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Which Features of Repetitive Negative Thinking and Positive Reappraisal Predict Depression? An In-Depth Investigation Using Artificial Neural Networks With Feature Selection

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Emotion regulation habits have long been implicated in risk for depression. However, research in this area traditionally adopts an approach that ignores the multifaceted nature of emotion regulation strategies, the clinical heterogeneity of depression, and potential differential relations between emotion regulation features and individual symptoms. To address limitations associated with the dominant aggregate-level approach, this study aimed to identify which features of key emotion regulation strategies are most predictive and when those features are most predictive of individual symptoms of depression across different time lags. Leveraging novel developments in the field of machine learning, artificial neural network models with feature selection were estimated using data from 460 participants who participated in a 20-wave longitudinal study with weekly assessments. At each wave, participants completed measures of repetitive negative thinking, positive reappraisal, perceived stress, and depression symptoms. Results revealed that specific features of repetitive negative thinking (wondering "why cannot I get going?" and having thoughts or images about feelings of loneliness) and positive reappraisal (looking for positive sides) were important indicators for detecting various depressive symptoms, above and beyond perceived stress. These features had overlapping and unique predictive relations with individual cognitive, affective, and somatic symptoms. Examining temporal fluctuations in the predictive utility, results showed that the utility of these emotion regulation features was stable over time. These findings illuminate potential pathways through which emotion regulation features may confer risk for depression and help to identify actionable targets for its prevention and treatment.

General Scientific Summary
How people regulate their emotions plays an important role in depression. This study leveraged advancements in data science to uncover *which* characteristics of emotion regulation strategies are most predictive and *when* those characteristics are most predictive of depressive symptoms. The findings revealed that patterns of repetitive negative thinking that are marked by feeling stuck and not understanding why as well as perceptions of loneliness may be particularly harmful and set the stage for various symptoms of depression. Looking for positive sides of a negative or stressful

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This study's protocol was not preregistered. Anonymized data and sample analysis code are provided in Supplement 7. Data and code are available on the Open Science Framework (osf.io/jqsvb) and Code Ocean (https://codeocean.com/capsule/2835363/tree/v2). The study materials are protected by copyright and are not freely available without permission from the author.

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situation was also important to detect depressive symptoms such as sadness, loss of pleasure, and loss of interest. These characteristics were stable predictors over time and represent potential targets for effective prevention and treatment.

Keywords: artificial neural networks, depression, emotion regulation, positive reappraisal, repetitive negative thinking

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Depression is among the most prevalent forms of psychopathology and causes severe personal suffering and high societal costs (James et al., 2018; World Health Organization, 2017). Considerable scientific inquiry has focused on identifying mechanisms of depression to develop effective prevention and treatment approaches. Emotion regulation difficulties are purported to play a prominent role in the etiology and maintenance of this burdensome mental health condition (Campbell-Sills & Barlow, 2007; Gross & Jazaieri, 2014; Hofmann et al., 2012; Joormann & Vanderlind, 2014). In depression, emotion regulation is characterized by problematic patterns of emotion regulation strategy use to downregulate negative emotional experiences (Gotlib & Joormann, 2010; Rottenberg, 2017). Two of the most widely researched regulatory strategies that are important in depression are the habitual use of repetitive negative thinking and the lower propensity to use positive reappraisal in response to distressing events (Aldao et al., 2010; Liu & Thompson, 2017; Visted et al., 2018; Watkins, 2008).

Repetitive negative thinking refers to a process of excessive thinking about negative topics that is passive and difficult to control (Watkins, 2008). Increased repetitive negative thinking is associated with inertia of negative emotions (Waugh et al., 2017), impaired stress recovery (Watkins, 2008), and cognitive biases (Joormann et al., 2006). Positive reappraisal involves reinterpreting the meaning of a negative emotion-eliciting stimulus in a less negative and more positive manner to reduce its emotional impact (Garnefski & Kraaij, 2006; Ochsner & Gross, 2008). Habitual use of positive reappraisal has been associated with increased positive emotions (Brans et al., 2013), more positive interpretations of ambiguity (Everaert et al., 2020), better stress recovery (Jamieson et al., 2012), and improved psychological adjustment (Nezlek & Kuppens, 2008).

Importantly, longitudinal research suggests that the propensity to use more repetitive negative thinking and less positive reappraisal may confer risk for depression and more severe symptoms. Studies have shown that repetitive negative thinking predicts increases in depressive symptoms as well as both the maintenance and relapse of clinical depression (Raes, 2012; Spinhoven et al., 2018; Topper et al., 2014). Conversely, habitual positive reappraisal use may predict decreases in depressive symptom severity over time (Brewer et al., 2016; Garnefski & Kraaij, 2007; Haga et al., 2012), albeit its predictive magnitude may be less strong compared with repetitive negative thinking (Aldao et al., 2010).

Despite advances in elucidating the role of repetitive negative thinking and positive reappraisal in depression, research has yet to uncover how these emotion regulation difficulties are connected to individual symptom dimensions of depression. This is because most research has studied emotion regulation difficulties at the level of diagnostic categories or overall symptom severity levels of depression. This focus on the disorder-level may be problematic because depression is a highly heterogeneous condition with many possible symptom profiles (Fried, 2017; Fried & Nesse, 2015; Zimmerman et al., 2015). The lack of consideration given to the clinical heterogeneity of depression in research on emotion regulation difficulties represents an important limitation because it may conceal differential associations between individual emotion regulation strategies and the clinically diverse cognitive, affective, and somatic symptoms (Gross & Jazaieri, 2014). This seems highly plausible because prior research has shown that individual symptoms of depression are differentially related to adverse life events (Keller et al., 2007) and cognitive risk factors (Beevers et al., 2019; Marchetti et al., 2018). Examining potential differential relations for emotion regulation strategies, a recent cross-sectional study found that positive reappraisal was negatively related to pessimism, whereas repetitive negative thinking was positively related to guilty feelings, changes in appetite, agitation, self-criticalness, and sadness (Everaert & Joormann, 2019). This initial finding suggests that not all symptoms of depression have similar relations with repetitive negative thinking and positive reappraisal. This warrants an approach that considers the symptom level of depression in research on emotion regulation.

Similarly, researchers increasingly argue that studies on emotion regulation should also consider the complex multifaceted nature of regulatory strategies (Bernstein et al., 2019; Smith & Alloy, 2009). Emotion regulation strategies are typically treated and studied as unitary constructs. Yet, their various components (e.g., behavioral tendencies, metacognition, controllability, etc.) could differentially affect clinical outcomes. To date, one study examined relations among constituting parts of rumination (Bernstein et al., 2019), which is a form of repetitive negative thinking focused on past or current distress. Using psychometric network modeling, this study found that thinking about the lack of motivation, ability to concentrate in the future, analyzing personality to understand why one is depressed, and wondering why one is not better able to cope with stressors are particularly important features of rumination. In addition, this research observed differential relations between several aspects of rumination. Stronger relations occurred between brooding about feelings of sadness and loneliness, between repetitive self-criticism with self-directed anger and wishing recent situations had gone or been handled better (Bernstein et al., 2019). These findings point to the importance of considering individual facets of rumination to gain a better understanding of this construct and its role as a risk factor for depression. However, similar research on positive reappraisal use is currently lacking even though this emotion regulation strategy is regarded as a regulatory process involving multiple tactics (for example, reappraising the valence versus significance of a negative event; McRae et al., 2012; Uusberg et al., 2019).

Taken together, adopting a more detailed level of analysis that considers *both* specific features of emotion regulation and individual symptoms of depression may be important to advance contemporary theories and research on mechanisms of risk for depression. Knowledge of how features of complex and multifaceted emotion regulation processes such as repetitive negative thinking and positive reappraisal predict individual symptoms of depression may unlock a fine-grained understanding of how emotion regulation difficulties fuel depression. Identifying such predictive relations may provide actionable targets for the prevention and treatment of depression.

