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Difficulty in updating positive beliefs about negative cognition is associated with increased depressed mood

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ABSTRACT

Background and objectives: Depressed people hold positive beliefs about negative cognition (e.g., rumination is useful to find a solution), which may motivate those individuals to engage in sustained negative thinking. However, in reality, rumination often leads to unfavorable outcomes. Thus, such beliefs create a large discrepancy between one's expectations and the actual outcome. Therefore, we hypothesized that this prediction error would be associated with increased depressed mood.
Methods: We observed how people update their positive beliefs about negative cognition within a volatile environment, in which negative cognition does not always result in a beneficial outcome. Forty-six participants were offered two response options (retrieving a negative or positive personal memory) and subsequently provided either an economic reward or punishment. Retrieving a negative (rather than positive) memory was initially reinforced, although this action-outcome contingency was reversed during the task. In the control condition, positive memory retrieval was initially reinforced, although a contingency reversal was employed to encourage negative memory retrieval.
Results: Model-based computational modeling revealed that participants who showed a delay in switching from negative to positive (but not from positive to negative) responses experienced increased levels of depressed mood. This delay in switching was also found to be associated with depressive symptoms and trait rumination.
Limitations: The non-clinical nature of the sample may limit the clinical implications of the results.
Conclusions: Difficulty in updating positive beliefs (or outcome predictions) for negative cognition may play an important role in depressive symptomatology.

1. Introduction

Persistent negative cognition, such as depressive rumination (Nolen-Hoeksema, Wisco, & Lyubomirsky, 2007), is recognized as one of the most important risk factors for depression. Rumination is defined as repetitively attending to one's feelings and problems, and is predominantly characterized by excessive automatic negative thoughts (Nolen-Hoeksema, 1991, 2000). Cognitive theories of depression emphasize the role of biased emotional information processing, including the preferential recall of negative compared to positive memories (Gotlib & Joormann, 2010; Mathews & MacLeod, 2005). A meta-analytic study has suggested that people with depression remember more negative than positive information. Conversely, non-depressed individuals tend to possess a normative positivity bias, i.e., they recall more positive than negative information (Matt, Vazques, & Campbell, 1992). This normative positive bias could serve as a shield against negative depressive processing, while preserving and promoting positive mental states (Mezulis, Abrahamson, Hyde & Hankin, 2004).

One critical issue with depressive cognition is that it is persistent and uncontrollable; moreover, combined with a negativity bias it can progress into depressive rumination (e.g., Koster et al., 2011). The "sticky" nature of depressive cognition can be partly explained by a persistent "positive" belief that negative cognitive activities lead to beneficial outcomes. Papageorgiou and Wells (2001, 2003) have suggested that people with depression tend to regard rumination as a useful coping strategy to find a solution in difficult or otherwise distressing situations. These positive beliefs often appear at the beginning of an episode of persistent negative thinking, through which the individual aims to minimize discrepancies between their expected (or desired) and actual states (Roelofs et al., 2007). This positive belief is

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consistent with the extant learning theory on depression, which has proposed that (a) negative, depressive thoughts are initially reinforced by "rewarding" experiences, such as successful problem solving (Watkins, 2008), and concern and compassion from others following negative self-disclosure (Coyne, 1976; Ramnerö, Folke, & Kanter, 2016); (b) the acquired negative thinking is maintained through an avoidance mechanism that motivates people to postpone overt actions and avoid risking failure and humiliation (Watkins & Nolen-Hoeksema, 2014). Kingston, Watkins, and Nolen-Hoeksema (2014) experimentally manipulated rumination, which indeed increased justification for not taking or avoiding overt actions. Avoidance can temporarily reduce distress because depressed individuals perceive taking action to be even more aversive than ruminating (Nolen-Hoeksema et al., 2007). However, withdrawing from aversive situations (or choosing rumination instead of active problem solving) ironically results in fewer chances to engage in potentially pleasant and rewarding activities and to interact with positive environmental stimuli (Ramnerö et al., 2016). Nevertheless, the acquired negative thinking is difficult to extinguish, as depressed people may maintain a higher "reward" expectancy for ruminating than for taking other types of actions (including other types of thinking, e.g., positive).

Importantly, negative cognitive activities are inherently aversive experiences as they arouse negative affect. Moreover, excessive use of negative self-reference can lead to social rejection from others (e.g., Coyne, 1976). Given such unfavorable outcomes, people who hold positive beliefs about negative cognition should often experience a large discrepancy between their expected (positive) outcomes and the actual (negative) consequences. For example, people may initially ruminate because they believe it will help them solve their current problems and thus, provide them with a sense of control and confidence. However, in reality, their ruminative thinking will only increase depressed mood and inactivity, and consequently impair their problem-solving capabilities (Lyubomirsky & Nolen-Hoeksema, 1995).

In learning psychology, this discrepancy is referred to as *prediction error* (e.g., Schultz, 2016). Typically, people (or rational learning agents) attempt to minimize prediction error through learning or action-feedback processes. If an agent is punished (or experiences a negative outcome) for a particular action, they will adopt a downward prediction, and thus believe that such an action no longer leads to a beneficial outcome. Consequently, the frequency with which they take that action will decrease. By updating their action-outcome prediction, people can optimize their behavior to maximize the benefits obtained by taking a certain action. However, regarding depression, this updating function seems to be blunted, because depression and/or rumination is associated with reduced sensitivity to reward (e.g., Pizzagalli, Jahn, & O'Shea, 2005) and with difficulty adapting a learned cognitive set to changing environmental contingencies (Davis & Nolen-Hoeksema, 2000; McAuliffe, Hughes, & Barnes-Holmes, 2014).

