

Computational Models for Precision Psychiatry

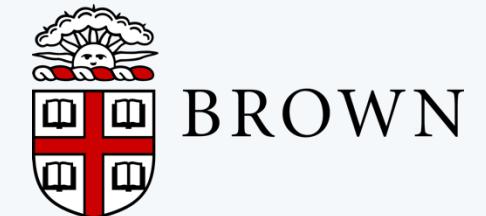


PEAC Lab

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The Goal: Precision Psychiatry



The goal is
to provide the **right treatments**
to the **right patients**
at the **right time**.

The goal is Precision Psychiatry, what are the hurdles?

- **Lack of mechanistic understanding**
→ Heterogeneity
- **Lack of predictors**
→ Trial and error treatment
- **Lack of effective treatments**



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1. Disease insights

Mechanistic Models



2. Predictive validity

Data-driven Models



1. Disease insights

Mechanistic Models



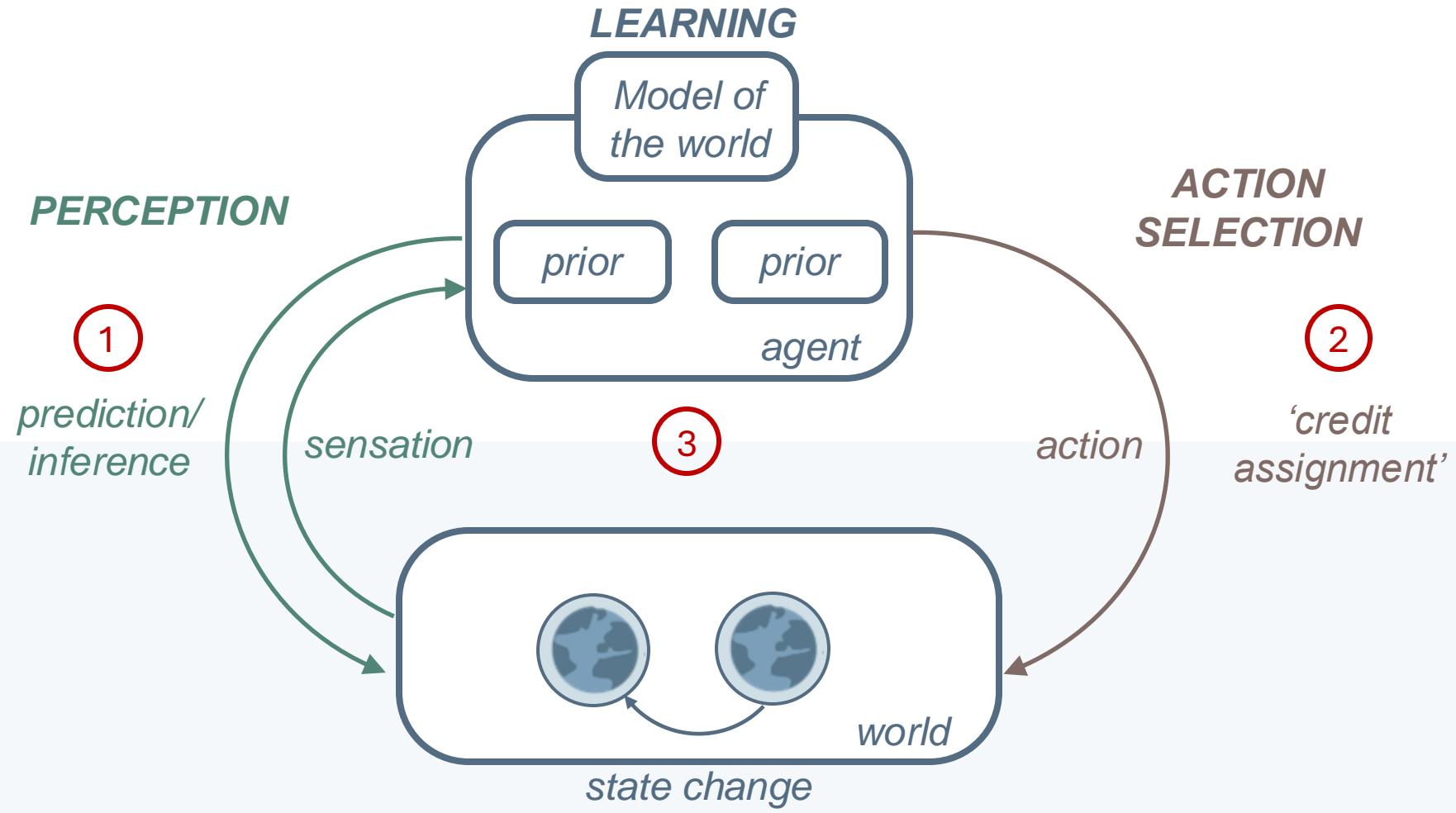
2. Predictive validity

Data-driven Models

Combination

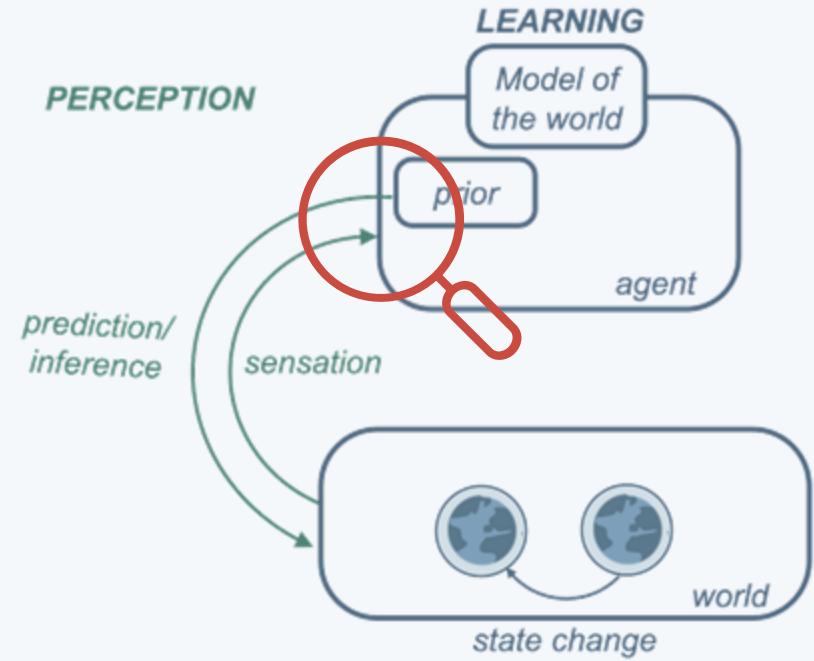
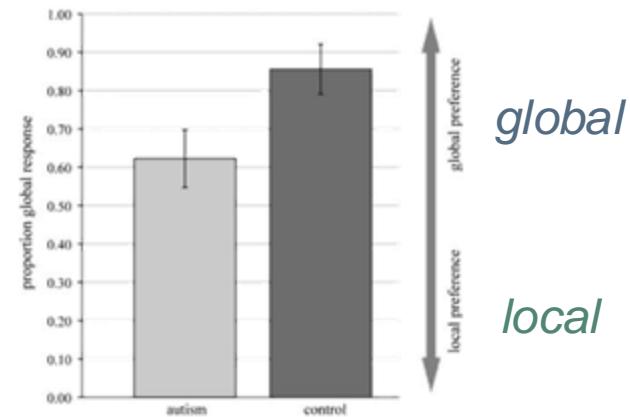
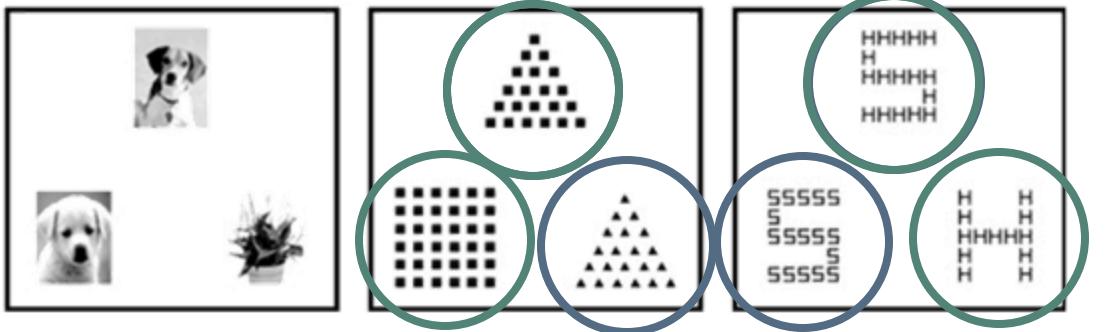


*Bordersen et al., PlosCB, 2011
Huys et al., Nat. Neuro., 2016;
Geana et al., Biol. Psych., 2021;
Wiecki et al. Plos One, 2016;
Wiecki et al., Clin Psychol Science, 2015*

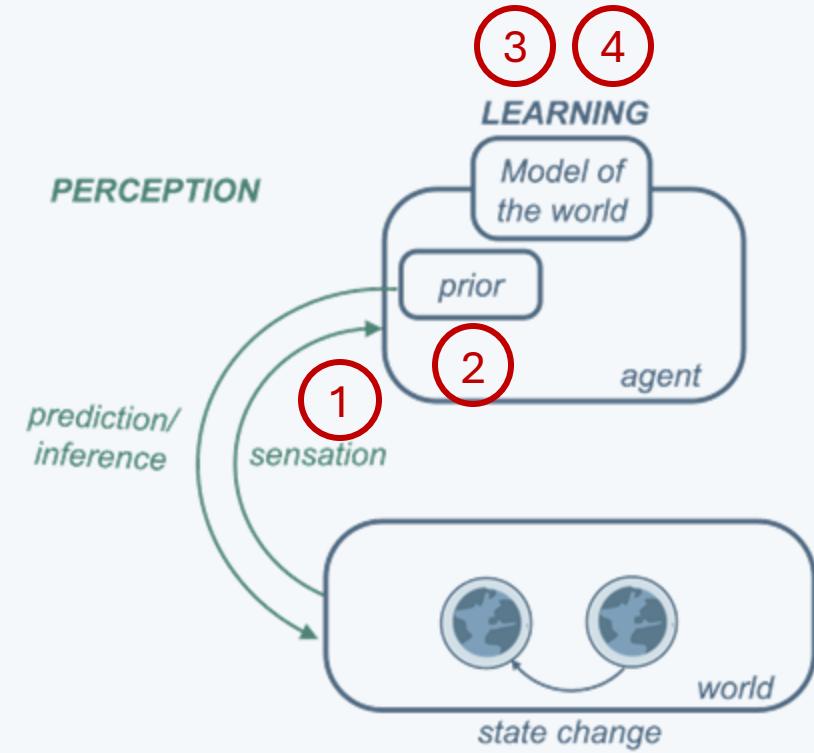
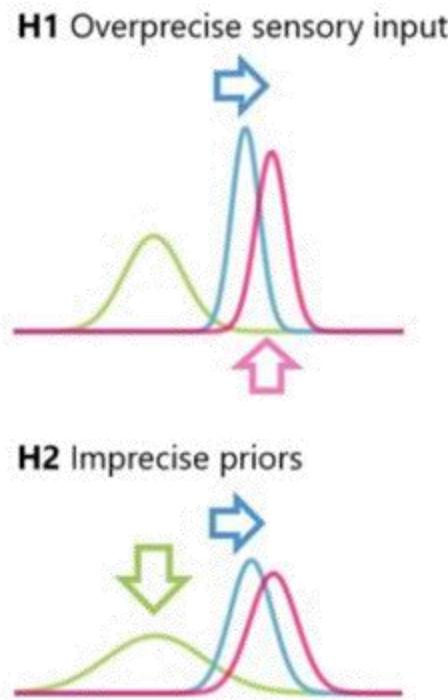


Autism Spectrum Disorder

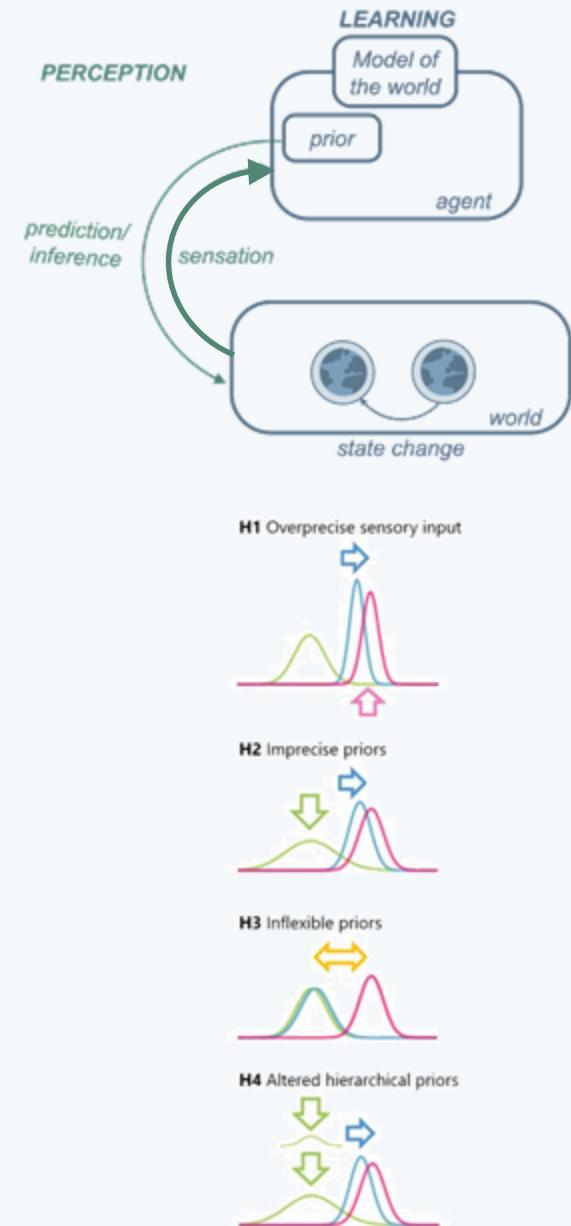
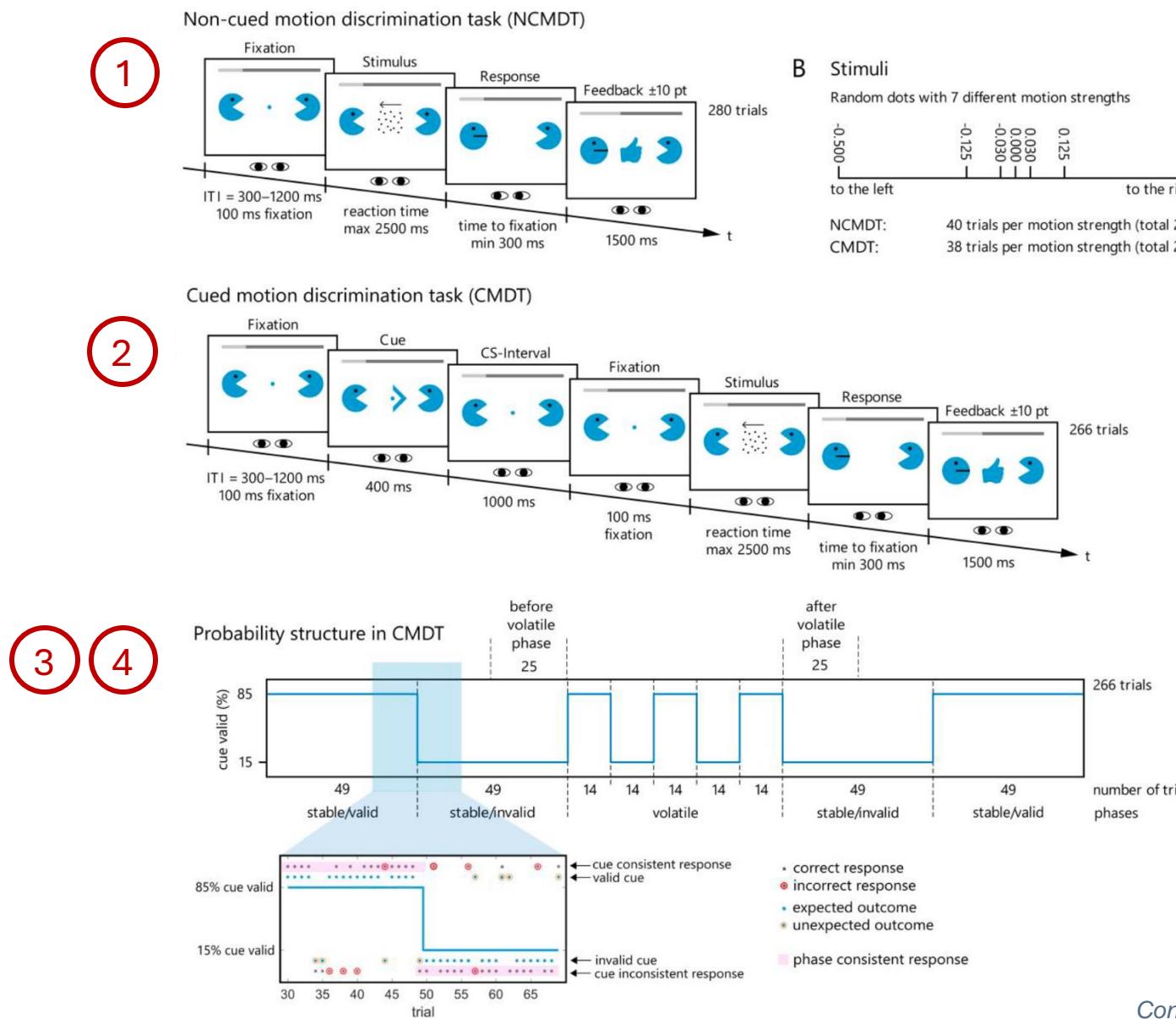
Which one matches?



