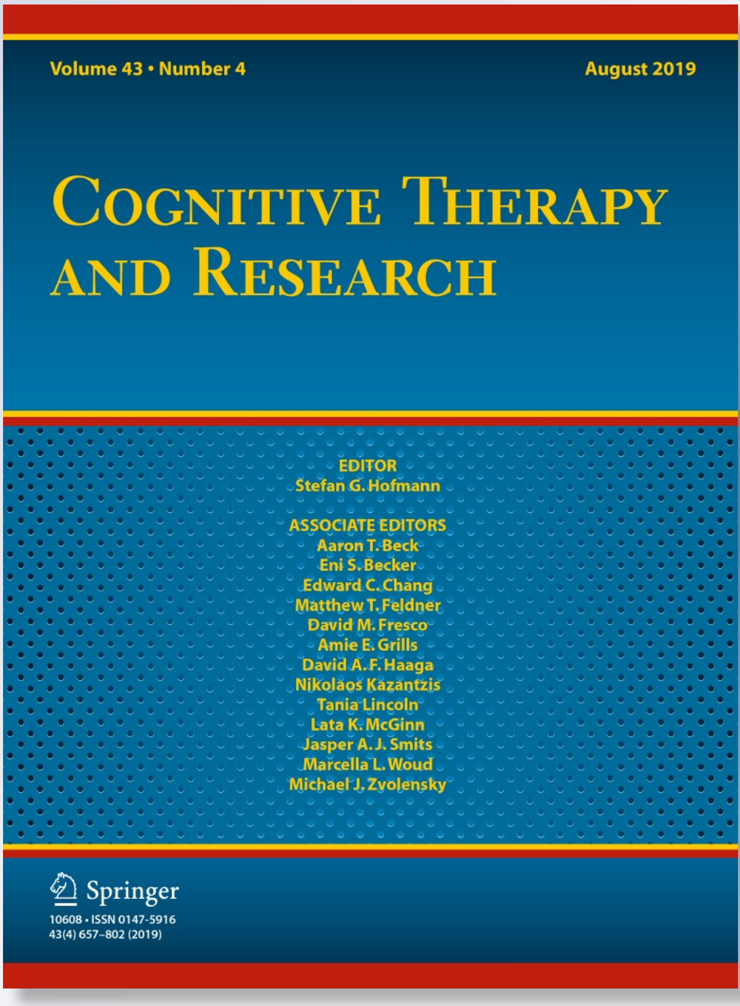
#Sad: Twitter Content Predicts Changes in Cognitive Vulnerability and Depressive Symptoms

Maria P. Sasso, Annaleis K. Giovanetti, Anastasia L. Schied, Hugh H. Burke & Gerald J. Haeffel

Cognitive Therapy and Research

ISSN 0147-5916
Volume 43
Number 4

Cogn Ther Res (2019) 43:657-665
DOI 10.1007/s10608-019-10001-6



Springer

Cognitive Therapy and Research (2019) 43:657–665
https://doi.org/10.1007/s10608-019-10001-6

ORIGINAL ARTICLE

#Sad: Twitter Content Predicts Changes in Cognitive Vulnerability and Depressive Symptoms

Maria P. Sasso[1] · Annaleis K. Giovanetti[1] · Anastasia L. Schied[1] · Hugh H. Burke[1] · Gerald J. Haeffel[1]

Published online: 31 January 2019

Abstract
Research shows that social media networks can affect both the physical and mental health of its users. We hypothesized that social media would also be associated with cognitive vulnerability to depression. To test this hypothesis, we used a 3-month pre-post prospective longitudinal design with a sample of undergraduates (n = 105). Results showed that participants who had tweets with a "past focus" (as determined by LIWC software) were more likely to exhibit increases in cognitive vulnerability and depressive symptoms than participants who did not have tweets with a past focus. Increases in cognitive vulnerability were associated with increases in depressive symptoms. However, the effect of Twitter content on future depressive symptoms was not accounted for by increases in cognitive vulnerability. Rather, one's past focus Twitter content had an effect on future depressive symptoms that was independent of its effect on future cognitive vulnerability levels. These results provide further support for the plasticity of cognitive vulnerability in early adulthood as well as corroborate emerging evidence for the association between social media and mental health risk factors.

Keywords Cognitive vulnerability · Depression · Twitter · Social media · Contagion

Introduction

Depression is a common and recurrent disorder affecting more than 300 million people around the globe (World Health Organization 2004). It is the leading cause of disability in the world for people ages 15–44 (World Health Organization 2004). Depression can also be lethal; it is among the strongest predictors of suicide (Kessler et al. 1999), which is the second leading cause of death in college-aged students (Turner et al. 2013). Moreover, the rates of depression continue to rise. Between 2005 and 2015, there was an 18% increase in individuals diagnosed with clinically significant depression (World Health Organization 2004). Clearly, it is critical to understand what factors influence risk and resilience to this global mental health concern.

According to the hopelessness theory of depression (e.g., Abramson et al. 1989), some individuals are at elevated risk for depression because they have a *cognitive vulnerability*. Specifically, some people are vulnerable to depression because they have a tendency to generate interpretations of stressful life events that have overly negative implications for their future and for their self-worth. Recent research has provided strong support for hopelessness theory's cognitive vulnerability hypothesis (see Haeffel et al. 2008 for review). Prospective studies have consistently found that cognitive vulnerability interacts with stressful events to predict the development of depressive symptoms and depressive disorders (Abramson et al. 1999; Hankin et al. 2004). These studies (e.g., Alloy et al. 2006) have shown that it is possible to take a group of individuals and predict which of them are at heightened risk for a first episode of clinically significant depression based on their cognitive style for interpreting life events (i.e., their level of cognitive vulnerability).

