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Review article

Mapping the scientific landscape of artificial intelligence in mental health

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ABSTRACT

Artificial Intelligence (AI) has gained increasing popularity in contemporary scientific research; however, its application in mental health still requires a consolidated understanding of existing findings regarding effectiveness. This bibliometric study aims to synthesize current knowledge and explore research trends related to AI's role in mental health. It investigates how advancements in modern technologies are used to predict, prevent, and treat mental disorders, and evaluates their effectiveness. A literature search was conducted using Lens software to retrieve peer-reviewed empirical studies in English from highly ranked databases, covering the period from 2005 to 2025. A total of 97 relevant publications were identified and analyzed for patterns, trends, and associations using the Bibliometrix package in R. Results reveal a sharp increase in publications after 2020. Clinical and applied psychology emerged as dominant fields. *Eating and Weight Disorders* is the leading journal (n=22), followed by the *Journal of Psychopathology and Behavioral Assessment* (n=19) and *Cognitive Therapy and Research* (n=17). The United States is both the most productive (n=149) and most cited country (n=8,896). AI has demonstrated promise in detecting symptoms of depression and suicidal behavior, preventing mental health disorders, and enhancing traditional psychological interventions. Nonetheless, several gaps remain, including the underrepresentation of diverse populations and a limited understanding of factors influencing user acceptance of AI-based tools. This study provides researchers with an overview of publication trends, collaboration networks, keyword analysis, and future research directions. It also supports practitioners in selecting appropriate AI-based interventions to improve mental health outcomes and overall well-being within healthcare systems.

Keywords: artificial intelligence, mental health, depression

1. Introduction

The use of artificial intelligence (AI) in mental health shows potential in diagnosing, preventing, and treating various psychological disorders. AI serves as a valuable supportive tool in psychological interventions for improving mental health, psychological well-being, and overall quality of life among patients. While numerous studies exist on AI's role in clinical psychology, there is no extensive research that brings together findings about its effectiveness, benefits, and future research paths. Some researchers have explored the broader role of technology in mental health [1, 2], while others have specifically examined AI's use in detecting depression [3, 4], preventing it [5, 6], or identifying suicidal behaviors [7, 8]. Other studies have also looked at AI's ef-

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fectiveness in dealing with eating disorders [9], anorexia [10], and obesity [11]. Additionally, some efforts have been made to use AI to predict generalized anxiety disorder [12]. However, a comprehensive investigation into the link between AI and mental health remains limited. Therefore, more empirical research is needed to better understand how AI can be effectively applied in the diagnosis, prevention, and treatment of mental disorders. This bibliometric study aims to collect, assess, and combine findings from existing literature to create a full understanding of the correlation between mental health and AI. The study also intends to outline publication patterns and trends in the field, identify knowledge gaps, improve detection of mental disorders, relieve symptoms, and enhance psychological and overall well-being.

2. Theoretical framework

One major direction in current research focuses on exploring the relationship between AI and mental health. For instance, Higgins et al. [1] examined AI's supportive role in the mental health field and identified several practical challenges in its implementation. Similarly, Ramshaw et al. [2] conducted a comparative analysis of traditional and AI-assisted diagnostic methods, highlighting key barriers to accurate mental health diagnosis. Shan et al. [13] conducted a systematic review of interventions targeting student mental health and emphasized the need for further investigation in this area.

Some studies have specifically assessed the effectiveness of AI in psychological interventions. For example, research suggests that AI can contribute to more personalized and efficient treatment approaches [5]. Evidence highlights the integration of an internet-based cognitive behavioral therapy (CBT) and computer-assisted therapy, although limitations such as the inability to convey body language were noted. A study on AI's role in predicting GAD symptoms found that AI is effective in collecting data critical to risk management for the disorder [12]. In contrast, a study by Maslej et al. [14] indicated that psychiatrists tend to prefer human-based support for patients with depression. Meanwhile, Blease et al. [15] explored psychology students' familiarity with AI, revealing a wide range of opinions and highlighting the importance of integrating AI-related content into academic curricula.

Research has also extensively examined the utilization of AI in the prevention, detection, and treatment of various mental illnesses, including depression [3], suicidal behavior [7, 16, 17], anxiety [12], stress [18], eating disorders [9], and generalized anxiety disorder (GAD) [19], among others. Research has shown that not only CBT and mindfulness-based interventions can be effective in treating mental health conditions, but also social support—whether in person or delivered through AI—can be effective [19].

Another prominent area of research involves the use of AI-based tools to detect various mental health disorders, particularly depression and suicidal behavior. Joshi and Kanoongo [3] analyzed the role of images, facial expressions, the text from social media, and emotional chatbots in detecting depression and emotions, concluding that AI can effectively identify emotional states through multiple modalities, including speech, text, and video. Barros et al. [7] examined factors influencing suicide risk, such as gender, age, psychiatric diagnosis, and type of therapeutic intervention, suggesting that Bayesian networks can either support or hinder psychotherapy outcomes. Similarly, Fonseka, Bhat, and Kennedy [20] evaluated AI's predictive capabilities for suicide risk and stressed the importance of both individual and social dimensions, acknowledging both the strengths and limitations of AI tools [16, 17]. Buddhitha and Inkpen [21] also investigated how AI can detect suicidal ideation among social media users.

Liu et al. [6] argued that AI and related technologies will likely play a larger role in predicting and preventing depression in the future, due to their impartiality in decision-making. Their study analyzed how non-pathological variables such as gender, academic year, lifestyle, and social media use influence depression risk. Inkster, Kadaba, and Sybramanian [22] reported that AI tools helped reduce depressive symptoms among mothers. Kelley et al. [4] also examined the role of social media in recognizing signs of depression and other mental disorders.

The application of AI in identifying and treating eating disorders has gained attention as well. Studies have confirmed AI's efficacy in the identification, prevention, and treatment of such disorders [9]. Noguero et al. [10] focused on gender bias in AI tools used for patients with anorexia, emphasizing the importance of equitable application. Fang et al. [11] evaluated AI-enhanced CBT in treating obesity and reported significant improvements in body weight and body fat percentage.

