Supplementary Text and Figures

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# 1 Supplementary Information about Participants

To ensure the relevance of our findings to the broader psychiatric population, we included individuals with R-AN who had comorbid psychiatric conditions. The presence of comorbidities was assessed by specialized psychiatrists and psychologists at the Specchidacqua Institute (Montecatini, Pistoia) and the Gruber Center, Outpatient Clinic (Bologna). Among the 40 individuals with R-AN, comorbidities included anxiety disorder (n=16), obsessive-compulsive disorder (OCD) (n=8), social phobia (n=1), and depressive and anxiety disorders (n=1). Some R-AN patients were also taking medication, including anxiolytic antidepressants (n=10), selective serotonin reuptake inhibitors (SSRIs) (n=6), benzodiazepines (n=1), and mood stabilizers (lithium) (n=1).

To be eligible for participation, individuals needed to be proficient in spoken and written Italian. Exclusion criteria for all participants included a history of alcohol or drug abuse or dependence, neurological disorders, and intellectual or developmental disability. Cognitive function within the normal range was assessed using the Raven’s Standard Progressive Matrices test (Raven, 2000). The eligibility criteria for all participants were evaluated through psychologist interviews. Body mass index (BMI) values were determined in the laboratory.

The study included a predominantly Caucasian sample, with 97.7% of the participants identifying as Caucasian. A smaller proportion of participants identified as Asian-Italian (1.7%) and African-Italian (0.6%). Additionally, all selected participants were right-handed and were unaware of the specific objectives of the study, ensuring a blind study design.

# 2 Sample size

Before conducting the present study, we conducted a parallel but separate study with two distinct groups. The first group included 29 anorexic patients, and the second group consisted of 124 healthy controls (these participants were different from those in the current study). In this prior study, each participant completed 160 trials per condition in a PRL task, where the content of the pair of images presented in each trial was manipulated. In both groups, the difference in the learning rate (which is the main focus of the current study) was measured to be 0.54 (on a logit scale).

To determine the sample size needed to detect a similar effect, we carried out a parameter recovery study following the method outlined by Pedersen & Frank (2020). We simulated the data of two groups of 30 participants with different values of (lower and higher) with a difference of 0.54. The other parameters of the RLDDM model (i.e., , , ) were set to the values estimated from the empirical data of the 29 anorexic patients and 124 healthy controls. For the simulation, we used the hddm.generate.gen\_rand\_rlddm\_data function of the hddm module with following parameters:

subjects = 30  
trials = 160  
  
data = hddm.generate.gen\_rand\_rlddm\_data(  
 a=1.5,  
 alpha=0.79, # or 0.25  
 scaler=2.25,  
 t=0.25,  
 size=trials,  
 subjs=subjects,  
 p\_upper=0.7,  
 p\_lower=0.3,  
)

We used the HDDMrl function of the hddm module to estimate the RLDDM parameters based on the simulated data. We repeated this procedure 100 times, and in each iteration, the parameters for the lower and higher values of were completely separated. This simulation suggest that our study had enough participants and trials to detect the effect size on that had been observed in the previous study.

A parameter recovery study and a frequentist power analysis are two distinct approaches. However, since Bayesian methods prioritize estimation over hypothesis testing, it is comforting to see that with the current number of participants and trials, the RLDDM model can detect an effect size similar to the one found in a separate study with a different group of participants but with a similar experimental manipulation.

# 3 Demographic and psychopathology measures

Mean age and Body Mass Index (BMI) for each group of participant were as follows: patients with AN, mean age = 21.18 (SD = 2.41), average Body Mass Index (BMI) = 16.88 (SD = 1.55); patients with BN, mean age = 20.39 (SD = 1.88), average BMI = 30.09 (SD = 5.47); HCs, mean age = 19.77 (SD = 1.06), average BMI = 21.62 (SD = 3.03); healthy individuals at risk of developing eating disorders, mean age = 20.36 (SD = 1.44), average BMI = 22.41 (SD = 4.79).

