Journal Club Report

State anxiety biases estimates of uncertainty and impairs reward learning in volatile environments

Thomas P. Hein, Jan de Fockert , Maria Herrojo Ruiz *

Reporter: Haoran Dou; Date:2021/4/8

Backgrounds

- Anxiety is characterised by excessive worry about negative possibilities (Grupe and Nitschke, 2013). IU is also related to anxiety disorder(Carleton, 2016).

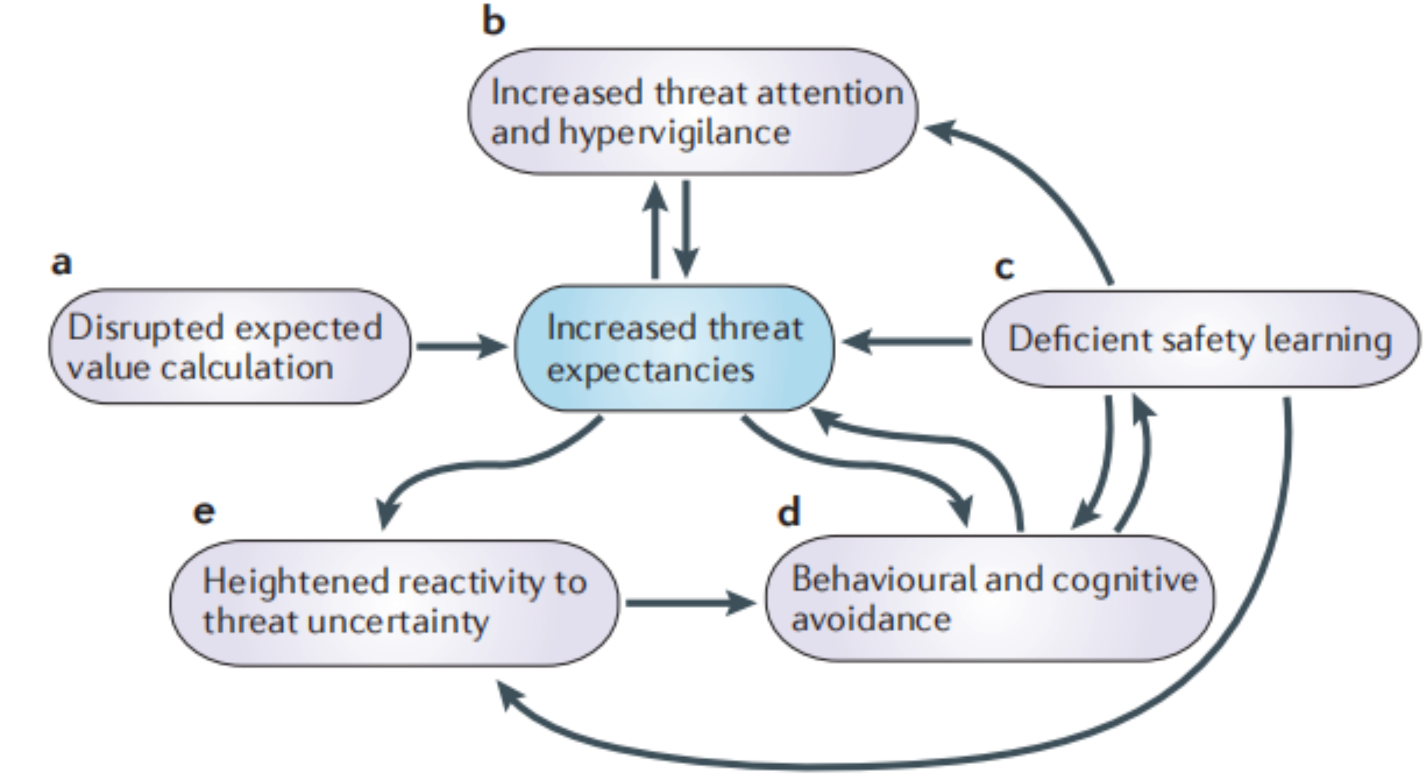


Figure 2 | **Altered anticipatory processes in response to threat uncertainty in anxiety.** Dynamic interactions among five key psychological processes (in grey) allow

Grupe, D. W., & Nitschke, J. B. (2013). Uncertainty and anticipation in anxiety: an integrated neurobiological and psychological perspective. *Nature Reviews Neuroscience*, *14*(7), 488-501.
Carleton, R. N. (2016). Into the unknown: A review and synthesis of contemporary models involving uncertainty. *Journal of anxiety disorders*, *39*, 30-43.

Backgrounds

- Previous computational work has identified three types of uncertainty during decision-making and learning:

1. expected (irreducible) uncertainty
2. estimation (informational) uncertainty
3. unexpected (environmental) uncertainty

To reduce uncertainty, the brain is thought to appraise the inherent statistical structure of the world using probability distributions, continuously updating and inverting a hierarchical model of the causes of the sensory inputs it receives.

- Examinations of belief, uncertainty, and precision estimates using Bayesian formulations in perceptual and learning tasks are increasingly used to provide mechanistic explanations for an array of neuropsychiatric conditions, such as Parkinson’s disease, schizophrenia, autism and anxiety.

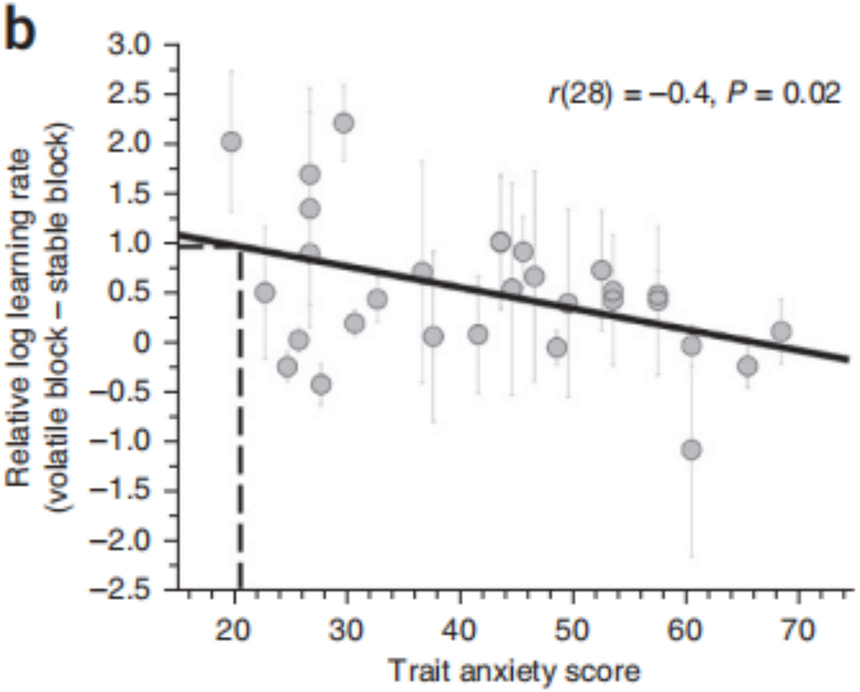
.

Anxious individuals have difficulty learning the causal statistics of aversive environments

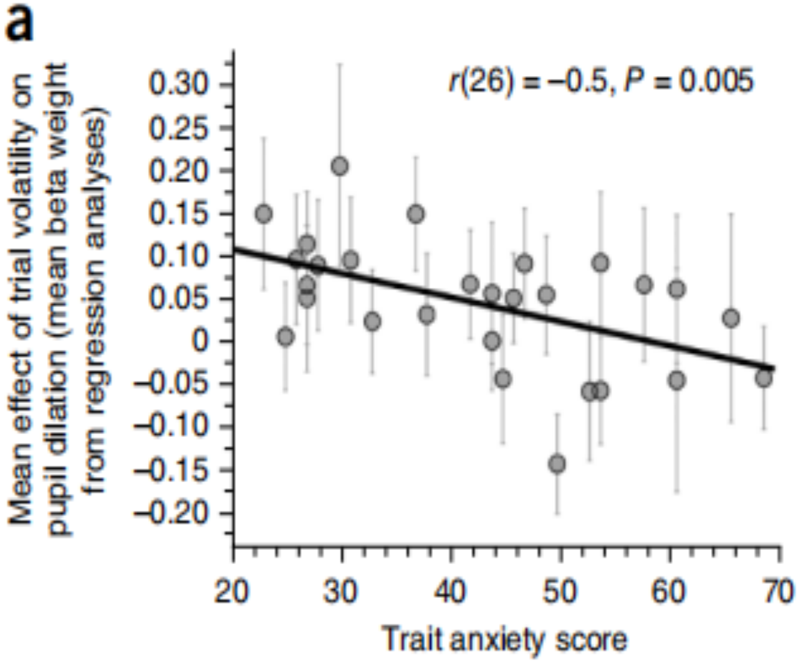
nature neuroscience

Michael Browning[1], Timothy E Behrens[1], Gerhard Jocham[1,2], Jill X O'Reilly[1] & Sonia J Bishop[1,3]

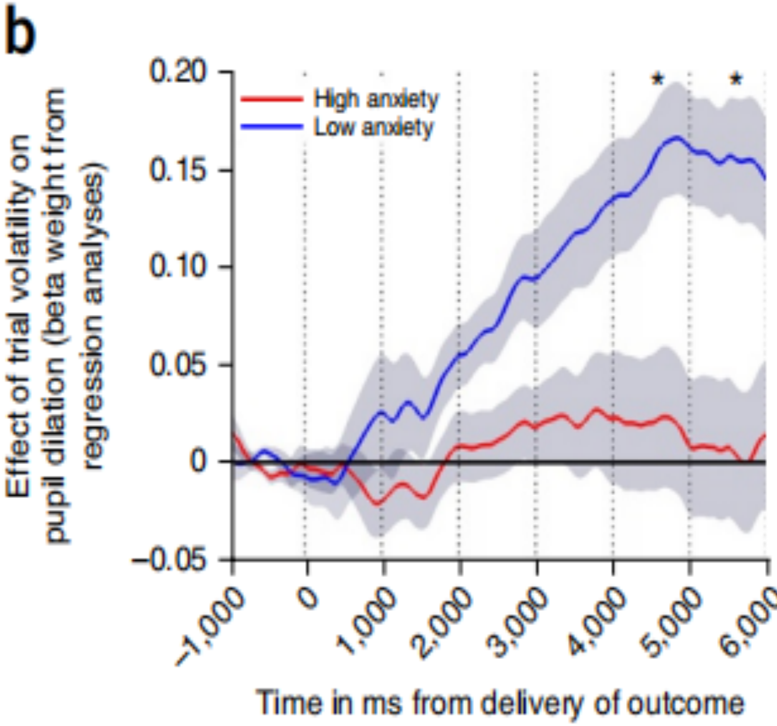
b



a



b



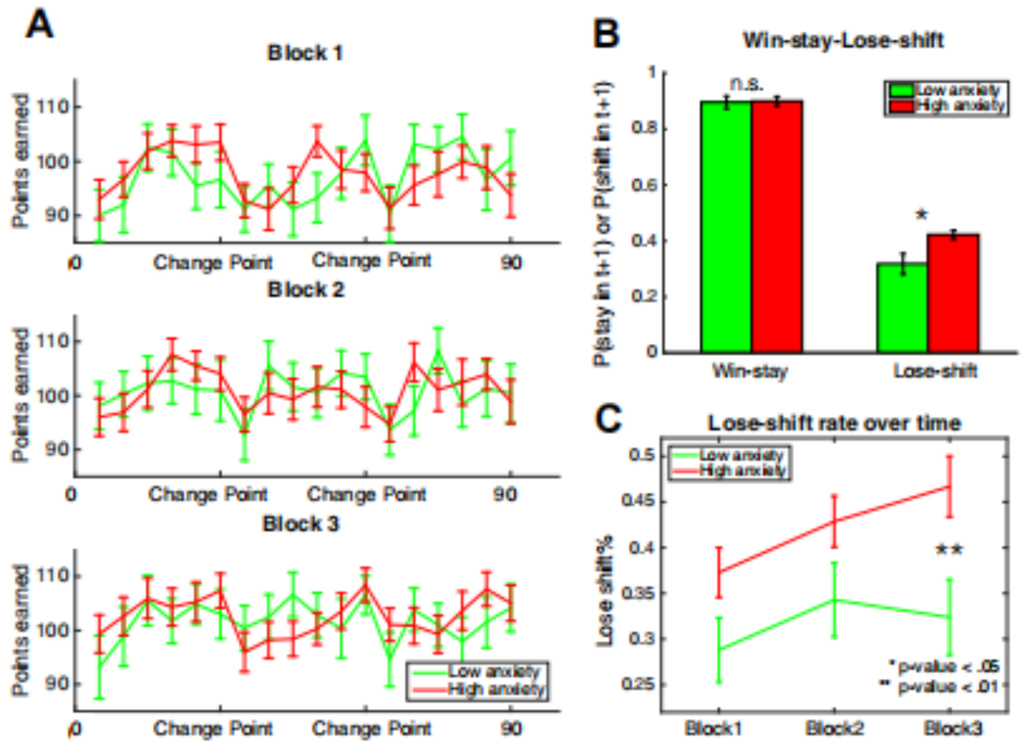
Received 3 August 2014; accepted 29 January 2015; published online 2 March 2015; doi:10.1038/nn.3961

Archival Report

Biological Psychiatry

Computational Dysfunctions in Anxiety: Failure to Differentiate Signal From Noise

He Huang, Wesley Thompson, and Martin P. Paulus



Conclusion:

Anxious subjects' exaggerated response to uncertainty leads to a suboptimal decision strategy that makes it difficult for these individuals to determine whether an action is associated with an outcome by chance or by some statistical regularity.

