Adult age differences in learning and decision-making: From descriptive decisions to complex state spaces

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Structure

Theoretical ideas

- Decisions from **description**
  - Risk
  - Delay
  - Effort

  Summary / Critique

- Decisions from **experience**
  - Learning associations
  - Learning rates
  - Learning structure

  Summary / Critique

The future

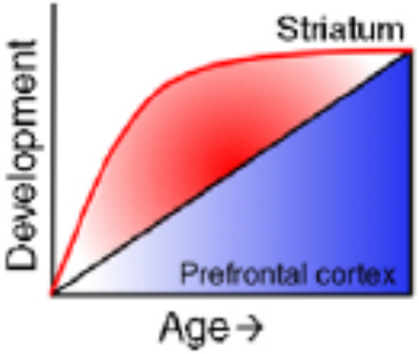
- Arbitration of strategies
- Learning in multidimensional environments
- Social influences on learning

Theoretical ideas

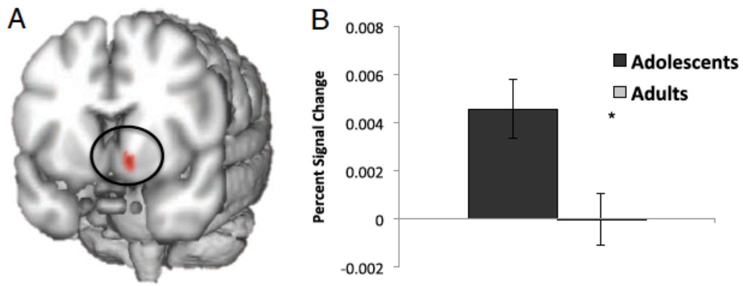
Specificity problem

Heuristic theory ⟹ Cognitive theory (Puntam, 1960) ⟹ Cognitive neuroscience theory (Marr & Poggio, 1976)

- Computational
- Algorithmic
- Implementation



Enhanced striatal activity
In teenagers



Explains greater risk taking, steeper discount rates etc.

Van den Bos & Eppinger, 2016

Theoretical ideas

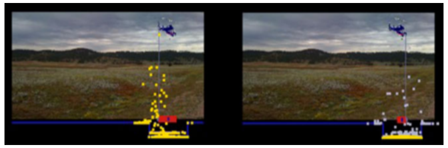
The identity problem

We are unable to identify the processes underlying developmental changes in behavior.

Van den Bos et al., in prep

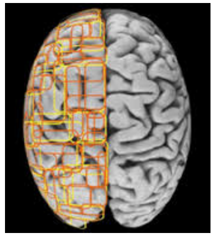
Theoretical ideas
computational methods as one solution

Theory and Behavior

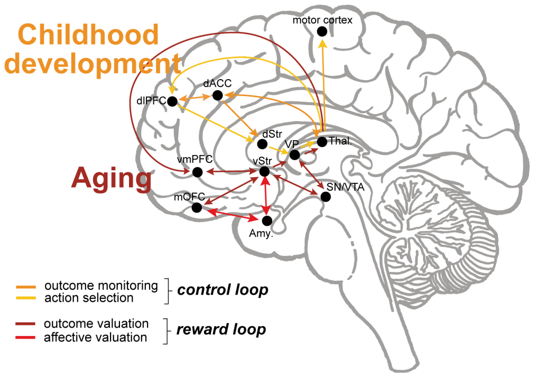


Computational models

$$\delta(t) = r(t) + \gamma * V(t+1) - V(t)$$



Neuroscience data



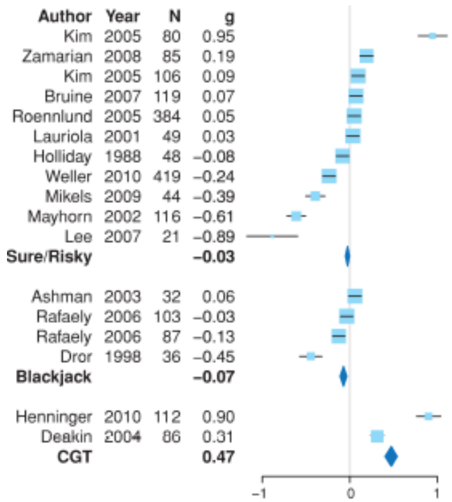
Models provide **specificity** and, if you include assumptions about developmental change they can help to solve the **identity** problem

Decisions from description: Risk

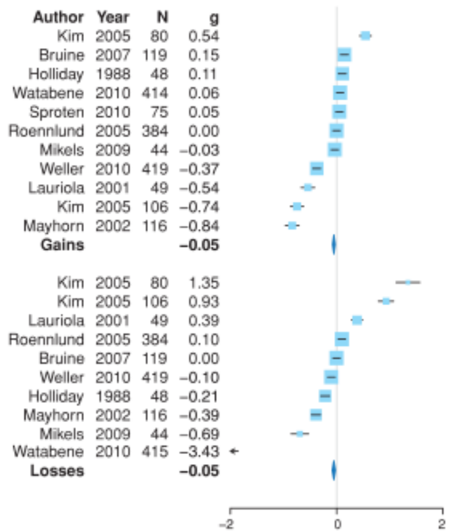
risk advantageous | risk disadvantageous

€10 Euro EV 10 | €30 Euro EV 15 | €10 Euro EV 10 | €30 Euro EV 7.5

Risky decisions



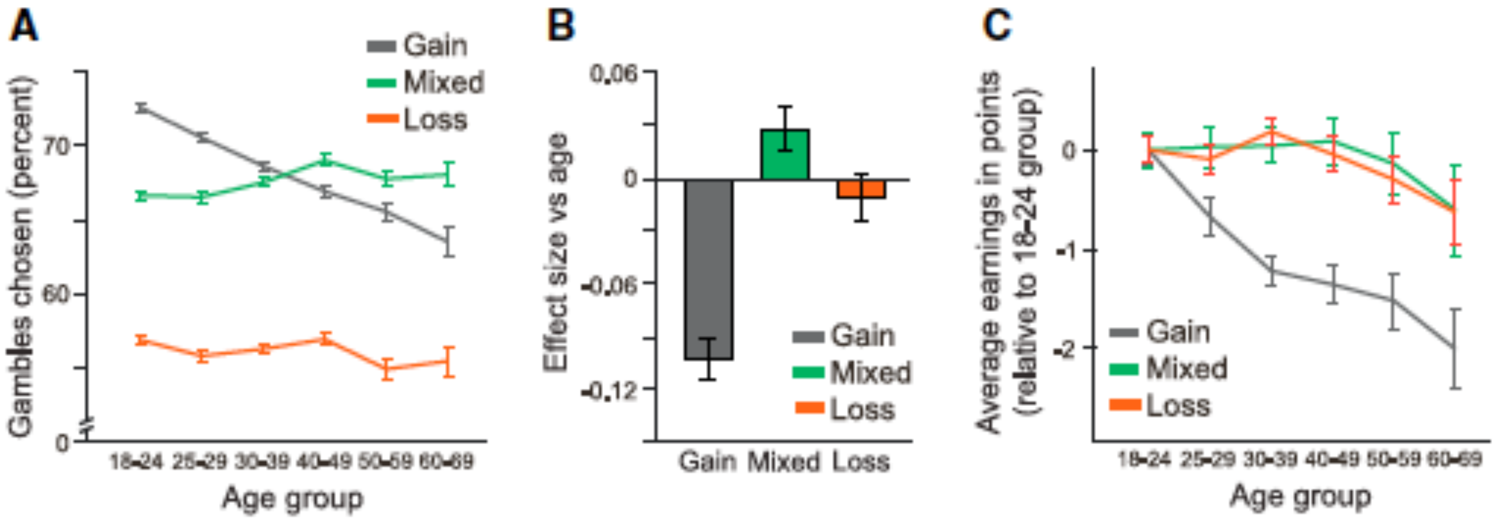
Gains and losses



Mata et al., 2011

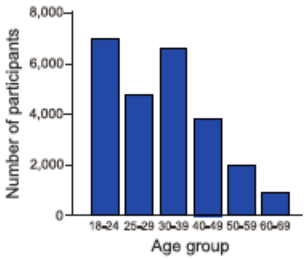
Decisions from description: Risk

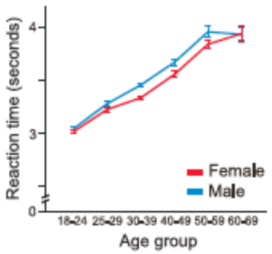
Less risk taking in older adults in the gain domain



Rutledge et al., 2016

Sample size





Impact of this bias depends on the framing of the question.

Summary and Critique

Findings are inconsistent. Effects are small.

- What do these experiments tell us about real world risk-taking?
- What is the algorithmic level of descriptive decisions?

Problems of multi-shot experiments:

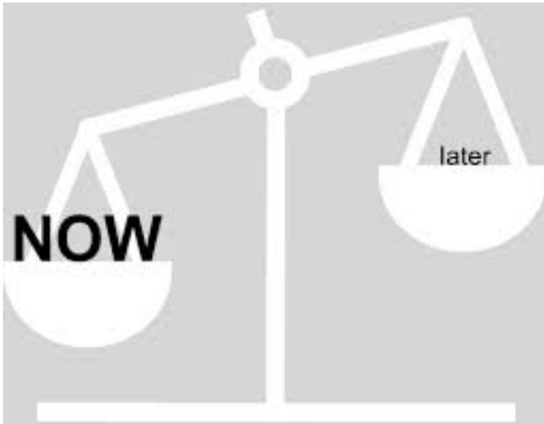
- 140 risky decisions in 20 minutes?
- Reference points

What about incentive compatibility?

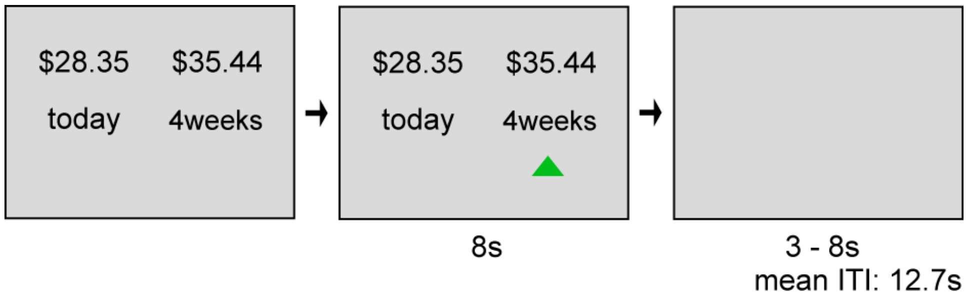
Suggestion: *Large scale behavioral assessments with single shot, incentive compatible tasks and then use subsample follow-ups with neuroscience studies using paradigms that we understand.*