Bayesian statistical analysis revealed no credible age differences among the four groups (AN, BN, HC, and RI). AN participants displayed a lower mean BMI than HC participants, while BN participants had a higher mean BMI than HC participants. No noteworthy difference in BMI was observed between HC and RI participants. Furthermore, there is credible evidence that the Rosenberg Self-Esteem Scale scores of all three groups (AN, BN, and RI) are smaller than those of the HC group. We also found credible evidence that individuals with AN, BN, and RI exhibited higher levels of dissatisfaction with their body shape, as measured by the BSQ-14 questionnaire, when compared to the HCs. Individuals with AN displayed higher stress, anxiety, and depression levels (as measured by the DASS-21) than HCs. Additionally, individuals with AN showed credibly higher levels of social interaction anxiety (as measured by the SIAS) than HCs. All three AN, BN, and RI groups exhibited higher levels of Concerns over mistakes and doubts scores of the MPS scale compared to HCs. Individuals with AN also showed higher levels of Personal standard scores of the MPS scale compared to HCs. Moreover, individuals with AN displayed higher values on all three subscales of the EAT-26 questionnaire (Garner et al., 1982) relative to HCs.

Sixteen individuals with R-AN were diagnosed with a comorbid anxiety disorder, 8 with OCD, 1 with social phobia, and 1 with DAP.

# 4 Psychometric questionnaires

The *Eating Attitude Test-26* (EAT-26, Garner et al., 1982) consists of 26 items assessing levels and types of eating disturbances in the past three mouths. The EAT-26 is characterized by three subscales: the Dieting Scale, the Bulimia and Food Preoccupation Scale and the Oral Control Scale. Scores point out the presence of an eating disorder. Respondents are required to rate intensity associated with the items on a 6-point Likert scale (0 = never, rarely, sometimes; 3 = always). The Italian version of the EAT-26 demonstrated good psychometric properties (Dotti & Lazzari, 1998). In fact, Cronbach’s alpha was high in an undergraduate sample for the Dieting scale (.87), for Bulimia and Food Preoccupation scale (.70), for Oral Control Scale (.62). Cronbach’s alpha for the total scores was 0.86.

The *Body Shape Questionnaire-14* [BSQ-14; Dowson & Henderson (2001)] is a 14-item self-report scale assessing the global body satisfaction in the past two weeks. Respondents are required to rate intensity of concerns about own appearance associated with the items on a 6-point Likert scale (1 = never, 6 = always). The Italian version of the BSQ-14 demonstrated good psychometric properties (Matera et al., 2013). In the present sample, = 0.978. For the 40-item BSQ, a score below 80 is considered “no concern”, a score of 80 to 110 is considered “slight concern”, a score of 111 to 140 is considered “moderate concern”, and a score above 140 is considered “marked concern”.

The *Social Interaction Anxiety Scale* [SIAS; Mattick & Clarke (1998)] is a 20-item self-report questionnaire assessing social interaction anxiety. Respondents are required to rate intensity associated with the items on a 4-point Likert scale from 0 (not at all true) to 4 (extremely true). Higher scores denote greater social interaction anxiety levels. Both original version and the Italian version (Sica et al., 2007) show acceptable psychometric properties (in the present sample = 0.938). Heimberg et al. (1992) have suggested a cut-off of 34 on the 20-item SIAS to denote a clinical level of social anxiety (32.3 for the Italian 19 item version).

The *Depression Anxiety Stress Scale-21* [DASS-21; Lovibond & Lovibond (1995)] is a 21-item self-report measure assessing depression, anxiety, and stress over the previous week. Items are rated on a 4-point scale ranging from 0 (did not apply to me at all) to 3 (applied to me very much). Both the original and the Italian version (Bottesi et al., 2015) demonstrate adequate reliability. In the present sample = 0.875, = 0.914, = 0.899; for the total scale, = 0.945.

The *Rosenberg Self-Esteem Scale* [RSES; Rosenberg (1965)] is a 10-item scale designed to assess person’s overall self-esteem. It comprises five straightforwardly worded and five reverse-worded items each rated on a 4-point Likert scale ranging from 4 (strongly agree) to 1 (strongly disagree). Increased values indicate increased self-esteem. In the present sample, = 0.949.

