# Anxiety and depression are associated with more distorted thinking on social media: Longitudinal Observational Study

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## *Abstract*

**Background:** Depression and anxiety are associated with patterns of negative thinking that can be targeted through cognitive restructuring as a part of cognitive behavioral therapy (CBT). Our team has created a set of cognitive distortion schemata (CDS) n-grams based on theories underlying CBT to measure the linguistic markers that indicate cognitive vulnerability to depression. These CDS were specifically designed to examine online language.

**Objective:** Our prior work supports a relationship between CDS and a diagnosis of depression, but less is known about the relationship between online language, CDS, and anxiety. The current study measures if CDS can be detected in people who report an anxiety symptoms, and if CDS increase with symptom severity.

**Methods:** 691 participants were recruited from a study assessing social media use and mental health symptoms, the Studies of Online Cohorts of Internalizing Symptoms and Language (SOCIAL). We used bootstrap resampling to compare differences in CDS prevalence in anxious and depressed participants.

**Results:** CDS can be observed in anxiety disorders, increase as a function of anxiety symptom severity, and are related to depression and anxiety comorbidity.

**Conclusions:** Using behavioral, affective, and cognitive indicators of distorted thinking from social media may yield new insight into the trajectories of depression and anxiety. This work has implications for the future of CBT and other online interventions that target distorted thinking styles. Clinical Trial: n/a

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# Anxiety and depression are associated with more distorted thinking on social media: Longitudinal Observational Study

## Introduction

Anxiety and mood disorders, also known as internalizing disorders, are among the most common mental disorders and leading contributors to the burden of disability worldwide [16, 17, 22]. Internalizing disorders are heterogeneous in their symptoms [31, 14, 28], prognosis [27], and impact multiple bodily systems including: circadian cycles [48], emotion processing [40, 41, 43, 38, 42], hormones [15, 50], physical health [44, 5], and even language [3, 8]. Regarding language, prior work has shown that individuals with symptoms of depression more frequently use first-person pronouns, absolutist language, and terms that describe negative emotions [6, 36, 35, 47]. These findings are consistent with research suggesting that internalizing disorders are characterized by a self-focus and negative affectivity. Individuals with a diagnosis of depression also display more distorted negative thinking in real life [4], and in their online worlds [3].

Aspects of distorted thinking manifest by distinctive word choices and sentence structure are often targeted directly in therapy. Indeed, the leading evidence-based treatment for internalizing disorders is cognitive behavioral therapy (CBT), which aims to restructure negative thinking and change associated behaviors [29, 30]. Investigating the language of individuals with internalizing disorders may assist understanding this heterogeneous and complex disorder. Major depression, for example, is often underdetected and thus, under-treated [34]. A better understanding of language indicative of depression and related disorders could assist in early detection or more individualized treatments. Social media provides a platform where researchers can learn more about the language of depression and anxiety, as it occurs naturalistically. In the United States, over 70% of individuals are on a social media platform. The insights gained from social media data can have direct impacts on treatment of internalizing disorders through use machine learning and AI tools that can detect depressive thinking styles and could be used for the purposes of prevention and early intervention [9, 2]. This work has opportunities to contribute to the growing field of large language models (LLMs) in mental health [24]. Moreover, understanding vulnerability to internalizing disorder is important because social media itself may be associated with internalizing symptoms [44].

Grounded in CBT, we have previously demonstrated that cognitive distortion schemata (CDS), or the patterns of thought represented by sequences of words (n-grams), differ between a depressed sample and a random sample on Twitter [3]. We created the CDS among a team of clinical psychologists and experts in natural language processing (NLP). We employed a theory-driven approach in creating the CDS, derived to measure the linguistic markers that indicate cognitive vulnerability to depression. The CDS categories we developed are 12 widely accepted styles of distorted thinking, including allor-nothing thinking, catastrophizing, fortune telling, and others. Previous results that show CDS are higher in depressed individuals compared to a random sample of adults while controlling for other elements of depressogenic language including first-person pronouns and more negative language [18, 47]. In other words, our findings *could not be explained* by higher use of ”I/me/my” or more words like ”sad/lonely/depressed.” Rather, differences can be more appropriately explained by language structure and patterns themselves. Indeed, we have also found evidence that this kind of language may be increasing over time [8], which connects with concerns about the negative effects of social media.

