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Article

Applications of Transformer-Based Language Models for Depression Detection: A Scoping Review

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Abstract: Depression is a substantial public health issue, with global ramifications. Transformer-Based Language Models (TBLM), with their ability to capture nuanced emotional and semantic information, are particularly well-suited for identifying depressive states from such unstructured textual data. The objective of this scoping review is to examine the usefulness of TBLM in detecting depression on text-based data. This study is based on a comprehensive search of Web of Science Core Collection, which includes studies that focused on the application of TBLM in diagnosing and classifying depression through social media texts. Our findings indicate that models such as BERT and its variants predominate in the existing literature, due to BERT's demonstrated generalizability in natural language understanding and its capacity to capture semantic and affective features in social media texts. However, generative models like GPT are rarely exploring. Twitter was the most frequently used data source, attributed to its public accessibility, real-time content generation, and large user base. Domain-adapted models, including MentalBERT and RedditBERT, demonstrate promising capabilities through fine-tuning on mental health-related corpora, potentially enhancing the detection of context-specific linguistic cues. This study further suggests that TBLM are increasingly being incorporated into psychiatric practice, with evidence of rapid advancements and encouraging outcomes.

Keywords: Transformer-Based Language Models; depression detection; BERT; GPT; mental health

1. Introduction

Depressive disorder, commonly known as depression, has become a pressing issue in contemporary society and represents a substantial challenge for global healthcare systems due to its high prevalence and profound impact on individuals' daily functioning. According to the World Health Organization (WHO), more than 280 million people globally suffer from depression, making it one of the leading causes of disability and a major contributor to the global burden of disease and suicide. Clinically, depression is characterized by a persistent low mood or a significant reduction in interest or pleasure in most activities over a prolonged period. Numerous studies have established strong associations between depression and various physical health conditions, including cardiovascular disease, cancer, diabetes, and respiratory illnesses [1]. Despite an estimated 5% of adults experiencing depressive symptoms, a substantial number of cases remain undiagnosed or inadequately treated. This treatment gap exists despite the disorder's severe societal impact, largely due to limited healthcare resources allocated for mental health care. Barriers such as societal stigma, discrimination, and financial

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constraints frequently deter individuals from seeking timely and appropriate treatment [2]. The COVID-19 pandemic has further strained mental health services, intensifying the urgency for innovative, scalable, and accessible approaches to the early detection and management of mental health conditions, including depressive disorders [3].

Traditionally, the diagnosis of depressive disorders has been primarily guided by standardized criteria outlined in the International Classification of Diseases (ICD) and the Diagnostic and Statistical Manual of Mental Disorders (DSM). However, these diagnostic frameworks are inherently dependent on available healthcare resources, the clinical expertise of practitioners, and are subject to individual biases in interpretation [4]. In response to these limitations, recent developments have increasingly explored the potential of artificial intelligence (AI) and machine learning technologies to improve the early detection and diagnostic accuracy of depression. The integration of AI into mental health care is gaining significant recognition among psychiatrists, who anticipate its transformative role in enhancing diagnostic precision and therapeutic interventions [5].

Among emerging technologies, Transformer-Based Language Models (TBLM)—a class of advanced neural networks trained on vast corpora of text—have demonstrated exceptional capabilities in understanding and generating human-like language. Due to ethical concerns, privacy restrictions, and the difficulty of acquiring labeled clinical data, most publicly available depression detection datasets remain small and limited in diversity [6]. Nonetheless, TBLM offer considerable potential to generate high-quality synthetic data to address such data scarcity challenges. Social media platforms, where individuals frequently share thoughts, emotions, and personal experiences, have emerged as valuable data sources for mental health research. Linguistic patterns in posts by individuals with depression often contain subtle semantic and emotional cues that can serve as indicators of psychological distress [7]. TBLM, with their ability to capture nuanced emotional and semantic information, are particularly well-suited for identifying depressive states from such unstructured textual data. Given that language serves as a reliable predictor of mood disorders, analyzing how individuals communicate provides critical insights into their mental health status [8]. Overall, the advancement of TBLM has opened new frontiers in health-related AI applications, particularly in three key domains: language comprehension, text generation, and knowledge inference. AI-driven models hold the promise of enabling rapid, accessible, and unbiased approaches to depression detection, offering a potentially powerful complement to traditional clinical assessments.

