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Review

Application of Artificial Intelligence in Social Media Depression Detection: A Narrative Review from Temporal Analysis

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Abstract

Background: Depression remains a major global mental health concern, significantly intensified during the COVID-19 pandemic. As social media usage surged during this period, it emerged as a valuable source for identifying early signs of depression. Artificial intelligence (AI) offers powerful tools to analyze large volumes of user-generated content, enabling timely and effective detection of depressive symptoms. This review aims to preliminarily explore and compare evidence on the use of AI models for detecting depression in social content across the pre-, during, and post-pandemic phases, assessing their effectiveness and limitations. Methods: A narrative literature review was conducted using PubMed and Scopus, following the SANRA guidelines to ensure methodological quality and reproducibility. The study was pre-registered in the OSF database and employed the PICOS framework for the strategy. Inclusion criteria comprised studies in English from the past 10 years that analyzed depression detection via AI, machine learning (ML), and deep learning (DL) applied to textual data, images, and social metadata. This review addresses the following four research questions: (1) whether AI models improved effectiveness in detecting depression during/after the pandemic vs. pre-pandemic; (2) whether textual, visual, or multimodal data approaches became more effective during the pandemic; (3) whether AI models better addressed technical challenges (data quality/diversity) post-pandemic; and (4) whether strategies for responsible AI implementation improved during/after the pandemic. Results: Out of 349 identified records, nine primary studies were included, as most excluded articles had a predominantly technical focus and did not meet the clinical relevance criteria. AI models demonstrated strong potential in detecting depression, particularly through text-based classification and social content analysis. Several studies reported high predictive performance, with notable improvements in accuracy and sensitivity during and after the pandemic, although evidence remains limited. Conclusions: Our preliminary analysis suggests that AI-based depression detection on social media shows potential for clinical use,

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highlighting interdisciplinary collaboration, ethical considerations, and patient-centered approaches. These findings require confirmation and validation through larger, well-designed systematic reviews.

Keywords: depression; COVID-19; mental health; social media; artificial intelligence; narrative review

1. Introduction

Mental disorders are a major cause of the global burden of disease. The 2019 Global Burden of Diseases (GBD), Injuries, and Risk Factors Study found that depressive disorders are among the top twenty-five leading causes of global health burden [1,2]. According to the Fifth American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM-5), depressive disorders are divided into five categories, characterized by common symptoms such as sadness, feelings of emptiness or irritable mood, combined with somatic and cognitive changes that significantly affect the individual's daily functions [3]. An estimated 280 million people worldwide suffer from this condition, with a prevalence that is 50% higher in women than in men. It is estimated that 5% of the world's adult population is affected, with a distribution of 4% among men and 6% among women, while 5.7% of people over 60 years of age have the condition [World Health Organization (WHO)] [4]. With the COVID-19 pandemic, cases have increased significantly, with an estimated 53.2 million new patients with the major depressive disorder globally in 2020 alone [5]. In the same year, the US faced some of the highest social, economic, and health care costs in the world due to the pandemic. The spike in unemployment claims and severe financial hardship for workers and companies had a negative impact on mental health [6]. Many countries responded to the pandemic by imposing national lockdowns, which included social isolation measures such as closing schools and workplaces. Young people, who have a higher risk of developing mental health problems than adults [7], may be particularly vulnerable to the negative effects of such isolation [8]. In this context, social media platforms have played a key role as a constantly available communication tool [9]. The number of users amounted to 4.55 billion in October 2021 compared to 3.8 billion in January 2020 [10]. However, numerous studies have revealed that high consumption of social media is correlated with an increase in media addiction, especially among adolescents, and an increased risk of anxiety, loneliness, and depression [11,12]. In the face of these growing mental health problems, early screening plays a crucial role [13]. The diagnosis of depressive disorder is mainly based on clinical assessments conducted by health professionals using psychodiagnostic tests [14,15] and standardized questionnaires or scales [16] such as the Hamilton Depression Rating Scale (HDRS) [17], the Beck Depression Inventory-II [18], and the Patient Health Questionnaire-9 (PHQ-9) [19]. Despite this, depression often remains underdiagnosed and poorly managed due to psychosocial limitations, reduced access to mental health care services, and diagnostic and therapeutic inconsistencies [20]. The increase in data finding use of social media post-pandemic allows online monitoring to detect mental disorders, such as depression, at an early stage. [21,22]. In this context, artificial intelligence (AI) offers new perspectives and methods to address depressive disorders, complementing and enhancing traditional diagnostic techniques [23]. For instance, AI can employ automated algorithms that analyze sentiment and emotional tone, which can reveal the presence of depression, such as sadness or despair [24]. In addition, deep learning (DL) and machine learning (ML) techniques are used and can identify linguistic clues that suggest the presence of a mental disorder [25,26]. Despite concerns about privacy and ethics in the use of social media data that may limit research [27,28], the adoption of AI in social media could radically transform the diagnosis and treatment of depression, improving access to personalized resources for millions of people. The primary objective of this narrative review is to preliminarily explore temporal trends in AI model effectiveness for detecting depression on social media, using the COVID-19 pandemic as a contextual reference point for understanding potential changes in performance and methodological approaches.

