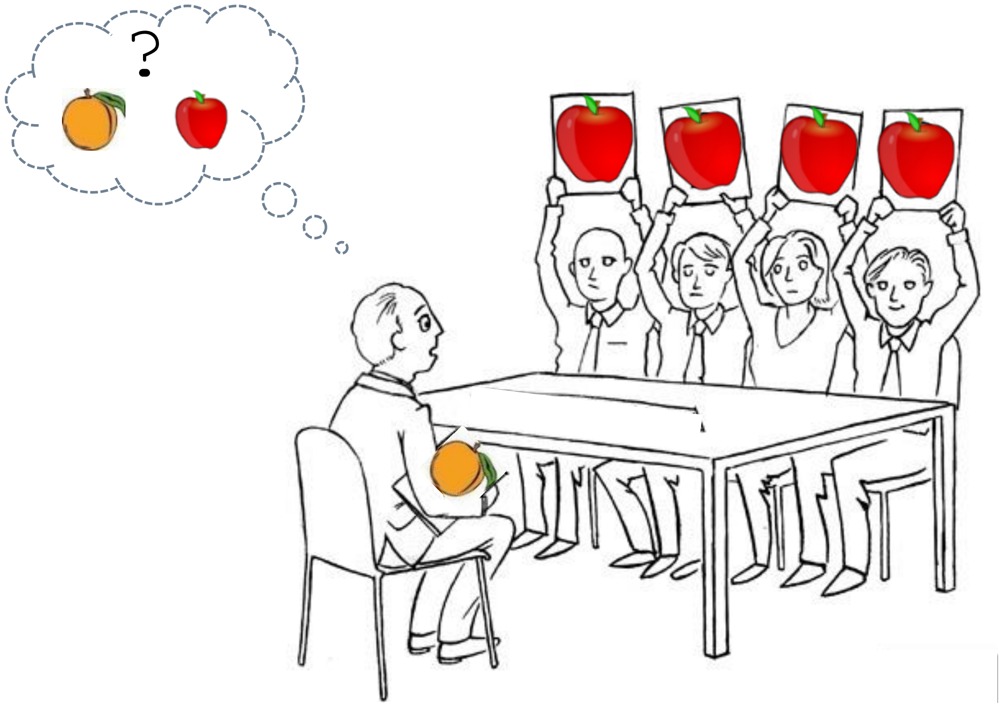

Multiple facets of social influence in goal-directed learning

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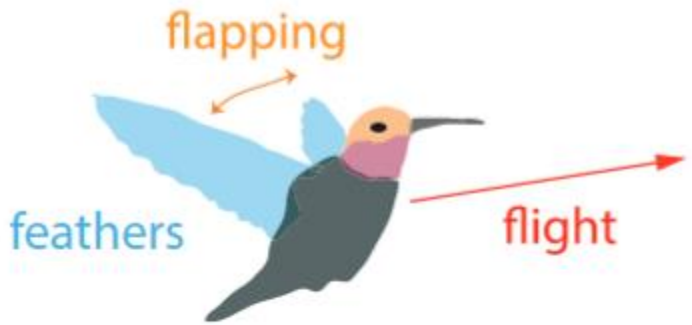
Marr's 3 levels

	LEVELS	
Computation	1	why (problem)
Algorithm	2	what (rules)
Implementation	3	how (physical)



Computational theory	Representation and algorithm	Hardware implementation
What is the goal of the computation, why is it appropriate, and what is the logic of the strategy by which it can be carried out?	How can this computational theory be implemented? In particular, what is the representation for the input and output, and what is the algorithm for the transformation?	How can the representation and algorithm be realized physically?

Figure 1–4. The three levels at which any machine carrying out an information-processing task must be understood.

[…] "trying to understand perception by understanding neurons is like trying to understand a bird's flight by studying only feathers. It just cannot be done"

Marr, 1982

Marr's 3 levels

(A) 

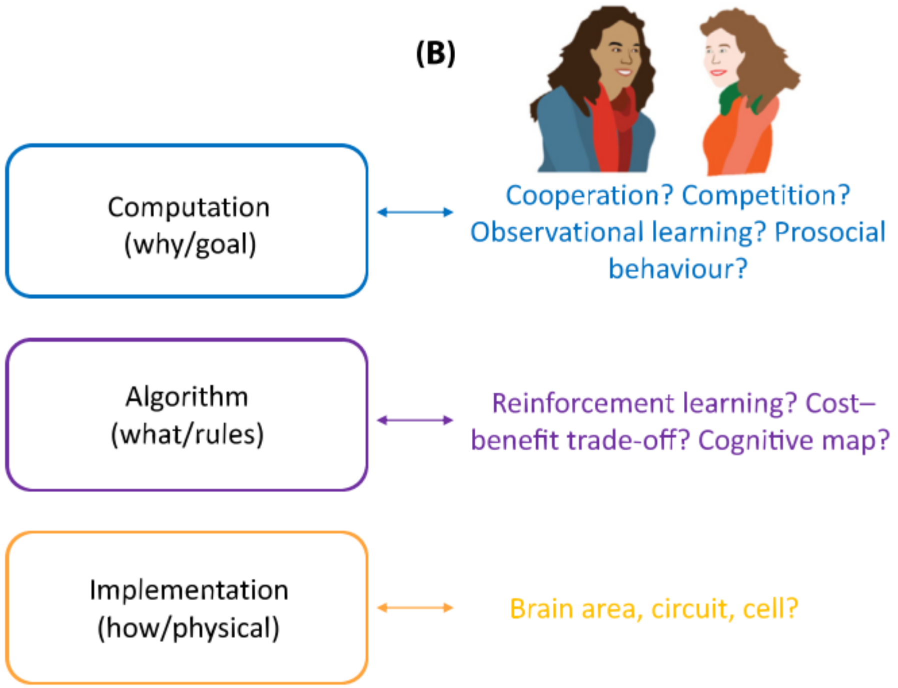
(B) 

Flight ⟷	Computation (why/goal)	⟷ Cooperation? Competition? Observational learning? Prosocial behaviour?
Flapping ⟷	Algorithm (what/rules)	⟷ Reinforcement learning? Cost–benefit trade-off? Cognitive map?
Feathers ⟷	Implementation (how/physical)	⟷ Brain area, circuit, cell?

Lockwood et al., 2020

My own research

(B)



Overarching goal:
uncover the neuro-computational mechanisms underlying social decision-making

→ social specificity?


Hamburg
26
Hamburg


ASTRA
URTYP


PILSENER
RATSHERRN
4,9
PILSENER


PILSENER
RATSHERRN
4,9
PILSENER


PILSENER
RATSHERRN
4,9
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PILSENER
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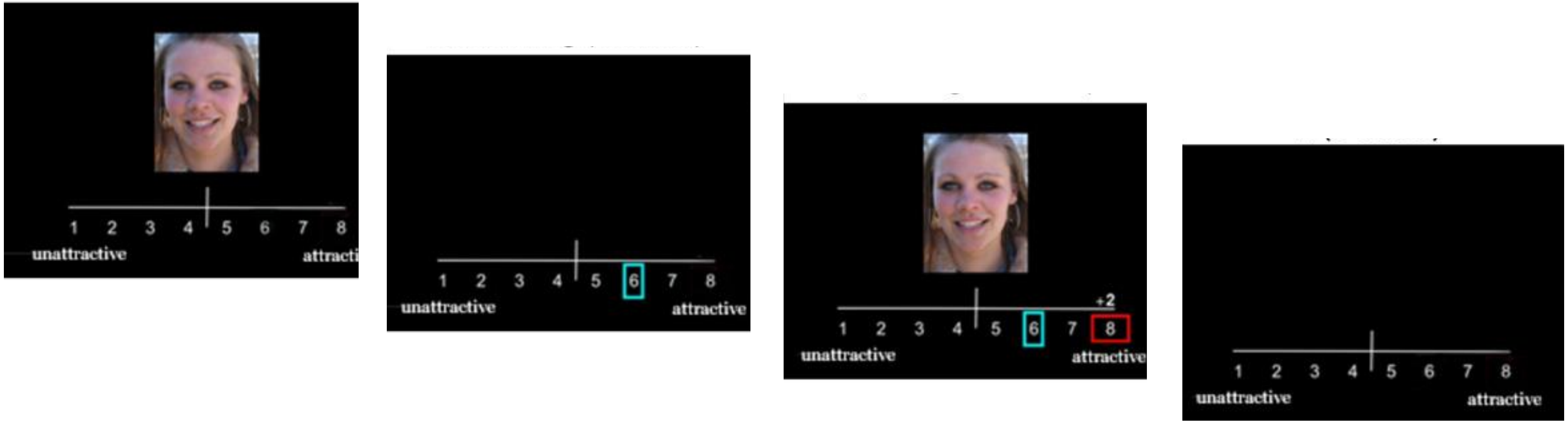
4,9
PILSENER


Hamburg
26
Hamburg


SOCIAL INFLUENCE

Social influence

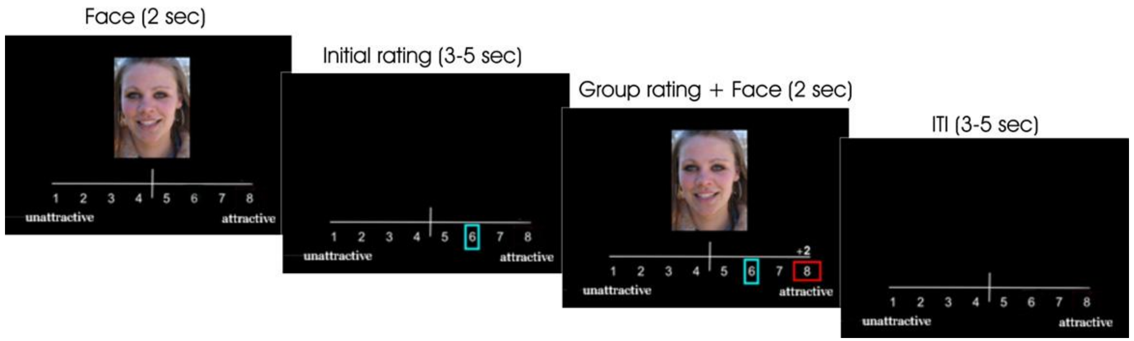


1st choice | social info | 2nd choice

<u>Challenge:</u> **no feedback** is given in subjective decisions, hence direct no measure of internal value representation