Hypothesis about Perceptual Deficits in Autism Spectrum Disorder

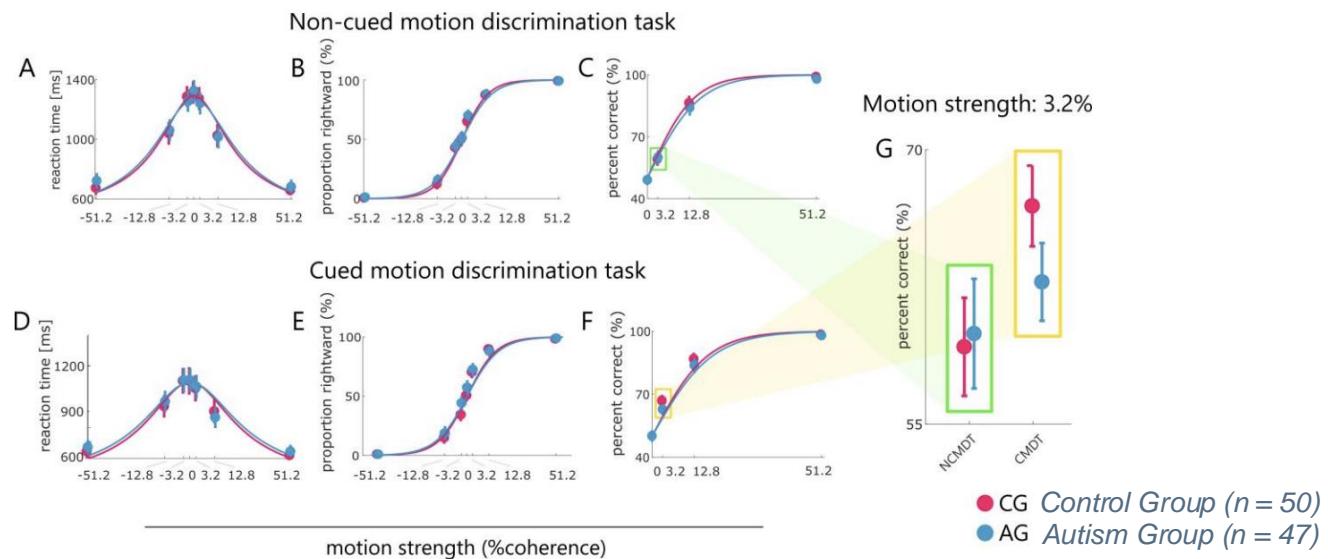


Testing the Hypothesis for Autism Spectrum Disorder

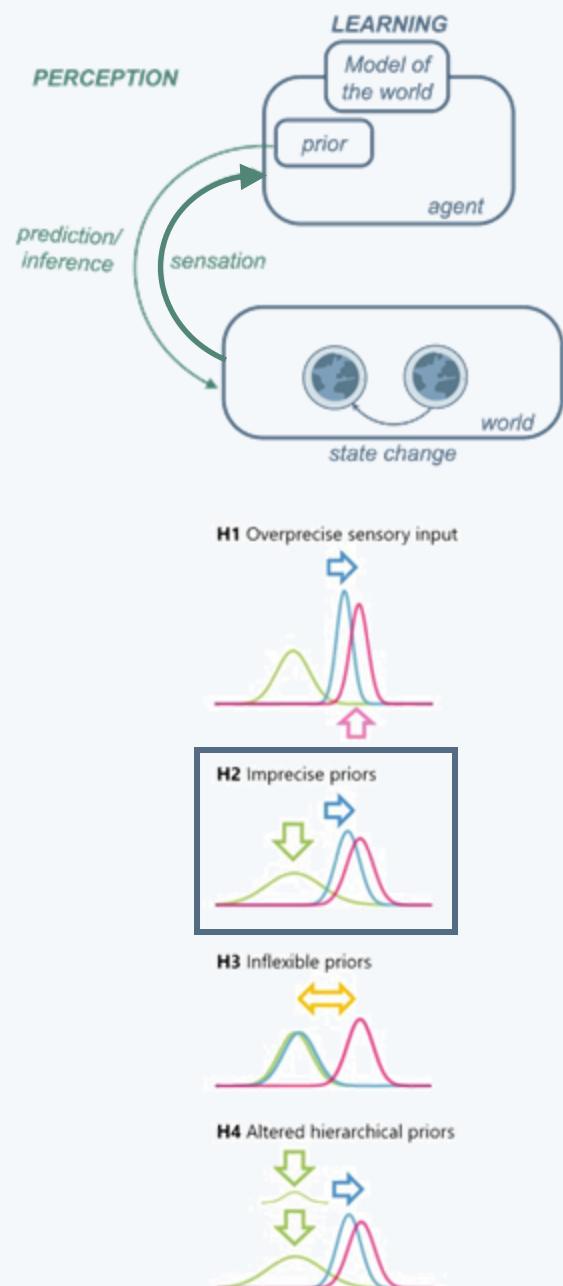
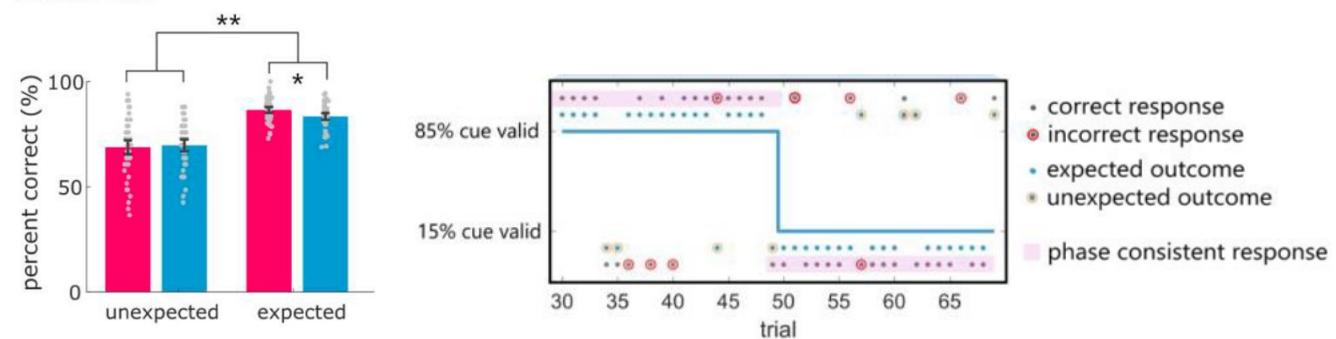


Maladaptive inference in Autism Spectrum Disorder

Patients with ASD rely less on prior information with sensory uncertainty is high



ASD did benefit less in trials where the cue was reliable

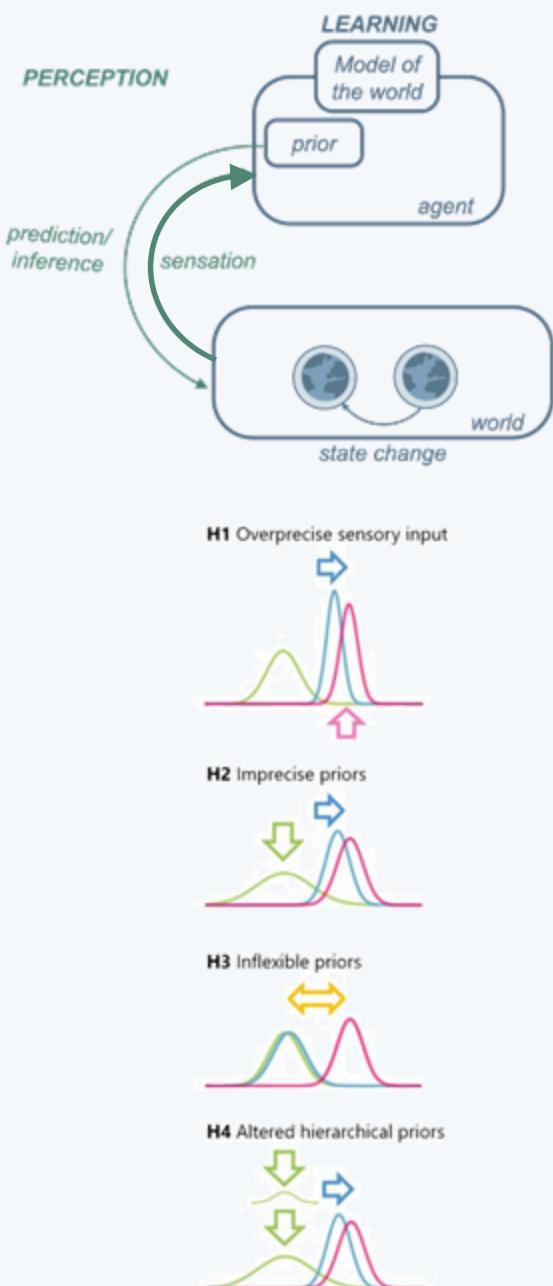


Maladaptive inference in Autism Spectrum Disorder

H1: Overprecise sensation hypothesis	H2: Imprecise prior hypothesis	H3: Inflexible prior hypothesis	H4: Hierarchical learning of priors
Does sensory processing and evidence accumulation differ between the AG and CG in the NCMDT?	Does the AG use contextual prior information less than the CGs?	Does the AG have more difficulties than the CG in updating a contextual prior after learning it initially?	Is the use of prior information in the AG less modulated by the volatility of the contextual cue than in the CG?
<p>✗ H1a The AG and CG differ in accuracy and RT.</p> <p>✗ H1b The AG and CG differ in DDM parameter estimates (drift, threshold).</p>	<p>✓ H2a The AG benefits less than the CG from prior information provided by cues.</p> <p>✓ H2b The AG shows a smaller difference in accuracy between expected and unexpected stimuli than the CG.</p> <p>✓ H2c Responses of the AG are less phase-consistent on zero-coherence trials than response of the CG.</p> <p>✓ H2d Responses of the AG are less phase-consistent on question trials than those of the CG.</p> <p>✓ H2e The AG reports lower cue confidence than the CG on question trials.</p>	<p>✗ H3a The AG chooses options consistent with the cue more frequently (are more cue consistent) than the CG.</p> <p>✗ H3b The AG is more cue consistent in their reports on question trials than the CG.</p>	<p>✓ H4a Stability modulates the accuracy difference between expected and unexpected trial outcomes less in the AG than in the CG.</p> <p>✗ H4b Stability modulates the phase consistency less in the AG than in the CG.</p> <p>✗ H4c Stability modulates the reported phase consistency less in the AG than in the CG.</p> <p>✓ H4d Stability of the phase modulates the reported cue confidence less in the AG than in the CG.</p>



Autism Paper



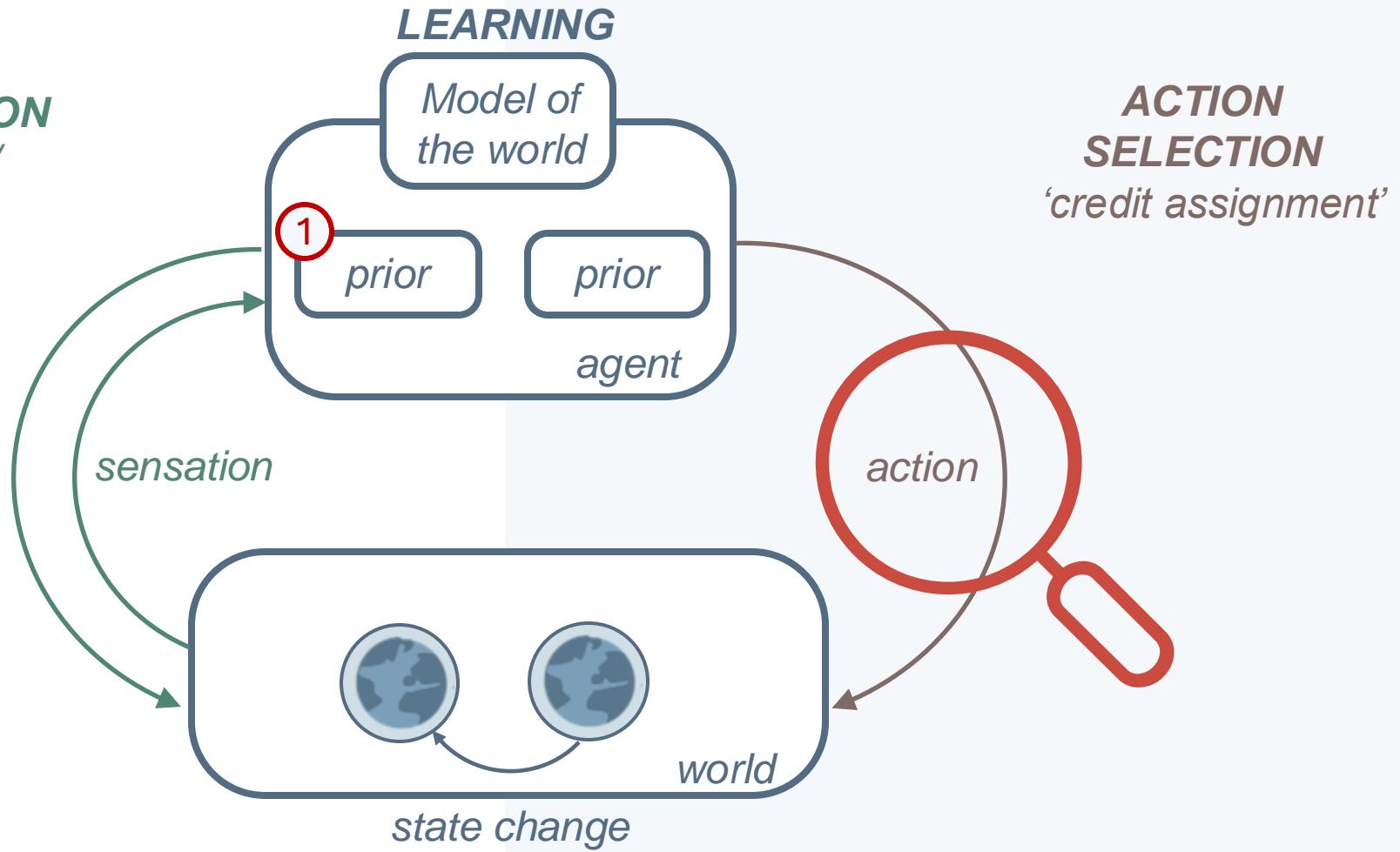
PERCEPTION
*prediction/
inference*

1

*Autism: Imprecise priors may
underlie perceptual symptoms
in Autism Spectrum Disorder*



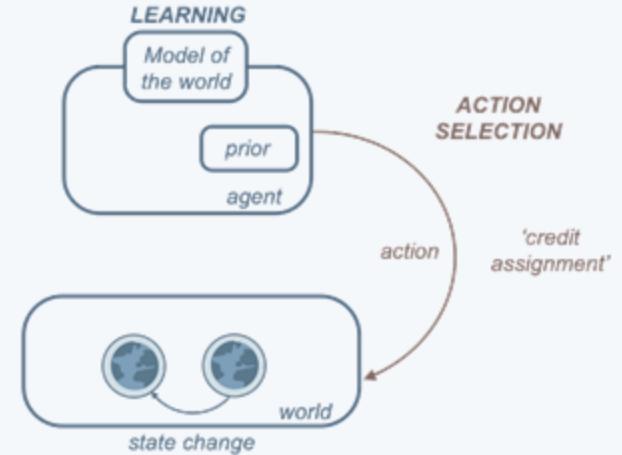
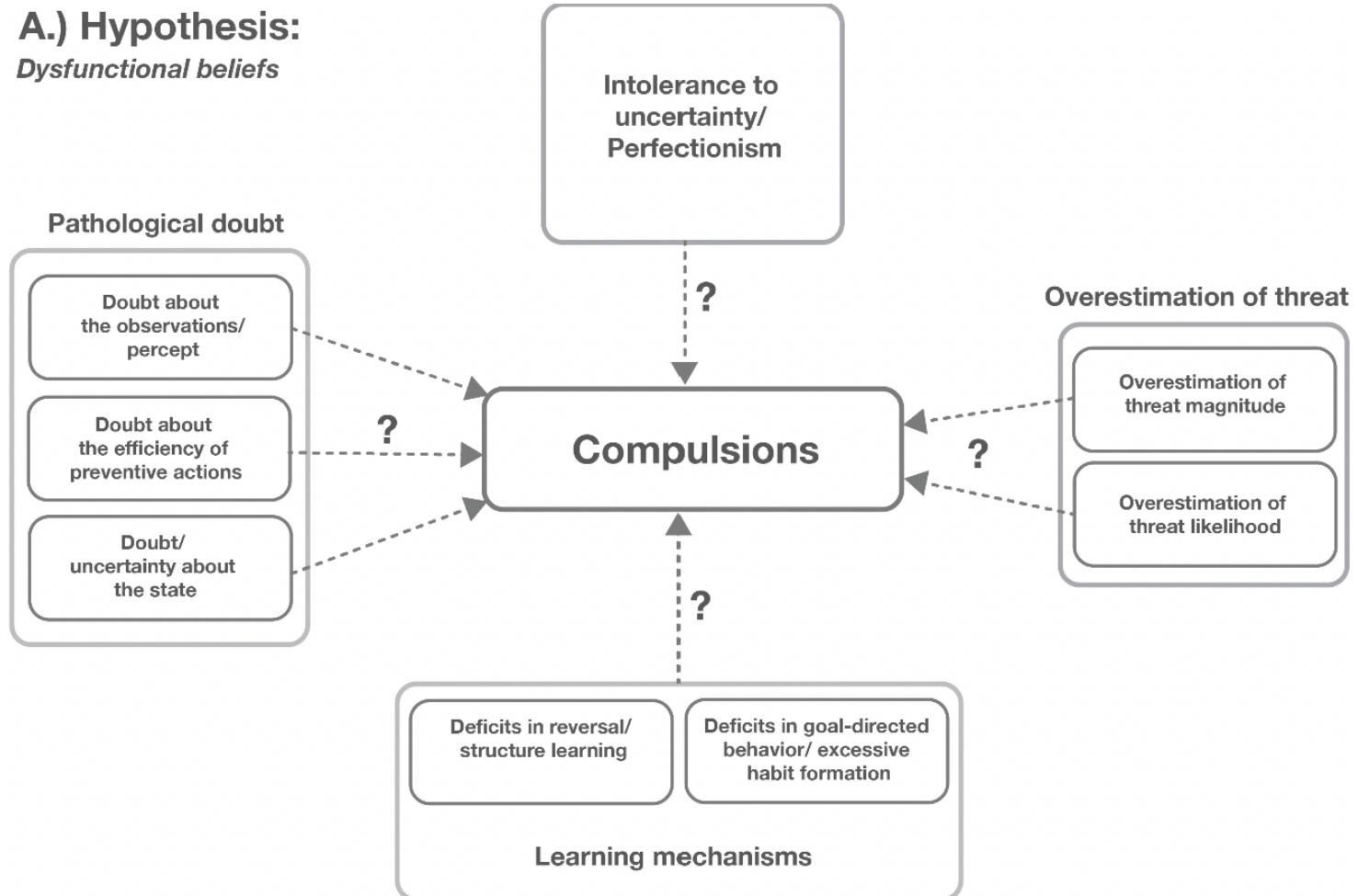
Autism Paper



