

SMHD: A Large-Scale Resource for Exploring Online Language Usage for Multiple Mental Health Conditions

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Abstract

Mental health is a significant and growing public health concern. As language usage can be leveraged to obtain crucial insights into mental health conditions, there is a need for large-scale, labeled, mental health-related datasets of users who have been diagnosed with one or more of such conditions. In this paper, we investigate the creation of high-precision patterns to identify self-reported diagnoses of nine different mental health conditions, and obtain high-quality labeled data without the need for manual labelling. We introduce the SMHD (Self-reported Mental Health Diagnoses) dataset and make it available. SMHD is a novel large dataset of social media posts from users with one or multiple mental health conditions along with matched control users. We examine distinctions in users' language, as measured by linguistic and psychological variables. We further explore text classification methods to identify individuals with mental conditions through their language.

1 Introduction

Mental health is a significant challenge in healthcare. Mental disorders have the potential to tremendously affect the quality of life and wellness of individuals in society (Strine et al., 2008; Mowery et al., 2017a). Social media have become an increasingly important source of data related to mental health conditions (Cohan et al., 2017; Mowery et al., 2017b; Coppersmith et al., 2017; Yates et al., 2017), as it is now a prominent platform for individuals to engage in daily discussions, share information, seek advice and simply communicate with peers that have shared interests. In addition to its ubiquity and ease of access, the possibility to disclose mental health matters anonymously or pseudo-anonymously further drives users to online self-disclosure.

At the same time, the close connection between language and mental health makes social media an invaluable resource of mental health-related data. Lack of data has been one of the key limitations to understanding and addressing the challenges the domain is facing (Coppersmith et al., 2014a). Data from social media can not only be used to potentially provide clinical help to users in need, but also to broaden our understanding of the various mental health conditions. Social media analysis has already been proven valuable for identifying depression (Coppersmith et al., 2014a; Yates et al., 2017), suicide ideation (Cohan et al., 2017; De Choudhury and Kıcıman, 2017; Kshirsagar et al., 2017; Desmet and Hoste, 2018), and other conditions such as schizophrenia (Mitchell et al., 2015). While social media data is abundantly available, the amount of labeled data for studying mental health conditions is limited. This is due to the high cost of annotation and the difficulty of access to experts.

Prior research has investigated self-disclosure as a means of obtaining labeled data from social media. De Choudhury et al. (2013a) used it to identify new mothers and track post-partum changes in emotions.

* Equal contribution.

Condition	Twitter, (Coppersmith et al, 2015)	Reddit, SMHD (ours)
ADHD	102	10,098
Anxiety	216	8,783
Autism	n/a	2,911
Bipolar	188	6,434
Borderline	101	n/a
Depression	393	14,139
Eating	238	598
OCD	100	2,336
PTSD	403	2,894
Schizophrenia	172	1,331
Seasonal Affective	100	n/a

Table 1: Comparison between the number of self-reported diagnosed users per condition in the dataset of Coppersmith et al. (2015a) and ours (SMHD).

I was officially diagnosed with ADHD last year.
I have a diagnosed history of PTSD.
my dr just diagnosed me as schizo.

Figure 1: Examples of self-reported diagnoses statements.

Coppersmith et al. (2014a) specifically focused on self-reports of mental health diagnoses. In particular, Coppersmith et al. (2015a) constructed a dataset of various mental health conditions using Twitter statements. Finally, Yates et al. (2017) introduced a large dataset of depressed users obtained from Reddit.

We extend the previous efforts on addressing the lack of large-scale mental health-related language data. Particularly, we propose improved data collection methods through which we can obtain high-quality large-scale datasets of labeled diagnosed conditions paired with appropriate control users. Consequently, we introduce SMHD (Self-reported Mental Health Diagnoses), a large dataset of diverse mental health conditions that can provide further insight into the mental health-related language. We leverage self-reported diagnosis statements where a user declares to have been diagnosed with a mental health condition such as depression. Examples of self-reported diagnoses are shown in Figure 1. Our dataset can be used not only to develop methods for better identifying mental health conditions through natural language, but also allows us to investigate the characteristics of language usage within each condition. We hope the availability of this new resource will foster further research into these problems and enhance reproducibility of suggested approaches.

Our work has the following significant distinctions compared to existing social media datasets related to mental health. Previous work has studied self-reported diagnosis posts in Twitter (Coppersmith et al., 2015a), where the post length is limited to 140 characters.¹ This makes the Twitter language use rather different from real life discussions. Instead, we use data from Reddit, an interactive discussion-centric forum without any length constraints. Our dataset contains up to two orders of magnitude more diagnosed individuals for each condition than the Twitter dataset by Coppersmith et al. (2015a), making it suitable for exploring more recent data-driven learning methods (see Table 1). We choose our control users in a systematic way that makes classification experiments on the dataset realistic.