Depressive rumination has core features of habitual behavior, which is known to be resistant and insensitive to changes in goals and (de) valuation of outcomes (e.g., Watkins & Nolen-Hoeksema, 2014). The habit account of rumination provides an intriguing prediction; that is, individuals with depressive symptoms maintain a relatively high reward expectancy (or positive beliefs) for rumination, even when rumination is actually associated with unfavorable outcomes. Therefore, such individuals continuously experience a large discrepancy between their predicted and actual outcomes for negative thinking. This repetitive prediction error would be associated with increased depressed mood and a sense of helplessness, as people will find that their behavior (or rumination) cannot control reinforcement. Thus, in the present study, we tested the hypothesis that people with difficulty updating their beliefs regarding negative cognitive processing (for example, negative memory retrieval) would experience increased levels of depressed mood. This is likely due to a discrepancy between the actual negative outcomes of such negative thinking behavior and their more positive outcome expectations. Simultaneously, we explored whether there was any evidence of associations between this updating difficulty and depressive symptomatology.

To test these hypotheses, we developed a laboratory model to capture one's persistent positive beliefs, or difficulty updating action-outcome predictions, regarding negative cognition. In this pursuit, we employed an emotional version of the probabilistic reversal learning paradigm (cf. Izquierdo & Jentsch, 2012). In a classic reversal learning task, participants have to choose between two options. One option is associated with a higher probability of reward, while the other is associated with a higher probability of punishment. Typically, over the course of the training period, participants learn which of the two response options is more likely to result in a beneficial outcome. However, during the task, the learned response-reward contingency is reversed. To perform this task well, participants have to adapt their response behaviors to the contingency reversal and switch to the other, more beneficial, response option.

For the current "emotional" version of the task, participants were offered two response options, retrieving either a negative or positive personal memory. For example, if participants chose the "negative" option, they were asked to retrieve a memory related to a given negative word (e.g., "sad"). These personal memory recalls were probabilistically reinforced by an economic reward and punishment. Initially, participants were reinforced to retrieve a negative (rather than positive) personal memory. However, in the middle of the task, the action-outcome contingencies were reversed. As a result, negative memory retrieval was no longer the "correct" response, and was thus more likely to be punished. Therefore, participants were supposed to switch to "positive" memory retrieval, which was subsequently the correct response. To achieve this, participants had to update their beliefs (or outcome predictions) according to the contingency reversal. However, people who have difficulty updating their beliefs for negative memory retrieval would be more likely to experience increased levels of depressed mood, as they continuously remember personal negative memories and receive punishment. As a control condition, we established a positive-to-negative transition, in which positive memory retrieval was more likely to be rewarded in the first half of the trials, while the contingency reversal reinforced participants to choose the negative counterpart in the latter half. Because the resultant updating delay can lead to persistent positive memory retrieval, the speed of updating is not associated with depressed mood.

The emotional reversal learning task is an experimental analogy of persistent negative thinking and rumination because (a) retrieving negative memories is part of rumination (e.g., *Think about a recent situation, wishing it had gone better*; Nolen-Hoeksema, 1991); (b) a rumination induction is known to facilitate the recall of negative past events (e.g., Nolen-Hoeksema et al., 2007); and most importantly, (c) insensitivity to changes in outcome is a central feature of habitual behavior, and rumination is considered a mental habit that is difficult to oppose despite its negative consequences (Hertel, 2004; Watkins & Nolen-Hoeksema, 2014). Indeed, depressed individuals "choose to ruminate" (Papageorgiou & Wells, 2004, p. 12) because they maintain positive beliefs about rumination (they expect better outcomes than if they would make alternative behavioral choices, e.g., thinking about positive events). Another factor that promotes rumination is negative reinforcement through the avoidance of alternative actions, which are often perceived as aversive and difficult, but are potentially pleasant and rewarding (e.g., Nolen-Hoeksema et al., 2007). It has been established that individuals with depressive symptoms prefer negative to positive self-reference when they have to choose between negative and positive valence (Takano, Iijima, Sakamoto, Raes, & Tanno, 2016), and they also tend to experience difficulty updating their beliefs about their negative (vs. positive) self-reference when the outcome is variable (Iijima, Takano, Boddez, Raes, & Tanno, 2017).

Thus, we formulated the hypothesis that delayed belief updating would be associated with increased levels of depressed mood only in the experimental condition (which reinforces participants to switch from negative to positive memory retrieval), whereas this association would not emerge in the control condition with the reversed reinforcement schedule. The speed of belief updating was indexed using learning rates, which are latent parameters estimated by the Q-learning model (e.g., Watkins & Dayan, 1992). A learning rate represents the extent to which a participant updates their reward expectancy after experiencing an unexpected outcome (i.e., prediction error). As a larger value for a learning rate indicates faster belief updating, we specifically expected a negative association between a learning rate and depressive symptoms in the experimental, but not control, condition.

2. Method

2.1. Participants

Forty-six participants (9 men and 37 women; mean age = 23.1, *SD* = 5.6 years) were recruited from a large sample pool at the University of Leuven, comprising university students and others in the Leuven community. No inclusion/exclusion criteria were used, except that all participants had to be fluent Dutch speakers. Participants were randomly allocated to one of two conditions, Negative-to-Positive (*N* = 23) or Positive-to-Negative (*N* = 23), which used different learning schedules for the emotional reversal learning task (ERLT). Groups were not explicitly matched based on gender, age, level of depressive symptoms, or level of ruminative tendencies; no significant differences between the conditions were found for any of these variables (Table 1). Participants received monetary compensation (10 or 20 euros) for their participation, depending on their performance on the emotional reversal learning task.

