When Food Becomes a Distraction: The Impact of Food-Related Information on Reward Learning in Anorexia Nervosa

Corrado Caudek[1] & Ernst-August Doelle[1,2]

[1] Wilhelm-Wundt-University

[2] Konstanz Business School

Author Note

Add complete departmental affiliations for each author here. Each new line herein must be indented, like this line.

Enter author note here.

The authors made the following contributions. Corrado Caudek: Conceptualization, Writing - Original Draft Preparation, Writing - Review & Editing; Ernst-August Doelle: Writing - Review & Editing, Supervision.

Correspondence concerning this article should be addressed to Corrado Caudek, Postal address. E-mail: my@email.com

Abstract

Objective: This study utilized a within-subject design to examine whether individuals with restrictive anorexia nervosa (R-AN; $n = 40$) perform similarly to healthy controls (HCs; $n = 45$) and healthy controls at risk of eating disorders in reinforcement learning (RL; $n = 36$) tasks. Specifically, we aimed to determine if RL performance is comparable between groups for disorder-unrelated choices, but significantly impaired for disorder-related choices. **Method:** RL performance was assessed using a Probabilistic Reversal Learning (PRL) task, where participants were asked to perform disorder-related choices or disorder-unrelated choices. **Results:** R-AN individuals demonstrated lower learning rates for disorder-related decisions, while their performance on neutral decisions was comparable to participants with Bulimia Nervosa, Healthy Controls (HCs), and HCs at risk of eating disorders. Additionally, only AN patients exhibited reduced learning rates for outcome-irrelevant food-related decisions in reward-based learning, as opposed to food-unrelated decisions. **Discussion:** Impaired RL task performance in individuals with AN may be attributed to external factors rather than compromised learning mechanisms. These findings indicate that AN may significantly impact the cognitive processing of food-related information, even when AN patients do not show learning rate disadvantages compared to HCs in decision-making involving food-unrelated information. This study provides valuable insights into the reinforcement learning processes of individuals with AN and emphasizes the need to consider the influence of food-related information on cognitive functioning in this patient population. The findings have potential implications for the development of interventions targeting decision- making processes in individuals with AN

Keywords: keywords

Word count: X

When Food Becomes a Distraction: The Impact of Food-Related Information on Reward Learning in Anorexia Nervosa

Introduction

Anorexia Nervosa (AN) is one of the most common eating disorders characterized by distorted body perception and pathological weight loss, particularly in its restricting type (R-AN) (American Psychiatric Association, 2022). Lifetime prevalence for AN has been reported at 1.4% for women and 0.2% for men (Galmiche, Déchelotte, Lambert, & Tavolacci, 2019; Smink, Hoeken, & Hoek, 2013), with a mortality rate that can be as high as 5-20% (Qian et al., 2022). Treating AN is extremely challenging (Atwood & Friedman, 2020; Linardon, Fairburn, Fitzsimmons-Craft, Wilfley, & Brennan, 2017), highlighting the importance of gaining a deeper understanding of its underlying mechanisms (Chang, Delgadillo, & Waller, 2021).

Executive functions have gained significant attention in the research on understanding the mechanisms underlying anorexia nervosa (AN). Impairments in executive processes, such as cognitive inflexibility, decision-making difficulties, and inhibitory control problems, have been identified as potential risk and perpetuating factors in AN (Bartholdy, Dalton, O'Daly, Campbell, & Schmidt, 2016; Guillaume et al., 2015; Wu et al., 2014). Within this domain, Reinforcement Learning (RL) in the context of associative learning has received considerable interest. In fact, the presence of persistent maladaptive eating behaviors in individuals with AN, despite experiencing negative consequences, along with indications of altered reward and punishment sensitivity, has led to the proposal of abnormal reward responsiveness and reward learning in AN (Schaefer & Steinglass, 2021). While there is strong evidence supporting the presence of anomalies in reward responsiveness in individuals with AN, our current understanding of potential abnormalities in AN-related reward learning remains limited.

In relation to the dysfunctions observed in reward responsiveness among individuals with AN, research has revealed that the intense levels of dietary restriction and physical activity characteristic of AN can indeed activate reward pathways (Keating, 2010; Keating, Tilbrook, Rossell, Enticott, & Fitzgerald, 2012; Selby & Coniglio, 2020). Additionally, individuals with AN may exhibit diminished reward responses specifically towards food (Wierenga et al., 2014). In a broader sense, research has shown that AN is associated with reduced subjective reward sensitivity and decreased neural response to rewarding stimuli. Moreover, individuals with AN may experience disruptions in processing aversive stimuli, leading to heightened harm avoidance, intolerance of uncertainty, increased anxiety, and oversensitivity to punishment (Fladung, Schulze, Schöll, Bauer, & Groen, 2013; Jappe et al., 2011; Keating et al., 2012; O'Hara, Campbell, & Schmidt, 2015). These factors contribute to an altered response to negative feedback and a tendency to avoid aversive outcomes (Jonker, Glashouwer, & Jong, 2022; Matton, Goossens, Braet, & Vervaet, 2013). Neuroimaging studies have further supported these findings by revealing neural dysfunction in AN's response to loss and aversive taste (Bischoff-Grethe et al., 2013; Monteleone et al., 2017; Wagner et al., 2007).

However, when it comes to reward learning abnormalities in AN (Bernardoni et al., 2018; Foerde et al., 2021; Foerde & Steinglass, 2017), the reported results have been inconsistent (Caudek, Sica, Cerea, Colpizzi, & Stendardi, 2021). For example, some studies have suggested RL deficits, while others have found no significant differences. [bla bla] Given the critical role of RL in learning from experience, understanding these processes is essential in elucidating the mechanisms underlying maladaptive eating behavior in AN (Bischoff-Grethe et al., 2013; Glashouwer, Bloot, Veenstra, Franken, & Jong, 2014; Harrison, Genders, Davies, Treasure, & Tchanturia, 2011; Jappe et al., 2011; Matton et al., 2013).