Obsessive-Compulsive Disorder

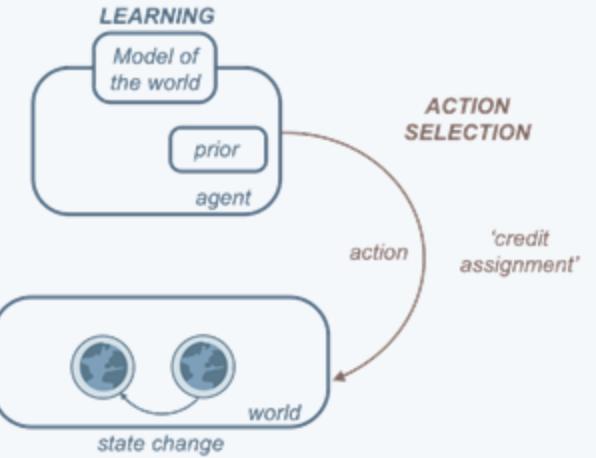
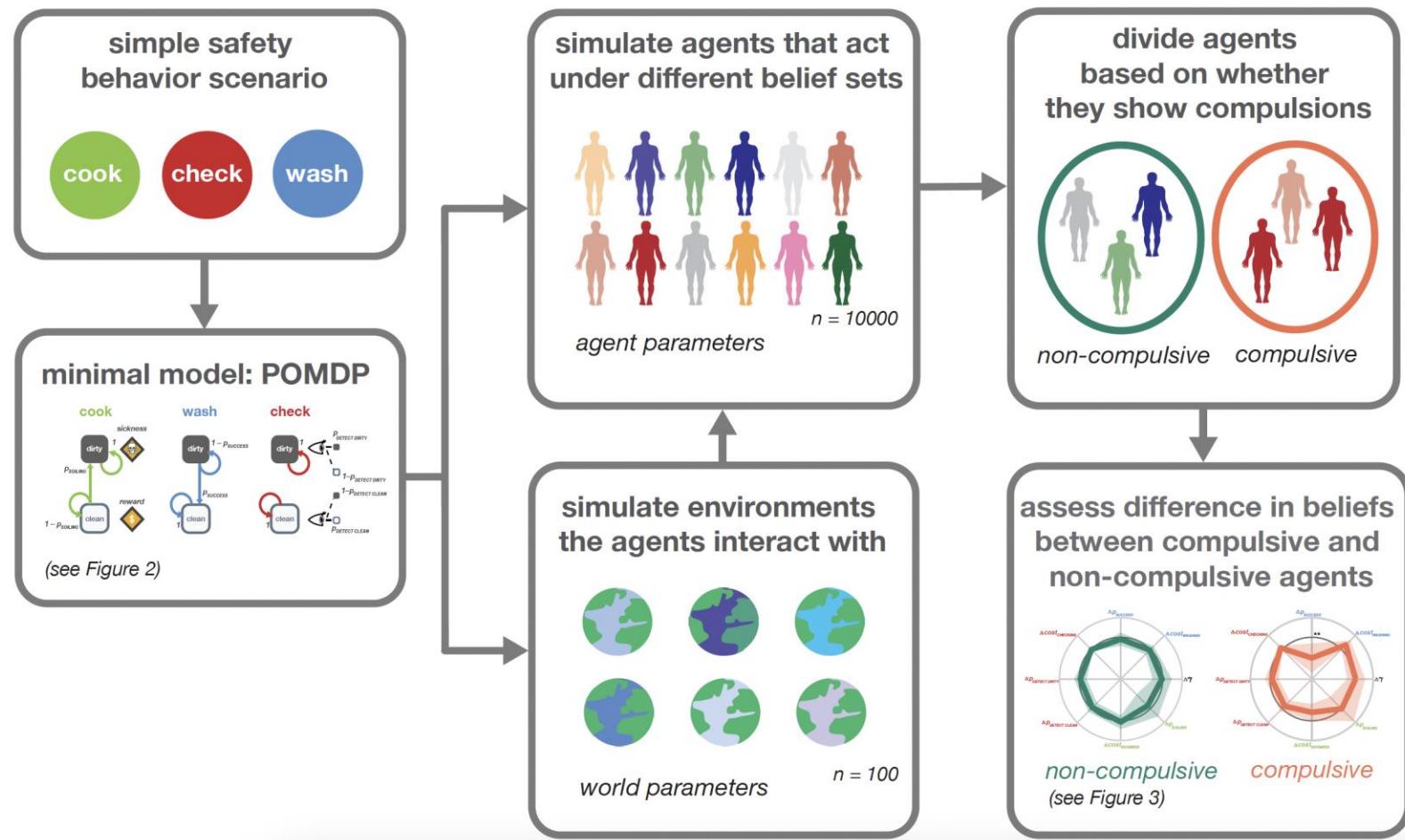
A.) Hypothesis:

Dysfunctional beliefs

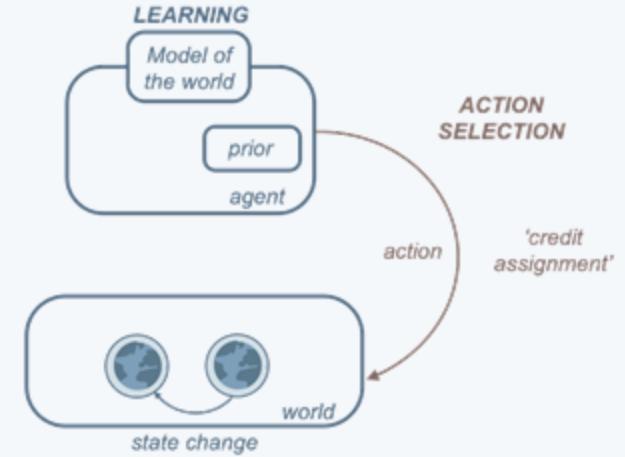
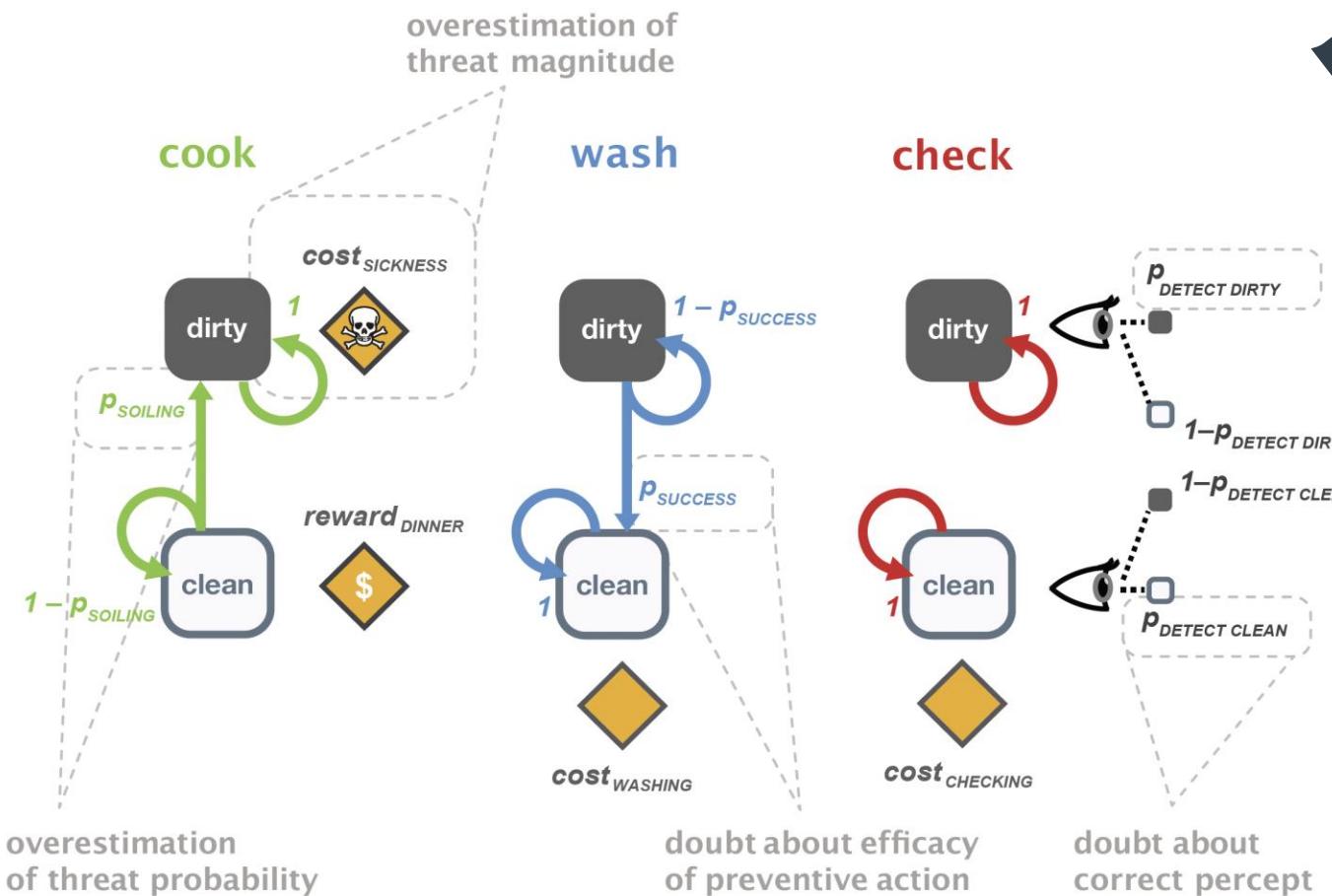


Klaas Enno Stephan Lionel Rigoux

A model of compulsions

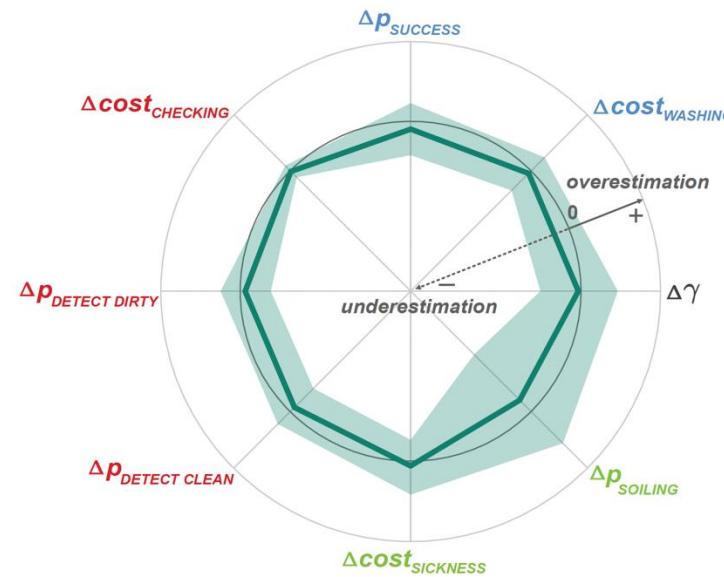


Modeling the impact of beliefs on behavior

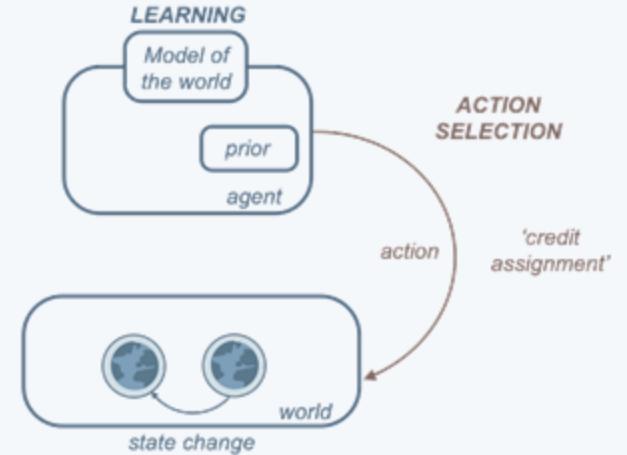
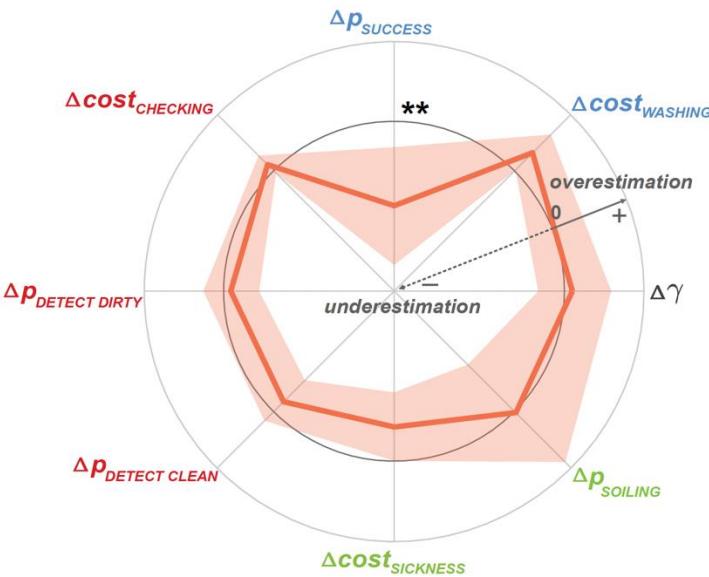


Compulsive behavior is driven by a distrust in effective avoidance

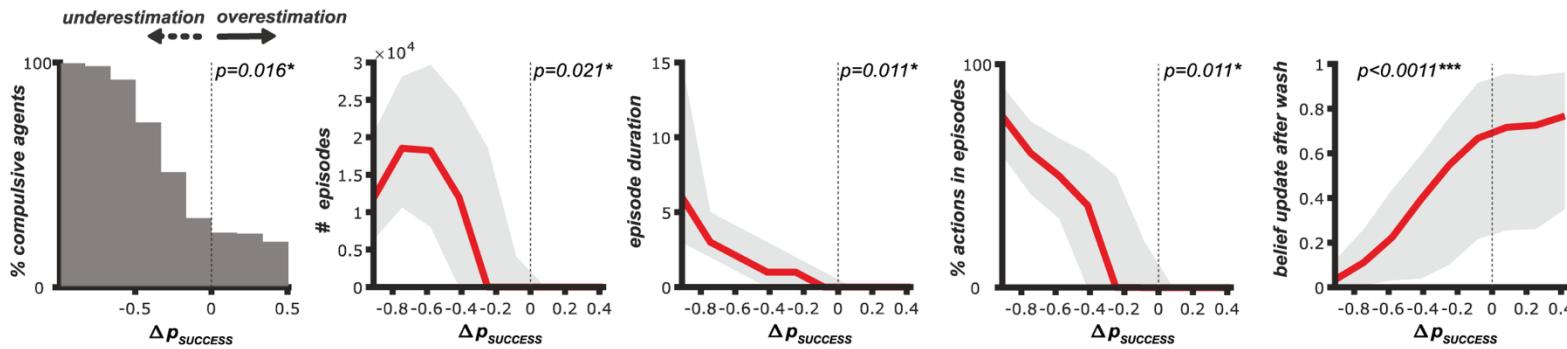
A. belief distortion for non-compulsive group