The present study goes beyond traditional approaches that consider emotion regulation and depression at the aggregate level of analysis. Instead, this study aimed to identify which features of repetitive negative thinking and positive reappraisal in response to stressful experiences are relevant to predicting individual symptoms of depression. Their unique predictive information above and beyond perceived stress was investigated because stress may be reciprocally related to both depressive symptoms and habitual emotion regulation strategy use (Hankin & Abramson, 2001; Liu & Alloy, 2010; Monroe & Reid, 2009). In examining predictive relations, this study considered various time lags to uncover potential temporal changes in the capacity of certain emotion regulation features to predict depressive symptoms. Because emotion regulation processes and depressive symptoms may change at varying rates over time (Everaert & Joormann, 2020), the strength of their temporal association may fluctuate and alter which emotion regulation features are good predictors at certain time lags (Dormann & Griffin, 2015). However, no study to date has examined potential temporal fluctuations in the predictive utility of emotion regulation features. Yet, such knowledge of predictive relations over time may aid in future theory-building regarding the role of emotion regulation in depression.

To determine which emotion regulation features and when those features predict affective, cognitive, and somatic symptoms of depression, this study leveraged novel developments in machine learning to construct artificial neural network models with feature selection. Artificial neural networks map input features into outputs through a multilayer network structure that captures hidden patterns within the data. Such neural networks are highly successful in machine learning tasks such as prediction, forecasting, or classification, and are increasingly used in research on mental health (Ophir et al., 2020; Richter et al., 2021; Schultebraucks et al., 2020; Sheetal et al., 2020). In contrast to traditional regression-based methods that detect only linear relationships, artificial neural networks effectively model interactions and other nonlinearities as well as multicollinear and high-dimensional data. Indeed, artificial neural networks typically outperform other statistical methods (Urban & Gates, 2021).

Artificial neural networks are commonly criticized as being a black box that lacks interpretability (Ribeiro et al., 2016). To shed light on what specific features are important, this study used a novel feature selection mechanism that examines redundancy and identifies the most important features for prediction (Yamada et al., 2020). By incorporating eight different time lags (0, 1, 2, 3, 4, 8, 12, and 16 weeks), this study aimed to provide the first attempt to illuminate potential temporal fluctuations in predictive relations to identify the right timescale to understand the predictive utility of emotion regulation features. In this way, this study aimed to establish predictive relations between individual depressive symptoms and features of crucial emotion regulation difficulties over time to advance both theory and clinical practice.

Method

Participants and Sampling Strategy

A sample of 460 adults was recruited through Amazon's Mechanical Turk (MTurk) between October 2016 and July 2017. MTurk provides an online crowdsourcing platform with access to large samples suitable for clinical research collecting mental health data (Chandler & Shapiro, 2016; Gillan & Daw, 2016). Table 1 provides demographic information. Participation in the study was restricted to MTurk users who were 18 years or older, resided in the United States, and had a history of providing good-quality responses (i.e., an acceptance ratio of ≥ 95%). A strict data-quality assurance protocol was applied (see Supplement 1). All participants gave informed consent in accordance with the Institutional Review Board at Yale University. Participants were remunerated up to a total of 15.20 USD for completing all surveys.

Table 1
Demographic Characteristics and Descriptive Statistics for Baseline Study Variables

Variable	*N* or *M* (*SD*)
Age	34.29 (11.99)
Gender	
Male	140
Female	328
Race	
White or Caucasian	367
Black or African American	35
American Indian/Alaska Native	1
Asian American	30
Hispanic American	8
Other	27
Education	
No high school degree	4
High school graduate	49
Some college	129
Two-year college graduate	50
Four-year college graduate	162
Master's degree	59
Doctoral degree	11
Professional degree	4
Baseline study variables	
Depressive symptom severity (BDI-II)	15.43 (12.59)
Perceived stress (PSS)	18.43 (7.86)
Repetitive negative thinking (RTQ)	71.09 (26.89)
Positive reappraisal (CERQ)	14.29 (4.08)

Note. BDI-II = Beck Depression Inventory second edition; RTQ = Repetitive Thinking Questionnaire; CERQ = Cognitive Emotion Regulation Questionnaire; PSS = Perceived Stress Scale.

Procedure and Questionnaires

This longitudinal study consisted of twenty waves of data collection separated by one-week time intervals.[1] In the first wave, participants completed a survey that began with demographic questions (age, gender, race, education level) followed by established questionnaires about depression, perceived stress, positive reappraisal, and repetitive negative thinking. Participants completed the same set of questionnaires in all subsequent waves. To standardize the temporal orientation across questionnaires and waves of data collection, participants were instructed to fill out all questionnaires *about the past week* (see Supplement 2 for the instructions). Questionnaires were presented in randomized order. Importantly, participants' scores on measures of repetitive negative thinking, positive reappraisal, perceived stress, and depressive symptom severity represented almost the full range of scores at each wave of data collection. At baseline (wave 1), a total of 232 respondents reported minimal (range: 0–13), 75 reported mild (range: 14–19), 79 reported moderate (range: 20–28), and 74 reported severe (range: 29–58) depressive symptom levels. Descriptive statistics per wave of data collection are provided in Supplement 3.

Severity of Depressive Symptoms

The Beck Depression Inventory—II (Beck et al., 1996) is a frequently used self-report measure of depressive symptom severity. On 21 items, respondents indicate the degree to which they have experienced a certain symptom on a 4-point scale from 0 to 3 (during the past week), yielding a total score ranging from 0 to 63. The cognitive, affective, and somatic symptoms assessed by the BDI-II align with the criteria of major depression from the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 2013). The BDI-II has been shown to have the largest overlap in symptoms with other common depression measures (Fried, 2017). The reliability and validity of the BDI-II has been extensively supported in both nonclinical and clinical adult samples (Joiner et al., 2005). In this study, the internal consistency of the BDI-II varied between MacDonald's $\omega = .96$ and $\omega = .97$ across the twenty waves.

Repetitive Negative Thinking

The repetitive negative thinking subscale of the Repetitive Thinking Questionnaire (McEvoy et al., 2010) is a transdiagnostic measure of the tendency for repetitive negative thinking. All 27 items of the subscale are scored on a five-point scale from 1 (*not true at all*) to 5 (*very true*) in reference to distressing or upsetting situations that happened during the past week. Psychometric research evaluating the repetitive negative thinking subscale in nonclinical and clinical samples has demonstrated that the subscale has a good to excellent high internal consistency as well as validity (Mahoney et al., 2012; McEvoy et al., 2010). In this study, the subscale had excellent internal consistency (MacDonald's ω varied between .97 and .98 across waves).

Positive Reappraisal

The use of positive reappraisal was measured using the subscale of the Cognitive Emotion Regulation Questionnaire (Garnefski et al., 2001). This four-item scale specifically measures the aspects of positive reappraisal (*learning something from the situation*, *becoming a stronger person*, *thinking about positive sides*, *looking for positive sides*) in response to negative events during the past week. On each of the 4 items, respondents rate the extent to which they engage in positive reappraisal using a 5-point scale from 1 (*almost never*) to 5 (*almost always*). The positive reappraisal subscale has good to excellent internal consistency, acceptable test–retest reliability, and both convergent and divergent validity (Garnefski et al., 2001; Garnefski & Kraaij, 2007; Ireland et al., 2017). In the present study, the internal consistency (MacDonald's ω) varied between .94 and .98.

Perceived Stress

The Perceived Stress Scale (Cohen et al., 1983) is a commonly used measure of stress perception. Respondents indicate the degree to which they appraise situations in their lives as stressful on a 5-point scale from 0 (*never*) to 4 (*very often*). Participants completed all ten items of the questionnaire in reference to the past week. The total score ranges from 0 to 40. Research has shown that the questionnaire has an adequate internal consistency (Roberti et al., 2006) and convergent validity (Pbert et al., 1992). In this study, the internal consistency of the scale varied between MacDonald's $\omega = .93$ and $\omega = .96$.