Biological Psychiatry September 15, 2017; 82:440–446 www.sobp.org/journal

Purpose

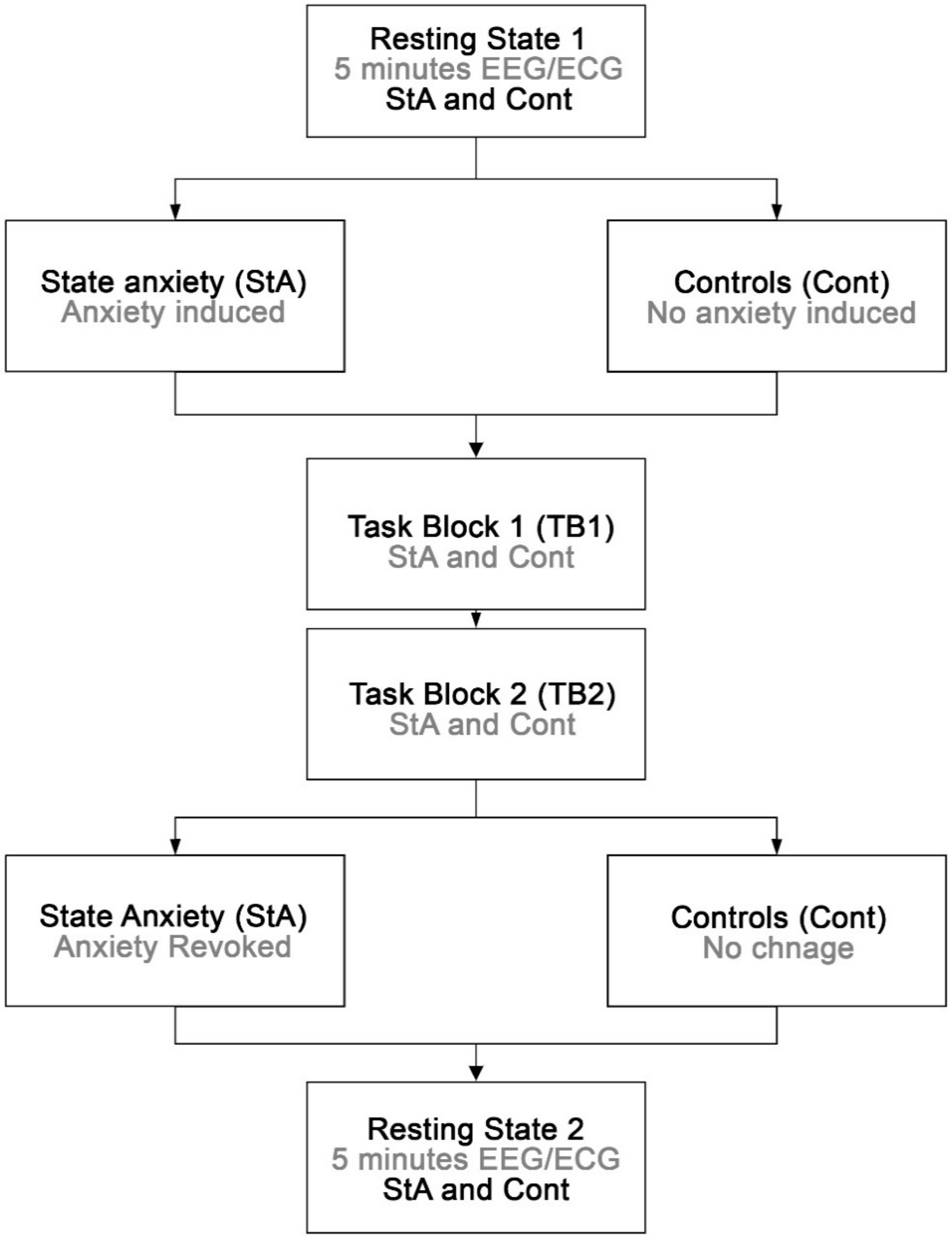
- Less understood is how temporary states of anxiety in healthy subjects interfere with optimal learning and belief updating in the brain.
- Expanding on those findings, here we evaluated whether temporary anxious states in healthy individuals influence reward learning in a volatile environment through changes in informational and environmental uncertainty.
- Error related negativity (ERN, or feedback ERN) and P300 are closely related to prediction error. After a temporary anxious states, whether the precision-weighted prediction errors （pwPE）modulated the EEG processing?

The main questions

1. State anxiety vs information uncertainty
2. State anxiety vs environment uncertainty
3. State anxiety vs learning rate
4. State anxiety vs EEG & pwPE

Methods

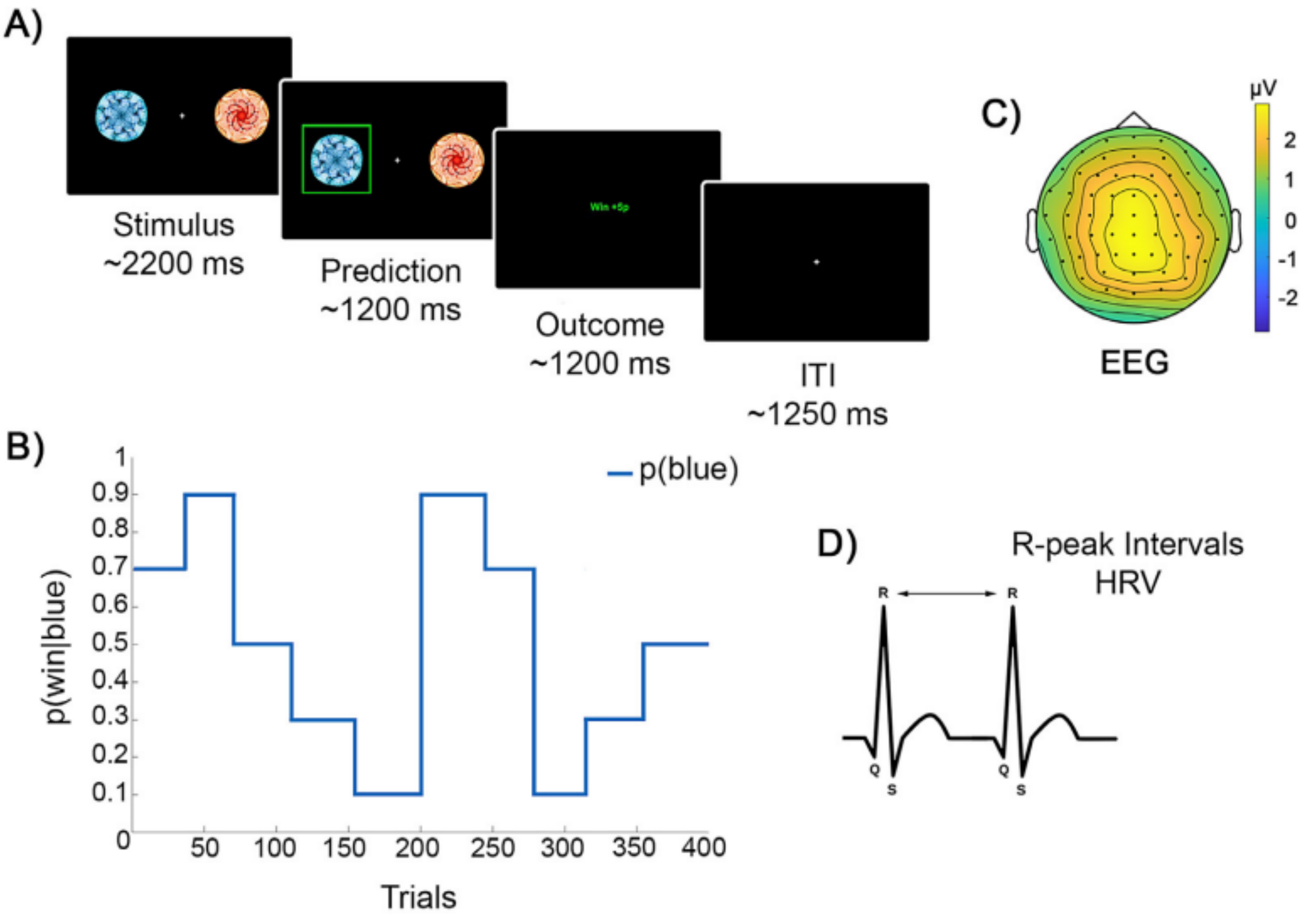
- *Participants*
- Forty-two healthy individuals (age 18–35, 28 females, mean age 27). All participants were healthy volunteers, with no past neurological or psychiatric disorders.
- Spielberger’s Trait Anxiety Inventory (STAI); The sample population range was between 34 and 68 (Low trait = 34–42, High trait = 43–68). The mean trait anxiety score in the StA group was 47 (SEM = 2.1), while it was 46 (SEM = 2.2) in the Cont group. Individual trait anxiety levels did not exceed the clinical level.
- The ages(mean 27.7, SEM = 1.2) and sex (13 female, 8 male) of the Cont group were commensurate with those from StA (mean 27.5, SEM = 1.3, sex 14 female, 7 male).



Anxiety induced

1. Participants in the StA group were informed that they had been randomly selected to complete a public speaking task after finishing the reward learning task .
2. They were told they would be required to present a piece of abstract art and would be allowed to prepare for 3 min for a 5 min public presentation of this artwork to a panel of academic experts. In the control group were instead informed that they would be given a piece of abstract art, but they were to give a mental description of it for the same time privately to themselves.
3. After completing the reward-based learning blocks, StA participants were informed of the sudden unavailability of the assessment panel and were ultimately instructed to describe the artwork privately in line with the Cont group.

Procedure



A)
Stimulus
~2200 ms
Prediction
~1200 ms
Outcome
~1200 ms
ITI
~1250 ms
C)
μV
2
1
0
-1
-2
EEG
B)
p(blue)
p(win|blue)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
50
100
150
200
250
300
350
400
Trials
D)
R-peak Intervals
HRV
R
R
Q
S
Q
S

Bayesian learner problems :

- computational complexity
- questionable biological implementation
- failure to account for individual differences

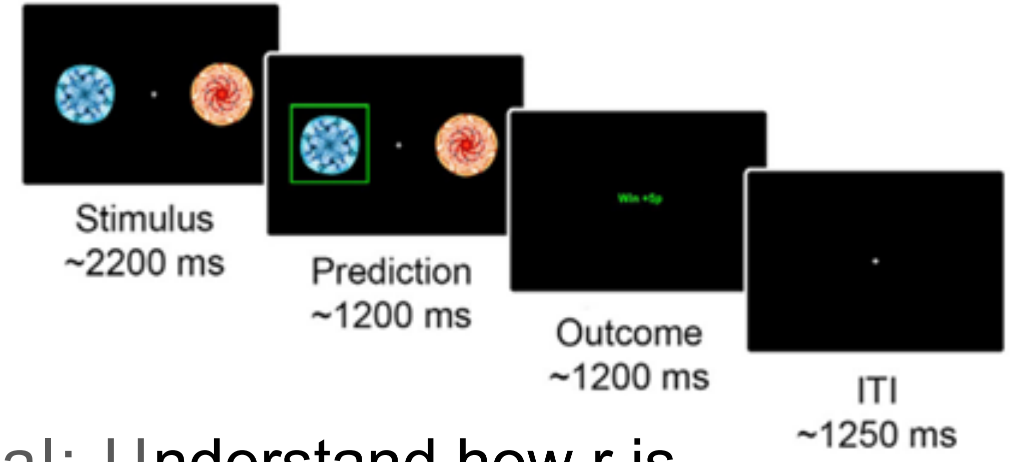
RW model limitations (Rescorla&Wagner , 1972)

- On the theoretical side, it is a heuristic approach that does not follow from the principles of probability theory.
- In practical terms, it often performs badly in real-world situations where environmental states and the outcomes of actions are not known to the agent, but must also be inferred or learned.

Hierarchical Gaussian Filter (HGF) model(Mathys, 2011,2014)

- Any Bayesian learning scheme relies upon the definition of a so-called “generative model,” i.e., a set of probabilistic assumptions about how sensory signals are generated.
- The generative model we propose is inspired by the seminal work of Behrens et al. (2007) and comprises a hierarchy of states that evolve in time as Gaussian random walks, with each walk’s step size determined by the next highest level of the hierarchy.
- Using Mean-field approximation and a novel approximation to replace conventional Laplace approximation. This enables us to derive closed-form update equations for the posterior expectations of all hidden states governing contingencies in the environment. This results in extremely efficient computations that allow for real-time learning.
- The form of these update equations is similar to those of Rescorla–Wagner learning, providing a Bayesian analogon to RL theory.