Recently, it has been proposed that the inconsistency in the results regarding potential anomalies in RL processing in AN may be explained by the assumption that RL is a context-independent unitary process. This assumption attributes RL anomalies in R-AN to deficits in the underlying RL mechanism [ref]. Instead, an alternative perspective posits that atypical RL behavior in R-AN may arise from the interference of extraneous contextual factors, even in the presence of intact RL mechanisms (Haynos, Widge, Anderson, & Redish, 2022). This hypothesis suggests that contextual factors, encompassing personal characteristics, long-term goals, and situational influences, can exert a negative impact on RL performance, regardless of the presence of an underlying RL deficit. Individuals with R-AN, being particularly susceptible to the influence of symptom-related information such as food, body weight, and social pressure [ref], may experience heightened vulnerability to these interfering contextual factors.

To investigate the influence of contextual factors on decision-making in R-AN, we conducted a study using a Probabilistic Reversal Learning (PRL) task. This task measures RL and cognitive flexibility by allowing participants to learn from feedback and adjust their behavior based on reward probabilities. The task reflects real-life situations where outcomes are uncertain, requiring individuals to make decisions based on probabilities. By presenting uncertain and varying reward probabilities, the task captures the complexities of decision-making under uncertainty and provides insights into how individuals integrate probabilistic information to guide their behavior. The PRL task involves unannounced reversals of contingencies, demanding behavioral adaptation to changing environments. This reversal learning aspect measures cognitive flexibility – i.e., the ability to shift behavior in response to changing environmental demands. The PRL task has been extensively used in neuroscience research and has shown associations with specific brain regions involved in reinforcement learning and cognitive flexibility [ref]. Neuroimaging techniques like fMRI have revealed neural activations and connectivity patterns during the task, corresponding to reward processing, error monitoring, and cognitive control mechanisms.

In contrast to previous studies that utilized general stimuli (Schaefer & Steinglass, 2021), our study implemented the PRL task with two distinct conditions. Participants were asked to complete the PRL task under two different scenarios: one condition involved choices between a stimulus related to the disorder and a stimulus unrelated to the disorder, while the other condition involved choices between two stimuli unrelated to the disorder.

The putative learning process involves a computational mechanism known as the reward prediction error (PE). Derived from the RL framework, PE quantifies the disparities between received outcomes and expected outcomes, enabling the updating of stimulus, state, or action values (Rescorla & Wagner, 1972; Sutton & Barto, 2018). The neural manifestation of the PE during reversal learning consistently emerges in the ventral frontostriatal circuitry of the human brain (O'Doherty et al., 2003). In the RL framework, PEs are solely dependent on the relationship between outcomes and choices, making the image content irrelevant in a PRL task. As a result, previous studies have not explored the impact of contextual factors on learning rates using the PRL task.

However, recent research suggests that outcome-irrelevant information can influence PRL performance. For example, Shahar et al. (2019) showed that spatial-motor associations, which are irrelevant to the outcomes, can affect PRL performance. While optimal decision-making should prioritize rewards regardless of spatial-motor associations, such as the choice of a response key in the previous trial, Shahar et al. (2019) found that rewards had a more pronounced influence on the likelihood of choosing between two images when the chosen image was associated with the same response key in both the "n-1" and "n" trials.

The present study aimed to investigate the influence of outcome-irrelevant and disorder-relevant information on PRL performance in three groups: individuals with DSM-5 restricting-type AN, healthy controls (HCs), and individuals at risk of developing eating disorders (RIs). The primary objective was to utilize computational models of reinforcement learning to analyze and compare learning outcomes in two distinct contextual conditions: decision-making involving disorder-relevant information and decision-making without disorder-relevant information.

Based on the evidence suggesting that outcome-irrelevant information can impact PRL performance, the study hypothesized that differences in RL between R-AN patients and the control groups would primarily emerge in the disorder-relevant condition. Conversely, no substantial differences were expected in the disorder-unrelated condition. By incorporating both disorder-relevant and disorder-unrelated stimuli, the study aimed to examine and quantify anomalies in RL performance among individuals with R-AN, thereby shedding light on the role of contextual factors in their decision-making processes.

Evidence of contextual factors on RL learning in AN

TODO

Developing flexibility in decision-making necessitates acquiring knowledge about the most rewarding choices in the current context and adjusting one's decision-making accordingly.

...

Concerning cognitive flexibility, research has produced mixed results for the influence of disorder-related information.

...

The inconsistent findings in behavioral experiments can be partly explained by the predominant use of general stimuli in the studies, as opposed to disorder-relevant stimuli (Schaefer & Steinglass, 2021). Furthermore, when disorder-related information is utilized, it is typically provided solely in the feedback following the participant's choice, while the stimuli presented during the decision-making process are unrelated to the disorder. Consequently, the manipulation primarily emphasizes the consequences of the choices rather than the contextual factors surrounding the decision-making process. However, recent theoretical developments have emphasized the significant role of context in RL (e.g., Collins

& McDougle, 2021). Regarding motor learning, for example, it has been shown that contextual cues affect learning rate (Castro, Hadjiosif, Hemphill, & Smith, 2014; Herzfeld, Vaswani, Marko, & Shadmehr, 2014). In line with these findings, we propose that contextual cues, specifically disorder-related information, have the potential to activate a dysfunctional "learning mode" in individuals with R-AN, even in the absence of a general deficit in the unedrlying RL mechanisms.

Implications for treatment

The hypothesis of contextual maladaptive RL in R-AN has potential implications for treatment. In fact, attempts are made, for individuals with R-AN, to strenghten their cognitive flexibility so as to address their maladaptive eating behavior. But these intervenctions have focused on behaviora choices in disorder-unrelated contexts only.

Methods

The study, which adhered to the Declaration of Helsinki, was approved by the University of Florence's Ethical Committee (Prot. n. 0178082). All eligible participants provided informed consent and willingly agreed to participate in the study.