Data-Analysis

Artificial Neural Networks

Artificial neural networks are networks composed of interconnected computational units termed *hidden units*. These hidden units are organized in layers. A *deep* neural network is composed of *multiple* hidden layers and is typically designed as a feedforward neural network in which there are no cycles or loops (i.e., the input at each layer is the output of the previous layer). This study used fully connected feedforward networks in which the layers are densely connected. That is, all the outputs of one layer were connected to all the inputs of the next layer. The output of each layer is computed as an affine mapping of the previous layer followed by a nonlinear function:

$$a^{(l+1)} = \sigma\left(W^{(l)}a^{(l)} + b^{(l)}\right),$$

where $a^{(l)}$ is termed the activation of the hidden units at layer l, $W^{(l)}[i,j]$ denotes the weight associated with the connection between unit j in layer l and unit i in layer $l+1$, $b^{(l)}$ is a bias vector, $\sigma(\cdot)$ is a nonlinear function applied element-wise, and the input to the first layer is the data: $a^{(0)} = X$. For this study, we used a Rectified Linear Unit (ReLU) nonlinearity for the nonlinear activation $\sigma(x) = ReLU(x) = max\{0, x\}$.

[1] This study used data from a larger a longitudinal study on emotion regulation, depression, and anxiety. Portions of this data have been published elsewhere (Everaert & Joormann, 2019, 2020). These prior publications reported on the longitudinal stability of emotion regulation strategy use (Everaert & Joormann, 2020) or cross-sectional relations between emotion regulation strategies and symptoms of depression and anxiety using data from the first wave (Everaert & Joormann, 2019).

Neutral network models are trained to optimize model performance on a given task, in this case, binary classification. Training is performed by optimizing the set of parameters θ such that a loss function is minimized. Minimizing the loss function is usually done by stochastic gradient descent (SGD). The task the network performs is determined by the output layer and the loss function minimized over the network. This study used the cross-entropy loss for binary classification defined by:

$$\mathcal{L}_0 = \sum_i \mathrm{y}_i \log(\hat{y}_i) + (1 - \mathrm{y}_i)\log(1 - \hat{y}_i),$$

Where y_i are the actual binary label and $\hat{y}_i$ is the estimated label generated by the network. The gradient of the loss function relative to the weights is computed efficiently using backpropagation (Rojas, 1996), starting from the output layer backward to the input.

Feature Selection Using Stochastic Gates

Although neural networks are a powerful tool for training classifiers, their main drawback is lack of model interpretability. Layers of nonlinear units can be most effective for successful classification but do not shed light on specific patterns or trends on which the network relies for classification. Stochastic gates (STG) is a recent method that performs feature selection. It limits the number of input features used for classification (Yamada et al., 2020). The STG formulation presents two important merits, namely a straightforward way for quantifying the importance of each input feature and a regularized training process to avoid overfitting which is imperative when the available data for training is small. The STG framework includes a set of units termed gates weighting each input feature before entering the classification network as shown in Figure 1.

During training, the gates are modeled as Gaussian variables: $z_i = \mathcal{N}(\mu_i, \epsilon)$, where the variance ϵ is kept fixed and the mean μ_i are trained (along with θ_i) to minimize the following cost:

$$\mathcal{L}(\theta, \boldsymbol{z}) = \mathcal{L}_0 + \lambda \sum_i P(z_i > 0)$$

where $\mathcal{L}_0$ is the classification loss, and λ is a tradeoff factor tuning between no feature selection (setting λ to 0) and enhanced regularization ($\lambda >> 1$). Given an input feature vector $\boldsymbol{x}$ every element i is multiplied by $\alpha_i = max(0, min(1, \mu_i))$ to ensure that all gates are between 0 and 1. Therefore α_i approaching 1 would mean that the feature x_i is selected whereas $\alpha_i \sim 0$ would indicate that x_i is not. Importantly, promoting sparsity during training forced the models to minimize the number of relevant features. If two input features are highly correlated, the model would choose the feature that contributes most to learning the task. Therefore, features that were not selected might be informative on their own, but in the presence of others they are redundant.

Input and Output Variables

Each model included 27 items of the repetitive negative thinking subscale of the RTQ and four items of the positive reappraisal subscale of the CERQ as input variables (predictors). Importantly, 10 items of the PSS were included in each model to ensure that features of repetitive negative thinking and positive reappraisal would predict depression symptoms above and beyond features of perceived stress. The individual items of the BDI-II served as output variables. To account for temporal trends, we used the first derivative of each feature over time, $x_i(n) = r_i(n) - r_i(n-1)$ where $r_i(n)$ is the (scaled) response to item i on week n. Output variables were dummy-coded into binary responses indicating that a symptom was present (1) or absent (0). Input variables were not binarized. Table 2 in Supplement 4 provides descriptive statistics for all input features at each time lag considered. Scores of negative questions were not reversed. Of note, as opposed to linear models where direction of correlation can be extracted based on the sign of regression weights, neural networks comprise several nonlinear layers where such interpretation is not possible. Moreover, the trained transformation, including the sign of the coefficients is learned through the optimization process given the input data. Missing data points were not interpolated. To maximize the amount of data used in the analyses, sequences of input and output data were extracted from participants according to their available data. On average, participants completed 12.45 of the 20 waves of data collection (SD = 5.29; Md = 20). Complete data were available for 52.17% of the participants (see Table 1 in Supplement 3 for more information). Note that there were no differences in patterns between completers versus noncompleters.

Trained Models

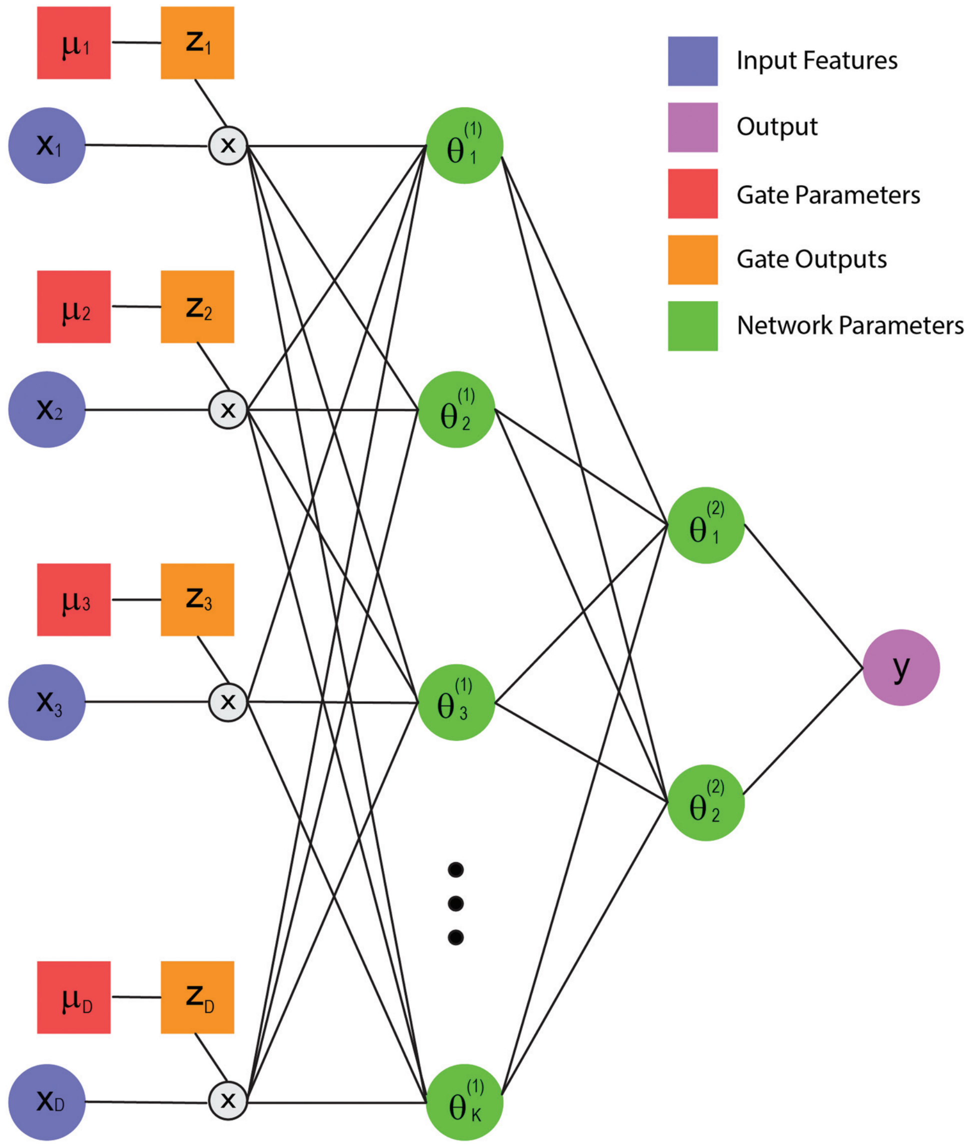
The relevance of emotion regulation features to individual depressive symptoms was examined by training a set of neural networks, each trained for detection of a specific symptom of depression. For this study, models were trained with a built-in lag L to evaluate the relevance of past emotion regulation features to current depression symptoms. We examined 8 different lags between input and output variables $L = \{0, 1, 2, 3, 4, 8, 12, 16\}$. Setting $L = 0$ stands for no lag between input and output variables, that is, detection of depression symptoms based on input features of the same week. The other lags stand for training the network to detect depression symptom occurrences based on emotion regulation features reported 1, 2, 3, 4, 8, 12, or 16 weeks prior to symptom occurrence. Overall, we trained a neural network for each of the 21 examined depressive symptoms and 8 lags resulting in 8 × 21 = 168 networks. The trained neural network models did not account for the nested structure of the data (that is, measurement waves nested within individuals). Because of constraints to the amount of data per participant, the trained neural network models included all time-series of all participants in this study. Therefore, the results are best interpreted as between-person differences.

