Behaviour Research and Therapy 165 (2023) 104307

Contents lists available at ScienceDirect

Behaviour Research and Therapy

journal homepage: www.elsevier.com/locate/brat

Perseverative thinking is associated with features of spoken language[☆]

Elizabeth C. Stade[a,*], Lyle Ungar[b], Shreya Havaldar[b], Ayelet Meron Ruscio[a]

[a] Department of Psychology, University of Pennsylvania, 425 South University Avenue, Philadelphia, PA, 19104-6018, USA
[b] Department of Computer and Information Science, University of Pennsylvania, 504 Levine Hall, 3330 Walnut Street, Philadelphia, PA, 19104-6018, USA

ARTICLE INFO

Keywords:
Worry
Rumination (cognitive process)
Major depression
Generalized anxiety disorder
Natural language processing
Machine learning

ABSTRACT

Perseverative thinking (PT), such as rumination or worry, is a transdiagnostic process implicated in the onset and maintenance of emotional disorders. Existing measures of PT are limited by demand and expectancy effects, cognitive biases, and reflexivity, leading to calls for unobtrusive, behavioral measures. In response, we developed a behavioral measure of PT based on language. A mixed sample of 188 participants with major depressive disorder, generalized anxiety disorder, or no psychopathology completed self-report PT measures. Participants were also interviewed, providing a natural language sample. We examined language features associated with PT, then built a language-based PT model and examined its predictive power. PT was associated with multiple language features, most notably *I-usage* (e.g., "I", "me"; $\beta = 0.25$) and *negative emotion* language (e.g., "anxiety", "difficult"; $\beta = 0.19$). In machine learning analyses, language features accounted for 14% of the variance in self-reported PT. Language-based PT predicted the presence and severity of depression and anxiety, psychiatric comorbidity, and treatment seeking, with effects in the $r = 0.15$–0.41 range. PT has face-valid linguistic correlates and our language-based measure holds promise for assessing PT unobtrusively. With further development, this measure could be used to passively detect PT for deployment of "just-in-time" interventions.

1. Introduction

Perseverative thinking (PT) is a process involving difficulty disengaging from negative thinking (McEvoy et al., 2013). Two common forms of PT are worry, or difficult-to-control negative thinking about uncertain future events (Borkovec et al., 1983), and rumination, or negative thinking about one's feelings or past events (Nolen-Hoeksema, 1991). PT plays an important role in the onset, maintenance, and recurrence of numerous mental disorders (Ehring & Watkins, 2008; Harvey et al., 2004). Despite its importance, progress in understanding and treating PT has been hampered by the challenge of measuring this covert process.

PT is typically assessed using trait questionnaires. Although these global assessments are reliable and convenient, they are biased by errors related to recall, averaging, and meta-cognitive appraisals (Fahrenberg et al., 2007; Mathersul & Ruscio, 2020; Wells, 2013). State measures sample PT periodically in daily life (e.g., Ruscio et al., 2015) or in real- or next-to-real time in the laboratory (e.g., Stade et al., 2022). While these methods circumvent some limitations of global ratings, they likely are still affected by recall errors and lack of insight, especially in clinical populations (Mineka et al., 2003). These methods also run the risk of "reflexivity" (Watkins & Roberts, 2020), wherein the natural thought process is disrupted or altered as individuals reflect and report on their thoughts.

1.1. A behavioral measure based on natural speech

Given these limitations, theorists have called for the development of an implicit behavioral measure of PT (Watkins & Roberts, 2020). Elsewhere in the field, researchers seeking behavioral measures of covert psychological processes have drawn on computational linguistics (Kern et al., 2016; Schwartz et al., 2013). Computational linguistics involves automated processing and analysis of human language using interdisciplinary methods based in linguistics, cognitive science, and artificial intelligence (Clark et al., 2010). In recent years, researchers have made progress in identifying language markers and building language-based

☆ Author Note: Portions of this research were presented at the annual meeting of the Society for Research in Psychopathology, Philadelphia, PA, September 2022. This work was supported by the National Institute of Mental Health [grant R01-MH094425 to A.M.R.] and the National Science Foundation [grant DGE-1845298 to E.C.S.].

* Corresponding author. University of Pennsylvania, Stephen A. Levin Building, 425 South University Avenue, Philadelphia, PA, 19104-6018, USA.
E-mail addresses: elizwade@sas.upenn.edu (E.C. Stade), ungar@cis.upenn.edu (L. Ungar), shreya@cis.upenn.edu (S. Havaldar), ruscio@psych.upenn.edu (A.M. Ruscio).

https://doi.org/10.1016/j.brat.2023.104307
Received 26 August 2022; Received in revised form 7 March 2023; Accepted 23 March 2023
Available online 31 March 2023
0005-7967/

models of depression (Guntuku et al., 2017) and psychosis (Hitczenko et al., 2021). The verbal-linguistic nature of PT (Ehring & Watkins, 2008) makes this construct well-positioned for linguistic investigation; however, to our knowledge, no study has undertaken a thorough exploration of language as a behavioral indicator of PT.

Several lines of research hint that PT may have natural language correlates. First, findings suggest that negative thoughts may "spill out" into day-to-day conversations. The self-reported tendency to discuss personal concerns excessively with friends—a process termed "co-rumination"—shares a moderate to strong correlation with self-reported trait rumination (Jose et al., 2012; Rose, 2002). Furthermore, in conversations between romantic partners about a topic of shared concern, self-rated worry exhibits moderate to large associations with partner- and observer-rated expressed worry (Parkinson et al., 2016). These results suggest that there exists an "expressed PT" behavior that a) is related to internally-experienced PT and b) is detectable by both familiar and unfamiliar outside observers. However, neither the co-rumination nor the expressed worry literatures have quantified this effect in natural language by searching for linguistic markers of trait perseveration.

Further indirect evidence comes from work on linguistic markers of disorders in which PT is heightened. First-person singular pronoun use (e.g., "I," "my"; "*I-usage"*) is robustly related to depression (Edwards & Holtzman, 2017). Notably, research linking *I-usage* to depression grew out of early research on the association depression shares with self-focused attention and repetitive negative thinking (Ingram & Smith, 1984; Pyszczynski & Greenberg, 1987), and some researchers have posited that increased *I-usage* in depression reflects rumination (Nalabandian & Ireland, 2019). *Negative emotion* language has also been associated with depression, though less reliably than *I-usage* (Ireland & Mehl, 2014). Experimental research suggests that depression may interact with rumination to produce *negative emotion* language (Lyubomirsky et al., 1999).

Research on generalized anxiety disorder (GAD) may offer further clues, given the central role of worry in this disorder. Mothers with GAD show heightened use of present- and future-tense verbs when interacting with their children (Geronimi & Woodruff-Borden, 2015), and patients with GAD show increases in past-tense verbs over the course of therapy (Dirkse et al., 2015). Together these results suggest a relationship between worry and language oriented toward the present and future, rather than the past. Additionally, our group found that *I-usage* and *negative emotion* words were shared by GAD and depression (Stade et al., under review), hinting that these linguistic markers reflect transdiagnostic process(es). Similar conclusions are suggested by research showing a relationship between *I-usage* and neuroticism (Tackman et al., 2019), a common factor underlying depression and anxiety.

PT is a transdiagnostic risk factor for depression and anxiety (Spinhoven et al., 2018) that loads highly on neuroticism (du Pont et al., 2019), and many of the linguistic markers revealed in prior studies (e.g., *I-usage*, *negative emotion* words, and *temporal orientation* of speech) are conceptually related to PT (Ehring & Watkins, 2008). This raises the possibility that PT shares a direct relationship with, or is even driving, these language features.

We are aware of only one prior attempt to investigate linguistic markers of PT. Brockmeyer et al. (2015) examined language use during recall of negative and positive memories among depressed and healthy individuals, reporting mixed results for a relationship between trait rumination and *I-usage*. However, *I-usage* was the only language feature examined, rumination was assessed via a single short-form questionnaire, and the diagnostic groups were very small, limiting statistical power to detect an effect. Furthermore, the study's focus on rumination left open the question of whether *I-usage* is unique to rumination or is characteristic of the broader construct of PT. Finally, as only one linguistic feature was investigated, the study was unable to move beyond descriptive analyses to building a predictive model. Prior evidence for verbal expressions of PT in natural conversation hints that a behavioral measure of PT could be extracted from spoken language and, in turn, used to predict clinical outcomes.

