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Transdiagnostic latent factors dissociating depression and anxiety through reinforcement learning

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Abstract

Background The comorbidity of depression and anxiety has long been recognized. While mainly characterized as mood dysregulation, depression and anxiety symptoms are also manifested in learning and decision-making deficits. However, the specific cognitive mechanisms that are common to both disorders, as well as those that distinguish them, remain poorly understood. Here, we propose reinforcement learning (RL) as a unifying computational framework to disentangle the shared and distinct cognitive processes underlying depression and anxiety.

Methods We adopted a probabilistic instrumental learning task in which subjects repeatedly chose between alternative options to earn rewards (Gain) or avoid losses (Loss) in two experiments ($n = 190$ in experiment 1, $n = 361$ in experiment 2). Classic psychiatric questionnaires about depression and anxiety traits were also collected from participants.

Results We discovered a dissociation where depression traits correlated negatively with learning rates, while anxiety traits showed the opposite pattern in two separate experiments. Experiment 2 further identified transdiagnostic latent factors of depression and anxiety traits that drove the dissociation of depression and anxiety traits on learning rates. Specifically, somatic symptoms and anhedonia were found to be the main contributors to the negative correlation between learning and depression traits. In contrast, cognitive symptoms and negative affects showed a positive correlation with learning rates.

Conclusions The dissociation between transdiagnostic factors may reflect a trade-off wherein excessive internal focus diminishes the capacity for external information processing. Together, our findings demonstrate how the transdiagnostic approach under a unified computational framework can elucidate distinct cognitive profiles of depression and anxiety.

Clinical trial number Not applicable.

Keywords Transdiagnostic latent factors · Reinforcement learning · Depression · Anxiety · Computational psychiatry

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Introduction

Depression and anxiety are among the most prevalent mental disorders, with significant clinical and subclinical impacts [36]. Depression and anxiety share numerous overlapping emotional and cognitive symptoms and exhibit a high comorbidity rate [47], but also embody distinct features such as anhedonia for depression and heightened fear experience for anxiety [62, 73]. Moreover, depression is characterized by dysfunctional reward processing [2, 29, 40], whereas anxiety is associated with abnormal aversive learning and threat processing [9, 69, 85]. These features indicate impaired processing of appetitive and aversive information (e.g., reward or threat), which is frequently explored through learning-based approaches [68, 71]. Despite the existing evidence, a unified framework to support the understanding of the overlapping and distinct characteristics of depression and anxiety is still lacking. Recently, however, the emergence of computational psychiatry may hold the promise to offer a more quantitative approach to diagnose and disentangle distinct cognitive components in mental disorders such as depression and anxiety [1, 31, 34, 44, 60, 65].

Reinforcement learning (RL), which describes how agents interact with an uncertain environment to update expectations and maximize rewards [80], may provide a unified framework to study how people respond to appetitive or aversive feedback and learn, enabling a computational characterization of the cognitive processes in depression and anxiety. Numerous studies have adopted RL tasks to quantify the learning and decision-making deficits in depression and anxiety, yielding mixed results [4, 10, 13, 31, 34, 51, 61, 72, 82, 87]. For instance, depression and anxiety were found to be associated with exaggerated responses to adverse outcomes, manifested as increased aversive learning rates [4, 82, 87]. Conversely, other studies suggested a decrease in learning rates in depression and anxiety disorders, indicating a general impairment regarding appetitive and aversive outcomes [13, 51, 61]. The investigation of RL in depression/anxiety has been further confounded by the fact that depression and anxiety were either studied as one compound psychiatric disorder [4, 31, 34, 72] or separately in studies focusing exclusively on either depression or anxiety [10, 13, 51, 61, 82, 87].

Here, we aim to reconcile the discrepancies in the literature through the computational framework of RL targeting transdiagnostic dimensions underlying depression and anxiety. Since similar psychiatric symptoms can be found in both depression and anxiety (for example, negative affect and sleep deficits), identifying common factors across diagnostic boundaries may help to discover important dimensions that directly relate to cognitive dysfunctions. Such an approach has been endorsed by the Research Domain Criteria (RDoC) initiative and could be critical to revealing the shared and heterogeneous cognitive mechanisms [21, 22, 50] involved in depression and anxiety. Moreover, by linking the transdiagnostic factors to RL, we can potentially elucidate which specific dimensions contribute to the learning deficits observed in depression and anxiety.

In the current study, we investigated the learning processes associated with depression and anxiety traits through two preregistered studies (https://osf.io/xumzk). Depression and anxiety traits refer to the extent of depression and anxiety in individuals in the general population. We adopted a probabilistic instrumental learning task where subjects had to choose repeatedly from alternative options to earn rewards (Gain) or avoid losses (Loss) to depict the learning process of individual subjects from a general population subject pool. Standard psychiatric questionnaires about depression and anxiety traits were also collected from these subjects. In Experiment 1, we found that the scores from the self-report questionnaires of depression and anxiety traits had dissociative effects on learning rates: while depression trait scores were negatively correlated with learning rates across subjects, anxiety scores and learning rates showed a positive correlation. In Experiment 2, with a wider selection of questionnaires measuring a variety of depression and anxiety-related symptoms (see Methods for details), we identified four transdiagnostic latent factors, including somatic symptom (SOM), anhedonia (ANH), cognitive symptoms (COG), and negative affect (NEG). First, the SOM factor, which captured the somatic aspects of depression and anxiety traits, was negatively associated with the learning rates. Furthermore, the ANH factor described a general lack of hedonic experience and showed a context-specific relationship to the learning rates. Finally, the NEG and COG

factors, which loaded more heavily on depression and anxiety measurements, respectively, showed a positive correlation trend with learning rates.

Experiment 1: Dissociation of learning rates related to depression and anxiety

Methods

Participants

Behavioral data were collected online using the Naodao online experiment platform (www.naodao.com). Power analysis (G*Power 3.1.9.4) indicated that 177 participants would provide 80% power (α = 0.05, two-tailed) to detect similar effects as previous studies ($\Delta R^2 = 0.04$, $f^2 \approx 0.045$; [34, 85]) in a 5-predictor multiple regression. Thus, we recruited a total of 200 participants in Experiment 1 based on the power analysis and earlier similar studies about computational psychiatry [85]. Participants were sampled from the general population because we focused on psychopathological traits on a continuum that varies across clinical and subclinical levels. Participants who failed the attentional check in the questionnaire session or chose the same slot machine in > 90% of trials in the learning task session were excluded, resulting in the final sample size of 190 (93 females, mean age 23.55 ± 5.73). All participants were paid a base amount of ¥20 plus a bonus of ¥10 on average based on their performance in the learning task.

Self-report psychiatric questionnaires

We employed the Self-rating Depression Scale (SDS, [89]) and the State-Trait Anxiety Inventory-Trait (STAI-T, [78]) to assess depression and anxiety traits, respectively. Both the SDS (20 items; Cronbach's α = 0.88) and the STAI-T (20 items; Cronbach's α = 0.91) demonstrated strong internal consistency. We inserted attentional checks in several questionnaires, instructing participants to select a specific option (e.g., "please choose 'not very often' for this question"). Participants who failed the attentional check in ≥ 1 question were excluded from the following analysis. Additionally, Intelligence Quotient (IQ) was measured using the abbreviated nine-item form of the Raven's Standard Progressive Matrices Test [8]. We controlled for the effect of IQ in our analyses to account for its potential confounding influence on cognitive task performance, as suggested by previous literature [37].

Procedure

All participants went through a probabilistic instrumental learning task to characterize RL ([54, 63]; Fig. 1a-c). The learning task was carried out in two contexts corresponding to different outcome valence: in the Gain context, participants were required to choose between two slot machines to earn monetary rewards, while in the Loss context, they were required to learn to avoid monetary losses. Both the Gain and Loss conditions comprised a total of 100 trials each. Within each condition, a trial started with two slot machines appearing on the screen. Participants were asked to choose either the left or the right slot machine by pressing the corresponding buttons on the keyboard. Upon pressing a button, the chosen slot machine was highlighted for 1 s. Subsequently, the monetary outcome of the selected slot machine was revealed and lasted for 1.5 s. A fixation cross appeared signaling the inter-trial-interval (ITI) period and lasted for 0.5 s between trials (Fig. 1a). If participants' response time was faster than 2.5 s, the remaining time was added to the ITI duration to discourage relentless button-pressing behavior. In the RL framework, participants were assumed to use the monetary outcome of each trial to update the expectations of each slot machine and adjust their choice accordingly.