While we have previously shown higher rates of CDS in depressed Twitter users compared to a random sample [3, 8], we have not explored cognitive distortions online among anxious people. This is a major gap in the literature, given the high comorbidity of anxiety and depressive disorders [37, 39, 32]. Moreover, while we have previously examined prevalence rates of CDS, we have not examined if their use is related to symptom severity on a continuum which comports with a modern understanding of depression and anxiety. We would expect that more severe symptoms of anxiety and depressive psychopathology is associated with greater use of cognitive distortions. Thus, the current study was centered on two main research questions. First, does CDS prevalence increase as a function of anxiety severity (RQ1)? Second, how is CDS prevalence related to anxiety and depression comorbidity (RQ2)? For both of these research questions, we proposed a hypothesis. First, we expected that the prevalence of cognitive distortions in online language (calculated based on proportion of tweets containing CDS n-grams/total tweets) could be observed in individuals with anxiety disorders. and we hypothesized that CDS prevalence would increase as anxiety symptom severity increased. Second, we hypothesized that we would observe a relationship between depression severity and CDS prevalence, with higher levels of depression and anxiety associated with the highest proportion of distorted thinking in online language.

# Method

This study was approved by the institutional review board of Indiana University (2002549202 and 2005948214).

## Participants

We recruited participants for a study on social media and mental health. Participants are part of the Survey Online Cohorts for Internalizing Symptoms and Language (SOCIAL), described in prior work [32, 39]. Participants in the current study were 691 individuals from SOCIAL-I, a nationally representative sample drawn from Qualtrics panels. Participants were asked to provide their Twitter handle in addition to answering a variety of self-report questions addressing mental health. From the provided Twitter handles, personal Twitter timelines were harvested and evaluated for being human vs. bot-like (see Lorenzo-Luaces et al., 2023 for more detailed analysis). All study participants who provided a valid Twitter handle were included in our analysis. Demographic information is included in Table 1.

## Measures

*Severity Measure for Generalized Anxiety Disorder* The severity measure for generalized anxiety disorder (GAD) consists of 10 items rated on a 5-point Likert scale ranging from 0 (“never”) to 4 (“all of the time”). The participants are asked to rate the frequency of worry and associated symptoms over the past 7 days. Total scores range from 0 - 40. Higher scores indicate a greater severity of GAD symptoms. The average score (total raw score/number of items answered) can be used as a proxy for GAD severity: 0 indicates none, 1 indicates mild, 2 indicates moderate, 3 indicates severe, and 4 indicates extreme anxiety. In our sample, Cronbach’s alpha was .92 for SOCIAL-I indicating excellent internal consistency.

*Severity Measure for Depression* The severity measure for depression is also known as the Patient Health Questionnaire-9 (PHQ-9) [23] and consists of 9 items rated on a 4-point Likert scale. Items are rated based on symptoms over the last 7 days, and range from 0 (“not at all”) to 3 (“nearly every day”). The PHQ-9 has excellent psychometric properties. We scored the PHQ-9 to align with the severity scores of the GAD-10, described above, and based on established scoring such that overall PHQ scores correspond with an aggregate severity measure as follows: 0-4: none (0), 5-9: mild (1), 10-14: moderate (2), 15-19: severe (3), and 20-27: extreme (4). In our sample, Cronbach’s alpha was .87 for SOCIAL-I suggesting that this measure was internally consistent.

