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Testing Bayesian models of belief updating in the context of depressive symptomatology

Matthias Feldmann[1,2] | Tobias Kube[3] | Winfried Rief[1] | Eva-Lotta Brakemeier[1,2]

[1]Department for Clinical Psychology and Psychotherapy, Philipps University Marburg, Marburg, Germany

[2]Department for Clinical Psychology and Psychotherapy, University of Greifswald, Greifswald, Germany

[3]Pain and Psychotherapy Research Lab, University of Koblenz-Landau, Landau, Germany

Correspondence
Matthias Feldmann, Department of Clinical Psychology and Psychotherapy, Gutenbergstr 18, Marburg 35032, Germany.
Email: matthias.feldmann@uni-marburg.de

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Abstract

Objectives: Predictive processing approaches to belief updating in depression propose that depression is related to more negative and more precise priors. Also, belief updating is assumed be negatively biased in comparison to normative Bayesian updating. There is a lack of efficient methods to mathematically model belief updating in depression.

Methods: We validated a novel performance belief updating paradigm in a nonclinical sample ($N = 133$). Participants repeatedly participated in a non-self-related emotion recognition task and received false feedback. Effects of the feedback manipulation and differences in depressive symptoms on belief updating were analysed in Bayesian multilevel analyses.

Results: Beliefs were successfully manipulated through the feedback provided. Depressive symptoms were associated with more negative updating than normative Bayesian updating but results were influenced by few cases. No evidence of biased change in beliefs or overly precise priors was found. Depressive symptoms were associated with more negative updating of generalised performance beliefs.

Conclusions: There was cautious support for negatively biased belief updating associated with depressive symptoms, especially for generalised beliefs. The content of the task may not be self-relevant enough to cause strong biases. Further explication of Bayesian models of depression and replication in clinical samples is needed.

KEYWORDS
Bayesian modelling, belief updating, depression, precision, predictive processing

1 | BACKGROUND

Theories of the brain as an active Bayesian inference machine are very popular and are still gaining importance (Clark, 2013; Rescorla, 2021). Bayesian approaches have a strong foundation in the field of sensory processing and motor control, but they have also been expanded to the field of information updating and cognition (Adams et al., 2013; Chater et al., 2010; Hohwy, 2017; Williams, 2020). In simpler terms, individuals create predictions (i.e., beliefs) about themselves and the world, referred to as "prior". The precision of that prior is thought to reflect the certainty with which a belief is held. A more precise prior is more resistant to change when encountering divergent information. All new information that is encountered is perceived with a certain precision as well. Thus, the integration of prior and (new) data depends on a weighting of the precision of old and new information. Bayesian updating rules provide a normative mathematical formula for computing updated or posterior beliefs after seeing (new) data that is optimal within the mathematical model.

Active inference is a popular framework that draws onto this Idea of a "Bayesian brain". According to this framework people seek to minimise errors between predictions generated by their mental model of the world and the real world. Beliefs are thought to be structured hierarchically, with more specific beliefs at the bottom and more generalised beliefs at the top of the hierarchy. Generalised beliefs may shape situation-specific predictions from top-down, whereas prediction errors arising from specific predictions may change more generalised beliefs from bottom-up (Friston, 2008; Pezzulo et al., 2015; Williams, 2020).

1.1 | Active inference approaches to depression

Recently, active inference theories have been extended to explain mental disorders such as psychosis (Corlett et al., 2019; Fletcher & Frith, 2009; Sterzer et al., 2018), autism (van de Cruys et al., 2014), posttraumatic stress disorder (PTSD; Kube, Berg, et al., 2020; Lyndon & Corlett, 2020) and depression (Barrett et al., 2016; Kube, Schwarting, et al., 2020). Kube, Schwarting et al. (2020) assume that depressed individuals form very precise negative priors concerning their own performance and attributes. Due to the high precision of these priors, new information is disregarded, and reduced updating occurs in comparison to healthy individuals. Additionally, cognitive processes summarised as cognitive immunization (Rief & Joormann, 2019) are thought to reduce the precision of received feedback. Thereby they further hinder belief updating in line with positive information in depression. Depressed individuals may also actively seek information supporting their prior predictions and avoid discrepant information, reflecting the "active" part of active inference (Kube, Schwarting, et al., 2020).

Expectations as future-oriented beliefs may implement priors in a Bayesian sense and, thus, partly bridge the gap between active inference accounts of psychopathology and clinical-psychological and psychiatric research (Kube, Rozenkrantz, et al., 2020). Depressive individuals have more negative (Strunk et al., 2006) and less positive self-related future expectations than healthy individuals (Horwitz et al., 2017). Some studies found evidence for reduced updating of negative expectations in depressive individuals when confronted with more positive evidence (positive expectation violation) (Everaert et al., 2018; Korn et al., 2014; Kube et al., 2018; Teachman et al., 2019). Often there was no reduced updating of positive expectations when confronted with more negative evidence (negative expectation violation) (Kube et al., 2019; Takano et al., 2019).

