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REVIEW

Mapping and Visualizing the Intersection of Sentiment Analysis and Mental Health

Mapeo y visualización de la intersección del análisis de sentimientos y la salud mental

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ABSTRACT

Introduction: sentiment analysis, a computational approach to evaluating emotions in textual data, has gained significance in mental health research. It assesses public sentiments on mental health issues and aids in early disorder detection through social media and digital platforms.
Objectives: this study aims to analyze the intersection of sentiment analysis and mental health research, identifying key scholarly trends, thematic developments, and global collaborations from 2013 to 2024.
Method: a bibliometric analysis was conducted using 521 documents from Scopus, including journal articles, book chapters, and conference papers. Biblioshiny, VOSviewer, and CiteSpace were used to analyze publication trends, co-authorship networks, and keyword co-occurrences.
Results: the field has grown at an annual rate of 42,45 %, with research output peaking in 2023 (134 articles). Key themes include AI applications in mental health, sentiment-based diagnosis, and the impact of COVID-19. China, the USA, and Australia are the leading contributors, while Bangladesh and Switzerland have the highest citation impact per article. The study maps extensive international research collaborations.
Conclusions: sentiment analysis is an evolving field with global collaboration. Advances in machine learning and NLP enhance its potential for real-time mental health monitoring and predictive analysis. Future research should focus on personalized AI-driven interventions, ethical considerations, and expanding datasets to improve diagnostic accuracy. This study provides insights for researchers, practitioners, and policymakers in leveraging sentiment analysis for mental health advancements.

Keywords: Sentiment Analysis; Mental Health; Bibliometric Analysis; Biblioshiny; VOSviewer; Citespace.

RESUMEN

Introducción: el análisis de sentimientos, un enfoque computacional para evaluar las emociones en datos textuales, ha cobrado relevancia en la investigación en salud mental. Evalúa la opinión pública sobre temas de salud mental y facilita la detección temprana de trastornos a través de redes sociales y plataformas digitales.
Objetivos: este estudio busca analizar la intersección entre el análisis de sentimientos y la investigación en salud mental, identificando tendencias académicas clave, desarrollos temáticos y colaboraciones globales entre 2013 y 2024.

Método: se realizó un análisis bibliométrico con 521 documentos de Scopus, incluyendo artículos de revistas, capítulos de libros y ponencias de congresos. Se utilizaron Biblioshiny, VOSviewer y CiteSpace para analizar las tendencias de publicación, las redes de coautoría y la coocurrencia de palabras clave.
Resultados: el campo ha crecido a una tasa anual del 42,45 %, alcanzando su pico de producción investigadora en 2023 (134 artículos). Los temas clave incluyen las aplicaciones de la IA en salud mental, el diagnóstico basado en sentimientos y el impacto de la COVID-19. China, EE. UU. y Australia son los principales contribuyentes, mientras que Bangladesh y Suiza tienen el mayor impacto de citas por artículo. El estudio mapea extensas colaboraciones internacionales de investigación.
Conclusiones: el análisis de sentimientos es un campo en evolución con colaboración global. Los avances en aprendizaje automático y PLN aumentan su potencial para la monitorización de la salud mental en tiempo real y el análisis predictivo. Las investigaciones futuras deben centrarse en intervenciones personalizadas basadas en IA, consideraciones éticas y la expansión de los conjuntos de datos para mejorar la precisión diagnóstica. Este estudio proporciona información a investigadores, profesionales y legisladores sobre cómo aprovechar el análisis de sentimientos para impulsar avances en salud mental.

Palabras clave: Análisis de Sentimientos; Salud Mental; Análisis Bibliométrico; Biblioshiny; VOSviewer; Citespace.

INTRODUCTION

Sentiment analysis, a branch of natural language processing (NLP), has gained significant importance in the field of mental health. This technology is utilized to examine textual data from diverse sources, including social media, therapy sessions, and online communications, to detect and monitor mental health conditions. These are also used for the identification and prediction of disorders related to depression, anxiety, and stress. Sentiment analysis also demonstrates promising results for its application in the real-time monitoring of mental health. The tools of sentiment analysis review online material, mainly social media and online forums, for their analysis emotional status. Kakde et al., discussed applying the SA-mental health management systems to detect and monitor stress, anxiety, and depression related ailments using online communications.[1] Similarly, Verma et al. proposed a system to predict mental health using the sentiment analysis technique NLP technique with the support vector machine to find the probability of having mental health issues.[2]

This development in machine learning and deep learning has brought forth unprecedented advances in sentiment analysis accuracy in mental health applications. Zhang discusses recent studies on the application of methods that were developed using machine learning to perform sentiment analysis in mental health, especially during the period of the COVID-19 pandemic. This is a reflection of the need for accurate sentiment analysis models to know and effectively manage mental health challenges caused by this new pandemic.[3] The effort of Fatima et al. proposed the semi-supervised machine learning model DASentimental, which can predict the features of depression, anxiety, and stress from written sentences with state-of-the-art accuracy.[4] Over time, in the clinical domain also, work on sentiment analysis is being developed in such a way that it would ameliorate therapies for mental health. Empirical validation of automated sentiment analysis in online cognitive behavioral therapy (iCBT) is the study conducted by the group Provoost et al. Their study introduced the capability of extracting useful knowledge from a patient's emotional state, hence enhancing the effectiveness of interventions delivered through iCBT.[5] Shickel et al. applied deep transfer learning to predict emotional valence in mental health texts; applications can be extended to online therapy sessions.[6]

Social media sites provide a great deal of data, which may be considered as a source for sentiment analysis in mental health. Saraff et al. review how the sentiment analysis of social media can be utilized to make sense of human emotions and behavior in pandemic situations, especially in smart city scenarios.[7] Dixit et al. explored the detection of SESD to monitor mental health based on continuous data tracking from social media and wearable devices, which enhances the system's transparency and assures robust and general performance of the models.[8] Given the normal use of sentiment analysis for diagnosis, two of the most common conditions are: Depression Anxiety Zucco et al. mentioned a possible use of sentiment analysis in affective computing to maintain appropriate depression monitoring. They proposed a multimodal system that incorporates sentiment analysis to enhance the detection and monitoring of depression.[9] In another work, Srivastava et al. looked into the integration of multiple biomarkers of acoustic and visual clues for the enhancement of depression detection through sentiment analysis.[10] Despite the progress, significant challenges still persist in the application of sentiment analysis to mental health.

These models have normally suffered from low accuracy due to the intricacy of human sentiments and contexts in which sentiments are made. The work by Nandwani and Verma reviewed challenges found in sentiment analysis and emotion detection from text, pointing to the challenges in accurately detecting emotions and sentiments across different pieces of unstructured data from social media.[11] On the other hand, the literature suggests great values of sentiment analysis in monitoring and predicting states of mental health. Advanced machine learning techniques have increased its accuracy and applicability, especially for social media analysis and clinical applications. However, a few challenges remain, such as the need for more specialized datasets and the complexity of human emotions, in order to realize the full potentials of sentiment analysis in mental health.