2. Materials and Methods

2.1. Study Design

This study uses a narrative review [29] and follows the Scale for the Evaluation of Narrative Review Articles (SANRA) to ensure the quality of the study (Supplementary File S1). The aim is to provide a comprehensive quantitative and qualitative synthesis of the literature regarding the use of AI models for the identification of depression through social media, analyzing data collected before, during, and after the COVID-19 pandemic.

2.2. Defining the Research Question

The research questions that guided this preliminary narrative review are as follows:

- Have AI models improved effectiveness in detecting depression on social media during and after the pandemic compared to the pre-pandemic period?
- During and after the pandemic, have AI models that utilize textual, visual, or multimodal data been more effective in detecting depression on social media compared to the pre-pandemic period?
- Have AI models updated or developed during and after the pandemic shown improvements in addressing technical challenges such as data quality and diversity compared to pre-pandemic models?
- Have the strategies implemented to improve AI models in detecting depression on social media during and after the pandemic been more effective in promoting responsible and inclusive use of AI compared to pre-pandemic strategies?

This research was developed using the PICOS framework [30] to ensure a structured and scientifically valid approach to the identified topic:

P (Population): social media users;
I (Intervention): AI models to detect signs of depression in social media during and after the pandemic;
C (Comparison): AI models used pre-pandemic for depression detection;
O (Outcome): improvement in detection effectiveness (accuracy, sensitivity, and specificity);
S (Study Type): primary studies.

2.3. Inclusion and Screening Criteria

The study included a preliminary registration in the OSF database with the code https://doi.org/10.17605/OSF.IO/VQRY5 (accessed on 16 April 2025). The inclusion criteria encompassed primary studies published in English within the last 10 years, relevant to the study's objectives. Exclusion criteria eliminated other types of studies (e.g., editorials, commentaries, reviews, and protocol studies). The search strategy was conducted using the PubMed–Medline and Scopus databases, aiming to select primary studies published in the last 10 years. These databases were selected because they are among the most relevant and authoritative for biomedical and mental health research and they index the majority of clinically oriented studies in this field. In the initial search to identify the total number of records, the screening process was conducted blindly by two reviewers. In case of disagreement between the two, and to reach the necessary consensus for inclusion, a third researcher was involved in the selection process. After selecting the articles to be included from the specified databases, the search was extended to the gray literature and proceedings from sector conferences that met the inclusion criteria. Mendeley Reference Manager (free version, accessed May 2025) [31] was used for the bibliographic management of the analyzed records, and specific search strings were applied with principal keywords "Artificial Intelligence", "Deep Learning", "Machine Learning", "Natural Language Processing", "Cognitive Dysfunction", "Mental Disorders", "Psychological Distress", "Depression", "Depressive Disorder", "Affective Disorders, Psychotic", "Anxiety Disorders", "Phobia, Social", "Neurocognitive Disorders", "Executive Function", "Memory, Short-Term", "Problem Solving", "Social Media", "Internet Addiction Disorder", "Media Exposure", "Social Networking", "Social Network Analysis" combined with Boolean operators. The search was updated through 31 May 2025 (Supplementary File S2).

2.4. Data Synthesis and Risk of Bias

The selected studies underwent rigorous analysis in two phases. Initially, they were categorized based on author and year, country, study design, sample, type of AI, objective, results, and limitations. This categorization has ensured a structured approach to synthesizing the identified literature. Subsequently, a comprehensive narrative synthesis was conducted, integrating the results of the selected primary studies and providing an overall perspective on the topic, while also highlighting the unique characteristics and complexities of each included study. The risk of bias and the methodological quality of the included studies were independently assessed by two researchers using the Critical Appraisal Skills Program (CASP) checklists [32] (CASP Checklist for included studies: Supplementary File S3).

3. Results

From the search strategy, 349 records were identified from the PubMed–Medline and Scopus databases. After excluding 287 articles based on title and abstract, of which 29 duplicates, 62 articles were selected for screening. Of these, 25 were deemed irrelevant and 37 texts were assessed for suitability, with an additional 30 removed after review and expert opinion: 14 focused on mental health conditions other than depression specifically; 8 used AI for treatment/intervention rather than detection; 5 were conference abstracts without complete methodological details; and 3 had insufficient AI implementation description. The screening process ultimately included 7 primary studies and 2 from other sources added (Figure 1).

