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Wearables, IoT, and Artificial Intelligence for Mental Health Monitoring: A Systematic Review.

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Abstract*– Digital technologies have begun to represent an important option for improving mental health monitoring, which has become a fundamental challenge worldwide. This study presents a systematic review of the use of wearable sensors, the Internet of Things (IoT), and artificial intelligence (AI) for monitoring and early detection of mental health problems. To this end, 30 studies were analyzed using the PRISMA method and filtered using PICOC criteria. The results show that the most studied disorders are anxiety, stress, and depression. In addition, the most used sensors are those for heart rate, sound, physical activity, and EEG, as they allow for continuous and non-invasive data collection. In terms of AI techniques, most studies use conventional techniques such as SVM, regression, and XGBoost; however, other studies already incorporate more advanced models that combine neural networks and attention mechanisms. These technologies often offer advantages such as early detection, continuous monitoring, and personalized follow-up. However, there are other limitations related to privacy, data variability, and lack of clinical validation. In short, it is concluded that the integration of sensors, AI, and IoT has great potential, but greater standardization and research in diverse populations is required for its real-world application in mental health.

Keywords—Mental health; wearable sensors; Internet of Things; artificial intelligence; monitoring.

I. INTRODUCTION

Mental health has become one of the top priorities on the global public health agenda. According to the World Health Organization (WHO), more than one billion people worldwide live with some form of mental health disorder, representing a social, economic, and clinical challenge of critical proportions. Despite this magnitude, mental health care remains insufficient, and in many countries, specialized services are limited, costly, or inaccessible [1]. The most common problems continue to be anxiety and depression, which account for more than two-thirds of all cases recorded in 2021. In fact, it is estimated that around $1 trillion is lost each year due to the low productivity caused by these disorders [1]. Furthermore, it is estimated that by 2030, total costs related to mental health could exceed $16 trillion, considering both healthcare expenses and indirect economic losses. All of this makes it even more urgent to seek new technological tools to help address this problem [2]. Mental health care is usually based on interviews and questionnaires. However, these methods are accurate and depend heavily on what the patient says at the time, making it more difficult to detect problems early on [3]. For this reason, technological solutions have begun to be sought that allow for continuous and more accurate monitoring.

In this regard, wearable devices and smart sensors have become quite useful options. Today, there are smartwatches, activity trackers, and other sensors that can collect real-time data on heart rate, heart rate variability (HRV), skin conductance, sleep, and physical activity [2]. This data has proven to be very useful in identifying signs of stress, anxiety, or depression [4]. In addition, recent studies show that different types of sensors can provide valuable information. For example, the portable biosensor that serves as a stress indicator collects information on electrodermal activity (EDA), while accelerometers and gyroscopes record the patient's movement and daily activity [5]. PPG sensors are also used to help calculate heart rate and its variability, which is related to different emotional states [6]. Together, these technologies interconnect physical and mental health and allow for the analysis of a person's condition based on various criteria.

On the other hand, the use of sensors is further enhanced when integrated with the Internet of Things (IoT). In healthcare, this is known as the Internet of Medical Things (IoMT), which allows various devices to be connected and send data continuously and securely to cloud platforms [7]. Thanks to this, it has become possible to monitor patients remotely and generate early warnings when something seems to be wrong [8]. Reducing unnecessary in-person visits, early detection of crises, and the ability to tailor interventions to each person's needs are some of the benefits of IoT in mental health [9]. However, significant challenges remain, such as data security, device compatibility, and user acceptance [10].

Artificial Intelligence (AI) is another important factor. Deep learning and machine learning algorithms have made it possible to analyze large volumes of data from IoT systems and sensors. These methods enable the discovery of complex patterns, the prediction of critical events, and support for healthcare professionals in their decision-making process [11]. Positive results have been observed from the application of artificial intelligence to mental health, such as the diagnosis of depression based on information about physical activity, the detection of stressful episodes using electrodermal signals, and the determination of anxiety using measures of heart rate variability [12]. Similarly, some practices already include artificial intelligence chatbots that communicate with patients, offer suggestions, and automatically notify doctors if a high risk is detected [13].

Despite this progress, there are still significant limitations. Some of the most important problems are the lack of standardization in methods, the inaccuracy of algorithms, the uneven quality of data obtained through sensors, and ethical issues related to privacy [14]. All of this has meant that these technologies are not widely used in clinical settings. However, recent studies indicate a growing interest in integrating sensors, IoT, and AI into a single system [15].

Although there are already systematic reviews examining the use of sensors in mental health [2], of the IoT in remote monitoring [7], or AI in the detection of psychiatric disorders [11], no systematic review has been identified that integrates these three dimensions together. This lack represents a gap in literature and is the reason for conducting this study.

Therefore, the objective of this systematic review is to identify and analyze the tools and architectures that use artificial intelligence, IoT, and wearable devices for mental health monitoring and control. It also seeks to summarize their benefits, limitations, and performance metrics to provide guidance that will help create more effective and secure solutions.

II. METHODOLOGY

This research is being conducted in accordance with the Systematic Literature Review (SLR) format.

A. *PICOC formulation*

The PICOC method was used to determine the scope of the research.

TABLE I
PICOC COMPONENTS

Component	Description
P (Problem / Population)	People at risk or in need of mental health monitoring.
I (Intervention)	Use of portable sensors, IoT, and artificial intelligence algorithms to monitor physiological and emotional indicators.
C (Comparison)	Traditional psychological assessment methods or non-integrated technologies.
O (Results)	Improved tracking, early detection, and continuous monitoring of mental health, accurate predictions, and support for clinical decisions.
C (Context)	Clinical and non-clinical context.

B. *Formulating questions*

After identifying the components of the PICOC method, the general research question (RQ) for this systematic review was formulated:

"What architectures and tools based on artificial intelligence, IoT, and wearable sensors are used for mental health monitoring and control, and what are their benefits and limitations compared to traditional assessment methods?"

Based on the general question, specific questions were formulated.