A growing body of literature has also begun to explore the intersection of AI and psychological well-being. Chen [23], for instance, studied the effectiveness of AI-based interventions in improving students' well-being during the COVID-19 pandemic. Sabour et al. [24] assessed the impact of chatbots on mental health, showing that they can play a practical role in reducing psychological distress. Similarly, Yorita et al. [25] investigated how chatbots and robots support occupational stress self-management. Tanaka et al. [26] demonstrated AI's ability to reduce anxiety and traumatic memory in children undergoing distressing medical experiences, thereby enhancing their overall well-being. He et al. [27] found that AI could mitigate depression among elderly individuals by reducing social isolation through the analysis of so-called "information cocoons". Another study explored the option of recognizing depression on Twitter [28] or using a smartphone application for the prevention of suicidal episodes among adolescents [29].

Li et al. [30] conducted a meta-analysis on AI's role in promoting well-being, concluding that relationship quality, effective communication, and meaningful content engagement are key factors in users' experiences. Another investigation emphasized the effectiveness of a digital CBT-based resilience intervention for children, recommending the implementation of the CUES program in schools [31]. Jeong et al. [32] showed that AI can enhance students' psychological well-being by increasing motivation, and a similar study [33] found that AI can effectively monitor emotional states, academic performance, university transition, and interpersonal relationships [34, 35, 36, 37, 38, 39].

3. Methodology

3.1 Methodology of bibliometric analysis

A bibliometric study utilizes statistical methods to analyze research outputs published in peer-reviewed journals, conference proceedings, reviews, and other scholarly sources. This approach enables a comprehensive examination of both theoretical and empirical data, categorized by subject areas, publication years, citation metrics, keywords, and contributions from leading authors, institutions, sources, and countries, and evaluates the impact of these studies. Bibliometric analysis facilitates the identification of prevailing trends and patterns within a specific research domain and related fields over a defined time period. To carry out such an analysis, access to a well-structured and comprehensive research database is essential [40, 41, 42].

3.2 Data collection and analysis

Using Lens to access prestigious databases (e.g., PubMed, Crossref, Microsoft Academic, and CORE), we collected recently published papers. Various types of sources—including scholarly works and patents—were statistically analyzed to present datasets with unique content. We adopted a bibliometric method to extract descriptive data on publications, author and co-author metrics, source evaluations, and keyword, thematic map, and network analyzes. Data visualization was performed using Bibliometrix, an R package designed for in-depth bibliometric analysis.

The following parameters were used for the search:

- **Search query:** `Scholarly Works (97) = Artificial AND intelligence OR (digital AND (media AND (impact AND (mental AND health))))`
- **Filters:** Year Published = 2005–2025
- **Field of Study:** Clinical Psychology
- **Subject:** Clinical Psychology

The search for the current bibliometric paper was conducted to retrieve data in plain text (.txt) and Microsoft Excel (.csv) files for analysis and presentation in this paper. Descriptive and bibliometric data analysis was conducted using RStudio in combination with the Bibliometrix package.

3.3 Research questions and objective

The purpose of a bibliometric study is to examine publication patterns in the field concerning the use of AI in mental health. It intends to evaluate how the current body of literature helps uncover research gaps and informs potential future research directions. In line with the purpose and scope of this study, the following research questions have been designed:

- RQ1: What are the descriptive characteristics of the publications in this field, including the number of studies published and cited between 2005 and 2025?
- RQ2: What trends can be observed in terms of the most productive authors and co-authors, dominant research themes, key journals, and contributing countries? How do citation metrics reflect the impact of this body of work?
- RQ3: Which keywords are most commonly associated with the published studies, and what do they reveal about the thematic focus of the field?
- RQ4: What patterns of collaboration and research networks exist among the authors of these publications?

4. Results

4.1 Publication descriptives

A total of 97 relevant studies published between 2005 and 2025 within the explored research domain were identified using Lens (Figure 1). The data sources contributing to this dataset included Microsoft Academic (61 results), PubMed (57), OpenAlex (37), PubMed Central (32), and CORE (14). Due to overlapping entries across databases, duplicates were removed, resulting in a final set of 97 unique publications. The included papers were published with an annual growth rate of 4.33%. The majority of these works were authored in English by 410 authors and co-authors publishing in 10 different sources. Only three papers were written by single authors, and no international co-authorship was identified. Authors used 186 keywords; their papers received 3,871 citations (an average of 39.64 each) and used 6,559 references overall. The average age of each published study is 6.71 years.

4.2 Published papers trends over time

The publication records by year, starting from 2005 to 2025, are presented in Figure 2, demonstrating changing trends in interest in conducting studies on the use of AI in mental health. According to Figure 2, two phases can be distinguished. The first phase was between 2005 and 2019, when the publication record ranged from 0 to 6 per year, demonstrating comparatively low interest in research on AI in mental health. The second phase, between 2020 and 2025, shows a sharp increase (in 2020,

Figure 1. Overview of publications included into the analysis.

$n = 12$; in 2024, $n = 13$), indicating growing scholarly interest among researchers within the field. Figure 2 illustrates the increasing popularity of AI in mental health as a research subject.

Figure 3 visualizes the publication trends on AI in mental health in selected journals over the past two decades, underlining the dynamics of scholarly output. A significant increase after 2019 reflects growing interest in exploring AI in mental health, likely influenced by the COVID-19 pandemic. The Journal of Psychopathology and behavioral Assessment consistently ranks among the top sources, serving as a key outlet for research on AI in mental health. Cognitive Therapy and Research began contributing after 2014, reaching 16 papers published by 2025. Eating and Weight Disorders published its first relevant paper in 2012 and has emerged as the leading journal over the past three years.

4.3 Distribution of productive authors, countries, and collaboration network

Figure 4 highlights the most productive authors over the past two decades and their collaboration networks in the research field of utilizing AI for mental health. It illustrates the publication output of the top 10 authors between 2005 and 2025. Most of them published one or two papers and received low to modest citation counts, reflecting an emerging research dynamic. All authors were active during varying periods, either briefly or over a few years. Boris Birmaher was particularly productive between 2009 and 2016, contributing foundational work that helped shape the direction of future studies. Authors like Barnaby D. Dunn and Anna Brytek-Matera were active primarily between 2015 and 2019, while others have emerged more recently, contributing between 2020 and 2025, indicating increasing interest in this research field. Figure 4 also illustrates temporal trends in research and author involvement, showing the appearance of recent contributors after 2020. The total citation count remains low, likely suggesting that the domain is still evolving.