Bibliometric analysis is considered a very powerful and effective quantitative approach to the analysis of publication trends within the corpus of literature, basing closely on dynamics research output in every detail.[12,13,14,15,16] It allows for a systematic review of publications, citations, and other forms of scholar outputs with the view to enabling researchers to identify patterns that could be emerging, seminal works highlighting, and outlining the intellectual structure underlying a particular discipline.[17,18,19,20,21] This approach and rationale will be particularly valuable in mapping how knowledge within a field evolved and has traced its growth trajectory.

The highly accessible web-based interface of Biblioshiny, which is used for the R-based bibliometric package, further enhances this process by enabling researchers with relatively sparse programming skills to run an in-depth analysis and visualization in a most professional-looking way.[22,23,24,25] This democratizes access to high-level bibliometric analysis and enables more researchers to do sophisticated interpretation and visualization tasks.[26,27,28]

Complementarily, VOSviewer is the other important tool that widely constructs and analyzes bibliometric networks in co-authorship, co-citation, and keyword co-occurrence aspects.[29,30,31] With its powerful visualization capability, VOSviewer provides intuitive, insightful representations of complex research landscapes to researchers and also tells meaningful insights with detection of underlying relationships within a field of study.[32,33,34,35] This range of tools significantly expands the possibility of investigation and understanding of the highly complicated dynamics that typify scholarly communication and collaboration.

Similarly, CiteSpace is a widely used bibliometric tool that excels in tracking the evolution of scientific knowledge, identifying research frontiers, and visualizing intellectual structures through co-citation and burst detection analyses.[36,37] By mapping citation networks and detecting emerging trends, CiteSpace aids researchers in systematically understanding the development of a research field, revealing key contributors, and recognizing gaps in the literature.[38,39] Together, these tools significantly enhance bibliometric research, enabling deeper insights into scholarly communication and collaboration.

The main objective of this study is to analyze the research landscape when it comes to sentiment analysis in mental health using bibliographic data from Scopus. Mapping the evolution of research topics, co-authorship networks, and keyword co-occurrences by employing advanced tools like VOSviewer, Citespace, and Biblioshiny is designed to transmit the global and interdisciplinary nature of the research domain from 2013 to 2024. More than this, the attempt is directed toward finding new and disappearing themes, the impact of studies across countries in the field, and sharing insights into collaboration that will drive this research agenda further. Ultimately, the study will advance a detailed overview of the current state and future direction for sentiment analysis and mental health research, with broader value to researchers, practitioners, and policymakers.

METHOD

Scopus was selected to be used as the primary bibliographic data source due to its large collection of high-quality journals, offering more comprehensive coverage compared to other databases. The method of retrieving data employed the keywords “Sentiment Analysis” AND “Mental Health” without using language limits. The initial yield was 563 documents. Filtering results to restrict to Articles, Book Chapters, and Conference Papers, excluding Reviews, Editorials, Letters, Notes, and Short Surveys, resulted in a final dataset of 521 documents from 330 unique sources between 2013 to 2024. The filtered data was exported in CSV format, and analysis was done using VOSviewer, Citespace and Biblioshiny tools to visualize research patterns in the field.

Table 1 provides a detailed summary of the key findings from the analysis. The data spans from 2013 to 2024, covering a total of 330 sources, including journals, books, and other types of publications. The analysis includes 521 documents, with an impressive annual growth rate of 42,45 %, reflecting the increasing interest in sentiment analysis and mental health research. The average age of the documents is 2,05 years, indicating that the field is relatively new and rapidly evolving. On average, each document has received 13,12 citations. The dataset includes a vast array of keywords, with 2521 Keywords Plus (ID) and 1306 Author’s Keywords (DE), showing the diversity and breadth of the research topics covered. The analysis also highlights the significant collaboration in the field, with 1910 authors contributing to the documents. Despite this, there are 17 single-authored documents, with 16 authors contributing to these. The average number of co-authors per document is 4,09, and 19,77 % of the documents result from international co-authorship, underscoring the global nature of the research. The document types analyzed include 278 articles, 28 book chapters, and 215 conference papers, illustrating the varied dissemination of research findings across different formats.

Table 1. Important aspects of the analysis

Description	**Results**
MAIN INFORMATION ABOUT DATA	
Timespan	2013:2024
Sources (Journals, Books, etc)	330
Documents	521
Annual Growth Rate %	42,45
Document Average Age	2,05
Average citations per doc	13,12
References	1
DOCUMENT CONTENTS	
Keywords Plus (ID)	2521
Author's Keywords (DE)	1306
AUTHORS	
Authors	1910
Authors of single-authored docs	16
AUTHORS COLLABORATION	
Single-authored docs	17
Co-Authors per Doc	4,09
International co-authorships %	19,77
DOCUMENT TYPES	
article	278
book chapter	28
conference paper	215

RESULTS

Annual scientific production

Figure 1 illustrates the annual scientific production in the field of sentiment analysis and mental health from 2013 to 2024. The data reveals a significant upward trend, particularly from 2020 onwards. The number of articles published each year has grown substantially, peaking at 134 articles in 2023. This represents a notable increase in scholarly activity and interest in the intersection of sentiment analysis and mental health, with a marked acceleration in research output over the last four years. In 2024, the number of published articles is slightly lower at 98, reflecting a potential stabilization after the peak in 2023. The years 2022 and 2021 also saw high levels of publication, with 119 and 92 articles respectively, indicating a sustained interest in the topic. Before 2020, the output was significantly lower, with only a few articles published each year. This trend highlights the relatively recent emergence of sentiment analysis as a critical tool in mental health research, gaining momentum and scholarly attention rapidly over the past few years.

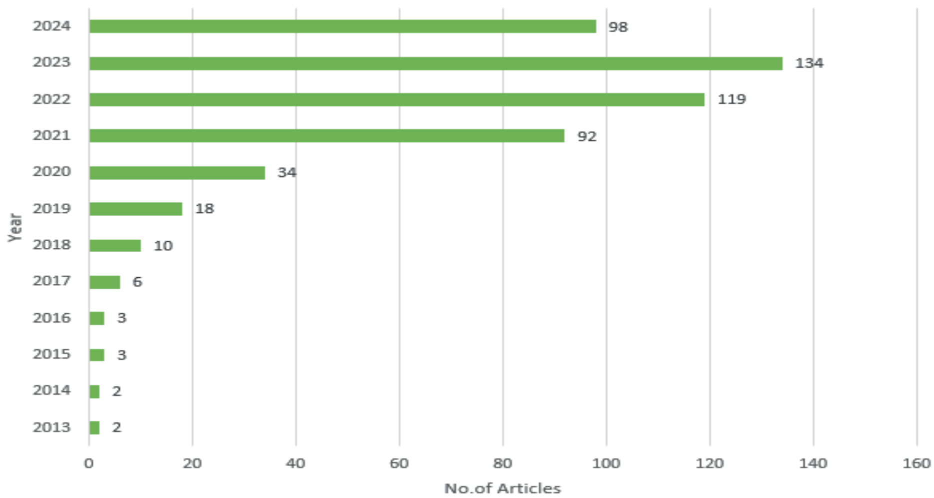

Figure 1. Annual Scientific Production

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Most Relevant Authors

Table 2 highlights the most prolific authors in the field of sentiment analysis and mental health research, showcasing those with the highest number of published articles. Leading the list is Wang Y, who has authored 7 articles, making them the most prominent contributor to this field. Following closely are Kumar S, Liu J, and Singh P, each with 5 articles to their credit. Several other authors, including Kumar A, Singh J, Singh S, Wang H, Wang S, and Wang X, have all made significant contributions, each authoring 4 articles. The presence of multiple authors with the surname "Wang" suggests that this surname is common among contributors in this research area, possibly indicating a geographical concentration of research activity. The diversity of the authors listed reflects the collaborative and interdisciplinary nature of research in sentiment analysis and mental health, drawing on expertise from a variety of fields and regions.

