Angiotensin blockade enhances motivational reward learning via enhancing ventral striatal prediction error and frontostriatal communication

Authors

Ting Xu[1], Xinqi Zhou[1], Jonathan W. Kanen[2,3], Lan Wang[1], Zhiyi Chen[4,5], Ran Zhang[1], Guojuan Jiao[1], Feng Zhou[4,5], Weihua Zhao[1], Shuxia Yao[1], Benjamin Becker[1,*]

Affiliations

[1] The Clinical Hospital of the Chengdu Brain Science Institute, MOE Key Laboratory for Neuroinformation, University of Electronic Science and Technology of China, Chengdu, China

[2]Department of Psychology, University of Cambridge, Cambridge, UK

[3]Behavioural and Clinical Neuroscience Institute, University of Cambridge, Cambridge, UK

[4]Faculty of Psychology, Southwest University, Chongqing, China

[5]Key Laboratory of Cognition and Personality, Ministry of Education, China

***Correspondence to**

Benjamin Becker

University of Electronic Science and Technology

Xiyuan Avenue 2006, 611731 Chengdu, China

mail: ben_becker@gmx.de

ABSTRACT

Adaptive human learning utilizes reward prediction errors (RPEs) that scale the differences between expected and actual outcomes to optimize future choices. Depression has been linked with biased RPE signaling and an exaggerated impact of negative outcomes on learning which may promote amotivation and anhedonia. The present proof-of-concept study combined computational modelling and multivariate decoding with neuroimaging to determine the influence of the angiotensin II type 1 receptor antagonist losartan on learning from positive or negative outcomes and the underlying neural mechanisms in healthy humans. In a double-blind, between-subjects, placebo-controlled pharmaco-fMRI experiment, 61 healthy male participants (losartan, n=30; placebo, n=31) underwent a probabilistic selection reinforcement learning task incorporating a learning and transfer phase. Losartan improved choice accuracy for the hardest stimulus pair relative to the placebo group during learning. Computational modelling revealed that losartan reduced the learning rate for negative outcomes and increased exploitatory choice behaviors while preserving learning for positive outcomes. These behavioral patterns were paralleled on the neural level by increased RPE signaling in orbitofrontal-striatal regions and enhanced positive outcome representations in the ventral striatum (VS) following losartan. In the transfer phase, losartan accelerated response times and enhanced VS functional connectivity with left dorsolateral prefrontal cortex when approaching maximum rewards. These findings elucidate the potential of losartan to reduce the impact of negative outcomes during learning and subsequently facilitate motivational approach towards maximum rewards in the transfer of learning. The mechanism could help to normalize biased reward learning characteristic of depression.

Key words: Angiotensin, Losartan, Depression, Reinforcement learning, Reward Prediction Error, Functional magnetic resonance imaging, Ventral Striatum

Introduction

Human learning is driven by reward prediction errors (RPE) that signal the discrepancy between expected and actual outcomes. Computational approaches have closely linked RPEs to dopaminergic signaling in the midbrain-striatum circuitry and to motivation and reward seeking (1, 2). Deficits in these domains, in particular amotivation and anhedonia, represent key symptoms of unipolar depression and dysregulated RPE signaling has been proposed as a potential underlying neurocomputational candidate mechanism (3). Specifically, within a computational reinforcement learning (RL) framework, depressed individuals showed enhanced sensitivity to negative information while they concomitantly discounted positive feedback leading to reduced learning from positive events (4, 5). On the neural level this learning bias was often accompanied by blunted RPE signaling in the ventral striatum and reduced fronto-striatal connectivity during reward feedback (6, 7). These neural dysregulations have been associated with depressive symptom load, specifically anhedonia and persistent negative mood (8), and could predict anti-depressive treatment response (9). As such, distorted learning from negative and positive outcomes may play a key role in the pathophysiology of depression and may represent a promising target for novel antidepressive treatments.

Accumulating evidence suggests that the renin-angiotensin system plays a key role in learning. Preclinical work in rodents and humans has utilized the selective competitive angiotensin II type 1 receptor (AT1R) antagonist losartan (LT) - an approved treatment for hypertension with an excellent safety record (10, 11) - to modulate learning from negative or positive events (12, 13). Recent human studies have demonstrated that a single dose of LT selectively suppressed memory encoding of threatening materials (14) and accelerated threat extinction learning (15, 16). Moreover, LT specifically affected probabilistic learning from negative outcomes by reducing the degree to which participants learned from loss feedback, while leaving learning from positive outcomes unaffected (12). An initial neuroimaging study moreover reported modulatory effects of LT on mesocorticolimbic functional connectivity during social reward and punishment processing (17).

Given the pivotal role of dopamine (DA) in RPE signaling and modulation of mesocorticolimbic circuits (18), these results may indicate a downstream effect of LT on DA

signaling and in turn on learning from positive and negative outcomes. Support for a potential DA-mediated mechanism of action is provided by studies suggesting an important role of the AT1R in regulating central dopaminergic neurotransmission (19), high co-expression of AT1R and DA receptors (20) and evidence for functionally interactions between AT1R and DA receptors in the striatum (21).

Against this background, the present proof-of-concept study combined computational modelling and functional MRI, with a preregistered between-subjects randomized double-blind placebo-controlled pharmaco-fMRI design in n=61 healthy participants to determine modulatory effects of LT-induced AT1R blockade on RL model parameters and the underlying neural mechanisms. We utilized a validated probabilistic selection RL paradigm with two stages: a learning phase in which participants learned to make better choices for fixed pairs of stimuli according to reward or loss feedback, and a subsequent transfer phase in which participants applied the learned optimal choices to novel combinations of stimuli without feedback. Behavioral responses during learning were fit using a computational RL model to describe the dynamic learning process. Effects of LT on learning were examined by means of comparing RL model parameters and neural activity related to model-derived estimates of RPE. Effects of LT on learning transfer were examined by comparing choices and functional connectivity in cortico-striatal pathways when participants approached the best or avoided the worst stimulus. Based on previous literature (12, 16, 17), we predicted that LT would: 1) reduce learning from negative outcomes, increase the RPE-associated signaling in the ventral striatum (VS) and its neural expression for positive outcomes during the learning phase and 2) increase selection of the best stimulus in the context of increased fronto-striatal coupling during learning transfer.

Methods and Materials

Participants and study protocols

Seventy right-handed healthy male Chinese participants were screened according to evaluated enrollment criteria (see **Supplemental Methods**). The study focused on male individuals to control for sex differences in response to RA blockade (22) and menstrual cycle-dependent variations in reward processing (23). Nine participants were excluded due

to poor learning (LT, n=4; Placebo, n=4; see choice accuracy criteria **Fig. 1**) or excessive head movement (LT, n=1) leading to a final sample of n = 61 (mean±SD, age=20.89±2.32 years).

All participants provided written informed consent, protocols were pre-registered on Clinical Trials.gov (https://clinicaltrials.gov/ct2/show/NCT04604938) and approved by the local ethics committee (Approval 355).

Using a double-blind randomized, placebo-controlled, between-subjects pharmacological fMRI design, participants were administered either a single oral dose of LT (50mg) or placebo (PLC) packed in identical capsules. Capsules were dispensed by an independent researcher based on a computer-generated randomization sequence to implement double blinding. Consistent with the pharmacodynamics profile of LT (LT crosses the blood brain barrier and reaches peak plasma levels after 90 minutes and eliminates between 1.5-2.5h (24-27)), treatment was administered 90min before fMRI acquisition. Participants first performed a reinforcement learning task (duration 30min) followed by an emotional memory task (reported in Xu et al., 2021). To control for nonspecific effects of LT, assessments of mood, attention and memory were incorporated at baseline and after the experiment, while cardiovascular activity (i.e., blood pressure, heart rate) was measured at baseline, after drug administration and after the experiment (see **Fig. 1a** and **Supplemental Methods**). To ensure double blinding participants were asked to guess treatment after the experiment (treatment guess χ^2=0.40, p=0.53; confirming successful double-blinding).

