Datasets for Depression Modeling in Social Media: An Overview

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Abstract

Depression is the most common mental health disorder, and its prevalence increased during the COVID-19 pandemic. As one of the most extensively researched psychological conditions, recent research has increasingly focused on leveraging social media data to enhance traditional methods of depression screening. This paper addresses the growing interest in interdisciplinary research on depression, and aims to support early-career researchers by providing a comprehensive and up-to-date list of datasets for analyzing and predicting depression through social media data. We present an overview of datasets published between 2019 and 2024. We also make the comprehensive list of datasets available online as a continuously updated resource, with the hope that it will facilitate further interdisciplinary research into the linguistic expressions of depression on social media.

1 Introduction

Depression is the most common mental health disorder, and its prevalence has increased further during the COVID-19 pandemic (Wolohan, 2020; Kaseb et al., 2022; Bucur et al., 2025). Depression is also one of the most extensively researched mental health disorders in the field of psychology (Xu et al., 2021). Since the past decade, interdisciplinary researchers have explored this widespread mental disorder using data from social media (De Choudhury et al., 2013; Yates et al., 2017; Orabi et al., 2018; Aragón et al., 2019; Fine et al., 2020; Uban et al., 2021; Nguyen et al., 2022; Wang et al., 2024; Raihan et al., 2024; Abdelkadir et al., 2024). The language used on social media has been shown to predict future depression diagnoses recorded in medical files, suggesting that social media data could be a valuable supplement to traditional depression screening methods (Eichstaedt et al., 2018).

Interdisciplinary research has gained popularity through workshops and shared tasks focused on computational approaches for analyzing mental disorders, including CLPsych (Chim et al., 2024), LT-EDI (Kayalvizhi et al., 2023), eRisk (Parapar et al., 2024), and MentalRiskES (Mármol-Romero et al., 2023). As the research community shows increasing interest in examining how depression is expressed in social media language, we aim to support early-career researchers and anyone interested in this field by providing a comprehensive list of datasets for analyzing or predicting depression using social media data. Our motivation stems from recent changes in the terms of service and API rate limits for popular social media platforms, such as Twitter and Reddit, which have been the primary sources for data collection (Harrigian et al., 2021). These changes have made it more challenging and costly to gather new data. Therefore, we focus on the availability of the datasets in this overview.

The most recent review of social media data for mental health research was conducted by Harrigian et al. (2021), which covered datasets published between 2014 and 2019. Our current work aims to provide an updated overview of social media datasets specifically related to depression research. Since the latest dataset included by Harrigian et al. (2021) is from 2019, our focus will be on datasets published between 2019 and 2024.

This paper contributes to the computational research in depression by providing a meticulously curated, up-to-date, and continuously updated list of data collections.[1] We hope that the resources presented in this overview will further contribute to the interdisciplinary research on depression manifestations in social media language and aid in developing effective interventions for those affected by depression.

[1]We make the list available online at https://github.com/bucuram/depression-datasets-nlp.

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2 Methodology

We have conducted a comprehensive literature search on the major publication databases, including ACL Anthology, IEEE Xplore, Scopus, ACM Digital Library, Springer Nature Link, ScienceDirect, and Google Scholar to search for papers using NLP models for depression modeling or papers presenting novel depression-related data collections from social media. We formulated the following search query to retrieve relevant papers:
("depression" OR "depression detection" OR "depression prediction" OR "depression monitoring" OR "depression analysis") AND ("social media" OR "online" OR "Twitter" OR "Reddit" OR "Facebook")

For this overview, we selected papers published between 2019 and 2024 that specifically analyze depression using social media data. We excluded any papers not written in English. To determine if the retrieved papers included analyses related to depression based on social media data or described new data collections, we manually inspected the full texts. We focused on data in the English language. In total, we identified 310 relevant papers, of which 59 proposed new data collections for depression-related research using social media data.