Table 2. Most Relevant Authors

Authors	No. of Articles
Wang Y	7
Kumar S	5
Liu J	5
Singh P	5
Kumar A	4
Singh J	4
Singh S	4
Wang H	4
Wang S	4
Wang X	4

Most Relevant Sources

Table 3 presents the most relevant sources for publications in the field of sentiment analysis and mental health. The International Journal of Environmental Research and Public Health leads the list with 25 articles, indicating its significant role in disseminating research related to this topic. The Journal of Medical Internet Research follows with 20 articles, underscoring its focus on the intersection of technology and health, which includes sentiment analysis as an emerging tool in mental health research. The Lecture Notes in Networks and Systems ranks third with 19 articles, reflecting its contribution to the dissemination of research at the nexus of network systems and health applications. The ACM International Conference Proceeding Series and Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) are also prominent, with 13 and 9 articles respectively, highlighting the importance of conference proceedings and specialized lecture notes in this evolving field. Other notable sources include Plos One and Communications in Computer and Information Science, each contributing 9 and 8 articles, respectively. Frontiers in Psychology is also a key source with 7 articles, showing the relevance of psychological perspectives in sentiment analysis studies. Finally, CEUR Workshop Proceedings and Procedia Computer Science each have 6 articles, further indicating the importance of workshop and conference proceedings in shaping research trends in sentiment analysis and mental health.

Table 3. Most Relevant Sources

Sources	No. of Articles
International Journal of Environmental Research and Public Health	25
Journal of Medical Internet Research	20
Lecture Notes in Networks and Systems	19
ACM International Conference Proceeding Series	13
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	9
Plos One	9
Communications in Computer and Information Science	8
Frontiers In Psychology	7
CEUR Workshop Proceedings	6
Procedia Computer Science	6

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Trend Topics

Figure 2 illustrates the trend topics in sentiment analysis and mental health research from 2013 to 2024. The visualization highlights the evolution of key terms over time, with each bubble representing the frequency of the term's occurrence in the literature. The term "suicide" was a trending topic in more recent years, having a surge of interest in particular in 2023 and 2024. "Social media analysis" and "deep learning" are also prevalent themes that have been of great interest since 2021, a reflection of the growing use of advanced computational approaches in social media mental health trend analysis. "Artificial intelligence" and "depression detection" have also been of great interest, beginning in 2021, indicating a high interest in applying AI to diagnose mental health. The application of "sentiment analysis" and "mental health" was at its peak around 2022 and 2023, indicating their primary place in the sphere of interest during that period. Other prevalent themes are "COVID-19", having gained a high interest starting in 2020, as scholars explored the impact of the pandemic on mental health, and "data mining", having been of high interest each year starting in 2019. "Affective computing" and "healthcare" used to be of interest but have been of decreasing interest in more recent years, possibly indicating a trend towards more specialist themes of interest in the sphere. The trend analysis is a distinct graphical display of the dynamic nature of the sphere, indicating how specific themes have become more prevalent over time and how the sphere has evolved over time.

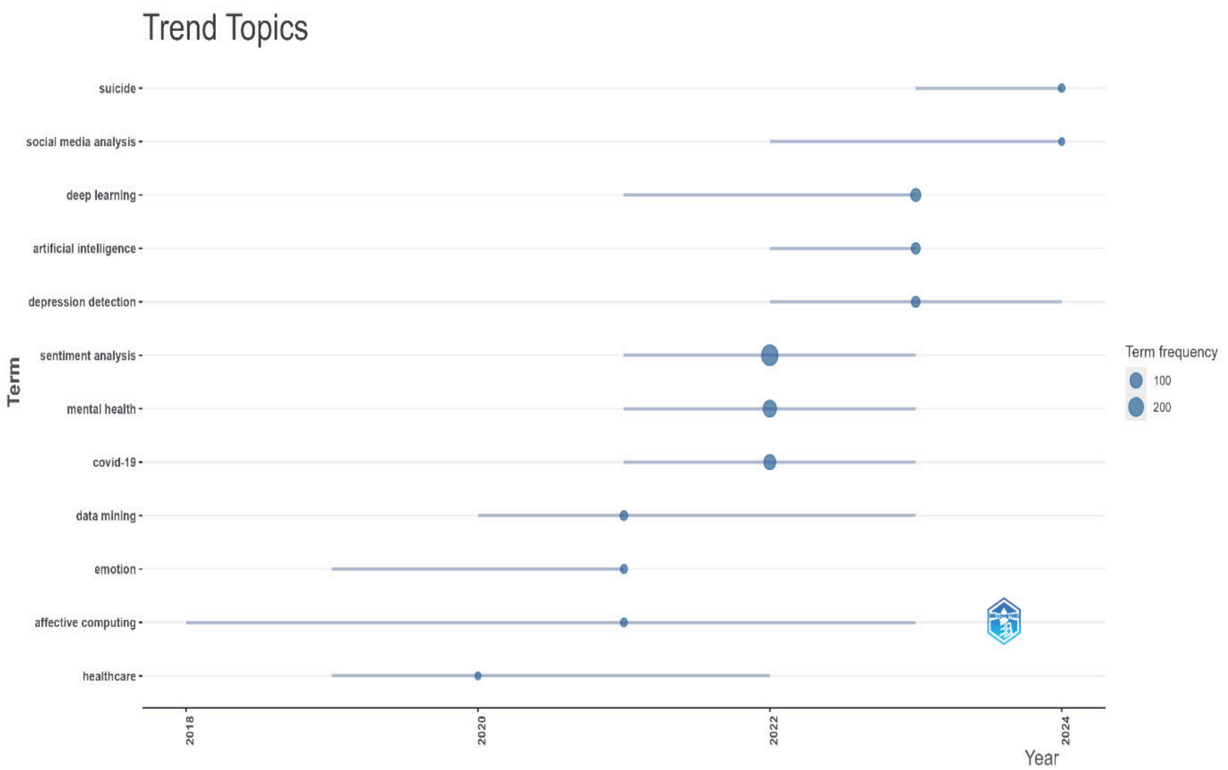

Figure 2. Trend Topics

Thematic Map

Figure 3 is a thematic map that differentiates various topics in sentiment analysis and mental health studies based on their level of development (density) and centrality (relevance). The map is divided into four quadrants, each of which is related to different themes of different nature. In the upper right-hand side of the map, there are highly developed and central themes such as "sentiment," "thematic analysis," and "health" that are key and developed areas of research. The upper left-hand side of the map is occupied by Niche Themes such as "suicide," "AI," and "mental disorder" that are highly developed but not that central, suggesting that these are specialist areas of the field. The lower left-hand side of the map is occupied by Emerging or Declining Themes such as "chatbots," "conversational agents," and "mental healthcare" that are less developed and not that central, possibly suggesting that these areas of work are in their beginning or in decline. Lastly, in the lower right-hand side of the map, there are Basic Themes such as "sentiment analysis," "mental health," and "COVID-19" that are central to the research field but in the process of full development, suggesting their fundamental nature and potential to be developed in the future. The thematic map is a complete picture of existing studies, indicating key areas of interest, specialist areas, and areas of new trend in sentiment analysis and mental health studies.