Figure 5 visualizes the geographic distribution of corresponding authors, along with their overall productivity and collaboration types—single-country publications (SCP) and multiple-country publications (MCP). Authors from the USA contributed the highest number of papers ($n = 149$), most of which were written by American authors (SCP $n = 94$), followed by China ($n = 85$) with a similar distribution between SCP ($n = 40$) and MCP ($n = 45$), Spain ($n = 70$) with a prevalence of SCP ($n = 20$), and Brazil ($n = 65$) with a strong prevalence of SCP ($n = 48$), emphasizing their prominent role in exploring links between AI and mental health. Notably, Poland, Sweden, and Turkey had fewer papers (13, 14, and 15, respectively). The results suggest that SCP publications play key roles in research collaboration on AI and mental health, with the exception of China, the UK, and Chile, where MCP is more prominent. These findings reveal not only where research is being produced, but also how globally integrated each country is in advancing the AI and mental health domain.

Figure 6 illustrates the data on co-authorship collaboration networks within the studied research area, where each node represents an author, and the relationships between them show co-author connections.

The majority of nodes are fragmented or have weak connections, suggesting a growing but still limited collaboration landscape, where a few co-author nodes play a key role in developing thematic clusters, while most research is conducted by isolated author groups. For instance, in research on AI and mental health, the authors' collaboration network is largely concentrated in a few clusters established by Jahrami H and Ricca V, suggesting foundational influence. Clusters with authors like Porter A.L., Merigó J.M., and Kumar S. demonstrate both higher productivity and broader collaborative reach, indicating their foundational impact on shaping this research area. Overall, while collaboration networks are emerging, the landscape remains relatively fragmented, highlighting opportunities for greater international and interdisciplinary collaboration.

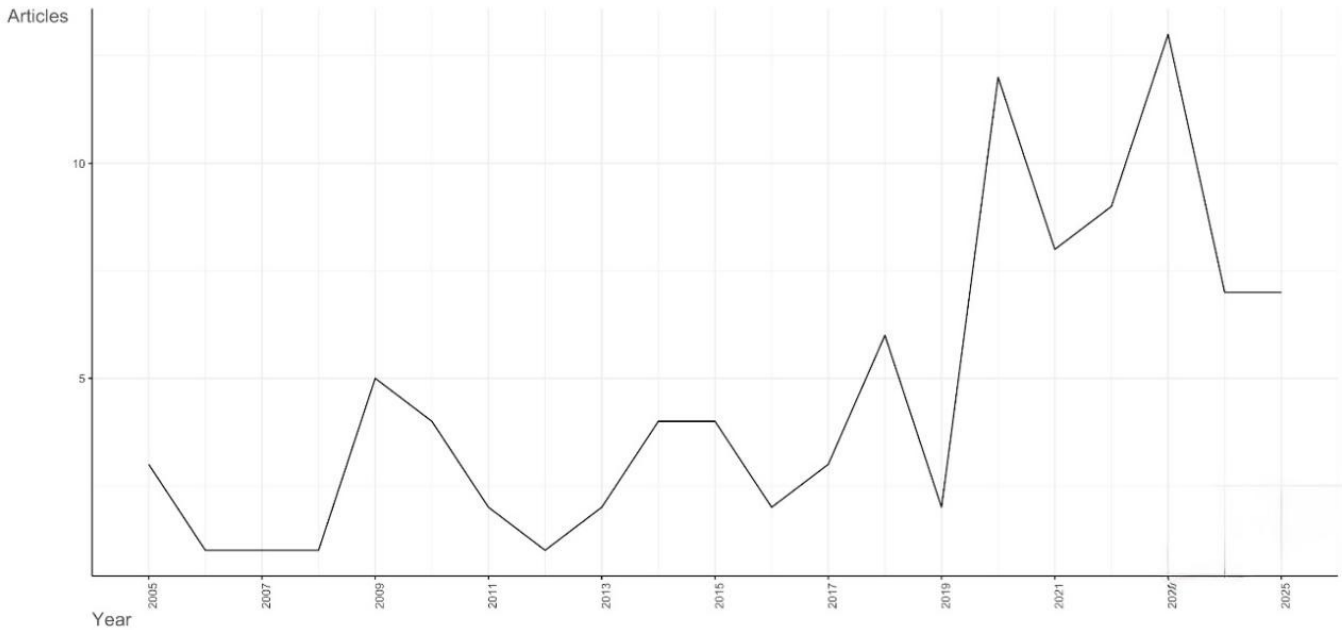

Figure 2. Changes in document counts by publication year within the top 10 subjects' areas (2005-2025).

4.4 Keyword analysis and trend topics

Figure 7 visualizes the keyword usage dynamics in studies on the use of AI in the mental health field from 2005 to 2025, highlighting shifts in research interests over time. Starting in 2016, keywords such as "adolescent," "orthorexia nervosa," and "depression" appeared in the domain. After 2022, "eating disorders," "orthorexia nervosa," "depression," and "systematic review" gained prominence, suggesting rising interest in these topics. The increase in the keyword "orthorexia nervosa" may reflect its emerging niche within the domain, potentially driven by novel diagnostic awareness and its correlation with digital cognitive and behavioral patterns. Overall, the findings point to a chronological transition in keyword usage—from more general concepts to a research focus increasingly centered on eating disorders and depression over the past three years—triggering the development of AI-driven diagnostic, preventive, and supportive tools.

Figure 8 illustrates the frequency with which keywords co-occur in research on AI and mental health, presented as nodes. The size of each cluster reflects keyword frequency, and the thickness of the connections indicates the frequency of co-occurrence.

Based on our findings (Figure 8), the keyword co-occurrence network emphasizes the thematic structure of studies on AI applications in mental health. The core concept is "eating disorders," connected with several other keywords, such as "anorexia nervosa" through the "application of AI" and "treatment approaches," and "orthorexia nervosa" via "diagnostic criteria," reflecting a significant research focus on the detection and classification of mental disorders. The keyword "eating disorders" is also connected to "depression," "body image," "self-monitoring," and "obesity," indicating comorbidity and the use of self-tracking technologies in treatment or assessment. Another thematic cluster connects "depression" to "children" through "maltreatment," extending to "CBT" and "unemotional traits," pointing to a developmental and clinical treatment focus among youth. A significant but separate node on "systematic review" indicates the growing number of evidence studies synthesizing data for conceptual consolidation within the field. Moreover, a few weakly connected and peripheral clusters—such as "attitudes toward psychological help-seeking," "childhood trauma," "parents' distress," and "autism spectrum disorder"—represent underexplored or emerging areas within the domain. The structure of the nodes suggests an evolving network in the research domain on AI-driven interventions for mental health (mainly eating and mood disorders), with growing interest in diagnostic, monitoring, and treatment-oriented directions.