Taken together, prior studies indicate that high levels of cognitive vulnerability, as defined in the hopelessness theory, precede and predict future depressive symptoms. Thus, it is critical to understand what influences the development and maintenance of this risk factor. Prior research suggests that the development and consolidation of cognitive vulnerability depends, at least in part, on early social environments, particularly negative interpersonal contexts (e.g., early life stress; direct inferential feedback from parents). Research has shown that children's cognitive

✉ Gerald J. Haeffel
ghaeffel@nd.edu

[1] Department of Psychology, The University of Notre Dame, Notre Dame, IN 46556, USA

vulnerability levels are influenced by the cognitive vulnerability levels of their parents, as well as the direct feedback they receive about stress from their parents, peers, and teachers (Alloy et al. 2001; Garber and Flynn 2001; Seligman et al. 1984; Stark et al. 1996; Mezulis et al. 2006). Cognitive vulnerability solidifies in early adolescence (Cole et al. 2008; Nolen-Hoeksema et al. 1992) and tends to be stable throughout late adolescence and into adulthood (see Romens et al. 2009 for review).

Given its stability over time, cognitive vulnerability is often viewed similarly to a genetic diathesis in that an individual's risk level is "fixed." However, recent work suggests that cognitive vulnerability is not unchangeable. For example, Haeffel and Hames (2014) found that cognitive vulnerability reveals its plasticity if there is a significant change in environmental context, such as moving away to college. Specifically, they showed that cognitive vulnerability was "contagious" between freshman college roommates. In just 3 months, students randomly assigned to live with a high cognitively vulnerable roommate were likely to exhibit an increase in their own cognitive vulnerability level compared to students randomly assigned to live with a low cognitively vulnerable roommate. Importantly, increases in cognitive vulnerability were associated with increased risk for future depressive symptoms, particularly in individuals who experienced high stress. This study highlights the potential influence the social environment can have on cognitive vulnerability even in adulthood.

This preliminary work suggests cognitive vulnerability has some plasticity after it solidifies in early adolescence. However, the specific environmental and social factors that influence cognitive vulnerability in adulthood are still not well understood. It appears that major life changes (e.g., moving to an entirely new place and living with a stranger) can impact cognitive vulnerability levels (Haeffel and Hames 2014). However, this type of major life upheaval in one's life is somewhat rare (e.g., you only move away from home for the first time once; Gray et al. 2013). The question remains if more commonly occurring environmental and interpersonal factors can also influence cognitive vulnerability levels.

One environmental factor that is becoming increasingly important in modern society is social media. Since its inception, social media has transformed modern communication, relationships, and content exposure while creating new landscapes for communal influence not previously possible. Worldwide, there are over 2 billion Facebook members and 330 million Twitter users (Statista 2017). Eighty-three percent of young adults in America use social networking sites and have an average of seven social media accounts (Lehart et al. 2010). As noted by Ferrara and Yang (2015), social media platforms such as Twitter and Facebook provide users "…with nearly unlimited access to information and connectivity."

Despite the increasingly important role that social media plays in people's everyday lives, there is a relative paucity of research examining its association with depression and its antecedents. To our knowledge, there are no studies specifically examining the association between social media and cognitive vulnerability to depression; however, there are a number of related findings to suggest that social media content may be associated with this important trait-like risk factor. Recent research shows that social media can influence both physical and mental health. For example, Eichstaedt et al. (2015) examined data from 1346 U.S. counties (> 88% of the U.S. population) and found that use of negative-emotion language on Twitter was associated with heart disease mortality risk on a community level. Impressively, Twitter content was a stronger predictor of heart-disease mortality than 10 other covariates including family income, obesity, and hypertension.

Social media content has also been shown to affect emotional well-being. There is an emerging body of empirical work showing an association between social media and negative moods such as loneliness, anxiety, suicide rates, and depressive symptoms (Lin et al. 2016; Kross et al. 2013; Twenge et al. 2018; Verduyn et al. 2015). For example, Reece et al. (2017) demonstrated that Twitter content could be used to predict self-reported onsets of depressive episodes up to six months into the future (see also Reece and Danforth 2017). It appears that social media may be contributing to these negative moods via an emotional contagion effect (when one person's emotional state triggers the same emotional state in another person or group of people). According to Coviello et al. (2014), "…what people feel and say in one place may spread to many parts of the globe on the very same day." Indeed, Kramer et al. (2014) provided causal evidence for the emotional contagion effect of social media. Using an experimental design, they manipulated the newsfeed of over 500,000 Facebook users. Results showed that those randomly assigned to received newsfeeds with fewer positive expressions produced fewer positive posts and more negative posts. These findings support the assertion that social contagion of moods can occur over social media in the absence of direct interpersonal contact and nonverbal cues.

The purpose of this study was to examine the effect of social media content on cognitive vulnerability to depression. Specifically, we hypothesized that individuals who had more negative Twitter content would exhibit higher levels of cognitive vulnerability prospectively, and in turn, report greater levels of depressive symptoms. We chose to examine the social media site of Twitter. Twitter is the eighth most popular website in the United States and the third most popular social media site, ranking only behind Facebook and Instagram (Statista 2017). One in four online adults use Twitter (nearly 700 million users total) and over 350,000 tweets are sent every minute (Internet Live Statistics 2018). The highest percentage of Twitter users are young Americans; nearly 40% of those between the ages of 18 and 29 use the social media site (Harvard IOP 2018). Within this age range, Twitter is more popular among college students (with 47% using Twitter) than those not in college (Harvard IOP 2018). Twitter's easily searchable timelines as well as the ability for users to publish and retweet unlimited content make it an ideal social media site to test our hypothesis.