Decisions from description: Time

Immediate temptations vs. delayed rewards

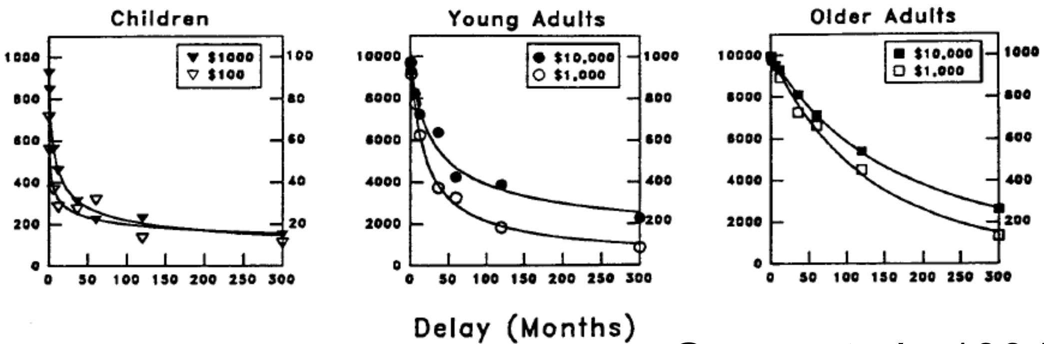


Canonical delay discounting task



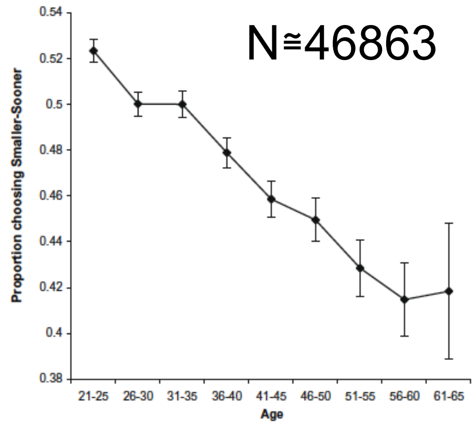
Decisions from description: Time

Lifespan age difference



Green et al., 1994

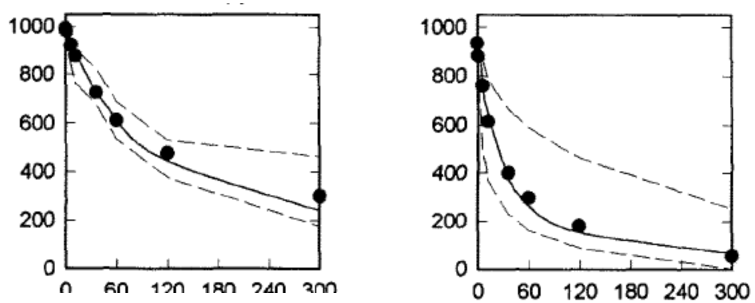
One-shot



Reimers et al., 2009

Confounded by income

High income OA   Low income OA



Green et al., 1996

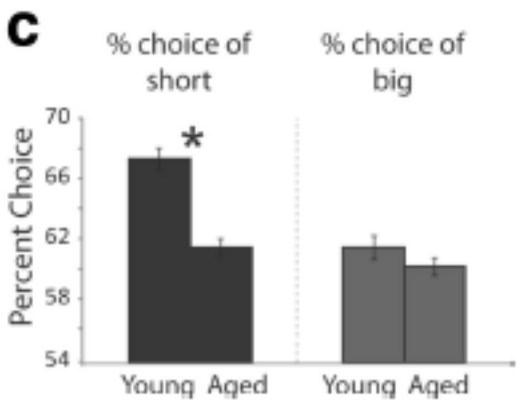
Impulsive choice is associated with:

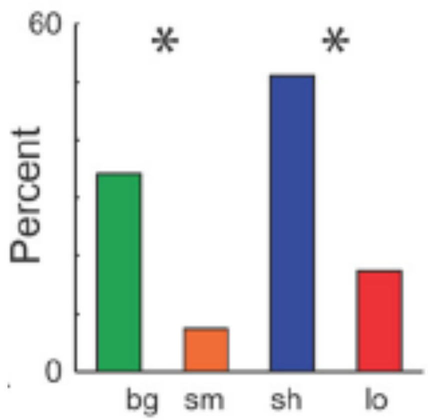
- Younger age
- Lower income
- Lower education
- Risky behavior

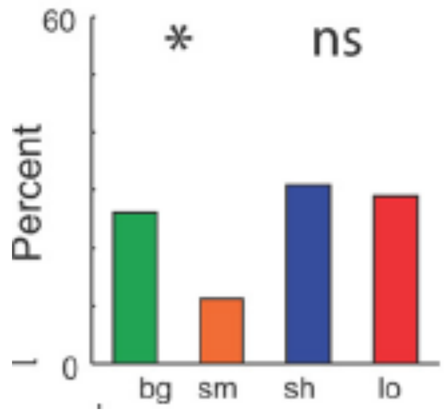
Decisions from description: Time

Younger rats

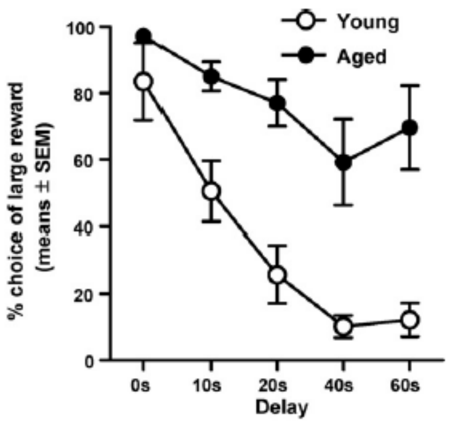
Older rats







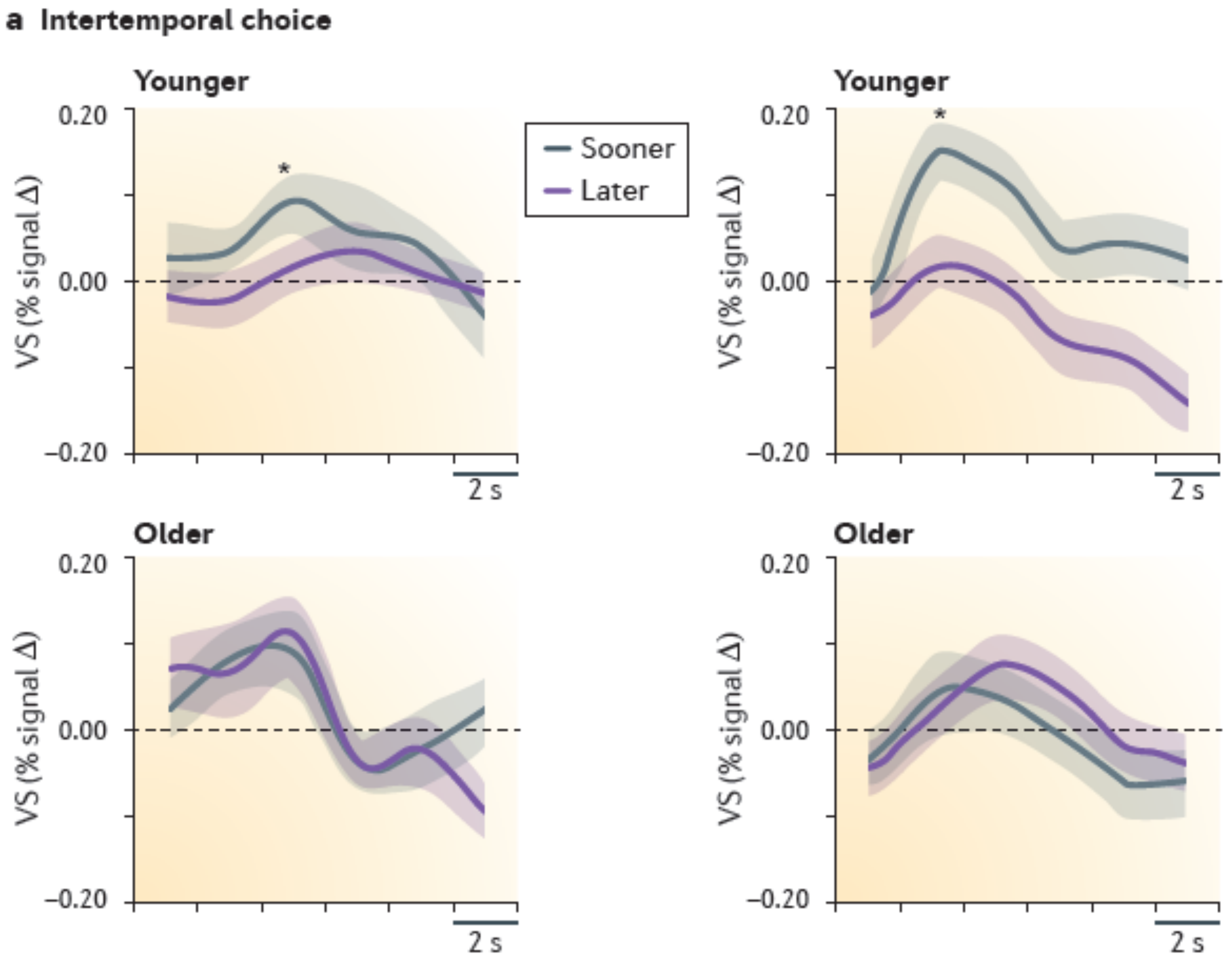
Roesch et al., 2012



Similar results in older rats

Simon et al., 2012

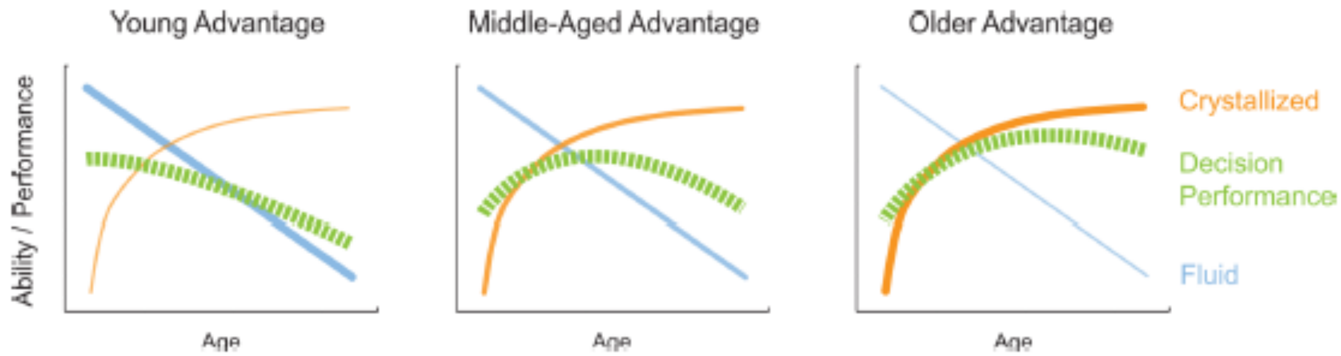
Decisions from description: Time



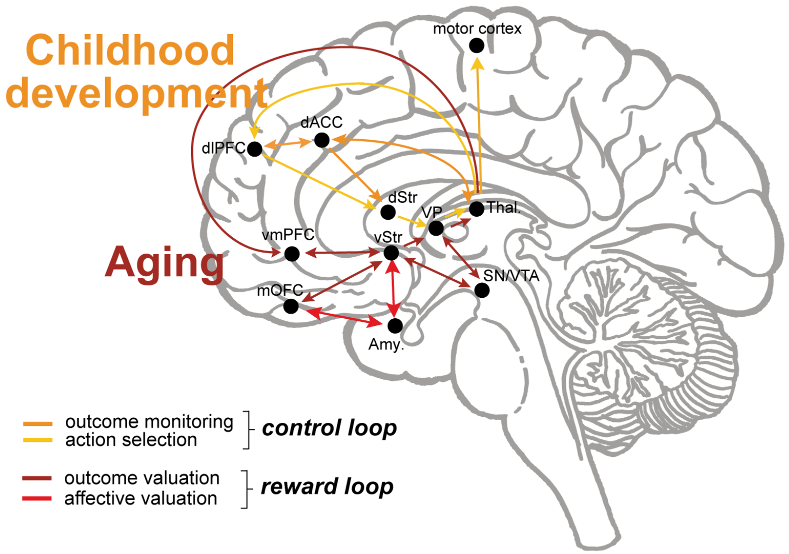
Samanez-Larkin et al., 2011

Eppinger et al., 2012

Decisions from description: Time



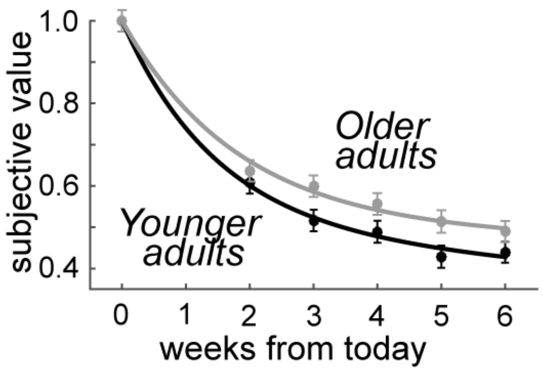
Samanez-Larkin & Knutson, 2015



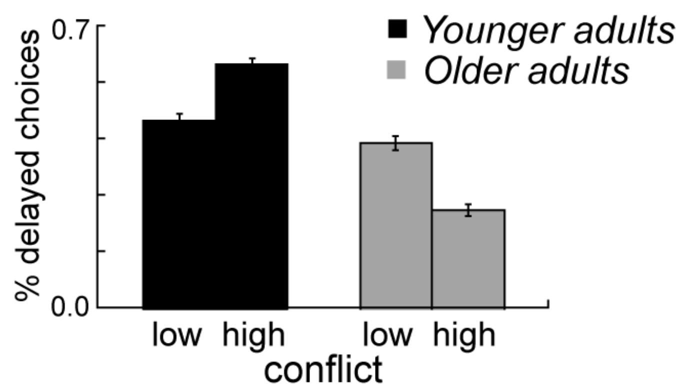
Hämmerer & Eppinger, 2012
Eppinger et al., 2011