4.5 Thematic clustering

Studied themes were categorised as motor, basic, niche, and emerging (Figure 9) using two criteria: centrality and density, offering significant insights into the structure of scholarly work on AI and mental health. According to our analysis, the categories focused on "depression," "adolescents," and "anxiety" belong to motor themes, meaning they are central and well-developed. Their location underlines their foundational role in the domain, especially regarding the use of AI tools in diagnosing and treating adolescent mood and eating disorders. However, their positioning also highlights the need for further exploration and development. Moreover, the positioning of the categories "unemotional traits" and

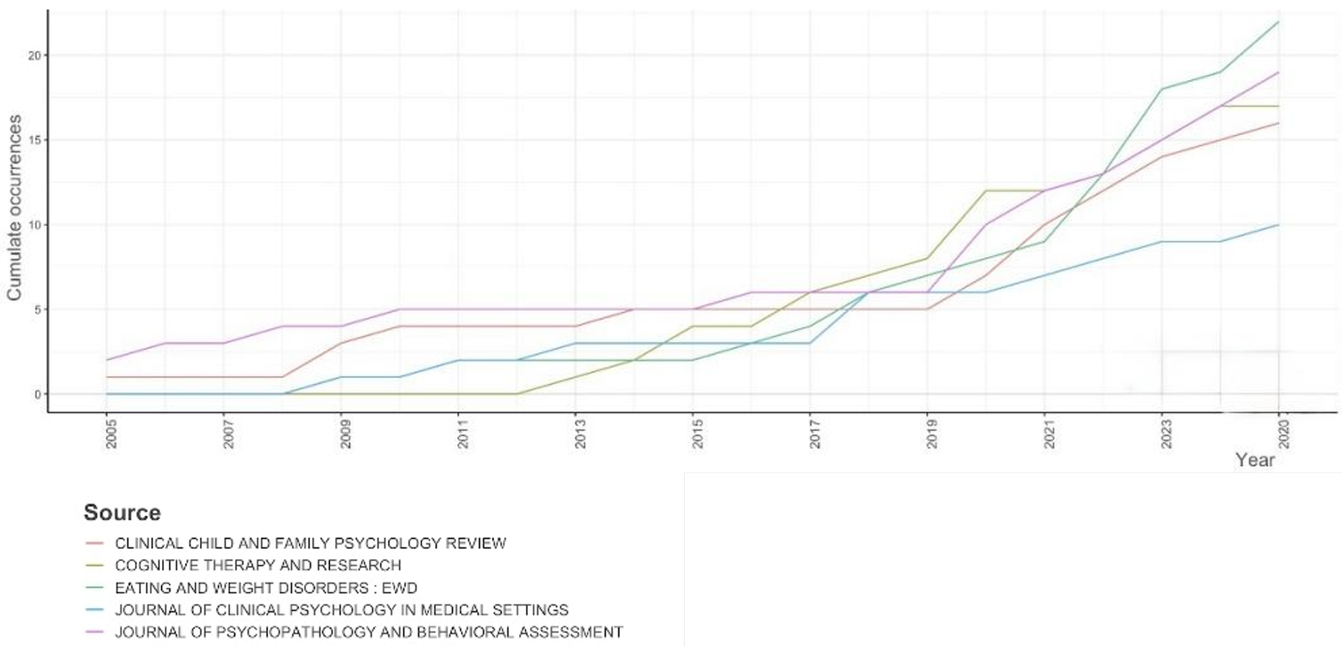

Figure 3. Annual publication output of key journals on AI in mental health (2005–2025).

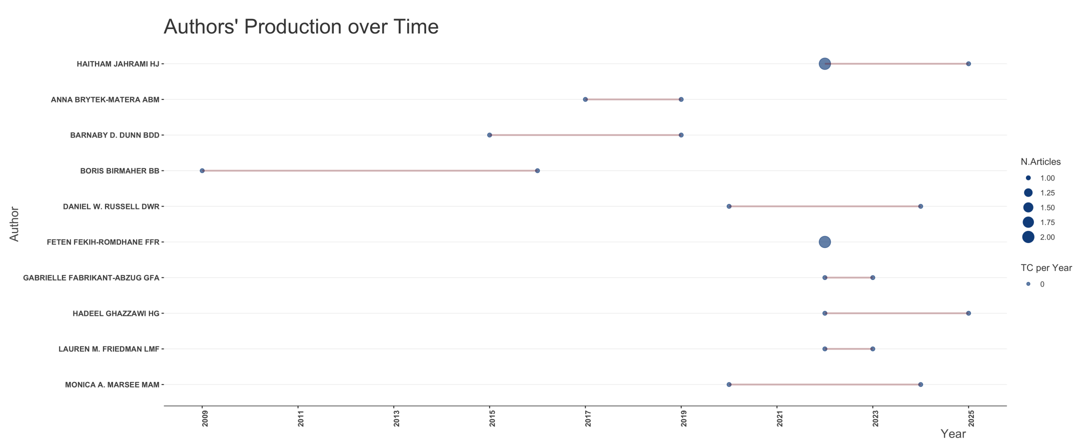

Figure 4. Authors' publication output over time (2005-2025).

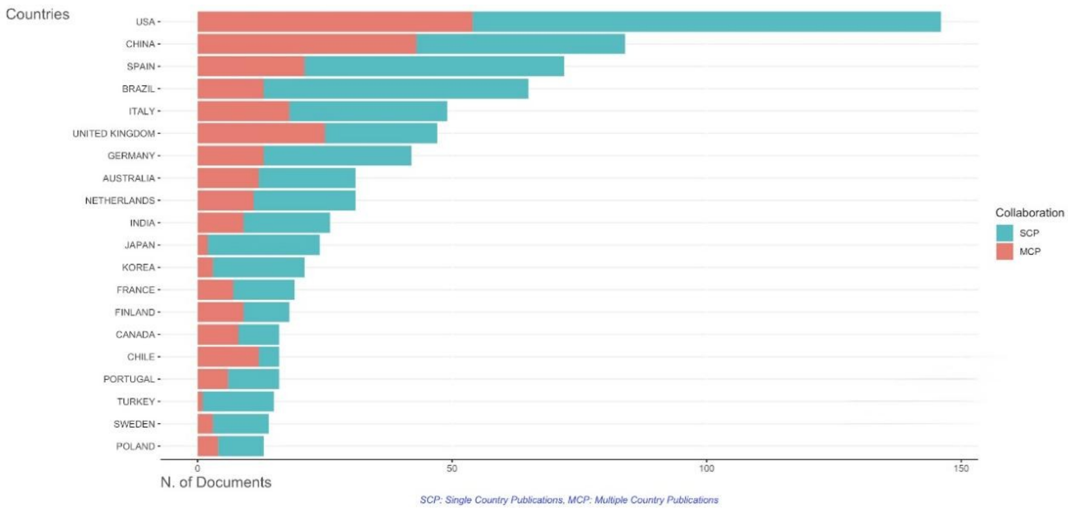

Figure 5. Geographic distribution of corresponding authors' contributions and collaboration types.