Two contexts (Gain vs. Loss) and two types of outcomes (Good vs. Bad) formed a total of four combinations: in the Gain context, Good outcome corresponded to gaining one coin while Bad outcome corresponded to no

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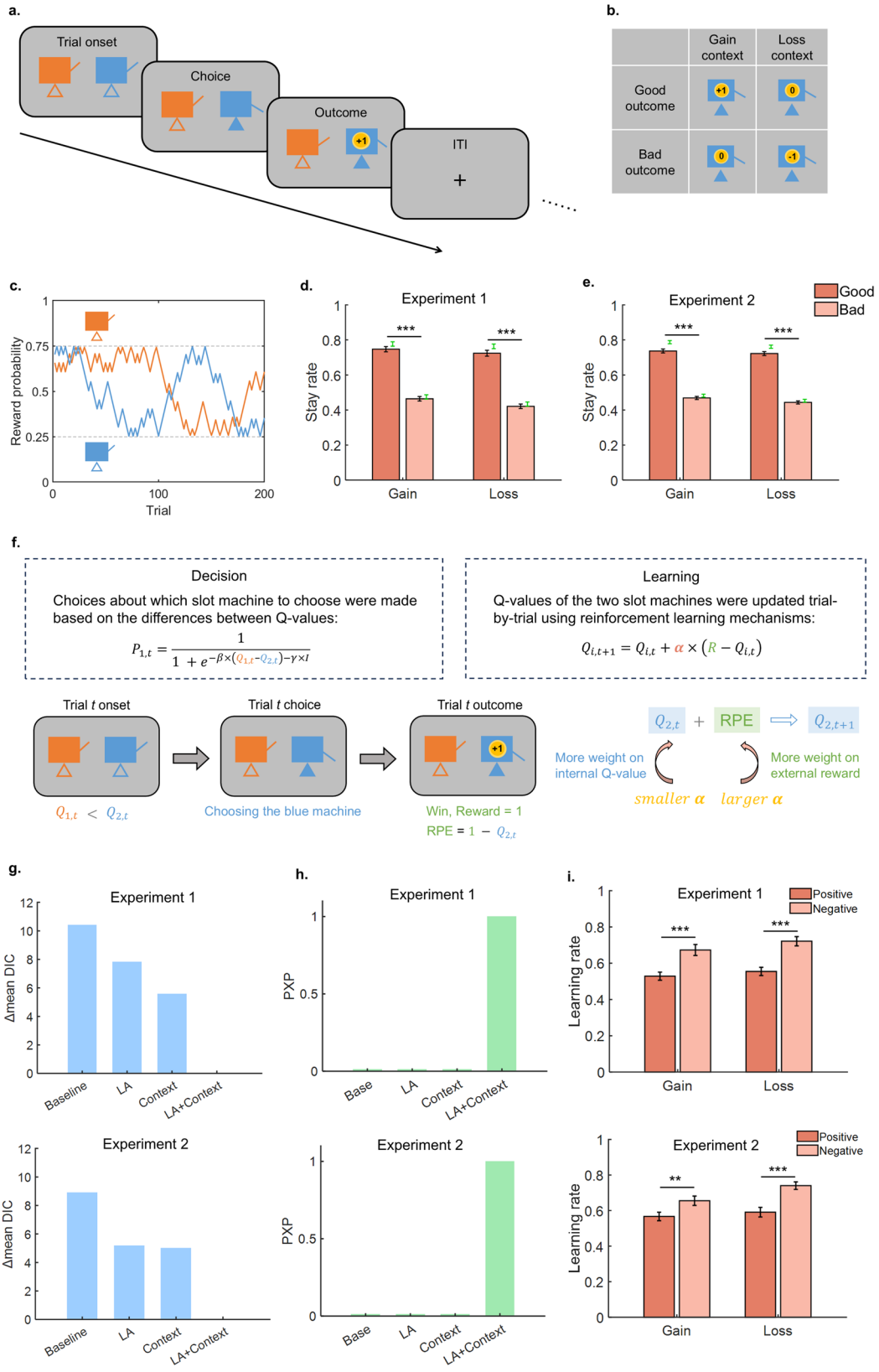

Fig. 1 The probabilistic instrumental learning task. **a** An example trial of the probabilistic instrumental learning task. After the trial onset, participants chose between two slot machines. Only the outcome of the selected machine was revealed. **b** Four different outcomes of slot machines, including a 2 × 2 combination of two different contexts (Gain or Loss) and two types of outcomes ('Good' or 'Bad'). **c** An example demonstrating that the reward probabilities of the two slot machines fluctuate independently throughout the task with a random-walk procedure. **d-e.** Model-free stay rates of experiments 1 and 2, respectively. In both Gain and Loss contexts, participants exhibited a higher stay rate after a 'Good' outcome than after a 'Bad' outcome. Error bars indicate standard errors. The green bars represent model-predicted stay rates. **f.** The Q-learning model consists of a choice component and a learning component. The choice component made choices about which slot machine to choose based on the Q-values of each slot machine. The learning component updated the Q-values using reward prediction errors (RPE) weighted by learning rates. **g.** Model comparison results, depicted as the difference in mean DIC between candidate models and the best-fitting model. LA: learning asymmetry model. **h.** Model comparison results, depicted as the protected exceedance probability (PXP). The model comparison revealed that the full model, which distinguished between both Context and Learning Asymmetry, provided the best fit. **i.** Positive and negative learning rates in both the Gain and the Loss conditions. The error bars represent standard errors. In Figures **g**, **h**, and **i**, the upper panels correspond to the results of Experiment 1, and the lower panels show the results of Experiment 2

monetary gain, whereas in the Loss context, Good outcome corresponded to no monetary loss and Bad outcome refered to the loss of one coin (Fig. 1b). The probability of getting a Good outcome from each slot machine fluctuated independently throughout the 100 trials within each condition. Specifically, the starting probabilities were sampled from a uniform distribution with boundaries of [0.25, 0.75]. The probabilities would then change trial by trial following a random-walk procedure. After each trial, the probabilities were diffused either up or down equally likely by adding or subtracting 0.05 from the current probability. The updated probabilities were then reflected off the boundaries of [0.25, 0.75] to maintain within the probability range (Fig. 1c). Reward probability schedules were generated randomly for each participant. The color of slot machines was randomly selected, and the order of the Gain and Loss conditions was counterbalanced across subjects.

All participants completed both conditions (200 trials in total) after a practice of 12 trials. After the probabilistic instrumental learning task, participants completed the above self-report questionnaires. Experiment 1 lasted 45 min on average.

Computational modeling of RL

The Q-learning model Q-learning models were used to quantify the RL process [80]. Participants were assumed to maintain and update the estimated Q-value of each slot machine throughout the task. The Q-value of slot machine i in trial t is denoted as $Q_{i,t}$ ($i = 1, 2$), and is updated using the following formula:

$$Q_{i,t+1} = \begin{cases} c\,Q_{i,t} + \alpha_P \times (R_t - Q_{i,t}) & if\ R_t > Q_{i,t} \\ Q_{i,t} + \alpha_N \times (R_t - Q_{i,t}) & if\ R_t < Q_{i,t} \end{cases} \quad (1)$$

In the above equation, Q-value in the $t+1$ trial is derived from a combination of Q-value in the previous trial, $Q_{i,t}$, and the reward prediction error (RPE), $R_t - Q_{i,t}$, weighted by the learning rate, α (between [0, 1]). Larger learning rates place greater emphasis on the RPE, while smaller learning rates give more weight to the current Q-value (Fig. 1f). α_P denotes the positive learning rate when the RPE is positive, while α_N represents the negative learning rate when the RPE is negative. The differentiation between positive and negative learning rates helps to detect potential learning asymmetry [53, 63, 67]. The RPE is determined by subtracting the Q-value from the monetary outcome R_t obtained in trial t. In the Gain condition, R_t is assigned a value of either 1 or 0, whereas in the Loss condition, it takes on a value of 0 or -1. Q-values are initiated by 0.5 in the Gain condition and − 0.5 in the Loss condition.

