Linguistic Expressions of Depressogenic Schemata

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ABSTRACT

Examinations of the words we use in our daily lives have shown that certain linguistic patterns may be indicators of underlying depressogenic schemata. The Linguistic Inquiry and Word Count (LIWC) and multidimensional scaling (MDS) have been used as methods of computerized text analysis to yield insight into how people's language use may be reflective of maladaptive psychological processes, including self-focused attention, rumination, and absolutist thinking, which are all associated with the depressogenic schemata. These findings demonstrate the significance of analyzing people's language use in the mental health profession. Research in this interdisciplinary field of natural language processing, applied linguistics, and mental health not only corroborates psychological theories regarding depression but further yields implications for prevention, diagnosis, and outcome predictions of mental health depression and anxiety.

Keywords: computational psychotherapy, affective computing, computerized text analysis, natural language processing, mental health, depression

INTRODUCTION

The words we use in our daily lives can reveal certain aspects of our mental states and worldviews (Tausczik & Pennebaker, 2010). For those who must accurately understand and analyze the mental health of others, such as mental health counselors or clinical psychologists, linguistic analyses promise to be an invaluable method to decrease subjective biases which can lead to misdiagnoses and mistreatments. Given the wealth of data available on the Internet for linguistic analyses, along with the advancement of higher-speed processors and natural language processing models, certain linguistic patterns have been detected as signs for given mental health markers such as self-focused attention, rumination, and negativity, all of which are known to be symptoms of depression (Beck, 1967). These linguistic insights may help clinicians with prompt and accurate diagnoses, treatments, and preventions.

This paper will address the question: How does language reflect the presence of schemata of maladaptive cognitive processes, known as the *depressogenic schemata*, which are related to some of the most prevalent mental health disorders such as depression, anxiety, posttraumatic stress disorder, and eating disorders among individuals? In the first section of this paper, I briefly explain the depressogenic schemata and describe two major models of computational text

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analyses used for mental health research including the Linguistic Inquiry and Word Count and Multidimensional Scaling (Calvo & D'Mello, 2010; Tausczik & Pennebaker, 2010). Next, I give examples of the ways in which language can detect certain psychological processes by drawing on different empirical studies to present a multidimensional and nuanced understanding of how language use relates to certain aspects of our mental health and how computational text analyses can validate psychological constructs and correlations between word usage and depressogenic schemata. These studies reveal an optimistic future for the application of computational linguistic analyses in the mental health realm.

THE DEPRESSOGENIC SCHEMATA AND ITS CONSTRUCTS

Depressogenic schemata are maladaptive schemata, associated with many different mental health disorders, including anxiety and depression (Beck, 1967). In Beck's (1967) cognitive theory of depression, depressogenic schemata are the main and necessary components that put individuals at risk for mental health disorders. They are a set of extremely rigid patterns of reactions that are triggered by stressors (Ruiz & Odriozola-Gonzalez, 2016), and they are dysfunctional, given that they often yield cognitive distortions that produce a negative view of the world and the self (Beck, 1967). This cognitive theory of depressogenic schemata has been acknowledged and expanded on by many studies (Alloy et al., 1999; Bhar, Brown, & Beck, 2008; Forgeard et al., 2011; Ruiz & Odriozola-Gonzalez, 2016). Depressogenic schemata are associated with other maladaptive psychological processes including self-focused attention, rumination, and absolutist thinking (Molendijk et al., 2010). Each of these processes plays a role in developing and strengthening the depressogenic schemata (Ruiz & Odriozola-Gonzalez, 2016).

Self-focused attention is defined as the awareness of information regarding the self (Brockmeyer et al., 2015). It can lead people to notice discrepancies between their perceptions of their actual self and their ideal self (Brockmeyer et al., 2015). Although this prompts people to engage in discrepancy-reducing behaviors in order to attempt to subdue the discomfort, people are not always able to successfully subdue it, resulting in negative affect (Mor & Winquist, 2002). When this self-regulatory cycle yields perpetual negative affect, however, people develop a maladaptive cycle in which they begin to repetitively internalize their negative self-perceptions, which, in turn, magnifies their negative affect (Mor & Winquist, 2002). This spirals into a compulsive negative reflection and awareness of oneself, eventually leading to the loss of one's self-worth (Brockmeyer et al., 2015; Rude, Gortner, & Pennebaker, 2004). As a trans-diagnostic symptom, self-focused attention has been associated with multiple mental health disorders including depression, anxiety, and eating disorders (Mor & Winquist, 2002).

