learning computations and the development of psychopathology

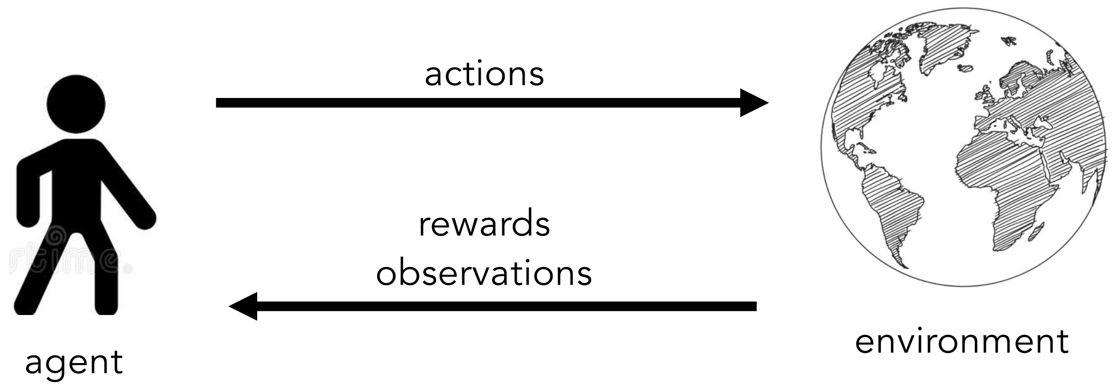
catherine hartley
new york university

CPC 2024

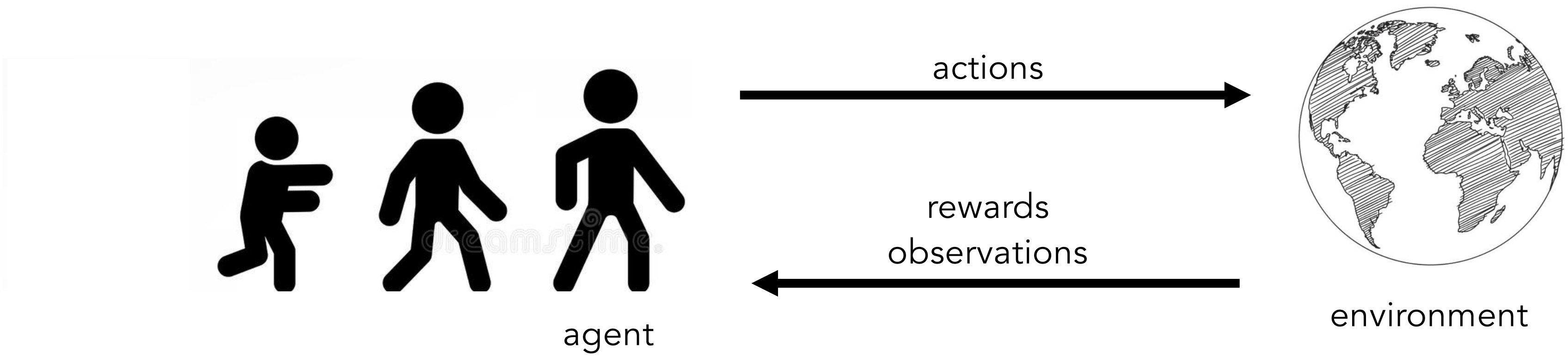
reinforcement learning supports adaptive action

learn the values of states or actions

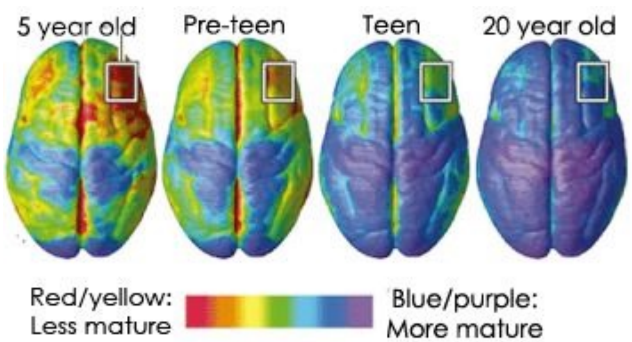
learn model of the environment



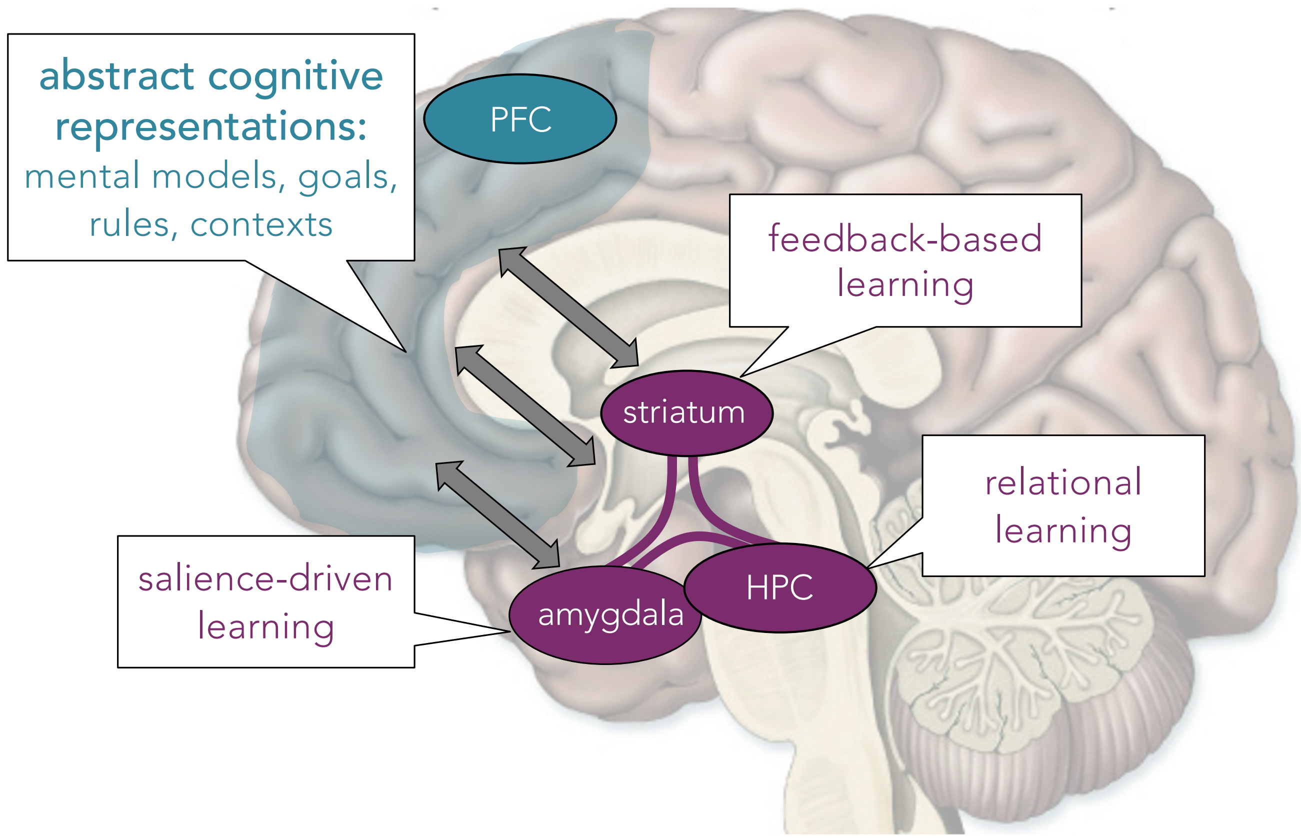
reinforcement learning supports adaptive action



developmental changes in reinforcement learning circuitry

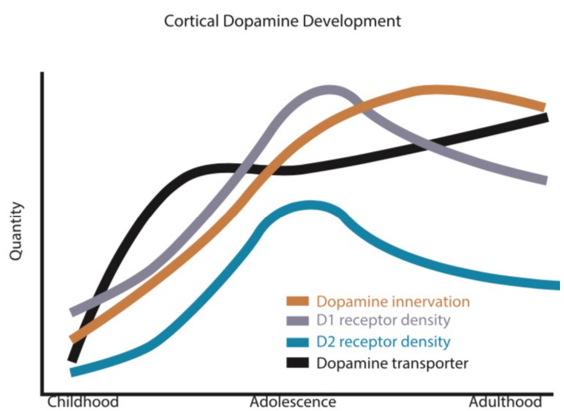


from Gogtay et al., 2004

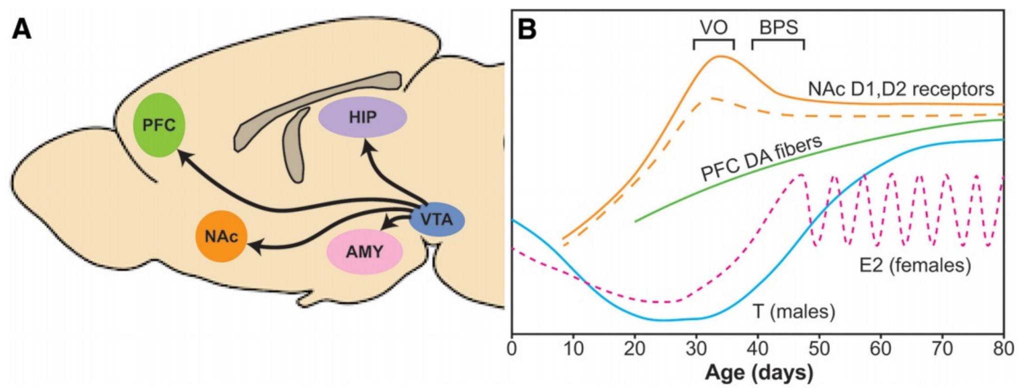


see Somerville, 2016, *Neuron*

developmental changes in reinforcement learning circuitry



from Larsen and Luna, 2018

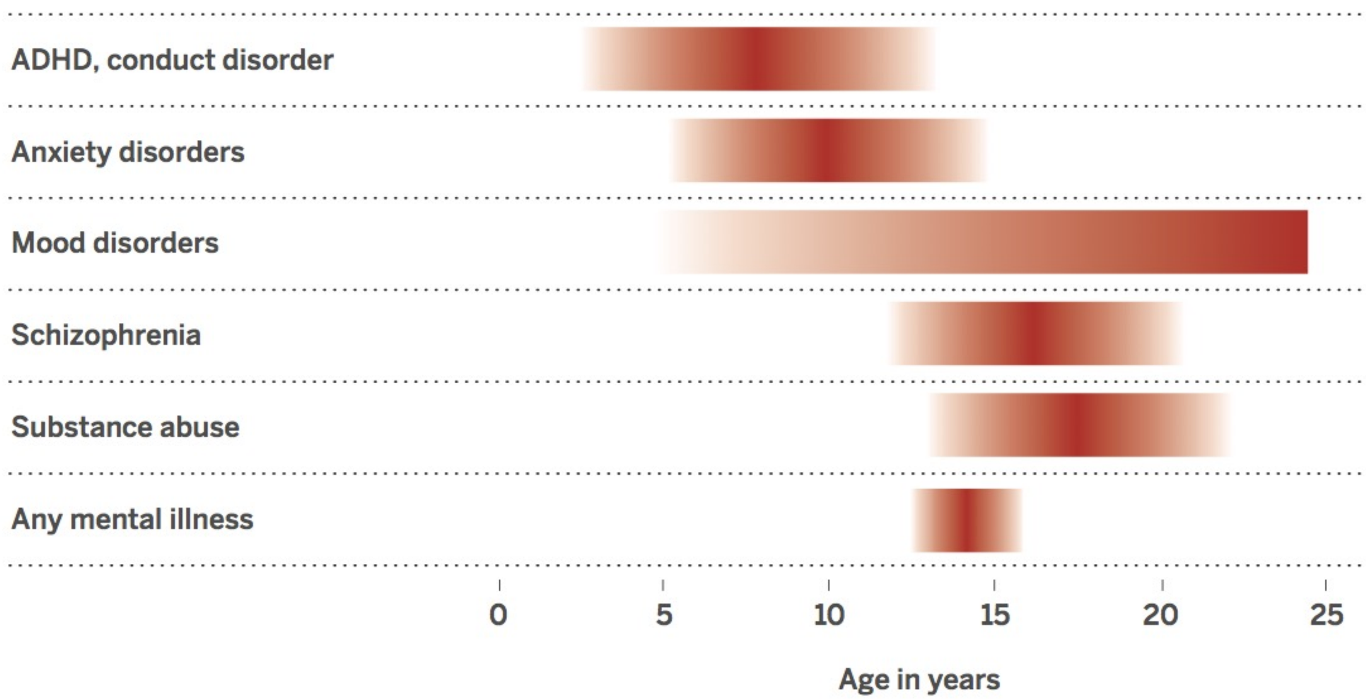


from Walker et al., 2017

adolescent-specific changes in dopaminergic signaling, corticostriatal connectivity, and pubertal hormones

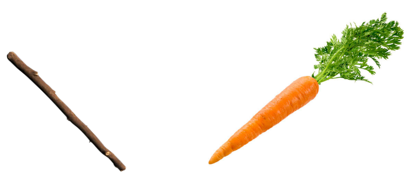
Gee et al., *2019, J Neuro*

many mental illnesses associated with altered reinforcement learning emerge during adolescence

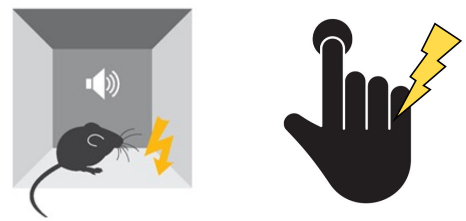


from Lee et al., *Science*, 2015

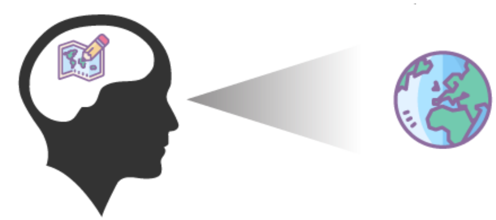
multiple dimensions of reinforcement learning



weighting of positive versus negative outcomes



learning the value of states versus actions



using structured knowledge or cached values

how do these processes change with age?

how do these changes relate to clinical symptomatology?

how does early experience influence learning phenotypes?

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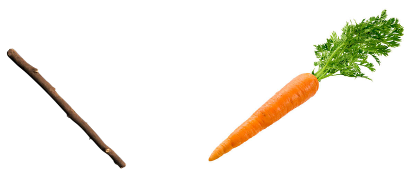

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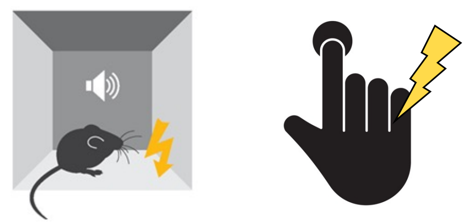

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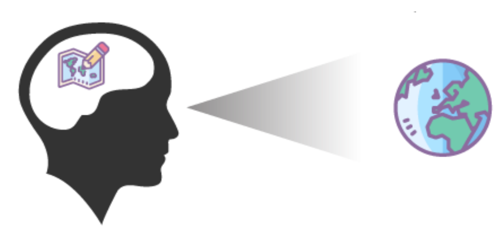
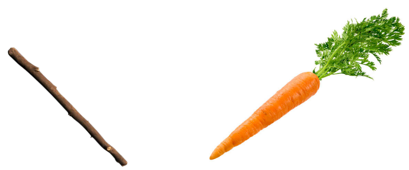


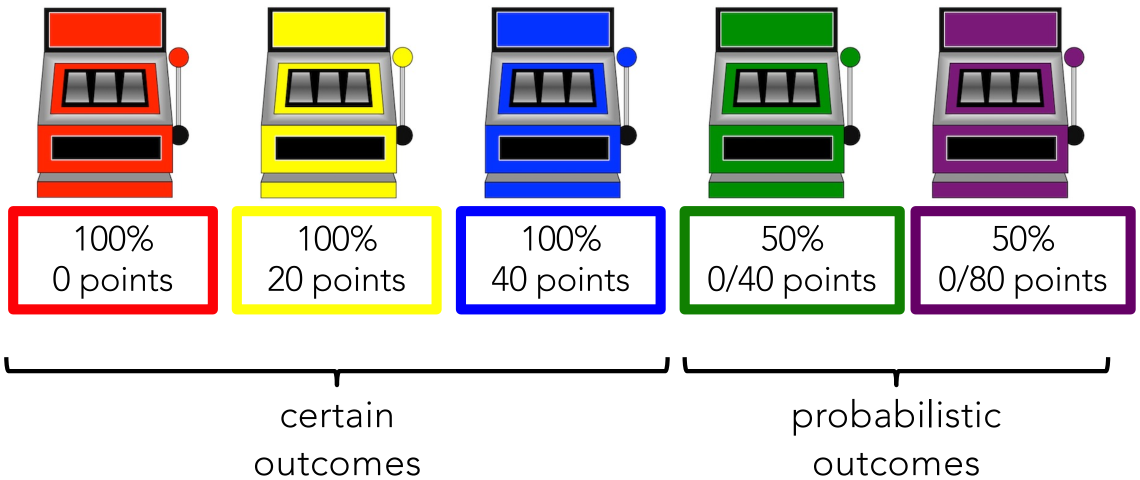
using structured knowledge or cached values

valence asymmetries in reinforcement learning



- healthy adults tend to overweight recent positive experiences relative to negative experiences (Sharot and Garrett, 2016; Palminteri and Lebreton, 2022)
- anxious adults show the opposite tendency (Pike and Robinson, 2022)