TABLE II
PICOC QUESTIONS

RQ1	What types of mental health issues have been addressed with these technologies?
RQ2	What portable sensors and physiological indicators are used?
RQ3	What IoT architectures and platforms are implemented to collect and transmit data?
RQ4	What artificial intelligence techniques are applied to mental health data processing?
RQ5	What advantages and limitations have been reported compared to traditional diagnostic or self-assessment methods?

C. *Identification of keywords*

The identification of keywords corresponding to each component of the PICOC method aims to construct effective search equations in databases.

TABLE III
KEYWORDS WITH BOOLEAN OPERATORS

P	"mental health" OR "psychological disorders" OR "stress" OR "anxiety" OR "depression"
I	"wearable sensors" OR "wearables" OR "smart devices" OR "IoT" OR "artificial intelligence" OR "machine learning" OR "deep learning"
C	"psychological questionnaires" OR "clinical interviews" OR "self-report" OR "traditional methods" OR "diagnosis"
O	"remote monitoring" OR "continuous monitoring" OR "early detection" OR "prediction" OR "decision support" OR "digital health" OR "telemedicine"
C	"clinical context" OR "healthcare" OR "mental healthcare" OR "digital health" OR "community care"

D. *PICOC search formula*

Once the components of the PICOC question and the keywords were identified, we proceeded to develop the search formula that would allow us to find the most relevant literature for this systematic review. To do this, the terms of each component were combined using the Boolean operators "OR" to combine the keywords and "AND" to link the components.

TABLE IV
SEARCH EQUATION

Search equation	
Scopus	TITLE-ABS-KEY (("MENTAL HEALTH" OR "PSYCHOLOGICAL DISORDERS" OR "STRESS" OR "ANXIETY" OR "DEPRESSION") AND ("WEARABLE SENSORS" OR "WEARABLES" OR "SMART DEVICES" OR "IOT" OR "ARTIFICIAL INTELLIGENCE" OR "MACHINE LEARNING" OR "DEEP LEARNING") AND ("PSYCHOLOGICAL QUESTIONNAIRES" OR "CLINICAL INTERVIEWS" OR "SELF-REPORT" OR "TRADITIONAL METHODS" OR "DIAGNOSIS") AND ("REMOTE MONITORING" OR "CONTINUOUS MONITORING" OR "EARLY DETECTION" OR "PREDICTION" OR "DECISION SUPPORT" OR "DIGITAL HEALTH" OR "TELEMEDICINE") AND ("CLINICAL CONTEXT" OR "HEALTHCARE" OR "MENTAL HEALTHCARE" OR "DIGITAL HEALTH" OR "COMMUNITY CARE")) AND PUBYEAR > 2015 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE , "AR")) AND (LIMIT-TO (OA , "ALL"))
Web of Sciencie	(((((((((TS = "MENTAL HEALTH") OR (TS = "PSYCHOLOGICAL DISORDERS")) OR (TS = "STRESS")) OR (TS = "ANXIETY")) OR (TS = "DEPRESSION")) AND ((((((TS = "WEARABLE SENSORS") OR (TS = "WEARABLES")) OR (TS = "SMART DEVICES")) OR (TS = "IOT")) OR (TS = "ARTIFICIAL INTELLIGENCE")) OR (TS = "MACHINE LEARNING")) OR (TS = "DEEP LEARNING"))) AND (((((TS = "PSYCHOLOGICAL QUESTIONNAIRES") OR (TS = "CLINICAL INTERVIEWS")) OR (TS = "SELF-REPORT")) OR (TS = "TRADITIONAL METHODS")) OR (TS = "DIAGNOSIS"))) AND (((((((TS = "REMOTE MONITORING") OR (TS = "CONTINUOUS MONITORING")) OR (TS = "EARLY DETECTION")) OR (TS = "PREDICTION")) OR (TS = "DECISION SUPPORT")) OR (TS = "DIGITAL HEALTH")) OR (TS = "TELEMEDICINE"))) AND (((((TS = "CLINICAL CONTEXT") OR (TS = "HEALTHCARE")) OR (TS = "MENTAL HEALTHCARE")) OR (TS = "DIGITAL HEALTH")) OR (TS = "COMMUNITY CARE")))

E. *Inclusion and Exclusion Criteria*

To ensure that the selected studies are valid and relevant, specific inclusion and exclusion criteria were defined.

Studies dealing with mental health monitoring or follow-up were included, as well as research using or describing the use of wearable sensors, IoT devices, and artificial intelligence algorithms in this field. In addition, studies reporting quantitative or qualitative data on prediction, early detection, continuous monitoring, or clinical decision support were considered. Studies conducted in both clinical and non-clinical settings, published between 2021 and 2025, and written in English were accepted.

On the other hand, research focused exclusively on physical illnesses unrelated to mental health was excluded, as was research that did not incorporate wearable sensors, IoT, or artificial intelligence as part of its methodology. In addition, publications that were not scientific articles.

The implementation of these criteria allowed us to precisely establish the scope of the analysis, ensuring that the studies included in the review were consistent both thematically and methodologically.

F. *PRISMA Statement*

The PRISMA statement is an international manual that helps ensure transparency, accuracy, and replicability in systematic reviews. This tool provides a checklist that guides each stage of the review process, from identifying and selecting articles to assessing their eligibility and synthesizing the results. According to Page et al. [16], the 2020 version of PRISMA modified the original 2009 guidelines to include technological and methodological advances in the search and analysis of scientific evidence, resulting in a more comprehensive and organized report. Likewise, its ability to improve the quality and credibility of publications has led many scientific journals and organizations to adopt it for its capacity to increase the quality and credibility of publications [16].

According to this study, the PRISMA statement was essential for organizing the selection and analysis process of research related to portable sensors, IoT, and artificial intelligence used in mental health monitoring in an orderly manner. This guide was used to determine clear criteria in the selection, exclusion, and final screening stages of articles, ensuring the methodological consistency of the study. According to Hutton et al. [17], The use of PRISMA also promotes understanding and comparison of results in various areas, as it encourages clear presentation of the techniques used. In this way, PRISMA not only supports transparency in the research process, but also helps to strengthen confidence in the results obtained, enabling future research to replicate and expand on the findings more reliably.

