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Transdiagnostic latent factors dissociating depression and anxiety through reinforcement learning

Running Title: Transdiagnostic latent factors of depression and anxiety

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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 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.

Keywords

Transdiagnostic latent factors, Reinforcement learning, Depression, Anxiety, Computational psychiatry

1. Introduction

Depression and anxiety are among the most prevalent mental disorders, with significant clinical and subclinical impacts (GBD 2017 DALYs and HALE Collaborators, 2018). Depression and anxiety share numerous overlapping emotional and cognitive symptoms and exhibit a high comorbidity rate (Kaiser et al., 2021), but also embody distinct features such as anhedonia for depression and heightened fear experience for anxiety (Prenoveau et al., 2010; Naragon-Gainey et al., 2016). Moreover, depression is characterized by dysfunctional reward processing (Henriques & Davidson, 2000; Admon & Pizzagalli, 2015; Eshel & Roiser, 2018), whereas anxiety is associated with abnormal aversive learning and threat processing (Britton et al., 2011; Wise & Dolan, 2020; Peng et al., 2023). These features indicate impaired processing of appetitive and aversive information (e.g., reward or threat), which is frequently explored through learning-based approaches. 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 (Montague et al., 2012; Adams et al., 2016; Huys et al., 2016; Gagne et al., 2020; Ossola & Pike, 2023; Fang et al., 2024).

Reinforcement learning (RL), which describes how agents interact with the uncertain environment to update expectations and maximize rewards (Sutton & Barto, 1998), may provide a unified framework to study how people respond to appetitive or aversive feedbacks 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, often yielding mixed results (Chase et al., 2010; Browning et al., 2015; LaFreniere & Newman, 2018; Aylward et al., 2019; Gagne et al., 2020; Mukherjee et al., 2020; Pike & Robinson, 2022; Vandendriessche et al., 2022; Yamamori et al., 2023; Fang et al., 2024). For instance, depression and anxiety were found to be associated with exaggerated responses to adverse outcomes, manifested as increased aversive learning rates (Aylward et al., 2019; Vandendriessche et al., 2022; Yamamori et al., 2023). Conversely, other studies suggested a decrease in learning rates in depression and anxiety disorders, indicating a general impairment regarding appetitive and aversive outcomes (Chase et al., 2010; LaFreniere & Newman, 2018; Mukherjee et al., 2020). 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 (Aylward et al., 2019; Gagne et al., 2020; Pike & Robinson, 2022; Fang et al., 2024) or separately in studies focusing exclusively on either depression or anxiety (Chase et al., 2010; Browning et al., 2015; LaFreniere & Newman, 2018; Mukherjee et al., 2020; Vandendriessche et al., 2022; Yamamori et al., 2023).

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 (Cuthbert & Insel, 2013; Cuthbert, 2014; Kotov et

al., 2021) 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 among 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 in both Gain and Loss conditions. Furthermore, the ANH factor described a general lack of hedonic experience and showed a context-specific relationship to the learning rates in the Loss condition. Finally, the NEG and COG factors, which loaded more heavily on depression and anxiety measurements, respectively, showed a positive correlation trend with learning rates.

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

2.1. Methods

2.1.1. 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 ($\alpha = .05$, two-tailed) to detect similar effects as previous studies ($\Delta R^2 = 0.04$, $f^2 \approx 0.045$; Wise & Dolan, 2020; Gagne et al., 2020) 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 (Wise & Dolan, 2020). 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 $> 90\%$ 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.

2.1.2. Self-report psychiatric questionnaires

We employed the Self-rating Depression Scale (SDS, Zung et al., 1965) and the State-Trait Anxiety Inventory-Trait (STAI-T, Spielberger, 1983) to assess depression and anxiety traits, respectively. Both the SDS (20 items; Cronbach's $\alpha = 0.88$) and the STAI-T (20 items; Cronbach's $\alpha = 0.91$) demonstrated strong internal consistency. A set of questionnaires designed to assess additional prevalent psychiatric conditions was also employed in Experiment 1 (see supplementary methods S1 and supplementary results S5). 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 (Bilker et al., 2012). We controlled for the effect of IQ in our analyses to account for its potential confounding influence on cognitive task performance suggested by previous literatures (Gillan et al., 2016).