From a clinical perspective, asymmetrical belief updating, that is reduced expectation updating only after positive prediction errors may pose an important challenge to the psychological treatment of depression (Rief & Joormann, 2019).

In summary, active inference theories of depression may offer great potential but there is still a large gap between the complexity of the theories and the paradigms used to test them in the scope of thought and conscious beliefs. Especially, it remains an open empirical question what mechanisms are involved in biased belief updating in depression: First, Bayesian updating incorporates prior knowledge. It follows from this proposed mechanism directly that individuals with more negative priors should update their expectations less in response to positive feedback than individuals with more positive priors. In other words, the normative Bayesian integration of prior experience may sufficiently explain the biases found in depressive individuals without assuming distorted updating processes per se. On the other hand, additional processes such as cognitive immunisation may cause updating even more negative than expected in a normative Bayesian framework. The mathematical formulation of Bayesian updating makes it possible to formulate stronger numerical hypotheses about belief updating processes and distinguish between these two possible mechanisms.

However, such a mathematical formulation depends on a successful elicitation of the precision of the participant's prior belief distribution. To describe this distribution, at least a measure of centrality and a measure of precision or variance is necessary. Precision elicitation is challenging (Boukhelifa & Duke, 2009; Greis et al., 2017; Meyniel et al., 2015). While most research is focused on prior elicitation by experts (Stefan et al., 2020), Muthukrishna et al. (2018) successfully used a method in which laymen distributed coins into several bins that formed a discretized scale. Based on this input, precision could be computed. In an input comparison on a previous belief updating task with laymen, more efficient elicitation techniques depending only on a measure of centrality and a measure of variance showed a similar performance (Kim et al., 2019).

1.2 | Aims of the current work

In this study, we designed a novel paradigm for the mathematical modelling of performance belief update processes. Our long-term goal is to advance research on biases in belief updating in depression. We evaluated the feasibility of inducing positive and negative expectation violations in the same individuals. For this, we assessed whether manipulated feedback influenced specific and generalised expectations about individuals' own emotion recognition ability.

Finally, we examined the influence of depressive symptoms on performance belief updating. We hypothesised individuals with higher depressive symptoms to report more negative and more precise expectations and to change their expectations in a negatively biased way. We also assumed belief updating to be negatively biased in comparison to a normative model performing Bayesian updating using the prior specified by the participant. This pattern of results would imply additional processes involved such as cognitive immunisation.

2 | METHODS

Ethical approval was granted by the university ethical committee (reference 2020-41k). The study was preregistered under https://aspredicted.org/cd8pm.pdf. Materials, data, code, and model outputs for this study can be found at https://osf.io/kdgj2/. The study was implemented using formr and jspsych (Arslan et al., 2020; de Leeuw, 2015).

2.1 | Sample

Participants were recruited online using university and depression-related mailing lists. A total of 148 individuals completed the study. One individual was excluded for technical difficulties and three more (2.0%) guessed that the feedback was manipulated and were therefore excluded as well. Further, we excluded individuals who indicated that they answered at least "rather" randomly for the graphical distribution input ($n = 11$). Thus, data from 133 individuals was analysed. Of these, 96 (72.2%) were female. Participants were on average 28.5 years old (SD = 10.5, range = [18; 66]). The level of education was high, with 125 (94.0%) reporting at least a high school degree and 57 (43%) a university degree. Participants showed on average mild levels of depressive symptoms (PHQ-9 $M = 7.8$, SD = 5.7, range = [0; 25]) with 93 (69.9%) reporting minimal to mild symptoms (PHQ-9: 0–9) and 40 (30.1%) reporting moderate to severe symptoms (PHQ-9: 10–27).

2.2 | Performance belief updating task

The purpose of the performance belief updating task was to mathematically model performance belief updating processes on a non self-related task. In each of 12 trials, participants entered their prior belief distribution (prior mode and precision) about how many of 20 forced-choice questions they would answer correctly in a difficult emotion recognition test (Figure 1). After performing the test, participants were asked if they completed this trial in a sincere and concentrated manner. If they agreed, they were presented fake feedback (e.g. "12 of 20 answers were correct") and otherwise no feedback. At the end of a trial, they were asked for their performance beliefs in the following trial (posterior).

2.2.1 | Prior and posterior mode

The modes of the user elicited prior and posterior distributions were assessed using a visual analogue slider ranging from 0 to 20. The numbers referred to the expected amount of correct answers in the next trial of the belief updating task (specific expectations). Expectation change was defined as the difference between posterior mode and prior mode.

