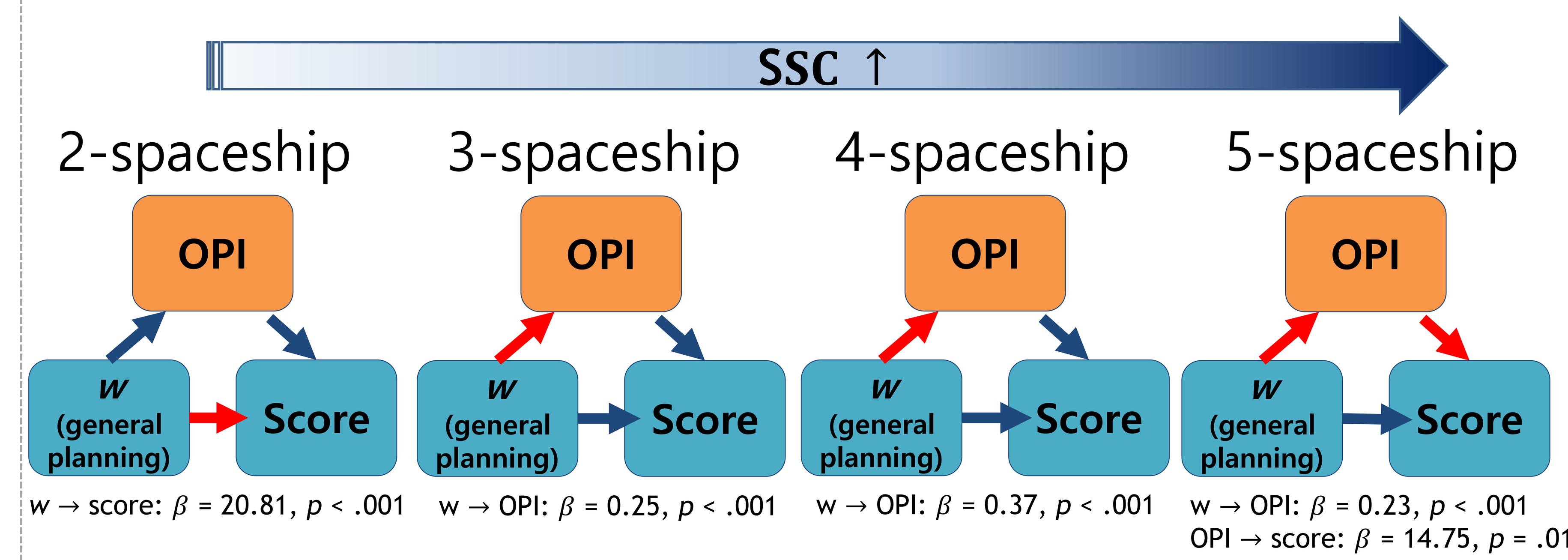
▪ Assumption: options with similar values lead to longer RTs
▪ Formula:

$$RT_1 = \beta_{MB} \times (Q^1_{MB} - Q^2_{MB}) + \beta_{MF\,\times}(Q^1_{MF} - Q^2_{MF})$$

$$OPI = \frac{1-\beta_{MB}}{1-\beta_{MF}}$$

RESULTS

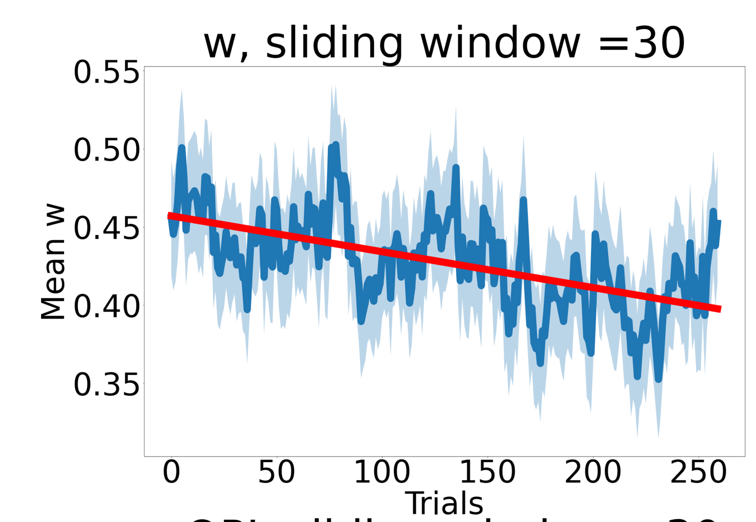
1. Participants were more likely to use online planning as a function of **SSC**

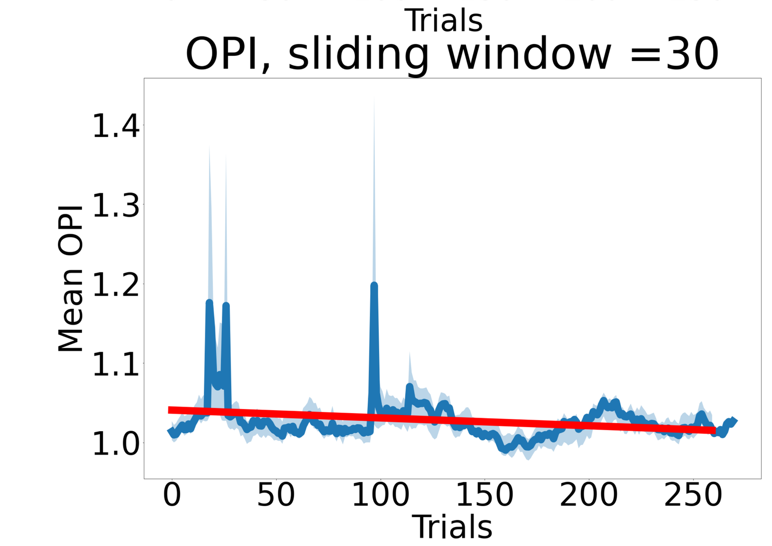


▪ The planning tendency in general (*w*) was directly related to performance in the canonical TST
▪ In more complex variants this relationship grew progressively more mediated by the degree of online planning, to the extent that
▪ **A mediation effect was observed in the 5-spaceship TST**

2. The influence of online planning increases within general planning, as a function of **within-task experience**

Within – task experience ↑





▪ Consistent with uncertainty-weighted arbitration theory, model-based influence on choice decreases with experience

▪ However, consistent with previous observations that w measures model use, but not model learning (Konavalov & Krajbich 2020), OPI remains steady across experience

▪ These results suggest that 1) OPI could be a more stable measure of model use (vs. model learning), and 2) since OPI remains constant while general planning tendency decreases, its influence vs. offline planning increases with experience

CONCLUSIONS

▪ These results suggest that humans learn to use online planning in complex environments.
▪ Our findings have implications for the generalizability of decision-making models to naturalistic settings, and for the correspondence between decision-making in humans and artificial agents.

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