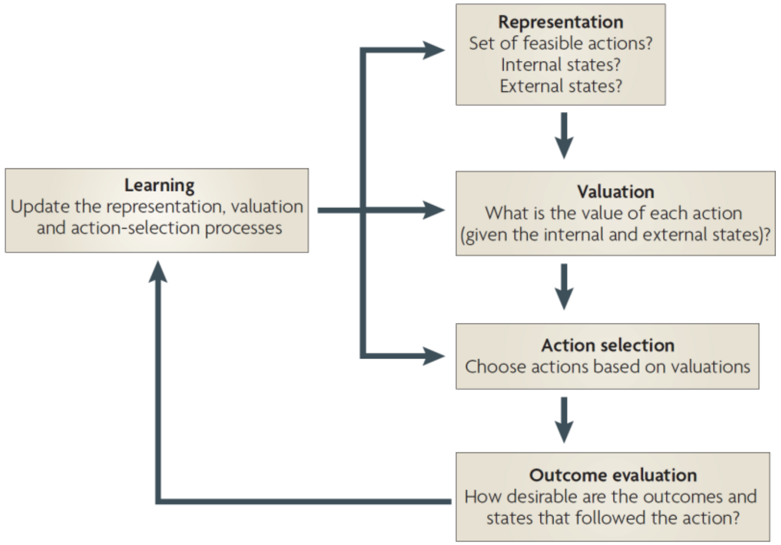
Klucharev et al, 2009

social influence



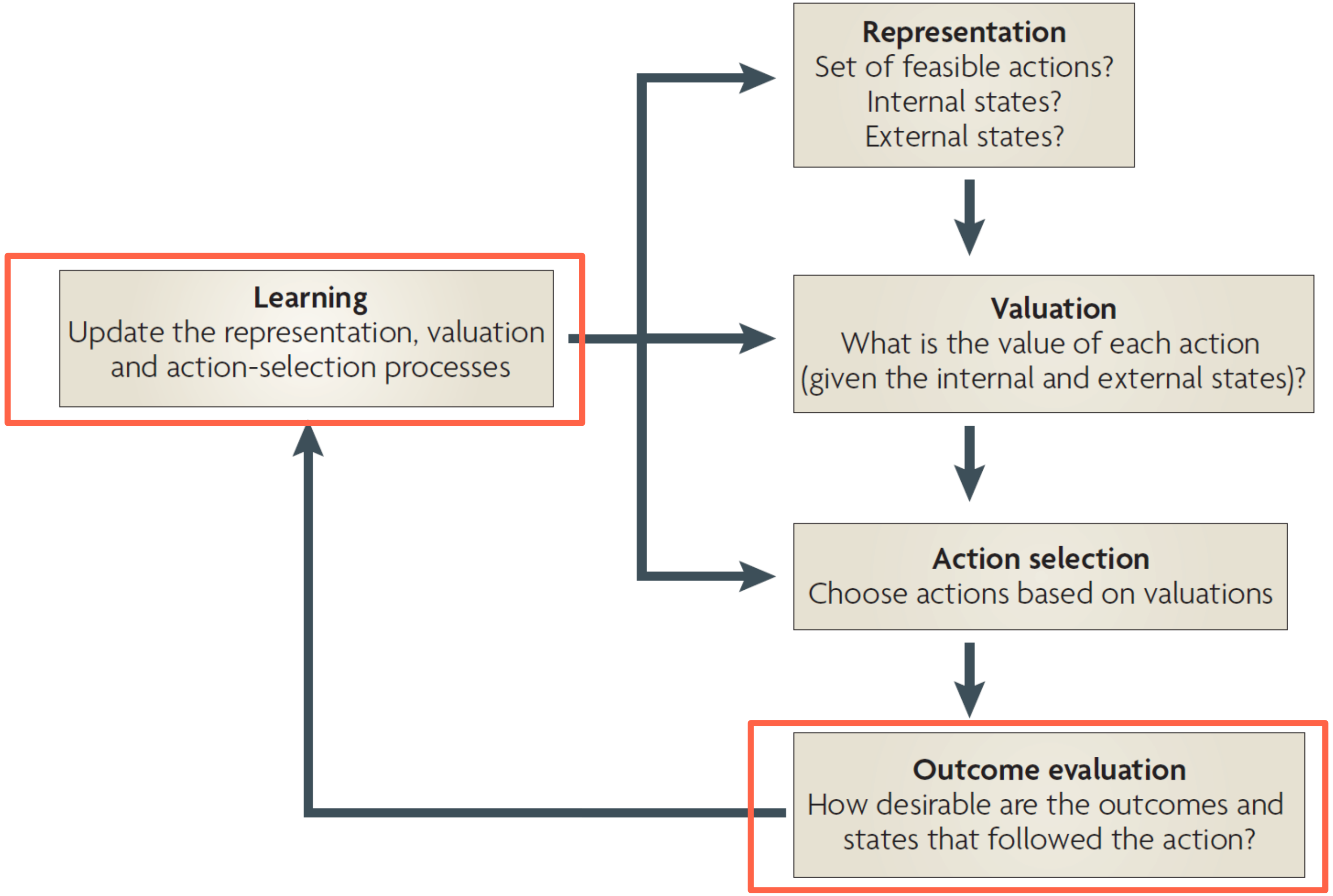
Klucharev et al, 2009

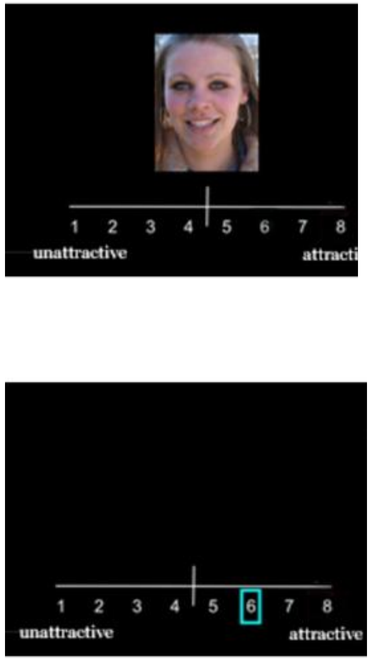
goal-directed learning



Rangel et al, 2008

Goal-directed learning



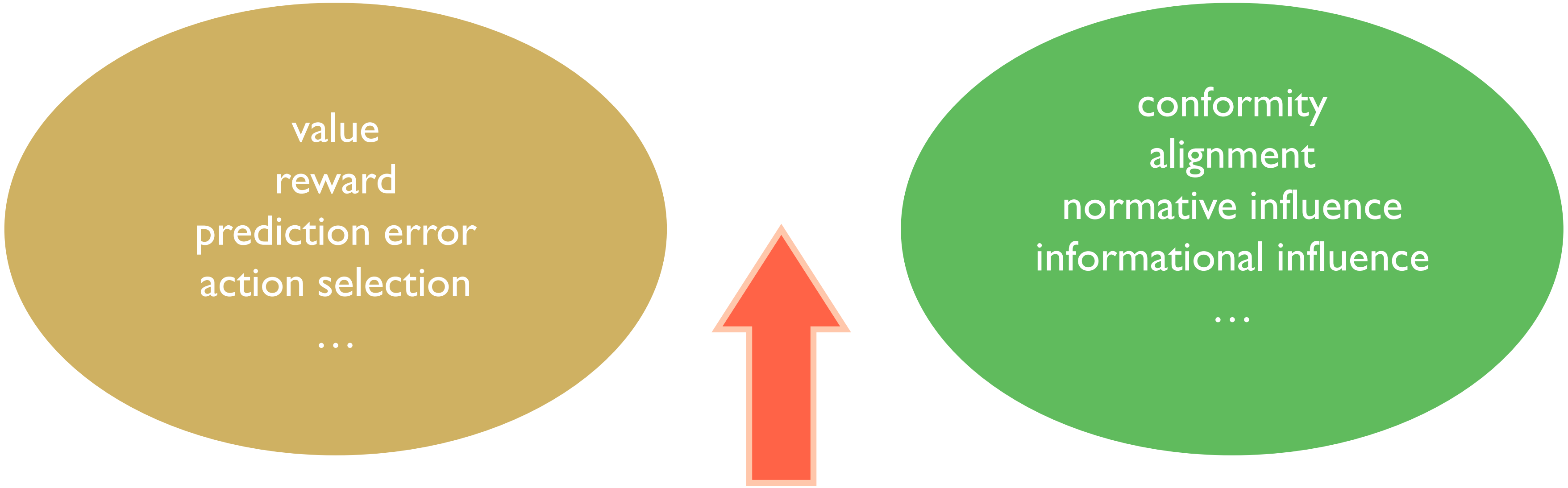


Rangel et al, 2008

The current study

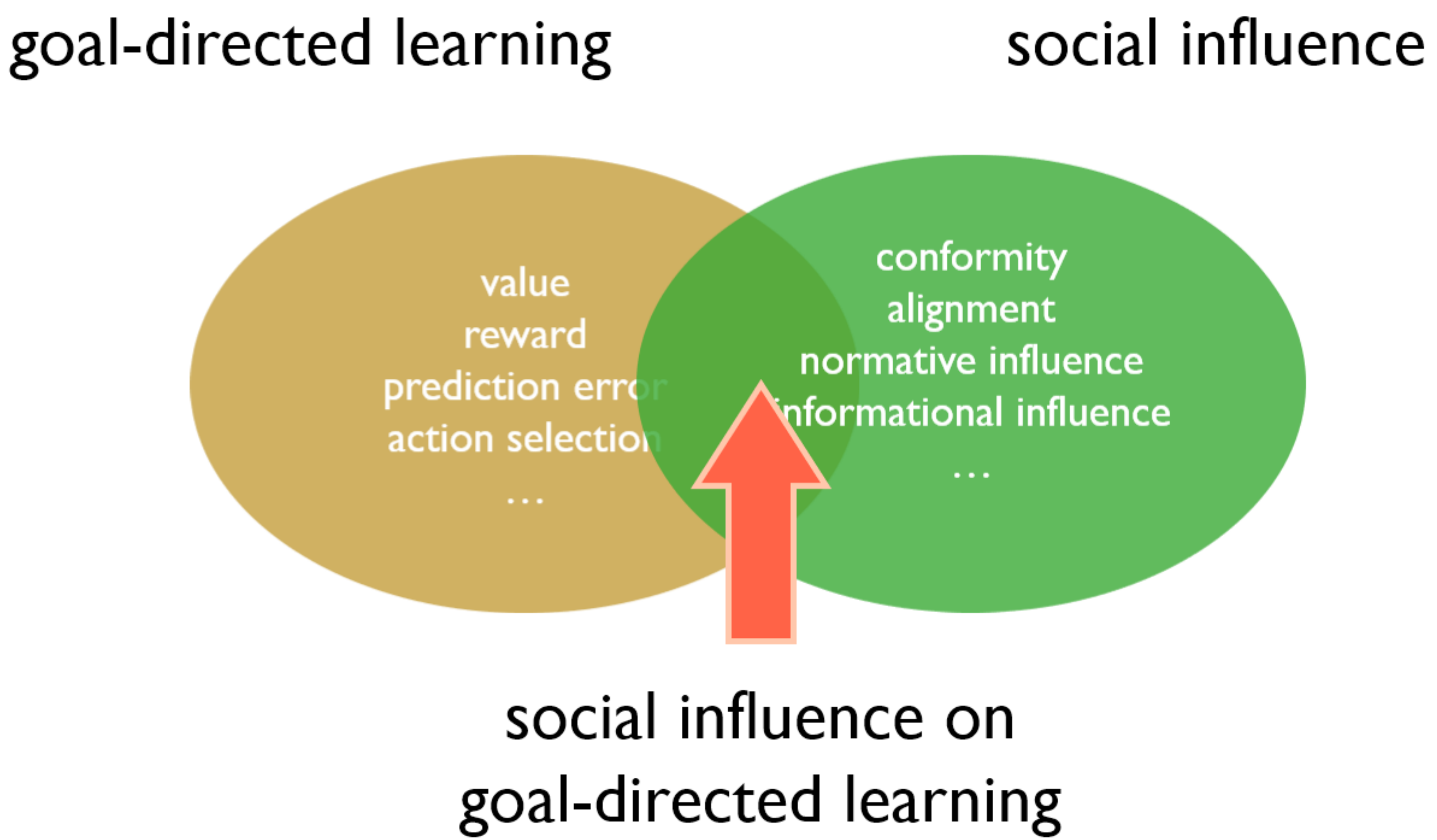
goal-directed learning

social influence



social influence on
goal-directed learning

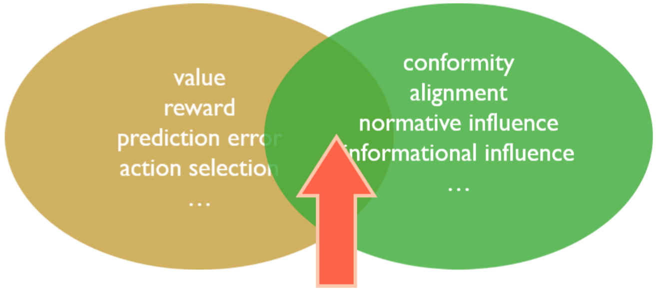
The current study



Where does social influence come from?

goal-directed learning

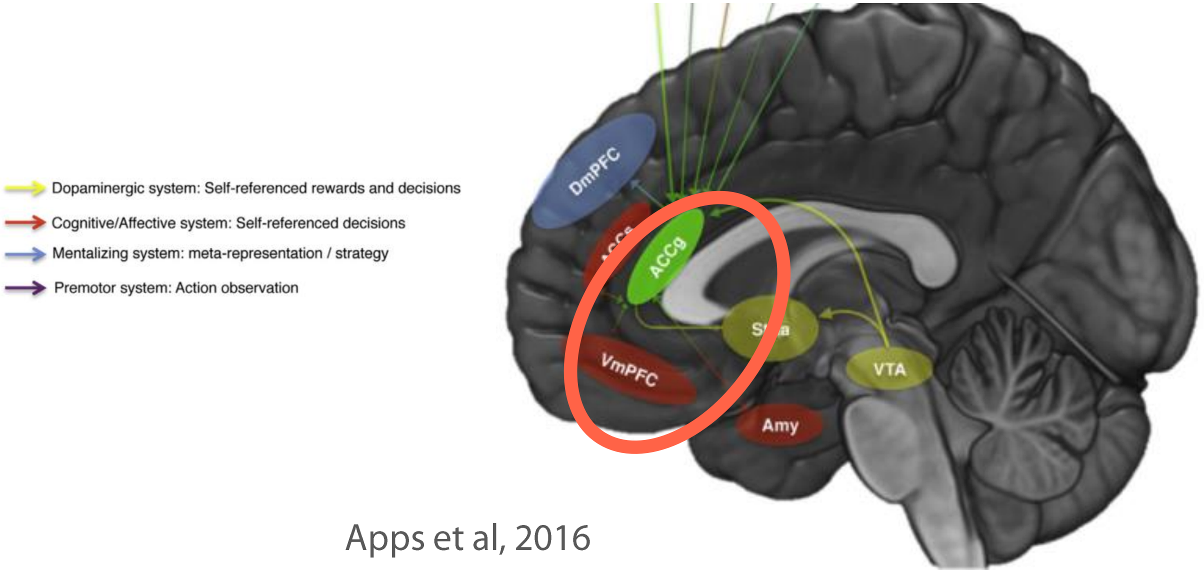
social influence



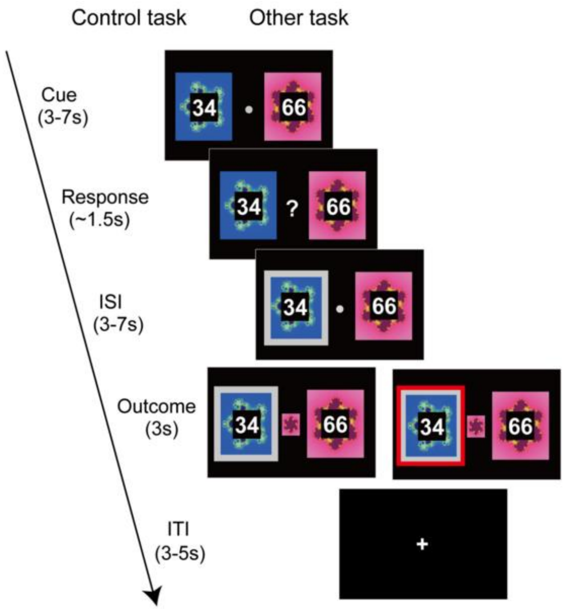
Direct learning

Social learning / observational learning

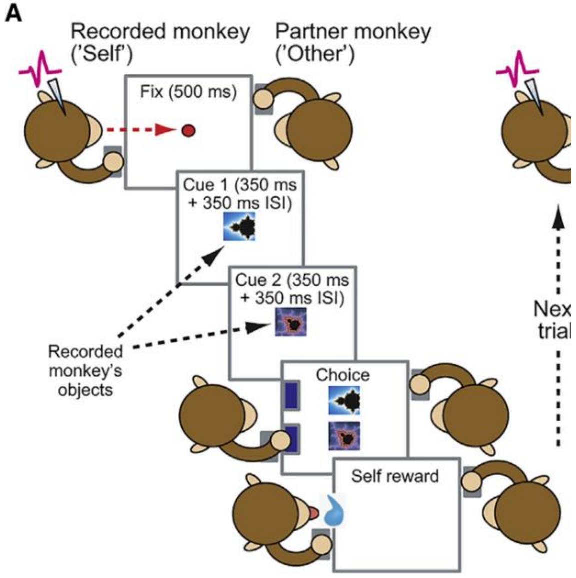
direct vs social learning



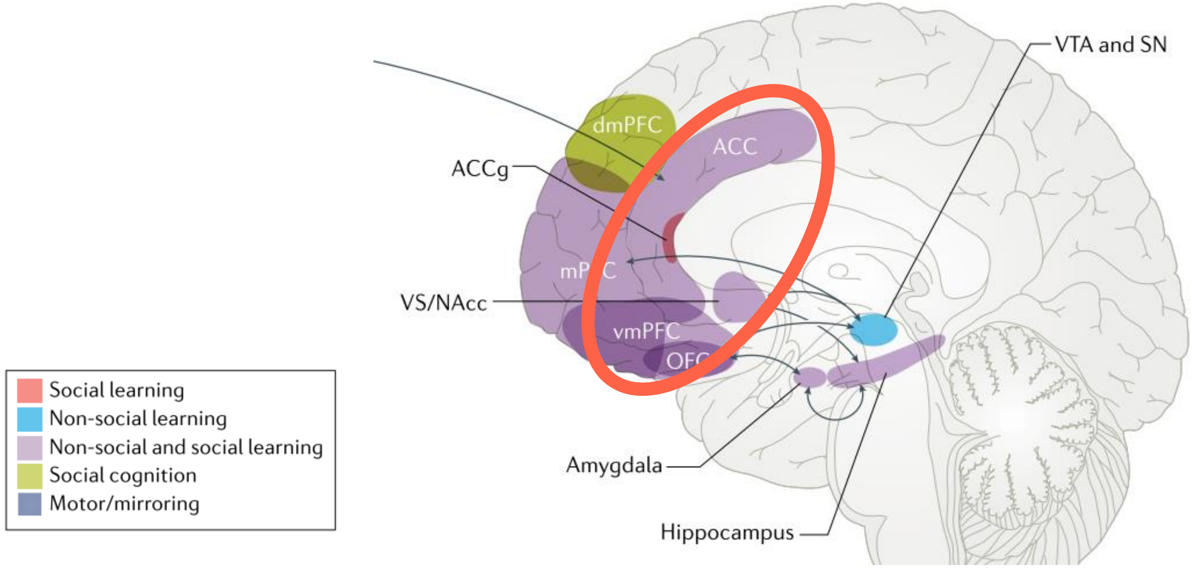
Apps et al, 2016



Suzuki et al, 2012



Grabenhorst et al, 2019



Olsson et al, 2020

Research Question

How does knowing about other people's decisions influence my own choices in the same environment?

behavioral readouts

Computation (why/goal)

What is the underlying algorithm by which social influence is integrated into my own decision-making?

computational modeling

Algorithm (what/rules)

How such computation is implemented in the brain?