We normalize language usage between the users: by removing specific mental health signals and discussions, we focus on patterns of language in normal (general) discussions. While our dataset creation method is close to Yates et al. (2017), we extend theirs by investigating multiple high-precision matching patterns to identify self-reported diagnoses for a range of conditions. Part of our patterns are obtained through synonym discovery. Considering relevant synonyms from reliable sources increases the variety of the diagnosed users and linguistic nuances. We also explore nine common mental health

¹This limitation was doubled to 280 characters in late 2017.

conditions while Yates et al. (2017) focus only on depression. We explore classification methods for identifying mental health conditions through social media language and provide detailed analysis that helps us understand the differences in language usage between conditions, and between diagnosed users and controls.

Our contributions are as follows: (i) We investigate the creation of high-precision matching patterns to identify self-reported diagnoses of nine different mental health conditions. (ii) We introduce a large-scale dataset of nine mental health conditions that has significant extensions to existing datasets and we make our data publicly available. Our dataset includes users who might suffer from more than one condition, thus allowing language study of interacting mental conditions. (iii) We investigate language characteristics of each mental health group. (iv) We explore classification methods for detecting users with various mental health conditions.

2 Related work

Social media offers a considerable amount of accessible common language, attracting the attention of those who study the language of individuals with mental health conditions. Twitter is a natural source, being a popular platform that enables users to share short messages publicly. Early work used crowdsourcing to identify Twitter users who report a depression diagnosis in a survey, and proposed features that are able to identify depressed users prior to the onset of depression (De Choudhury et al., 2013b). Others found that these characteristics hold in both English and Japanese tweets (Tsugawa et al., 2015), indicating similar cross-cultural tendencies.

Due to the cost and bias introduced by relying on surveys, work shifted to identifying mental health conditions by examining the content shared by social media users. Coppersmith et al. (2014a) identified approximately 1,200 Twitter users with 4 mental health conditions (bipolar, depression, PTSD, SAD) using diagnosis statements found in tweets (e.g., “I was diagnosed with depression”). Following this work, detailed studies were conducted on users experiencing PTSD (Coppersmith et al., 2014b), and schizophrenia (Mitchell et al., 2015; Ernala et al., 2017). The shared task at the 2nd Computational Linguistics and Clinical Psychology Workshop (CLPsych 2015) focused on identifying depression and PTSD users on Twitter (Coppersmith et al., 2015b). This included a set of approximately 1,800 Twitter users with self-identified diagnoses. Leading submissions to CLPsych 2015 relied on the LIWC lexicon (Pennebaker et al., 2015), topic modeling, manual lexicons, and other domain-dependent features (Resnik et al., 2015; Preotiuc-Pietro et al., 2015). Coppersmith et al. (2015a) expands the research on Twitter to eleven self-identified mental health conditions. (Benton et al., 2017) uses this dataset (and others) with a neural multi-task learning approach to identify language characteristics. Mowery et al. (2016) investigates specific symptoms of depression in tweets, including depressed mood, disturbed sleep, and loss of energy.

While the abundant short texts of Twitter can provide some insight into language characteristics of those with mental health conditions, long-form content can provide additional linguistic insights. Some have investigated the language of users of an online crisis forum to identify posts of users who are at highest risk to allow for faster intervention (Milne et al., 2016; Cohan et al., 2017). Losada and Crestani (2016) applied the self-reported diagnosis strategy to identify approximately 150 Reddit users who suffer from depression, and paired them with 750 control users. Yates et al. (2017) also used self-reported diagnoses to identify clinically depressed users, but applied it to a larger set of Reddit, yielding the Reddit Self-reported Depression Diagnosis (RSDD) dataset of over 9,000 users with depression and over 100,000 control users (using an improved user control identification technique). The corpus was also used to study the temporal aspects of self-reported diagnoses (MacAvaney et al., 2018).

Others have used data sources beyond social media to examine the language of people with mental health conditions. Resnik et al. (2013) uses topic models to predict depression and neuroticism based on student-written essays, finding clear clusters of words when students are asked to write about their feelings in a stream-of-consciousness setting. Althoff et al. (2016) uses text message conversations from a mental health crisis center to improve counseling techniques.

This work addresses important limitations of previous efforts. Similar to RSDD (Yates et al., 2017), we

build our corpus from Reddit using self-reported diagnoses. This results in a large amount of long-form post content that is not constrained by a character limit. Furthermore, because there are no character limits (as exist for Twitter), the mode of language is more typical of general writing. Unlike Yates et al. (2017), we investigate extended self-diagnoses matching patterns derived from mental health-related synonyms. We also focus on nine mental health conditions (rather than just a single condition). This results in a collection that can be used to compare and contrast the language characteristics of each condition.

