A Survey on Multilingual Mental Disorders Detection from Social Media Data

Ana-Maria Bucur[1,2,3], Marcos Zampieri[4], Tharindu Ranasinghe[5], Fabio Crestani[1]
[1]Università della Svizzera italiana, Switzerland
[2]Interdisciplinary School of Doctoral Studies, University of Bucharest, Romania
[3]PRHLT Research Center, Universitat Politècnica de València, Spain
[4]George Mason University, USA [5]Lancaster University, UK
ana-maria.bucur-cosma@usi.ch

Abstract

The increasing prevalence of mental disorders globally highlights the urgent need for effective digital screening methods that can be used in multilingual contexts. Most existing studies, however, focus on English data, overlooking critical mental health signals that may be present in non-English texts. To address this gap, we present a survey of the detection of mental disorders using social media data beyond the English language. We compile a comprehensive list of 108 datasets spanning 25 languages that can be used for developing NLP models for mental health screening. In addition, we discuss the cultural nuances that influence online language patterns and self-disclosure behaviors, and how these factors can impact the performance of NLP tools. Our survey highlights major challenges, including the scarcity of resources for low- and mid-resource languages and the dominance of depression-focused data over other disorders. By identifying these gaps, we advocate for interdisciplinary collaborations and the development of multilingual benchmarks to enhance mental health screening worldwide.

1 Introduction

Nearly half of the global population risks developing at least one mental disorder by age 75 (McGrath et al., 2023). Many individuals avoid seeking help due to stigma, which varies across cultures and is shaped by cultural norms, religious beliefs, and social attitudes (Ahad et al., 2023). Due to several challenges, including the stigma surrounding mental health, limited access in certain areas, economic factors, and a high global demand for services, the World Health Organization advocates for improved delivery of mental health services, including digital technologies to deliver remote care.[1] Furthermore, integrating remote screening tools and culturally adapted digital interventions is crucial (Bond et al., 2023), as remote screening can detect language patterns linked to mental disorders from short essays (Rude et al., 2004), text messages (Nobles et al., 2018), or social media (Eichstaedt et al., 2018). However, developing effective screening tools for mental disorders heavily relies on the availability of data. Therefore, in this work, we present the datasets that can be used to train models for screening in languages other than English.

The first well-known study on the detection of mental disorders using social media was conducted by De Choudhury et al. (2013). Subsequent research has shown that the language used on Facebook can predict future depression diagnoses found in medical records, indicating that social media data could serve as a valuable complement to depression screening (Eichstaedt et al., 2018). Methods used for social media screening focus mainly on English data (Skaik and Inkpen, 2020; Harrigian et al., 2021), and workshops and shared tasks addressing NLP applications to mental health, such as eRisk (Parapar et al., 2024; Crestani et al., 2022), CLPsych (Chim et al., 2024) and LT-EDI (Kayalvizhi et al., 2023) also primarily use English data.

Current NLP models face major limitations in mental disorders detection in languages other than English. Studies show that cultural differences shape how mental disorders are expressed in language (De Choudhury et al., 2017; Aguirre and Dredze, 2021; Rai et al., 2024), which means that markers predictive in English often do not generalize well across different cultures (Aguirre et al., 2021; Abdelkadir et al., 2024). Even one of the best predictors of depression in language, the use of the first person pronoun “I” (Rude et al., 2004), for example, has different degrees of association with the severity of depression across different demographic groups (Rai et al., 2024). This suggests that markers of mental disorders in language are

[1]https://www.who.int/news/item/17-06-2022-who-highlights-urgent-need-to-transform-mental-health-and-mental-health-care

Proceedings of the 19th Conference of the European Chapter of the Association for Computational Linguistics
Volume 1: Long Papers, pages 893–918
March 24-29, 2026 ©2026 Association for Computational Linguistics

not universal. In addition, self-disclosure rates vary across cultures; collectivist cultures tend to exhibit lower self-disclosure rates than individualist cultures in online settings (Tokunaga, 2009). Furthermore, non-native English speakers tend to use their native language for more intimate self-disclosures on social media, with higher rates of negative disclosure compared to posts in English (Tang et al., 2011). This could have substantial implications for English-based social media screening tools, as they may overlook signals of mental disorders that are present in posts written in languages other than English.

Recently, there have been efforts to develop detection models that focus on languages other than English, such as Portuguese (Santos et al., 2024), German (Zanwar et al., 2023), Arabic (Almouzini et al., 2019), and Chinese (Zhu et al., 2024). There have also been shared tasks specifically designed to address these issues, such as MentalRiskES (Mármol-Romero et al., 2025), which focuses on the early detection of depression, suicide, and eating disorders in Spanish. To further contribute to these important efforts, we present the first survey on the detection of mental disorders from social media data beyond English. This survey aims to promote the development of multilingual NLP models that account for cross-cultural and cross-linguistic differences in online language.

This paper makes the following contributions:

1. We provide a comprehensive list of multilingual mental health datasets that capture linguistic diversity and can be used for developing multilingual NLP models.[2]

2. We discuss cross-cultural and cross-language differences in the manifestations of mental disorders in social media.

3. We identify and describe several research gaps and future directions in the detection of mental disorders using online data beyond English.

2 Related Surveys

In this section, we analyze related surveys on the analysis of mental disorders from social media data. Calvo et al. (2017) is considered one of the first comprehensive surveys, presenting the datasets and NLP techniques used for mental health status detection and intervention. The survey explores research on various mental health conditions and states, including depression, mood disorders, psychological distress, and suicidal ideation, specifically in non-clinical texts such as user-generated content from social media and online forums. Similarly, recent surveys (Skaik and Inkpen, 2020; Harrigian et al., 2021; Ríssola et al., 2021; Zhang et al., 2022; Garg, 2023; Bucur et al., 2025a,b) present the datasets, features, and models used to detect mental disorders from online content, with a primary focus on English language data. Dhelim et al. (2023) and Bucur et al. (2025b) focus on studies that were published during the COVID-19 pandemic that address mental well-being, loneliness, anxiety, stress, PTSD, depression, suicide, and other mental disorders. In addition to these surveys, Chancellor and De Choudhury (2020) provides a critical review of the study design and methods used to predict mental health status, along with recommendations to improve research in this field.

Our paper fills an important gap in the literature by offering the first comprehensive survey of research on detecting mental disorders in languages other than English. The most related survey to ours is the one conducted by Garg (2024), which focuses solely on low-resource languages and only discusses datasets in Thai, Bengali, Hindi, Japanese, and Korean. In contrast, our survey has a broader scope, covering research on a variety of languages, regardless of their resource availability. Our work complements previous surveys by providing an important data-centric foundation for researchers seeking to deploy and validate NLP methods in non-English contexts.

3 Mental Disorders Detection Tasks Overview

In this section, we discuss common tasks related to predicting mental disorders, emphasizing research available in non-English languages where applicable. The prediction of mental disorders via social media typically involves a supervised *binary classification* task, in which online posts are used to determine the presence or absence of disorders (Figure 1). This can be performed at the post level for predicting suicidal ideation (Huang et al., 2019) and depression (Uddin et al., 2019; Bucur et al., 2023), or at the user level for conditions like depression (Hiraga, 2017), anxiety (Zarate

[2]We make the list publicly available, and we will continuously update it: https://github.com/bucuram/multilingual-mental-health-datasets-nlp

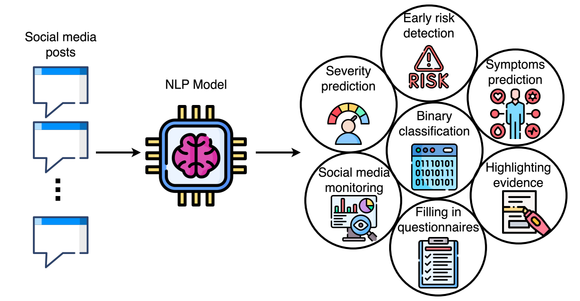

Figure 1: Overview of tasks related to detecting mental health problems from social media.