*Cognitive Distortion Schemata* Beck proposed the concept of cognitive distortions to characterize the thinking of individuals with depression [4]. We drew on these latest lists of cognitive distortions, which consist of 12 cognitive distortions categories. We (L.A.R., L.L-L., and J.B.) iteratively designed a list of CDS n-grams and consulted with CBT experts to land on a set of 241 cognitive distortion schemata (CDS) n-grams, each geared to express at least one type of cognitive distortion. The CDS were formulated to capture the minimal semantic building blocks of distorted thinking while avoiding expressions that are specific to depression-related topics, such as poor sleep or ongoing health issues. Where possible, higher-order n-grams were chosen to capture as much of the semantic structure of one or more distorted schemata as possible[3]. For example, the 3-gram ‘everyone will believe’ captures both ‘overgeneralizing’ and ‘mindreading’. For more details on CDS construction, as well as a details on CDS n-grams and relevant grammatical features, see Bathina et al., 2021. While our initial work examined CDS across the 12 categories, the current project collapses all CDS categories into one, representing all types of distorted thinking. We did this for ease of analysis, interpretation, and because we did not make conceptual distinctions between the categories based on our hypotheses. To collapse CDS categories into one metric of CDS, we simply calculate the proportion of all tweets that contain any occurrence of a CDS n-gram.

## Data Analysis

We report descriptive statistics for the demographic variables of participants in SOCIAL-I. Then, we used bootstrap resampling to compare differences in CDS prevalence by anxiety and depression severity. We calculate the between-group CDS prevalence as the proportion of CDS-containing tweets produced by the subset of the re-sampled group with a given severity score. In other words, for each severity class $C$ we have a corresponding set of tweets $T_C$, the set of all tweets produced by the individuals in $C$. Our CDS n-gram schemata is a function $F(t) \rightarrow \{0,1\}$ that maps each tweet $t$ to 1 if it contains any CDS n-gram or 0 otherwise. The prevalence for each severity class $C$ is thus calculated as $P_C = \frac{\sum_{t \in T_C} F(t)}{|T_C|}$. To establish accuracy of these prevalence calculations, we apply bootstrap re-sampling. Our bootstrap analysis comprised randomly re-sampling with replacement $n$ individuals from our sample population, where $n$ is the size of our sample. This bootstrap estimates are calculated by resampling repeated $B$ = 10,000 times, and the CDS prevalence recorded at each step. Our bootstrap analysis thus produces a distribution of CDS prevalence estimates $\{P^*_{C,1}, P^*_{C,2}, ..., P^*_{C,B}\}$ such that overlap of inner 95 percentile interval of the distribution of prevalence estimates for one class with the median of another class is considered to be indicative of non-significant differences between severity groups. As noted above, there were 5 severity groups for GAD (none, mild, moderate, severe, extreme) with CDS prevalence calculated for each (Fig. 2).