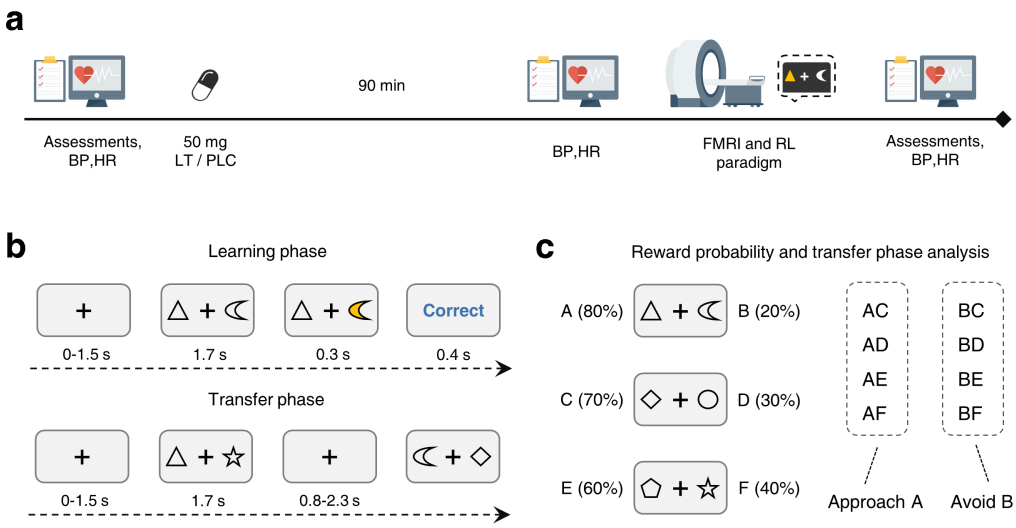

Fig. 1 Experimental timeline and paradigm. **(a)** Experimental timeline. (**b**). The reinforcement learning paradigm consisted of two subsequent phases. During the learning phase participants were presented with one of three different pairs of six stimuli (denoted as AB, CD and EF) on each trial in a randomized order. Participants were instructed to learn to choose the best option within each stimulus pair based on the feedback presented (i.e., 'correct' or 'wrong' presented as text, which indicated that 0.5 RMB or nothing were added to the total payment). To avoid choice preference or reward associations with one stimulus, stimulus pairs were presented in a counterbalanced order across subjects. During the transfer phase, participants were presented with all permutations of combinations with A and B - corresponding to the stimuli with the highest or lowest reward probability, respectively - and were instructed to choose the better option according to their previous learning experience. **(c)** The probabilities of acquiring reward for pairs AB, CD and EF were 80:20, 70:30 and 60:40, respectively, during the learning phase. The easiest condition was therefore the AB pair while the EF pair was the hardest one to learn because of the relatively equivalent reward probabilities between the two stimuli. A performance criterion (i.e., choosing 65% A in AB, 55% C in CD, 50% E in EF, a similar approach to that used by Frank et al., 2007) was initially used to ensure successful learning in the subjects who entered the final analysis, n = 4 subjects in each treatment group did not fulfill this criterion and were excluded from further analysis. The analysis in the transfer phase was conducted on trials in which A was correctly chosen or B was avoided when being paired with another stimulus.
Abbreviations: BP, blood pressure; HR, heart rate; LT, losartan; PLC, placebo; FMRI, functional magnetic resonance imaging; RL, reinforcement learning. License: Image in 1a were designed by DinosoftLabs and obtained from Flaticon.com under the free use license.

Reinforcement learning paradigm

A validated probabilistic selection reinforcement learning paradigm was employed (28-31). This paradigm consisted of two stages: an initial reinforcement learning phase and a subsequent transfer phase. During the learning phase, participants were presented with one of three different pairs of six shape stimuli (denoted as AB, CD and EF, **Fig. 1c**) on each trial in

a randomized order. Participants were instructed to learn to choose the better option of each stimulus pair based on feedback (**Fig .1b**). Learning difficulty varied for the stimulus pairs in terms of reward contingency (80:20, 70:30 or 60:40, for AB, CD or EF, respectively). A total of 240 trials – dispersed across two fMRI runs with 120 trials each (40 trials per stimulus pair, trial mean duration 4s) – were presented during the learning phase. Each trial began with a fixation cross presented for a jittered interval of 0, 500, 1000, or 1500ms (**Fig. 1b**) followed by the presentation of two shapes displayed to the left and right of the fixation cross (side was counterbalanced). Stimuli were presented until participants made a response or 1700ms elapsed. The choice was visually confirmed by highlighting the chosen shape in yellow for 300ms, followed by 400ms feedback presentation ('correct' or 'wrong'). Then, the fixation cross was displayed again until the whole trial duration was reached. In addition, 12 null trials without stimulus presentation of the same duration were randomly interspersed in each fMRI run to improve the model fitting of the rapid event-related fMRI design.

For the transfer phase, the six shape stimuli were recombined to constitute fifteen stimulus pairs. Each stimulus pair permutation was presented 8 times (side was counterbalanced) leading to 120 trials in the transfer phase, also with 12 null trials interspersed in a random order. Duration of each trial was 1700ms and no feedback was provided (**Fig. 1b**). Participants were told to choose the better option in each stimulus pair according to what they had learned in the learning phase.

Computational modeling of learning behavior

We explored the learning rate in terms of choice behavior by using a Q-learning algorithm (32). The Q-learning algorithm has been widely employed to model learning behavior and serves to model the change in choice behavior based on trial-by-trial updates of the expected value of choice options (30, 33, 34). The corresponding model contains three free parameters: learning rate for positive (α_{Gain}) and negative (α_{Loss}) RPEs and estimation of explore-exploit tendency (β). For details of modeling procedures, model estimation and comparison see **Supplemental Methods**.

Statistical analyses on the behavioral level

All analyses were performed in R (R development core and team, 2017). For the learning phase, we employed a multilevel Bayesian linear model to analyze trial-by-trial choice behavior using the Bayesian regression model in Stan (brms) R package (35). Main effects of treatment, stimulus pair and fMRI run, as well as the interaction of stimulus pair and treatment on parameters were considered as credibly different when more than 95% of the posterior distribution was above/below zero. In the transfer phase, we performed similar analyses for trials including stimuli with the highest and lowest reward probability (A, 80% or B, 20%) (**Fig. 1c**) to examine LT effects on choosing the best and avoiding the worst option. An exploratory model additionally examined effects of LT on choice times with choice (choose A, avoid choosing B) and treatment (LT, PLC) as fixed factors and subject as random factor. Main effects of treatment, choice behavior and their interaction were considered significant using the same 95% posterior distribution criterion (details **Supplemental Methods**). Treatment effects on computational modeling indices of choice behavior (learning rate, explore-exploit tendency) were examined by using two sample t tests.

MRI acquisition, preprocessing and first level analysis

MRI data were acquired on a 3.0-T GE Discovery MR system (General Electric Medical System, Milwaukee, WI, USA) and preprocessed using standard procedures in SPM 12 (Statistical Parametric Mapping; http://www.fil.ion.ucl.ac.uk/spm/; Wellcome Trust Centre for Neuroimaging) (see **Supplemental Methods**).