Bayesian learner

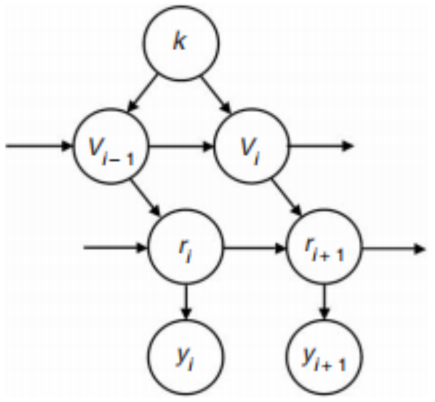


- yi=1(blue color win, 0 orange win)
- Blue win r_i, Orange win $1-r_i$
- Task of subject: find r_{i+1} Through y_{0-I}
- in a time-varying environment, r changes by trial; Understand how r is changing is good. Recent trial might more important in r changes trial.
- Markovian fashion. When an outcome is observed, the new outcome probability depends only on this observed outcome and on the previous outcome probability, but not on the full history of previous outcome probabilities.
- In Markovian setting, r is represented by $p(r_{i+1} | r_i)$, The distribution is centred on r_i, r_{i+1} depends upon r_i
  V:width of the distribution, also volatility.

$$p(r_{i+1} | r_i, v) \sim \beta(r_i, V)$$

- In Markovian setting, the changeability of v is represented as $p(v_{i+1} | v_i)$.
- K: controls the rate of change of volatility

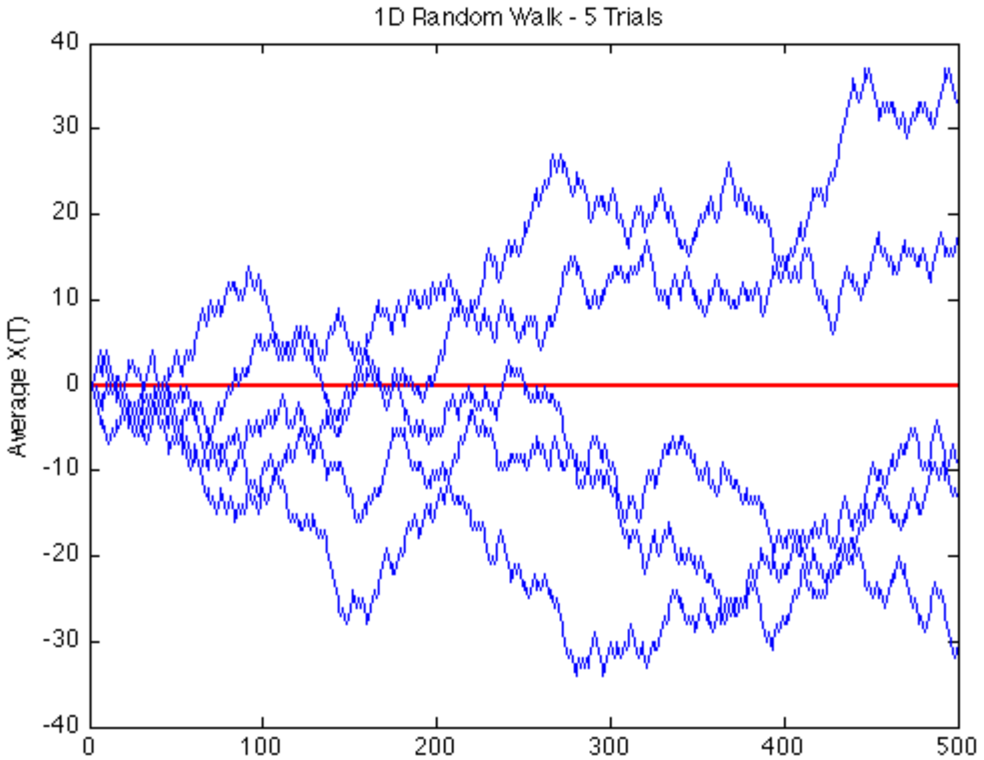
$$p(v_{i+1} | v_i, k) \sim N(v_i, K)$$



- K larger means an environment moves quickly between stable and volatile periods

Random walk(随机漫步)

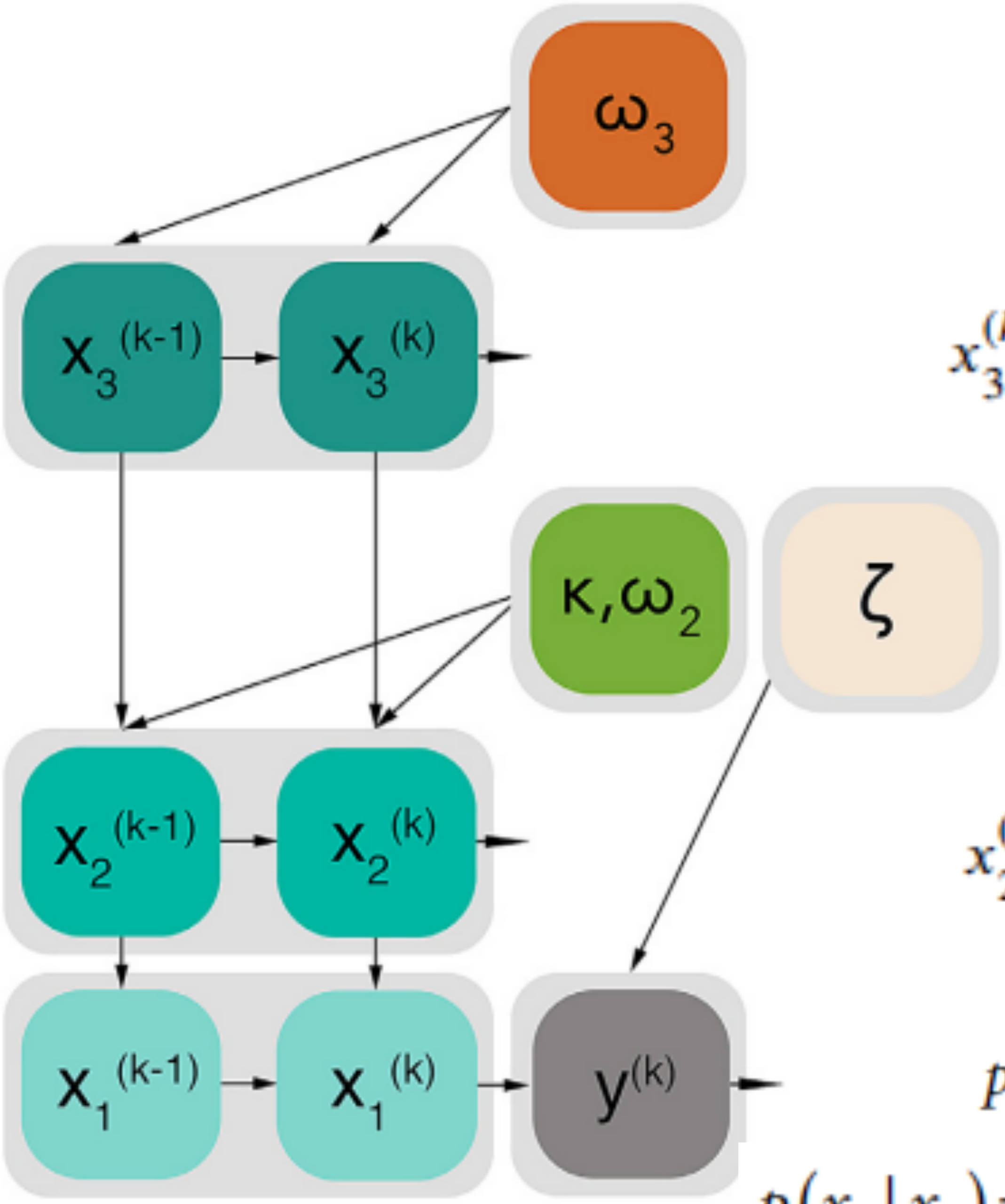
随机行走等是指基于过去的表现，无法预测将来的发展步骤和方向。核心概念是指任何无规则行走者所带的守恒量都各自对应着一个扩散运输定律，接近于布朗运动，是布朗运动理想的数学状态.



Gaussian Random walk

A random walk having a step size that varies according to a normal distribution is used as a model for real-world time series data such as financial markets.

$$Z \sim \mathcal{N}(0, n\sigma^2).$$



$$x_3^{(k)} \sim N\left(x_3^{(k-1)}, \exp(\omega_3)\right)$$

$$x_2^{(k)} \sim N\left(x_2^{(k-1)}, \exp(\kappa x_3 + \omega_2)\right)$$

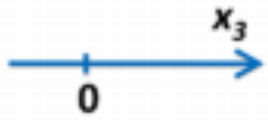
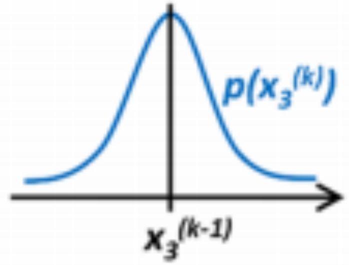
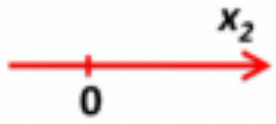
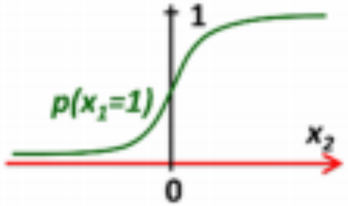
$$p(u \mid x_1) = (u)^{x_1}(1-u)^{1-x_1} \qquad s(x) \stackrel{\text{def}}{=} \frac{1}{1+\exp(-x)}$$

$$p(x_1 \mid x_2) = s(x_2)^{x_1}(1-s(x_2))^{1-x_1} = \text{Bernoulli}(x_1; s(x_2)) \qquad (2)$$

- At the lowest level of the model, the hidden state x1 corresponds to **the binary categorical variable of the experimental stimuli**: whether the blue symbol is rewarded in trial k (x1 (k)= 1; hence, orange would be non-rewarding) or not rewarded (x1 (k)= 0; orange is rewarded).
- State x2 describes **the true value of the tendency of the stimulus outcome contingency**.

This is defined as the sigmoid transformed difference between μ2 before seeing the input and after seeing it, relative to the difference between the observed inputs μ and its predictions.

- State x3 Represents the phasic log-volatility within the task environment; that is, **the rate of change** on the second level.

Level	State of the world	Variable	Possible values	Generative model	
3	Log-volatility of tendency	x_3	Real number 	Gaussian random walk with constant step size ϑ	$p(x_3^{(k)}) \sim N(x_3^{(k-1)},\vartheta)$ 
2	Tendency towards category "1"	x_2	Real number 	Gaussian random walk with step size $\exp(\kappa x_3+\omega)$	$p(x_2^{(k)}) \sim N(x_2^{(k-1)}, \exp(\kappa x_3+\omega))$ 
1	Stimulus category	x_1	"1", "0" 	Sigmoid trans-formation of x_2	$p(x_1{=}1) = s(x_2)$ $p(x_1{=}0) = 1-s(x_2)$ 

Unpacking the learning rate, we see:

$$\Delta\mu_i \propto \frac{\hat{\pi}_{i-1}}{\pi_i}\delta_{i-1}$$

Prediction error

Precisions determine learning rate

outcome uncertainty

$$\frac{\hat{\pi}_u}{\pi_1^{(k)}} = \frac{\hat{\pi}_u}{\hat{\pi}_1^{(k)} + \hat{\pi}_u} = \frac{\hat{\pi}_u}{\dfrac{1}{\sigma_1^{(k-1)} + \exp\left(\kappa_1\mu_2^{(k-1)} + \omega_1\right)} + \hat{\pi}_u}$$

informational uncertainty

environmental uncertainty

(instead of the constant ϑ in the Kalman filter)

Update equations for expectations

Level 3	$\Delta\mu_3 = \sigma_3 \cdot \frac{\kappa}{2} \cdot w_2 \cdot \delta_2$	with	$\Delta\mu_3 = \mu_3^{(k)} - \mu_3^{(k-1)}$ $\sigma_3 = \sigma_3^{(k)}$ $w_2 = \frac{e^{\kappa\mu_3^{(k-1)}+\omega}}{\sigma_2^{(k-1)} + e^{\kappa\mu_3^{(k-1)}+\omega}}$ $\delta_2 = \frac{\sigma_2^{(k)} + \left(\mu_2^{(k)} - \mu_2^{(k-1)}\right)^2}{\sigma_2^{(k-1)} + e^{\kappa\mu_3^{(k-1)}+\omega}} - 1$
Level 2	$\Delta\mu_2 = \sigma_2 \cdot \delta_1$	with	$\Delta\mu_2 = \mu_2^{(k)} - \mu_2^{(k-1)}$ $\sigma_2 = \sigma_2^{(k)}$ $\delta_1 = \mu_1^{(k)} - s\left(\mu_2^{(k-1)}\right)$

Expectation update
(Unweighted) learning rate
Weighting factor
Prediction error

FIGURE 4 | Interpretation of the variational update equations in terms of Rescorla–Wagner learning. The Rescorla–Wagner update is Δprediction = learning rate × prediction error. Our expectation update equations can be interpreted in these terms.