All models were trained using balanced training and testing sets with fivefold cross validation where the data was divided into 5 disjoint sets of participants; on each fold one set was set aside for testing and the rest were used for training. The neural network configuration included a single hidden layer of 32 hidden units with an SGD optimizer and a learning rate of .1.

Quantification of Performance

Because output variables were mapped to 0 or 1, the neural networks were trained for binary classification. The performance of the models was evaluated based on the commonly used receiver operating characteristic (ROC). A ROC curve captures the true

Figure 1
Neutral Network Configuration With Two Hidden Layers and STG



Note. STG = stochastic gates. See the online article for the color version of this figure.

positive rate versus the false positive rate, obtained by shifting the final decision threshold from a very small value leading to zero detection (true positive rate = 0) to a very high threshold leading to constant detection (false positive rate = 1) resulting with a curve connecting (0,0) and (1,1) on the false-positive–true-positive axes. The Area Under the ROC Curve (AUC) was evaluated to quantify the true-positive–false-positive rates into a single score. A perfect classifier would have AUC = 1 whereas a random (that is, untrained) classifier would lead to AUC = .5.

Transparency and Openness

This study's protocol was not preregistered. Anonymized data and sample analysis code are provided in Supplement 7. Data and code are also available on the Open Science Framework (osf.io/jqsvb) and Code Ocean (https://codeocean.com/capsule/2835363/tree/v2). The study materials are protected by copyright and not freely available without permission from the author.

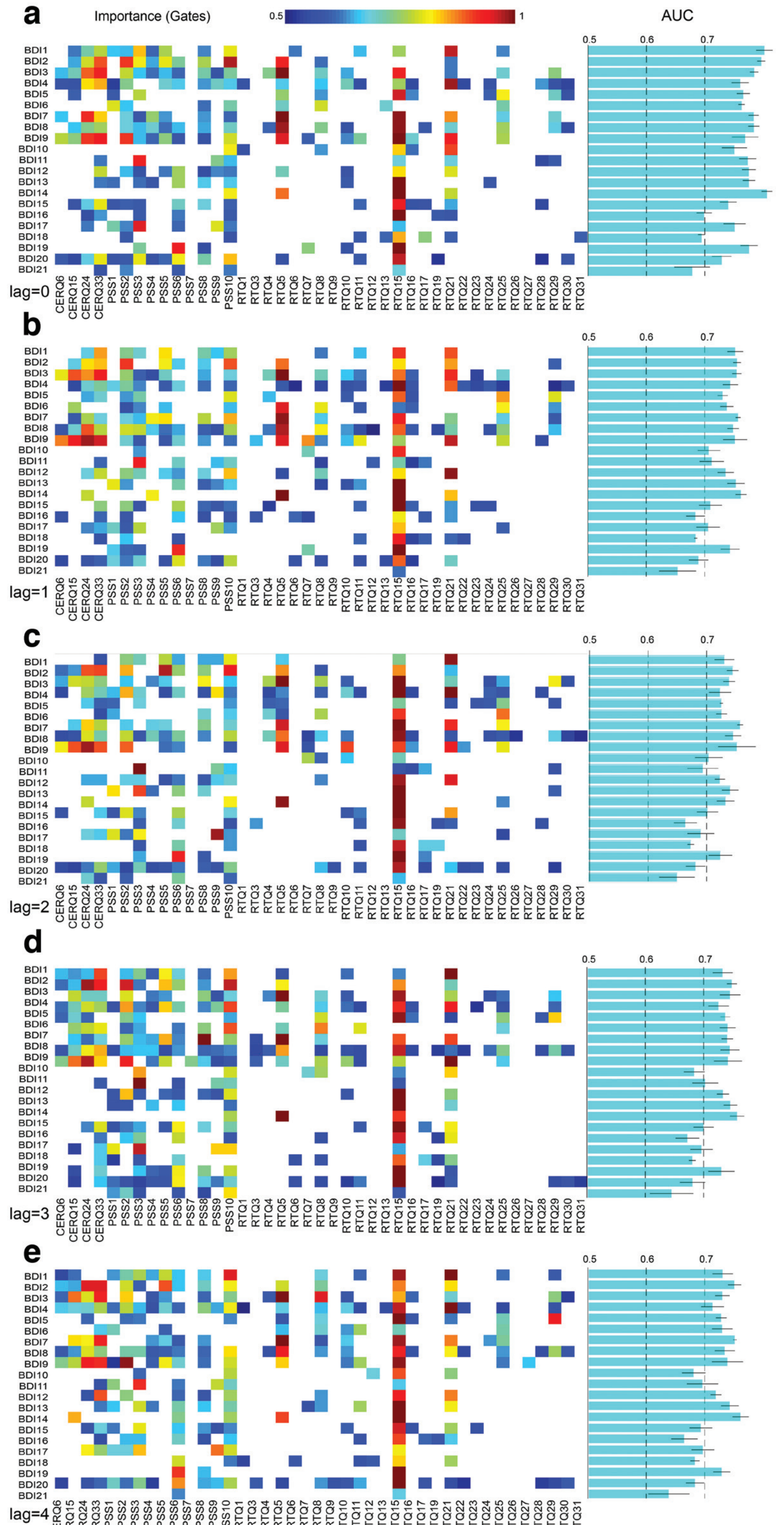
Results

Performance of Trained Neural Network Models

Figures 2 and 3 present the prediction performance of the trained models for detection of depression symptoms. All trained models achieved significantly higher detection rates than chance level (chance level is .50, since data sets were balanced, $p < .006$ (.05/8 lags) to correct for multiple comparisons) for all values of L

