LEARNING UNDER UNCERTAINTY:
IMPACT OF ANXIETY IN A CHANGE POINT DETECTION TASK

CRANE HUANG & MARTIN PAULUS

COMPUTATIONAL PSYCHIATRY COURSE, ZURICH, 2016

HIGHLIGHT

- Anxious subjects may **use sub-optimal strategy** to achieve decent performance.
- Anxious subjects have **difficulty to differentiate signal from noise** in the environment.
- Anxious subjects have **worse reaction** to uncertainty **over time**.

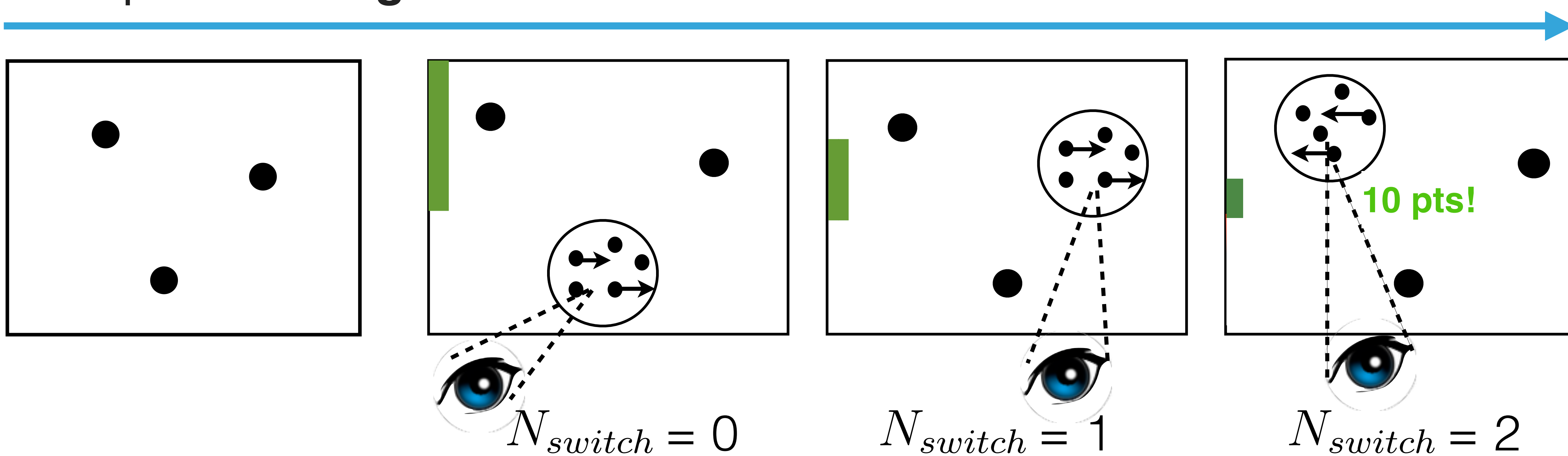
GOAL

- If and how does **anxiety** affect **performance**?
- If and how does **anxiety** affect **decision strategy**?
- Can we explain behavioral difference **computationally**?

EXPERIMENT DESIGN (1) – VISUAL SEARCH TASK

Task: locate the **target** among three possible locations.
Target: one patch with **a specified coherent motion direction.**
Distractors: two other patches with the opposite direction.

Example trial: **Target** with **left** coherent motion.



Points $= 100 - 25 \times N_{switch} - 12.5 \times RT \pm 50$ (+if correct, - if incorrect response)

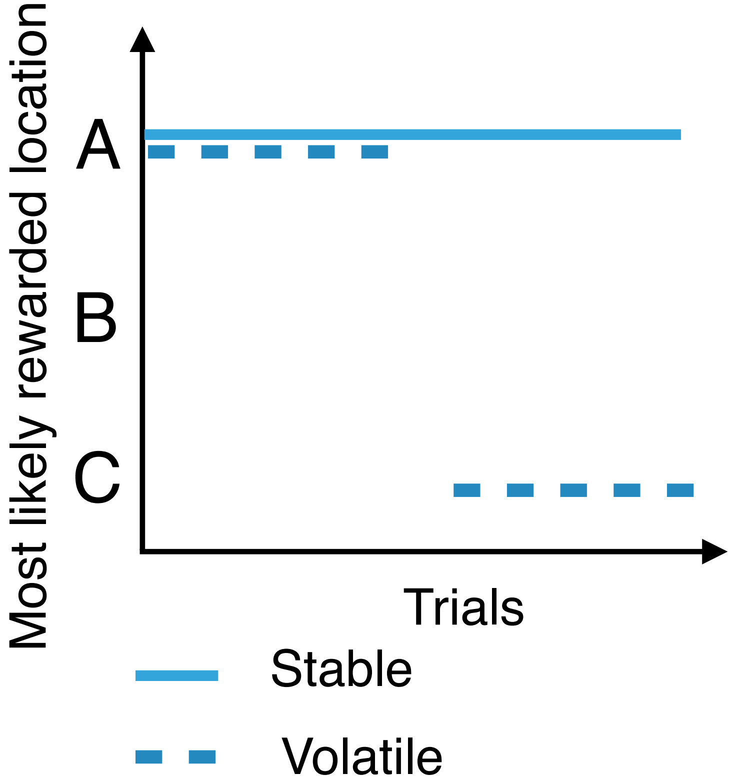
Higher points $\Longleftarrow$ Search the most likely rewarded location first.

(Yu & Huang, 2014)