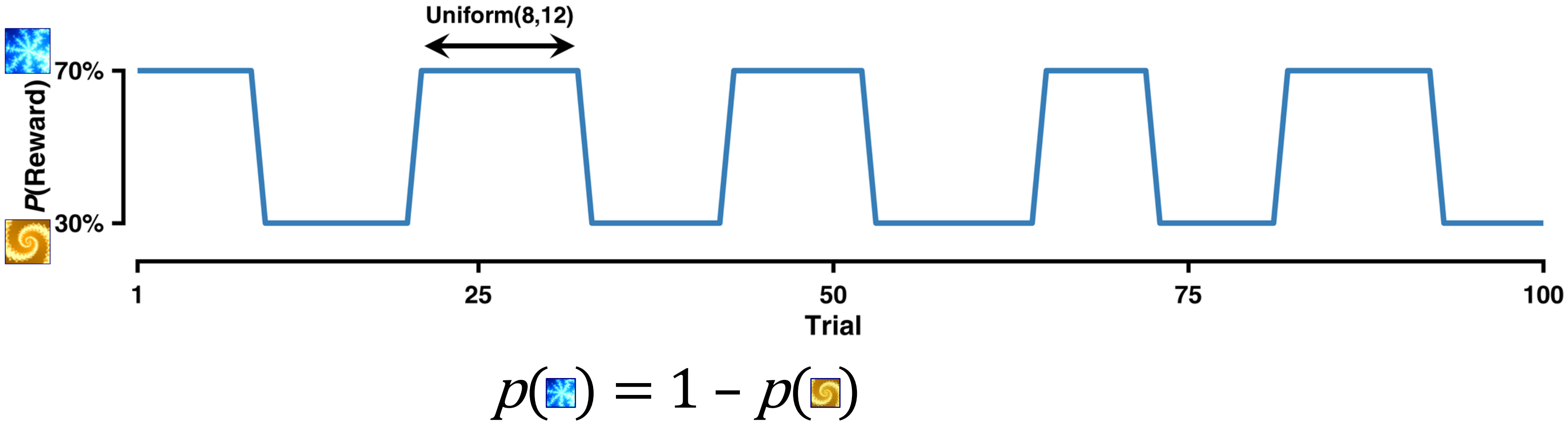
functional neuroimaging

Implementation (how/physical)

Paradigm

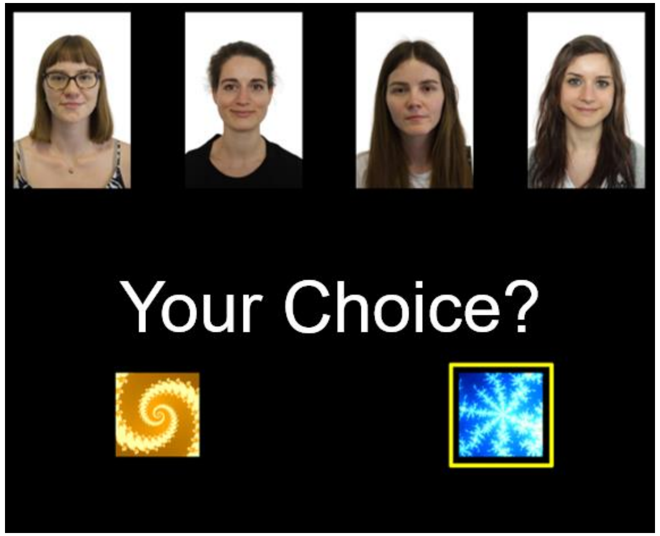
- **Probabilistic reversal learning task**
- Goal: maximize the outcome

- **Group decision-making**
  - 5 same-gender subjects / group
- 185 participants (95 F, 18-37 yrs)
- Truly real-time communication via intranet



Zhang & Gläscher, *in press*

Procedure

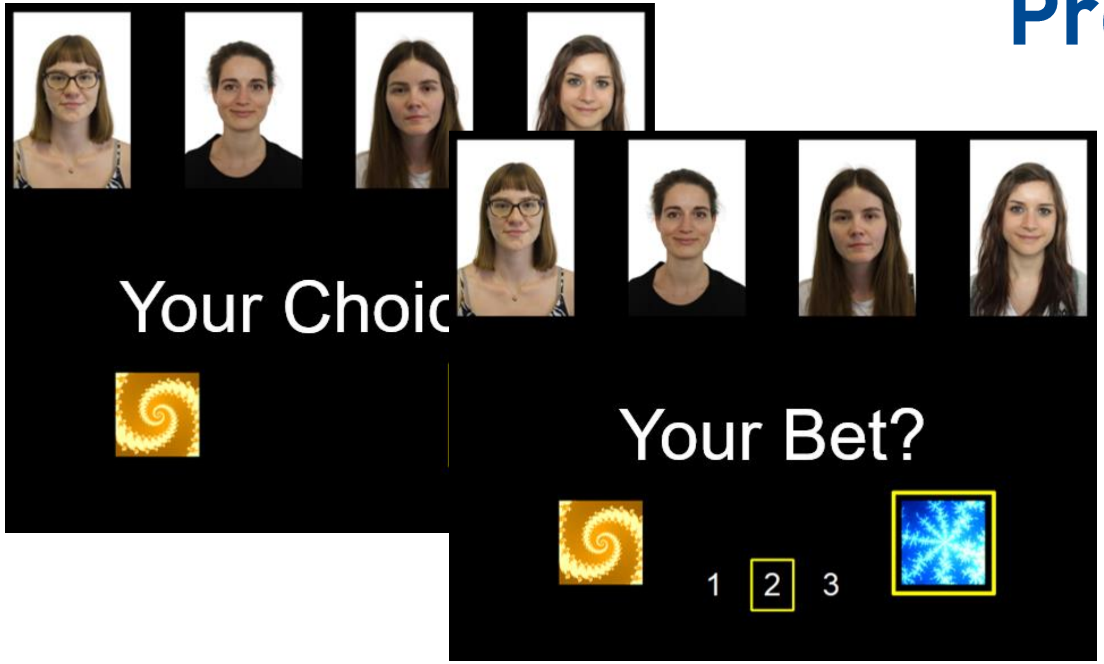


1st choice

*post-decision wagering metric (Persaud et al., 2007)

** 2nd choice and 2nd bet

Procedure



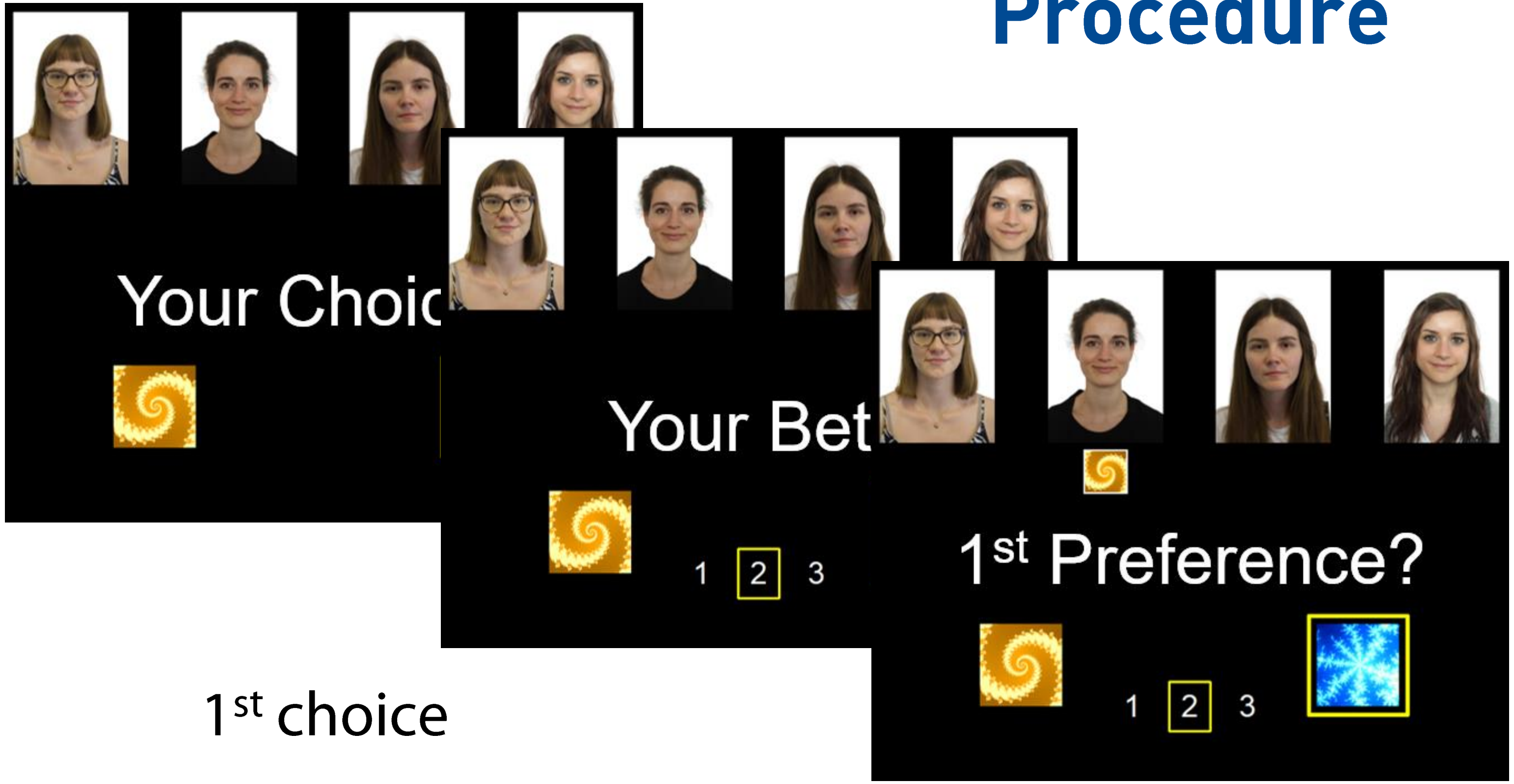
1st choice

1st bet*

*post-decision wagering metric (Persaud et al., 2007)

** 2nd choice and 2nd bet

Procedure



1st choice

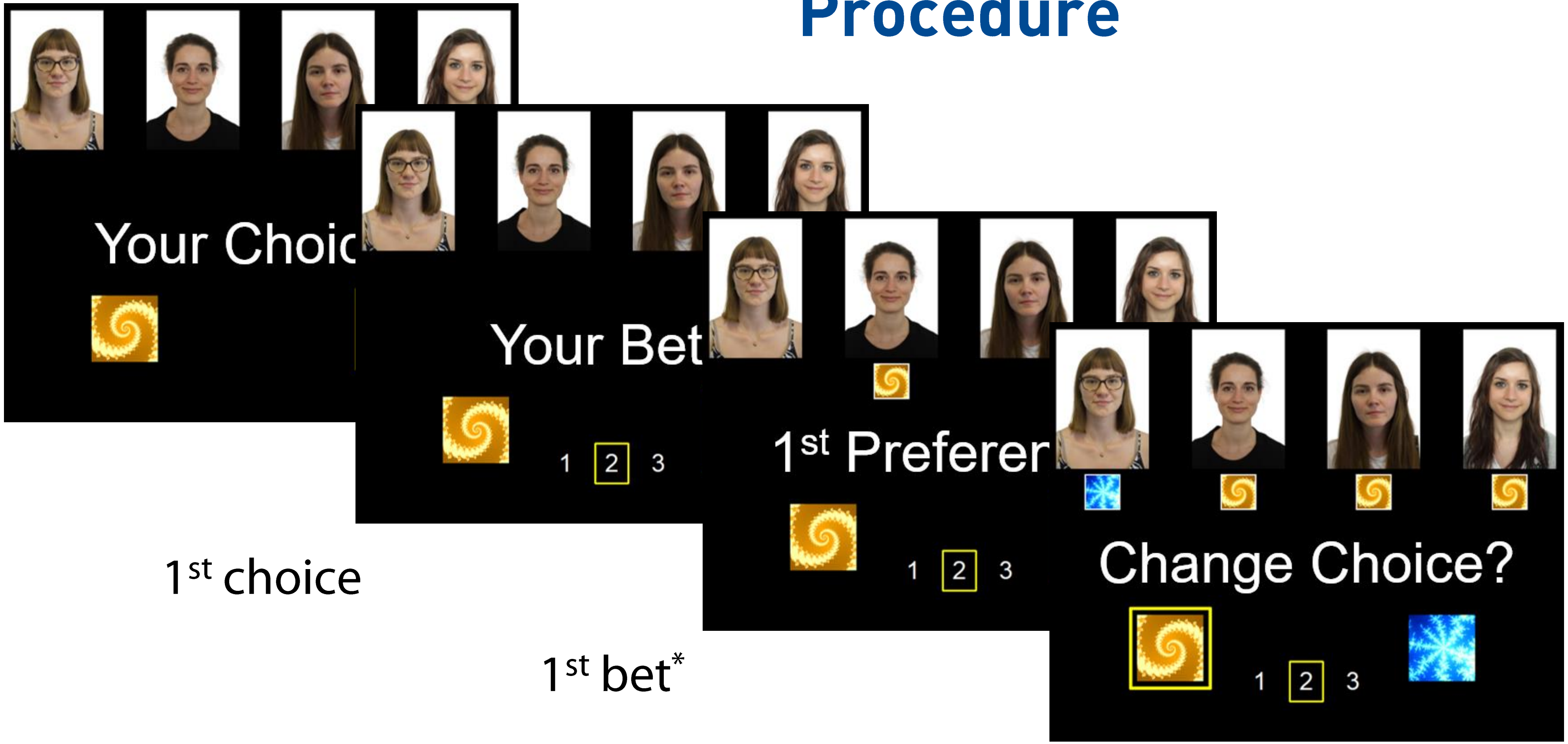
1st bet*

preference

*post-decision wagering metric (Persaud et al., 2007)

