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Depression Diagnosis with Artificial Intelligence: A Bibliometric Analysis

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Abstract

Background: Depression, a severe psychological disorder, exerts profound effects on an individual's life. It saps energy, pleasures, and motivation leading individuals to helplessness and hopelessness, strained relationships, and increased thoughts of suicide ideation. Artificial intelligence has emerged as a potential tool in predictive analysis. With the analysis of big data, AI can detect patterns and indicators that aid in identifying depression with improved accuracy and efficacy. Since 2012, diagnosing depression with AI tools has become a hot topic of research. This study is a bibliometric analysis of the literature on diagnosing depression with artificial intelligence (AI) tools.
Methods: The authors geared up the four digital libraries: Pub Med, Web of Science, Google Scholar and Science Direct databases and applied filters to select relevant publications from 2014 to 2022. They used Microsoft Excel to analyze the data on publication growth, top contributors, keywords, and citations. VOSviewer was used to visualize collaborative maps between authors, institutions, affiliations, and hot topics related to the field.
Results: A total of 476 publications were used for this Bibliometric analysis. From 2019 to 2022, the growth of publications trend has seen a steady increase. The USA is the leading country in terms of publication count. The most cited author was Perlis, who published seven papers on depression and AI. The most affiliated institution was Harvard Medical School, which produced 28 publications. The most common keyword was "depression", which appeared in 260 publications. The highly contributed journal was "Frontiers in Psychology" and the most cited paper was by Kessler et al., (2015).

- **Introduction**

Psychological disorders, including depression, have a significant impact on individuals worldwide. Depression affects a substantial portion of the population, with approximately 10-20% of women and 5-12% of men experiencing this condition . Depression is characterized by symptoms such as low mood, reduced energy and appetite, changes in sleep patterns, decreased interest in daily activities, and thoughts of suicide. It is a prevalent mental health condition, affecting over 300 million people globally. The COVID-19 pandemic has further exacerbated the burden of depression on individuals, adding to the challenges they already face . The economic costs of global mental health are projected to reach trillions of dollars annually by 2030, surpassing the expected costs of diabetes, respiratory diseases, and cancer combined . Accurate diagnosis is crucial for effective treatment of depression. However, many individuals struggle to access medical attention due to factors such as transportation limitations, financial constraints, and lack of motivation. Long-term follow-ups and effective assessment are essential for a patient's recovery, but traditional retrospective methods often suffer from recall bias and hinder accurate characterization and understanding of the condition.
Ecological momentary assessment (EMA) has emerged as an alternative approach for assessing depression. This method allows for repeated sampling of thoughts, emotions, and behaviors in real-time, capturing the experiences as they occur in individuals' natural environments . EMA has shown superiority over traditional paper and pencil approaches for assessment . Although there are no approved biomarkers for diagnosing psychiatric disorders like depression, speech, text, and expression are widely used as potential biomarkers by psychiatrists and clinicians . The popularity and extensive use of social media platforms and wearable devices have made them potential sources of these biomarkers . Artificial Intelligence (AI) and machine learning techniques, such as Convolution Neural Networks (CNN), Deep Convolution Neural Networks (DCNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), have been employed to predict and assess depression using these biomarkers. The demand and preference for online mental health services have led to the development of prototypes and studies using AI models to predict and estimate depression .
Bibliometric analysis is a quantitative research method that involves analyzing and measuring scientific publications and their impact within a specific field (Yao et al., 2013). It utilizes statistical analysis of bibliographic data to evaluate researchers, institutions, or scientific journals. Common metrics include the number of publications, citations, co-authorship patterns, and other related indicators. Several software tools like VOSviewer, CiteSpace, and SciVal are

available for conducting Bibliometric analysis. These software tools enable researchers to explore publication and citation data, identify influential papers and authors, understand research trends, and assess research impact. Although there are a few reviews available; they are limited to using only speech text, or expression as specific biomarkers of depression. However, there is a need for a comprehensive Bibliometric analysis that assesses the recent trends, and key contributors and discovers the main topics of related research. To date, existing reviews have focused on specific biomarkers, such as speech or text or expression analysis, and have not provided a comprehensive overview of all relevant studies. This study aims to fill this gap by conducting a Bibliometric analysis of studies that assess the recent trends, and key contributors and discover the main topics of related research.

- **Methods and Materials**

- **Search process**

On August 29, 2023, the researcher conducted an advanced search process on 4 digital libraries; Pub Med, Web of Science, Google Scholar and Science Direct by entering the search formula "(Depressed) OR (Depression) OR (Depressive) OR (Major Depressive Disorder) AND (Artificial Intelligence) OR (AI) OR (Machine Learning) OR (ML)" to identify the research articles related to depression diagnosis with Artificial Intelligence (AI) methods. The filters used were date (1999-2023), language type (English only), and the document types included review and research articles only. To better shape and understand the search process and study design of this Bibliometric analysis, the data is provided in Figure 1. As shown in Figure 1, the researcher identified 2861 records from the Web of Science database. Once the author used the filters of date (2012-2023), access type (only open access), document type (review and articles), and language (English), the researchers excluded 1192 records and retrieved 1669 records only. In the second stage, the researchers read the titles and abstracts (title & abstract screening) of these 1669 records and excluded 1193 research papers which led to the number of final records as 476 for this Bibliometric analysis.