1.2. The present study

Here, we present the first comprehensive study of linguistic markers of PT in natural language. Given evidence that the common factor of repetitive negative thinking, rather than worry- and rumination-specific factors, accounts for most of the variance in psychopathological outcomes (Samtani et al., 2022), we elected to study PT as a unitary construct. We recruited a mixed clinical sample that varied widely in self-reported trait PT. Participants engaged in an interview in which they provided free-form, spoken responses to a series of questions about changes or difficulties in various life domains. We transcribed their language and subjected it to computational linguistic analysis. After examining relationships between self-reported PT and a variety of language features, we built and tested a language-based model of PT.

1.2.1. Hypotheses

We preregistered our hypotheses and analysis plan on the Open Science Framework (https://osf.io/qmwn5). Following APA Style Journal Reporting Standards (Kazak, 2018), we posed primary and secondary hypotheses. Primary hypotheses tested language features previously associated with depression and/or anxiety that have a conceptual relationship with PT. We hypothesized that trait PT would be related to *I-usage,* reflecting increased self-focus, and *negative emotion* language, reflecting PT's focus on negative content (Ehring & Watkins, 2008). We also expected to find a relationship of PT with *cognitive processes* language, which has been posited to index rumination (Eichstaedt et al., 2018).

Secondary hypotheses tested language features that are consistent with definitions of PT but have less extant support. We predicted that PT would be related to reduced *concreteness*, capturing its abstract quality (Watkins, 2008), as well as increased *comparisons,* given claims that PT results from discrepancies arising from mental comparisons between an actual and ideal state (Carver & Scheier, 1990). Finally, we examined the sentence-to-sentence *coherence* of speech using sentence embeddings (Iter et al., 2018). This technique measures the semantic relation between each possible sentence pair in a given text. Although it has previously been used to study cognition and communication in psychosis (Tang et al., 2021) and autism (Lee et al., 2018), embedding-based coherence could also capture the perseverative quality of PT.

Worry and rumination are commonly described as focusing on the future and past, respectively (Borkovec et al., 1983; Nolen-Hoeksema et al., 2008). Consequently, we suspected that trait PT would be associated with *future*- and *past*-, rather than *present-,* focused language. We further proposed the primary hypotheses that worry would share a stronger relationship with *future*-focused language than rumination, and that rumination would share a stronger relationship with *past*-focused language than worry.

1.2.2. Exploratory analyses

In exploratory analyses, we examined relationships between trait PT and all available language features. This allowed us to search for novel language correlates of PT in a data-driven manner. Leveraging these correlates, we then built a language-based model of PT. Such models are trained using language features to predict a psychological construct of interest, and thus can be used to estimate an individual's score on the construct based on language alone. In the present study, language features served as input to the model, which output a continuous score estimating each participant's PT severity. To test the predictive power of this model, we examined the ability of the language-based estimates of PT to predict relevant clinical outcomes.

2. Method

2.1. Participants

We recruited adult participants from the Philadelphia community via online and in-person advertisements. Those who passed an initial screening were invited to the lab, where we obtained informed consent prior to administering the Anxiety and Related Disorders Interview Schedule for *DSM-5*–Lifetime Version (ADIS-5L; Brown & Barlow, 2014). To enroll a sample that varied widely in PT, we recruited a mixed sample ($N = 188$) that included clinical participants ($n = 148$) who had a current, principal (most severe) diagnosis of either major depressive disorder (MDD) or generalized anxiety disorder (GAD) along with nonclinical participants ($n = 40$) who had no current or past psychopathology. We permitted psychotropic medications at a stable dosage, but excluded individuals with current suicidal intent, acute psychosis, or substance-related disorders (other than tobacco) within the past month.

Participants were primarily female (65%) and ranged in age from 18 to 80 ($M = 33.01$, $SD = 13.16$). The sample was racially diverse: 61% of participants identified as White, 18% as Black, 11% as Asian, and 10% as a different race; 7% of participants reported their ethnicity as Hispanic/Latinx. Most participants completed college (66%), and self-reported household income ranged from \$0 to \$200,000 (*Mdn* = \$32,750, *SD* = \$34,623).

2.2. Measures

2.2.1. Trait PT measures

Participants completed four self-report measures of PT. The Perseverative Thinking Questionnaire (Ehring et al., 2011) is a 15-item scale that measures PT transdiagnostically, emphasizing key process characteristics such as repetitiveness, intrusiveness, and uncontrollability. Participants rate how they typically think about negative experiences or problems using a scale from 0 (*never*) to 4 (*almost always*).

The Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990) is a 16-item measure of pathological worry. Items assess the frequency, intrusiveness, and pervasiveness of worry, rated on a scale from 1 (*not at all typical of me*) to 5 (*very typical of me*).

The Ruminative Responses Scale (RRS; Nolen-Hoeksema et al., 1993) is the most widely used measure of rumination. It consists of 22 statements describing styles of cognitive responding when depressed. Items are rated on a scale from 1 (*almost never*) to 4 (*almost always*).

The Rumination-Reflection Questionnaire (Trapnell & Campbell, 1999) contains rumination and reflection subscales that have been shown to tap different underlying constructs and consequently are scored separately. Here we used the rumination subscale, which contains 12 items assessing a general tendency to ruminate, rated on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*).

The four PT questionnaires had excellent reliability in the present sample (Cronbach's $\alpha = 0.94–0.97$) and were strongly correlated ($r = 0.71–83$). Following Stade et al. (2022), we created a PT composite by summing the standardized scores of the four questionnaires to provide broad coverage of the PT construct, reduce the number of analyses, and ensure that findings reflected the PT construct rather than idiosyncratic properties of any particular questionnaire. The PT composite had high internal consistency ($\alpha = 0.93$). Subsequent analyses used this composite variable to represent PT, apart from analyses testing worry- and rumination-specific hypotheses, for which we used the PSWQ ($\alpha = 0.97$) and RRS ($\alpha = 0.94$) total scores, respectively.

2.2.2. Clinical outcomes

MDD and GAD Diagnosis and Severity. We used the ADIS-5L to assess current mental disorders according to *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* (*DSM-5*; American Psychiatric Association, 2013) criteria. In addition to categorical diagnoses, the ADIS-5L yields a clinical severity rating for each disorder on a scale from 0 (*none*) to 8 (*very severely disturbing/disabling*). Interviewers were Master's- or Bachelor's-level diagnosticians trained to a high level of reliability with an expert rater. Diagnostic decisions and clinical severity ratings for each participant were finalized in weekly consensus meetings of the assessment team.

We focused on MDD and GAD given the particularly close relationship of PT to these disorders. Interrater reliability was high for MDD diagnosis (Κ = 0.88) and severity (ICC = 0.95) as well as for GAD diagnosis (Κ = 1.00) and severity (ICC = 0.95) based on blind, independent ratings of recorded interviews ($n = 32$) selected at random from studies in our lab.

Global Depression and Anxiety Severity. We used the clinician-administered Hamilton scales to capture depression and anxiety severity extending beyond MDD and GAD. The Hamilton Rating Scale for Depression (Hamilton, 1960) is a 17-item scale assessing depressive symptoms experienced in the past week, whereas the Hamilton Anxiety Rating Scale (Hamilton, 1959) is a 14-item scale assessing symptoms of anxiety experienced in the past week. Interrater agreement was excellent for both scales (ICC = 0.96–0.97).

Total Disorders. We calculated the number of mental disorders (out of 13) diagnosed on the ADIS-5L to serve as an overall index of psychopathology. These included MDD, GAD, persistent depressive disorder, bipolar or cyclothymic disorder, posttraumatic stress disorder, acute stress disorder, panic disorder, agoraphobia, social anxiety disorder, specific phobia, separation anxiety disorder, obsessive-compulsive disorder, and any other disorder identified during the interview (most commonly tobacco use disorder). As other substance-related disorders were exclusion criteria for the study, these disorders were not included in the calculation. We summed the number of current disorders for which *DSM-5* diagnostic criteria were met.