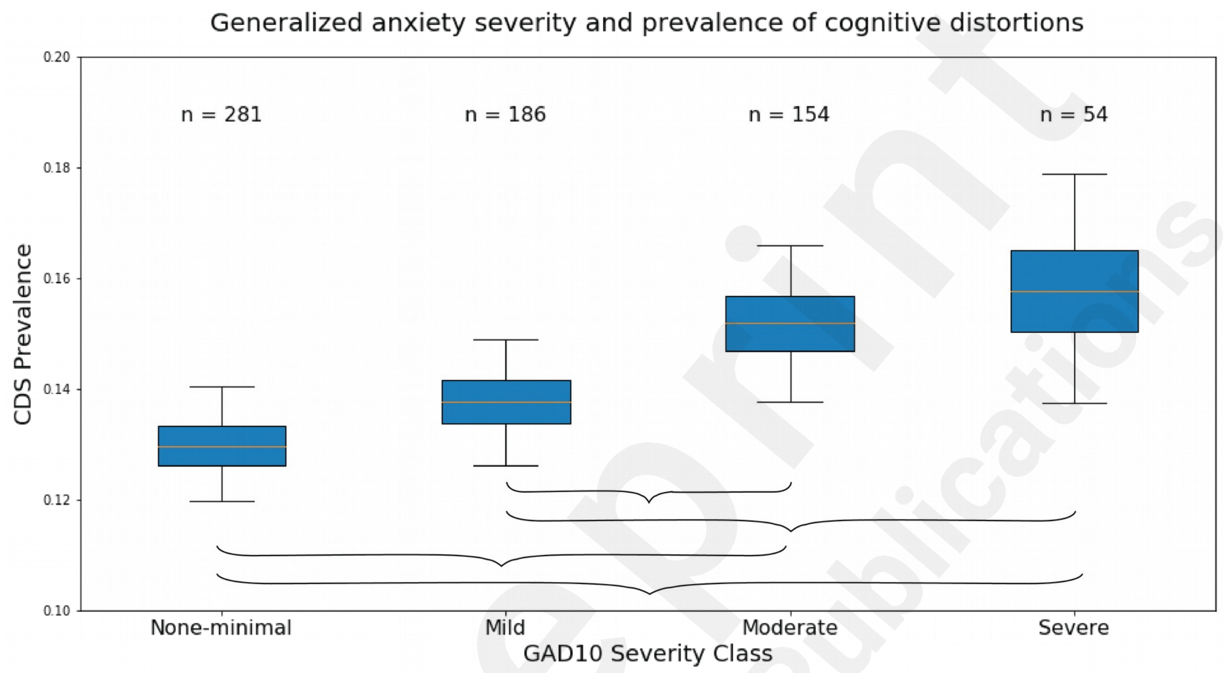
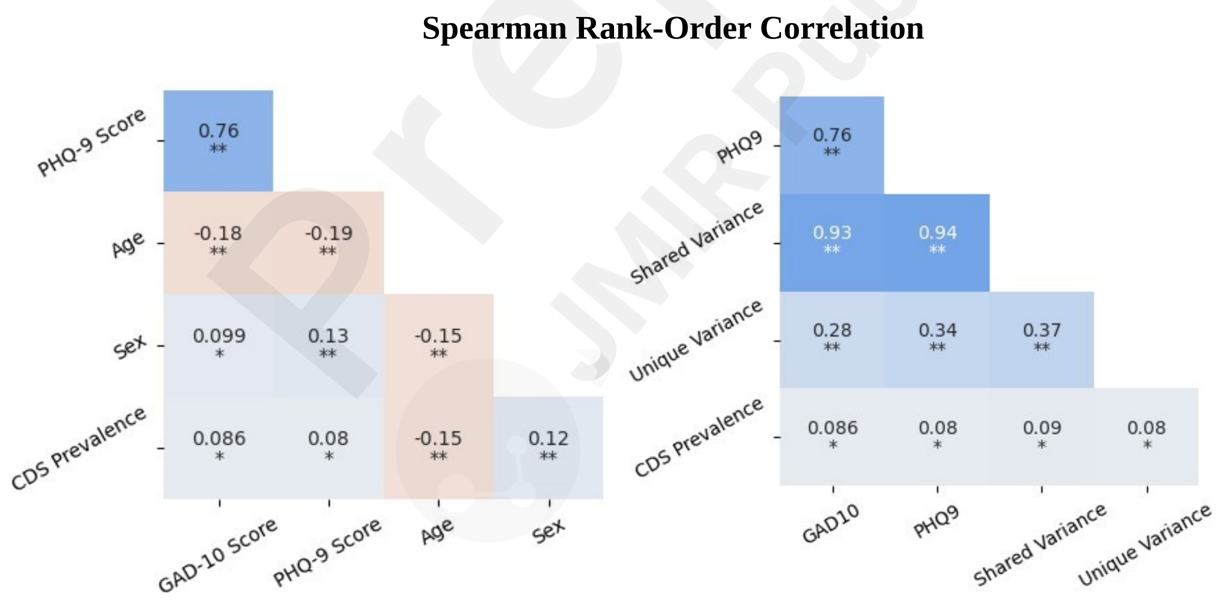



Figure 2: Bootstrapped aggregate CDS prevalence distributions for each GAD-10 severity class. Each bar above with the sample size of the corresponding severity class. The colored box represents interquartile range, while the horizontal lines correspond to 95% CI. Our results show a trend of increasing CDS prevalence as severity increases, with pairwise significant differences denoted by curly braces.