3 Data

In this section we describe the construction and characteristics of the Self-reported Mental Health Diagnoses (SMHD) dataset. The studied conditions correspond to branches in the DSM-5 (American Psychiatric Association, 2013), an authoritative taxonomy for psychiatric diagnoses. Six conditions are top-level DSM-5 disorders: schizophrenia spectrum disorders (*schizophrenia*), bipolar disorders (*bipolar*), depressive disorders (*depression*), anxiety disorders (*anxiety*), obsessive-compulsive disorders (*ocd*) and feeding and eating disorders (*eating*). The three other conditions are one rank lower: post-traumatic stress disorder (*ptsd*) is classified under trauma- and stress-related disorders, and autism spectrum disorders (*autism*) and attention-deficit/hyperactivity disorder (*adhd*) under neurodevelopmental disorders. We use these lower-rank conditions to provide more definition when they are clearly distinguishable from sibling disorders.

3.1 Dataset construction

The SMHD dataset was created by using high precision patterns to identify Reddit users who claimed to have been diagnosed with a mental health condition (*diagnosed users*) and using exclusion criteria to match these diagnosed users with control users who are unlikely to have one of the mental health conditions studied (*control users*). SMHD consists of user labels indicating the mental health condition(s) associated with each user and all Reddit posts made by each user between January 2006 and December 2017 (inclusive). Users and posts were extracted from a publicly available Reddit corpus². This approach is based on the method used to create the Reddit Self-reported Depression Diagnosis (RSDD) dataset (Yates et al., 2017). SMHD expands on RSDD by incorporating synonyms in matching patterns and including diagnoses for eight new conditions in addition to depression.³

Diagnosed users were identified using high precision diagnosis patterns in a manner similar to that used in prior work that studied depression on Reddit (Yates et al., 2017); we describe these patterns in more detail in section 3.2. After identifying candidate diagnosed users who matched a diagnosis pattern (see Figure 1), we removed any candidates who (1) matched a negative diagnosis pattern⁴ or (2) had fewer than 50 posts talking about topics other than mental health (*mental health posts*). This is done to ensure enough data remains for a diagnosed user after removing their mental health-related content. After removing these candidate diagnosed users, 36948 diagnosed users remain.

Mental health posts were defined as posts that were either made to a subreddit (i.e., a subforum devoted to a specific topic) related to mental health or that included language related to mental health, such as the name of a condition (e.g., *OCD*) and general terms like *diagnosis*, *mental illness*, or *suffering from*. We constructed a list of subreddits related to mental health by beginning with lists from prior work studying depression on Reddit (Pavalanathan and De Choudhury, 2015; Yates et al., 2017) and expanding them to include discussion and support subreddits for each of the other mental health conditions. All mental health posts are removed for diagnosed users and control users alike. Classification therefore happens on the set of posts that do not contain any of the mental health terms, and that have not been posted in any of the mental health-related subreddits. Our methodology does not guarantee, however, that all potentially relevant terms or subreddits have been excluded.

Control users were chosen from a pool of candidate control users based on their similarity with

²<https://files.pushshift.io/reddit/>

³Patterns are available from <http://ir.cs.georgetown.edu/data/smhd/>.

⁴e.g., *I was never clinically diagnosed*.

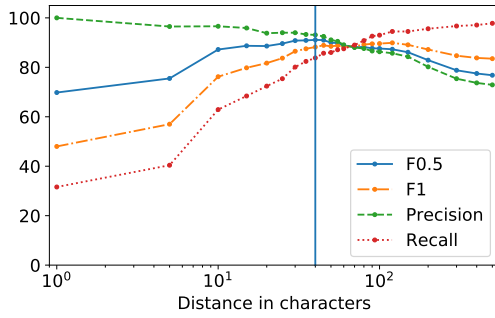


Figure 2: Precision, recall, F1 and F0.5 of the condition diagnosis patterns as a function of the maximum allowable distance (in characters) between a diagnosis and a condition keyword. Chosen threshold indicated at 40 characters.

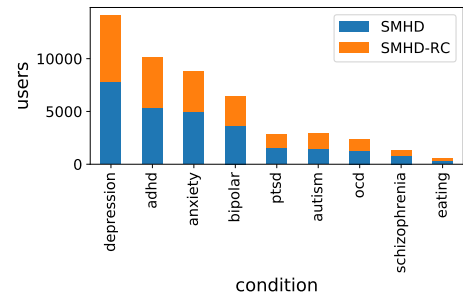


Figure 3: Number of users per condition for SMHD (in blue) and SMHD-RC (in orange).

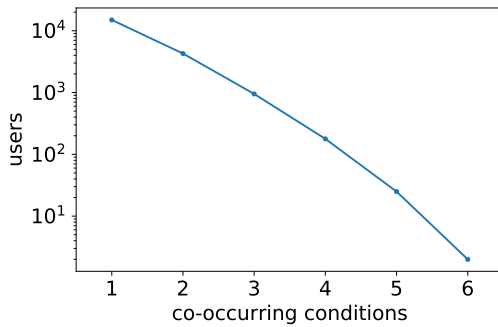


Figure 4: Number of users with a single or multiple co-occurring conditions.

