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Review

Review on the use of AI-based methods and tools for treating mental conditions and mental rehabilitation

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Abstract This review provides a thorough examination of recent developments in artificial intelligence analysis methods within mental and psychiatry field. By analyzing and comparing results obtained with various tools and techniques, we provide a comprehensive and systematic understanding of applications. Our main methods include meta-analysis, search queries with the keywords and network-based approach. In our analysis, we observed that terms associated with robotics, human–computer interaction, speech perception, and certain applications, such as chronic fatigue syndrome and psychological adaptation, have been gradually losing prominence. And conversely, techniques such as deep learning, virtual reality, and virtual assistance are gaining traction, and increasing interest was noted for applications involving autistic spectrum disorders, mild cognitive impairments, and psychiatric research areas. The structured and organized presentation of information, along with the accompanying visualizations and diagrams, makes it a valuable resource for scientists and researchers working in the domains of artificial intelligence.

Abbreviations

Add/adhd	Attention-deficit disorder or attention-deficit hyperactivity disorder
AI	Artificial intelligence
AR	Augmented reality
ASD	Autism spectrum disorder
BCI	Brain–computer interface
CBT	Cognitive and behavioral therapy
CNN	Convolutional neural network
CVA	Computer virtual assistant or chatbot
DL	Deep learning
FC	Functional connectivity
MCI	Mild cognitive impairments
II	Image interpretation
ML	Machine learning

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NLP	Natural language processing
OCD	Obsessive–compulsive disorder
PTSD	Post-traumatic stress disorder
SVM	Support vector machine
VG	Video games
VR	Virtual reality
XAI	Explainable artificial intelligence

1 Introduction

Artificial intelligence (AI) in psychiatry has become increasingly prominent as a tool for diagnosis [1–5], treatment planning [6–9], and patient monitoring [10–13]. AI technologies, such as machine learning algorithms and natural language processing, are being integrated into psychiatric practice to enhance the accuracy and efficiency of psychiatric assessments, predict disease progression, and personalize treatment plans. In addition, AI-driven virtual assistants are being explored for their potential in providing remote mental health support.

Among mental health patients, AI can be particularly helpful for:

- Individuals with complex mental health disorders, where AI-driven tools can improve the accuracy of diagnosis and enhance personalized treatment plans for conditions such as schizophrenia [14–18], bipolar disorder [19–21], severe depression [22–28], autism spectrum disorder [29, 30];
- Treatment-resistant conditions: AI algorithms can help identify patterns in patient data to suggest novel treatment approaches or combinations of medications for individuals who do not respond to traditional therapies [31–37];
- Remote or hard-to-reach populations: AI-powered virtual assistants and telehealth platforms can increase access to mental health services for individuals who live in remote areas or face mobility challenges [38–41].

These advances span across various fields, including:

- Psychiatry and psychology: improving diagnostic accuracy and personalized treatment planning for mental health disorders [42, 43];
- Neuroscience and cognitive psychology: enhancing understanding of brain functioning and cognitive processes [44–46];
- Computational and data sciences: developing advanced AI algorithms for data analysis, pattern recognition, and predictive modeling [47–51].

There is an increasing use of AI for addressing issues in the fields of psychology and psychiatry, suggesting a trend towards more widespread adoption of this technology in mental health care (see Fig. 1). By examining the uses of AI in the treatment of various mental disorders, it is possible provide insight into the potential benefits and limitations of this technology and its usefulness for improving clinical outcomes. AI-based methods can be used for more precise adjustment of psychological testing, taking into account the individual mental characteristics of patients [52–54].

A large number of systematic reviews on AI in medicine have been created, which tend to have a specific and limited focus on solving a particular issue or addressing a specific problem [40, 55–64]. Existing works cover a broader range of AI applications and their effectiveness across different patient populations. But meta-reviews on AI in mental rehabilitation are important because they provide a comprehensive assessment of the current state of research and application in this domain. Such reviews can help identify trends, gaps, and future directions in the research by synthesizing findings across multiple studies. They can also highlight methodological limitations and ethical concerns in existing studies and thus guide future research and practice in the field. In addition, meta-reviews can provide an objective evaluation of the efficacy and effectiveness of AI-based interventions in mental rehabilitation, which is crucial for informing evidence-based decision-making.

Certain gaps where AI integration in psychiatry warrants further review and exploration include:

- Limited ethical guidelines for AI-driven mental health services, particularly regarding data privacy and consent [65–71];
- Limited generalizability of AI-powered tools across different populations and cultures;
- Need for user-friendly AI applications that integrate smoothly into clinical workflows without disrupting established care models;

– Further research into the specific benefits of AI-driven mental health services, in terms of cost-effectiveness and improved patient outcomes compared to traditional approaches.