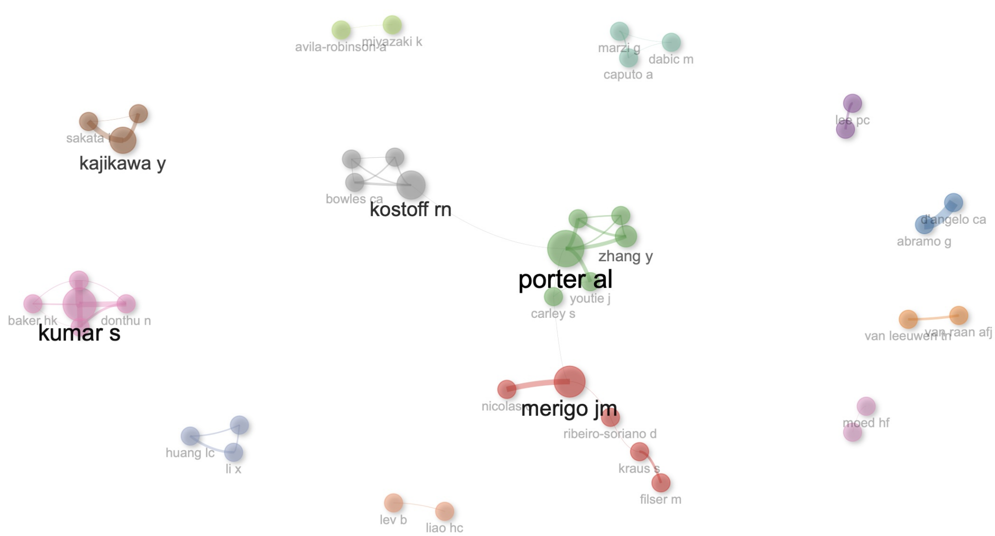

Figure 6. Author collaboration network in AI in mental health research.

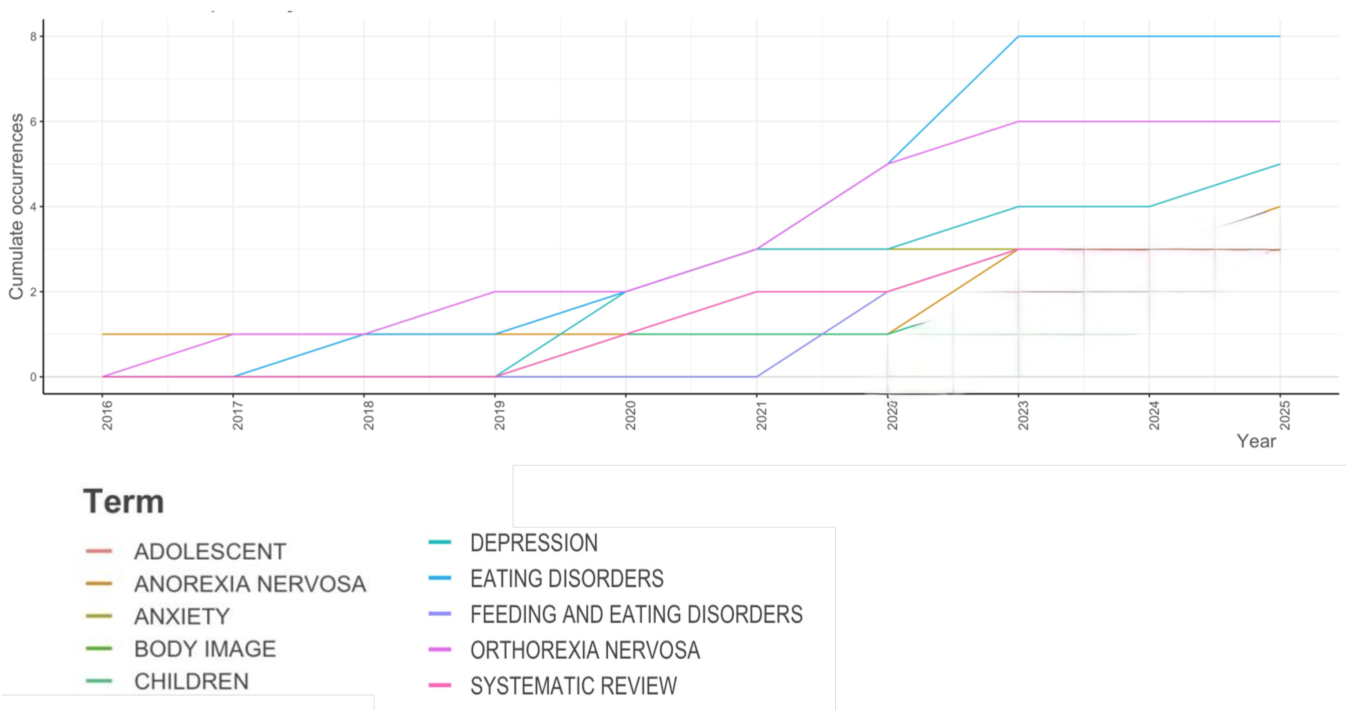

Figure 7. Evolution of keywords in publications on AI and Mental Health (2005-2025).