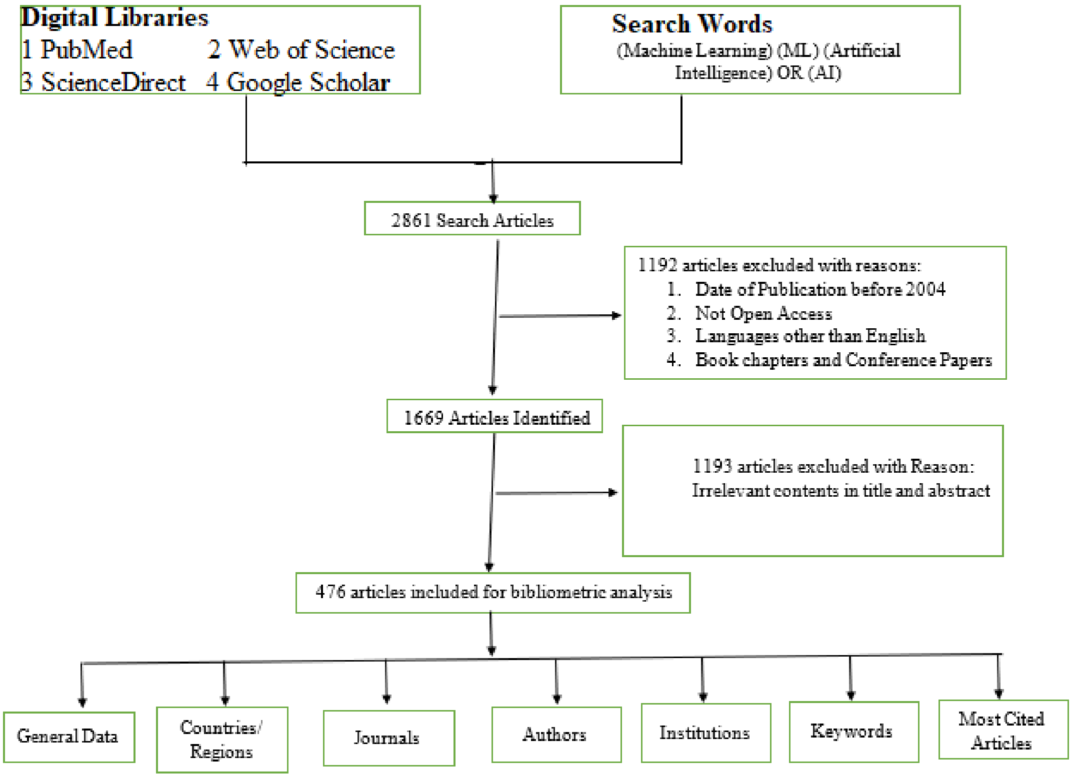


FIGURE 1. Flow chart of screened data.

- **Data analysis tools**

The researchers used two tools (Microsoft Excel 2010 &VOSviewer) for this bibliometric analysis. The Microsoft Excell 2010 (Redmond, Washington, United States) was used to identify publication growth and the top contributors in terms of countries, journals, authors, institutions, keywords, and most cited articles. The VOSviewer was used to map the network collaborations among countries, journals, authors, institutions, and keywords.

- **Results**

- **General data**

Figure 2 represents the publication growth and general data of the included 476 records. (**A)** Represents the publication growth from 2012-2023. It is observed that there is a growing trend of research in depression diagnosis with AI in recent years (2019-2022). The year 2022 is worth noting because this year there is the highest number of publications (n=141) related to this field. However, after further investigation, it was seen that the topics of research in the last 4 years were Depression, Suicide, bipolar disorder, and neuropsychiatric disorders. (**B)** It represents general data as 62 countries/regions, 190 journals, 2848 authors,1085 institutions/affiliations, 1354 keywords, and 6716 citations in total.