3 Datasets

In Figure 1, we show the number of papers on depression modeling from social media data published each year.

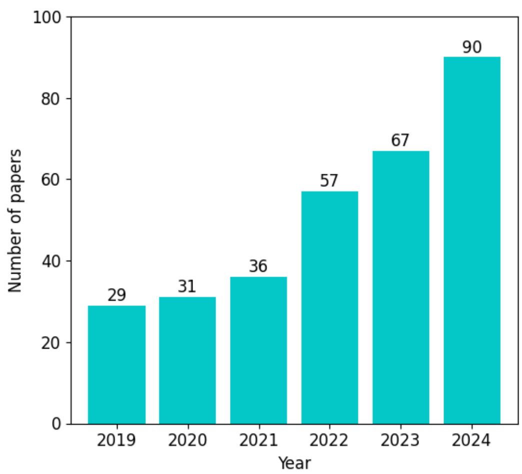

Figure 1: Number of papers on depression modeling published each year in peer-reviewed conferences or journals.

We observe a growing trend in interdisciplinary research on depression, which may have been partly influenced by the COVID-19 pandemic, as there has been an increase in depression rates during this time (Wolohan, 2020; Kaseb et al., 2022). In addition, there has been more research focused on using NLP models for mental health surveillance on social media platforms to assess the pandemic's impact on the population (Dhelim et al., 2023).

In Figure 2, we present the most used datasets in the 310 papers found through our search. Most of the papers have used the datasets from the LT-EDI Workshop (DepSign dataset (Sampath and Durairaj, 2022)), the eRisk Lab (Losada et al., 2017, 2018, 2019, 2020; Parapar et al., 2021; Crestani et al., 2022), or the CLPsych 2015 Shared Task dataset (Coppersmith et al., 2015). All the aforementioned datasets were released as part of shared tasks or competitions, and the data was a valuable resource that was further used after the end of the shared task. Other benchmark datasets are from Shen et al. (2017), Pirina and Çöltekin (2018), or RSDD (Yates et al., 2017).

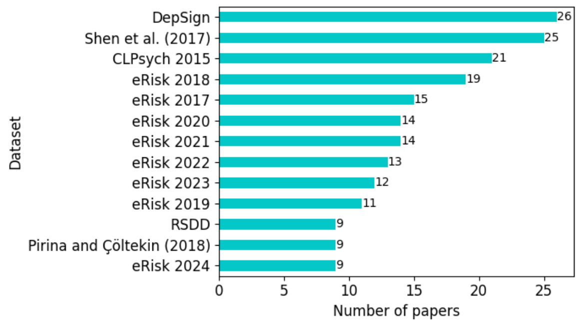

Figure 2: The most used datasets for depression modeling.

The availability of data collections has advanced the development of state-of-the-art depression prediction models. Of the 310 papers published during 2019 and 2024, 59 of them collect and annotate new data from online platforms. In Appendix 6 Table 1, we present detailed information for each of the data collections, such as the platform used for data gathering, the annotation procedure, and the level of annotation (either for each post or user), the labels that are provided for the data, the size of the dataset and its availability.

Platform In Figure 3, we present the social media platforms used for gathering datasets for depression modeling. Reddit and Twitter were the most commonly used platforms for data collection due to easy access to dedicated APIs. However, recent changes in the terms of service and API rate limits for both Twitter / X[2] and Reddit[3] have complicated data collection from these platforms. These updates may hinder the reproduction of datasets where authors only provide Twitter or Reddit IDs instead of the raw text. In addition, these changes make the process of collecting new data more challenging, costly and time-consuming.