valence asymmetries in reinforcement learning

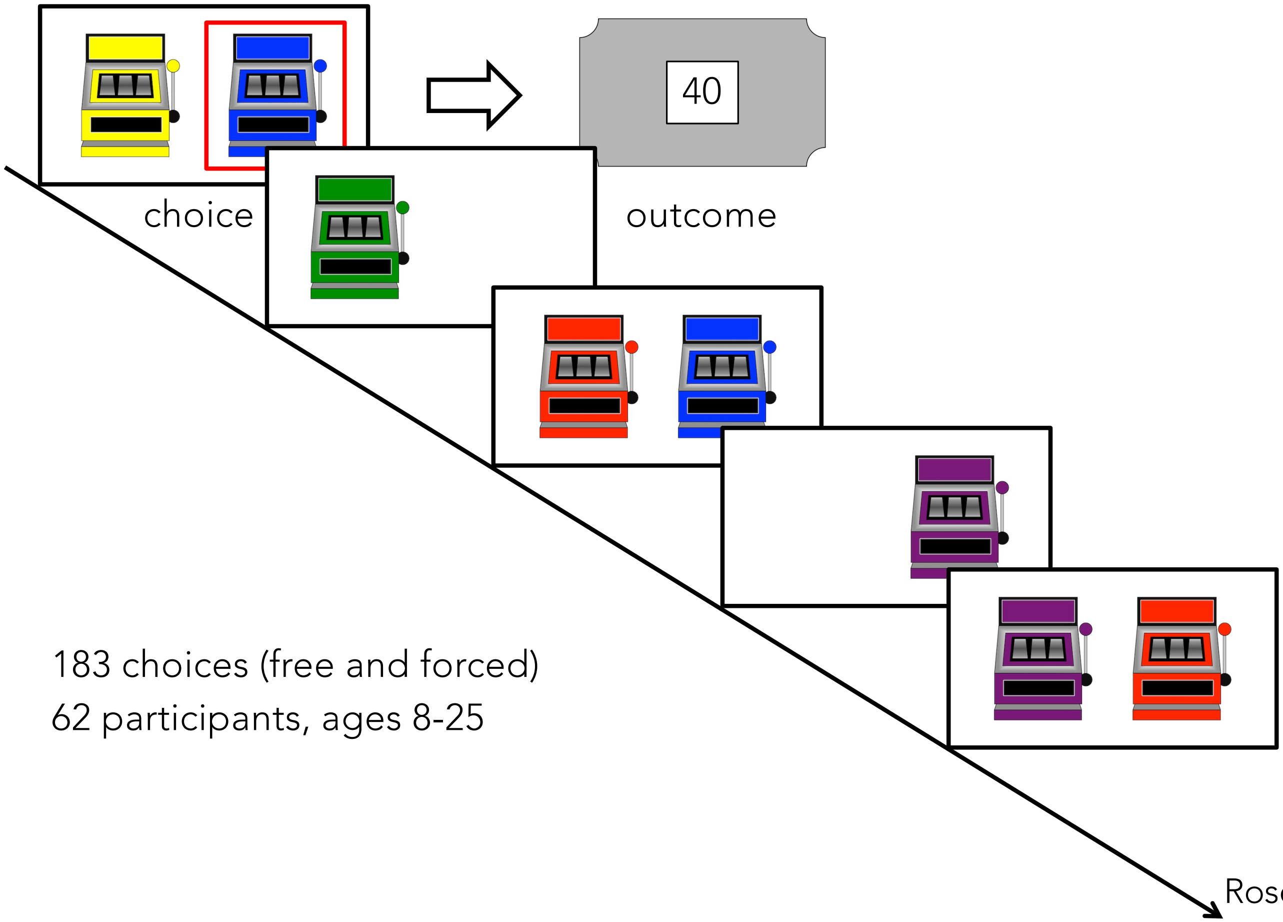


Gail Rosenbaum

Rosenbaum et al., 2022, *eLife*

adapted from Niv et al., 2012, *J Neuro*

valence asymmetries in reinforcement learning



183 choices (free and forced)
62 participants, ages 8-25

Rosenbaum et al., 2022, *eLife*

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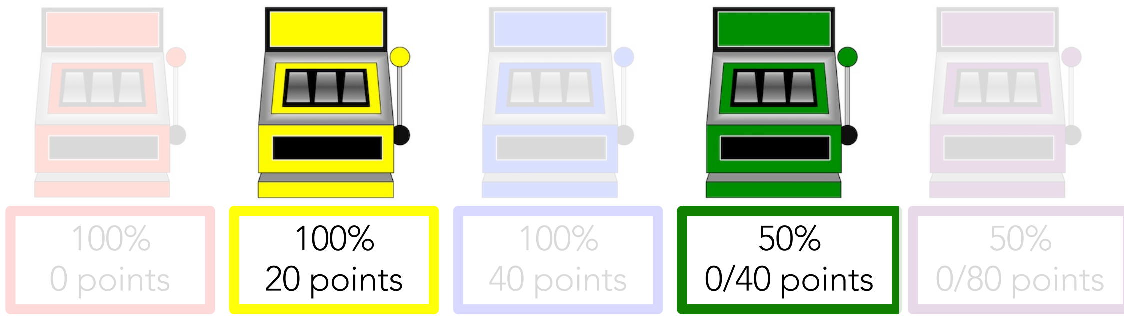
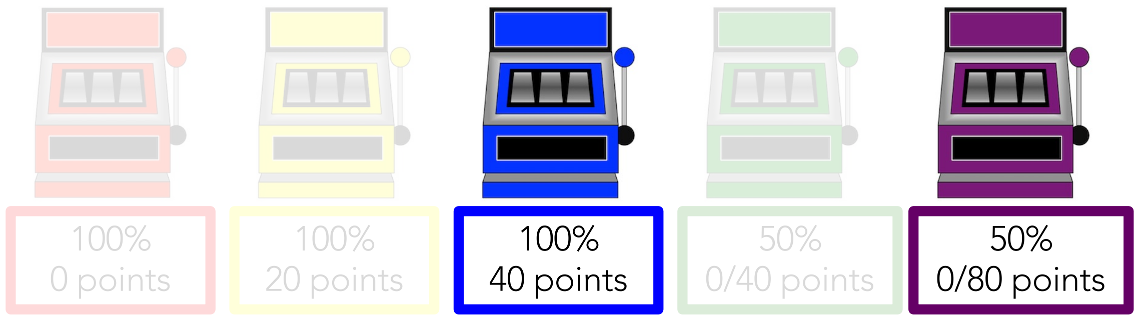


expected value = .5 * (0) + .5 * (40) = 20

Rosenbaum et al., 2022, *eLife*

valence asymmetries in reinforcement learning



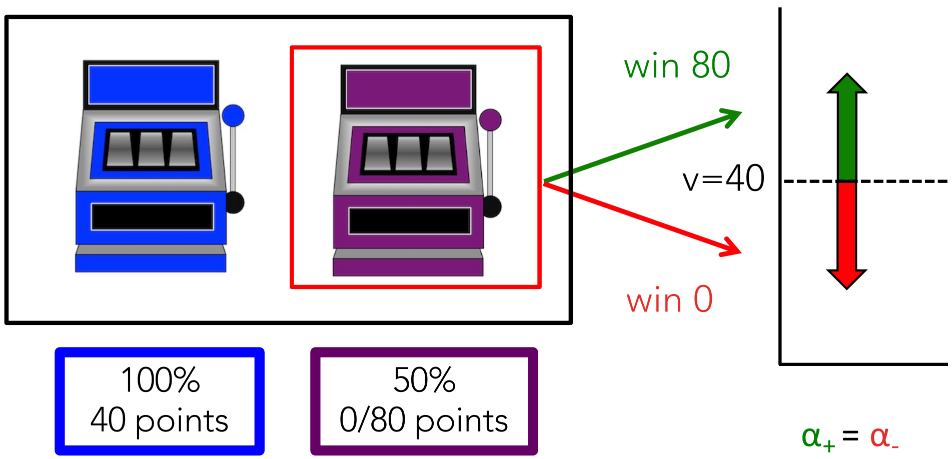
expected value = .5 * (0) + .5 * (80) = 40

Rosenbaum et al., 2022, *eLife*

risk preferences as valenced learning asymmetries

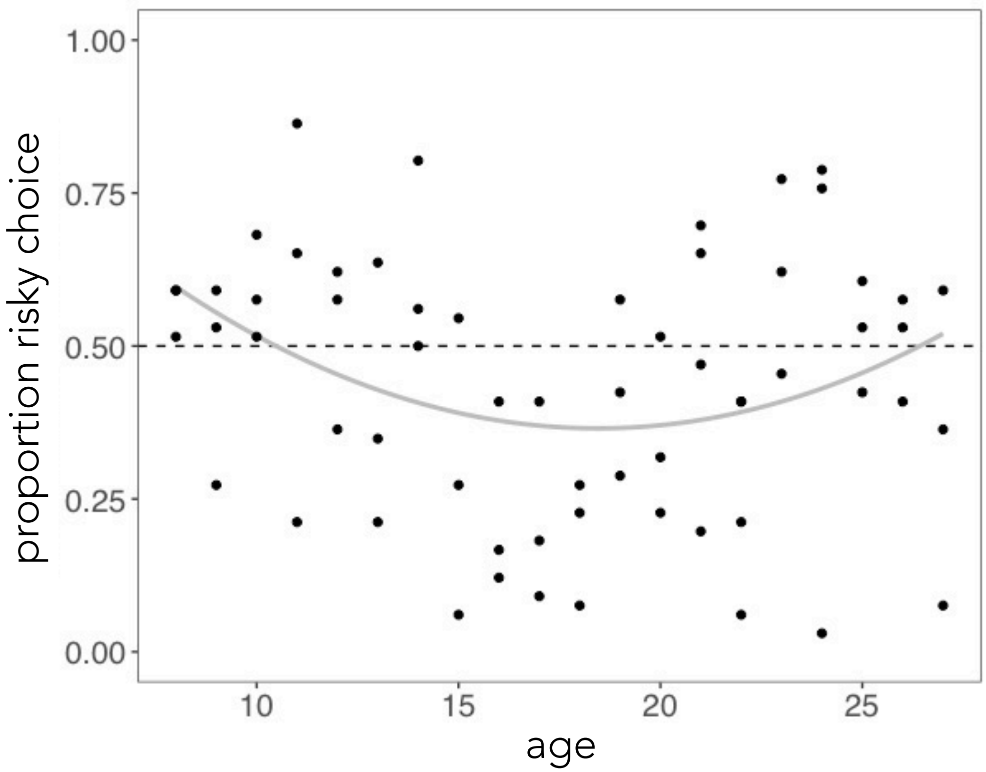
$$v_{new}(\text{chosen}) = v_{old}(\text{chosen}) + \alpha_{+} * \delta, \text{ if } \delta > 0$$

$$= v_{old}(\text{chosen}) + \alpha_{-} * \delta, \text{ if } \delta \leq 0$$



Rosenbaum et al., 2022, *eLife*

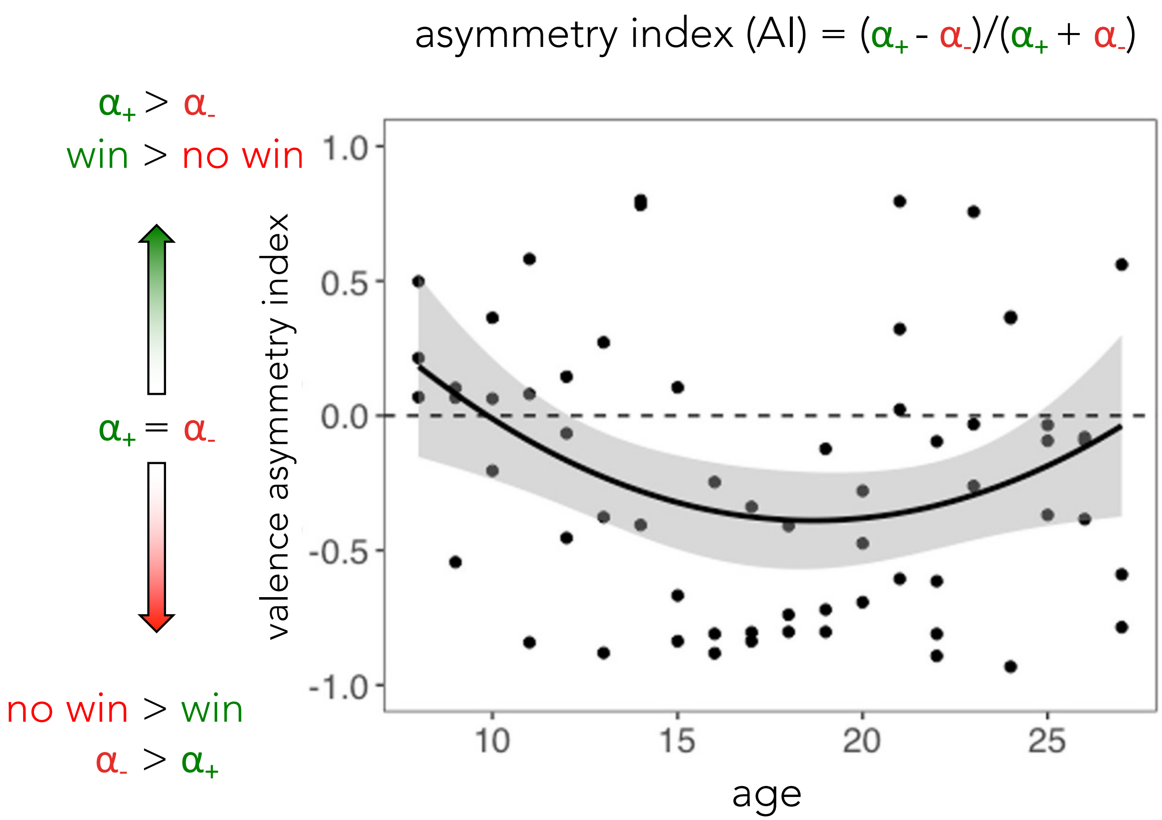
risk preferences varied nonlinearly with age



age² effect:
p = .045

Rosenbaum et al., 2022, *eLife*

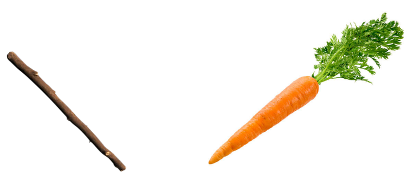
valence asymmetries in reinforcement learning shifted with age



age² effect:
p = .018

Rosenbaum et al., 2022, *eLife*

multiple dimensions of reinforcement learning



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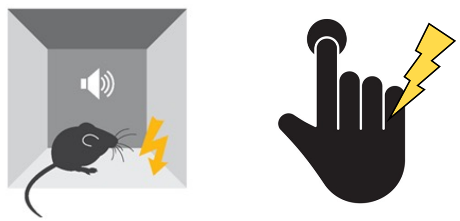

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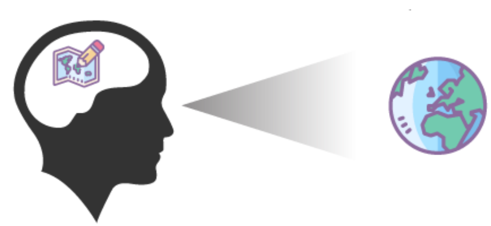
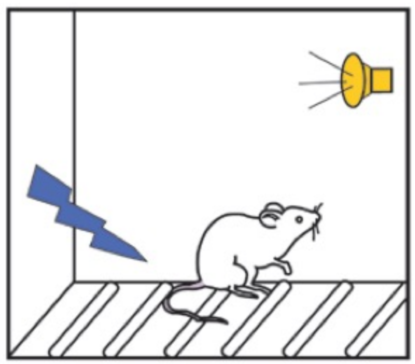


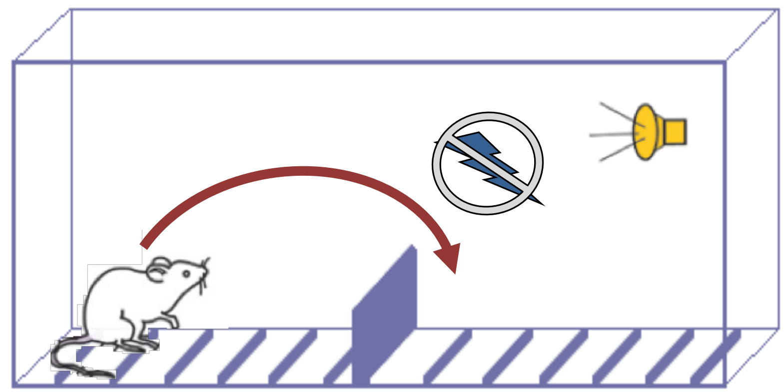
using structured knowledge or cached values

learning the values of states versus actions



pavlovian
learning

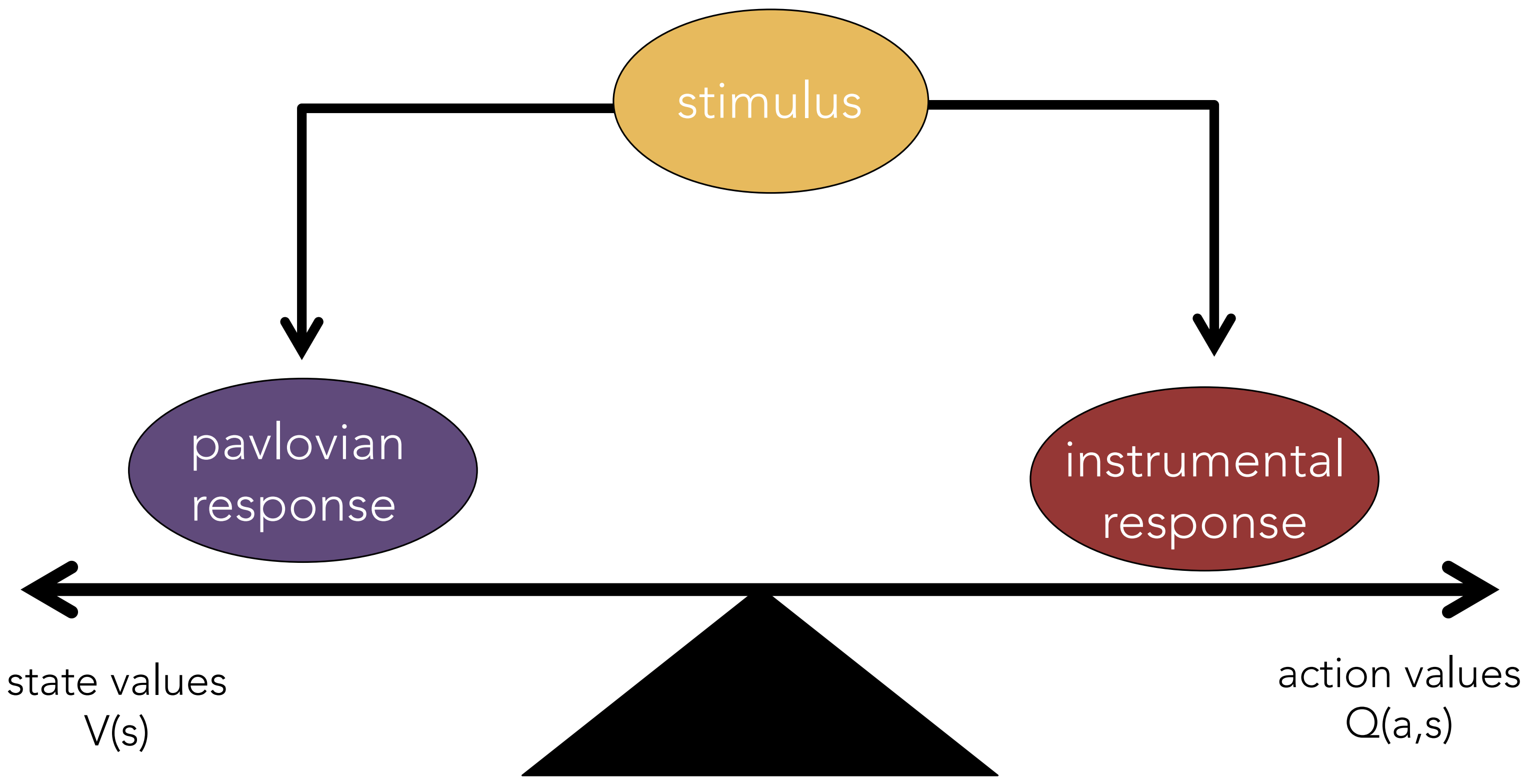
"default" behavioral reactions
to anticipated events