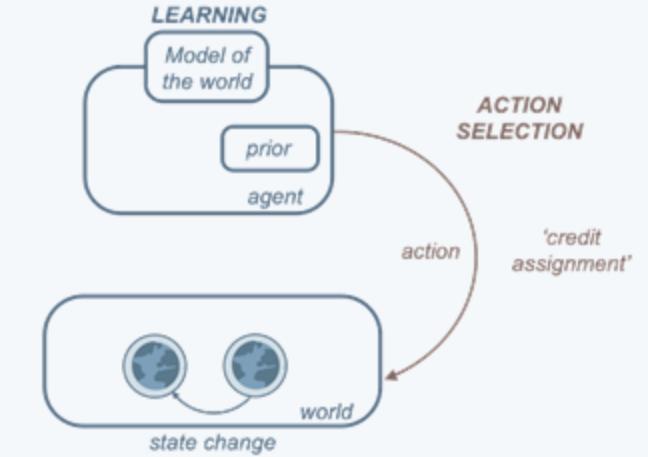
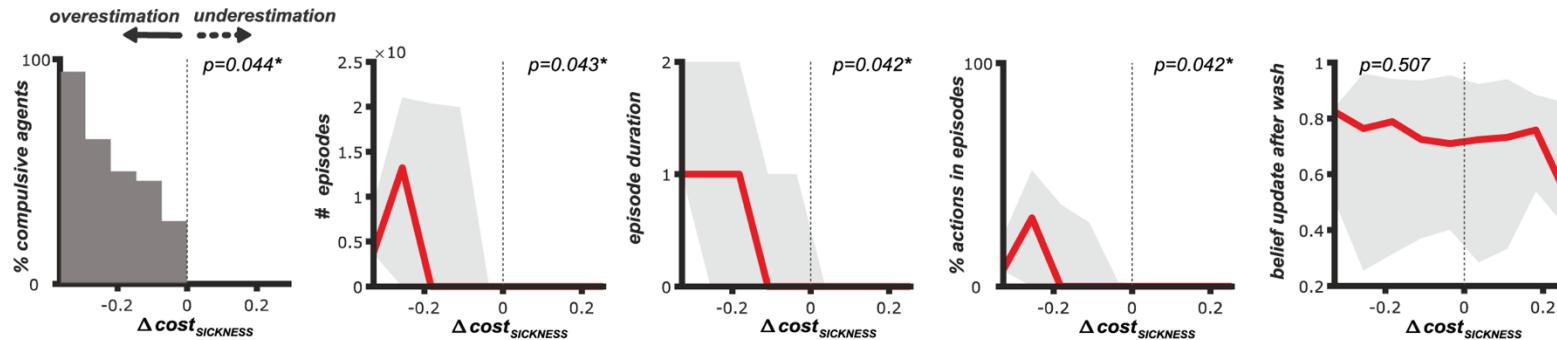
B. belief distortion for compulsive group



Distrust in avoidance effectiveness is sufficient to cause compulsions and correlated with increases in compulsion severity.

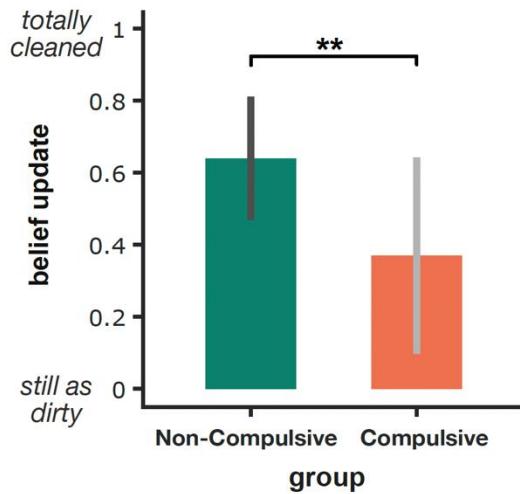


Overestimation of threat can trigger the onset of compulsive episodes, but does not sustain compulsions

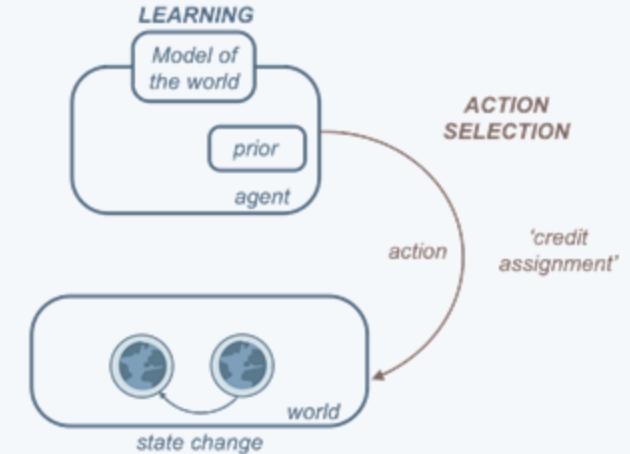
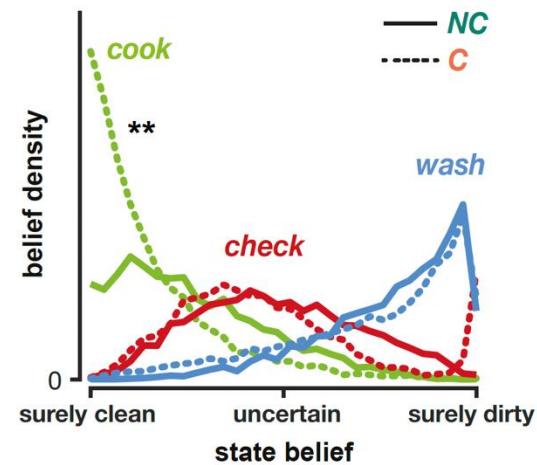


Underestimation of avoidance success leads to slowed belief updating and pathological doubt

A. belief updating after wash

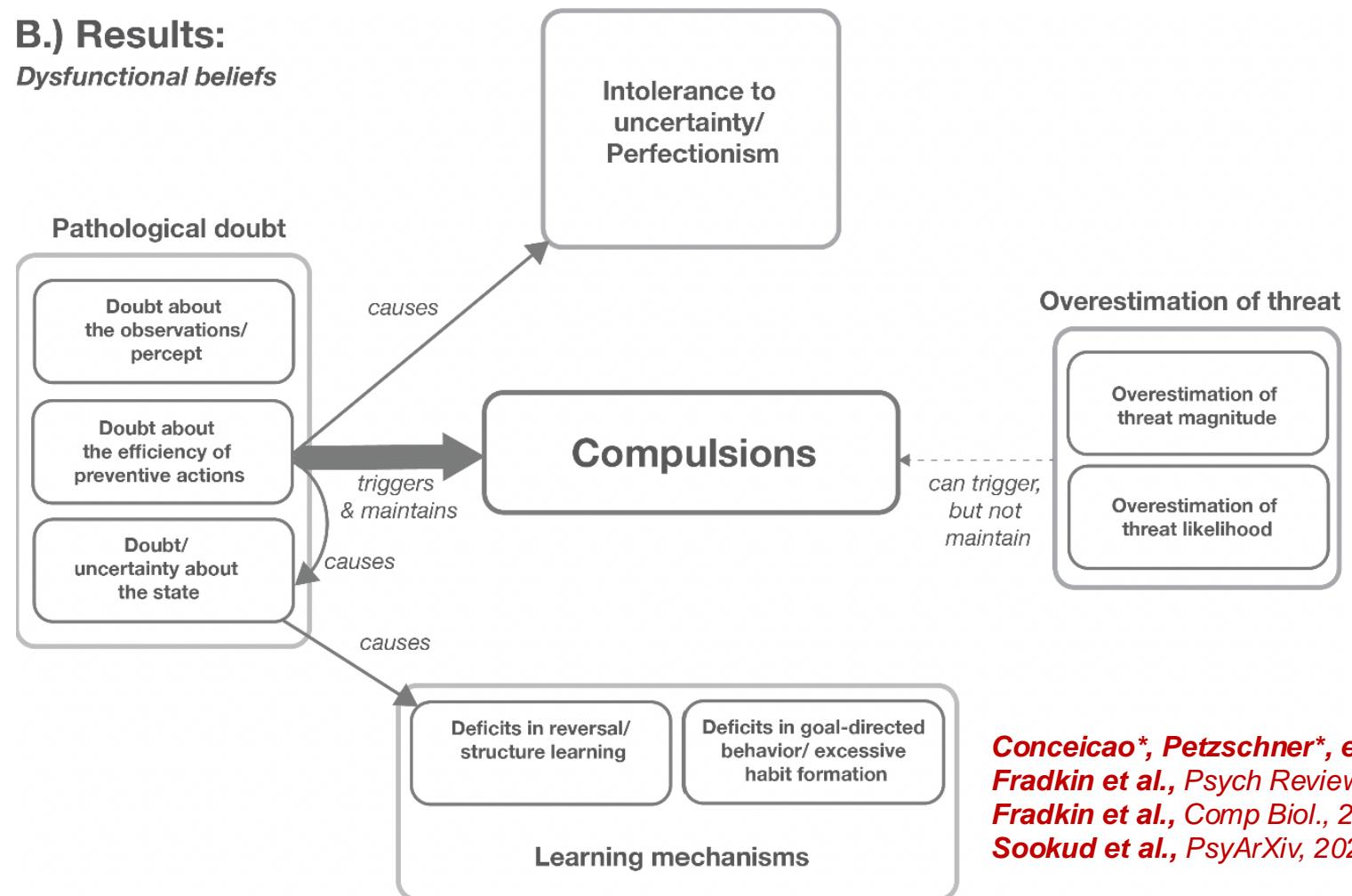


B. average belief per action



B.) Results:

Dysfunctional beliefs

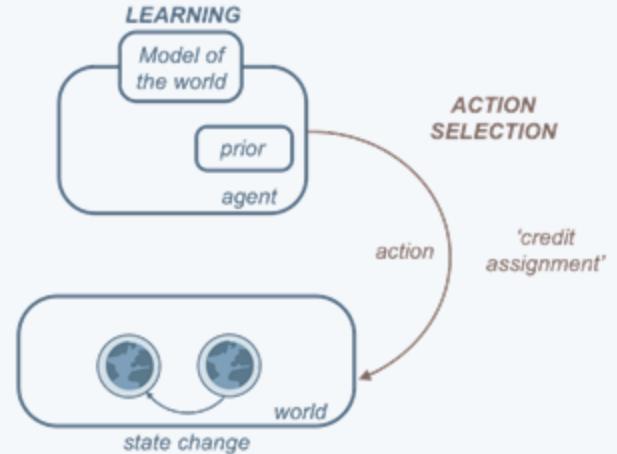


Conceicao*, Petzschner*, et al., BioRxiv, 2023

Fradkin et al., Psych Review, 2020

Fradkin et al., Comp Biol., 2020

Sookud et al., PsyArXiv, 2024

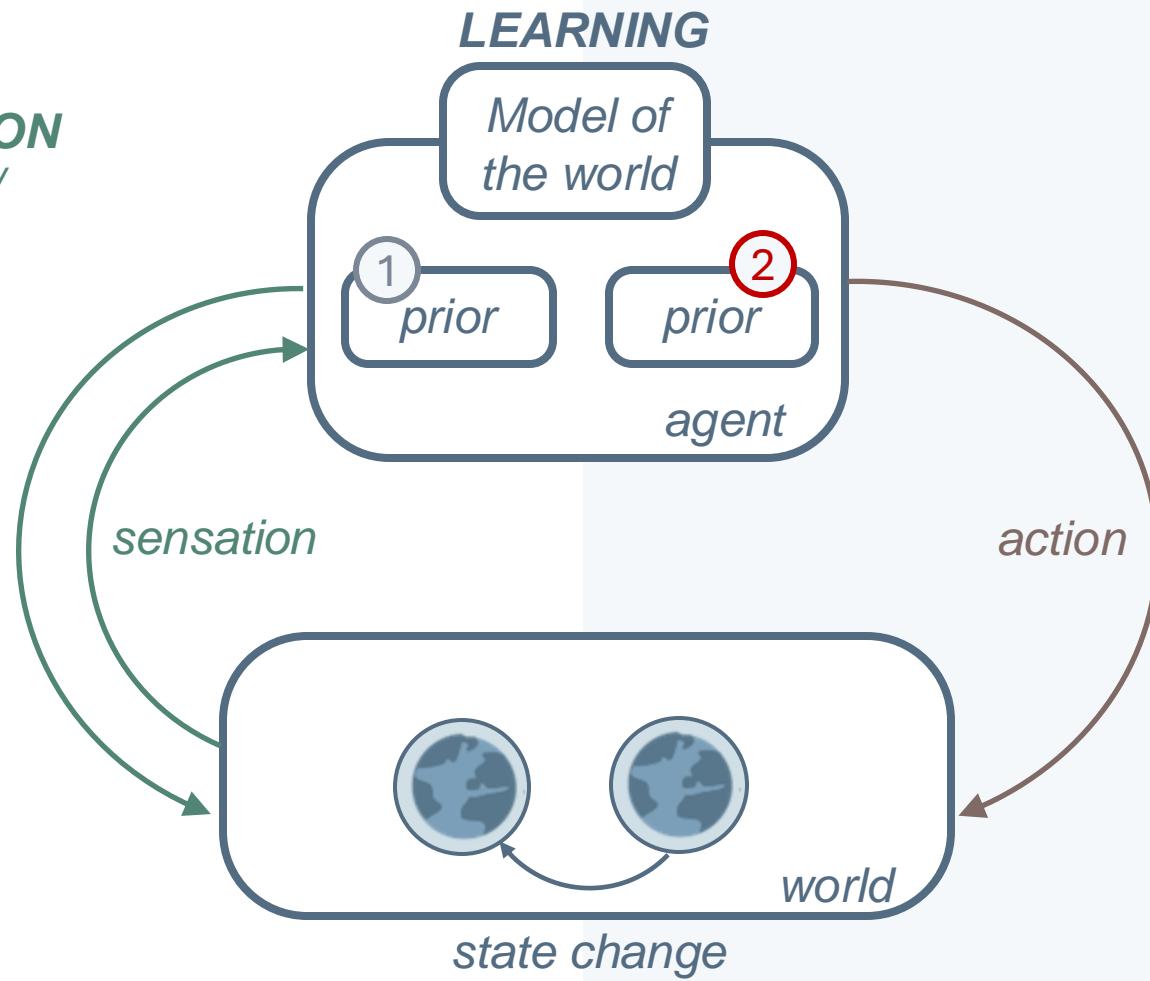


Get the Paper

PERCEPTION *prediction/ inference*

1

Autism: Imprecise priors may underlie perceptual symptoms in Autism Spectrum Disorder



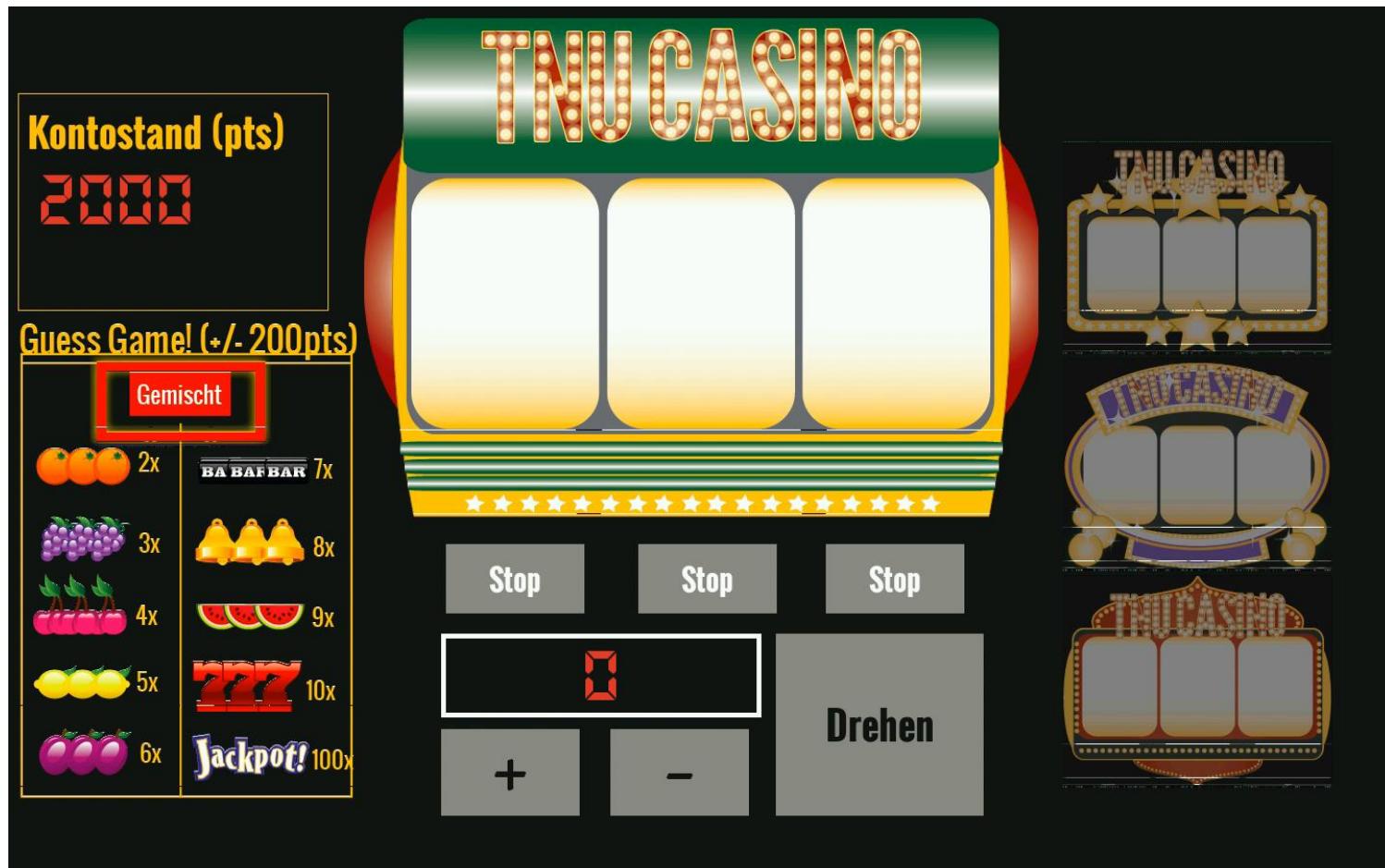
ACTION SELECTION *'credit assignment'*

2

OCD: decreased belief about control can cause compulsion (harm avoidance)