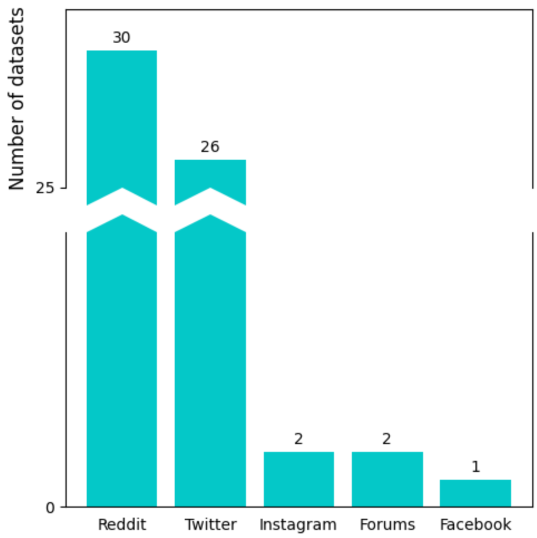

Figure 3: The most used platforms for the data collections presented in this overview.

Annotation procedure and labels For depression detection from social media data, the most common method of annotation from the datasets presented in this work is the annotation based on self-disclosure (Figure 4), labeling users binary, depending on whether they mention online a depression diagnosis or not. In 20 of the data collections, researchers use self-mentions of depression diagnoses (e.g., "I was diagnosed with depression") for their annotation processes. This approach allows for the compilation of large datasets containing hundreds of thousands of users.

Another common annotation procedure is manual annotation, used for 18 of the data collections. These annotations can be performed by mental health experts, graduate students, or laypeople. Most procedures for manual annotations are performed at the post level. Manual annotation is used

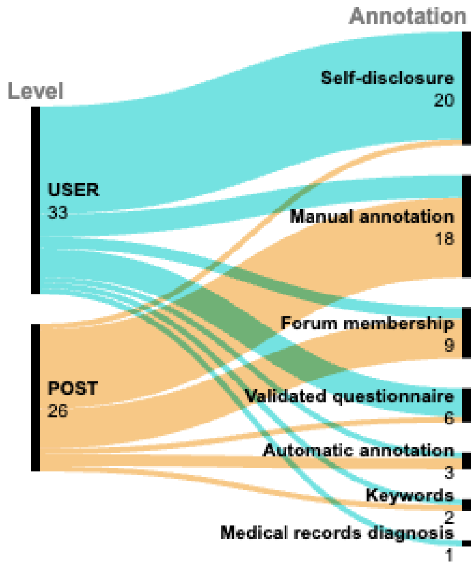

Figure 4: Overview of the annotation levels within each dataset, at either the user or post level, along with the procedures used for annotation.

to label the data binary (depression vs. control), to label data for depression severity (no signs of depression, mild, moderate, severe, etc.), and for symptoms measured by different validated questionnaires, or symptoms from The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-V) (American Psychiatric Association, 2013). Recently, datasets have shifted from binary labeling to labeling based on depression symptoms, leading to the development of explainable methods for depression modeling (Pérez et al., 2023c; Bao et al., 2024).

Data annotation can also be performed by asking social media users to fill in validated self-report questionnaires, such as the Beck's Depression Inventory (BDI) or Patient Health Questionnaire-9 (PHQ-9). However, even if psychometric tools produce a more reliable assessment of depression, fewer people are willing to participate in the data collection, resulting in small sample sizes. Only six datasets rely on self-report questionnaires for the annotation procedure, and one of them relies on the diagnosis from medical records.

Another method for annotation, which is noisier and more prone to errors, is labeling posts by the presence of specific depression-related keywords or automatic annotation performed via an NLP model trained on mental health data. These methods are used less frequently in the data collections included in this overview, with only three data collections being labeled automatically and two datasets being

[2] https://developer.twitter.com/en/docs/twitter-api/rate-limits

[3] https://support.reddithelp.com/hc/en-us/articles/16160319875092-Reddit-Data-API-Wiki

labeled using depression-related keywords.