instrumental
learning

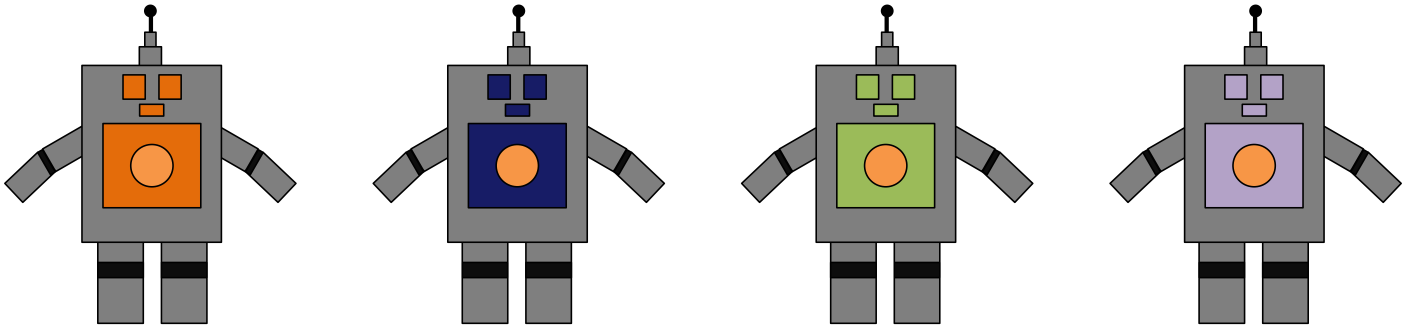
flexible actions that
achieve desired outcomes

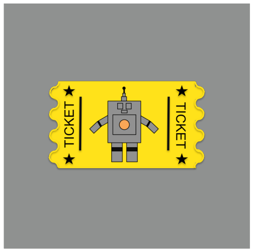
learning the values of states versus actions

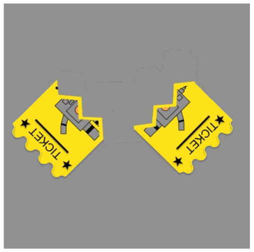


pavlovian bias and psychopathology

- passive avoidance is increased in anxiety disorders (Mkrtchian et al., 2017)
- pavlovian influence on instrumental action is increased in substance use disorders (Garbusow et al., 2014)
- pavlovian biases are greater in individuals with trauma exposure (Ousdal et al., 2018)



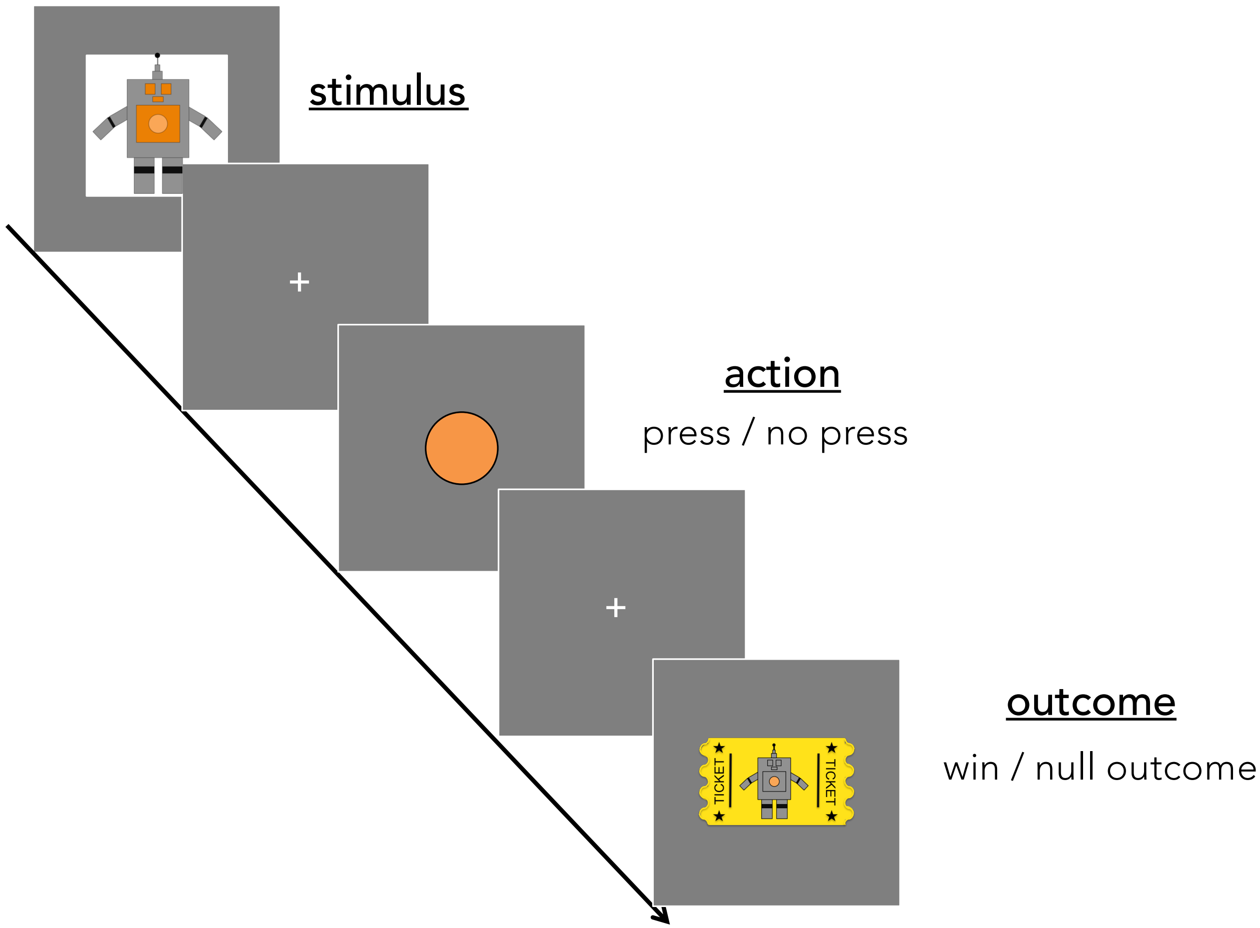




Hillary Raab

Raab and Hartley, 2020, *Scientific Reports* ; adapted from Guitart-Masip et al., 2012

assessing pavlovian influence on instrumental learning across development



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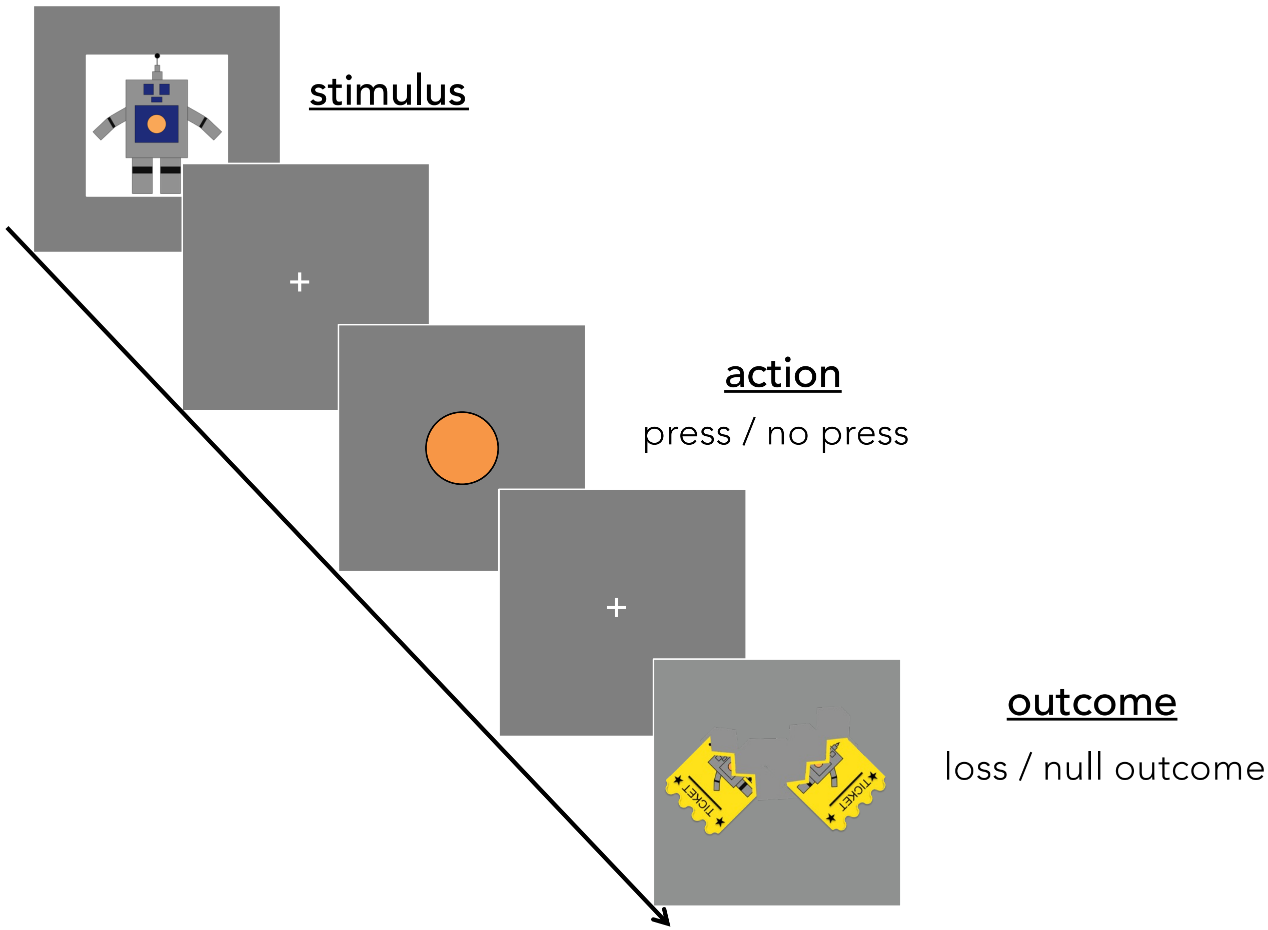

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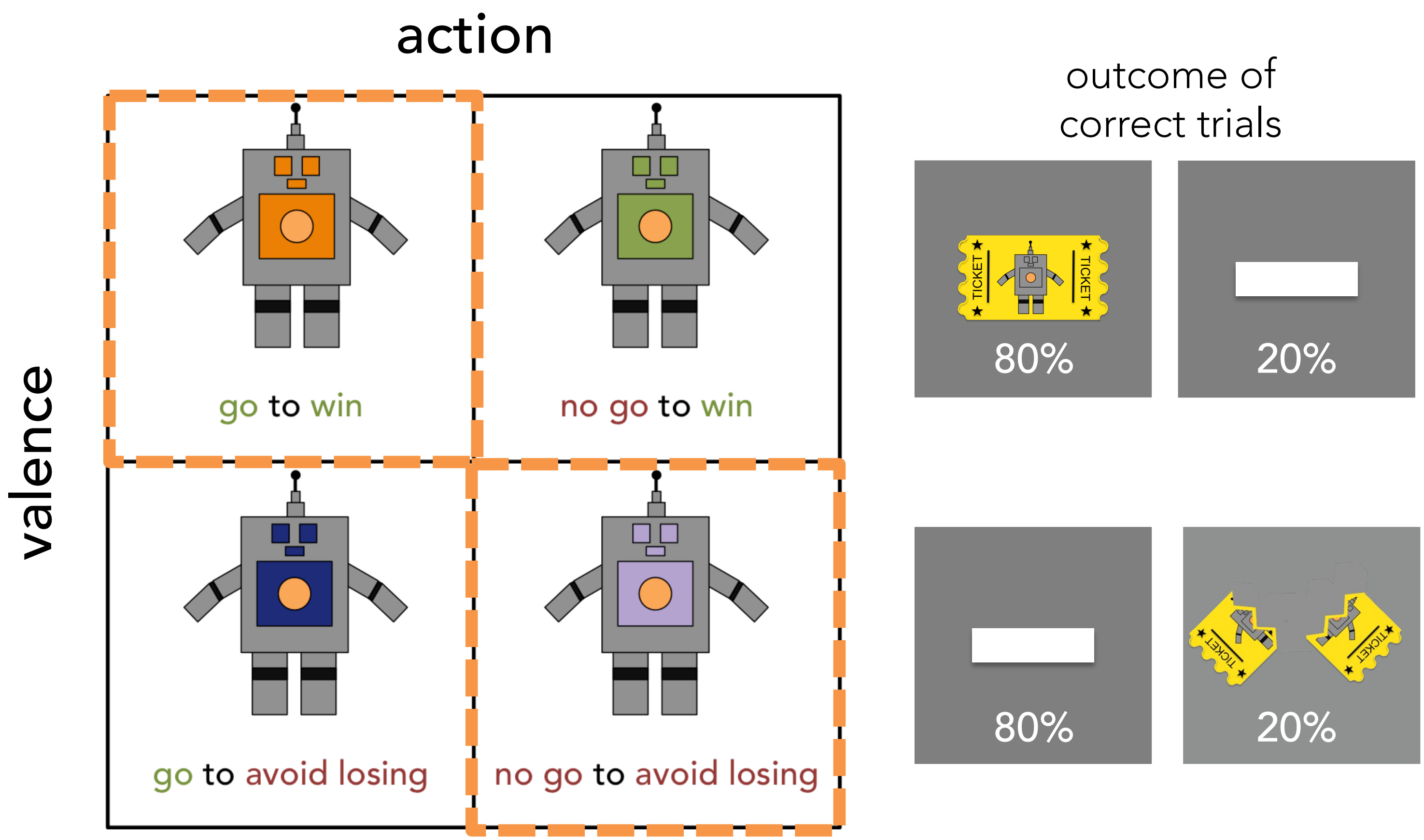
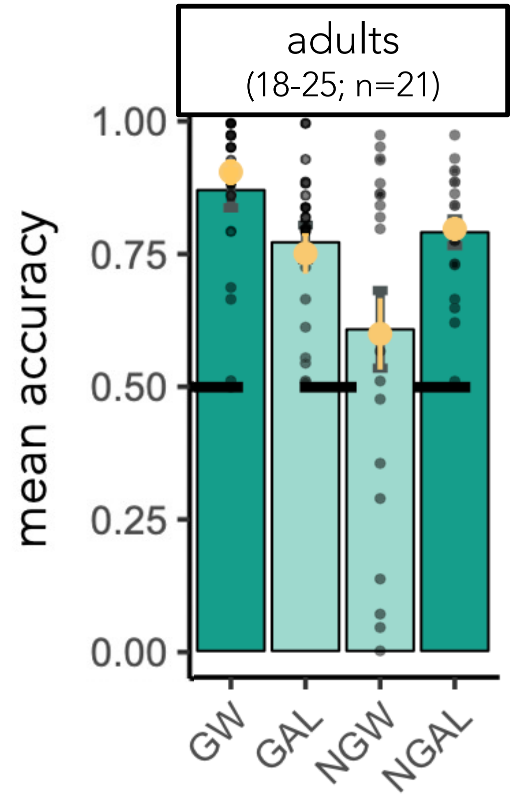


pavlovian influence on instrumental learning is attenuated in adolescence



valence x action x age^2, $p < .001$

Raab and Hartley, 2020, *Scientific Reports*

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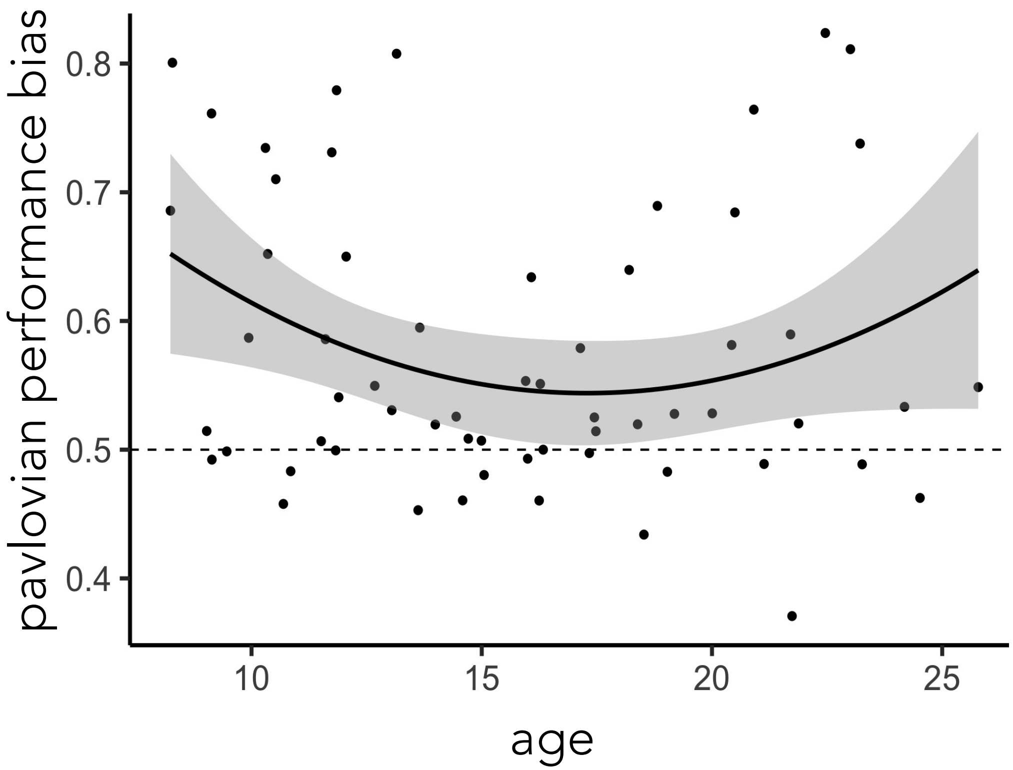


