
ON THE STATE OF SOCIAL MEDIA DATA FOR MENTAL HEALTH RESEARCH

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A FIELD AT A CROSSROADS

- Adoption of computational methods for mental health in the clinical setting remains limited, despite almost a decade of active research
- Several challenges plague data acquisition in this domain
 - Variable clinical presentation of psychiatric conditions
 - Sensitive nature of annotated data & robust privacy regulations
 - Proxy-based annotation mechanisms are necessary to achieve scale

To what extent have data-related challenges hindered research progress and slowed the transition of computational methods into the clinical setting?



METHODS

LITERATURE SEARCH & ANNOTATION SCHEMA

LITERATURE SEARCH

Term Lists

Depression	Suicide	Anxiety	Bipolar
Mood	PTSD	OCD	Addiction
ADHD	Eating	Panic	Mental Health
Borderline Personality		Schizophrenia	

Social Media

Electronic Media

Machine Learning

Inference

Prediction

Detection

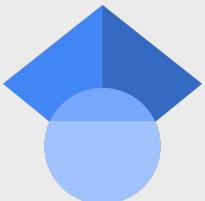
Query Pool



JMIR Publications
Advancing Digital Health & Open Science



arXiv.org



Query Structure



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SELECTION CRITERIA AND EXCLUSIONS

I. Must contain non-clinical electronic media (e.g., social media, SMS, search query text)

2. Must contain written language (i.e., text) within each unit of data

3. Must contain dependent variable that captures or proxies a condition listed in DSM-5

Electronic Health Records (EHR) & transcribed interviews

Search query volume, mobile activity, images, speech

Date of diagnosis, unlabeled data dumps

ANNOTATION SCHEMA

Field	Description	Example
Platform(s)	Electronic media source(s)	Twitter, SMS
Task(s)	Mental health condition(s) included as dependent variables	Depression, suicidal ideation, PTSD
Annotation Method(s)	Method for defining and annotating mental health variable(s)	Regular expressions, community participation, clinical diagnosis
Annotation Level	Resolution at which ground-truth annotations are made	Individual, document
Size	Number of data points at each annotation resolution for each task class	673 users, 576k comments
Language(s)	Primary language(s) of text in the dataset	English, Japanese, Portuguese
Availability	Whether the dataset can be shared and, if so, by what mechanism	Data usage agreement, IRB review, distribution prohibited