Another psychological process related to the depressogenic schemata, which is also a subcomponent of self-focused attention, is *rumination*. Rumination is a specific type of self-focused attention that is defined as "a pattern of responses to distress in which individuals passively and persistently focus on their selves, their symptoms, as well as possible causes and consequences of these symptoms" (Brockmeyer et al., 2015, p. 2). Rumination is a predictor of the onset of depression and is also a factor that maintains depression (Brockmeyer et al., 2015). It is a costly, self-regulatory cycle that absorbs one's attentional resources and thereby, hinders adaptive emotional processing to regain one's self-worth (Burwell & Shirk, 2007).

Rumination further includes two distinct components: *brooding* and *reflection* (Burwell & Shirk, 2007). Reflection is the "purposeful turning inward to engage in cognitive problem solving to alleviate one's depressive symptoms" (Treynor, Gonzalez, & Nolen-Hoeksema, 2003,

p. 256). Brooding is "the passive comparison of one's current state with desired but unreached states" (Brockmeyer et al., 2015, p. 2). Brooding is known to be maladaptive, while reflection can be adaptive (Brockmeyer et al., 2015; Burwell & Shirk, 2007).

Often emerging from rumination is another cognitive bias known as *absolutist thinking* (Ostell & Oakland, 1999). Absolutist thinking is expressed when people think in extreme, black-and-white ways (Ostell & Oakland, 1999). It is not necessarily related to the strength of someone's belief in their thoughts or perspectives but, instead, denotes the high polarization of the perspective or thoughts themselves (Al-Mosaiwi & Johnstone, 2018). Absolutist thinking also involves thinking in a dichotomous way when the reality is more spectral or nuanced (Ostell & Oakland, 1999). Although self-focused attention, rumination, reflection, brooding, and absolutist thinking are all common psychological processes of the depressogenic schemata and, as such, are most often associated with depression, they have also been known to exist in other mental health disorders such as anxiety, eating disorders, posttraumatic stress disorder, and borderline personality disorder (Beck, 1967; Brockmeyer et al., 2015; Molendijk et al., 2010).

One way in which depressogenic schemata (i.e., self-focused attention, rumination, reflection, brooding, and absolutist thinking) reveal themselves is through language (Tausczik & Pennebaker, 2010). The language that people use can tell us about their psychological worlds (Tausczik & Pennebaker, 2010). It reveals what people are paying attention to, what their personalities and emotions might be like, and how they are processing information, ultimately revealing aspects of their mental health (Brockmeyer et al., 2015; Tausczik & Pennebaker, 2010). Therefore, studying the language use of people with mental health disorders known to have depressogenic schemata can give us insights into understanding their psychological processes (Tausczik & Pennebaker, 2010).

NATURAL LANGUAGE PROCESSING

In order for researchers to analyze the language of individuals with depressogenic schemata, computational linguistic analyses have become a crucial tool as an unobtrusive and more objective measure of psychological constructs (Calvo, Milne, Hussain, & Christensen, 2017). With the wealth of textual data in the Internet era, many studies have found significant patterns in the language use of those with depression, providing insight into the interaction among people's psychological, cognitive, and linguistic worlds (Calvo et al., 2017).

Text analysis itself is a very old concept and the idea that language reveals aspects about our psychological worlds is also nothing new (Tausczik & Pennebaker, 2010). Tausczik and Pennebaker (2010) pointed out that dating back to 1901, Freudian slips were examined for psychological meanings of motivations, beliefs, and intentions, and in 1921, the Rorschach Test similarly used people's language and tried to explain what they might mean (Rorschach, 1921). Before the availability of computerized text analysis, trained raters conducted text analyses (Calvo et al., 2017). However, computational text analysis in psychological research was especially needed, given that trained judges often were, themselves, emotionally affected by much of the depressing content (Tausczik & Pennebaker, 2010). Computational text analysis also increased internal reliability and efficiency since it no longer relied on self-reports of observations and moods (Brockmeyer et al., 2015). Additionally, given the difficulty of recruiting patients and engaging them for full studies, text analysis also offered the opportunity to study larger data sets and populations for longer periods of time (Calvo et al., 2017).