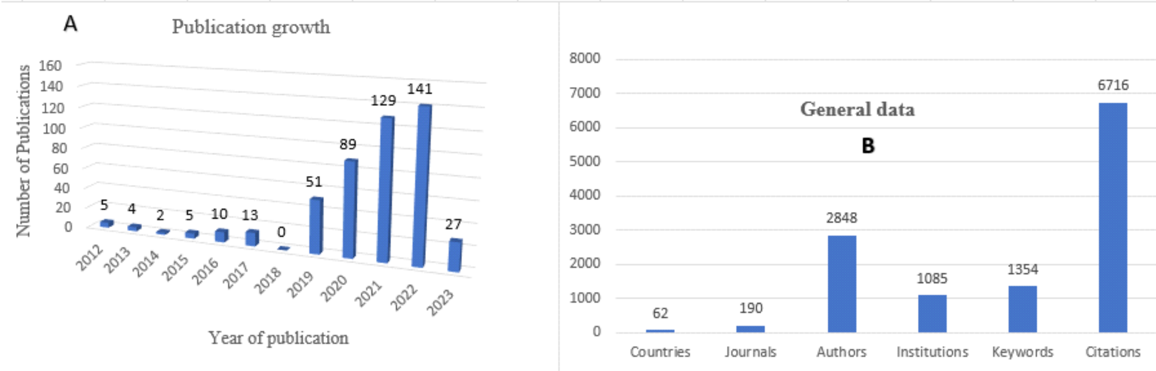


Figure 2 A&B Represents the publication growth and General data of the included studies

- **Top contributing countries**

Figure 3 represents the top 10 productive countries in terms of the count of publications and the network collaboration among them. The USA ranked number one with 222 publications (46.93), followed by China with 85 publications (17.85%), and at third number, England came up with 57 publications (11.95%). As for total citations, the USA again ranked at the top with 4687 citations (21.11 CPP), followed by England with 1408 citations (24.7 CPP), and then Germany with 1149 citations (23.44 CPP). To represent the inter-countries collaboration network, the researchers used the co-authorship analysis in terms of countries in VOSviewer. Assigning the minimum number of publications to an author as 5, only 31 countries formed a collaborative network. In this map, the USA, China, England, Germany, and South Korea are large nodes with relatively thicker lines. The size of the nodes represents the concentration of publications for each country. The distance from one node to another node is negatively associated with the collaboration strength between them. The color displays the cooperation between different clusters of countries.

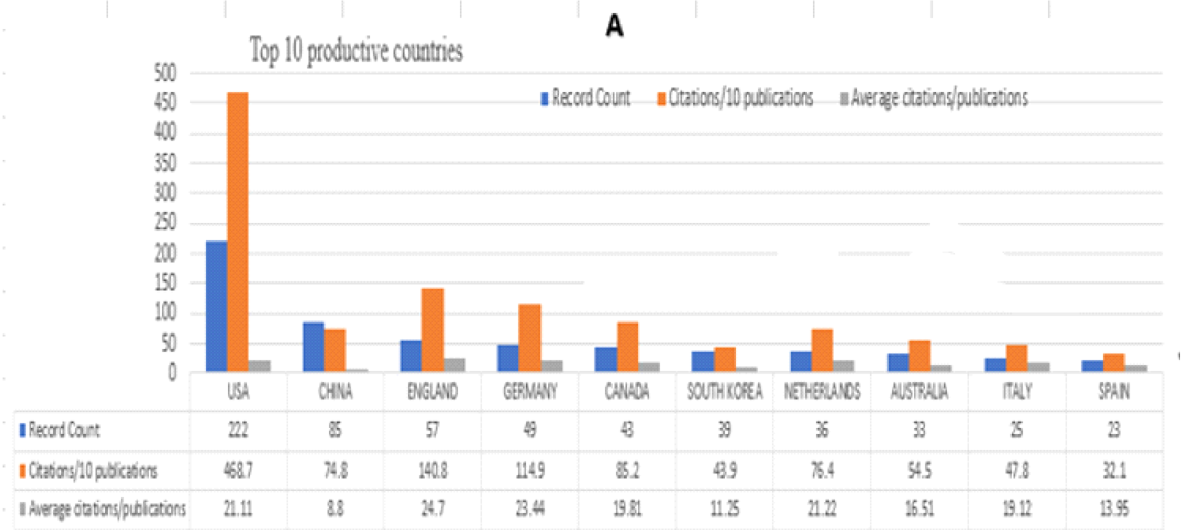


Figure 3 Top 10 productive countries and inter-countries co-operation relationship on depression diagnosis with AI.