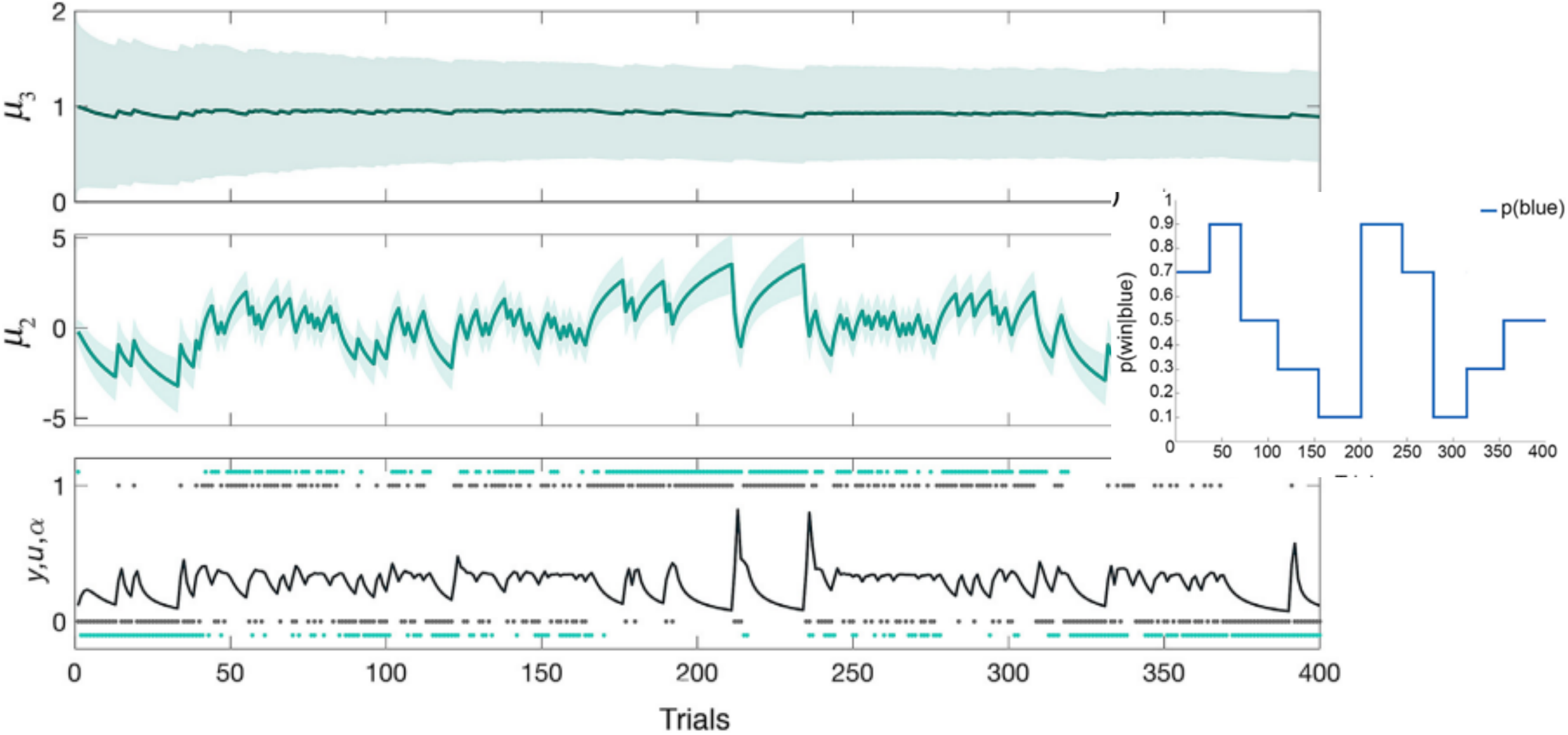


Fig. 2. Three-level Hierarchical Gaussian Filter for binary outcomes. Bottom panel. Representation of the three levels of the HGF for binary outcomes and the associated belief trajectories across the total 400 trials in a representative participant. At the lowest level, the inputs u correspond to the rewarded outcome of each trial (1 = blue, 0 = orange; shown as black dots). The participant's responses y are shown in light blue dots tracking those trial outcomes. The learning rate (α) about stimulus outcomes at the lowest level is also given in black. The belief on the second level, μ_2 (σ_2), represents the participant's estimate of the stimulus tendency x_2 and the step size or variance of the Gaussian random walk for x_2 depends on parameters κ and ω_2, in addition to the estimates of the level above, x_3. The belief on the third level, μ_3 (σ_3), represents estimates of volatility x_3, whose step size is governed by parameter ω_3. Top panel. Schematic representation of the 3-level HGF model with relevant parameters modulating each level. In our study, ω_2, ω_3 and the response parameter ζ were free parameters and were estimated by fitting the HGF to the individual responses and observed inputs. Generally, parameters ω_2, ω_3 describe an individual's learning motif (see the section below for further details).

$$p(u|x_1)=(u)^{x_1}(1-u)^{1-x_1} \qquad p(x_1|x_2)=s(x_2)^{x_1}(1-s(x_2))^{1-x_1}=\text{Bernoulli}(x_1;s(x_2)) \qquad (2)$$

$$x_2^{(k)} \sim N\left(x_2^{(k-1)}, \exp\left(\kappa x_3+\omega_2\right)\right) \qquad (1) \qquad s(x)\stackrel{\text{def}}{=}\frac{1}{1+\exp(-x)}$$

$$x_3^{(k)} \sim N\left(x_3^{(k-1)}, \exp\left(\omega_3\right)\right) \qquad (2)$$

$$\exp\left(\kappa\mu_3^{(k-1)}+\omega_2\right) \qquad (3)$$

$$\Delta\mu_i^k=\mu_i^{(k)}-\mu_i^{(k-1)} \propto \frac{\hat{\pi}_{i-1}^{(k)}}{\pi_i^{(k)}}\delta_{i-1}^{(k)} \qquad (4)$$

$$\pi_i^{(k)}=1/\sigma_i^{(k)} \qquad (5)$$

$$\mu_1^{(k)}=u^{(k)} \qquad (6)$$

$$\mu_2^{(k)}=\mu_2^{(k-1)}+\sigma_2^{(k)}\delta_1^{(k)} \qquad (7)$$

$$\sigma_2^{(k)}=\frac{1}{1/\hat{\sigma}_2^{(k)}+\hat{\sigma}_1^{(k)}} \qquad (8)$$

$$\delta_1^{(k)} \underline{\underline{\mathrm{def}}} \mu_1^{(k)} - \hat{\mu}_1^{(k)} \tag{9}$$

$$\hat{\sigma}_1^{(k)} \underline{\underline{\mathrm{def}}} \hat{\mu}_1^{(k-1)} \left(1 - \hat{\mu}_1^{(k-1)}\right) \tag{10}$$

$$\hat{\sigma}_2^{(k)} \underline{\underline{\mathrm{def}}} \sigma_2^{(k-1)} + e^{\kappa \mu_3^{(k-1)} + \omega_2} \tag{11}$$

$$\pi_2^{(k)} = \hat{\pi}_2^{(k)} + \frac{1}{\hat{\pi}_1^{(k)}} \tag{12}$$

$$\mu_3^{(k)} = \mu_3^{(k-1)} + \sigma_3^{(k)} \frac{\kappa}{2} w_2^{(k)} \delta_2^{(k)} \tag{13}$$

$$\pi_3^{(k)} = \hat{\pi}_3^{(k)} + \frac{\kappa^2}{2} w_2^{(k)} \left(w_2^{(k)} + r_2^{(k)} \delta_2^{(k)} \right) \tag{14}$$

$$\hat{\pi}_3^{(k)} \underline{\underline{\mathrm{def}}} \frac{1}{\sigma_3^{(k-1)} + exp(\omega_3)} \tag{15}$$

$$w_2^{(k)} \underline{\underline{\mathrm{def}}} \frac{e^{\kappa \mu_3^{(k-1)} + \omega_2}}{\sigma_2^{(k-1)} + e^{\kappa \mu_3^{(k-1)} + \omega_2}} \tag{16}$$

$$\varepsilon_2^{(k)} = \mu_2^{(k)} - \mu_2^{(k-1)} = \sigma_2^{(k)} \delta_1^{(k)} \tag{19}$$

$$\varepsilon_3^{(k)} = \mu_3^{(k)} - \mu_3^{(k-1)} = \sigma_3^{(k)} \frac{\kappa}{2} w_2^{(k)} \delta_2^{(k)} \tag{20}$$

$$p(y|m,\zeta) = \left(\frac{m^{\zeta}}{m^{\zeta} + (1-m)^{\zeta}}\right)^{y} \cdot \left(\frac{(1-m)^{\zeta}}{m^{\zeta} + (1-m)^{\zeta}}\right)^{1-y} \tag{21}$$

As response model we used the unit-square sigmoid observation model for binary responses (Iglesias et al., 2013; Mathys et al., 2014). This transforms the predicted probability *m(k)* that the stimulus (e.g.blue) is rewarding on trial *k* (outcome = 1)—which is a function of the current beliefs—into the probabilities p(y(k) = 1) and p(y(k) = 0) that the participant will choose that stimulus (blue, 1) or the alternative (orange, 0):

Higher values of the response parameter ζ lead to the participants being more likely to choose the response that corresponds with their current belief about the rewarded stimulus.

Parameters used in statistics

- model parameters $\omega 2$ (tonic volatility estimate) ; noise from the response model, ζ ; posterior mean on beliefs about volatility ($\mu 3$), environmental uncertainty, and the variances on levels 2 and 3 ($\sigma 2$, $\sigma 3$) as a measure of (informational) uncertainty.

- Note that due to the poor estimation of $\omega 3$ (‘meta-volatility’), which directly modulates precision in level 3 and thus the update steps on the expectation of volatility, $\mu 3$, interpretation of between-group results for $\mu 3$ and $\sigma 3$ should be treated with care.

- precision-weighted prediction errors （pwPE） trajectories from levels 2 and 3 (labeled ε 2, $\varepsilon 3$, Eqs. [19] and [20]);.

Model space

- They tested five computational models of learning.

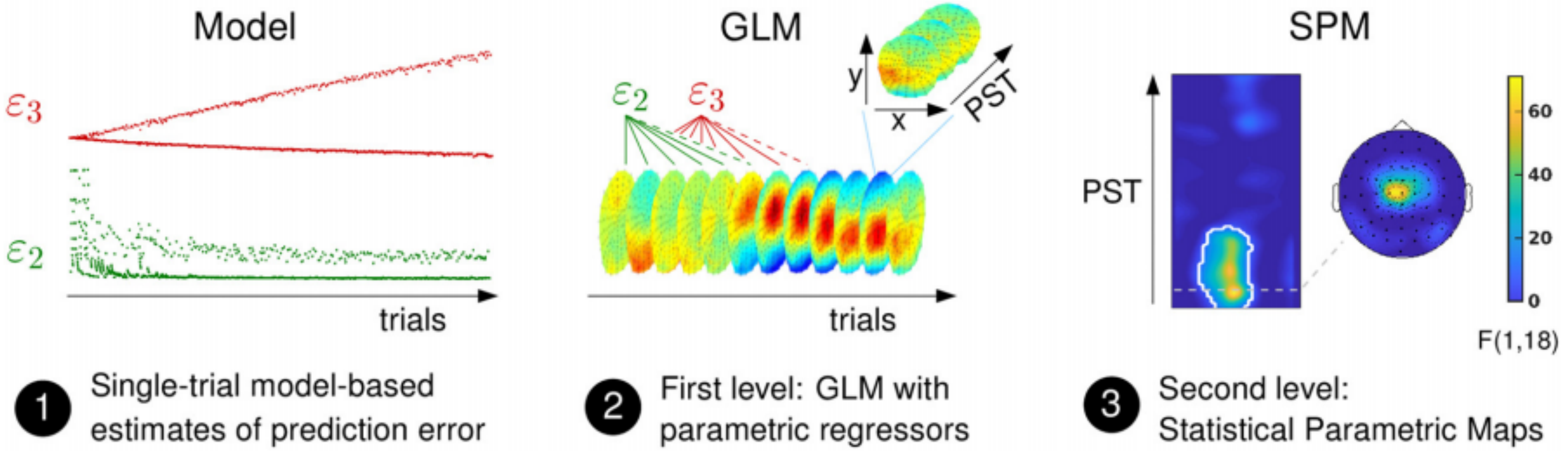
1. a 3-level HGF (with volatility on the third level: HGF3),
2. a reduced 2-level HGF excluding volatility (HGF2)
3. a modified 3-level HGF where the decision noise parameter that maps beliefs to choices (ζ) depends on trial-by-trial estimates of volatility ($\mu 3$)(here termed HGF$\mu 3$).
4. a Rescorla Wagner (RW) where PEs drive belief updating but with a set learning rate (Rescorla and Wagner, 1972);
5. a Sutton K1 model (SK1) that permits the learning rate to change with recent prediction errors (Sutton, 1992).

- Models were then compared at the group level for fit using random effects Bayesian model selection (BMS; Stephan et al., 2009; code from the freely available MACS toolbox; Soch and Allefeld, 2018). BMS provided model frequencies and exceedance probabilities, reflecting how optimal each model or family of models performed.