EXPERIMENT DESIGN (2) – CHANGE OF REWARD CONTINGENCY

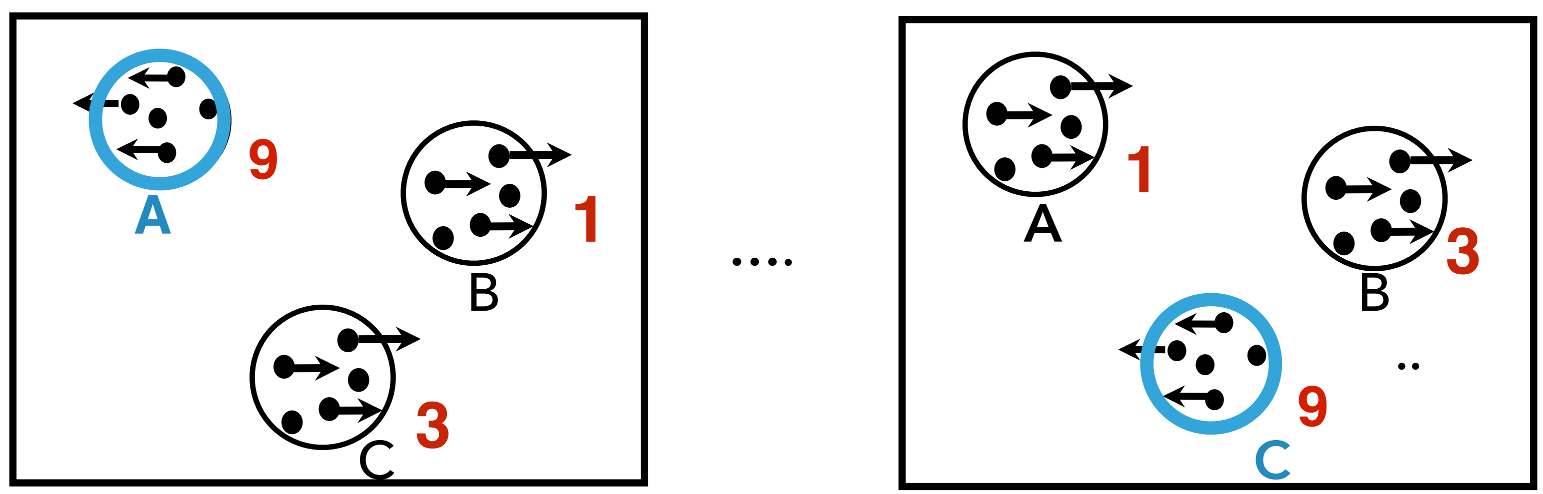
Reward frequency at three locations: **1:3:9**

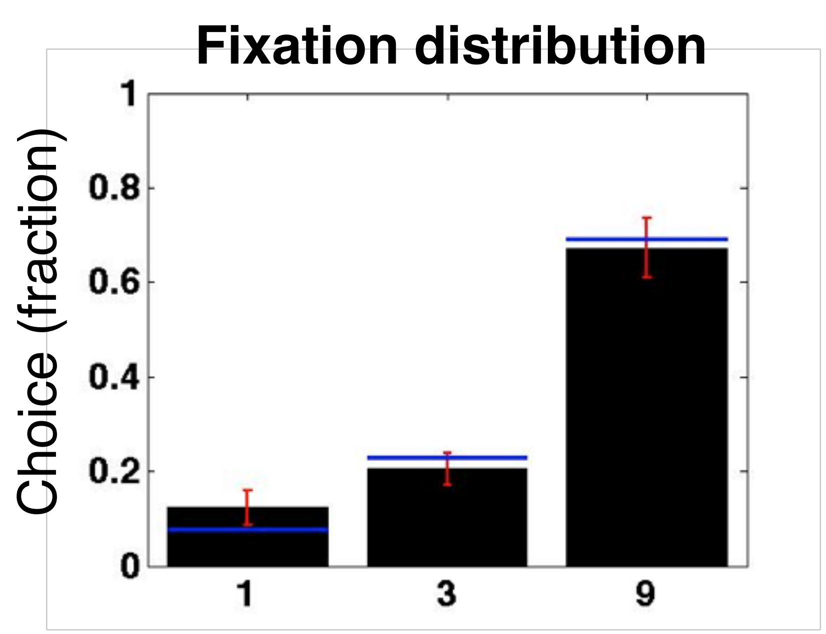
Volatility conditions



Change of reward contingency

Change ~ N(30,1), 90 trials/block





(Yu&Huang, 2014)

Questions:

- Can subjects use the **reward contingency** to optimize search strategy?
- How does **anxiety** affect performance and decision-making process?

SUBJECT INFORMATION

- N = 122 subjects (from Mood/anxiety group in T1000 project)
- Age: 35.03 (+/- 11.08) years
- Gender: 84/38 (Female/Male)
- Low anxiety (OASIS* $\leq$ 8): n = 45, mean OASIS 5.5 $\pm$ 2.5
- High anxiety (OASIS $\geq$ 9): n = 77, mean OASIS 11.5 $\pm$ 2.5