age^2, $p < .05$

Raab and Hartley, 2020, *Scientific Reports*

modeling pavlovian influence on instrumental learning

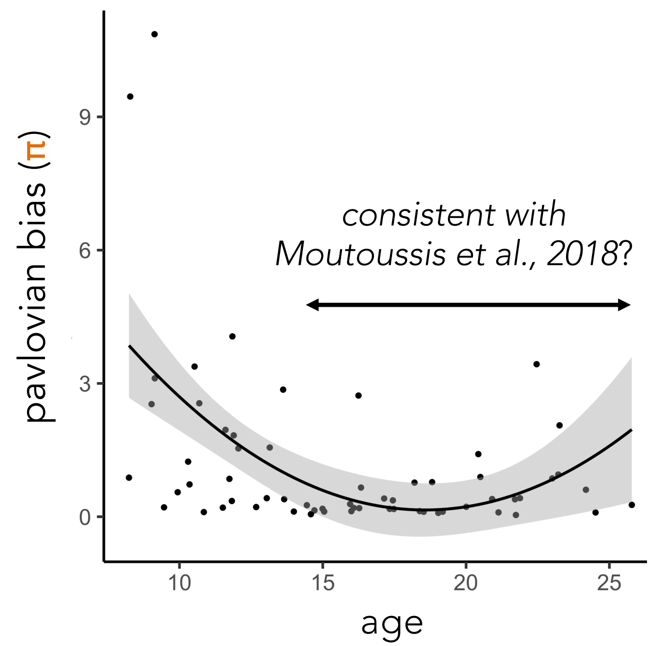
action value estimate
learning rate
prediction error

$$Q_{t+1}(\text{go},) = Q_t(\text{go},) + \alpha * \delta$$

go bias
state value estimate

$$W_t(\text{go},) = Q_t(\text{go},) + \gamma + \pi * V_t( )$$

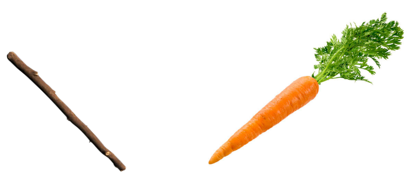
action value estimate
pavlovian bias



age^2, p = .001

Raab and Hartley, 2020, *Scientific Reports*

multiple dimensions of reinforcement learning



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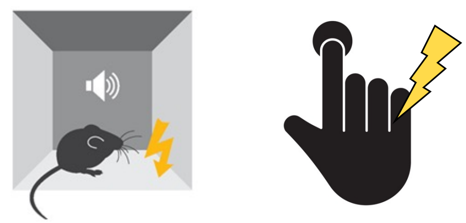

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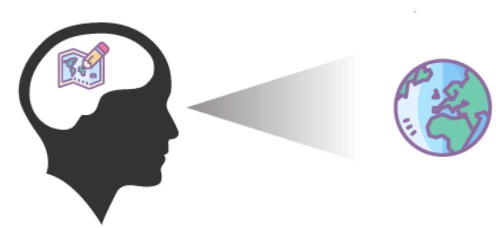
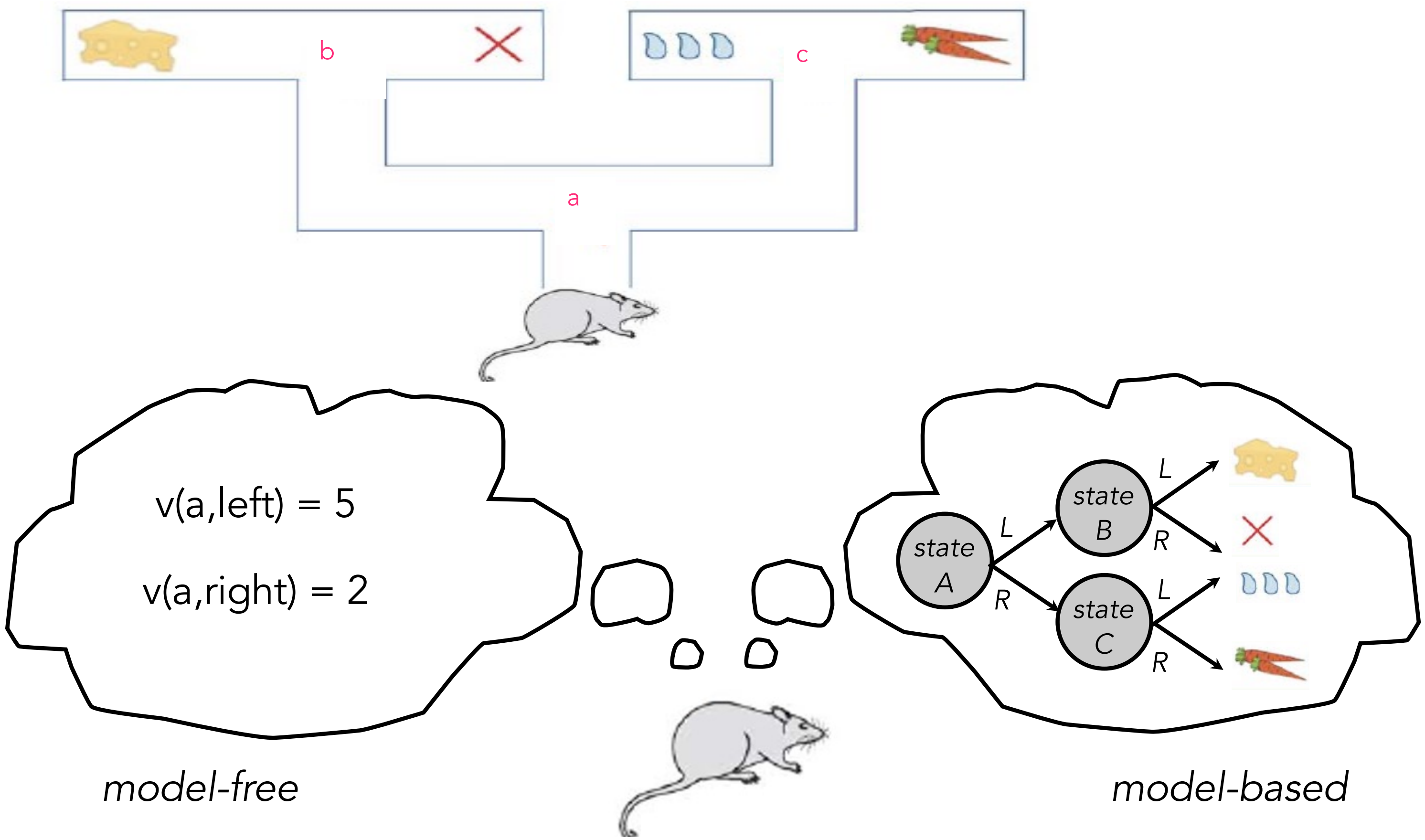


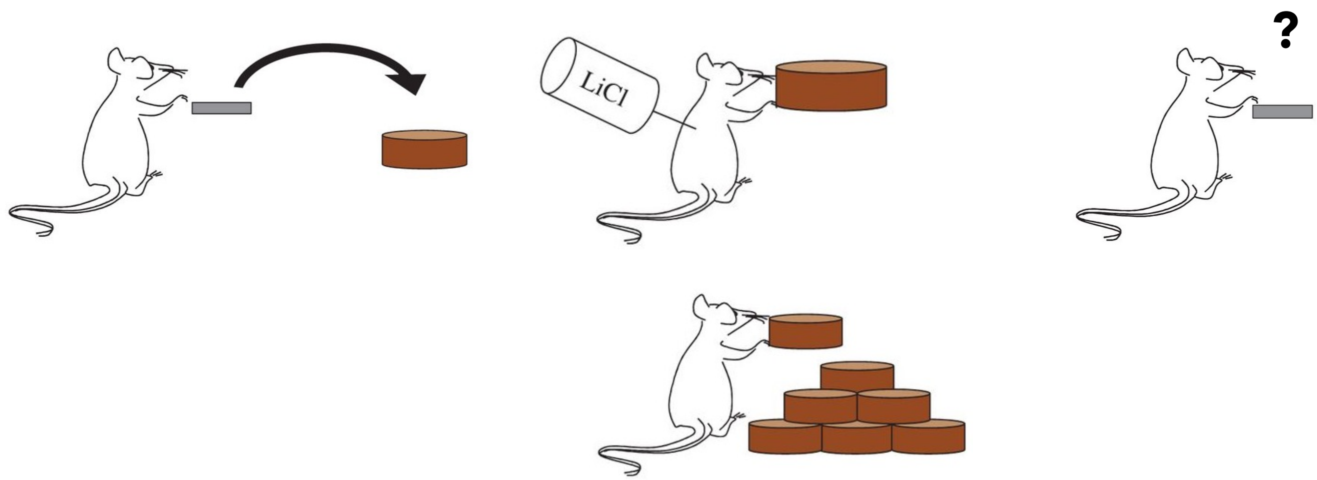
using structured knowledge or cached values

learning values or mental models?



goals versus habits

training devaluation test



from Gillan and Robbins, 2014

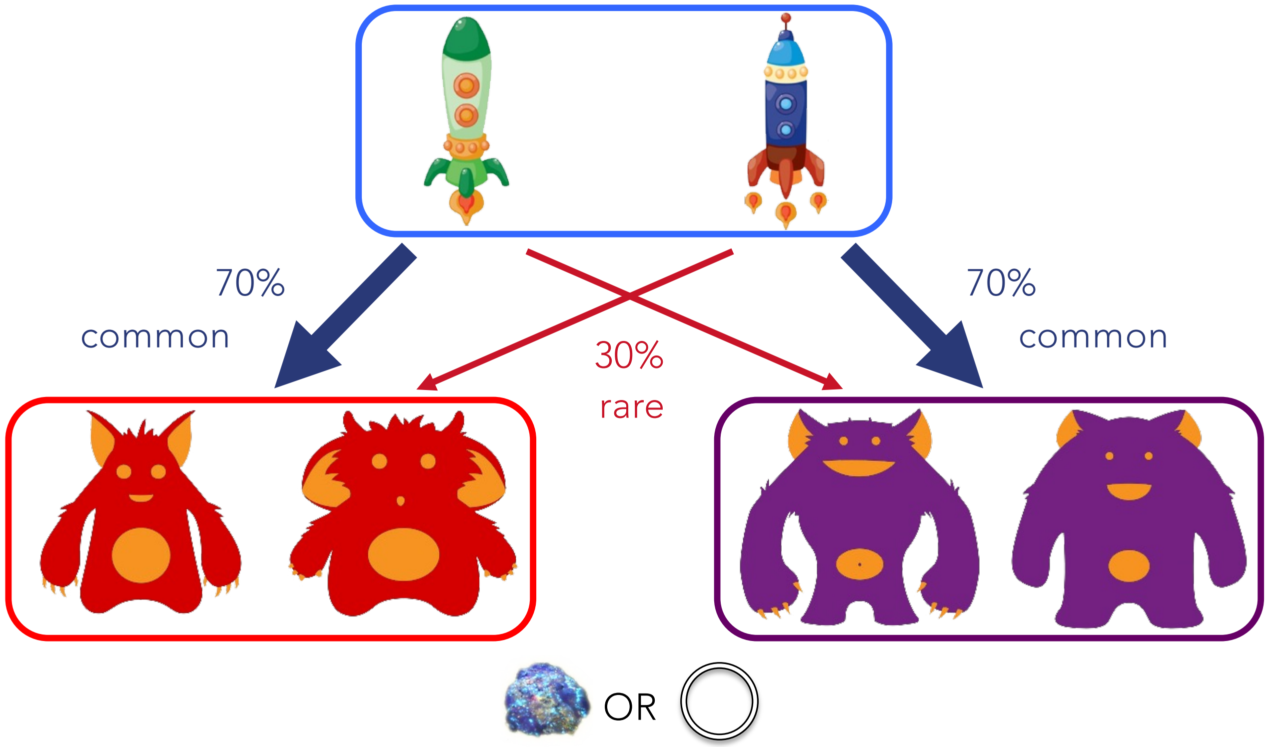
decreased model–based learning relates to a transdiagnostic compulsivity phenotype



- avoidance habits
- binge eating
- substance abuse

see Robbins et al., 2012; Gillan et al., 2013; Voon et al., 2014

dissociating learning strategies

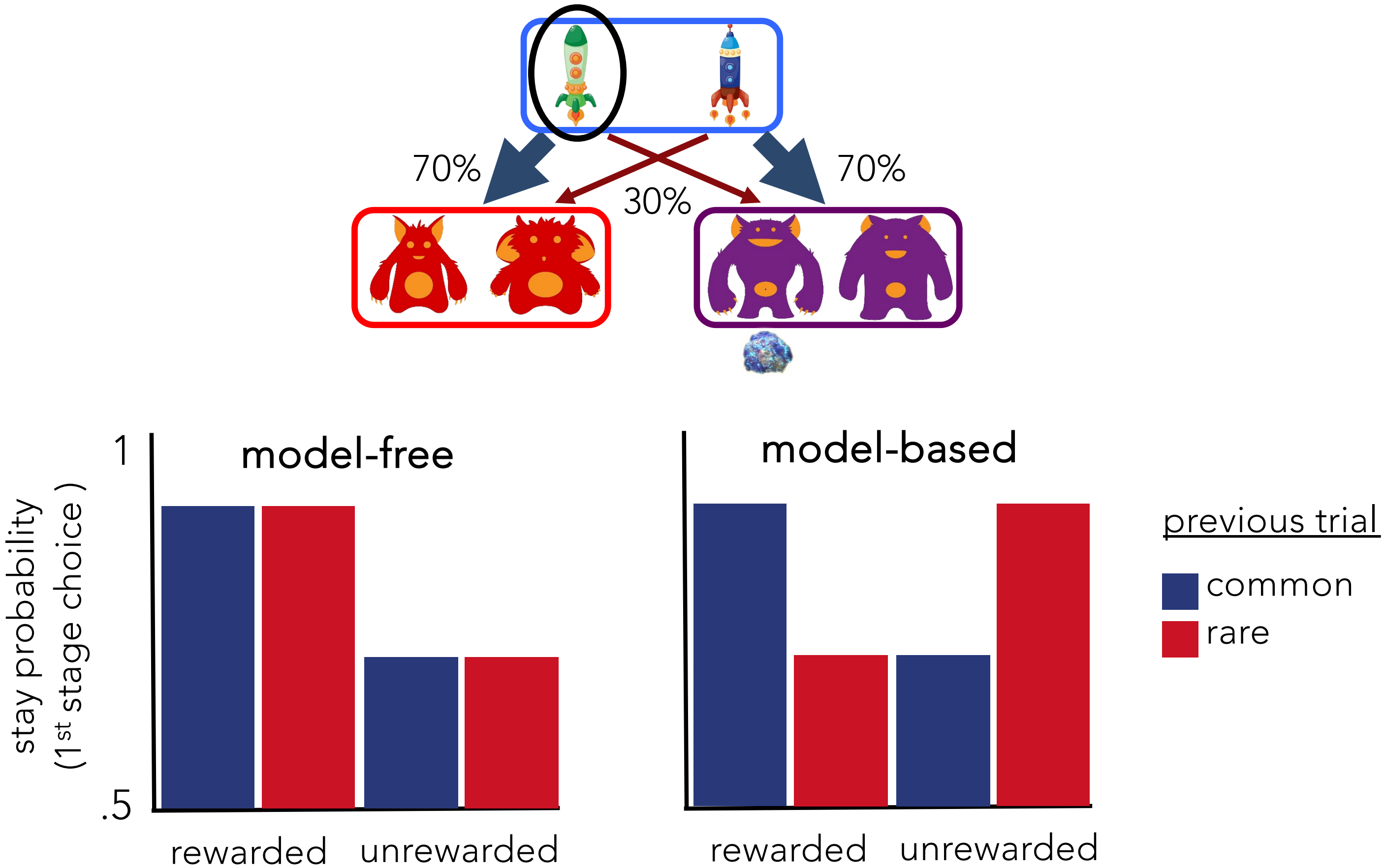


Hugo Decker

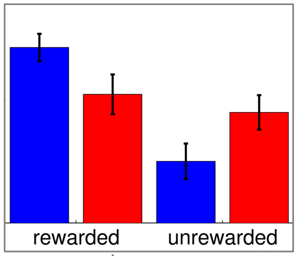
Decker et al., 2016, *Psych Science*

adapted from Daw et al., 2011, *Neuron*

dissociating learning strategies

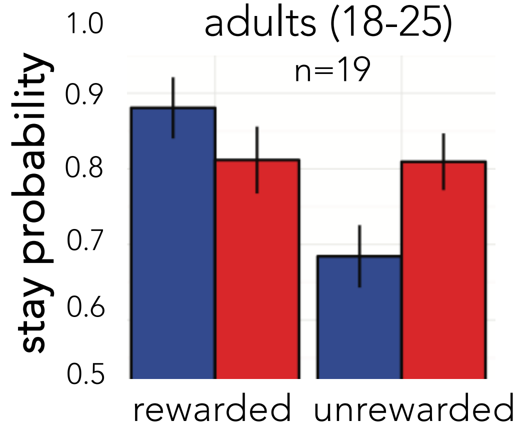


model-based learning emerges over development



Daw et al., *Neuron*, 2011

previous trial: common rare



model-free: $p < .0001$

model-based: $p < .0001$

Decker et al., 2016, *Psych Science*

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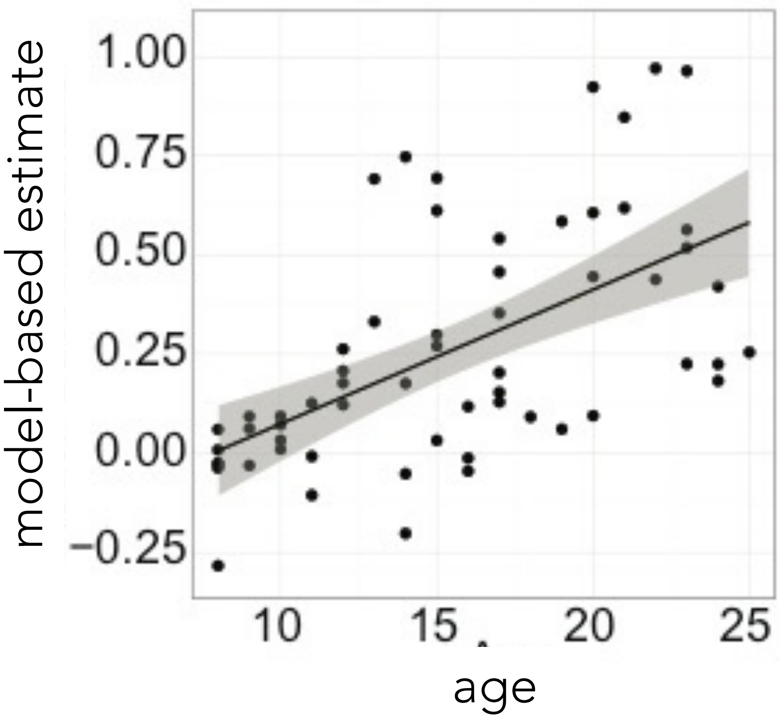
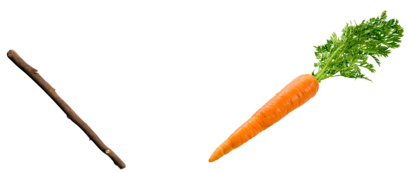


model-based x age:
p = .0004

model-free x age:
p = .124

Decker et al., 2016, *Psych Science*

multiple dimensions of reinforcement learning



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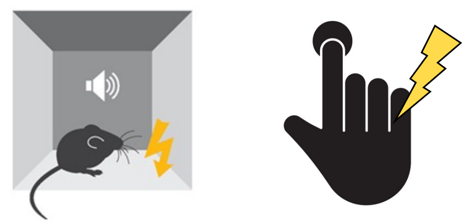