2.2. Measures

2.2.1. Beck Depression Inventory II (BDI-II)

Depressive symptoms were measured using the BDI-II (Beck, Steer, & Brown, 1996; Van der Does, 2002b), which consists of 22 items representing typical depressive symptoms. Each item was rated on a 0–3 scale. The BDI-II showed good internal consistency in the current study (α = 0.90).

2.2.2. Ruminative Response Scale (RRS)

The tendency to ruminate was assessed using the RRS brooding subscale (Treynor, Gonzalez, & Nolen-Hoeksema, 2003; see also; Schoofs, Hermans, & Raes, 2010; Raes & Hermans, 2007), which consists of five items. Each item was rated on a 5-point scale (1 = *almost never*, 5 = *almost always*). Internal consistency for the RRS brooding subscale in the current study was good (α = 0.71).

Table 1
Means and SDs of questionnaires and task performances for the negative-to-positive (NtP) and positive-to-negative (PtN) Condition.

	NtP (*N* = 23)		PtN (*N* = 23)	
	Mean	*SD*	*Mean*	*SD*
BDI-II	10.04	8.59	8.04	6.32
RRS Brooding	10.17	2.87	10.13	3.49
POMS-D pre	2.78	4.16	2.09	3.19
POMS-D post	2.17	4.74	2.00	2.86
Performance on the ERLT				
Choice frequency of the “Negative” option				
Phase 1 (Acquisition, 1–13th trial)	0.59	0.25	0.23	0.18
Phase 2 (Acquisition, 14–26th trial)	0.72	0.21	0.17	0.16
Phase 3 (Reversal, 27–39th trial)	0.36	0.21	0.46	0.23
Phase 4 (Reversal, 40–52nd trial)	0.23	0.22	0.59	0.32
Q-learning parameters				
Learning rate (α_{reward})	0.35	0.12	0.32	0.12
Learning rate (α_{punish})	0.53	0.18	0.39	0.25
Exploitation (β)	3.99	1.83	3.53	1.35

Note. BDI-II = Beck Depression Inventory-II; POMS-D Pre, Post = Profile of Mood States Depression subscale, administered before and after the emotional reversal learning task; RRS = Ruminative Response Scale.

2.2.3. Profile of mood state – depressed mood subscale (POMS-D)

The POMS-D (Wald, 1984) was administered before and after the ERLT to assess the level of depressed mood. The POMS-D consists of 8 items rated on a 5-point scale (0 = *not at all*, 4 = *very much*). The POMS-D showed good internal consistency for the current data (α = 0.90).

2.3. The emotional reversal learning task (ERLT)

At the start of each trial, participants were asked to choose between two options: “negative” or “positive” memory retrieval (Fig. 1 A; “valence choice”), by pressing the “8” or “9” key. Participants were informed that if they chose the “negative” option, they would be asked to retrieve a memory in response to a negative cue word in the following display and that, on the other hand, if they chose the “positive” option, they would be asked to recall a memory in response to a positive cue word. Following this valence choice, participants were provided with a question containing an emotional cue word with the valence of their choice. This question probed whether they could retrieve the specific memory that they would need to retrieve based on the presented emotional cue word (e.g., “Can you remember an episode that made you feel *unhappy*?” or, “Can you remember an episode that made you feel *happy*?”). If participants thought that they could retrieve a specific memory in response to the presented cue word, they pressed the *yes* “8” key. However, if they could not come up with a memory, they pressed the *no* “9” key. Emotional cue words were randomly selected from a cue-word list, which consisted of 52 pairs of Dutch antonyms, such as *sad* vs. *happy* and *passive* vs. *active*. All cue words used in the present study were confirmed to have negative or positive valence in a pre-established database of Dutch emotional words (Moors et al., 2013).

After making the yes/no response for memory retrieval, participants received feedback in the form of either a reward or a punishment (as +5 or −5 point tokens). The reward/punishment was provided probabilistically depending on the participants' valence choices. Participants were explicitly informed that: (a) one of the two valence options was more likely to be associated with reward than the other option; (b) this option-reward contingency could change during the task; and (c) if participants indicated “no memory”, they would always receive punishment. Participants were also informed that if the total amount of points that they acquired during the task exceeded a certain criterion, they would receive an extra monetary compensation (10 euros) on top of the base amount (10 euros). The researcher did not mention the exact criterion to prevent participants’ reward devaluation during the task.

The current experiment had two conditions in terms of the reinforcement schedule: Negative-to-Positive (NtP) and Positive-to-Negative (PtN) condition (Fig. 1 B). In the NtP condition, participants were initially reinforced to choose the “negative” option, which was followed by a reward or punishment at the probabilities of 80:20% (i.e., the acquisition phase). After the halfway point (or the 26th trial), this contingency was reversed, as the “negative” option was more likely to be punished at the reward-punishment probabilities of 20:80% (i.e., the reversal phase). Conversely, the PtN condition initially reinforced choosing the “positive” option, and subsequently switched to the “negative” option.