However, in our data sample the extreme severity class comprised only 16 individuals. This sample size was too small to be considered valid for bootstrap analysis and so was excluded from the final results of that analysis. We followed this same process to examine depression severity and CDS prevalence, again using bootstrapping and examining 95% confidence interval overlaps (Fig. 3).

To further test the relationships between variables, we next conducted Spearman rank-order correlation between anxiety, depression, age, sex, and CDS prevalence (Fig. 1a). This correlation measure was selected due to concerns with respect to the underlying assumptions of aggregate Likert-scale questionnaire scores as linear measures of symptom severity. Rank-order correlation preserves ordering of severity without relying on the assumption that such questionnaire measures are linear metrics of underlying psychological traits [26]. We further examine the relationship between comorbidity of anxiety and depression with CDS prevalence by computing Spearman rank-order correlations over the shared and unique variance [20] between anxiety and depression (Fig. 1ab). Here, we calculate the shared variance between GAD-10 score and PHQ-9 score as $\frac{z_d+z_a}{2}$ and unique variance as $\frac{z_d-z_a}{2}$, where $z_d$ is the z-scored PHQ-9 score and $z_a$ is the z-scored GAD-10 score. These values thus account for the shared and marginal effects of depression and anxiety.




(a) Rank-order correlation (b) Z-scored Rank-order correlation

Figure 1: Pairwise Spearman rank-order correlation coefficients between (a) GAD10, PHQ9 and confounding variables and (b) accounting for shared and unique variance between PHQ9 and

GAD10.

## Results

Demographic information is shown in Table 1.

Table 1: Demographics information of the two cohorts analyzed in this study. Note that 19 participants did not respond to the demographic portion of the survey, so total for each demographic category is 672 participants of total 691.

| **Variable** | **Value** |
|---|---|
| Age (years), mean (SD) | 34.46(13.30) |
| **Race, n(%)** | |
| White | 481(69.0) |
| Black or African American | 82(11.86) |
| American Indian or Alaska Native | 5(0.71) |
| Asian | 41(6.43) |
| Hispanic or Latino/a | 58(8.29) |
| Other | 5(3.71) |
| **Sex, n(%)** | |
| Male | 241(34.71) |
| Female | 430(62.14) |
| Prefer not to say | 1(0.14) |
| **Gender, n(%)** | |
| Male | 246(35.43) |
| Female | 418(60.43) |
| Other | 1(0.145) |
| Non-binary, genderqueer, or agender | 7(1.0) |

| | |
|---|---|
| **Sexual Orientation, n(%)** | |
| Bisexual/pansexual | 85(12.14) |
| Heterosexual/straight | 541(78.29) |
| Homosexual/gay | 27(3.86) |
| Other (e.g., queer, questioning, asexual) | 12(1.71) |
| Prefer not to say | 7(1.0) |
| **Annual household income (US $), n(%)** | |
| Less than $10,000 | 61(8.71) |
| $10,000 to $19,999 | 72(10.29) |
| $20,000 to $29,999 | 97(14.43) |
| $30,000 to $39,999 | 64(9.29) |
| $40,000 to $49,999 | 39(5.57) |
| $50,000 to $59,999 | 48(6.86) |
| $60,000 to $69,999 | 37(5.29) |
| $70,000 to $79,999 | 47(6.71) |
| $80,000 to $89,999 | 30(4.29) |
| $90,000 to $99,999 | 40(5.86) |
| $100,000 to $149,999 | 75(10.86) |
| $150,000 or more | 62(8.86) |

To test our first hypothesis that CDS was related to anxiety symptom severity, we conducted regression. As shown in Figure 2, there is a relationship between anxiety and online cognitive distortions which can be observed by increased prevalence of CDS, with individuals with no/minimal anxiety having the lowest CDS prevalence. There is an apparent increasing trend of CDS prevalence rising with GAD severity class, with moderate and severe GAD scores showing significantly greater prevalence than none-minimal and mild GAD. However, differences of none-minimal versus mild or moderate versus severe do not reach significance. In general, we found support for our hypothesis, showing that CDS prevalence increases with increases in anxiety severity.