Maladaptive Credit Assignment in Pathological Gambling

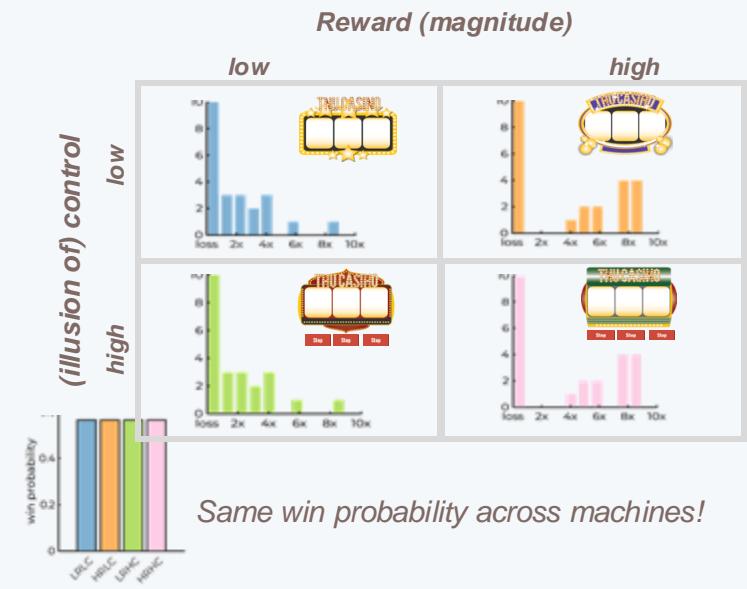


Recreational Gamblers ($n = 43$)
Pathological Gamblers ($n = 44$)

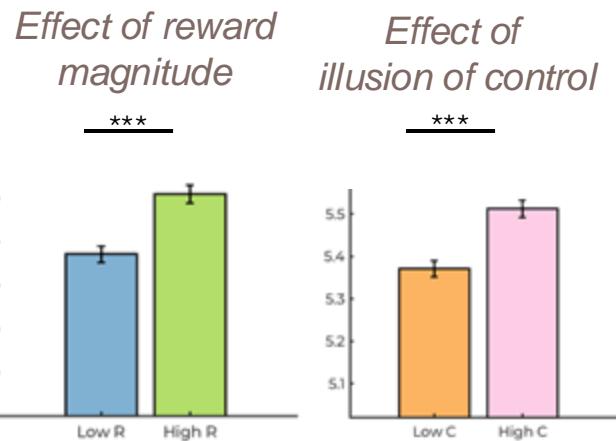
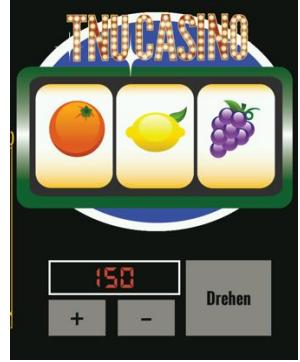


Saeed Paliwal Gina Paolini Stephanie Olayia

Independent manipulation of reward and control



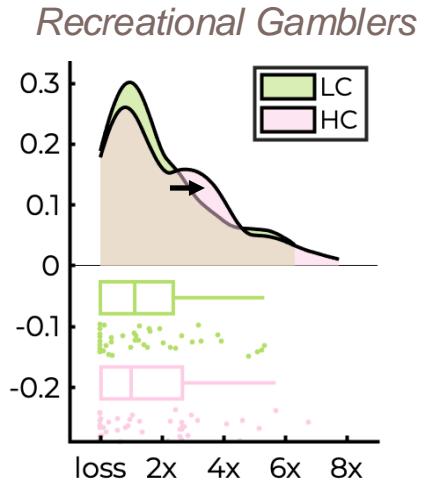
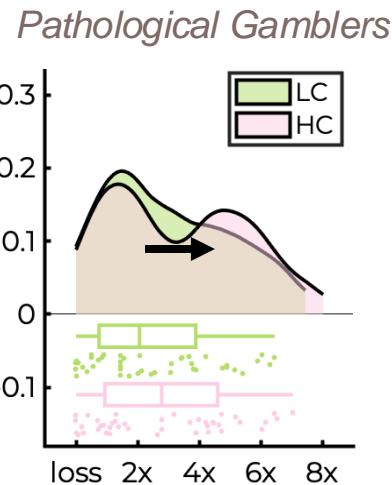
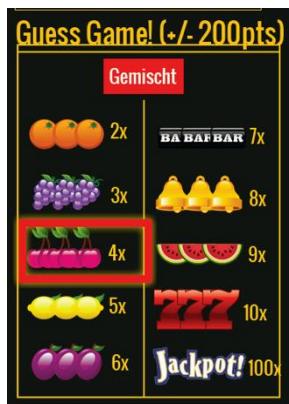
Beliefs about control increase bet size



LME for log(betsize):
 *** Main effect of reward magnitude
 *** Main effect of control illusion
 * Main effect of patient
 ** Interaction reward magn. x control illusion
 ** Interaction patient x control illusion
 n.e. Interaction patient x reward magnitude

reward magnitude	
(illusion of) control	
Low/Low	Low/High
High/Low	
High/High	

Beliefs about control increase outcome prediction

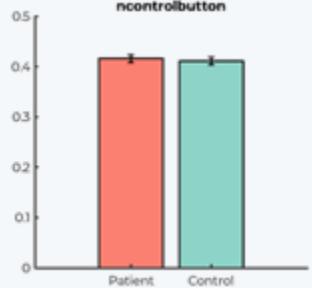


True Control:
 $P_{obj}(\text{Outcome}|\text{Action})$

Illusion of control belief:
 $P_{subj}(\text{Outcome}|\text{Action})$

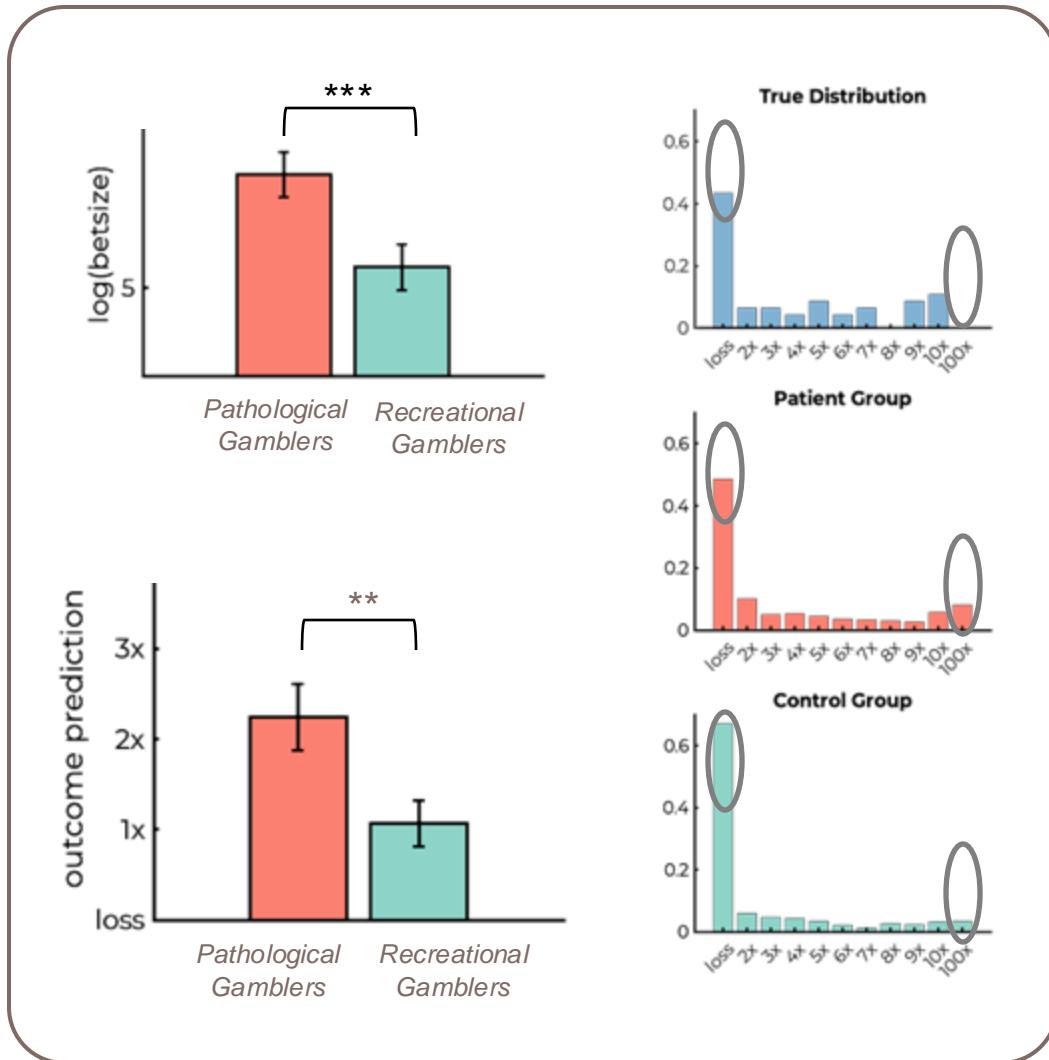
LME gamma link for outcome prediction:
 * Main effect of control illusion
 *** Main effect of reward magnitude
 ** Main effect of patient
 n.s. Interaction reward x control illusion
 *** Interaction patient x reward
 n.s. Interaction patient x control illusion

The effect of control does not depend on whether we execute control!

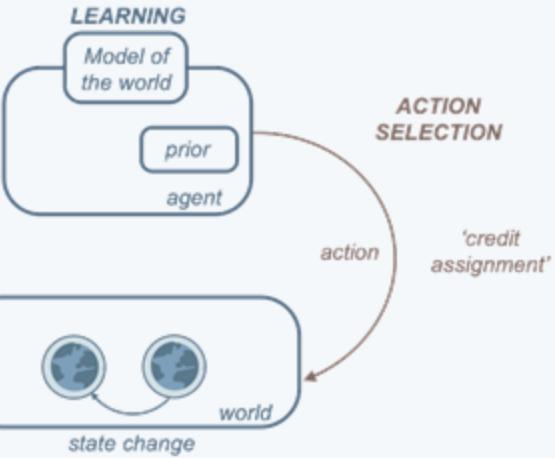
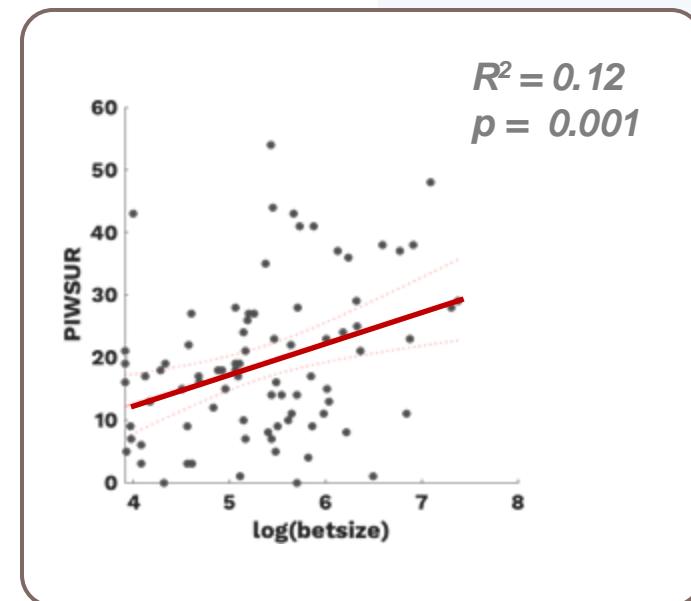


Recreational Gamblers ($n = 43$)
 Pathological Gamblers ($n = 44$)

Group Differences



*Baseline number of button
presses should relate to
compulsivity*



Recreational Gamblers ($n = 43$)
Pathological Gamblers ($n = 44$)

Group Differences

Computational Model: RL

No learning

Model 1: $\log(b_i) \sim \beta_1$

Model 2: $\log(b_i) \sim \beta_1 + \beta_2 \cdot r_{t-1}$

Learning a value of the machine (context)

Model 3: $\log(b_i) \sim \beta_1 + \beta_2 \cdot V_t$

$$V_{t+1}(s) = V_t(s) + \alpha_1 \delta_{V,t}$$

Model 4: $\log(b_i) \sim \beta_1 + \beta_2 \cdot V_t$

$$\text{if } \delta_{V,t} \geq 0: V_{t+1}(s) = V_t(s) + \alpha_1 \delta_{V,t}$$

$$\text{if } \delta_{V,t} < 0: V_{t+1}(s) = V_t(s) + \alpha_2 \delta_{V,t}$$

Learning + Control as Value increase

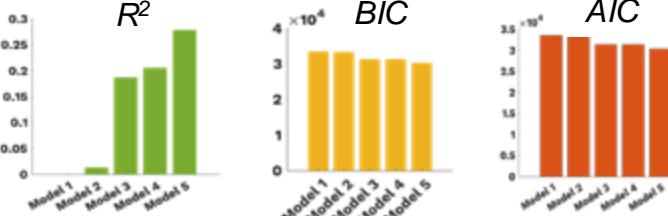
Model 5: $\log(b_i) \sim \beta_1 + \beta_2 \cdot V_t$

$$\text{if } \delta_{V,t} \geq 0: V_{t+1}(s) = V_t(s) + \alpha_1 \delta_{V,t}$$

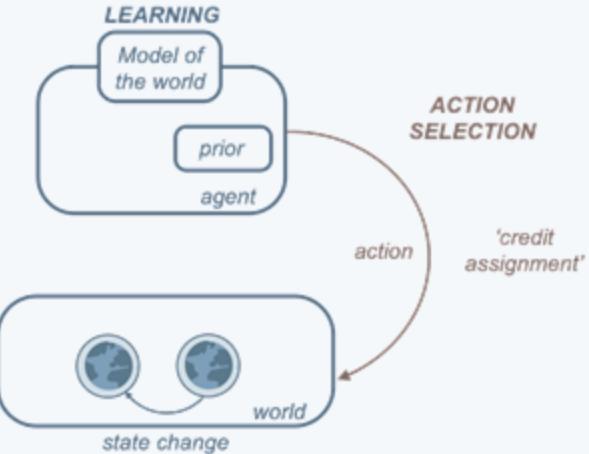
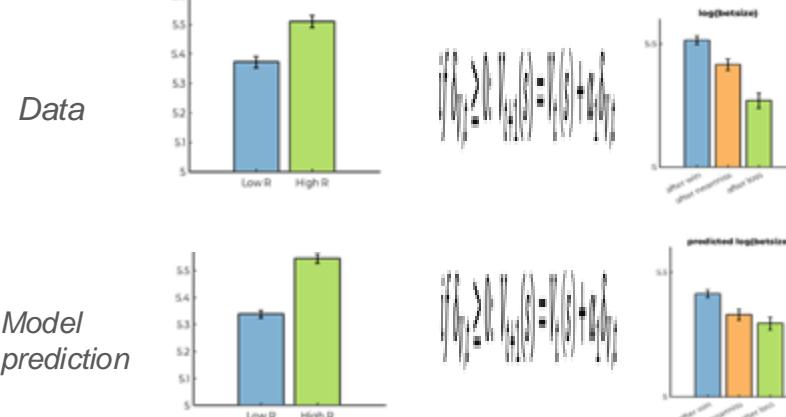
$$\text{if } \delta_{V,t} < 0: V_{t+1}(s) = V_t(s) + \alpha_2 \delta_{V,t}$$

$$\text{if control high: } V_{t+1}(s) = V_t(s) + \alpha_3 V_t(s)$$

Model 5 with learning and control is winning model



Winning model can capture the main effects in the data



PERCEPTION *prediction/ inference*

1 *Autism: Imprecise priors may underlie perceptual symptoms in Autism Spectrum Disorder*