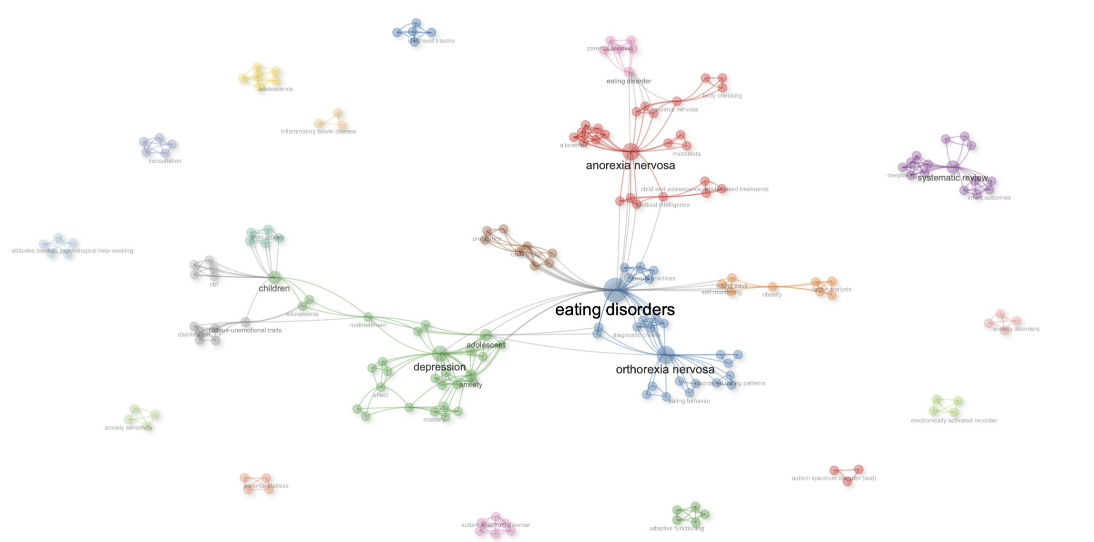

Figure 8. Keywords co-occurrence network.

the cluster joining "anorexia nervosa," "bulimia," and "AI" on the border of the motor and basic themes suggests their developing relevance in clinical profiling and predictive modelling. A category with "eating disorders" and "orthorexia nervosa" belongs purely to the basic themes, reflecting central but still developing concepts, especially in relation to the diagnostic area. In contrast, the niche themes are well-developed but less central—specialized and methodologically mature. This category includes "body image," "feeding and eating," and "body mass index." A second cluster, "eating disorder," is located near the emerging/declining themes and illustrates the rare development of this topic in the research area. Lastly, the emerging/declining themes include two categories: "obesity" and "systematic reviews." These may indicate either underdeveloped or outdated areas of research.

4.6 Citations and co-citations, influential scores and countries

Figure 10 illustrates the top 10 most productive journals that published relevant papers on the use of AI in mental health between 2005 and 2025. *Eating and Weight Disorders* is the leading journal, contributing 22 publications, underlining a significant record of research interest in AI applications for identifying, monitoring, and treating eating disorders. *Journal of Psychopathology and behavioral Assessment* published 19 relevant studies, and *Cognitive Therapy and Research* published 17 papers, suggesting an influential focus on cognitive, behavioral, and clinical appraisal approaches enhanced by AI tools. *Clinical Child and Family Psychology Review* published 16 relevant studies, and *Journal of Clinical Psychology in Medical Settings* contributed 10, indicating ongoing exploration of AI applications in child and family mental health contexts and integrated interventions. Other journals contributed six or fewer studies each, showing a less frequent record of research interest across related psychological, psychiatric, and interdisciplinary topics. Overall, the prevalence of clinically focused and disorder-specific journals indicates that the area is rooted in applied mental health research, with a strong focus on cognitive assessment, eating disorders, and adolescent psychopathology.

Figure 11 shows the top 10 countries by total citation count in the research field of applying AI in mental health.

The United States is leading with 8,896 citations, reflecting its strong position in publishing highly influential studies. This may be a result of the country's large research output, funding capacity, and concentration of top academic and scientific institutions. Spain (n = 2,843), the United Kingdom (n = 2,143), and the Netherlands (n = 2,110) have demonstrated strong academic impact, showing their prominent contribution to establishing scholarly discourse in this area. China, while being one of the major contributors, demonstrates a comparatively lower citation count (n = 1,939), suggesting a potential gap in international visibility or publication impact. Other countries, including Italy (n = 1,564), Germany (n = 1,447), Japan and Slovenia (n = 1,104 each), and Brazil (n = 1,070), round out the list, emphasizing the global significance and international collaborative nature of studies on AI in mental health. Overall, the citation data illustrates that the U.S. maintains a leadership position; however, the presence of several European and Asian countries in the top 10 reflects increasingly influential contributions to the developing domain of AI in mental health research.

5. Discussions and conclusions

This bibliometric study reveals a growing upward tendency in the number of publications on the application of AI in mental health from 2005 to 2025, with a notable increase in publication volume after 2020. This trend is consistent with global tendencies toward using digital health solutions after the COVID-19 pandemic, as reflected in recent reviews [13, 23]. The rise in scholarly output reflects the growing role of AI in diagnostic, preventive, and therapeutic mental health applications, as highlighted in multiple empirical studies and systematic reviews [3, 5, 9].

The prevalence of clinical topics such as eating disorders, depression, and anxiety is a key finding. Depression—its diagnosis and treatment—emerges as the most frequently addressed condition, with numerous studies leveraging AI's utility for early detection, suicide risk assessment, and digital intervention delivery [6, 12, 16, 17, 27]. The thematic map further validates the centrality and advancement of these areas, with "depression" and "anxiety" appearing in the motor themes category, indicating both centrality and maturity in this research area. Conversely, the increasing applicability of AI in addressing "eating disorders" and "orthorexia nervosa," identified as basic yet emerging themes, supports recent findings highlighting its diagnostic, preventive, monitoring, and therapeutic potential in addressing mental disorders [9, 10].

Keyword co-occurrence analysis emphasizes the following findings. The keyword "eating disorders" frequently co-occurs with "anorexia nervosa," "orthorexia nervosa," and "AI," mediated by co-words like "treatment" and "diagnostic criteria." This aligns with studies by Fang et al. [11], who demonstrate the use of AI-enhanced CBT and identify gender biases in AI tools, respectively. The frequent appearance of "systematic review" as an independent, high-frequency keyword highlights the evolving community's effort to consolidate fragmented results and evaluate the clinical reliability of AI tools [13, 28].