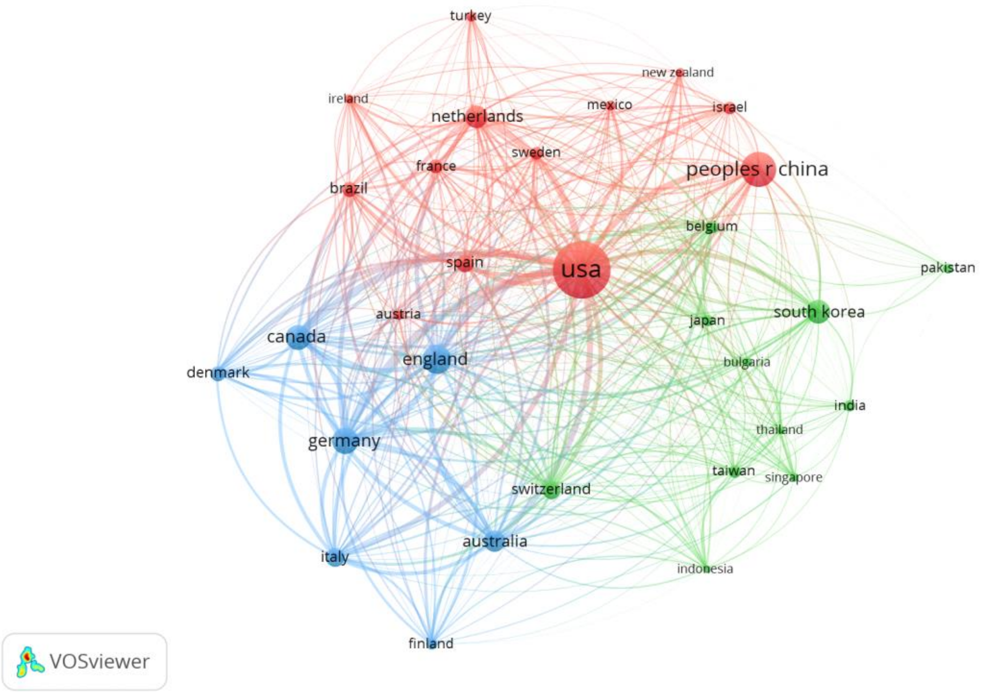


Figure 3 (B) Top 10 productive countries and inter-countries co-operation relationship on depression diagnosis with AI.

- **Top Contributing Journals**

Table 1 exhibits the 10 top-ranked journals in terms of the number of publications and co-cited journals in terms of the highest number of co-citation counts. Among them, the highest number of research articles were published by Frontiers in Psychiatry (35 publications, TC= 180) followed by Translational Psychiatry (21 publications, TC=308) and PLOS One (19 publications, TC=307). But, in terms of average citations per document, the Journal of Medical Internet Research (30.16 CPP), followed by Psychological Medicine (25.5 CPP), and the Journal of Affective Disorders (18.41 CPP) ranked as the top three productive journals. However, in terms of co-cited journals, the Journal of Affective Disorders (944 co-citations), followed by the American Journal of Psychiatry (603 co-citations) and Psychological Medicine (430 co-citations), ranked the top three co-cited journals in the list of top ten co-cited journals. Figure 4 represents the network visualization map of collaboration between different journals. The node size shows the publication intensity in the field of depression diagnosis with AI. The distance from one node to another node is negatively associated with journal cooperation. The early stage of publication date is represented by blue color while as latest publications color is represented by yellow color.

Table 1. Top 10 productive journals and co-cited journals

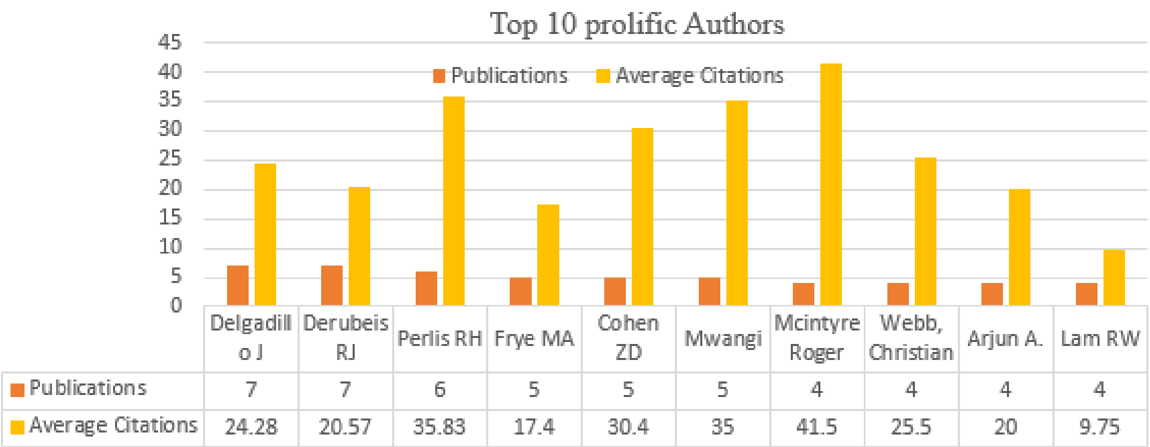
Publication Titles	Record Count	Total Citations	Average Citations/Publication	Co-cited Journals	Co-citations
Frontiers in Psychiatry	35	180	5.14	Journal of Affective Disorders	944
Translational Psychiatry	21	308	14.66	American Journal of Psychiatry	603
PLOS One	19	307	16.15	Psychological Medicine	430
Journal of Affective Disorders	17	313	18.41	PLOS One	422
Journal of Medical Internet Research	12	362	30.16	Biological Psychiatry	413
Journal of Psychiatric Research	12	163	3.58	Jama Psychiatry	336
Psychological Medicine	12	306	25.5	Archives of General Psychiatry	336
BMC Psychiatry	9	123	13.66	Journal of Clinical Psychiatry	300
International Journal of Environmental Research and Public Health	9	74	8.22	British Journal of Psychiatry	283
Scientific Reports	9	85	9.44	Psychiatry Research	270