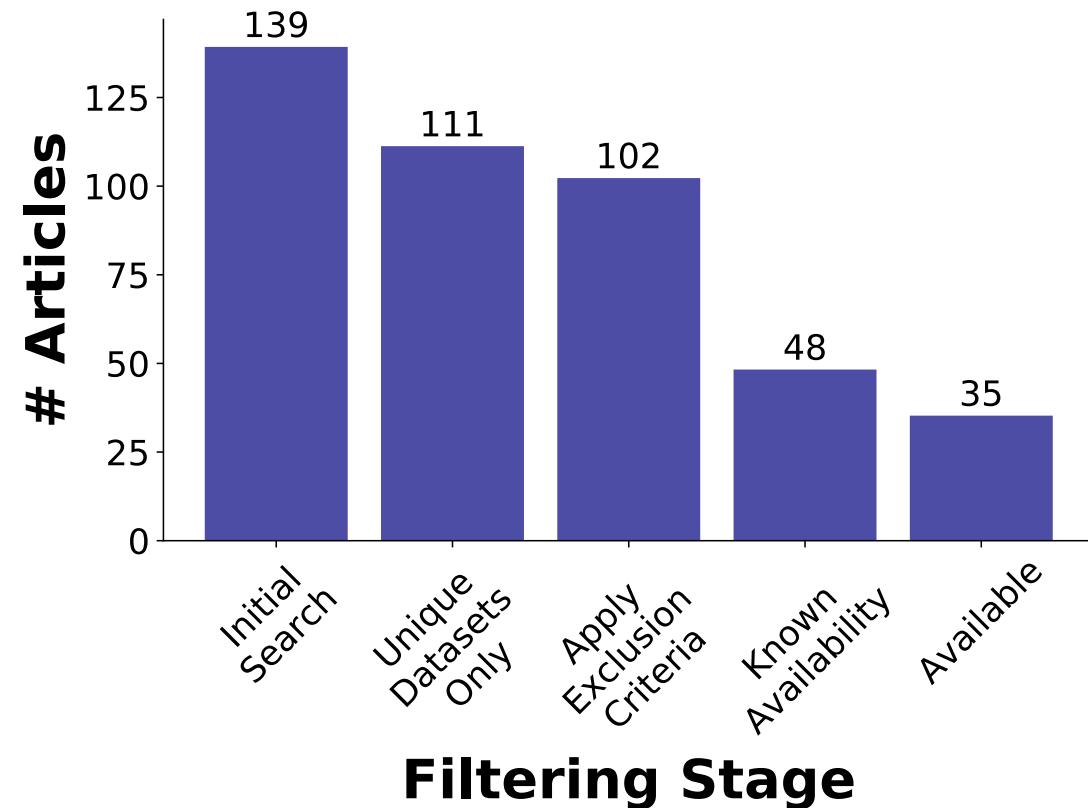
RESULTS

SUPPORTING DATA & ANALYSIS

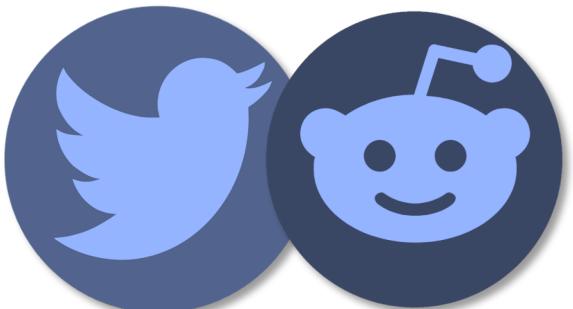


RESULTS

- Identified 102 unique datasets that meet our selection criteria
- Found an average of 12.75 new datasets released per year
- 2015 CLPsych Shared Task was the most reused resource¹
- Unable to identify any accessible datasets with clinically-derived annotations

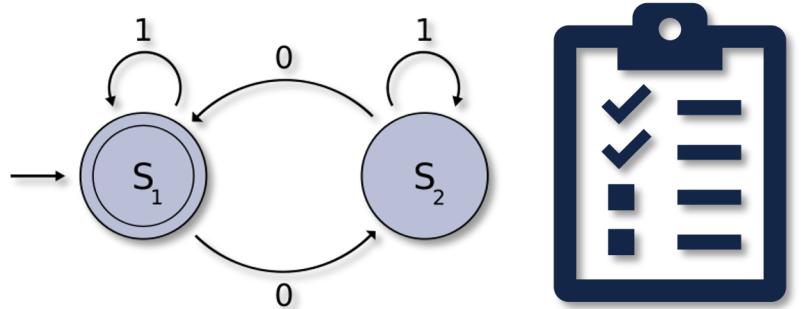


¹“CLPsych 2015 shared task: Depression and PTSD on twitter.” Coppersmith et al., 2015.



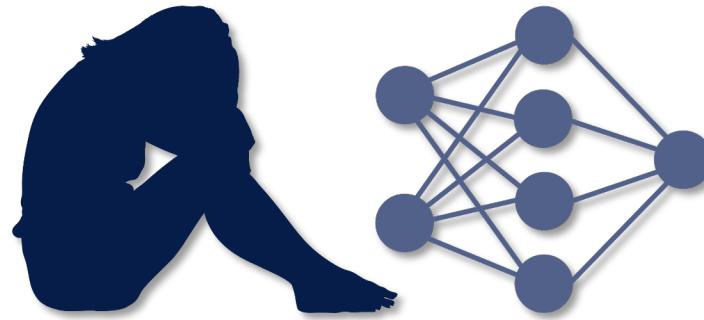
20 Platforms

Twitter and Reddit were most used;
noticeable dearth of Facebook, Instagram, and
YouTube



24 Annotation Mechanisms

Frequent use of regular expressions, clinical
surveys, & community participation



36 Modeling Tasks

Depression, suicidal ideation, PTSD, bipolar
disorder, self harm, & eating disorders were
most common



6 Languages

English, Chinese, Japanese, Korean, Spanish,
Portuguese (though mostly English)