The *Multidimensional Perfectionism Scale* [MPS-F; Frost et al. (1990)] is a 35-item assessing perfectionism tendencies. According to Stöber (1998), MPS-F is composed of four underlying factors: Concerns over Mistakes and Doubts (CMD), Parental Expectations and Criticism (PEC), Personal Standards (PS), and Organization (O). Both the original MPS-F and the Italian version (Lombardo, 2008) demonstrate adequate reliability. In the present sample, = 0.919, = 0.851, = 0.946, = 0.931; for the total scale, = 0.932.

# 5 Additional Information about the Task

Participants were introduced to the study as a way to evaluate their cognitive functions using a computer-based “game” and additional questionnaires. Their goal in the PRL task was to maximize their earnings, which were shown at the end of each trial block. When participants felt uncertain, they were instructed to rely on their instincts. During the PRL task, feedback was provided in a probabilistic manner. The correct image was rewarded in 70% of the trials, while negative feedback was given in the remaining 30% of the trials. Each block of the task consisted of four epochs, with 40 trials in each epoch where the same image was considered correct. Within each block, there were three rule changes known as reversal phases. Participants were aware that the stimulus-reward contingencies would change, but they were not provided with specific details about when or how these changes would occur. Prior to the actual experiment, participants underwent a training block consisting of 20 trials. The PRL tasks were programmed using the Psychtoolbox extensions in MATLAB (MathWorks) (Brainard & Vision, 1997).

# 6 Statistical Methods

We analyzed our data using R-Studio (R version 4.4.0) and Python, employing Bayesian statistics to prioritize estimation over Null Hypothesis Significance Testing (NHST). This approach offers several advantages that enhance interpretability and flexibility, making it particularly appropriate for our study:

1. **Emphasis on Estimation**: Bayesian methods focus on estimating the parameters of interest directly, providing a richer understanding of the data than the binary outcomes of null hypothesis testing. This approach aligns with our goal of understanding the underlying mechanisms rather than merely testing for the presence or absence of a statistical effect.
2. **Credible Intervals**: Bayesian credible intervals offer a more intuitive interpretation compared to frequentist confidence intervals (Gelman et al., 2021). An 95% credible interval, for instance, directly reflects the probability that the parameter lies within this range, given the data. This is more informative than a confidence interval, which does not offer a direct probability statement about the parameter.
3. **Accommodation of Non-Gaussian Models**: Bayesian methods easily accommodate non-Gaussian statistical models, allowing us to better capture the complexities of the data without being constrained by assumptions of normality. This flexibility is crucial in accurately modeling the diverse and often non-normal distributions encountered in psychological data (as in the present case).
4. **Hierarchical Models**: Bayesian hierarchical models provide a robust framework for analyzing data with nested structures (Gelman et al., 1995). This approach allows for the inclusion of multiple levels of variability and provides more accurate parameter estimates by borrowing strength across different levels of the hierarchy, which is particularly beneficial in the present study for better estimation of the DDMRL model. Hierarchical modeling of reinforcement learning tasks has been demonstrated to yield superior predictive accuracy compared to alternative methods (Geen & Gerraty, 2021; Gershman, 2016).

# 7 Computational Models

The main goal of this study was to use computational models of reinforcement learning to compare the learning outcomes of two different decision-making contexts: those involving disorder-relevant information and those that did not. We used a reinforcement learning drift diffusion model [RLDDM; Pedersen & Frank (2020)] to investigate the impact of disorder-related information (which is irrelevant to the outcome) on decision-making in individuals with restrictive eating disorders (R-AN).

## 7.1 RLDDM

The RLDDM consists of two key components: one describes how reward feedback is employed to update value expectations and the other describes how an agent uses these expectations to arrive at a decision.

The model assumes that subjective option values (Q values) are learned through reward prediction errors (PEs), which measure the disparity between expected and obtained outcomes (Sutton & Barto, 2018). The update of subjective option values follows a delta learning rule (Rescorla & Wagner, 1972):

where refers to the expected values for option on trial , represents the reward (with values 1 or 0), and is the leaning rate, which scales the difference between the expected and actual rewards. A higher learning rate results in rapid adaptation to reward expectations, while a lower learning rate results in slow adaptation. We included in the model different learning rates for positive and negative prediction errors: The parameter is computed from reinforcements, whereas is computed from punishments.