TBLM distinguish themselves from traditional language models through their massive scale—often encompassing billions of parameters—and their architectural foundation in Transformer networks. This architecture utilizes a self-attention mechanism, enabling parallel processing of input data and thereby significantly enhancing both computational efficiency and contextual language understanding. Prominent examples of TBLM include Bidirectional Encoder Representations from Transformers (BERT), Generative Pre-trained Transformer (GPT), and Large Language Model Meta AI (LLaMA). The suitability of TBLM for depression detection arises from their capacity to process and analyze large volumes of natural language data, identifying subtle linguistic cues associated with mental health conditions. Recent research has demonstrated that TBLM can effectively utilize a wide range of data sources for depressive symptom analysis, including social media posts, narrative clinical notes, transcribed clinical interviews, patient diaries, simulated datasets, and speech transcripts [6]. Comparative studies have evaluated different model architectures and explored strategies to optimize performance and augment training data for improved accuracy in depression detection. These findings consistently highlight the potential of TBLM as reliable tools for identifying depressive symptoms in various textual contexts. This study seeks to provide a comprehensive scoping review of the application of TBLM for depression detection specifically on social media platforms. In doing so, it aims to address a notable gap in the existing literature, as few scoping reviews have systematically examined the capabilities and challenges of TBLM in this emerging area of mental health research.

2. Methods

2.1. Search Strategy

A literature search was conducted on Web of Science, covering the publication period from 2020 to 2025.

Carefully designed Boolean search strings were tailored to each database to ensure precision and relevance, with a particular focus on studies exploring the application and impact of TBLM in detecting depression using data derived from social media platforms. The search strategy incorporated three primary categories of terms. For TBLM -related terminology, the following keywords were used: “Large Language Model” OR “LLM” OR “Generative Pre-trained Transformer” OR “GPT” OR “GPT-2” OR “GPT-3” OR “GPT-3.5” OR “GPT-4” OR “ChatGPT” OR “Transformer models” OR “BERT” OR “BARD” OR “Gemini”. To capture literature focused on depression detection, the search included: “Depression” OR “Depressive disorder” OR “Major depressive disorder” OR “Clinical depression” OR “Mood disorder”. This systematic approach ensured the inclusion of relevant studies.

2.2. Study Screening and Selection

This study included only theses, dissertations, conference proceedings, and technical reports. Publications such as reviews, conference abstracts, proposals, books, and editorials were excluded from the analysis. The study selection process was conducted in three sequential stages: (1) identification of studies, (2) title and abstract screening, and (3) full-text review. Two independent reviewers were involved throughout the screening process. Duplicate records were identified and removed in the initial stage. During the second stage, titles and abstracts of all retrieved records were screened for relevance. In the final stage, the full texts of the remaining studies were independently assessed by both reviewers. Any discrepancies in the inclusion decisions were resolved through discussion and consensus. Data extraction was independently conducted by two reviewers using a structured Excel spreadsheet. Extracted information included the general characteristics of each study, the specific predictive models employed, and the data sources used for model training. A narrative synthesis approach was adopted to analyze and integrate findings from the included studies. For each study, the following information was recorded: the specific large language model applied (e.g., BERT, GPT), publication or submission date, the data source used for model training (e.g., Facebook, Twitter), the method of data collection (e.g., participant-recruited data through depression surveys and social media sharing vs. data obtained from publicly available online sources), and the evaluation metrics employed (e.g., accuracy, F1-score, precision, recall).

3. Results

3.1. Search Results

A total of 173 articles were initially retrieved through systematic searches of three major bibliographic databases: Web of Science Core Collection. Following the removal of 11 duplicate records, 135 unique articles remained for screening. Title and abstract screening resulted in the exclusion of 119 articles based on the following criteria: lack of relevance to the research topic, absence of social media data, non-focus on depression, or unavailability of full-text access. Additionally, reviews, books, and book chapters were excluded from consideration. After full-text screening and application of all inclusion and exclusion criteria, a total of 16 articles were deemed eligible and included in this scoping review.

3.2. Overview of Included Studies

This scoping review includes 21 studies published between July 2020 and April 2025 that examine the application of TBLM in depression-related research utilizing social media data. Table 1 shows the key characteristics of the included studies. These studies feature a wide range of sample sizes, spanning from several thousand to tens of millions of social media posts. The primary platforms used for data collection were Twitter, Reddit, and Facebook. The studies predominantly focused on tasks related to the detection of depression and the classification of its severity. Specifically, four studies employed TBLM to classify the severity of depression based on detected depressive symptoms. An additional four studies investigated the capacity of TBLM to identify signs of comorbid mental disorders alongside depression. One study explored the temporal dynamics of depression using TBLM to analyze changes in language patterns over time. A diverse array of TBLM was applied across the included studies, including foundational models such as BERT and RoBERTa, as well as domain-specific adaptations like MentalBERT. Various iterations of the Generative Pre-trained Transformer (GPT) models were also utilized. Among these, BERT emerged as the most frequently employed model, demonstrating considerable effectiveness in analyzing textual data to detect indicators of depression.

Table 1. Key characteristics of the included studies.