***O**verall **A**nxiety **S**everity and **I**mpairment **S**core, cutoff based on L Campbell-Sills et al. 2009

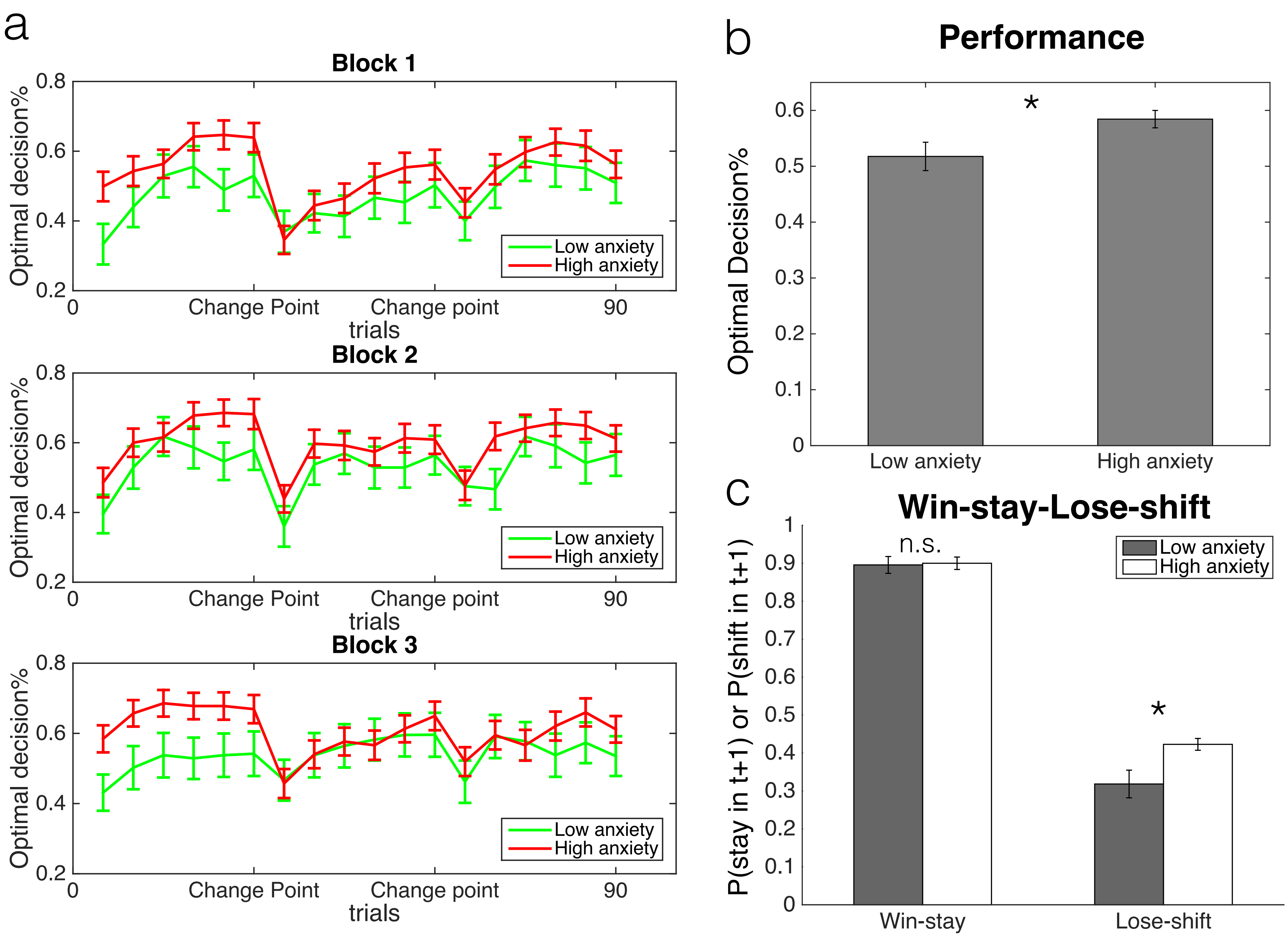
BEHAVIORAL RESULT

Questions:

- Can subjects use the **reward contingency** to optimize search strategy?
- How does **anxiety** affect performance and decision-making process?

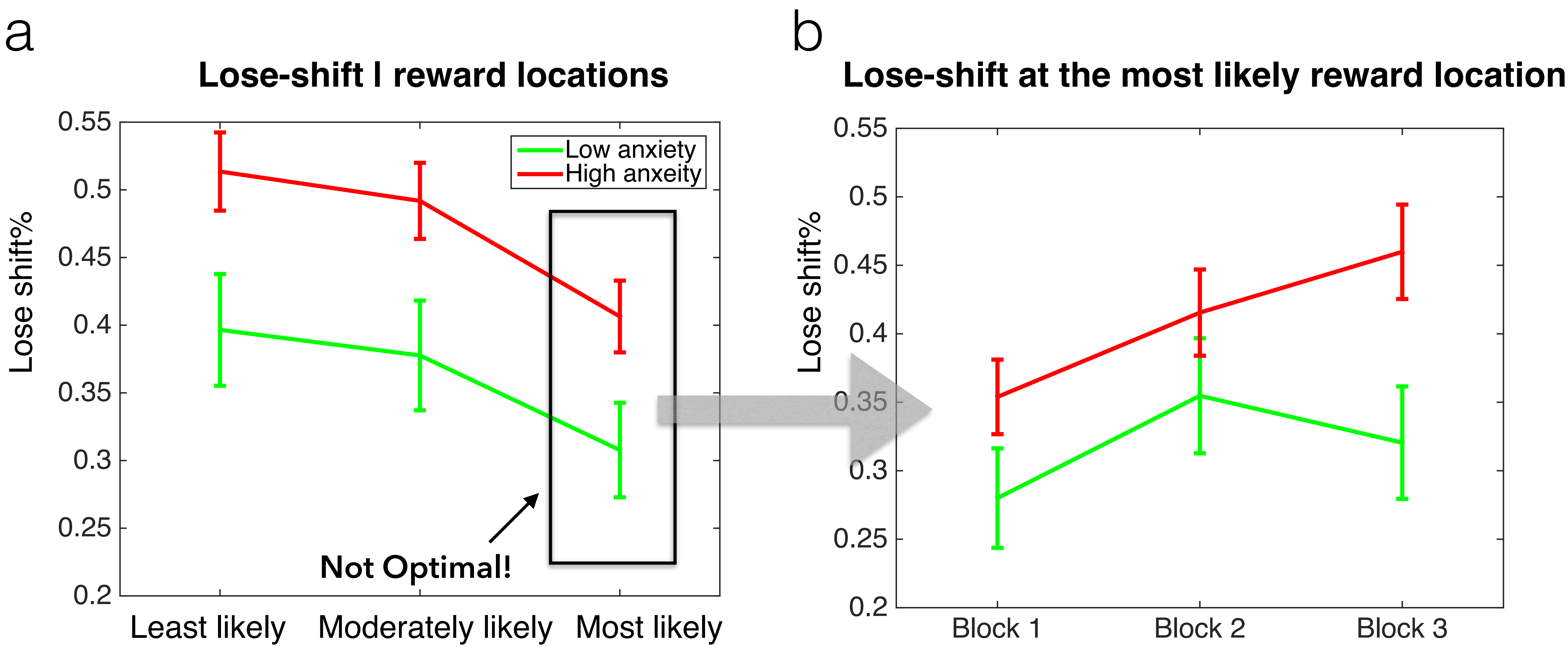
Behavioral measure	f(x)
Optimal decision%	$P(Choice_t = argmax_{i \in A,B,C}\{P_i(Reward)\})$
	Fraction of trials where the 1st choice was at the most likely rewarded location (e.g. The patch with reward probability 9/13)
Lose-shift%	$P(Choice_{t+1} = Target_t \| Choice_t \neq Target_t)$
	Fraction of trials where the 1st choice in next trial followed current trial's target if the 1st choice in the current trial was not the target

BEHAVIORAL RESULT (1)



- Small but significant higher optimal decision rate.
- Significant higher lose-shift rate.

BEHAVIORAL RESULT (2)



- Higher lose-shift rate regardless of the underlying probability.
- Sub-optimal decision strategy worsens over time.

BEHAVIORAL RESULT (SUMMARY):

- Higher anxious subjects have:
  - Slightly higher optimal decision rate
  - Higher lose-shift rate regardless of the underlying probability
  - Sub-optimal strategy worsens over time (higher lose-shift rate at the most likely rewarded location)

Can we use **computational models** to explain:

- higher lose-shift rate?
- change over time?

COMPUTATIONAL MODELS

- **Fix RL*:** Rescorla-Wagner (R-W) model with a constant learning rate.
- **Cho-Tar RL:** R-W with a learning rate for chosen option and a learning rate for non-chosen target.
- **Vmax RL:** R-W with a sensitivity adjustment rate that is based on argmax{**V**} (change of the option with the max value)
- **DBM*:** Bayesian model with a belief of environmental stationarity.