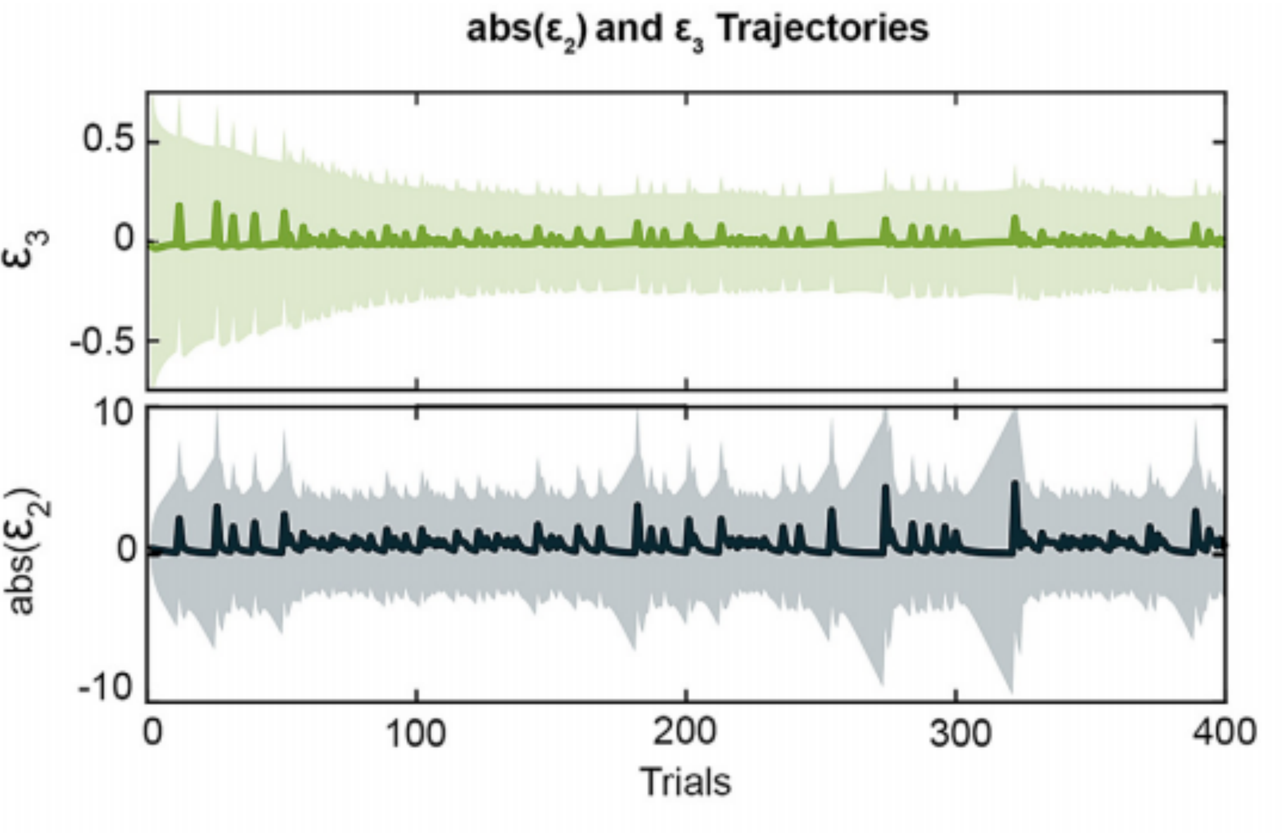
Means and variances of the priors on perceptual parameters and starting values of the beliefs of the HGF models.

Model	Prior	Mean	Variance
3-level HGF			
	κ	1	0
	ω_2	-4	16
	ω_3	-7	16
	${\mu_2}^{(0)}$	0	0
	${\sigma_2}^{(0)}$	0.1	0
	${\mu_3}^{(0)}$	1	0
	${\sigma_3}^{(0)}$	1	0
	ζ	48	1
2-level HGF			
	κ	0	0
	ω_2	-4	16
	ω_3	-7	0
	${\mu_2}^{(0)}$	0	0
	${\sigma_2}^{(0)}$	0.1	0
	${\mu_3}^{(0)}$	1	0
	${\sigma_3}^{(0)}$	1	0
	ζ	48	1
HGFμ_3			
	κ	1	0
	ω_2	-4	16
	ω_3	-7	16
	${\mu_2}^{(0)}$	0	0
	${\sigma_2}^{(0)}$	0.1	0
	${\mu_3}^{(0)}$	1	1
	${\sigma_3}^{(0)}$	1	1

EEG analysis and the General Linear Mode



Weber, L. A., Diaconescu, A. O., Mathys, C., Schmidt, A., Kometer, M., Vollenweider, F., & Stephan, K. E. (2020). Ketamine affects prediction errors about statistical regularities: a computational single-trial analysis of the mismatch negativity. Journal of Neuroscience, 40(29), 5658-5668.



The Pearson correlation coefficient ranged from 0.67 to 0.96 across all 42 participants, mean 0.86, median 0.88; and the correlation was significant in all participants ($p < 0.05$).

Regressors in GLM

1:absolute values of pwPEs in level 2 ($\varepsilon 2$),

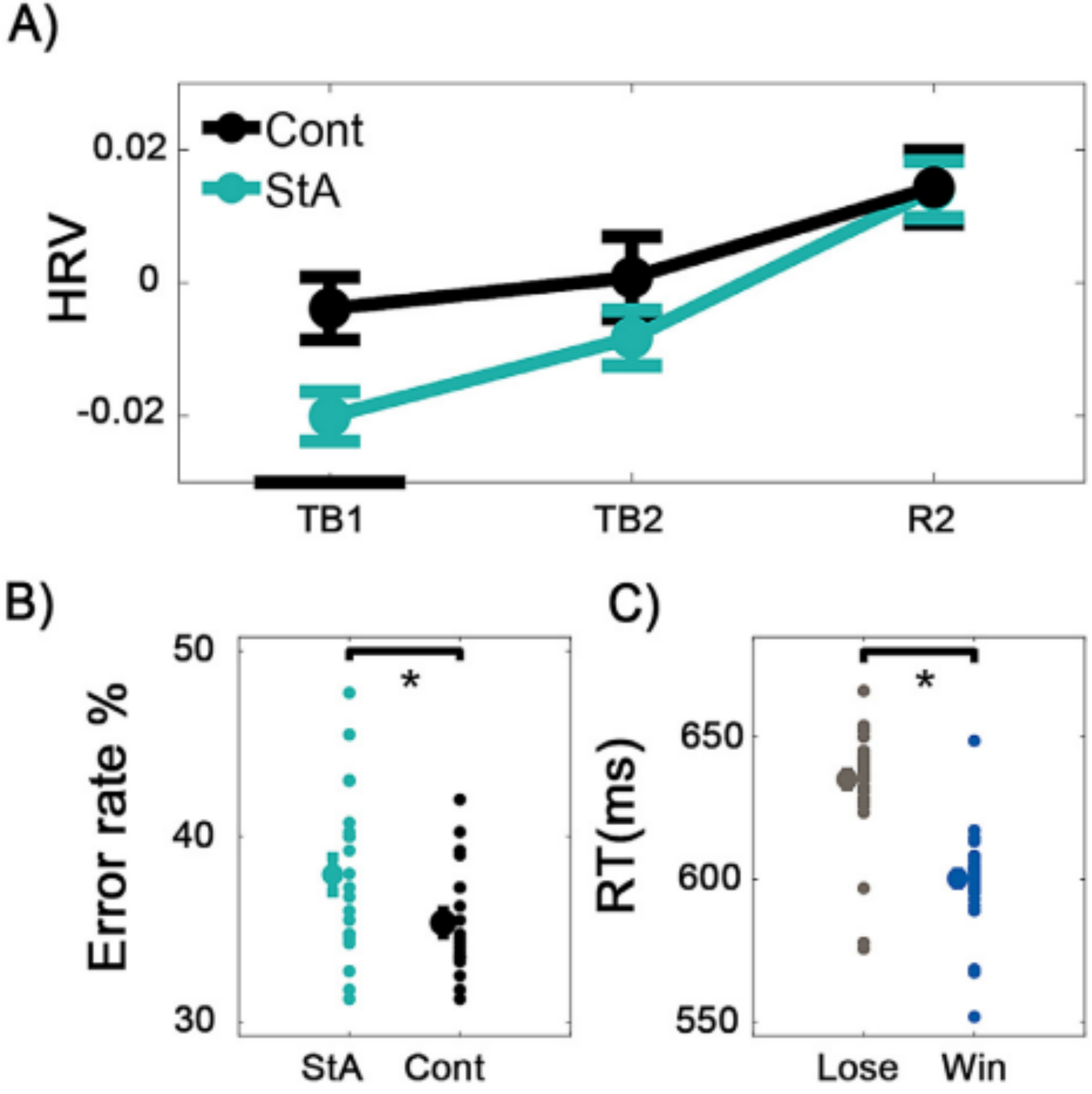
The absolute value of $\varepsilon 2$ was selected because its sign is arbitrary: the quantity x2 is related to the tendency of one choice (e.g. blue stimulus) to be rewarding (x1 = 1); yet this choice and equivalently the sign of the pwPE at this level was arbitrary (see for instance Stefanics et al., 2018).

2: pwPEs in level 3 ($\varepsilon 3$). (removed)

3:the trial-wise win/lose outcome values

- A common practice is to orthogonalise collinear regressors in the model to solve the problem of reduced power and unreliable parameter estimates in the GLM (Mumford et al., 2015).
- However, other authors argue that despite the potential appeal of orthogonalisation of regressors does not improve the overall fit of the model, and in most cases, it can lead to a misleading interpretation of the resulting inferences (Vanhove, 2020).