Decisions from description: Time

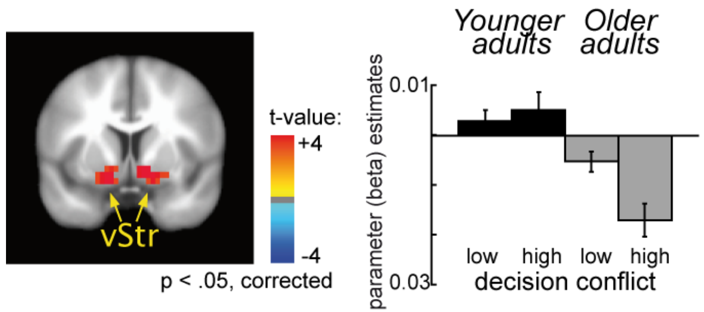
Session 1



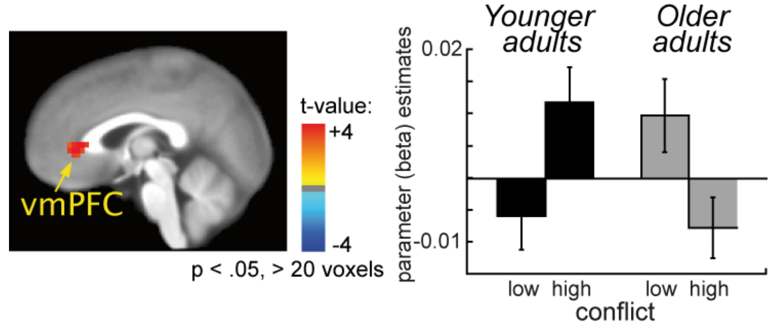
Session 2



Age effects – ventral striatum



Value effects - vmPFC



Eppinger et al., under revision

Summary and Critique

Unclear whether age differences in discounting result from reduced impulsivity or greater experience.

Older adults have a limited time horizon, how does that fit to reduced discounting?

Table 1 Potential confounds that may arise in attempts to measure discount rates in laboratory studies

Factor	Description
Unreliability of future rewards	A subject may prefer an earlier reward because the subject thinks she is unlikely to actually receive the later reward. For example, the subject may perceive an experimenter as unreliable.
Transaction costs	A subject may prefer an immediate reward because it is paid in cash, whereas the delayed reward is paid in a form that generates additional transaction costs. For example, a delayed reward may need to be collected, or it may arrive in the form of a check that needs to be cashed.
Hypothetical rewards	A subject may not reveal her true preferences if she is asked hypothetical questions instead of being asked to make choices with real consequences. However, researchers who have directly compared real and hypothetical rewards have concluded that this difference does not arise in practice (Johnson and Bickel, 2002).

Chabris et al., 2008

Solutions:

- *Careful designs,*
- *Greater age ranges,*
- *Species comparisons,*
- *DA manipulations,*
- *PET measurements.*

Decisions from description: Effort

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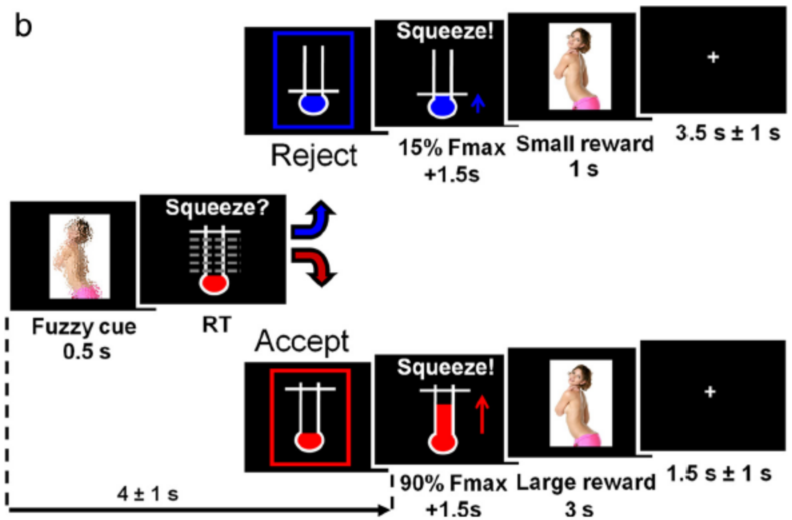
Cognitive effort

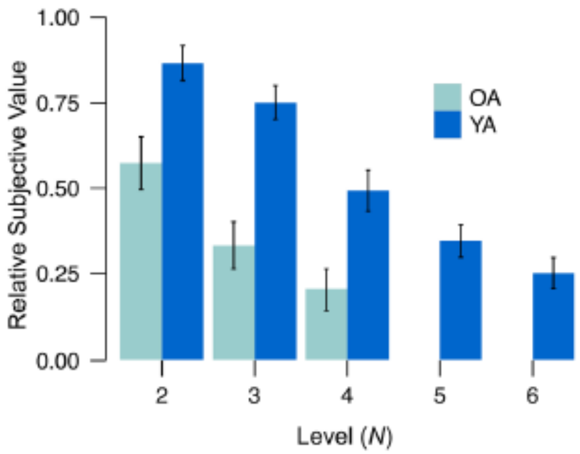
Westbrook et al., 2013

Physical effort

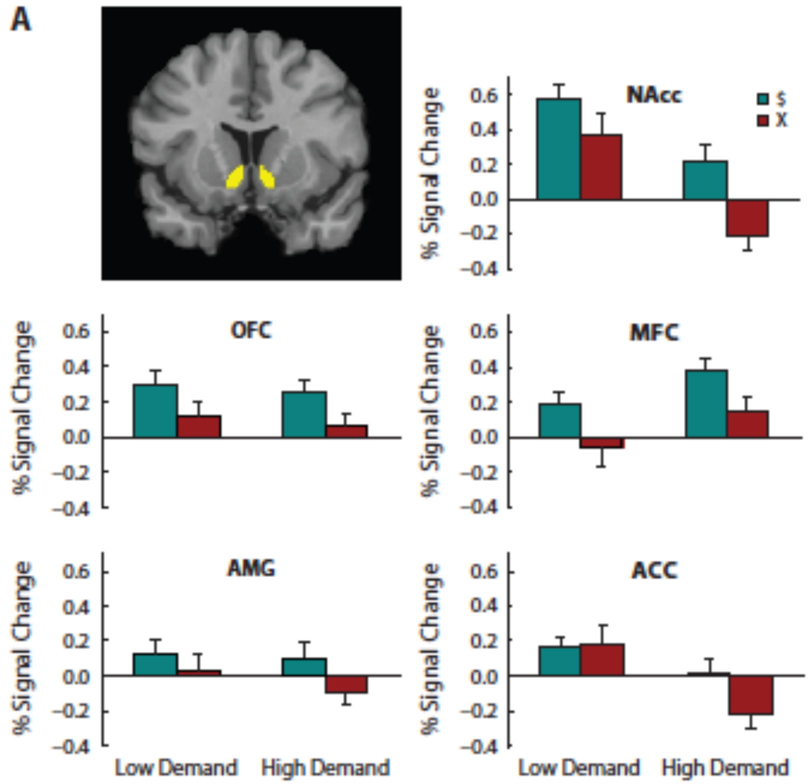


Prevost et al., 2010

Decisions from description: Effort



Westbrook et al., 2013



Botvinick et al., 2009

Summary and Critique

There is not (yet) much to say about age differences in effort discounting.

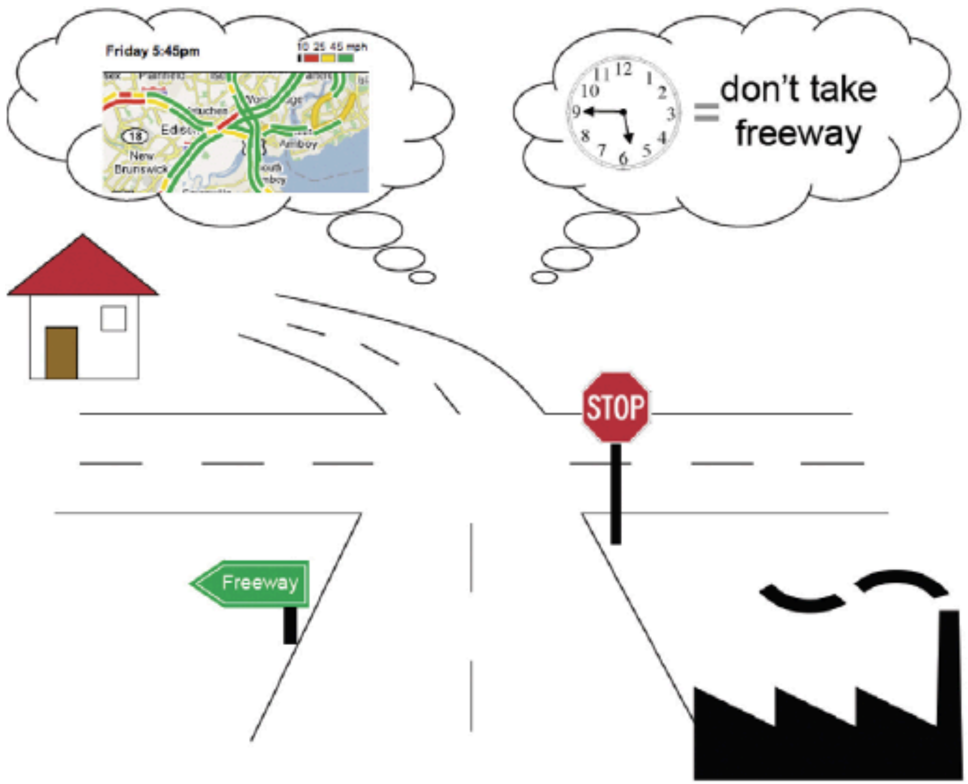
The general problem:
Is it about cognitive abilities or about preferences?
Is it because older adults can’t or because they don’t want to?

More specific problems:
Operationalization of effort:

- Pinky presses?
- Grip strength?
- Cognitive effort ?