Reference	Publication Date	Large Language Models	Datasets Size with Data Sources
Mohmand et al. [9]	December 2024	BERT	25,004 posts from Twitter
Beniwal et al. [10]	December 2024	BERT RoBERTa DistilBERT	11,199 posts from Instagram, Twitter, Reddit, and LinkedIn
Zeberga et al. [11]	March 2022	BERT Distilled_BERT	75,000 posts from Reddit 25,000 posts from Twitter
Bokolo et al. [12]	October 2024	RoBERTa DeBERTa DistilBERT SquuezeBERT	632,528 posts from Twitter
Burbano et al. [13]	March 2025	DEENT-Bert MentalBERT	70,509 depression-oriented posts and 53,475 non-depressive posts from Twitter
Tiwari et al. [14]	February 2024	E-CLS BERT	12,029 posts from Twitter
Buchem et al. [14]	July 2024	RedditBERT	6600 annotated messages from Reddit
Ilias et al. [15]	June 2023	BERT MentalBERT	1482 non-depressive posts and 1340 depressive posts
Jain et al. [16]	June 2024	BERT RoBERTa DeBERTa	50,000 posts from Twitter
Bokolo et al. [17]	October 2023	DistilBERT SqueezeBERT RoBERTa DeBERTa	632,000 posts from Twitter
Wang et al. [18]	July 2020	BERT BERT_IDP RoBERTa RoBERTa_IDP	13,993 microblogs from Weibo
Pourkeyvan et al. [19]	February 2024	distilbert-base-uncased-finetuned-sst-2-english Bert-Base-Uncased Distil Roberta Base Mental-Bert-Base-Uncased	11,890,632 posts from Twitter
Khan et al. [20]	October 2023	BERT	Posts from Twitter
Xin et al. [21]	October 2024	MentalBERT BERT	7731 messages from Reddit 8463 posts from Twitter Mental Health Corpus (27,977)
Zhou et al. [22]	April 2025	BERT	20,000 posts from Twitter
Abbas et al. [23]	April 2024	BERT	20,000 tagged tweet user profiles from Twitter

3.3. Predictive Models

The reviewed studies primarily utilized TBLM to detect depression using specific social media datasets. Among these, BERT emerged as the most frequently adopted model, appearing in 13 studies, thereby affirming its central role in depression detection tasks. Variants of BERT, such as RoBERTa and DistilBERT, were employed in 7 studies, demonstrating their efficacy as streamlined or enhanced alternatives to the original model. MentalBERT, a domain-specific adaptation of BERT, was applied in 5 studies, highlighting the value of task-oriented model customization in mental health research. Several studies introduced hybrid models, reflecting a growing trend toward integrating TBLM with other algorithms. For example, combinations such as BERT-MobileNet, BERT-SVM, and BERT-KNN were utilized to process multi-modal data comprising both textual and visual inputs.

Other studies enhanced predictive accuracy by incorporating complementary technologies, such as the NRC emotion lexicon and Latent Dirichlet Allocation (LDA) topic modeling. Emerging approaches, including DEENT-BERT, illustrate ongoing innovation in this area. Although only one study explored the application of GPT-2 for depression detection, base Transformer architectures remain dominant due to their flexibility and effectiveness. Lightweight versions of these models are often preferred for their computational efficiency, while domain-specific adaptations continue to show promise, though they require broader empirical validation. Additionally, six studies leveraged BERT as a feature extractor or for generating embeddings, contributing to overall model performance and reinforcing the utility of TBLM in supporting downstream predictive tasks.

3.4. Data Source

The studies included in this scoping review employed both self-constructed and pre-existing datasets to develop predictive models for depression detection. Specifically, eight studies constructed their own datasets, while one study combined a ready-made dataset with a self-built dataset. Additionally, datasets from Kaggle, a well-known platform for machine learning and data science communities, were utilized in seven studies. Social media platforms served as the primary data sources across the studies, with Twitter being the most frequently used (n = 11/16, 68.8%), followed by Reddit (n = 4/16, 25%), Weibo (n = 1/16, 6.3%), and Facebook (n = 1/16, 6.3%). Some studies incorporated data from multiple platforms; for instance, three studies (18.75%) utilized both Twitter and Reddit, while one study integrated posts from Twitter, Reddit, Instagram, and LinkedIn. Regarding the language of the datasets, English was the most commonly used (n = 12/16, 75%), followed by Roman Urdu (n = 2/16, 12.5%). Chinese and Hindi were each used in one study. In addition to textual data, some studies incorporated other forms of content to enrich model performance. For example, one study included image-based posts, while another utilized bio-descriptions extracted from user profiles to enhance the contextual understanding of the models.