- **Top Contributed Authors**

Table 2 displays the top 10 contributed authors in terms of publication count. Delgadillo Jaime (University of Sheffield, England) has the highest number of publications (n = 7, TC = 170) on his name, he was followed by Derubeis Robert (University of Pennsylvania, USA) with the same number of publications (n = 7, TC = 144). The dispute of rank between these two authors was assigned after further investigation of total citation counts and average citations per document. And then Perlis R comes with 6 publications with 215 total citations. However, for total citation counts, Perlis R. has the highest number of citations (n = 215), followed by Mwangi (n = 175), and then Delgadillo J. has 170 total citations to his publications. Although, Mcintyre Roger has only 4 publications in his name, but has the highest average citations per document (41.50). this was followed by Perlis R. with 35.83 citations per document. The node size shows the author's contribution to the field of depression diagnosis with AI. The distance from one node to another node is negatively associated with journal cooperation. The color displays the cooperation between different clusters of countries.

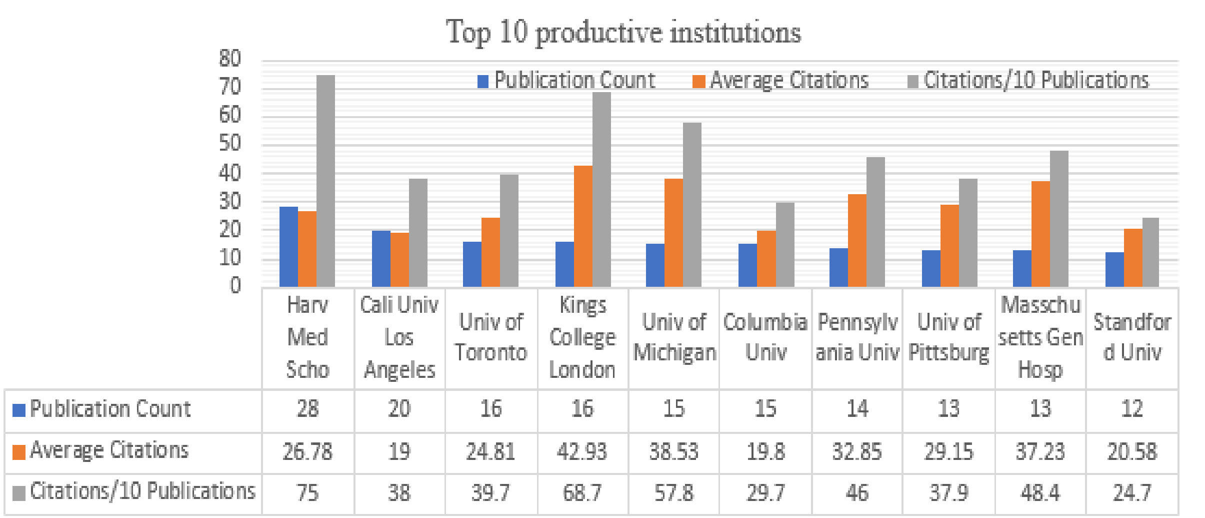
Table 2 Top 10 contributed authors

Authors	Publications	Total Citations	Average Citations
Delgadillo J	7	170	24.28
Derubeis RJ	7	144	20.57
Perlis RH	6	215	35.83
Frye MA	5	87	17.40
Cohen ZD	5	152	30.40
Mwangi	5	175	35.00
Mcintyre Roger	4	166	41.50
Webb, Christian	4	102	25.50
Arjun A.	4	80	20.00
Lam RW	4	39	9.75



- **Top Contributing Institutions/Organizations**

Figure 6 **(A)** displays the top 10 prolific organizations/institutions. Harvard Medical School ranked first with 28 publications, followed by California University, Los Angeles with 20 Publications, and then the University of Toronto with 16 publications at the third number as top-ranked organizations/institutions. In terms of citations, Harvard Medical School ranked on top of the list with 750 citations, followed by Kings College London with 687 citations, and then the University of Michigan with 5768 citations. However, for average citations, Kings College London ranked first with 42.93 citations per document. Figure 6 **(B)** represents the co-authorship network visualization map of the institutions for depression diagnosis with AI. The size of the nodes represents the number of articles published by the institute or organization. The color represents the cooperation among the different clusters of institutions.