2.1.3. Procedure

All participants went through a probabilistic instrumental learning task to characterize RL (Li & Daw, 2011; Ni et al, 2023; Fig. 1a-c). The learning task was composed of two conditions corresponding to different outcome valence: in the Gain condition, participants were required to choose between two slot machines to earn monetary rewards, while in the Loss condition, 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 second. Subsequently, the monetary outcome of the selected slot machine was revealed and lasted for 1.5 seconds. A fixation cross appeared signaling the inter-trial-interval (ITI) period and lasted for 0.5 seconds 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 in the next trial.

Two conditions (Gain vs. Loss) and two types of outcomes (Good vs. Bad) formed a total of four combinations: in the Gain condition, Good outcome corresponded to gaining one coin while Bad outcome corresponded to no monetary gain, whereas in the Loss condition, Good outcome corresponded to no monetary loss and Bad outcome referred 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). 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 minutes on average.

2.1.4. Computational modeling of RL

The Q-learning model

Q-learning models were used to quantify the RL process (Sutton & Barto, 1998). 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:

$$Q_{i,t+1} = Q_{i,t} + \alpha \times (R_t - Q_{i,t}) \quad (1)$$

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 (ranged 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). 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 a free parameter q_0 , i.e., $Q_{1,0} = Q_{2,0} = q_0$. The initial value q_0 ranges between $[0, 1]$ in the Gain condition, and $[-1, 0]$ in the Loss condition.

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

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

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 , named 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 learning 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 full model has four free parameters corresponding to α , q_0 , γ , and β . Gain and Loss conditions are assumed to possess a distinct set of parameters.

Alternative models were constructed for model comparison. The baseline model encompasses only the learning rate and the inverse temperature (the Base model). The following models were all constructed based on the Base model, adding the initial values (the Initial model), the perseverance (the Persev model), or both (the full model). Additionally, we also compared models that distinguished between positive and negative learning rates based on the full model (see Results and Supplementary).

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 (Ahn et al., 2017; Ni et al., 2023). 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, 12,000 samples were collected after a burn-in of 4,000 samples on each of the four chains, resulting in a total of 48,000 posterior samples collected for each parameter. 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 (Stephan et al., 2009; Rigoux et al., 2014).

Additionally, we conducted model simulations and parameter recovery to assess the stability of the Q-learning model. The results for parameter recovery are shown in supplementary results S3.

2.1.5 Bayesian regression models

We ran a series of Bayesian regressions to investigate the relationship between learning and psychopathological measures (Wise & Dolan, 2020). Bayesian regressions were used to mitigate the multiple comparisons problem. The same set of analyses was conducted under both the Gain and Loss conditions. Learning rates were regressed against the SDS score and the STAI-T score as the main independent variables, with Sex, Age, and IQ in the regression model as covariates of no interest. Age, IQ, the SDS score, and the STAI-T score were Z-transformed before entering the regressions. 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. We report the means of the posterior distributions as estimates of each coefficient, along with the 95% highest posterior density interval (HPDI), representing the points between which 95% of the posterior distribution's density lies. The regression coefficients of control variables were reported in supplementary results S4. The regressions of other parameters from the learning model on psychiatric measures were reported in supplementary results S6.