Participants were explicitly informed beforehand that they would be tested on whether they actually retrieved their specific personal memories during the ERLT. After completion of this task, participants underwent two manipulation-check tasks: a recognition task and a description task. In the recognition task, positive and negative words were sequentially presented on a computer screen. These words were selected from the antonymous word list used in the ERLT. Either the negative or positive word was randomly selected from each of the 52

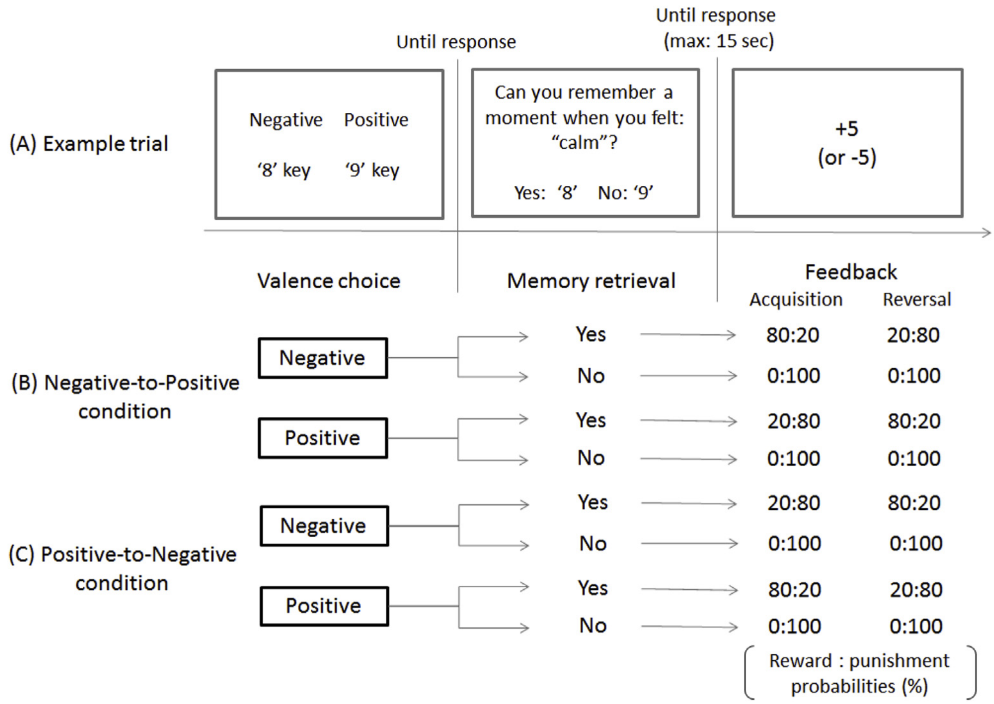

Fig. 1. Schematic flow of the Emotional Reversal Learning Task (Panel A) and learning schedules in the Negative-to-Positive and Positive-to-Negative condition (Panels B and C).

antonymous word pairs. For each presented word, participants were asked to indicate whether they saw it during the ERLT. Because self-reference and autobiographical encoding (e.g., Klein, Loftus, & Burton, 1989) produce recall enhancement of encoded words, it was expected that the words for which participants retrieved personal memories during the ERLT would be more accurately recognized than words for which they could not retrieve a personal memory. In the description task, participants were provided with 10 word pairs from the same antonymous word list. For each of the presented word pairs, participants first had to indicate which word in the pair was displayed during the task. Next, they were asked to describe the memory that they had retrieved. All participants provided written memories for this description task (participants' responses were not scored for statistical analyses). For all the tasks, instructions and stimuli were displayed on a computer screen in Dutch, using E-prime 2.0 software (Psychology Software Tools, Pittsburgh, PA).

2.4. Procedure

Participants were invited to the laboratory individually. On arrival, they provided written informed consent. Participants completed a set of questionnaires, including the BDI-II, RRS, and POMS-D, following which they completed the ERLT.[1] Immediately after the task, participants completed the POMS-D a second time, and subsequently engaged in the manipulation-check tasks. At the end of the experiment, participants in the PtN condition received a mood-lifting manipulation (Hepburn, Barnhofer, Williams, 2006; Nelis, 2014). All participants were sufficiently debriefed and received monetary compensation for their participations. All study protocols were approved by an institutional review board.

2.5. Statistical analyses

Our statistical analyses consisted of two steps: (a) modeling trial-by-trial choice behaviors to parameterize the delay in updating outcome predictions, and (b) testing the association between the updating delay and depressed mood. For the first step, we indexed the updating delay using a *learning rate*, which was estimated by fitting the Q-learning model to individual participants' choice responses. As this parameter reflects the extent to which participants overwrite their old outcome predictions after experiencing a new actual outcome, lower learning rates indicate greater delays in updating outcome predictions. For the second step of our analyses, we tested the association between participants' updating delay and depressed mood using a multiple regression model in which post-task depressed mood is predicted by an interaction between the condition (NtP vs. PtN) and the updating-delay index (learning rate). In the NtP condition, individuals with low learning rates should persistently choose to retrieve negative memories, and would experience greater discrepancies between their predicted and actual outcomes for negative memory retrieval. Therefore, we predicted that the learning rate would be associated with increased levels of depressed mood in the NtP condition, but not in the PtN condition, where low learning rate contributes to persistent positive memory retrieval.