Treatment Seeking. Participants were asked about their treatment utilization in the Medical History module of the ADIS-5L. We analyzed dichotomous variables reflecting current use of psychotropic medication and psychotherapy, respectively, for any mental health problem.

Symptom Dimensions. Participants completed the Mood and Anxiety Symptom Questionnaire (MASQ; Watson, Clark, et al., 1995; 1995b), a self-report measure assessing overlapping and distinct symptoms of depression and anxiety. The General Distress: Mixed Symptoms subscale captures symptoms largely overlapping between depression and anxiety, while the General Distress: Depressive Symptoms and General Distress: Anxious Symptoms subscales capture symptoms that are somewhat more specific to one construct versus the other. The Anhedonic Depression and Anxious Arousal subscales capture symptoms that are unique to depression and anxiety, respectively. All MASQ subscales had excellent reliability in the present sample (Cronbach's $\alpha = 0.88–0.95$).

2.3. Procedure

All procedures were approved by the University of Pennsylvania Institutional Review Board. The ADIS-5L interview began with an Introduction section containing open-ended questions about life changes or difficulties. First, participants were asked: "I would like to get a general idea of what sorts of problems you have been having recently. What have they been?" This was followed by: "What would you say is the main thing that is bothering you right now?" Participants subsequently were asked about stressors in each of seven life domains: family, social life, romantic relationships, work/school, finances, health, and legal matters (e.g., "In the past year, have you had any changes in or difficulties with … family?"). Four follow-up questions that we added to the Introduction section asked about employment or schooling (e.g., "What kind of work/schooling are you in now?" "What are your short-term educational or employment goals?"). After the Introduction section, participants completed the remainder of the ADIS-5L interview, followed by the Hamilton scales. The entire interview session was audio recorded. Participants returned to the lab approximately three weeks later and completed self-report measures, including the trait PT measures and the MASQ.

2.4. Data processing

2.4.1. Interview transcription

Trained research assistants blind to participants' clinical status transcribed the audio recordings of the ADIS-5L Introduction section using XTrans software (Glenn et al., 2009). Transcription was carried out following a transcription protocol developed by the Linguistic Data Consortium (LDC) at the University of Pennsylvania and adapted for this project with guidance by the LDC. For each participant, we produced a verbatim transcript of all participant and interviewer speech. A second independent transcriber listened to each audio recording, correcting the transcript as needed. When participants' enunciation or audio quality made transcription more challenging, a third independent transcriber performed an extra check of the transcription. The transcribing team met weekly to prevent transcriber drift from this protocol.

2.4.2. Linguistic feature extraction

We next converted participants' language into variables or features for use in subsequent analyses. We deleted end-of-sentence punctuation, retaining only language, then separated the language into "n-grams," i.e., words and two-to three-word phrases (Schwartz et al., 2013). We extracted language features (e.g., *I-usage*, *negative emotion* words, *cognitive processing* words) using the unweighted Linguistic Inquiry and Word Count lexica (Pennebaker et al., 2015), the weighted National Research Council Canada affect intensity and valence/arousal lexica (Mohammad, 2018a; 2018b), and a weighted *concreteness* lexicon (Brysbaert et al., 2014). For unweighted lexica, we counted the relative frequency with which terms from the lexicon were used by the participant, producing a lexicon score. For weighted lexica, we counted the relative frequency with which each lexicon term was used by the participant, multiplied it by the predetermined term weight, then summed the frequency-by-term-weight products to produce a lexicon score, similar to a regression equation. Additionally, we derived several language ratios (e.g., non-present-focused versus present-focused language) from the lexicon-based assessments, along with meta-language features (i.e., total words, average word length). Finally, we calculated sentence-to-sentence *coherence* across the two Introduction section questions that assessed general problems. Additional details about the linguistic feature extraction process appear in the online supplement.

2.5. Data analysis

Analysis code is available on the Open Science Framework (https://osf.io/d4cxa). We performed analyses using R, version 4.0.3. (R Core Team, 2019), and the Differential Language Analysis ToolKit, version 1.2.6 (Schwartz et al., 2017). The present sample of 188 individuals included all participants who spoke a minimum of 200 words in the Introduction section, as this threshold followed published recommendations while retaining the largest sample possible (Kern et al., 2016). Participants spoke an average of 891 words ($SD = 752$).

Using OLS regression, we quantified the relationship of PT with each language feature. Using the *pwr.r.test* function from the *pwr* package in R (Version 1.3.0, Champely, 2020), power was estimated to be 0.79 to detect an effect of $\beta = 0.20$ using a sample as large as ours. To retain maximum power for our primary hypotheses, we applied the standard $p < .05$ threshold without correction for multiple comparisons. For secondary hypotheses and exploratory analyses, we applied Benjamini and Hochberg (1995) false discovery rate correction. All analyses controlled for age and sex, as language use varies by these demographic features (Schwartz et al., 2013).

Lastly, we used machine learning to build a predictive model of PT using language alone. We used regression with elastic-net regularization (Zou & Hastie, 2005) to select language features that predict PT, submitting all language features described above for evaluation as predictors in the model. We used 10-fold cross validation, which repeatedly divides the dataset into a "training set" and a "test set" to better estimate the generalizability of the model to new datasets. R^2 values yielded by these analyses convey the average accuracy of the model across 10 repetitions of cross validation in predicting self-reported trait PT using language features. To evaluate predictive power, we examined the ability of the language-based model to predict a range of clinical outcomes, including concurrent and subsequent depression and anxiety, total number of mental disorders, and treatment-seeking behavior.

3. Results

3.1. A priori analyses

3.1.1. Primary hypotheses

We began by examining language features that were hypothesized to be related to PT. Effects are reported as standardized beta weights (β), which can be interpreted analogously to Pearson's r. Language terms shown in parentheses are the top three words that appeared most often in our dataset from each category (or, in the case of weighted lexica, the words that had the highest frequency-by-term-weight product in our dataset from each category).

As hypothesized, there was a significant association (95% CI in brackets) between trait PT and *I-usage* (e.g., I, my, I'm), $\beta = 0.25$ [0.11, 0.38], $p = .001$. Also as expected, PT was significantly related to *negative emotion* language (e.g., anxiety, bad, difficult), $\beta = 0.19$ [0.05, 0.32], $p = .010$. However, contrary to expectations, trait PT was not related to *cognitive processes* language (e.g., but, know, not), $\beta = 0.01$ [-0.14, 0.15], $p = .910$.

We next examined whether specific forms of PT, worry and rumination, had different associations with temporal orientation language. Worry ($\beta = -0.04$) and rumination ($\beta = -0.06$) each had very small, negative associations with *future focus* language (e.g., then, going, will). Worry shared a small, positive association ($\beta = 0.08$), and rumination shared a near-zero, negative association ($\beta = -0.02$), with *past focus* language (e.g., was, had, been). None of these coefficients differed reliably from zero (all $p > .277$) or from each other (both $t < 1.77$, both $p > .077$), contrary to the expected pattern of greater *future focus* in worry and *past focus* in rumination.

3.1.2. Secondary hypotheses

To test whether high perseverators (i.e., individuals higher in trait PT) talked more about the past or future relative to the present, we constructed a ratio of non-present-focused language to present-focused language. PT shared a small, nonsignificant relationship with this ratio, albeit in the expected direction, $\beta = .07$ [-0.08, 0.21], $p = .460$. There were similarly small, nonsignificant effects in the predicted direction for *concreteness* (e.g., I, um, a; $\beta = -0.12$ [-0.26, 0.02]) and *comparison* (e.g., like, as, more; $\beta = 0.06$ [-0.09, 0.20]) language, and for sentence-to-sentence *coherence* ($\beta = 0.12$ [-0.02, 0.26]), all $p > .201$.