Method

Participants

Participants were 105 undergraduates (60 females, 45 males; M_{age} at baseline = 19 years old) undergraduates from a private, midsized university in the Midwestern United States. The self-reported ethnicity of the final sample was 78% Caucasian, 13% African American, 2% Asian-American, 2% Native American, and 4% "Other." Participants were recruited through the University's online volunteer participant pool; only participants who self-identified as active Twitter users were invited to participate in the study. Participants were given extra credit for their participation. All procedures were approved by the university's human subject review board.

Measures

Depressive Symptoms

The Beck Depression Inventory-I (BDI-I; Beck et al. 1979) is a widely used 21-item self-report inventory that assesses depressive symptoms. Participants rate symptoms of depression (e.g., negative mood, pessimism, sleep disturbance) on 0 to 3 scales. Total scores on the BDI can range from 0 to 63, with higher scores indicating greater levels of depressive symptoms. The BDI has high internal consistency (Chronbach's α is typically greater than 0.8) and good test–retest reliability (r = .60–.83 for nonpsychiatric samples); it also has strong levels of concurrent, criterion, and predictive validity with both college and psychiatric samples (see Beck et al. 1988 for a review). Internal consistency in the current sample was good with α = 0.87 at baseline and α = 0.92 at follow-up.

Cognitive Vulnerability

The Cognitive Style Questionnaire (CSQ; Haeffel et al. 2008) was used to assess the cognitive vulnerability factor featured in the hopelessness theory of depression (Abramson et al. 1989). The CSQ is a self-report questionnaire that presents participants with 12 hypothetical negative events (6 achievement and 6 interpersonal). For each hypothetical event, participants are first instructed to vividly imagine themselves in that situation, as if the situation were happening in real time (example event: *You take an exam and receive a low grade on it*). Next, they are instructed to write down what they believe to be the one major cause of the event. Participants then use a 7-point Likert-type scale to rate the cause that they have specified on dimensions of internality, stability, and globality. Finally, participants are asked to think about what the occurrence of the hypothetical situation would mean to them, and to use a 7-point Likert-type scale to rate the consequences and self-worth implications of the hypothetical event. An individual's CSQ score is their average rating across the scales relevant to the vulnerability factor featured in the hopelessness theory (stability, globality, consequences, and self-worth characteristics) for the 12 hypothetical negative life events. This composite score (total score divided by the number of items) can range from 1 to 7, with higher scores reflecting greater levels of cognitive vulnerability to depression. The CSQ has good internal consistency (α ranging from 0.88 to 0.96 across most studies; Haeffel et al. 2008) and test–retest reliability (0.80 test–retest for during a 1 year period; Alloy et al. 2000). It also has demonstrated predictive and construct validity (see Haeffel et al. 2008 for review). Specifically, the CSQ: (a) interacts with measures of negative life events to predict depressive symptoms and disorders, (b) is associated with hopelessness, which mediates the CSQ's relationship with depression, (c) is associated with event-specific negative inferences, and (d) is associated with hypothesized antecedents such as a history of emotional abuse. The internal consistency for the CSQ composite in the current sample was good with α = 0.89 at baseline and α = 0.91 at follow-up.

Twitter Content

Linguistic Inquiry and Word Count (LIWC; Tausczik and Pennebaker 2010) software was used to analyze participants' Twitter feeds. The LIWC software was used to categorize individual words in the tweets into existing dictionaries derived from prior research (Tausczik and Pennebaker 2010). The program then calculates the percentage of each LIWC category within that given text. We tested the following five derived categories: Use of "I", Past Focus (e.g., "learned," "remember") Future Focus (e.g., "hope," "tomorrow"), Negative Emotion (e.g., "exhausting," "fear"), and Positive Emotion (e.g., "favorite," "excited"). These categories were chosen a priori based on their theorized and empirical relevance to cognitive vulnerability and depressive symptoms more generally. Specifically, "use of I" was chosen because personal pronoun use in expressive writing has been linked to both positive (Klein and Boals 2001; Campbell and Pennebaker 2003) and negative (Rude et al. 2004) emotional states. We examined "past focus" because of its link to cognitive risk processes such as ruminative brooding, which is associated with cognitive vulnerability (Spasojevic and Alloy 2001) and risk for depressive symptoms and disorders (Nolen-Hoeksema 1991). "Future Focus" was chosen because of its possible association with the future consequences component of cognitive vulnerability of depression. The categories of "Positive Emotion" and "Negative Emotion" were chosen because people with depression tend to simultaneously exhibit high levels of negative emotions and low levels of positive emotions (Clark and Watson 1991).

Procedure

The study had two time points. At baseline, participants completed measures of cognitive vulnerability (CSQ) and depressive symptoms (BDI). They also provided consent to allow access to 1 month of their twitter content. At follow-up 3 months later, participants returned to the lab and again completed measures of cognitive vulnerability (CSQ) and depressive symptoms (BDI). The 3-month prospective interval was chosen because prior research (e.g., Haeffel and Hames 2014) testing the effect of social environment on changes in cognitive vulnerability also used this time frame.