Availability Due to the sensitive nature of the information in the datasets used for depression modeling, their availability varies. Our exploration of data availability was inspired by the work of Harrigian et al. (2021). However, unlike their study, we have decided not to consider datasets that can be reproduced using APIs from social media platforms as readily available. This decision was influenced by recent changes in the terms of service of platforms such as Reddit and Twitter / X, which have complicated the reproduction of data and made it difficult to retrieve social media posts using the IDs included in the data collections via APIs.

Out of the 59 papers proposing new datasets, 16 are publicly available and hosted online for anyone to use, 15 can be made available after signing a data usage agreement, and 11 collections can be made available by contacting the authors of the dataset. The availability of the rest of the datasets is unknown.

4 Discussion

Data availability One of the primary motivations for this overview were the recent changes in social media platforms, which may hinder the development of new research collections. Our aim was to provide the research community with a comprehensive list of data collections that can be used for interdisciplinary research on the manifestations of depression in social media. We included availability information for each dataset in this overview. We have found that 16 of the datasets are publicly available and free for anyone interested to download and use. As detailed in Section 3, data collections that were part of shared tasks or easily accessible were successfully used by the research community.

Annotation reliability One common method for user-level labeling involves relying on individuals to self-disclose their depression diagnoses. However, this approach is not reliable. Even when annotators manually review posts that contain self-disclosed information, there is no way to verify the authenticity of these disclosures or the accuracy of the users' statements. In addition, for the control group, which includes users who do not mention any depression diagnoses, their actual mental health status remains unknown. We cannot assume that these individuals do not suffer from mental disorders because they have not disclosed this information. It is essential to recognize that relying on self-reported diagnoses for mental health data collection can lead to self-selection bias (Amir et al., 2019). This means that the data obtained may only represent individuals who are willing to openly discuss their mental health issues, which may not accurately reflect the entire population of people with mental disorders.

5 Conclusion and Future Work

We presented a comprehensive and up-to-date overview of datasets used for depression modeling from social media data. We review papers published in international conferences and journals between 2019 and 2024. Due to the research community's efforts to organize shared tasks, the availability of benchmark datasets has increased, offering researchers the resources to build online screening methods for depression and to analyze the depression-related discourse online.

This paper not only aims to offer information about the available datasets for depression manifestation in social media language, but to encourage further interdisciplinary collaboration and exploration. We hope that the comprehensive list of resources provided will inspire researchers, particularly those in the early stages of their careers, to explore this field more deeply. This could lead to a better understanding of depression as expressed in social media and improved interventions.

In this overview, we focused on English datasets, as it is one of the languages that are most used for data collection (Harrigian et al., 2021; Skaik and Inkpen, 2020). However, studying the manifestations of mental health problems in low-resourced languages is an important step toward providing depression screening solutions that can improve the mental health outcomes of people from all around the world (Garg, 2024). In future work, we aim to extend this effort to include social media datasets in languages other than English. Furthermore, we would like to explore the relationship between datasets curated for depression detection and those used in related tasks. This would provide insights on the relationship between depression detection and related social media tasks (Bucur et al., 2021) as well as support multi-task learning efforts (Benton et al., 2017b; Kodati and Tene, 2025).

Limitations

In this paper, we aim to provide a comprehensive overview of the current state of social media data for computational research on depression and present a list of datasets available for researchers in this field. Our study includes 59 data collections, each of which has been carefully reviewed. However, it is possible that we may have overlooked some works that do not explicitly mention depression-related analyses using social media data in their titles or abstracts.

Ethical Considerations

Addressing ethical considerations in mental health research that uses social media data is essential for protecting the privacy, confidentiality, and well-being of individuals whose data is being analyzed (Chancellor and De Choudhury, 2020; Benton et al., 2017a; Chancellor et al., 2019). In this overview, we present the datasets available for studying the manifestations of mental disorders on social media. Although we do not conduct any analyses on the data presented in this work, we want to emphasize that collecting social media data from individuals affected by mental disorders must adhere to ethical research protocols (Benton et al., 2017a). Additionally, researchers who use these datasets should follow the same ethical guidelines and recommendations for health research involving social media.