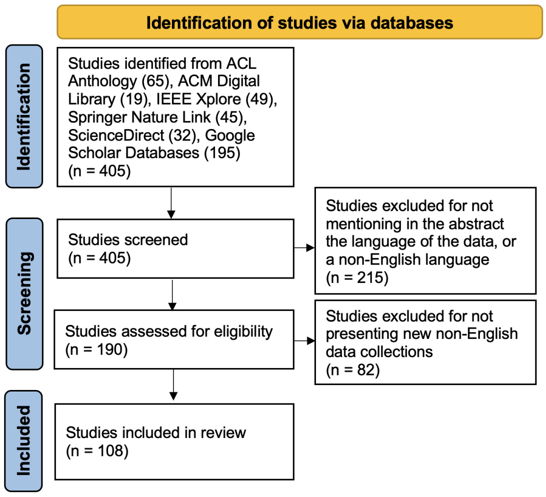

Figure 2: PRISMA flow diagram for our survey.

et al., 2023), and bipolar disorder (Sekulić et al., 2018). User-level prediction can serve as an *early risk prediction task*, facilitating timely assessments (Losada and Crestani, 2016; Bucur et al., 2021; Mármol-Romero et al., 2023). *Severity prediction* assesses the intensity of conditions such as depression (Naseem et al., 2022; Kabir et al., 2023; Sampath and Durairaj, 2022) or suicide risk (Benjachairat et al., 2024). Longitudinal analysis of social media helps detect *moments of change* in mental health (Tsakalidis et al., 2022). Other tasks focus on *symptom prediction* (Liu et al., 2023; Yadav et al., 2020) and *highlighting evidence* for mental health problems (Chim et al., 2024; Varadarajan et al., 2024). Mental health indicators from the social media timeline of an individual can be used to *fill in validated questionnaires*, with the goal of estimating symptoms of mental disorders that are usually assessed through survey-based methods such as BDI-II[3] for depression assessment (Parapar et al., 2021) or EDE-Q[4] for eating disorders (Parapar et al., 2024). Lastly, *mental health monitoring* uses aggregated detection results to estimate the prevalence of disorders, as demonstrated during the COVID-19 pandemic (Cohrdes et al., 2021).

Shared tasks have encouraged interdisciplinary collaborations between psychologists and computer scientists. English-based shared tasks, such as eRisk (Parapar et al., 2024), CLPsych (Coppersmith et al., 2015), and LT-EDI (Kayalvizhi et al., 2023) provided valuable benchmark datasets that the research community continues to use, even beyond the official competitions. MentalRiskES[5] (Mármol-Romero et al., 2025) is the only shared task focused on detecting mental disorders in languages other than English. MentalRiskES includes tasks such as the detection of depression, anxiety, eating disorders, and suicidal risk in the Spanish language (Mármol-Romero et al., 2023).

4 Methodology

Our primary objective is to catalog the available non-English resources derived from social media for the detection of mental disorders. We conducted a systematic search on major publication databases, including ACL Anthology, ACM Digital Library, IEEE Xplore, Springer Nature Link, ScienceDirect, and Google Scholar. Initially, 405 studies were identified through database searches. After screening the abstracts, 215 papers were excluded because they did not mention the language of the data or mention that the data was in English. Thus, following a review of the main body of the papers, the number of eligible studies was narrowed down to 108, which represents the final count of papers included in this survey. Papers that did not present new data collections in languages other than English were excluded during the screening process. The PRISMA flow diagram is presented in Figure 2. The search terms used in our survey are provided in the Appendix A.

5 Multilingual Datasets

In this section, we outline the datasets included in the current survey. The languages most frequently represented in these data collections are three high-resource languages: Chinese, Arabic, and Spanish. Although approximately half of the datasets were published in unranked venues, which diminishes

[3]https://naviauxlab.ucsd.edu/wp-content/uploads/2020/09/BDI21.pdf
[4]https://www.corc.uk.net/media/1273/ede-q_quesionnaire.pdf
[5]https://sites.google.com/view/mentalriskes2025

Language	Resource	Datasets
Arabic	High	Almouzini et al. (2019); Alghamdi et al. (2020); Alabdulkreem (2021); Musleh et al. (2022), CairoDep (El-Ramly et al., 2021), Almars (2022); Maghraby and Ali (2022); Baghdadi et al. (2022), Arabic Dep 10,000 (Helmy et al., 2024), Al-Haider et al. (2024); Abdulsalam et al. (2024); Al-Musallam and Al-Abdullatif (2022)
Chinese	High	Zhang et al. (2014); Huang et al. (2015); Cheng et al. (2017); Shen et al. (2018); Wu et al. (2018); Cao et al. (2019); Wang et al. (2019); Peng et al. (2019); Huang et al. (2019); Li et al. (2020), WU3D (Wang et al., 2020), Yao et al. (2020); Yang et al. (2021); Chiu et al. (2021); Sun et al. (2022); Cai et al. (2023); Li et al. (2023); Guo et al. (2023); Wu et al. (2023); Lyu et al. (2023); Yu et al. (2023); Zhu et al. (2024)
French	High	Tabak and Purver (2020)
German	High	Cohrdes et al. (2021); Baskal et al. (2022); Tabak and Purver (2020), SMHD-GER (Zanwar et al., 2023)
Japanese	High	Tsugawa et al. (2015); Hiraga (2017); Niimi (2021); Cha et al. (2022); Wang et al. (2023)
Spanish	High	Leis et al. (2019), SAD (López-Úbeda et al., 2019), Valeriano et al. (2020); Ramírez-Cifuentes et al. (2020, 2021); Villa-Pérez et al. (2023), MentalRiskES (Romero et al., 2024), Cremades et al. (2017); Coello-Guilarte et al. (2019)
Brazilian Portuguese	Mid to High	von Sperling and Ladeira (2019); Mann et al. (2020); Santos et al. (2020); de Carvalho et al. (2020), SetembroBR (Santos et al., 2024), Mendes and Caseli (2024); Oliveira et al. (2024)
Dutch	Mid to High	Desmet and Hoste (2014, 2018)
Code-Mixed Hindi-English	Mid to High	Agarwal and Dhingra (2021)
Italian	Mid to High	Tabak and Purver (2020)
Korean	Mid to High	Lee et al. (2020); Park et al. (2020); Kim et al. (2022b,a); Cha et al. (2022)
Polish	Mid to High	Wołk et al. (2021)
Russian	Mid to High	Stankevich et al. (2019); Baskal et al. (2022); Narynov et al. (2020); Stankevich et al. (2020); Ignatiev et al. (2022)
Turkish	Mid to High	Baskal et al. (2022)
Bengali	Mid	Uddin et al. (2019); Victor et al. (2020); Kabir et al. (2022); Tasnim et al. (2022), BanglaSPD (Islam et al., 2022), Ghosh et al. (2023); Hoque and Salma (2023), BSMDD (Chowdhury et al., 2024)
Indonesian	Mid	Oyong et al. (2018); Yoshua and Maharani (2024)
Filipino	Mid	Tumaliuan et al. (2024); Astoveza et al. (2018)
Greek	Mid	Stamou et al. (2024)
Hebrew	Mid	Hacohen-Kerner et al. (2022)
Roman Urdu	Mid	Rehmani et al. (2024); Mohmand et al. (2024)
Thai	Mid	Katchapakirin et al. (2018); Hemtanon and Kittiphattanabawon (2019); Kumnunt and Sornil (2020); Hemtanon et al. (2020); Wongaptikaseree et al. (2020); Hämäläinen et al. (2021); Mahasiriakalayot et al. (2022); Boonyarat et al. (2024); Benjachairat et al. (2024)
Cantonese	Low	Gao et al. (2019)
Norwegian	Low	Uddin et al. (2022); Uddin (2022)
Sinhala	Low*	Rathnayake and Arachchige (2021), EmoMent (Atapattu et al., 2022), Herath and Wijayasiriwardhane (2024)

*The classification of Sinhala is based on the work of Ranathunga and de Silva (2022), who identified the miscategorization of Sinhala in Joshi et al. (2020)'s classification.

Table 1: Datasets for detecting mental disorders in languages other than English included in the current survey. The availability of resources is based on Joshi et al. (2020).

their visibility, the other half were published in high-ranking journals and conferences (Figure 4 in Appendix A.