Participants

The study recruited a total of 40 individuals meeting criteria for DSM-5 restricting-type AN, 213 healty volunteers, and 36 healthy individuals at risk of developing eating disorders. Individuals with R-AN were recruited from three facilities in Italy, namely the Specchidacqua Institute in Montecatini (Pisa), the Villa dei Pini Institute in Firenze, and the Gruber Center, Outpatient Clinic in Bologna. The treatment approach consisted of Cognitive Behavioral Therapy and family-based treatment. Patients received treatment for 2 to 6 hours per day, 2 days per week. The treatment program included various components, such as individual therapy, family therapy, group therapy, nutritional counseling, psychiatric care, and medical monitoring. AN diagnosis was determined by semi-structured interview performed by specialized psychiatrists and psychologists at treatment admission according to the Diagnostic and Statistical Manual of Mental Disorders-5 (DSM-5) criteria.

Patients diagnosed with R-AN (Restrictive Anorexia Nervosa) were included in the study approximately 6 months (± 1 month) after starting treatment for eating disorders at one of the participating facilities. The assessment of comorbidities in R-AN patients was carried out by specialized psychiatrists and psychologists at the treatment centers using a comprehensive approach. This approach involved regular and ongoing monitoring of psychiatric symptoms and comorbid conditions throughout the treatment process. The assessment process encompassed clinical interviews and the administration of specific symptom inventories and rating scales to obtain a comprehensive evaluation of comorbid psychiatric disorders.

The HC (healthy control) group consisted of 310 adolescent or young-adult females recruited through social media or university advertisements. All participants completed the Eating Attitudes Test-26 (EAT-26; Garner et al., 1982) screening tool. Females who scored higher than 20 on the EAT-26 (Dotti & Lazzari, 1998) and did not report any current treatment for eating disorders were classified as “at-risk” for the study’s purposes and assigned to the RI (reference/independent) group, resulting in a total of 36 “at-risk” females. From the remaining participants who scored lower than 20 on the EAT-26 and did not report any current treatment for eating disorders, a random sample of 45 females was selected and assigned to the HC group. It was a requirement for both the HC and RI groups that participants have a normal Body Mass Index.

To be eligible for participation, individuals needed to demonstrate proficient command over both spoken and written Italian language. 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 et al., 2000). The eligibility criteria for all participants were evaluated through psychologist interviews by trained psychologists. 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 study's specific objectives, ensuring a blind study design.

Procedure

During the initial session, participants underwent a clinical interview to determine their eligibility for the study. Those who met the criteria and were selected proceeded to anthropometric measurements and were asked to complete the psychometric scales listed below. In a subsequent session, participants completed the PRL task and were subsequently provided with a debriefing.

We compared the characteristics of the clinical sample with the controls by administering the following scales: the EAT-26, the Body Shape Questionnaire-14 (BSQ-14; Dowson & Henderson, 2001), the Social Interaction Anxiety Scale (SIAS; Mattick & Clarke, 1998), the Depression Anxiety Stress Scale-21 (DASS-21; Lovibond & Lovibond, 1995), the Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965), the Multidimensional Perfectionism Scale (MPS-F; Frost et al., 1990), and the Raven's Standard Progressive Matrices (Raven et al., 2000). The results of these statistical analyses are provided in the Supplementary Information (SI).

During the Probabilistic Reversal Learning (PRL) task, participants were presented with two stimuli simultaneously on a screen and were instructed to select one within a 2.5-second time limit by pressing a key. Trials were presented in an interleaved manner, with a randomly drawn inter-trial interval ranging from 0.5 to 1.5 seconds. Following each trial, a euro coin image was displayed as a reward for correct responses, while a strike-through image of a euro coin served as a punishment for incorrect responses. Feedback was provided for 2 seconds after each trial.

The PRL task consisted of two blocks, each containing 160 trials. One block included pairs of food-related and food-unrelated images, while the other block exclusively used food-unrelated images. The images were selected randomly from sets of food-related and food-unrelated categories.

All images used in the study were obtained from the International Affective Picture System (IAPS) database (Lang et al., 2005). The food-related category consisted of images of french fries, cake, pancake, cheeseburger, and cupcake (IAPS #7461, 7260, 7470, 7451, 7405), while the food-unrelated category included images of a lamp, book, umbrella, basket, and clothespin (IAPS #7175, 7090, 7150, 7041, 7052). For the control task, five images were used for each of the two food-unrelated categories, i.e., five images of flowers (IAPS #5000, 5001, 5020, 5030, 5202) and five images of objects (IAPS #7010, 7020, 7034, 7056, 7170).

The PRL task comprised four epochs, each consisting of 40 trials where the same image was considered correct. Feedback during the task was probabilistic, with the correct image being rewarded in 70% of the trials, while negative feedback was provided in the remaining 30% of the trials. Both blocks of the task included three rule changes in the form of reversal phases. Participants were informed that stimulus-reward contingencies would change, but not the specifics of how or when this would occur. The objective of the participants was to maximize their earnings, which were displayed at the end of each block. Participants underwent a training block consisting of 20 trials prior to the start of the actual experiment. The Psychtoolbox extensions in MATLAB (MathWorks) were used to program the tasks (Brainard, 1997).

Data analysis

To model the two-choice decision over time in the PRL task, we used a hierarchical reinforcement learning drift diffusion model (RLDDM), as described in Pedersen, Frank, and Biele (2017) and Pedersen and Frank (2020). The RLDDM was estimated in a hierarchical Bayesian framework using the `HDDMrl` module of the `HDDM` (version 0.9.7) Python package (Fengler et al., 2021; Wiecki et al., 2013). It has been shown that hierarchical modeling of reinforcement learning task provides the best predictive accuracy compared to other methods (Geen & Gerraty, 2021; e.g., Gershman, 2016).

We chose a Bayesian approach for our study because estimating RLDDM models is currently limited to Markov Chain Monte Carlo (MCMC) procedures. Moreover, by prioritizing estimation over hypothesis testing, the Bayesian approach overcomes the binary nature of decision-making inherent in null hypothesis significance testing (NHST) (Kruschke & Liddell, 2018). We determined credible effects by examining 95% credible intervals or assessing the proportion of posterior samples (97.5%) indicating the direction of the effect.