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6 Appendix

Table 1: List of available datasets for depression modeling using data posted on online platforms. The labels for availability are the following: **FREE** - the dataset is publicly available and hosted online for anyone to access, **AUTH** - the data can be accessed by contacting the paper's authors, **DUA** - the data is available only after a data usage agreement is signed, **UNK** - the dataset availability is unknown; the authors do not mention if the data is available to the research community.

Dataset	Platform	Level	Annotation Procedure	Label	Size	Availab.
Gui et al. (2019)	Twitter	USER	Self-disclosure	Binary	2.8K users	UNK
Chandra Guntuku et al. (2019)	Twitter	USER	BDI	Binary	887 users	UNK
Almouzini et al. (2019)	Twitter	USER, POST	Manual annotation	Binary	89 users	UNK
eRisk2019 (Losada et al., 2019)	Reddit	USER	BDI-II	BDI filled-in	20 users	DUA
Owen et al. (2020)	Twitter	POST	Manual annotation	Binary	1K posts	FREE
Bathina et al. (2021)	Twitter	USER	Self-disclosure	Binary	1.2K users	AUTH
Ríssola et al. (2020)	Reddit	POST	Self-disclosure, heuristics	Binary	14K posts	DUA
Birnbaum et al. (2020)	Facebook	USER	Medical records diagnosis	Binary	223 users	AUTH
D2S (Yadav et al., 2020)	Twitter	POST	PHQ-9	PHQ-9 symptoms	12K posts	AUTH
eRisk 2020 (Losada et al., 2020)	Reddit	USER	BDI-II	BDI filled-in	90 users	DUA
Tabak and Purver (2020)	Twitter	USER	Self-disclosure	Binary	5K users	UNK
Yazdavar et al. (2020)	Twitter	USER	Manual annotation	Binary	8.7K users	DUA
Haque et al. (2021)	Reddit	POST	Subreddit participation	Depression vs. suicide	1.8K posts	FREE
Chiu et al. (2021)	Instagram	USER	Depression-related keywords	Binary	520 users	UNK
Nanomi Arachchige et al. (2021)	Online forums	POST	Manual annotation	Depression severity	2.1K posts	UNK
Sherman et al. (2021)	Reddit	USER	Self-disclosure	Binary	31K users	DUA
eRisk 2021 (Parapar et al., 2021)	Reddit	USER	BDI-II	BDI filled-in	170 users	DUA
Pirayesh et al. (2021)	Twitter	USER	Self-disclosure	Binary	817 users	AUTH
Guo et al. (2021)	Reddit	USER	Self-disclosure	Labels for multiple disorders	7.9 K users	UNK
Zhang et al. (2021)	Twitter	USER	Self-disclosure	Binary	5K users	UNK
Zhou et al. (2021)	Twitter	USER	Self-disclosure	Binary	1.8M posts	UNK
Safa et al. (2022)	Twitter	USER	Self-disclosure	Binary	1.1 K users	AUTH
Naseem et al. (2022)	Reddit	POST	Manual annotation	Depression severity	3.5 K posts	FREE
PsySym (Zhang et al., 2022)	Reddit	USER, POST	Automatic and manual annotation	DSM-5 symptoms for multiple disorders	26K users, 8.5K posts	AUTH
MHB (Boinepelli et al., 2022)	Online forums	USER	Forum participation	Only depression	9.3K users	FREE
CAMS (Garg et al., 2022)	Reddit	POST	Manual annotation	Causes for depression	3.1 K posts	FREE
Sotudeh et al. (2022)	Reddit	POST	Subreddit participation	Summarization	24 k posts	DUA
Sampath and Durairaj (2022)	Reddit	POST	Manual annotation	Depression severity	16K posts	FREE
eRisk2022 (Crestani et al., 2022)	Reddit	USER	Self-disclosure	Binary	3.1K users	DUA
Monreale et al. (2022)	Reddit	POST	Subreddit participation	Labels for multiple disorders	16 K posts	UNK
PRIMATE (Gupta et al., 2022)	Reddit	POST	Manual annotation	PHQ-9 symptoms	2K posts	DUA
PsycheNet-G (Mihov et al., 2022)	Twitter	USER	Self-disclosure	Binary	591 users	UNK
Twitter-STMHD (Singh et al., 2022)	Twitter	USER	Self-disclosure, manual annotation	Labels for multiple disorders	33K users	FREE
multiRedditDep (Uban et al., 2022)	Reddit	USER	Self-disclosure	Binary	3.7K users	AUTH
Davis et al. (2022)	Reddit	USER	Subreddit participation	Binary	81K users	UNK
Fernández-Barrera et al. (2022)	Flickr	POST	Depression tags	Only depression	14.5K posts	UNK
Cha et al. (2022)	Twitter, Everytime	POST	Lexicon-based automatic annotation	Binary	26M posts, 22K posts	AUTH