5.1 Data Sources

Most of the datasets in English are sourced from Twitter[6] and Reddit (Harrigian et al., 2021). Most non-English datasets in this section were also primarily collected from Twitter. However, Reddit was not as widely used for these data collections in non-English contexts. The data presented in this survey come from various populations and regions, and some of the sources are platforms that are exclusive to specific countries, such as Sina Weibo[7] used in China, VKontakte[8] used in Russia, Pantip[9] in Thailand, or Everytime[10] in Korea. Complete information about the sources of the data is presented in Table 2 in Appendix A.

The way individuals use social media platforms to share information about themselves varies not only by platform but also by culture. Twitter provides community and safety, helping raise awareness and combat stigma around mental health (Berry et al., 2017). In contrast, Reddit allows for greater anonymity with "throwaway" accounts, encouraging users to openly share their experiences in detailed posts on specific subreddits (De Choudhury and De, 2014). This longer format supports post-level mental health analysis (Chowdhury et al., 2024), while Twitter's shorter posts favor user-level insights, requiring longitudinal data to identify language patterns (Tumaliuan et al., 2024). Moreover, even when individuals come from the same cultural

[6]All the datasets were collected before Twitter changed its name to X, so we refer to it as 'Twitter' in this paper.

[7]https://weibo.com

[8]https://vk.com/

[9]https://pantip.com/

[10]https://everytime.kr/

background and speak the same language, the topics they choose to discuss are heavily influenced by the platform they use. For example, on Sina Weibo, users primarily talk about popular culture, while on Twitter, conversations in Chinese revolve more around politics (Zhang and Gonçalves, 2016). These differences, potentially shaped by platform governance and censorship, have direct implications for mental health data collection, as they influence the visibility, framing, and prevalence of mental health-related discourse across different platforms.

5.2 Languages

Table 1 presents all the datasets included in this survey. To classify the availability of resource types, we used the framework proposed by Joshi et al. (2020), which categorizes resources into six classes (from Rare to High) based on the availability of both labeled and unlabeled NLP data. The languages most frequently represented in the data collections are high-resource languages: Chinese appears in 25 data collections, Arabic is found in 11 datasets, and Spanish is included in 10 datasets. Even if most of the languages covered in the data are from high-, mid to high- and mid-resourced languages, we also have some languages with fewer resources, such as Cantonese, Norwegian and Sinhala. Most of the languages used in the data collections belong to some of the largest language families by number of speakers, specifically the Indo-European, Sino-Tibetan, and Afro-Asiatic language families. When analyzing the language resources based on speaker population and vitality according to Ethnologue (Eberhard et al., 2023), we find that all the languages listed in Table 1 are categorized as large-institutional. This classification indicates that these languages are supported and maintained by institutions beyond their respective communities and have a large number of speakers. The categorization of all listed languages as large-institutional by Ethnologue underscores a robust support system that enhances their viability in NLP applications. However, it also highlights the urgent need to address disparities in resource availability for less-represented languages, promoting inclusivity in NLP research.

5.3 Mental Disorders

Figure 3 shows the distribution of mental disorders in different languages within the datasets. Depression is the most common mental disorder and

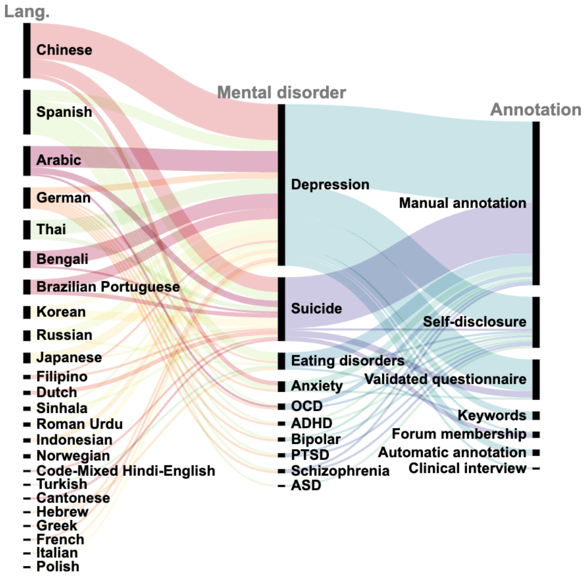

Figure 3: Overview of the mental disorders addressed in each dataset, along with the annotation procedures.

is well-represented in the data. The languages that lack data on depression are Cantonese, Dutch, Hebrew, Hindi, and Turkish. Suicide is another mental disorder that frequently appears in collections. In contrast, the mental health problems that are least represented include eating disorders, obsessive-compulsive disorder (OCD), attention deficit / hyperactivity disorder (ADHD), autism spectrum disorder (ASD), anxiety, bipolar disorder, and schizophrenia. (Hazell et al., 2022)

5.4 Annotation Procedure

Most data collections were manually annotated (Figure 3). Manual annotation was carried out by mental health experts or psychologists (Narynov et al., 2020; de Oliveira et al., 2022), graduate students who are native speakers of the language of interest (Boonyarat et al., 2024; Uddin et al., 2019), or nonexpert individuals. However, some datasets do not specify who the annotators were or what guidelines they followed during the annotation process. Most datasets that collect user-level data from online platforms rely on the self-disclosure of mental health statuses. For example, they rely on explicit mentions of diagnoses (e.g. "I was diagnosed with depression") (Tabak and Purver, 2020; Villa-Pérez et al., 2023). The third most common annotation method involves asking social media users to complete validated questionnaires to diagnose mental disorders. The most frequently used survey-based methods include the CES-D (Tsugawa et al., 2015; Lyu et al., 2023), BDI-II (Sun et al., 2022; Stankevich et al., 2019; Ignatiev et al., 2022) or tools specifically designed for certain populations, such as the Thai Mental Health Questionnaire (TMHQ) (Katchapakirin et al., 2018). Another reliable annotation approach is conducting clinical interviews to assess mental health problems (Wołk et al., 2021). Less common and noisier annotation methods include identifying posts based on the presence of specific keywords (López-Úbeda et al., 2019), by forum membership (Agarwal and Dhingra, 2021), or automatic annotation through another model trained on mental health data (Cohrdes et al., 2021).

Manual annotation and annotation based on self-disclosure of diagnosis rely on individuals' willingness to disclose personal information on social media. Research shows that collectivist cultures tend to have lower rates of self-disclosure compared to individualist cultures in online contexts (Tokunaga, 2009). However, there are notable differences within these cultures. For example, although Koreans are less likely to share personal information, they often provide more in-depth disclosures compared to individuals in the United States (Yoo, 2012). In addition, self-disclosure annotation relies on individuals explicitly naming their conditions, which may not occur in cultures where mental health is stigmatized. These annotation choices can have significant consequences for model behavior, potentially resulting in systematic false negatives for populations whose expressions of distress do not align with dominant annotation frameworks.

5.5 Availability of Data Collections

Out of the 108 datasets listed in Table 1, only 23 are publicly available for download without restrictions. This is not surprising, as mental health datasets are often subject to privacy, ethical, and legal concerns, unlike many other NLP domains. These open datasets focus on the detection of depression, suicide, or anorexia in various languages, including Arabic, Bengali, Brazilian Portuguese, Chinese, Hebrew, Hindi, Spanish, Russian, Roman Urdu, and Thai. For 15 of the datasets, access can be obtained by contacting the authors of the respective research papers, while four datasets require users to complete a data agreement to gain access. In addition, four datasets are unavailable due to the sensitive nature of the data. For the remaining datasets, the research papers do not provide any information on data availability. Details about the availability of data collections can be found in Appendix A, Table 2.

6 Mental Disorders Detection Approaches

In this section, we present the methods proposed for the datasets in Section 5. Most approaches are monolingual and specifically target only one non-English language. In Appendix A, Table 2, we include detailed information on the methods used and evaluation scores for all the datasets.