Cognitive modeling analysis allows us to deconstruct decision-making task performance into its component processes. This approach enables the identification of deviations in the underlying mechanisms that may not be evident in the overall task outcome. RLDDM has six basic parameters: positive learning rate ($alpha^+$), negative learning rate ($alpha^-$), drift rate (v), decision threshold (a), non-decision time (t), and starting point bias (z) parameters. The α parameter quantifies the learning rate in the Rescorla-Wagner delta learning rule (Rescorla & Wagner, 1972); a higher learning rate results in rapid adaptation to reward expectations, while a lower learning rate results in slow adaptation. The parameter α^+ is computed from reinforcements, whereas α^+ is computed from punishments. The drift rate v is the average speed of evidence accumulation toward one decision. The decision boundary is the distance between two decision thresholds; an increase of a increases the evidence needed to make a decision. The increase of a leads to a slower but more accurate decision; a decrease in a results in a faster but error-prone decision. The non-decision time t is the time spent for stimuli encoding or motor execution (*i.e.*, time not used for evidence accumulation). The starting point parameter z captures a potential initial bias toward one or the other boundary in absence of any stimulus evidence.

Transparency Openness

We report all data exclusion criteria and how the sample size was determined. All measures used in this study are reported. Data and analysis code are available upon request to the corresponding author. Data were analyzed using Python and R version 4.3.1. The study was not preregistered.

Results

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 relative to HCs. For more detailed information regarding these comparisons, please refer to the Supplementary Information (SI).

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

Reinforcement learning and drift diffusion modeling

To test the interference of disease-related information on the decision process, we compared several RLDDMs in which we conditioned either none, each or all model's parameters on group and context (disorder-related vs. disorder-unrelated information). For each model, we computed the Deviance Information Criterion (DIC), and we selected the model with the best trade-off between the fit quality and model complexity (i.e., the model with the lowest DIC). The following RLDDM models were examined.

1. Model M1: This is the standard RLDDM. DIC = 39879.444.
2. Model M2: Extending M1, it includes separate learning rates for positive and negative reinforcements. DIC = 39124.890
3. Model M3: In this model, the α^+ and α^- parameters are based on the diagnostic group. DIC = 39194.763.
4. Model M4: Building upon M3, the α^+ and α^- parameters are conditioned on both the diagnostic group and image category. DIC = 38197.467.
5. Model M5: Expanding on M4, it considers the potential influence of both the

diagnostic group and image category on the a parameter. DIC = 36427.448.

6. Model M6: Extending M5, it takes into account the possible influence of both the diagnostic group and image category on the drift rate (v) parameter. DIC = 36185.146.
7. Model M7: Building upon M6, it considers the potential influence of both the diagnostic group and image category on the non-decision time (t) parameter. DIC = 34904.053.
8. Model M8: Adding to Model M7, it estimates a potential bias in the starting point (z) parameter. DIC = 34917.762.

All the models were estimated using Bayesian methods with weakly informative priors. The model with the lowest DIC was Model M7. In Model M7, the parameters α^+, α^-, a, v, and t (excluding z) are conditioned on both the diagnostic group and image category.

Model M7 was estimated using 15,000 iterations, with a burn-in period of 5,000 iterations. Convergence of the Bayesian estimation was evaluated using the Gelman-Rubin statistic. For all parameters in Model M7, the $\hat{R}$ values were below 1.1 (maximum = 1.025, mean = 1.002), indicating no significant convergence issues. Collinearity and posterior predictive checks were also used to evaluate model validity (see SI).

To investigate the impact of disorder-related versus disorder-unrelated information on RL learning, we compared the posterior estimates of the RLDDM parameters of M7 between the two conditions (see Table 1).

Table 1

Posterior Parameter Estimates of DDMRL Model M7 by Group (R-AN, HC, RI) and Context of PRL Choice (disorder-related vs. disorder-unrelated information). The learning rates (α) are shown on a logit scale. The probability (p) describes the Bayesian test that the posterior estimate of the parameter in the disorder-related context is greater than the posterior estimate of the parameter in the disorder-unrelated context. Standard deviations are provided in parentheses.

Group	Par.	Neutral choice	Food choice	p	Cohen's d
R-AN	a	**1.273** (0.039)	**1.442** (0.040)	0.0013	0.802
R-AN	v	1.403 (0.320)	1.776 (0.342)	0.7907	0.190
R-AN	t	0.188 (0.011)	0.174 (0.011)	0.8311	-0.253
R-AN	α^-	1.815 (1.081)	0.738 (1.096)	0.2349	-0.432
R-AN	α^+	**1.006** (0.899)	**-1.786** (0.756)	0.0098	-1.206
HC	a	**1.222** (0.033)	**1.314** (0.034)	0.0256	0.474
HC	v	2.157 (0.265)	1.790 (0.263)	0.1606	-0.358
HC	t	0.183 (0.009)	0.172 (0.009)	0.8228	-0.280
HC	α^-	2.780 (0.874)	3.442 (0.980)	0.6993	0.298
HC	α^+	1.198 (0.680)	1.326 (0.700)	0.5544	0.071
RI	a	1.245 (0.041)	1.316 (0.039)	0.1026	0.403
RI	v	2.197 (0.322)	1.849 (0.307)	0.2133	-0.381
RI	t	0.188 (0.011)	0.186 (0.011)	0.5462	0.166
RI	α^-	2.857 (1.067)	2.904 (1.062)	0.5101	0.015
RI	α^+	1.573 (0.847)	0.739 (0.752)	0.2247	-0.438

The results reveal that the R-AN group exhibits a decreased learning rate following positive prediction errors (PEs) when making choices associated with disorder-related information, in contrast to choices linked to disorder-unrelated information (Cohen's d = 1.206, p =0.0098). Instead, there were no evidence of a credible difference in the learning rate between disorder-related and disorder-unrelated conditions in the HC and RI groups.

Moreover, we found that both the R-AN (Cohen's $d = 0.802$, $p = 0.0013$) and HC (Cohen's $d = 0.474$, $p = 0.0256$) groups showed a higher decision threshold when making choices related to disorder-related information compared to choices related to disorder-unrelated information. This finding aligns with the results reported in the studies by Caudek et al. (2021) and Schiff, Testa, Rusconi, Angeli, and Mapelli (2021), indicating a general tendency among individuals to adopt a more cautious decision-making approach in the context of food-related choices, as opposed to choices unrelated to food.