Dataset	Platform	Level	Annotation Procedure	Label	Size	Availab.
DEPTWEET (Kabir et al., 2023)	Twitter	POST	Manual annotation	Depression severity	40K posts	FREE
Alavijeh et al. (2023)	Twitter	USER	Self-disclosure	Labels for multiple disorders	1.5K users	FREE
Adarsh et al. (2023)	Reddit	POST	Subreddit participation	Binary	60K posts	UNK
Liu et al. (2023a)	Reddit	POST	Subreddit participation	Symptoms	1.3M posts	FREE
BDI-Sen (Pérez et al., 2023b)	Reddit	POST	Manual annotation	BDI-II symptoms	4.9K posts	DUA
Song et al. (2023)	Reddit	POST	Subreddit participation	Labels for multiple disorders	85K posts	UNK
RedditCE (Liang et al., 2023)	Reddit	POST	Manual annotation	Emotion-cause labels	35K posts	FREE
Liu et al. (2023b)	Reddit, Twitter	USER	Self-disclosure	Binary	205K users, 255 users	UNK
RESTORE (Yadav et al., 2023)	Reddit, Twitter, Pinterest	POST	Manual and automatic annotation	PHQ-9 symptoms	9.8K images	AUTH
Zogan et al. (2023)	Twitter	USER	Self-disclosure	Binary	1.4K users	UNK
Wu et al. (2023)	Twitter	USER	Self-disclosure, manual annotation	Binary	10K users	DUA
DepreSym (Pérez et al., 2023a)	Reddit	POST	Manual annotation	BDI-II symptoms	21K posts	DUA
Villa-Pérez et al. (2023)	Twitter	USER	Self-disclosure	Labels for multiple disorders	6K users	DUA
HelaDepDet (Priyadarshana et al., 2023)	Twitter, Reddit	POST	Manual annotation	Depression severity	40K posts	FREE
Anshul et al. (2023)	Twitter	USER	Self-disclosure, Manual annotation	Binary	1.5K users	FREE
RED (Welivita et al., 2023)	Reddit	POST	Subreddit participation	Labels for multiple disorders	1.2M posts	FREE
Alhamed et al. (2024)	Twitter	USER	Manual annotation	Before/After diagnosis	120 users	FREE
Milintsevich et al. (2024)	Reddit	POST	Manual annotation	Anhedonia	167 posts	DUA
MentalHelp (Raihan et al., 2024)	Reddit	POST	Automatic annotation	Binary	14M posts	FREE
Lee et al. (2024)	Reddit	USER	Manual annotation	Binary	1K users	DUA
Beniwal and Saraswat (2024)	Instagram	POST	Manual annotation	Binary	10K posts	AUTH
Tumaliuan et al. (2024)	Twitter	USER	PHQ-9	Binary	72 users	AUTH