Two of the most common text analysis models used to analyze language for mental health applications include the Linguistic Inquiry and Word Count (LIWC) and

Multidimentional Scaling (MDS). These analyses approach language through different methods and, therefore, can be used together on the same data to glean information from different angles.

Linguistic Inquiry Word Count

Perhaps the most widely used program for linguistic analyses is the Linguistic Inquiry and Word Count (LIWC; pronounced *Luke*) (Tausczik & Pennebaker, 2010). LIWC is a program that categorizes and counts words, giving an overview of what categories of words are mainly contained in a given text file (Tausczik & Pennebaker, 2010). LIWC is able to do this with its dictionary, against which words from an input text file are compared (Tausczik & Pennebaker, 2010). It parses each word of an input text file and increments the counters of each category to which the word belongs, such as function words, pronouns, impersonal pronouns, verbs, auxiliary verbs, past tenses, etc. (Tausczik & Pennebaker, 2010). After parsing an entire text file, LIWC is also able to provide overall percentages of the linguistic categories and words that appeared in the file (Tausczik & Pennebaker, 2010).

The 80 linguistic categories in LIWC vary greatly from simple grammatical categorizations such as articles (made up of only three words: *a, an, the*) to emotion categories or thinking style categories that include self-reflection or causal thinking (Tausczik & Pennebaker, 2010). These kinds of categories have also been linked to many psychological processes (Calvo et al., 2017; Tausczik & Pennebaker, 2010).

Two notable linguistic categories include broad terms of content and function words (Tausczik & Pennebaker, 2010). Content words are words that convey the topical meanings of sentences. These words are usually nouns, verbs, adjectives, and adverbs. Function words, on the other hand, include pronouns, prepositions, determiners, conjunctions, auxiliary verbs, and other syntactic categories that reveal the context and manner in which the topic is being conveyed. Many of these words are also deictic in that the interlocutors must have shared knowledge of referents for successful communication (Fillmore, 1971). For example, interlocutors must have ideas about who, where, or when words like *me, you, here,* or *later* refer to, in order to advance a conversation (Fillmore, 1971). Using these words and understanding them, then, require social and psychological perspectives, knowledge, and skills. Studying the use of these words, therefore, may reveal psychological and social aspects of a speaker's worldview (Tausczik & Pennebaker, 2010). According to Tausczik and Pennebaker (2010), even though function words make up only roughly 0.05% of our English vocabulary, they still make up approximately 55% of all the words we use in communication.

The way LIWC works, therefore, is quite straightforward and is useful for understanding frequencies of certain words, topics, or categories within a given text input. Because it also computes text data in percentages, it is useful for comparing text files written by different people to analyze differences or similarities in their psychological processes (Tausczik & Pennebaker, 2010).

Multidimensional Scaling

Multidimensional Scaling (MDS) is another way to analyze text (Calvo & D'Mello, 2010). The purpose of MDS in the natural language processing (NLP) context is to find semantic similarities or dissimilarities between words by creating word clusters (Imel, Atkins, & Steyvers, 2015). Dimensions, as determined by the variables (i.e., in the NLP context, words) are input to create mathematical space. For example, if 100 words are analyzed, a 100-dimension semantic space is created. In this space, MDS yields clusters by creating a graph of the most optimal distance among each object by moving them and reconfiguring them in the best way that maximizes the goodness-of-fit, using all the dimensions (Imel et al., 2015). MDS can also help simplify its plotted graph and, thereby, reduce the number of variables, which in turn will distill the data (Cheng, Li, Kwok, Zhu, & Yip, 2017). An advantage of MDS is that, while LIWC categories are pre-determined, clusters in MDS do not necessarily have to be predetermined and, as such, may allow for a more accurate representation of relationships between words.