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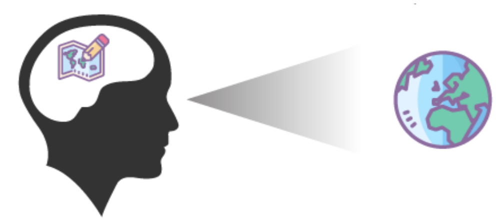

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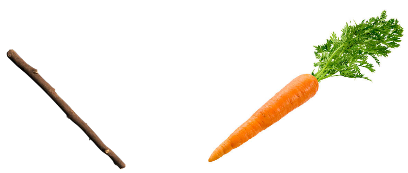

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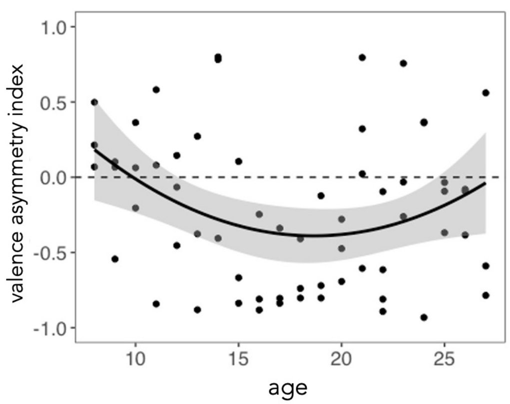

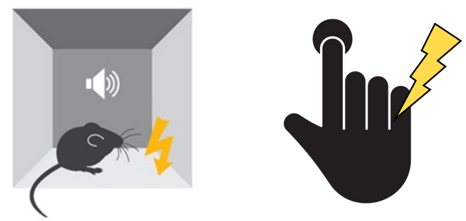

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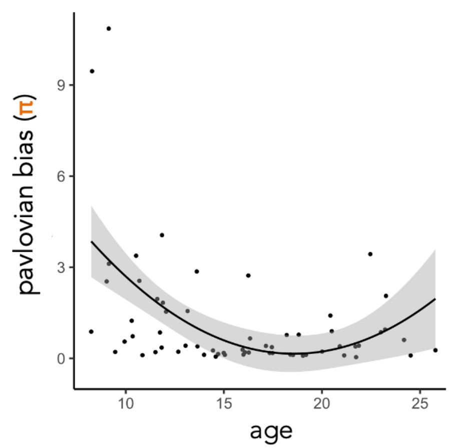

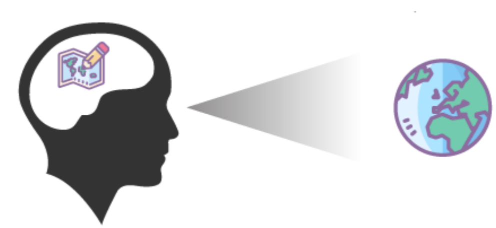

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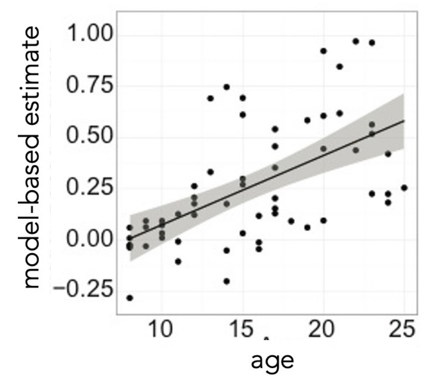

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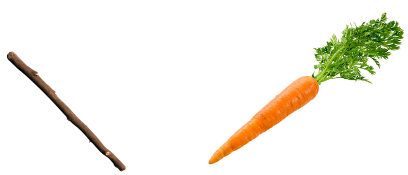

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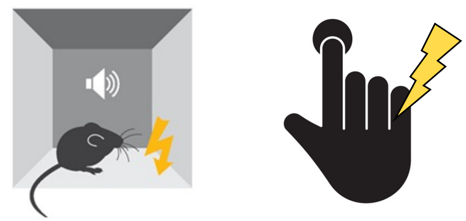

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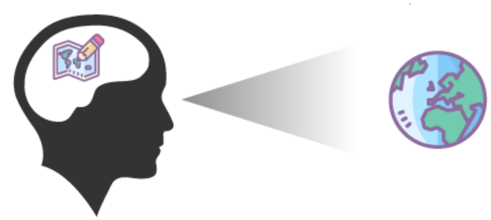

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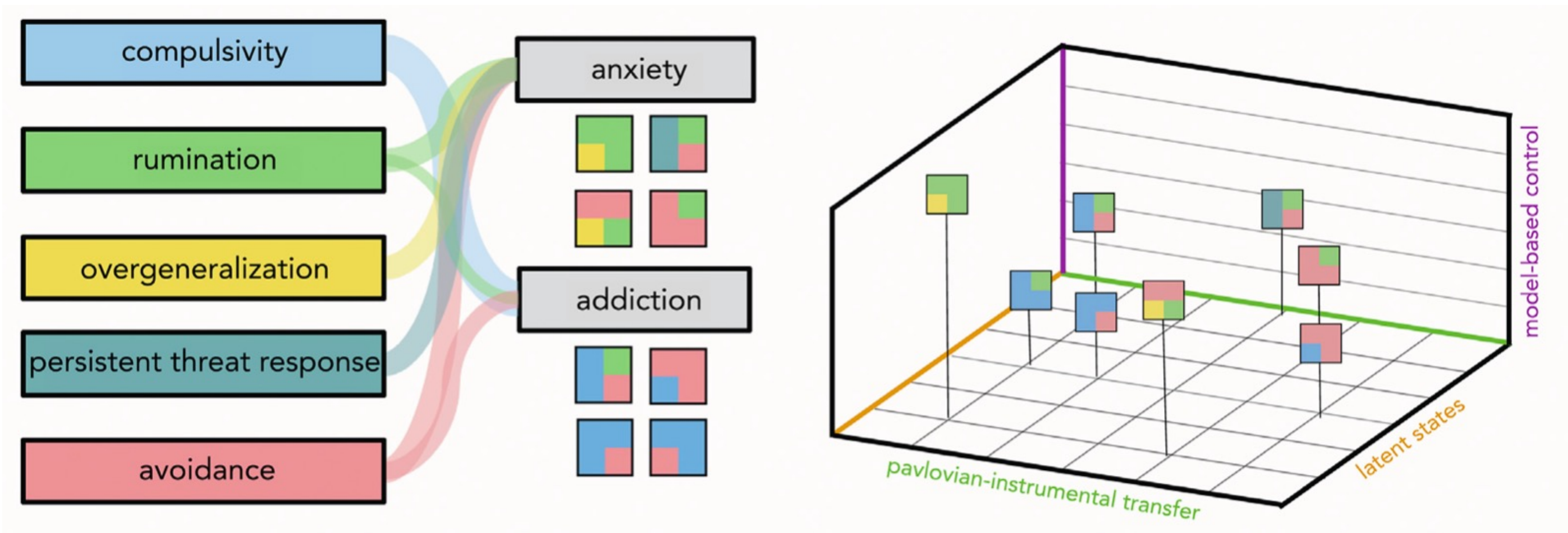

from Goldway et al. (2023), *Biological Psychiatry*

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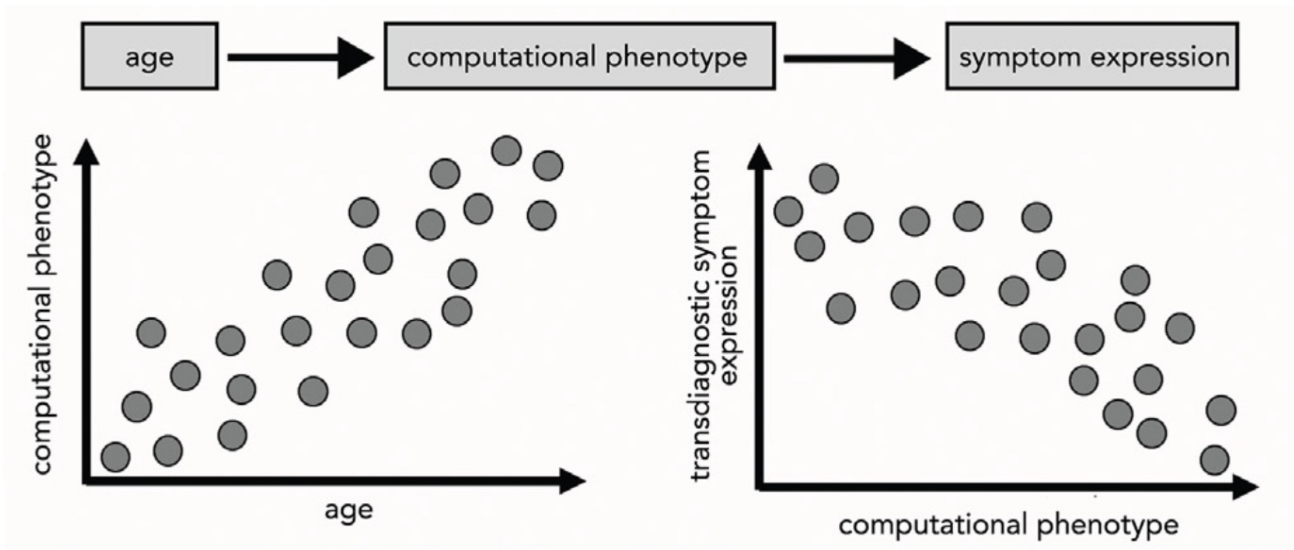

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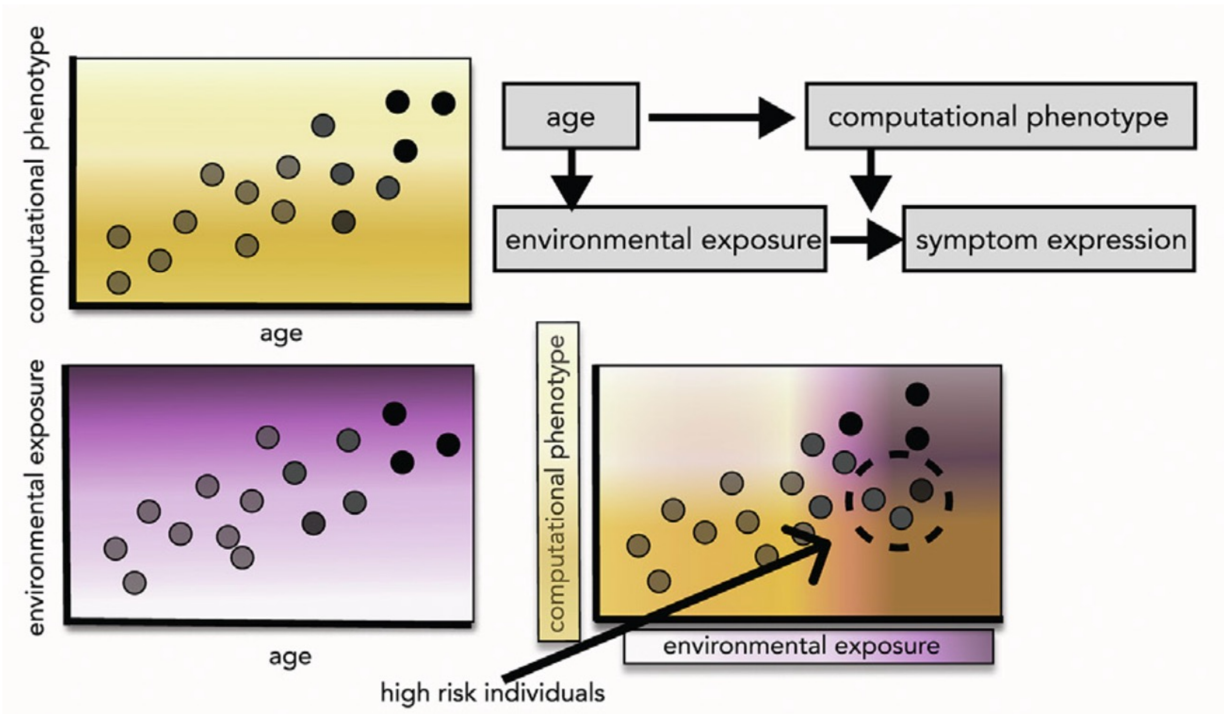

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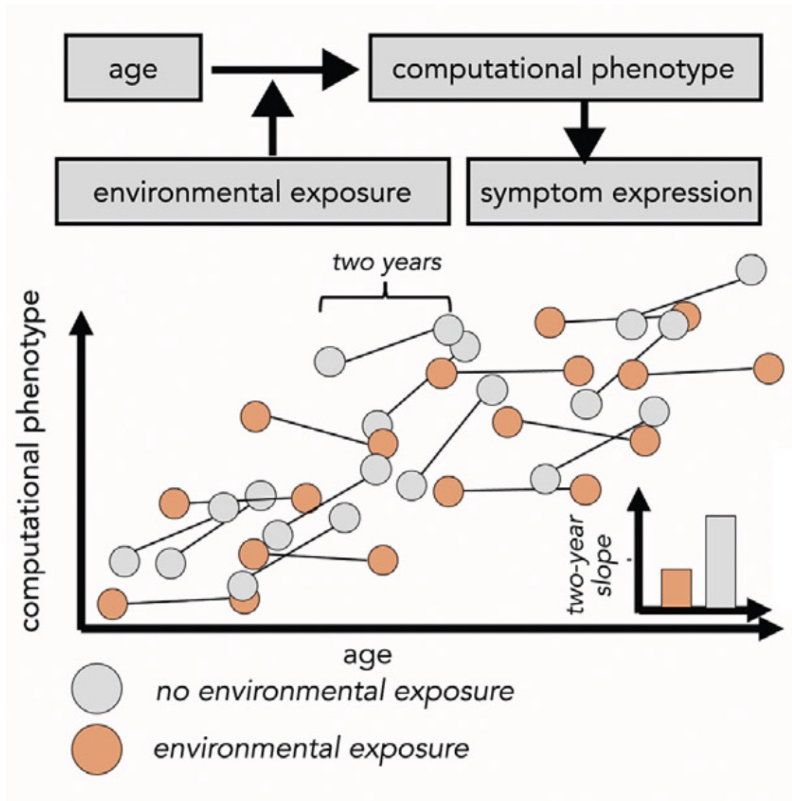

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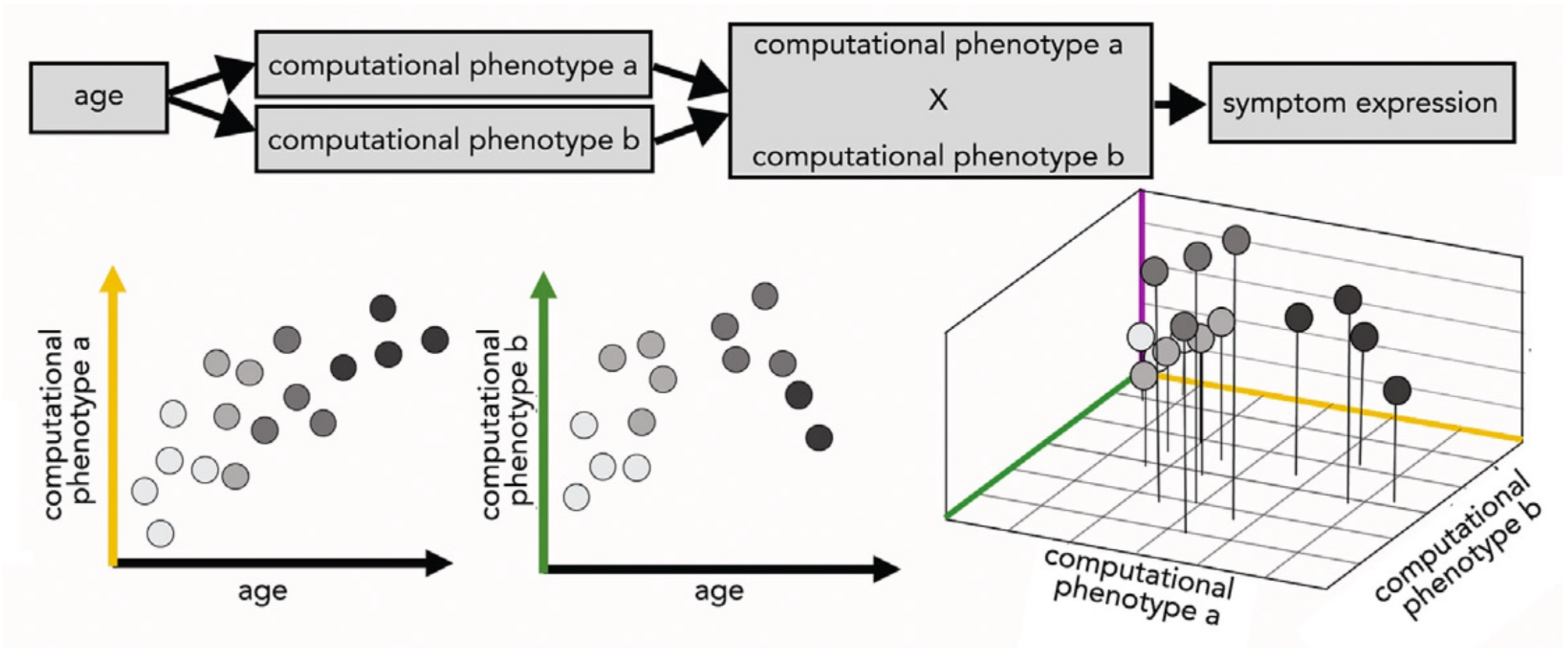


from Goldway et al. (2023), *Biological Psychiatry*

relating computational phenotypes to clinical symptoms across development

- longitudinal designs
- larger sample sizes (in-person vs. online studies)
- tasks administered within-subject
- no exclusions for clinical diagnoses
- reliable assessments of computational phenotypes

relating computational phenotypes to clinical symptoms across development

גהה
המרכז לבריאות הנפש

Noam (

RCNS R01MH125564

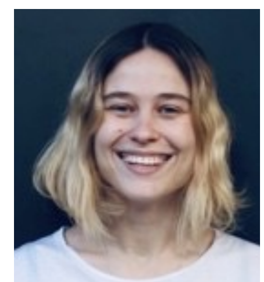
work in progress!