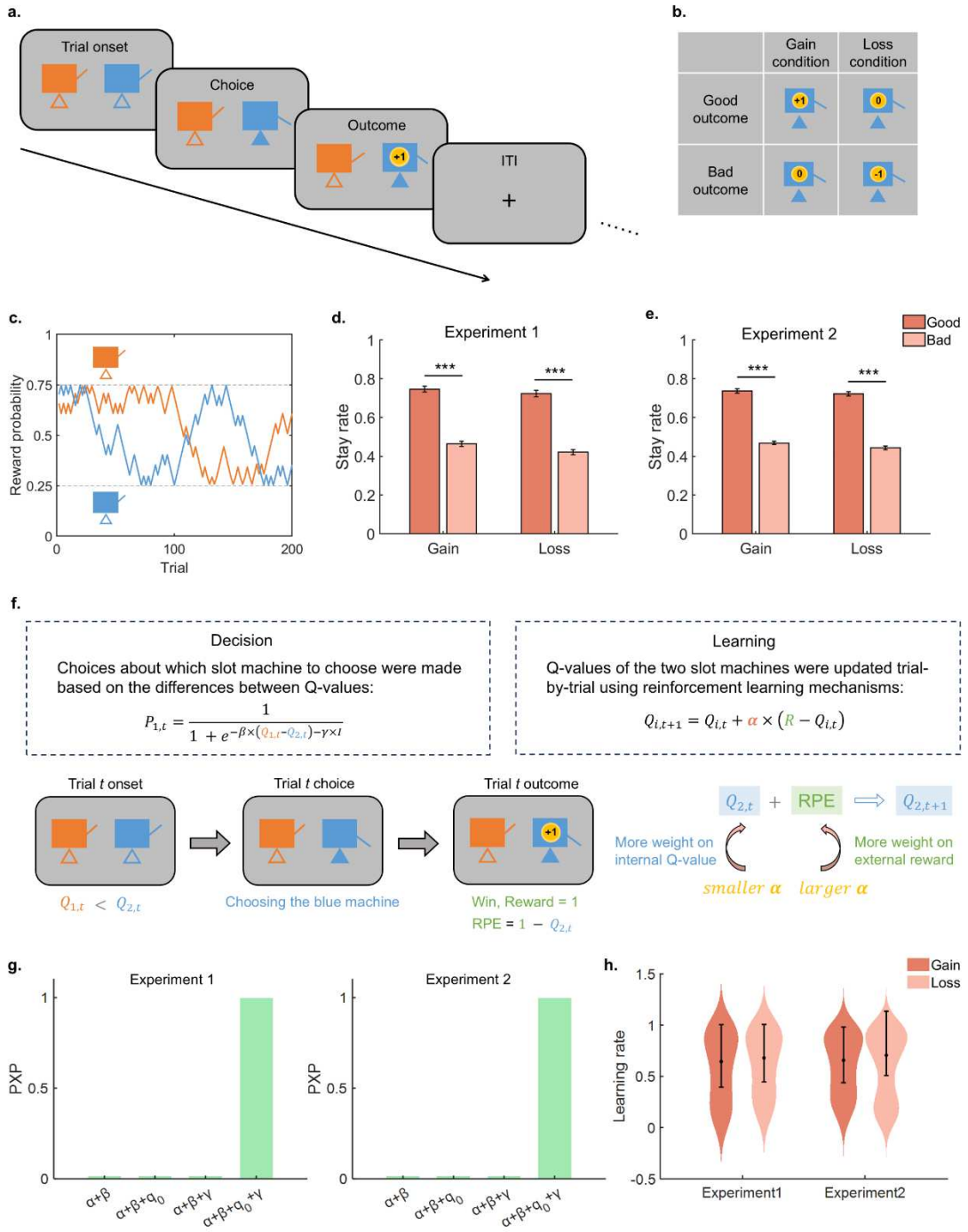


Figure 1. The probabilistic instrumental learning task. **a.** An example trial of the probabilistic instrumental learning task. After the trial onset, participants chose between two slot machines. Only the outcome of the selected machine was revealed. **b.** Four different outcomes of slot machines, including a 2×2 combination of two different conditions (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 conditions, participants exhibited a higher stay rate after a ‘Good’ outcome than after a ‘Bad’ outcome. Error bars indicate standard errors. **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 protected exceedance probability (PXP). The model comparison revealed that the full model, which included initial value and perseverance, provided the best fit. **h.** The violin plot of the fitted learning rates in Gain and Loss conditions. The width of the violin represents the density of the parameter distribution. Error bars represent the 25th and 75th percentiles of learning rates. The black dots show the median of learning rates in each condition and experiment.

2.2. Results

2.2.1. 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 and Fig. S1.

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 $\pm$ 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 $\pm$ 9.20
STAI-T	38.43 $\pm$ 10.03

2.2.2. 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 conditions ($F_{1,189} = 304.64, p < 0.001, \eta_p^2 = 0.617$) (Fig. 1d), indicating participants adopt the standard "win-stay-lose-shift" learning strategy. We further applied RL models (i.e., the Q-learning model) to quantify the learning process (Fig. 1f, also see methods). The

model comparison results showed that the full model provided the best fit, measured by the protected exceedance probability ($PXP > 0.99$) (Fig. 1g). There was no significant difference in learning rates between the gain and loss contexts ($p > 0.05$, Fig. 1h). We also ran models that distinguished between positive and negative learning rates. However, the effects of depression and anxiety traits on positive and negative learning rates showed similar trends (see Supplementary results S7). Thus, we carried out further analyses using a single learning rate model in the main text.