DEPRESSOGENIC SCHEMATA REFLECTED THROUGH NLP

When applying NLP to the language used by people with and without depression or anxiety, studies have revealed differences between the two populations, attributable to their having or not having depressogenic schemata (Brockmeyer et al., 2015; Cheng et al., 2017; Molendijk et al., 2010; Rude et al., 2004). This has also increased validation for our understanding of the psychological processes of people who suffer from depression and anxiety, as well as other diagnoses that involve the depressogenic schemata (Calvo et al., 2017; Tausczik & Pennebaker, 2010). Many empirical studies have applied NLP to the abundant text data that have become available through the advancement of the Internet (Calvo et al., 2017).

Multiple studies have found that people with depression use more first person singular pronouns (i.e., *I, me, my, mine*) compared to people without depression (Fast & Funder, 2010; Pyszcynski & Greenberg, 1987; Weintraub, 1981). Rude et al. (2004) further built on these studies to examine whether people who recovered from depression still carried aspects of the depressogenic schemata, by comparing their language use to that of people with depression and people who have never had depression. They recruited college students who fell into one of these categories and prompted them with: "Write about your deepest thoughts and feelings about coming to college" (Rude et al., 2004, p. 1123). Their main interest was to examine whether previously depressed people might show tendencies of people with depression or people who had never had depression.

After analyzing their essays using LIWC, Rude et al. (2004) found several interesting differences. Although the authors were able to replicate former studies that found that individuals with depression used more of the first person singular pronouns than did individuals without depression, they also realized that the first person singular pronoun *I* was so significantly different that it skewed the statistics for the entire category of first person singular pronouns. That is, when teasing out each of the first person singular pronouns, only *I* was significantly different (t (121) = 2.70, $p < 0.01$). The other first person singular pronouns, *me, myself,* and *my*, were not significantly different (Rude et al., 2004). Rude et al. suggested that this may be due to the fact that *I* takes on an agent or subject role more often, while the other pronouns are more likely to be objects in sentences. This finding could be the manifestation of self-focused attention, a construct of depression. However, further research needs to be conducted to clearly understand and interpret this difference.

Additionally, Rude et al. (2004) compared previously depressed individuals with individuals who had never been depressed and found that, although when looking at the essay as a whole there seemed to be no significant differences, when comparing different sections of the essay, the endings of the essays differed such that those who had previously experienced depression used more *I* than those who had never been depressed. When Rude et al. analyzed this further, they noticed through their topic categories a heightened sense of conflict over expressing negative emotions, as well as a heightened self-awareness. This is consistent with previous research that found that previously depressed individuals often engage in negative thought suppression as a strategy to resist falling back into depression (Wenzlaff & Wegner, 2000). Additionally, this finding also supports the idea that formerly depressed individuals are more vulnerable to depression than individuals who have never been depressed, as there may be remnants of depressogenic schematic patterns (Alloy et al., 1999; Ruiz & Odriozola-Gonzalez, 2016; Wenzlaff & Wegner, 2000).

Finally, Rude et al. (2004) were also able to replicate findings that depressed individuals used more negative valence words than those who were never depressed ($t(121) = 5.86$, $p < .001$). Each of these findings is a crucial validation of the theoretical understandings of depression. They align with Beck's (1967) theory of the depressogenic schemata and the increased use of *I* and also support Pyszczynski and Greenberg's (1987) model of heightened self-focused attention in depression.

Molendijk et al. (2010) replicated Rude et al.'s (2004) study with a similar prompt. They asked their participants to write an essay with the following prompt: "Try to describe your life, what kind of person you are, how you became this way, how you experience life nowadays, and how you see your future" (p. 46). Like in Rude et al.'s study, Molendijk et al. found differences in the use of *I*, most significantly towards the last section of the participants' essays.

Additionally, Molendijk et al. (2010) found that the use of negative and positive valence words was equally used by non-depressed individuals. However, among individuals with depression, there was an over-use of negative valence words as compared to positive valance words. Once again, Molendijk et al.'s study also supports the construct of self-focused attention of the depressogenic schemata, with an increased pattern of negative information processing among individuals with depression.