Separate general linear models (GLM) were designed for the learning and transfer phase. For the learning phase, outcome onsets for positive and negative feedback were separately modeled, each modulated by the corresponding RPE estimated from the computational model. The highlight-period and six head motion parameters were included as covariates of no interest. Given that the choice accuracy in both treatment groups rapidly approached a ceiling effect in the second run (**Fig. S2**) the first and second fMRI run were modeled separately, and analyses focused on the first run to increase the sensitivity for learning-associated treatment effects. During the transfer phase, approach A and avoid B were modeled as separate conditions, and the six head motion parameters were included as nuisance regressors.

Examining neural effects of LT on RPE signaling and learning transfer

Effects of LT on RPE signaling during early learning were examined by subjecting the corresponding first level contrasts to voxel-wise two sample t tests. Effects on the transfer of optimal choice behavior were examined by means of separate two sample t-tests for choosing A or avoiding B, respectively. Whole brain analyses thresholded at cluster level family-wise error (FWE) corrected $p<0.05$ were employed (initial cluster threshold, $p<0.001$ uncorrected; see recommendations in Slotnick, 2017 (36)).

Effects of LT on feedback-sensitive neural expressions in the VS

Given the higher sensitivity of multivariate neurofunctional representations for a given mental process including reward and RPEs in the VS (37, 38), multi-voxel pattern analysis (MVPA) was employed. We initially developed a decoder on the whole brain neural pattern that differentiated positive versus negative outcomes during early learning and tested it in an independent sample to validate brain systems strongly involved in differentiating reward versus loss. Next, treatment effects on the corresponding expression in the VS were examined (details **Supplemental Methods**). The VS region of interest included the ventral caudate and nucleus accumbens, defined from the brainnetome atlas (39), which was functionally validated in our previous work (40, 41).

Functional connectivity analysis

Given that animal and human studies indicate that reinforcement learning is critically mediated by the functional communication between the VS and frontal regions (42, 43), treatment effects on frontal-VS functional connectivity during transfer phase were examined. Treatment effects on frontal-VS functional networks were determined by performing two sample t tests on choosing A or avoid choosing B events. Within the brainnetome atlas-defined prefrontal cortex (39), results were thresholded at $p<0.05$ FWE corrected at peak level with small volume correction (SVC).

Results

Demographics and potential confounders

The LT (n = 30) and PLC (n = 31) groups were comparable with respect to sociodemographics and mood and cardiovascular indices arguing against nonspecific treatment effects (**Table 1**; all ps>0.10).

Table 1. Sociodemographic and Bio-psychometric assessments in the two groups

	Time	LT(M±SD)	PLC(M±SD)	t	p
Age		20.63±2.17	21.13±2.47	0.83	0.41
BMI		21.64±2.21	21.15±2.12	-0.87	0.39
HBP	Before	119.87±7.28	118.29±6.64	-0.88	0.38
	Drug peak	115.07±9.36	116.16±7.11	0.52	0.61
	After experiment	119.20±6.73	119.45±5.89	0.16	0.88
LBP	Before	70.43±6.83	70.77±7.17	0.19	0.85
	Drug peak	69.77±6.92	69.23±7.61	-0.29	0.77
	After experiment	69.63±6.05	72.26±6.54	1.63	0.11
HR	Before	75.00±11.09	76.10±10.51	0.40	0.69
	Drug peak	68.03±9.69	70.10±8.62	0.88	0.38
	After experiment	68.27±9.54	69.52±10.28	0.49	0.63
PANAS-P	Before	27.37±4.10	27.77±6.88	0.28	0.78
	After experiment	17.20±6.85	15.19±5.10	-1.30	0.20
PANAS-N	Before	24.5±4.98	26.84±7.23	1.47	0.15
	After experiment	14.33±5.93	13.13±5.04	-0.86	0.40
SAI	Before	41.77±9.62	38.58±9.80	-1.28	0.21
	After experiment	39.9±8.56	37.39±8.12	-1.18	0.24
TAI	Before	41.73±9.47	40.13±8.02	-0.72	0.48
	After experiment	41.33±8.46	39.26±8.40	-0.96	0.34
BDI II	Before	9.13±7.16	8.61±8.82	-0.25	0.80
	After experiment	6.83±6.06	6.39±7.21	-0.26	0.80
D-CAT1	Before	39.83±8.81	38.06±5.77	-0.93	0.36
	After experiment	45.47±6.67	47.16±6.20	1.03	0.31
D-CAT2	Before	55.1±8.19	56.16±8.96	0.48	0.63
	After experiment	58.03±8.29	61.45±9.65	1.48	0.14
D-CAT3	Before	63.93±12.03	65.35±12.48	0.45	0.65

	After experiment	68.10±9.30	70.71±12.34	0.93	0.36
WM	Before	0.91±0.11	0.92±0.04	0.55	0.58
	After experiment	0.94±0.04	0.96±0.03	1.31	0.20

Values are presented as mean ± SD.

Abbreviations: PLC, placebo; LT, Losartan; PANAS, Positive and Negative Affect Schedule; STAI, Spielberger State-Trait Anxiety Inventory; BDI, Beck Depression Inventory II; D-CAT 1-3, Digit cancellation test 1-3; WM, working memory. LT, Losartan, PLC, placebo.

LT increases choice accuracy for the hardest stimulus pair during early learning

The choice accuracy indicates the proportion of trials on which subjects chose the option with higher probability for reward in a stimulus pair (e.g., choose A in AB). Here we observed a significant main effect of stimulus pair (β=0.19, 95% confidence interval [CI], [0.16, 0.22], **Fig. S1**) such that participants exhibited the highest choice accuracy for the easy stimulus pair. The main effect of treatment did not reach significance (β=0.02, 95% CI, [-0.02, 0.06], **Fig. S1**), but the main effect of fMRI run (β=0.12, 95% CI, [0.11, 0.13], **Fig. S1**) was significant. Further inspection revealed that participants in both groups rapidly reached a ceiling effect during the second fMRI run (**Fig. S2**) which may critically reduce the sensitivity of detecting learning-related treatment effects. This pattern was confirmed by a robust treatment × stimulus pair interaction effect in the first (β=-0.05, 95% CI, [-0.07,-0.03], **Fig. 2a**) but not the second fMRI run (β=0.01, 95% CI, [-0.01, 0.03], **Fig. 2b**), with further analyses indicating that compared to PLC – LT increased choice accuracy for the most difficult (EF, β=0.09, 95% CI, [0.01, 0.18], **Fig. 2c**), but not the easier pairs (AB, β=-0.01, 95% CI, [-0.07,0.05]; CD, β=0.03, 95% CI, [-0.05, 0.10], **Fig. 2c**) during the first run. To increase the sensitivity to determine learning-related treatment effects, all subsequent behavioral and neural analysis consequently focused on the early learning phase (run 1).

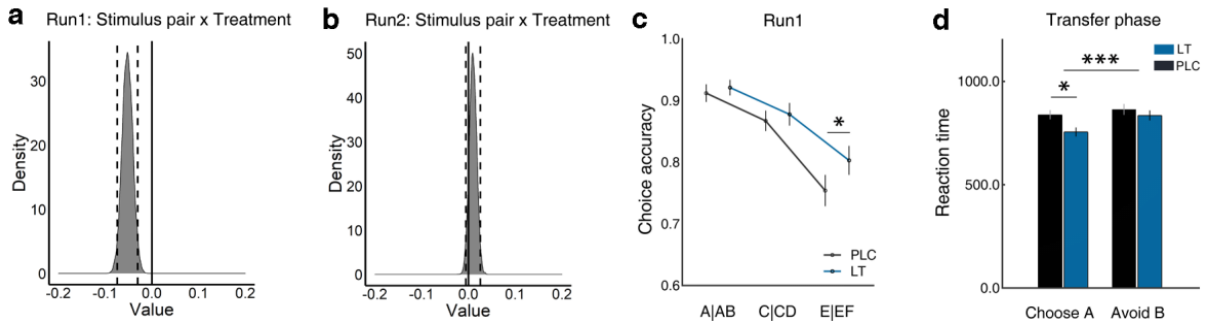

Fig. 2 Behavioral effects of Losartan on choice accuracy and choice time. (a, b) A significant interaction between treatment and stimulus pair was observed in the first but not the second fMRI run of the learning phase. (**c**) During the first fMRI run of the learning phase, losartan-treated participants increased the choice accuracy for the hardest stimulus pair (EF) relative to the placebo group. (**d**) In the transfer phase, all participants responded quickly when choosing stimulus A or avoiding stimulus B, and relative to the placebo group, the losartan group exhibited faster responses for approaching stimulus A in a novel environment. The error bars denote standard error of the mean. Statistical significance was estimated from t tests or analysis of variance models and presented for visualization purpose. PLC, placebo; LT, losartan, *p<0.05.***p<0.001