Further evidence of context-dependent learning emerges from between-groups comparisons. When confronted with choices related to disorder-related information, individuals with R-AN displayed a decreased learning rate following positive prediction errors (PEs) compared to both HC and RI. Specifically, the learning rate after positive PEs was lower for R-AN compared to HC, $p = 0.0009$, Cohen's $d = 1.498$. Similarly, R-AN exhibited a lower learning rate after positive PEs compared to RI ($p = 0.0085$, Cohen's d = 1.209). In contrast, no credible difference in the learning rate after positive PEs was found between R-AN and HC ($p = 0.4325$), as well as between R-AN and RI ($p = 0.3232$), for choices unrelated to disorder information.

Concerning the learning rate after negative PEs, we found that R-AN showed a lower learning rate compared to HC, but only when making choices related to disorder-related information: ($p = 0.0274$, Cohen's $d = 1.144$).

Individuals with R-AN also showed a higher decision threshold when making choices related to disorder-related information compared to choices compared to both HC (Cohen's d $= 0.622$, $p = 0.0068$) and RI (Cohen's $d = 0.454$, $p = 0.0118$) participants. No credible group differences were found when considering choices unrelated to disorder information.

Additionally, we observed that both HC (Cohen's $d = 0.520$, $p = 0.0344$) and RI (Cohen's $d = 0.529$, $p = 0.0392$) participants exhibited a faster accumulation of evidence and more confident decision-making, as indicated by a higher average drift rate parameter, compared to individuals with R-AN. This difference was only evident for choices unrelated to disorder information.

Finally, no credible differences were found, both within-group and between-group, regarding the non-decision time parameter (t).

Biased choices

To investigate a potential bias against food choices in individuals with R-AN during the PRL task, regardless of their past action-outcome history, we examined the frequency of food choices in PRL blocks where a food image was paired with a neutral image. Our findings indicate no bias against the food image in the AN-R group, with a proportion of food choices of 0.49, 95% CI [0.46, 0.51]. Moreover, there were no credible differences between groups: contrast R-AN - HC = -0.007, 95% CI [-0.037, 0.024]; contrast R-AN - RI = 0.013, 95% CI [-0.019, 0.046].

Comorbidity

To ensure the broader applicability of our findings to the psychiatric population (Woodside & Staab, 2006), we included individuals with R-AN who also had comorbid psychiatric conditions. Among the 40 individuals with R-AN in our study, comorbidities included anxiety disorder (n=16), OCD (n=8), social phobia (n=1), and DAP (n=1). In a further statistical analysis, we examined whether these comorbid conditions influence the conservative learning behavior observed in individuals with R-AN when making disorder-related choices. We applied model M7 to the individuals with R-AN and categorized them based on the presence or absence of diagnosed comorbidities. Our statistical analysis revealed no credible differences in parameters between the two groups. For the disorder-related context, the parameter differences were as follows: $\Delta\alpha^{-}$ = 2.614, 95% CI [-3.173, 8.364]; $\Delta\alpha^{+}$ = -0.635, 95% CI [-4.301, 2.449]; Δa = -0.034, 95% CI [-0.188, 0.124]; Δv = 0.230, 95% CI [-1.203, 1.586]; Δt = 0.002, 95% CI [-0.050, 0.055]. For the disorder-unrelated context, the parameter differences were: $\Delta\alpha^{-}$ = -0.768, 95% CI [-6.570, 4.401]; $\Delta\alpha^{+}$ = -1.739, 95% CI [-6.184, 1.654]; Δa = -0.126, 95% CI [-0.281, 0.025]; Δv = 0.744, 95% CI [-0.453, 1.886]; Δt = -0.003, 95% CI [-0.057, 0.052].

Discussion

In this within-subjects study, we examined how disorder-related information impacts probabilistic reversal learning in individuals with restrictive anorexia nervosa (R-AN), healthy female participants (HC), and females at-risk of developing eating disorders (RI). Our findings supported our hypotheses, revealing that R-AN patients exhibited slower learning after positive prediction errors (positive outcomes) related to the disorder, compared to when the outcomes were unrelated to the disorder. Instead, we did not find any difference in the learning rate between disorder-related and disorder-unrelated information in the HC and RI groups.

Furthermore, we noticed that individuals with R-AN exhibited lower learning rates for both positive and negative prediction errors in comparison to the HC group. However, this discrepancy was observed only when the choices were related to disorder-related information. When it came to making choices based on images displaying disorder-unrelated information, no substantial difference in learning rates was observed between the R-AN and HC groups. When comparing the RI and R-AN groups, we found that individuals with R-AN exhibited slower learning rates than RI participants when they experienced positive prediction errors associated with the disorder. However, this difference was not found when the choices involved disorder-unrelated information.

We also observed significant contextual effects on the DDM parameters of the hDDMrl model. Specifically, we found that, on average, the R-AN group had a higher decision threshold (parameter "a" in the hDDMrl model) compared to the HC and RI groups, but only when making choices related to disorder-related information. This indicates that individuals with R-AN displayed a more cautious or conservative decision-making behavior than the HC and RI groups specifically in situations involving disorder-related information.

Furthermore, we found that both the R-AN and HC groups showed a higher decision threshold when making choices related to disorder-related information compared to choices related to disorder-unrelated information. This finding aligns with the results reported in the studies by Caudek et al. (2021) and Schiff et al. (2021), indicating a general tendency among individuals to adopt a more cautious decision-making approach in the context of food-related choices, as opposed to choices unrelated to food.

Additionally, we observed that both HC and RI participants exhibited a faster accumulation of evidence and more confident decision-making, as indicated by a higher average drift rate parameter, compared to individuals with R-AN. However, this difference was only evident for choices unrelated to disorder information.

There is a growing consensus that reward and punishment processing in anorexia nervosa (AN) is not a generic process, but rather influenced by complex interactions between stimulus properties (e.g., type of reward/punishment cue) and contextual factors (e.g., long-term objectives, personality traits, temperamental dispositions, physiological states like hunger, etc.). A recent comprehensive review by @Haynos, Lavender, Nelson, Crow, and Peterson (2020) demonstrated that how individuals with AN perceive their experiences as rewarding or punishing is influenced by factors such as predictability, controllability, immediacy, and effort. For instance, behaviors associated with AN that are predictable, controllable, and immediate (e.g., calorie counting or purging) may be rewarding, providing a sense of control and accomplishment. Conversely, behaviors that are unpredictable and uncontrollable (e.g., social outcomes) may be perceived as punishing, leading to increased anxiety and distress.