Brockmeyer et al. (2015) further looked at whether the association between depressogenic schemata and the use of first person singular pronouns was simply between groups of people who had depression versus people who did not, or whether this association carried further to the intrapersonal level where the frequency of the use of first person singular pronouns could also differ, depending on the valence of the topic. They recruited participants who met the criteria for depression and anxiety as according to the Diagnostic and Statistical Manual of Mental Disorders- IV (American Psychological Association, 2000), as well as healthy participants who did not have depression or anxiety and asked them to write about their saddest and happiest moments of their lives. All participants, including the healthy individuals, took a symptoms severity test of depression and anxiety. Brockmeyer et al. referred to the *Emotions Interview* (Rottenberg, Hildner, & Gotlib, 2006) that included questions such as, "Can you describe why this event made you feel sad/happy?," "As you think about this sad/happy event now, what thoughts or feelings come to mind?" Brockmeyer et al. found that the frequency of the first person singular pronouns was positively correlated with the participants' severity of symptoms of depression and anxiety, even for the healthy individuals, when they were writing about their saddest moment. While this correlation was also seen when participants with depression were writing about their happiest moment, for healthy individuals the correlation was no longer significant when they were writing about their happiest moments (Brockmeyer et al., 2015). Therefore, this study showed that the difference in the use of the first person singular pronouns can be seen not only between individuals with and without depression but also among healthy individuals, depending on the negative or positive valence associated with the recall (Brockmeyer et al., 2015). In other words, the frequency of the use of first person pronouns not only depends on the depressogenic schemata (i.e., one's mental health) but also on whether the task elicits a negative or positive response. Depending on these differences, the frequency of the first person singular pronoun between depressed and non-depressed individuals may be weaker or stronger. This study, therefore, highlights the importance of *relative* frequency. Because "relative frequency of first person singular pronouns in natural language is regarded as an objective, linguistic marker of SFA [self-focused attention]" (Brockmeyer et al., 2015, p. 1), the study can be interpretable in terms of SFA. SFA increases in negative event recalls for people in general; however, while the use of language related to SFA is task-dependent in healthy individuals, the use of language related to SFA seems to be operating at all tasks for individuals with depression, although to different degrees.

Brockmeyer et al. (2015) further looked at two dimensions of rumination, namely, brooding and reflection. They found that for, healthy individuals, while the frequency of the use of first person singular pronouns in negative memory recalls correlated with the levels of brooding, it did not correlate with levels of reflection. However, among individuals with depression, because there was no difference in the context of recalls, this effect was not seen. This finding supports the construct validity of brooding and how it is considered maladaptive, as well as the construct validity of reflection and how it considered adaptive. It is only when reflection turns to brooding that it can be considered maladaptive. Overall, the psychological processing involved, whether it is brooding or reflection, seems to be context dependent for healthy individuals while for depressed individuals, their default information processing seems to be constantly negative.

Brockmeyer et al. (2015) and Molendijk et al. (2010) looked at multiple first person pronouns (i.e., *I, me, my, mine*), instead of just the pronoun *I*. Because Rude et al. (2004) found that the pronoun *I* is the pronoun driving the statistical significance, this study should perhaps be re-analyzed, to test whether the significance lies in simply the pronoun *I* or whether the other first-person pronouns are also significant.

Molendijk et al. (2010), Brockmeyer et al. (2015), and Rude et al. (2004) also all found that individuals with depression used significantly more negative valence words than individuals without depression. Al-Mosaiwi and Johnstone (2018) further established a connection between negative valence words and absolutist thinking styles.

Absolutist words are words that indicate a certainty in the degree of probability (Ostell & Oakland, 1999). These words include words such as *always, totally, constantly, forever, completely*, and *entire*. Non-absolutist words are more nuanced and include words such as *rather, somewhat*, and *likely*, with an acknowledgement of an alternative or a varying degree of probability (Ostell & Oakland, 1999).

Unlike previous studies, Al-Mosaiwi and Johnstone (2018) did not elicit their data but rather investigated naturalistic data as gleaned from Internet forums of anxiety, depression, suicidal ideation, and recovery groups as well as control groups which included cancer, asthma, and diabetes forums. This research design helps interpret the data in such a way that the language use is, indeed, attributable to mental health related depressogenic schemata, as opposed to other physical illness. In Internet forums, members can begin new topics or respond to topics that have already been posted to contribute to and develop a discussion (Al-Mosaiwi & Johnstone, 2018). These posts were analyzed using LIWC.