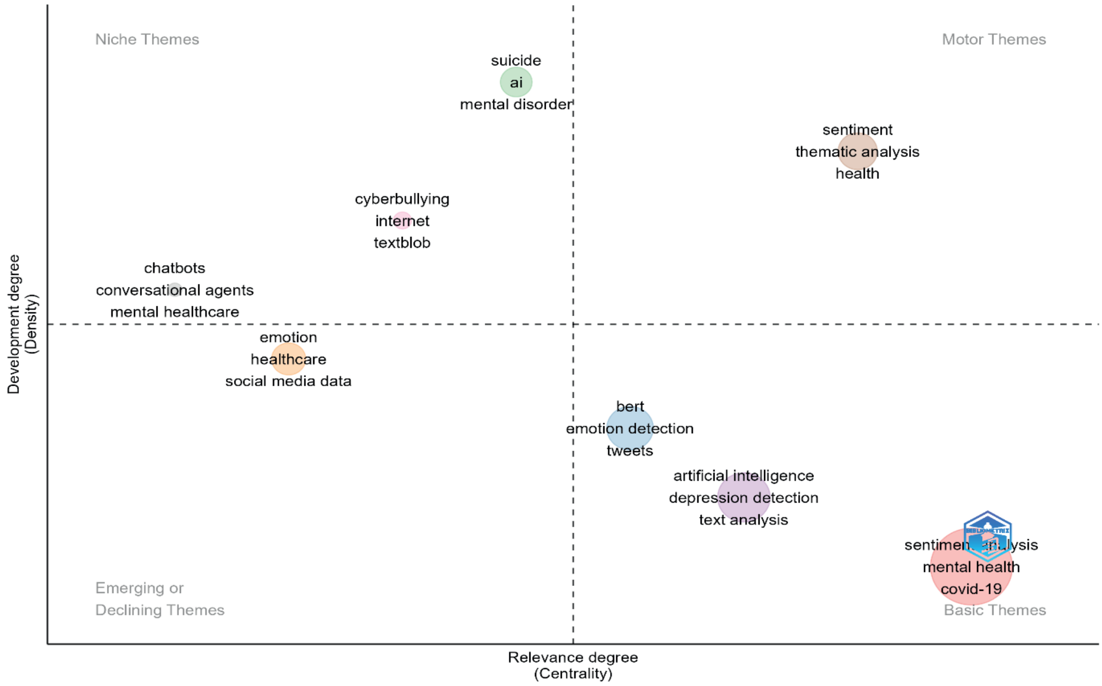

Figure 3. Thematic Map

Three Field Plot

Figure 4 presents a three-field plot visualizing the relationships between keywords (left), authors (middle), and sources (right) in the context of sentiment analysis and mental health research. This plot depicts how certain keywords are related to certain authors and how these authors, in turn, are involved with various academic sources. On the left are keywords, such as “BERT,” representing social media, Sentiment Analysis, and Data Mining, reckoned with heavy links to various authors in the middle field. It tells us that these topics are at the center of the research conducted by these authors. Let’s take, for instance, the keyword “BERT”: on this chart, this keyword is right on Gupta MK because this researcher is focusing on this advanced language processing model in his research. In the middle field, the big contributors such as Singh P and Wang S and Wang H emanate; each of them connects to a variety of topics and sources. The links to the right-hand field reveal that these authors are highly productive in prominent sources: International Journal of Environmental Research and Public Health, Communications in Computer and Information Science, and Lecture Notes in Computer Science. The plot efficiently maps the interrelationships between research topics, authors, and publication venues; thus, it provides insight into the collaboration networks and publication patterns of the respective fields under survey. This visualization acts like a roadmap to understand the landscape of sentiment analysis and mental health research; it helps identify the major contributors and hails influential sources in the domain.

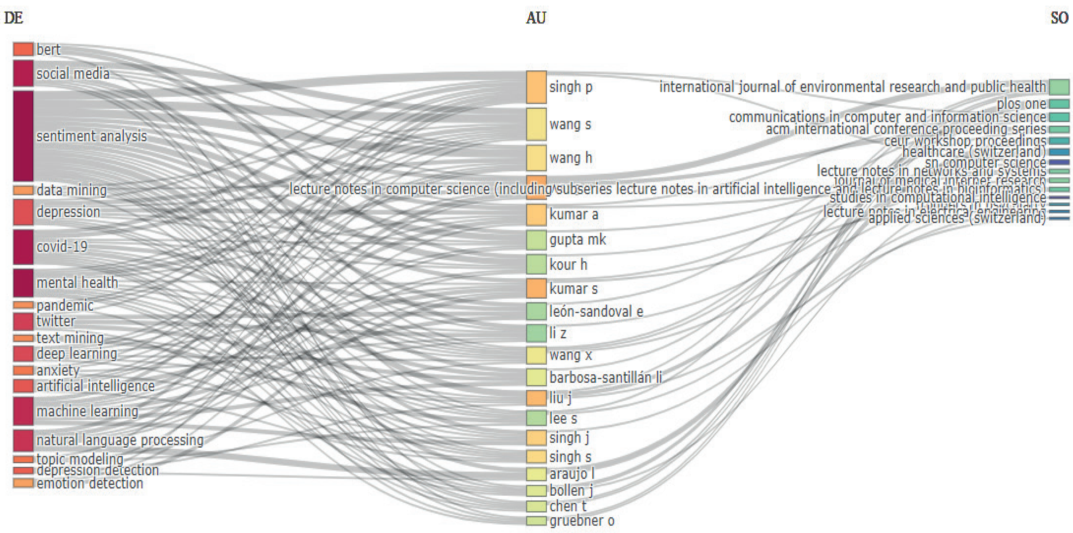

Figure 4. Three-Field Plot Visualizing the Connections Between Keywords (Left), Authors (Middle), and Sources (Right) in Sentiment Analysis and Mental Health Research

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Most Cited Countries

The most cited countries on sentiment analysis and mental health research are presented in Table 4, both regarding the number of total citations and average citations per article. China takes precedence with 1685 citations, having its works cited an average of 31,8 times each. Thus, it is predictable to note that there is a high impact emanating from works coming from the country. The USA follows with 1100 total citations and an average of 19,3 citations per article, showing its strong contribution in the field. Australia is also notable, having 442 total citations and an average of 24,6 citations per article, showing substantial influence. Bangladesh, though much lower in total citations at 270, boasts the highest average of 54 citations per article, showing highly impactful research emanating from Bangladesh. Switzerland also possesses a high average citation rate of 47,5 with 95 total citations. India and Spain, though contributing a very high number of articles, have lower average citations of 4,3 and 8,8 per article, respectively. Other countries in strong position include the United Kingdom, Canada, and Italy with average citation rates of 13,9, 22,1, and 20,3, respectively. The following table shows this research area in sentiment analysis and mental health is global, with contributions from a wide variety of countries, each with its unique impact.