However, most previous studies have primarily focused on exploring the subjective value assigned to various experiences by individuals with AN, regardless of their inherent rewarding or punishing properties. In contrast, the current study investigates the impact of contextual factors on reinforcement learning (RL). To our knowledge, this is the first study to demonstrate that individuals with R-AN exhibit slower learning specifically for disorder-related choices, while maintaining intact RL performance for disorder-unrelated choices. These findings challenge the notion of a domain-general RL mechanism impairment in this population.

It is important to acknowledge that the experimental manipulation employed in this study is irrelevant to the task outcome, meaning that optimal reinforcement learning (RL) performance should not be affected by it. However, we observed a significant impact of this manipulation on the PRL performance of individuals with R-AN, while no such impact was observed in the performance of healthy controls (HCs) and healthy controls at risk of eating disorders. In the existing literature, there are limited pieces of evidence regarding the influence of outcome-irrelevant information on RL in the general population. Notably, Shahar et al. (2019) demonstrated that image/effector response mapping can affect associative learning in a PRL task, even if only image identity predicts rewards. As detailed in the Supplementary Information (SI), we successfully replicated these findings across all three groups included in our study, thus further supporting the notion that various forms of outcome-irrelevant information can impact RL learning, both in the general population and in individuals with eating disorders. It is noteworthy that the effects of image/effector response mapping described by Shahar et al. (2019) appear to be similar in both the general population and the patient groups, whereas the effects of outcome-irrelevant disorder-related information were specific to the R-AN group.

Otherr recent studies have focused on investigating context-specific learning in eating disorders. One task specifically designed for this purpose is the two-step Markov decision task, which distinguishes between automatic or habitual (model-free) learning and controlled or goal-directed (model-based) learning. For instance, studies conducted by Foerde et al. (2021) and Onysk and Seriès (2022) employed similar experiments using the two-step task paradigm. Foerde et al. (2021) compared a monetary two-step task and a food-related two-step task, while Onysk and Seriès (2022) utilized stimuli unrelated to food or body images (i.e., pirate ships and treasure chests) with rewards associated with body image dissatisfaction.

The results of these studies consistently demonstrated that individuals with AN tend to exhibit a stronger inclination towards habitual control over goal-directed control across different domains compared to healthy controls. However, no significant differences were observed in learning rates as a function of context, nor between AN patients and healthy controls, according to these findings. In contrast, the present study reveals that the learning process itself in individuals with R-AN can be influenced by disorder-related information, even when such information is not directly relevant to the task outcome.

The implications of the present findings, if replicated by future studies, are relevant to the treatment of anorexia nervosa (AN). Current treatment practices address the issue of cognitive inflexibility in AN, with Cognitive Remediation Therapy (CRT) being proposed as an adjunct treatment targeting specific cognitive processes in AN and other eating disorders. CRT involves cognitive exercises and behavioral interventions aimed at improving central coherence abilities, reducing cognitive and behavioral inflexibility, and enhancing thinking style comprehension (Tchanturia, Davies, Reeder, & Wykes, 2010). A key aspect of CRT is to avoid focusing on symptom-related themes and instead utilize neutral stimuli in cognitive and behavioral exercises. This approach aims to establish a therapeutic alliance and reduce drop-out rates, particularly among AN patients.

However, recent evidence suggests that CRT may not consistently enhance central coherence abilities, cognitive flexibility, or symptoms associated with eating disorders (Hagan, Christensen, & Forbush, 2020; Tchanturia, Giombini, Leppanen, & Kinnaird, 2017). In response to this, Trapp, Heid, Röder, Wimmer, and Hajak (2022) have proposed improvements to address practical issues encountered in the application of CRT. They question the use of neutral stimuli and draw support from Beck's cognitive theory of depression (Beck & Alford, 2009).

The proposition presented by Trapp et al. (2022) aligns with the hypothesis of our study, which suggests that contextual factors play a crucial role in the maladaptive eating behavior observed in individuals with R-AN, extending beyond deficits in the underlying reinforcement learning mechanism alone. If abnormal reward learning is indeed identified as a significant anomaly among individuals with R-AN, particularly in relation to disorder-relevant choices, it would imply that treatments focused on enhancing cognitive flexibility and reinforcement learning processes specific to disorder-relevant stimuli could hold significant promise for this population.

There are several important questions that remain for future research. 1) One aspect to consider is the use of symbolic rewards and punishments in our study, represented by images of a one euro coin and a barred representation of a one euro coin, respectively. These rewards and punishments were merely symbolic, and it is unclear how the use of concrete, non-symbolic rewards and punishments would impact the findings. Additionally, the subjective value of one euro, or the loss of one euro, may vary among participants. Therefore, future studies could aim to determine the equivalence of subjective values for rewards and punishments to enhance the understanding of the underlying processes. 2) Our study only included individuals with R-AN who were not in the most severe stage of the illness, as they were recruited from a center for voluntary medical and psychological support. We did not examine R-AN patients who require hospitalization due to the life-threatening nature of their illness. It is possible that at the later stages of the illness, associative learning abilities, which were preserved in the present sample under neutral conditions, may become impaired. Therefore, investigating the impact of illness severity on context-dependent learning in R-AN patients is an important avenue for future research. 3) While we observed no difference in the choice behavior of R-AN patients, as measured by the relative frequency of image choices, when selecting between a neutral image and a food image, we did find a slower learning rate and lower decision threshold for R-AN patients compared to healthy controls in the RLDDM model when compared to choosing between two neutral images. It is possible that the higher "salience" of food images compared to neutral images could be better captured by other measures, such as fixation length or the number of fixations, rather than solely relying on the relative frequency of image choices. This warrants further exploration in future studies. 4) It is worth noting that our study excluded women under the age of 18. However, this age range is a critical period as the onset of AN during this stage may have a more profound impact on associative learning, given the ongoing cognitive development and less-developed protective factors. Therefore, future studies should take into consideration the inclusion of participants in this age range to better understand the influence of context-dependent learning in R-AN.