** 2nd choice and 2nd bet

Procedure



1st choice

1st bet*

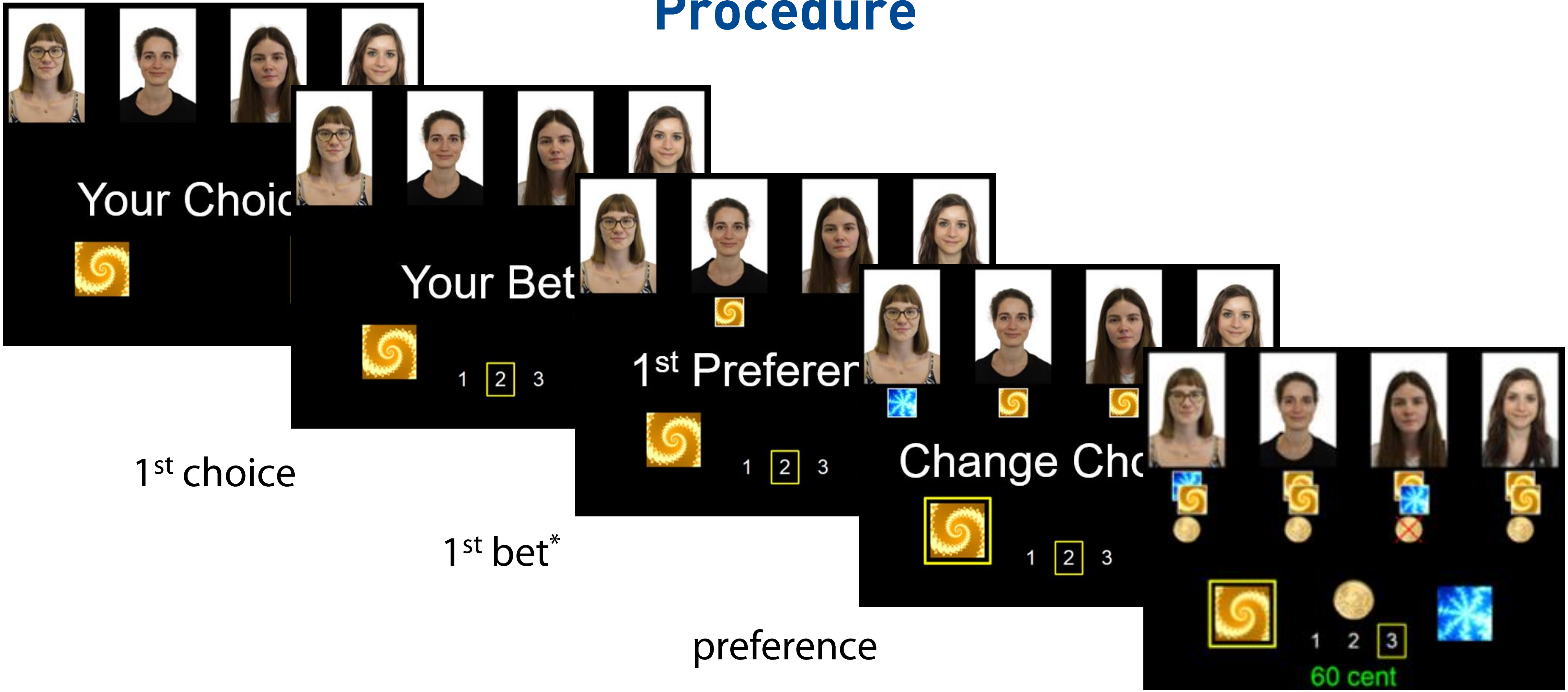
preference

adjustment**

*post-decision wagering metric (Persaud et al., 2007)

** 2nd choice and 2nd bet

Procedure



1st choice

1st bet*

preference

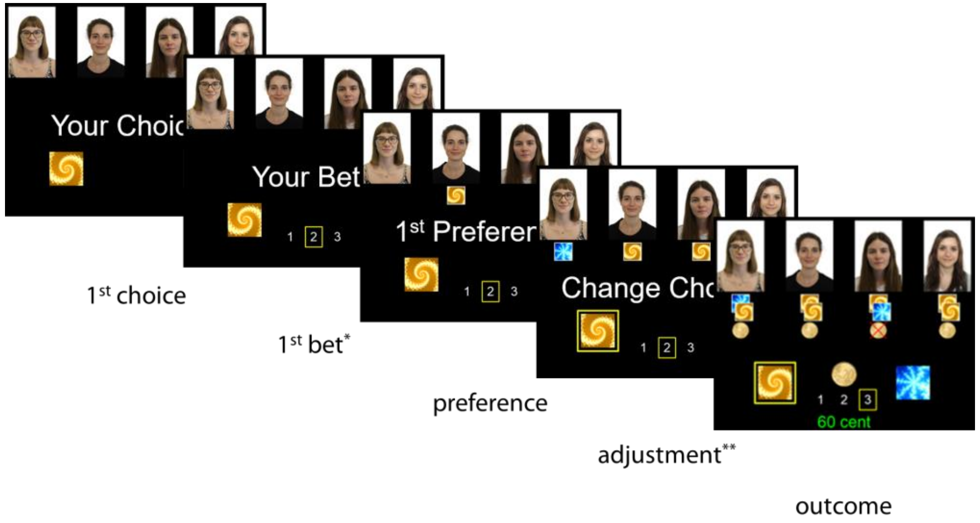
adjustment**

outcome

*post-decision wagering metric (Persaud et al., 2007)

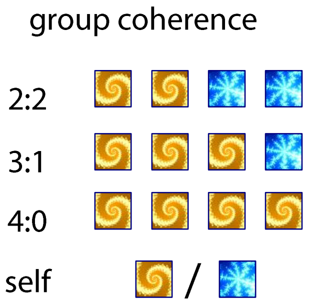
** 2nd choice and 2nd bet

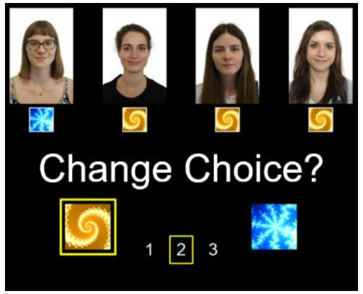
Why bother?

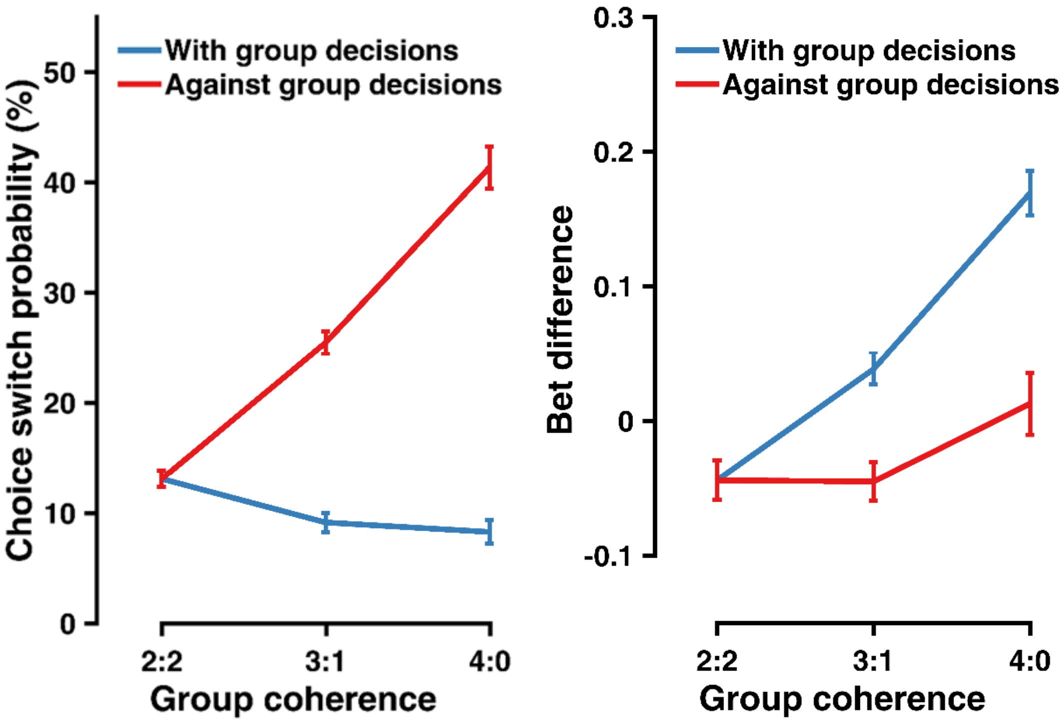


- Enhances ecological validity
- Allows to dissociate reward-based info and socially-based info
- Suitable for applying computational modeling
- Enables to parametrically test the effect of group coherence

Behavioral Results

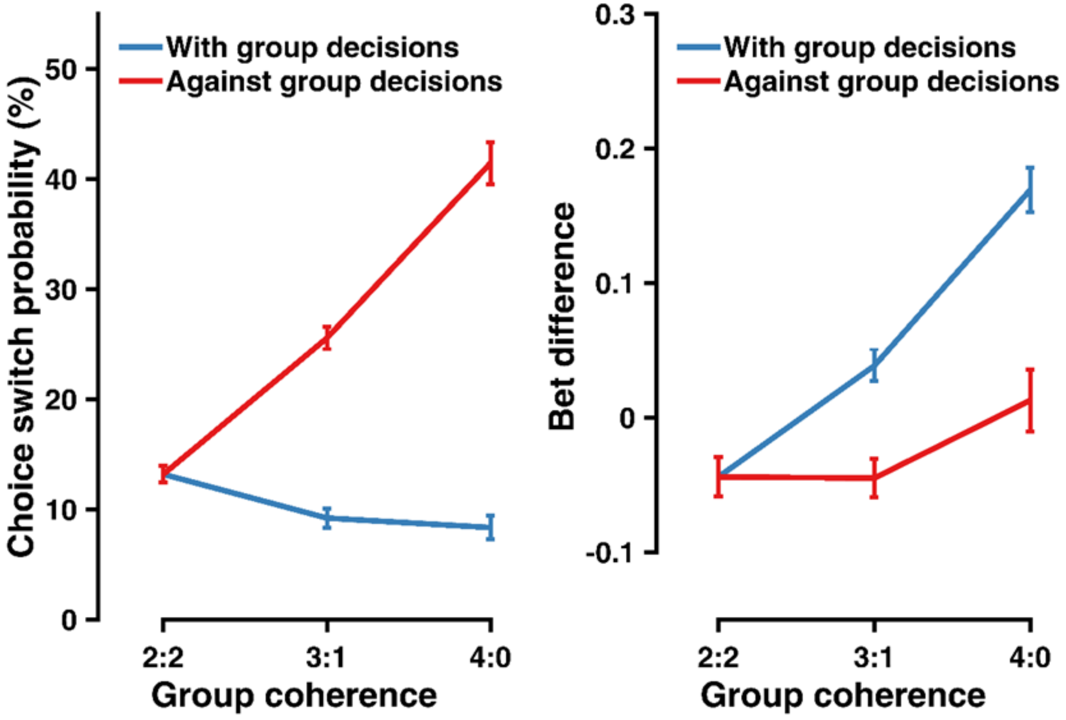






Computational Modeling

What to be modeled?

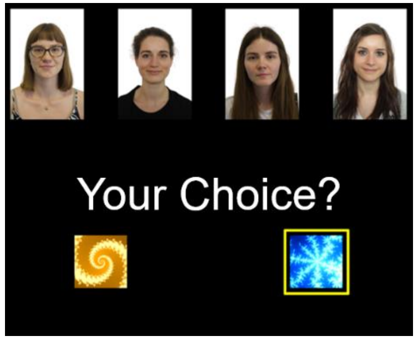


Computational Modeling

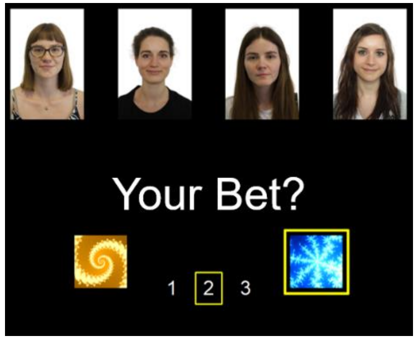
What to be modeled?