Table 4. Most Cited Countries

Country	Total Citations	Average Article Citations
CHINA	1685	31,8
USA	1100	19,3
AUSTRALIA	442	24,6
INDIA	360	4,3
UNITED KINGDOM	278	13,9
BANGLADESH	270	54
CANADA	199	22,1
ITALY	122	20,3
SWITZERLAND	95	47,5
SPAIN	88	8,8

Co-authorship between Countries

Figure 5 illustrates the co-authorship network between countries in sentiment analysis and mental health research, visualized using VOSviewer. The network shows the collaborative relationship between authors from different countries, where each node indicates one country and lines link the nodes of collaborating countries. The United States and China are closer to the center in this network, which means that these two countries are crucial in international collaborations. The tight links between these two and other countries such as Australia, Canada, Italy, and India further suggest that these countries often cooperate in research within this area. India also shares strong connections with its neighbors Bangladesh and Pakistan, as well as with Saudi Arabia and Singapore, thus confirming active regional collaboration. European nations such as Germany, Switzerland, Italy, France, and Spain are also among the densely connected countries, therefore reflecting a dense European research network. It also shows good collaboration among the Southeast Asian countries like Malaysia, Indonesia, Thailand, and South Korea. In general, this map of co-authorship shows the research on sentiment analysis and mental health to be global and interconnected, with many countries participating in collaborative effort intercontinentally.

Co-occurrence of keywords

Figure 6 presents the Keyword Co-occurrence Network, where the keywords of the sentiment analysis and mental health research are visualized in VOSviewer. In this network of connected keywords, one can see depicted the thematic structure of the research. The central cluster, dominated by the keyword "sentiment analysis," includes other important words such as "natural language processing," "social networking (online)," and "artificial intelligence."; it therefore characterizes the core area of research, concerning both computational issues of sentiment analysis and its applications in social media and online platforms. The blue cluster has the center on "social media," in which the key terms included are "Twitter" and "topic modeling"; thus, it provides an idea that the research will dwell on analyzing social media data through various computational methods. The green cluster is about "human" and "pandemic," including keywords such as "coronavirus disease 2019," "public health," and "anxiety." This cluster describes the sentiment analysis that became related to, or actually has been intertwining with, the issues of mental health during the COVID-19 pandemic. That is why this kind of thematic sentiment analysis has gained especial relevance in the last few years. The co-occurrence map below visualizes the diversity and interconnected nature of research themes in sentiment analysis and mental health, mapping key areas of focus and relationships between diverse themes of research. The dense interconnectedness of the keywords shows that this is a highly interdisciplinary area of collaboration.