In the transfer phase, both choosing A and avoiding B were significantly higher than chance level (50%) regardless of treatment (choose A: t=15.07, p<0.001, avoid B: t=15.16, p<0.001). The main effect of treatment on choice accuracy was not significant (β=-0.03, 95% CI, [-0.13, 0.06]). However, analyzing choice reaction times revealed a significant main effect of choice behavior (β=-12.70, 95% CI, [-23.18, -1.94]) and an interaction effect of treatment with choice behaviors (β=-27.36, 95% CI, [-42.41, -12.41]). Relative to PLC, LT accelerated choice times for choosing A (β=-83.52, 95% CI, [-147.03, -18.08], **Fig. 2d**), reflecting facilitated approach of the previously learned best option following LT.

LT reduces the learning rate for negative outcomes during early learning

In line with our hypothesis, LT significantly reduced learning rate from negative outcomes ($t_{(59)}$=-2.40, p=0.02, d=-0.61, **Fig. 3b**) but did not affect learning from positive outcomes ($t_{(59)}$=-1.84,p=0.07,d=-0.47, **Fig. 3a**). Moreover, LT enhanced the explore-exploit parameter ($t_{(59)}$=3.83, p<0.01, d=0.98, **Fig. 3c**), reflecting increased exploitatory choice behavior in terms of more consistent selection of options with higher expected reward values.

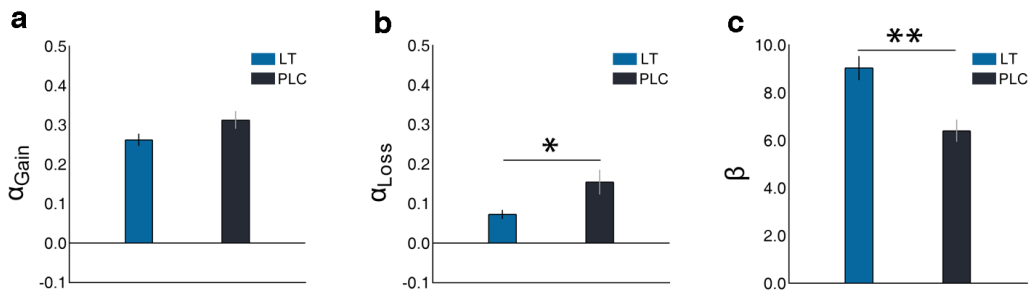

Fig. 3 Losartan effects on computational model parameters. (a) Losartan and placebo groups showed equivalent learning rate for positive outcome. **(b)** Compared to the placebo group, losartan-treated individuals exhibited a reduced learning rate for negative outcomes. **(c)** Moreover, losartan enhanced exploitatory decisions relative to placebo group. The error bars denote standard error of the mean. PLC, placebo; LT, losartan; **p<0.01, *p<0.05.

LT increases RPE signaling during early learning

We initially examined brain regions that scaled positive and negative RPEs independent of treatment. A corresponding one sample t-test confirmed previous studies suggesting that activity in striatal and frontal regions linearly increased with the strength of the RPEs (**Fig. S4, Table S1-S2**). Examining treatment effects by means of a two sample t-test revealed that LT enhanced RPE associated neural responses in the left VS (peak Montreal Neurological Institute (MNI): x,y,z=-8,0,8, $t_{(59)}$=4.24,k=243, $P_{FWE\text{-}cluster}$<0.05, **Fig. 4a**) and bilateral orbitofrontal cortex (left OFC, peak MNI: x,y,z =-40,54,-16, $t_{(59)}$=4.35, k=655, $P_{FWE\text{-}cluster}$<0.05; right OFC, peak MNI, x,y,z=44,40,-14, $t_{(59)}$=4.24,k=326, $P_{FWE\text{-}cluster}$<0.05, **Fig. 4a**). Examination of extracted parameter estimates (spherical masks, radius: 6mm) revealed that these regions signaled positive but not negative RPEs under PLC whereas the LT-induced increase further enhanced positive RPE and instated negative RPE signaling in these regions (**Fig. 4b**).

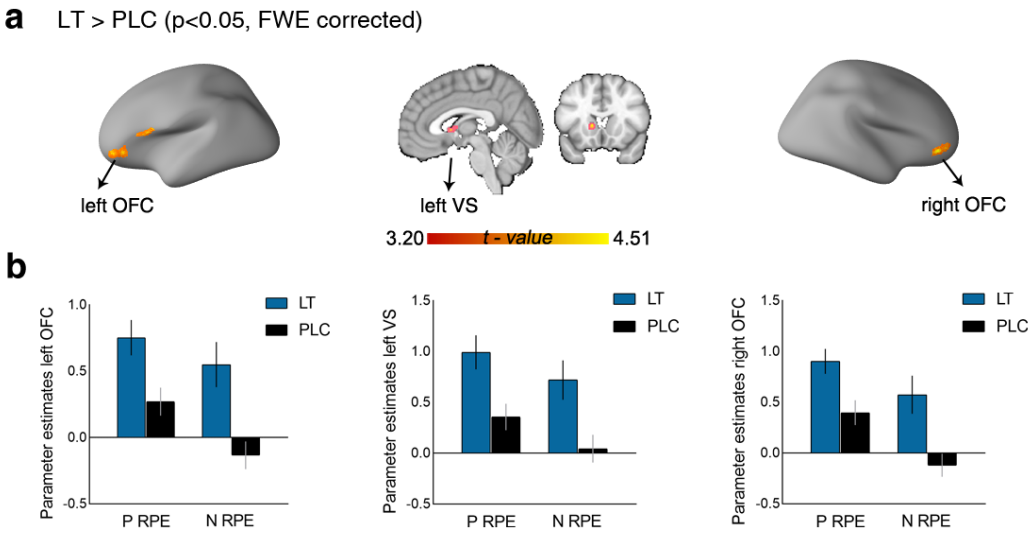

Fig. 4 Losartan modulation on RPE-related neural response. (a) Comparison of losartan and placebo groups in RPE-related response suggested a losartan-triggered increased activation of bilateral orbitofrontal cortex and left ventral striatum**. (b)** For illustration purpose, parameter estimates extraction from spherical masks (radius: 6 mm) of identified left or right orbitofrontal cortex as well as left ventral striatum showed that losartan enhanced activation in these regions to RPE for both positive and negative outcomes. The error bars denoted standard error of the mean. LT, losartan; PLC, placebo. FWE-family-wise error, OFC-orbitofrontal cortex, VS-ventral striatum, PRPE-positive reward prediction error, NRPE-negative reward prediction error.

LT sharpens differential neural representations for positive vs negative outcomes in the VS

We initially established an accurate whole brain multivariate predictive pattern for classifying positive and negative outcomes (accuracy, 89.34%, sensitivity and specificity, 88.52% and 90.16%, respectively **Fig. 5b**). Applying thresholding (bootstrapped 10,000 samples) and multiple comparisons correction (false discovery rate [FDR] corrected, p<0.001) revealed that a network including the VS, ventromedial prefrontal cortex, dorsomedial prefrontal cortex and middle frontal gyrus strongly contributed to the prediction of positive or negative outcomes during early learning (**Fig. 5a**, for a validation in an independent dataset see **Fig. S5**).