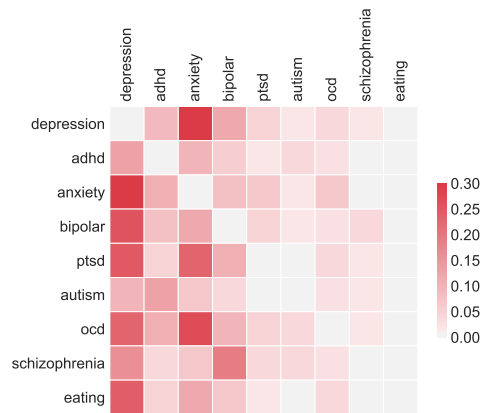


Figure 5: Concomitance of condition diagnoses. Rows contain relative co-occurrences of the row condition with other conditions.

the diagnosed users as measured by their number of posts and the subreddits they posted in. This is done to prevent biases between the control and diagnosed groups in the dataset and prevent making the task of identifying such users artificially easy. In more detail, every Reddit user who (1) had no mental health post⁵ and (2) had at least 50 posts became a candidate control user. Given this pool of candidate control users, we matched each diagnosed user with 9 candidate control users (on average) after excluding controls who had never posted in the same subreddit as the diagnosed user or who had more than twice as many posts or less than half as many posts as the target diagnosed user.

The selection criteria for potential control users are stringent: users are removed if they do not have the required subreddit overlap or minimum post count, or if they use any of the mental health-related terms in any of their posts. The latter is necessary because we found that the prior probability of using an exclusion term in any given subreddit (e.g. *depressed*) is almost always higher for diagnosed users than for controls, even in popular subreddits on general topics (e.g. *r/politics*). As a result, the pool of candidate controls for matching to diagnosed users is significantly diminished. Because control users are picked from the pool without replacement, we were unable to meet the target of 9 appropriate controls for some of the diagnosed users. We release the users who have at least 9 control users as SMHD, and use this

⁵When defining language related to mental health, we consider *add* to be a mental health term. However, this term is often used as a verb that does not refer to Attention Deficit Disorder. We therefore do not exclude candidate control users who have used this term. We instead remove any post containing the term *add*, which matches our treatment of the diagnosed users where all mental health posts are removed.

dataset for all analyses in this paper. It contains 20,406 diagnosed users and 335,952 matched controls. A secondary dataset containing the remaining 16,542 diagnosed users with fewer than 9 controls will be made available as SMHD-RC (*Relaxed Controls*) for studies that require additional data for analysing differences between mental health conditions, rather than between diagnosed users and controls.

3.2 Diagnosis patterns

To identify Reddit users who report a diagnosis for one or more mental health conditions, we developed detection patterns with a focus on high precision. The patterns consist of two components: one that matches a self-reported diagnosis, and another that maps relevant diagnosis keywords to the 9 mental health conditions. A user is included for a condition if one of the condition keywords occurs within a certain distance of the diagnosis pattern (as discussed below).

For each condition, a seed list of diagnosis keywords was collected from the corresponding DSM-5 headings. To increase the likelihood of matching diagnostic posts, we expanded each set of medical expressions to include synonyms, common misspellings, vernacular terms and abbreviations. Our steps mirror the ones of Soldaini and Yom-Tov (2017), who were also interested in identifying self-diagnosed users, albeit on query logs. In particular, we leveraged two synonym mappings to generate alternative formulations of the disorders of interest:

- *MedSyn* (Yates and Goharian, 2013) is a laypeople-oriented synonym mapping ontology. It was generated from a subset of *UMLS*⁶ filtered to remove irrelevant semantic types.
- *Behavioral* (Yom-Tov and Gabrilovich, 2013) maps expressions commonly used by laypeople to describe their medical condition to concepts in *UMLS*. The synonyms were generated by first identifying the most frequent search terms Yahoo! search used to retrieve Wikipedia medical pages. Then, frequent lexical affinities (Carmel et al., 2002) to the aforementioned were added to synonyms lists.

The resulting expansions were vetted manually to remove terms that did not describe the condition precisely (e.g., hypernyms) or that were ambiguous (e.g., “add”), and missing items were added.

Using the diagnosis patterns without condition keywords, all self-reported diagnosis posts were collected from the Reddit dataset, and 500 posts were randomly sampled for manual annotation. False positive matches were found in 18 of those, i.e. the precision for self-diagnosis detection was 96.4%. False positives included negations, hypotheticals (e.g., “I’m not sure if I was diagnosed”), and diagnoses that are uncertain or wrong (“I was diagnosed with autism, then undiagnosed.”). Out of 500 diagnosis posts, 241 reported a mental health condition. The ones that were annotated as belonging to one of the 9 conditions were used to tune the condition term lists and the optimal distance between a diagnosis pattern and a condition term. Figure 2 plots the effect of this distance on precision, recall, F1 and F0.5 (which emphasizes precision). A maximum distance of 40 characters was chosen, where F0.5 score is highest. We thus achieve high precision (93%) with good recall (84%). Since the optimal distance threshold was tuned on this development set, it may overfit the data and the reported scores should be considered a ceiling performance.