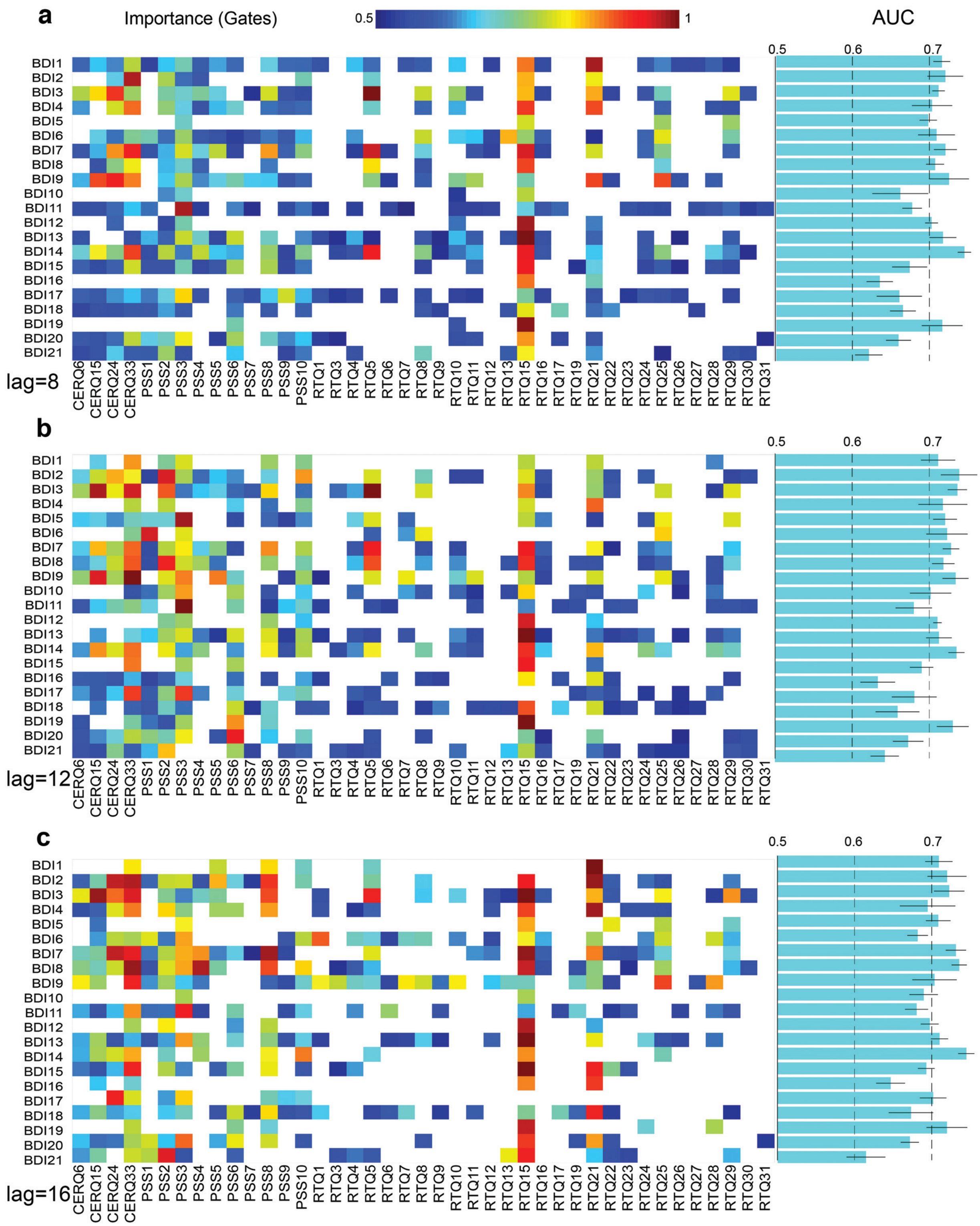
Figure 2

Neutral Network Models for L = 0, 1, 2, 3, and 4 Weeks



Note. BDI = Beck Depression Inventor; RTQ = Repetitive Thinking Questionnaire; CERQ = Cognitive Emotion Regulation Questionnaire; PSS = Perceived Stress Scale; AUC = Area Under the ROC Curve. See the online article for the color version of this figure.

Figure 3
Neutral Network Models for L = 8, 12, and 16 Weeks



Note. BDI = Beck Depression Inventor; RTQ = Repetitive Thinking Questionnaire; CERQ = Cognitive Emotion Regulation Questionnaire; PSS = Perceived Stress Scale; AUC = Area Under the ROC Curve. See the online article for the color version of this figure.

(lag) and all output variables (BDI-II items). AUC values ranged from .63 to .81, suggesting that all models achieved reasonable accuracy for detecting individual depressive symptoms across the different time lags considered in this study.

Importance of Individual Emotion Regulation Features for Predicting Depressive Symptoms

The importance of individual repetitive negative thinking and positive reappraisal features for every depression symptom across each time lag was quantified based on the trained gates values. An input feature was considered important if its gate was significantly larger than .5 (paired t test, $p < .05$, across 5-folds). Figures 2 and 3 present the importance of each input feature for each output feature at the different lags. Table 2 presents the three best emotion regulation features selected as relevant for detection per BDI-II symptom of depression, sorted by descending order of importance. This results section focuses on the BDI-II cognitive-affective and somatic symptoms that align with the diagnostic criteria for major depressive disorder from the *DSM–5* (American Psychiatric Association, 2013).

Cognitive-Affective Symptoms

Inspecting the cardinal symptoms of depression, results showed that the hallmark symptom of sadness (BDI-II item 1) was consistently predicted by ‘thoughts/images about feelings of loneliness’ (RTQ item 21) at each of the eight time intervals. Also, “wondering ‘why cannot I get going?’” (RTQ item 15) emerged as an important indicator for detecting sadness at multiple time lags. Finally, the positive reappraisal feature “looking for positive sides” (CERQ item 33) was a relevant indicator of sadness (at lags 0, 1, 3, 4, 8, 12).

Similarly, the symptoms of anhedonia, namely loss of pleasure (BDI-II item 4) and loss of interest (BDI-II item 12), were best detected by repetitive thinking features ‘thoughts/images about feelings of loneliness’ (RTQ item 21) and “wondering ‘why cannot I get going?’” (RTQ item 15) as well as the positive reappraisal feature “looking for positive sides” (CERQ items 33; at lag 0, 1, 4, 8, 12, 16) at most time lags. In addition, the positive reappraisal feature of ‘thinking about positive sides’ (CERQ items 24) was relevant in predicting loss of pleasure at lags 0, 2, and 3 and loss of interest at lag 16.

Moreover, the symptom feelings of worthlessness (BDI-II item 14) was consistently detected at each time lag by the repetitive thinking feature ‘wondering “why cannot I get going?”’ (RTQ item 15). In addition, the feature “thoughts/images about shortcomings, failings, faults, mistakes” (RTQ item 5) emerged among the best three indicators at lags 0, 1, 2, 3, 4, and 8. Of note, the repetitive thinking feature ‘thoughts/images about feelings of loneliness’ (RTQ item 21) was only among the best predictors for lags 0 and 1. Also, the feature “looking for positive sides” (CERQ items 33) was only among the best predictors at time lags 8, 12, and 16.

As for feelings of guilt (BDI-II item 5), “wondering ‘why cannot I get going?’” (RTQ item 15) emerged as the best predictor at all time lags except lag 12. The features ‘thoughts/images about feelings of loneliness’ (RTQ item 21) and “looking for positive sides” (CERQ item 33) were not among the best predictors of guilty feelings at any of the time lags. Instead, repetitive thinking features “thoughts/images about being angry with oneself” (RTQ item 25) at lags 0, 1, 2, 8, 12, and 16 as well as “wondering ‘Why do I always react this way?’” (RTQ item 29) at lags 1, 3, 4, 8, and 12 were among the most important features to detect feelings of guilt.

Indecisiveness (BDI-II item 13) was best predicted by “wondering ‘why cannot I get going?’” (RTQ item 15). This feature of repetitive negative thinking emerged as the best predictor across all time lags. The features “thoughts/images about feelings of loneliness” (RTQ item 21; lags 0, 3, 4, and 16) and “looking for positive sides” (CERQ items 33; lag 0 and 12) was among the best three features for detecting indecisiveness for only a small number of time lags.

Finally, for suicidal thoughts and wishes (BDI-II item 9), several positive reappraisal features were identified as relevant, including “looking for positive sides” (CERQ item 33; at time lag 0, 1, 4, 12, and 16) and “thinking about positive sides” (CERQ item 24; at time lag 1, 2, 3, 4 and 8).) Interestingly, the repetitive thinking feature “wondering ‘why cannot I get going?’” (RTQ item 15) was only among the best indicators for detecting suicidal thoughts and wishes at lags 0 and 4. The repetitive thinking feature “thoughts/images about feelings of loneliness” (RTQ item 21) emerged as a better predictor and was among the best three features for detecting suicidal ideation at time lag 1, 2, 3, and 8.