	Harv Med Scho	Cali Univ Los Angeles	Univ of Toronto	Kings College London	Univ of Michigan	Columbia Univ	Pennsylvania Univ	Univ of Pittsburg	Masschusetts Gen Hosp	Standford Univ
Publication Count	28	20	16	16	15	15	14	13	13	12
Average Citations	26.78	19	24.81	42.93	38.53	19.8	32.85	29.15	37.23	20.58
Citations/10 Publications	75	38	39.7	68.7	57.8	29.7	46	37.9	48.4	24.7

Figure 6 A, Top 10 prolific institutions in terms of the number of publications related to depression diagnosis with AI

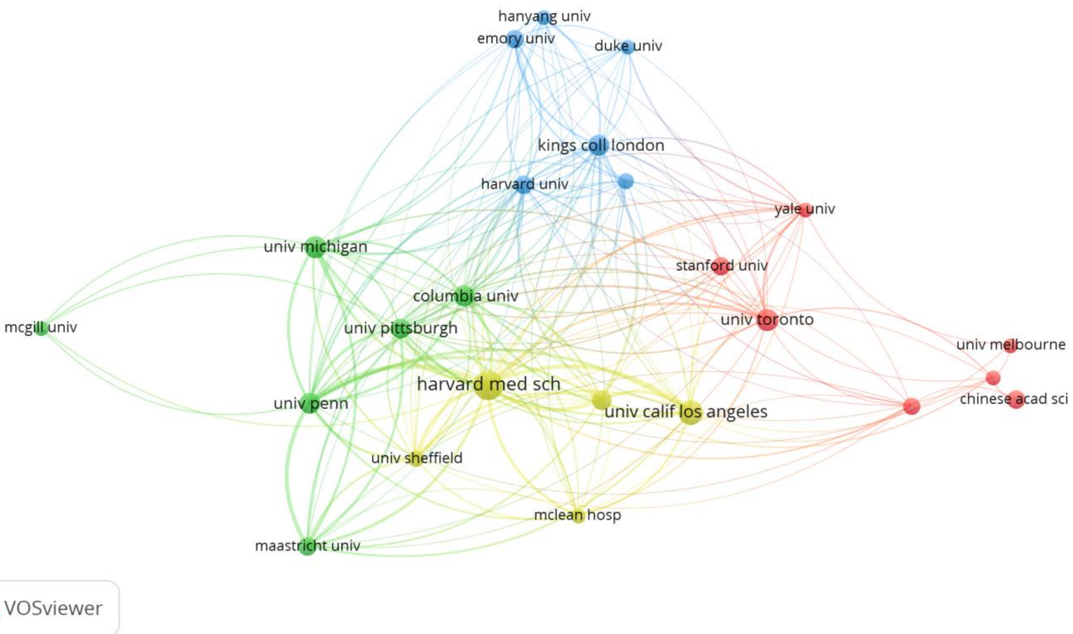


Figure 6 (B) The co-authorship network visualization map of the institutions for depression diagnosis with AI

- **Keyword Analysis**

Keyword analysis was done by VOSviewer and is represented in Figure 7. Only 45 keywords appeared more than 115 times out of 1354 total keywords and were categorized into 4 clusters. The most appeared keywords were "depression" (n=260), followed by "Machine Learning" (n=206), and then "Symptoms" (n=57) in the list. The node size shows the keyword occurrence intensity in the field of depression diagnosis with AI. The distance from one node to another node is negatively associated with other keywords. The early stage of keyword occurrence is represented by blue color while as latest keywords are represented by yellow color.