To validate the final diagnosis matching approach on a held-out set, 900 posts (corresponding to 9 samples of 100 diagnosis posts, one for each condition) was manually checked for false positives. We obtain high precision, with a minimum precision of 90% for *anxiety* and macro-averaged precision of 95.8%. Most false positives are caused by terms for a condition occurring close to a diagnosis for another condition (e.g. “My doctor diagnosed me with depression, and I also have an anxiety problem.”). While a user might also suffer from these conditions, they are not explicitly reporting a diagnosis.

3.3 Dataset statistics

Figure 3 shows the distribution of diagnosed users per condition in both datasets. Users who self-reported a diagnosis of depression, ADHD, anxiety or bipolar are most common. Interestingly, 26.7% of diagnosed users in the dataset reported more than one diagnosis (Figure 4). Such concomitant conditions are not uncommon, and were also reported in the work of Coppersmith et al. (2015a). As can be seen in

⁶Unified Medical Language System

condition	posts		tokens		characters
	per user	total	per post	total	per post
control	310.0 (157.8)	115,669k	26.2 (48.3)	3,031.6M	133.9 (252.9)
depression	162.2 (84.2)	1,272k	45.1 (80.0)	57.4M	227.5 (406.9)
adhd	164.7 (83.6)	872k	46.5 (82.7)	40.5M	237.5 (433.5)
anxiety	159.7 (83.0)	795k	46.4 (83.0)	36.9M	233.9 (422.8)
bipolar	157.6 (82.4)	575k	45.5 (86.5)	26.2M	230.6 (447.0)
ptsd	160.7 (84.7)	258k	53.1 (114.0)	13.7M	267.8 (581.7)
autism	168.3 (84.5)	248k	46.5 (82.3)	11.6M	237.9 (434.0)
ocd	158.8 (81.4)	203k	46.4 (90.1)	9.4M	234.2 (459.5)
schizophrenia	157.3 (80.5)	123k	49.2 (105.6)	6.1M	253.8 (566.6)
eating	161.4 (81.0)	53k	46.3 (73.7)	2.5M	232.6 (372.8)

Table 2: Average (Stdev.) and count of posts, tokens and characters for diagnosed and control users.

Figure 5, depression co-occurs with high frequency with most of the other conditions, almost 30% of users with depression, OCD or PTSD also suffer from anxiety, and schizophrenia is most likely to be diagnosed alongside bipolar disorder.

An important characteristic of the SMHD dataset is its scale. Reddit allows its users to write long-form posts, so unlike datasets collected on Twitter, a large amount of text is available for each diagnosed user. Table 2 gives an overview of the average and total number of posts, tokens and characters per condition, and for controls. Control users post on average twice as many posts as diagnosed users, but these posts tend to be considerably shorter. Although this may be a valid signal for certain mental health conditions, it can be removed for classification experiments by truncating the length and number of posts. This is common practice for technical reasons, and truncating post length has been shown in previous work to improve classification performance (Yates et al., 2017).

3.4 Ethics and privacy

Even though we rely on publicly available Reddit posts in our work, mental health is a sensitive matter and measures to prevent risk to individuals in social media research should always be considered (Hovy and Spruit, 2016; Šuster et al., 2017). The risks associated with the data collection methods and our resulting SMHD dataset is minimal. We refrain from publicly posting any excerpts of the data, we made no attempt to contact users, and we made no attempt to identify or link users to other social media accounts. We further replace usernames with random identifiers to prevent users’ identities from being known without the use of external information. The SMHD dataset is available through a Data Usage Agreement (DUA)⁷ protecting the users’ privacy. In particular, the DUA specifies that no attempt should be made to publish portions of the dataset (which could result in users being identified), contact users, identify them, or link them with other user information.

4 Analysis

To investigate the differences between the language of mental health condition groups and the control group, we categorize language of users based on measures of psycholinguistic attributes through the LIWC lexicon (Pennebaker et al., 2015). These categories include variables that characterize linguistic style as well as psychological aspects of language (e.g., cognitive attributes and affective attributes). For each user, we obtain LIWC categories based on their posts and then compare these categories across users in each mental health condition group versus the control group using Welch’s t-test (Welch, 1947). We adjust p-values with Bonferroni correction. To better see the differences between the categories, we also report the Cohen’s *d* statistic (Cohen, 1988). Table 3 shows the results.