LEARNING

*Model of
the world*

1 prior

2 prior

3

agent

sensation

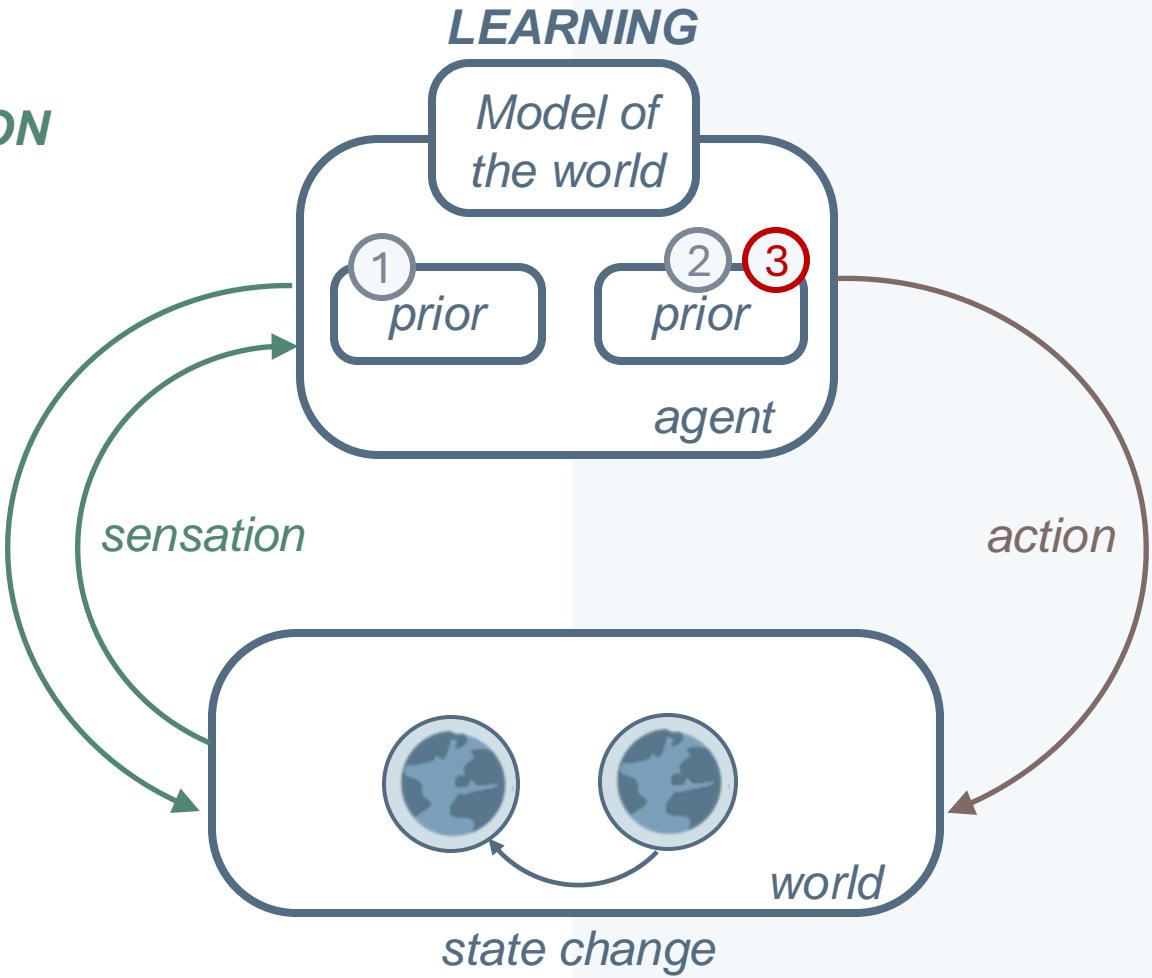
action

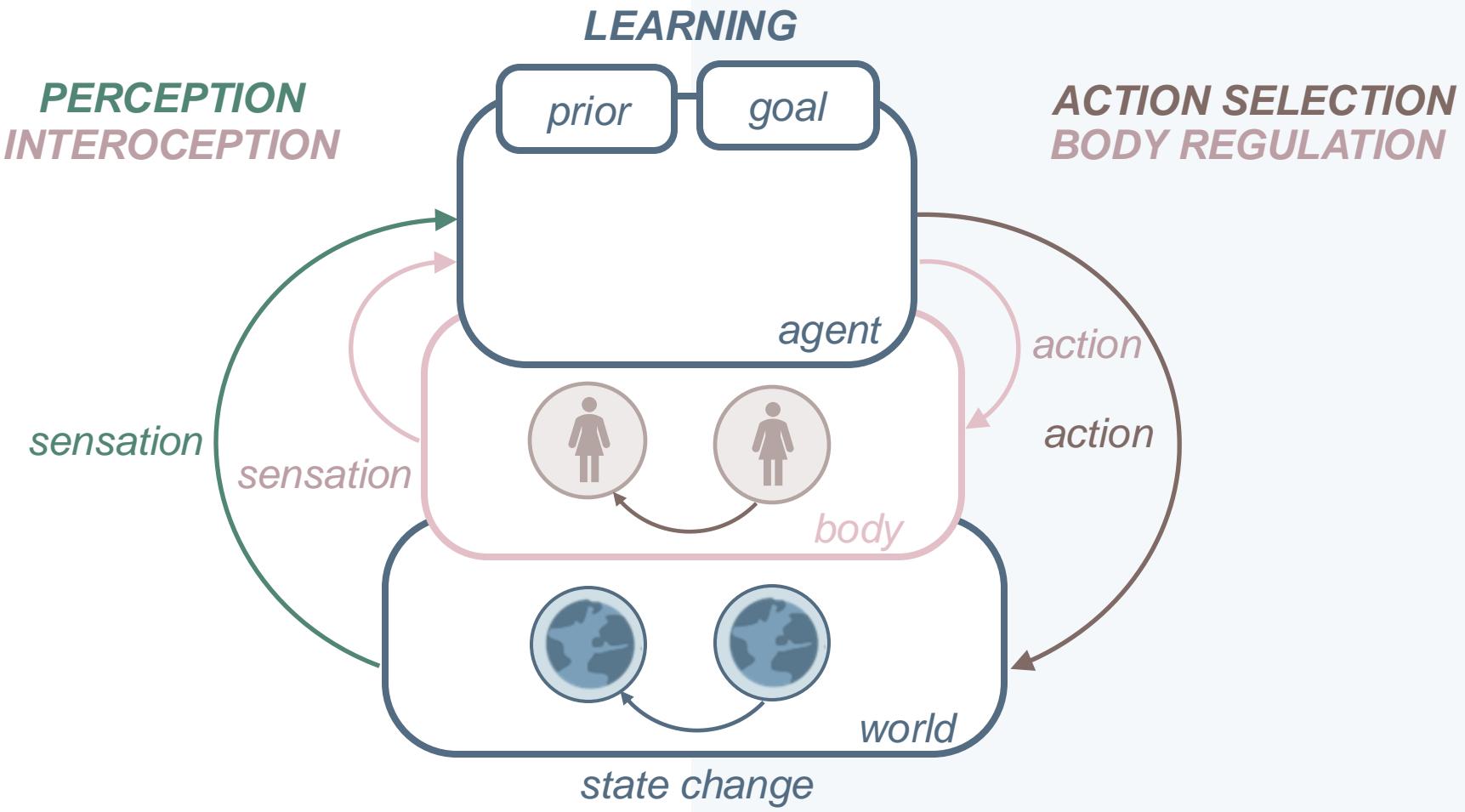
state change

ACTION SELECTION *'credit assignment'*

2 *OCD: decreased belief about control can cause compulsion (harm avoidance)*

3 ***Pathological Gambling:***
increased belief about control can cause compulsion (reward seeking)





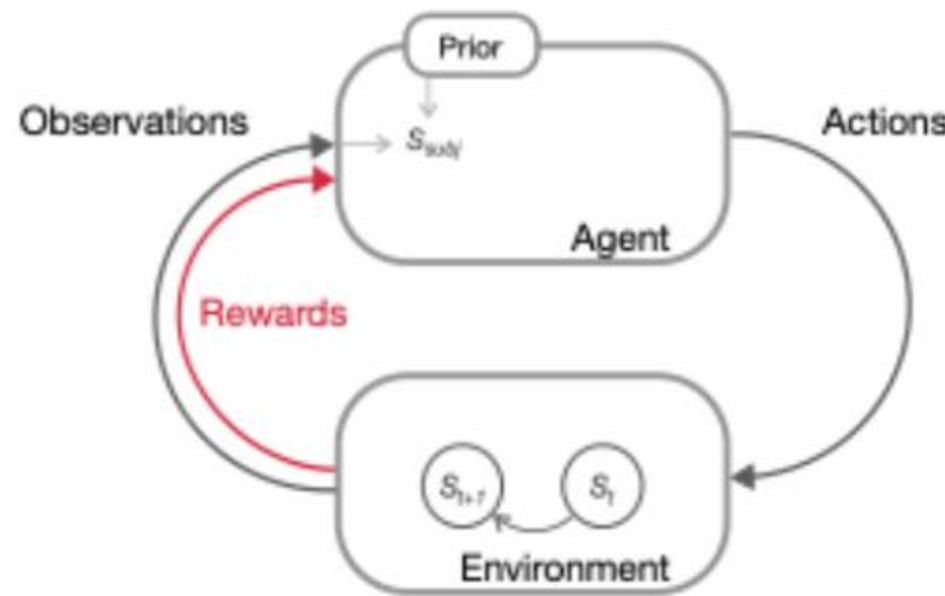
Seth, TiCS, 2012

Khalsa et al., Biol Psych, 2018

Petzschnner, Weber et al., Biol Psych, 2017

Petzschnner et al. TINS, 2021

New Preprint:
“Rethinking reinforcement learning: The interoceptive origins of reward”



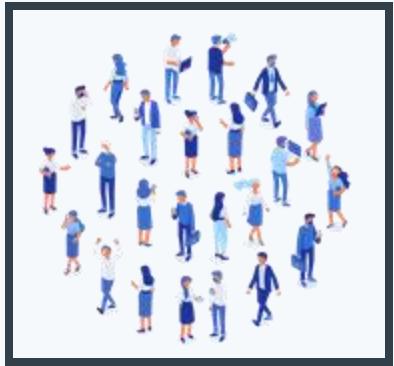
Reward Paper

1. Disease insights

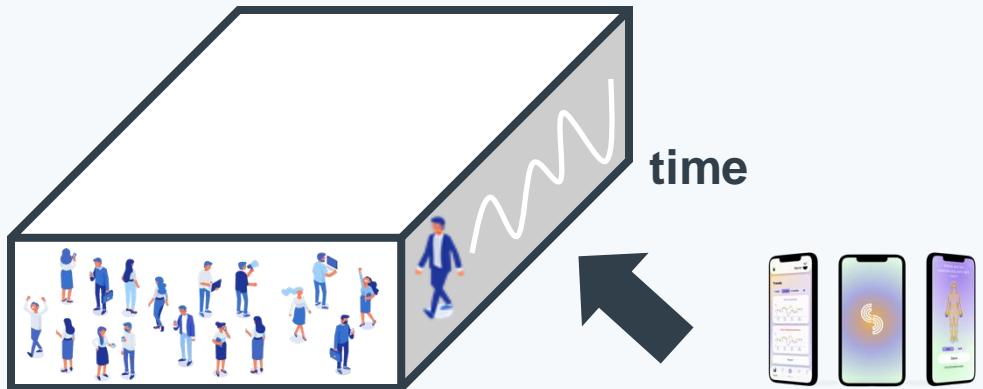
Mechanistic Models



Big data

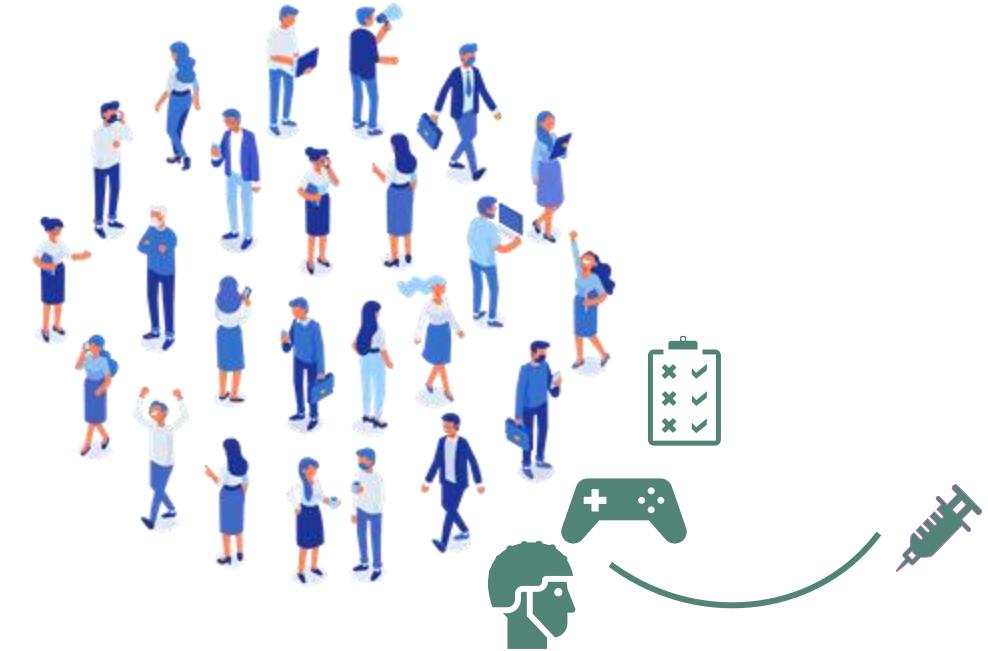


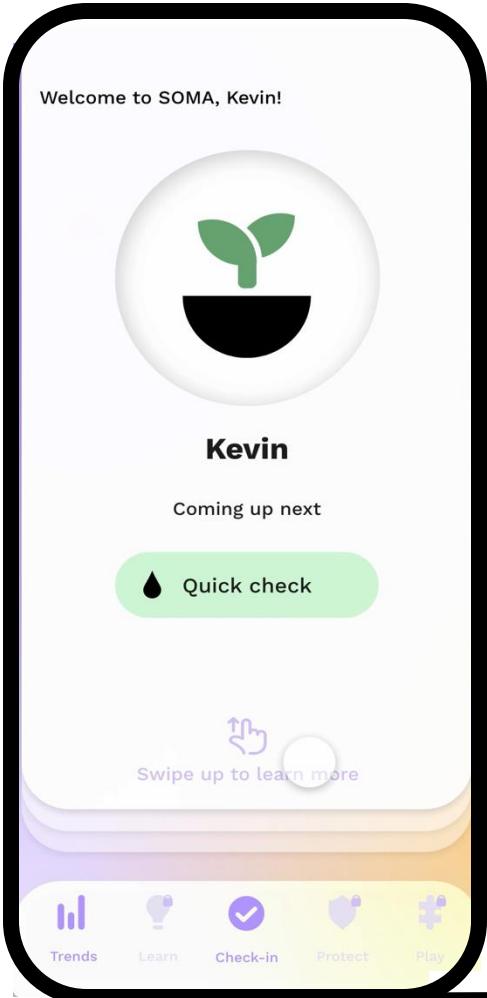
Prediction needs: Deep & wide data



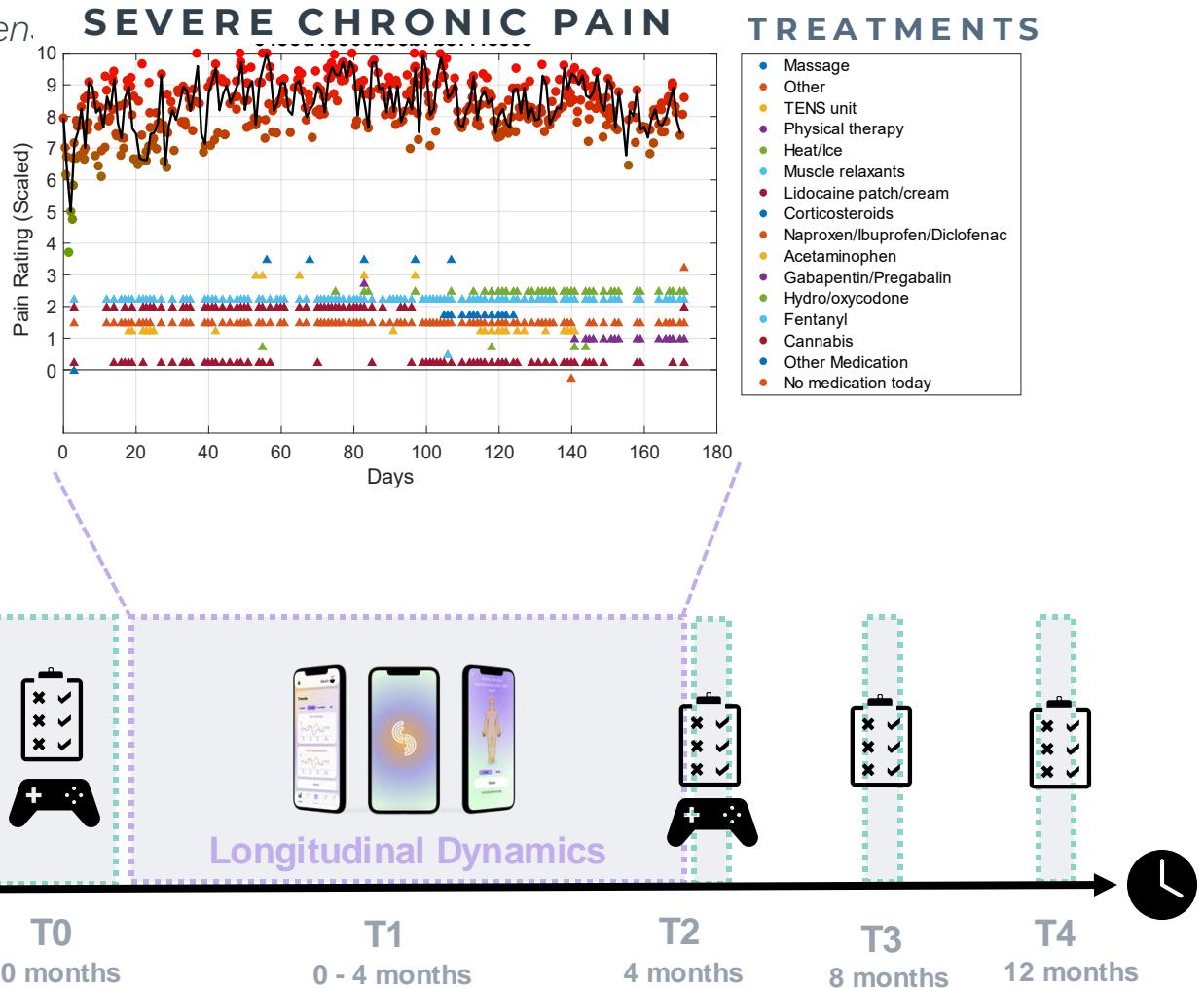
2. Predictive validity

Data-driven Models





- Pain intensity
- Pain intensity
- Pain intensity
- Pain intensity
- Mood
- Emotions
- Medications
- Treatments
- Activities
- Pain intensity