G. *PRISMA process*

The PRISMA process was used to review this research. A total of 614 articles were identified: 398 from Scopus and 216 from Web of Science. After removing duplicates and applying the inclusion and exclusion criteria, the remaining studies were evaluated by reading the titles, abstracts, and full texts.

Finally, 30 articles were selected that met the study objectives and provided the most important evidence on the use of wearable sensors, IoT, and artificial intelligence for mental health monitoring.

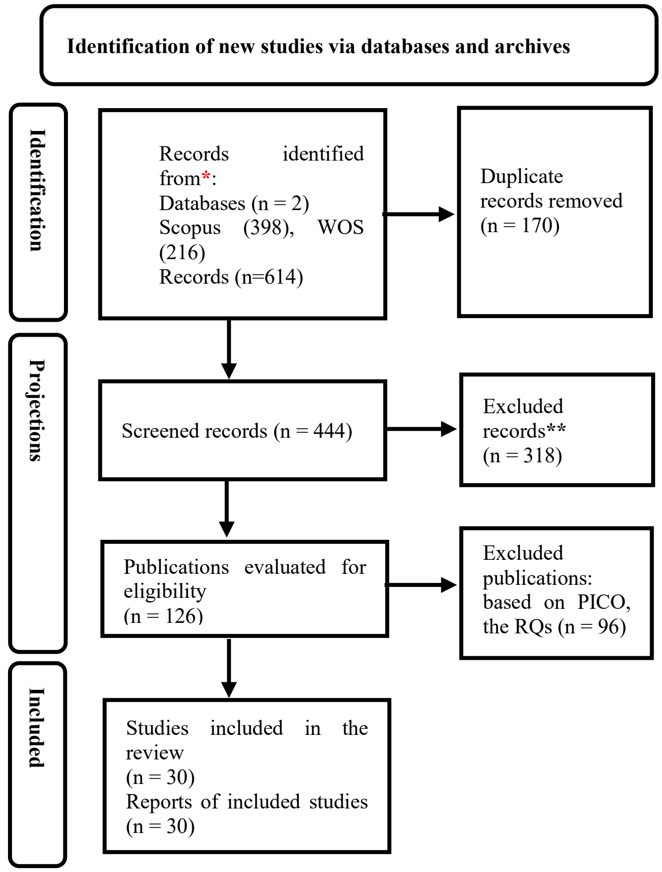

Fig. 1 PRISMA Process Diagram

H. *Assessment of methodological quality*

To assess the methodological quality of the 30 studies included in this review, we followed the guidelines of the Joanna Briggs Institute (JBI)[18]. Accordingly, six aspects were considered: whether the population or sample is correctly defined; whether the data used are adequate; whether the methodology is clearly explained; whether there is validation of the model or results; whether clear metrics or robust results are reported; and finally, whether the study's limitations are discussed. Each of the defined criteria was assessed on a binary scale, that is, using 0 and 1, thereby allowing the studies to be classified according to their quality.

I. *Bibliometrix*

In the bibliometric analysis of various branches of knowledge, the use of Bibliometrix in R Studio has become an essential tool. This methodology enables the observation of research trends, scientific productivity, and collaborative networks in a visual and organized manner. Understanding citation and authorship patterns helps to identify factors that affect the quality and impact of research, showing how bibliometric analysis can uncover links between variables such as total authors, citations, and funding. This type of analysis provides a better understanding of the development and evolution of emerging fields, such as artificial intelligence, in high-impact journals [19].

In this scenario, R Studio and the Bibliometrix package provide a powerful, open-source platform for working with and observing data from databases such as Scopus and Web of Science. In recent studies, such as that on trends in critical thinking in English language teaching, functions such as worldcloud, threefieldPlot, and co-occurrence network were used to determine the most influential authors, countries, and keywords [20], their use has been fundamental.

In conclusion, bibliometric analysis using R Studio is valuable because it has the ability to combine complex data and convert it into information that can be used to make decisions in the scientific field. In addition to co-authorship networks and keywords, tools such as tracking authors' output over time and thematic maps can be used to examine the thematic evolution of studies and the functioning of academic collaboration. R Studio is an essential tool for mapping and scientific review studies thanks to its bibliometric approach, which allows us to understand the interactions between authors and institutions and the structure of knowledge [21].

III. Results

Articles that met the review objectives were selected after using the PRISMA model to apply inclusion and exclusion criteria. In total, research combining artificial intelligence, mobile devices, and IoT structures for mental health monitoring and assessment was examined. The information collected was organized considering the technologies used, the physiological indicators measured, the difficulties reported, and the types of mental health problems addressed.

Furthermore, the assessment of the methodological quality of the JBI revealed that most of the included studies are of good quality. Of the 30 studies, 21 were categorized as high quality, meeting all JBI criteria. On the other hand, 7 studies were classified as moderate quality, and only 2 were of low quality. Most of the weaknesses identified were concentrated in the criteria for model or outcome validation and in the reporting of metrics. Despite this, overall, the analyzed studies ensure the reliability of this review.

The following table presents a summary of the reviewed studies, structured according to country of origin, corresponding author, and the primary mental health issues studied. This compendium helps identify the most common research trends and contextual variations related to the mental disorders studied in various areas of the world.