3.1. Characteristics of the Included Studies

Among the nine primary studies included [33–41], two were conducted in India [34,35], two in the USA [36,40], two in China [37,38], while one study each was conducted in Australia [33], Spain [39], and Bangladesh [41]. Of the nine studies, six were experimental/clinical [34,36,37,39,41] and three were observational [35,38,40]. The quality of the study design was assessed as high in all studies. (Tables 1 and 2).

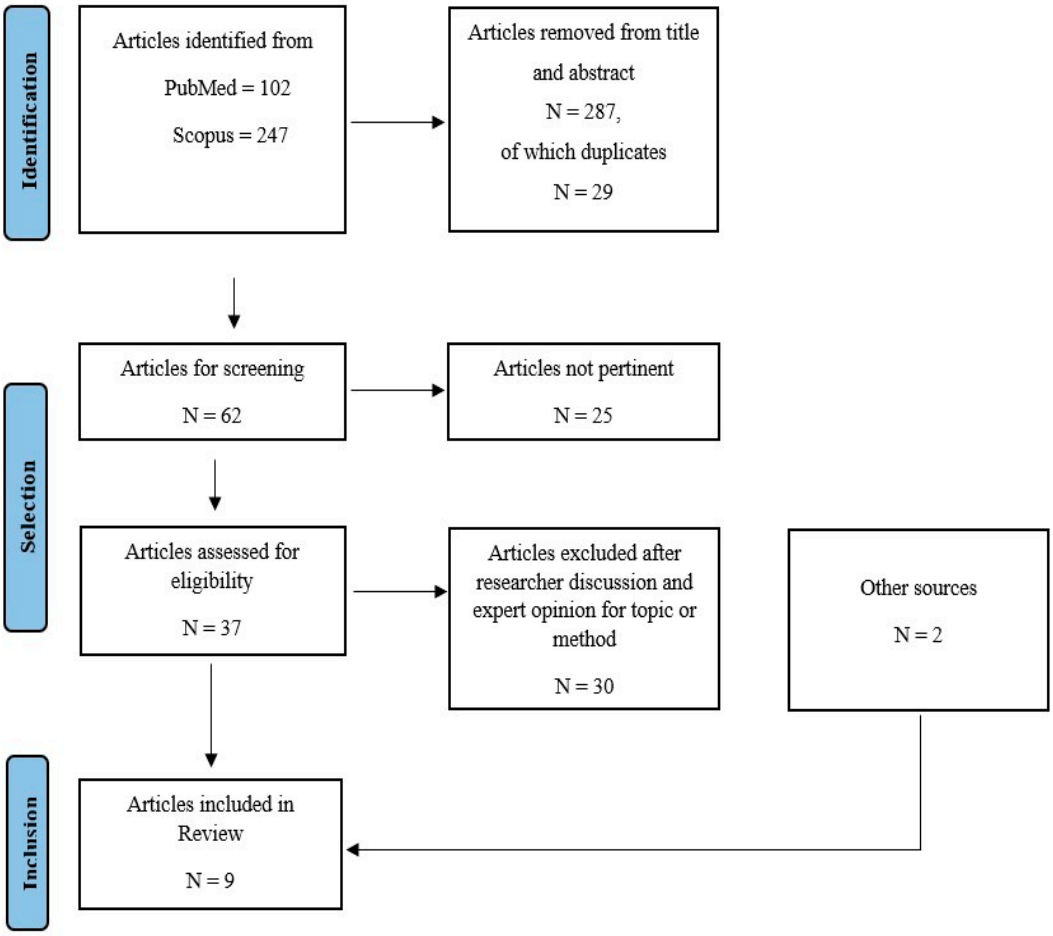

Figure 1. Flowchart selection.