References

American Psychiatric Association. (2022). *Diagnostic and Statistical Manual of Mental Disorders* (5th ed., Text Revision). Arlington, VA: American Psychiatric Publishing.

Atwood, M. E., & Friedman, A. (2020). A systematic review of enhanced cognitive behavioral therapy (CBT-e) for eating disorders. *International Journal of Eating Disorders*, *53*(3), 311–330.

Bartholdy, S., Dalton, B., O'Daly, O. G., Campbell, I. C., & Schmidt, U. (2016). A systematic review of the relationship between eating, weight and inhibitory control using the stop signal task. *Neuroscience & Biobehavioral Reviews*, *64*, 35–62.

Beck, A. T., & Alford, B. A. (2009). *Depression: Causes and treatment.* University of Pennsylvania Press.

Bernardoni, F., King, J. A., Geisler, D., Birkenstock, J., Tam, F. I., Weidner, K., … Ehrlich, S. (2018). Nutritional status affects cortical folding: Lessons learned from Anorexia Nervosa. *Biological Psychiatry*, *84*(9), 692–701.

Bischoff-Grethe, A., McCurdy, D., Grenesko-Stevens, E., Irvine, L. E. Z., Wagner, A., Yau, W.-Y. W., et al.others. (2013). Altered brain response to reward and punishment in adolescents with anorexia nervosa. *Psychiatry Research: Neuroimaging*, *214*(3), 331–340.

Castro, L. N. G., Hadjiosif, A. M., Hemphill, M. A., & Smith, M. A. (2014). Environmental consistency determines the rate of motor adaptation. *Current Biology*, *24*(10), 1050–1061.

Caudek, C., Sica, C., Cerea, S., Colpizzi, I., & Stendardi, D. (2021). Susceptibility to eating disorders is associated with cognitive inflexibility in female university students. *Journal of Behavioral and Cognitive Therapy*, *31*(4), 317–328.

Chang, P. G., Delgadillo, J., & Waller, G. (2021). Early response to psychological treatment for eating disorders: A systematic review and meta-analysis. *Clinical Psychology Review*, *86*, 102032.

Collins, A. G., & McDougle, S. D. (2021). *Context is key for learning motor skills.* Nature Publishing Group UK London.

Fladung, A.-K., Schulze, U. M., Schöll, F., Bauer, K., & Groen, G. (2013). Role of the ventral striatum in developing anorexia nervosa. *Translational Psychiatry*, *3*(10), e315–e315.

Foerde, K., Daw, N. D., Rufin, T., Walsh, B. T., Shohamy, D., & Steinglass, J. E. (2021). Deficient goal-directed control in a population characterized by extreme goal pursuit. *Journal of Cognitive Neuroscience*, *33*(3), 463–481.

Foerde, K., & Steinglass, J. E. (2017). Decreased feedback learning in anorexia nervosa persists after weight restoration. *International Journal of Eating Disorders*, *50*(4), 415–423.

Galmiche, M., Déchelotte, P., Lambert, G., & Tavolacci, M. P. (2019). Prevalence of eating disorders over the 2000–2018 period: A systematic literature review. *The American Journal of Clinical Nutrition*, *109*(5), 1402–1413.

Geen, C. van, & Gerraty, R. T. (2021). Hierarchical bayesian models of reinforcement learning: Introduction and comparison to alternative methods. *Journal of Mathematical Psychology*, *105*, 102602.

Gershman, S. J. (2016). Empirical priors for reinforcement learning models. *Journal of Mathematical Psychology*, *71*, 1–6.

Glashouwer, K. A., Bloot, L., Veenstra, E. M., Franken, I. H., & Jong, P. J. de. (2014). Heightened sensitivity to punishment and reward in anorexia nervosa. *Appetite*, *75*, 97–102.

Guillaume, S., Gorwood, P., Jollant, F., Van den Eynde, F., Courtet, P., & Richard-Devantoy, S. (2015). Impaired decision-making in symptomatic anorexia and bulimia nervosa patients: A meta-analysis. *Psychological Medicine*, *45*(16), 3377–3391.

Hagan, K. E., Christensen, K. A., & Forbush, K. T. (2020). A preliminary systematic review and meta-analysis of randomized-controlled trials of cognitive remediation therapy for anorexia nervosa. *Eating Behaviors*, *37*, 101391.

Harrison, A., Genders, R., Davies, H., Treasure, J., & Tchanturia, K. (2011). Experimental measurement of the regulation of anger and aggression in women with anorexia nervosa. *Clinical Psychology & Psychotherapy*, *18*(6), 445–452.

Haynos, A. F., Lavender, J. M., Nelson, J., Crow, S. J., & Peterson, C. B. (2020). Moving towards specificity: A systematic review of cue features associated with reward and punishment in anorexia nervosa. *Clinical Psychology Review*, *79*, 101872.

Haynos, A. F., Widge, A. S., Anderson, L. M., & Redish, A. D. (2022). Beyond description and deficits: How computational psychiatry can enhance an understanding of decision-making in anorexia nervosa. *Current Psychiatry Reports*, 1–11.

Herzfeld, D. J., Vaswani, P. A., Marko, M. K., & Shadmehr, R. (2014). A memory of errors in sensorimotor learning. *Science*, *345*(6202), 1349–1353.

Jappe, L. M., Frank, G. K., Shott, M. E., Rollin, M. D., Pryor, T., Hagman, J. O., … Davis, E. (2011). Heightened sensitivity to reward and punishment in anorexia nervosa. *International Journal of Eating Disorders*, *44*(4), 317–324.

Jonker, N. C., Glashouwer, K. A., & Jong, P. J. de. (2022). Punishment sensitivity and the persistence of anorexia nervosa: High punishment sensitivity is related to a less favorable course of anorexia nervosa. *International Journal of Eating Disorders*, *55*(5), 697–702.