3.2. Exploratory analyses

3.2.1. Language features of perseverative thinking

Next, taking an exploratory approach, we identified the top language features related to PT by examining associations between the trait PT composite and all possible features, including lexicon-based features and feature ratios, language-based estimates, *coherence*, and meta-language features. To control the false discovery rate, we report only effects that were significant at Benjamini-Hochberg corrected levels. These analyses revealed several additional language features related to PT. Trait PT was positively related to *feelings* (e.g., feel, hard, pain; $\beta = .23$ [0.09, 0.36], $p = .032$) and *sadness* (e.g., lost, sorry, low; $\beta = 0.21$ [0.07, 0.35], $p = .044$) words. Trait PT was inversely related to *anticipation* (e.g., what, about, hm; $\beta = -0.25$ [-0.38, -0.11], $p = .024$) and *work* (e.g., work, school, working; $\beta = -0.25$ [-0.38, −0.11], $p = .032$) words. Lastly, high trait perseverators used more *prepositions* (e.g., like, to, of; $\beta = 0.24$ [0.10, 0.37], $p = .035$) and fewer *negations* (e.g., not, no, don't; $\beta = -0.26$ [-0.38, −0.12], $p = .024$) during the interview.

3.2.2. Language-based model of PT

We next built a predictive model of PT by entering all language features (93 in total) as predictors in an elastic net model using 10-fold cross validation. Language features collectively accounted for 14% of the variance in the self-reported PT composite. To further assess the robustness of our model, we tested whether language accounted for variance beyond easy-to-obtain demographic variables. We first fit a model using age and sex to predict self-reported PT, then built a second model predicting the first model's residuals using language features alone. Language features accounted for 13% of the variance in PT above and beyond these demographic variables.

Elastic net models weight each language feature according to its informativeness. To understand the inner workings of our model, we examined the features that received the highest weights. In addition to the features revealed in earlier exploratory correlational analyses, several new features were identified through the modeling process. PT not only was predicted by *I-usage* (namely, first-person singular pronouns), but also was positively predicted by *first-person plural pronouns* (e.g., we, we're, our) and negatively predicted by *second-person pronouns* (e.g., you, your, you're). Other new features that positively predicted PT included *anxiety* (e.g., anxiety, worry, anxious), *affiliation* (e.g., we, family, friends), *sexual* (e.g., sex, hiv, prude), *religion* (e.g., god, hell, rabbinical), and *space* (e.g., in, on, at) words. Other new features that negatively predicted PT included *death* (e.g., died, dead, die), *health* (e.g., life, health, living), *home* (e.g., family, house, home), *discrepancies* (e.g., would, want, if), and *hear* (e.g., say, said, saying) words, as well as the emotions *surprise* (e.g., was, actually, trying) and *joy* (e.g., with, life, family).

3.2.3. Predictive power of the language-based model

Finally, we assessed the predictive power of our language-based PT model by examining its relationship with a range of clinical outcomes. The model significantly predicted all concurrent, clinician-assessed outcomes, with effects mostly in the moderate range (median $r = .32$; see Table 1). Specifically, the model-generated PT score robustly predicted GAD and MDD status and severity. The associations were similarly robust with global anxiety and depression measured via the Hamilton scales. The model predicted the total number of mental disorders that were diagnosed during the interview, and it predicted which participants were currently receiving psychotherapy and pharmacotherapy. Language-based PT also predicted subsequent self-reported depression and anxiety symptoms on the MASQ, with small to moderate effects (median $r = 0.25$). The strongest association was with General Distress: Mixed Symptoms, followed by Anhedonic Depression, General Distress: Anxiety Symptoms, and General Distress: Depressive Symptoms. The weakest association was with Anxious Arousal.

Table 1
Predictive power of the language-based perseverative thinking model.

Method	Clinical Outcome	*r*	95% CI
Clinician-rated	GAD severity	.41	[.28, .52]
	GAD diagnosis	.33	[.20, .45]
	Syndromal anxiety	.36	[.23, .48]
	MDD severity	.32	[.19, .45]
	MDD diagnosis	.24	[.10, .37]
	Syndromal depression	.37	[.24, .49]
	Psychiatric comorbidity	.24	[.08, .39]
	Current psychotherapy use	.17	[.03, .31]
	Current psychotropic medication use	.15	[.00, .28]
Self-reported	General Distress: Mixed Symptoms	.30	[.16, .42]
	General Distress: Anxious Symptoms	.25	[.11, .38]
	General Distress: Depressive Symptoms	.25	[.11, .38]
	Anhedonic Depression	.26	[.12, .39]
	Anxious Arousal	.18	[.04, .32]

Note. GAD = generalized anxiety disorder, MDD = major depressive disorder. Syndromal anxiety and depression were measured using the Hamilton Anxiety Rating Scale and Hamilton Rating Scale for Depression, respectively. All other clinician-rated outcomes were measured using the Anxiety and Related Disorders Interview Schedule for *DSM-5*–Lifetime Version. Self-reported symptoms were measured using the Mood and Anxiety Symptom Questionnaire. All effect sizes are significant at Benjamini-Hochberg corrected significance levels.

4. Discussion

Perseverative thinking is a transdiagnostic process that plays an important role in depression, anxiety, and other forms of psychopathology. Novel, behavioral methods of assessing PT hold the potential to yield new insights into this construct. Here, we investigated language features associated with PT. We found several correlates of PT in spoken language expressed during a brief interview, including hypothesized features such as *I-usage* and *negative emotion* language, as well as novel features such as *prepositions* use, *we-usage,* and (lack of) *you-usage.* A language-based model capitalizing on these features captured meaningful variance in self-reported PT, above and beyond demographic variables. This model, in turn, predicted a variety of clinical outcomes. These results provide proof of concept for a clinically relevant measure of PT based in natural language, opening up new avenues for theory, research, and practice.

4.1. Language correlates of PT

As expected, *negative emotion* words were related to PT, and exploratory analyses revealed other emotion categories as predictors of PT: *feelings, sadness, anxiety,* and (lack of) *joy*. These findings likely reflect the important role of negative valence in PT (Watkins, 2008) as well as PT's deleterious effects on mood (McLaughlin et al., 2007). Our results add to this literature by showing that PT is related to the expression, as well as the experience, of adverse emotional states. However, it remains to be seen whether these language features, detected in an interview about recent stressors, reflect a dispositional style of responding or an objectively higher level of stress in the lives of high trait perseverators. Future analyses controlling for the number or severity of life stressors could help disentangle these possibilities.

Other language correlates observed here may reveal insights about the nature of PT. For example, the relationship of PT with *space* and *preposition* words, which refer to physical space or location (Pennebaker & King, 1999), could reflect looming cognitive style, a cognitive vulnerability related to PT involving a sense of impending or rapidly approaching threat (e.g., "I am <u>in</u> deep trouble," "I am running <u>out</u> of options"; Hughes et al., 2008). Other findings appear to reflect the context in which language was expressed. Decreased *negation* words (e.g., not, no, don't), spoken in response to direct questions about problems or difficulties, may indicate that individuals with higher PT were less likely to deny problems during the interview. Increased *religion* words (e.g., god, hell, praying) may reflect reactions to the difficult life circumstances participants were describing, but may also have been driven by the use of the word *god* to express disbelief, frustration, or anger.

4.2. Construal level and other cognition language in PT

We had predicted that PT would be associated with high-level, abstract construals in language. Although we found a small effect in this direction for *concreteness*, the lexicon we used to index level of construal, the effect was nonsignificant. Notably, in the PT literature, level of construal is typically measured during the act of perseverative thinking. It is possible that measuring construal level outside "bouts" of PT hindered our ability to detect an effect. Alternatively, the *concreteness* lexicon may not map perfectly onto level of construal as operationalized by PT theorists, who define abstract construals as focused on the desirability and importance of outcomes, while concrete construals are focused on the feasibility and planning of outcomes (Watkins, 2008). Lastly, perhaps features of the interview context—such as being prompted to reflect on specific life domains, or expressing concerns out loud—led participants to be more concrete than when they perseverate internally without direction.

Along similar lines, we found no relationship between PT and *cognitive processes* language and actually observed an inverse relationship with *discrepancies*. This was surprising given prior evidence for a positive relationship between depression and *discrepancies* language in social media posts (Eichstaedt et al., 2018). It could be that *discrepancies* and its parent category *cognitive processes*, which reflect attempts to understand, explain, or reason about events, may have been used at a low level given the contextual demand for relatively focused, concise responses in the overview section of this lengthy interview. For both construal level and cognitive processing language, it would be valuable to replicate results in a different context, such as giving participants an extended period to describe a specific past event or anticipated future event, which may offer more opportunity for elaborate cognitive processing.