To test RQ2, we examined the relationship between CDS prevalence and depression severity. In examining CDS prevalence and depression severity, we did not see as clear of a linear increase in CDS prevalence by severity (Fig. 3).

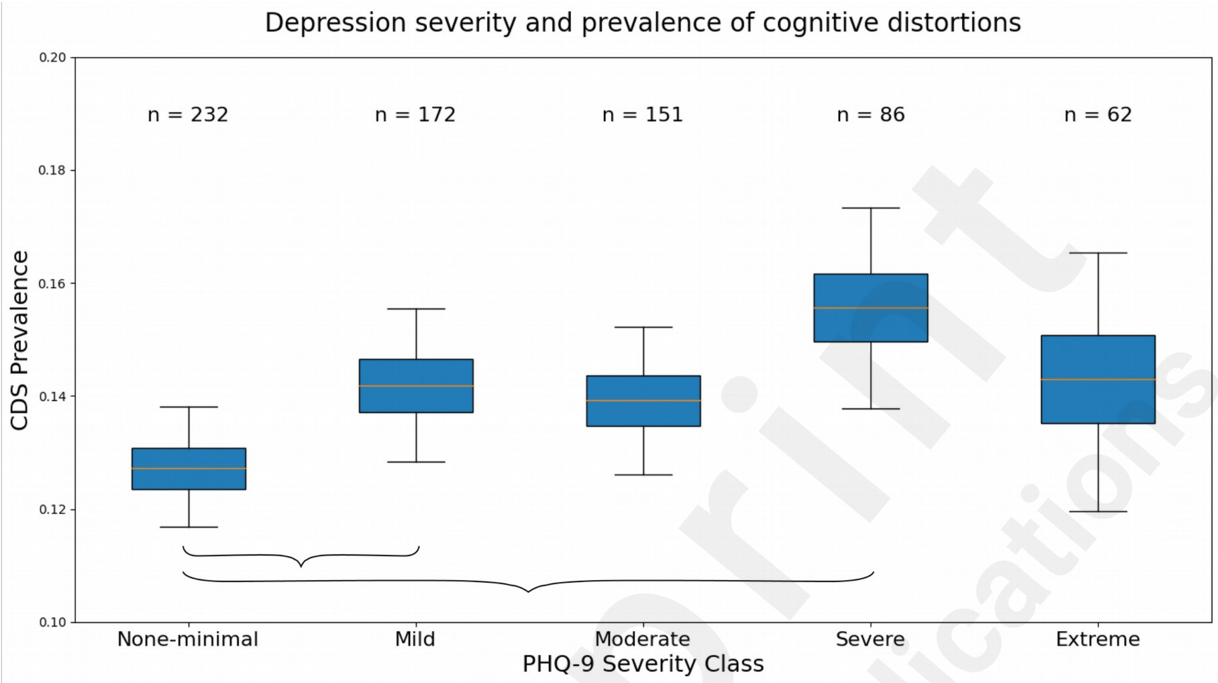



Figure 3: Bootstrapped aggregate CDS prevalence distributions for each PHQ-9 severity class. Each bar is annotated above with the median and 95% CI bounds in brackets. The colored box represents interquartile range, while the horizontal lines correspond to 95% CI. Pairwise significant differences denoted by curly braces.

In fact, there were not significant differences high levels of depression and mild and moderate levels of depression or severe and extreme levels. We attribute this to the heterogeneous nature of depression, as well as small sample size at extreme levels, and is discussed below.