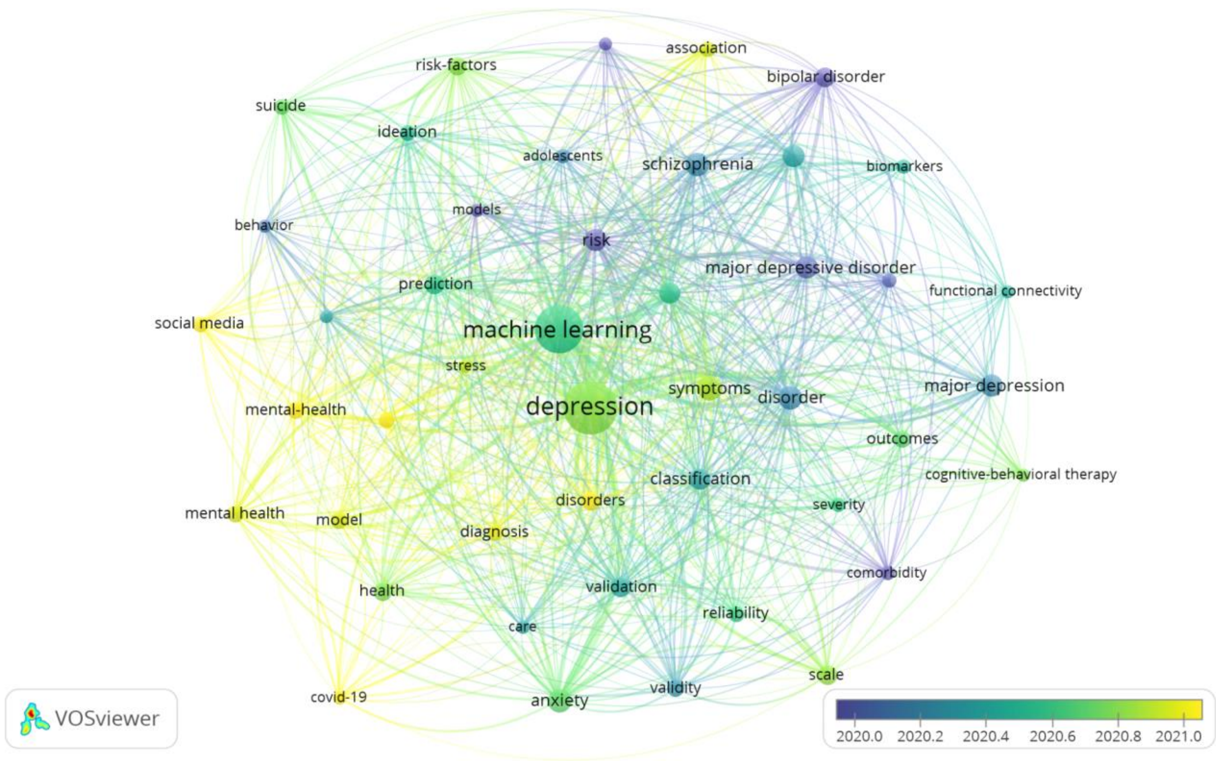


Figure 7 Co-occurrence network visualization map of keyword analysis related to depression diagnosis with AI.

VII. Most Cited Articles

In the words of Gonzales-Alcaide et al., (2016), the term citation is used to indicate the utility, interest, and value of that publication in terms of the advancement of knowledge. Table 3 displays the top 10 publications in terms of citation count. The highest number of citations (n=271) was achieved by the study of Kessler, R. et al., (2015) entitled "Predicting Suicides After Psychiatric Hospitalization in US Army Soldiers The Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS) which was published by JAMA Psychiatry, followed by 167 citations to the study carried out by de Almeida JRC et al., (2013) entitled "Distinguishing between Unipolar Depression and Bipolar Depression: Current and Future Clinical and Neuroimaging Perspectives" published by Biological Psychiatry, and then the study with 147 citations which was done by Chekroud, AM et al., in 2017 entitled "Reevaluating the Efficacy and Predictability of Antidepressant Treatments A Symptom Clustering Approach) and was published in the journal of JAMA Psychiatry.

Table 3 represents the most cited publications.

Rank First Author	Publication Title	Journal	TC	Publication/Year
1. Kessler, et al., (2015)	Predicting Suicides After Psychiatric Hospitalization in US Army Soldiers The Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS)	JAMA Psychiatry	271	2015
2. de Almeida, et al., (2013)	Distinguishing between Unipolar Depression and Bipolar Depression: Current and Future Clinical and Neuroimaging Perspectives	Biological Psychiatry	167	2013
3. Chekroud, et al., (2017)	Reevaluating the Efficacy and Predictability of Antidepressant Treatments A Symptom Clustering Approach	JAMA Psychiatry	147	2017
4. Le, TT et al., (2020)	Scaling tree-based automated machine learning to biomedical big data with a feature set selector	Bioinformatics	131	2020
5. Kessler, RC. et al., (2016)	Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports	Molecular Psychiatry	124	2016
6. Maj, M, et al., (2020)	The clinical characterization of adult patients with depression aimed at the personalization of management	World Psychiatry	120	2020

7. (2012)	Perlis, RH, et al.,	Using electronic medical records to enable large-scale studies in psychiatry: treatment resistant depression as a model	Psychological Medicine	114	2012
8. (2013)	Perlis, RH, et al.,	A Clinical Risk Stratification Tool for Predicting Treatment Resistance in Major Depressive Disorder	Biological Psychiatry	112	2013
9. (2017)	Cheng Q J, et al.,	Assessing Suicide Risk and Emotional Distress in Chinese Social Media: A Text Mining and Machine Learning Study	Journal Of Medical Internet Research	111	2017
10. (2020)	Joel, S, et al.,	Machine learning uncovers the most robust self-report predictors of relationship quality across 43 longitudinal couples studies	Proceedings Of The National Academy Of Sciences Of The United States Of America	105	2020

- **Discussion**

- **Research growth and General data**

The comprehensive bibliometric analysis presented here offers valuable insights into the landscape of depression diagnosis with AI, highlighting trends, key contributors, and significant publications. This study not only contributes to understanding the current state of research but also provides directions for future investigations in this domain.
The findings of this study align with existing literature on depression diagnosis and AI. The increasing trend in research output from 2019 to 2023 corroborates the growing interest in utilizing AI techniques for mental health assessment, especially depression. This trend resonates with previous studies emphasizing the potential of AI in mental health diagnostics (Chekroud et al., 2016; Pan et al., 2020).