2.6. Q-learning model

Choice responses of individual participants were modeled using the Q-learning technique (Daw, 2011; Sutton & Barto, 1998; Watkins & Dayan, 1992). Q-learning is an algorithm of reinforcement learning, which assumes that (a) a learning agent internally maintains outcome predictions for each response option (i.e., Q value), and (b) the outcome predictions are sequentially updated after receiving an actual outcome (reward or punishment). Based on the difference in Q value between the (two) response options, the agent makes a choice, which further influences the outcome predictions for the next trial. The Q updating policy is defined by the Rescola-Wagner rule, which is represented as follows:

[1] In between the questionnaire and ELRT, participants engaged in a dot-probe task (MacLeod & Mathews, 1986), which was used as a filler task for a subsequent self-verification manipulation (Giesler, Josephs, & Swann, 1996). Because we did not find an effect of self-verification on the questionnaire responses and ELRT task performances, we do not report those results here.

$$Q_{nwg}(t+1) = Q_{neg}(t) + \alpha_{reward}(R(t) - Q_{neg}(t))$$

or

$$Q_{nwg}(t+1) = Q_{neg}(t) + \alpha_{punish}(R(t) - Q_{neg}(t))$$

where Q_{neg} *(t + 1)* is the outcome prediction of the "negative" option for trial *t + 1*. The outcome prediction is determined by the prediction error, i.e., the difference between the actual outcome, *R(t)*, and outcome prediction of the previous trial, Q_{neg} *(t)*. The prediction error is weighted by a learning rate, α_{reward} and α_{punish}, which defines the speed of updating the outcome predictions. We assumed different learning rates for rewarded and punished trials, because it has been suggested that the updating speed of an outcome prediction can differ across different outcome values (Jahfari & Theeuwes, 2017). Similarly, the outcome prediction for positive memory retrieval, Q_{pos} *(t),* is also updated by the Rescola-Wagner rule, with variable updating speeds for rewarded and punished trials.

The probability of choosing the "negative" option is represented by a softmax function of the difference between the outcome predictions of the two options:

$$P_{neg}(t) = \frac{1}{1 - \exp(-\beta(Q_{neg}(t) - Q_{pos}(t)))}$$

where an exploration-exploitation parameter, β, reflects a learning history, with a larger value indicating greater sensitivity to the difference in outcome predictions.

When estimating the parameters, we fit the same Q-learning model to the data for both the NtP and PtN conditions. It is important to note that the two learning rates have different meanings for each of these conditions. The learning rate for the punished trials (α_{punish}) influences the speed of *decreasing* reward expectancy for a chosen option; it mainly controls the updating processes for (a) the negative response option in the NtP condition and (b) the positive option in the PtN condition after the contingency reversal. Therefore, α_{punish} in the NtP condition is of particular interest, as it codes the speed of updating (or down-revising) the outcome prediction for negative memory retrieval.

2.7. Parameter estimation

We used a Hierarchical Bayes (HB) estimation to obtain the optimal parameter estimates of α_{reward}, α_{punish}, and β for each participant. In the HB approach, each parameter is assumed to follow multi-level distributions, wherein parameters of individual participants were drawn from a group-level distribution shared by all participants. In our analysis, each of the three free parameters was treated deterministically; however, we modeled their respective probit transformations (α'_{reward}, α'_{punish}, and β′) to follow a normal distribution with a group mean (μ) and standard deviation (σ): $\alpha'_{\text{reward}} \sim$ Normal ($\mu_{\alpha'\text{ reward}}$, $\sigma_{\alpha'\text{ reward}}$), $\alpha'_{\text{punish}} \sim$ Normal ($\mu_{\alpha'\text{ punish}}$, $\sigma_{\alpha'\text{ punish}}$), and β' ~ Normal ($\mu_{\beta'}$, $\sigma_{\beta'}$). The group means and standard deviations also had priors, which were assumed to be constant between the NtP and PtN conditions: $\mu_{\alpha'\text{ reward}}$, $\mu_{\alpha'\text{ punish}}$, $\mu_{\beta'}$ ~ Normal (0, 1), and $\sigma_{\alpha'\text{ reward}}$, $\sigma_{\alpha'\text{ punish}}$, $\sigma_{\beta'}$ ~ Uniform (0, 1.5). These parameter settings were adapted from previous studies that used similar estimation approaches (Jahfari & Theeuwes, 2017; Katahira, 2016; Steingroever, Wetzels, & Wagenmakers, 2013; Wetzels, Vandekerckhove, Tuerlinckx, & Wagenmakers, 2010). This HB Q-learning model was implemented in Stan (Hoffman & Gelman, 2014; Stan Development Team, 2015). Three Hamiltonian-Monte-Carlo chains were run to evaluate convergence, which showed that Rhats for all parameters were close to 1 (indicating convergence to a stationary distribution; Gelman & Rubin, 1992).

2.8. Sample size calculation

Our main hypothesis was tested using a multiple regression model, in which post-task depressed mood was predicted by the interactions between the condition (NtP vs. PtN) and learning rates. Although we did not have good prior information for the expected effect size, a power analysis with G*power (Faul, Erdfelder, Buchner, & Lang, 2009) indicated that the required sample size was *N* = 26–55 (total for the two conditions) to detect a moderate to large effect (f^2 = 0.15–0.35) under alpha = .05 and power = .80.

3. Results

3.1. Manipulation check

Participants indicated that they could retrieve specific memories in response to most of the negative and positive cue words (*M* = 86.8%, *SD* = 11.2%, for a total of 52 trials). However, it is possible that participants pretended to retrieve a memory just by pressing the "yes" key in the memory retrieval display. Therefore, as a manipulation check, we tested the effect of autobiographical encoding on performance in a recognition task. It was expected that if participants actually retrieved a memory for each cue word, their recognition performance would be enhanced by the memory traces of retrieving a personal memory. We found a slightly (but statistically significantly) higher recognition performance for the memory-recalled than not-memory-recalled words (69.2 and 62.7%, respectively; χ^2 = 5.60, *p* = .02, Cramer's V = 0.05).