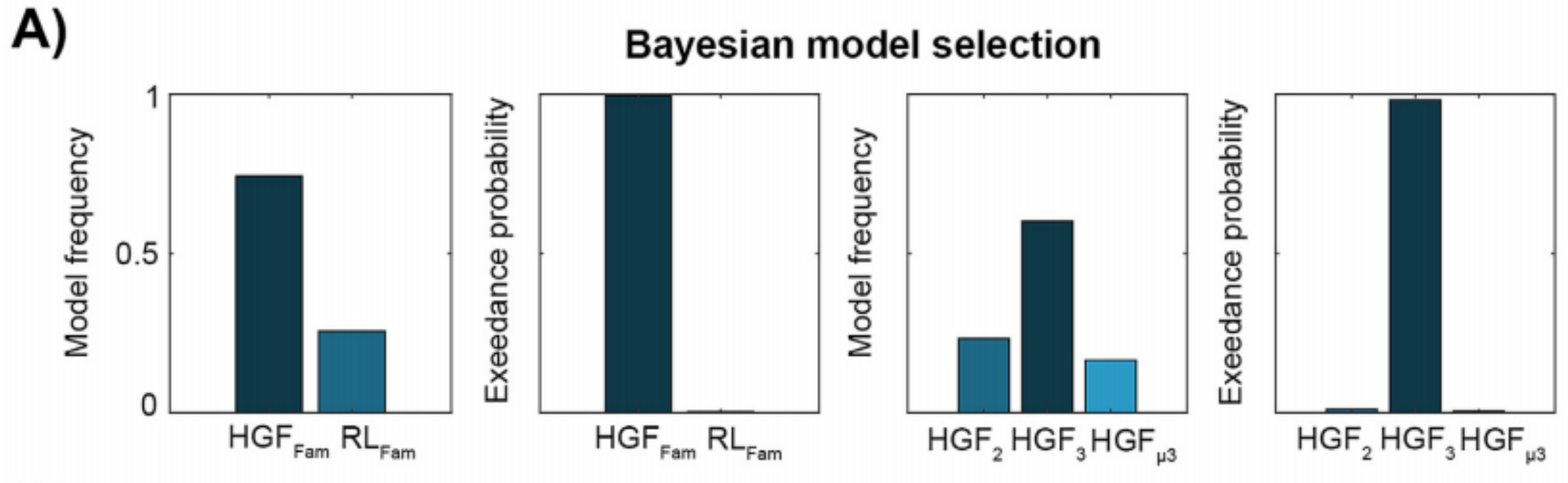
Results

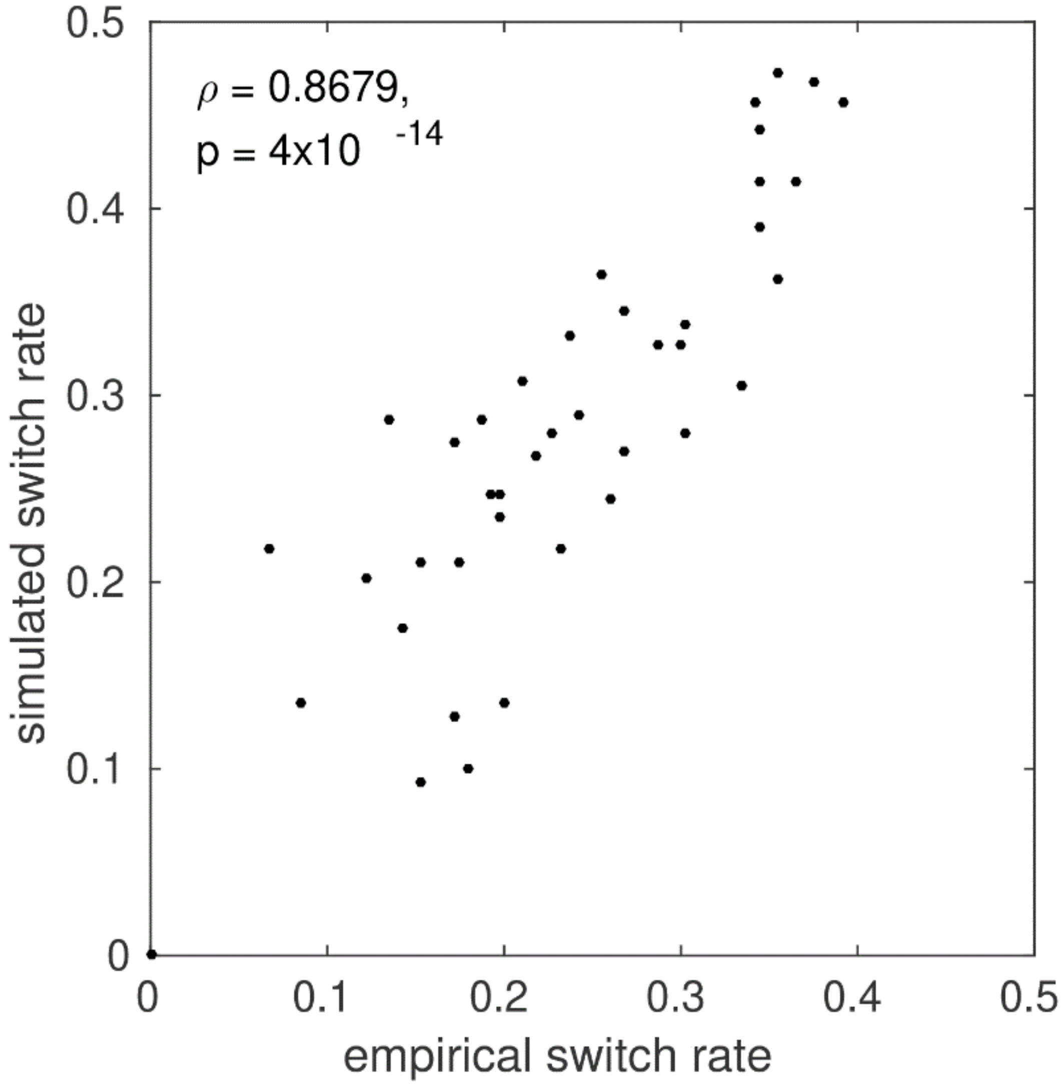


A)
Cont
StA
0.02
0
-0.02
HRV
TB1
TB2
R2
B)
50
40
30
Error rate %
*
StA
Cont
C)
650
600
550
RT(ms)
*
Lose
Win

Model fit

- After fitting each model (HGF: 3-Levels [HGF3], 2-Levels [HGF2], HGFμ3, the Rescorla Wagner [RW], and Sutton K1 [SK1]) individual in each of the 42 participants and obtaining log-model evidence (LME) values for each, we compared the five models using Bayesian model selection (BMS).

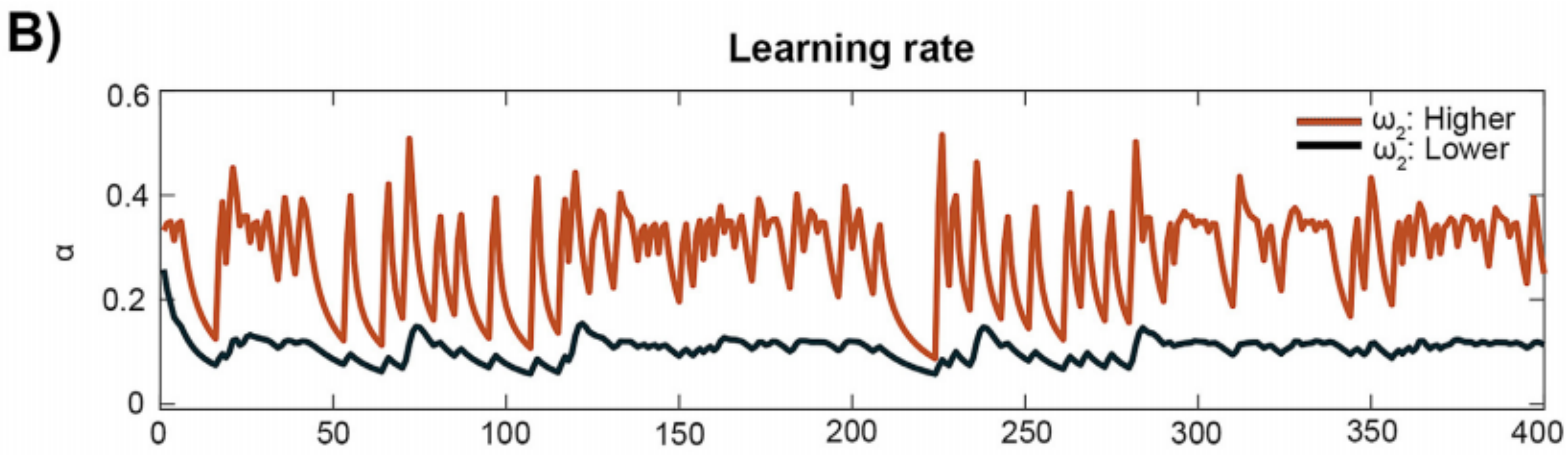




To further determine the quality of the fit of the winning HGF3 model, simulated responses were generated using the estimated model parameters for each individual (ω_2, ω_3, ζ). We compared the probability of trial-to-trial response switch (Orange, Blue) between simulated and empirical data across participants computing the non-parametric Spearman rank correlation. There was a very high and significant rank correlation between both variables (N = 42): $\rho = 0.8679$, $P = 4 \times 10^{-14}$. Inspection of this association within each participant group revealed similar values (N = 21 in each case): $\rho_{Cont} = 0.8263$, $P_{Cont} = 4 \times 10^{-6}$; $\rho_{StA} = 0.8355$, $P_{StA} = 2.5 \times 10^{-6}$.

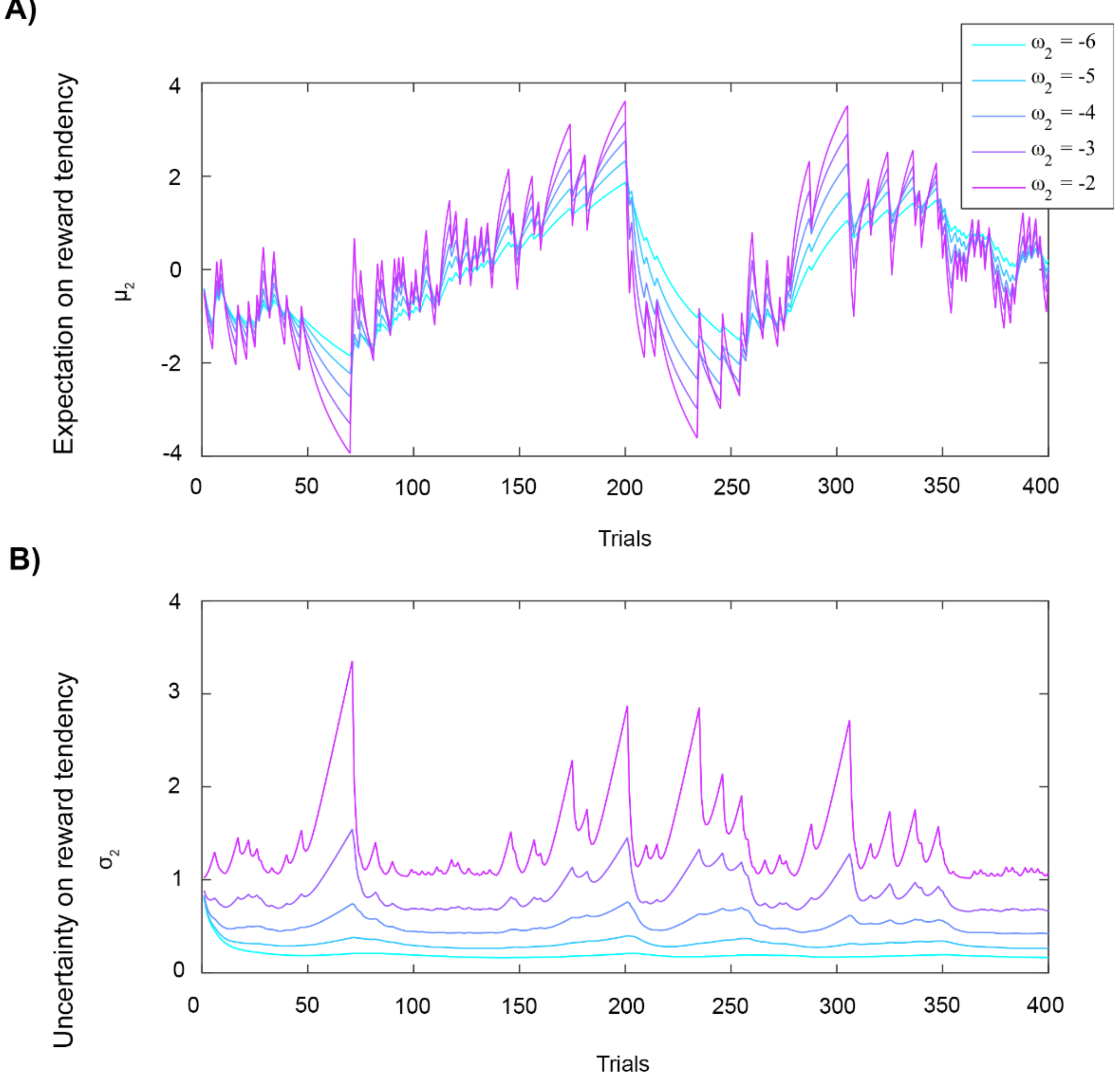
Model-based analysis

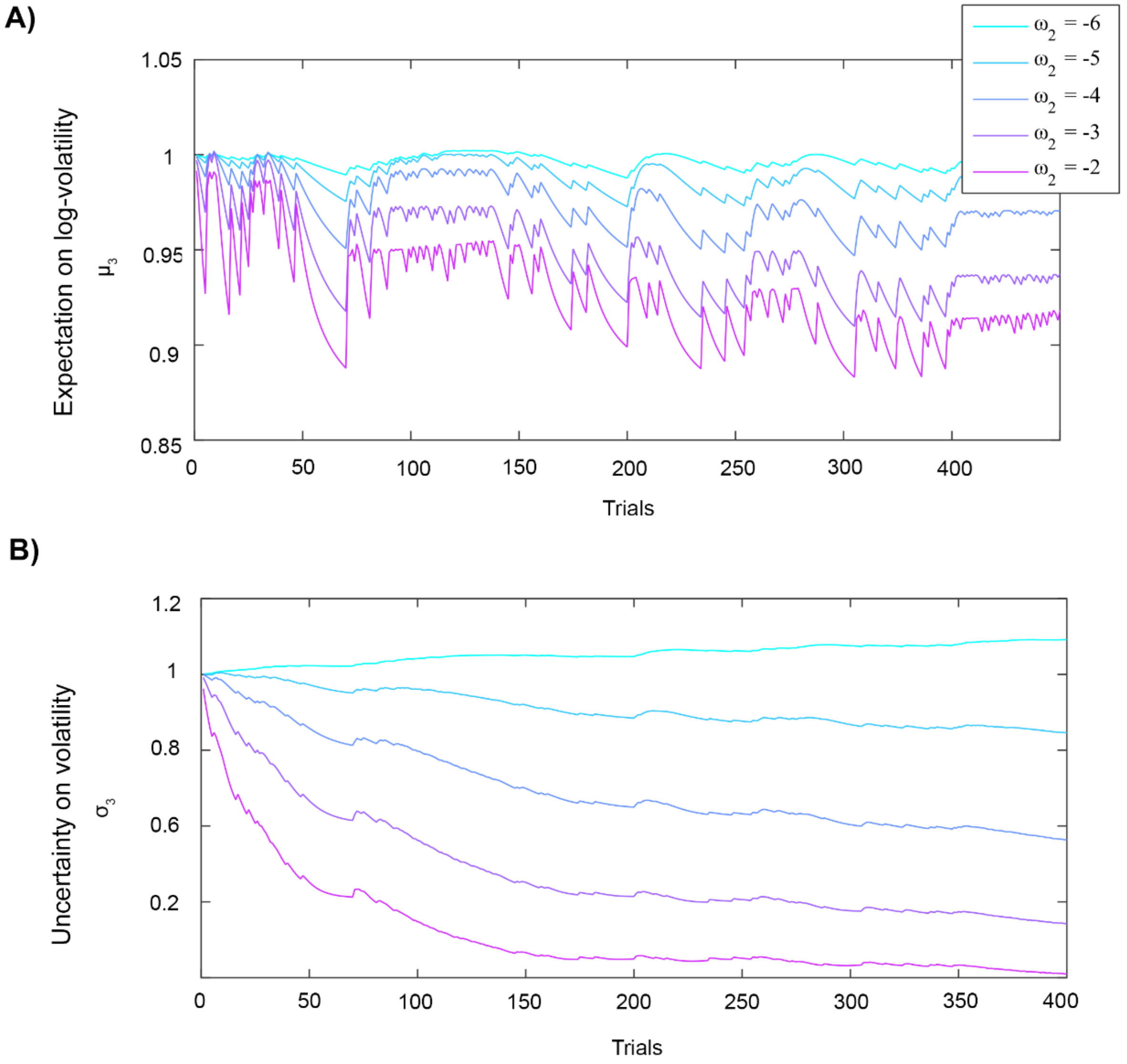
1, State anxiety is associated with a lower learning rate about stimulus outcomes