Model	**F(x)**	**Parameters**
Fix RL	$V_i^{t+1} = V_i^t + \eta(R_t - V_i^t)$	η
Cho-Tar RL	$V_{Cho}^{t+1} = V_{Cho}^t + \eta_{Cho}(R_t - V_{Cho}^t)$ $V_{Tar}^{t+1} = V_{Tar}^t + \eta_{Tar}(1 - V_{Tar}^t)$	η_{Cho}, η_{Tar}
Vmax RL	$V_i^{t+1} = \begin{cases} V_i^t + \eta_0(R_t - V_i^t), & argmax_i\{\mathbf{V}_i^t\} = argmax_i\{\mathbf{V}_i^{t-1}\} \\ V_i^t + (\eta_0 + \eta_d)(R_t - V_i^t), & argmax_i\{\mathbf{V}_i^t\} \neq argmax_i\{\mathbf{V}_i^{t-1}\} \end{cases}$	η_0, η_d
DBM	$P(b_k, \gamma_k \mid s_{k-1}) = \alpha P(b_{k-1}, \gamma_k - 1 \mid s_{k-1}) + (1-\alpha)P_0(b_k, \gamma_k)$	α

Decision model (softmax)	$q(i) = \frac{e^{\beta V_i}}{\sum_j e^{\beta V_i}}(RL), or\ q(i) = \frac{e^{\beta P_i}}{\sum_j e^{\beta P_i}}(DBM)$	β

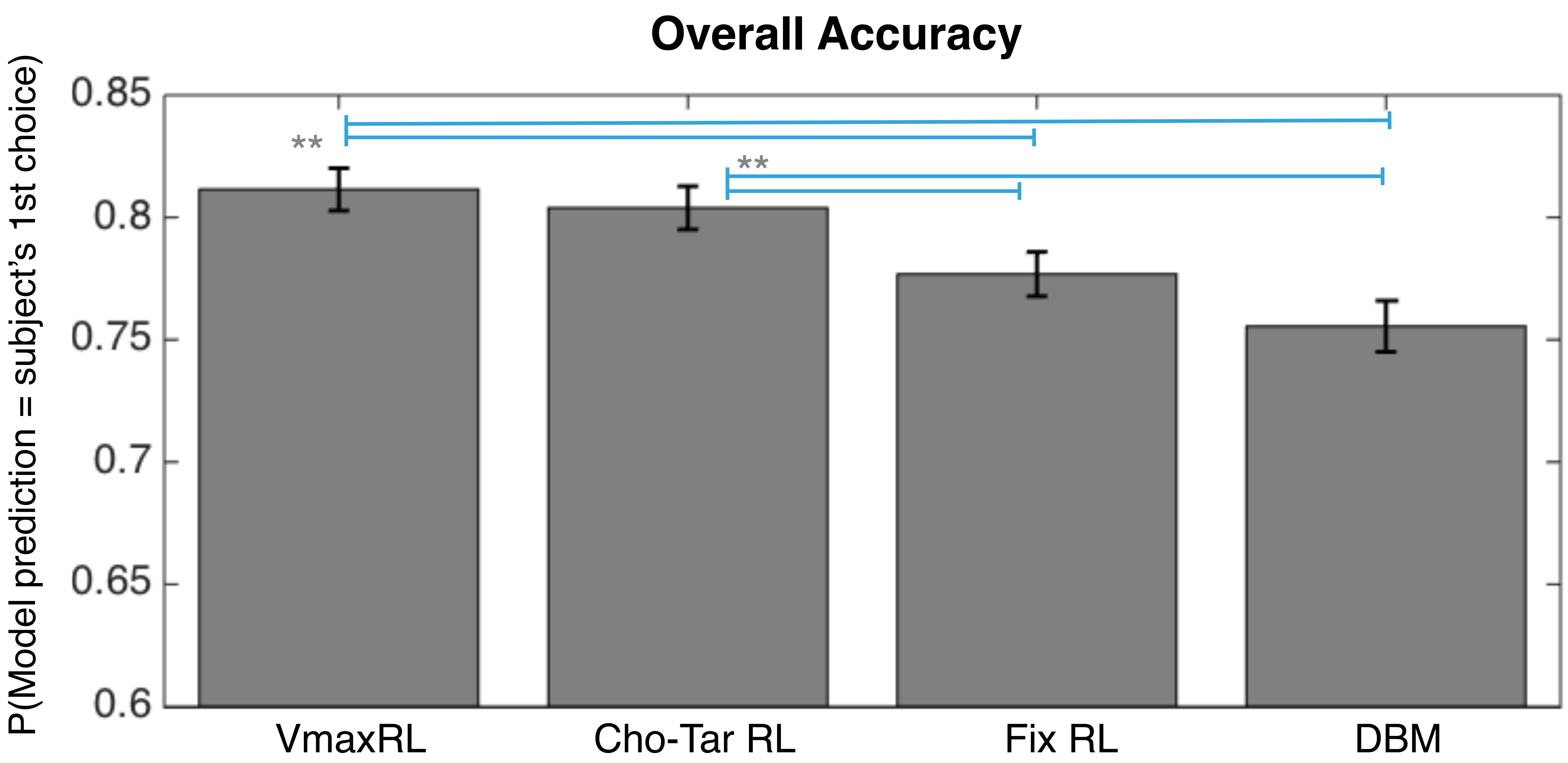
(Behrens et al. 2007, Browning et al. 2015, Niv et al. 2015)

(*Yu & Huang, 2014; Huang & Paulus, NIPS 2016, to appear)

COMPUTATIONAL MODELS

- Model accuracy
- Group difference in model parameters
- Model parameter vs. Behavioral measures