In general, we observe a variety of differences in language use between the diagnosed and the control groups. The effect sizes range from a very small effect to medium ($0.05 < d < 0.5$), which is typical of large datasets (Sakai, 2016). These differences span across both the linguistic style and psychological

⁷<http://ir.cs.georgetown.edu/resources/>

LIWC category	depression	adhd	anxiety	bipolar	ptsd	autism	ocd	schizophrenia	eating
<i>Summary Language Variables</i>									
Clout	-0.06 [‡]	-	-0.1 [‡]	-	-	-	-	-	-
Authentic	0.2 [‡]	0.15 [‡]	0.22 [‡]	0.18 [‡]	0.21 [‡]	0.14 [‡]	0.23 [‡]	-	0.24 [*]
WPS	0.08 [‡]	0.1 [‡]	0.08 [‡]	0.06 [‡]	0.1 [‡]	0.12 [‡]	0.08 [‡]	-	-
Dictionary words	0.27 [‡]	0.22 [‡]	0.28 [‡]	0.24 [‡]	0.31 [‡]	0.2 [‡]	0.28 [‡]	0.22 [‡]	0.3 [‡]
Total function words	0.27 [‡]	0.21 [‡]	0.28 [‡]	0.24 [‡]	0.3 [‡]	0.26 [‡]	0.28 [‡]	0.23 [‡]	0.27 [‡]
Total pronouns	0.22 [‡]	0.14 [‡]	0.24 [‡]	0.2 [‡]	0.25 [‡]	0.17 [‡]	0.26 [‡]	0.18 [‡]	0.26 [‡]
Personal pronouns	0.23 [‡]	0.14 [‡]	0.26 [‡]	0.21 [‡]	0.22 [‡]	0.14 [‡]	0.23 [‡]	0.2 [‡]	0.27 [‡]
1st pers singular	0.23 [‡]	0.16 [‡]	0.28 [‡]	0.22 [‡]	0.23 [‡]	0.17 [‡]	0.26 [‡]	0.17 [‡]	0.28 [‡]
3rd pers singular	0.09 [‡]	-	0.1 [‡]	0.08 [*]	0.17 [*]	-	-	-	-
Impersonal pronouns	0.06 [‡]	0.05 [*]	0.07 [‡]	-	0.11 [‡]	0.09 [*]	0.13 [‡]	-	-
Prepositions	0.12 [‡]	0.12 [‡]	0.12 [‡]	0.12 [‡]	0.16 [‡]	0.12 [‡]	0.11 [‡]	-	-
Auxiliary verbs	0.12 [‡]	0.1 [‡]	0.14 [‡]	0.11 [‡]	0.14 [‡]	0.15 [‡]	0.13 [‡]	-	-
Common Adverbs	0.09 [‡]	0.07 [‡]	0.08 [‡]	0.06 [*]	-	-	-	-	-
Conjunctions	0.17 [‡]	0.14 [‡]	0.18 [‡]	0.16 [‡]	0.17 [‡]	0.13 [‡]	0.11 [‡]	-	0.3 [‡]
<i>Other Grammar</i>									
Common verbs	0.15 [‡]	0.11 [‡]	0.17 [‡]	0.13 [‡]	0.15 [‡]	0.13 [‡]	0.19 [‡]	-	-
Numbers	-0.1 [‡]	-0.09 [‡]	-0.11 [‡]	-0.09 [‡]	-0.11 [‡]	-	-0.1 [‡]	-	-0.13 [‡]
<i>Psychological Variables</i>									
Positive emotion	-	-	-	-	-	-0.08 [*]	-	-	-
Anxiety	0.07 [‡]	-	0.07 [*]	-	-	-	-	-	-
Social processes	0.11 [‡]	0.07 [‡]	0.11 [‡]	0.1 [‡]	0.15 [‡]	-	-	-	-
Family	0.06 [‡]	-	0.06 [*]	-	0.12 [‡]	-	-	-	-
Female references	0.13 [‡]	0.07 [‡]	0.1 [‡]	0.13 [‡]	0.22 [‡]	-	-	-	-
Cognitive processes	0.12 [‡]	0.13 [‡]	0.14 [‡]	0.09 [‡]	0.12 [‡]	0.16 [‡]	0.13 [‡]	-	-
Insight	0.09 [‡]	0.07 [‡]	0.1 [‡]	0.08 [‡]	-	0.1 [*]	0.17 [‡]	-	-
Discrepancy	-	0.06 [*]	-	-	-	-	-	-	-
Tentative	0.07 [‡]	0.08 [‡]	0.08 [‡]	0.07 [*]	-	-	-	-	-
Differentiation	0.08 [‡]	0.08 [‡]	0.1 [‡]	-	-	0.09 [*]	-	-	-
Biological processes	0.06 [‡]	-	-	-	-	-	-	-	-
Health	0.08 [‡]	0.07 [‡]	0.08 [‡]	0.11 [‡]	-	-	-	-	-
<i>Time orientation</i>									
Past focus	0.08 [‡]	0.05 [*]	0.09 [‡]	0.08 [‡]	0.09 [*]	-	0.11 [*]	-	-
Present focus	0.09 [‡]	0.06 [‡]	0.1 [‡]	0.07 [*]	-	-	-	-	-
<i>Personal concerns</i>									
Relativity	0.05 [‡]	0.06 [‡]	-	-	-	-	-	-	-
Time	0.06 [‡]	-	0.06 [*]	-	-	-	-	-	-
Work	-	0.06 [*]	-	-	-	-	-	-	-
Leisure	-0.07 [‡]	-0.07 [‡]	-0.07 [‡]	-0.09 [‡]	-0.12 [‡]	-0.09 [‡]	-	-	-
Money	-0.06 [‡]	-	-0.05 [‡]	-0.06 [‡]	-	-0.1 [‡]	-	-	-0.12 [‡]
Informal language	-0.07 [‡]	-0.07 [‡]	-0.06 [‡]	-	-0.12 [‡]	-	-0.09 [*]	-	-
Netspeak	-0.07 [‡]	-0.06 [‡]	-0.06 [‡]	-0.06 [*]	-0.1 [‡]	-0.08 [*]	-	-	-0.15 [‡]
Assent	-	-	-	-	-0.06 [*]	-	-	-	-