TABLE V
Results Of Articles By Mental Health Issues

Corresponding author	Country	Mental health issues addressed
Shin Y. et al [22]	South Korea	Depression, anxiety, comorbidity
Aledavood T. et al [23]	Finland	Major depressive episode, major depressive disorder (MDD), bipolar disorder (BD), borderline personality disorder (BPD)
Kondylakis H. et al [24]	Greece	Stress, anxiety, depression, pain, psychological well-being
Epperson C. et al [25]	United States	Major depression, bipolar disorder I and II, other mood disorders, anxiety, suicidal ideation
Bai S. [26]	China	Psychological stress, depression, anxiety, phobia, psychosis, interpersonal problems, emotional well-being
Presby D. et al [27]	Switzerland	Depression, anxiety, stress
Georgiou D. et al [28]	Greece	Psychotic disorders, early detection, relapse prevention
Dubey P. et al [29]	India	Stress, depression, general mental disorders (early detection and prediction)
Lee M. et al [30]	United States	Low mood, risk of depression, and emotional disturbances related to circadian misalignment
Lee J. et al [31]	South Korea	Major depressive disorder in older adults
O'Leary A. et al [32]	United States	Depression, anxiety, and emotional disorders in children
Loftness B. et al [33]	United States	Anxiety, depression, and ADHD in early childhood
Rashid Z. et al [34]	United Kingdom	Major depressive disorder (MDD), ADHD, autism, eating disorders, Alzheimer’s disease, and other mental disorders
Kargarandehkordi A. et al [35]	United States	Chronic stress and its physiological effects on blood pressure
Datar D. et al [36]	India	Prediction of mental states (neutral, focused, relaxed), useful for stress management, concentration, and relaxation
Baumann H. et al [37]	Germany	Occupational stress and coping with emotional distress among healthcare professionals
Sadhu S. et al [38]	United States	Anxiety disorders, stress, and depression through the analysis of patients’ physiological data
Kishimoto T. et al [39]	Japan	Depression, bipolar disorder, and other mood-related psychiatric disorders
Lemos R. et al [40]	Portugal	Depression, anxiety, and quality of life in breast and lung cancer survivors
Kathan A. et al [41]	Germany	Depression
Iqbal T. et al [42]	Ireland	Stress in students and workers during experimental induction tasks (e.g., Trier Social Stress Test)
de Angel V. et al [43]	United Kingdom	Depression and comorbid anxiety disorders
de Angel V. et al [44]	United Kingdom	Depression (primary) and anxiety as a frequent comorbidity
Naregalkar P. et al [45]	India	Stress and anxiety

Pinge A. et al [46]	India	Stress, anxiety, emotional burden
Chen J. et al [47]	China	Depression, anxiety, insomnia
Moshe I. et al [48]	Finland	Depression, anxiety, stress
Choudhary S. et al [49]	United States	Depression
Modi N. et al [50]	India	Stress
Shaik T. et al [51]	Australia	Stress and depression

As can be seen, the most common disorders in the studies analyzed are stress, anxiety, and depression, followed by bipolar disorder and other related emotional problems. This pattern reflects a global concern for the identification, monitoring, and treatment of these conditions, particularly through approaches based on digital technologies and portable devices that enable constant monitoring of people's physiological and mental states.

The following table describes the sensors and devices used by the authors in their studies, as well as the key physiological indicators that were recorded. This information facilitates recognition of the technologies most frequently used in monitoring variables related to mental health.

TABLE VI
PHYSIOLOGICAL SENSORS AND INDICATORS

Corresponding author	Sensors used	Physiological indicators
Shin Y. et al [22]	Wearables: Apple Watch, Galaxy Watch; motion sensors, GPS	Cardiovascular, sleep and activity, respiratory, temperature
Aledavood T. et al [23]	Smartphone, actigraph, bed sensor	Activity, sleep, mobility, communication, location patterns
Kondylakis H. et al [24]	Smartphone, integrated clinical sensors	Neuropsychological/emotional, pain, stress
Epperson C. et al [25]	Smartphone (internal sensors)	Sleep, mood, anxiety, depression, mania, suicidal ideation
Bai S. [26]	Wearables, behavioral sensors	Cardiovascular, stress/anxiety, neuropsychological, activity
Presby D. et al [27]	Wearables, smart band	Cardiovascular, sleep, physical activity
Georgiou D. et al [28]	Wearables, tablet	Cardiovascular, sleep, activity, behavior, clinical questionnaires
Dubey P. et al [29]	Physiological devices (HR, HRV, sleep)	Cardiovascular, sleep, physical activity
Lee M. et al [30]	Fitbit, wearable	Cardiovascular, sleep, activity, circadian rhythm
Lee J. et al [31]	Wearables, smartphone	Cardiovascular, sleep, daily activity
O'Leary A. et al [32]	Wearables, smartphone	Cardiovascular, sleep, movement, stress/attention
Loftness B. et al [33]	Smartphone	Movement, voice, motor responses
Rashid Z. et al [34]	Wearables, smartphone	Cardiovascular, sleep, physical activity, voice, location
Kargarandehkordi A. et al [35]	Wearables: Fitbit, Empatica E4, Omron	Cardiovascular, blood pressure, EDA, activity, stress
Datar D. et al [36]	Portable EEG	EEG, mental state
Baumann H. et al [37]	Wearables, mobile app	Cardiovascular, activity, stress
Sadhu S. et al [38]	Wearable wristband	Cardiovascular, activity, sleep
Kishimoto T. et al [39]	PPG wristband	Cardiovascular, sleep, movement
Lemos R. et al [40]	Fitbit, smartphone	Sleep, activity, voice, ambient light
Kathan A. et al [41]	Smartphone	Sleep, activity, voice, EMA self-reports
Iqbal T. et al [42]	Empatica E4 wristband	Cardiovascular, respiratory, pulse volume
de Angel V. et al [43]	Wearables, mobile apps	Sleep, activity, voice, socialization
de Angel V. et al [44]	Fitbit, smartphone	Sleep, activity, sociability, stress, cognition
Naregalkar P. et al [45]	ECG, EMG, GSR, RESP	Cardiovascular, respiratory, muscle activity, EDA
Pinge A. et al [46]	Wearables, ECG, PPG, EDA, EEG, EMG, IMU	Cardiovascular, respiratory, activity, temperature, pressure, EDA
Chen J. et al [47]	Clinical data and self-reports	Activity, sleep, BMI, insomnia, age, chronic diseases
Moshe I. et al [48]	Oura Ring, iPhone	Cardiovascular, sleep, activity
Choudhary S. et al [49]	Smartphone	Digital behavioral indicators: app usage, sleep, movement
Modi N. et al [50]	Multichannel EEG	EEG, stress
Shaik T. et al [51]	PPG wearables, respiratory and temperature sensors	Cardiovascular, respiratory, body temperature

In the studies reviewed, it can be observed that physiological heart rate sensors, accelerometers, and wearable devices, such as smart watches or bracelets, are the most used to identify signs related to mental health problems such as stress, depression, and anxiety. This demonstrates that there is a preference for non-invasive technologies that are also easy to use for continuous monitoring of mental and emotional state.