Decisions are made by comparing the Q-values of each slot machine in the current trial. The difference of Q-values is subsequently transformed using a softmax rule:

$$P_{1,t} = \frac{1}{1 + exp\left(-\beta \times \left(Q_{1,t} - Q_{2,t}\right) - \gamma \times I\right)} \quad (2)$$

The above equation specifies the probability of choosing the left slot machine (specified as option 1) by computing the difference of Q-values between the left slot machine and the right one (option 2), weighted by an inverse temperature parameter, β. The inverse temperature parameter captures choice stochasticity and ranges between [0, 20]. An additional parameter, γ, choice perseverance, accounts for the propensity to simply repeat the previous action. Perseverance varies between [-5, 5], allowing for subjects' idiosyncratic behavioral tendency of either repeating or switching to the other option during the task. The indicator function I assigns a value of 1 if the left slot machine is chosen in the last trial, and -1 if the right slot machine is chosen instead. In summary, the model has four free parameters corresponding to α_P, α_N, γ, and β.

Four models were constructed for model comparison, depending on whether to distinguish between Gain and Loss contexts and whether to use separate learning rates for positive and negative RPEs. The Baseline model uses a single set of parameters across both contexts and does not distinguish between positive and negative RPEs, comprising 3 parameters (α, γ, β). The Learning Asymmetry (LA) model includes positive and negative learning rates, but does not distinguish between Gain and Loss contexts (4 parameters, α_P, α_N, γ, β). The Context model, by contrast, uses separate sets of parameters for different contexts but applies a single learning rate within each context (6 parameters, $G-\alpha$, $G-\gamma$, $G-\beta$, $L-\alpha$, $L-\gamma$, $L-\beta$; G stands for Gain while L stands for Loss). The Learning Asymmetry + Context model is the full model, which distinguishes contexts and considers asymmetry in learning rates (8 parameters, $G-\alpha_P$, $G-\alpha_N$, $G-\gamma$, $G-\beta$, $L-\alpha_P$, $L-\alpha_N$, $L-\gamma$, $L-\beta$).

Model fitting and model comparisons Parameters of the Q-learning models were fitted using the Hierarchical Bayesian Model (HBM). This method generates the posterior distribution of the parameters at both the individual and the group levels [3, 63]. The hierarchical structure indicates that the individual-level parameters are drawn from corresponding hyper-distributions of $N(\mu, \sigma^2)$. Normal priors are assigned to all hyper means $\mu \sim N(0, 1)$ and half-Cauchy priors to all hyper standard deviations $\sigma \sim C(0, 5)$. Individual-level parameters are transformed using the Φ transformation, the cumulative density function of the standard normal distribution, to constrain the parameters within their corresponding boundaries.

Model fitting was performed using the *rstan* package in R. The outcome obtained and choice made at each trial were entered into the stan( ) function as behavioral data. For each model, 10,000 samples were collected after a burn-in of 4,000 samples on each of the four chains, resulting in a total of 40,000 posterior samples collected for each parameter. R-hat was computed to diagnose model convergence. For each parameter, we computed the mean of posterior samples to obtain the estimation of the corresponding parameter.

Given the parameter samples, we computed the deviance information criterion (DIC) for each model and used it to compare the performances of our candidate models (Spiegelhalter et al., 2002). The protected exceedance probability (PXP) was calculated based on DIC. PXP indexed the probability that a specific model is the best among the candidate models, providing a group-level Bayesian model selection method to identify the best model [75, 79].

Additionally, we conducted model simulations and parameter recovery to assess the stability of the winning model. The results for parameter recovery are shown in supplementary results S5.

Bayesian regression models

We ran a series of mixed-effect Bayesian regressions to investigate the relationship between learning and psychopathological measures [85], as well as how their relationship varies across context and learning asymmetry (LA). Bayesian regressions were used to mitigate the multiple comparisons problem. Learning rates (LR) were regressed against the SDS score and the STAI-T score as the main independent variables, with Sex, Age, and IQ as covariates of no interest. Age, IQ, the SDS score, and the STAI-T score were Z-transformed before entering the regressions. Interaction terms between SDS/STAI-T scores and Context (gain vs. loss), as well as Learning

Asymmetry (positive vs. negative), were first included to determine whether the relationships between learning rates and psychopathological measures were condition-specific. The regression model was specified as Eq. (3):

$$\begin{aligned} LR \sim\ & Sex + Age + IQ + LA + Context \\ & + SDS + STAI - T + SDS * LA \\ & + SDS * Context + STAI - T * LA \\ & + STAI - T * Context + (1 + LA \\ & + Context|participant) \end{aligned} \tag{3}$$

In cases where no interaction effects reached significance, we reran the regressions excluding those interaction terms to estimate the main effects of SDS and STAI scores. Participant-level random intercepts and slopes were included to account for within-subjects variance. All Bayesian regressions were conducted using the *brms* package in R. The models were fitted using Markov chain Monte Carlo sampling, with each model having 8000 samples, of which 4000 were used for burn-in. Standard normal distributions were used as priors for regression coefficients [5]. We report the means of the posterior distributions as estimates of each coefficient, along with the 95% highest posterior density interval (HPDI). The regression coefficients of control variables were reported in supplementary results S6. The regression coefficients of other parameters from the learning model on psychopathological measures were reported in supplementary results S7.

Results

Demographic information and distributions of questionnaire scores

The demographic information of the population in Experiment 1 is presented in Table 1. Scores of self-report questionnaires are shown in Fig. 2a-b.

Quantification of reinforcement learning

Model-agnostic and model-based analyses were used to quantify subjects' learning processes based on the feedback they received in the Gain and Loss conditions. We calculated the stay rate as the proportion of trials in which the same slot machine was chosen as in the previous trial by the participants. The stay rate after 'Good' outcome was significantly higher than after the 'Bad' outcome in both contexts ($F_{1,189} = 304.64$, $p < 0.001$, $\eta_p^2 = 0.617$) (Fig. 1d), indicating participants adopt the standard "win-stay-lose-shift" learning strategy. The split-half reliability of stay rates is shown in supplementary results S2. We further applied RL models (i.e., the Q-learning model)

Table 1 Demographic information of the population in Experiment 1

	Exp 1 (n=190)
Gender (Female)	93 (48.9%)
Age ($M \pm SD$)	23.55 ± 5.73
Employment	
Working full-time	52 (27.4%)
Working part-time	7 (3.7%)
Unemployed	4 (2.1%)
Student	127 (66.8%)
Education	
High school or lower	6 (3.2%)
Undergraduate	165 (86.8%)
Postgraduate	18 (9.5%)
PhD or above	1 (0.5%)
Questionnaires ($M \pm SD$)	
SDS	34.98 ± 9.20
STAI-T	38.43 ± 10.03