3.2. Descriptive statistics

Table 1 shows the means and standard deviations for the questionnaire variables, the choice frequencies of the "negative" option in the ERLT, and the estimated Q-learning parameters. There were no statistically significant differences between the NtP and PtN conditions for BDI, RSQ, and baseline POMS-D scores, *ts* < 1.22, *ps* > 0.22. We calculated the mean "negative" choice frequency for each quarter of the ERLT trials (i.e., Phase 1 and 2 = the first and latter half of the acquisition phase; Phase 3 and 4 = the first and latter half of the reversal phase) to ensure that the contingency reversal reinforced a decrease in "negative" choices in the NtP condition and an increase in "negative" choices in the PtN condition. A one-way ANOVA for the "negative" choice frequency across the four phases indicates that participants adapted their choice behaviors after the contingency reversal, *F*(1.3, 28.8) = 19.45, *p* < .001, for the NtP, and *F*(2.1, 45.6) = 28.82, *p* < .001, for the PtN condition. More specifically, there was a significant increase in the number of "negative" responses from Phase 2 to 3 in the NtP condition, *t*(22) = 4.66, *p* < .001, *dz* = 0.97, and a significant decrease from Phase 2 to 3 in the PtN condition, *t*(22) = 5.69, *p* < .001, *dz* = 1.19.

The delay in switching from an old to new response was represented by a low learning rate for punished trials (i.e., α_{punish}). Supporting this notion, the learning rate for punished trials was significantly negatively correlated with the "negative" responses in Phase 3 (first half of the reversal phase) of the NtP condition, *r* = −0.56, 95%CI [-0.79, −0.20], *p* = .005, and with the Phase 3 "positive" responses in the PtN condition, *r* = −0.78, 95%CI [-0.90, −0.54], *p* < .001. These significant correlations suggest that the low learning rate for punished trials captures the delayed transition (a) from the negative to positive response in the NtP condition (in which the negative response was punished in the reversal phase), and (b) from the positive to negative response in the PtN condition (in which the positive response was be punished in the reversal phase).

3.3. Individual differences in the learning rate and depressive symptoms

Subsequently, we examined the associations between the learning parameters and depressive symptoms. The results indicate that the learning rate for the punished trials was significantly associated with depressive symptoms, ruminative tendencies, and post-task depressed mood in the NtP condition (Table 2). As previously noted, the low

Table 2
Correlations between learning parameters and depression measures.

	Learning rate: reward (α_{reward})	Learning rate: punishment (α_{punish})	Exploitation (β)
Negative-to-positive condition (*N* = 23)			
BDI-II	−0.08	−0.47*	0.03
RRS Brooding	0.00	−0.43*	−0.07
POMS-D Pre	0.26	−0.27	0.08
POMS-D Post	0.20	−0.49*	0.04
Positive-to-negative condition (*N* = 23)			
BDI-II	−0.03	−0.29	−0.12
RRS Brooding	0.30	−0.13	0.12
POMS-D Pre	0.39	−0.15	0.17
POMS-D Post	0.33	−0.11	−0.01

Note. BDI-II = Beck Depression Inventory-II; POMS-D Pre, Post = Profile of Mood States Depression subscale, administered before and after the emotional reversal learning task; RRS = Ruminative Response Scale. *$p < .05$.

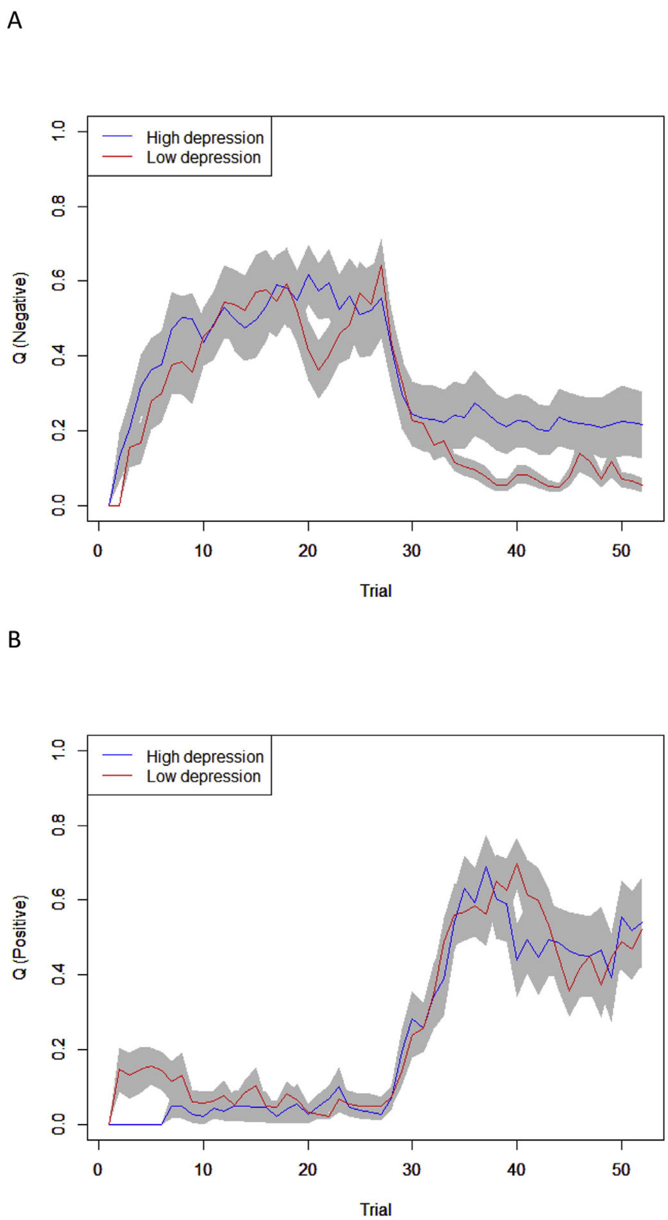

Fig. 2. Mean Q values (reward expectancies) for the negative (Panel A) and positive option (Panel B) as a function of trials for participants with high (i.e., BDI-II > 9) and low levels of depressive symptoms in the Negative-to-Positive condition. Gray fields indicate standard errors.