Instantaneous social info

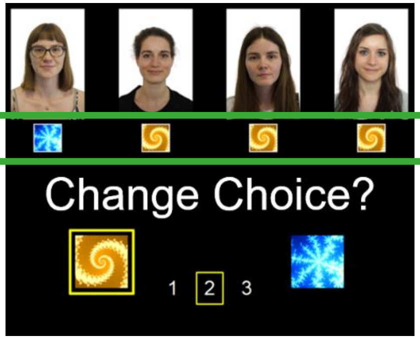
Social learning



1st choice

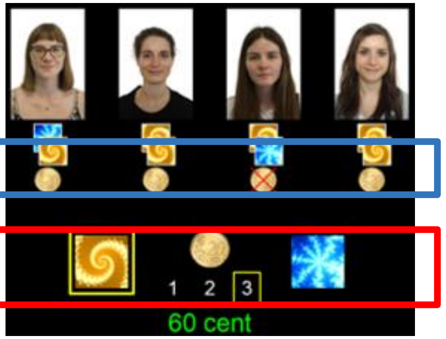


1st bet



2nd choice

2nd bet



Direct learning

Instantaneous social info

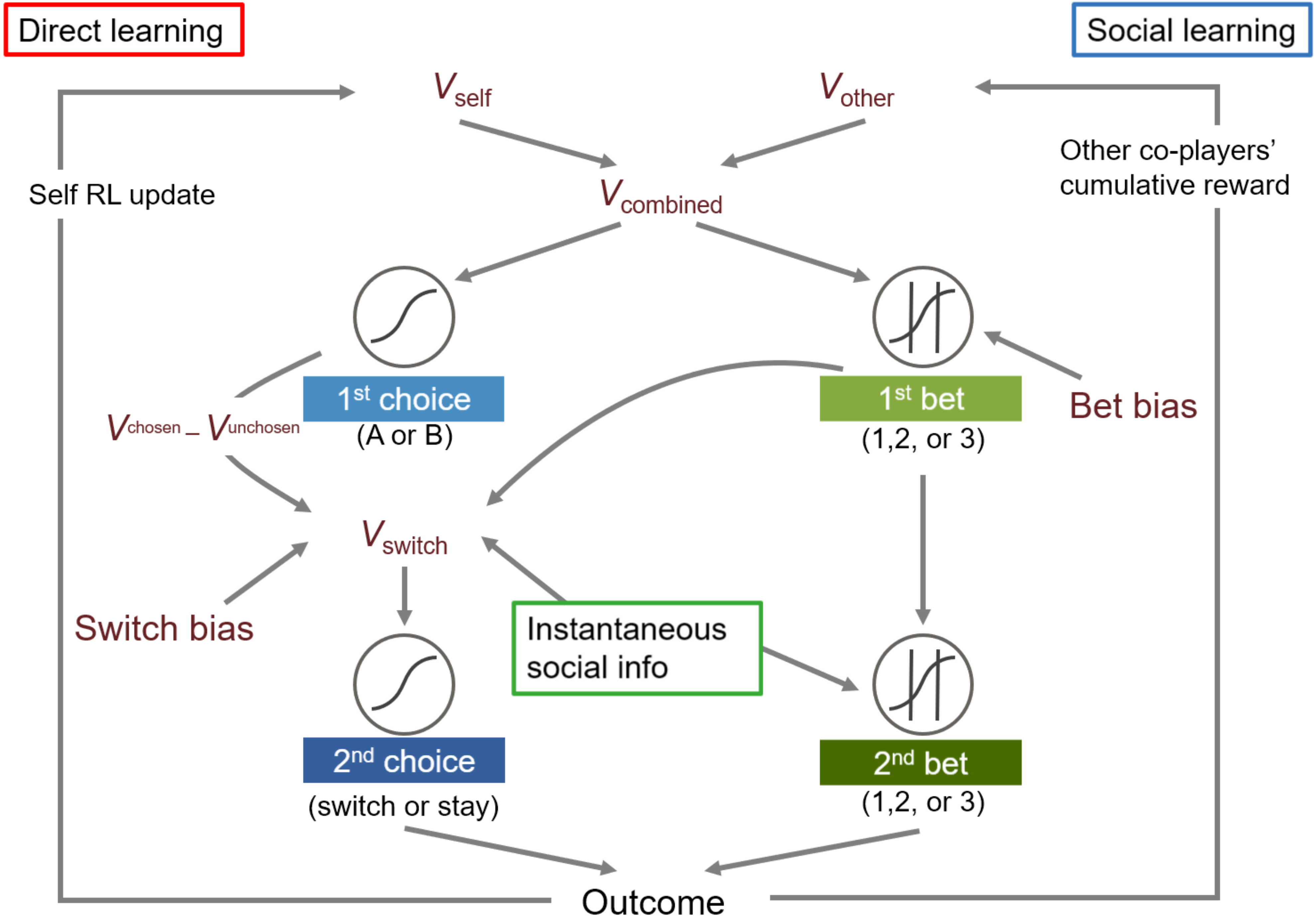
1st choice

1st bet

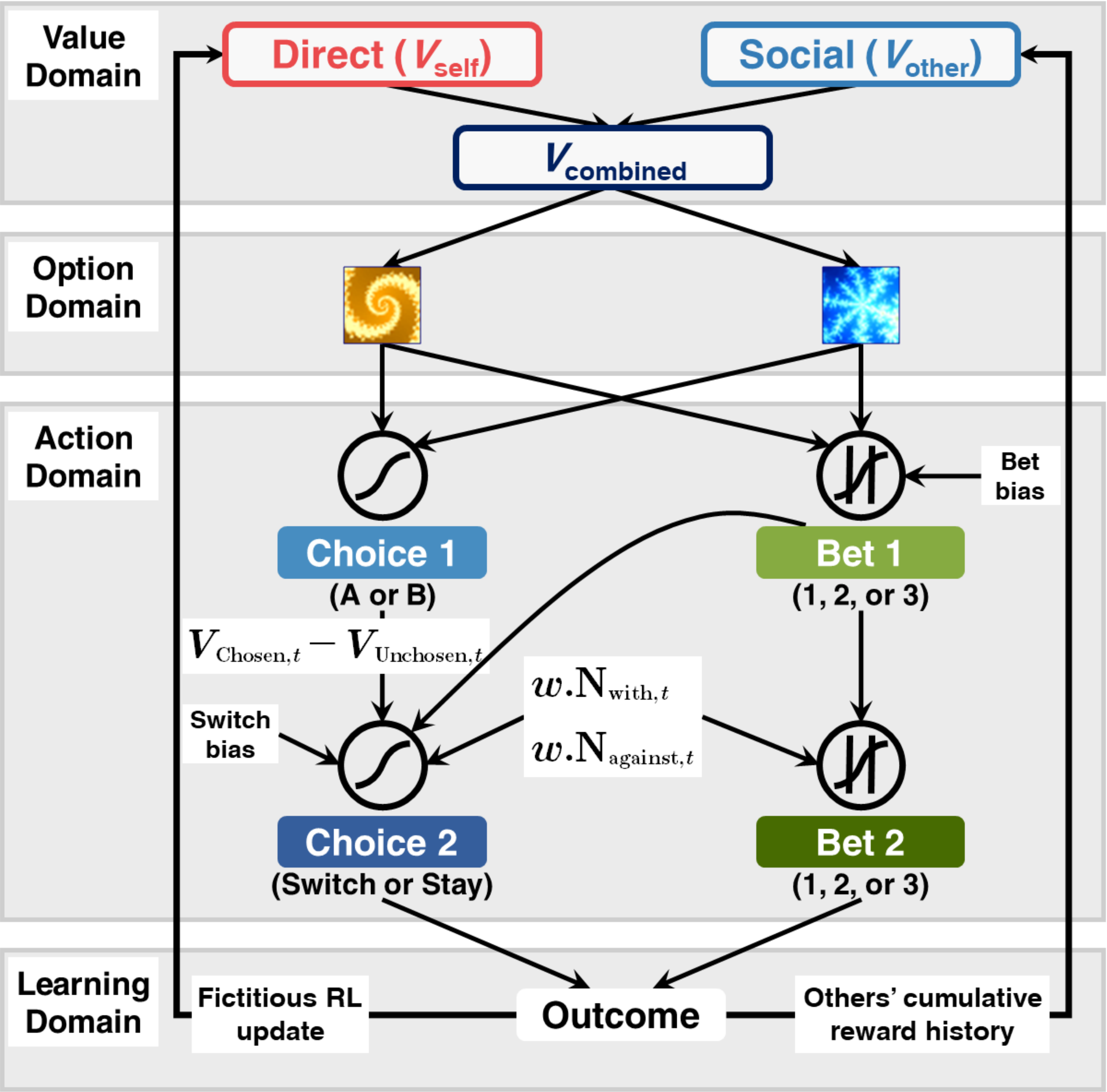
2nd choice

2nd bet

Direct learning

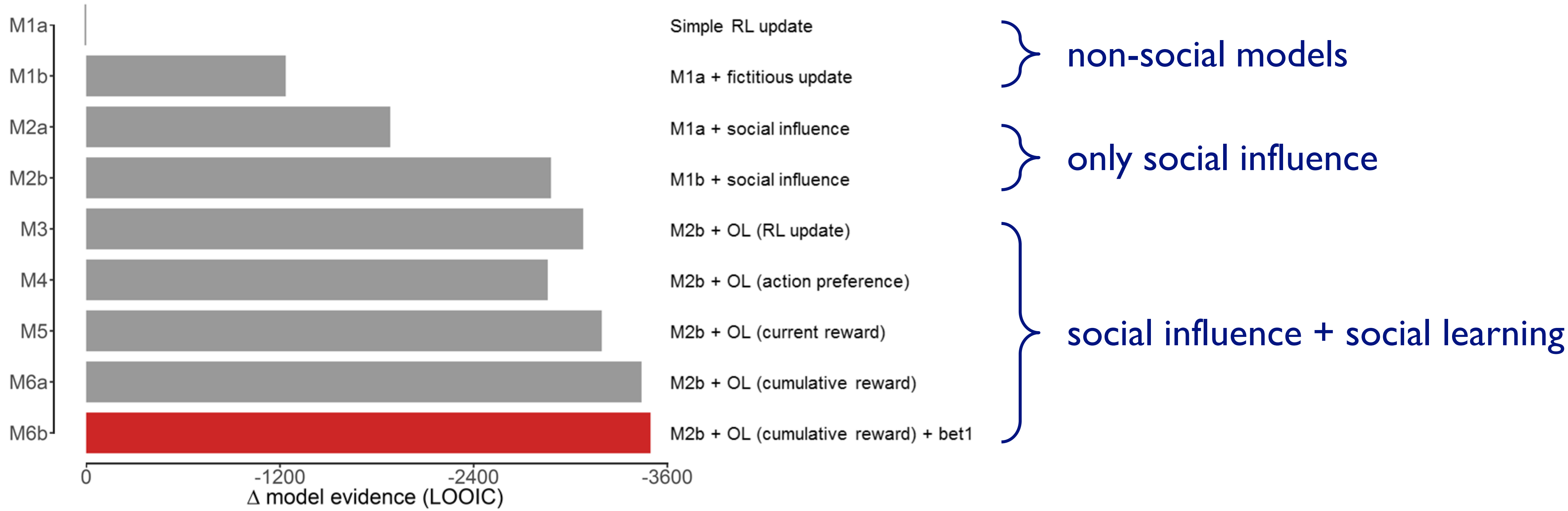


Direct learning
Social learning
V_{self}
V_{other}
Self RL update
Other co-players' cumulative reward
$V_{combined}$
$V_{chosen} - V_{unchosen}$
1^{st} choice
(A or B)
1^{st} bet
(1,2, or 3)
Bet bias
V_{switch}
Switch bias
Instantaneous social info
2^{nd} choice
(switch or stay)
2^{nd} bet
(1,2, or 3)
Outcome



Value Domain
Direct (V_{self})
Social (V_{other})
$V_{combined}$
Option Domain
Action Domain
Bet bias
Choice 1
(A or B)
Bet 1
(1, 2, or 3)
$V_{\text{Chosen},t} - V_{\text{Unchosen},t}$
$w.\text{N}_{\text{with},t}$
$w.\text{N}_{\text{against},t}$
Switch bias
Choice 2
(Switch or Stay)
Bet 2
(1, 2, or 3)
Learning Domain
Fictitious RL update
Outcome
Others' cumulative reward history

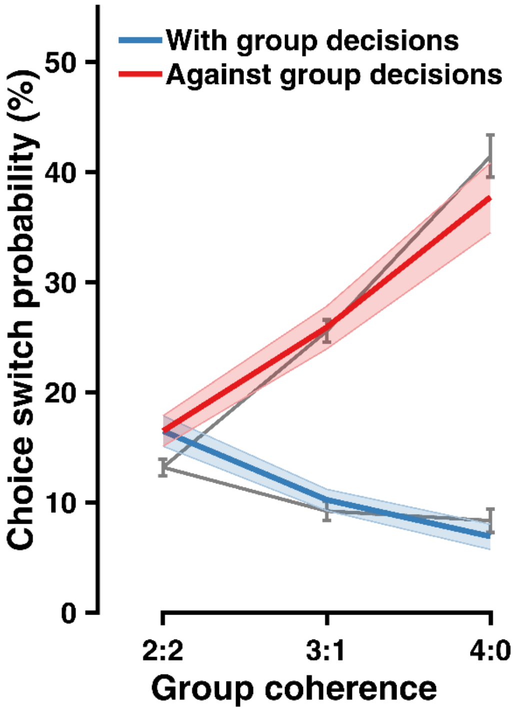
Model Comparison

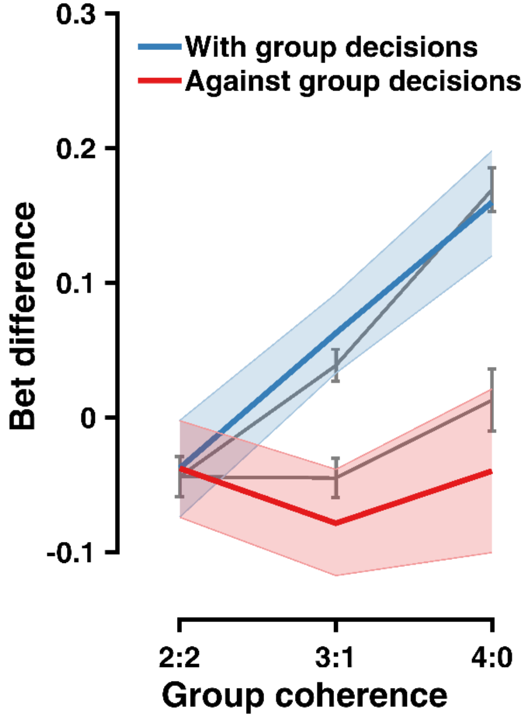


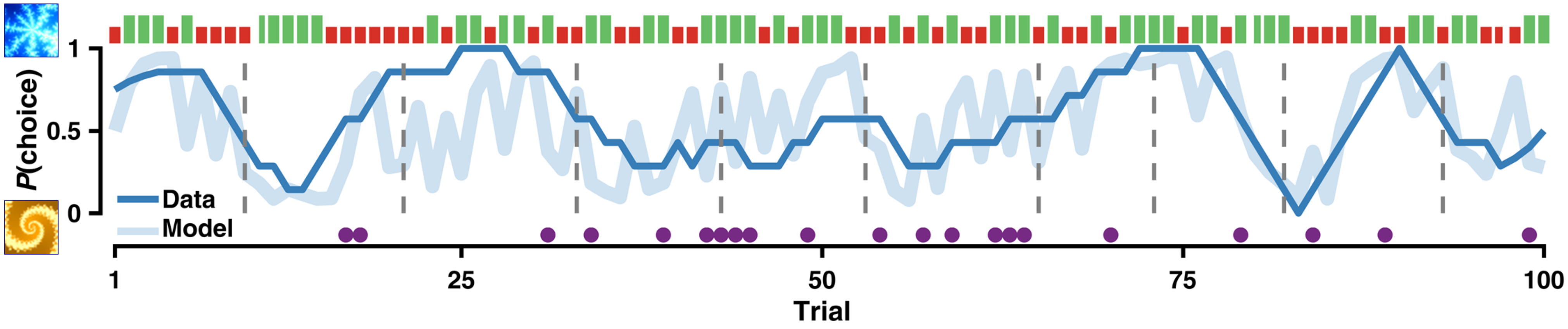
Hierarchical Bayesian Modeling (MCMC)
+ Leave-one-out model prediction