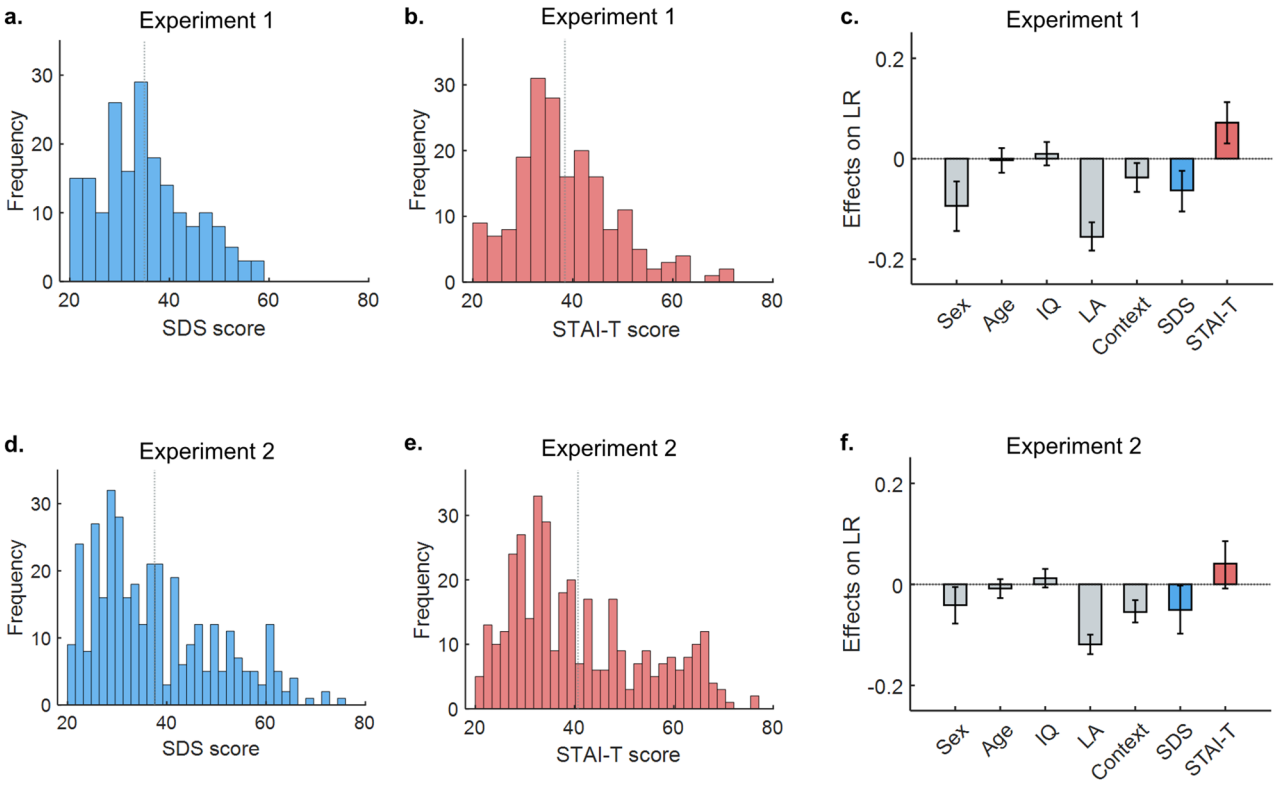

Fig. 2 Dissociation of the depression and anxiety traits on learning rates (LR). **a-b.** The sample distribution of the SDS score and the STAI-T score in experiment 1. **c.** The effects of Sex, Age, IQ, Learning Asymmetry (LA), Context, the SDS score, and the STAI-T score on the learning rates in Experiment (1) **d-e.** The sample distribution of the SDS score and the STAI-T score in experiment (2) **f.** The effects of Sex, Age, IQ, Learning Asymmetry (LA), Context, the SDS score, and the STAI-T score on the learning rates in Experiment 2. The gray dashed line denotes the mean of scores in **a-b** and **d-e**. In **c** and **f**, Error bars represent the 95% highest posterior density interval (HPDI) of posterior samples of each regression coefficient

to quantify the learning process (Fig. 1f; also see methods). The R-hat statistic was below 1.05 for all models, indicating the sampling chains have converged (R-hat = 1.01 for the best-fitting model). The model comparison results showed that the LA + Context model with four learning rates provided the best fit, measured by mean DIC and the protected exceedance probability (PXP > 0.999) (Fig. 1g-h). The negative learning rates were higher than the positive learning rates ($F_{1,189} = 125.84,\ p < 0.001,\ \eta_p^2 = 0.400$), exhibiting a negative bias [63] (Fig. 1i). Further, all parameters in the LA+Context model were well recovered (supplementary results S5). The model-predicted stay rates showed similar trends as the empirical stay rates, such that stay rates were higher after 'Good' outcome than 'Bad' outcome ($F_{1,189} = 651.52,\ p < 0.001,\ \eta_p^2 = 0.775$) (green bars in Fig. 1d).

Bayesian regression models of the SDS and STAI-T scores

Participants' learning rates were regressed against the SDS and STAI-T scores. Because the winning model distinguished learning rates across Context and Learning Asymmetry (LA), we first ran models with interactions between SDS/STAI-T scores and Context/Learning Asymmetry. No significant interaction effects were found (all 95% HPDIs of the coefficients crossed zero, see supplementary results S6 for details). Therefore, we fitted a model without interactions to capture the main effects of SDS and STAI scores on learning rates. The regression coefficients indicated a negative correlation between the SDS score and learning rates (β_{SDS} = -0.0631, 95% HPDI = [-0.105, -0.0243]), whereas the the STAI-T score demonstrated a positive correlation (β_{STAI-T} = 0.717,

95% HPDI = [0.0303, 0.113]) (Fig. 2c). In summary, the divergent effects of the SDS and STAI-T scores on learning rates highlighted dissociative effects of depression and anxiety traits on learning processes.

Moreover, both Learning Asymmetry (β_{LA} = -0.156, 95% HPDI = [-0.183, -0.127]) and Context ($\beta_{Context}$ = -0.0375, 95% HPDI = [-0.0661, -0.00872]) exhibited negative effects. Specifically, learning rates were higher following negative reward prediction errors than positive ones, and were also elevated in the Loss context relative to the Gain context. We additionally examined the correlations between SDS/STAI-T scores and behavioral measures (i.e., win-stay and lose-shift rates), with the results reported in supplementary results S4.

It was worth noting that in our datasets, depression or anxiety traits alone did not show a consistent correlation with learning rates. Specifically, except for a significant correlation between STAI-T scores and negative learning rate in the Loss condition ($r = 0.194$, $p = 0.007$), none of the other correlation analyses yielded significant results ($ps > 0.05$). On the other hand, we observed a strong positive correlation between the SDS and STAI-T scores ($r = 0.807$, $p < 0.001$). Thus, we speculated that the dissociative effects of depression and anxiety on learning rates might be attributed to the unique variance of the two scores after controlling for their covariance. It could be argued that the significant effects of SDS and STAI-T scores on learning rates may result from the strong collinearity between SDS and STAI-T scores, thereby generating a spurious correlation in the multivariate model —a phenomenon known as the suppression effect [56]. The Variance Inflation Factors (VIF) indeed indicated moderate multicollinearity (VIFs were 3.01 for the SDS score and 2.95 for the STAI-T score). To address this question, we used factor analysis to extract common factors in the questionnaires in Experiment 2.

Experiment 2: Identification of latent factors underlying depression and anxiety

In Experiment 1, we found dissociative effects of depression and anxiety traits on learning processes and suggested that the comorbidity and heterogeneity of depression and anxiety traits should be considered jointly while exploring the underlying cognitive mechanisms. To further elucidate the role of transdiagnostic latent factors of depression and anxiety on learning rates, in Experiment 2, we collected a wider range of questionnaires representative of depression and anxiety [34, 37, 73]. Here, we aimed to discover transdiagnostic latent factors underlying depression and anxiety that might provide explanations about the dissociative associations between learning and depression/anxiety.

Methods

Participants

Data were again collected online using the Naodao online experiment platform (www.naodao.com). We recruited a total of 400 participants in Experiment 2. This number exceeds the 300-case threshold recommended for exploratory factor analysis when communalities are medium to high (≥ 0.50) [18]. Data exclusion was the same as in Experiment 1, resulting in the final sample size of 361 (176 females, mean age 25.17 ± 6.92). All participants were paid a base amount of ¥20 plus a bonus of ¥10 on average based on their performance in the learning task.

Self-report psychiatric questionnaires

Participants completed self-report questionnaires after the probabilistic instrumental learning task. We implemented a wider range of questionnaires concerning depression and anxiety in Experiment 2. Besides the SDS (Cronbach's α = 0.94) and STAI-T (Cronbach's α = 0.95), the Beck Depression Inventory-II (BDI, [7]; 21 items, Cronbach's α = 0.95), the Self-rating Anxiety Scale (SAS, [90]; 20 items, Cronbach's α = 0.92), and the Penn State Worry Questionnaire (Penn, [59]; 16 items, Cronbach's α = 0.94) were also included. We carried out attentional

checks the same as in Experiment 1. The IQ was measured using the nine-item form of the Raven's Standard Progressive Matrices Test.