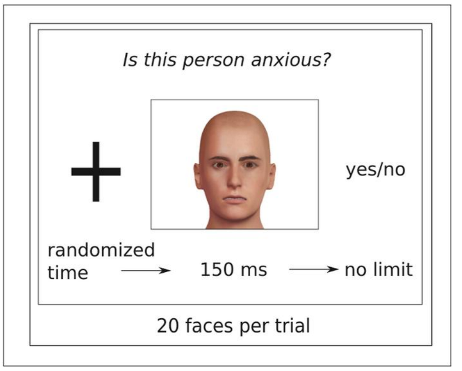

FIGURE 1 Emotion recognition test. Participants were shown 20 images of faces with emotional expressions for 150 ms each. Of the faces shown, 10 expressed the target emotion (2 × 10% intensity, 4 × 20%, 4 × 30%) and 10 did not (each 2 with 30% intensity out of happiness, anger, sadness, fear, disgust and surprise excluding the target emotion). Faces for the emotion recognition test were generated using the 3D rendering software makehuman (http://www.makehumancommunity.org) and the extension faret (Hays et al., 2020) by interpolating between a neutral and an emotional face model in 10% steps

2.2.2 | Prior and posterior standard deviation

The precision of the prior and posterior distributions was specified using a graphical input method. Instructions were formulated in discrete numbers for an easier understanding (Hullman et al., 2018). Participants were asked about information on the distribution of the hypothetical outcomes of the next 20 trials in the belief updating task for the same target emotion. In this regard, participants were shown a quantile dot plot with 20 dots (Fernandes et al., 2018) of a beta distribution around the mode they entered before. They were asked to manipulate the variance of the distribution by interactively moving an analogue slider labelled "spread out" to "dense". The quantile dot plot would update interactively to represent the variance currently entered. The distribution input method is depicted in Figure 2. Additionally, we collected data with a textual form of precision measurement. We included a comparison between these two forms of measurement in Supporting Information S1.

2.2.3 | Normative Bayesian posterior

We compared participants' belief updating with a normative model of belief updating. A normative model is not informed by data, but by theoretical considerations of what the optimal solution for a certain problem is (Baron, 2012). The normative model in this case uses Bayesian updating rules:

$$\text{posterior} = \frac{\text{prior} \times \text{data}}{\text{marginal likelihood}}$$

In the normative model, Bayesian updating is based on the feedback received and conditioned on the prior expectations that

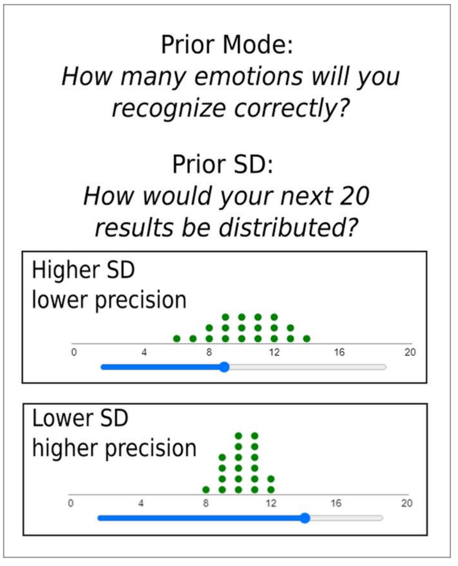

FIGURE 2 Elicitation of the prior belief distributions. Precision was assessed with a graphical elicitation method. The distribution of green dots could interactively be changed by moving the slider below. SD, Standard deviation

participants indicated using the distribution input method. When so-called conjugate prior is used, the posterior can be described in a closed form independent of the marginal likelihood, which is often hard to estimate (Gelman et al., 2003):

$$\text{posterior} = \text{prior} \times \text{data}$$

For this model, we used the Beta (alpha, beta)-Distribution as a conjugate prior. The Beta (alpha, beta)-Distribution describes the knowledge about a percentage of correct answers after seeing *alpha* correct answers and *beta* false answers (Gelman et al., 2003).

$$\text{posterior} = \text{Beta}\left(\text{alpha}_{\text{prior}}\ \text{beta}_{\text{prior}}\right) \times \text{Beta}\left(\text{alpha}_{\text{data}},\ \text{beta}_{data}\right)$$

In each trial, a participant receives (fake) information about the outcome of 20 successes (feedback) or failures (20-feedback). The information gain (data) can thus be described by a Beta (feedback, 20-feedback) distribution. We use the distribution elicited via the graphical distribution input described above as the prior. Hence, all necessary information to compute a normative posterior distribution are available:

$$\text{posterior} = \text{Beta}\left(\text{alpha}_{\text{elicited}}, \text{beta}_{\text{elicited}}\right) \times \text{Beta}(\text{feedback},\ 20 - \text{feedback})$$

Finally, we computed the difference between the posterior mode as elicited by the participants and the mode of the posterior distribution as computed by the normative model. The mode of the posterior distribution was multiplied by 20 to match the scale of the participants' input. We refer to the result as the difference from the normative posterior (DNP). A negative DNP means that the update is more negative than the normative solution (see Figure 3).