Classical Monolingual Approaches Most approaches rely on feature-based text representations such as Bag-of-Words, TF-IDF, and Word2Vec, combined with traditional classifiers like SVM, Logistic Regression (Almouzini et al., 2019; Alghamdi et al., 2020; Helmy et al., 2024) or deep learning models (Mann et al., 2020; Tasnim et al., 2022; Ghosh et al., 2023). These methods are straightforward and can be adapted to any language, making them suitable for the detection task.

Monolingual pre-trained models With the rise of large pre-trained transformers, language-specific models such as Chinese BERT (Yao, 2024), AraBERT (Abdulsalam et al., 2024), German BERT (Zanwar et al., 2023), Bangla BERT (Chowdhury et al., 2024), BERTimbau (Santos et al., 2024), IndicBERT (Agarwal and Dhingra, 2021) are being used for detecting mental disorders. However, a significant limitation of these pre-trained transformer-based models is that they are available only for a limited number of high- and mid-resource languages, rendering them impractical for use with low-resource languages.

Multilingual models Methods developed for multiple languages simultaneously are rare. Some approaches use cross-lingual embeddings and leverage information from languages with more extensive mental health-related resources, such as English, to make predictions on Spanish data (Coello-Guilarte et al., 2019). Lee et al. (2020) developed a cross-lingual model for suicidal ideation by translating data from Korean to English and Chinese. Although multilingual pre-trained models like XLM-Roberta and Multilingual BERT are frequently used, they often perform worse than language-specific models, such as BERTimbau and HeBERT (Oliveira et al., 2024; Hacohen-Kerner et al., 2022). This discrepancy suggests that adapting models to specific cultural and linguistic contexts is often more effective than relying solely on general multilingual pre-training. Consequently, relying on a single model for multiple languages can increase the likelihood of errors.

Translation-based Zahran et al. (2025) conducted a comprehensive evaluation of LLMs on Arabic data related to depression, suicidal ideation, anxiety, and other mental disorders. The authors showed that LLMs performed better on original Arabic datasets than on data that had been translated into English. Some studies also use data translated from the target language to English (Vajrobol et al., 2023). When developing mental health models in languages other than English, certain studies use translations from English to the target language, as seen with Greek (Skianis et al., 2024) and various Indian languages (Rajderkar and Bhat, 2024). However, Schoene et al. (2025) has shown that automatically translating suicide-related dictionaries from English to low-resource languages often results in spelling errors and fails to capture the cultural nuances of speakers in the target language.

LLMs While LLMs have been successfully used in mental health tasks in English (Wang et al., 2024b; Shah et al., 2025), research for other languages is limited. For instance, Zahran et al. (2025) evaluated LLMs on Arabic data and found that slight changes in instructions could harm performance, leading to parsing errors and prompt adherence issues. There are also concerns about increased hallucinations (Lauscher et al., 2025) and unsafe responses (Wang et al., 2024b) in languages other than English. Consequently, the use of LLMs in mental health tasks for non-English languages should be approached with caution.

Performance across different languages As mentioned in Section 3, the detection of mental disorders is primarily approached as a classification task and evaluated using standard metrics such as Accuracy, Precision, Recall, and F1-score. Detailed performance scores can be found in Table 2 in Appendix A. The availability of resources has a significant impact on the performance of supervised or pre-trained language models. High-resource languages, such as Japanese, Chinese, and Arabic, generally yield strong results, indicating that larger and well-annotated datasets contribute to more reliable detection. In contrast, some languages, such as Sinhala, Brazilian Portuguese, and Bengali, show highly variable performance when comparing the detection of depression and suicidal ideation. For other languages included in this survey, such as French, German, Russian, and Italian, the performance in detecting depression is relatively low. Current methods demonstrate unequal effectiveness, which may leave speakers of certain languages without appropriate mental health screening tools. The success of these models is influenced by factors such as language-specific methodologies, the quality of datasets, the availability of resources, and cultural differences in expression. In addition, performance may vary depending on whether the task is binary classification, multiclass classification, or regression. Performance can also vary depending on whether the prediction is based on a single post (post-level classification) or multiple posts from the same user (user-level classification).

7 Cross-cultural and Cross-language Differences in Mental Health Expression

Culture influences the sources of distress, how it is expressed, how it is interpreted, the process of seeking help, and the responses of others (Kirmayer et al., 2001). In addition, the way people perceive themselves influences their mental health. In Western cultures, there is a strong emphasis on personal narratives, and people tend to express their emotions more openly, a trend that is reflected in online posts (Tokunaga, 2009). In contrast, in Asian societies, individuals often internalize their emotional struggles or express them indirectly, influenced by their collectivist values (Hu et al., 2014). Although negative self-thoughts are a common characteristic of depression, in East Asian contexts, self-criticism is often viewed as a sign of healthy functioning (Gotlib and Hammen, 2008).

Symptoms of mental disorders Cultural differences in the interpretation of mental health symptoms can lead some individuals to minimize psychological distress, often reporting socially acceptable somatic symptoms such as body pain or fatigue (Kirmayer et al., 2001). While somatic symptoms are common across cultures, their expression and understanding can vary. Culturally specific idioms of distress, such as ”nervios”[11] in Latin American communities, illustrate this, as they encompass both psychological and somatic symptoms and show a high comorbidity with anxiety

[11]Translated as “nerves” in English.

and mood disorders (De Snyder et al., 2000). The DSM-V (APA, 2013) includes cultural concepts of distress to aid clinicians in recognizing diverse expressions of psychological issues. In addition, Rai et al. (2025) found that Indian social media users on Reddit are more focused on seeking help than on discussing their symptoms or diagnoses.

Mental health expressions in online language Online expression varies between cultures and has been extensively studied among English-speaking individuals from different regions (De Choudhury et al., 2017; Aguirre and Dredze, 2021; Rai et al., 2024). When analyzing data from a peer-support mental health community, Loveys et al. (2018) found that manifestations of negative emotions differ between demographic groups. Moreover, Pendse et al. (2019) found that users in the US, UK, and Canada employed more clinical language to express mental distress compared to users from India, Malaysia, and the Philippines.

Variation of features across cultures The tendency for self-focused attention, often referred to as "I"-language, is considered one of the strongest predictors of depression in language (Mihalcea et al., 2024). As a result, the frequency of the pronoun "I" has been used in previous studies as a feature for detecting depression in English. However, it is crucial to carefully consider the applicability of this marker to non-English languages. This association has not been observed in non-Western individuals (Rai et al., 2024) or in speakers of Chinese (Lyu et al., 2023) or Romanian (Trifu et al., 2024). While the pronoun "I" serves as an indicator of depression in English, its usage in other languages requires special attention due to linguistic differences. For example, English requires nouns or pronouns to be explicitly included as subjects in sentences. In contrast, some languages, such as Chinese and Romanian, are pro-drop languages, which allow the subject of the action to be omitted (Koeneman and Zeijlstra, 2019), resulting in a lower frequency of the personal pronoun "I" in these languages.

Mental health metaphors Indicators of mental disorders are often displayed through metaphors. Depression is often described as weight, pressure, or darkness, and is often portrayed using containment metaphors (Charteris-Black, 2012). Metaphors are used by individuals to articulate their experiences, and psychologists use them in the therapeutic process (Mould et al., 2010). Mental illness metaphors have been extensively studied in English (Charteris-Black, 2012; Lazard et al., 2016) and have been used to predict mental states (Shi et al., 2021; Zhang et al., 2021). With the exception of research in Spanish (Coll-Florit and Climent, 2023), there is a lack of resources to understand metaphors of mental illness beyond English.

Considering cultural and multilingual differences is crucial when developing automated methods for predicting mental disorders based on language. These variations may explain the failure of many predictive models to generalize effectively (Aguirre et al., 2021; Abdelkadir et al., 2024).

8 Research Gaps

In this section, we highlight several research gaps that we hope will be explored in future studies.

Linguistic features used in English do not transfer reliably across languages Many commonly used linguistic markers of mental disorders, such as the use of first-person singular pronouns or sentiment polarity, are often considered universal features. However, these markers are actually dependent on language and shaped by cultural contexts, as previous research has indicated (Trifan et al., 2020; Rai et al., 2024). While many studies have investigated markers of depression in language across cultures, most have focused primarily on individuals from various cultures who communicate in English (Aguirre et al., 2021; Abdelkadir et al., 2024; Rai et al., 2025). There is a significant lack of research on how cross-cultural factors influence the expression of mental disorders in individuals' native languages on social media, as well as how these factors affect the identification of such disorders.