3.2. Pre-Pandemic Evolution: Foundations and Initial Applications of AI

In a diagnostic experimental study conducted in Bangladesh, Islam et al. [41] used advanced ML techniques [Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNNs), and Ensemble methods] to analyze 7145 Facebook comments in order to identify signs of depression. It has emerged that the DT, with a precision of 0.59, a recall of 0.99, and a F measure of 0.73, has proven particularly effective in recognizing psycholinguistic indicators of depression, managing to identify almost all relevant comments. This approach has demonstrated a high rate of correct identification of comments indicative of depression, suggesting the effectiveness of such methodologies in the analysis of social content for diagnostic purposes. In parallel, Ricard et al. [40] conducted an observational study on 749 Instagram users in the USA, using the Patient Health Questionnaire-8 (PHQ-8) as a reference to assess the ability of community-generated content to predict depression. The developed ML models have demonstrated significant predictive capabilities, with a combined model of user-generated and community-generated data achieving an area under the curve (AUC) of 0.72, surpassing the model that uses only community-generated data (AUC = 0.71) and the model based solely on user-generated data (AUC = 0.63). These results reinforce the idea that community-generated data can serve as valuable resources for identifying signals of depression. Meanwhile, Cacheda et al. [39] conducted an observational study in Spain involving 887 social media users and applied the Random Forest (RF) algorithm with a "time-aware approach." This study showed that the dual model improves the detection of major depressive disorder (MDD) by over 10% compared to current standard models, highlighting the importance of timeliness in detection through social media. In parallel, Tadesse et al. [38] conducted an experimental study analyzing posts on Reddit to identify linguistic markers of depression, employing natural language processing (NLP) techniques and ML classifiers [Support Vector Machine (SVM) and Multilayer Perceptron (MLP)]. The results demonstrated that linguistic features can indicate the presence of depression with an accuracy of 91%, an F1-score of 0.93, a precision of 90%, and a recall of 91% using the MLP classifier, confirming the effectiveness of combining different feature extraction methods and ML algorithms. Finally, Sun et al. [37] conducted an experimental study in China developing a diagnostic network that uses "domain-adversarial" neural networks to improve depression diagnosis through skew-robust adversarial domain adaptation. The proposed method demonstrated performance comparable to the baseline, surpassing other DL models in depression diagnosis. The performance indicators used, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), provided standard metrics to evaluate the precision of a model's predictions. Without top-down selection, the severity assessment network based on robust adversarial domain adaptation (SRADDA) achieved an RMSE of 6.38 and a MAE of 4.93. With top-down selection, the RMSE improved to 5.13 and the MAE to 4.08.

Table 1. Characteristics of the included studies.

Characteristic	**Frequency (n = 9)**	**Percentage**
	Publication year	
2024	1	11.1%
2023	2	22.2%
2021	1	11.1%
2019	3	33.3%
2018	2	22.2%
	Country	
USA	2	22.2%
China	2	22.2%
Australia	1	11.1%
Spain	1	11.1%
India	2	22.2%
Bangladesh	1	11.1%
	Study Design	
Experimental study	6	66.7%
Observational study	3	33.3%
	Type of AI	
HCN	1	11.1%
NLP	1	11.1%
ML	4	44.4%
DL	3	33.3%
	Quality of study	
Positive	9	100%
Negative	0	0%
Unknown	0	0%

Legend. HCN: hierarchical convolutional network; NLP: natural language processing; ML: machine learning; and DL: deep learning.

Table 2. Summary of included studies.

Author and Year	Country	Study Design	Sample	Type of AI	Objective	Results	Limitations
Zogan et al. [33] 2024	Australia	Experimental study	Tweets from depressed and non-depressed users	HCN	Develop a model to detect depression in social media users by analyzing changes in behavior and tweet content during the COVID-19 pandemic	The HCN model demonstrated high effectiveness in identifying depression, with an increase in depression rates among users during the pandemic	Limited generalization of results; bias in the dataset; technical limitations; problematic labeling
Chatterjee et al. [34] 2023	India	Experimental study	Depressive symptoms tweet	ML (SVM classifier)	Develop a real-time depression detection model through multimodal analysis of Twitter posts	The model showed an accuracy of 89% in detecting depression, combining sentiment analysis and user interaction data to track mental health trends	Selection bias; limited reliability; linguistic interpretation; limited generalization; lack of clinical comparison
Anshul et al. [35] 2023	India	Experimental study	Depressed and non-depressed social media users	DL (VNN and textual analysis)	To detect depression among social media users using a novel AI framework	Achieved high accuracy with 93.1% on the Tsinghua dataset and 91.7% on the novel COVID-19 dataset, demonstrating the effectiveness of the multimodal approach	Limited data from social media; self-selection bias; classification accuracy; difficult multimodal interpretation; non-generalizable results
Zhang et al. [36] 2021	USA	Observational study	5150 Twitter users	DL (BERT, RoBERTa, XLNet)	Monitor depression trends on Twitter during the pandemic by identifying depressed users through AI	The fusion model achieved an accuracy of 78.9%, identifying key linguistic and psychological markers related to depression	Limited representativeness; uncertain identification; control group contamination; linguistic limitations; analysis based on social media
Sun et al. [37] 2019	China	Experimental study	Various datasets	DL (Domain-adversarial neural networks)	Improving depression diagnosis through a skew-robust adversarial domain adaptation network	The study showed performance comparable to the baseline, surpassing other DL models in depression diagnosis	Dimensional discrepancy between datasets; distribution variations; dependence on pre-selection; limited generalization; bias in model training
Tadesse et al. [38] 2019	China	Experimental study	Reddit posts	NLP; ML (SVM, MLP, etc.)	Identify linguistic markers of depression in Reddit posts	Linguistic features indicate depression with 91% accuracy and F1-score 0.93 using MLP	Dependence on self-reports; linguistic and cultural biases; limitations of NLP models; ethical issues; variability in user behavior

Table 2. *Cont.*

Table 3. Summary of included studies.