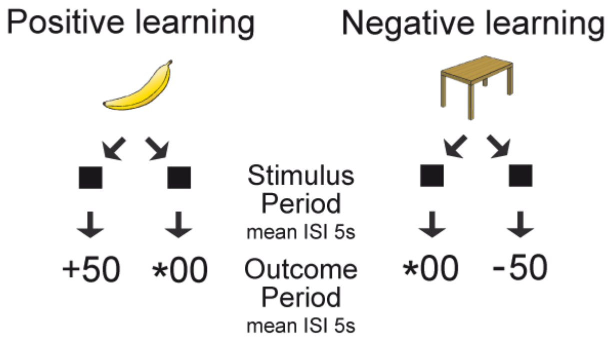
Decisions from experience:

model-based RL　　model-free RL

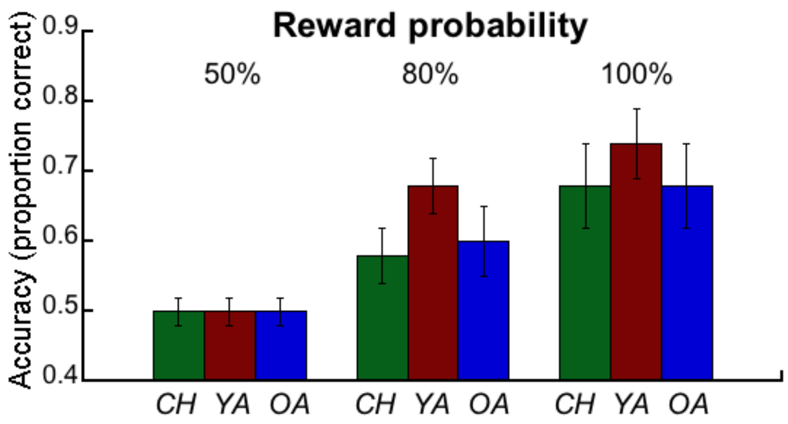


Dayan & Niv, 2008

Decisions from experience: Model-free RL

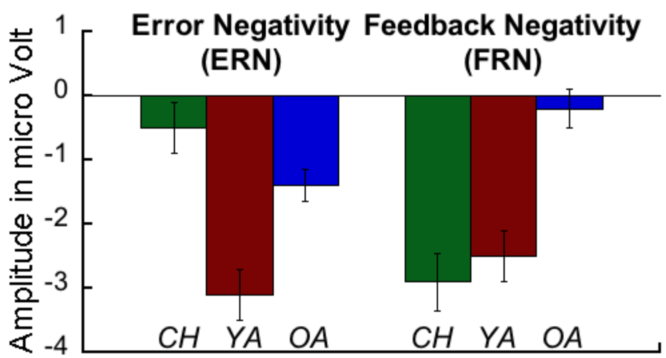


Learning under uncertainty



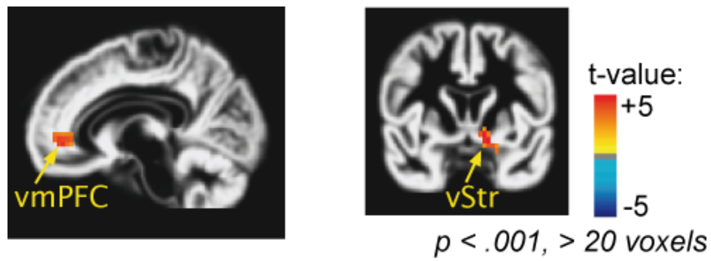
Medial frontal ERPs

80% reward probability



Learning from reward Pes

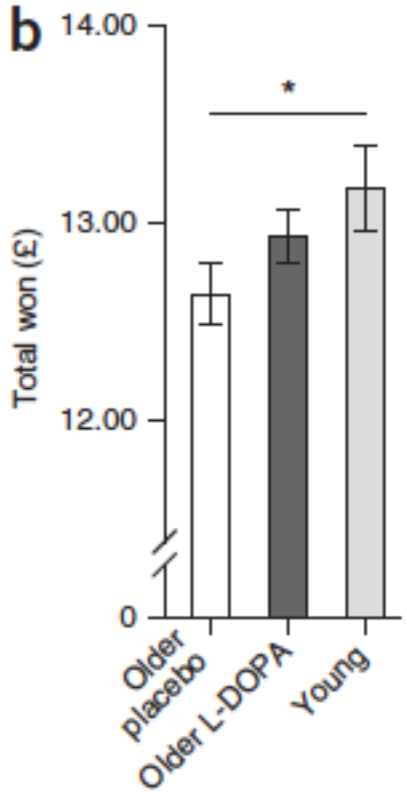
YA > OA

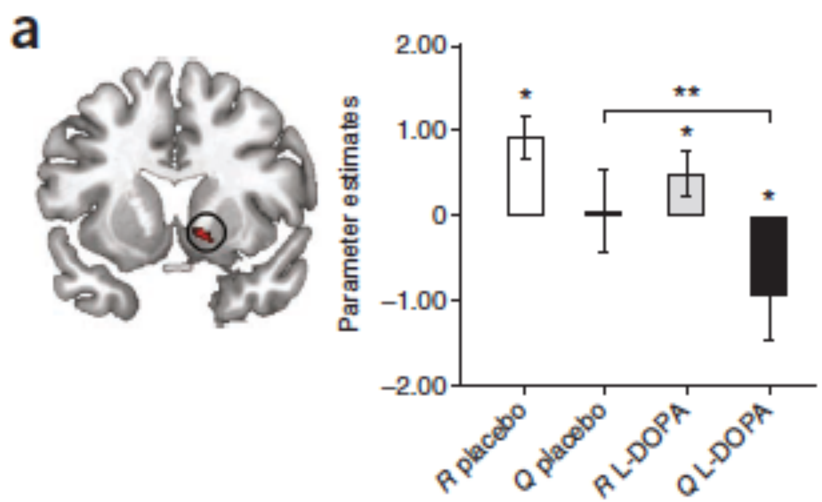


Eppinger et al., 2008; 2009

Eppinger et al., 2013

Decisions from experience: Model-free RL



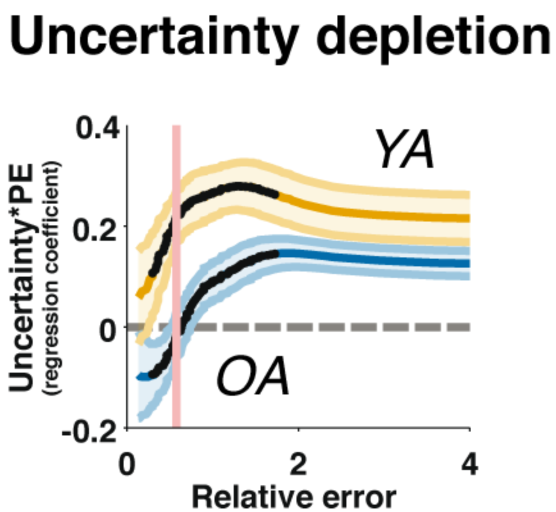


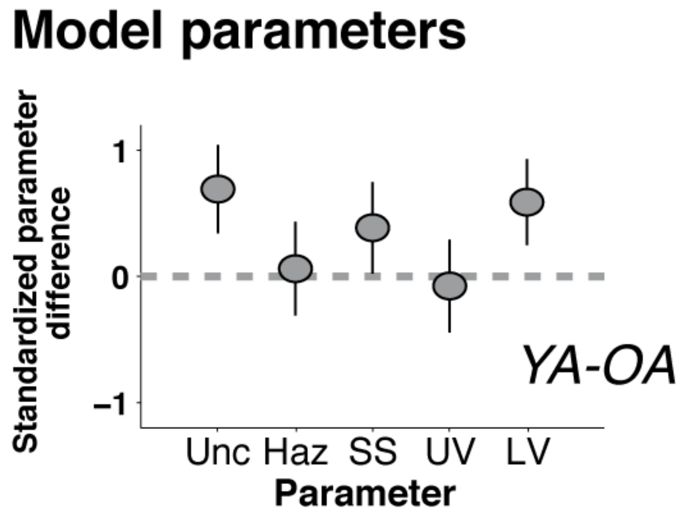
Chowdhury et al., 2013

Changes in bottom up DA signals or top-down down prefrontal influences (e.g. learning rates)?

Decisions from experience: Model-free RL

- Uncertainty
- Surprise
- Hazard rate

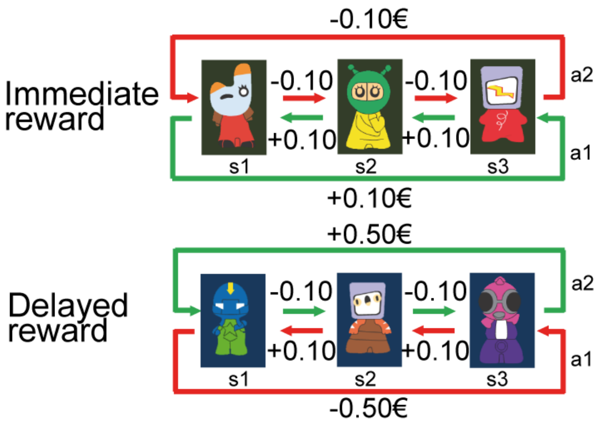


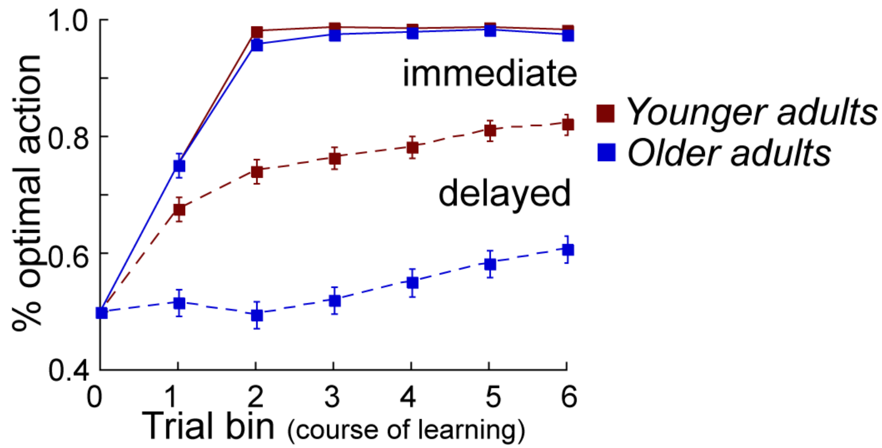


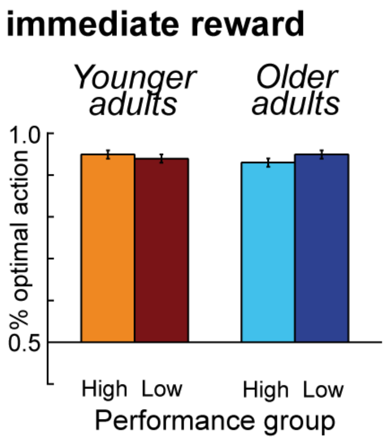
Unc = Uncertainty depletion
Haz = Hazard rate
SS = Surprise sensitivity
UV = update variability
LV = learning rate variability

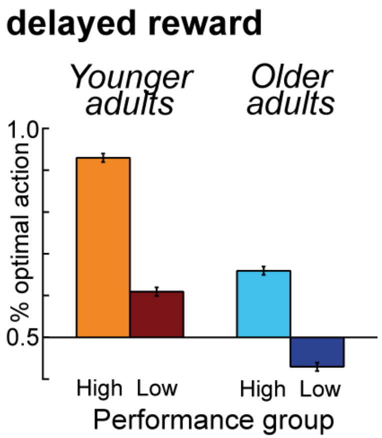
Nassar et al., 2016

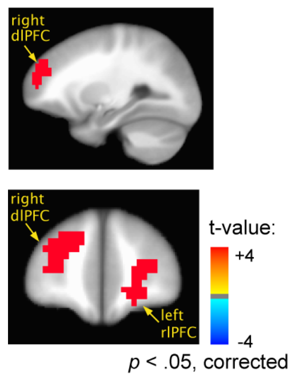
Decisions from experience: Model-based RL