Lack of mental health-related data for low-resource languages As presented in Section 5, most datasets are often from mid- and high-resourced languages, with the exception of Cantonese, Norwegian, and Sinhala. Currently, many languages remain underrepresented, including high-resource languages like French and mid-to-high-resource languages such as Finnish, Croatian, and Vietnamese. Moreover, there is a lack of datasets in low-resource languages, which may hinder the development of online screening tools for individuals who speak these languages. While some studies have attempted to use automatic translation to build datasets in languages other than English, this approach often fails to accurately capture the cultural nuances of native speakers of the target language (Schoene et al., 2025).

Multilingual approaches As highlighted in Section 6, most NLP approaches have focused on processing data in a single target language, with multilingual approaches being almost nonexistent. Most existing NLP models developed for mental disorders detection do not support multiple languages effectively, which limits their applicability in multicultural and multilingual settings where mental health issues may manifest differently. While multilingual and cross-lingual approaches are often proposed as solutions to data scarcity, generalizability failures may stem not only from resource limitations but also from unmodeled cultural variation.

Annotation transparency and consistency Although most of the datasets presented in this paper rely on manual annotation for labeling the data related to mental disorders, it is often unclear who performed the annotations. The authors of the research papers should provide specific details about the annotation process, such as whether the annotators are mental health experts or non-experts, if they are native speakers of the target language, and whether they understand the cultural differences in the manifestations of mental disorders. These factors significantly impact the quality and reliability of the data, as understanding cultural nuances is essential in interpreting mental health expressions. For annotations based on questionnaires, it is crucial to use validated questionnaires specific to the target language rather than general English versions. Previous research has demonstrated that incorporating information about cultural idioms of distress in psychological assessments for mental disorders can enhance their validity (Cork et al., 2019). Therefore, such considerations should also be integrated into the annotation process for mental disorders across cultures.

Explainability While many mental health studies in English emphasize the importance of explainable approaches (Yang et al., 2023; Souto et al., 2023; Yang et al., 2024), there is a significant opportunity for applying explainable approaches to non-English languages. This could enhance our understanding of how mental disorders manifest culturally in social media language and provide insights into the diverse expressions of mental disorders. Currently, few studies have examined model explainability in Bengali (Ghosh et al., 2023) and Thai (Vajrobol et al., 2023).

9 Conclusion

In this paper, we presented a comprehensive survey of research for mental disorders detection in social media data beyond English. We highlight cross-cultural and multilingual differences in mental health expressions and provide a comprehensive list of datasets that can be used to develop multilingual NLP models for online mental health screening. Our focus was on non-English resources, as most previous research has focused on English (Skaik and Inkpen, 2020; Harrigian et al., 2021). Lastly, we identified several gaps in current research that we hope will be addressed in future interdisciplinary studies.

Future Directions and Calls to Action We aim to encourage researchers to develop mental health datasets in languages other than English, fostering interdisciplinary collaborations with experts from psychology and mental health organizations, as seen in successful previous projects like REMO COST Action[12], and PsyMine (Ellendorff et al., 2016), which have primarily focused on English. By involving community members, multilingual shared tasks can be organized to identify mental disorders across different languages, inspired by successful SemEval multilingual tasks for offensive language (Zampieri et al., 2020) and emotion detection (Muhammad et al., 2025a,b). Researchers can work together to annotate data in underrepresented languages while adhering to ethical protocols. By participating in these tasks, members of the ACL community can gain access to datasets that are essential for developing multilingual models. Such initiatives will improve the visibility of multilingual mental disorder detection and encourage further collaborations, providing researchers with more opportunities to address challenges in this field. Researchers can focus on building datasets for underrepresented mental disorders beyond depression, adhering to ethical guidelines and providing transparency in the annotation process (Benton et al., 2017). Recent advances in explainability can also be applied to better understand the cultural manifestations of mental disorders.

[12]https://projects.tib.eu/remo

Limitations

Our paper aims to provide a comprehensive survey of cross-cultural language differences and the datasets available for developing multilingual NLP models. We included 108 data collections in this study and carefully reviewed each paper cited in our survey. However, it is possible that we may have overlooked some works that do not explicitly mention in their title or abstract that they focus on languages other than English.

Ethical Considerations

Data Collection We recognize that using online data to identify mental disorders is a promising approach for early screening, but it also presents several ethical challenges (Benton et al., 2017; Chancellor and De Choudhury, 2020). To ensure that research protocols in this area comply with ethical guidelines, researchers must take the following steps: (1) obtain Institutional Review Board (IRB) approval, (2) follow ethical research protocols to protect sensitive data, as outlined by Benton et al. (2017), (3) obtain consent from participants, (4) de-anonymize the data and store it on a secure server. Any further sharing of the data with other researchers must adhere to the same ethical protocols. From our survey of 108 datasets, we found that only 18 received ethical approval from an IRB. In addition, 19 papers indicated that they anonymized the data to protect user privacy. It is concerning that only about 35% of the papers adhered to ethical practices in their research, highlighting the urgent need for a greater emphasis on ethical standards, especially since ethical disclosures were expected to gradually increase over time (Ajmani et al., 2023).

Potential Consequences Moreover, the ethical implications extend beyond data collection and storage. Researchers should consider the potential consequences of their findings on the populations studied and ensure that their work does not inadvertently stigmatize or harm individuals with mental health disorders. Incorrect predictions can have harmful effects on individuals' lives. For instance, if a system falsely predicts that someone shows signs of mental disorders, it can adversely impact their well-being due to the stigma associated with such labels. This may lead individuals to believe there is something wrong with them, ultimately lowering their self-esteem (Chancellor et al., 2019b). A false negative prediction occurs when the system fails to identify significant signs of distress, preventing the individual from receiving the necessary treatment or interventions. False negative predictions are particularly critical in cases of suicidal ideation, where a person's life may be at risk. Chancellor et al. (2019a) critically discuss how subjects are represented in this area of research, highlighting the risk of inadvertently dehumanizing individuals. The language used in mental health-related papers can unintentionally perpetuate stigma, often referring to those involved in data collection as "sufferers" of mental disorders while labeling others as "normal." Engaging with the community and stakeholders during the research process can help mitigate these risks and foster a more responsible approach to using online data in mental health research (Chancellor et al., 2019b).

Model Validity There are ongoing concerns regarding the construct validity of models trained on data collected from social media, specifically whether these models effectively measure the manifestations of mental disorders (Chancellor and De Choudhury, 2020). The datasets used in this survey predominantly rely on manual annotation or labeling through validated questionnaires, which are considered more reliable methods for annotation. However, it is essential to conduct interdisciplinary research and ground the constructs being measured in both theoretical and clinical frameworks. For example, clinical depression (or major depressive disorder) is fundamentally different from merely "feeling depressed." The latter may refer to temporary feelings, while clinical depression encompasses a range of persistent symptoms. These symptoms may include depressed mood, loss of interest in previously enjoyed activities, changes in body weight, sleep disturbances, fatigue, psychomotor agitation or retardation, feelings of guilt, and thoughts of death or suicidal ideation (APA, 2013). To be diagnosed with depression, these symptoms must be persistent and significantly impair an individual's ability to function. Prioritizing interdisciplinary collaboration and rigorous validation methods is essential in addressing the complexities of mental health.

Representativeness It is important to note that individuals active on social media represent only a subset of the overall population. As a result, there may be differences in how mental disorders are expressed among social media users compared to the general population. Using social media data can introduce bias, as it tends to reflect the experiences of younger and more technologically literate individuals who are more likely to engage with these platforms (Chancellor et al., 2019b). In addition, datasets that include self-disclosure of a mental health diagnosis often come from individuals who are more likely to have sought professional help for their diagnosis and/or treatment. Furthermore, not everyone feels comfortable sharing sensitive information about their mental health online (Chancellor et al., 2019b).