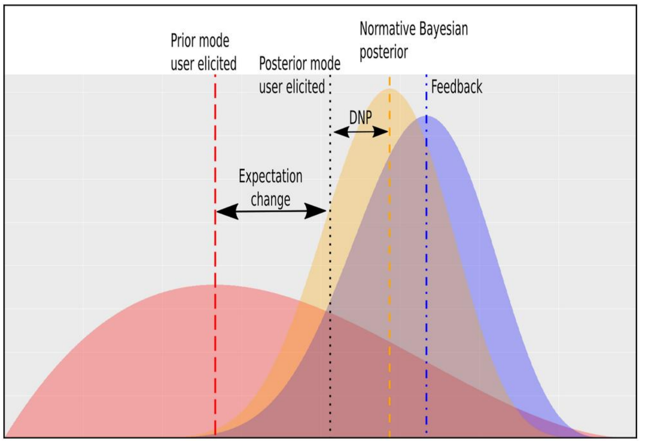

FIGURE 3 Bayesian belief updating. Schematic depiction of the variables elicited and computed in each trial of the performance belief updating task. DNP, difference of the user elicited posterior mode from the Bayesian normative posterior mode

2.3 | Measures

2.3.1 | Depressive symptoms

Depressive symptoms were measured using the mood scale of the German version of the patient health questionnaire (PHQ-9; Gräfe et al., 2004). The PHQ-9 is a brief self-report scale measuring the DSM-5 criteria of major depressive disorder. The internal consistency in this sample was Cronbach's $\alpha = 0.89$.

2.3.2 | Generalised expectations

Participants' generalised expectation about their emotion recognition ability was assessed using a single item on a seven-point Likert-scale. The scale was labelled from "not at all" to "completely" for each of the 4 target emotions (happiness, sadness, anxiety, and anger, e.g. "I will be able to recognise sadness well in other people", Cronbach's $\alpha = 0.80$). This assessment was adapted from a previous study on the revision of generalised performance expectations in response to (fake) performance feedback in the context of depressive symptoms (Kube et al., 2018).

2.4 | Procedure

Participants gave informed consent on participating in the study (30 min). However, they were not informed that feedback would be manipulated. Instead, the study goal was described as the calibration of a novel test for emotion recognition ability in depression. Participants first completed a demographic questionnaire and the PHQ-9. They rated their generalised expectations before and after completing the performance belief-updating task. In the performance belief-updating task, they were presented fake feedback in a randomized ABCA/ACBA crossover design with three trials per block (see Table 1). Afterwards, participants described the study goal in a free text entry. Participants were then debriefed and informed about the true study goal. Finally, they had the opportunity to submit their email address to enter in a lottery for a tablet.

2.5 | Statistical analysis

All analyses were performed using the statistical processing language R with the packages *tidyverse* and *psych* (Revelle, 2020; Wickham et al., 2019). We used Bayesian multilevel modelling using the package *brms* with weakly informative priors for all analyses (Bürkner, 2018). One-sided posterior probabilities (PP) were computed for preregistered hypotheses, while otherwise two-sided 95% credible intervals are reported. They reflect that the true parameter value lies within this interval with a 95% probability if the model is correctly specified.

2.5.1 | Multi-level models of the trial based update parameters

Influence of fake feedback. For each of the outcomes of interest in the performance belief-updating task (posterior mode, posterior SD and DNP), we computed a multilevel model of the same structure: Each outcome was predicted by a fixed intercept, the feedback valence, and the experimental group. Feedback valence (low, medium, high) was dummy coded using medium as the base category. To account for the interdependency between observations due to repeated measurement, we introduced varying intercepts for the observations of the same person. We also included random slopes by person for the effect of the level of feedback. Thus, for every person three variables were estimated: an individual intercept, an individual effect for positive feedback, and an individual effect for negative feedback.

Additionally, we expected the outcomes to differ systematically due to the fake feedback given and introduced varying intercepts for the observations of the same trial.

A similar model was built for the outcome expectation change. However, we used the average in expectation change over the three trials per emotion and omitted the varying intercepts by trial because the dependence between the three trials for the same emotion was too strong.

Influence of the depressive symptoms. In a next step, we added depressive symptoms as an additional linear predictor in each of the previous models and an additional model for the outcome prior mode. In a last, exploratory step, we tested for an interaction between depressive symptoms and feedback level.

2.5.2 | Models of pre-post generalised expectations

Generalised expectations were only measured at two time points. First, we tested for an influence of the fake feedback between the measurements on the adaptation of generalised expectations. Thus, emotion recognition ability was predicted by time of measurement (before or after the emotion recognition test), feedback (low/high) and their interaction. Again, we added varying effects by person to account for dependence between observations. The outcome generalised expectation was measured with one Likert scaled item per emotion and time point. Therefore it was modelled as a cumulative ordinal variable (Bürkner & Vuorre, 2019).

Additionally, depressive symptoms were added as a predictor with all interactions into the analysis of the generalised expectation change described above.

TABLE 1 Feedback shown in the performance belief-updating task

	Feedback level	
Emotion	**Group A**	**Group B**
Anxiety	Medium	Medium
Anger	High	Low
Sadness	Low	High
Joy	Medium	Medium

3 | RESULTS

3.1 | Trial based update parameters

Influence of fake feedback. When modelling the effect of the randomised feedback conditions on the specific expectations in the next trial (posterior mode), high feedback had a positive effect (b = 1.20, 95% CI = [0.23; 2.15]), while low feedback had a negative effect (b = −2.08, 95% CI = [−3.07; −0.1.09]).