3.5. Performance

Model performance was evaluated in nearly all of the reviewed studies using a variety of metrics, with the F1-score emerging as the most commonly employed primary evaluation criterion—underscoring an emphasis on balanced performance between precision and recall. Both precision and recall were independently reported in 18 studies, reflecting a strong methodological focus on the accurate identification of the positive class, i. e., individuals potentially experiencing depression. BERT has achieved high levels of precision and F1-score (up to 95% and 93%, respectively) when applied to multilingual data, including Hindi-English code-switched social media posts [10]. Both BERT and MentalBERT showed robust effectiveness in differentiating between forum users with a clinical depression diagnosis and those without; in Owen's study, both models achieved a mean F1-score of 0.64 for binary classification tasks.

Lightweight models such as DistilBERT, optimized through knowledge distillation, maintained high performance (F1-score = 97.44% on Twitter data) while offering reduced computational cost—demonstrating the practical advantages of model compression techniques [24]. RoBERTa also exhibited exceptional performance [25]. For example, in the study conducted by Bokolo [17], RoBERTa achieved the highest classification accuracy of 0.981 and a mean accuracy of 0.97 across ten cross-validation folds for detecting depressive content in tweets. Beyond classification, TBLM have demonstrated notable advantages in feature extraction. The CDME-GAT model, which incorporates a graph attention network and multi-embedding representations, achieved a state-of-the-art F1-score of 96.7%. Similarly, Abbas' evaluation of a BERT-RF hybrid model for feature engineering enabled logistic regression to outperform other state-of-the-art approaches, achieving a peak accuracy of 99% [23]. Consequently, studies show the effectiveness of the approach provided and can help medical professionals diagnose depression with precision.

4. Discussion

This scoping review evaluated the efficacy of TBLM in the detection of depression using social media data, highlighting their transformative potential for mental health care. The analysis focused on the most frequently employed TBLM, the performance evaluation metrics utilized, and their applications across popular social media platforms, with a particular emphasis on English-language datasets. Our findings indicate that models such as BERT and its variants predominate in the existing literature, likely due to BERT's demonstrated generalizability in natural language understanding and its capacity to capture semantic and affective features in social media texts. However, an overreliance on BERT may constrain exploration into the unique strengths of alternative TBLM architectures. The widespread adoption of lightweight models like DistilBERT reflects the practical demand for computational efficiency. Given the immense volume and velocity of social media data, such models offer a pragmatic balance between performance and resource consumption, aligning well with real-time processing needs and industrial requirements for edge computing and low-latency deployment.

Domain-adapted models, including MentalBERT and RedditBERT, demonstrate promising capabilities through fine-tuning on mental health-related corpora, potentially enhancing the detection of context-specific linguistic cues. Nevertheless, their adoption remains limited. Most studies utilized data from individual social media platforms—such as Twitter, Reddit, Facebook, Instagram, Weibo, and LinkedIn—to train and evaluate predictive models. Among these, Twitter was the most frequently used data source, attributed to its public accessibility, real-time content generation, and large user base. The platform's dynamic and anonymized content facilitates the extraction of meaningful insights while reducing risks of privacy infringement and personal bias.

This review further suggests that TBLM are increasingly being incorporated into psychiatric practice, with evidence of rapid advancements and encouraging outcomes. When compared to non-transformer-based models and even human evaluators, TBLM exhibit superior capabilities in information retrieval, contextual analysis, and the generation of clinically relevant outputs. These advantages position TBLM as valuable tools for the identification and prediction of mental health conditions based on large-scale, real-world data. Their integration into psychiatric care is progressing in a measured and evidence-informed manner, with careful attention to issues of safety, effectiveness, and ethical implementation.

5. Conclusions

The application of TBLM in the domain of depression detection is undergoing rapid expansion. Nonetheless, the field remains largely reliant on earlier models such as BERT, reflecting a delayed integration of more advanced technologies like GPT-4. This trend suggests that although the potential of newer models is acknowledged, their widespread adoption and systematic evaluation within depression detection research remains limited. TBLM have demonstrated significant value in processing unstructured text and monitoring social media platforms, offering practical utility in real-time mental health assessments. These models are adept at analyzing large-scale datasets, discerning complex patterns, and generating insights that are critical to understanding and addressing mental health challenges. Their integration into clinical environments holds substantial promise, with the potential to transform current approaches to the detection, diagnosis, and management of depression and related conditions. However, the implementation of TBLM in healthcare also raises important ethical and privacy concerns. These issues necessitate rigorous investigation through well-designed methodologies and clinical trials to ensure their responsible and effective application in patient care. Addressing such concerns is vital for fostering trust among patients, clinicians, and other stakeholders, and for ensuring that the benefits of these advanced technologies are realized without compromising individual privacy or ethical standards.

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Conflicts of Interest

The authors declare no conflict of interest.

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