Results

Descriptive statistics for the study variables are listed in Table 1. We hypothesized that individuals with high amounts of negative content in their Twitter feeds would exhibit greater levels of cognitive vulnerability in the future and, in turn, greater levels of depressive symptoms than those with low amounts of negative Twitter content. We tested this hypothesis using ordinary least squares (OLS) regression-based path analysis modeling using bootstrapping confidence intervals (Hayes 2018). In the model (see Fig. 1), the dependent variable was level of depressive symptoms (BDI) at time 2. Baseline level of depressive symptoms (BDI) was entered as a covariate to control for any individual differences in depressive symptoms and to create

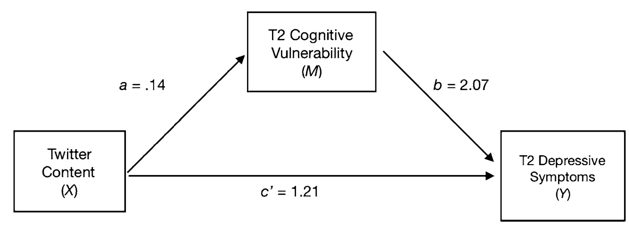


Fig. 1 OLS regression-based path analysis using bootstrapping confidence intervals testing the direct and indirect effects of Twitter content on cognitive vulnerability and depressive symptoms 3 months later (controlling for total Twitter word count, cognitive vulnerability at baseline, and depressive symptoms at baseline). Path coefficients listed are for analyses testing the effect of "past focused" Twitter content (*X*). All path effects were significant at $p < .01$ level. The indirect effect ($ab = 0.28$) of past focused Twitter content on depressive symptoms (mediated by cognitive vulnerability) was not significant

Table 1 Means, standard deviations, and correlations for study 1

	1	2	3	4	5	6	7	8	9
1 BDI	–								
2 CSQ	**.43**	–							
3 "I"	.07	**.19**	–						
4 Past	.07	.07	.12	–					
5 Future	− .08	.02	− .05	**.27**	–				
6 Negative	.17	.05	**.34**	.14	− .11	–			
7 Positive	− .09	− .06	.13	**.28**	− .16	.03	–		
8 BDI 2	.35	.17	.11	**.35**	.12	.17	.10	–	
9 CSQ 2	.15	**.61**	.14	**.46**	.11	.11	.19	.29	–
Mean	5.46	4.01	5.83	2.71	2.08	2.32	4.76	8.44	4.09
	5.48	0.8	3.18	1.98	9.59	1.53	2.51	8.01	0.99

BDI Beck depression inventory at baseline, *CSQ* cognitive style questionnaire at baseline. *I* LIWC "I" category, *Past* LIWC past focus category, *Future* LIWC future focus category, *Negative* LIWC negative emotion category, *Positive* LIWC positive emotion category, *BDI T2* Beck depression inventory at follow-up, *CSQ 2* Cognitive Style Questionnaire at follow-up

Higher scores on BDI and CSQ indicate greater levels of the construct being measured. Correlations in bold are significant at the 0.05 level a residual change score. The independent variable was each Twitter content score, respectively (LIWC score—Use of "I", past focus, future focus, negative emotion, and positive emotion, respectively). Thus, five separate regression analyses were conducted. The mediator was cognitive vulnerability score at time 2. Cognitive vulnerability score at baseline was entered as a covariate in order to create a lagged score (Valente and MacKinnon 2017). Total Twitter word count was also entered as a covariate to control for any individual differences in overall Twitter use.

Results showed that the LIWC categories of "I", negative emotion, and positive emotion had no significant direct or indirect effects on future cognitive vulnerability scores or depressive symptom scores (see Table 2). Only the LIWC category of past focus had a direct effect on both future cognitive vulnerability (coefficient = 0.14, $t = 2.02$, $p = .05$, CI 0.01–0.27; Model $R^2 = 0.43$, $F[4, 56] = 10.72$, $p < .001$) as well future depressive symptoms (coefficient = 1.21, $t = 2.43$, $p = .02$, CI 0.21–2.21; Model $R^2 = 0.34$, $F[5, 55] = 5.55$, $p < .001$) over the 3-month interval. Participants with greater focus on the past exhibited higher levels of cognitive vulnerability and higher levels of depressive symptoms than those with less focus on the past. As expected, cognitive vulnerability had a direct effect on depressive symptoms (coefficient = 2.07, $t = 2.16$, $p = .04$, CI 0.15–3.99). However, the indirect effect (the path from past focus to cognitive vulnerability to depressive symptoms) was not statistically significant from zero as the 95% bootstrap confidence interval included zero (− .03 to.82). This means that past focus Twitter content had an effect on future depressive symptoms that was independent of its effect on future cognitive vulnerability levels (i.e., cognitive vulnerability did not mediate the effect of past focus Twitter content on future depressive symptoms).

Table 2 Model coefficients

	Consequent							
	M (cognitive vulnerability)				*Y* (depressive symptoms)			
Antecedent		Coeff	SE	p		Coeff	SE	p
X (Twitter "I")	a	0.02	0.03	.60	c'	−0.29	0.21	.19
M (Cog Vul)		–	–	–	b	2.76	0.96	.01
Constant	i_M	1.31	0.50	0.01	i_Y	3.42	3.79	.37
	$R^2 = 0.40$				$R^2 = 0.29$			
	$F(4, 56) = 9.16$, $p < .001$				$F(5, 55) = 4.43$, $p = .002$			
X (Twitter past)	a	0.14	0.07	.05	c'	1.21	0.50	.02
M (Cog Vul)		–	–	–	b	2.07	0.96	.04
Constant	i_M	1.14	0.49	.03	i_Y	1.70	3.66	.64
	$R^2 = 0.43$				$R^2 = 0.34$			
	$F(4, 56) = 10.72$, $p < .001$				$F(5, 55) = 5.55$, $p < .001$			
X (Twitter future)	a	0.00	0.10	.98	c'	0.14	0.71	.84
M (Cog Vul)		–	–		b	2.67	0.97	.01
Constant	i_M	1.35	0.5	0.01	i_Y	2.67	3.85	.49
	$R^2 = 0.39$				$R^2 = 0.26$			
	$F(4, 56) = 9.04$, $p < .001$				$F(5, 55) = 3.95$, $p < .004$			
X (Twitter negative)	a	0.05	0.06	0.38	c'	0.23	0.44	.60
M (Cog Vul)		–	–	–	b	2.61	0.98	.01
Constant	i_M	1.21	0.51	.02	i_Y	2.23	3.94	.57
	$R^2 = 0.40$				$R^2 = 0.27$			
	$F(4, 56) = 9.36$, $p < .001$				$F(5, 55) = 4.01$, $p < .004$			
X (Twitter positive)	a	0.06	0.04	.10	c'	0.58	0.27	.33
M (Cog Vul)		–	–	–	b	2.22	0.96	.02
Constant	i_M	1.09	0.51	.04	i_Y	0.87	3.76	.82
	$R^2 = 0.42$				$R^2 = 0.32$			
	$F(4, 56) = 10.19$, $p < .001$				$F(5, 55) = 5.24$, $p < .001$			