Procedure

All participants went through the probabilistic instrumental learning task, whose procedure was the same as Experiment 1. Participants completed the self-report questionnaires after the learning task. Experiment 2 lasted 45 min on average.

Factor analysis

We implemented exploratory factor analysis (EFA) to explore possible transdiagnostic latent factors across depression and anxiety in Experiment 2. Factor analysis was conducted using the fa() function from the *Psych* package in R. Ninety-seven individual items of the five questionnaires were entered as measured variables into the factor analysis. Response categories endorsed by under 2% of participants were collapsed into the adjacent category to reduce severe skewness. Polychoric correlations were used to adjust for categorical item responses [34]. Factors were extracted using the minimum residual estimation method (*minres*) with an oblique rotation. Factor selection was based on Parallel Analysis [25], which was realized using the parallel() function from the *nFactors* package in R. This method determined the number of factors by comparing the distribution of the eigenvalues between the real data and a randomly generated dataset. Eigenvalues surpassing the threshold delineated by the randomly generated data signified that the corresponding factors account for a substantial amount of variance within the data (Fig. 4a). The Parallel Analysis revealed a 4-factor latent structure, which comprised factors that we labeled as Anhedonia (ANH), Cognitive Symptoms (COG), Somatic Symptoms (SOM), and Negative Symptoms (NEG). These factors were named according to the individual items that belonged to this factor (see results). An item belonged to a factor if (1) the loading of this item on this factor was > 0.3 or < -0.3, and (2) this item loaded the highest on this factor (Fig. 4b).

Next, we performed confirmatory factor analysis (CFA) to assess the reliability of the four-factor structure. The dataset was divided into two parts. We conducted EFA on the first half of the data ($n = 185$), which yielded a four-factor model similar to the one using the full sample. Subsequently, we applied CFA with diagonally weighted least squares (DWLS, [55]) to the second half of the data ($n = 176$), using the four-factor model derived from the first part. Three metrics were used to evaluate the CFA model fitting [86]: Comparative fit index (CFI), Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA). The CFI and TLI range from 0 to 1, with a larger value indicating a better model fit. The RMSEA ranges from 0 to 1, with a smaller value indicating a better model fit. CFA was conducted using the *lavaan* package in R. The results of the CFA analysis are shown in the supplementary results S3.

RL computational modeling and Bayesian regression models

As in Experiment 1, we constructed Q-learning models to quantify the process of reinforcement learning. Model comparisons were conducted the same as in Experiment 1. We also conducted the regression of learning rates on the SDS score and the STAI-T score to validate the results of Experiment 1. Moreover, to investigate the relation between learning and the transdiagnostic structure of depression and anxiety, learning rates were regressed on the four factors extracted by factor analysis, adding Sex, Age, and IQ as covariates of no interest. The interactions between transdiagnostic factors and Learning Asymmetry/Context were included to detect potential effects that varied across the two variables, as specified in Eq. (4). The other settings of the Bayesian regression models were the same as Experiment 1.

$$\begin{aligned} LR \sim\ & Sex + Age + IQ + LA + Context \\ & + ANH + COG + SOM + NEG \\ & + ANH * LA + ANH * Context \\ & + COG * LA + COG * Context \\ & + SOM * LA + SOM * Context \\ & + NEG * LA + NEG * Context \\ & + (1 + LA + Context|participant) \end{aligned} \tag{4}$$

Partial least squares regression

We further adopted the partial least squares (PLS) regression to validate the structure of transdiagnostic factors and their relationship with learning rates. PLS regression was utilized to identify dimensions of covariance between psychiatric symptoms and learning rates through a data-driven approach [85]. PLS regression was conducted using the *pls* package in R. Principal components were extracted from the covariance matrix between question items (predictors) and the four learning rates (positive and negative learning rates in the Gain and Loss conditions) (response variables). Residuals from the predictors and the response variables were then used to extract additional components. This iteration continues with each new component being added to the model. Consequently, the components not only captured the dimensional information across mental disorders but also reflected variations in learning rates. The optimal number of components was determined based on a 10-fold cross-validation, fitting the model on 90% of the training data and evaluating its performance on the left-out 10%. The model's predictive accuracy was assessed by the mean squared error with different numbers of components (Fig. 4a). The procedure of PLS regression proceeded with the optimal number of components, yielding distinct components with varying loadings across the ninety-seven question items. The top 20 items with the largest loadings were identified as belonging to each respective component.

Additionally, to verify the consistency between the results obtained from different methods, we examined the overlap of items between factors extracted from factor analysis and components derived from PLS regression. The proportion of overlap was calculated as the ratio of the number of overlapping items to the total number of items in a PLS component. The statistical significance of this overlap proportion was assessed using a permutation test, in which PLS regression was performed 1000 times with randomly shuffled predictors and response variables.

Results

The demographic information of the population in Experiment 2 is presented in Table 2. Scores of self-report questionnaires are shown in Fig. 2d-e and Fig. S1.

Quantification of reinforcement learning

The stay rate after 'Good' outcome was significantly higher than after the 'Bad' outcome in both conditions ($F_{1,360} = 556.00$, $p < 0.001$, $\eta_p^2 = 0.607$) (Fig. 1e), indicating successful learning. Again, the model comparison results showed that the full model provided the best fit (PXP > 0.999) (Fig. 1g-h). All models were well converged (all R-hat < 1.05; R-hat = 1.03 for the best-fitting model). As in Experiment 1, the negative learning rates were higher than the positive learning rates ($F_{1,360} = 142.79$, $p < 0.001$, $\eta_p^2 = 0.284$, Fig. 1i). Moreover, all parameters in the best-fitting model were well recovered (supplementary results S5). The model-predicted stay rates were higher after 'Good' outcome than 'Bad' outcome as the empirical stay rates ($F_{1,360} = 1445.13$, $p < 0.001$, $\eta_p^2 = 0.801$) (green bars in Fig. 1e).

Table 2 Demographic information of the population in Experiment 2

	Exp 2 (n = 361)
Gender (Female)	176 (48.8%)
Age ($M \pm SD$)	25.17 ± 6.92
Employment	
Working full-time	131 (36.3%)
Working part-time	14 (3.9%)
Unemployed	4 (1.1%)
Student	212 (58.7%)
Education	
High school or lower	5 (1.4%)
Undergraduate	316 (87.5%)
Postgraduate	32 (8.9%)
PhD or above	8 (2.2%)
Questionnaires ($M \pm SD$)	
SDS	37.55 ± 12.21
STAI-T	40.68 ± 13.34
BDI	10.48 ± 10.29
SAS	35.51 ± 10.89
Penn	45.51 ± 13.72

Bayesian regression models of the SDS and STAI scores

The regressions of the SDS and STAI-T scores replicated the findings in Experiment 1. The interaction terms between SDS/STAI scores and Learning Asymmetry/Context were not significant (all 95% HPDIs of the coefficients crossed zero, see supplementary results S6 for details), so we again fitted a model without interaction effects. The SDS score was negatively associated with learning rates (β_{SDS} = -0.0506, 95% HPDI = [-0.0977, -0.00254]), whereas the STAI-T score was positively correlated with learning rates at 90% confidence level (β_{STAI-T} = 0.0411, 95% HDPI = [-0.00805, 0.0855], 90% HDPI = [0.00444, 0.0819]) (Fig. 2f). Both Learning Asymmetry (β_{LA} = -0.119, 95% HPDI = [-0.138, -0.0994]) and Context ($\beta_{Context}$ = -0.0547, 95% HPDI = [-0.0754, -0.0314]) exhibited negative effects. Learning rates were higher following negative reward prediction errors than positive ones, and were also elevated in the Loss context relative to the Gain context.