Somatic Symptoms

Features of repetitive negative thinking and positive reappraisal also predicted various somatic symptoms of depression. Changes in appetite (BDI-II item 18) were predicted by “why cannot I get going?” (RTQ item 15) at all time lags. Also, the repetitive negative thinking features “continuously thinking about something” (RTQ item 17; lags 0, 2, 3, 8, and 12) and “thoughts/images about feelings of loneliness” (RTQ item 21; at lags 1, 3, 4, 12, 16) were relevant. Notably, the positive reappraisal feature “looking for positive sides” (CERQ item 33) did not emerge as an important predictor of changes in appetite.

Moreover, the symptom changes in sleeping pattern (BDI-II item 16) was consistently detected by “wondering ‘why cannot I get going?’” (RTQ item 15) at all time lags. The features “thoughts/images about feelings of loneliness” (RTQ item 21; at lags 1, 3, 4, 8, 12, and 16) and “looking for positive sides” (CERQ item 33; at lags 0, 3, 8, 12, and 16) were also among the best three indicators at most time lags.

Agitation (BDI-II item 11) or restlessness was detected by the feature “looking for positive sides” (CERQ item 33) at lags 0, 1, 3, 4, 8, 12, and 16 as well as the feature “wondering ‘why cannot I get going?’” (RTQ item 15) at lags 0, 1, 3, 4, and 8. The feature “thoughts/images about feelings of loneliness” (RTQ item 21) was among the best indicators only at time lag 0.

Both tiredness/fatigue (BDI-II item 20) and loss of energy (BDI-II item 15) were predicted by “wondering ‘why cannot I get going?’” (RTQ item 15) at each time lag. The feature “thoughts/images about feelings of loneliness” (RTQ item 21) was in particular important to predict loss of energy at time lags 1, 2, 3, 4, 8, 12, and 16. This repetitive thinking feature predicted tiredness/fatigue at time lags 1, 2, 12, and 16. The positive reappraisal feature “looking for positive sides” (CERQ item 33) was a relevant

Table 2
Emotion Regulation Features Selected as Relevant for Detection per Depressive Symptoms, Sorted by Descending Order of Importance

Depressive symptom	Input elements detected as important							
Lag (weeks)	0 (No lag)	1	2	3	4	8	12	16
BDI-II 1 sadness	RTQ21	RTQ15	RTQ21	RTQ21	RTQ21	RTQ21	CERQ33	RTQ21
	CERQ33	RTQ21	RTQ15	CERQ33	RTQ15	RTQ15	RTQ21	CERQ33
	RTQ15	CERQ33	RTQ5	CERQ6	RTQ8	CERQ33	RTQ15	RTQ5
BDI-II 2 pessimism	RTQ5	RTQ5	CERQ33	CERQ24	CERQ24	CERQ33	CERQ24	RTQ21
	CERQ33	RTQ21	CERQ24	CERQ33	CERQ33	RTQ15	CERQ33	CERQ33
	CERQ24	CERQ33	RTQ5	RTQ15	RTQ15	RTQ21	RTQ15	CERQ24
BDI-II 3 past failure	RTQ5	RTQ5	RTQ15	RTQ5	RTQ5	RTQ5	RTQ5	RTQ15
	CERQ33	CERQ33	RTQ5	RTQ15	RTQ8	CERQ24	CERQ15	CERQ15
	RTQ15	RTQ21	RTQ29	CERQ15	CERQ33	RTQ21	CERQ33	CERQ33
BDI-II 4 loss of pleasure	RTQ21	RTQ15	RTQ15	RTQ21	RTQ21	RTQ15	RTQ21	RTQ21
	CERQ33	RTQ21	RTQ21	RTQ15	RTQ15	RTQ21	RTQ15	RTQ15
	CERQ24	CERQ33	CERQ24	CERQ24	CERQ33	CERQ33	CERQ33	CERQ33
BDI-II 5 guilty feelings	RTQ15	RTQ15	RTQ25	RTQ15	RTQ15	RTQ15	RTQ25	RTQ15
	RTQ25	RTQ25	RTQ15	RTQ29	RTQ29	RTQ25	RTQ5	RTQ22
	RTQ5	RTQ29	CERQ24	RTQ8	CERQ33	RTQ29	RTQ29	RTQ25
BDI-II 6 punishment feelings	RTQ8	RTQ5	RTQ15	RTQ8	RTQ11	RTQ13	RTQ25	RTQ1
	RTQ25	RTQ25	RTQ25	CERQ33	RTQ25	RTQ25	RTQ8	RTQ15
	RTQ5	RTQ8	RTQ8	RTQ11	RTQ15	RTQ8	CERQ33	RTQ25
BDI-II 7 self-dislike	RTQ5	RTQ5	RTQ15	RTQ5	RTQ5	RTQ5	RTQ15	RTQ15
	RTQ15	RTQ15	RTQ5	RTQ21	RTQ15	RTQ15	RTQ5	CERQ24
	CERQ24	CERQ24	RTQ21	RTQ15	CERQ33	CERQ33	CERQ33	CERQ33
BDI-II 8 self-criticalness	RTQ15	RTQ5	RTQ15	RTQ15	RTQ5	RTQ15	RTQ15	CERQ33
	RTQ5	CERQ24	RTQ5	RTQ5	RTQ15	RTQ5	RTQ5	RTQ15
	CERQ33	RTQ15	CERQ24	CERQ33	RTQ21	CERQ33	CERQ33	CERQ24
BDI-II 9 suicidal thoughts or wishes	RTQ15	CERQ24	CERQ24	RTQ21	RTQ15	CERQ24	CERQ33	CERQ33
	RTQ5	RTQ21	RTQ5	CERQ24	CERQ24	RTQ21	CERQ15	RTQ25
	CERQ33	CERQ33	RTQ21	CERQ15	CERQ33	CERQ15	RTQ7	RTQ28
BDI-II 10 crying	RTQ21	RTQ15	RTQ7	RTQ21	RTQ15	RTQ15	RTQ15	RTQ15
	RTQ15	RTQ7	RTQ15	RTQ8	RTQ21	RTQ25	RTQ24	RTQ25
	RTQ25	RTQ16	RTQ10	RTQ7	RTQ12	RTQ8	RTQ16	RTQ8
BDI-II 11 agitation	RTQ21	RTQ15	RTQ17	CERQ33	RTQ15	RTQ15	CERQ33	CERQ33
	RTQ15	RTQ17	RTQ8	RTQ15	CERQ33	CERQ33	CERQ24	RTQ6
	CERQ33	CERQ33	RTQ29	CERQ24	RTQ8	RTQ29	CERQ15	RTQ19
BDI-II 12 loss of interest	RTQ15	RTQ21	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15
	RTQ21	RTQ15	RTQ21	RTQ21	CERQ33	CERQ33	RTQ21	CERQ33
	CERQ33	CERQ33	CERQ33	RTQ5	RTQ21	RTQ21	CERQ33	CERQ24
BDI-II 13 indecisiveness	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15
	CERQ33	RTQ11	RTQ8	RTQ21	RTQ21	RTQ10	CERQ33	RTQ21
	RTQ21	RTQ10	RTQ29	RTQ8	RTQ11	RTQ4	CERQ15	CERQ15
BDI-II 14 worthlessness	RTQ15	RTQ5	RTQ15	RTQ5	RTQ15	RTQ15	RTQ15	RTQ15
	RTQ5	RTQ15	RTQ5	RTQ15	RTQ5	RTQ5	CERQ33	CERQ33
	RTQ21	RTQ21	CERQ24	RTQ8	CERQ15	CERQ33	CERQ15	CERQ24
BDI-II 15 loss of energy	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15
	CERQ33	CERQ33	RTQ21	RTQ21	RTQ21	CERQ33	CERQ33	RTQ21
	CERQ24	RTQ21	CERQ33	CERQ33	CERQ33	RTQ21	RTQ21	CERQ33
BDI-II 16 changes in sleeping pattern	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ21
	CERQ33	RTQ21	RTQ3	RTQ21	RTQ21	RTQ21	RTQ21	RTQ15
	RTQ19	RTQ6	RTQ11	CERQ33	RTQ17	CERQ33	CERQ33	CERQ33
BDI-II 17 irritability	CERQ33	RTQ15	RTQ15	CERQ33	CERQ24	RTQ15	CERQ33	CERQ24
	RTQ15	CERQ33	CERQ24	RTQ15	RTQ15	CERQ33	CERQ24	CERQ33
	CERQ24	CERQ24	CERQ33	CERQ24	CERQ33	CERQ24	CERQ6	RTQ28
BDI-II 18 changes in appetite	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ21
	RTQ17	RTQ21	RTQ19	RTQ21	RTQ21	RTQ17	RTQ21	CERQ15
	RTQ13	RTQ11	RTQ17	RTQ17	RTQ12	RTQ22	RTQ17	RTQ15
BDI-II 19 concentration difficulty	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15
	RTQ7	RTQ7	RTQ17	CERQ33	RTQ17	RTQ10	CERQ33	CERQ33
	CERQ33	RTQ11	CERQ33	RTQ21	CERQ33	CERQ33	CERQ15	RTQ28
BDI-II 20 tiredness or fatigue	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15	CERQ33	RTQ15
	CERQ33	RTQ21	CERQ33	CERQ33	RTQ11	CERQ33	RTQ15	RTQ21
	CERQ24	CERQ33	RTQ21	RTQ11	RTQ8	CERQ24	RTQ21	CERQ33
BDI-II 21 loss of interest in sex	RTQ15	RTQ15	CERQ24	RTQ15	RTQ15	RTQ15	RTQ15	RTQ15
	CERQ24	CERQ33	RTQ15	RTQ31	RTQ21	RTQ8	CERQ24	RTQ13
	CERQ33	RTQ21	RTQ3	RTQ13	CERQ24	CERQ24	RTQ13	CERQ33