4.3. What do pronouns reveal about the nature of PT?

Pronouns carry crucial information about what has been and what will be the center of focus in any utterance or written phrase (Gordon et al., 1993; Grosz et al., 1995). As expected, *I-usage* was related to PT in both correlational and predictive analyses. Previously identified as one of the strongest linguistic correlates common to depression and anxiety (Stade et al., under review), *I-usage* likely reflects the self-referential nature of PT. Importantly, in this interview about recent life difficulties, all participants were prompted to reflect on themselves and their problems. Nevertheless, it was the highest perseverators who spoke the most about themselves and their negative emotions.

Unexpectedly, two other classes of pronouns emerged as predictors of PT: PT was positively predicted by first-person plural pronouns (e.g., we, we're, our; "*we-usage*") and negatively predicted by second-person singular pronouns (e.g., you, your, you're; "*you-usage*"). Whereas *I-usage* is shared with depression and anxiety, these other pronouns appear to be relatively specific to PT, representing a novel contribution of our study. Increased *we-usage* is surprising given evidence that, in the context of close relationships, *we-usage* reflects connectedness and affiliation (Horn & Meier, 2022); as high perseverators report more interpersonal conflict (Nolen-Hoeksema & Davis, 1991), we might have expected *we-usage* to relate negatively to PT. Perhaps in the context of an interview about difficulties, *we-usage*—and also *affiliation* words (e.g., we, family, friends), which positively predicted PT—index interpersonal conflict or shared problems (e.g., "We were fighting," "My family has been struggling"). A similar explanation could account for the increased use of *sexual* words (e.g., sex, hiv, prude) by high perseverators, which may reflect concerns about sexual health and intimate relationships. Alternatively, perhaps *we-usage* and *affiliation* words came up in the context of participants worrying about the well-being of loved ones, given that other people and relationships are a common source of worry for individuals with GAD (Roemer et al., 1997).

Conversely, *you-usage* was a negative predictor of PT in our model. This is also surprising, as *you-usage* has been associated with negative communication between romantic partners and is thought to index blaming (Horn & Meier, 2022). However, unlike prior studies which investigated *you-usage* in conversations between intimates, we studied language in a context akin to a first clinical encounter, wherein individuals provided a series of largely one-sided responses to questions posed by an unfamiliar professional. Perhaps high perseverators were more likely to become absorbed in their own problems and focus less on the clinician during the interview, resulting in fewer attempts to engage the clinician or check understanding ("you know?") through *you-usage*. Given the limited range of contexts in which dyadic communication has been studied in computational linguistic research on psychopathology, it is an open question whether *you-usage* is adaptive or maladaptive. Future research should systematically explore the use of different classes of pronouns across diverse contexts, including a wide range of topics (e.g., problems/difficulties, positive life events, neutral topics) and partners (e.g., peers, intimates, strangers, clinicians; see Meier et al., 2021).

4.4. Temporal orientation is not evident in the language of PT

We found that worry and rumination are not differentiated by temporal orientation of language, and that their parent construct PT is not associated with increased use of non-present-focused language. Although temporal orientation is often pointed to as a difference between worry and rumination, there is a risk of reification given that most studies have used definitions and measures of the constructs that reference the future (for worry) or past (for rumination; Hallion et al., 2022; McEvoy et al., 2010). On the other hand, our failure to detect a temporal effect may reflect the difficulty of measuring temporal orientation via language. For example, we can compare two statements using the present-tense verb "*am*"—"I am reading the article" versus "I am a reader"—and notice that only the former conveys information about what is happening in the present, while the latter conveys a persistent truth claim with little information about the here and now. A final possibility is that our interview, which prompted all participants to focus on the past (i.e., changes/difficulties that occurred "recently" or "in the past year"), may have led everyone to talk more about the past and thereby flattened individual differences in preferential focus on the past, present, or future. Eliciting language using more open-ended prompts, or recording natural language in participants' daily environments (Mehl et al., 2001), would be a valuable next step in adjudicating among these explanations. More generally, studying spontaneous utterances in the natural environment could help reveal whether the context in which language is spoken shapes the linguistic correlates of PT.

4.5. Language-based model of PT

Our language-based model of PT successfully predicted clinically relevant outcomes across multiple measures and methods of assessment. The score yielded by this language-based measure was moderately associated with clinician ratings rendered later in the interview; robust associations were observed for GAD and MDD, the disorders most strongly linked to PT, as well as for broader syndromal measures of anxiety and depression. In line with evidence that PT, as a transdiagnostic process, is associated with comorbidity (McEvoy et al., 2013; Ruscio et al., 2011) and help-seeking behavior (Patel et al., 2021), language-based PT predicted total number of mental disorders and use of psychotherapy and pharmacotherapy, respectively.

Language-based PT also shared small-to-moderate associations with self-reported depression and anxiety symptoms assessed three weeks later. These analyses served as a particularly conservative test of predictive validity, as they employed a new method (self-report) and were separated temporally from when language was collected. We found particularly strong relationships of language-based PT with subscales reflecting general distress symptoms that are relatively nonspecific to depression and anxiety, consistent with studies showing that PT is a common risk factor for these conditions (e.g., McLaughlin et al., 2007; Ruscio et al., 2015; Spinhoven et al., 2018). By contrast, language-based PT shared the smallest association with MASQ Anxious Arousal, in line with research showing anxious arousal to be relatively weakly related (Brown et al., 1995) or even unrelated (Naragon-Gainey et al., 2016) to worry.

Our language-based model represents a meaningful first step toward the development of an unobtrusive, behavioral measure of PT. The variance explained by our model, corresponding to a medium-sized effect (14% or $r = 0.37$), compares favorably to the weaker associations more typically observed between self-report and behavioral measures of the same construct ($r < 0.20$; Dang et al., 2020). Our model also performed well compared to other language-based models of psychological constructs (e.g., $r = 0.39$; Schwartz et al., 2014).

Although these results are promising, further work is needed on two fronts before our model can be ready for real-world applications. First, the model will need to be strengthened by incorporating additional linguistic correlates of PT, including smaller effects that add incrementally to prediction as well as different types of effects (at the level of specific words or phrases, rather than broad categories) that we were not powered to detect. Detecting these sorts of effects using a data-driven approach will require sample sizes in the thousands as well as language sources with more words per participant. Social media posts afford these benefits, though the extent to which our interview-based language model translates to social media language remains to be seen. Given that intake interviews are a staple of clinical practice, a different strategy may be to encourage routine recordings of these interviews that could be aggregated, perhaps through practice research networks (Parry et al., 2010), to construct the large dataset this work requires.

Second, more research is needed to validate the language-based model of PT. As the field has raced ahead in developing novel behavioral, passive measures of psychopathology constructs, guidelines for evaluating the convergent validity of such measures have lagged. Typically, behavioral measures are compared exclusively to self-report measures of the same construct (mono-trait, hetero-method correlations), despite the added importance of mono-trait, mono-method comparisons for establishing convergent validity (Campbell & Fiske, 1959). Guidelines are needed to help researchers select appropriate validators when developing behavioral measures. For our measure, candidate validators include behaviors that would be expected to relate to PT, such as distracted communication during interpersonal encounters (Merolla et al., 2019) or time spent indoors or physically inactive, measured via smartphone sensor (Mohr et al., 2017).

Work is also needed to evaluate the discriminant validity of our language-based PT model vis-à-vis closely-related psychopathology constructs. Such tests have been rare in the literature on natural language processing and psychopathology, where language is commonly examined vis-à-vis a single construct without performing tests of specificity. The few studies that have made these comparisons suggest that some of the same language features are implicated in different forms of psychopathology (e.g., Stade et al., under review), raising the possibility that transdiagnostic processes or co-occurring conditions account for a subset of observed effects. In the case of our language-based PT model, appropriate tests of discriminant validity will require a very large dataset and measures of a range of psychopathological constructs to which we did not have access here. For example, we might expect language-based PT to share smaller correlations with more distal constructs like externalizing disorders, intermediate correlations with fear-based internalizing disorders such as phobias, and the highest correlations with distress disorders such as GAD and MDD. Even more fine-grained discriminant tests, such as between cognitive and noncognitive features of these disorders, will require even larger datasets to provide the necessary statistical power.