Author and Year	Country	Study Design	Sample	Type of AI	Objective	Results	Limitations
Cacheda et al. [39] 2019	Spain	Observational study	887 users from social media	ML (RF Algorithm)	Improve early diagnosis of MDD with social data	The dual model showed an improvement of over 10% compared to current standard detection models	Data selection and limited self-reporting; linguistic focus; non-generalizable results; bias in machine learning models; timing of predictions
Ricard et al. [40] 2018	USA	Observational study	749 Instagram users	ML	Evaluate Instagram content for depression detection using PHQ-8.	Model with AUC 0.73 demonstrates predictive capability; data combination slightly improves AUC to 0.71	Limited participant selection; limited data from Instagram; lack of demographic data; limited use of comment data; small sample of depressed individuals
Islam et al. [41] 2018	Bangladesh	Experimental study	7145 comments from Facebook	ML (DT, SVM, KNN, Ensemble methods)	Detect depression among Facebook users by analyzing comments for psycholinguistic features.	The DT highlighted maximum precision, recall, and F-measure of 0.59, 0.99, and 0.74, identifying key psycholinguistic markers in depressive comments	Limited data source; lack of external validation; reliance on self-reporting; label imbalance; limited linguistic interpretation

Legend. AI: artificial intelligence; HCN: hierarchical convolutional network; SVM: support vector machine; KNN: K-nearest neighbors; ML: machine learning; DL: deep learning; VNN: visual neural network; BERT: bidirectional encoder representations from transformers; RoBERTa: robustly optimized BERT approach; RF: random forest; XLNet: generalized autoregressive pretraining method; MLP: multilayer perceptron; AUC: area under curve; PHQ-8: Patient Health Questionnaire-8; MDD: major depressive disorder; NLP: natural language processing.

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3.3. Impacts of the Pandemic: Adaptations and Challenges of AI in Depression Detection

Zhang et al. [36] conducted an observational study involving 5150 Twitter users to monitor depression trends during the COVID-19 pandemic. To analyze the data, advanced DL models [Bidirectional Encoder Representations from Transformers (BERT), robustly optimized BERT approach (RoBERTa), and a generalized autoregressive pretraining method (XLNet)] were employed. The fusion model achieved an accuracy of 78.9%, while the chunk-level results (data divided into segments of text) showed significant improvements in classification as the size of the training and validation set increased. In particular, the XLNet model demonstrated the highest performance, with an AUC of 84.9%, a precision of 78.1%, an F1-score of 79.2%, and an accuracy of 78.4% when trained on a sample of 4650 users. These data underscore how the integration of sophisticated DL models and a large dataset can significantly improve accuracy in classifying depressive states based on the language used by users on social media platforms like Twitter. In a similar context, Zogan et al. [33] conducted an experimental study developing a model called "Hierarchical Attenuation Convolutional Neural Network" (HCN), designed to identify and analyze depression among social media users. Focusing on the repercussions of the COVID-19 pandemic on user behavior and the content of their tweets, the model detected an increase in depression rates during the pandemic period. The HCN demonstrated high effectiveness in identifying depression, using metrics such as accuracy (93.4%), precision (85.6%), recall (91.8%), and F1-score (89.7%), providing a detailed overview of how changes in digital behavior can reflect significant depressive states.

3.4. Post-Pandemic: Advances of AI in Monitoring Mental Health

Anshul et al. [35] conducted an experimental study in India using a DL methodology that integrates Visual Neural Network (VNN) and textual analysis. The study aimed to detect depression among social media users by leveraging a new framework based on AI. The results showed a high accuracy of 93.1% on the Tsinghua dataset and 91.7% on a new COVID-19 dataset, demonstrating the effectiveness of the multimodal approach. The evaluation criteria used in the study include accuracy, precision, recall, and F1 score. Meanwhile, another experimental study conducted in India by Chatterjee et al. [34] led to the creation of a model for real-time depression detection through the analysis of tweets that exhibit depressive symptoms. Using advanced ML techniques and an SVM classifier, the study developed a model based on sentiment analysis and user interactions on social media to track trends in mental health. The model recorded an accuracy of 89%, with precision, recall, and F1-score values highlighting its ability to detect signals of depression from Twitter posts. The maximum accuracy achieved was 89%, and the F1 score was 0.88, representing the best performance among the tested classifiers.

4. Discussion

The adoption of AI techniques in mental health diagnosis through social media analysis has garnered significant attention, particularly in understanding temporal trends across different periods [42]. This discussion systematically addresses our four research questions by examining the limited evidence from our nine included studies, while acknowledging the preliminary nature of these findings (Figure 2).

These models have demonstrated a remarkable ability to identify indicators of depression based on linguistic patterns, user sentiment analysis, and interaction data [41]. However, the advent of the COVID-19 pandemic has led to a reevaluation of these methods, particularly regarding their effectiveness before and during the post-pandemic period. While the pandemic provided a natural experiment with increased social media data, it remains unclear whether observed improvements in AI performance reflect pandemic-specific methodological advances or the natural evolution of AI technology that would have occurred regardless [33,36].