Al-Mosaiwi and Johnstone (2018) not only found that absolutist words were used more frequently among depression, anxiety, and suicidal ideation groups compared to other groups, but they found that the use of absolutist words was a stronger predictor of depression, anxiety, and suicidal ideation than the use of negative valence words or first person singular pronouns. Although depressogenic schemata may be more associated with the experience of negative valence in general, absolutist thinking seems to be the factor that strengthens the schemata. Moreover, absolutist words were most frequent in suicidal ideation, which aligns with previous research that had already established the strong association between suicidal ideation and absolutist thinking (Ostell & Oakland, 1999).

Moreover, in the recovery forums of depression and anxiety, despite the high frequency of positive valence words, use of absolutist words did not differ from anxiety and depression forum groups. This finding aligns with Beck's (1967) cognitive model of depression that posits that a depressive episode increases the risk of another depressive episode in the future. It further gives support for Rude et al.'s (2004) study, which showed that, according to their word usage, depressed, never-depressed, and recovering individuals are three distinct populations and, thereby, distinct in some of their psychological processes.

While these studies showed that analyzing word usage was, indeed, promising to be revealing of depressogenic schemata, Van der Zanden et al. (2014) further looked at data from a web-based depression treatment. They chose Master Your Mood (MYM) as their platform—an online cognitive-behavioral group course guided by a chat box and geared to young adults with depressive symptoms. Van der Zanden et al. reasoned that, since differences in individuals' language use revealed aspects of their psychological processes at given points in time, perhaps a longitudinal study could be conducted to investigate trajectories of individuals' psychological states by examining their language use. Changes in their language use could also help predict treatment adherences and outcomes, since they are also intertwined with a progression of psychological processes (Raue, Schulberg, Heo, Klimstra, & Bruce, 2009). Treatment adherences are the degree to which individuals follow through with their treatments (Raue et al., 2009). Treatment outcomes are the degree to which the treatment is successful in helping to move the individual to the goal of the treatment (Raue et al., 2009).

Van der Zanden et al. (2014) obtained data of baseline language by analyzing the answers to prompts written on the application forms for the course. The baseline application forms consisted of two prompts: "What is your reason for applying to MYM?" and "Please briefly describe the kinds of problems or symptoms you've been having" (Van der Zanden et al., 2014, p. 11). The authors also analyzed transcriptions of chat sessions themselves. They wanted to test: (1) if certain word usages at baseline could predict baseline outcome variables such as level of mastery and symptom severity, (2) whether baseline word use correlated with treatment adherence, and (3) whether baseline and changing word usages correlated with changes in outcome variables. *Mastery* refers to the amount of control one feels that one has over one's own environment (Van der Zanden et al., 2014). LIWC was used to analyze all text data.

Two categories known as *discrepancy words* and *social process words* proved fruitful when analyzing the results (Van der Zanden et al., 2014). LIWC lumps the words such as *should*, *would, could,* or *wish* that indicate an alternative possibility into the category of discrepancy words (Tausczik & Pennebaker, 2010). Social process words are words that indicate the acknowledgement of another person in relation to the self, such as *they, others, we,* and *share* (Van der Zanden et al., 2014). At baseline, the use of fewer negative emotion words and more discrepancy words correlated with greater levels of mastery, also at baseline (Van der Zanden et al., 2014). Van der Zanden et al. (2014) also found that fewer discrepancy words and more social words at baseline correlated with higher levels of adherence. Furthermore, they found that an increase in the use of discrepancy words correlated positively with a decrease in depression severity, higher adherence to treatment, and greater mastery.

A possible explanation that Van der Zanden et al. (2014) posited was that discrepancy words could be an indication of higher motivation. They also hypothesized that, although discrepancy words express a condition lacking in the present, they also express a possibility of an optimistic and improved future condition. Van der Zanden et al., therefore, showed that these word usages revealed not only the psychological processes of the moment but also could predict the psychological processes of the future.

Given that there were promising results from studies showing that language use could, indeed, be reflective of psychological processes, some studies began to test whether predictive modeling could be successful. For these studies, researchers used not only LIWC but also other techniques, such as MDS.