The second component describes the selection rule for reinforced options. Typically, a softmax function is used, where the probability of selecting option depends on its expected value relative to other options , scaled by the inverse temperature parameter :

In the RLDDM, instead, this second component of decision-making is replaced by a Drift-Diffusion Model [DDM; Ratcliff & McKoon (2008)] which assumes a stochastic accumulation of evidence on each trial.

The RLDDM encompasses six key parameters:

* and : Represent learning rates for rewards and punishments, respectively. We predict lower and in AN-R compared to HCs, specifically for food-related choices. Additionally, we expect a reduced within the AN-R group for food-related versus unrelated decisions, but not for (see also Bernardoni et al., 2021).
* : Denotes the drift rate or speed of evidence accumulation. No differences are expected between conditions or between groups (Weider et al., 2015).
* : Indicates the decision boundary, affecting both decision speed and accuracy. Elevated aa values are anticipated in mixed-food versus no-food conditions, signifying decreased choice confidence (Lee et al., 2023).
* : Represents non-decision time, accounting for stimulus encoding and motor execution. No condition or group differences are anticipated (Weider et al., 2015)..
* : Captures the starting point, or initial decision bias. No initial bias is expected between conditions or groups.

## 7.2 Estimation

The RLDDM is the most advanced method for analyzing performance in the probabilistic reversal learning (PRL) task. We estimated the RLDDM using a hierarchical Bayesian framework with the module of the (version 0.9.7) Python package (Fengler et al., 2021; Wiecki et al., 2013). The posterior distribution of group and individual parameters was also estimated using the module of the (version 0.9.8) Python package. For a detailed description of the model, refer to (Pedersen & Frank, 2020; Wiecki et al., 2013).

## 7.3 Priors

The Bayesian posterior estimations of the RLDDM rely on informative priors for the DDM component, obtained from a prior meta-analysis (Wiecki et al., 2013). For the learning rate parameters (positive and negative), we used non-informative broad normal distributions, centered at 0.5 after transformation.

# 8 Data analysis

## 8.1 Quality Control

To ensure data quality, we excluded participants who performed below chance level (50%) in the probabilistic reversal learning (PRL) task (e.g., Geisler et al., 2017). Additionally, two participants with R-AN who exhibited convergence problems, indicated by a large R-hat diagnostic, were excluded. Consequently, the final sample for subsequent analyses consisted of 117 participants: 36 individuals with R-AN, 45 healthy controls (HC), and 36 healthy controls at risk of developing eating disorders (RI).

## 8.2 Model Comparison

The study used the Rescorla-Wagner model as a foundation to develop new RLDDM models. In these models, all parameters were allowed to vary by condition (i.e., food-related vs. food-unrelated information) and group due to the absence of prior evidence indicating specific parameter effects or group variations related to food information.

Markov chain Monte Carlo (MCMC) sampling was employed to estimate these models. Initially, 2000 traces were sampled following a 500-trace burn-in period. The Deviance Information Criterion (DIC) was calculated for each model, and the model with the lowest DIC was selected. The selected model was then re-estimated using 15,000 traces with a 5,000-trace burn-in period (Kruschke & Liddell, 2018).

The Rescorla-Wagner and the following RLDDM models were examined:

* Model M0: Standard Rescorla-Wagner model. DIC = 39506.552.
* Model M1: RLDDM without conditioning. DIC = 39879.444.
* Model M2: Separate learning rates for positive and negative reinforcements. DIC = 39124.890.
* Model M3: Group-based and parameters. DIC = 39194.763.
* Model M4: Group and stimulus-based and parameters. DIC = 38197.467.
* Model M5: Group and stimulus-based , , and decision threshold (a) parameters. DIC = 36427.448.
* Model M6: Group and stimulus-based , , , and drift rate (v) parameters. DIC = 36185.146.
* Model M7: Group and stimulus-based , , , , and non-decision time () parameters. DIC = 34904.053.
* Model M8: Group and stimulus-based , , , , , and starting point () parameters. DIC = 34917.762.