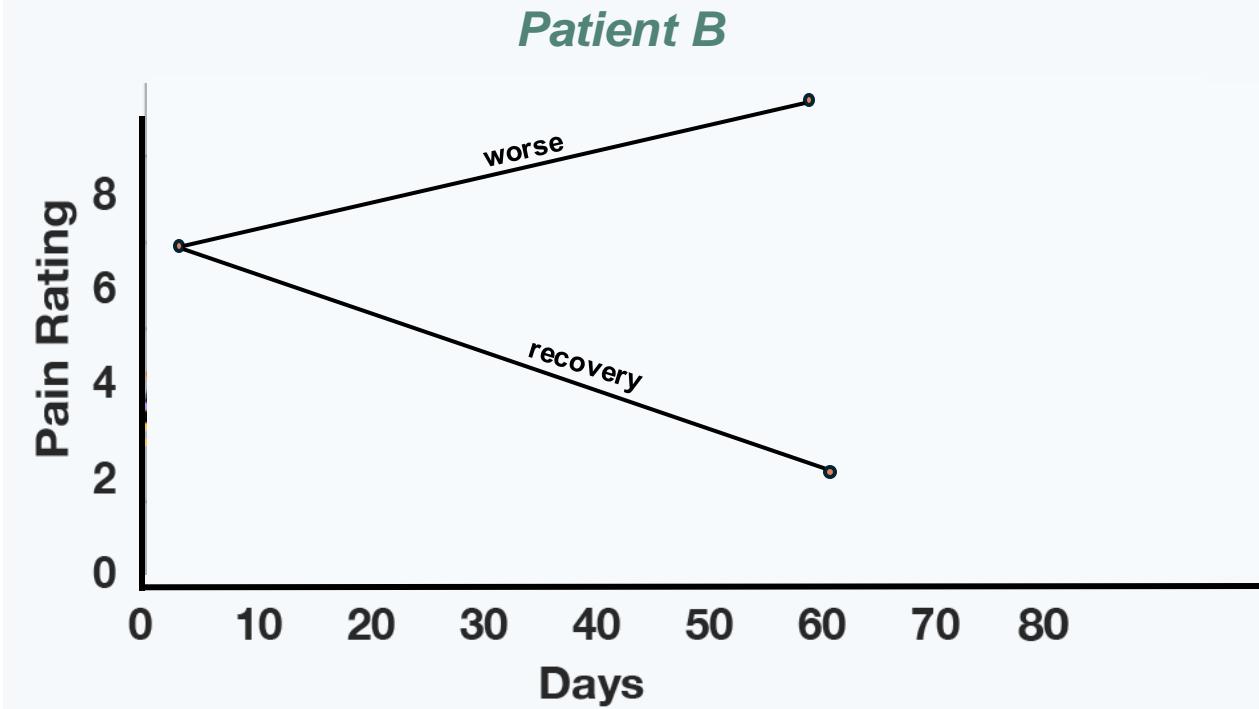
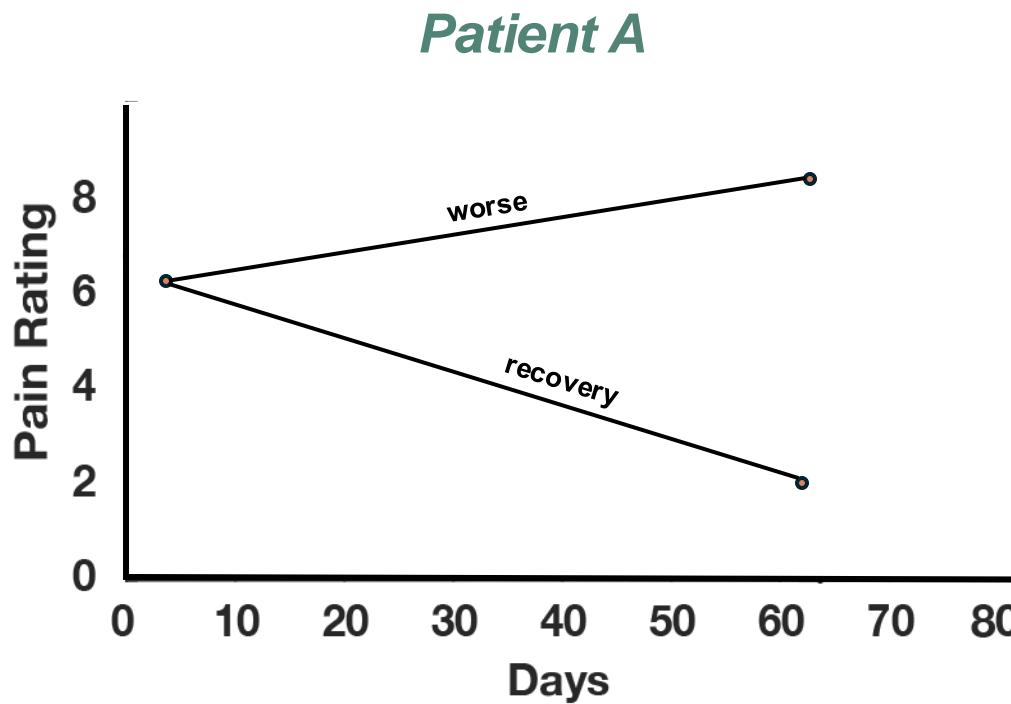
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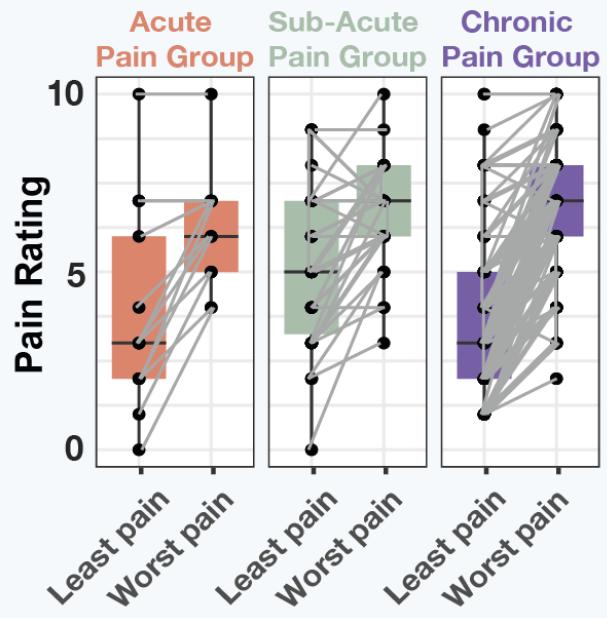


Pain and Mood are highly variable. Single ratings often fail to give a full picture of recovery.

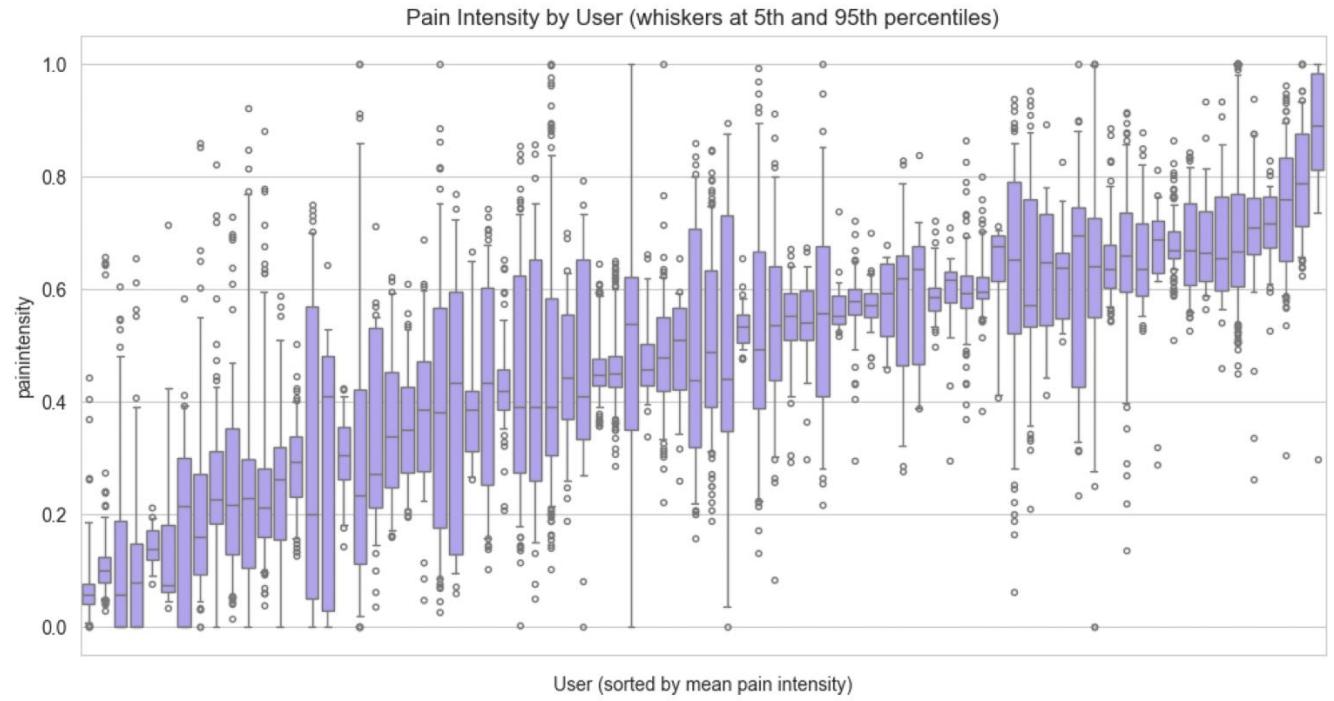


Variability with days and across months

Within 24h



Within 4 month

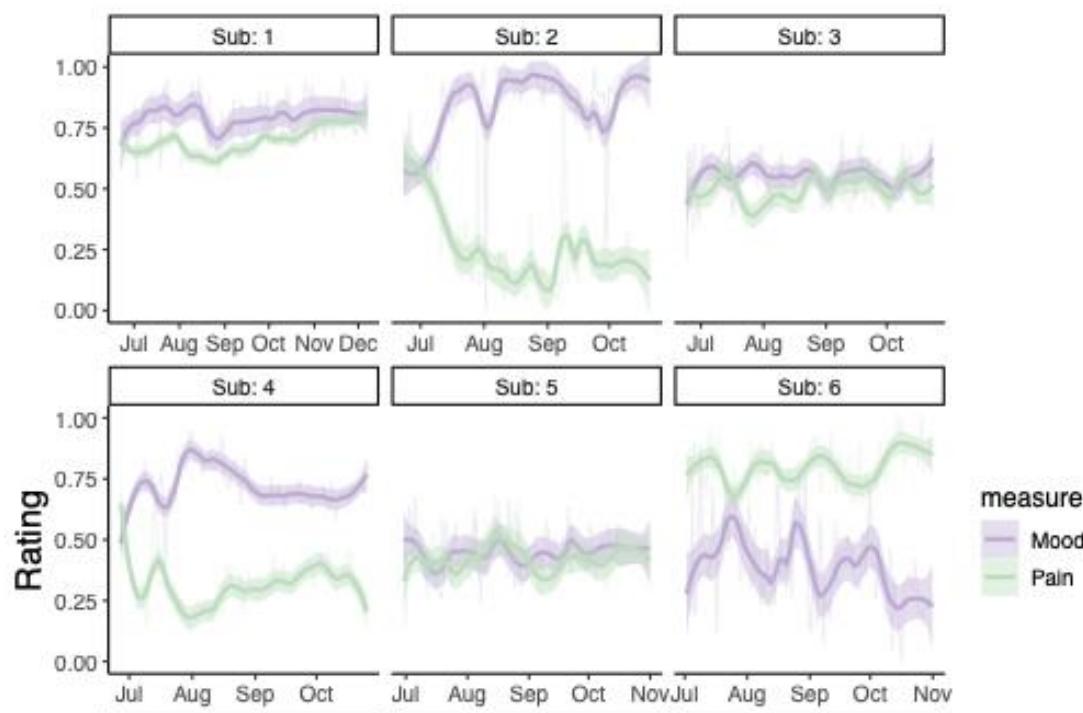




What predicts pain change over time?

day to day

SHORTTERM:

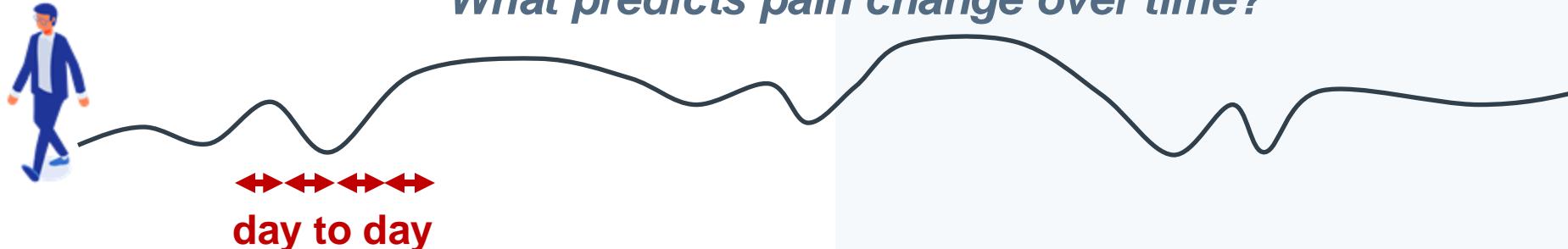


Chloe Gunsilius



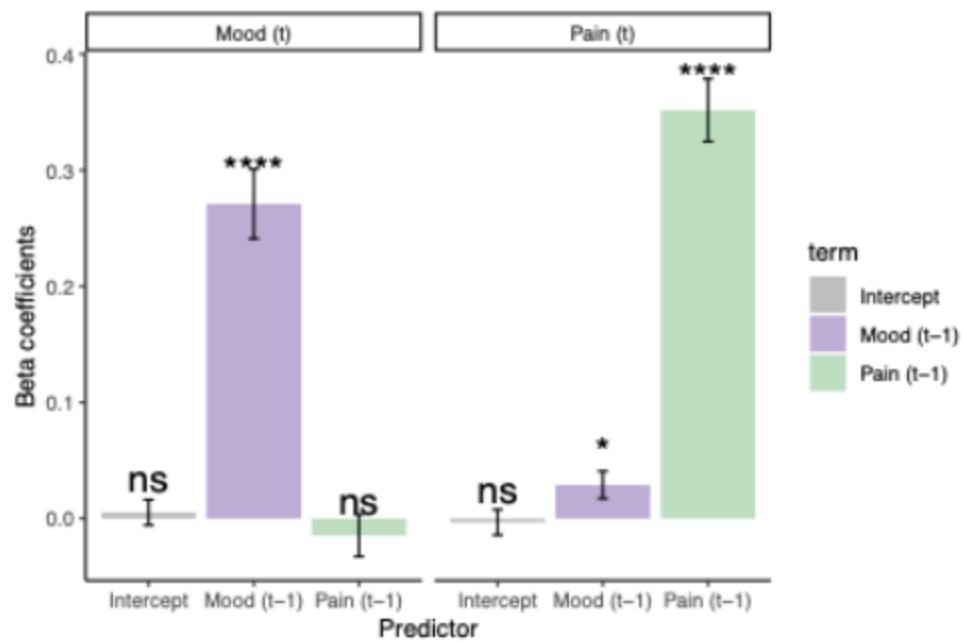
Joseph Heffner

What predicts pain change over time?