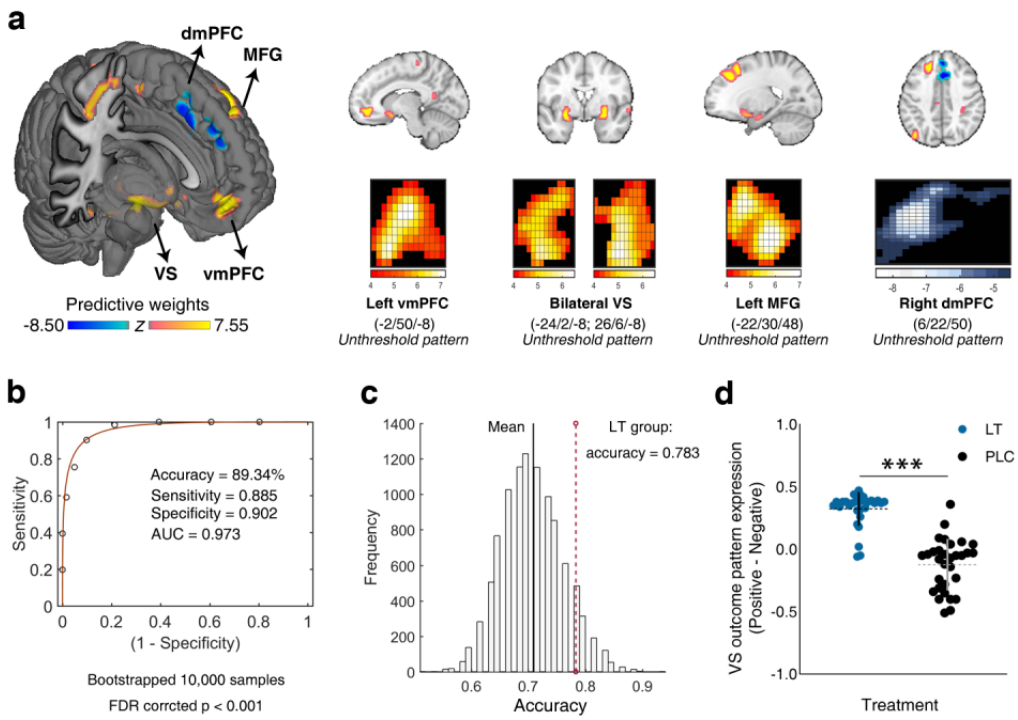

Fig. 5 Multivariate neural predictive pattern results. (a) Neural predictive pattern consists of voxels in which activity reliably predicted positive versus negative outcomes during early phase of learning. This map shows weights that exceed a threshold (p<0.001, FDR corrected based on bootstrapped 10,000 samples) for display only. Hot color indicates positive weights and cold color indicates negative weights. **(b)** ROC plot. This neural predictive pattern yields a classification accuracy of 89.34% in a leave-one-subject-out cross validation procedure. **(c)** The histogram of classification accuracy of ventral striatum neural expression for positive and negative outcome from permutation test. The red line shows the classification accuracy in losartan group. **(d)** Losartan treatment increases the neural pattern of ventral striatum for positive outcome. The error bars denoted standard error of the mean and the black line shows the mean value. VS-ventral striatum, vmPFC-ventromedial prefrontal cortex, dmPFC-dorsomedial prefrontal cortex, MFG-middle frontal gyrus, AUC-area under curve, FDR-False discovery rate, LT-losartan, PLC-placebo. ***p<0.001.

Based on our a priori regional hypothesis about the crucial role of VS in reward learning we examined effects of LT on VS neural representations for positive outcomes. Our results suggested that only following LT - but not PLC - the VS expression accurately differentiated positive from negative outcomes (accuracy=78.33%, p<0.001, sensitivity=0.83, specificity=0.73, AUC=0.88; PLC, accuracy=56.45%, p=0.37, sensitivity=0.55, specificity=0.58, AUC=0.68), with a direct comparison between the treatment groups suggesting that LT specifically enhanced the VS representation for positive outcomes ($t_{(59)}$=9.92,p<0.001,d=1.29, **Fig. 5c-5d**). A group comparison on classification accuracy using permutation-inference further confirmed a significant treatment effect (t=-15.53, p<0.001, 95% CI, [-0.013, -0.010]).

LT increased VS-dlPFC coupling when approaching maximum rewards during transfer

On the neural activation level, no treatment effects of LT during learning transfer were observed. However, on the level of VS functional connectivity LT increased functional connectivity between the VS and left dorsolateral prefrontal cortex (left dlPFC, peak MNI: x,y,z=-48,22,28, $t_{(59)}$=5.15, k=197, $P_{svc\text{-}FWEpeak}$=0.01, **Fig. 6**), reflecting an LT-induced enhancement of VS-dlPFC communication when approaching maximum rewards during learning transfer.

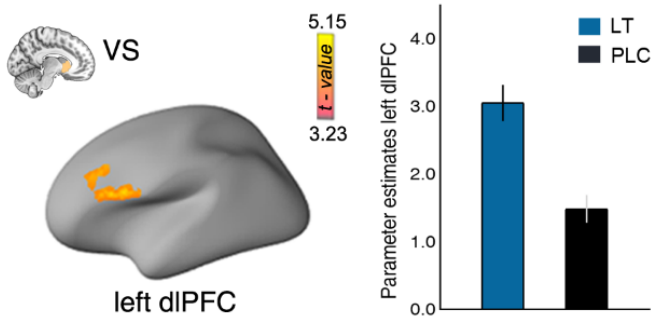

Fig. 6 Functional connectivity results. For illustration purpose parameter estimates were extracted from a spherical (radius: 6 mm) ROI in the identified left dorsolateral prefrontal cortex (dlPFC) region. Losartan increased functional coupling between the ventral striatum and left dlPFC when participants choose A stimuli in the transfer phase. The statistical map of the left dlPFC was thresholded at p<0.001 uncorrected (whole-brain level) for display purpose. The error bars denoted standard error of the mean. VS-ventral striatum; dlPFC-dorsolateral prefrontal cortex; LT, losartan; PLC, placebo.

Discussion

The present pharmacological study utilized computational modeling in combination with fMRI to examine the effects of transient LT-induced AT1R blockade on reinforcement learning and the underlying neural mechanism in healthy individuals. On the behavioral level LT facilitated choice accuracy in the most difficult reward condition while it specifically reduced learning from negative outcomes and enhanced exploitatory choice behaviors. On the neural level, the behavioral effects were paralleled by regional-specific effects on ventral striatal-orbitofrontal reward systems, such that LT increased RPE signaling in these regions and sharpened the fine-grained neurofunctional distinction between positive and negative outcomes in the VS. During learning transfer, LT facilitated approach of the maximum

rewarding option and enhanced VS-dlPFC functional connectivity. Overall, these findings indicate that LT-attenuated learning from negative feedback in the context of general positive outcome learning and a subsequent increased motivation to obtain maximum rewards during learning transfer, which on the neural level was accompanied by enhanced RPE and functional communication in fronto-striatal circuits.