The following table presents the Internet of Things (IoT) architecture and technology platforms used in the studies reviewed for the collection and transmission of behavioral and physiological data. In addition, the main artificial intelligence methods used to analyze and process mental health-related information are described.

TABLE VII
IOT ARCHITECTURES AND AI TECHNIQUES

Author	IoT Architecture / Platform	Applied AI techniques
Shin Y. et al [22]	PixelMood App + Cloud (Apple/Samsung Health)	Random Forest, SVM, Gradient Boosting, Neural Networks, Anomaly Detection

Aledavood T. et al [23]	Mobile platform + cloud + sensors (PHQ-9)	Linear mixed models, statistical and correlational analysis
Kondylakis H. et al [24]	CARINAE platform + hospital cloud + app	LMM, ANOVA, Tukey, XGBoost
Epperson C. et al [25]	Rhythms + hospital cloud + MHC app	Alert algorithms, descriptive and correlational analysis
Bai S. [26]	IoT platform + cloud AI + rehabilitation programs	Psychological recognition, ACO, optimized SVM, regression, correlation
Presby D. et al [27]	Cloud + mobile app + wearable devices	SEM, cross-correlation, longitudinal analysis
Georgiou D. et al [28]	e-Prevention platform (Elastic Stack)	Anomaly detection and real-time analytics
Dubey P. et al [29]	Federated network + central server	CNN, LSTM, multimodal fusion, SHAP, ROC
Lee M. et al [30]	Wearable IoT + synchronized cloud	Kalman filter, regression, GEE, LME
Lee J. et al [31]	App + Samsung Health + cloud + social networks	Regression, SVM, RNN, PCA, NLP, clustering
O'Leary A. et al [32]	DPST system + cloud + clinical notes	AI for automated interpretation and clinical reporting
Loftness B. et al [33]	mHealth platform + cloud analytics	XGBoost, Naïve Bayes, KNN, SHAP, CCA
Rashid Z. et al [34]	RADAR-Base IoT platform (multiple devices)	Feature extraction and ML for biomarkers
Kargarandehkordi A. et al [35]	CardioMate + IoT devices	Deep Learning, self-supervision, ROC/AUC analysis
Datar D. et al [36]	Local EEG processing (Python)	XGBoost, Random Forest, SVM, hyperparameter optimization
Baumann H. et al [37]	mHealth with sensors and biofeedback	Adaptive algorithms, MANOVA, post hoc analysis
Sadhu S. et al [38]	mHealth + sensors + CarePortal dashboard	Clinical data visualization and analysis
Kishimoto T. et al [39]	Silmee Cloud + research cloud	XGBoost, SVM, Gradient Boosting, Deep Learning
Lemos R. et al [40]	FAITH (4-layer) + Google Fit + Apple HealthKit	Feature selection, time series, clustering, neural networks, federated learning
Kathan A. et al [41]	Smartphones + digital platform	GRU, transfer learning, personalized models
Iqbal T. et al [42]	Empatica Connect Cloud	Bayesian EM analysis, adaptive physiological ranges
de Angel V. et al [43]	RMT + apps + cloud	No direct AI; future-oriented framework
de Angel V. et al [44]	IoT (Fitbit, smartphones, KCL cloud)	Multivariate ML, latent class analysis, structural equation modeling
Naregalkar P. et al [45]	Physiological database + Python	Decision tree, SVM, cross-validation
Pinge A. et al [46]	Wearables (Empatica, Polar, Garmin, etc.)	ML: SVM, KNN, neural networks, logistic regression
Chen J. et al [47]	Digital nomogram + clinical database	LightGBM, XGBoost, SVM, SHAP
Moshe I. et al [48]	Delphi App + Oura Ring + cloud	Multilevel models, EMA–sensor correlation
Choudhary S. et al [49]	Android + servers (MHSS)	Random Forest, XGBoost, SVM, Gini analysis
Modi N. et al [50]	Local EEG + CNN-MLP	Deep Learning: CNN, MLP, LSTM, RNN, GRU, Transformer
Shaik T. et al [51]	Gym-like simulated environment + sensors	Multi-agent Deep Reinforcement Learning (DRL)

As can be seen, IoT architecture based on cloud services and mobile applications are the most widely used for the continuous collection of physiological information. In terms of artificial intelligence techniques, machine learning and deep learning schemes dominate, including SVM, XGBoost, and neural networks. These techniques focus on early identification, categorization, and prognosis of mental disorders. This demonstrates a shift toward systems that are increasingly automated, intelligent, and personalized for mental health monitoring.

The reviewed analyses reveal that the use of artificial intelligence algorithms, IoT platforms, and wearable sensors offers clear benefits compared to traditional methods of self-assessment or diagnosis in terms of mental health.

Some of these include early detection of crises or symptoms, constant non-invasive monitoring, personalized interventions, and greater accuracy and objectivity in relation to subjective reports. These technologies also enable real-time data collection, integration with community and clinical environments, and support for medical decision-making.

However, studies indicate that there are significant limitations, including the need to protect sensitive information, technological dependence, and large-scale clinical validation. Other limitations include participant dropout, small sample sizes, population biases, and individual variability in physiological signals, which can impact the accuracy of models. The intricate technical nature and challenge of fully automating the analysis are also obstacles to large-scale implementation.

In summary, these technologies provide more impartial, consistent, and flexible monitoring than conventional methods; however, technical, clinical, and ethical aspects must be considered, and robust validations must be performed to ensure reliable results that can be used in different situations.