We also include Spearman rank-order correlation as shown in Figure 1a. Rank correlation demonstrates statistically significant relationships across all variables, although the effects are small as has previously been reported when correlating NLP metrics with self-report [18]. Anxiety (GAD-10) and depression (PHQ-9) scores were highly correlated with a correlation coefficient of 0.76, closely reflecting comorbidity rates between anxiety and depression. These severity scores were also correlated with CDS prevalence at a rate of 0.086 and 0.080, respectively. These correlation values are consistent with prior studies applying NLP to self-reported mental health data[10, 33].

Overall, our results supported our hypotheses. First, CDS increase as anxiety severity increases. Support of our second hypothesis that GAD and depression comorbidity would produce high levels of CDS is more mixed. However, the covariance rank order correlations shown in the heatmap show a significant effect of comorbidity that is roughly equal to the effects of depression or anxiety.

## Discussion

To the best of our knowledge, this is the first study to examine cognitive distortions in online language in mood and anxiety disorders using natural language processing (NLP) and a theory-based lexicon of n-grams. While some prior work using natural language processing has shown differences in language and thinking styles in depressed vs. random cohorts, less focus has been given to anxiety. This is a critical gap in our understanding of the thinking styles across internalizing disorders, especially considering that anxiety disorders increase risk for mood disorders [7, 19, 12], and that anxiety disorders alone are associated with a very high level of distress, impairment, and disability [17].

Our primary finding was that CDS increase as levels of generalized anxiety symptoms increase. We observed a similar trend with major depression symptoms as based on the PHQ-9: as symptoms of depression increased, prevalence of distorted thinking increased, controlling for age and sex covariates. While shared variance of anxiety and depression symptoms contribute to overall CDS prevalence, the size of the effect is roughly similar to unique variance, according to Spearman rank-order correlations (.09 = shared vs. .08 = unique). Regarding the size of the effects we observed, there are many reasons why variance in CDS prevalence that is explained by severity is expected to be low. For example, there are many other variables that impact expression of CDS including time of year and the content of the post. Indeed, in a recent study examining emotion connectivity and symptoms of depression, sizes of the effect were similarly small [21].

Based on the CDS construction, which was informed by Beck's original cognitive distortion categories [4], and expanded by 10 CBT experts in our team [3], we provide validation of distorted thinking in anxiety disorders in online language. This work sheds additional light on the degree to which cognitively distorted and depressogenic language occurs colloquially in social media platforms. Moreover, our work can be used in tandem with emerging work using LLMs applied to support mental health [24]. There is the potential for large-scale societial relevance of our work: as individuals connect across the globe, they may use distorted language in specific ways within their social networks [49, 13]. There may be elements of contagion [35, 25] of distorted language within certain communities with depression and anxiety disorders, but this remains to be tested.

Despite the novelty of our research, using a theory-driven approach to capture distorted language, there are several limitations to consider. First, we relied on self-reported depression and anxiety symptoms. While this is an expansion of our prior work that relied on self-disclosure of diagnoses, there are still problems with self-report [39], as compared to clinician-based severity ratings. Clinical diagnoses of GAD and depression were not confirmed in our sample. Second, our sample was drawn from an online Qualtrics panel, and data may be limited by low-incentive to complete the research accurately [11]. Third, we had low proportions of individuals with extreme levels of depression and anxiety symptoms. While this is to be expected, the bootstrapping produced large confidence intervals, which limited interpretation of CDS at extreme levels of symptoms.

This work has many implications for the future of evidence-based treatments including online interventions that engage individuals with internalizing symptoms. Characterizing the relationship between distorted language and depression and anxiety symptoms may help in the development of automated interventions such as chatbots, see[1] for a recent review. Moreover, the extent to which CDS prevalence occurs in the population at large can be used as a passive index of vulnerability to depression and anxiety disorders. This vulnerability index is expected to change as individuals progress through treatment, or go through major stressors, such as a global pandemic, but this is yet to be explored. Using online language to distinguish trajectories of symptoms in individuals with internalizing symptoms is still a relatively novel research area [45, 46]. More work is needed to understand cognitive distortions in colloquial language use [8] and how these distortions can change with age, symptoms, context, and treatment.

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