Factor analysis

The exploratory factor analysis (EFA) across the 97 questionnaire items with 5 questionnaires revealed that a structure comprising four latent factors best explained the covariance structure of the questionnaire data (Fig. 3a), which were then labeled based on the similarities of individual items that had high loadings to each factor (Fig. 3b). Factors were ranked by the proportion of variance explained. The first factor, which was predominantly characterized by reversed-coding items from the SDS and STAI-T questionnaires and described the general lack of hedonic experience, was designated as the 'Anhedonia (ANH)' factor. The second factor, which encompassed items from the STAI-T and the Penn questionnaires and mainly reflected dysfunctional cognitive processes, was labeled as 'Cognitive Symptoms (COG)'. The third factor, which included questionnaire items about physical discomfort, was designated as 'Somatic Symptom (SOM)'. Lastly, the fourth factor corresponded primarily to the BDI questionnaire and was labeled 'Negative Affect (NEG)'. The four factors explained 61% of the total variance of the items.

Bayesian regression models of the transdiagnostic factors

To explore how the transdiagnostic latent factors might explain the individual learning differences associated with depression and anxiety traits, we again conducted Bayesian regressions to test the specific effects of the four

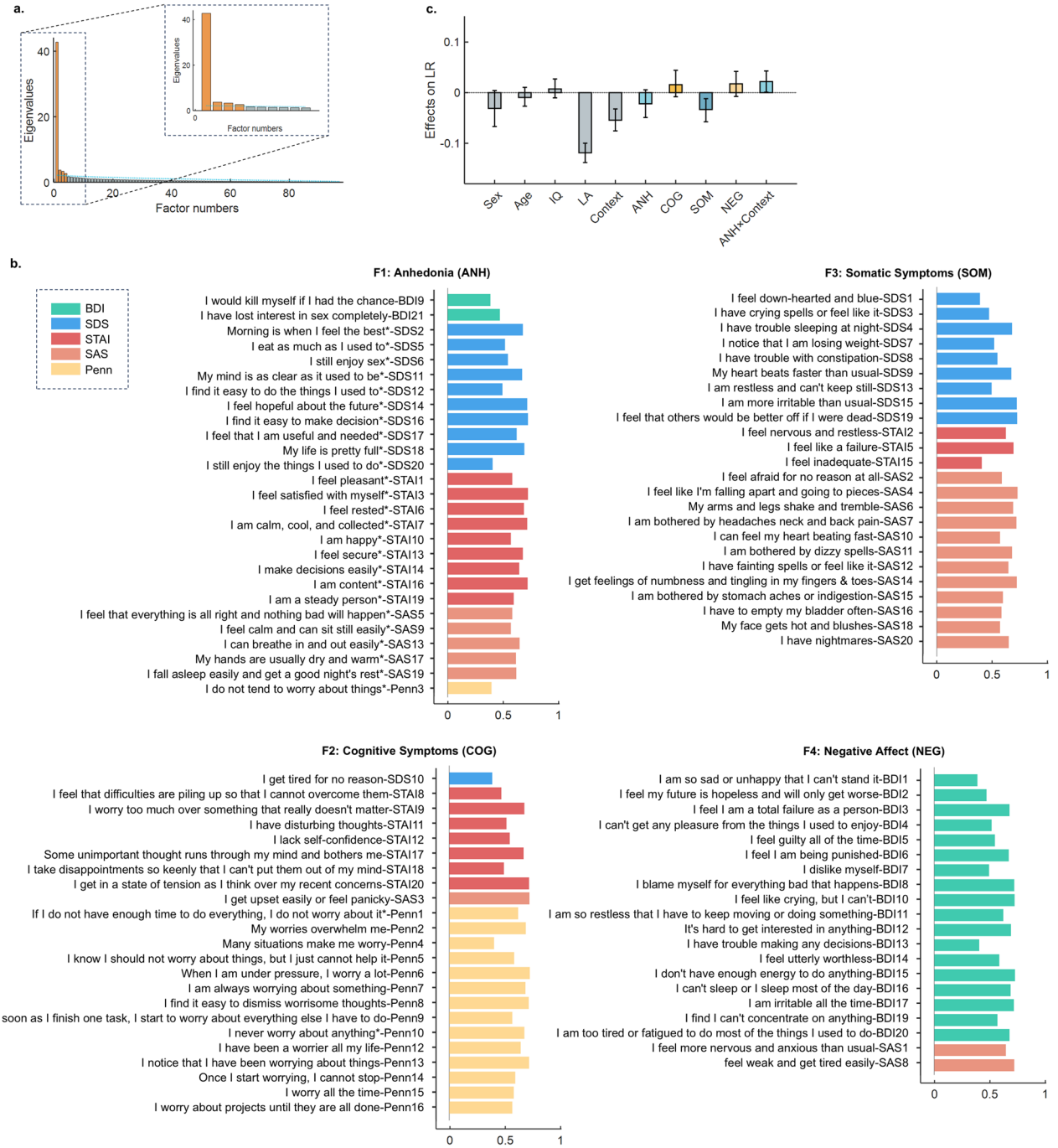

Fig. 3 Results of the factor analysis and Bayesian regression in Experiment 2. **a**. The scree plot illustrates the change of eigenvalues as the number of factors increases. The blue dotted line represents the permutated eigenvalues from the parallel analysis. Eigenvalues that exceed this line indicate that the factors explain more variance than factors generated by random data. Parallel analysis indicated that a four-factor solution was appropriate. **b**. Loadings of items on the four factors, namely 'Anhedonia', 'Cognitive Symptoms', 'Somatic Symptoms', and 'Negative Affect'. Only items with loading greater than 0.3 or lower than −0.3 are shown. **c**. The effects of Sex, Age, IQ, Learning Asymmetry (LA), Context, and the four factors on the learning rates. Error bars represent the 95% HPDI of posterior samples of each regression coefficient

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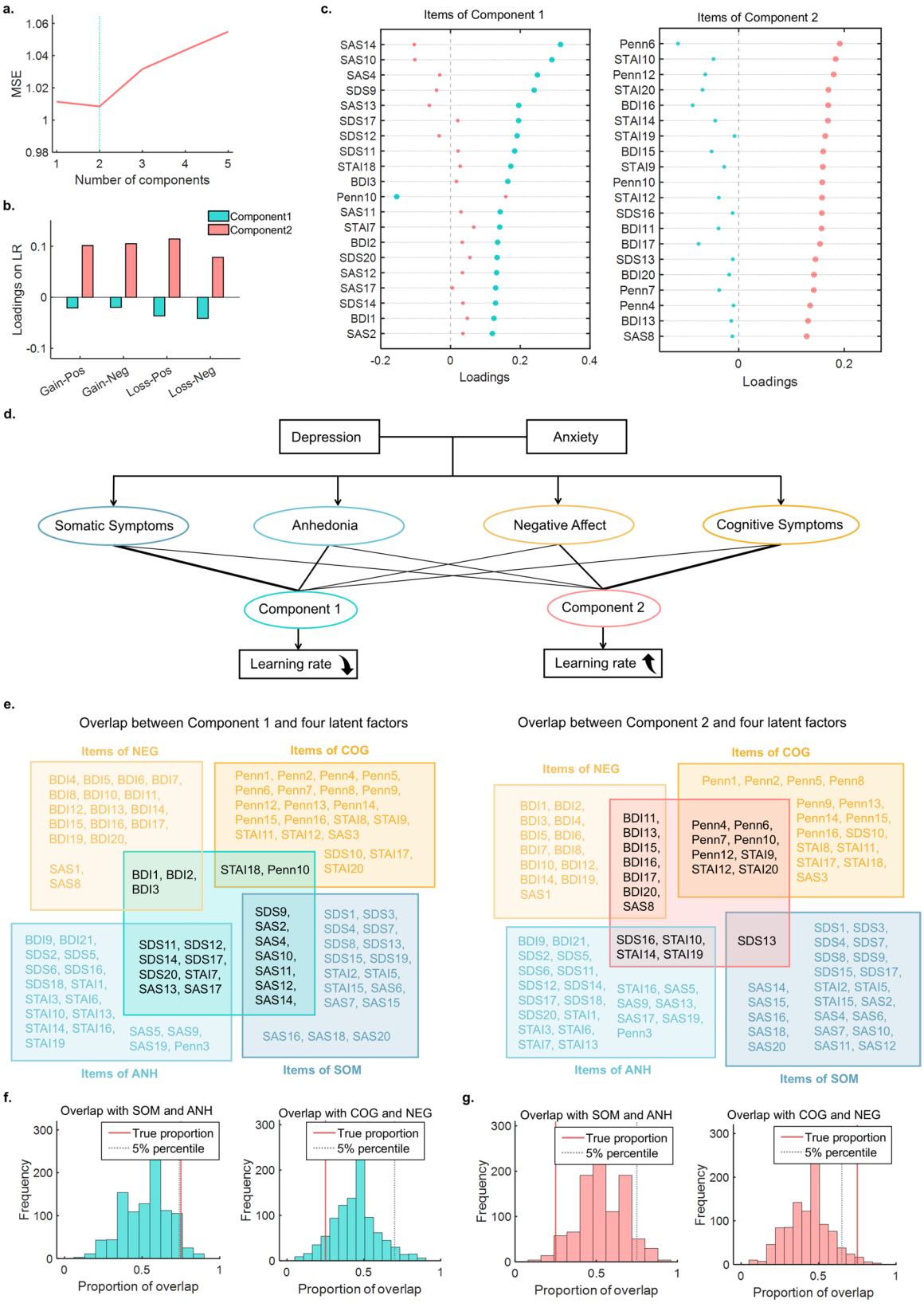