Cog Vul cognitive vulnerability. All indirect effects (*ab*) of *X* on *Y* mediated by cognitive vulnerability were not significant

Discussion

Prior research shows that cognitive vulnerability precedes and predicts future depressive symptoms and episodes (Abramson et al. 1999). Thus, it is critical to understand what influences the development and maintenance of this risk factor. The purpose of this study was to test the effect of Twitter content on prospective changes in cognitive vulnerability and depressive symptoms. Specifically, we hypothesized that those with more negative Twitter content would report greater levels of cognitive vulnerability and depressive symptoms over a 3-month prospective interval. The hypothesis was supported for only one of the Twitter content categories (derived from LIWC dictionaries)—a "past focus." Participants who had tweets with high levels of past focus were more likely to exhibit prospective increases in cognitive vulnerability and depressive symptoms than participants with low levels of past focus. Further, those who reported increases in cognitive vulnerability were more likely to report increases in depressive symptoms. However, changes in cognitive vulnerability did not mediate the effect of past focus Twitter content on changes in depressive symptoms. Rather, one's Twitter content had an association with future depressive symptoms that was independent of its association with future cognitive vulnerability.

Our results add to a growing body of research showing that social media content is associated with variety of mental health factors ranging from sleep to loneliness to suicide risk. In light of this work, some researchers have proposed a "big data" approach (e.g., data mining, machine learning) to examining social media content in order to target mental health problems on a population-level. Conway and O'Connor (2016) argued that Twitter may be specifically useful in this regard because it is a "broadcast social network" and has a publicly accessible data base. Supporting the big-data approach, Bollen et al. (2011) showed that collective public mood derived from Twitter feeds could predict the value of the Dow Jones Industrial Average over time. Large-scale data analyses of social media content have also been used to track the spread of influenza (Broniatowski et al. 2013) and even assess the safety of pharmaceuticals (Freifeld et al. 2014). Of particular relevance to the current findings, Jashinsky et al. (2014) showed that it may be possible to monitor suicide risk on a large scale. Specifically, they developed a set of terms related to suicide risk factors that were then used to analyze over one million tweets. Results showed a correlation between Twitter derived risk and state age-adjusted suicide data from the U.S. Centers for Diseases Control and Prevention. Taken together with the current findings, it appears that continued research on social media content may have important implications for understanding mental health issues on both a population and individual level.

It is important to underscore that the other four a priori chosen LIWC categories did not predict changes in depressive symptoms or cognitive vulnerability (with the exception of future focus, which only had an effect on cognitive vulnerability). Thus, the current results should be interpreted with caution until replicated. Further research is also needed to pinpoint the mechanism by which past focus content predicted increases in depressive symptoms as it was not mediated by cognitive vulnerability (which exerted its own separate effect). It is unclear why past focus was the only predictor of both cognitive vulnerability and depressive symptoms. We suspect it is because past focus is most conceptually related to the ruminative response of brooding, which is strongly associated with cognitive vulnerability and depressive symptoms (e.g., Spasojevic and Alloy 2001). The next logical step in this work is to examine brooding in relation to social media, cognitive vulnerability, and depressive symptoms.

Another direction for future research is to examine the possible reinforcing nature of social media. Many social media sites (e.g., Facebook) use algorithms that highlight or favor news and content that they believe will be of most interest to the user. However, these types of algorithms may create a reinforcing cycle that continuously presents the user with one particular type of content rather than a wide variety of information. For example, Del Vicario et al. (2016) showed that Facebook users "…tend to aggregate in communities of interest which causes reinforcement and fosters confirmation bias, segregation, and polarization" (p. 558). It is possible that a similar type of vicious cycle may be occurring for mood content on social media. Future research needs to determine if individuals expressing or viewing depressogenic content are more likely to continue to be presented with such content. The inundation of negative content could further accelerate the development of depression and anxiety in those who are already at heightened risk for mood disorders.