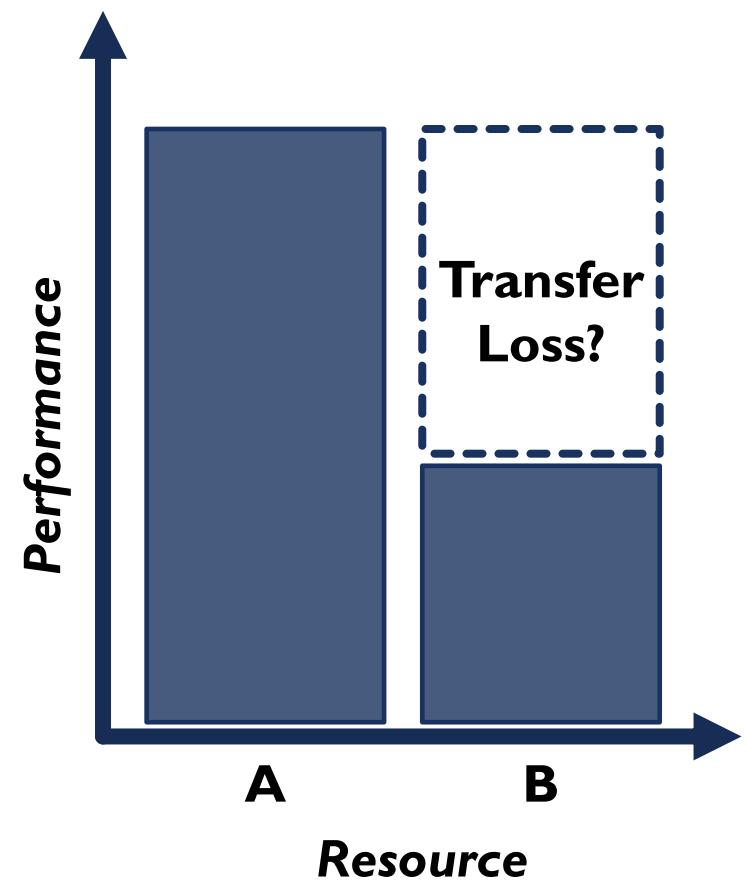


DISCUSSION

3 RECOMMENDATIONS FOR FUTURE DATASET CURATION

I. UNIFY TASK DEFINITIONS

- Over 20 unique annotation mechanisms identified (conservative estimate)
- Becomes difficult to contextualize algorithmic performance across studies
- Community needs **standardized** (and fair) benchmarks to inform interpretation of results as models are transitioned into the clinic



2. DEVELOP MECHANISMS FOR SHARING SENSITIVE DATA

- Recent research has called into question the strength of proxy-based annotations^{1,2}
- Existing datasets with clinically-derived annotations are not currently shareable
- Leverage **privacy-preserving technology** to share patient-generated data or make data available via **secure computing environments**



¹“Methodological gaps in predicting mental health states from social media: Triangulating diagnostic signals.” Ernala et al., 2019.

²“Do models of mental health based on social media generalize?” Harrigan et al., 2020.

3. CURATE DATASETS WITH POPULATION DIVERSITY IN MIND

- Several datasets sample demographically-matched or activity-matched individuals
- However, no dataset was specifically sampled to be representative of the general population
- Machine learning models underperform for people of color, even after addressing sample size issues¹
- Leverage **self-disclosed demographics** when possible and start looking **beyond English**



¹“Gender and racial fairness in depression research using social media.” Aguirre et al., 2021.

MENTAL HEALTH DATASET DIRECTORY



Screenshot of the GitHub repository page for [kharrigian/mental-health-datasets](#).

The repository has 2 unwatched stars, 83 forks, and 16 open issues. It contains 4 branches and 0 tags. The master branch has 53 commits from kharrigian, last updated on Apr 24. The commits include updates to analysis, reference, supplemental_data, .gitignore, README.md, data_sources.xlsx, excel_to_markdown.py, and requirements.txt.

About: An evolving list of electronic media data sets used to model mental-health status.

Readme: Available.

Releases: No releases published. Create a new release.

Packages: No packages published. Publish your first package.

Access and contribute to our directory of annotations at:
github.com/kharrigian/mental-health-datasets

THANK YOU FROM OUR TEAM



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