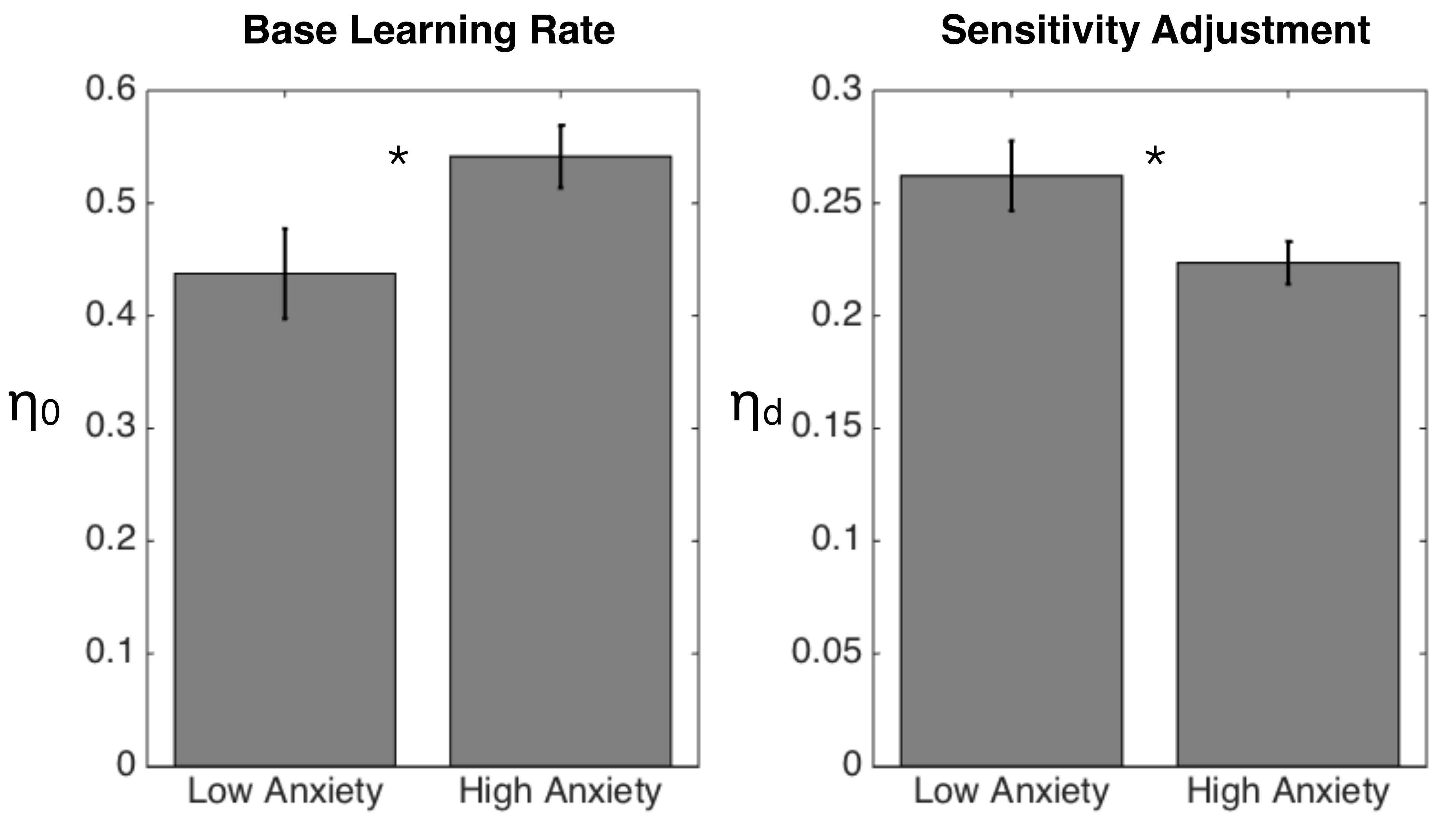
MODELING RESULT (1): OVERALL ACCURACY



Vmax and **Cho-Tar** have significantly higher overall accuracy than Fix RL and DBM.

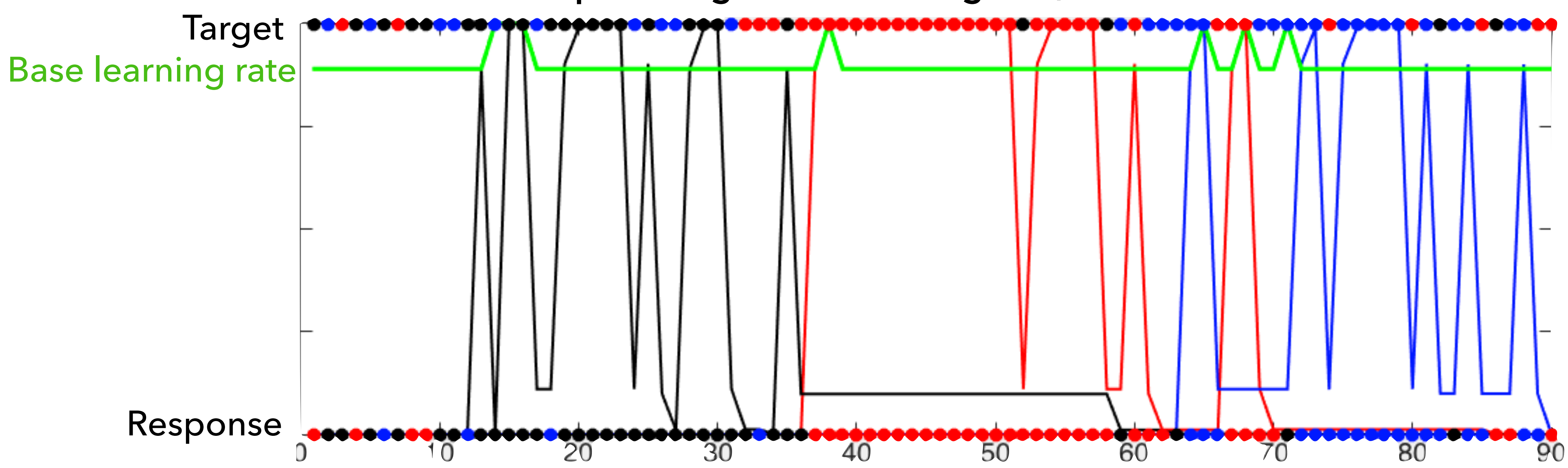
MODELING RESULT (2): GROUP DIFFERENCE-1

- **Vmax RL**: Higher anxious individuals have higher base-learning rate, and lower sensitivity adjustment rate.