Yael Niv

Eran Eldar

Gal Shoval

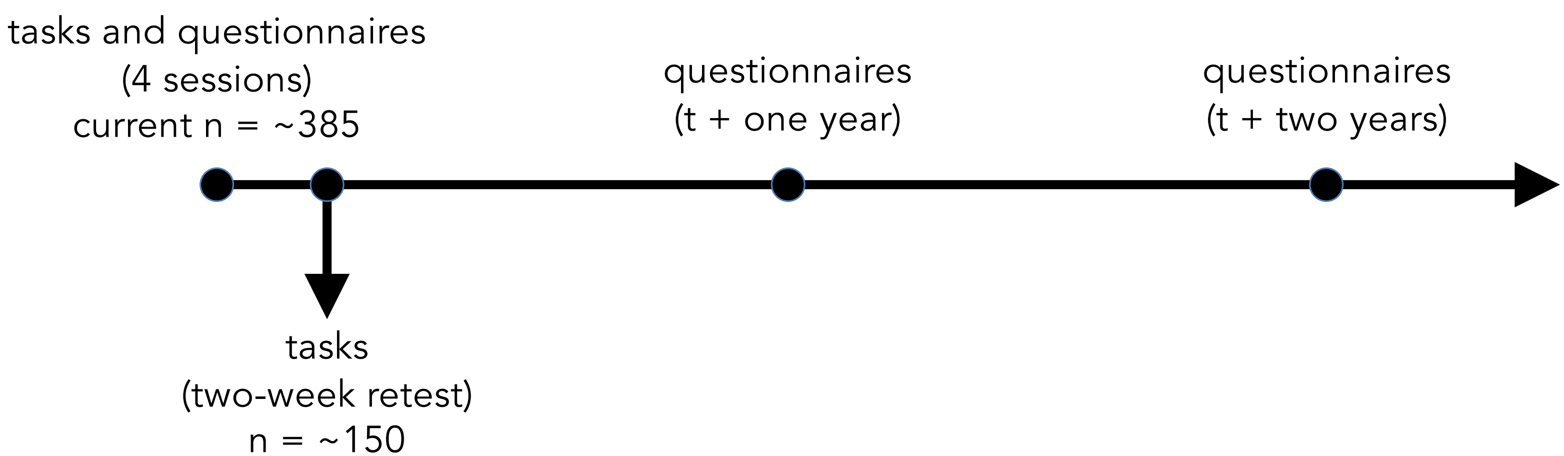
Levi Solomyak



Gili Karni

relating computational phenotypes to clinical symptoms across development

- n = 1000 (n=500 discovery/replication samples), ages 10-25, online study
- tasks assessing multiple RL dimensions
- transdiagnostic symptom assessment
- accelerated longitudinal design



relating computational phenotypes to clinical symptoms across development

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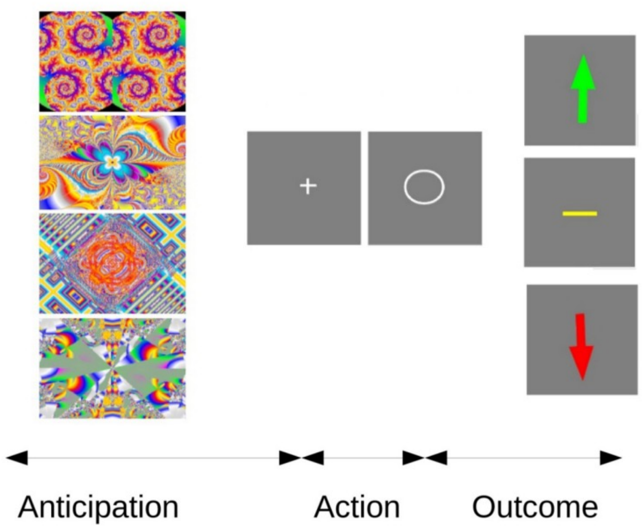
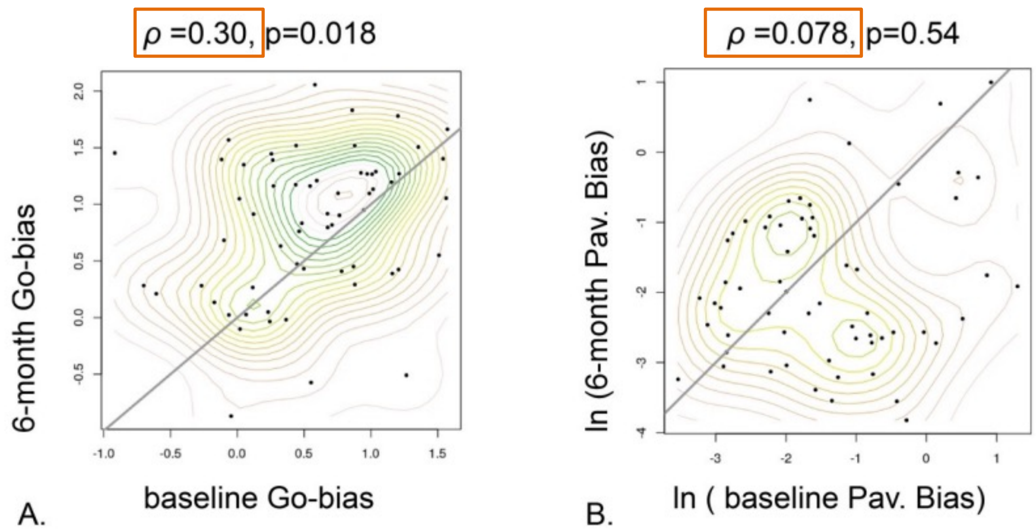
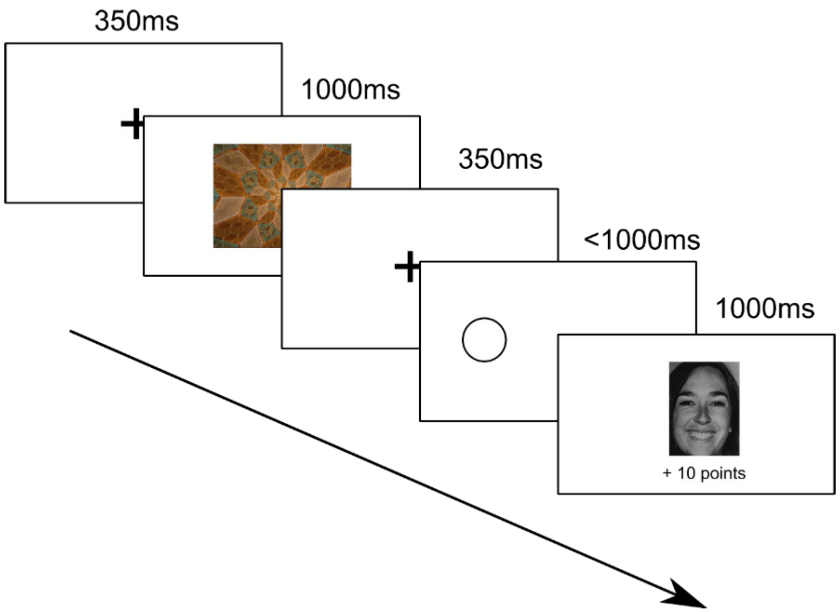
poor test-retest reliability in pavlovian bias task

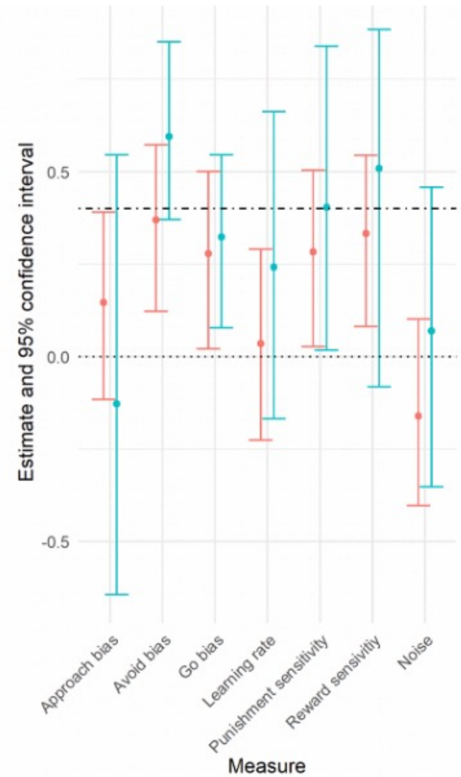




Moutoussis, M. et al. (2018). *PLoS Computational Biology*

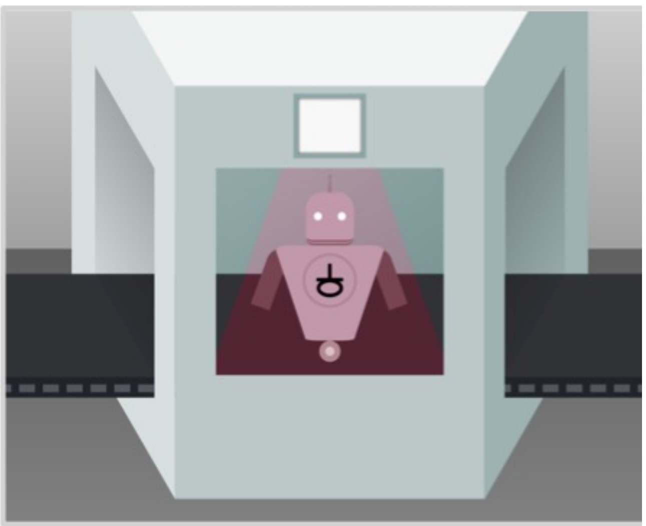
poor test-retest reliability in pavlovian bias task



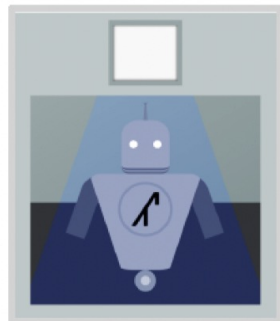


Pike et al., (2022). *PsyArXiv*

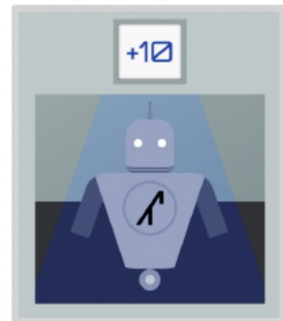
task modifications to improve parameter recovery and reliability



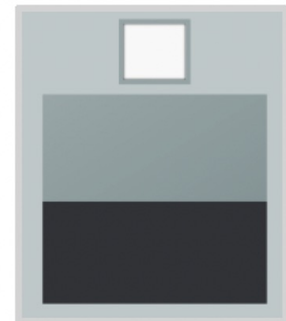
gamificiation



Response window



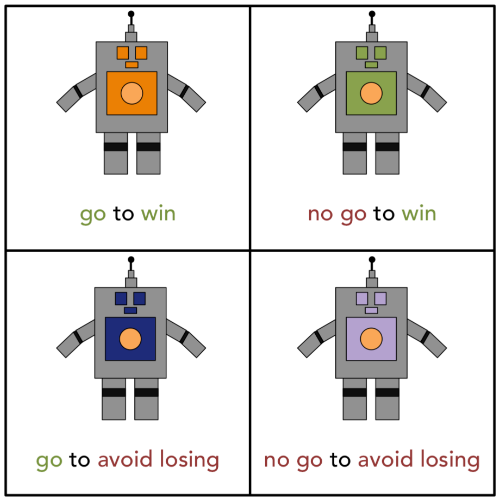
Outcome Displayed

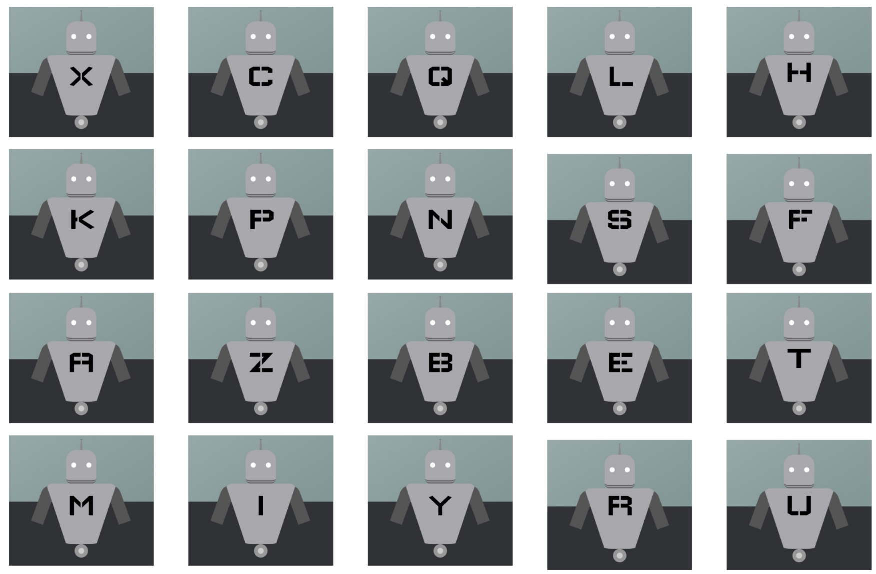


Inter-trial interval

Sam Zorowitz

task modifications to improve parameter recovery and reliability



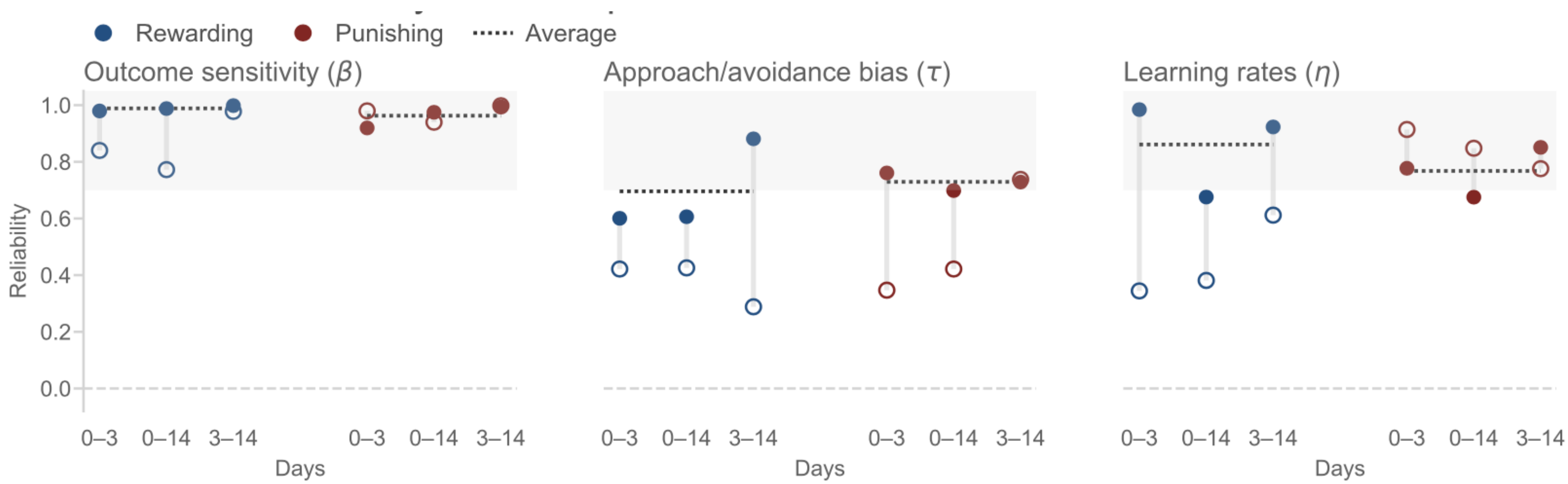


"infinite" learning

- 20 unique stimuli (5 of each type)
- 10-15 repetitions of each stimulus

Sam Zorowitz

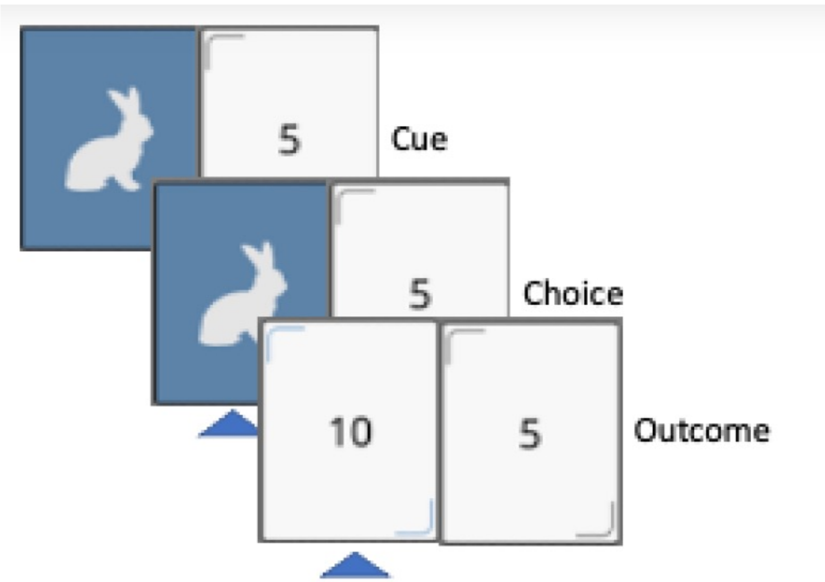
increasing number of learning "problems" improved reliability of parameter estimates in adults