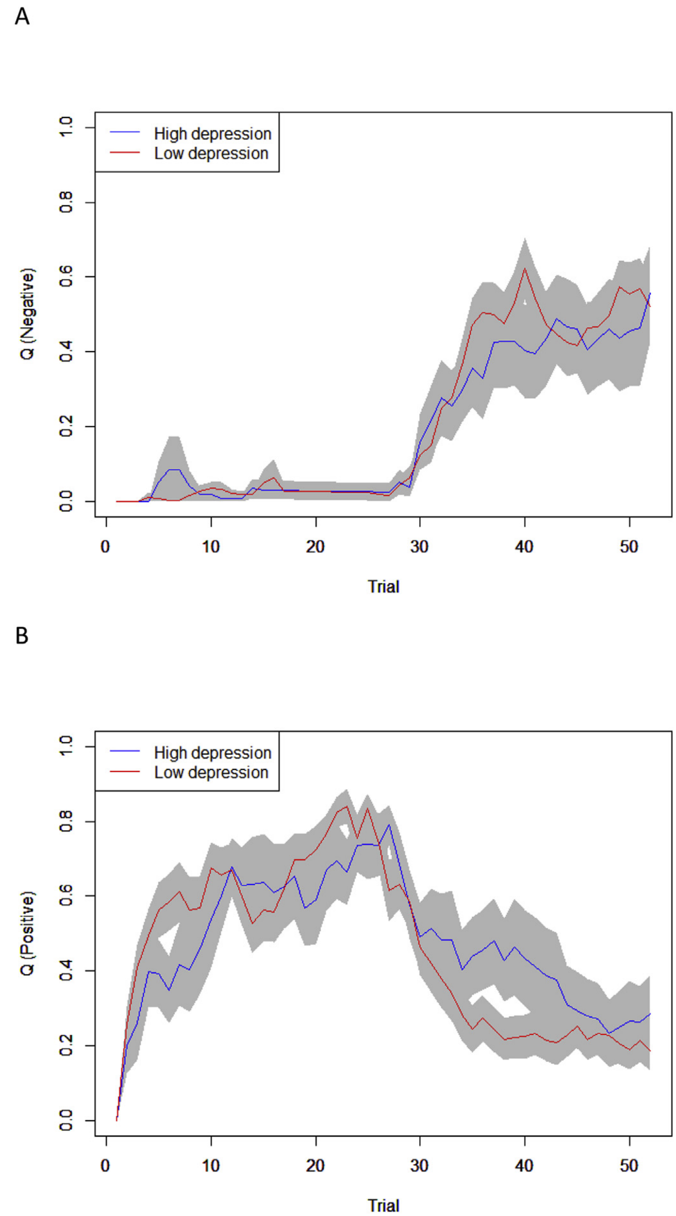

Fig. 3. Mean Q values (reward expectancies) for the negative (Panel A) and positive option (Panel B) as a function of trials for participants with high (i.e., BDI-II > 9) and low levels of depressive symptoms in the Positive-to-Negative condition. Gray fields indicate standard errors.

learning rate for punished trials reflects the degree of delay in disengaging from a previously reinforced response. To visualize this delay, we depicted trajectories of outcome predictions (i.e., Q values) for participants with higher and lower levels of depressive symptoms (split by the mean of the BDI-II scores). As described in the Method section, Q values reflect participants' reward expectancies for negative and positive response options (i.e., the extent to which participants believe that retrieving a negative or positive memory leads to a beneficial outcome). Fig. 2 illustrates the Q trajectories in the NtP condition, which indicate that people with high levels of depressive symptoms maintained high reward expectancy for the negative option even after the contingency reversal (Panel A), whereas individuals with low levels of depressive symptoms decrease their reward expectancy rapidly after the contingency reversal (Panel A). Fig. 3 also depicts the Q trajectories in the PtN condition, which indicate that the delay for people with high levels of depressive symptoms is less evident; reward expectancy dropped to the same level as for the less depressed group by the end of the reversal phase.[2]

3.4. Depressed mood and delayed updating of outcome prediction

Finally, we tested whether the low learning rate for punished trials is associated with increased levels of depressed mood in the NtP condition. A multiple regression model was estimated, in which post-task depressed mood was predicted by the two learning rates, the condition (dummy coded as NtP = 1, PtN = 0), and their interactions, after controlling for the pre-task levels of depressed mood and the BDI-II score. All predictors except for the condition were standardized for ease of interpretation. The results revealed a significant interaction between the condition and the learning rate for punished trials (Table 3), indicating a significant effect of the learning rate on post-task depressed mood in the NtP condition, B = −9.38, 95%CI [-16.13, −2.63], $t = 3.34$, $p = .008$, but not in the PtN condition, B = −0.28, 95%CI [-5.83, 5.27], $t = 0.10$, $p = .919$. These results suggest that the delay in updating outcome predictions is associated with increased levels of depressed mood, particularly when the reward expectancy for negative (but not positive) memory retrieval has to be decreased (as coded by α_{punish} in the NtP condition).