Figure 2 shows the number of studies per country included in the review. The United States stands out with seven studies, followed by India with five and the United Kingdom with three. Other countries such as Germany, China, South Korea, Finland, and Greece contributed two studies each, while Australia, Ireland, Japan, Portugal, and Switzerland presented one study each. This distribution reflects a greater concentration of research in technologically advanced nations, especially those with well-established digital health infrastructures.

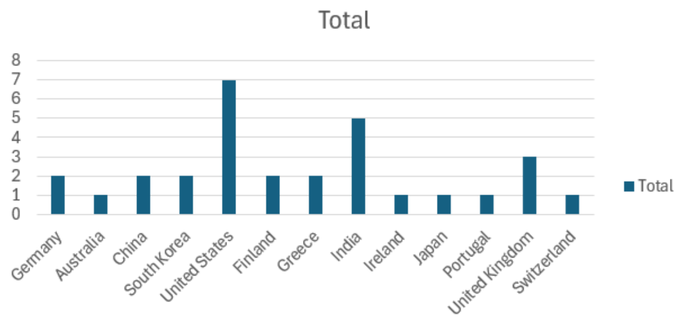

Fig. 2 Number of studies per country included in the review.

Figure 3 shows the relationship between countries, co-authors, and keywords identified through bibliometric analysis. The United Kingdom stands out as the country with the strongest presence in the collaboration network, while the predominant keyword is “mHealth,” reflecting the main focus of the research analyzed.

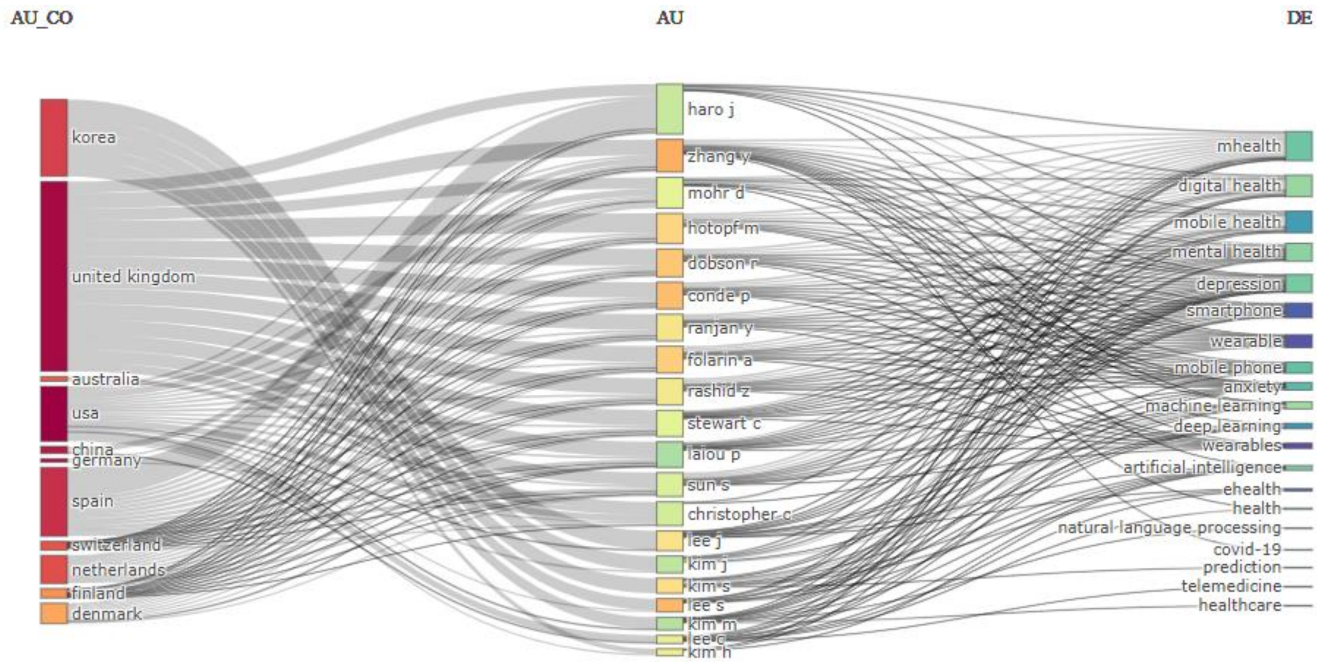

Fig. 3 Relationship between countries, co-authors, and keywords.

Figure 4 shows the co-occurrence map of the authors' keywords, grouped into different colored clusters representing the main lines of research. Among the most prominent words are “digital health,” “mHealth,” “machine learning,” and “depression,” highlighting the interdisciplinary approach of studies on the use of artificial intelligence and digital health.

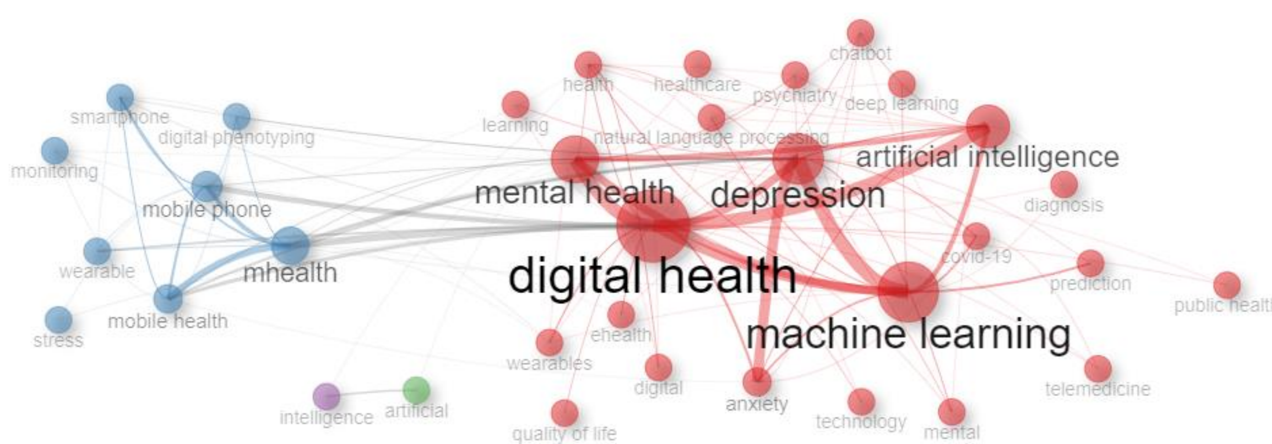

Fig. 4 Keyword overlap.