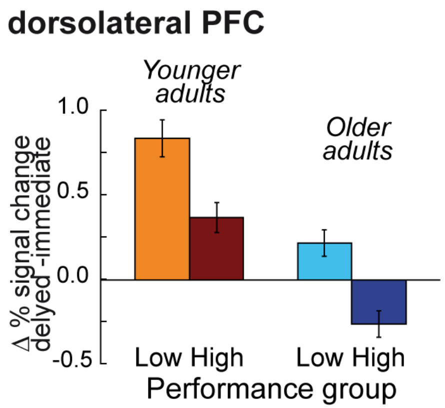








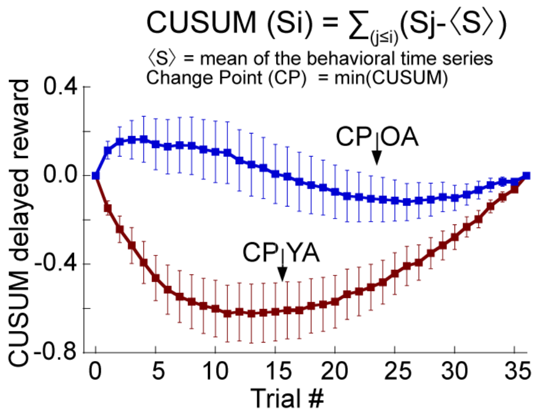




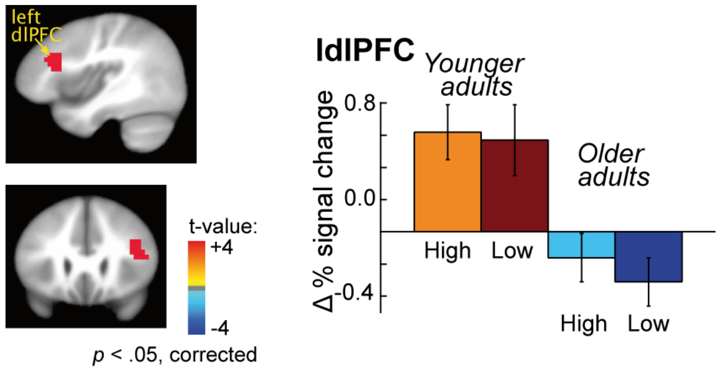
Eppinger et al., 2015

Decisions from experience: Model-based RL

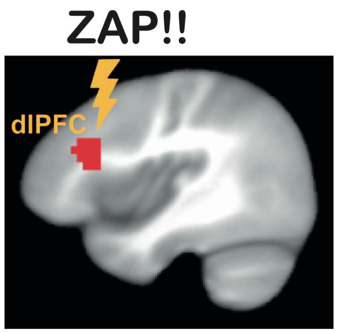
Behavioral change points



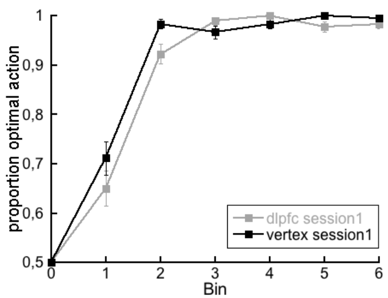
Neural change points



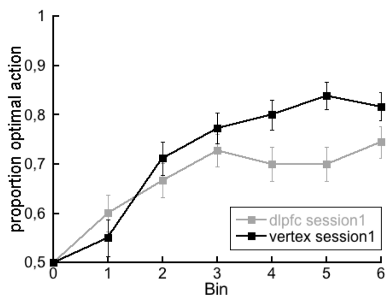
TMS in younger adults



Immediate reward



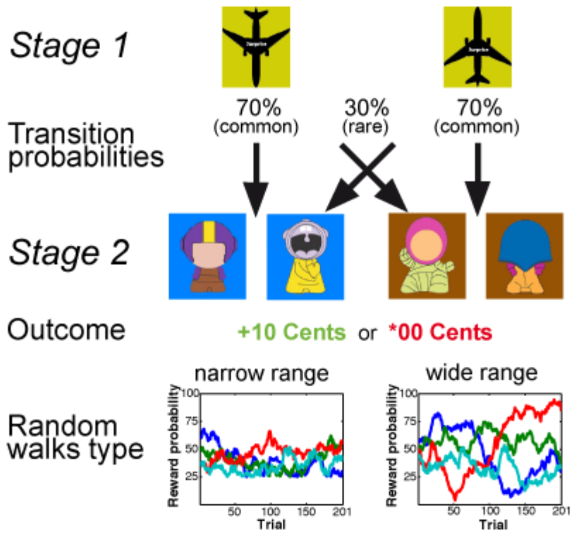
Delayed reward



Wittkuhn et al., *in prep*

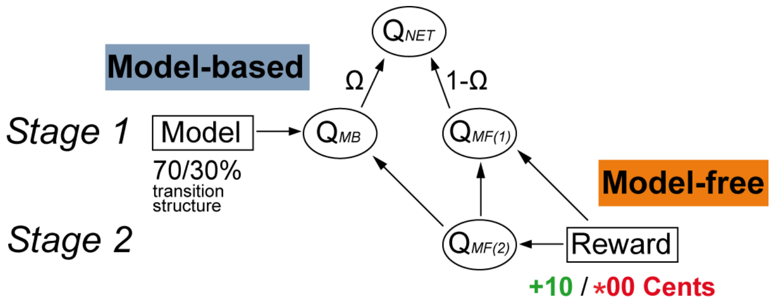
Interactions between MB and MF

2-stage Markov task

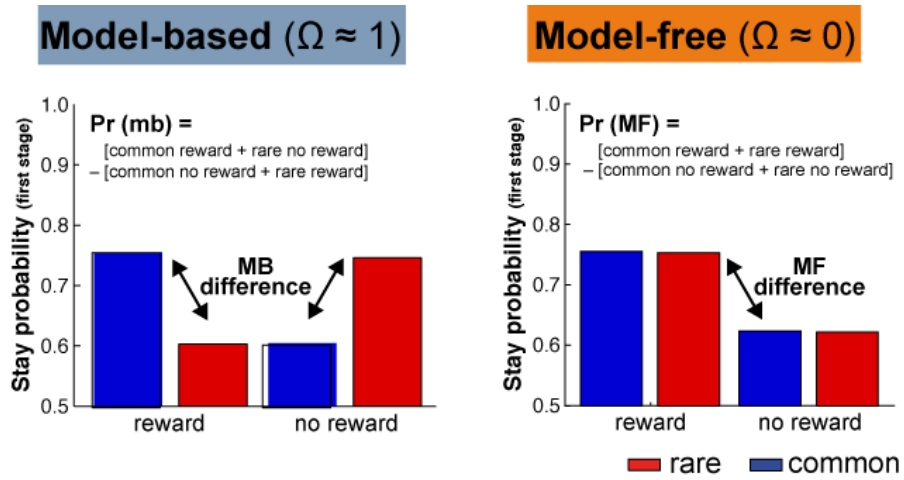


Daw et al., (2011)

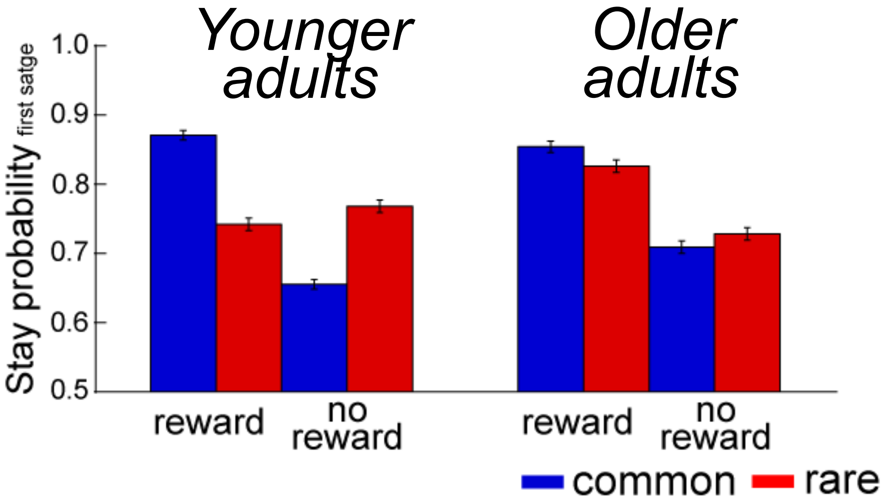
Computational model



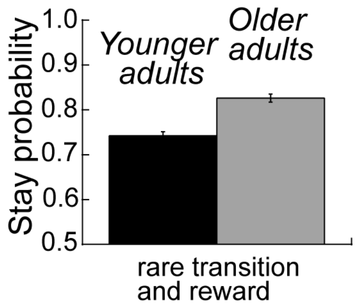
Simulations



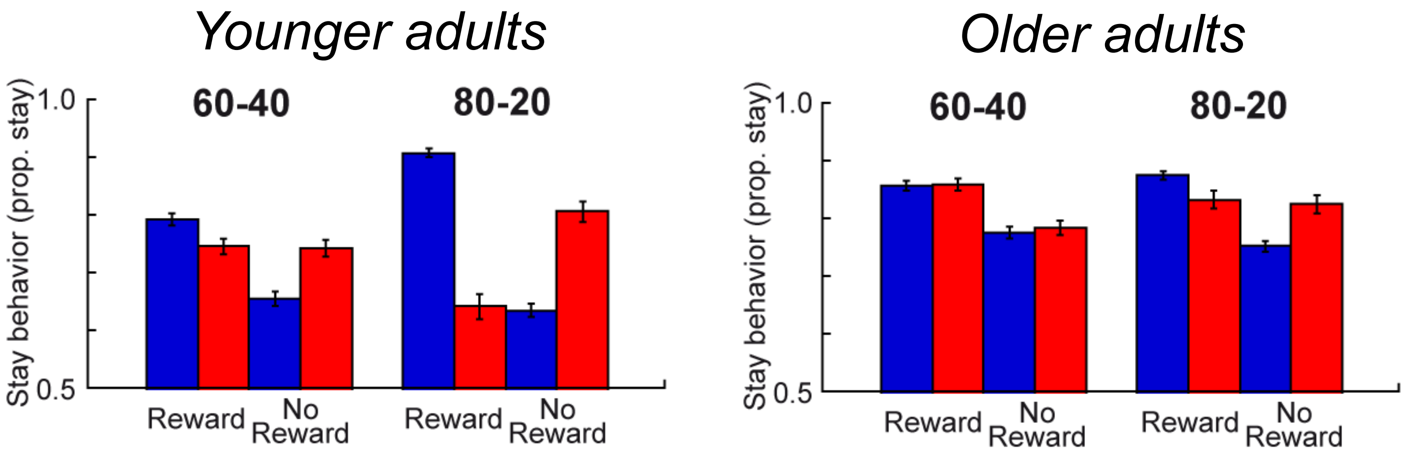
Interactions between MB and MF



Perseveration in older adults



Eppinger et al., 2013



Eppinger et al., in prep

Summary and Critique

Age-related deficits in MF learning are reflected in diminished striatal responses to RPe's. These signals can be partially restored with l-DOPA.

It is unclear whether they result from changes in DA signaling or from age differences in upstream processes.

Substantial impairments of older adults in learning task structures. These deficits are reflected in reduced prefrontal activity.

The underlying computational deficits are unclear: Is this a deficit in extracting state transition structures or is it a representational deficit?

- Need to go beyond correlational methods.
- Strong focus on RL and DA prediction error signals.
- Tasks tend to be static and uni-dimensional.