The study had both strengths and limitations. Strengths include a prospective longitudinal design and the use of a priori empirically derived Twitter content categories. Indeed, the LIWC software provides an objective and unbiased coding of written language. However, a weakness of the software is that it cannot detect sarcasm, humor, some internet-speak, and other subtleties of language. Although the software recognizes some common internet-speak and emoticons (such as "lol" and ":"), there are inevitably some words, phrases and "nonsense words" that are incorrectly categorized, which may dilute the results. It is also necessary to note that Twitter content was only measured at baseline. We conceptualized the Twitter content measure (the LIWC content score for a month of tweets) similarly to a "trait-like" indicator. In other words, the Twitter analysis was capturing a representative sample of each individual's typical Twitter content. We considered this akin to measuring a child's average parental environment by sampling a month's worth of parenting behaviors. This means that Twitter content was treated as a between-subject variable. We did not examine individual (idiographic) change in Twitter content. Thus, it is unclear if daily or weekly fluctuations predict prospective changes in cognitive vulnerability and depressive symptoms. Also, we cannot make definitive statements about whether or not changes in cognitive vulnerability preceded changes in depressive symptoms because the two constructs were measured at the same time points. Results also may have underestimated the effect of cognitive vulnerability on depressive symptoms because stress was not directly assessed. The hopelessness theory of depression is a vulnerability-stress model in which stress activates cognitive vulnerability to confer risk for depression. Although prior studies (e.g., the cognitive vulnerability to depression project; Abramson et al. 1999; Alloy et al. 2000) have found a main effect of cognitive vulnerability on depressive symptoms, a stronger test of the theory would examine the vulnerability by stress interaction.

Another possible limitation is that the participants were not new Twitter users. This means that participants may have already been well immersed in their "Twitter environment." Results likely would be amplified if participants had been new to Twitter, which would be similar to experiencing a significant change in social environment (as studied in prior research [e.g., moving to college]). Additionally, we could not control for total number of tweets because all Twitter content was extracted into a single text document. However, because Twitter posts cannot exceed 140 characters (at the time the study was conducted), the total word count is reflective of total number of posts (because any single post could not have a large number of words, which eliminates the possibility of any long outlier posts). That said, some information may have been lost using this strategy.

It is important to highlight that the current findings apply specifically to undergraduates using Twitter. Although Twitter is used by approximately half of college internet users (Harvard IOP 2018), the results may not generalize to non-college Twitter users (or to college students using other social media sites). That said, there is a growing body of work indicating that multiple forms of social media may be related to negative moods and depression. For example, Reece and Danforth (2017) used machine learning tools to identify individuals with depression based on the photographs that they posted to Instagram.

In conclusion, social media has become ubiquitous and has led to many positive outcomes from documenting political uprisings (e.g., the Egyptian revolution in 2011) to facilitating solidarity in response to human suffering (Smith et al. 2018). However, like most technological advances, social media also has the potential for negative outcomes. Social media has been used to spread false information that can influence political elections (Metaxas and Mustafaraj 2012) and recent work shows that its contagion effects can lead to negative moods and poor health (e.g., sleep disturbance; Levenson et al. 2016). The results of this study provide proof of principle that Twitter content may be one factor associated with changes in cognitive vulnerability (as well as depressive symptoms). It will be important for future research to continue to try to understand the contexts and mechanisms by which Twitter content affects negative and positive moods.

Funding The study did not receive funding.

Compliance with Ethical Standards

Conflict of Interest Maria P. Sasso, Annaleis K. Giovanetti, Anastasia L. Schied, Hugh H. Burke, and Gerald J. Haeffel declare that there are no conflicts of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

References

Abramson, L. Y., Alloy, L. B., Hogan, M. E., Whitehouse, W. G., Donovan, P., Rose, D., … Raniere, D. (1999). Cognitive vulnerability to depression: Theory and evidence. *Journal of Cognitive Psychotherapy, 13*, 5–20.

Abramson, L. Y., Metalsky, G. I., & Alloy, L. B. (1989). Hopelessness depression: A theory-based subtype of depression. *Psychological Review, 96*(2), 358–372. https://doi.org/10.1037/0033-295X.96.2.358.

Alloy, L. B., Abramson, L. Y., Hogan, M. E., Whitehouse, W. G., Rose, D. T., Robinson, M. S., … Lapkin, J. B. (2000). The Temple-Wisconsin Cognitive Vulnerability to Depression (CVD) Project: Lifetime history of Axis I psychopathology in individuals at high and low cognitive vulnerability to depression. *Journal of Abnormal Psychology, 109*, 403–418. https://doi.org/10.1037/0021-843X.109.3.403.

Alloy, L. B., Abramson, L. Y., Tashman, N. A., Berrebbi, D. S., Hogan, M. E., Whitehouse, W. G., … Morocco, A. (2001). Developmental origins of cognitive vulnerability to depression: Parenting, cognitive, and inferential feedback styles of the parents of individuals at high and low cognitive risk for depression. *Cognitive Therapy and Research, 25*, 397–423. https://doi.org/10.1023/A:1005534503148.

Alloy, L. B., Abramson, L. Y., Whitehouse, W. G., Hogan, M. E., Panzarella, C., & Rose, D. T. (2006). Prospective incidence of first onsets and recurrences of depression in individuals at