Fig. 4 Partial least squares regression results in Experiment 2. **a**. The optimal number of components was determined based on a 10-fold cross-validation. The mean squared errors across models between one and five factors were represented. The model with two components yielded the best performance. **b**. Loadings of the two components on the learning rates. Component 1 was negatively correlated with learning rates, while Component 2 was positively correlated with learning rates. **c**. Loadings of individual items on the two components. Green dots represented loadings on Component 1, while red dots represented loadings on Component 2. **d**. The relationship between depression/anxiety, the four latent factors, and the two PLS components. **e**. The overlap of items between the two components and the factors extracted from factor analysis. **f-g.** Permutation test of the overlaps of items between Component 1 & 2 and SOM plus ANH (left panel), or COG plus NEG (right panel). In **f** and **g**, the red line denotes the true proportion of overlap, while the gray dashed line denotes the 5% percentile. True proportions that exceeded the 5% line indicated that the proportion of overlap was significantly large enough

latent factors on learning rates in both the Gain and Loss conditions of Experiment 2. We first fitted regression models that included interactions between the four symptom factors and Learning Asymmetry/Context. ANH showed a significant interaction with Context ($\beta_{ANH\times Context}$ = 0.0314, 95% HPDI = [0.000806, 0.0617]), whereas all other interaction effects were non-significant (all 95% HPDIs included zero; see Supplementary Results S6). We subsequently reran the regression model with non-significant interactions removed, allowing us to estimate the main effects of COG, SOM, and NEG (Fig. 3c). SOM showed a significant negative correlation with learning rates (β_{SOM} = -0.0332, 95% HPDI = [-0.0576, -0.0118]). The positive correlation between COG and NEG with learning rates was not significant (β_{COG} = 0.0158, 95% HPDI = [-0.00809, 0.0442]; β_{NEG} = 0.0175, 95% HPDI = [-0.00756, 0.0420]). The interaction between ANH and Context remained significant ($\beta_{ANH\times Context}$ = 0.0218, 95% HPDI = [0.000951, 0.0429]). When examing the effect of ANH on learning rates separately in Gain and Loss contexts, ANH showed negative correlation in the Loss condition (β_{ANH} = -0.0289, 95% HPDI = [-0.0571, -0.000620]) but not in the Gain condition (β_{ANH} = 0.00482, 95% HPDI = [-0.0244, 0.0373]). In summary, context moderated the association between ANH and learning rates, such that this association was more negative in the Loss context than in the Gain context. SOM was negatively associated with learning rates across contexts. The correlation between COG, NEG, and learning rates showed a positive trend.

PLS regression

PLS regression was adopted to validate the items of transdiagnostic factors and their relationship with learning rates. Ninety-seven individual questionnaire items were entered as the predictive variables, and positive and negative learning rates in the Gain and Loss contexts were entered as response variables. A 10-fold cross-validation process showed that two components provided the best fit (Fig. 4a). Component 1 exhibited a negative correlation with learning rates ($\beta_{Gain-Pos}$ = -0.0207, $\beta_{Gain-Neg}$ = -0.0196, $\beta_{Loss-Pos}$ = -0.0364, $\beta_{Loss-Neg}$ = -0.0413), whereas Component 2 demonstrated a positive correlation ($\beta_{Gain-Pos}$ = 0.101, $\beta_{Gain-Neg}$ = 0.105, $\beta_{Loss-Pos}$ = 0.114, $\beta_{Loss-Neg}$ = 0.0782) (Fig. 4b). We further interpreted the two components based on the 20 largest loading items for each component (Fig. 4c). Component 1 encompassed items from the SAS and the SDS questionnaires, which mainly contributed to the SOM and ANH factors in our previous factor analysis. Component 2 was characterized by items from the STAI-T, the Penn, and the BDI questionnaires, aligning well with the COG factor and the NEG factors (Fig. 4e). Specifically, Component 1 had a 75% proportion of items overlapping with the SOM and ANH factors (permutation test p = 0.036), but only 25% of items overlapping with the COG and NEG factors (permutation test p = 0.886) (Fig. 4f). On the other hand, Component 2 had 75% of items aligning with the COG and NEG factors (permutation test p = 0.009), but only 25% with the SOM and ANH factors (permutation test p = 0.957) (Fig. 4g). The PLS results are consistent with the factor analysis and further supported that the learning processes of depression and anxiety could be characterized by the transdiagnostic components underlying depression and anxiety traits.

In summary, among the four latent factors extracted from the factor analysis, the ANH and SOM factors reproduced the negative correlation with learning rate as observed in the depression scale (SDS). Importantly, these latent factors were further validated by the PLS regression. The PLS approach identified one component

corresponding to somatic symptoms and anhedonia, which was negatively correlated with the learning rate, and another element related to cognitive symptoms and negative affect, showing a positive correlation with the learning rate (Fig. 4d).

Discussion

In this study, we explored the shared and distinct characteristics of depression and anxiety traits under the reinforcement learning framework. Despite high comorbidity between depression and anxiety, Experiment 1 showed dissociable effects on learning rates regarding depression and anxiety traits. Specifically, depression traits were negatively associated with learning rates, and anxiety traits showed the opposite pattern. Importantly, depression traits or anxiety traits alone did not exhibit significant correlations with learning rates, but only revealed their dissociative effects when considered together with regard to individual learning rates, indicating that the dissociated characteristics may stem from transdiagnostic dimensions of depression and anxiety. Furthermore, Experiment 2 took a transdiagnostic approach to uncover four latent factors underlying depression and anxiety traits, including SOM, ANH, COG, and NEG factors. Among the four factors, SOM and ANH were negatively associated with learning rates, which may contribute to the negative association between depression traits and learning rates, whereas COG and NEG showed a positive correlation trend with learning rates. The dissociative effect among the transdiagnostic factors was further supported by the PLS analysis.

The distinct effects of depression and anxiety traits on learning rates provided preliminary evidence for the dissociation of the two disorders in interacting with the outside environment and adjusting behaviors based on the feedback from the environment. It is worth noting that this dissociation was consistent in both the gain and loss domains, regardless of positive or negative learning rates. This indicates that depression and anxiety traits were not simply associated with reward or punishment processing, but with RL itself. Our results echoed well with previous research that suggested general learning deficits in depression and anxiety [13, 51, 61], instead of increased aversive learning rates [4, 82, 87].

More importantly, we demonstrated a critical difference between depression and anxiety traits in the learning environments. Specifically, the negative correlation between depression traits and learning rates aligns with previous clinical studies [13, 61]. In an RL framework, lower learning rates imply reduced sensitivity and slow adaptation to the environment. The negative correlation between depression traits and learning rates indicates diminished reinforcement sensitivity in depression traits, consistent with depression's core anhedonia characteristic [13, 40]. Interestingly, the anhedonia factor from transdiagnostic analysis also revealed such a negative correlation and was more significant in the loss condition (Fig. 3c). Anhedonia, characterized by a reduced interest or pleasure, is associated with lower reward sensitivity in learning tasks [42, 45]. Thus, we speculate that decreased learning rates in depression traits might be partially driven by anhedonia, which disrupts motivation and reward-based learning, limiting new information integration and adaptive behaviors.