The future

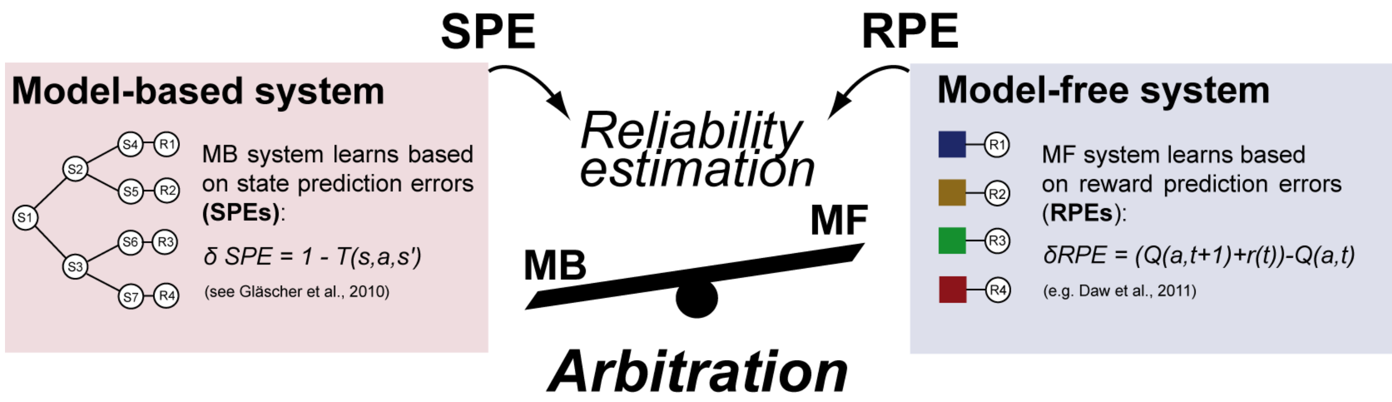
Questions that I am working on / I find interesting:

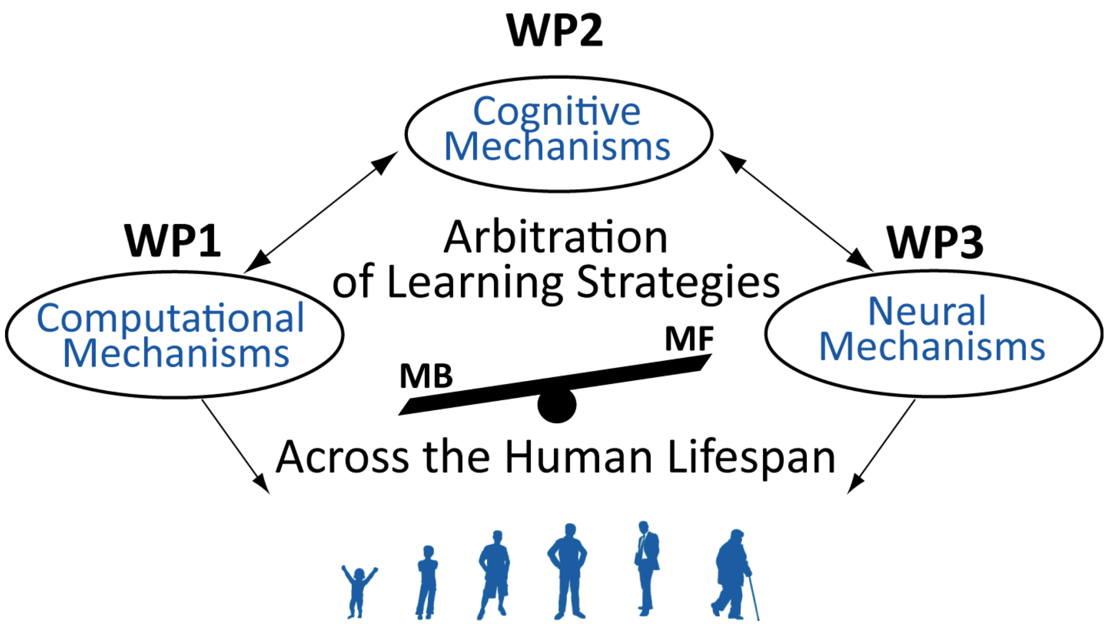
Learning strategies. How do we know which learning strategy to engage in? How does the ability to arbitrate between strategies change with age? How do learning strategies change in partially observable environments

Multi-dimensional environments. How do older adults differ from younger adults in the ability to prioritize and/or integrate information from multiple sources during learning.

Social influences on learning

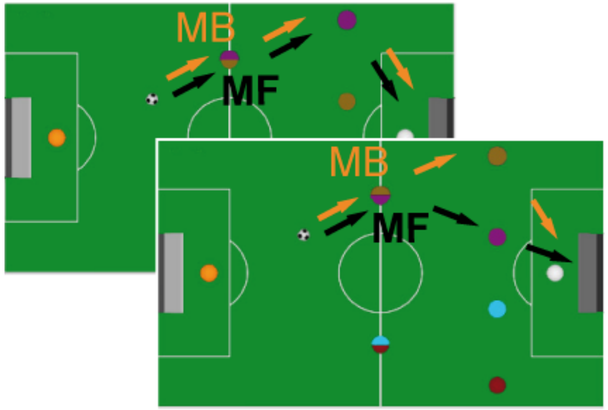
Arbitration of learning strategies



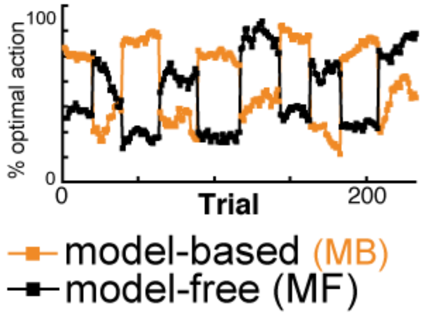


Age differences in the arbitration of learning strategies

Dynamic Markov decision task

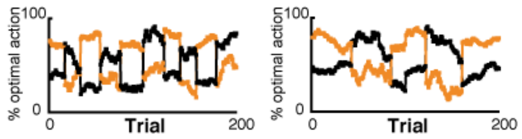


Learning strategies

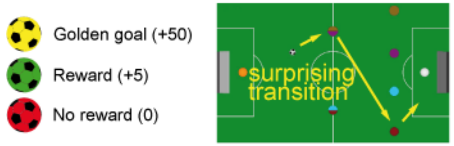


Manipulations

Volatility



Surprise



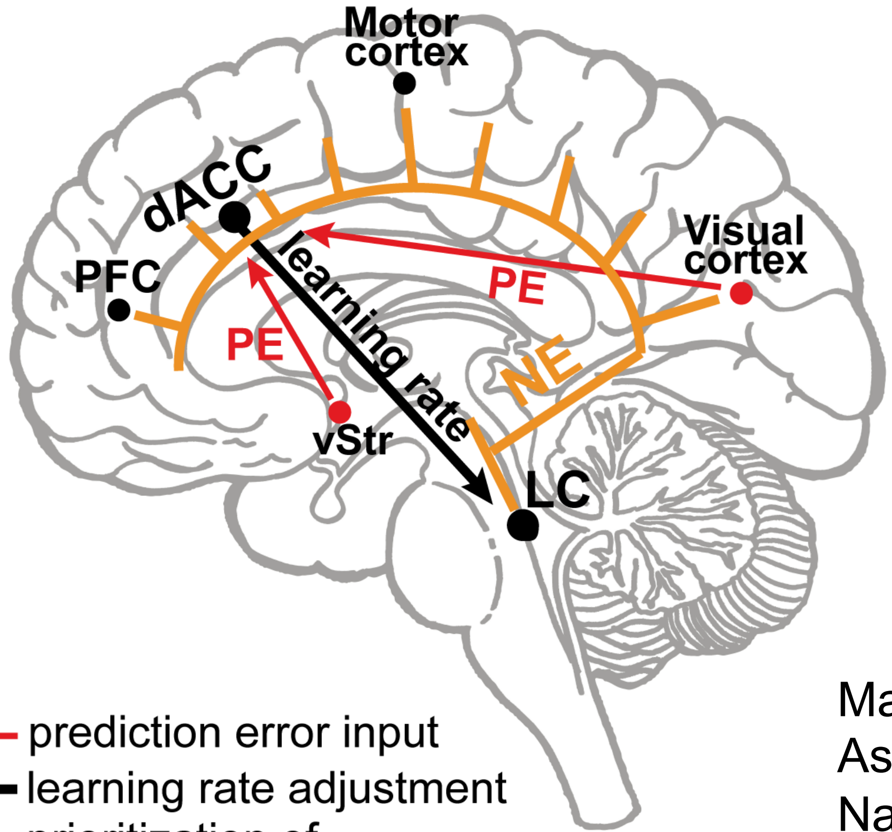
Learning of latent structures

Additional manipulations

Size of the state space
Social manipulations

Prioritization and integration of information during learning

A cognitive neuroscience framework of adaptive learning



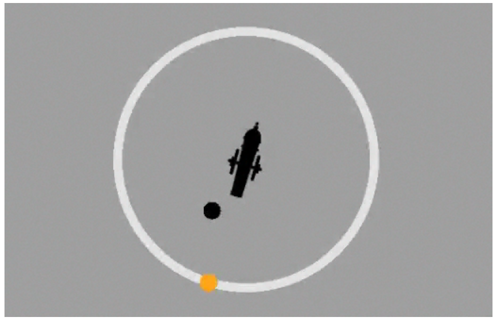
- prediction error input
- learning rate adjustment
- prioritization of representations

Mather et al., in press
Aston-Jones & Cohen, 2005
Nassar et al.2012;2016

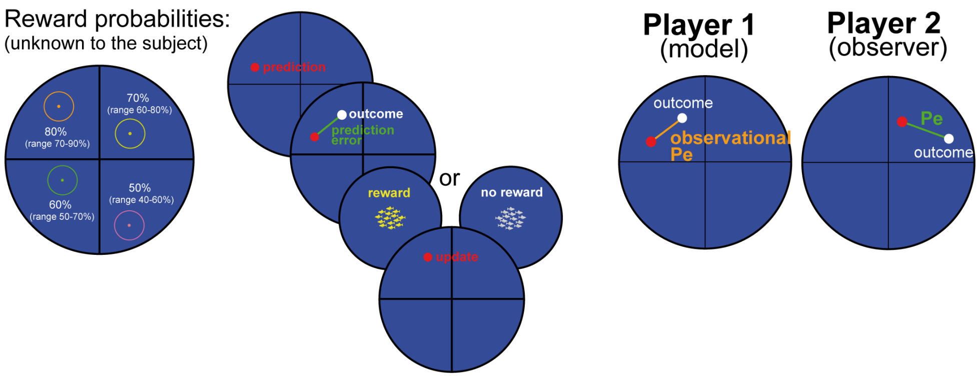
Age differences in adaptive learning

Helicopter task

Cannonball task
(Uncertainty and prefrontal theta)

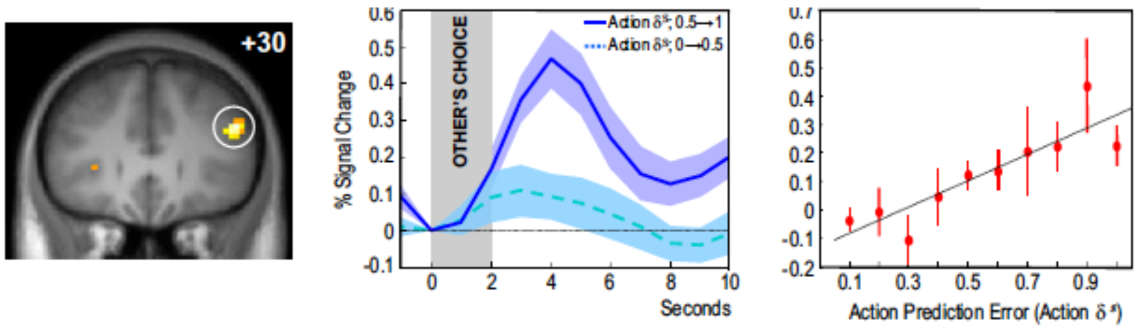


Fishing task
Multi-dimensional learning



Social influences on learning

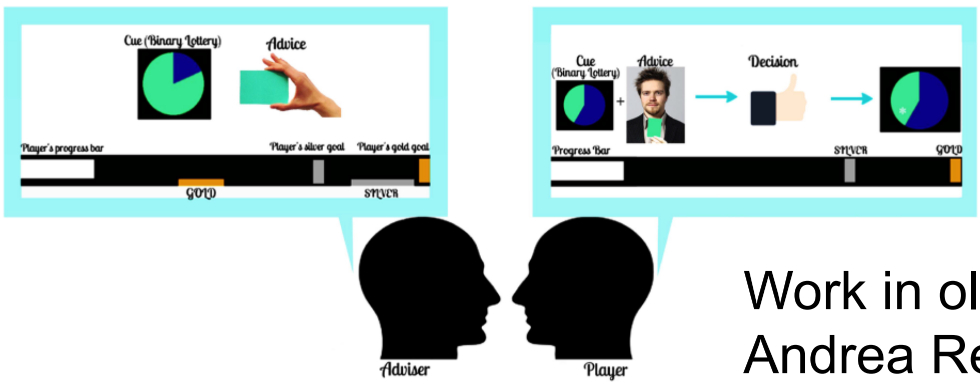
Observational action prediction error



Work in kids: Rodriguez-Buritica et al., 2016; under review

Burke et al., 2011

Advice



Work in older adults: Collaboration with Andrea Reiter & Andreea Diaconescu

Woodrow Wilson:

"I not only use all the brains that I have, but all that I can borrow."