Cultural and Linguistic Variation Understanding cultural and linguistic variations is crucial when developing automated methods for predicting mental disorders, as they help explain why many predictive models struggle to generalize effectively on data from different demographics (Aguirre et al., 2021; Aguirre and Dredze, 2021; Abdelkadir et al., 2024). Furthermore, each individual's experience with depression is unique, and it is important to consider their distinct experiences and symptomatology. Algorithmic representations and abstractions play a crucial role in the understanding of mental illness and well-being by providing a framework for generalization (Chancellor et al., 2019a). While these simplifications can help identify trends and better understand complex individual experiences, they also risk oversimplifying those experiences. It is important to recognize that generalizing can sometimes lead to misunderstandings regarding the unique nuances of mental health experiences and symptoms. Each person's experience with mental health disorders is unique, and acknowledging this is essential for a deeper understanding of mental health.

Acknowledgments

We sincerely appreciate the insightful feedback provided by the anonymous reviewers, which has greatly contributed to the improvement of this paper.

Tharindu Ranasinghe is partially supported by the CA21167 COST action UniDive, funded by COST (European Cooperation in Science and Technology).

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A Appendix

A.1 Methodology details

The search terms used in our survey are the following: (“mental disorder” OR “mental illness” ” OR “mental health” OR “depression” OR “anxiety” OR “bipolar” OR “ptsd” OR “post traumatic stress disorder” OR “suicide” OR “suicide ideation” OR “ocd” OR “obsessive compulsive disorder” OR “schizophrenia” OR “eating disorder” OR “anorexia” OR “bulimia”) AND “social media” AND (“multilingual” OR the list of languages provided in Joshi et al. (2020)).

A.2 Rankings of the publication venues for the multilingual datasets

Figure 4 presents an overview of these languages along with the ranking of the publications in which they appeared. The rankings for conferences are categorized as A*, A, B, and C, following the CORE Rankings Portal.[13] For journals, the rankings are classified as Q1, Q2, Q3, and Q4, based on the Journal Citation Reports.[14] There are also datasets published in unranked conferences or journals. While about half of the datasets appeared in unranked venues, leading to lower visibility for the research, the other half were published in high-ranking journals and conferences.

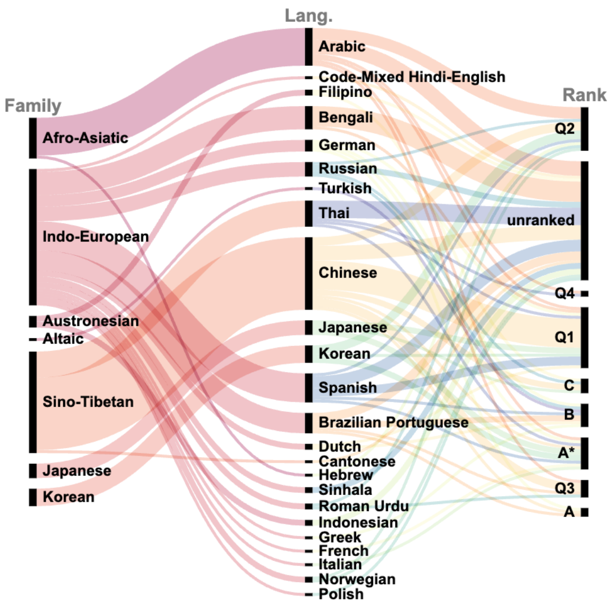

Figure 4: Overview of the languages in the datasets, their language families, and the ranking of their publication venues.

[13] https://www.core.edu.au/conference-portal
[14] https://jcr.clarivate.com/

Table 2: List of Non-English available datasets for mental disorders-related tasks using data posted on online platforms.

Dataset	Language	Mental disorder	Platform	Annotation Procedure	Label	Dataset Size	Availab.	Method	Performance
Almouzini et al. (2019)	Arabic	depression	Twitter	Self-disclosure	Binary	89 users, 2.7K posts	UNK	Bag-of-Unigrams, Linear SVM	Accuracy: 87.5%, F1-score: 87.5%
Alghamdi et al. (2020)	Arabic	depression	Online forums	Manual annotation	Binary	20K posts	UNK	Lexicon-based	Accuracy: 80.45%, F1-score: 80.81%
Alabdulkreem (2021)	Arabic	depression	Twitter	Manual annotation	Binary	200 users	UNK	Word2Vec, RNN-LSTM	Accuracy: 72%, F1-score: 69%
Musleh et al. (2022)	Arabic	depression	Twitter	CES-D and self-disclosure	Binary, DSM-5 symptoms	4.5K posts	UNK	TF-IDF, RF	Accuracy: 82.39%, F1-score: 82.53%
CairoDep (El-Ramly et al., 2021)	Arabic	depression	Twitter, Reddit, Online forums	Keywords, Manual annotation	Binary	2.4K posts	FREE	AraBERT	Accuracy: 96.93%, F1-score: 96.92%
Almars (2022)	Arabic	depression	Twitter	Manual annotation	Binary	6.1K posts	UNK	Attention BiLSTM	Accuracy: 83%, F1-score: 83%
Maghraby and Ali (2022)	Arabic	depression	Twitter	PHQ-9	PHQ-9 symptoms	1.2K posts	FREE	-	-%
AraDepSu (Hassib et al., 2022)	Arabic	depression, suicidal ideation	Twitter	Manual annotation	Depression, depression with suicidal ideation, or non-depression	20K posts	UNK	MARBERT	Accuracy: 91.20%, F1-score: 88.75%
Arabic Dep 10,000 (Helmy et al., 2024)	Arabic	depression	Twitter	Manual annotation	Binary	10K posts	FREE	TF-IDF, RBF SVM	F1-score: 96.6%
Al-Haider et al. (2024)	Arabic	OCD	Twitter	Manual annotation	Binary	8.7K posts	UNK	fastText, RF	F1-score: 80%
Baghdadi et al. (2022)	Arabic	suicidal ideation	Twitter	Manual annotation	Binary	2K posts	FREE	AraBERT	Accuracy: 96.06%, F1-score: 95.86%
Abdulsalam et al. (2024)	Arabic	suicidal ideation	Twitter	Manual annotation	Binary	5.7K posts	UNK	AraBERT	Accuracy: 91%, F1-score: 88%
Al-Musallam and Al-Abdullatif (2022)	Arabic	depression	Twitter	Manual annotation	Binary	6k posts	UNK	TF-IDF, LR	Accuracy: 82%, F1-score: 81%
Uddin et al. (2019)	Bengali	depression	Twitter	Manual annotation	Binary	1.1K posts	FREE	GRU	Accuracy: 75.7%
Victor et al. (2020)	Bengali	depression	Facebook, Twitter	Manual annotation	Binary	30K posts	UNK	TF-IDF, RF	Accuracy: 90%
Kabir et al. (2022)	Bengali	depression	Facebook	Manual annotation	Depression severity	5K posts	FREE	BiGRU	Accuracy: 81%, F1-score: 81%
Tasnim et al. (2022)	Bengali	depression	Facebook	Manual annotation	Binary	7K posts	UNK	BOW, TF-IDF, DT	Accuracy: 97%, F1-score: 97%
BanglaSPD Islam et al. (2022)	Bengali	suicidal ideation	Facebook	Manual annotation	Binary	1.7K posts	UNK	fastText, CNN-BiLSTM	Accuracy: 61%, F1-score: 61%
Ghosh et al. (2023)	Bengali	depression	Facebook, Twitter, YouTube	Manual annotation	Binary	15K posts	AUTH	fastText, BiLSTM-CNN	Accuracy: 94.32%
Hoque and Salma (2023)	Bengali	depression	Facebook	Manual annotation	Depression severity	2.5K posts	UNK	XLM-RoBERTa	Accuracy: 61.11%, F1-score: 60.89%
BSMDD (Chowdhury et al., 2024)	Bengali	depression	Reddit, Twitter	Manual annotation	Binary	28K posts	FREE	GPT 3.5	Accuracy: 97.96%, F1-score: 98.04%
von Sperling and Ladeira (2019)	Brazilian Portuguese	depression	Twitter	Self-disclosure	Binary	2.9K users	UNK	Hand-crafted features, SVM	F1-score: 79.8%