The two values on ω 2 used in the simulated trajectories are -2 (orange) and -4 (black)

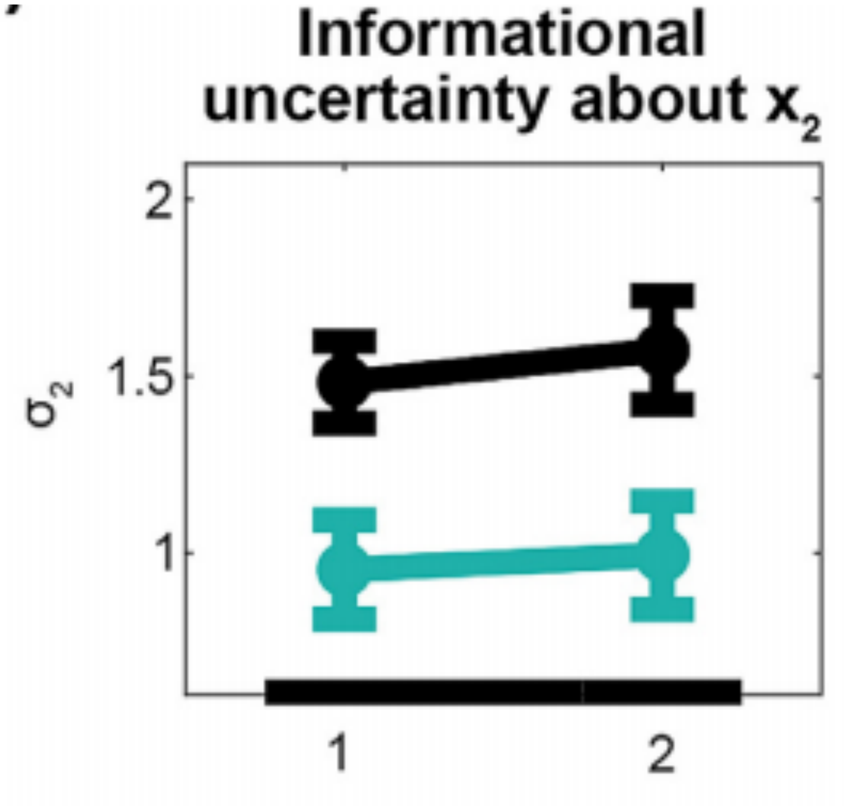
1. The perceptual model parameter $\omega 2$, with smaller values obtained in StA (mean -3.1, SEM 0.23) when compared to the Cont group (mean -2.0, SEM 0.15, p = 0.002, effect size: Δ = 0.75, CI = [0.55, 0.90]).
2. The decision noise parameter, ζ, did not differ between groups (p = 0.62), and was moderately low in both groups: Cont (mean 1.98 [0.26]) and StA (2.20 [0.41]).
3. The values of $\omega 2$ influence, among other HGF trajectories, the learning rate at the lowest level, α (through modulation of $\mu 2$), driving the step of the update about stimulus outcomes (Mathys et al., 2014). More negative $\omega 2$ values—as found in StA—lead to smaller updates, and thus to smaller learning rates (See Fig. 4B).





To illustrate the impact that this has on the evolution of beliefs about reward contingencies and environmental volatility in our task, we additionally provide simulations of belief trajectories for both $\mu 2$ ($\sigma 2$) and the log-volatility μ 3 ($\sigma 3$)

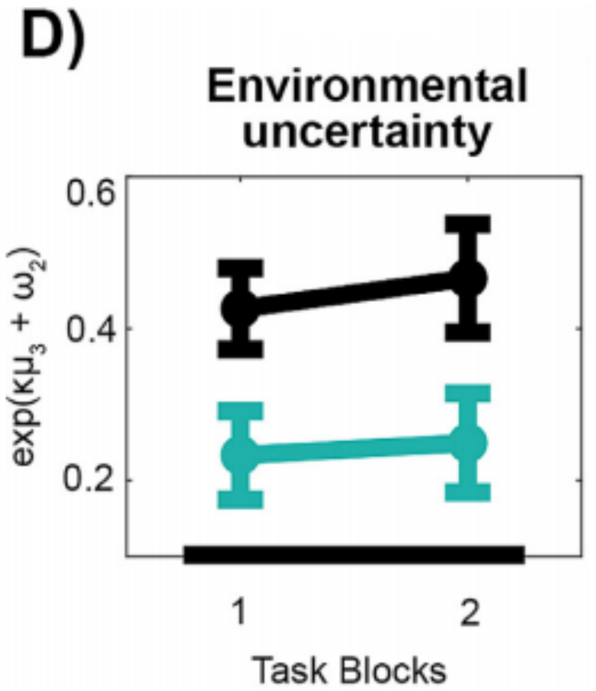
2. *Informational uncertainty about the outcome tendency is lower in state anxious individuals*



- Here we found a significant main effect of factor Group on $\sigma 2$ (p = 0.008). There were no significant effects of block and no interaction effect (p = 0.58, p = 0.78). In addition, planned comparisons showed that anxiety significantly owered the total average $\sigma 2$ for StA in comparison to Cont, as expected from the lower $\omega 2$ values in StA.

- A lower belief uncertainty about the outcome tendency in StA individuals means that new information had a smaller impact on the update equations for beliefs about x_2 in this group.

3. Environmental uncertainty is underestimated in state anxiety

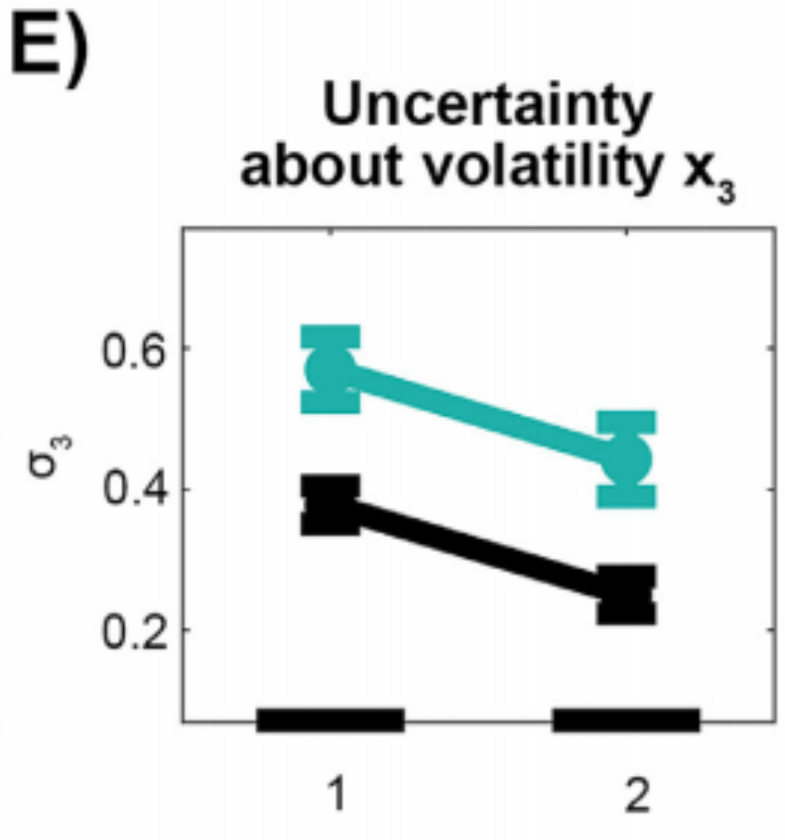


•Environmental uncertainty—induced by changes in the environment—depends on the tonic volatility estimate, $\omega 2$, and the trial-wise volatility estimate $\mu 3_{\text{(k-1)}}$ (see Eq. 3 above; the coupling constant κ was fixed to one).

•More volatile environments lead to greater environmental uncertainty. We found that environmental uncertainty was significantly modulated by factor Group (p = 0.02), while there was no significant main effect for factor Block or interaction effect (p = 0.58, p = 0.75).

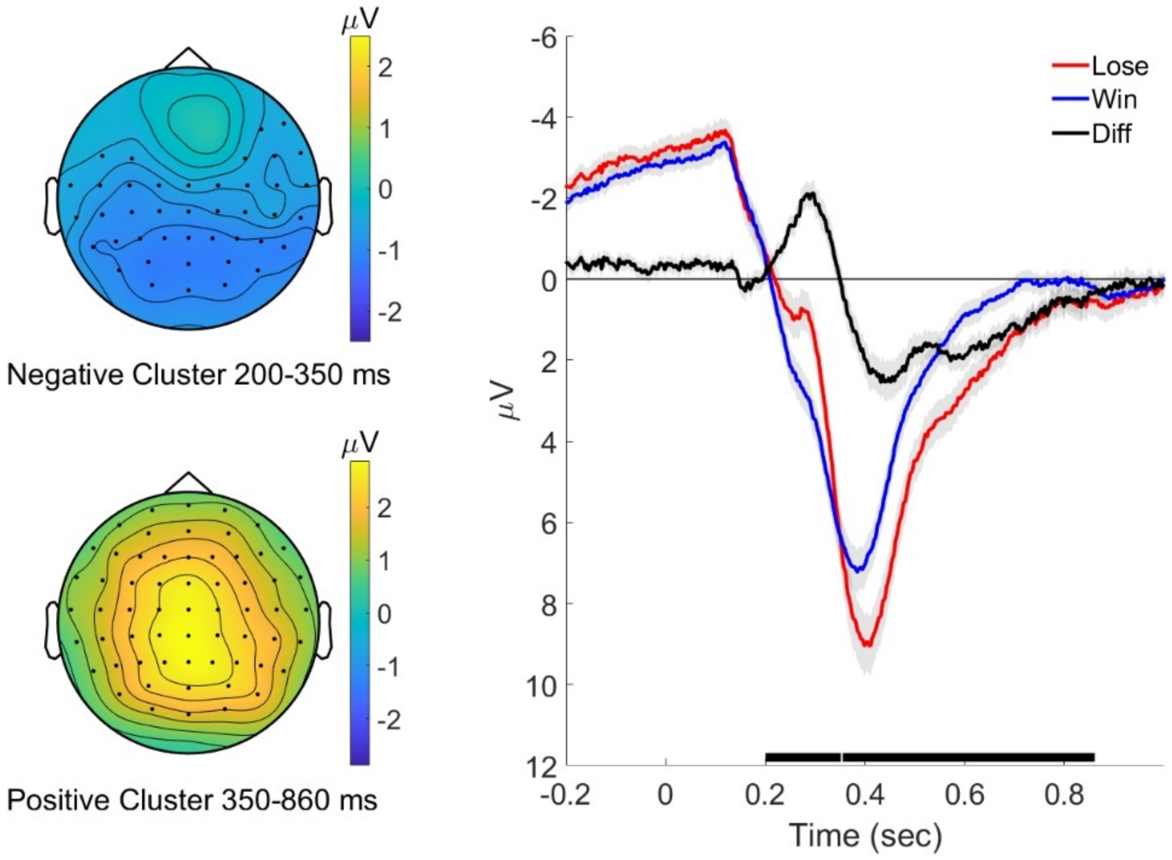
•Further pair-wise analyses demonstrated that the StA group underestimated the environmental uncertainty, relative to control participants, when averaging across both experimental blocks.

4.Uncertainty about volatility is higher in state anxious individuals



- In contrast to the effect on $\sigma2$ reported above, state anxiety increased belief uncertainty on level 3 ($\sigma3$; uncertainty about volatility).
- We found both a significant main effect of Block (p = 0.0006) and Group on this parameter (p = 0.0002), yet no interaction effect (p = 0.99).
- Across blocks, the uncertainty about volatility generally decreased. Planned comparisons demonstrated that separately in the first and second task blocks anxiety significantly increased $\sigma3$ in the StA group when compared to the Cont group (Fig. 4E; $P_{FDR} < 0.05$, effect size for TB1: $\Delta = 0.73$, CI = [0.53, 0.89]; TB2: $\Delta = 0.74$, CI = [0.53, 0.89]).