4.6. Strengths and limitations

Our study had several strengths. We used multiple analytic approaches (correlational analyses, multivariate machine learning modeling) to uncover novel language features associated with PT. We analyzed PT as a dimensional, transdiagnostic construct using a composite measure offering excellent coverage of the PT construct. We recruited individuals with disorders in which PT is a prominent clinical feature, as well as individuals without psychopathology. This yielded a sample of individuals with widely varying levels of PT, thereby maximizing range and increasing statistical power. Lastly, we analyzed clinical interview language, which may be more sensitive to individuals' current experiences and concerns than the social media language commonly used in linguistic analyses.

Nevertheless, our conclusions are tempered by several limitations. Our measurements of language and PT were separated by approximately three weeks, which may have weakened our ability to detect effects. Furthermore, our sample, although of reasonable size given its clinical nature, was relatively small for computational linguistic analysis. Power calculations indicated that we were adequately powered to detect effects as small as .20, but language features with smaller effects may have been missed, especially given our conservative analytic approach using FDR correction. Equally important was that, although we controlled for age and sex, we lacked the statistical power to covary potential third variables that may be driving the relationship between PT and language features. This means our language-based model could be tapping into constructs closely related to PT, such as depression, anxiety, or life stress. Additional validation work using larger samples is required to rule out this possibility.

All of our high perseverators had GAD or MDD, and nonclinical participants made up a small portion of the sample. Consequently, our results are best understood as characterizing PT in the context of psychopathology, and may not represent features of high worriers or high ruminators whose experiences fall within the normal range. Relatedly, our results may be less representative of PT occurring in other disorders (e.g., insomnia) or of forms of PT not explicitly included in our composite measure (e.g., obsessions). Further research is needed to determine the generalizability of our language-based PT measure to other samples and clinical conditions.

4.7. Conclusions

We conducted the first comprehensive computational linguistic investigation of perseverative thinking. We found that PT has a linguistic signature in a clinical interview setting, including *negative emotion* language and a unique pattern of *pronoun* use. Several language features revealed new insights, such as that use of *space* or *location* words could convey a cognitive style related to PT. These findings highlight the promise of computational linguistics for advancing understanding of covert processes like PT. Furthermore, a model of PT based solely on language features predicted outcomes of interest to clinicians. Although additional work is needed to further refine and validate our measure, these results show proof of concept of unobtrusive, behavioral, and fully automated detection of PT. By circumventing the limitations of self-report, this measure could facilitate mechanistic research on PT and the delivery of just-in-time adaptive interventions for this deleterious cognitive process.

CRediT authorship contribution statement

Elizabeth C. Stade: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Validation, Writing – original draft, Writing – review & editing. **Lyle Ungar:** Conceptualization, Formal analysis, Methodology, Resources, Supervision, Writing – review & editing. **Shreya Havaldar:** Formal analysis, Methodology. **Ayelet Meron Ruscio:** Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgements

We thank Auburn Stephenson and Joe Friedman for their assistance with data organization and cleaning, and Garrick Sherman for his help with implementing analyses. We gratefully acknowledge the research assistants who transcribed the interview data, without whom this project would not have been possible: Alex Aceves, Bridget Yu, Catherine Shi, Claire Marucci, Danny Chiarodit, Elisa Xu, Emma Palermo, Grace Daley, Isabella Schlact, and Sophia Glinski.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.brat.2023.104307.

References

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.).

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B, 57*(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Borkovec, T. D., Robinson, E., Pruzinsky, T., & DePree, J. A. (1983). Preliminary exploration of worry: Some characteristics and processes. *Behaviour Research and Therapy, 21*(1), 9–16. https://doi.org/10.1016/0005-7967(83)90121-3

Brockmeyer, T., Zimmermann, J., Kulessa, D., Hautzinger, M., Bents, H., Friederich, H.-C., Herzog, W., & Backenstrass, M. (2015). Me, myself, and I: Self-referent word use as an indicator of self-focused attention in relation to depression and anxiety. *Frontiers in Psychology, 6*. https://doi.org/10.3389/fpsyg.2015.01564

Brown, T. A., & Barlow, D. H. (2014). Anxiety and related disorders interview Schedule for DSM-5 (ADIS-5L). In *Lifetime version. Client interview schedule*. Oxford University Press.

Brown, T. A., Marten, P. A., & Barlow, D. H. (1995). Discriminant validity of the symptoms constituting the DSM-III-R and DSM-IV associated symptom criterion of generalized anxiety disorder. *Journal of Anxiety Disorders, 9*(4), 317–328.

Brysbaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. *Behavior Research Methods, 46*(3), 904–911. https://doi.org/10.3758/s13428-013-0403-5

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin, 56*(2), 81–105.

Carver, C. S., & Scheier, M. F. (1990). Origins and functions of positive and negative affect: A control-process view. *Psychological Review, 97*(1), 19–35. https://doi.org/10.1037/0033-295X.97.1.19

Champely, S. (2020). Pwr: Basic functions for power analysis. R package version 1.3-0. https://CRAN.R-project.org/package=pwr.

Clark, A., Fox, C., & Lappin, S. (Eds.). (2010). *The handbook of computational linguistics and natural language processing*. Wiley-Blackwell.

Dang, J., King, K. M., & Inzlicht, M. (2020). Why are self-report and behavioral measures weakly correlated? *Trends in Cognitive Sciences, 24*(4), 267–269. https://doi.org/10.1016/j.tics.2020.01.007

Dirkse, D., Hadjistavropoulos, H. D., Hesser, H., & Barak, A. (2015). Linguistic analysis of communication in therapist-assisted internet-delivered cognitive behavior therapy for generalized anxiety disorder. *Cognitive Behaviour Therapy, 44*(1), 21–32. https://doi.org/10.1080/16506073.2014.952773

Edwards, T., & Holtzman, N. S. (2017). A meta-analysis of correlations between depression and first person singular pronoun use. *Journal of Research in Personality, 68*, 63–68. https://doi.org/10.1016/j.jrp.2017.02.005

Ehring, T., & Watkins, E. R. (2008). Repetitive negative thinking as a transdiagnostic process. *International Journal of Cognitive Therapy, 1*(3), 192–205. https://doi.org/10.1680/ijct.2008.1.3.192

Ehring, T., Zetsche, U., Weidacker, K., Wahl, K., Schönfeld, S., & Ehlers, A. (2011). The Perseverative Thinking Questionnaire (PTQ): Validation of a content-independent measure of repetitive negative thinking. *Journal of Behavior Therapy and Experimental Psychiatry, 42*(2), 225–232. https://doi.org/10.1016/j.jbtep.2010.12.003

Eichstaedt, J. C., Smith, R. J., Merchant, R. M., Ungar, L. H., Crutchley, P., Preoţiuc-Pietro, D., Asch, D. A., & Schwartz, H. A. (2018). Facebook language predicts depression in medical records. *Proceedings of the National Academy of Sciences, 115* (44), 11203–11208. https://doi.org/10.1073/pnas.1802331115

Fahrenberg, J., Myrtek, M., Pawlik, K., & Perrez, M. (2007). Ambulatory assessment—monitoring behavior in daily life settings. *European Journal of Psychological Assessment, 23*(4), 206–213. https://doi.org/10.1027/1015-5759.23.4.206

Geronimi, E. M. C., & Woodruff-Borden, J. (2015). The language of worry: Examining linguistic elements of worry models. *Cognition & Emotion, 29*(2), 311–318. https://doi.org/10.1080/02699931.2014.917071

Glenn, M. L., Strassel, S. M., & Lee, H. (2009). XTrans: A speech annotation and transcription tool. *Interspeech*, 2855–2858. https://doi.org/10.21437/Interspeech.2009-729, 2009.