2.2.3. Bayesian regression models of the SDS and STAI-T scores

Participants' learning rates in both the Gain and Loss conditions were regressed against the SDS and STAI-T scores. In the Gain condition, the regression coefficients indicated a negative correlation between the SDS score and learning rates ($\beta_{SDS} = -0.118$, 95% HPDI = $[-0.195, -0.0439]$), whereas the STAI-T score demonstrated a positive correlation ($\beta_{STAI-T} = 0.131$, 95% HPDI = $[0.0538, 0.207]$) (Fig. 2c). In the Loss condition, the SDS score was also negatively correlated with learning rates ($\beta_{SDS} = -0.0791$, 95% HDPI = $[-0.154, -0.0127]$). In contrast, the STAI-T score was positively correlated with learning rates ($\beta_{STAI-T} = 0.125$, 95% HDPI = $[0.0497, 0.196]$) (Fig. 2d). 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.

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 learning rates in the Loss condition ($r = 0.193$, $p = 0.008$), all other correlation analyses did not yield 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 (MacKinnon et al., 2000). 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.

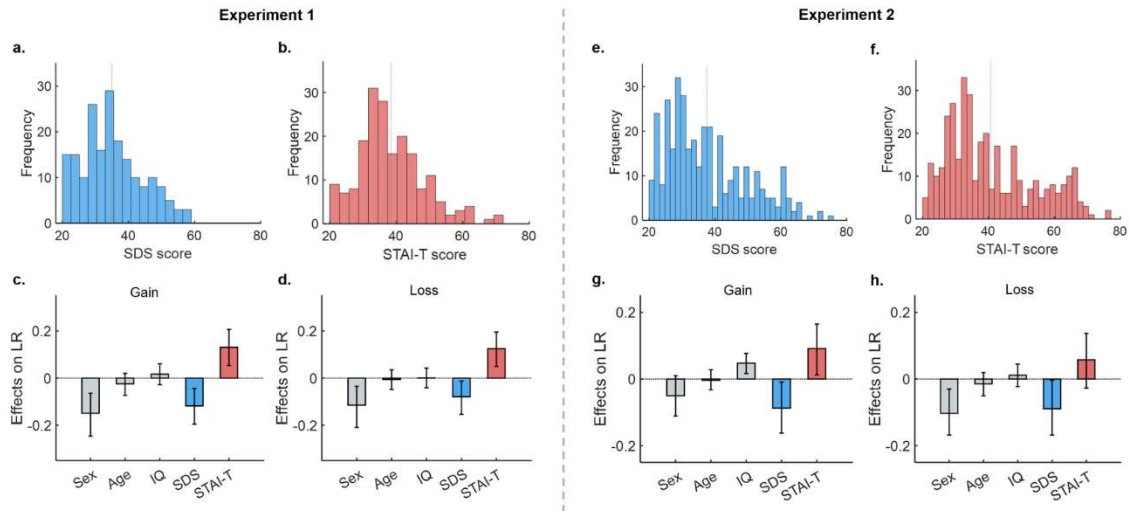


Figure 2. Dissociation of the depression and anxiety traits on learning rates (LR). **a-b.** The sample distribution of the SDS score and the STAI-T score in experiment 1. **c-d.** The effects of Sex, Age, IQ, the SDS score, and the STAI-T score on the learning rates in the Gain and the Loss conditions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

3. 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 (Prenoveau et al., 2010; Gillan et al., 2016; Gagne et al., 2020). 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.

3.1. Methods

3.1.1. 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 ($\geq .50$) (Comrey & Lee, 2013). Data exclusion was the same as 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.

3.1.2. 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 $\alpha = 0.94$) and STAI-T (Cronbach's $\alpha = 0.95$), the Beck Depression Inventory-II (BDI, Beck et al., 1996; 21 items, Cronbach's $\alpha = 0.95$), the Self-rating Anxiety Scale (SAS, Zung, 1971; 20 items, Cronbach's $\alpha = 0.92$), and the Penn State Worry Questionnaire (Penn, Meyer et al., 1990; 16 items, Cronbach's $\alpha = 0.94$) 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.