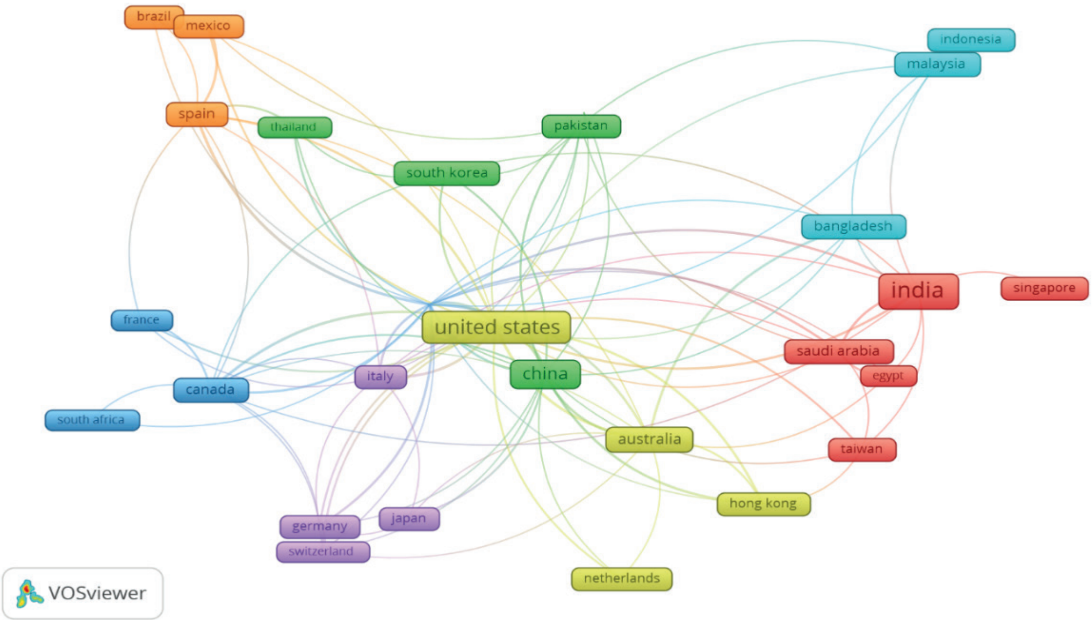

Figure 5. Co-authorship between Countries

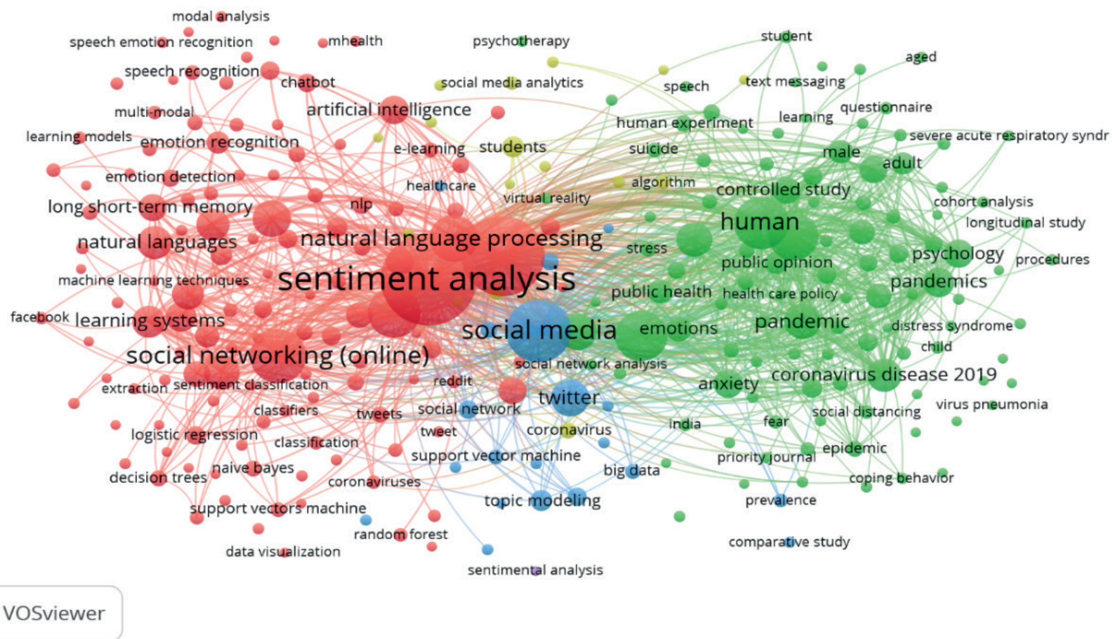

Figure 6. Co-occurrence of keywords

Network Visualization Co-Citation of Cited Authors

Figure 7 shows the co-citation network cited authors reveals 15 distinct clusters, each representing a major research focus on the realm of research. The largest cluster (#0), Computational Intelligence, includes 58 members and highlights the role of AI-driven sentiment analysis techniques, particularly deep learning models like BERT and Transformer-based architectures. The most cited scholars in this cluster, such as Devlin J (54 citations) and Mikolov T (25 citations), have significantly contributed to the development of these computational methods. Major citing articles, including Arias (2022) and Wang (2024), emphasize social media-based sentiment tracking for mental health applications. Similarly, Cluster #1, Using Natural Language (51 members), focuses on linguistic and affective text analysis, with highly cited authors such as Pennebaker JW (40) and Blei DM (39) leading research on topic modeling and psychological language processing in online communities.

The COVID-19 Pandemic Cluster (#2) (44 members) examines the mental health impact of the pandemic through sentiment analysis. Highly cited scholars such as Liu Y (36) and Xue J (24) have contributed to studies analyzing public sentiment shifts during COVID-19. Papers like Arias (2022) and León-Sandoval (2022) discuss the role of sentiment analysis in monitoring mental distress and misinformation during global crises. Similarly, Cluster #3, Unified Deep Neuro-Fuzzy Approach (41 members), focuses on hybrid AI techniques combining fuzzy logic and deep learning for improved sentiment classification. Highly cited members like Reece AG (19) and Chakraborty K (12) highlight the use of neuro-fuzzy models in mental health prediction.

The Language Use Cluster (#4) (39 members) explores linguistic indicators of mental health disorders, emphasizing the role of word choice, syntax, and emotion detection in social media text. Scholars such as De Choudhury M (51) and Coppersmith G (35) have been instrumental in developing computational models for identifying depression and suicidal tendencies in online communities. Meanwhile, Cluster #5, Online Cognitive Behavioral Therapy (CBT) (36 members), investigates sentiment analysis in digital mental health interventions, with key contributors like Wang X (39) and Pang B (15) leading research on emotion detection in therapy chatbots and automated patient support systems.

Clusters #6 (Depression Detection, 35 members) and #7 (Suicidal Ideation, 29 members) focus on sentiment analysis for early identification of mental health disorders. These clusters highlight machine learning-based depression screening models, with top-cited scholars like Tadesse MM (18) and Islam MR (17) working on AI-based depression monitoring. Similarly, studies in suicidal ideation detection, led by Zhang Y (30) and Cambria E (21), explore the role of sentiment tracking in suicide prevention efforts. Cluster #8, Knowledge-Based Tweet Classification (23 members), emphasizes disease sentiment monitoring using Twitter and social media data, with scholars like Barbieri F (10) and Collier N (3) working on real-time mental health event detection.

The final set of clusters—Enhanced Feature Selection (#9, 20 members), Depression Contagion (#10, 19 members), AI in Mental Health Aid (#11, 16 members), Using Social Media (#12, 13 members), Topic Patterns (#13, 12 members), and Robustness Uncertainty Quantification (#14, 6 members)—deal with advanced AI techniques and emerging challenges in sentiment analysis. Notable themes include mental health sentiment contagion in social networks (Xu, 2013), AI-driven therapy solutions (D'Alfonso, 2017), and ethical considerations in AI-powered mental health analysis (Denecke, 2024). These clusters demonstrate the interdisciplinary nature of sentiment analysis in mental health, integrating AI, linguistics, social sciences, and clinical psychology to address mental well-being challenges.

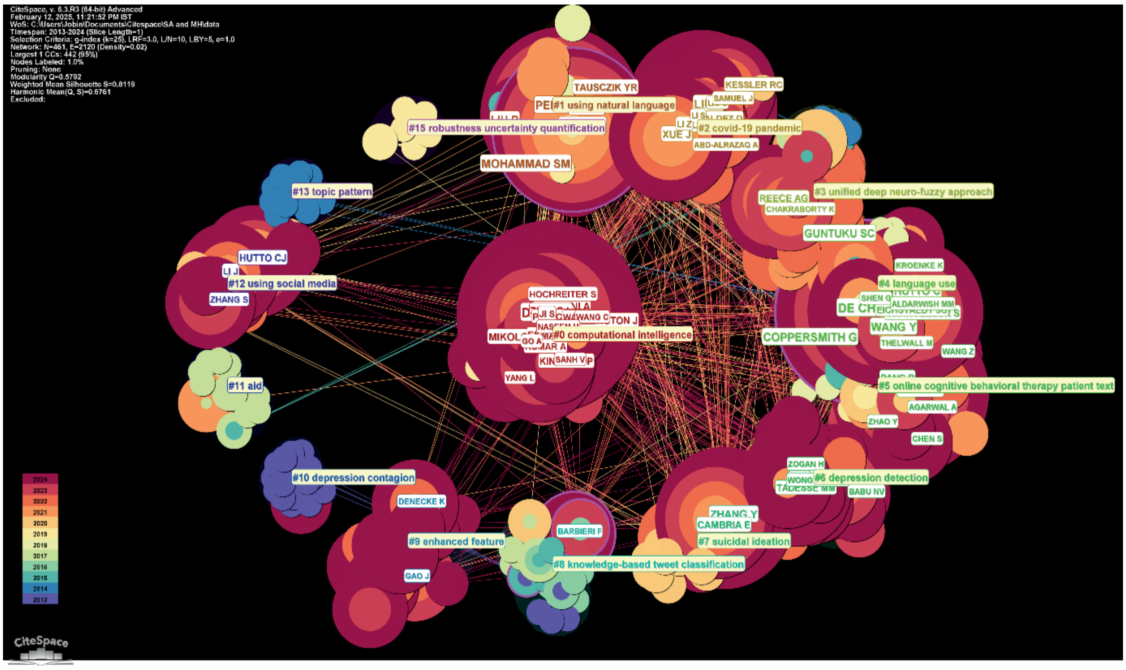

Figure 7. Network Visualization Co-Citation of Cited Authors

Timezone Network Visualization of Cited Journals

Figure 8 illustrates the co-citation network of cited journals consisting of 10 clusters representing key academic sources in sentiment analysis and mental health research. Each cluster highlights specific research areas, showcasing frequently cited journals that serve as foundational literature in the field. The largest cluster (#0), COVID-19 Tweet (111 members), focuses on sentiment analysis of COVID-19-related tweets and their impact on public mental health. Highly cited journals in this cluster include PLOS ONE (135 citations), Journal of Medical Internet Research (55), and Proceedings of the International AAAI Conference on Web and Social Media (40). Influential citing articles, such as Nanath (2023) and Wongkoblap (2021), emphasize the role of social media discourse in pandemic-related emotional well-being. Cluster #1, Public Social Media (78 members), similarly explores mental health trends in social media platforms, with major citing journals like IEEE Access and Social Science and Medicine contributing to studies on online discourse, misinformation, and emotional contagion.