Gordon, P. C., Grosz, B. J., & Gilliom, L. A. (1993). Pronouns, names, and the centering of attention in discourse. *Cognitive Science, 17*(3), 311–347. https://doi.org/10.1207/s15516709cog1703_1

Grosz, B. J., Weinstein, S., & Joshi, A. K. (1995). Centering: A framework for modeling the local coherence of discourse. *Computational Linguistics, 21*(2), 203–225.

Guntuku, S. C., Yaden, D. B., Kern, M. L., Ungar, L. H., & Eichstaedt, J. C. (2017). Detecting depression and mental illness on social media: An integrative review. *Current Opinion in Behavioral Sciences, 18*, 43–49. https://doi.org/10.1016/j.cobeha.2017.07.005

Hallion, L. S., Wright, A. G. C., Joormann, J., Kusmierski, S. N., Coutanche, M. N., & Caulfield, M. K. (2022). A five-factor model of perseverative thought. *Journal of Psychopathology and Clinical Science, 131*(3), 235–252.

Hamilton, M. (1959). The assessment of anxiety states by rating. *British Journal of Medical Psychology, 32*(1), 50–55. https://doi.org/10.1111/j.2044-8341.1959.tb00467.x

Hamilton, M. (1960). A rating scale for depression. *Journal of Neurology Neurosurgery and Psychiatry, 23*(1), 56–62.

Harvey, A. G., Watkins, E., Mansell, W., & Shafran, R. (2004). *Cognitive behavioural processes across psychological disorders: A transdiagnostic approach to research and treatment*. Oxford University Press.

Hitczenko, K., Mittal, V. A., & Goldrick, M. (2021). Understanding language abnormalities and associated clinical markers in psychosis: The promise of computational methods. *Schizophrenia Bulletin, 47*(2), 344–362. https://doi.org/10.1093/schbul/sbaa141

Horn, A. B., & Meier, T. (2022). Language in close relationships. In M. Dehghani, & R. L. Boyd (Eds.), *Handbook of language analysis in psychology* (pp. 102–124). Guilford Press.

Hughes, M. E., Alloy, L. B., & Cogswell, A. (2008). Repetitive thought in psychopathology: The relation of rumination and worry to depression and anxiety symptoms. *Journal of Cognitive Psychotherapy, 22*(3), 271–288. https://doi.org/10.1891/0889-8391.22.3.271

Ingram, R. E., & Smith, T. W. (1984). Depression and internal versus external focus of attention. *Cognitive Therapy and Research, 8*(2), 139–151. https://doi.org/10.1007/BF01173040

Ireland, M. E., & Mehl, M. R. (2014). Natural language use as a marker of personality. In T. M. Holtgraves (Ed.), *The oxford handbook of language and social psychology*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199838639.013.034.

Iter, D., Yoon, J., & Jurafsky, D. (2018). Automatic detection of incoherent speech for diagnosing schizophrenia. In *Proceedings of the Fifth workshop on computational linguistics and clinical psychology: From keyboard to clinic* (pp. 136–146). https://doi.org/10.18653/v1/W18-0615

Jose, P. E., Wilkins, H., & Spendelow, J. S. (2012). Does social anxiety predict rumination and co-rumination among adolescents? *Journal of Clinical Child and Adolescent Psychology, 41*(1), 86–91. https://doi.org/10.1080/15374416.2012.632346

Kazak, A. E. (2018). Editorial: Journal article reporting standards. *American Psychologist, 73*(1), 1–2. https://doi.org/10.1037/amp0000263

Kern, M. L., Park, G., Eichstaedt, J. C., Schwartz, H. A., Sap, M., Smith, L. K., & Ungar, L. H. (2016). Gaining insights from social media language: Methodologies and challenges. *Psychological Methods, 21*(4), 507–525. https://doi.org/10.1037/met0000091

Lee, M., Martin, G. E., Hogan, A., Hano, D., Gordon, P. C., & Losh, M. (2018). What's the story? A computational analysis of narrative competence in autism. *Autism, 22*(3), 335–344. https://doi.org/10.1177/1362361316677957

Lyubomirsky, S., Tucker, K. L., Caldwell, N. D., & Berg, K. (1999). Why ruminators are poor problem solvers: Clues from the phenomenology of dysphoric rumination. *Journal of Personality and Social Psychology, 77*(5), 1041–1060.

Mathersul, D. C., & Ruscio, A. M. (2020). Forecasting the future, remembering the past: Misrepresentations of daily emotional experience in generalized anxiety disorder and major depressive disorder. *Cognitive Therapy and Research, 44*, 73–88. https://doi.org/10.1007/s10608-019-10048-5

McEvoy, P. M., Mahoney, A. E. J., & Moulds, M. L. (2010). Are worry, rumination, and post-event processing one and the same? Development of the repetitive thinking questionnaire. *Journal of Anxiety Disorders, 24*(5), 509–519. https://doi.org/10.1016/j.janxdis.2010.03.008

McEvoy, P. M., Watson, H., Watkins, E. R., & Nathan, P. (2013). The relationship between worry, rumination, and comorbidity: Evidence for repetitive negative thinking as a transdiagnostic construct. *Journal of Affective Disorders, 151*(1), 313–320. https://doi.org/10.1016/j.jad.2013.06.014

McLaughlin, K. A., Borkovec, T. D., & Sibrava, N. J. (2007). The effects of worry and rumination on affect states and cognitive activity. *Behavior Therapy, 38*(1), 23–38. https://doi.org/10.1016/j.beth.2006.03.003

Mehl, M. R., Pennebaker, J. W., Crow, D. M., Dabbs, J., & Price, J. H. (2001). The electronically activated recorder (EAR): A device for sampling naturalistic daily activities and conversations. *Behavior Research Methods, Instruments, & Computers, 33* (4), 517–523. https://doi.org/10.3758/BF03195410

Meier, T., Milek, A., Mehl, M. R., Nussbeck, F. W., Neysari, M., Bodenmann, G., Martin, M., Zemp, M., & Horn, A. B. (2021). I blame you, I hear you: Couples' pronoun use in conflict and dyadic coping. *Journal of Social and Personal Relationships, 38*(11), 3265–3287. https://doi.org/10.1177/02654075211029721

Merolla, A. J., Hall, J. A., & Bernhold, Q. (2019). Perseverative cognition, distracted communication, and well-being in everyday social interaction. *Personal Relationships, 26*(3), 507–528. https://doi.org/10.1111/pere.12286

Meyer, T. J., Miller, M. L., Metzger, R. L., & Borkovec, T. D. (1990). Development and validation of the Penn state worry questionnaire. *Behaviour Research and Therapy, 28* (6), 487–495. https://doi.org/10.1016/0005-7967(90)90135-6

Mineka, S., Rafaeli, E., & Yovel, I. (2003). Cognitive biases in emotional disorders: Information processing and social-cognitive perspectives. In R. Davidson, K. Scherer, & H. Goldsmith (Eds.), *Handbook of affective sciences* (pp. 976–1009). Oxford University Press.

Mohammad, S. (2018a). Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 English words. *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, 1*, 174–184. https://doi.org/10.18653/v1/P18-1017. *Long Papers*.

Mohammad, S. M. (2018b). Word affect intensities. In *Proceedings of the 11th edition of the Language Resources and evaluation conference. LREC-2018)*.

Mohr, D. C., Zhang, M., & Schueller, S. M. (2017). Personal sensing: Understanding mental health using ubiquitous sensors and machine learning. *Annual Review of Clinical Psychology, 13*(1), 23–47. https://doi.org/10.1146/annurev-clinpsy-032816-044949

Nalabandian, T., & Ireland, M. (2019). Depressed individuals use negative self-focused language when recalling recent interactions with close romantic partners but not family or friends. *Proceedings of the Sixth Workshop on Computational Linguistics and Clinical Psychology*, 62–73.

Naragon-Gainey, K., Prenoveau, J. M., Brown, T. A., & Zinbarg, R. E. (2016). A comparison and integration of structural models of depression and anxiety in a clinical sample: Support for and validation of the tri-level model. *Journal of Abnormal Psychology, 125*(7), 853–867. https://doi.org/10.1037/abn0000197

Nolen-Hoeksema, S. (1991). Responses to depression and their effects on the duration of depressive episodes. *Journal of Abnormal Psychology, 100*(4), 569–582.