Table 3: Differences between the linguistic and psycholinguistic variables obtained from LIWC between users treatment groups and control users. Statistical significance is based on t-test with Bonferroni adjustment. Numbers in the cells are effect sizes (Cohen’s d). \star , \dagger , and \ddagger respectively show adjusted p-values of <0.01 , <0.001 and <0.0001 . This is also indicated by shading colors, red shading shows that the corresponding category is observed with more intensity in the treatment group, where as blue shading shows more significance in the control group. For brevity, only significant attributes are shown.

attributes. Particularly, we observe that clout, an attribute regarding language that indicates high social status, is more prominent among control users compared to the depression and anxiety groups. Related work in psychology shows that depression and anxiety are more prevalent in lower socioeconomic status demographics (Murphy et al., 1991), which is in line with the observation in our dataset. Next, authentic language is stronger among most of the mental health groups compared with control groups. This correlates with the use of personal and first person pronouns. This is backed by prior research showing that fewer self-references are associated with unauthentic language (Newman et al., 2003). We also observe that among most of the conditions the usage of first-person singular pronouns is higher than in control groups. Related studies arrive at the same conclusion that people with mental health conditions tend to use more first-person pronouns and references, possibly because mental health conditions result in greater self-focused attention and rumination (Bucci and Freedman, 1981; Pennebaker et al., 2015; Watkins and Brown, 2002; Van der Zanden et al., 2014).

Social processes, the language related to human interaction and sharing, appears to be higher in depressed, anxiety and PTSD users. A potential explanation for this is that sharing and support-seeking behaviors have been shown to improve an individual’s state of mind (Turner et al., 1983; De Choudhury and Kiciman, 2017). People with conditions such as bipolar, depression and anxiety show significantly

	Depression	ADHD	Anxiety	Bipolar	PTSD	Autism	OCD	Schizophrenia	Eating	Multi-label
Logistic Regression	P=85.00	P=88.60	P=85.80	P=87.06	P=92.44	P=93.18	P=95.00	P=100.00	P=0.00	P=17.22
BoW features	R=28.65 F=42.85	R=19.22 F=31.59	R=27.04 F=41.13	R=21.57 F=34.58	R=19.71 F=32.50	R=7.93 F=14.62	R=4.87 F=9.27	R=2.25 F=4.40	R=0.00 F=0.00	R=24.38 F=19.72
XGBoost	P=81.40	P=85.71	P=83.52	P=84.94	P=89.83	P=84.09	P=86.96	P=86.84	P=94.12	P=16.87
BoW features	R=29.49 F=43.29	R=21.25 F=34.05	R=31.46 F=45.71	R=30.31 F=44.68	R=37.99 F=53.40	R=21.47 F=34.21	R=25.64 F=39.60	R=24.72 F=38.48	R=14.29 F=24.81	R=29.38 F=20.51
Linear SVM	P=78.70	P=83.74	P=81.76	P=84.36	P=93.12	P=91.19	P=86.29	P=93.06	P=100.00	P=19.20
BoW features	R=39.75 F=52.82	R=30.69 F=44.92	R=39.88 F=53.61	R=37.21 F=51.64	R=41.22 F=57.14	R=28.05 F=42.90	R=27.44 F=41.63	R=25.09 F=39.53	R=13.39 F=23.62	R=34.86 F=23.71
Supervised FastText	P=66.80	P=62.11	P=67.63	P=62.63	P=70.76	P=68.47	P=65.02	P=69.23	P=64.15	P=23.02
	R=44.70 F=53.56	R=37.77 F=46.98	R=44.54 F=53.71	R=42.74 F=50.81	R=48.57 F=57.60	R=39.07 F=49.75	R=33.85 F=44.52	R=33.71 F=45.34	R=30.36 F=41.21	R=44.44 F=27.83
Convolutional Neural Network (CNN)	P=45.85	P=37.86	P=51.33	P=37.21	P=47.00	P=30.82	P=22.97	P=30.12	P=38.56	P=20.65
	R=56.07 F=50.45	R=32.77 F=35.13	R=45.01 F=47.96	R=39.53 F=38.34	R=65.95 F=54.88	R=50.68 F=38.33	R=57.95 F=32.90	R=47.94 F=36.99	R=52.68 F=44.53	R=48.12 F=26.55