high and low cognitive risk for depression. *Journal of Abnormal Psychology, 115*, 145–156. https://doi.org/10.1037/0021843X.115.1.145.
Beck, A. T., Rush, A. J., Shaw, B. F., & Emery, G. (1979). *Cognitive therapy of depression*. New York: Guilford.
Beck, A. T., Steer, R. A., & Garbin, M. G. (1988). Psychometric properties of the BDI: Twenty-five years of evaluation. *Clinical Psychology Review, 8*, 77–100. https://doi.org/10.1016/02727358(88)90050-5.
Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computer Science, 2*, 1–8. https://doi.org/10.1016/j.jocs.2010.12.007.
Broniatowski, D. A., Paul, M. J., & Dredze, M. (2013). National and local influenza surveillance through Twitter: An analysis of the 2012–2013 influenza epidemic. *PLoS ONE, 8*, 1–8. https://doi.org/10.1371/journal.pone.0083672.
Campbell, R. S., & Pennebaker, J. W. (2003). The secret life of pronouns: Flexibility in writing styles and physical health. *Psychological Science, 14*(1), 60–65. https://doi.org/10.1111/1467-9280.01419.
Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine, 32*(4), 556–577. https://doi.org/10.1002/sim.5408.
Clark, L. A., & Watson, D. (1991). Tripartite model of anxiety and depression: Psychometric evidence and taxonomic implications. *Journal of Abnormal Psychology, 100*(3), 316–336. https://doi.org/10.1037/0021-843X.100.3.316.
Cole, D. A., Ciesla, J. A., Dallaire, D. H., Jacquez, F. M., Pineda, A. Q., LaGrange, B., … Felton, J. W. (2008). Emergence of attributional style and its relation to depressive symptoms. *Journal of Abnormal Psychology, 117*, 16–31. https://doi.org/10.1037/0021-843X.117.1.16.
Conway, M., & O'Connor, D. (2016). Social media, big data, and mental health: Current advances and ethical implications. *Current Opinion in Psychology, 9*, 7–82. https://doi.org/10.1016/j.copsyc.2016.01.004.
Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H. E., & Quattrociocchi, W. (2016). The spreading of misinformation online. *Proceedings of the National Academy of Sciences, 113*, 554–559. https://doi.org/10.1073/pnas.1517441113.
Eichstaedt, J. C., Schwartz, H. A., Ker, M. L., Park, G., Labarthe, D. R., Merchant, R. M. … Seligman, M. E. (2015). Psychological language on Twitter predicts county-level heart disease mortality. *Psychological Science, 26*(2), 159–169. https://doi.org/10.1177/0956797614557867.
Freifeld, C. C., Brownstein, J. S., Menone, C. M., Bao, W., Filice, R., Kass-Hout, T., & Dasgupta, N. (2014). Digital drug safety surveillance: monitoring pharmaceutical products in twitter. *Drug Safety, 37*, 343. https://doi.org/10.1007/s40264-014-0155-x.
Garber, J., & Flynn, C. (2001). Predictors of depressive cognitions in young adolescents. *Cognitive Therapy and Research, 25*, 353–376. https://doi.org/10.1023/A:1005530402239.
Gray, R., Vitak, J., Easton, E. W., & Ellison, N. B. (2013). Examining social adjustment to college in the age of social media: Factors influencing successful transitions and persistence. *Computers & Education, 67*, 193–207. https://doi.org/10.1016/j.compedu.2013.02.021.
Haeffel, G. J. (2010). Cognitive vulnerability to depressive symptoms in college students: A comparison of traditional, weakest-link, and flexibility operationalizations. *Cognitive Therapy and Research, 34*, 92–98. https://doi.org/10.1007/s10608-008-9224-8.
Haeffel, G. J., Abramson, L. Y., Brazy, P., Shah, J., Teachman, B., & Nosek, B. (2007). Explicit and implicit cognition: A preliminary test of a dual-process theory of cognitive vulnerability. *Behaviour Research and Therapy, 45*, 1155–1167. https://doi.org/10.1016/j.brat.2006.09.003.
Haeffel, G. J., Eastman, M., & Grigorenko, E. L. (2012). Using a cognitive endophenotype to identify risk genes for depression. *Neuroscience Letters, 510*, 10–13. https://doi.org/10.1016/j.neulet.2011.12.060.
Haeffel, G. J., Gibb, B. E., Metalsky, G. I., Alloy, L. B., Abramson, L. Y., Hankin, B. L., … Swendsen, J. D. (2008). Measuring cognitive vulnerability to depression: Development and validation of the cognitive style questionnaire. *Clinical Psychology Review, 28*(5), 824–836. https://doi.org/10.1016/j.cpr.2007.12.001.
Haeffel, G. J., & Hames, J. L. (2014). Cognitive vulnerability to depression can be contagious. *Clinical Psychological Science., 2*, 75–85. https://doi.org/10.1177/2167702613485075.
Haeffel, G. J., & Vargas, I. (2011). Resilience to depressive symptoms: The buffering effects of enhancing cognitive style and positive life events. *Journal of Behavior Therapy and Experimental Psychiatry, 42*, 13–18. https://doi.org/10.1016/j.jbtep.2010.09.003.
Hankin, B. L., Abramson, L. Y., Miller, N., & Haeffel, G. J. (2004). Cognitive vulnerability-stress theories of depression: Examining affective specificity in the prediction of depression versus anxiety in three prospective studies. *Cognitive Therapy and Research, 28*(3), 309–345. https://doi.org/10.1023/B:COTR.0000031805.60529.0d.
Harvard, I. O. P. (2018). http://www.iop.harvard.edu/use-social-networking-technology.
Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis*. New York: Guildford Press.
Internet Live Statistics (2018) http://www.internetlivestats.com/.
Jashinsky, J., Burton, S. H., Hanson, C. L., West, J., Giraud-Carrier, C., Barnes, M. D., & Argyle, T. (2014). Tracking suicide risk factors through Twitter in the US. *Crisis, 35*, 51–59. https://doi.org/10.1027/0227-5910/a000234.
Kessler, R. C., Borges, G., & Walters, E. E. (1999). Prevalence of and risk factors for lifetime suicide attempts in the National Comorbidity Survey. *Arch Gen Psychiatry, 56*, 617–626. https://doi.org/10.1001/archpsyc.56.7.617.
Klein, K., & Boals, A. (2001). Expressive writing can increase working memory capacity. *Journal of Experimental Psychology: General, 130*(3), 520–533. https://doi.org/10.1037//0096-344S.130.3.520.
Kramer, A. D., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences of the United States of America, 111*(24), 8788–8790. https://doi.org/10.1073/pnas.1320040111.
Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D. S., Lin, N., Shablack, H., Jonides, J., & Ybarra, O. (2013). Facebook use predicts declines in subjective well-being in young adults. *PLoS ONE, 8*, e69841. https://doi.org/10.1371/journal.pone.0069841.
Lehart, A., Purcell, K., Smith, A., & Zickuhr, K. (2010). Social media & mobile internet use among teens and young adults. *Pew Internet & American Life Project*. http://pewinternet.org/Reports/2010/Social-Media-and-Young-Adults.aspx.
Levenson, J. C., Shensa, A., Sidani, J. E., Colditz, J. B., & Primack, B. A. (2016). The association between social media use and sleep disturbance among young adults. *Preventative Medicine, 85*, 36–41. https://doi.org/10.1016/j.ypmed.2016.01.001.
Metalsky, G. I., & Joiner, T. E. (1992). Vulnerability to depressive symptomatology: A prospective test of the diathesis-stress and causal mediation components of the hopelessness theory of depression. *Journal of Personality and Social Psychology, 63*, 667–675. https://doi.org/10.1037/0022-3514.63.4.667.
Metaxas, P. T., & Mustafaraj, E. (2012). Social media and elections. *Science, 338*, 472–473. https://doi.org/10.1126/science.1230456.
Mezulis, A. H., Hyde, J. S., & Abramson, L. Y. (2006). The developmental origins of cognitive vulnerability to