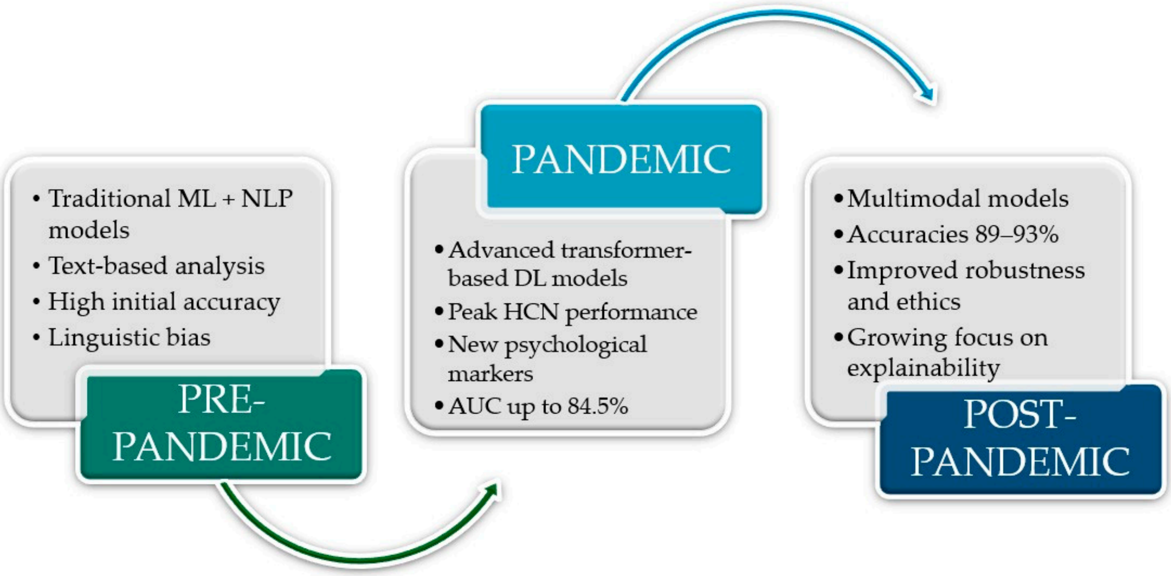

Figure 2. Graphical representation of data finding. Legend. ML: machine learning; NLP: natural language processing; DL: deep learning; HCNs: hierarchical convolutional Network; AUC: area under curve.

4.1. AI Model Effectiveness Evolution (Pre vs. During/Post-Pandemic)

Our analysis suggests potential improvements in AI model performance over time, though attribution to pandemic-specific factors remains uncertain. Pre-pandemic studies showed moderate effectiveness, with Islam et al. [41] achieving an F-measure of 0.73 using Decision Tree algorithms on Facebook data, and Benjamin et al. [40] reaching an AUC of 0.72 with Instagram content analysis. Before the pandemic, the effectiveness of AI models in detecting depression in social networks was primarily based on the various types of data that these models processed. Previous studies [40] predominantly leveraged textual data from user posts, analyzed through NLP techniques. These techniques, along with ML, have been crucial for analyzing the emotional states represented in online interactions [43]. The initial efforts highlighted the development of models capable of identifying linguistic signals and patterns related to depressive symptoms, with flexible methodologies that allowed for the incorporation of various types of data, including text, images, and even behavioral signals [44].

During the pandemic, Zhang et al. [36] reported improved accuracy of 78.9% using advanced transformer models (BERT, RoBERTa, and XLNet), while Zogan et al. [33] achieved notably high performance metrics (accuracy: 93.4%, F1-score: 89.7%) with their Hierarchical Convolutional Network. Post-pandemic studies by Anshul et al. [35] demonstrated accuracy rates of 93.1% and 91.7% on different datasets, and Chatterjee et al. [34] achieved 89% accuracy. In this pre-pandemic era, the data landscape was relatively stable, characterized by well-defined markers of depressive behavior that could be easily captured through existing technologies [38]. Platforms like Twitter and Facebook were primarily used for personal expression, making the data more accessible for AI analysis [45]. However, the onset of the pandemic introduced variables that significantly altered the types of data and the performance of the resulting model. The mental health crisis due to isolation, widespread fear, and uncertainty increased the volume and variance of data available for AI models, as users shared emotionally charged content as their mental states deteriorated [46].

Assessment of Hypothesis 1: The evidence suggests improved performance metrics in later studies, but this trend likely reflects natural AI technological evolution rather than pandemic-specific improvements. The progression from traditional machine learning approaches to deep learning and transformer models represents expected technological advancement that would have occurred regardless of the pandemic context.