The Language Use Cluster (#2, 77 members) examines how linguistic patterns in online communication reflect psychological distress. IEEE Access (126 citations) dominates this cluster, indicating that computational approaches to language modeling in sentiment analysis play a crucial role in mental health research. Studies such as Kim (2024) and Carpi (2022) analyze sentiment fluctuations and emotional expressions in different cultural contexts. Meanwhile, Cluster #3, Suicide-Related Tweet (69 members), focuses on suicide risk assessment using sentiment analysis on online forums. Journals such as Lancet (34 citations), International Journal of Environmental Research and Public Health (32), and Lancet Psychiatry (29) contribute significantly to this cluster, reflecting the growing intersection between medical research and computational sentiment analysis.

Cluster #4, Theory-Informed Assessment (44 members), explores AI-driven mental health assessment, with notable citing journals including Journal of Medical Internet Research (33 citations) and Advances in Neural Information Processing Systems (20). Research in this cluster, such as Miner (2016) and Balci (2024), focuses on automated depression detection and AI-enhanced therapeutic interventions. Cluster #5, Depression Contagion (21 members), investigates how online interactions influence the spread of depressive symptoms, with journals like Depression and Behavioral Sciences forming the core literature. Xu (2013) is a key study in this cluster, analyzing social network-based emotional contagion.

The final set of clusters includes Measuring Public Health Concern (#6, 11 members), Nonparametric Discovery (#7, 9 members), Analysis (#8, 9 members), and Mapping Emotion (#9, 6 members). These clusters focus on statistical and computational techniques in mental health sentiment analysis, with highly cited works like Ji (2015) (Twitter-based public health sentiment analysis) and Larsen (2015) (Mapping emotions on Twitter) shaping research in this area. Key journals in these clusters include Biometrics, IEEE Journal of Biomedical and Health Informatics, and Social Network Analysis and Mining. The overall network highlights the interdisciplinary nature of sentiment analysis in mental health, spanning computational linguistics, social science, public health, and AI-driven psychological research.

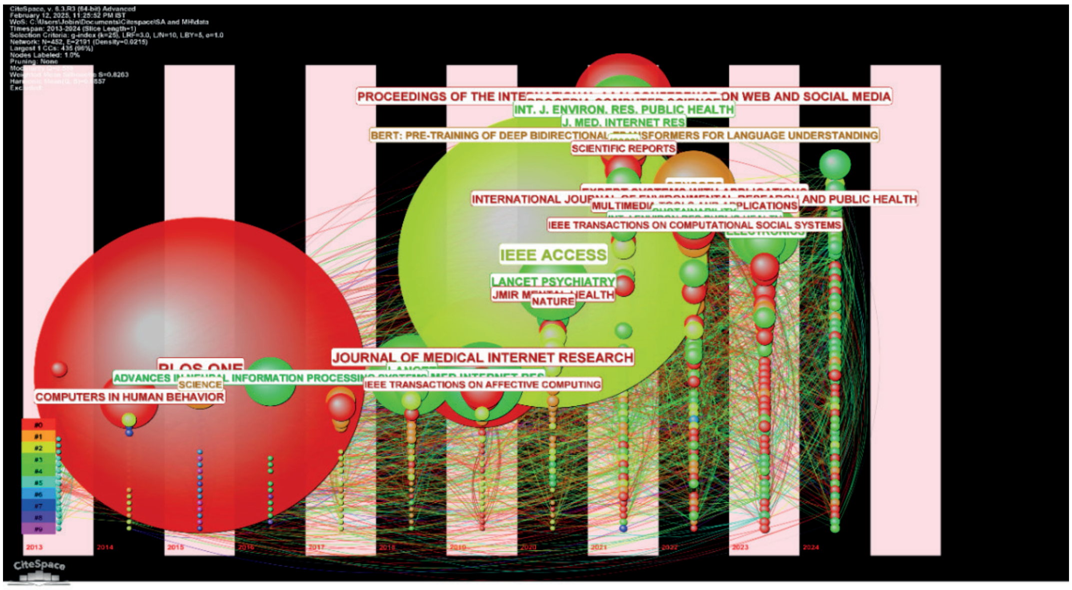

Figure 8. Timezone Network Visualization of Cited Journals

Timeline Network Visualization Countries Collaborations

Figure 9 shows the timeline network visualization of countries' collaborations in sentiment analysis and mental health research, revealing six key clusters, each representing a distinct research focus. The largest cluster (#0, Learning Technique, 15 members) highlights contributions from the United Kingdom (45 citations), Australia (30), and Bangladesh (18) in AI-driven sentiment analysis and deep learning applications for psychological assessments. Major works such as Wani (2024) and Mohmand (2024) explore machine learning frameworks for depression detection, emphasizing the growing role of computational techniques in mental health studies. Meanwhile, Cluster #1 (Reward-Related Mechanism, 13 members) sees major contributions from Spain (21 citations), Canada (18), and Mexico (11), focusing on emotional engagement, music therapy, and psychological reinforcement during crises like COVID-19. This cluster underscores how external stimuli influence mental well-

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being, with studies such as Mas-Herrero (2023) and Salazar (2021) analyzing emotional and sentiment-based responses in digital spaces.

The COVID-19 Pandemic Cluster (#2, 10 members) is dominated by India (186 citations), Malaysia (20), and Indonesia (12), reflecting Asia's leadership in pandemic-related mental health research. Key studies, such as Rastogi (2022) and Mazumdar (2024), analyze stress detection, panic responses, and misinformation-driven mental health issues using social media sentiment analysis. Cluster #3 (Social Gaming, 9 members), with the United States (115 citations) as a leading contributor, examines the psychological effects of digital gaming and online social interactions. Works such as Krittanawong (2022) and Gaurav (2024) suggest that gaming communities serve both as coping mechanisms and risk factors for mental health deterioration. Similarly, Cluster #4 (A Platform, 8 members) highlights China's dominance (70 citations) in digital mental health solutions, focusing on AI-powered mental health chatbots, online therapy platforms, and Q&A forums for psychological support.

Finally, Cluster #5 (Mental Health Prognosis, 7 members) features contributions from South Korea (16 citations), Pakistan (10), and Turkey (8), emphasizing predictive analytics in mental health monitoring. Studies like Noreen (2023) and Tuan (2024) explore early warning systems for stress, depression, and bipolar disorders using sentiment-based text analysis. The global distribution of research efforts suggests that different regions are specializing in unique aspects of sentiment analysis for mental health—Western countries lead in AI-driven methods, Asia dominates pandemic-related research, China is advancing digital mental health platforms, and South Korea and Pakistan focus on predictive analytics. This growing international collaboration highlights the increasing reliance on AI, NLP, and digital health technologies to tackle global mental health challenges.