3.1.3. 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 minutes on average.

3.1.4. 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. Factors were extracted using Maximum Likelihood Estimation (MLE) with an oblique rotation. Factor selection was based on Parallel Analysis (Dragow & Lissak, 1983), 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), Negative Symptoms (NEG), and Somatic Symptoms (SOM). 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 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 (Wu et al., 2024): 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 S2.

3.1.5. RL Computational modeling and Bayesian regression models

As in Experiment 1, we constructed Q-learning models to quantify the process of reinforcement learning. 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 other settings of the Bayesian regression models were the same as Experiment 1.

3.1.6. 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 (Wise & Dolan, 2020). PLS regression was conducted using the *pls* packages in R. Principal components were extracted from the covariance matrix between question items (predictors) and 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 with 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.

3.2. Results

The demographic information of the population in Experiment 2 is presented in Table 2. Scores of

self-report questionnaires are shown in Fig. 2a and Fig. S1.

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 $\pm$ 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 $\pm$ 12.21
STAI-T	40.68 $\pm$ 13.34
BDI	10.48 $\pm$ 10.29
SAS	35.51 $\pm$ 10.89
Penn	45.51 $\pm$ 13.72

3.2.1. 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 = 1) (Fig. 1g). There was no significant difference in learning rates between the gain and loss contexts ($p > 0.05$, Fig. 1h).

3.2.2. Bayesian regression models of the SDS and STAI scores

The regressions of the SDS and STAI-T scores replicated the findings in Experiment 1. In both the Gain and Loss conditions, the SDS score was negatively associated with learning rates (in the Gain condition, $\beta_{SDS} = -0.0875$, 95% HDPI = [-0.162, -0.00910]; in the Loss condition, $\beta_{SDS} = -0.0893$, 95% HDPI = [-0.168, -0.00351]), whereas the STAI-T score was positively correlated with learning rates (in the Gain condition, $\beta_{STAI-T} = 0.0915$, 95% HDPI = [0.0125, 0.165]; in the Loss condition, $\beta_{STAI-T} = 0.0578$, 95% HDPI = [-0.0273, 0.137]) (Fig. 2 g-h).

3.2.3. Factor analysis

We performed an exploratory factor analysis (EFA) across the 97 questionnaire items in 5 questionnaires. The factor selection process revealed that a structure comprising four latent factors

best explained the covariance structure of the questionnaire data (Fig. 3a), which were 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 they 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 corresponded primarily to the BDI questionnaire, and was labeled ‘Negative Affect (NEG)’. Lastly, the fourth factor, which included questionnaire items about physical discomfort, was designated as ‘Somatic Symptom (SOM)’. The four factors explained 52% of the total variance of the items.

3.2.4. 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 latent factors on learning rates in both the Gain and Loss conditions of Experiment 2 (Fig. 3c-d). SOM showed a significant negative correlation with learning rates in both the Gain and the Loss conditions (in the Gain condition, $\beta_{SOM} = -0.0692$, 95% HPDI = [-0.107, -0.0293]; in the Loss condition, $\beta_{SOM} = -0.0603$, 95% HPDI = [-0.104, -0.0170]). ANH showed negative correlation in the Loss condition ($\beta_{ANH} = -0.0554$, 95% HPDI = [-0.114, -0.00701]) but not in the Gain condition ($\beta_{ANH} = 0.0110$, 95% HPDI = [-0.0338, 0.0586]). The positive correlation between COG and NEG with learning rates was not significant (in the Gain condition, $\beta_{COG} = 0.0270$, 95% HPDI = [-0.0221, 0.0676]; $\beta_{NEG} = 0.0253$, 95% HPDI = [-0.0201, 0.0698]; in the Loss condition, $\beta_{COG} = 0.0334$, 95% HPDI = [-0.0158, 0.0811]; $\beta_{NEG} = 0.0449$, 95% HPDI = [-0.00426, 0.0983]). In summary, ANH was negatively correlated with learning rates only in the Loss condition. SOM was negatively associated with learning rates across the contexts. The correlation between COG, NEG, and learning rates showed a positive trend in both conditions.