Despite the increasing volume of publications in the domain of AI in mental health, the co-authorship network remains notably fragmented, with limited cross-national and inter-institutional collaboration. Only a few authors, such as Jahrami and Ricca, occupy central positions in the network, indicating localized clusters of expertise rather than a unified global research effort. This reflects a concentration of expertise within isolated

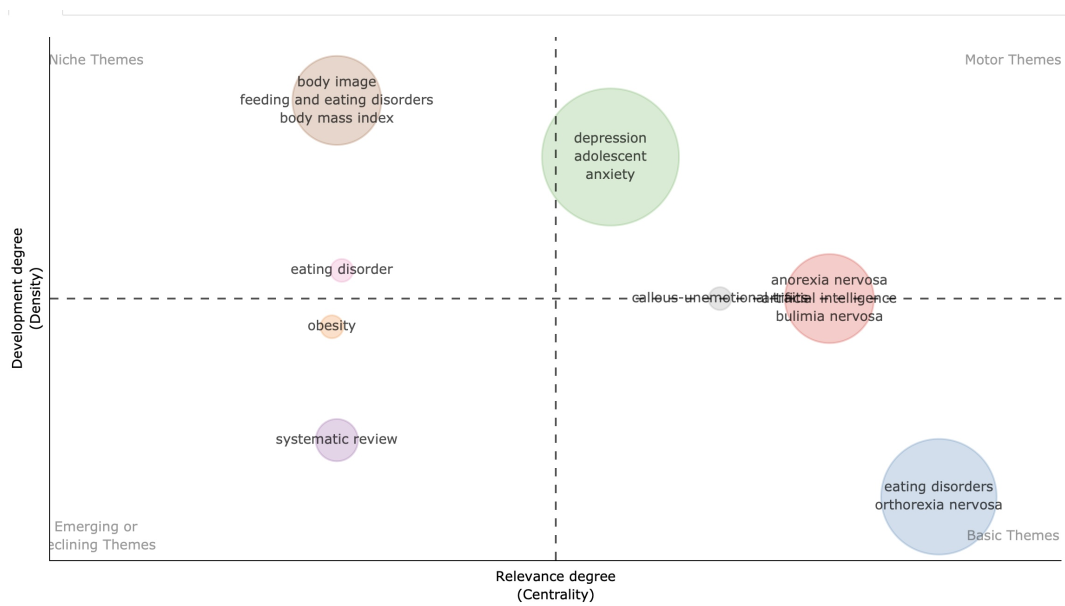

Figure 9. Thematic map of research themes in AI and mental health.

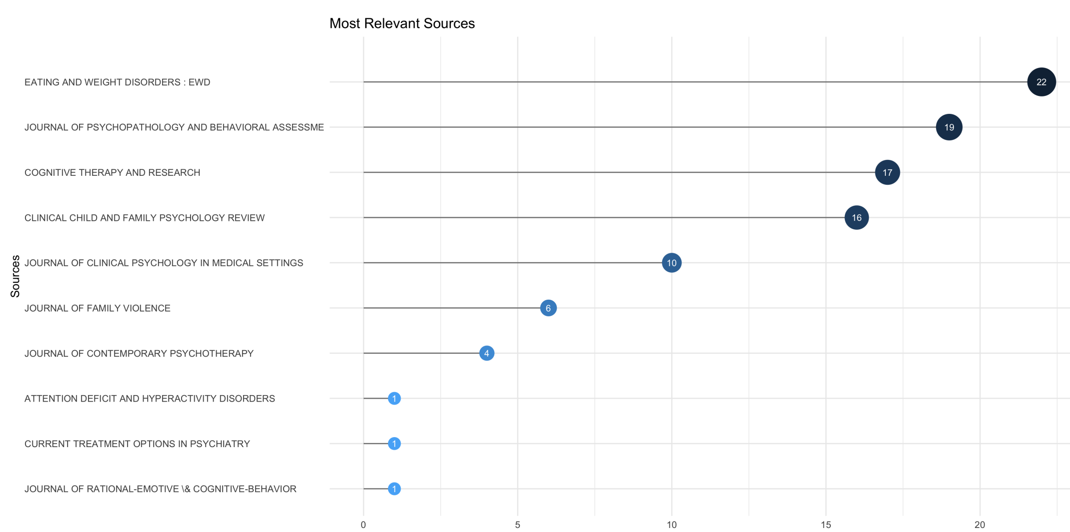

Figure 10. Most relevant journals publishing on AI and mental health (2005–2025).

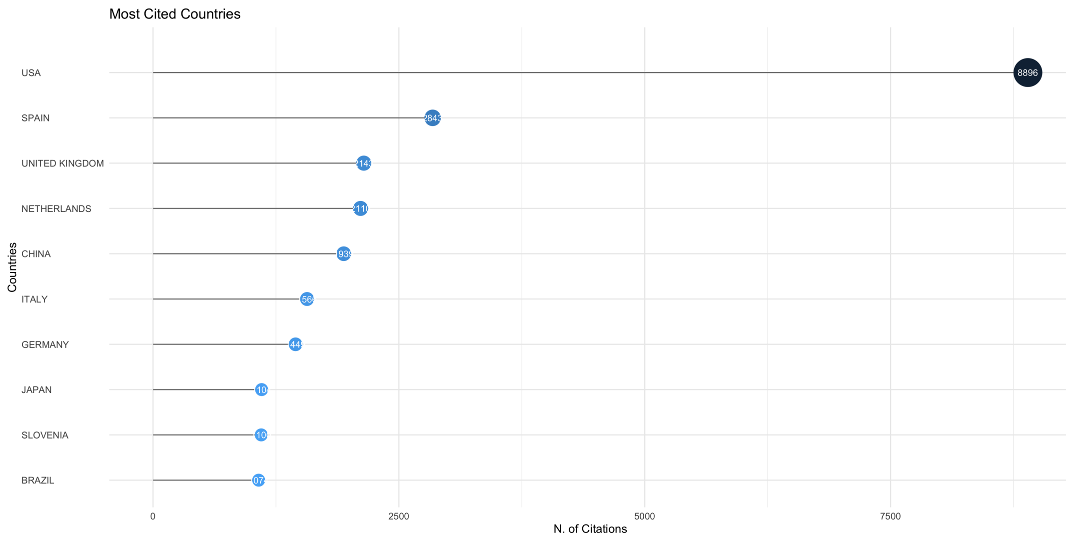

Figure 11. Top 10 most cited countries in AI and mental health research (2005–2025).

clusters, mirroring previous concerns about limited interdisciplinary and international integration in AI-based psychological research [14, 15]. The observed network structure suggests that although digital tools are globally applicable, the research remains largely restricted by national or institutional boundaries, potentially decreasing the generalizability and applicability of AI interventions in mental health.