RL: reinforcement learning
OL: observational learning

Posterior predictive check







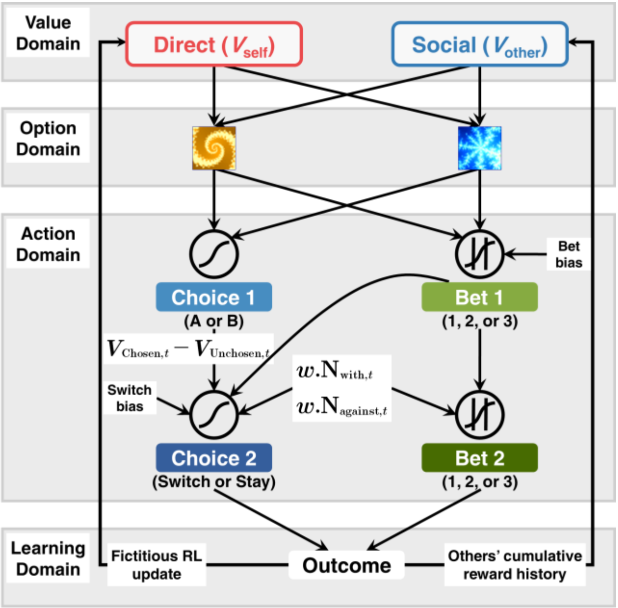
Summary

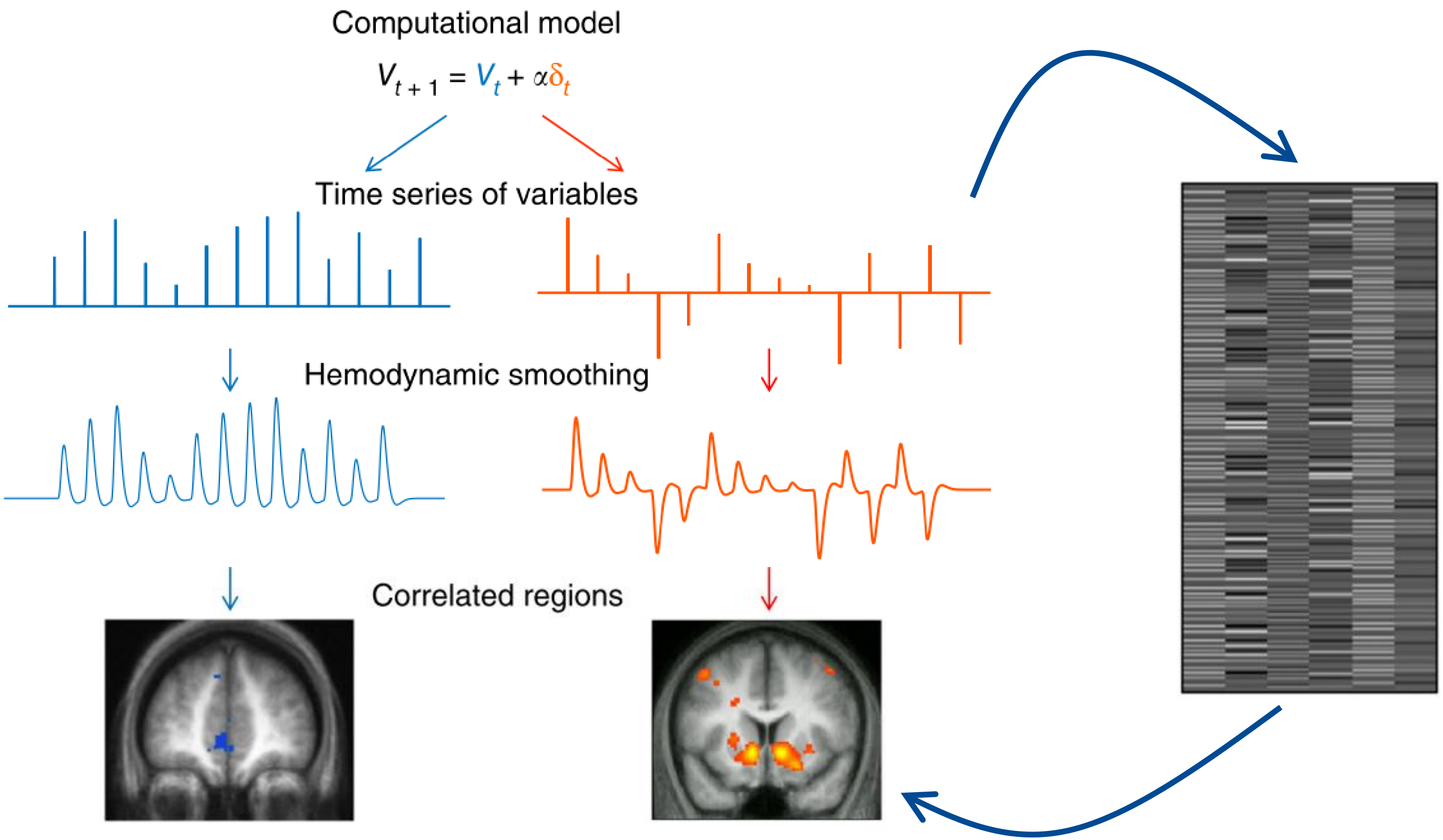
Social influence affects both choice and bet (computational).

Instantaneous social information predicts behavioral adjustment (algorithmic).

Learning is a weighted combination of direct learning and observational learning (algorithmic).

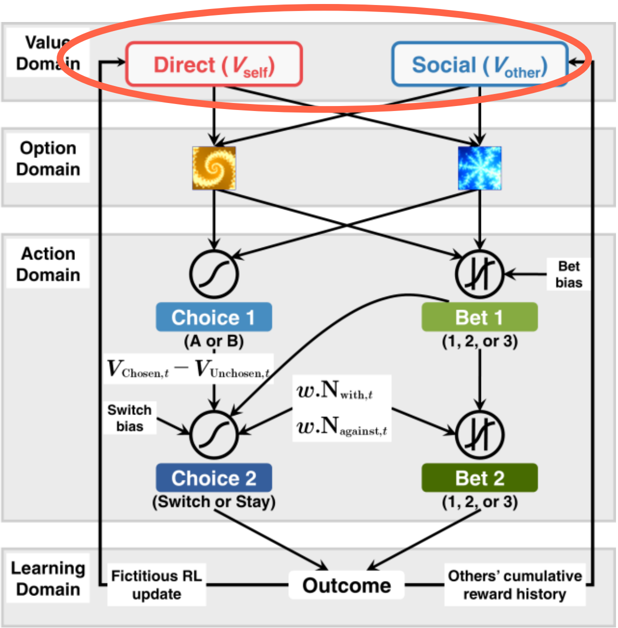
Model-based fMRI analysis

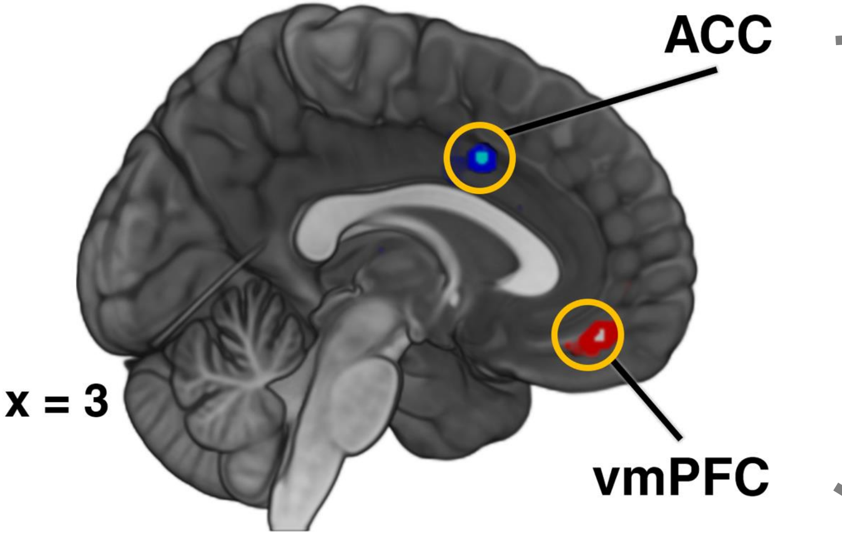




O'Doherty et al. (2007); Gläscher & O'Doherty (2010); Forstmann & Wagenmarkers (2015); Cohen et al. (2017)

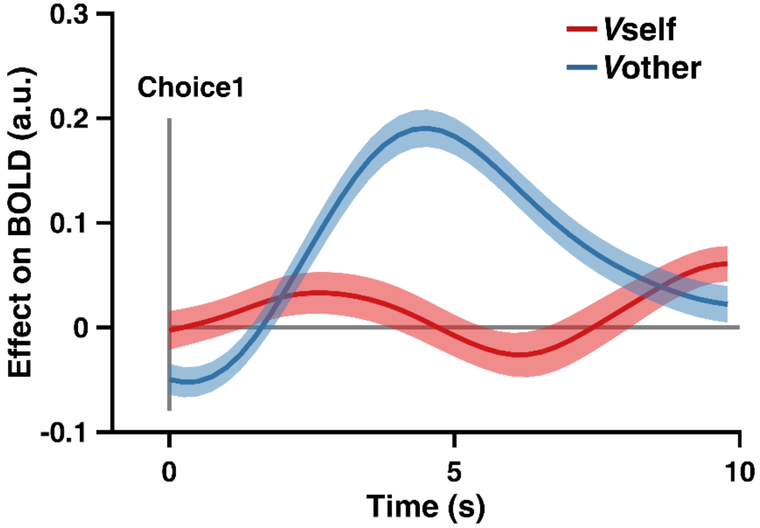
Dissociable value signals

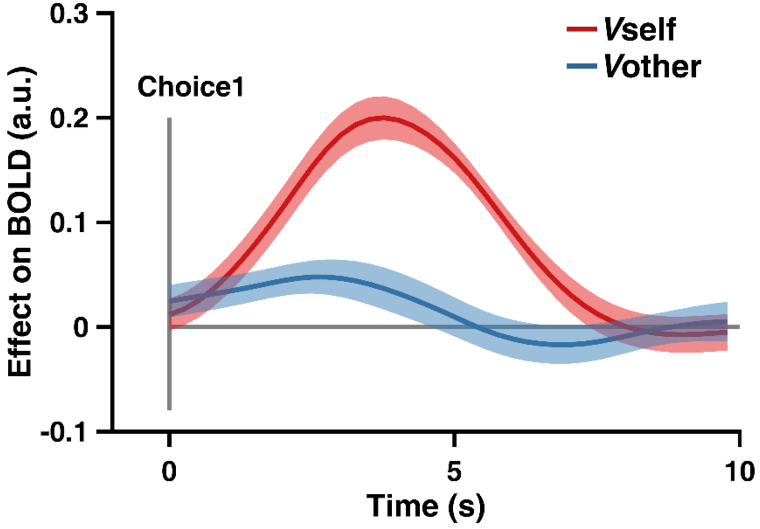




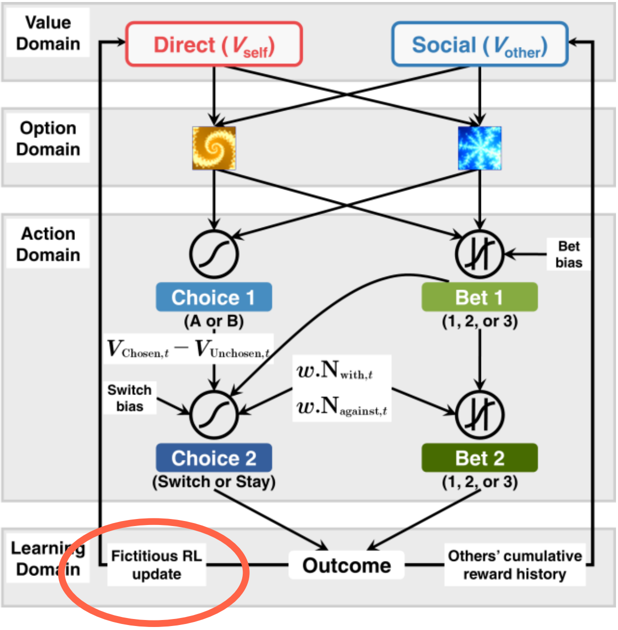
*V*self
: $p < 0.001$, SVC
: $p < 0.0001$, SVC