De Choudhury et al.'s (2013) study tested whether and how social media could help predict the onset of major depressive disorder. They reasoned that social media postings provide a naturalistic way to collect data regarding linguistic attributes indicative of the users' behavioral attributes such as activities, socialization, mood, and cognitive processes, and also, thereby, their depressogenic schemata. The authors chose to use Twitter as their platform to investigate. They wanted to identify the specific changes in language used on Twitter that would help construct a statistical classifier model to predict depression. Data were crowdsourced from Twitter and using the Twitter Firehose API (an Application Programming Interface, which is a system that allows the use of data for external innovations), to collect a year's worth of users' Twitter data from a year *before* their reported onset of depression up to the date *of* their reported onset of depression. One notable difference between De Choudhury et al.'s study and the others is that De Choudhury et al. focused on both function and content words, as opposed to function words only. They did this because they were not only interested in the psychological but also the behavioral attributes predictable by language use on Twitter.

Upon analyzing the user language, De Choudhury et al. (2013) found the following predictive features for the onset of depression: decrease in user engagement, increase in words with negative valence, and increase in first person pronouns. These factors map directly onto the psychological process of self-focused attention as well as behavioral processes of self-isolation and distancing (i.e., a drawing inward as opposed to outward), which aligns with Emile Durkheim's (1951) social integration/disengagement model of suicide.

Focusing on content words also helped draw on several topical themes that were found to be significant. The topical themes were: symptoms (some associated unigrams were *anxiety, withdrawal, delusions, weight, sleep, headache, psychosis*, etc.), disclosure (associated unigrams included *wants, enjoy, like, answer, care, discuss*), relationships (associated unigrams included *home, songs, party, favorite, friends, dating*) religion (associated unigrams included *Jesus, bible, lord, church*) and treatment (associated unigrams included *medication, side-effects, therapy, sedative, 40mg,* and *neurotransmitters*) (De Choudhury et al., 2013).

De Choudhury et al.'s (2013) work shows that both content and function words provide insight into people's lives such that it captures both psychological and behavioral attributes. Content words help us understand the topics that become important, while function words give us insight into the cognitive processes and the possible underlying development of depressogenic schemata. This study shows that language does, indeed, provide signals that can detect at-risk individuals who may have depressogenic schemata. Focusing on both attributes, De Choudhury et al. later constructed a support vector machine that could predict with about 70% accuracy the estimate of the risk of depression before onset.

For psychotherapists who mostly are not approached until after someone seeks treatment, De Choudhury et al.'s (2013) model offers clinicians the possibility of preventing at-risk individuals from the onset or further aggravation of mental health disorders, such as depression. This type of prevention intervention is helpful not only to the at-risk individuals, but also to the larger society.

The studies mentioned in this paper so far were conducted in English, German, and Dutch. Because these studies were able to replicate and contribute to the development of more nuanced findings, they indicate that the findings are not an English-specific phenomenon. Most of the literature in this field is dominated by studies conducted in Northern America or Europe. Because of the roles of culture and language in psychological processes, I was curious about the studies that were not only conducted in Western cultures.

A recent study by Cheng et al. (2017), which analyzed the Chinese social media platform Weibo by collecting data in order to find word-related depression and anxiety language features, concluded that findings such as the increased use of first person singular pronouns were not replicable in their study. Although most studies used Twitter and Facebook for NLP data analysis, China blocks those websites and instead uses Sina Weibo, more commonly known as Weibo (Cheng et al., 2017). The Simplified Chinese-Linguistic Inquiry and Word Count (SC-LIWC) was used despite the availability of locally developed dictionaries. Researchers chose to use the SC-LIWC so that results could be comparable to previous studies that used LIWC. Cheng et al. then analyzed the categories that were associated with depression and anxiety and further developed a support vector machine, similar to De Choudhury et al.'s (2013), to predict individuals who are experiencing depression or anxiety via their Weibo posts.

The language features of Weibo posts were extracted as independent variables or features for machine learning (Cheng et al., 2017). Weibo posts were first segmented using the Stanford Word Segmenter (Tseng, Chang, Andrew, Jurafsky, & Manning, 2005), which helps analyze Chinese texts, before being applied to the SC-LIWC. Similar to De Choudhury et al.'s (2013) study, Cheng et al. (2017) looked at both function and content words. Results showed that instead of the use of the first person singular pronouns, the use of second person plural, *you* (你们) ,was positively correlated with depression. Additionally, work-related words such as *salary, factory,* and *interview*, were negatively correlated with depression and anxiety, while achievement-related words such as *good at*, *responsible*, and *master* were positively correlated.