Nolen-Hoeksema, S., & Davis, C. G. (1991). "Thanks for sharing that": Ruminators and their social support networks. *Journal of Personality and Social Psychology, 77*(4), 801–814. https://doi.org/10.1037/0022-3514.77.4.801

Nolen-Hoeksema, S., Morrow, J., & Fredrickson, B. L. (1993). Response styles and the duration of episodes of depressed mood. *Journal of Abnormal Psychology, 102*(1), 20–28. https://doi.org/10.1037/0021-843X.102.1.20

Nolen-Hoeksema, S., Wisco, B. E., & Lyubomirsky, S. (2008). Rethinking rumination. *Perspectives on Psychological Science, 3*(5), 400–424. https://doi.org/10.1111/j.1745-6924.2008.00088.x

Parkinson, B., Simons, G., & Niven, K. (2016). Sharing concerns: Interpersonal worry regulation in romantic couples. *Emotion, 16*(4), 449–458. https://doi.org/10.1037/a0040112

Parry, G., Castonguay, L. G., Borkovec, T. D., & Wolf, A. W. (2010). Practice research networks and psychological services research in the UK and USA. In M. Barkham, G. E. Hardy, & J. Mellor-Clark (Eds.), *Developing and delivering practice-based evidence* (pp. 311–325). Wiley-Blackwell. https://doi.org/10.1002/9780470687994.ch12.

Patel, Z. S., Casline, E., Jensen-Doss, A., & Timpano, K. R. (2021). Parent distress intolerance, repetitive negative thinking, and mental health service use. *Child Psychiatry and Human Development, 52*(3), 365–375. https://doi.org/10.1007/s10578-020-01017-1

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*. Austin, TX: University of Texas at Austin.

Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology, 77*(6), 1296–1312.

du Pont, A., Rhee, S. H., Corley, R. P., Hewitt, J. K., & Friedman, N. P. (2019). Are rumination and neuroticism genetically or environmentally distinct risk factors for psychopathology? *Journal of Abnormal Psychology, 128*(5), 385–396. https://doi.org/10.1037/abn0000430

Pyszczynski, T., & Greenberg, J. (1987). Self-regulatory perseveration and the depressive self-focusing style: A self-awareness theory of reactive depression. *Psychological Bulletin, 102*(1), 122–138.

R Core Team. (2019). *R: a language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/.

Roemer, L., Molina, S., & Borkovec, T. D. (1997). An investigation of worry content among generally anxious individuals. *The Journal of Nervous and Mental Disease, 185*(5), 314–319.

Rose, A. J. (2002). Co–rumination in the friendships of girls and boys. *Child Development, 73*(6), 1830–1843. https://doi.org/10.1111/1467-8624.00509

Ruscio, A. M., Gentes, E. L., Jones, J. D., Hallion, L. S., Coleman, E. S., & Swendsen, J. (2015). Rumination predicts heightened responding to stressful life events in major depressive disorder and generalized anxiety disorder. *Journal of Abnormal Psychology, 124*(1), 17–26. https://doi.org/10.1037/abn0000025

Ruscio, A. M., Seitchik, A. E., Gentes, E. L., Jones, J. D., & Hallion, L. S. (2011). Perseverative thought: A robust predictor of response to emotional challenge in generalized anxiety disorder and major depressive disorder. *Behaviour Research and Therapy, 49*(12), 867–874. https://doi.org/10.1016/j.brat.2011.10.001

Samtani, S., Moulds, M. L., Johnson, S. L., Ehring, T., Hyett, M. P., Anderson, R., & McEvoy, P. M. (2022). Higher order repetitive negative thinking is more robustly related to depression, anxiety, and mania than measures of rumination or worry. *Cognitive Therapy and Research, 46*(1), 161–170. https://doi.org/10.1007/s10608-021-10235-3

Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Ramones, S. M., Agrawal, M., Shah, A., Kosinski, M., Stillwell, D., Seligman, M. E. P., & Ungar, L. H. (2013). Personality, gender, and age in the language of social media: The open-vocabulary approach. *PLoS One, 8*(9), 1–16. https://doi.org/10.1371/journal.pone.0073791

Schwartz, H. A., Eichstaedt, J., Kern, M. L., Park, G., Sap, M., Stillwell, D., Kosinski, M., & Ungar, L. (2014). Towards assessing changes in degree of depression through Facebook. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*, 118–125. https://doi.org/10.3115/v1/W14-3214

Schwartz, H. A., Giorgi, S., Sap, M., Crutchley, P., Ungar, L., & Eichstaedt, J. (2017). Dlatk: Differential Language Analysis ToolKit. In *Proceedings of the 2017 conference on empirical methods in natural language processing: System demonstrations* (pp. 55–60). https://doi.org/10.18653/v1/D17-2010

Spinhoven, P., van Hemert, A. M., & Penninx, B. W. (2018). Repetitive negative thinking as a predictor of depression and anxiety: A longitudinal cohort study. *Journal of Affective Disorders, 241*, 216–225. https://doi.org/10.1016/j.jad.2018.08.037

Stade, E. C., Cohen, R. T., Loftus, P., & Ruscio, A. M. (2022). A novel measure of real-time perseverative thought. *Clinical Psychological Science, 10*(3), 534–552. https://doi.org/10.1177/21677026211038017

Stade, E. C., Ungar, L., Eichstaedt, J. C., Sherman, G., & Ruscio, A. M. (under review). Depression and anxiety have distinct and overlapping language patterns: Results from a clinical interview.

Tackman, A. M., Sbarra, D. A., Carey, A. L., Donnellan, M. B., Horn, A. B., Holtzman, N. S., Edwards, T. S., Pennebaker, J. W., & Mehl, M. R. (2019). Depression, negative emotionality, and self-referential language: A multi-lab, multi-measure, and multi-language-task research synthesis. *Journal of Personality and Social Psychology, 116*(5), 817–834. https://doi.org/10.1037/pspp0000187

Tang, S. X., Kriz, R., Cho, S., Park, S. J., Harowitz, J., Gur, R. E., Bhati, M. T., Wolf, D. H., Sedoc, J., & Liberman, M. Y. (2021). Natural language processing methods are sensitive to sub-clinical linguistic differences in schizophrenia spectrum disorders. *Npj Schizophrenia, 7*(25), 1–8. https://doi.org/10.1038/s41537-021-00154-3

Trapnell, P. D., & Campbell, J. D. (1999). Private self-consciousness and the five-factor model of personality: Distinguishing rumination from reflection. *Journal of Personality and Social Psychology, 76*(2), 284–304. https://doi.org/10.1037/0022-3514.76.2.284

Watkins, E. R. (2008). Constructive and unconstructive repetitive thought. *Psychological Bulletin, 134*(2), 163–206. https://doi.org/10.1037/0033-2909.134.2.163

Watkins, E. R., & Roberts, H. (2020). Reflecting on rumination: Consequences, causes, mechanisms and treatment of rumination. *Behaviour Research and Therapy, 127*, 1–28. https://doi.org/10.1016/j.brat.2020.103573

Watson, D., Clark, L. A., Weber, K., & Assenheimer, J. S. (1995). Testing a tripartite model: II. Exploring the symptom structure of anxiety and depression in student, adult, and patient samples. *Journal of Abnormal Psychology, 104*(1), 15–25. https://doi.org/10.1037/0021-843X.104.1.15

Watson, D., Weber, K., Assenheimer, J. S., Strauss, M. E., & McCormick, R. A. (1995b). Testing a tripartite model: I. Evaluating the convergent and discriminant validity of anxiety and depression symptom scales. *Journal of Abnormal Psychology, 104*(1), 3–14. https://doi.org/10.1037/0021-843X.104.1.3

Wells, A. (2013). Advances in metacognitive therapy. *International Journal of Cognitive Therapy, 6*(2), 186–201. https://doi.org/10.1521/ijct.2013.6.2.186

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B, 67*(2), 301–320. https://doi.org/10.1111/j.1467-9868.2005.00503.x