Thanks for your attention!

Thanks to: Rasmus Bruckner, Julia Rodriguez, Matt Nassar, Josh Gold, Shu-Chen Li, and Hauke Heekeren, JDC, Leigh Nystrom, & Wouter van den Bos.

Funding: National Bernstein Network Computational Neuroscience

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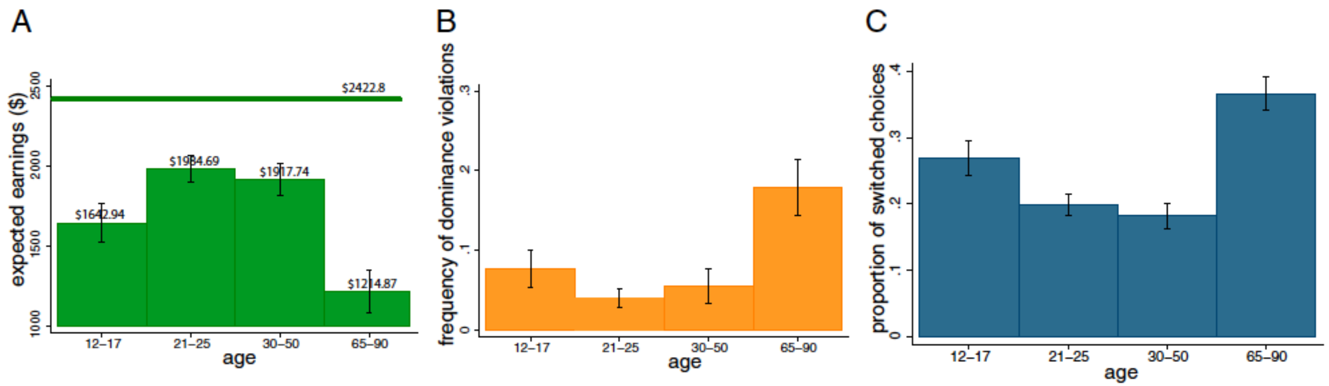
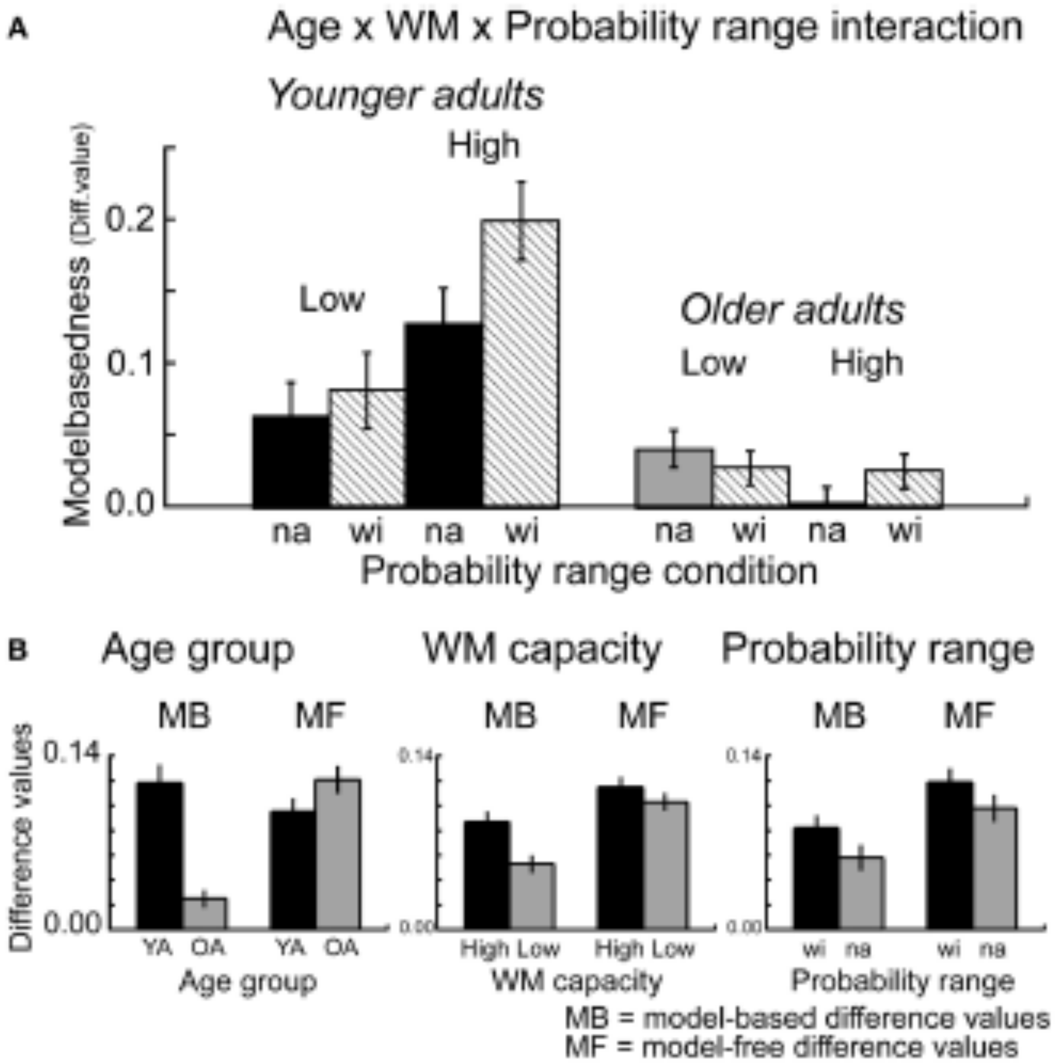
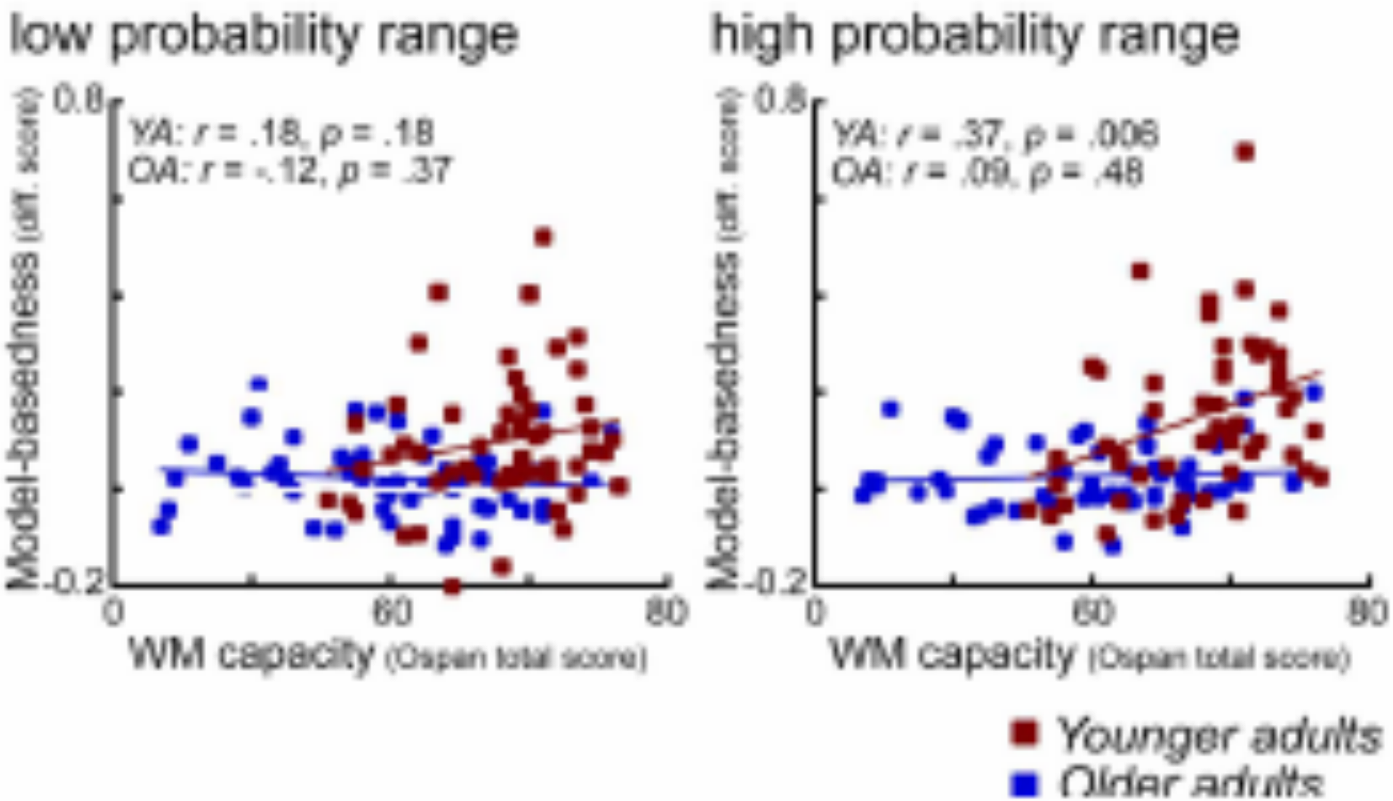
Decisions from description - Risk



Range manipulation





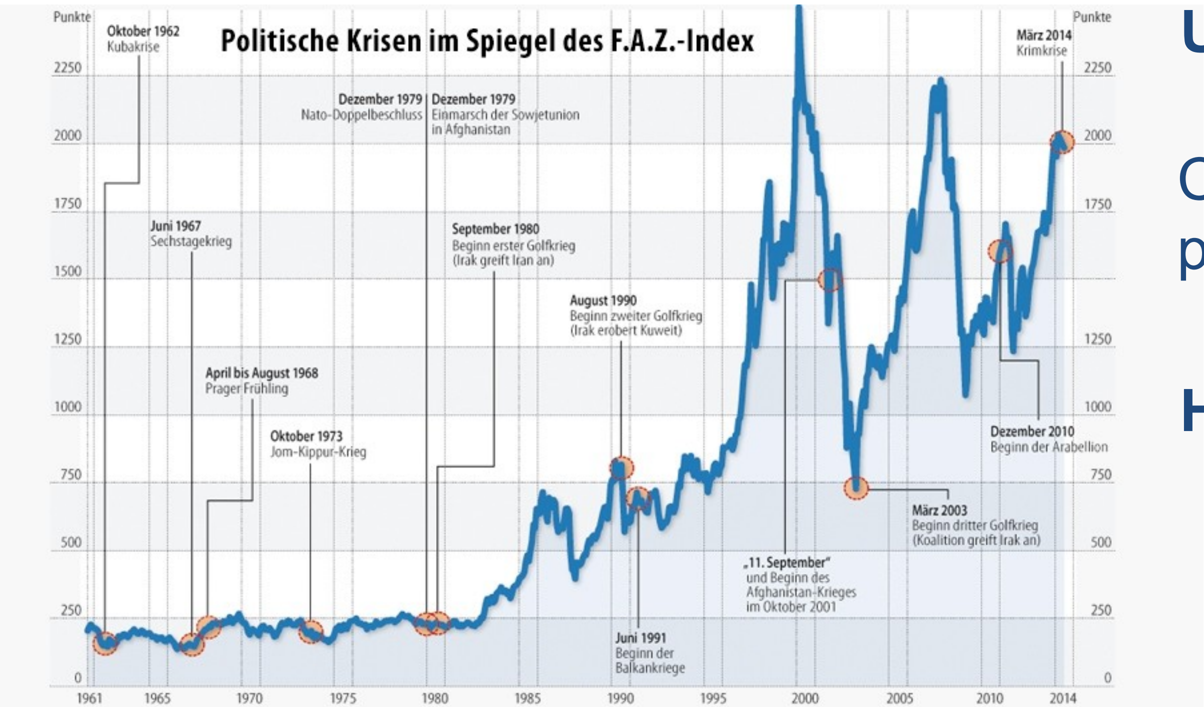
low probability range
high probability range
YA: r = .18, p = .18
OA: r = -.12, p = .37
YA: r = .37, p = .006
OA: r = .09, p = .48
Model-basedness (diff. score)
0.8
-0.2
0
60
80
WM capacity (Ospan total score)
Younger adults
Older adults

“Our behavior is purposeful; we live in a psychological reality or life space that includes not only those parts of our physical and social environment to us but also imagined states that do not currently exist.” Kurt Lewin

adaptive learning:

predicting latent states in changing environments based on (noisy) outcomes. *Examples: Wine, Restaurants, stock markets*

German stock market index



Uncertainty.