Dataset	Language	Mental disorder	Platform	Annotation Procedure	Label	Dataset Size	Availab.	Method	Performance
Mann et al. (2020)	Brazilian Portuguese	depression	Instagram	BDI	Binary	221 users	UNK	ELMo, ResNet, MLP	F1-score: 79%
Santos et al. (2020)	Brazilian Portuguese	depression	Twitter	Self-disclosure	Binary	224 users	UNK	TF-IDF, LR	F1-score: 69%
de Carvalho et al. (2020)	Brazilian Portuguese	suicidal ideation	Twitter	Manual annotation	Possibly/ Strongly concerning, Safe to ignore	2.4K posts	UNK	BERT-Portuguese	F1-score: 79%
SetembroBR (Santos et al., 2024)	Brazilian Portuguese	depression	Twitter	Self-disclosure	Binary	18.8K users	FREE	BERTimbau	F1-score: 63%
Mendes and Caseli (2024)	Brazilian Portuguese	depression symptoms	Facebook	Manual annotation	Depression symptoms	780 posts	UNK	BERTimbau	Precision: 76.14%
Oliveira et al. (2024)	Brazilian Portuguese	suicidal ideation	Twitter	Manual annotation	Binary	3.7K posts	FREE	GPT-4	F1-score: 98%
Gao et al. (2019)	Cantonese	suicidal ideation	Youtube	Manual annotation	Binary	5K posts	UNK	Word2vec, LSTM	Geometric mean of accuracies: 84.5%
Zhang et al. (2014)	Chinese	suicidal ideation	Sina Weibo	SPS	SPS score	697 users	UNK	LIWC, LR	RMSE: 11
Huang et al. (2015)	Chinese	suicidal ideation	Sina Weibo	Manual annotation	Binary	7.3K posts	UNK	Topic modeling, LibSVM	F1-score: 80.0%
Cheng et al. (2017)	Chinese	suicidal ideation	Sina Weibo	Suicide Probability Scale (SPS), DASS-21	Binary	974 users	UNK	LIWC, SVM	AUC: 61%
Shen et al. (2018)	Chinese	depression	Sina Weibo	Self-disclosure	Binary	1.1K users	UNK	Hand-crafted features, DNN	F1-score: 78.5%
Wu et al. (2018)	Chinese	depression	Facebook	CES-D	Binary	1.4K users	UNK	Word2vec, Hand-crafted features ,RNN	F1-score: 76.9%
Cao et al. (2019)	Chinese	suicidal ideation	Sina Weibo	Manual checking of self-report and/or appartenence to a suicide-related community	Binary	7K users	DUA	fastText, RNN	F1-score: 90.92%
Wang et al. (2019)	Chinese	depression	Sina Weibo	Manual annotation	Depression severity	13.9K users	UNK	BERT	F1-score: 53.8%
Peng et al. (2019)	Chinese	depression	Sina Weibo	Manual annotation	Binary	387 users	UNK	TF-IDF, SVM	F1-score: 76.12%
Huang et al. (2019)	Chinese	suicidal ideation	Sina Weibo	Manual annotation	Binary	18.5K posts	UNK	LIWC, Dictionary, LR, DT, SVM	F1-score: 88%
Li et al. (2020)	Chinese	depression	Sina Weibo	Self-disclosure	Binary	1.8K users	FREE	Lexicon-based, RF	F1-score: 76%
WU3D (Wang et al., 2020)	Chinese	depression	Sina Weibo	Depression-related keywords	Binary	32K users	FREE XLNet mebeddings, BiGRU		F1-score: 96.85%
Yao et al. (2020)	Chinese	depression	Sina Weibo	Manual, automatic annotation	Binary	2.7K users	UNK	-	-
Yang et al. (2021)	Chinese	depression	Sina Weibo	Manual annotation	Depression severity	6.1K posts	AUTH	BERT-based	F1-score: 65.7%
Chiu et al. (2021)	Chinese, English	depression	Instagram	Depression-related keywords	Binary	520 users	UNK	Multimodal features, Adaboost	F1-score: 83.5%
Sun et al. (2022)	Chinese	suicidal ideation, depression	Sina Weibo	BDI, SDS, Manual annotation	Binary / Possibly/Strongly concerning, Safe to ignore	203 users, 1.2K posts	UNK	Gradient Boosting	F1-score: 78.90%
Cai et al. (2023)	Chinese	depression	Sina Weibo	Self-disclosure and manual annotation	Binary	23K users	FREE	DNN	F1-score: 92.02%
Li et al. (2023)	Chinese	depression	Sina Weibo	Self-disclosure, manual annotation	Binary	4.8K users	UNK	Multimodal features, DNN	F1-score: 92.78%
Guo et al. (2023)	Chinese	depression	Sina Weibo	Manual annotation	Binary	3.1K users	UNK	Lexicon-based, XGBoost	F1-score: 93.22%

Dataset	Language	Mental disorder	Platform	Annotation Procedure	Label	Dataset Size	Availab.	Method	Performance
Wu et al. (2023)	Chinese	suicidal ideation	Dcard and PTT	Manual annotation	Risk levels	2K posts	UNK	-	-
Lyu et al. (2023)	Chinese	depression	Sina Weibo	CES-D	Binary	789 users	AUTH	LIWC, LR	Pearson correlation: 0.33
Yu et al. (2023)	Chinese	anxiety	Sina Weibo	Self-Rating Anxiety Scale	SAS score	1K users	N/A	LIWC, XGBoost	Pearson correlation: 0.32
Zhu et al. (2024)	Chinese	anxiety	Sina Weibo	Manual annotation	Binary	6K posts	UNK	LIWC, Word embeddings CNN	F1-score: 86.13%
Wang et al. (2024a)	Chinese	depression	Sina Weibo	Manual annotation	Binary	14.8K users	AUTH	Multimodal features, DNN	F1-score: 89.15%
Yao (2024)	Chinese	depression	Sina Weibo	Manual annotation	Binary	200 users	AUTH	BERT, DNN	Accuracy: 90%
Zhang et al. (2024)	Chinese	depression	Sina Weibo	Manual annotation	Binary	1.6K users	UNK	Tencent Embeddings, HTN	F1-score: 95.43%
Desmet and Hoste (2014)	Dutch	suicidal ideation	Online forums	Manual annotation	Fine-grained labels	1.3K posts	UNK	BOW, SVM	F1-score: 85.6%
Desmet and Hoste (2018)	Dutch	suicidal ideation	Online forums	Manual annotation	Fine-grained labels	10K posts	UNK	BOW, Topic modeling, LibSVM	F1-score: 92.69%
Abdelkadir et al. (2024)	English, but from different populations	depression	Twitter	Self-disclosure, Manual annotation	Binary	531 users	UNK	Mental Longformer	F1-score: 62%
Tumaliuan et al. (2024)	Filipino, English	depression	Twitter	PHQ-9	Binary	72 users	AUTH	-	-
Astoveza et al. (2018)	Filipino, Taglish	suicidal ideation	Twitter	Manual annotation	Binary	2.1K posts	UNK	BOW, MLP	Accuracy: 77.9%
Cohrdes et al. (2021)	German	depression	Twitter	Automatic annotation for PHQ-8 symptoms	Binary	88K posts	AUTH	–	–
SMHD-GER (Zanwar et al., 2023)	German	depression, ADHD, anxiety, bipolar, OCD, PTSD, schizophrenia	Reddit	Manual annotation	Labels for multiple disorders	28K posts	DUA	LIWC, BiLSTM	F1-score: 50.89%
Baskal et al. (2022)	German, Russian, Turkish, English	eating disorders	Reddit, Tumblr	Manual annotation	Binary	3K posts	AUTH	–	–
Tabak and Purver (2020)	German, French, Italian, Spanish, English	depression	Twitter	Self-disclosure	Binary	5K users	UNK	BOW, BiLSTM	F1-score: 69%
Hacohen-Kerner et al. (2022)	Hebrew	anorexia	Online forums	Manual annotation	Binary	200 posts	FREE	Hand-crafted features, RF	Accuracy: 90.63%
Agarwal and Dhingra (2021)	Code-Mixed Hindi-English	suicidal ideation	Reddit	Subreddit membership	Binary	6.4K posts	FREE	Indic BERT	Accuracy: 98.54%
Oyong et al. (2018)	Indonesian	depression	Twitter	Manual annotation	Binary	55 users	UNK	Hand-crafted depression score	F1-score: 50%
Yoshua and Maharani (2024)	Indonesian	depression	Twitter	DASS-42	Binary	184 users	UNK	Word2Vec, DT	F1-score: 94%
Tsugawa et al. (2015)	Japanese	depression	Twitter	CES-D, BDI	Binary	209 users	UNK	Hand-crafted features, Topic modeling, SVM	Accuracy: 66%
Hiraga (2017)	Japanese	depression	Online blogs	Self-disclosure	Binary	101 users	UNK	Part-of-speech, NB	Accuracy: 95.5%
Niimi (2021)	Japanese	depression	TOBYO	Blog theme	Binary	901 users	UNK	TF-IDF, SVM	F1-score: 96.2%