The following code snippet illustrates the estimation process for Model M7:

m7 = hddm.HDDMrl(  
 data,  
 depends\_on={  
 "a": ["group", "stim"],  
 "v": ["group", "stim"],  
 "t": ["group", "stim"],  
 "alpha": ["group", "stim"],  
 "pos\_alpha": ["group", "stim"],  
 },  
 dual=True,   
 p\_outlier=0.05,  
 informative=True,   
 include=["v", "a", "t"],  
)  
  
m7.find\_starting\_values()  
m7.sample(15000, burn=5000, dbname="models/ddm7\_final.db", db="pickle")

By comparing the DIC values, Model M7 was identified as the best-fitting model, capturing the complexity of group and stimulus-based variations in the learning parameters.

## 8.3 Model Evaluation and Hypothesis Testing

Convergence was assessed using the Gelman-Rubin statistic, with values for all parameters in Model M7 below 1.05, indicating good convergence. Collinearity and posterior predictive checks were also conducted to ensure model validity. To examine the impact of disorder-related versus neutral stimuli on reinforcement learning, we compared the posterior estimates of Model M7’s RLDDM parameters between the two conditions.

# 9 Additional figures

## 9.1 Within-group comparisons

![Plots of the posterior distribution of the within-group effects of parameter \alpha^{-} (\alpha^{-}_{food} - \alpha^{-}_{neutral}) across the three groups of participants.](data:application/pdf;base64,)

Plots of the posterior distribution of the within-group effects of parameter () across the three groups of participants.

![Plots of the posterior distribution of the within-group effects of parameter \nu (\nu_{food} - \nu_{neutral}) across the three groups of participants.](data:application/pdf;base64,)

Plots of the posterior distribution of the within-group effects of parameter () across the three groups of participants.

![Plots of the posterior distribution of the within-group effects of parameter t (t_{food} - t_{neutral}) across the three groups of participants.](data:application/pdf;base64,)

Plots of the posterior distribution of the within-group effects of parameter () across the three groups of participants.

## 9.2 Between-group comparisons

![Plots of the posterior distribution of the within-group effects of parameter \alpha^{-} (\alpha^{-}_{food} - \alpha^{-}_{neutral}) across the three groups of participants.](data:application/pdf;base64,)

Plots of the posterior distribution of the within-group effects of parameter () across the three groups of participants.

![Plots of the posterior distribution of the within-group effects of parameter \nu (\nu_{food} - \nu_{neutral}) across the three groups of participants.](data:application/pdf;base64,)

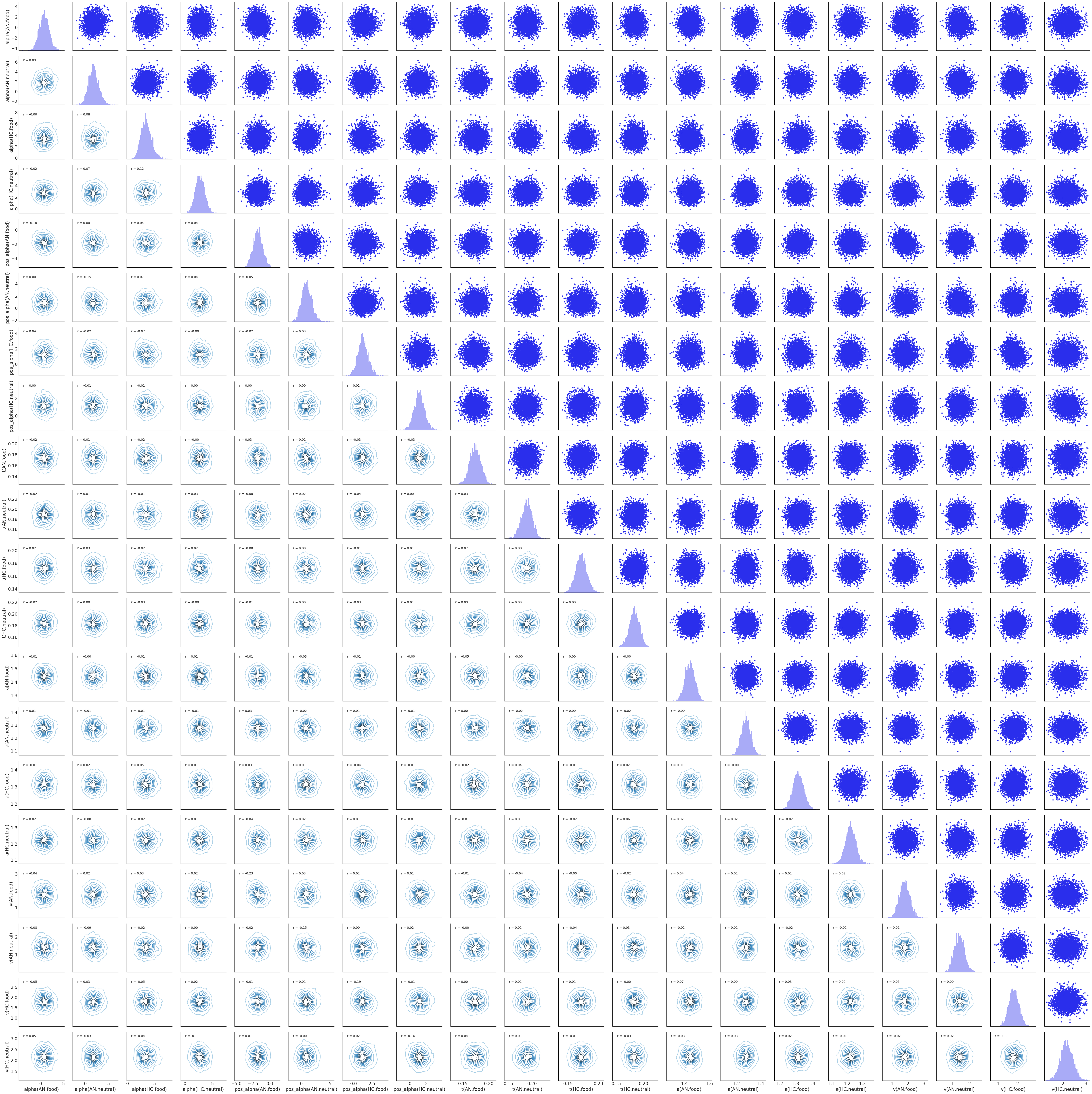
Plots of the posterior distribution of the within-group effects of parameter () across the three groups of participants.