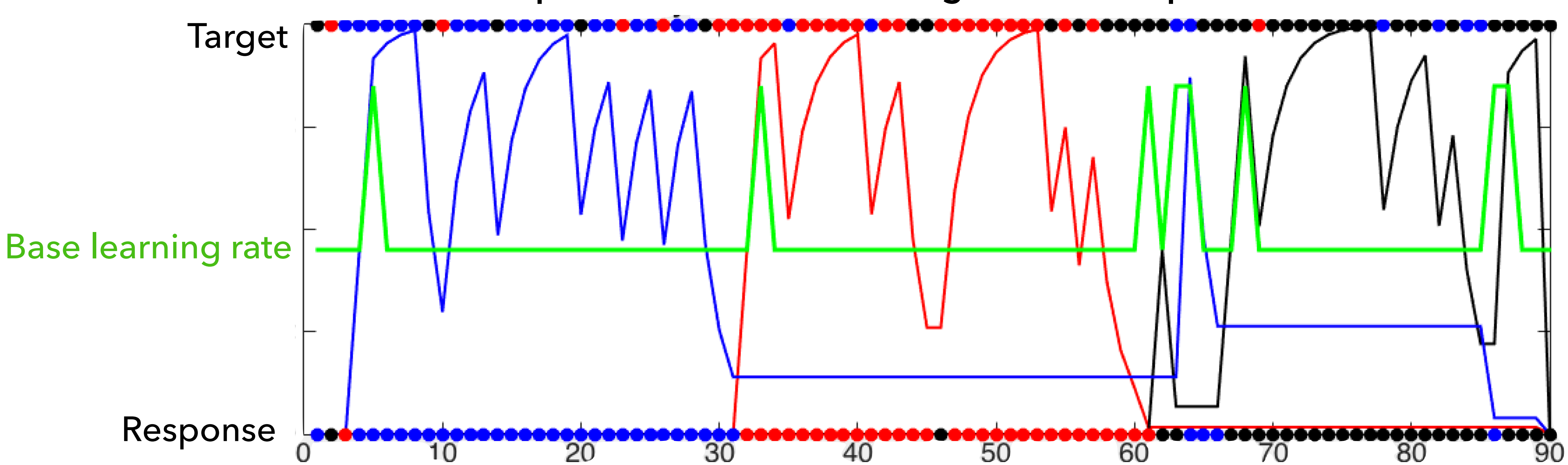


MODELING RESULT (2): GROUP DIFFERENCE-1

Example 1: High base-learning rate, WSLS like behavior

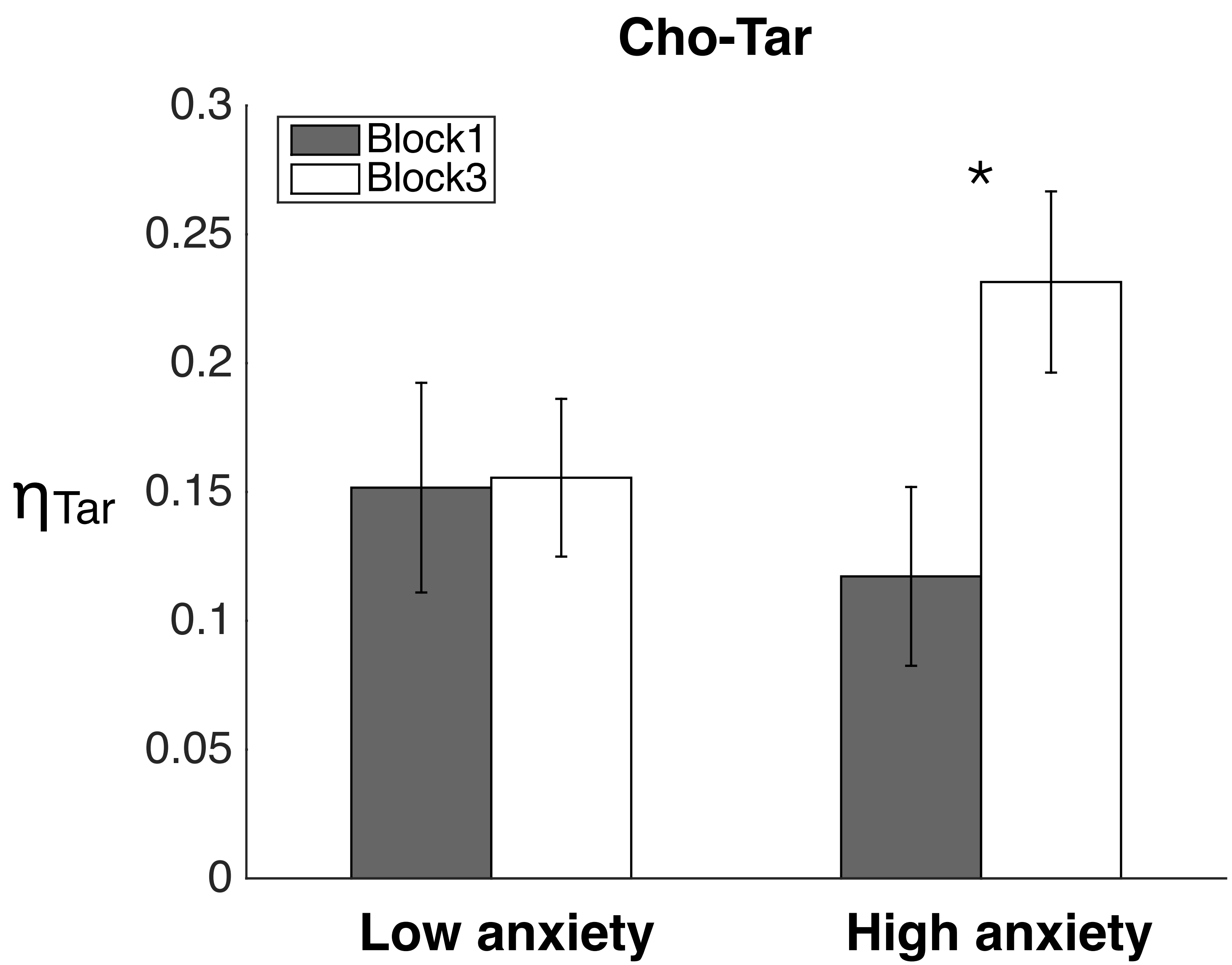


Example 2: Lower base-learning rate, more optimal behavior



MODELING RESULT (2): GROUP DIFFERENCE-2

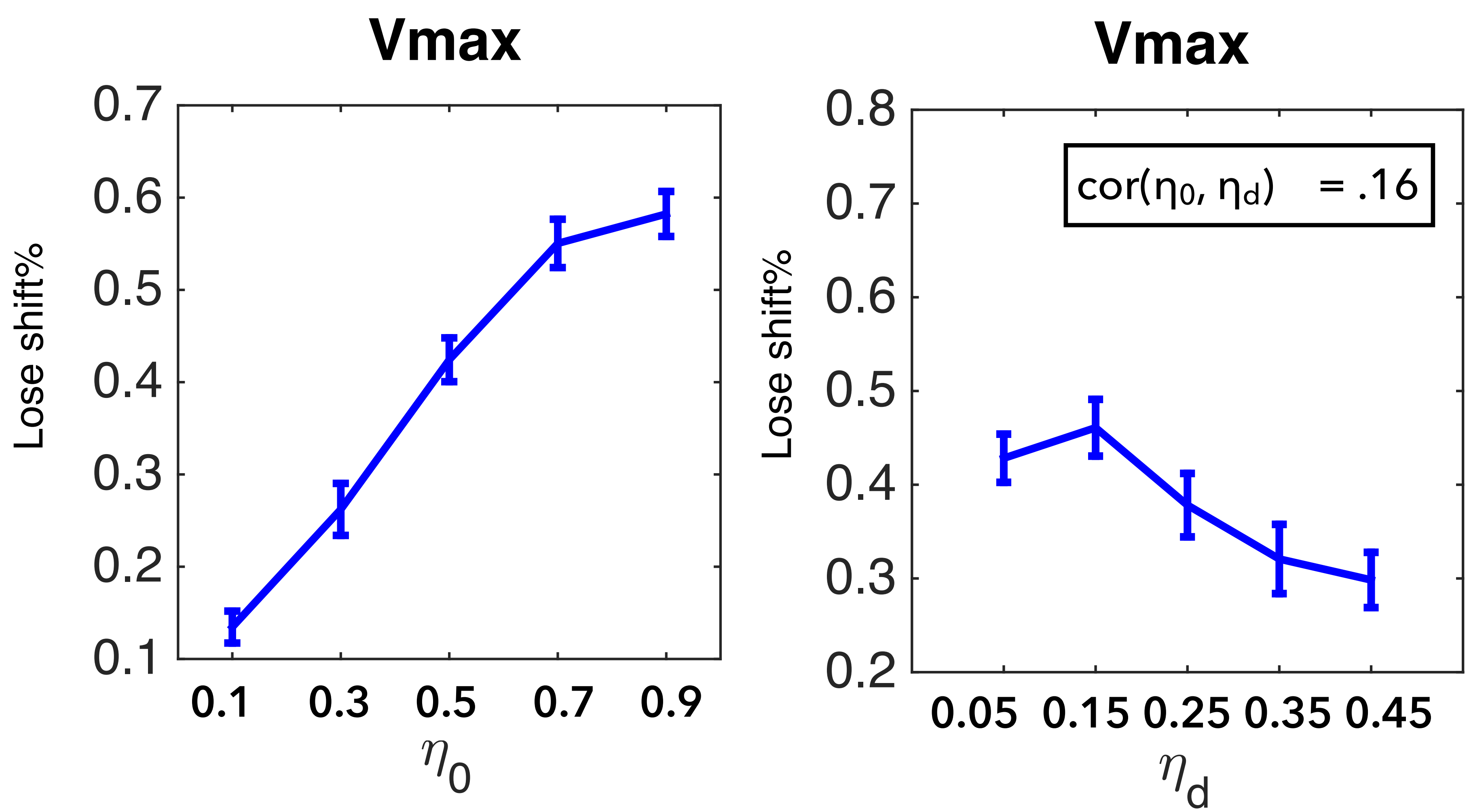
- **Cho-Tar RL:** Higher anxious individuals have increasing learning rate of non-chosen ‘target’.