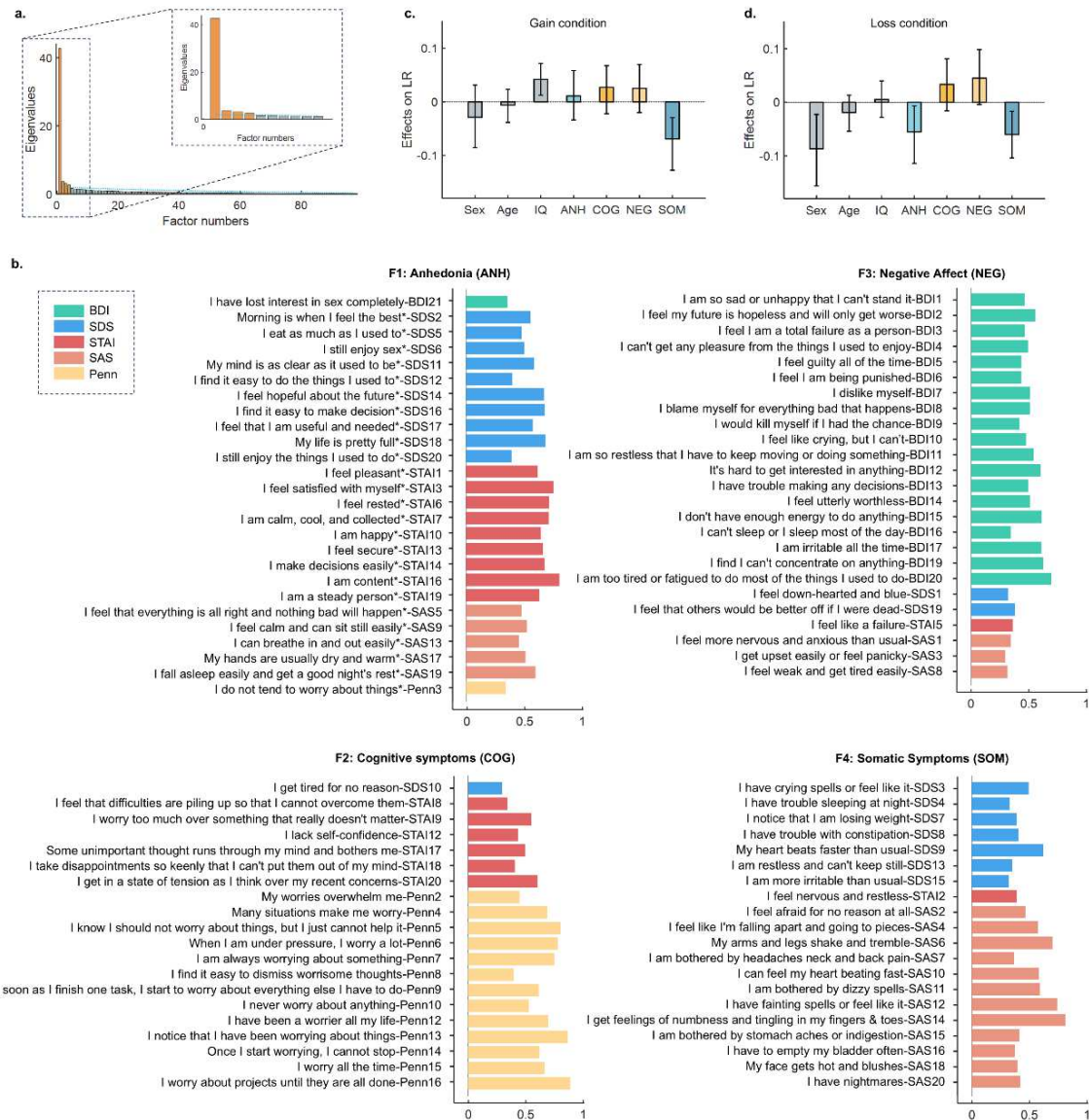


Figure 3. Results of the factor analysis and Bayesian regression in Experiment 2. **a.** The scree plot illustrates the change of eigenvalues as the number of factors increases. The blue dotted line represents the permutated eigenvalues from the parallel analysis. Eigenvalues that exceed this line indicate 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’, ‘Negative Affect’, and ‘Somatic Symptoms’. Only items with loading greater than 0.3 or lower than -0.3 are shown. **c-d.** The effects of Sex, Age, IQ, and the four factors on the learning rates in the Gain and the Loss conditions. Error bars represent the 95% HPDI of posterior samples of each regression coefficient.