![Plots of the posterior distribution of the within-group effects of parameter t (t_{food} - t_{neutral}) across the three groups of participants.](data:application/pdf;base64,)

Plots of the posterior distribution of the within-group effects of parameter () across the three groups of participants.

# 10 Collinearity check

As shown in the following figure, for all three groups the correlation between the parameters is generally low.



Joint posterior distribution of RLDMM parameters.

# 11 Posterior predictive checks

To assess model validity, we performed posterior predictive checks. This involved simulating data using estimated parameters and comparing observed and simulated results. We generated the simulated dataset by repeating the simulation process 500 times for each subject in a sample dataset.

## 11.1 PPC for learning rate

To evaluate the choice proportion for the best option across learning in both observed and simulated data, we binned the trials and plotted the 95% highest density intervals of the mean responses. The figures below illustrate the rate of selecting the best option during learning. The 95% highest density interval of the means across simulated datasets captures the uncertainty present in the generated data.

![Observed and predicted learning rates across conditions: R-AN group.](data:application/pdf;base64,)

Observed and predicted learning rates across conditions: R-AN group.

![Observed and predicted learning rates across conditions: HC group.](data:application/pdf;base64,)

Observed and predicted learning rates across conditions: HC group.

![Observed and predicted learning rates across conditions: RI group.](data:application/pdf;base64,)

Observed and predicted learning rates across conditions: RI group.

## 11.2 PPC for reaction times

The density plots of observed and predicted reaction times across conditions are presented in the following figures. To distinguish upper and lower bound responses, reaction times for lower boundary choices (i.e., worst option choices) were set to be negative (0-RT). The observed and predicted values show good agreement, indicating the model’s accuracy in capturing the reaction time distributions.

![Observed and predicted reaction times across conditions: R-AN group.](data:application/pdf;base64,)

Observed and predicted reaction times across conditions: R-AN group.

![Observed and predicted reaction times across conditions: HC group.](data:application/pdf;base64,)

Observed and predicted reaction times across conditions: HC group.

![Observed and predicted reaction times across conditions: RI group.](data:application/pdf;base64,)

Observed and predicted reaction times across conditions: RI group.