SHORTTERM:

*Mood and expected pain best predict current pain,
but current pain does not predict future mood*

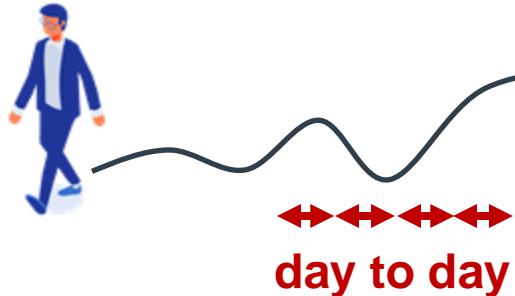


Chloe Gunsilius

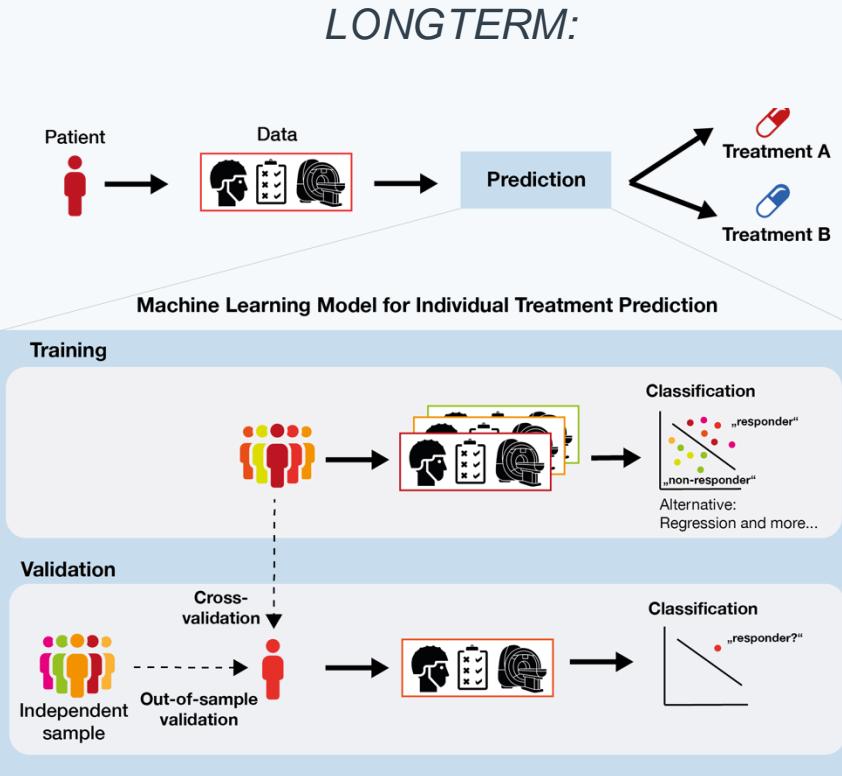
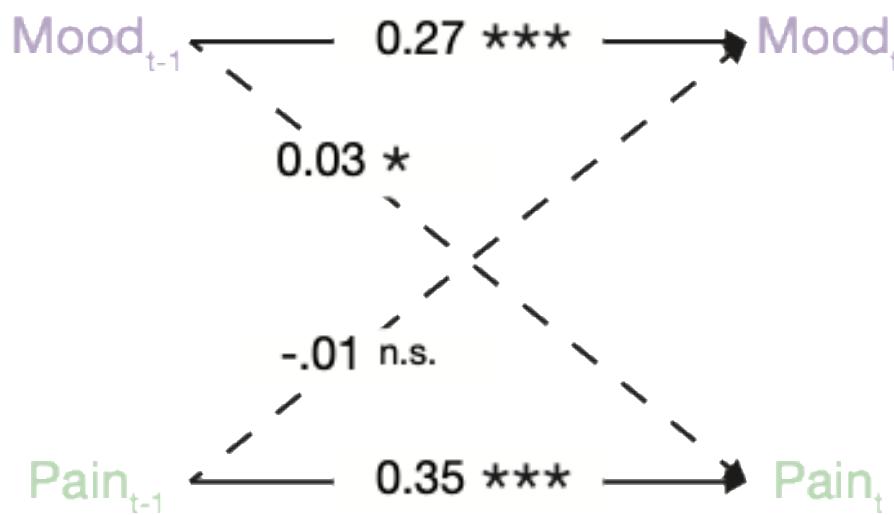


Joseph Heffner

What predicts pain change over time?



SHORTTERM:
Mood and expected pain best predict current pain,
but current pain does not predict future mood



Petzschnner, Science, 2024

n = 127



What predicts pain change over time?

day to day

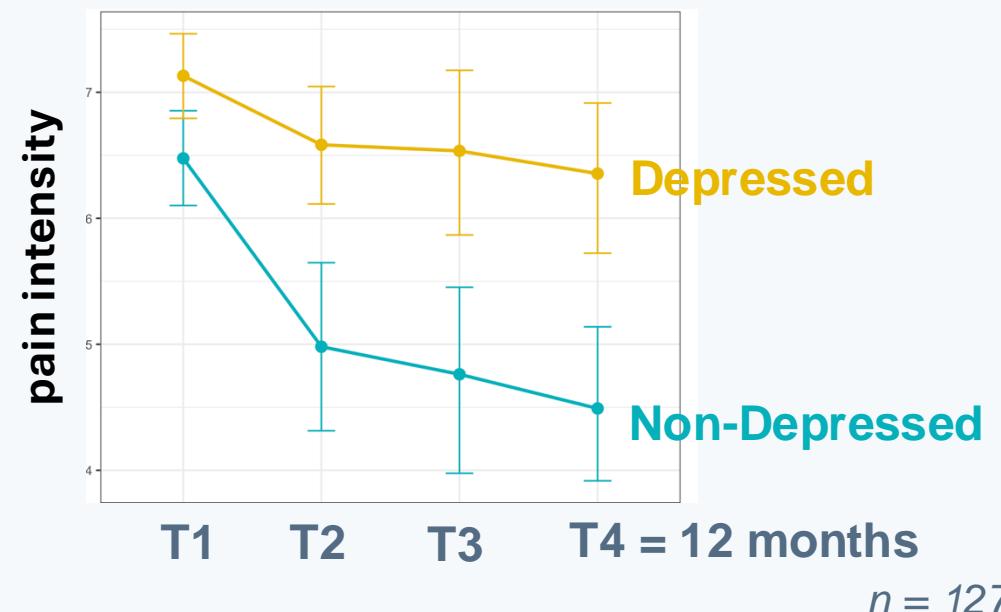
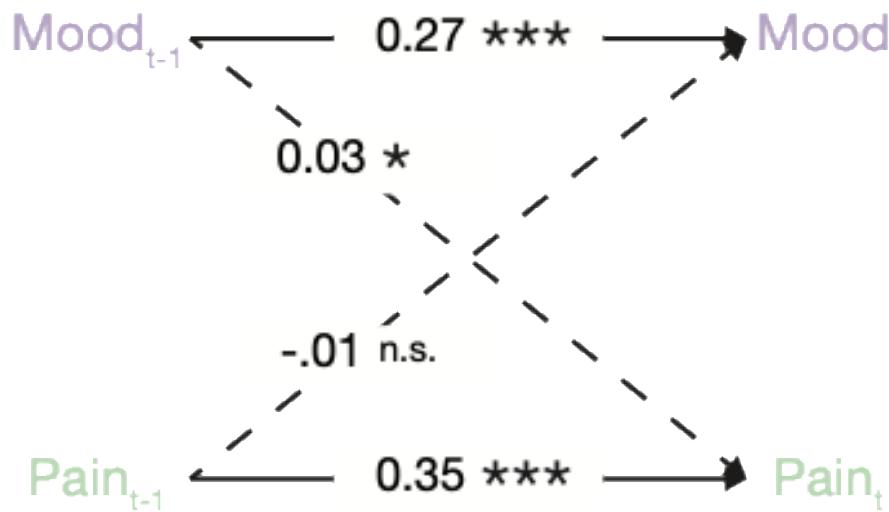


SHORTTERM:

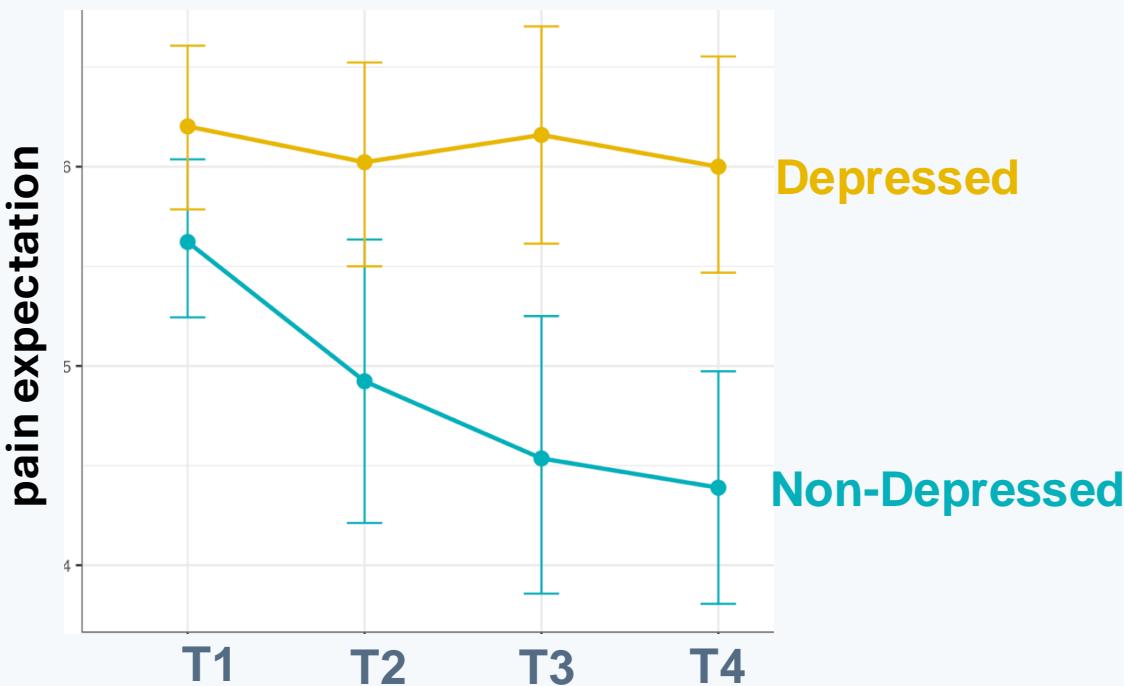
Mood and expected pain best predict current pain,
but current pain does not predict future mood

LONGTERM:

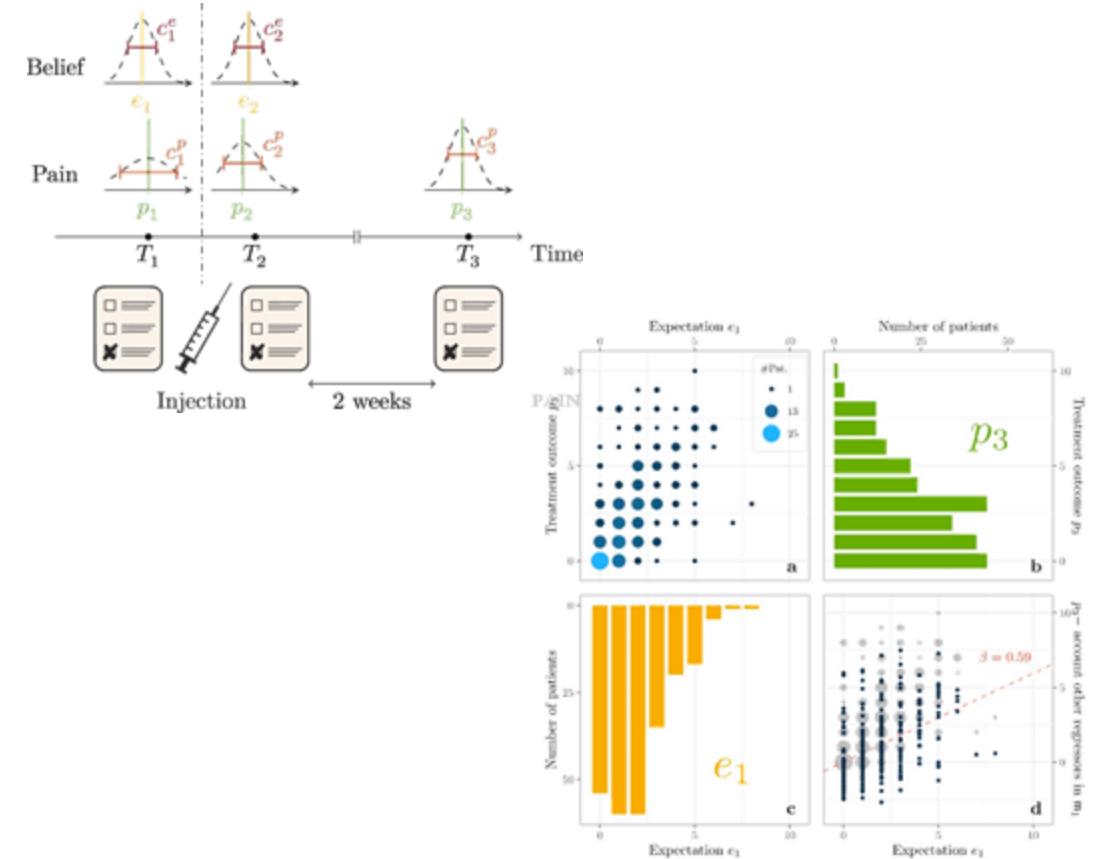
Depression and expected pain predict
pain change over 4 months



Depression relates to negative pain expectations



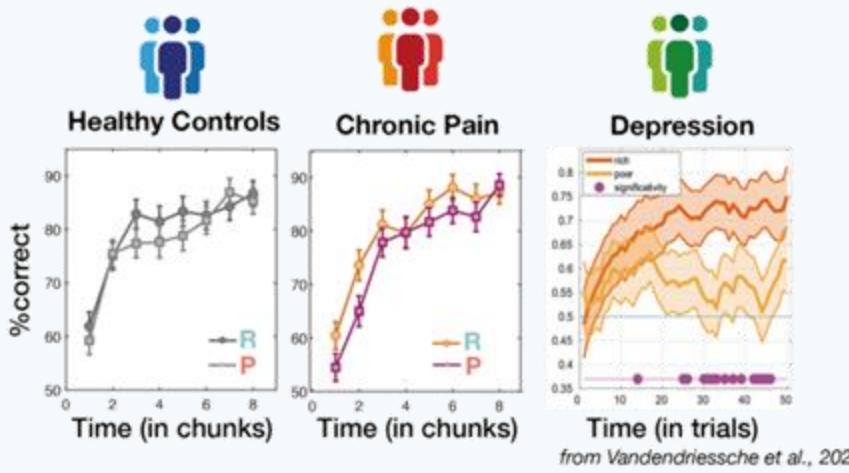
Negative pain expectations predict treatment response



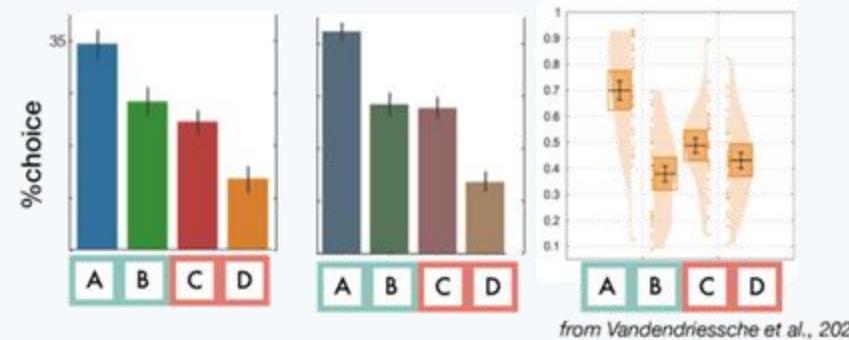
Next Steps

Understanding Comorbidity between Depression and Chronic Pain based on cortico-striatal function

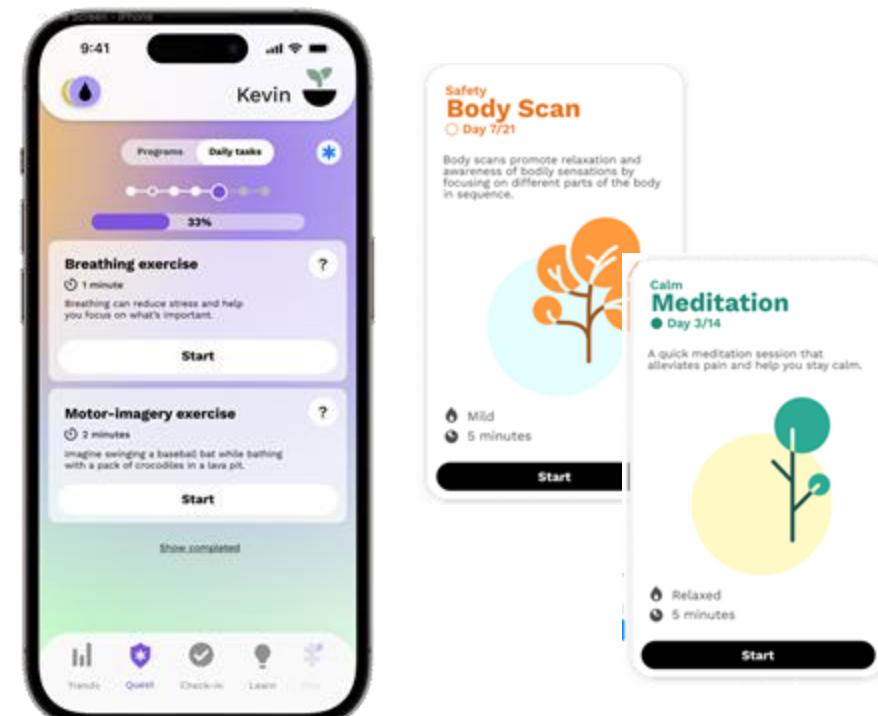
Learning Phase



Transfer Phase



Closed loop Mind-Body Intervention



1. Disease insights

Mechanistic Models



2. Predictive validity

Data-driven Models

Combination



Thank you!

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