- **Noise**: when (un-chosen) TARGET appears at less frequently rewarded location, which is about 30% of the time (i.e. 1/13+3/13).

MODELING RESULT (3): MODEL PARAMETER VS. BEHAVIORAL MEASURES-1

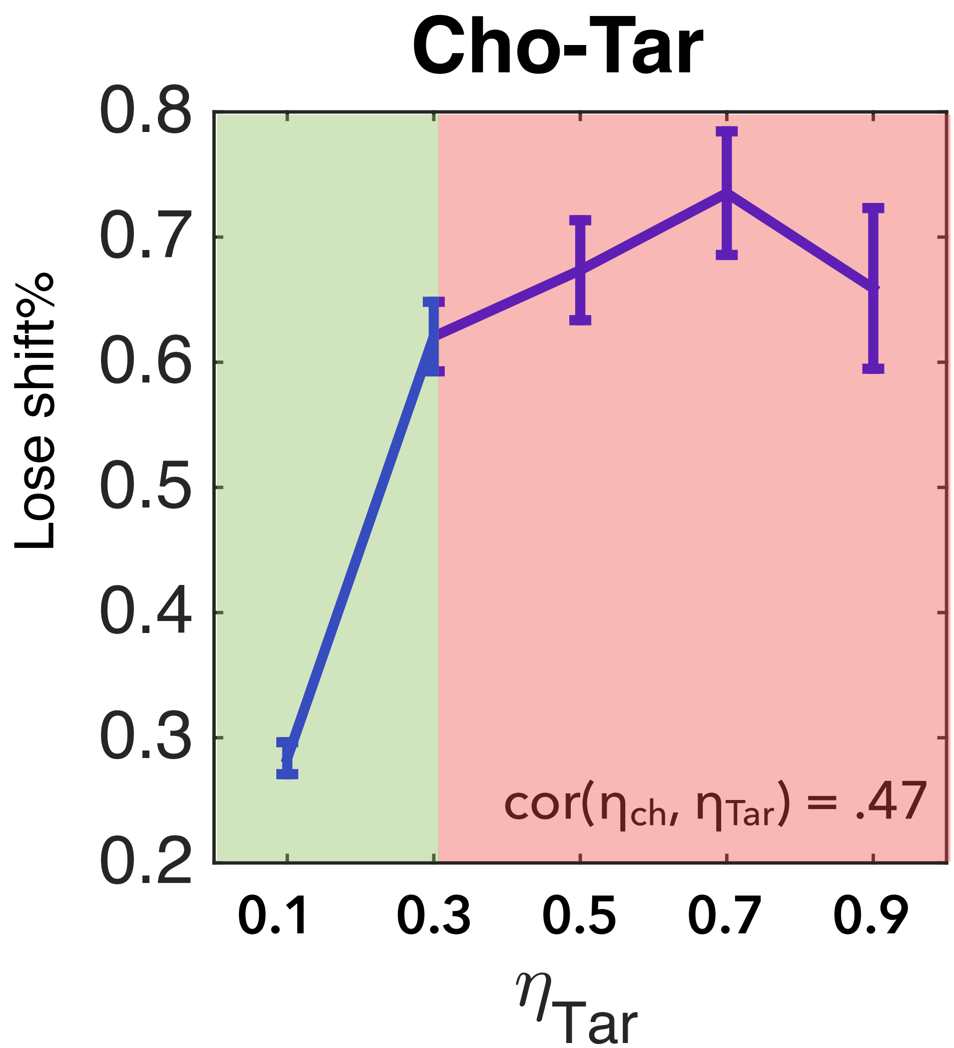
- **Vmax: lose-shift rate** positively correlates with the base learning rate and negatively correlates with sensitivity adjustment rate.



- Anxious subjects' **higher lose shift rate** may come from having higher base learning rate and lower sensitivity rate.