3.2.5 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 the learning rates in the Gain and Loss conditions 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 ($\beta_{Gain} = -0.0417$, $\beta_{Loss} = -0.0648$), whereas Component 2 demonstrated a positive correlation ($\beta_{Gain} = 0.0992$, $\beta_{Loss} = 0.0798$) (Fig. 4b). We further interpreted the two components based on the 20 largest loading items for each component (Fig. 4c). Component 1 mainly 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 (permutated $p = 0.022$), but only 25% of items overlapping with the COG and NEG factors (permutated $p = 0.897$) (Fig. 4f). On the other hand, Component 2 had 75% of items aligning with the COG and NEG factors (permutated $p = 0.028$), but only 25% with the SOM and ANH factors (permutated $p = 0.893$) (Fig. 4g). The PLS results are consistent with the factor analysis and further supported that the aptical learning processes of depression and anxiety could be characterized by the transdiagnostic components underlying depression and anxiety traits.

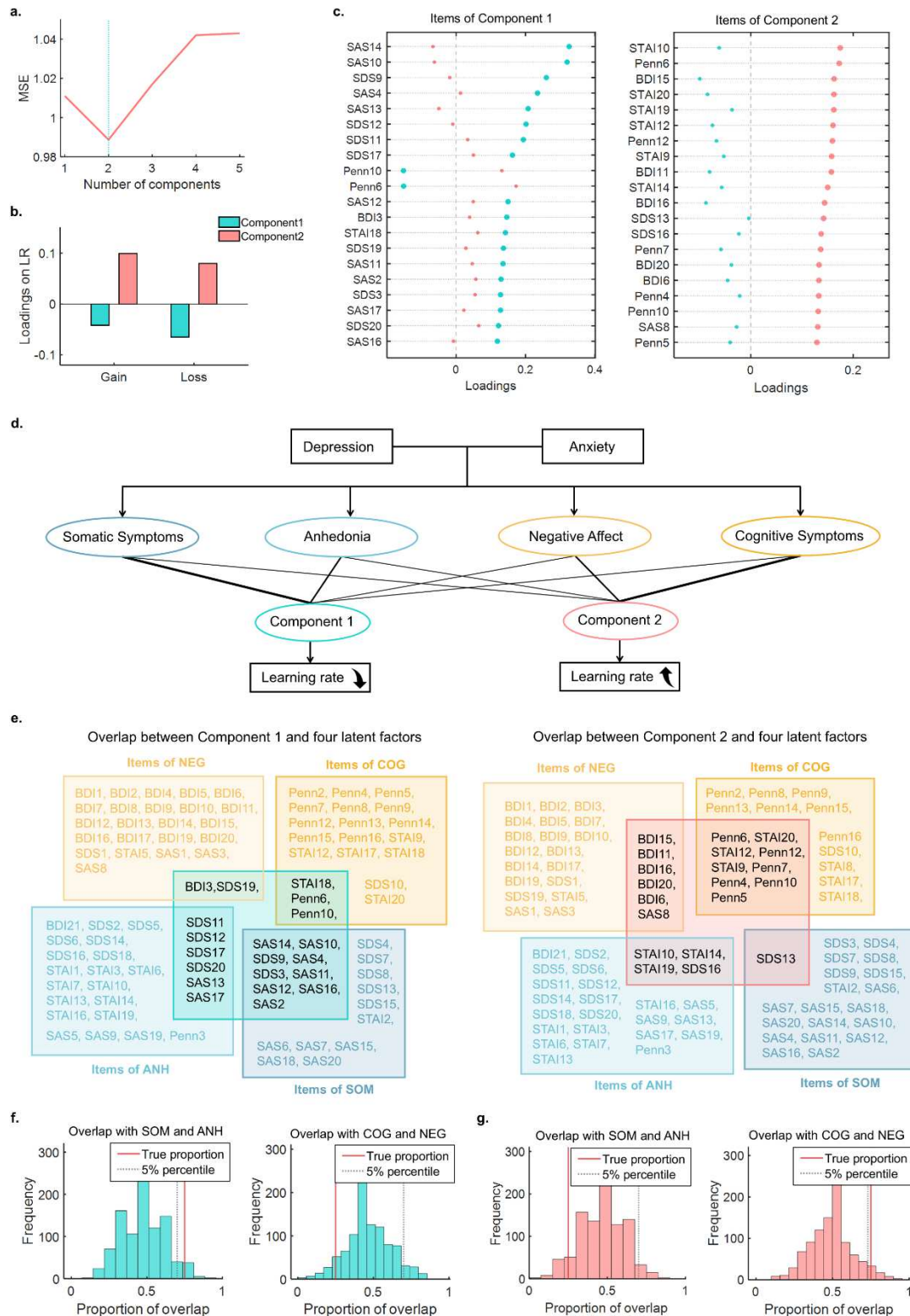


Figure 4. Partial least squares regression results in Experiment 2. **a.** The optimal number of components was determined based on a 10-fold cross-validation. The mean squared errors across models between one and five factors were represented. The model with two components yielded the best performance. **b.** Loadings of the two components on the learning rates in the Gain and Loss conditions. 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.

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 positive correlation with the learning rate (Fig. 4d).

4. 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 our results were consistent in both the gain and loss domains, regardless of positive or negative learning rates (see Supplementary results S7). 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 (Chase et al., 2010; LaFreniere & Newman, 2018; Mukherjee et al., 2020), instead of increased aversive learning rates (Aylward et al., 2019; Vandendriessche et al., 2022; Yamamori et al., 2023).

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 prior clinical studies (Chase et al., 2010; Mukherjee et al., 2020). 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 (Henriques & Davidson, 2000; Chase et al., 2010). Interestingly, the anhedonia factor from transdiagnostic analysis also revealed such a negative correlation. Anhedonia, characterized by a reduced interest or pleasure, is associated with lower reward sensitivity in learning tasks (Huys et al., 2013; Husain & Roiser, 2018). 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 (Hall et al., 2011). On the contrary, individuals with somatic symptoms tend to concentrate more on their inner states and feelings (Cioffi, 1991; Van Den Houte et al., 2017). 