We found that LT specifically enhanced choice accuracy for the most difficult condition suggesting that LT specifically improved learning under a low reinforcement probability. Computational modeling additionally allowed a more fine-grained examination of the behavioral effects by fitting trial-by-trial learning behavior and revealed that LT specifically reduced the learning rate for negative outcomes and enhanced exploitatory choices. The optimal learning ability could be understood when learning rate and other free parameters are considered simultaneously (e.g., explore-exploit tendency) in the RL model and the reward schedule (44). Effects of LT on learning rate were outcome dependent, such that LT specifically decreased learning from negative outcomes, indicating an attenuated influence of negative information on reinforcement learning. Within the context of a stable reinforcement schedule, it is adaptive for an agent to ignore relatively rare and potentially misleading negative feedback given that an oversensitivity to negative outcomes would cause suboptimal choice behaviors. Therefore, decreased negative learning rate may signal the relatively high approach for positive outcomes in a stable reward contingency, which in turn may facilitate an exploitatory choice tendency in terms of consistent decisions for options with a higher expected reward (31). Previous studies demonstrated that enhancing central dopaminergic activity increases choices towards monetary gains (1, 45). The current pattern of results may reflect modulatory effects of RAS blockade on dopaminergic neurotransmission given that LT has been shown to induce stronger D1 receptor expression (46) which has been associated with better reward-associative learning (47). These findings resonate with recent studies reporting an LT-induced enhancement of learning from positive relative to negative events (12) as well as an LT-induced shift from preferential social punishment towards social reward processing (17). Together, this pattern of effects suggests that LT can attenuate the impact of negative information thus promoting motivation to select rewarding options.

On the neural level LT increased orbitofronto-striatal RPE-signaling and induced a more distinct neural expression for positive outcomes in the VS. VS dopamine neurons are critically involved in RPE signaling and reward seeking (48), while the OFC is strongly implicated in computation of expected reward values and RPEs (49). An LT-induced enhancement of the neural RPE signal and the representation of rewarding outcomes may reflect the potential for the RAS to modulate central dopaminergic neurotransmission during reinforcement learning. The AT1R is expressed densely in dopamine-rich brain areas (20), particularly in the striatum (50) and plays a key role in dopaminergic function (51). Administering an antagonist of AT1R could increase D1 receptor activation (46) and block the functional response of the D2 receptor (21) - both of these receptors exhibit dense expression in ventral striatal and prefrontal regions crucially involved in reward learning (52-54). This may indicate a potential downstream effect of LT-induced AT1R blockade on DA signaling, in turn modulating reward learning within orbitofronto- striatal circuits, thus enhancing RPE encoding and reward representation in these regions.

During subsequent learning transfer, LT facilitated approach of the maximum reward in terms of accelerated decisions in the context of enhanced functional coupling of the VS with left dlPFC. Faster decisions for choosing the best options following LT may reflect an increased motivation to focus on maximizing rewards after reinforcement learning. The findings partly align with early research on dopaminergic modulation of reinforcement learning, which reported improved motivation for the highest-rewarding option during transfer, an effect that was explained as dopamine-dependent enhancement of learning signals (55). The important role of fronto-striatal connectivity in reinforcement learning has been extensively documented (42), indicating that reward associations initially formed in the striatum are subsequently used to guide learning and decisions engaging the dlPFC (56). To be specific, the dlPFC plays an important role in integrating and transmitting reward representations to the mesolimbic and mesocortical dopamine systems to initiate reward-motivated behaviors (57). Reduced striato-dlPFC connectivity has been observed in in disorders characterized by a dysfunctional DA system (58), and linked with impaired reinforcement learning (59). As such, the present findings of an LT-induced increase in VS-dlPFC connectivity when approaching rewards might reflect a modulatory role of angiotensin

signaling on fronto-striatal communication via effects on dopaminergic circuits.

Given the repeatedly observed hypersensitivity for negative information and an increased impact of negative information on learning in depression (60), the current pattern of behavioral effects may reflect potential for LT to normalize biased processing in depression and in turn improve motivational deficits. The therapeutic potential in depression is further supported by early animal models suggesting a crucial role of the RAS in depression (61, 62) and documenting potential antidepressant behavioral effects of LT (63, 64). Initial studies aimed at targeting reward processing and reinforcement learning impairments in depression via directly targeting the dopaminergic system (65, 66). These studies revealed initially promising evidence for a therapeutic potential of DA agonist in depression including normalized neural functioning in fronto-striatal reward systems (65, 66) and anhedonia improvement (5). However effects on impaired reward learning were not observed and the clinical utility of DA agonist is limited by adverse effects such as triggering impulsive behaviors (67) and abuse (68). The current pattern of results may point to a possibility that LT may represent a safe and potentially behavioral relevant strategy to modulate deficient reward learning and fronto-striatal functioning in depression.

While the current study found some evidence for a novel pathway to modulate reward learning, future studies are required to: (1) determine the potential of LT to influence reward learning and associated fronto-striatal deficits in depression, and (2) uncover the detailed interaction mechanism between the RAS with DA systems during reward learning such as incorporating receptor maps in combination with molecular imaging. In addition, future studies are required to demonstrate whether the observed effects generalize to women.

Taken together, we demonstrated that AT1R blockade via LT decreased negative learning rate but did not affect learning from positive outcomes, while increasing RPE signaling in orbitofronto-striatal regions and improving neural expression of positive outcomes in the VS. During the subsequent transfer, LT accelerated choices for maximizing rewards and increased VS-dlPFC functional coupling. Together, this pattern may reflect a promising mechanism of LT as a potential treatment to normalize impaired reward learning and fronto-striatal functioning in depression.

Funding

This work was supported by the National Key Research and Development Program of China (Grant No. 2018YFA0701400 [to BB]).

Contributions and data availability

TX and BB designed the study. TX, LW, GJ, YZ conducted the experiment and collected the data. TX, XZ, FZ performed the data analysis. TX and BB wrote the manuscript draft, JK, CZ, WZ and YS critically revised the manuscript draft. Unthresholded group-level statistical maps are available on NeuroVault (https://neurovault.org/collections/12001/). Additional data related to study is available from the corresponding author upon reasonable request. The authors report no biomedical financial interests or potential conflicts of interest. The presents study was pre-registered on Clinical Trials.gov (Trial name: The effects of losartan on reward reinforcement learning; Registration number: NCT04604938; URL: https://clinicaltrials.gov/ct2/show/NCT04604938).