Expectation change. There was positive expectation change in blocks with high feedback (b = 2.86, 95% CI = [2.34; 3.37]) and a negative expectation change in blocks with low feedback (b = −2.05, 95% CI = [−2.56; −1.54]). That is, participants updated their expectations in line with the feedback received, speaking to the validity of the paradigm.

Posterior SD. Posterior SD was unchanged in high feedback trials (b = −0.08, 95% CI = [−0.17; 0.01]) and in low feedback trials (b = 0.06, 95% CI = [−0.03; 0.16]).

DNP. DNP did not significantly differ in high feedback trials (b = −0.26, 95% CI = [−0.72; 0.19]) or low feedback trials (b = 0.22, 95% CI = [−0.24; 0.67]). The intercept for DNP was negative (b = −0.58, 95% CI = [−0.85; −0.30]), indicating that individuals on average updated more negatively than the normative Bayesian solution.

Exploratory analyses also showed that even individuals with none to mild depressive symptoms stated posterior predictions more negative than the feedback they received (b = −0.63, 95% CI = [−0.93; −0.34]) and predictions more negative in comparison to the normative Bayesian solution (b = −0.52, 95% CI = [−0.67; −0.37]).

Influence of depressive symptoms. Higher depressive symptoms were negatively associated with posterior mode (b = −0.24, 95% CI = [−0.50; 0.01], PP = 0.97) and the DNP (b = −0.11, 95% CI = [−0.24; 0.02], PP = 0.95). Higher depressive symptoms were not significantly associated with prior mode, although the was a trend (b = −0.20, 95% CI = [−0.49; 0.09], PP = 0.92). Against our hypotheses, depressive symptoms were not significantly associated with prior SD (b = −0.01, 95% CI = [−0.06; 0.03], PP = 0.65) or expectation change (b = −0.06, 95% CI = [−0.36; 0.23], PP = 0.72). The course of the specific expectations for individuals with low and high depressive symptoms is depicted in Figure 4.

Influence of depressive symptoms depending on feedback level. There were no significant interactions between feedback condition and depressive symptoms for any outcome. In other words, there was little evidence for an influence of depressive symptoms on the specific way positive or negative information was integrated. Population effects for models including interactions with feedback level and depressive symptoms repeated the same patterns and are summarised in Table 2.

3.2 | Generalised expectations

Effect of fake feedback. Generalised expectations decreased from before to after the belief updating task (b = −1.40, 95% CI = [−1.50; −1.30]). A positive interaction between time and feedback level (b = 0.87, 95% CI = [0.77; 0.97]) indicated changes in accordance with the feedback received.

Influence of depressive symptoms. Generalised expectations at baseline were not associated with depressive symptoms (b = −0.03, 95% CI = [−0.32; 0.38]) but decreased more strongly in individuals with higher depressive symptoms (b = −0.23, 95% CI = [−0.33; −0.13]). Changes in generalised expectations differing between high and low feedback were not associated with depressive symptoms (b = 0.08, 95% CI = [−0.02; 0.18]). Interactions of depressive symptoms and feedback level on generalised expectations are depicted in Figure 5.

3.3 | Sensitivity analyses

Excluding an influential person. When running sensitivity analyses excluding the individual with the most negative prior and posterior expectations as well as most negative DNP, the association between depressive symptoms and all trial-based parameters become non-significant.

Using the full sample. We also performed sensitivity analyses on the whole sample without filtering out those who replied "rather" randomly on the graphical distribution input but excluding the influential person described above (n = 143). Here, depressive symptoms were associated with lower prior and posterior expectations as well as lower DNP.

4 | DISCUSSION

In this study, we presented a novel experimental paradigm that allows modelling the update of participants' performance expectations on a linear scale. By providing participants with fake performance feedback, both specific and general expectations could be manipulated with a low rate of manipulation detection. Depressive symptom severity was associated with lower specific posterior expectations regardless of the feedback level and more negative deviance from a normative Bayesian solution. It showed no association with aberrant prior precision or absolute expectation change. Sensitivity analyses suggested that this pattern of results could be influenced by the inclusion or exclusion of few cases. Depressive symptoms were not associated with lower generalised expectations before the test but with a greater reduction after performing the test.

The manipulation of the performance feedback in this paradigm was successful. It induced positive and negative changes in both specific and generalised expectations. In contrast, the difference of the subjective posterior from the normative posterior did not significantly differ depending on the level of the performance feedback presented. This speaks for the validity of the DNP as a measure of a biased belief updating process independent of the feedback level. The induced changes in generalised expectations may be particularly important for the validity of the paradigm. They indicate that participants were likely to believe the fake feedback to the extent that they integrate new information into judgements of their general emotion recognition ability. However, generalised expectations decreased throughout the study. Slightly higher levels of performance feedback should be used to ensure that updating is balanced.