Keating, C. (2010). Theoretical perspective on anorexia nervosa: The conflict of reward. *Neuroscience & Biobehavioral Reviews*, *34*(1), 73–79.

Keating, C., Tilbrook, A. J., Rossell, S. L., Enticott, P. G., & Fitzgerald, P. B. (2012). Reward processing in anorexia nervosa. *Neuropsychologia*, *50*(5), 567–575.

Kruschke, J. K., & Liddell, T. M. (2018). Bayesian data analysis for newcomers. *Psychonomic Bulletin & Review*, *25*(1), 155–177.

Linardon, J., Fairburn, C. G., Fitzsimmons-Craft, E. E., Wilfley, D. E., & Brennan, L. (2017). The empirical status of the third-wave behaviour therapies for the treatment of eating disorders: A systematic review. *Clinical Psychology Review*, *58*, 125–140.

Matton, A., Goossens, L., Braet, C., & Vervaet, M. (2013). Punishment and reward sensitivity: Are naturally occurring clusters in these traits related to eating and weight problems in adolescents? *European Eating Disorders Review*, *21*(3), 184–194.

Monteleone, A. M., Monteleone, P., Esposito, F., Prinster, A., Volpe, U., Cantone, E., et al.others. (2017). Altered processing of rewarding and aversive basic taste stimuli in symptomatic women with anorexia nervosa and bulimia nervosa: An fMRI study. *Journal of Psychiatric Research*, *90*, 94–101.

O'Doherty, J., Winston, J., Critchley, H., Perrett, D., Burt, D. M., & Dolan, R. J. (2003). Beauty in a smile: The role of medial orbitofrontal cortex in facial attractiveness. *Neuropsychologia*, *41*(2), 147–155.

O'Hara, C. B., Campbell, I. C., & Schmidt, U. (2015). A reward-centred model of anorexia nervosa: A focussed narrative review of the neurological and psychophysiological literature. *Neuroscience & Biobehavioral Reviews*, *52*, 131–152.

Onysk, J., & Seriès, P. (2022). The effect of body image dissatisfaction on goal-directed decision making in a population marked by negative appearance beliefs and disordered eating. *Plos One*, *17*(11), e0276750.

Pedersen, M. L., & Frank, M. J. (2020). Simultaneous hierarchical bayesian parameter estimation for reinforcement learning and drift diffusion models: A tutorial and links to neural data. *Computational Brain & Behavior*, *3*, 458–471.

Pedersen, M. L., Frank, M. J., & Biele, G. (2017). The drift diffusion model as the choice rule in reinforcement learning. *Psychonomic Bulletin & Review*, *24*, 1234–1251.

Qian, J., Wu, Y., Liu, F., Zhu, Y., Jin, H., Zhang, H., . . . Yu, D. (2022). An update on the prevalence of eating disorders in the general population: A systematic review and meta-analysis. *Eating and Weight Disorders-Studies on Anorexia, Bulimia and Obesity*, *27*(2), 415–428.

Rescorla, R. A., & Wagner, A. R. (1972). A theory of pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. In A. H. Black & W. F. Prokasy (Eds.), *Classical conditioning II: Current research and theory* (pp. 64–69). New York, NY: Appleton-Century Crofts.

Schaefer, L. M., & Steinglass, J. E. (2021). Reward learning through the lens of RDoC: A review of theory, assessment, and empirical findings in the eating disorders. *Current Psychiatry Reports*, *23*, 1–11.

Schiff, S., Testa, G., Rusconi, M. L., Angeli, P., & Mapelli, D. (2021). Expectancy to eat modulates cognitive control and attention toward irrelevant food and non-food images in healthy starving individuals. A behavioral study. *Frontiers in Psychology*, *11*, 3902.

Selby, E. A., & Coniglio, K. A. (2020). Positive emotion and motivational dynamics in anorexia nervosa: A positive emotion amplification model (PE-AMP). *Psychological Review*, *127*(5), 853–890.

Shahar, N., Moran, R., Hauser, T. U., Kievit, R. A., McNamee, D., Moutoussis, M., ... Dolan, R. J. (2019). Credit assignment to state-independent task representations and its relationship with model-based decision making. *Proceedings of the National Academy of Sciences*, *116*(32), 15871–15876.

Smink, F. R., Hoeken, D. van, & Hoek, H. W. (2013). Epidemiology, course, and outcome of eating disorders. *Current Opinion in Psychiatry*, *26*(6), 543–548.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction.* Cambridge, MA: MIT Press.

Tchanturia, K., Davies, H., Reeder, C., & Wykes, T. (2010). *Cognitive remediation therapy for anorexia nervosa.* London: King's College London.

Tchanturia, K., Giombini, L., Leppanen, J., & Kinnaird, E. (2017). Evidence for cognitive remediation therapy in young people with anorexia nervosa: Systematic review and meta-analysis of the literature. *European Eating Disorders Review*, *25*(4), 227–236.

Trapp, W., Heid, A., Röder, S., Wimmer, F., & Hajak, G. (2022). Cognitive remediation in psychiatric disorders: State of the evidence, future perspectives, and some bold ideas. *Brain Sciences*, *12*(6), 683.

Wagner, A., Aizenstein, H., Venkatraman, V. K., Fudge, J., May, J. C., Mazurkewicz, L., et al.others. (2007). Altered reward processing in women recovered from anorexia nervosa.

American Journal of Psychiatry, *164*(12), 1842–1849.

Wierenga, C. E., Ely, A., Bischoff-Grethe, A., Bailer, U. F., Simmons, A. N., & Kaye, W. H. (2014). Are extremes of consumption in eating disorders related to an altered balance between reward and inhibition? *Frontiers in Behavioral Neuroscience*, *8*, 410.

Woodside, B. D., & Staab, R. (2006). Management of psychiatric comorbidity in anorexia nervosa and bulimia nervosa. *CNS Drugs*, *20*, 655–663.

Wu, M., Brockmeyer, T., Hartmann, M., Skunde, M., Herzog, W., & Friederich, H.-C. (2014). Set-shifting ability across the spectrum of eating disorders and in overweight and obesity: A systematic review and meta-analysis. *Psychological Medicine*, *44*(16), 3365–3385.