depression: Temperament, parenting, and negative life events in childhood as contributors to negative cognitive style. *Developmental Psychology, 42*(6), 1012–1025. https://doi.org/10.1037/0012-1649.42.6.1012.

Nolen-Hoeksema, S. (1991). Responses to depression and their effects on the duration of depressive episodes. *Journal of Abnormal Psychology, 100*, 569–582. https://doi.org/10.1037//0021-843X.100.4.569.

Nolen-Hoeksema, S., Girgus, J. S., & Seligman, M. E. P. (1992). Predictors of consequences of childhood depressive symptoms: A 5-year longitudinal study. *Journal of Abnormal Psychology, 101*, 405–422. https://doi.org/10.1037/0021-843X.101.3.405.

Nolen-Hoeksema, S., & Morrow, J. (1991). A prospective study of depression and posttraumatic stress symptoms after a natural disaster: The 1989 Loma Prieta earthquake. *Journal of Personality and Social Psychology, 61*, 115–121. https://doi.org/10.1037/0022-3514.61.1.115.

Reece, A. G., & Danforth, C. M. (2017). Instagram photos reveal predictive markers of depression. *EPJ Data Science, 6*, 15. https://doi.org/10.1140/epjds/s13688-017-0110-z.

Reece, A. G., Reagan, A. J., Lix, K. L., Dodds, P. S., Danforth, C. M., & Langer, E. J. (2017). Forecasting the onset and course of mental illness with Twitter data. *Nature, 7*, 13006. https://doi.org/10.1038/s41598-017-12961-9.

Romens, S. E., Abramson, L. Y., & Alloy, L. B. (2009). High and low cognitive risk for depression: Stability from late adolescence to early adulthood. *Cognitive Therapy and Research, 33*, 480–498. https://doi.org/10.1007/s10608-008-9219-5.

Rude, S. S., Gortner, E. M., & Pennebaker, J. W. (2004). Language use of depressed and depression-vulnerable college students. *Cognition and Emotion, 18*(8), 1121–1133. https://doi.org/10.1080/02699930441000030.

Seligman, M. E., Peterson, C., Kaslow, N. J., Tanenbaum, R. L., Alloy, L. B., & Abramson, L. Y. (1984). Attributional style and depressive symptoms among children. *Journal of Abnormal Psychology, 93*(2), 235–238. https://doi.org/10.1037//0021-843X.93.2.235.

Smith, L. G. E., McGarty, C., & Thomas, E. F. (2018). After Aylan Kurdi: How tweeting about death, threat, and harm predict increased expressions of solidarity with refugees over time. *Psychological Science, 29*, 623–634. https://doi.org/10.1177/0956797617741107.

Spasojevic, J., & Alloy, L. B. (2001). Rumination as a common mechanism relating depressive risk factors to depression. *Emotion, 1*, 25–37. https://doi.org/10.1037/1528-3542.1.1.25.

Stark, K. D., Schmidt, K. L., & Joiner, T. E. (1996). Cognitive triad: relationship to depressive symptoms, parents' cognitive triad, and percieved parental messages. *Journal of Abnormal Psychology, 24*(5), 615–631. https://doi.org/10.1007/BF01670103.

Statista. (2017). *Statista—The statistics portal for market data, market research and market studies*. Retrieved December 30, 2017, from, http://www.statista.com/.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29*(1), 24–54. https://doi.org/10.1177/0261927X09351676.

Treynor, W., Gonzalez, R., & Nolen-Hoeksema, S. (2003). Rumination reconsidered: A psychometric analysis. *Cognitive Therapy and Research, 27*, 247–259. https://doi.org/10.1023/A:1023910315561.

Turner, J. C., Leno, E. V., & Keller, A. (2013). Causes of mortality among American college students: A pilot study. *College Student Psychotherapy, 27*, 31–42. https://doi.org/10.1080/87568225.2013.739022.

Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among U.S. adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science, 6*, 3–17. https://doi.org/10.1177/2167702617723376.

Valente, M. J., & MacKinnon, D. P. (2017). Comparing models of change to estimate the mediated effect in the pretest-posttest control group design. *Structural Equation Modeling, 24*, 428–450. https://doi.org/10.1080/10705511.2016.1274657.

World Health Organization. (2004). *The Global Burden of Disease: 2004 Update* (Part 3). Retrieved from http://www.who.int/healthinfo/global_burden_disease/GBD_report_2004.update_full.pdf.