# 12 Comorbidity

Individuals with eating disorders often have comorbid psychiatric conditions, including depression (up to 75%), bipolar disorder (10%), anxiety disorders, obsessive-compulsive disorder (40%), panic disorder (11%), social anxiety disorder/social phobia, post-traumatic stress disorder (prevalence varies with eating disorder), and substance abuse (15-40%) (Woodside & Staab, 2006).

In this study, we included patients with comorbidities to increase the generalizability of our findings to the broader psychiatric population. Specifically, 16 individuals with R-AN were diagnosed with comorbid anxiety disorder, 8 with OCD, 1 with social phobia, and 1 with DAP.

We applied a modified version of model M7 to the R-AN data, categorizing patients into two groups based on the presence or absence of comorbidities. The potential effects of comorbidities were evaluated using the following model:

m = hddm.HDDMrl(  
 data,  
 depends\_on={  
 "a": ["comorbidity", "stim"],  
 "v": ["comorbidity", "stim"],  
 "t": ["comorbidity", "stim"],  
 "alpha": ["comorbidity", "stim"],  
 "pos\_alpha": ["comorbidity", "stim"],  
 },  
 dual=True,   
 p\_outlier=0.05,  
 informative=True  
)

The results show no credible differences in the posterior estimates of the model parameters between the group with comorbidities and those without comorbidities. Specifically, for disorder-related choices, the difference in the parameter was -0.034 (95% CI [-0.188, 0.124]), for it was 0.230 (95% CI [-1.203, 1.586]), for it was 0.002 (95% CI [-0.050, 0.055]), for it was 2.614 (95% CI [-3.173, 8.364]), and for it was -0.635 (95% CI [-4.301, 2.449]). For disorder-unrelated choices, the differences in the respective parameters were -0.126 (95% CI [-0.281, 0.025]) for , 0.744 (95% CI [-0.452, 1.885]) for , -0.003 (95% CI [-0.057, 0.052]) for , -0.768 (95% CI [-6.570, 4.401]) for , and -1.739 (95% CI [-6.184, 1.654]) for .

The 95% credible intervals of these parameter differences encompass zero, suggesting a lack of credible evidence for any substantial difference in the RLDDM parameters between patients with and without comorbid diagnoses. These findings indicate that the conservative RL patterns observed for disorder-related choices are not attributable to the presence of comorbidities in individuals with R-AN.

# 13 Medication

A similar statistical analysis to the previous section was conducted, categorizing individuals with R-AN into two groups based on the presence or absence of medication.

The results show no credible differences in the posterior estimates of the model parameters between the group with medication and those without. Specifically, for disorder-related choices, the difference in the parameter was -0.074 (95% CI [-0.233, 0.078]), for it was 0.370 (95% CI [-0.952, 1.701]), for it was 0.005 (95% CI [-0.048, 0.059]), for it was 1.010 (95% CI [-4.506, 6.468]), and for it was -0.440 (95% CI [-3.705, 2.547]). For disorder-unrelated choices, the differences in the respective parameters were -0.056 (95% CI [-0.208, 0.100]) for , 0.837 (95% CI [-0.360, 2.031]) for , -0.007 (95% CI [-0.066, 0.047]) for , -1.843 (95% CI [-7.674, 3.351]) for , and -3.346 (95% CI [-7.475, 0.241]) for .

The 95% credible intervals of these parameter differences encompass zero, suggesting a lack of credible evidence for any substantial differences in the RLDDM parameters between patients with and without medication. These findings indicate that the conservative RL patterns observed for disorder-related choices are not attributable to the presence of medication in individuals with R-AN.

# 14 Biased Choices

To investigate whether the conservative learning behavior observed in patients with R-AN during the PRL task, particularly when making disorder-relevant choices, could be due to a general preference for non-food-related images regardless of their past action-outcome history, we conducted a specific analysis. We focused on the frequency of food-related choices in the PRL blocks where participants chose between a food image and a neutral image. We aimed to determine if individuals with R-AN tended to choose the food image less frequently compared to the control groups.