In contrast to previous studies, there was no substantial evidence for negatively biased prior expectations neither on the specific nor on the generalised level (e.g. Sharot & Garrett, 2016; Zetsche et al., 2019) although there was a trend for negatively biased specific expectations. One explanation could be that the content of the performance beliefs, performing poorly at recognising other people's emotions, may not be relevant enough to cause strong biases. It may also not be associated with typical depressive thought content. Instead, "mind reading" as an overconfidence in estimating other people's state of mind is a cognitive distortion positively associated with depression and anxiety symptoms (Mercan et al., 2021). However, in a previous study performance expectations on an emotion recognition task were negatively associated with depressive symptoms (Kube et al., 2019). In contrast to the neutral question of how many emotions participants will recognize correctly in this study, Kube et al. (2019) asked "how successful" participants thought they would be in a task. This formulation may be more consistent with common core beliefs in depression ("I am incompetent", Beck, 1964). If possible, future studies should include both outcomes.

Higher levels of depressive symptoms were associated with a somewhat greater deviation from the normative Bayesian posterior and more negative posterior expectations. This is consistent with recent Bayesian approaches to depression and may be interpreted as evidence for processes like cognitive immunisation (Barrett

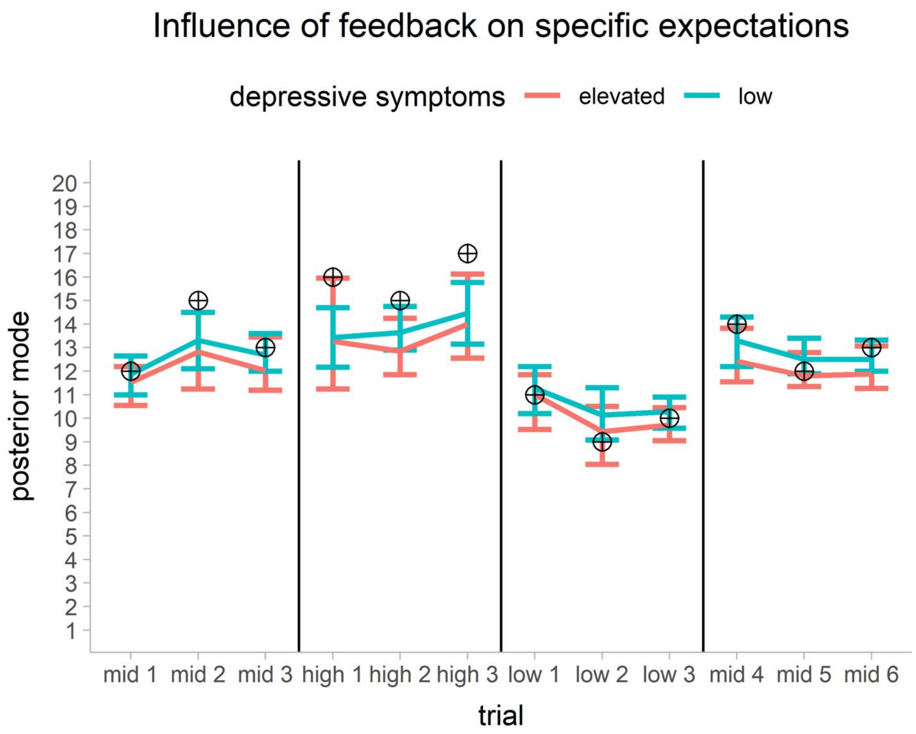

FIGURE 4 Influence of feedback and depressive symptoms on specific expectations. Mean and 50% quantile interval of the specific posterior expectation by trial and level of depressive symptoms. Elevated depressive symptoms were defined as a PHQ-9 score of at least 10. Circles indicate the feedback shown in each trial

TABLE 2 Influence of positive and negative feedback and the interaction with depressive symptoms on belief updating in the emotion recognition paradigm

	Posterior mode	Posterior SD	DNP	Expectation change
Intercept	12.5 [11.9; 13.1]	0.62 [0.55 0.68]	−0.59 [−0.86; −0.31]	−0.57 [−0.88; −0.26]
PHQ-9	−0.26 [−0.51; −0.00]	−0.01 [−0.05; 0.03]	−0.14 [−0.28; 0.01]	−0.11 [−0.43; 0.21]
High feedback	1.21 [0.24; 2.2]	−0.08 [−0.17; 0.00]	−0.26 [−0.73; 0.20]	2.86 [2.58; 3.14]
Low feedback	−2.09 [−3.06; −1.10]	0.06 [−0.03; 0.16]	0.22 [−0.23; 0.68]	−2.06 [−2.34; −1.77]
PHQ-9 * high feedback	0.07 [−0.16; 0.29]	0.00 [−0.03; 0.03]	0.08 [−0.12; 0.27]	0.26 [−0.03; 0.55]
PHQ-9 * low feedback	0.03 [−0.22; 0.28]	0.01 [−0.02; 0.05]	0.03 [−0.15; 0.22]	−0.09 [−0.39; 0.19]