- **Top contributing countries/organizations and authors**

Furthermore, the dominance of certain countries such as the USA, China, and England in research productivity is consistent with their strong investments in AI and mental health research infrastructure (Kessler et al., 2016). Institutions like Harvard Medical School and the University of Sheffield, as evidenced by their high publication counts and citations, reaffirm their leading roles in this field (Delgadillo et al., 2012; Kessler et al., 2015).

- **Keyword Analysis**

Keyword analysis sheds light on evolving research themes, with recent focus areas including social media, COVID-19, and personalized management. These findings resonate with the broader context of utilizing diverse data sources and tailoring interventions to individual needs, reflecting the interdisciplinary nature of contemporary mental health research (Maj et al., 2020; Cheng et al., 2017).

- **Analysis of Top Most Cited Publications**

Citations are quotations from one publication to another publication. They provide important details about the origin and credibility of the information and allow readers to verify and locate the sources. Citation analysis is a quantitative method used to evaluate and analyze the scholarly impact of research articles or publications. It provides insights into the influence and importance of a particular article or authors within a specific field of study (Gonzalez Alcaide et al., 2016). The most cited publications in the field of diagnosing depression with AI reveal various significant findings and approaches. it is evident in Table 4, that the article entitled “Predicting Suicides After Psychiatric Hospitalization in US Army Soldiers: The Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS)” is the most cited (266 citations) publication which was conducted by Kessler et al. in 2015. This study highlights the association between sunshine exposure and suicide rates, particularly noting increased risks in women during spring. Another notable work, "Distinguishing between Unipolar Depression and Bipolar Depression: Current and Future Clinical and Neuroimaging Perspectives" (2013), explores neuroimaging studies to differentiate between types of depression, advocating for personalized treatments based on objective markers.
"Reevaluating the Efficacy and Predictability of Antidepressant Treatments: A Symptom Clustering Approach" (Chekroud et al., 2017) identifies three symptom clusters in depression and suggests tailoring treatments accordingly. Le et al.'s (2020) study introduces features in TPOT, enhancing its efficiency in predicting major depressive disorder from biomedical data. Kessler et al.'s (2016) work proposes machine learning models to predict the course and severity of major depressive disorder based on patient self-reports, showcasing superior performance over conventional methods.
Maj et al. (2020) emphasize the need for personalized depression management based on individual patient features and available assessment tools. Perlis (2012) employs natural language processing on electronic medical records to study treatment-resistant depression, demonstrating its efficacy in analyzing patient data. Additionally, Kessler's (2013) clinical risk stratification tool for treatment-resistant depression aids in identifying patients who may not respond well to antidepressant treatment.

Lastly, Cheng's (2017) study on assessing suicide risk and emotional distress in Chinese social media users highlights the utility of language analysis and machine learning, although it acknowledges the need for further refinement.
These studies collectively advance our understanding of depression diagnosis with AI by exploring diverse methodologies, from neuroimaging to natural language processing and highlighting the importance of personalized approaches in depression management. They underscore the potential of AI in revolutionizing depression diagnosis and treatment, paving the way for more tailored and effective interventions.

• Conclusion

In conclusion, this bibliometric analysis underscores the growing interest and significance of leveraging AI techniques for depression diagnosis. This bibliometric analysis presents a comprehensive overview of the literature on depression diagnosis utilizing artificial intelligence (AI) methodologies. By examining a dataset spanning from 2012 to 2023 and analyzing 476 publications, this study sheds light on the evolving landscape of depression diagnosis, particularly focusing on the integration of AI tools. The findings reveal a notable surge in research activity in recent years, indicative of a concerted effort to harness technological advancements for mental health assessment. The dominance of countries like the USA, China, and England underscores the global collaboration and commitment to addressing mental health challenges through innovative means.
Furthermore, the identification of key authors, institutions, and journals provides valuable insights for stakeholders, guiding future research endeavors and collaborations. The prominence of certain keywords reflects the evolving discourse within the field, encompassing themes such as machine learning, social media, and COVID-19, underscoring the adaptability of AI methodologies to address contemporary challenges.
Overall, this study not only consolidates existing knowledge but also paves the way for future research directions and interdisciplinary collaborations aimed at enhancing the accuracy and efficacy of depression diagnosis. By harnessing the potential of AI in conjunction with traditional assessment methods, the field stands poised to usher in a new era of personalized and accessible mental healthcare.

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