We calculated the percentage of times each participant chose the food image in these specific PRL blocks and used this percentage as the dependent variable in a robust Bayesian regression model.

priors <- c(  
 set\_prior("student\_t(4, 0, 1.0)", class = "b")  
)  
  
bmod <- brm(  
 bf(  
 freq ~ diag\_cat,   
 sigma ~ diag\_cat  
 ),  
 data = bysubj\_freq,  
 family = student(),  
 control = list(adapt\_delta = 0.99),  
 prior = priors,  
 warmup = 1000,  
 iter = 5000,  
 cores = parallel::detectCores(),  
 seed = "12345",  
 chains = 4  
)

In the R-AN group, the proportion of food choices was 0.48, with an 95% credible interval ranging from 0.46 to 0.51. Since the 95% credible interval includes the value of 0.5, the data do not provide credible evidence of a bias away from food choices in the R-AN group.

The comparisons between the R-AN group and the two control groups are given by the following contrasts:

| Contrast | Estimate | Lower HPD | Upper HPD |
| --- | --- | --- | --- |
| R-AN - HC | -0.010 | -0.041 | 0.021 |
| R-AN - RI | 0.012 | -0.020 | 0.045 |

In both cases, the 95% credibility interval includes zero, indicating no credible difference between the R-AN group and the control groups in the likelihood of selecting the food image compared to the neutral image.

# 15 Outcome-irrelevant Learning: Spatial-Motor Associations

Shahar et al. (2019) investigated the impact of spatial-motor associations on reinforcement learning (RL). Optimal decision-making should prioritize rewards, irrespective of spatial-motor associations, such as the choice of response key in previous trials. Shahar et al. (2019) found that rewards had a greater impact on the probability of choosing between two images when the chosen image was linked to the same response key in both the n-1 and n trials.

To investigate whether the likelihood of selecting ‘stay’ (choosing the same image) was greater for ‘same’ versus ‘flipped’ response/key mapping in our data, we replicated the statistical analyses conducted by Shahar et al. (2019) and Ben-Artzi et al. (2022). We focused on contrasting rewarded and unrewarded responses in our probabilistic reversal learning (PRL) task.

We performed two Bayesian multilevel regression models using the brm function from the brms package in R, which utilizes Stan on the back-end. One model included a group effect (HC, RI, R-AN), while the other did not.

priors\_0 <- c(  
 set\_prior("student\_t(3, 0, 0.2)", class = "b", coef = "Intercept"),  
 set\_prior("student\_t(3, 0, 0.2)", class = "b"),  
 set\_prior("student\_t(3, 0, 0.2)", class = "sd"),  
 set\_prior("lkj(1)", class = "cor"),  
 set\_prior("gamma(0.01, 0.01)", class = "phi"),  
 set\_prior("beta(2, 2)", class = "coi"),  
 set\_prior("beta(2, 2)", class = "zoi")  
)  
  
mod\_0 <- brm(  
 stay ~ 0 + Intercept + mapping \* feedback \* group +   
 (1 + mapping \* feedback | subj\_idx),  
 family = zero\_one\_inflated\_beta(),  
 backend = "cmdstanr",  
 data = bysubj\_ed,  
 prior = priors\_0,  
 iter = 2000  
)

We observed no credible effect of group (HC, RI, R-AN) or a credible interaction between group, previous outcome, and mapping (ELPD difference = -4.5, SE = 2.8). The simpler model used stay as the dependent variable (1 if the same response key was chosen in trial as in trial , 0 otherwise), with mapping (repeated or flipped image-to-key mapping), feedback (reward, punishment), and their interaction as fixed effects, and subj\_idx as a random effect. The marginal effects of the mapping feedback interaction ( = 0.93, 95% CI [0.81, 1.06]) are shown in the following figure.

![](data:application/pdf;base64,)

The figure shows the probability of choosing the same image at trial + 1, depending on the outcome (rewarded vs. unrewarded) and mapping (flipped vs. same). Results indicate a tendency to repeat image selection after a rewarded trial. Notably, a stronger effect of reward was observed when the image was mapped to the same response key compared to the alternative key. Error bars represent 95% credibility intervals.

In conclusion, our study successfully replicated the findings reported by Shahar et al. (2019) and Ben-Artzi et al. (2022), providing evidence that the effects of reward extend not only to the relevant image but also to the outcome-irrelevant response key. This highlights the impact of outcome-irrelevant factors, such as contextual effects in our study and spatial-motor mapping in Shahar et al. (2019), on reinforcement learning in a PRL task.

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