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 (Ingram & Smith, 1984; Larsen & Cowan, 1988) and can be effectively treated with therapies that encourage an external focus (Nix et al., 1995). 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 (Davey & Harrison, 2022). Consistent with this perspective, our findings indicate that future treatments for depression should incorporate a somatic perspective.

On the contrary, our results suggested a positive correlation between anxiety traits and learning rates, consistent with prior research highlighting exaggerated responses to aversive stimuli in anxiety (Wise & Dolan, 2020; Yamamori et al., 2023). 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 (Showraki & Showraki, 2021; Cummings et al., 2024), extending to the RL 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 (Hirsch & Mathews, 2012), corroborating the increase in learning rates. Given that cognitive worry is a key feature of general anxiety (Wells, 1995; Goodwin et al., 2017), we surmised that cognitive symptoms might offer a mechanistic explanation for the positive correlation between learning rates and trait anxiety.

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 (Cuthbert & Insel, 2013; Cuthbert, 2014; Kotov et al., 2021). Several previous studies also took the transdiagnostic approach on depression and anxiety traits (Prenoveau et al., 2010; Naragon-Gainey et al., 2016) 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; Prenoveau et al., 2010).

Despite previous studies showing challenges in finding coherence between self-report and behavioral measures (Cyders & Coskunpinar et al., 2011; Duckworth & Kern et al., 2011; McHugh et al., 2011; Frey et al., 2017; Saunders et al., 2018; Eisenberg et al., 2019; 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; Peng et al., 2023). 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 has several limitations. First, our study did not include clinical cohorts. Future research should validate current findings in clinical populations, 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.

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.

Data and code availability

All data and codes for analysis can be found online at

https://osf.io/8ptk2/?view_only=fc9117a67a5b4e36970d8dcdd3893f29.

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Declaration of Competing Interest

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Ethics 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). All participants read the informed consent

form prior to the experiment and agreed to take part.

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