These findings were very interesting, given that this was the first study in which first person singular pronouns were not predictive of depressogenic schemata. Cheng et al. (2017) reason that this does not mean that depression does not include self-focused attention in China but rather suggest that this is because the first person singular pronoun in Chinese does not simply function as a self-referent but can also function as a self-referent in the communal context in which the person belongs. Therefore, the first person singular pronoun in Chinese evokes a sense of self within a social community, which then cannot serve as a linguistic feature to reflect the same kind of self-focused attention as do the first person pronouns in English (Cheng et al., 2017).

Cheng et al. (2017) also mention that, because depression and anxiety correlated with the use of *you*, users were more likely to speak directly to other people in their posts. The finding that achievement-oriented words were correlated with depressive symptoms matches previous literature which found that individuals who were highly achievement-oriented were at higher risk for depression (Canetto & Lester, 2002; Hull-Blanks, Kerr, & Robinson Kurpius, 2004). Cheng et al. explained the last finding that work-related words correlated negatively with depression and anxiety by hypothesizing that perhaps unemployed people were more likely to be depressed or anxious. More contextual data should be examined, however, to understand and make more conclusive remarks about this finding.

Finally, it should be noted that both Cheng et al. (2017) and De Choudhury et al. (2013) included classification models that used the predictive linguistic and behavioral features they found and support vector machines to validate their findings.

LIMITATIONS

Despite all the promising findings, these studies are not without limitations. First, we have already seen that there may be underlying cultural differences. As such, the studies which have been conducted mostly in Western cultures may not necessarily generalize to other cultures, as seen in Cheng et al.'s (2017) study. The generalizability of the correlational findings between language uses and their underlying psychological properties should be examined more in-depth. Just as there exist culture-bound syndromes, or words and expressions that do not exist in certain languages but exist in others, it seems highly likely that the correlations of language use and mental health processes may not generalize to other cultures.

Second, despite the seemingly effective appeal of computational text analyses like LIWC, they are still quite limited in what they are able to do (Tausczik & Pennebaker, 2010). For example, LIWC is unable to detect or compute for context, and, thereby, will not understand irony, sarcasm, and idioms (Tausczik & Pennebaker, 2010). In a similar vein, LIWC is not able to take into account negations, and qualifiers before words are not programmed to be further examined (Al-Mosaiwi & Johnstone, 2018). This may reveal inaccurate data. Al-Mosaiwi and Johnstone (2018) point out, however, that if there may have been other phrases that should have been removed but were not, the phrases are assumed to be left equally among each of the groups that they were studying.

Additionally, human pre-defined dictionaries of LIWC have the limitation that the dictionary is not broad enough to account for enough categories (Calvo & D'Mello, 2010). LIWC does not allow for the computer to create new categories. Additionally, these dictionaries are unable to analyze words in context and, thereby, are not flexible enough to account for changes in meaning depending on context (Calvo & D'Mello, 2010). This limitation, however, would not apply to other NLP models, especially those that are unsupervised.

Finally, another limitation lies in the fluidity and vagueness of language (Tausczik & Pennebaker, 2010). Although many studies have shown how words can be reflective of psychological attributes, the vague nature of words may prevent researchers from finding precise interpretations of what words may be reflecting psychologically (Tausczik & Pennebaker, 2010).

CONCLUSION

In sum, various studies have shown optimistic applications of the novel computational methodologies of analyzing language and also have demonstrated the importance of including both function as well as content words in studies. The interdisciplinary field of applied linguistic sciences to the mental health profession has the potential to yield many beneficial implications. This field of research not only helps us identify and validate the psychological processes that have been associated with the depressogenic schemata and mental health disorders in general, but it can further help with the prevention, detection, diagnoses, intervention, treatment, and outcome predictions of potentially various mental health disorders.

Researchers have lamented the lack of an integrated and organized literature due to the highly interdisciplinary field that includes mental health research, natural language processing, and applied linguistics (Calvo et al., 2017; De Choudhury et al., 2013). As such, the focus of this research has been largely dispersed. Due to the promising results that studies have shown, however, there is a real need for an integration of the different fields so that a more complete and holistic understanding can be gained.

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