Sam Zorowitz

from Zorowitz et al., 2023 PsyArxiv

task modifications to improve parameter recovery and reliability



– 15 unique stimuli (5 of each type)

– 16 repetitions of each stimulus

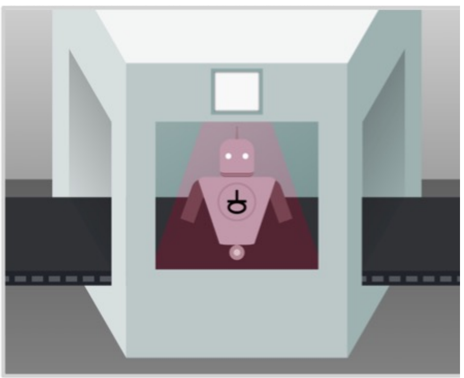
Sam Zorowitz

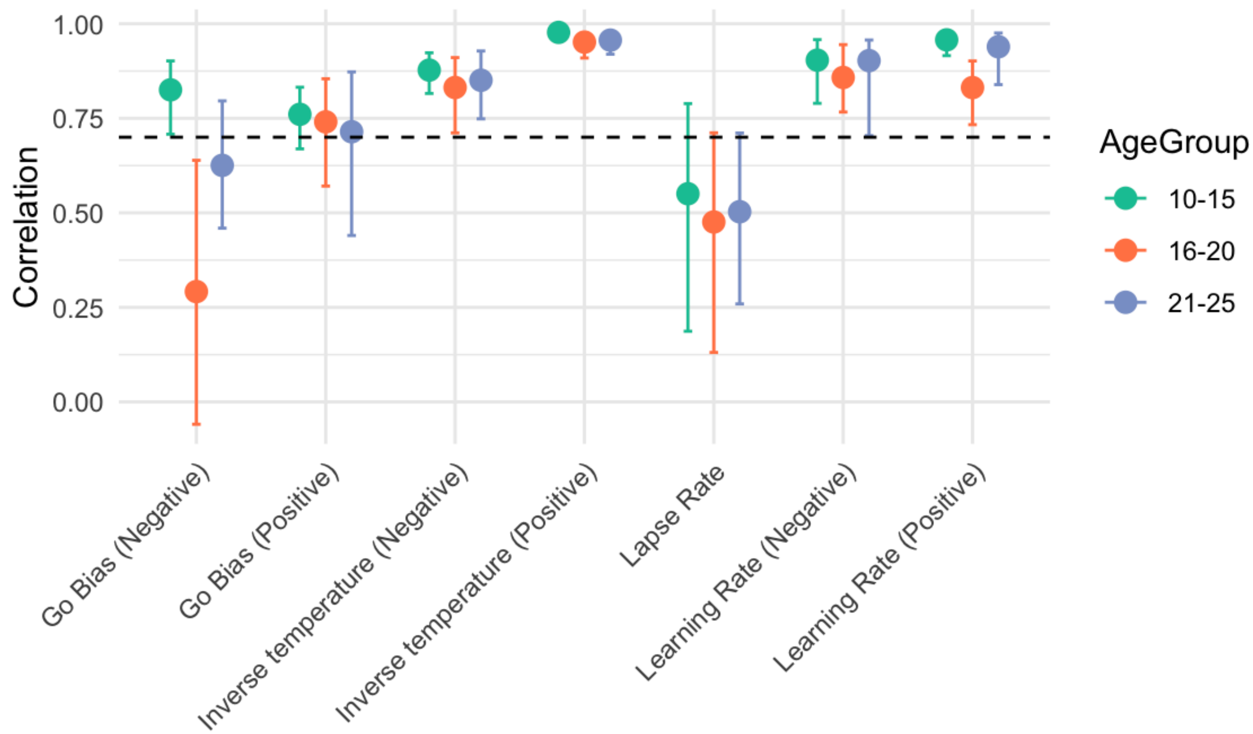
task modifications improved reliability of parameter estimates in adults

Parameter	Mean (SD)	Split-half reliability	Test-retest reliability
β_1	7.71 (3.35)	0.77 (0.69 – 0.84)	0.75 (0.60 – 0.86)
β_2	0.68 (0.37)	0.90 (0.86 – 0.93)	0.92 (0.86 – 0.96)
q_0	0.52 (0.10)	0.99 (0.99 – 0.99)	0.95 (0.91 – 0.98)
η_+	0.15 (0.03)	0.98 (0.98 – 0.99)	0.96 (0.92 – 0.97)
η_-	0.13 (0.01)	0.81 (0.72 – 0.87)	0.46 (0.15 – 0.71)
κ	0.04 (0.14)	0.96 (0.94 – 0.98)	0.72 (0.57 – 0.83)

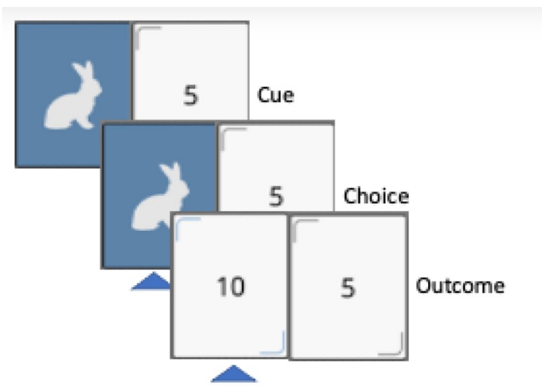
Sam Zorowitz

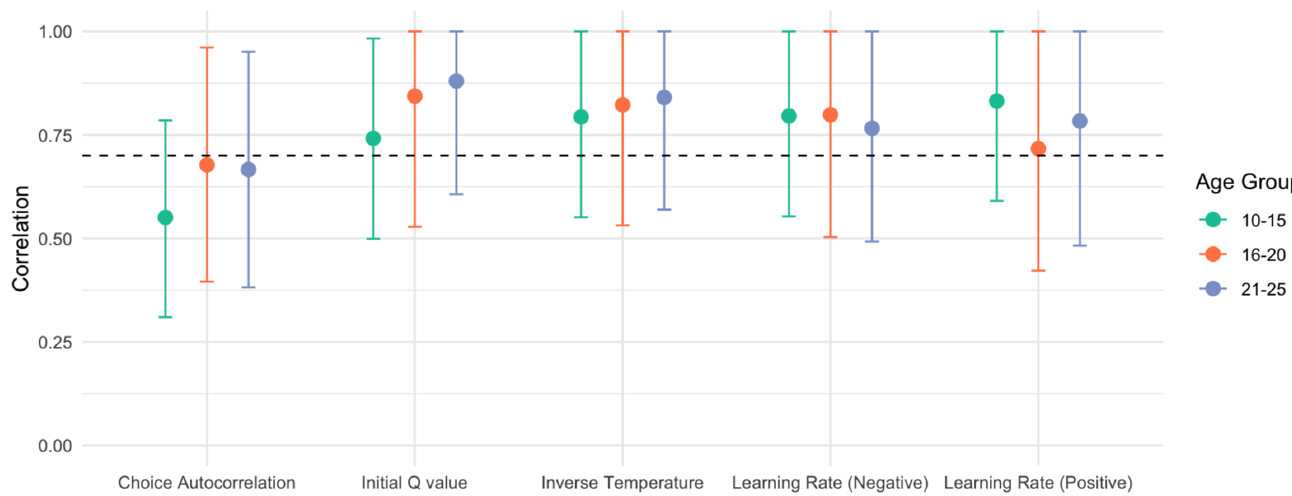
are parameter estimates reliable across development?



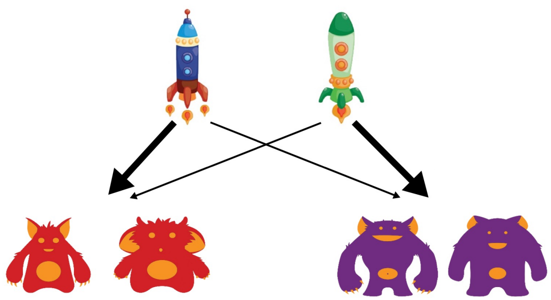


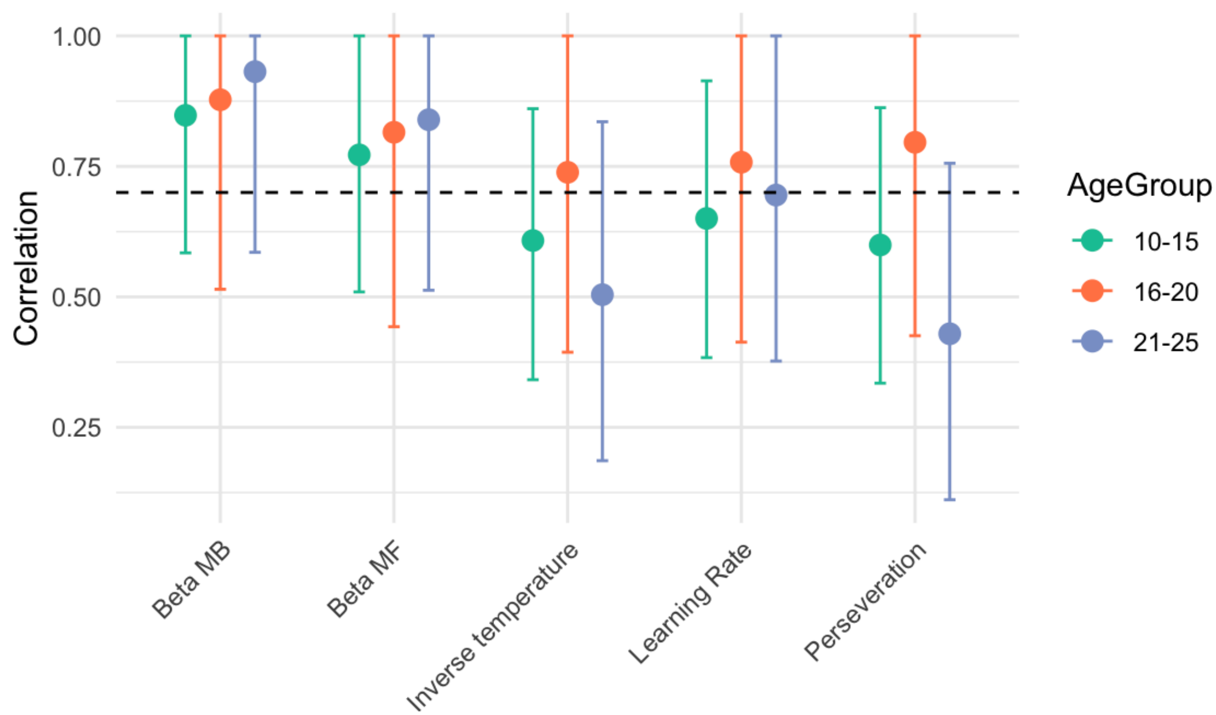
parameter estimates are reliable across age range





parameter estimates are reliable across age range



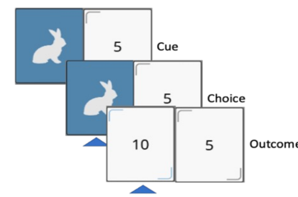


transdiagnostic self-report symptomatology

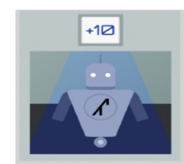
anxiety
depression
ADHD
OCD
impulsiveness
irritability and dysregulation
anhedonia
uncertainty intolerance
rumination

task-based learning phenotypes

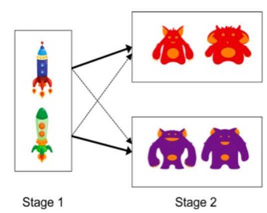
valence asymmetry



pavlovian go/nogo

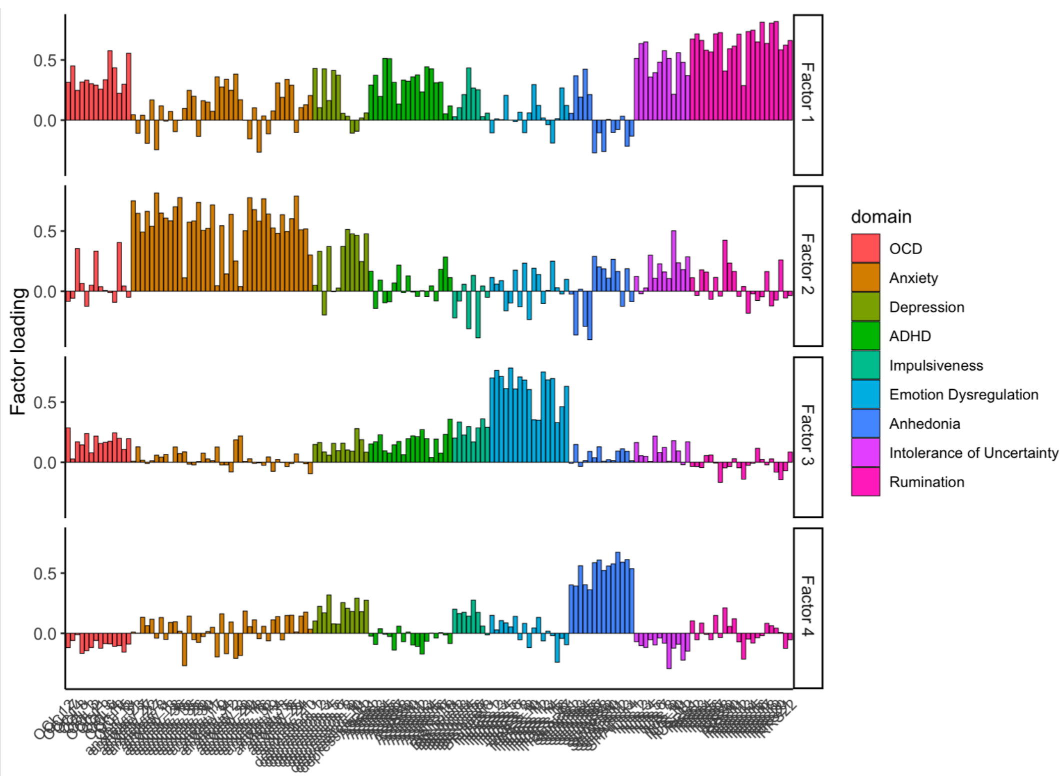


model-based/model-free



target n=1000 (740 collected), discovery sample n=500, replication sample, n=500, ages 10-25

transdiagnostic self-report symptomatology



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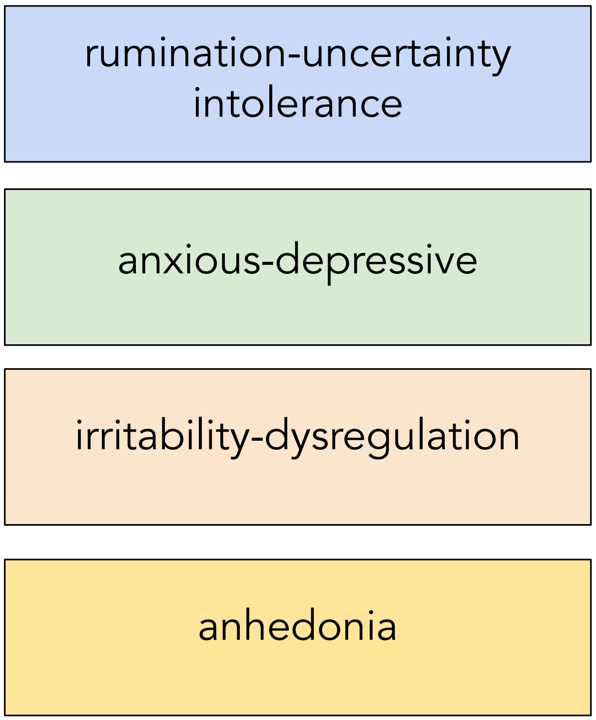


relating computational phenotypes to clinical symptoms across development*

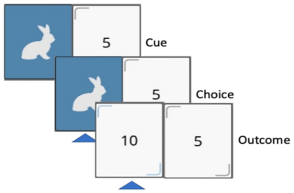
rumination-uncertainty intolerance

anxious-depressive

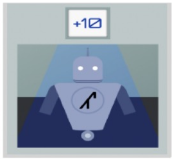
irritability-dysregulation

anhedonia

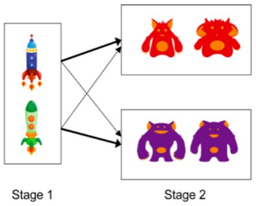
valence asymmetry



pavlovian bias



model-based effect



*very preliminary findings in discovery sample, n=~380

relating computational phenotypes to clinical symptoms across development

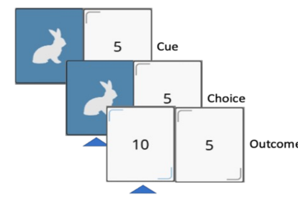
rumination-uncertainty intolerance

anxious-depressive

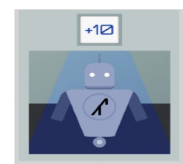
irritability-dysregulation

anhedonia

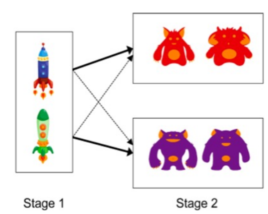
valence asymmetry



pavlovian bias



model-based effect



discovery sample n=380

relating computational phenotypes to clinical symptoms across development

rumination-uncertainty intolerance

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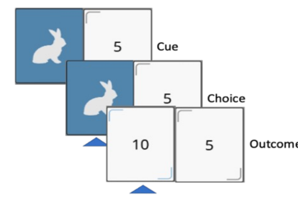
irritability-dysregulation