REFERENCES

1. Pessiglione, M., Seymour, B., Flandin, G., Dolan, R. J., & Frith, C. D. (2006). Dopamine-dependent prediction errors underpin reward-seeking behaviour in humans. *Nature, 442*(7106), 1042-1045.
2. Schultz, W. (2002). Getting formal with dopamine and reward. *Neuron, 36*(2), 241-263.
3. Husain, M., & Roiser, J. P. (2018). Neuroscience of apathy and anhedonia: a transdiagnostic approach. *Nature Reviews Neuroscience, 19*(8), 470-484.
4. Chen, C., Takahashi, T., Nakagawa, S., Inoue, T., & Kusumi, I. (2015). Reinforcement learning in depression: A review of computational research. *Neuroscience & biobehavioral reviews, 55*, 247-267.
5. Whitton, A. E., Reinen, J. M., Slifstein, M., Ang, Y.-S., McGrath, P. J., Iosifescu, D. V., . . . Schneier, F. R. (2020). Baseline reward processing and ventrostriatal dopamine function are associated with pramipexole response in depression. *Brain, 143*(2), 701-710.
6. Kumar, P., Goer, F., Murray, L., Dillon, D. G., Beltzer, M. L., Cohen, A. L., . . . Pizzagalli, D. A. (2018). Impaired reward prediction error encoding and striatal-midbrain connectivity in depression. *Neuropsychopharmacology, 43*(7), 1581-1588.
7. Reinen, J. M., Whitton, A. E., Pizzagalli, D. A., Slifstein, M., Abi-Dargham, A., McGrath, P. J., . . . Schneier, F. R. (2021). Differential reinforcement learning responses to positive and negative information in unmedicated individuals with depression. *European Neuropsychopharmacology, 53*, 89-100.
8. Brown, V. M., Zhu, L., Solway, A., Wang, J. M., McCurry, K. L., King-Casas, B., & Chiu, P. H. (2021). Reinforcement learning disruptions in individuals with depression and sensitivity to symptom change following cognitive behavioral therapy. *JAMA psychiatry, 78*(10), 1113-1122.
9. Queirazza, F., Fouragnan, E., Steele, J. D., Cavanagh, J., & Philiastides, M. G. (2019). Neural correlates of weighted reward prediction error during reinforcement learning classify response to cognitive behavioral therapy in depression. *Science advances, 5*(7), eaav4962.
10. Goldberg, A. I., Dunlay, M. C., & Sweet, C. S. (1995). Safety and tolerability of losartan potassium, an angiotensin II receptor antagonist, compared with hydrochlorothiazide, atenolol, felodipne ER, and angiotensin-converting enzyme inhibitors for the treatment of systemic hypertension. *The American journal of cardiology, 75*(12), 793-795.
11. Khoury, N. M., Marvar, P. J., Gillespie, C. F., Wingo, A., Schwartz, A., Bradley, B., . . . Ressler, K. J. (2012). The renin-angiotensin pathway in posttraumatic stress disorder: angiotensin-converting enzyme inhibitors and angiotensin receptor blockers are associated with fewer traumatic stress symptoms. *The Journal of clinical psychiatry, 73*(6), 17451.
12. Pulcu, E., Shkreli, L., Holst, C. G., Woud, M. L., Craske, M. G., Browning, M., & Reinecke, A. (2019). The effects of the angiotensin II receptor antagonist losartan on appetitive versus aversive learning: a randomized controlled trial. *Biological psychiatry, 86*(5), 397-404.
13. Ranjbar, H., Aghaei, I., Moosazadeh, M., & Shabani, M. (2018). Angiotensin II type 1 receptor blocker losartan attenuates locomotor, anxiety-like behavior, and passive avoidance learning deficits in a sub-chronic stress model. *Iranian Journal of Basic Medical Sciences, 21*(8), 856.
14. Xu, T., Zhou, X., Jiao, G., Zeng, Y., Zhao, W., Li, J., . . . Becker, B. (2021). Modulation of the renin-angiotensin system inhibits memory advantage for negative emotional material via decreasing hippocampus activation and its coupling with the amygdala. *bioRxiv*.
15. Stout, D. M., & Risbrough, V. B. (2019). Angiotensin II signaling and fear extinction: translational evidence and novel receptor targets. *Biological psychiatry, 86*(12), 874-876.
16. Zhou, F., Geng, Y., Xin, F., Li, J., Feng, P., Liu, C., . . . Ebstein, R. P. (2019). Human extinction learning is accelerated by an angiotensin antagonist via ventromedial prefrontal cortex and its connections with

basolateral amygdala. *Biological psychiatry, 86*(12), 910-920.

17. Zhou, X., Xu, T., Zeng, Y., Zhang, R., Qi, Z., Zhao, W., . . . Becker, B. (2021). The angiotensin antagonist Losartan shifts social reward motivation and punishment feedback sensitivity via modulating midbrain-striato-frontal circuits. *bioRxiv*.
18. Glimcher, P. W. (2011). Understanding dopamine and reinforcement learning: the dopamine reward prediction error hypothesis. *Proceedings of the National Academy of Sciences, 108*(Supplement 3), 15647-15654.
19. Kobiec, T., Otero-Losada, M., Chevalier, G., Udovin, L., Bordet, S., Menéndez-Maissonave, C., . . . Pérez-Lloret, S. (2021). The renin–angiotensin system modulates dopaminergic neurotransmission: a new player on the scene. *Frontiers in Synaptic Neuroscience, 13*, 16.
20. Saavedra, J. (2017). Beneficial effects of Angiotensin II receptor blockers in brain disorders. *Pharmacological research, 125*, 91-103.
21. Martinez-Pinilla, E., Rodriguez-Perez, A., Navarro, G., Aguinaga, D., Moreno, E., Lanciego, J., . . . Franco, R. (2015). Dopamine D2 and angiotensin II type 1 receptors form functional heteromers in rat striatum. *Biochemical Pharmacology, 96*(2), 131-142.
22. Miller, J. A., Cherney, D. Z., Duncan, J. A., Lai, V., Burns, K. D., Kennedy, C. R., . . . Scholey, J. W. (2006). Gender differences in the renal response to renin-angiotensin system blockade. *Journal of the American Society of Nephrology, 17*(9), 2554-2560.
23. Dreher, J.-C., Schmidt, P. J., Kohn, P., Furman, D., Rubinow, D., & Berman, K. F. (2007). Menstrual cycle phase modulates reward-related neural function in women. *Proceedings of the National Academy of Sciences, 104*(7), 2465-2470.
24. Getyala, A., V Gangadharappa, H., Sarat Chandra Prasad, M., Praveen Kumar Reddy, M., & M Pramod Kumar, T. (2013). Formulation and evaluation of non-effervescent floating tablets of losartan potassium. *Current drug delivery, 10*(5), 620-629.
25. Li, Z., Bains, J. S., & Ferguson, A. V. (1993). Functional evidence that the angiotensin antagonist losartan crosses the blood-brain barrier in the rat. *Brain research bulletin, 30*(1-2), 33-39.
26. Sica, D. A., Gehr, T. W., & Ghosh, S. (2005). Clinical pharmacokinetics of losartan. *Clinical pharmacokinetics, 44*(8), 797-814.
27. Samyuktha, M., Vasanth, P., Suresh, K., Ramesh, T., & Ramesh, M. (2013). Formulation and evaluation of gastroretentive floating tablets of losartan potassium. *Int J Biopharm, 4*, 18-26.
28. Frank, M. J., Moustafa, A. A., Haughey, H. M., Curran, T., & Hutchison, K. E. (2007). Genetic triple dissociation reveals multiple roles for dopamine in reinforcement learning. *Proceedings of the National Academy of Sciences, 104*(41), 16311-16316.
29. Frank, M. J., Woroch, B. S., & Curran, T. (2005). Error-related negativity predicts reinforcement learning and conflict biases. *Neuron, 47*(4), 495-501.
30. Jahfari, S., Theeuwes, J., & Knapen, T. (2020). Learning in visual regions as support for the bias in future value-driven choice. *Cerebral cortex, 30*(4), 2005-2018.
31. Van Slooten, J. C., Jahfari, S., Knapen, T., & Theeuwes, J. (2018). How pupil responses track value-based decision-making during and after reinforcement learning. *PLoS computational biology, 14*(11), e1006632.
32. Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*: MIT press.
33. Grogan, J. P., Tsivos, D., Smith, L., Knight, B. E., Bogacz, R., Whone, A., & Coulthard, E. J. (2017). Effects of dopamine on reinforcement learning and consolidation in Parkinson's disease. *Elife, 6*, e26801.
34. Jahfari, S., Ridderinkhof, K. R., Collins, A. G., Knapen, T., Waldorp, L. J., & Frank, M. J. (2019). Cross-task

contributions of frontobasal ganglia circuitry in response inhibition and conflict-induced slowing. *Cerebral cortex, 29*(5), 1969-1983.

35. Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of statistical software, 80*, 1-28.
36. Slotnick, S. D. (2017). Cluster success: fMRI inferences for spatial extent have acceptable false-positive rates. *Cognitive neuroscience, 8*(3), 150-155.
37. Kahnt, T. (2018). A decade of decoding reward-related fMRI signals and where we go from here. *Neuroimage, 180*, 324-333.
38. Zhou, F., Zhao, W., Qi, Z., Geng, Y., Yao, S., Kendrick, K. M., . . . Becker, B. (2021). A distributed fMRI-based signature for the subjective experience of fear. *Nature communications, 12*(1), 1-16.
39. Fan, L., Li, H., Zhuo, J., Zhang, Y., Wang, J., Chen, L., . . . Laird, A. R. (2016). The human brainnetome atlas: a new brain atlas based on connectional architecture. *Cerebral cortex, 26*(8), 3508-3526.
40. Zhao, Z., Ma, X., Geng, Y., Zhao, W., Zhou, F., Wang, J., . . . Kendrick, K. M. (2019). Oxytocin differentially modulates specific dorsal and ventral striatal functional connections with frontal and cerebellar regions. *Neuroimage, 184*, 781-789.
41. Zhou, X., Zimmermann, K., Xin, F., Zhao, W., Derckx, R. T., Sassmannshausen, A., . . . Kendrick, K. M. (2019). Cue reactivity in the ventral striatum characterizes heavy cannabis use, whereas reactivity in the dorsal striatum mediates dependent use. *Biological psychiatry: cognitive neuroscience and neuroimaging, 4*(8), 751-762.
42. Averbeck, B., & O'Doherty, J. P. (2022). Reinforcement-learning in fronto-striatal circuits. *Neuropsychopharmacology, 47*(1), 147-162.
43. Lowet, A. S., Zheng, Q., Matias, S., Drugowitsch, J., & Uchida, N. (2020). Distributional reinforcement learning in the brain. *Trends in Neurosciences, 43*(12), 980-997.
44. Zhang, L., Lengersdorff, L., Mikus, N., Gläscher, J., & Lamm, C. (2020). Using reinforcement learning models in social neuroscience: frameworks, pitfalls and suggestions of best practices. *Social Cognitive and Affective Neuroscience, 15*(6), 695-707.
45. Chowdhury, R., Guitart-Masip, M., Lambert, C., Dayan, P., Huys, Q., Düzel, E., & Dolan, R. J. (2013). Dopamine restores reward prediction errors in old age. *Nature neuroscience, 16*(5), 648-653.
46. Li, D., Scott, L., Crambert, S., Zelenin, S., Eklöf, A.-C., Di Ciano, L., . . . Aperia, A. (2012). Binding of losartan to angiotensin AT1 receptors increases dopamine D1 receptor activation. *Journal of the American Society of Nephrology, 23*(3), 421-428.
47. Beninger, R. J., & Miller, R. (1998). Dopamine D1-like receptors and reward-related incentive learning. *Neuroscience & biobehavioral reviews, 22*(2), 335-345.
48. Cox, J., & Witten, I. B. (2019). Striatal circuits for reward learning and decision-making. *Nature Reviews Neuroscience, 20*(8), 482-494.
49. Rolls, E. T. (2017). The roles of the orbitofrontal cortex via the habenula in non-reward and depression, and in the responses of serotonin and dopamine neurons. *Neuroscience & biobehavioral reviews, 75*, 331-334.
50. Garrido-Gil, P., Rodriguez-Perez, A. I., Fernandez-Rodriguez, P., Lanciego, J. L., & Labandeira-Garcia, J. L. (2017). Expression of angiotensinogen and receptors for angiotensin and prorenin in the rat and monkey striatal neurons and glial cells. *Brain Structure and Function, 222*(6), 2559-2571.
51. Rodriguez-Perez, A. I., Valenzuela, R., Villar-Cheda, B., Guerra, M. J., & Labandeira-Garcia, J. L. (2012). Dopaminergic neuroprotection of hormonal replacement therapy in young and aged menopausal rats: role of the brain angiotensin system. *Brain, 135*(1), 124-138.

52. Higa, K. K., Young, J. W., Ji, B., Nichols, D. E., Geyer, M. A., & Zhou, X. (2017). Striatal dopamine D1 receptor suppression impairs reward-associative learning. *Behavioural brain research, 323*, 100-110.
53. Keeler, J., Pretsell, D., & Robbins, T. (2014). Functional implications of dopamine D1 vs. D2 receptors: A 'prepare and select'model of the striatal direct vs. indirect pathways. *Neuroscience, 282*, 156-175.
54. Onge, J. R. S., Abhari, H., & Floresco, S. B. (2011). Dissociable contributions by prefrontal D1 and D2 receptors to risk-based decision making. *Journal of Neuroscience, 31*(23), 8625-8633.
55. Jocham, G., Klein, T. A., & Ullsperger, M. (2011). Dopamine-mediated reinforcement learning signals in the striatum and ventromedial prefrontal cortex underlie value-based choices. *Journal of Neuroscience, 31*(5), 1606-1613.
56. Pasupathy, A., & Miller, E. K. (2005). Different time courses of learning-related activity in the prefrontal cortex and striatum. *Nature, 433*(7028), 873-876.
57. Ballard, I. C., Murty, V. P., Carter, R. M., MacInnes, J. J., Huettel, S. A., & Adcock, R. A. (2011). Dorsolateral prefrontal cortex drives mesolimbic dopaminergic regions to initiate motivated behavior. *Journal of Neuroscience, 31*(28), 10340-10346.
58. Becker, A., Kirsch, M., Gerchen, M. F., Kiefer, F., & Kirsch, P. (2017). Striatal activation and frontostriatal connectivity during non-drug reward anticipation in alcohol dependence. *Addiction biology, 22*(3), 833-843.
59. Park, S. Q., Kahnt, T., Beck, A., Cohen, M. X., Dolan, R. J., Wrase, J., & Heinz, A. (2010). Prefrontal cortex fails to learn from reward prediction errors in alcohol dependence. *Journal of Neuroscience, 30*(22), 7749-7753.
60. Noworyta, K., Cieslik, A., & Rygula, R. (2021). Neuromolecular Underpinnings of Negative Cognitive Bias in Depression. *Cells, 10*(11), 3157.
61. Gironacci, M. M., Vicario, A., Cerezo, G., & Silva, M. G. (2018). The depressor axis of the renin–angiotensin system and brain disorders: A translational approach. *Clinical Science, 132*(10), 1021-1038.
62. Vian, J., Pereira, C., Chavarria, V., Köhler, C., Stubbs, B., Quevedo, J., . . . Fernandes, B. S. (2017). The renin–angiotensin system: a possible new target for depression. *BMC medicine, 15*(1), 1-13.
63. Gard, P. R. (2004). Angiotensin as a target for the treatment of Alzheimer's disease, anxiety and depression. *Expert opinion on therapeutic targets, 8*(1), 7-14.
64. Gard, P. R., Mandy, A., & Sutcliffe, M. A. (1999). Evidence of a possible role of altered angiotensin function in the treatment, but not etiology, of depression. *Biological psychiatry, 45*(8), 1030-1034.
65. Admon, R., Kaiser, R. H., Dillon, D. G., Beltzer, M., Goer, F., Olson, D. P., . . . Pizzagalli, D. A. (2017). Dopaminergic enhancement of striatal response to reward in major depression. *American Journal of Psychiatry, 174*(4), 378-386.
66. Schneier, F. R., Slifstein, M., Whitton, A. E., Pizzagalli, D. A., Reinen, J., McGrath, P. J., . . . Abi-Dargham, A. (2018). Dopamine release in antidepressant-naive major depressive disorder: a multimodal [11C]-(+)-PHNO positron emission tomography and functional magnetic resonance imaging study. *Biological psychiatry, 84*(8), 563-573.
67. Voon, V., Reynolds, B., Brezing, C., Gallea, C., Skaljic, M., Ekanayake, V., . . . Hallett, M. (2010). Impulsive choice and response in dopamine agonist-related impulse control behaviors. *Psychopharmacology, 207*(4), 645-659.
68. Evans, A. (2011). Dopamine agonist-induced substance addiction: the next piece of the puzzle. *Journal of Clinical Neuroscience, 18*(2), 191-192.