Change point probability / **Surprise**

Hazard rate

helicopter task

YA: N = 57; 20-30 years
OA: N = 57; 56-80 years

how does aging affect the computational mechanisms of adaptive learning?

three steps to take

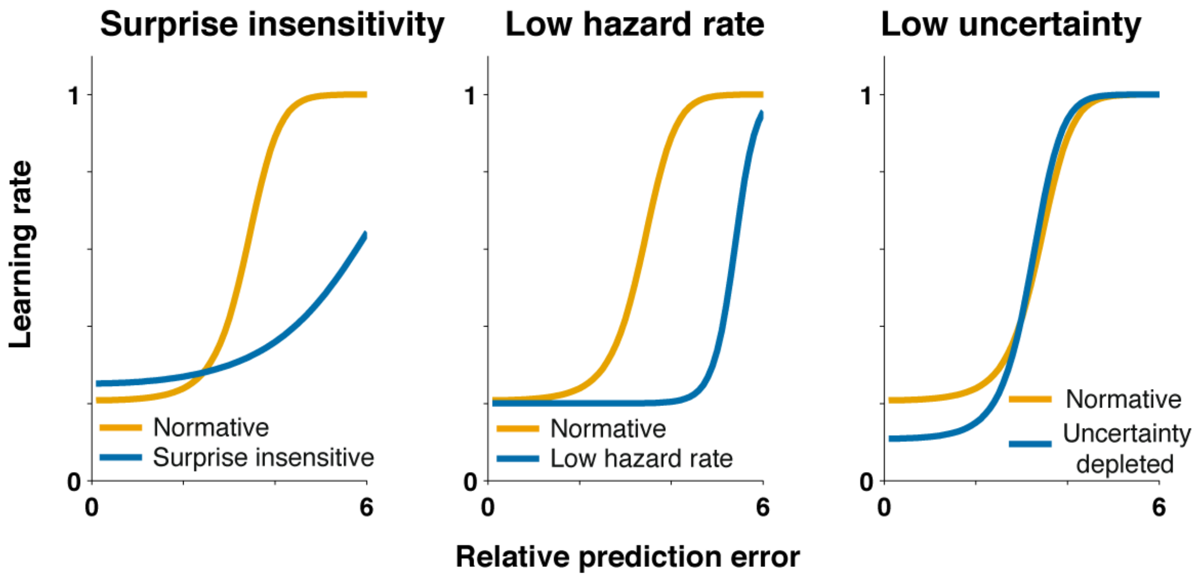
- Simulations
- Regression analysis
- Model fitting

normative computational model

Delta updating rule:

$$\text{Belief}_{t+1} = \text{Belief}_t + \mathbf{LR}_t \underbrace{(x_t - \text{Belief}_t)}_{\text{prediction error}} \qquad \mathbf{LR}_t = \text{surprise}_t + \text{uncertainty}_t(1-\text{surprise}_t)$$

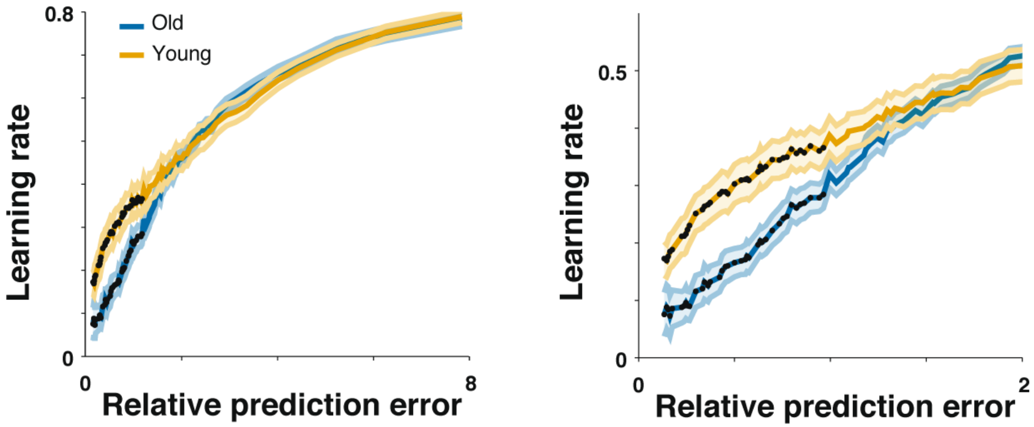
simulating possible age-related deficits



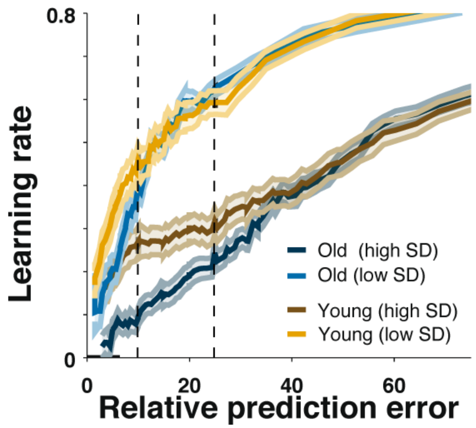
Depletion of each of the parameters leads to specific learning deficits.

learning rate against prediction error

age effects for small errors

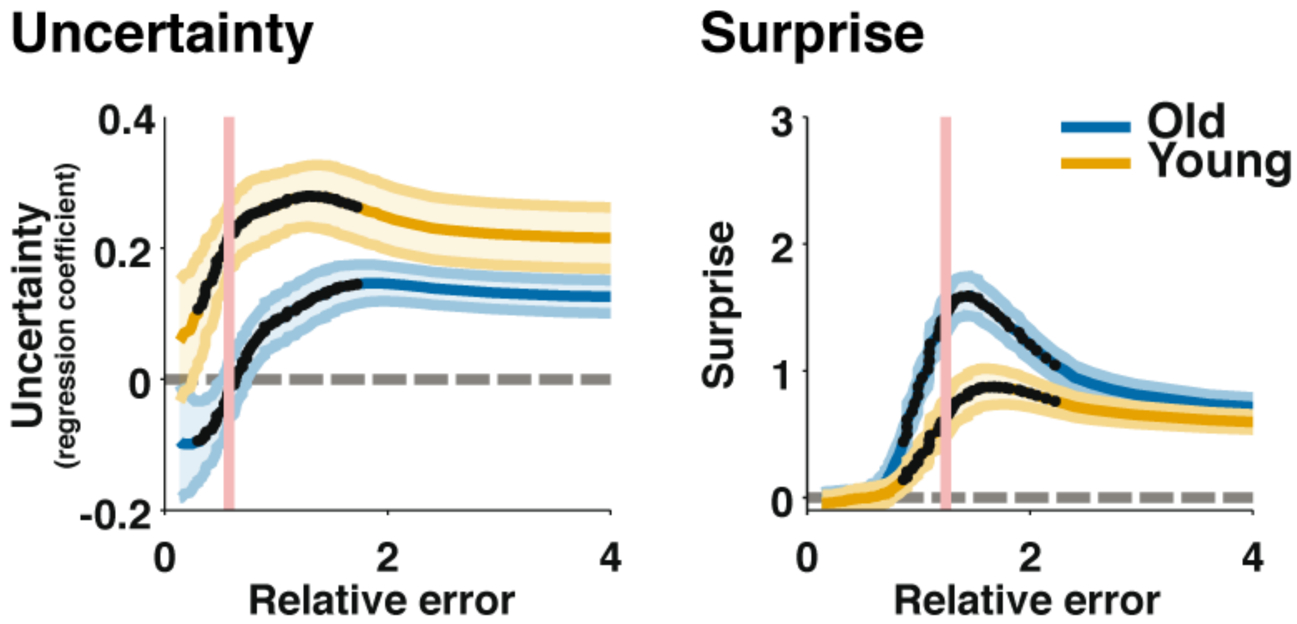


noise conditions



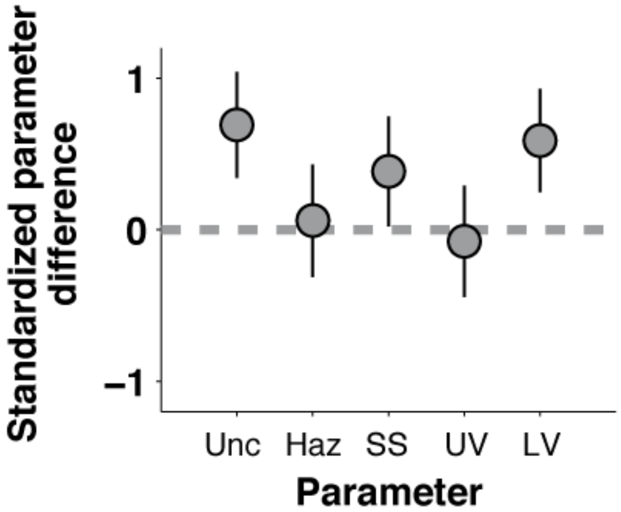
Lower learning rates for small prediction errors in older adults.

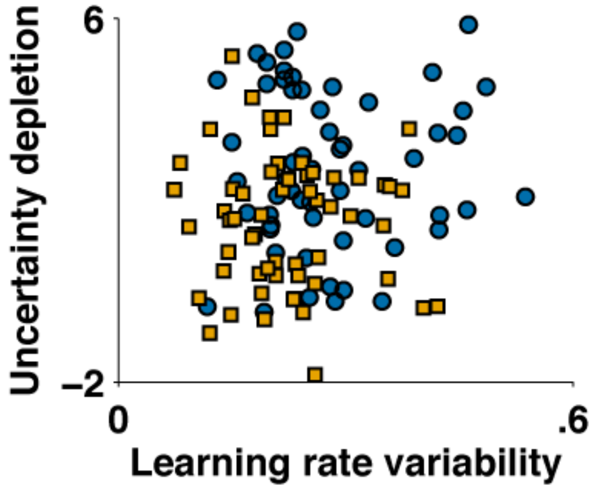
regression results



Older adults underestimate uncertainty and rely more on suprise during learning.

model fitting results





Unc = Uncertainty depletion Haz = Hazard rate SS = Surprise sensitivity
UV = update variability LV = learning rate variability

Diminished uncertainty representation and greater learning rate variability in older adults.

take home:

Older adults have a diminished capacity to represent and use uncertainty for learning.

This diminished capacity may reflect age-related functional decline in the medial PFC.

The diminished uncertainty model can explain a range of findings on learning impairments in older adults.

Nassar et al., (2016), *Nature Communications*
Nassar et al., (2016), *Behavioral and Brain Sciences*