anhedonia

valence asymmetry



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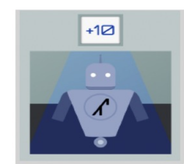
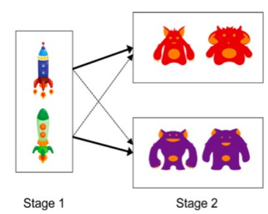


model-based effect



discovery sample n=380

stronger and unique relations among adolescents

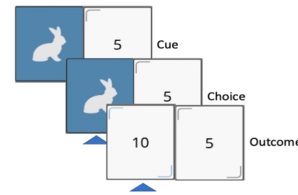
rumination-uncertainty intolerance

anxious-depressive

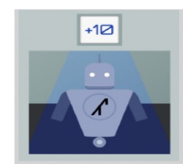
irritability-dysregulation

anhedonia

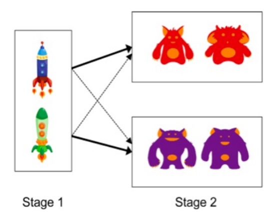
valence asymmetry



pavlovian bias



model-based effect



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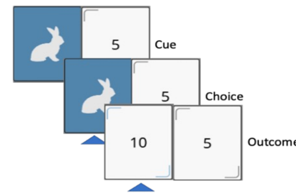
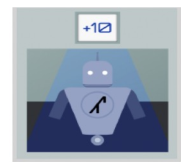
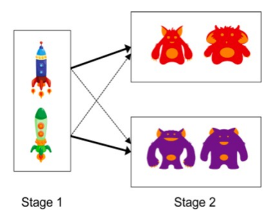


pavlovian bias

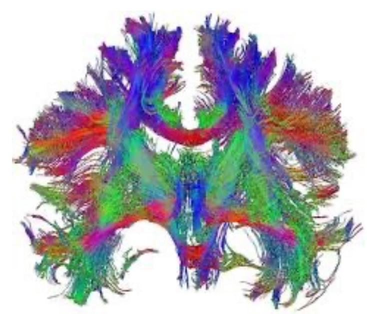
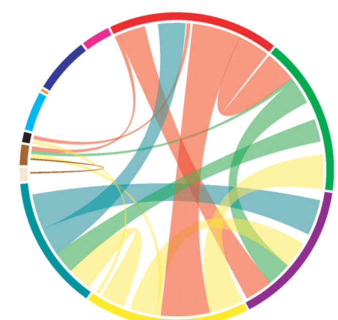


model-based effect

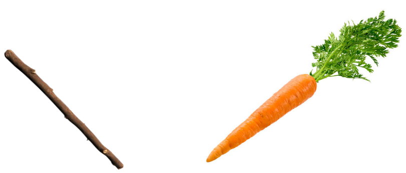


next steps

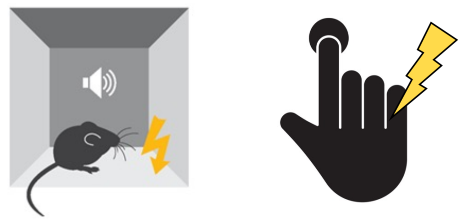
- dimensionality reduction in computational phenotypes
- relation to clinical symptoms at T1 and T2 (data collection underway)
- data collection in child and adolescent patients at Geha
- neuroimaging (n=120)

multiple dimensions of reinforcement learning



weighting of positive versus negative outcomes



learning the value of states versus actions

using structured knowledge or cached values

how do these processes change with age?

how do these changes relate to clinical symptomatology?

how does early experience influence learning phenotypes?

do dimensions of early-life experience relate to computational phenotypes?

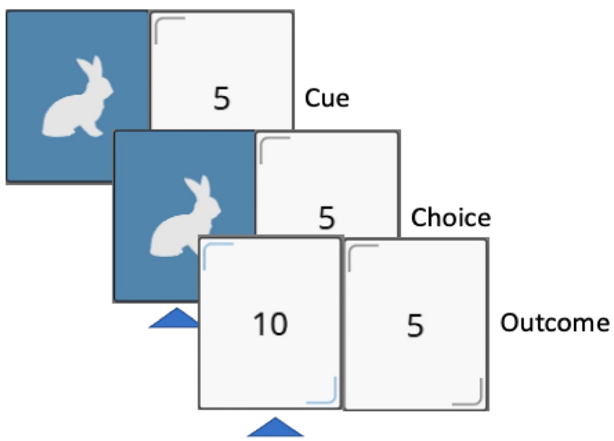
a priori dimensions

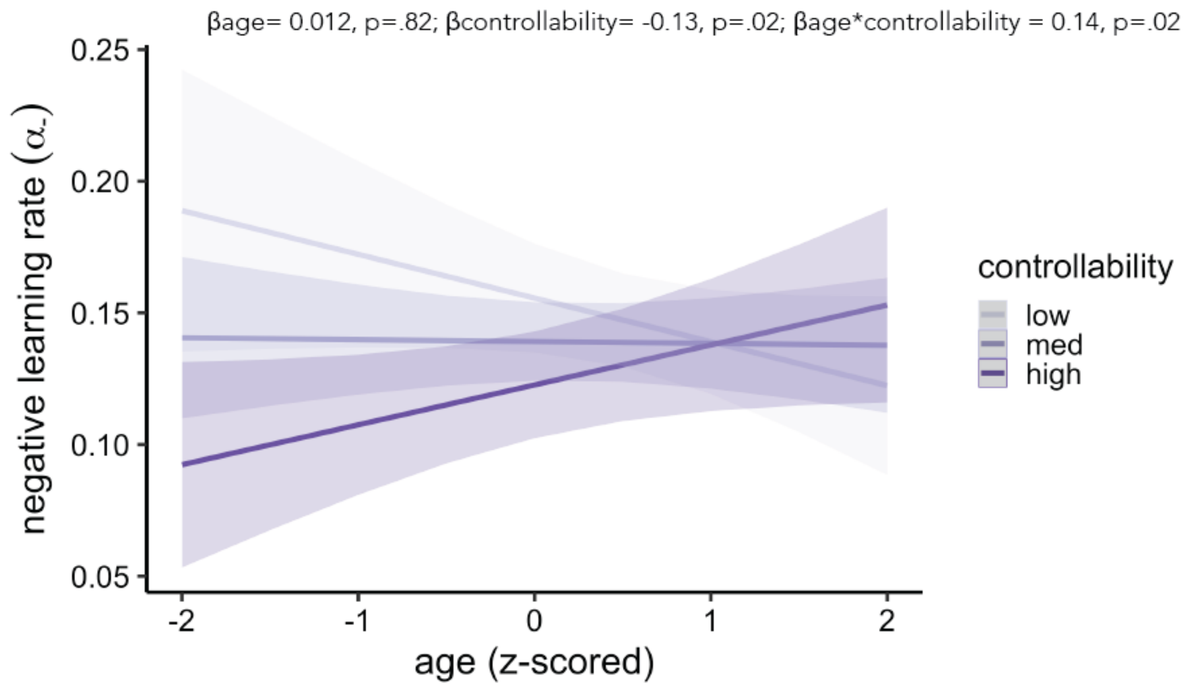
- reward prevalence
- threat prevalence
- unpredictability
- controllability

	Factor 1	Factor 2	Factor 3	Factor 4
Representative Question	Uncontrollable harshness	Adult support	Peer support	Resource unpredictability
How often did an adult shake, pinch, or slap you?	0.76			
My caregiver(s) was/were always trying to change me.	0.59			
When you got punished, how often did it seem like it was for no good reason at all?	0.49			
How often did a caregiver help you learn more about things you were interested in (e.g., dinosaurs, nature, outer space, etc.)?		0.70		
How often did a caregiver show an interest in your thoughts and feelings?		0.58		
My teacher(s) noticed when I was doing a good job and let me know about it.		0.39		
I felt comfortable being myself around my close friend(s).			0.81	
My close friend(s) regularly made plans to spend time with me.			0.65	
How often did you participate in structured activities outside of class (e.g., playing on a sports team, music lessons, etc.)?			0.37	
How often was your electricity, heat, or water turned off?				0.58
How often did you not have a permanent place to live?				0.37
How worried were you about having something of yours stolen or damaged?				0.46

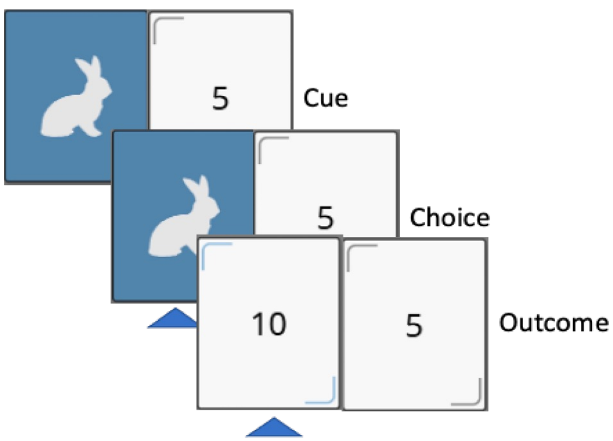
Nora Harhen

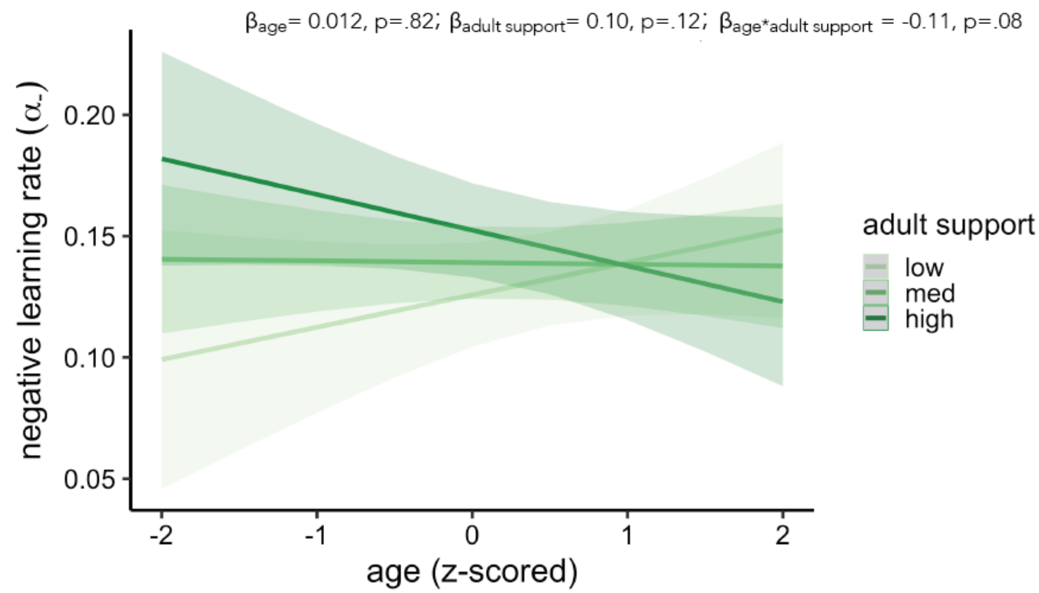
H1: less controllability will predict greater weighting of recent negative outcomes



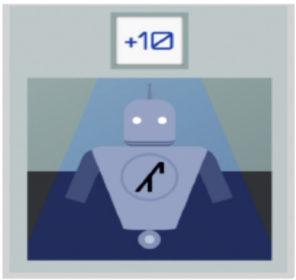


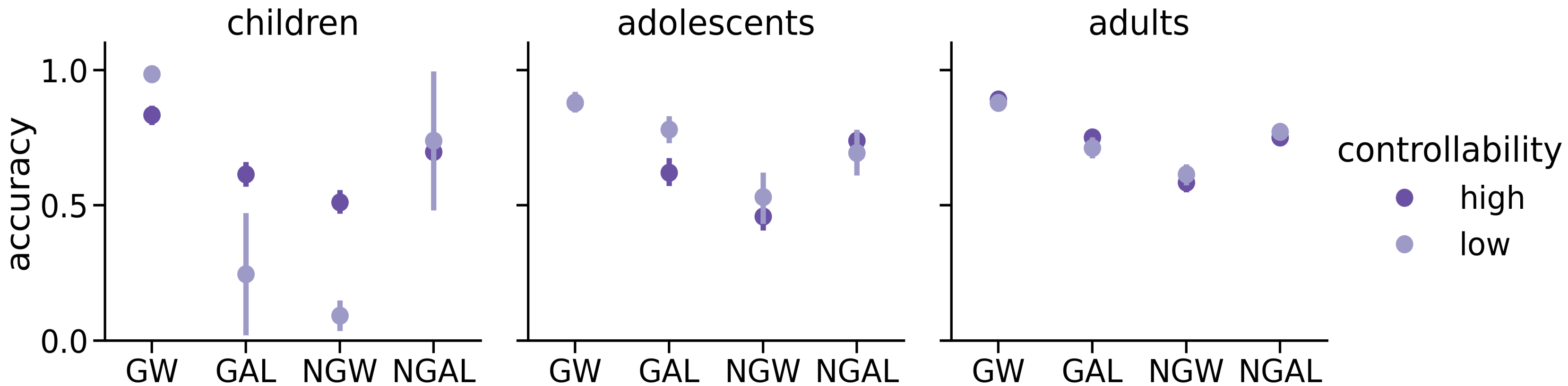
H2: greater reward prevalence will predict greater weighting of recent negative outcomes





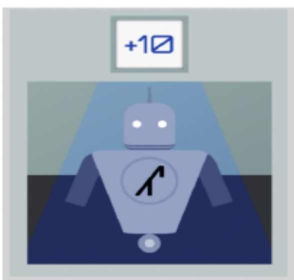
H3: less controllability will predict greater pavlovian bias

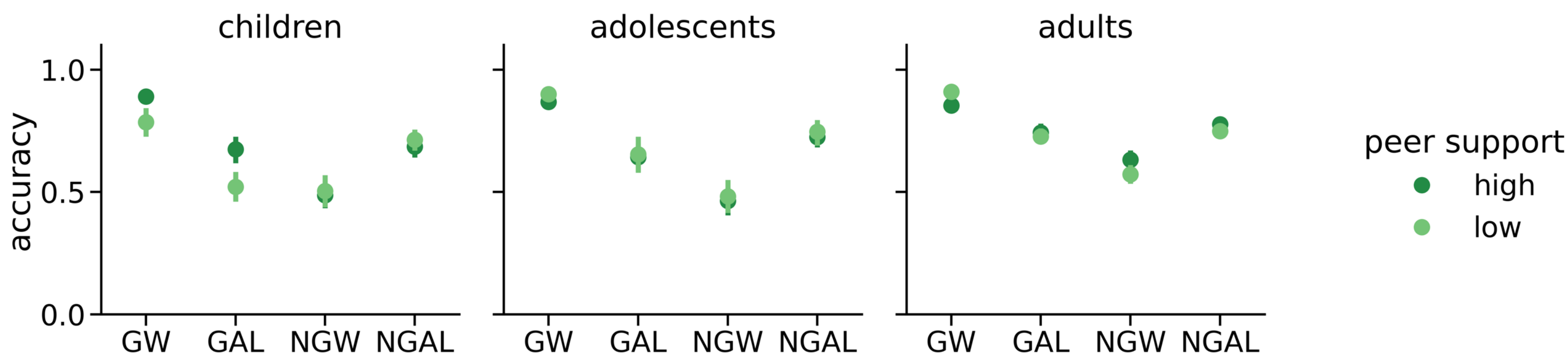




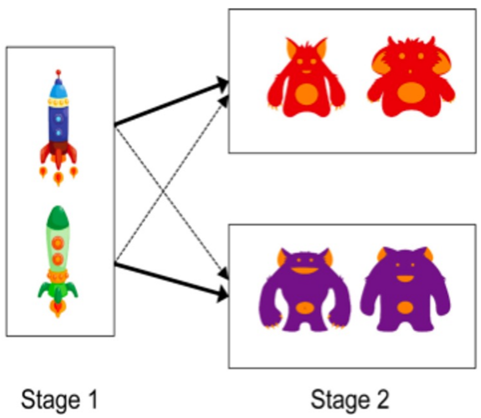
age*controllability, p<.001

H4: lower reward prevalence will predict less reactive approach behavior





H5: less predictability will predict less model-based control



no support for this hypothesis

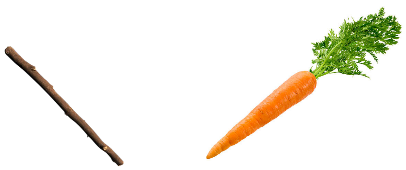
do dimensions of early-life experience relate to computational phenotypes?

- statistics of the early life environment relate to clinically relevant learning computations, but largely in younger individuals.

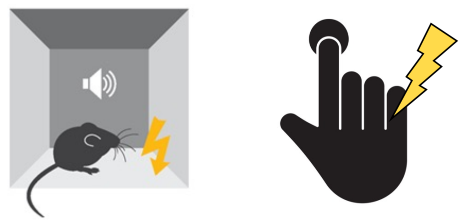
- how to reconcile these seemingly transient environmental effects on learning computations with its known enduring impacts on mental health?

Nora Harhen

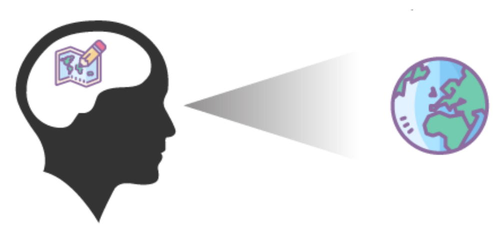
learning computations and the development of psychopathology



weighting of positive versus negative outcomes



learning the value of states versus actions



using structured knowledge or cached values

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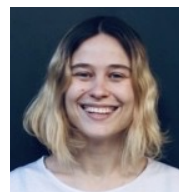
Gili Karni


Nathaniel Daw


Ross Otto

HARTLEY LAB

thank you for your attention!

acknowledgements

<u>funding</u>

NIMH CRCNS R01MH125564

NIMH BRAINS R01MH126183

NSF CAREER Award 1654393

NIDA I/START R03DA038701

NIH National Institute on Drug Abuse
Advancing Addiction Science

NIH National Institute of Mental Health

NSF CAREER Award

BRAIN & BEHAVIOR RESEARCH FOUNDATION

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The Vulnerable Brain Project

KLINGENSTEIN-SIMONS FELLOWSHIP AWARDS IN NEUROSCIENCE

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