Figure 5 shows the keyword cloud, which displays the most frequently used terms in the studies analyzed. The words “machine learning,” “digital health,” “mental health,” “AI,” and “depression” stand out, along with other related concepts, reinforcing the relevance of artificial intelligence and digital technologies in mental health research.

Fig. 5 Keyword cloud.

Figure 6 shows a thematic map displaying the main groups of keywords present in the reviewed studies. Each group is characterized by its centrality and density, indicating the importance and cohesion of the topics in literature. Groups such as digital health, human, disorder, and machine learning stand out, where centrality reflects the connection of each topic with others in the network, and density indicates the degree of internal development of each group.

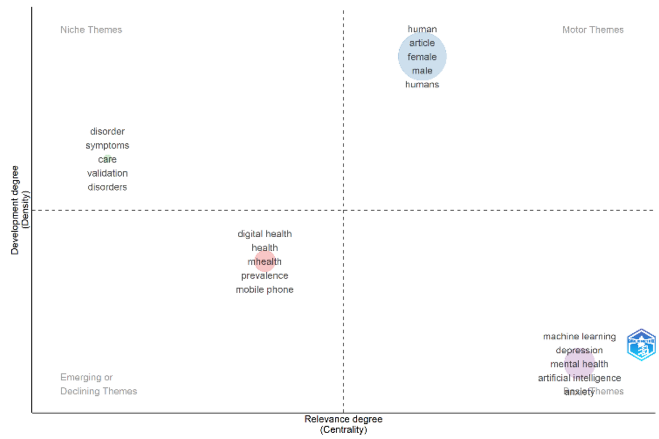

Fig. 6 Thematic Map.

Figure 7 shows a correspondence factor analysis of the keywords, grouped into three main clusters. Cluster 1 brings together terms related to artificial intelligence applied to mental health (machine learning, digital health, depression), cluster 2 includes concepts related to mobile devices and platforms (mHealth, smartphone, wearables), and cluster 3 groups together clinical and population terms (anxiety, psychiatry, suicidal ideation, digital mental health), reflecting the main areas of focus in the reviewed literature.

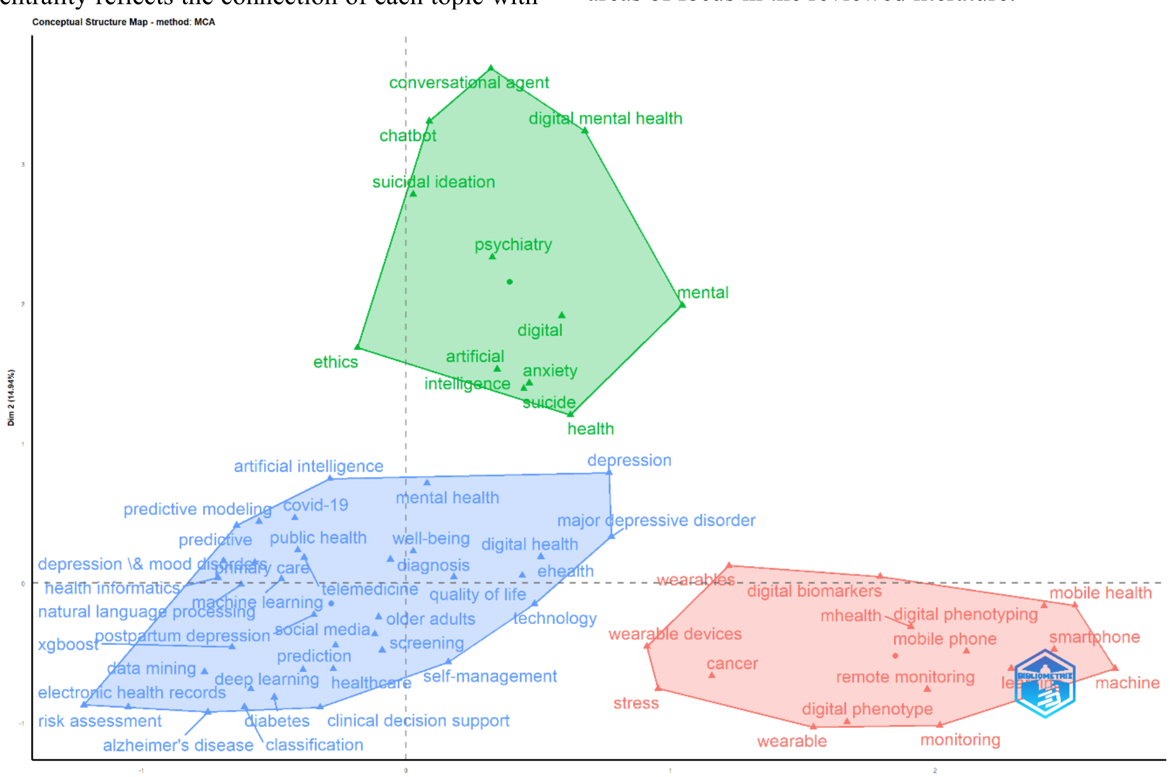

Fig. 7 Factor Analysis.

IV. Discussion

To begin with, in this review study, it can be observed that the disorders that appear most frequently in the studies are anxiety, stress, and depression, as they are present in almost all of the works reviewed. This is particularly evident in authors such as Moshe [48], Shin [22] and Kondylakis [24], in which these three problems are always present. By comparison, these disorders tend to be more detectable through continuous physiological signals, such as EEG or heart rate variability, compared to other less-represented disorders like ADHD or psychosis. Furthermore, the authors of the EmotionNet research focus solely on anxiety and stress, demonstrating that these are the most suitable for identification using EEG signals and deep learning models. They even state that they decided to concentrate on these emotions because they are easier to identify from physiological data and offer greater accuracy. This is consistent with our findings, as most of the articles we reviewed also prioritize these same factors, while other disorders such as ADHD or psychosis are less frequently presented. Therefore, we believe that our findings are consistent with what has been reported by EmotionNet [52], which shows that the topics most addressed today when using artificial intelligence and digital technologies for mental health are anxiety, stress, and depression.