Geographically, authors from the United States continue to dominate the field in terms of both productivity and citation impact. This trend aligns with other studies emphasizing the role of strong leadership, funding opportunities, developed research infrastructure, and early implementation of AI technologies [4, 20]. Nevertheless, countries such as the UK, Spain, the Netherlands, and China have also demonstrated impact within the field, supporting observations of international research efforts in AI-related suicide risk prediction [7, 16, 17, 21].

Finally, the growing interest in digital mental health diagnosis and prevention—such as chatbots, digital CBT, mood monitoring apps, and well-being platforms—is reflected in the keyword network and source analysis. Published papers have emphasized the essential role of AI in promoting psychological well-being, resilience, and stress management among children, students, and adolescents [24, 26, 22, 31]. Studies increasingly report that psychological interventions supported by AI are not only more accessible and cost-effective but also improve emotional resilience, reduce anxiety, enhance self-regulation, and mitigate social isolation [28, 29, 30].

In conclusion, the findings of this bibliometric study indicate both progress and limitations within the developing area of AI in mental health. While significant advancements have been made in terms of research output and thematic categorization, the domain would benefit greatly from more extensive and harmonized research methodologies, increased international collaboration, and the development of shared theoretical frameworks and technological standards. These steps are essential to fully harness the transformative potential of AI in advancing mental health care on a global scale.

5.1 Study limitations

This bibliometric review delivered significant findings as a synthesis of available data on publication patterns, productive authors, countries, sources, and collaboration networks. However, several limitations should be acknowledged. First, the database and query scope were limited to a selection of prestigious databases, including Crossref, Microsoft Academic, PubMed, OpenAlex, and CORE, with data extracted through Lens. Databases such as Scopus and Web of Science were not included in the search; therefore, non-indexed preprints and publications outside the selected databases may have been missed. Second, while the search query was carefully constructed to capture the most relevant studies, it relied on specific terminology. This approach may have excluded papers using alternative but related terms, thereby omitting some relevant studies.

Third, the analysis was limited to peer-reviewed publications written in English, leading to the exclusion of research published in other languages. Finally, a common concern in bibliometric studies is citation lag, in which newly published high-quality research may not have accumulated enough citations to fairly reflect its scholarly impact. This can result in the underrepresentation of recent contributions in the analysis.

5.2 Future research directions

The present bibliometric study highlights the necessity for further research into the effectiveness of utilizing AI to enhance the accuracy and efficiency of mental health detection, prevention, and professional treatment of various mental disorders. Such efforts may lead to improvements in psychological and overall well-being. The analysis of published research papers enabled us to formulate several significant recommendations for future studies within this domain.

Barros et al. [7] recommended conducting additional studies in varied environmental contexts, including educational institutions and primary health facilities, to assess the effectiveness of AI models with particular attention to the variable of age. Moreover, future research should explore the role of AI in detecting mental disorders by measuring responses across various categories of patients experiencing a wide range of emotions [3].

According to Liu et al. [6], personal preferences and individual differences should be considered when designing AI-supported prevention or treatment strategies for depression among college students [38, 39]. Da Fonseca, Bhat, and Kennedy [8] suggested integrating AI with electronic medical records (EMRs) to improve suicide prevention, while also emphasizing the need for further research on its safety and effectiveness.

Higgins et al. [1] noted that more studies are required to explore the impact of AI on treatment outcomes and the identification of missed care, as well as to better understand attitudes and beliefs related to the use of AI for promoting well-being [35, 37].

To conclude, further research is needed to understand the factors that increase acceptance of and engagement with AI in mental health contexts. This will require studies with larger and more diverse samples to assess whether AI applications can be generalized to broader populations.

Current research represents a significant step in the comprehensive exploration of publication trends related to the use of artificial intelligence in clinical psychology for the detection, prevention, and treatment of mental disorders from 2005 to 2025. Through bibliometric analysis, significant and relevant studies within the explored domains were systematically examined and synthesized, resulting in the establishment of a complex and comprehensive overview of the relationship between AI and mental health.

The identified research patterns and trends in the analyzed sources offer valuable insights for both clinical psychology practitioners and researchers, enabling them to be well-informed about existing knowledge, evidence, gaps, and emerging needs in the field. These findings can guide the development of more efficient interventions aimed at providing help to individuals struggling with mental health issues. Additionally, the analysis underscores the importance of further studies to estimate the practical impact of AI-based approaches in promoting psychological and overall well-being.

5.3 Conclusion

This bibliometric study highlights the rising scholarly interest in the use of artificial intelligence in mental health, particularly since 2020, indicating a significant shift likely influenced by the COVID-19 pandemic. The special focus on eating disorders, including emerging topics such as orthorexia nervosa, along with depression and adolescent mental health, suggests that these areas are well-established but still require greater clarity in research priorities to enable more targeted and effective development.

However, the fragmented author collaboration networks and the dominance of single-country publications reflect structural limitations in global research cooperation. While countries like the U.S. and Spain demonstrate high impact in terms of productivity and citation records, others such as China and Brazil face visibility challenges despite high productivity. These findings underscore the need for more integrative, international, and interdisciplinary approaches to strengthen the field.

Future research should also expand into underrepresented areas, such as digital diagnostics for autism, parental distress, and trauma-related disorders, to fully leverage AI's transformative potential in mental health care.

This study makes three major contributions. First, it provides a systematic mapping of the field's intellectual structure by identifying leading authors, institutions, sources, and countries, facilitating deeper insights into global collaboration patterns. Second, it uncovers thematic transitions from early-stage technological experimentation to the integration of AI into mental health diagnosis and interventions, demonstrating the theoretical advancement of the domain. Third, it serves as a reference point for academics, practitioners, researchers, and technology developers aiming to identify emerging areas for development, address knowledge gaps, and foster interdisciplinary partnerships.

Ethics statement

This study did not involve human participants or animals and therefore did not require ethical approval.

CRediT authorship contribution statement

Ivanna Shubina: conceptualization, methodology, software, validation, formal analysis, writing – original draft and final version, review & editing, and visualization. **Adrian Jarema Dzido**: software support, data processing, and assistance with data interpretation.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors declare that no generative AI or AI-assisted technologies were used in the writing of this manuscript. All text and figures were produced with the help of the Bibliometrix software. ChatGPT was used only for proofreading purposes.

Declaration of competing interest

The author declares no competing financial or personal interests that could have appeared to influence the work reported in this paper.

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