Table 3
Multiple regression predicting post-task depressed mood (POMS-D).

IVs	Estimates	*SE*	*t*	*p*	95% CI
BDI-II	−0.01	0.07	−0.11	.910	[-0.14, 0.13]
POMS-D	0.68	0.14	4.88	< .001	[0.40, 0.97]
Learning rate (reward)	1.08	5.86	0.18	.854	[-10.78, 12.95]
Learning rate (punish)	−0.28	2.74	−0.1	.919	[-5.83, 5.27]
Condition	3.25	2.78	1.17	.250	[-2.38, 8.87]
Learning rate (reward) * Condition	3.82	7.35	0.52	.607	[-11.06, 18.70]
Learning rate (punish) * Condition	−9.10	4.10	−2.22	.033	[-17.41, −0.79]
Adj R^2	0.55				

Note. $N = 46$. BDI-II = Beck Depression Inventory; POMS-D = Profile of Mood State Depressed Mood Subscale.

4. Discussion

We examined individuals' difficulty with updating outcome predictions for emotional memory retrieval, as an experimental analogy of persistent positive beliefs about negative cognition in depression (e.g., Papageorgiou & Wells, 2001). As expected, the results showed that the updating difficulty after receiving unfavorable outcomes (which is reflected by a low learning rate for punished trials) predicts increased levels of depressed mood when participants are reinforced to switch from negative to positive memory retrieval (i.e., NtP condition). In this condition, participants with updating difficulty maintained their "positive" belief (high reward expectancy or high Q value) that negative memory retrieval results in beneficial outcomes, even when the reality of choosing a negative response option was a form of punishment. These individuals would repetitively experience a discrepancy between their expected outcome and the actual outcome for negative memory retrieval, which might be associated with a sense of helplessness and depressed mood. Importantly, the updating delay was not associated with depressed mood when participants were reinforced to switch from positive to negative memory retrieval (i.e., PtN condition). This is likely because the updating delay in this condition increases the retrieval of positive memories, which might counteract the negative impact of the punishment feedback.

Another important finding is that individuals with higher levels of depressive symptoms and depressive rumination have lower learning rates for punished trials in the NtP condition. These significant correlations imply that vulnerable people tend to maintain a persistent "positive belief" that retrieving a negative memory leads to beneficial outcomes, even when it does not in reality. This tendency supports the argument that rumination is a mental habit (Ramnerö et al., 2016; Verplanken, Friborg; Wang, Trafimow, & Woolf, 2007; Watkins & Nolen-Hoeksema, 2014). In other words, negative thinking is less sensitive to changes in action-outcome contingencies, which makes it difficult to oppose depressive rumination despite its negative consequences (Hertel, 2004). However, it should be noted that rumination is not merely the memory recall of past negative episodes as we operationalized it here, although enhanced or biased recollection of negative information is suggested to play an important role in depressive rumination (e.g., Kuo et al., 2012). Nolen-Hoeksema et al. (2007), for example, note how rumination is about using negative thoughts and memories to make sense of current circumstances. Indeed, several scholars in the field of rumination have agreed that the sustained processing of negative self-related material from memory, in order to try to make sense of negative memories and current issues, is a central ingredient of depressive rumination (e.g., see Nolen-Hoeksema et al., 2007, p. 407).

As an alternative interpretation, the association between the low learning rate and depressive symptoms may be due to a general deficit in the updating function (see also Dombrovski et al., 2010; Kunisato et al., 2012), but not due to a valence-specific problem for negative memory retrieval. There seems to be a small updating delay for people with depressive symptoms also in the PtN condition (see Fig. 3B). More critically, the correlations between the learning rate and depressive symptoms were not statistically significantly different between the NtP and PtN condition ($rs = -0.47$ vs. -0.29, $p = .51$). This may be due to the small sample size in the current study, which was not large enough to detect a significant difference between the two correlations. Related to this point, the correlational analyses may be underpowered due to the small sample size in each condition. These results should be interpreted carefully as preliminary evidence, and future research (with a better statistical power) needs to replicate the observed associations between the learning rate and depressive symptoms.

Another important limitation is that our manipulation check tasks (i.e., recognition and description tests) cannot completely eliminate the possibility that participants did not retrieve their personal memories during the emotional reversal learning task. Because our primary interest was in the preference to (but not in the actual retrieval of) negative memories, we did not ask participant to report the contents of individual memories in the exact moments when participants indicated that they could retrieve a negative or positive memory. Thus, it should be noted that self-satisfying behavior (i.e., choosing "yes" without retrieving a target emotional memory) may contaminate the results.

Although the aforementioned limitations raise several alternative interpretations (particularly for the statistical power due to the small sample size), our data supports the association between difficulty in updating outcome predictions for negative memory retrieval and increased levels of depressed mood. Although the non-clinical nature of our sample limits the clinical implications, our methodology (i.e., the emotional reversal learning task) demonstrates a sound experimental analogy of persistent positive beliefs about negative cognition in depression.

Conflict of interest

The authors declare no conflict of interest.

[2] The mean splitting of participants was only done for visualization purposes. Following the dimensional view of psychopathology (Cuthbert, 2014), we performed all our statistical analyses on continuous (and not on dichotomized) measures (e.g., MacCallum, Zhang, Preacher, & Rucker, 2002).

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