Note. BDI-II = Beck Depression Inventory second edition; RTQ = Repetitive Thinking Questionnaire; CERQ = Cognitive Emotion Regulation Questionnaire.

predictor for both loss of energy and tiredness/fatigue at nearly all lags.

Finally, concentration difficulties (BDI-II item 19) were predicted by "wondering 'why cannot I get going?'" (RTQ item 15) at all time lags and "looking for positive sides" (CERQ item 33) at time lag 0, 2, 3, 4, 8, 12, and 16. The feature "thoughts/images about feelings of loneliness" (RTQ item 21) was among the best predictors only at time lag 3.

Additional Analyses

This pattern of findings from the artificial neural network models converged with results from multilevel linear regression models, which increases confidence in the findings. The results of the multilevel models are reported in Supplement 5. However, the results of multilevel modeling should be interpreted cautiously because these models were highly parametrized, consider only linear relations between the outcome and the predictors, and do not use a formal feature selection procedure to identify the most potent predictors. By contrast, the artificial neural network models with features selection effectively model interactions and other nonlinearities as well as multicollinear and high-dimensional data.

Additional neural network models were trained to include the lagged output variable as an input feature (see Supplement 6). The results indicated that the best feature for detecting an individual symptom is the level of the symptom at a prior time point. This is expected because the lagged BDI-II input feature shares the same information with the output variable because it measures the same construct. Inspecting emotion regulation features, the same three features (RTQ item 15, RTQ item 21, CERQ item 33) were frequently selected as relevant indicators for detecting depression symptoms. The emotion regulation features were relatively more important as the time lag increased. This finding substantiates the observations by this study.

Summary

The overall pattern showed that three emotion regulation features stood out and were frequently selected as among the best indicators for detecting various key *DSM–5* symptoms of depression. These features were "wondering 'why cannot I get going?'" (RTQ item 15), "thoughts/images about feelings of loneliness" (RTQ item 21), and "looking for positive sides" (CERQ item 33). It is to note that these features were identified as important in predicting individual symptoms of depression above and beyond when considering features of perceived stress. However, not all features of positive reappraisal and repetitive negative thinking were equally important to every *DSM–5* symptom of depression, and symptom-specific predictive relations emerged.

Temporal Changes in the Importance of Emotion Regulation Features

The obtained predictive pattern revealed that the predictive utility of the most potent emotion regulation features was relatively stable over the course of sixteen weeks. For most *DSM–5* symptoms of depression, no notable changes in the predictive utility were observed for "looking for positive sides" (CERQ item 33), "wondering 'why cannot I get going?'" (RTQ item 15) and "thoughts/images about feelings of loneliness" (RTQ item 21).

However, the predictive utility of some emotion regulation features for certain symptoms did vary over time. Some features such as "learning something from the situation" (CERQ item 6), "listening to sad music" (RTQ item 3), "thoughts/images to do something again but better" (RTQ item 4), "thinking 'why I feel this way'" (RTQ item 12), and "thoughts/images resulting in avoidance" (RTQ item 13) were only important to one *DSM–5* depressive symptom at one specific time lag (see Table 2). In addition, some other emotion regulation features may be better predictors at shorter time lags, such as the feature "thinking about positive sides" (CERQ item 24) for predicting loss of pleasure or suicidal thoughts and wishes. Conversely, other features emerged as good predictors at longer time lags, such as "looking for positive sides" (CERQ item 33) for feelings of worthlessness and changes in sleeping pattern. In sum, emotion regulation features differ in terms of the temporal stability of their predictive utility with respect to individual depressive symptoms.

Discussion

Leveraging recent advancements in machine learning, this study used artificial neural network modeling with feature selection to uncover which features of repetitive negative thinking and positive reappraisal and when those features are important predictors of individual symptoms of depression. The pattern of findings revealed three emotion regulation features as important indicators for detecting multiple *DSM–5* symptoms across time across individuals, but also symptom-specific predictive relations. Not all features of positive reappraisal and repetitive negative thinking were equally important to every symptom of depression. This finding underscores the importance of considering the clinically diverse symptoms of depression (Fried, 2017; Fried & Nesse, 2015; Zimmerman et al., 2015) as well as the multifaceted nature of emotion regulation strategies (Bernstein et al., 2019; Gross & Jazaieri, 2014; Smith & Alloy, 2009) to enable a more detailed understanding of how purported risk factors operate in depression. Indeed, such differential predictive relations would go unnoticed when research exclusively adopts the traditional disorder-level focus.

This study identified two features of repetitive negative thinking, namely wondering "why cannot I get going?" as well as thoughts and images about feelings of loneliness, as highly relevant to detecting *DSM–5* symptoms of depression. Wondering "why cannot I get going?" was consistently among the best indicators of all *DSM–5* symptoms of depression except suicidal thoughts and wishes. Notably, this repetitive negative thinking feature was the most important feature for detecting the cognitive-affective symptoms of loss of interest, worthlessness, guilty feelings, and indecisiveness across all considered time lags. In addition, this feature was the best indicator of many somatic symptoms including concentration difficulty, changes in appetite, changes in sleeping pattern, tiredness/fatigue, and loss of energy. The repetitive thinking feature "having thoughts and images about feelings of loneliness" was particularly relevant to the cardinal symptoms of sadness and loss of pleasure. This feature was also a good predictor of the following symptoms: loss of interest, suicidal thoughts and wishes, changes in sleeping pattern, changes in appetite, tiredness or fatigue, and loss of energy. However, having thoughts and images about feelings of loneliness was not consistently among the best three indicators for symptoms such as worthlessness, guilty feelings, agitation, and concentration difficulty. Collectively, these observations suggest that patterns of repetitive negative thinking that are characterized by feeling stuck and not understanding why or perceptions of loneliness may be particularly harmful and set the stage for various symptoms of depression.

These two repetitive negative thinking features are conceptually similar to the features identified as central aspects of rumination in prior cross-sectional research using psychometric network modeling (Bernstein et al., 2019). This prior work found that thinking about the lack of motivation and wondering why one is depressed and/or not able to cope with stressors are central features of rumination (Bernstein et al., 2019). Different from this earlier work, the present work did not identify features related to thinking about the ability to concentrate on the future as important. Instead, observations from the present study suggest that the social dimension of repetitive negative thoughts with a focus on loneliness is important in the prediction of hallmark depressive symptoms. This corresponds to interpersonal/social themes identified by cognitive models of depression (Beck & Haigh, 2014). Importantly, the current findings extend prior cross-sectional research (Bernstein et al., 2019) by showing that individual features of repetitive negative thinking can predict clinically important phenomena. The observed predictive relations between the repetitive negative thinking features and individual symptoms of depression elucidate potential pathways through which aspects of repetitive thought could fuel depression. This underpins the importance of considering individual facets of repetitive negative thinking to gain a better theoretical understanding of how it confers risk of experiencing this burdensome mental health condition.