Secondly, in the studies reviewed, we observed that the physiological sensors most used to monitor mental health are those that measure sleep, heart rate, heart rate variability (HRV), physical exercise, and sometimes EEG. They are mainly used in portable devices such as bracelets, smartwatches, and other wearables. Authors such as Dubey [29], Sadhu [38] and Kargarandehkordi [35] note this trend. When comparing these results with the analysis by Depressive-Deep [53], we observe that they also use HRV and EEG as primary signals, which is consistent with the technologies most used in our review. In their case, they combine both signals to generate 2D scalograms and improve the detection of depressive patterns, showing that these physiological indicators are not only popular but also useful for modern deep learning-based models. This reinforces what we found: that cardiac signals and EEG are the most preferred for analyzing emotions, stress, and depression, mainly because they allow for continuous, non-invasive monitoring that is compatible with wearables.

Likewise, in our analysis, we noticed that most studies use more traditional artificial intelligence techniques, such as SVM, regression, XGBoost, or mixed statistical models. In addition, they use simple neural networks to categorize emotions or states of mind. In research such as that by Lee J. [31], Loftness [33], Shin [22] and Bai [26], these methodologies are frequently repeated. In these studies, they are mainly used to detect states such as depression, stress, or anxiety based on data from portable devices and IoT. However, when we compare this with the external study of the Attention-Based CNN-BiLSTM-Transformer model, we observe that they use more sophisticated architectures by merging bidirectional recurrent networks, convolutions, and transformers with attention mechanisms for the integration of EEG, ECG, GSR, and EMG signals. While in our review the models tend to focus on a single type of technique or a simple combination (e.g., CNN-LSTM or SVM + feature extraction), the model in the article achieves better results, particularly in terms of classification performance reported in the study, because it captures spatial, temporal, and long-range relationships at the same time, outperforming SVM and Random Forest as well as more basic architectures such as CNN-LSTM. This shows that, although most of the studies in our analysis still rely on traditional or moderately complex methods, new trends are moving toward hybrid models and attention mechanisms, which seem to offer superior performance in emotion and mental health classification, as reported by the proposed Transformer model [54]. By comparison, deep learning-based approaches offer greater capacity for modeling complex patterns, while traditional methods stand out for their interpretability and lower computational cost. However, it is important to note that deep learning-based models, such as LSTM networks and attention mechanisms, can be difficult to interpret due to their internal workings, as it is not always clear how they arrive at their decisions—a phenomenon known as the “black box” problem. In the context of mental health, this can represent a significant limitation, because clinicians need to understand and trust the model’s results before applying them. For this reason, the use of explainable artificial intelligence (XAI) techniques becomes relevant, as they make decision-making processes more transparent and facilitate their application in clinical settings.

On the other hand, when analyzing security in the proposed IoT architectures, it is evident that there is a greater preference for using basic security solutions such as TLS and AES encryption in the cloud, and basic access controls on mobile devices. Although some propose anonymization or federated learning to protect privacy, there is a significant gap: very little is explained regarding data integrity. When analyzing vulnerabilities, this lack of precision indicates that security remains an afterthought rather than a core component of the design, which significantly limits the efficient management of such systems in a field as sensitive as mental health.

As Figure 2 illustrates, current scientific output is heavily concentrated in North America, Europe, and Asia. This is no minor detail; what we see in the data is a geographic bias that calls into question whether these artificial intelligence models truly serve everyone. The underlying problem is that, by training and testing algorithms on such specific groups of people, their ability to function in other environments is compromised. Ultimately, if AI is not used in diverse contexts, algorithmic bias ceases to be a theory and becomes a real flaw that completely limits its usefulness.

Finally, we note that solutions based on wearable devices, artificial intelligence, and the Internet of Things have clear advantages such as constant monitoring, early detection, and real-time data collection. However, we also find considerable limitations related to privacy, signal fluctuation, and lack of clinical validation on a large scale. Something similar is reported in the review by Jung et al. [55], where the authors explain that, although there is a set of physiological characteristics useful for predicting mood disorders, there are still many problems to be solved, especially heterogeneity between studies, restricted access to device data, and the absence of standardized frameworks for reporting and comparing results. The coincidence between both analyses shows that, despite the potential of these technologies, it is still necessary to improve transparency, standardization, and methodological quality to ensure that the models are truly reliable and applicable in different contexts.

V. Conclusions

This systematic review identified anxiety, stress, and depression as the most studied mental health problems when using sensors, artificial intelligence, and IoT. It also found that the most used sensors are those that measure heart rate, sleep, physical activity, and, in some cases, EEG, because they provide continuous, non-invasive information. In addition, most studies use traditional artificial intelligence techniques, although some studies are already using more modern models that combine several networks and achieve better results. In general, these technologies offer important benefits such as early detection and constant monitoring, but they still have limitations related to privacy, access to data, and lack of clinical validation.

Taken together, these findings show that the integration of sensors, AI, and IoT has great potential to improve how mental health is assessed and monitored, and that this study provides an overview of the tools and methods currently in use. However, the review also has limitations, such as the number of studies available and the diversity of methodologies among the articles included.

Therefore, it is recommended that future research continues to explore more robust models, including more diverse populations, and work on standards that help to compare results more clearly. In this regard, a future roadmap should focus on standardizing three key aspects: first, the interoperability of data from different IoT devices and platforms; second, the use of unified clinical metrics that allow for comparison across studies; and finally, the incorporation of evaluation criteria that integrate both the performance of artificial intelligence models and their interpretability and clinical validity, thereby facilitating their application in real-world mental health settings.

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