4.2. Data Modality Effectiveness Across Time Periods

Pre-pandemic approaches predominantly focused on textual analysis. Tadesse et al. [38] achieved 91% accuracy using natural language processing on Reddit posts, while Sun et al. [37] employed domain-adversarial neural networks primarily on textual data. During and post-pandemic periods showed increased adoption of multimodal approaches.

This change necessitated a reevaluation of existing models, as the nature and context of communication transformed. The incorporation of new types of data, such as emojis, memes, and engagement metrics (likes, shares, and comments), became essential to capture the nuanced expressions of mental distress that emerged during the pandemic. Consequently, AI models began to integrate multimodal approaches to data, seeking to synthesize textual and visual elements to improve precision [35,37,39].

Anshul et al. [35] explicitly integrated Visual Neural Network (VNN) with textual analysis, demonstrating the effectiveness of multimodal frameworks with accuracies exceeding 90%. However, Zhang et al. [36] during the pandemic period still relied primarily on textual analysis through transformer models, suggesting that the shift toward multimodal approaches was not universally adopted.

Moreover, hierarchical attention networks have significantly improved the detection of depression on social media during the pandemic [33].

Assessment of Hypothesis 2: Limited evidence suggests a trend toward multimodal approaches in later studies, but this appears to be part of general AI development rather than a pandemic-driven innovation. The small sample size prevents definitive conclusions about the superior effectiveness of multimodal versus text-only approaches across time periods.

4.3. Technical Challenges and Data Quality Improvements

Technical challenges remained consistent across all time periods. Pre-pandemic studies reported issues with data selection bias, limited generalization, and self-reporting limitations [40,41]. During pandemic studies faced similar challenges, with Zhang et al. [36] noting limited representativeness and uncertain identification issues. Post-pandemic studies continued to report comparable limitations, including selection bias and classification accuracy concerns [34,35].

Despite these advancements, several technical challenges persist in the deployment of AI models for mental health assessment. Data privacy and ethical concerns are paramount, especially when it comes to sensitive information on public platforms [47]. There is an ongoing debate about the robustness of algorithmic predictions, particularly to ensure that models are not biased by users' demographic characteristics [48]. Moreover, the need for explainability in AI models is fundamental, particularly in clinical applications where trust and transparency can significantly influence user acceptance and adherence to interventions [49].

All included studies, regardless of time period, struggled with similar fundamental challenges as follows: demographic bias, linguistic and cultural variability, privacy concerns, and generalization limitations. No clear evidence emerged of systematic improvements in addressing these technical challenges over time.

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Assessment of Hypothesis 3: The evidence does not support the hypothesis that pandemic-era models better addressed technical challenges. Fundamental methodological issues persisted across all time periods, suggesting that these challenges reflect inherent difficulties in social media-based mental health detection rather than time-specific problems.

4.4. Responsible AI Strategy Evolution

The period following the pandemic has seen a demand for responsible AI practices in mental health research. Incorporating ethical considerations into the design of AI models is essential to prevent potential harm associated with misdiagnoses or misinterpretation of results. Technologies must integrate principles of fairness and accountability to ensure equitable access to resources and demographic data processing options for all users [50].

Ethical considerations and responsible AI practices were discussed across all time periods without clear temporal progression. Pre-pandemic studies acknowledged privacy concerns and ethical issues [38,40]. Pandemic and post-pandemic studies continued to identify similar ethical challenges without evidence of substantially improved approaches to responsible AI implementation.

As mental health crises have been exacerbated by the pandemic, the importance of ongoing research into the social implications of AI detection models has never been clearer. Furthermore, the refinement of algorithms and their dependence on qualitative and quantitative data raise important discussions about the types of data used for analysis. Studies have shown multifaceted approaches that include the analysis of emotional language, pictorial content, and even online behavior on platforms like Twitter and Facebook [51].

The integration of interdisciplinary collaboration and user-centered approaches was mentioned across different time periods without clear indication that such practices became more prevalent or sophisticated in later studies. These different types of data provide AI models with a greater degree of contextual understanding, contributing to their overall effectiveness. For example, Chen et al. [52] highlighted the role of emotional AI in assessing interactions on social media, illustrating a comprehensive framework for monitoring mental health.

The era of the pandemic has also ushered in greater attention to interdisciplinary collaborations between mental health professionals and data scientists, promoting the development of robust AI solutions. Researchers have recognized that a multidimensional perspective is necessary to effectively identify and manage depression through social media. Furthermore, direct interaction with users to obtain feedback can enhance the performance and relevance of the model, indicating the need for user-centered approaches [53].

Assessment of Hypothesis 4: Based on our limited sample, there is insufficient evidence to support improved responsible AI strategies over time. Ethical considerations appear to be consistently acknowledged without clear indication of enhanced implementation approaches in later periods.