Note: Results from Bayesian multilevel models on four chains with 8000 iterations each with 95% credible intervals. Data was modelled with random intercepts for person and trial with random slopes by person for positive and negative feedback, except for the outcome expectation change.
Abbreviations: DNP, difference of the user elicited posterior from the normative Bayesian posterior; PHQ-9, patient health questionnaire; SD, standard deviation.

et al., 2016; Kube, Schwarting, et al., 2020). However, contrary to the hypothesis of predictive processing accounts of depression, depressive symptoms were not associated with higher prior precision, regardless of feedback level. Importantly, they did not influence the absolute change in specific expectations. Although posterior expectations were significantly associated with depressive symptoms and prior expectations were not, both effects were similar in size. At least part of the effect for negative posterior expectations and a more negative DNP may be attributable to a trend in more negative prior expectations. Therefore, we treat the evidence on distorted believe updating on the level of specific expectations very cautiously.

Previous studies reported biased belief updating in relation to depressive symptoms especially when unexpectedly high feedback was provided (Kube et al., 2019), although there are also inconclusive findings (Liknaitzky et al., 2017). In this study, the magnitude of the effects did not differ across the level of feedback. However, higher depressive symptoms were associated with a more negative change in generalised expectations. It is important to keep in mind that in the part of this study, in which specific expectations were assessed, was designed to inform a simple mathematical model. Only two numbers and estimates of precision had to be remembered for only a short amount of time to update one's prediction. Integrating the

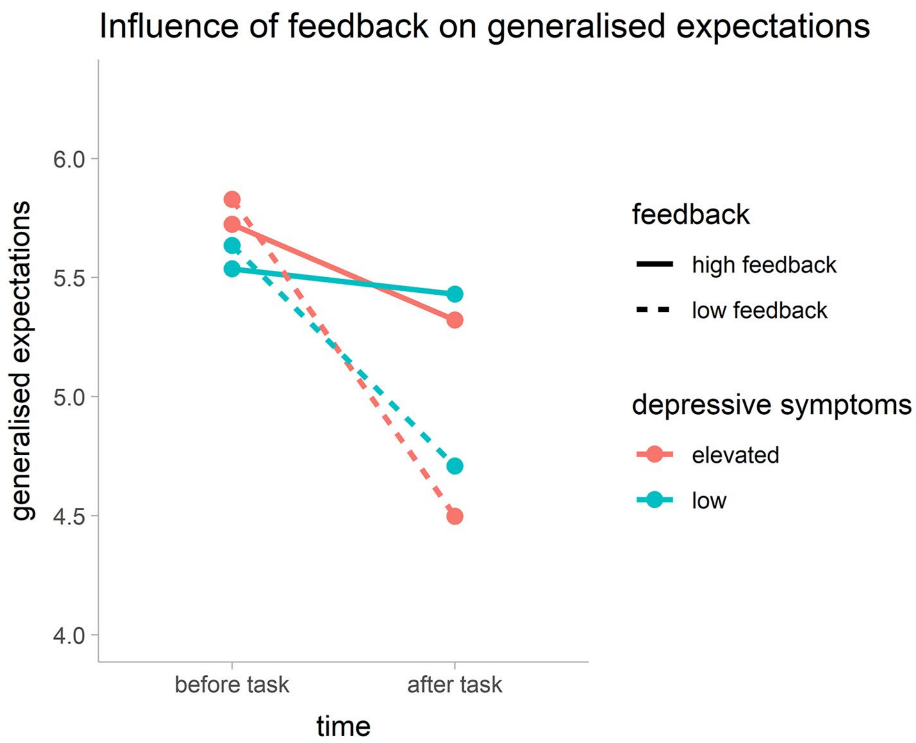

FIGURE 5 Influence of feedback and depressive symptoms on generalised expectations. Mean of the generalised emotion recognition performance expectations by time, group, feedback and level of depressive symptoms. Elevated depressive symptoms were defined as a PHQ-9 score of at least 10

information into more generalised expectations may offer more room for biases in memory retrieval and information selection. Cognitive immunization may also have a stronger influence. This difference in ambiguity may explain why the change in generalised expectations was biased in association with depressive symptoms, but not the change in situation-specific expectations.

An explanation with an only marginally biased belief integration process on the level of specific expectations would not contradict predictive processing accounts of depression per se. The proposed multilevel structure of the brain instead might offer a possible explanation: A precise negative prior on a higher level (e.g. "the self as deficient") could top-down influence lower-level expectations. The updating process on the lower level might still be intact. This idea of negative high-level cognitions that negatively influence lower-level cognitions is by no means new, going back to Beck's cognitive model of depression (Beck, 1964) and more recent applications of predictive processing (Clark, 2013; Fernández et al., 2017; Rauss et al., 2011). Predictive processing theories have been criticised for being overly flexible to the point of being non-falsifiable (Hohwy, 2020). This argument may apply here as well. It will be crucial for applied predictive processing research to formulate more specific theories of biased cognition in depression. They need to address on which level of a hypothesised hierarchically organised brain priors and especially prior precisions are biased in depressed individuals.