Additionally, the somatic symptoms factor consistently predicted lower learning rates, offering further insight into the negative relationship between depression traits and learning. Somatic symptoms might reflect insufficient external focus when interacting with an uncertain environment. Studies indicate that somatic symptoms (e.g., psychomotor retardation, chronic pain) are linked to slower cognitive processing and reduced engagement with external tasks, exacerbating functional impairments [39]. On the contrary, individuals with somatic symptoms tend to concentrate more on their inner states and feelings [14, 83]. This attentional bias could impair the effective processing of external reward information, ultimately leading to decreases in learning rates. Taken together, the reduced learning of anhedonia and somatic symptoms suggests a trade-off hypothesis for depression: The observed decline in learning rates may stem from depressive cognition's inward focus (e.g., rumination, self-monitoring of physical states), which competes with resources needed for external attention and memory encoding. This hypothesis aligns with earlier studies demonstrating that depression is characterized by an internal focus of attention [46, 52] and can be effectively treated with therapies that encourage an external focus [64]. A recent

study has proposed a 'self-axis' characterization of depression, positing that bodily sensations and interoceptive signals are at the core of depressive symptoms [24]. Consistent with this perspective, our findings indicate that future treatments for depression should incorporate a somatic perspective.

Our results also suggested a positive correlation between anxiety traits and learning rates, consistent with prior research highlighting exaggerated responses to aversive stimuli in anxiety [85, 87]. However, our results indicated a general increase in learning speed, regardless of whether feedback was aversive or appetitive. Our findings added evidence to the growing literature characterizing general anxiety disorder by sensory over-responsivity and mood overactivity across perception, emotion, and decision-making [20, 77], and extended to the learning domain. Additionally, the component associated with cognitive symptoms and negative affect, as identified by the PLS analysis, was also positively correlated with learning rates. Unlike somatic symptoms, individuals with high cognitive symptoms often overemphasize external stimuli [41], corroborating the increase in learning rates. Given that cognitive worry is a key feature of general anxiety [38, 84], we speculate that cognitive symptoms might offer a mechanistic explanation for the positive correlation between learning rates and trait anxiety.

It should be noted that although somatic symptoms were discussed primarily in relation to depression and cognitive symptoms to anxiety, this does not imply an exclusive correspondence between these symptom dimensions and diagnostic categories. In fact, both depression and anxiety include somatic and cognitive components [27, 49, 84]. Consistent with this transdiagnostic view, the somatic and cognitive factors derived from factor analysis and PLS regression in the present study were in fact composed of items from both depression and anxiety scales. This interpretation is also broadly consistent with evidence that different components of anxiety may relate differently to learning. For example, Wise and Dolan, [85] found that cognitive and somatic anxiety showed distinct associations with threat and safety learning rates in an avoidance learning task. Our results similarly suggest that cognitive and somatic symptom dimensions may have dissociable relationships with learning-related parameters. However, the specific pattern observed here appears more consistent with their findings on safety updating than on threat updating. This discrepancy could be due to differences in task context, as the present study used monetary gains and losses as reinforcers rather than threat and safety outcomes [11].

The four latent factors provide further insights into the transdiagnostic structure underlying depression and anxiety. Through exploratory factor analysis, we were able to identify four transdiagnostic factors specifically for the depression and anxiety trait items following the dimensional perspective of mental disorders [21, 22, 50]. Several previous studies also took the transdiagnostic approach on depression and anxiety traits [62, 73] and identified a general distress factor, as well as two unique factors of anhedonia and fear that mainly corresponded to depression and anxiety traits, respectively. The discrepancy between the factor structures identified by previous studies and the current study might be attributed to the fact that survey scales not specifically related to anxiety or depression were also included in the previous studies (e.g., the Fear Survey Schedule and the Albany Panic and Phobia Questionnaire; [73]).

Despite previous studies showing challenges in finding coherence between self-report and behavioral measures [23, 26, 28, 33, 57, 76]; Peng et al. 2021), the current study provided consistent correspondence between symptom dimensions and behavioral characteristics using a unified RL computational modeling approach. The results suggest that the RDoC approach can be successfully achieved through targeted and reliable modeling approaches that inherit robust construct coherence underlying mental disorders, conditions that minimize the influence of state effects, and greater numbers of repeated measures (Peng et al. 2021; [69]). The findings indicate that the RDoC and DSM-based approaches may ultimately reveal complementary information, leading to earlier screening and more personalized treatments for depression and anxiety disorders.

The current study adds to the literature on reinforcement learning in contexts with different valence. The processing of gains and losses involves both shared and distinct mechanisms. Reward learning has been associated with the ventral striatum and the dopaminergic system [71], whereas punishment avoidance has been linked to regions including the anterior insula and dorsal striatum [66]. At the same time, brain regions such as the mPFC appear to process both appetitive and aversive stimuli in a flexible manner, depending on a context-specific subjective reference point [70]. Consistent with this literature, the present study showed that a model distinguishing

between Gain and Loss contexts provided the best account of participants' behavior, suggesting partially distinct cognitive processes across the two contexts. Specifically, learning rates were higher in the Loss context than in the Gain context (see Fig. 2c and f), indicating heightened sensitivity to outcomes when learning to avoid losses. Although the present study did not include neural measures, our findings provide behavioral and computational evidence for distinct processing in reward and punishment learning [68], and further demonstrate context-dependent associations between transdiagnostic factors and learning processes.

The current study has several limitations. First, our study did not include clinical cohorts. Future research should validate current findings in the clinical population, with a specific focus on exploring the relationships between symptom dimensions and learning processes. Second, although we included representative scales of depression and anxiety, the current questionnaires were still limited in scope, which might lead to an insufficient characterization of cognitive symptoms and negative affect. Future work could expand the range of assessment tools to identify a broader spectrum of transdiagnostic factors. Third, the current cross-sectional evidence cannot provide causal links between psychiatric symptoms and learning deficits, beckoning future longitudinal investigations to reveal the causality between learning deficits and transdiagnostic symptoms. Lastly, learning tasks could involve both reinforcement learning and working memory systems [15, 16]. Previous work suggested that working memory contributes substantially to individual differences in reinforcement learning [88]. Although we assessed participants' IQ, which was demonstrated to be correlated with subjects' working memory capacity [17], we did not take direct measures of working memory in the present study. Future studies by collecting working memory assessment or directly manipulating working memory load will be needed to test the relationship between the working memory component and psychopathological measures in a learning environment.

Together, the results showed the promise of understanding the shared and distinct cognitive characteristics of depression and anxiety through a perspective of transdiagnostic latent factors in a unified RL computational framework. In the future, transdiagnostic approaches may provide critical evidence on specific characteristics and mechanisms underlying comorbid psychiatric challenges, and therefore provide insights into personalized intervention programs.

Abbreviations

RL	Reinforcement learning
LR	Learning rate
LA	Learning asymmetry
SDS	The Self-rating Depression Scale
STAI-T	The State-Trait Anxiety Inventory-Trait
ANH	Anhedonia
COG	Cognitive symptoms
SOM	Somatic symptom
NEG	Negative affect

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1186/s12888-026-08592-y.

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Author contributions Xinru Huang: Conceptualization; Methodology; Software; Formal analysis; Investigation; Data Curation; Writing - Original Draft; Writing - Review & Editing; Visualization; Project administration. Yinmei Ni: Conceptualization; Methodology; Resources; Formal analysis. Yuxi Wang: Conceptualization; Methodology; Resources; Formal analysis. Yujia Peng: Conceptualization; Methodology; Resources; Writing - Review & Editing; Supervision; Funding acquisition. Jian Li: Conceptualization; Methodology; Resources; Writing - Review & Editing; Supervision; Funding acquisition.

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Data availability All data and codes for analysis can be found online at the following URL: https://osf.io/8ptk2/overview.

Declarations

Ethics approval and consent to participate The study was approved by the Institutional Review Board of the School of Psychological and Cognitive Sciences, Peking University (#2021-10-12), under the principles of the Declaration of Helsinki. All participants read the informed consent form prior to the experiment and agreed to take part.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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