One positive reappraisal feature, looking for positive sides of a negative or stressful situation, was found to be among the three best indicators of various depressive symptoms. This feature, reflecting the process of actively searching for information and allocating attention toward to-be-identified positive aspects, was important to detect cardinal symptoms of depression including sadness, loss of pleasure, and loss of interest. In addition, looking for positive sides was also important for other key symptoms such as suicidal thoughts and wishes, worthlessness, agitation, changes in sleeping pattern, concentration difficulty, tiredness/fatigue, and loss of energy. Looking for positive sides may thus play a critical role in key cognitive, affective, and somatic symptoms of depression.

Importantly, various features of repetitive negative thinking and positive reappraisal were only important to some symptoms of depression. Of particular importance was the observation that the positive reappraisal feature of thinking about positive sides (which represents processing of already identified positive aspects) was related to suicidal thoughts and wishes. When combined with the feature looking for positive sides, positive reappraisal features were more important than features of repetitive negative thinking to predict concurrent and prospective suicidal ideation. This observation is consistent with recent longitudinal research indicating that interpretation processes predict increases in suicidal ideation (Everaert et al., 2021). This finding warrants further research exploring the etiological significance of the pathways from reappraisal or reinterpretation to suicidal ideation. Moreover, this study found that some specific features of repetitive negative thinking were relevant to predicting individual symptoms of depression. For example, thoughts or images about shortcomings, failings, faults, mistakes emerged among the best three indicators feelings of worthlessness and guilty feelings were detected by thoughts or images about being angry with oneself and wondering “Why do I always react this way?” Thus, these repetitive thinking features may not confer risk to depression as a clinical condition, but only to some of its symptoms. A more detailed level of analysis that considers both specific features of emotion regulation strategies and individual symptoms of depression may enable a more sophisticated theoretical understanding of risk for depression.

When inspecting changes in the predictive pattern over time, this study showed that the predictive utility of the most potent features of positive reappraisal and repetitive negative thinking was relatively stable over the course of sixteen weeks. Looking for positive sides, wondering “why cannot I get going,” and thoughts or images about feelings of loneliness were consistent predictors of future individual symptoms of depression across different time lags. Therefore, these features represent good and stable indicators to predict future maladaptation. Interestingly, the predictive utility of some features fluctuated over time. Features such as “thinking about positive sides” were better predictors of specific depressive symptoms at shorter time lags (3 weeks or less). By contrast, other emotion regulation features emerged as good predictors at longer time lags, namely looking for positive sides (for worthlessness). Such features may serve as additional early warning signals for future psychological maladaptation. The timescale should thus be considered to determine the utility of some emotion regulation features in predicting symptoms of depression across individuals. This is an intriguing observation because the predictive utility of purported risk factors for depression is generally assumed to reflect a stable characteristic. The literature currently lacks theoretical models that account for such temporal fluctuations in the predictive utility of emotion regulation features across individuals. Therefore, to enable theory-building efforts, future research could examine the temporal unfolding of individual emotion regulation features over shorter and longer periods to identify covarying factors (e.g., beliefs about emotions or symptoms, beliefs about the utility of emotion regulation strategies, emotion regulation repertoire) that account for potential fluctuations in their predictive utility. This work may further benefit from applying neural network modeling to examine within-person changes in temporal unfolding of the predictive utility of emotion regulation features to complement the between-person approach of this study.

The present findings have several implications for clinically applied settings. Identifying which features of purported risk factors such as repetitive negative thinking and positive reappraisal consistently predict individual symptoms of depression across individuals provides important clues to enhance prevention and treatment approaches to target depression. The study identified a small set of emotion regulation features as important to detect concurrent and future depressive symptoms across individuals. This set of items, as well as the information about the timescale of their predictive utility, may be useful for mental health professionals to identify (groups of) individuals who may be at risk for developing depressive symptoms over the course of several weeks. Targeting those emotion regulation features that are most relevant in predicting certain symptoms of depression holds the potential to prevent the onset of depression and suicidality effectively. For example, this study suggests that therapeutic techniques focused on improving emotion regulation (Ellard et al., 2010) and negative self-referential processing (Mennin & Fresco, 2013) should aim to reduce specific aspects of repetitive negative thinking such as wondering "why cannot I get going?" to prevent the onset of various symptoms of depression and potentially enhance treatment success.

Moreover, the present findings may also improve clinical decision-making by informing behavioral diagnostic tools for depression (Richter et al., 2021) and informing the selection of treatment targets once depressive symptoms have been developed using a process-based therapy approach (Hofmann & Hayes, 2019). That is, neural network modeling tools integrating behavioral data (e.g., emotion regulation strategy use) could be harnessed to accurately diagnose depressive symptoms. Based on the symptom profile of a patient experiencing depression, mental health professionals could select emotion regulation features that are concurrently and prospectively linked to the symptoms as treatment targets. Targeting those symptoms through changing underlying processes may effectively reduce current depressive symptoms as well as block the development of future symptoms connected to the emotion regulation features.

The present study has several limitations that point to directions for future research. First, this study recruited an online general population sample of individuals reporting depressive symptoms along the continuum of severity levels. Though almost the full range of depressive symptom severity scores was represented at each wave, the nature of the sample feature may limit the generalizability of the findings to non-crowdsourced and clinical samples. However, the dimensional approach adopted by this study seems particularly suited to document varying degrees of emotion regulation problems along the continuum of minimal to severe depressive symptoms. This approach aligns with contemporary dimensional approaches to studying risk for psychopathology (for example, research domain criteria; (Sanislow, 2020) and may further help to better understand the heterogeneous nature of conventional diagnostic categories (Fried, 2017; Fried & Nesse, 2015; Zimmerman et al., 2015). In moving forward, future research could replicate the present findings in non-crowdsourced and clinical samples of depression. Second, this study is limited by its focus on two prominent emotion regulation strategies in depression. Features of other emotion regulation strategies that are used at various stages of the emotion generative process (i.e., situation selection, situation modification, attentional deployment, cognitive change, response modulation; Gross, 2015) may also be important in predicting individual cognitive, affective, and somatic symptoms of depression. It is possible that the predictive utility of repetitive negative thinking and positive reappraisal features changes when considering a larger and more diverse set of emotion regulation features. Therefore, future work could integrate a broader set of emotion regulation strategies to examine which features are important for detecting individual symptom dimensions of depression. Third, the longitudinal design to examine the utility of emotion regulation features in predicting depressive symptoms precludes claims about causation. Experimental manipulation is required to establish the causal impact of identified emotion regulation features on individual depressive symptoms. The identified potent emotion regulation features could be investigated as potential causal factors underlying symptoms of depression. Finally, it is possible that the observed relations between emotion regulation strategies and depressive symptoms are specific to the questionnaires used for this study. Self-report instruments often differ in the set of items that are measured. This restricts the relations that can be detected by the artificial neural network models. However, the questionnaires used in this study are widely used self-report measures that were selected carefully based on their psychometric properties and the variety in common cognitive, affective, and somatic symptoms assessed. Therefore, the current study contributes to knowledge of emotion regulation features that may predict common symptoms of depression. The findings may serve as an impetus for future studies that use other questionnaires on depression and emotion regulation strategy use to determine the robustness of the initial observations reported by this study.

Despite these limitations, this study substantially advances the understanding of the relevance of emotion regulation features for depression in important ways. Using artificial neural network modeling with feature selection, this study showed that features of positive reappraisal and repetitive negative thinking were differentially important to detect individual symptoms of depression. Particularly important features that consistently predicted a variety of depressive symptoms were wondering "why cannot I get going?," thoughts or images about feelings of loneliness, and "looking for positive sides." However, the predictive utility of some other features of repetitive negative thinking and positive reappraisal fluctuated over time. Collectively, the results highlight the importance of considering individual facets of emotion regulation to predict depressive symptoms and gain a better understanding of how it may confer risk of experiencing this mental health condition.

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