MODELING RESULT (3): MODEL PARAMETER VS. BEHAVIORAL MEASURES-2

- **Cho-Tar: lose-shift rate** increases significantly when > 0.3 (Cho-Tar)

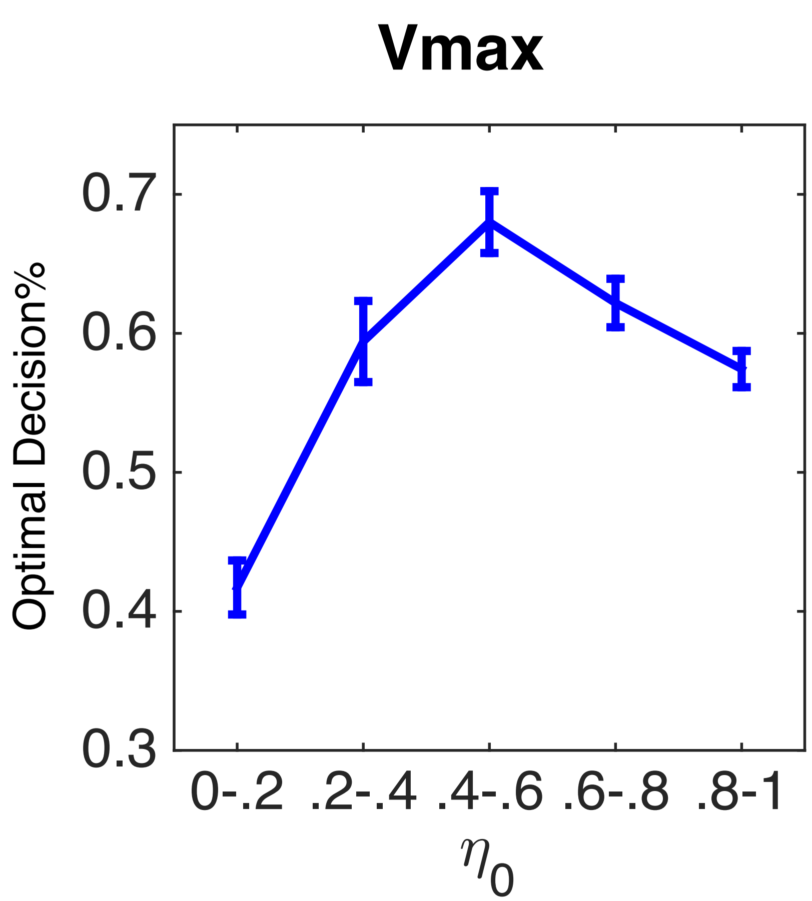


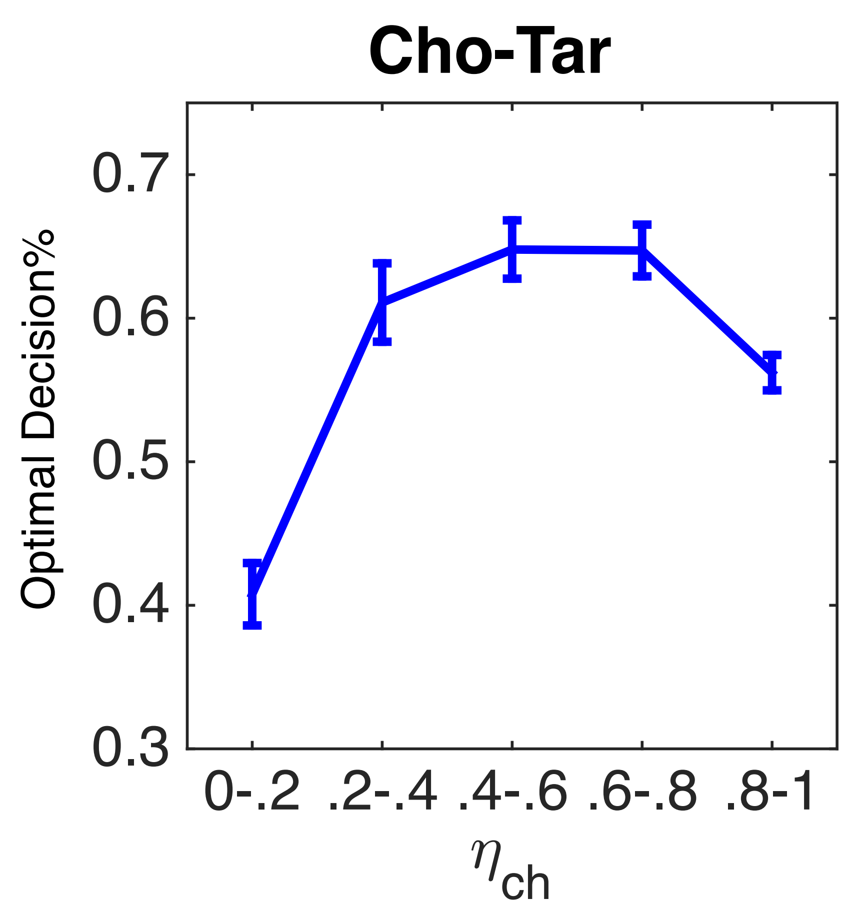
- Recall: **noise** is present in about 30% of trials.

- Anxious subjects' **increasing lose-shift rate** may come from over-learning from noise in the environment over time.

MODELING RESULT (3): MODEL PARAMETER VS. BEHAVIORAL MEASURES-3

- **Optimal decision rate** has an inverse U shape with base learning rate (Vmax) and choice learning rate (Cho-Tar)





- Note: similar result for fixed R-W model (Huang & Paulus, NIPS 2016, to appear)

MODELING RESULT SUMMARY

- **Behavior:**
  - **Higher lose-shift rate** regardless of the underlying reward probability.
  - Sub-optimal strategy **worsens over time.**

- **Model:**
  - **Higher base learning rate** and **lower adjustment rate**.
  - **Higher learning rate** from **noise over time.**

FUTURE WORK

- **Experiment:** compare across different volatility conditions
- **Modeling:**
  - Combine Vmax and Cho-Tar:

$$V_{Cho}^{t+1} = V_{Cho}^{t} + \eta_{Cho}(R_t - V_{Cho}^{t})$$

$$V_{Tar}^{t+1} = \begin{cases} V_{Tar}^{t} + \eta_{Tar}(1 - V_{Tar}^{t}) & argmax_i\{\mathbf{V}_i^t\} = argmax_i\{\mathbf{V}_i^{t-1}\} \\ V_{Tar}^{t} + (\eta_{Tar} + \eta_d)(1 - V_{Tar}^{t}) & argmax_i\{\mathbf{V}_i^t\} \neq argmax_i\{\mathbf{V}_i^{t-1}\} \end{cases}$$

  - Dynamic RL that allows trial-by-trial continuous fluctuation of the learning rate.
  - Hierarchical model (e.g. HGF, Mathys et al. 2014)
  - DBM with a dynamic belief of environmental stability.

CONCLUSION

Why is this important?

- Both anxious and non-anxious individuals **learn** about the underlying statistics of the change point detection task.
- Anxious individuals **over-interpret** statistical fluctuations as a sign of meaningful change.
- Most modern treatments of anxiety are based on re-learning fear-related content. New **behavioral or pharmacological strategies** need to be developed if anxious individuals do not learn appropriately.
- The computational approach allows us to **precisely quantify** the degree of learning **dysfunction** and to determine how much intervention may correct it.

Questions?