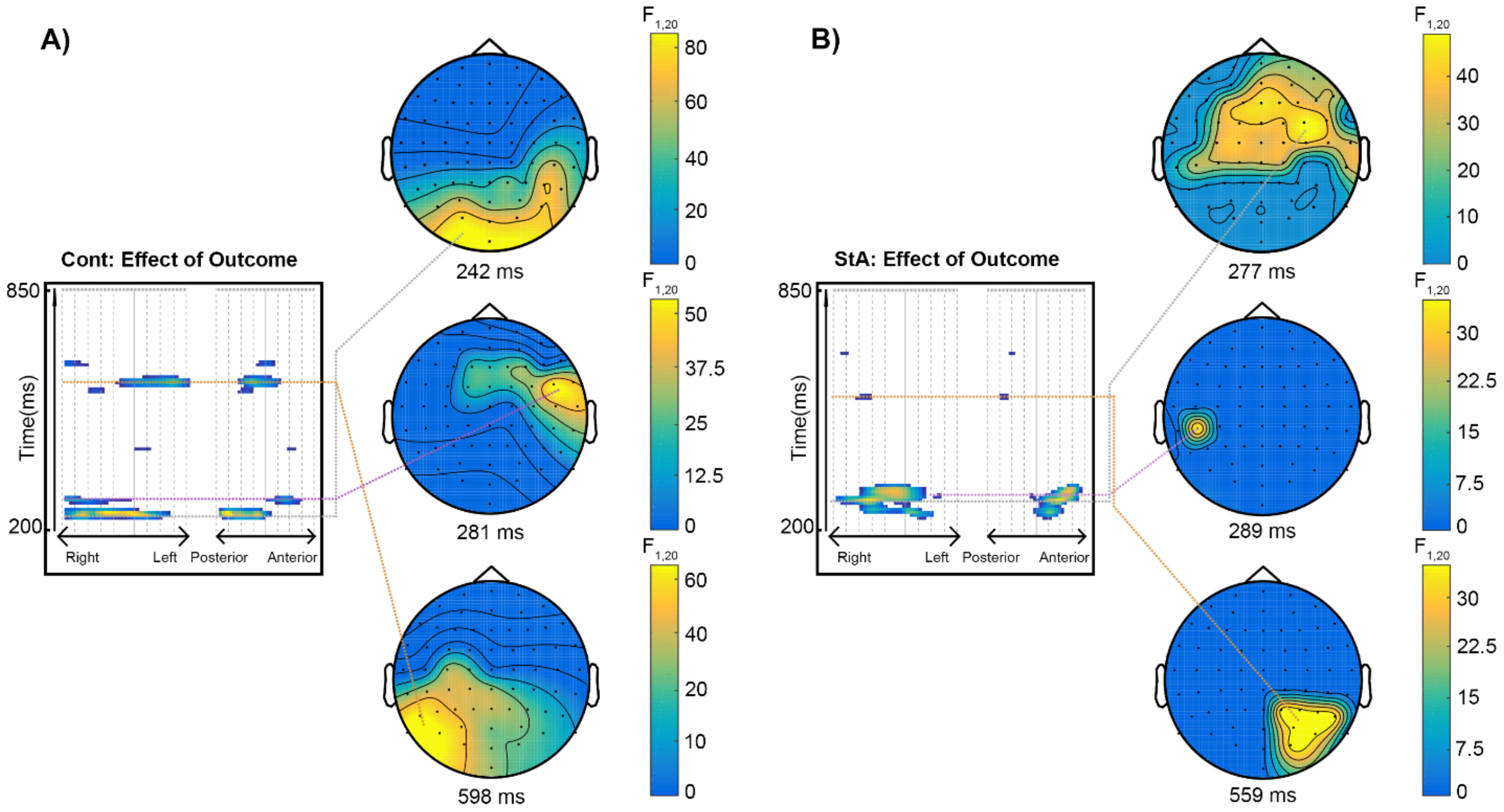
Standard Lose versus Win ERP results



Left panels. Cluster-based random permutation analysis of ERP responses was carried out in the total population (N= 42) to assess the effect of the outcome (win, lose). Maps given for each cluster show the scalp topography of the significant cluster ERP differences between outcomes (win, lose). Black dots on the topographical maps indicate electrodes pertaining to a significant cluster (*P* < 0.025, two-tailed test).

Right panel. Grand-mean ERP waveforms of the two outcomes (lose, red; win, blue) and the difference (lose minus win, black) are presented from all electrodes between -0.2 and 1 seconds, with SEM given as grey shaded areas. Significant clusters are denoted by black bars on the x-axis.

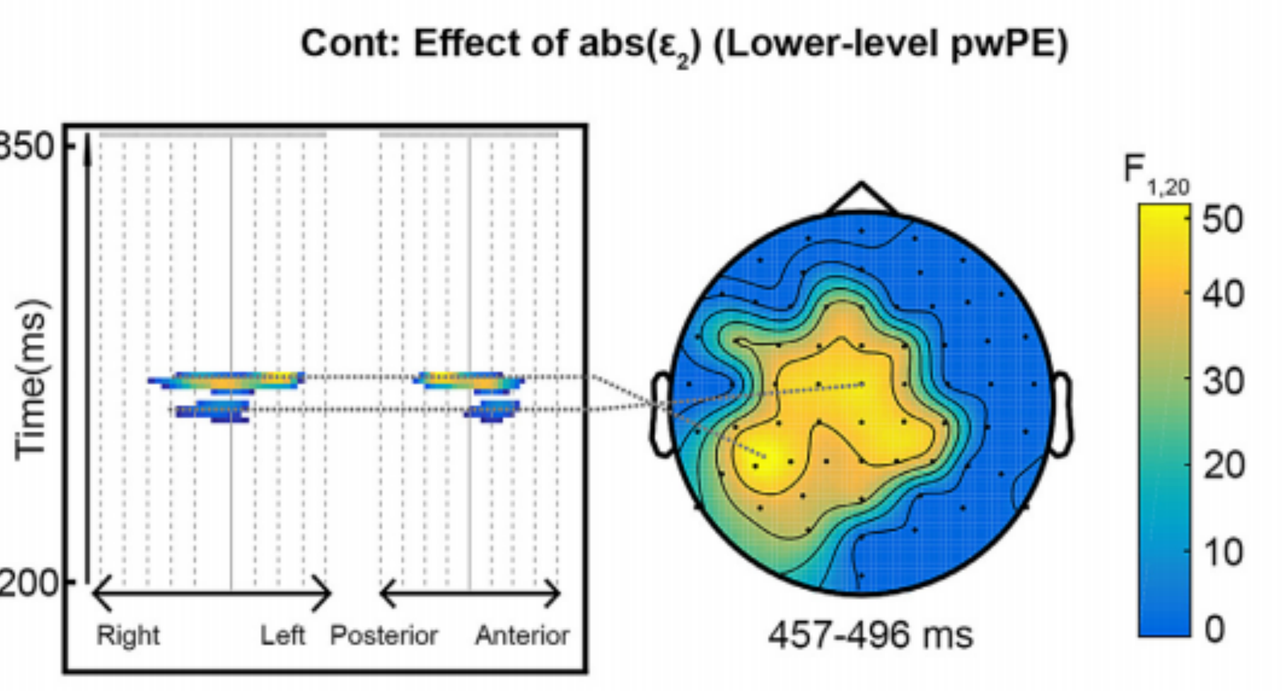
Signatures of the representation of trial outcomes on trial-wise ERPs.



A) Effect of trial outcomes in controls (Cont) correlated with EEG response changes across parietal-occipital and central-parietal electrodes).

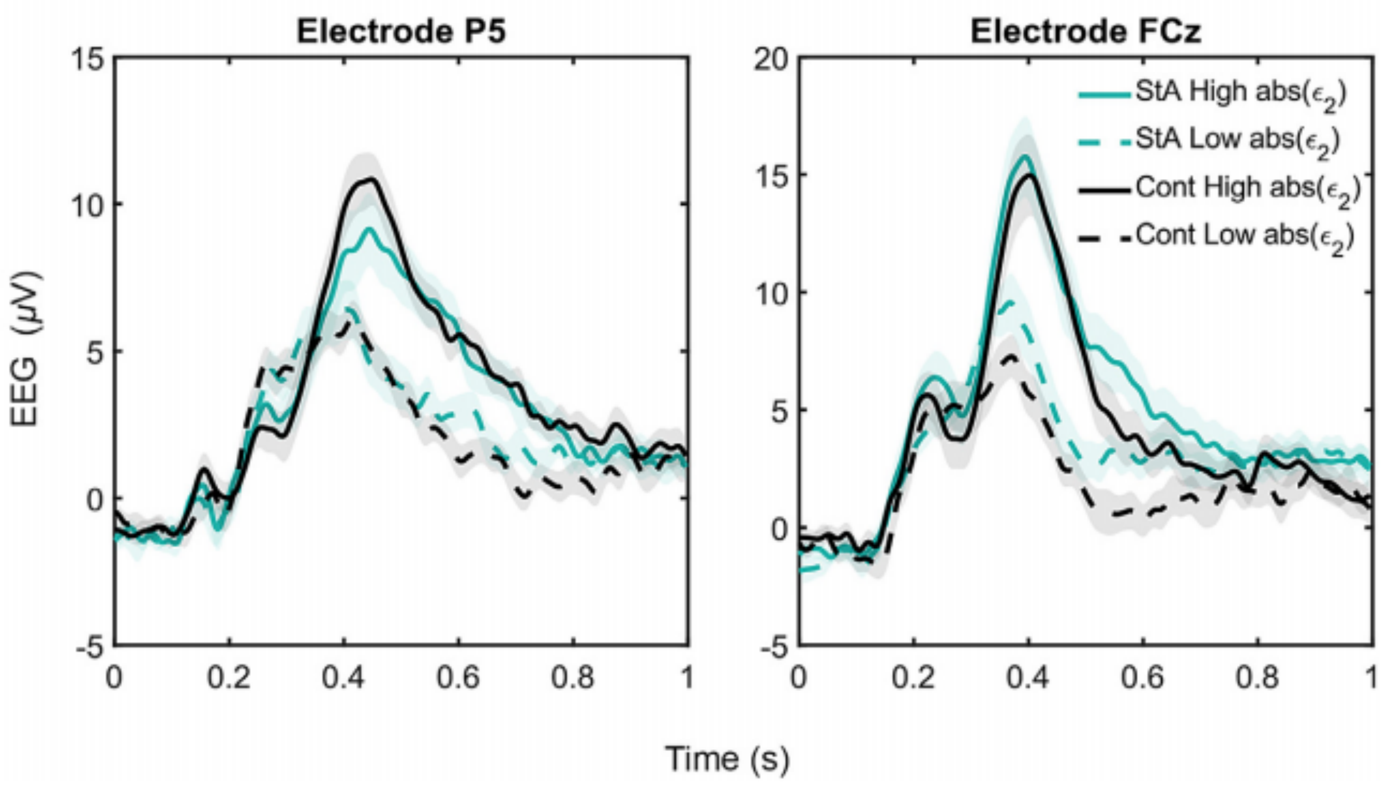
B) Effect of trial outcomes on EEG activity during state anxiety

Low-level precision-weighted prediction errors



•In the Cont group, abs(ε2) significantly modulated trial-wise EEG responses from 475 ms to 503 ms post timulus over central and parietal electrodes, with a maximum effect at 496 ms across a left parietal region (P_{FWE} < 0.0001). An additional significant effect of a smaller cluster size was found earlier between 425–464 ms with a peak at 457 ms (P_{FWE} = 0.001). Across central and frontal electrodes (Fig. 5B).

•Precision-weighted PEs about the stimulus tendencies abs(ε2) did not significantly modulate the ERP responses in the StA group. When directly contrasting the groups, there were no significant differences in the representation of abs(ε2) in EEG activity.



The bottom panels show the average EEG response to the 40 highest ("High") and 40 lowest ("Low") pwPE values from each participant, and at P5 and FCz electrodes—representing the significant GLM cluster obtained in Cont participants (shown in B). The averaged EEG responses are displayed separately for StA High, StA Low, Cont High, and Cont Low. Both participant groups show an increased response in EEG activity during "High" relative to "Low" abs(ε2) trials at both electrode locations and between 475−503 ms.

Main results

1. state anxiety was associated with a reduced estimate of tonic volatility, which resulted in an overall lower learning rate, and corresponded to a significant underestimation of environmental and informational uncertainty. At the same time, a reduction of tonic volatility in our paradigm led to a decrease in learning about phasic volatility, a higher-level belief about the current rate of change in the environment. Our modeling results offer a mechanistic explanation for the increase in error rate that we observed in the anxiety group.
2. Precision-weighted PEs (pwPEs) about the stimulus-reward contingency explained trial-wise modulation of observed ERP responses in control participants only.

- Taken together, the data suggest that temporary anxious states in healthy individuals impair reward-based learning in volatile environments, primarily through changes in uncertainty estimates, potentially mediated by a degraded neuronal representation of lower-level pwPEs about reward contingencies, although the latter remains speculative given the lack of significant differences in pwPE representation between the groups.

- https://medicine.yale.edu/psychiatry/media-player/6164/
- **Chris Mathys. Hierarchical Gaussian Filters (HGFs) for behavioral modeling in computational psychiatry**

- **Mathys, C**., Daunizeau, J., Friston, K. J., & Stephan, K. E. (2011). A Bayesian foundation for individual learning under uncertainty. *Frontiers in human neuroscience*, *5*, 39.

- **Toolbox HGF(based on matlab)**
- https://github.com/translationalneuromodeling/tapas/blob/master/HGF/README.md

Thank you!

Questions

- 4 level hgf ?
- Why kappa was set to constant 1? Did this parameter has difference between two groups?