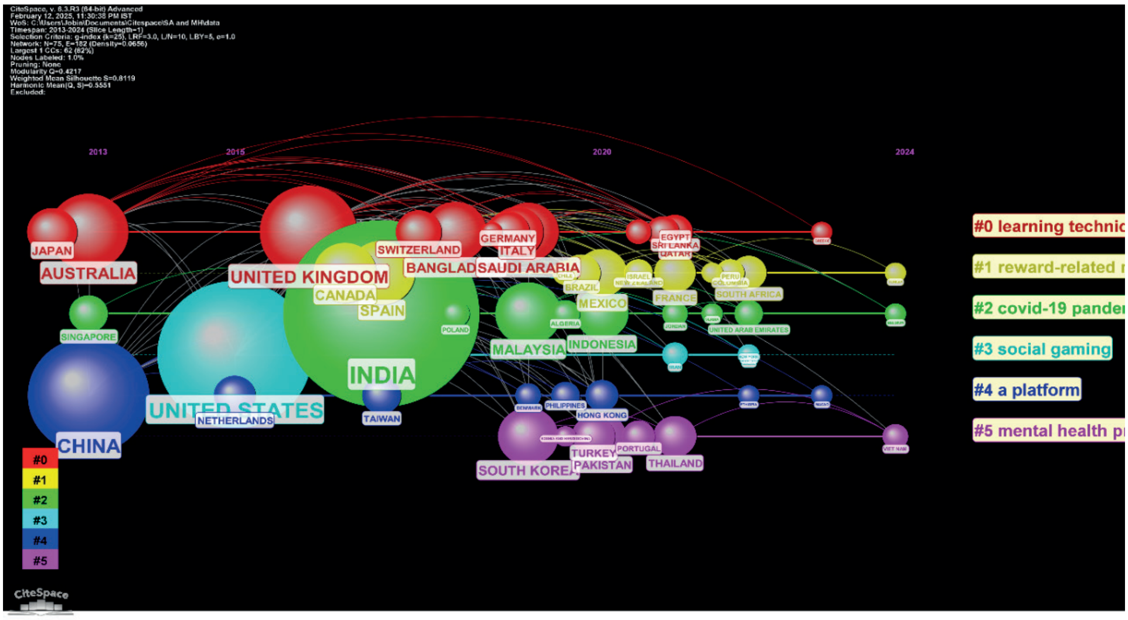

Figure 9. Timeline Network Visualization Countries Collaborations

DISCUSSION

This study provides a comprehensive bibliometric analysis of sentiment analysis in mental health research, identifying key trends, thematic evolutions, and collaborative networks. The findings indicate a rapid expansion in this field, particularly post-2020, driven by advancements in artificial intelligence, natural language processing, and the increasing use of social media as a data source for mental health monitoring. The significant growth in research output reflects a growing recognition of sentiment analysis as a valuable tool for understanding mental health trends, diagnosing disorders, and improving digital interventions.

A notable shift in research focus has been observed, moving from general sentiment analysis applications to more specialized AI-driven approaches for mental health detection and intervention. The prominence of deep learning models, including transformer-based architectures such as BERT, underscores the technological advancements shaping the field. Furthermore, the integration of sentiment analysis in clinical settings, such as online cognitive behavioral therapy (CBT) and predictive analytics for depression and anxiety, highlights its potential to revolutionize mental health care. However, despite these advancements, significant challenges remain, including the need for context-aware sentiment detection models, ethical concerns regarding data privacy, and the risk of algorithmic bias in mental health assessments.

The global character of the study field is clear in the heavy cross-country collaborations that manifest in the patterns of joint authoring. The top countries include the likes of the US, China, and Australia and smaller study centers of Bangladesh and Switzerland that demonstrate a high-impact per study output. This signifies that the caliber of the study and not the quantum of the study plays a vital role in defining the discourse of this field of study. The increasing interaction among the technology-rich countries and the emerging study centers opens doors of cross-field innovations and enhancement of AI-aided models of sentiment analysis among diversified populations.

A critical limitation in the existing body of research is the over-reliance on social media data, which, while abundant, may not accurately represent broader mental health trends. The emphasis on publicly available datasets poses risks related to selection bias and privacy concerns. Additionally, most studies focus on sentiment analysis as a diagnostic or predictive tool rather than exploring its integration into long-term mental health interventions. Future research should prioritize the ethical implications of using AI in mental health assessments and develop methodologies that incorporate multimodal data sources, including speech and physiological indicators, to enhance sentiment analysis accuracy.

Overall, the findings emphasize the interdisciplinary nature of sentiment analysis in mental health research, spanning computer science, psychology, and public health. The continued evolution of this field will depend on addressing ethical challenges, improving model interpretability, and ensuring inclusivity in dataset development. Future studies should explore the long-term efficacy of AI-driven interventions and establish frameworks for responsible sentiment analysis applications in mental health. By fostering stronger collaborations and integrating diverse data sources, sentiment analysis can play a pivotal role in advancing mental health research and interventions.

Practical Implications and Future Directions

These findings have several practical implications for researchers, practitioners, and policymakers. First, the centrality of themes such as social media analysis and deep learning in the thematic map suggests that embedding these technologies may be useful in future mental health interventions. For instance, real-time monitoring of social media may facilitate early identification of at-risk individuals who can then receive timely interventions. Advanced machine learning procedures, including deep learning, allow the enhancement of sentiment analyses and, therefore, the consistency and accuracy of the former with which mental health will be assessed. Perhaps in the future, it will even be possible to provide individual treatment plans that are truly personalized.

This therefore calls for further research in this area to be purposed toward investigating nascent-but nonetheless promising-areas that the thematic map indicates, such as conversational agents and chatbots for mental health. In turn, this benefits people at large through accessible scales of mental health support, especially in resource-poor healthcare settings. Second, the heavy representation of COVID-19 studies and its relation to mental health issues suggests more work on the long-term psychological effects of the pandemic and other various global disasters. Researchers can also expand to include a wider range of diverse populations and settings, consider potential biases in the data, and ensure that benefits from sentiment analysis tools are widely shared.

Most important, perhaps, was the strong international collaboration in the co-author network, which could further be enhanced through more cross-border partnerships in future research endeavors. In this regard, such cross-border research collaboration pools experiments and resources needed for developing more comprehensive and culturally sensitive mental health interventions. Policymakers and funding agencies should support these kinds of collaborative works since it may help solve the global issue concerning mental health. Building on such trends permits further advancement of the field toward more innovative, effective, and inclusive ways of care for mental health conditions.

CONCLUSION

This review outlines the trends and developments in scholarship at the intersection of sentiment analysis and mental health. Indeed, it has seen a growing research output, especially in recent years. The analysis underlines that sentiment analysis has emerged as one of the increasingly important means for diagnostics in mental health and public health monitoring, particularly in the context of global challenges such as the COVID-19 pandemic. Thematic and Co-authorship Analysis Thematic and co-authorship analysis has pointed out the following key areas: application of AI, social media analysis, and global research collaboration. Among them, countries like China, the USA, and Australia have emerged as top contributors in this field, while Bangladesh and Switzerland convincingly show high impact research output. The findings of this study map the current state of research, underlining a number of emerging trends likely to feature heavily in the future of sentiment analysis within mental health. Further interdisciplinary collaboration and enhancement of computational techniques are needed in the future to take the application of sentiment analysis in mental health research forward.

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CONFLICT OF INTERESTS

The authors declare no conflicts of interest.

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