4.5. Limitations and Implications

Several critical limitations must be acknowledged in interpreting these findings:

1. Sample Size Limitations: With only nine studies, our analysis lacks the statistical power to draw robust conclusions about temporal trends in AI effectiveness for depression detection.
2. Attribution Challenges: While the pandemic provided increased social media data availability, observed improvements in AI performance likely reflect natural technological evolution (e.g., advancement from traditional ML to deep learning and transformers) rather than pandemic-specific innovations.

3. Review design constraints: Although we applied structured methods (PICOS, independent screening, and PRISMA-like flow), the restricted time frame, English-only inclusion, and limited database search prevent classification as a true scoping review. These methodological constraints, together with study heterogeneity, justify the narrative approach and are now explicitly acknowledged to enhance transparency.
4. Methodological Heterogeneity: Differences in datasets, evaluation metrics, and study populations across the included studies limit direct comparisons and trend analysis.
5. The persistent technical and ethical challenges across all time periods suggest that fundamental issues in social media-based depression detection, including privacy concerns, cultural bias, and generalization limitations, require ongoing research attention rather than representing time-specific problems.
6. Missing Literature: Our exclusion of key technical databases such as ACL Anthology, IEEE Xplore, and major AI conferences represents a significant limitation. This may have led to the omission of important developments in computational approaches to mental health detection. While this is acknowledged as a limitation, it also frames a future research perspective.

These limitations should be considered in interpreting the findings; they highlight the preliminary nature of this narrative review, while also informing directions for future research.

4.6. Future Research Directions

The intersection of AI and technological support in general consolidated in chronic care [54–60] presents multifaceted opportunities for future research, particularly in the areas of privacy, model strength, and integration of multimodal data. Based on our preliminary data findings, future research should prioritize:

- These reflections also align with earlier critical insights, which highlight the need for clearer framing when interpreting temporal trends in AI-based analyses;
- Comprehensive Systematic Reviews: Larger studies incorporating computational linguistics conferences and AI research databases to provide more robust evidence about temporal trends;
- Longitudinal Validation Studies: Research designed specifically to distinguish between technological evolution and contextual factors (such as increased data availability during the pandemic) in AI performance improvements;
- Ethical Framework Development: Systematic approaches to responsible AI implementation in mental health applications, moving beyond acknowledgment of ethical concerns to practical implementation strategies;
- Cross-Cultural Validation: Studies addressing linguistic and cultural biases that persist across all time periods in our review;
- As artificial intelligence technologies evolve, ensuring the privacy of sensitive mental health data becomes fundamental, necessitating robust methodologies that preserve confidentiality while leveraging vast data sets. In addition, improving the robustness of the model against adversarial attacks is essential to maintain trust and effectiveness in therapeutic contexts. The integration of multimodal data—signs of voice, text, and physiological data—can enrich the assessments of mental health; however, the challenges in the harmonization of disparate data types require further exploration;
- The interdisciplinary collaboration between IT, psychologists, and doctors is essential to encourage innovative solutions that are ethically sound and clinically relevant. Incorporating user feedback into the development of the AI model can help align technological progress with the needs of the real-world practice [61]. Finally, understanding post-pandemic behavioral changes will inform artificial intelligence applications

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that address mental health problems emerging in an increasingly digital landscape in clinical procedure in general [62–65];

- Our analysis represents an exploratory examination that requires validation through more comprehensive research before definitive conclusions can be drawn about temporal trends in AI-based depression detection on social media;
- The advancements of AI models for detecting depression on social media have evolved significantly, particularly in response to the COVID-19 pandemic. The effectiveness of these models heavily relies on the integration of various types of data, addressing the technical challenges of bias, privacy, and interpretability. As AI continues to play a crucial role in mental health research, responsible strategies must be prioritized to ensure that these innovations serve the best interests of all users. Exploring these dynamics will be fundamental in shaping the future of mental health interventions in social media contexts, facilitating timely support for individuals struggling with depression. The research landscape continues to generate insights that can lead to better health outcomes, further strengthening the critical intersection between technology and mental well-being [66–68].

5. Conclusions

The use of AI for detecting depression through social media has gained attention for its potential relevance to mental health care. Despite early technological advances, clinical application remains central, requiring careful attention to ethical, privacy, and cultural considerations. Our analysis of nine studies highlights the need for interdisciplinary collaboration and cautious interpretation. These reflections also align with earlier critical insights, linking temporal trends in AI analyses to potential future developments in clinical practice. Future research should focus on patient-centered outcomes and clinically applicable strategies to support multidisciplinary mental health care. Finally, a clear and structured ethical action is urgently needed to ensure that AI applications evolve responsibly alongside their rapid technological advancement.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/psychiatryint7010024/s1, File S1: SANRA; File S2: Search Strategy; File S3: CASP checklist.

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