The interpretation of the results of this study—as well as a test of the predictive processing framework in general—hinge on the question of the quality of precision assessments. As described in Supporting Information S1, the graphical distribution input seems to provide estimations of precision similar to those estimated in a non-linear model. However, improvements over the alternative textual distribution input seem to be at best small, and the usability was even rated worse. Moreover, previous studies could not identify a clearly superior method (Johnson et al., 2010; Kim et al., 2019). Producing precision estimates may be a computationally effortful process and individuals tend to replace such processes with simpler heuristics (Kahneman & Frederick, 2002). Thus, the slightly better precision estimates yet poorer usability ratings of the graphical distribution input in this study may reflect a cost/benefit trade-off between computational effort and reliable precision estimates (Wesslen et al., 2020). Introducing monetary incentives rewarding the accuracy of predictions may lead individuals to invest more resources into the estimation process. Indeed, individuals with monetary incentives indicated more uncertainty about their predictions than without (Muthukrishna et al., 2018). Future studies might benefit from a similar approach.

4.1 | Strengths

We presented a paradigm that allows analysing performance belief updating processes on a linear scale. To the best of our knowledge, this is the first paradigm to numerically differentiate updating according to Bayesian laws from depressive biases in performance belief updating. Robust methods were used and the multilevel structure of the data was considered in the statistical analysis. By preregistering the study and sharing materials, data, and codes for the analysis, we contribute to establishing open science practices in clinical psychological and psychiatric research. We validated the paradigm by randomizing the fake feedback in a crossover design and assessing the effects of the fake feedback on specific and generalised expectations. The paradigm presented can be implemented online with few resources and allows for various extensions and variations.

4.2 | Limitations

As a major limitation, the performance belief updating task in its current form measures performance beliefs that are not central to depressive psychopathology. Another significant limitation of the current study refers to the assessment of depressive symptomatology via self-report alone and the low occurrence of severe depressive symptoms. This limits the generalisation of the results to belief updating in depression. Additionally, results of the trial-based outcomes depended on the inclusion or exclusion of few influential cases. Thus, replication is needed. Given that all data was collected in an online sample, no biological markers were measured and no interviews on appraisals of the task were conducted. More research on the elicitation of prior precisions is needed. As the computation of the normative posterior was derived from user elicited prior precisions, these measures should be interpreted with care as well. Generalised expectations were assessed only with a single-item measurement, limiting the evaluation of the psychometric properties of the assessment tools. Additionally, the feedback given was not balanced around the centre of the expectation answering scale. Instead, it was higher, such that a preference for answering close to the centre of a scale might have introduced a pessimistic bias. Furthermore, the mathematical models used were based only on simple Bayesian updating and not on the more complex free-energy updating (Bogacz, 2017; Clark, 2013).

4.3 | Future research

The paradigm should be replicated using a sample of individuals with confirmed diagnoses of depression in comparison to a healthy control group. Associations with the chronicity of depression and childhood maltreatment should be examined. Fake tasks more closely related to core depressive cognitions should be investigated. In Addition, it would be interesting to measure both the precision of the generalised expectations and the estimation of the precision of the feedback. This would allow to build a more complete model of individual updating processes. That way, immunisation could be framed as a selective reduction of data precision when encountering new data. It may also be possible to tailor the prior of healthy and depressive participants so that they are approximately the same. That would allow producing expectation violations that do not differ in prior belief. The trial-based design also makes it possible to measure changes within individuals for example, by experimentally manipulating mood or immunizing thought between trials.

5 | CONCLUSION

In this study, we introduced a novel paradigm that investigated performance belief updating after receiving fake feedback. Individuals with higher levels of depressive symptoms showed negatively biased situation-specific posterior expectations with unbiased precision. Absolute expectation change was biased on the level of generalised expectations but not on the level of situation-specific expectations. Further advancement in methods of assessing precision are needed. Theories in predictive processing should specify biases in different levels of a hierarchical brain structure to advance research in this area. We hope that the presented paradigm can be a valuable tool in the further specification of these theories.

AUTHOR CONTRIBUTIONS

Matthias Feldmann: Writing—original draft, Conceptualisation, Methodology, Visualization; Tobias Kube: Conceptualisation, Writing—review & editing; Winfried Rief: Conceptualisation, Writing—review & editing, Supervision; Eva-Lotta Brakemeier: Conceptualisation, Writing—review & editing, Supervision.

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CONFLICT OF INTEREST

The authors declare no conflict of interest. The study received no external funding.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the open science framework at https://osf.io/kdgj2/ with reference number DOI 10.17605/OSF.IO/KDGJ2.

ORCID

Matthias Feldmann https://orcid.org/0000-0002-0493-4949

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SUPPORTING INFORMATION

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