Dataset	Language	Mental disorder	Platform	Annotation Procedure	Label	Dataset Size	Availab.	Method	Performance
Wang et al. (2023)	Japanese	suicidal ideation	Twitter	Manual annotation	Binary	30K posts	N/A	–	–
Lee et al. (2020)	Korean	suicidal ideation	Naver Cafe	Membership in a forum	Binary	31K posts	UNK	Word2Vec, RNN	F1-score: 87.49%
Park et al. (2020)	Korean	suicidal ideation	Online forums	Manual annotation	Risk levels	2.7K posts	AUTH	KoBERT	F1-score: 88%
Kim et al. (2022a)	Korean	suicidal ideation	Twitter	Manual annotation	Binary	20K posts, 414 users	UNK	–	–
Kim et al. (2022b)	Korean	depression	Online forums	PHQ-9, Manual annotation	PHQ-9 score, PHQ-9 symptoms	60 users, 28K posts	UNK	BERT-based	F1-score: 93%
Jung et al. (2023)	Korean	suicidal ideation	Twitter	Manual annotation	Binary	20k posts	UNK	Metadata, word count, XGBoost	F1-score: 83.57%
Cha et al. (2022)	Korean, Japanese, English	depression	Twitter, Everytime	Lexicon-based automatic annotation	Binary	26M posts, 22K posts	AUTH	BERT-based	F1-score: 99%
Stamou et al. (2024)	Modern Greek	depression	Twitter	Self-disclosure	Binary	78 users	AUTH	–	–
Uddin (2022)	Norwegian	depression	Online forums	Manual annotation	Binary	21.8K posts	UNK	TF-IDF, LSTM	F1-score: 97%
Uddin et al. (2022)	Norwegian	depression	Online forums	Manual annotation	Binary	30K posts	UNK	Hand-crafted depression features; LSTM	F1-score: 98%
Wołk et al. (2021)	Polish	depression	Facebook, Reddit	Self-disclosure, clinical interview	Binary	262 users	UNK	Hybrid Model; BERT	Accuracy 71%
Rehmani et al. (2024)	Roman Urdu	depression	Facebook	Manual annotation	Depression severity	3K posts	AUTH	SVM	F1-score: 70.3%
Mohmand et al. (2024)	Roman Urdu	depression	Twitter	Keywords-based annotations + Expert review	Depression severity	25K posts	FREE	Transfer learning; BERT	F1-score: 99%
Stankevich et al. (2019)	Russian	depression	VKontakte	BDI	BDI score	531 users	UNK	Psycholinguistic Markers	F1 Score: 65%
Narynov et al. (2020)	Russian	depression	VKontakte	Manual annotation	Binary	34K posts	FREE	–	–
Stankevich et al. (2020)	Russian	depression	VKontakte	BDI	BDI score	1.3K users	UNK	–	–
Ignatiev et al. (2022)	Russian	depression	VKontakte	BDI	Binary	619 users	DUA	CatBoost	F1 Score: 69%
Rathnayake and Arachchige (2021)	Sinhala	depression	Twitter, Facebook	Manual annotation	Binary	1K posts	UNK	KNN	F1-score: 68.5%
EmoMent (Atapattu et al., 2022)	Sinhala, English	mental illness	Facebook	Manual annotation	mental illness, sadness, suicidal, anxiety/stress, psychosomatic, other, irrelevant	2.8K posts	AUTH	RoBERTa	F1 Score: 76%
Herath and Wijayasiriwardhane (2024)	Sinhala	suicidal ideation	Facebook	Manual annotation	Binary	300 posts	UNK	SVM	F1-score: 76%
Leis et al. (2019)	Spanish	depression	Twitter	Self-disclosure, manual annotation	Binary	540 users, 1K posts	FREE	–	–
SAD López-Úbeda et al. (2019)	Spanish	anorexia	Twitter	Hashtags	Binary	5.7K posts	FREE	SVM	F1-score: 91.6%
Valeriano et al. (2020)	Spanish	suicidal ideation	Twitter	Manual annotation	Binary	2K posts	FREE	Word2Vec; LR	F1-score: 79%
Ramírez-Cifuentes et al. (2020)	Spanish	suicidal ideation	Twitter	Manual annotation	Binary	252 users	N/A	Psychological features, LR	F1-score: 80%
Ramírez-Cifuentes et al. (2021)	Spanish	anorexia	Twitter	Manual annotation	Anorexia, control, under treatment, recovered, doubtful	645 users	N/A	CNN, LR	F1-score: 98%

Dataset	Language	Mental disorder	Platform	Annotation Procedure	Label	Dataset Size	Availab.	Method	Performance
Villa-Pérez et al. (2023)	Spanish, English	depression, ADHD, anxiety, ASD, bipolar, eating disorders, OCD, PTSD, schizophrenia	Twitter	Self-disclosure	Labels for multiple disorders	6K users	DUA	N-Grams; XGBoost	F1-score: 82.4%
MentalRiskES Romero et al. (2024)	Spanish	depression, anxiety, suicidal ideation, eating disorders	Telegram	Manual annotation	Binary + suffer + in favour (sf), suffer + against (sa), suffer + other (so) for Depression	1.2K users	AUTH	Social media text; mDeBERTa	F1 Score: 46%
Cremades et al. (2017)	Spanish, English	suicidal ideation	Facebook, Twitter, Blogspot, Reddit, Pinterest	Manual annotation	Binary	97 posts	FREE	–	–
Coello-Guilarte et al. (2019)	Spanish, English	depression	Twitter	Self-disclosure	Binary	316 users	FREE	BOW, SVM	F1 Score: 78%
Katchapakirin et al. (2018)	Thai	depression	Facebook	TMHQ	Binary	35 users	UNK	RF	F1 Score: 88.9%
Hemtanon and Kittiphattanabawon (2019)	Thai	depression	Facebook	Manual annotation	Binary	1.5K posts	UNK	SVM	F1 Score: 94%
Kumnunt and Sornil (2020)	Thai	depression	Pantip	Hashtags	Binary	31K posts	UNK	CNN-LSTM	F1 Score: 83.1%
Hemtanon et al. (2020)	Thai	depression	Facebook	PHQ-9	Binary	160 users	UNK	Social media features	F1 Score: 91.4%
Wongaptikaseree et al. (2020)	Thai	depression	Facebook	TMHQ	Binary	600 users	UNK	–	–
Hämäläinen et al. (2021)	Thai	depression	Online blogs	Manual annotation	Binary	900 posts	FREE	BERT	Accuracy: 77.53%
Mahasiriakalayot et al. (2022)	Thai	depression	Twitter	Manual annotation	Depression symptoms	3.1K posts	UNK	LSTM	F1-score: 81.06%
Boonyarat et al. (2024)	Thai	suicidal ideation	Twitter	Manual annotation	Binary	2.4K posts	FREE	Linguistic features; BERT	F1-score: 93%
Benjachairat et al. (2024)	Thai	suicidal ideation	Twitter	Manual annotation	C-SSRS Labels	5.1K posts	AUTH	Text features; LSTM	F1-score: 93.88%