*V*other
: $p < 0.001$, SVC
: $p < 0.0001$, SVC



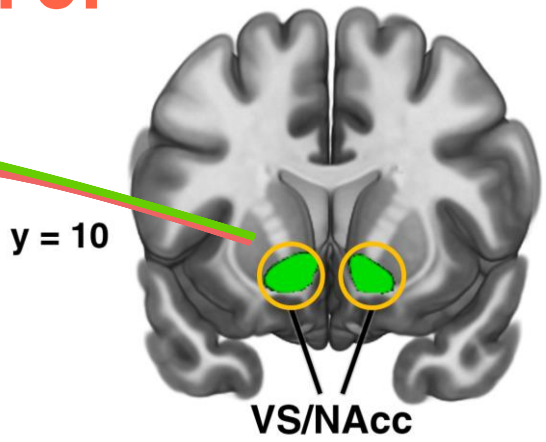


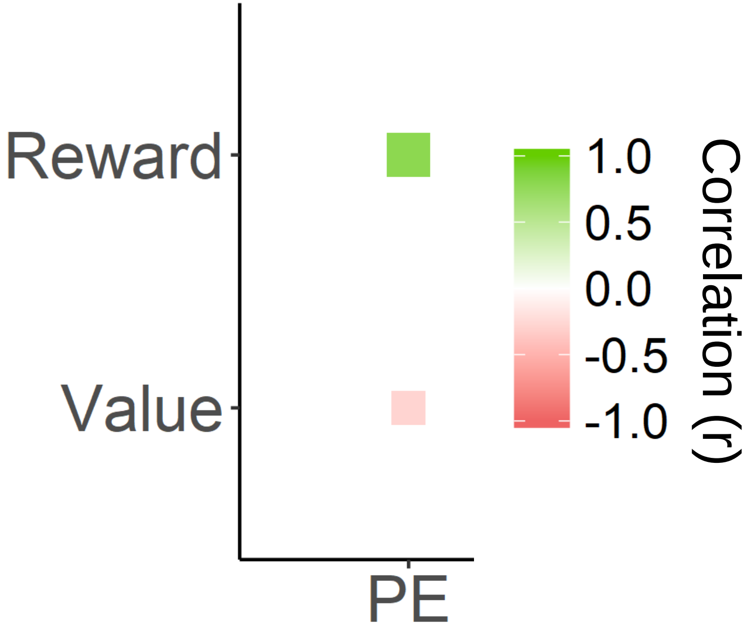
Reward prediction error

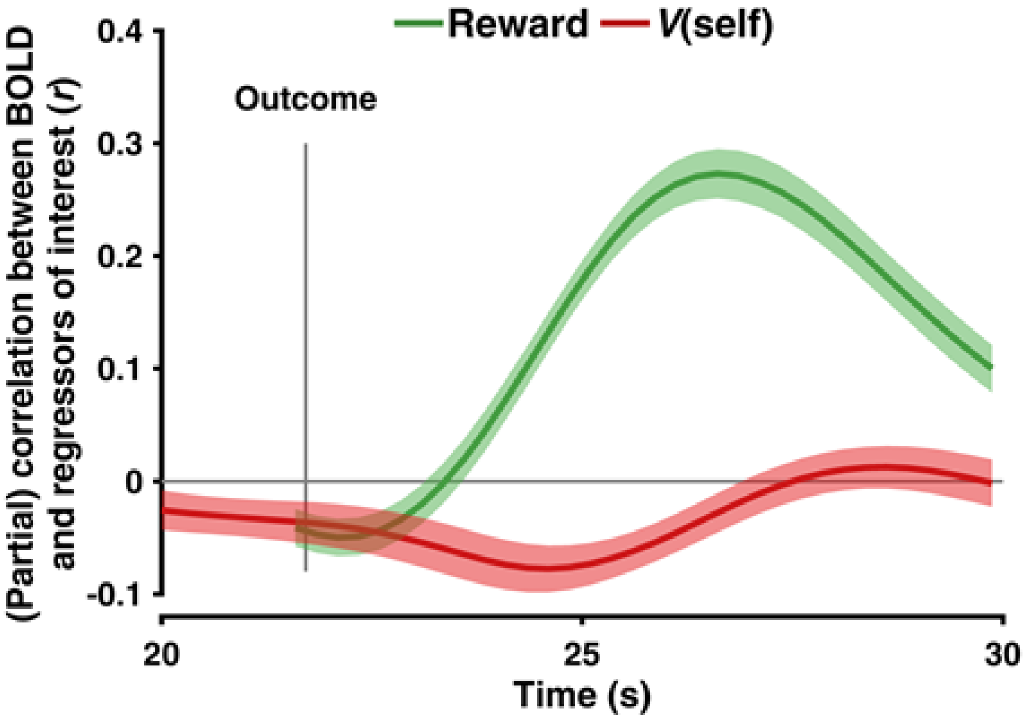


$$PE = R_t - V_t$$

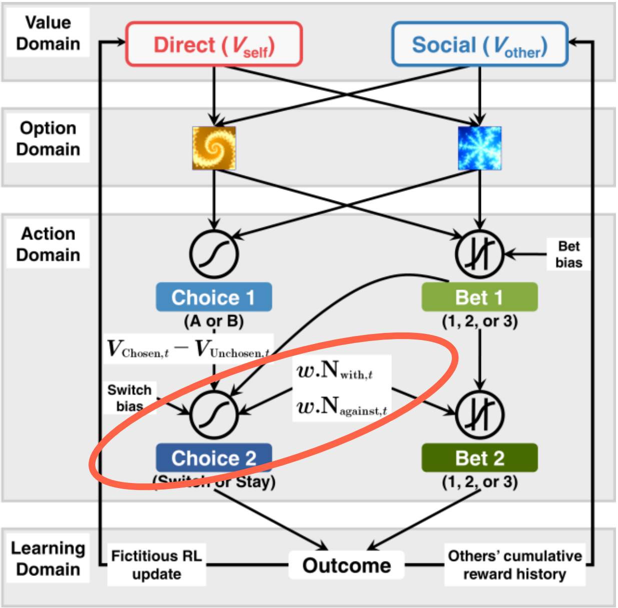
+
−
+
−

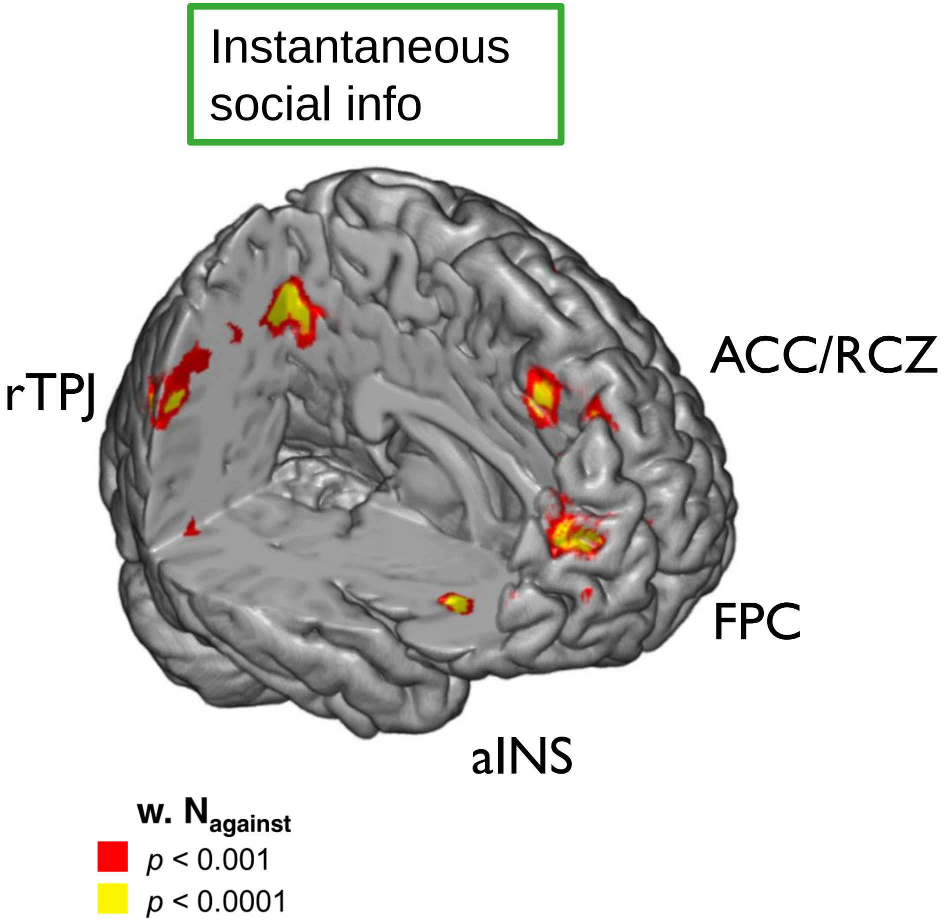


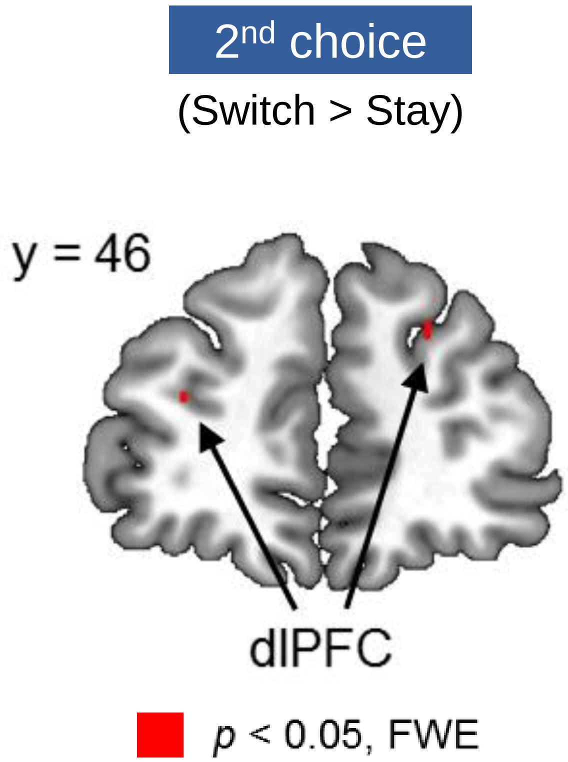




Conflicting social information and action adjustment







Klucharev, et al., 2009; Berns et al., 2010; Tomlin et al., 2013; Park et al., 2017

Cools et al., 2002; O'Doherty et al., 2003; Gläscher et al., 2009

How do these regions interact?

Whether / how behavioral adjustment modulates the functional link between the brain's social hub and reward hub?

	Social info ⊗ Behavioral change
PPI	rTPJ Switch > Stay
PhiPI	dlPFC

reward-related regions
(vmPFC, ACC, NAcc)

PPI: psycho-physiological interaction
PhiPI: physio-physiological interaction

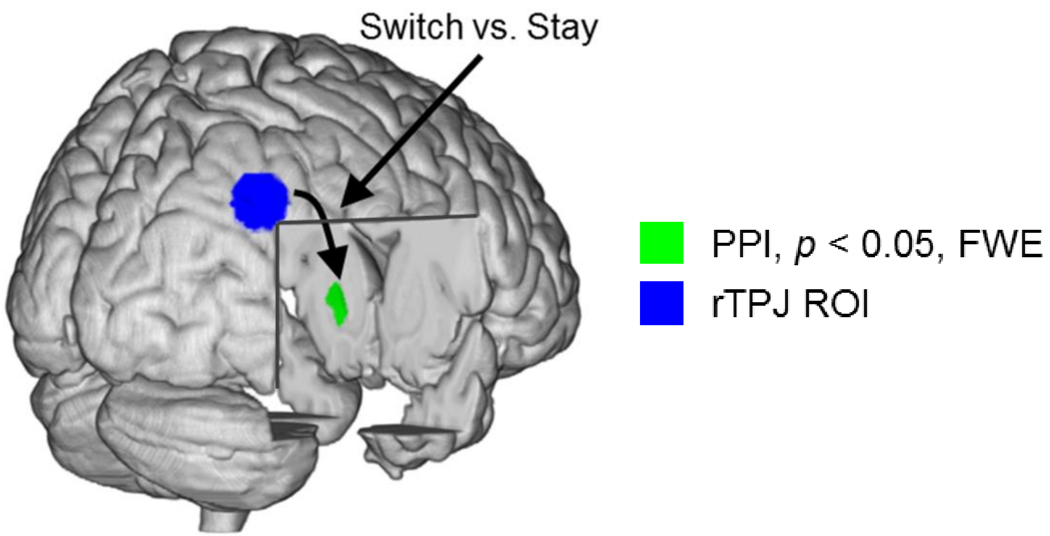
PPI reveals social prediction error

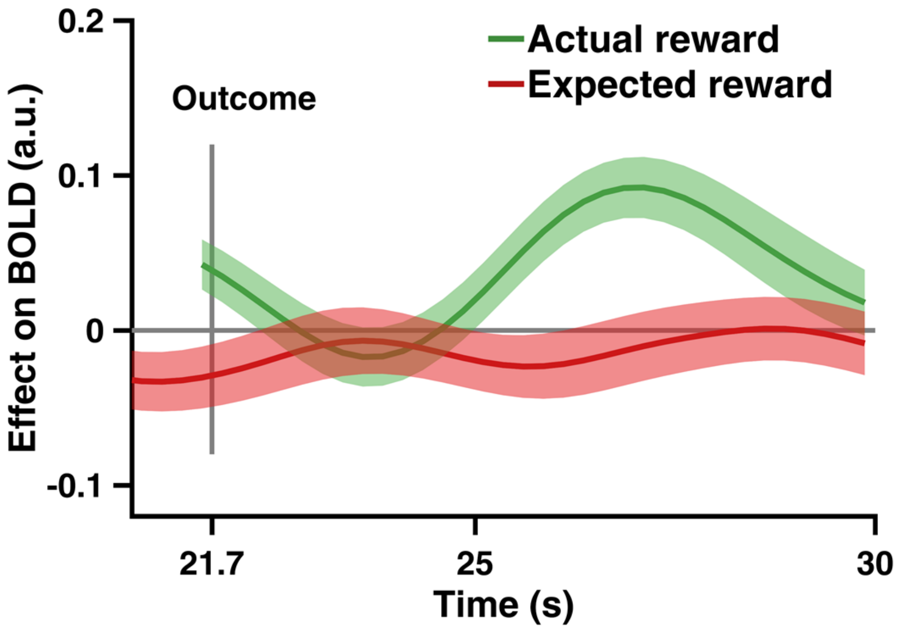
Prediction error:

$$PE = R_t - V_t$$

+

−





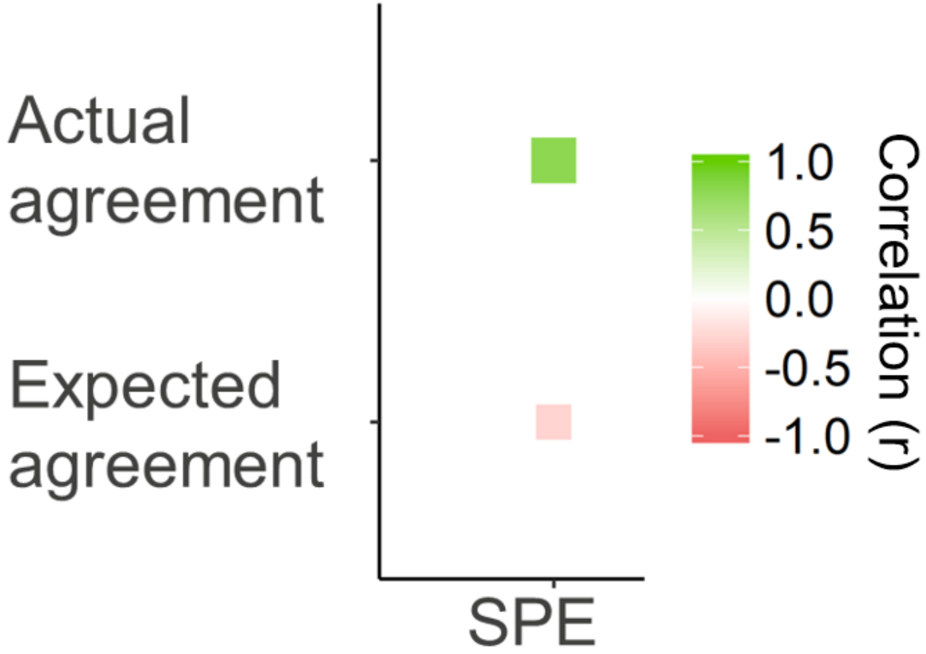
PPI reveals social prediction error

Social prediction error:

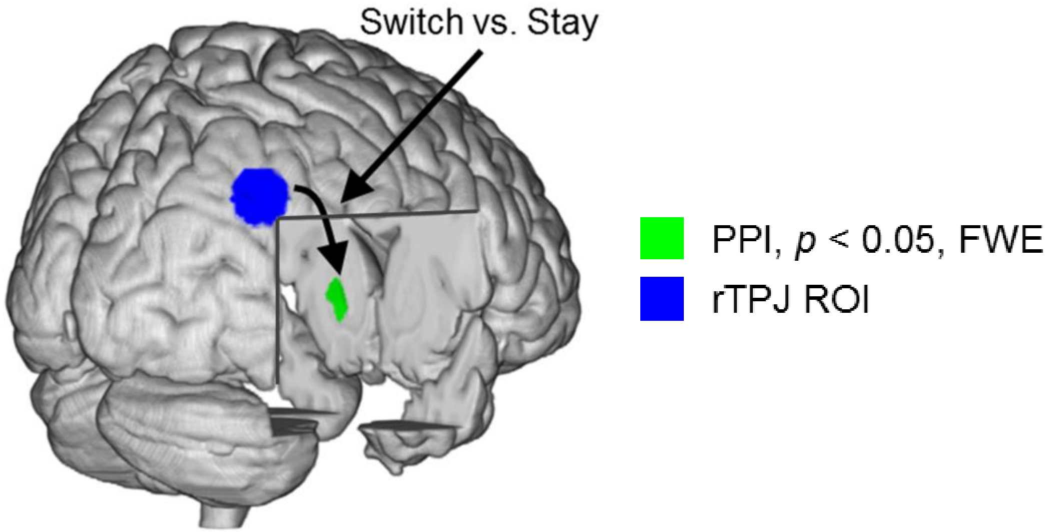
$$SPE = Agr_t - \Phi(Vdiff)_t$$

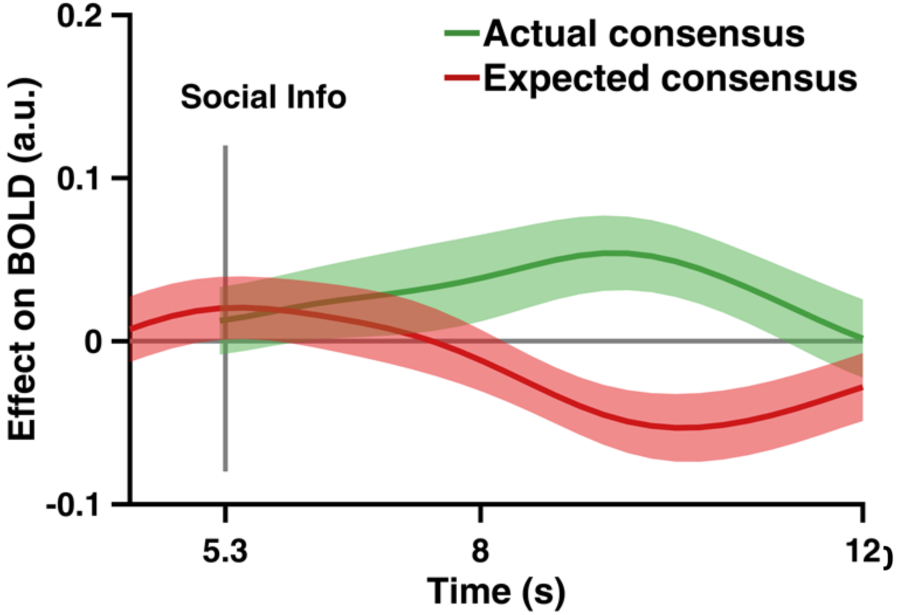
+

−

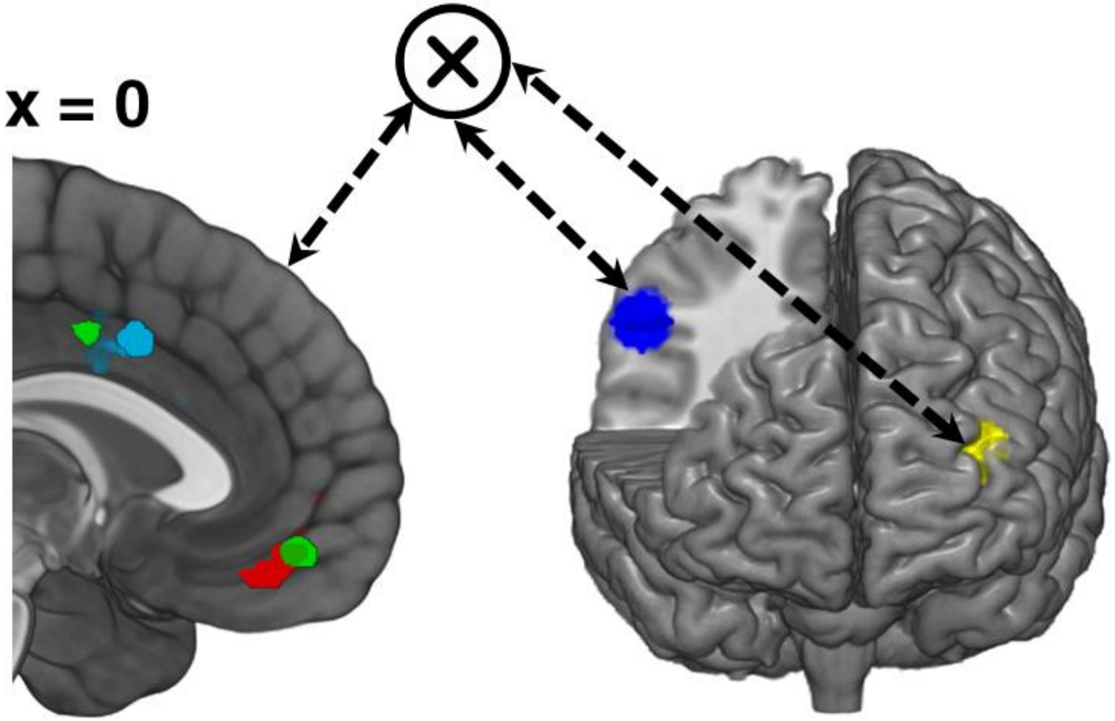


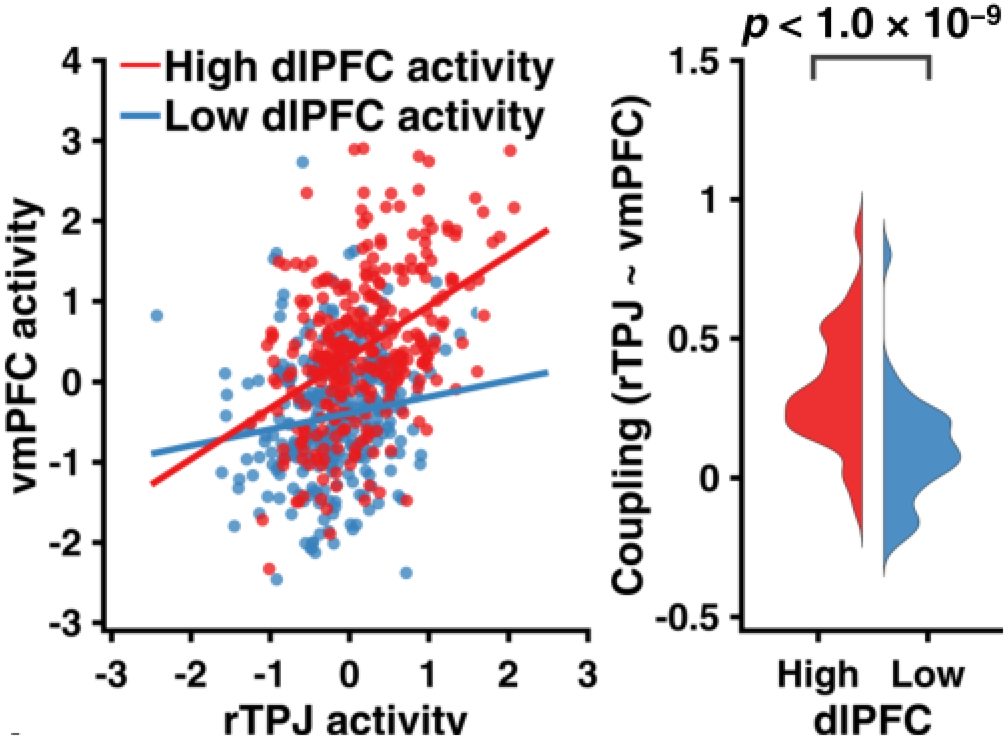
$$\Phi(x) = \frac{1}{1+e^{-x}}$$



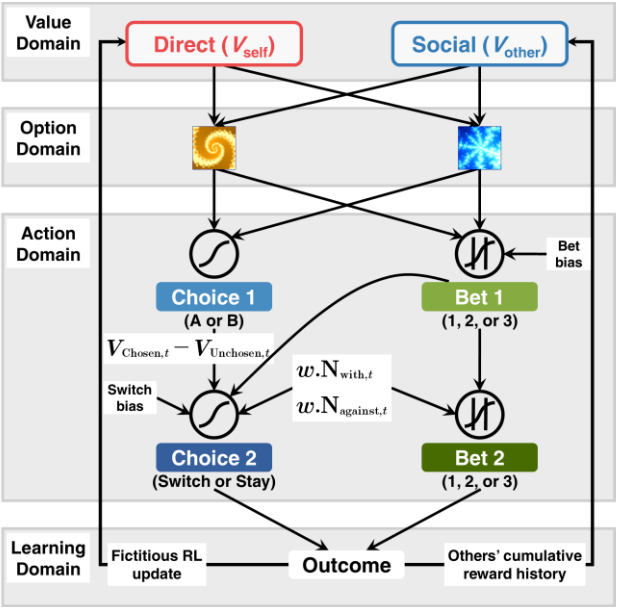


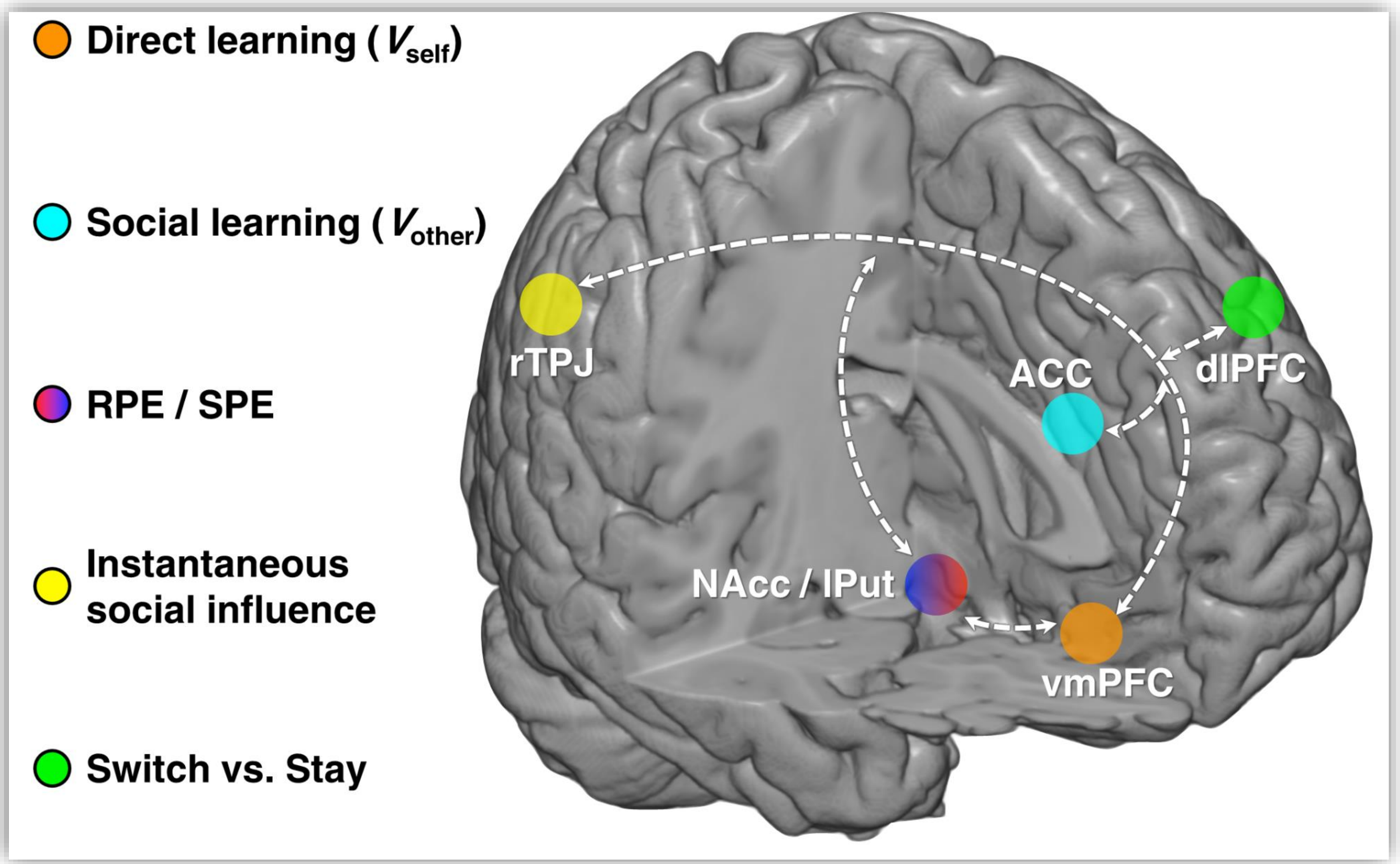
Functional connectivity (PhiPI)





A network of social decision-making





Summary

Social influence affects both choice and bet (computational).

Instantaneous social information predicts behavioral adjustment (algorithmic).

Learning is a weighted combination of direct learning and observational learning (algorithmic).

These dissociable value signals are respectively represented in vmPFC and ACC (implemental).

Connectivity reveals a network of social influence in decision-making (implemental).

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A brain network supporting social influences in human decision-making

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Abstract | Full Text | Info/History | Metrics | Preview PDF

Abstract

Humans learn from their own trial-and-error experience and from observing others. However, it remains unanswered how brain circuits compute expected values when direct learning and social learning coexist in an uncertain environment. Using a multi-

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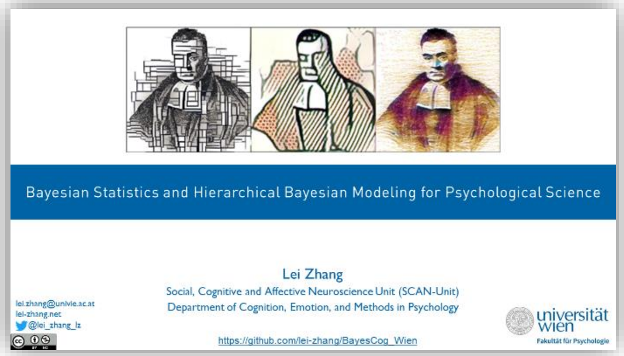

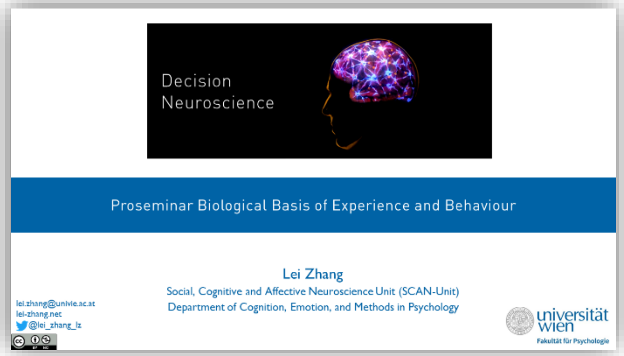

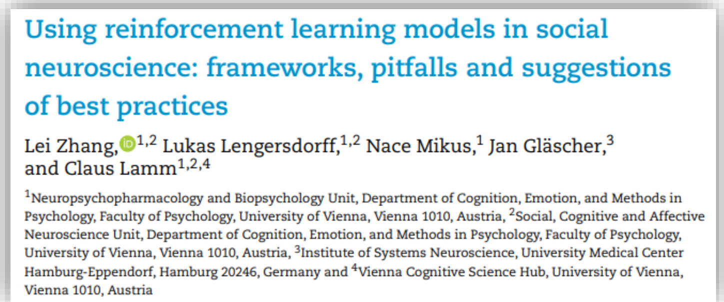

Using reinforcement learning models in social neuroscience: frameworks, pitfalls and suggestions of best practices

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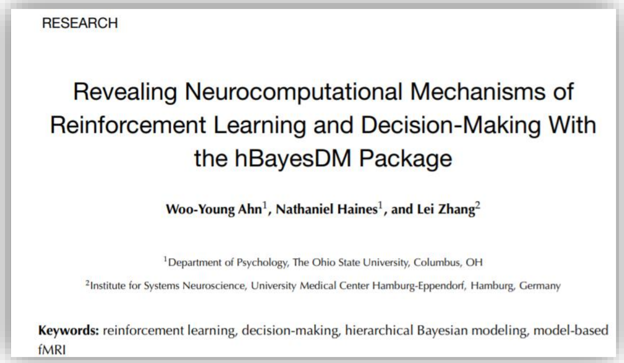

RESEARCH

Revealing Neurocomputational Mechanisms of Reinforcement Learning and Decision-Making With the hBayesDM Package

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Thank you

Presented by
Lei Zhang