Table 4: Classification performance on target users in SMHD. All methods rely on the official SMHD split introduced in Section 3 for training, tuning, and testing. We report the performance of each classifier as binary predictor (i.e., given a condition, predict if a user belongs to the diagnosed or control group) as well as in a multi-label, multi-class setting (i.e., given a user, predict if and which conditions they were diagnosed with).

more female references. This might point to a gender bias in the corpus towards males, which would shift an increased preoccupation with romantic relationships towards references of female partners. Cognitive processes (markers of cognitive activity associated with rational thought and argumentation) are also observed more in people with mental health conditions. This could be due to the observation that these groups tend to express their feelings more. Other attributes such as health, focus on past time, and biological processes are observed more in conditions such as depression. Unsurprisingly, attributes like leisure and money are more prevalent among controls.

5 Experiments

In order to provide a more thorough understanding of SMHD, we explored several classification methods for each of the conditions included in the dataset. We train our classifiers both in a binary and multi-label multi-class setting. For the binary tasks, all classifiers are trained only on the subset of diagnosed users in SMHD who are associated with any condition and their respective control users. Recall that, as discussed in 3.3, users can be diagnosed with one or more conditions; as such, we also evaluate the baseline classifiers in a multi-class, multi-label setting. In other words, given a user, classifiers are trained to predict if and which conditions the user was diagnosed with. In detail, we consider the following methods:

Logistic regression: we trained a simple discriminative model using bag-of-words features extracted over all posts by all users in the training set. Posts were concatenated and split on non-alphanumeric characters; we normalized tokens by folding them to lowercase. Words occurring less than 20 times in the training set were removed. Features were weighted using *tf-idf* and ℓ_2 -normalized.

XGBoost (Chen and Guestrin, 2016): we evaluated the performance of an ensemble of decision trees. For this model, the same features described above were used. We set the number of estimators to 100.

Support vector machine (SVM): we included a SVM classifier with linear kernel among our baselines. Like the methods above, this model was trained on *tf-idf* bag-of-words features.

Supervised FastText (Joulin et al., 2016): we trained a shallow neural net model using FastText. After tuning on the development set, we set the dimension of the hidden layer to 100. The model leverages sub-word information by using character ngrams of size 3 to 6; it was trained for 100 epochs.

Convolutional neural network (CNN): Finally, we tested a CNN approach to learn ngram sequences indicative of each condition. We used a model architecture based on the work of Kim (2014), with

a filter size of 3 and a pooling size of 4. A model was trained for each condition, and each model was trained for 100 epochs. Each user’s posts are concatenated and truncated to 15,000 tokens. This representation combines tractability with density. We do not pad posts individually hence no space is wasted by including short posts. Each token is represented by the FastText embeddings from above.

Results of the classification methods are reported in Table 4. All classifiers are trained, tuned, and tested on binary labels, except for the results reported in the rightmost column (“multi-label”). Overall, FastText obtained the best performance in terms of F1 score across all conditions except bipolar, in which it is outperformed by the SVM model, and eating disorder, where it is outperformed by a CNN. FastText also outperforms all other classifiers in the multi-label, multi-class test setting. We observe that models trained on bag-of-words features favor precision over recall, while the two neural models we tested offer more balanced performance. This can be explained by the fact that bag-of-words models are more likely to give more weight to strongly indicative text features, potentially causing some overfitting on the training data.

Comparing across conditions, we note that the performance on models is strongly affected by the number of diagnosed users in the training set. All classifiers struggle on the three conditions with fewest users (OCD, schizophrenia, and eating). This observation is consistent with the analysis on LIWC categories reported in Section 4.

Finally, we note that the simpler neural model (FastText) outperformed the richer CNN method. We explain this result by observing that FastText considers all posts by a user, while CNN samples a portion of them. This strategy, which is motivated by efficiency reasons, was based on the work of Yates et al. (2017), in which sampling was found to be an effective strategy to make the classification problem tractable. However, this result suggests that novel methods ought to be studied to achieve a robust sampling strategy across all conditions included in SMHD.

6 Conclusion

We presented SMHD, a large dataset of Reddit users with diverse mental health conditions and matched control users. Our dataset was constructed using high-precision diagnosis patterns and carefully selected control users. To our knowledge, SMHD is the largest dataset that supports a variety of mental health conditions and is up to two orders of magnitude larger than the largest published similar resource. We further examined differences in language use between mental health condition (diagnosed users) and control groups as measured by various linguistic and psychological signals. Several text classification methods were explored to identify the diagnosed users, with FastText being the most effective approach overall. We make our dataset available to the community, and hope that it will foster further research into these problems and enhance reproducibility of suggested approaches.

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