In this review, we aim to explore the tendencies of using AI in psychiatry from data science perspective. We identify and compare technologies for different applications used by researchers in different branches of medicine. We analyzed the results obtained from PubMed database using thoroughly constructed search queries based on keywords to obtain the most conclusive results with each query.

2 Materials and methods

As part of the methodology implementation, published articles were retrieved from scientific databases for the last 30 years using PubMed search engine (https://pubmed.ncbi.nlm.nih.gov, accessed on 20 May 2024). The following terms were used in the construction of search queries to conduct an analytical review of the current scientific and technical, regulatory, methodological literature addressing the scientific and technical problem of AI for the rehabilitation, as well as the prevention of cognitive disorders and diagnosis of patients with motor or cognitive disorders within the framework of rehabilitation medicine: ("AI" or "Artificial Intelligence" or "Machine Learning") and "rehabilitation" and ("cognitive" or "mental disorder" or "mental impairment" or "neurodegeneration" or "cognitive impairment") keywords were mandatory part of the query, while terms for the methods (e.g., "Virtual reality"), and application (e.g., "dementia") were combined pairwise as shown in Table 1.

At the initial stage of our review, we have identified and highlighted the following key issues that we wish to address:

– Which types of AI methods are the most frequently utilized for treating mental conditions?
– Are there varying preferences for them in different areas of medicine? If so, what are the reasons behind these discrepancies?
– which types of AI methods correspond to which fields of application?

During the research phase, we carefully reviewed papers that met the criteria of having one of the search queries or equivalent restatements in their title, abstract, or key words. In addition, we excluded papers with the types "Book", "Chapter", and "Monograph" from our final sample using PubMed search filters. Following the collection of the number of relevant papers found for each query, we chose the most significant results and features, and then performed a more specific review to identify the causes behind these findings on the basis of specific examples.

We created a keyword co-occurrence network which used information gathered from around 700 papers found in PubMed by using a search query using VOSviewer version 1.6.20 (Center for Science and Technology Studies, Leiden University, The Netherlands) [72]. This network provides a visual representation of the frequency with which certain terms appeared together in the studies analyzed, offering a clearer understanding of the overarching trends and connections that exist within the field. The methodology of VOSviewer visualization technique is provided in details in Ref. [73]. We have previously used a similar network-based approach to analyze AI methods in biomedical research [74]

By employing network visualization techniques, it became possible for us to detect clusters or communities within the keyword co-occurrence network by assigning a color code to each item based on the cluster to which it belongs. In our research, we utilized the VOSviewer algorithm which employs a modularity function to identify these groups [75]. The extracted clusters offer further information and insights regarding the relationship between keywords within the field being studied.

Table 1 List of the used keywords

AI methods and AI-based techniques	Application
Brain–computer interface; deep learning; functional connectivity; image interpretation; machine learning; robotics; virtual reality; natural language processing; support vector machine; computer/virtual assistant/chatbot; video games;	Aging; neurodegenerative diseases; add or adhd or attention-deficit disorder or attention-deficit hyperactivity disorder; ASD or autism spectrum disorders; stroke; depression; anxiety; Alzheimer; aphasia; bipolar disorder; dementia; mci or mild cognitive impairments; OCD or obsessive–compulsive disorder; Parkinson disease; psychotherapy; post-traumatic stress disorder or PTSD; schizophrenia

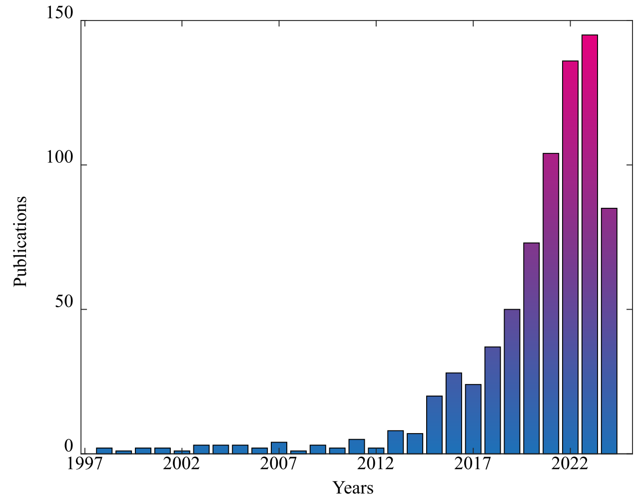


Fig. 1 Amount of relevant publications (including ("AI" or "Artificial Intelligence" or "Machine Learning") and "rehabilitation" and ("cognitive" or "mental disorder" or "mental impairment" or "neurodegeneration" or "cognitive impairment") keywords) over years

3 Review

3.1 Fundamentals of AI

By artificial Intelligence, we understand methods and algorithms, systems, or models that enable machines to perform tasks that typically require human-like intelligence, such as learning [76], problem-solving [77], decision-making [68, 71, 78–80], and perception [81–83]. AI methods encompass a wide range of techniques, including machine learning, natural language processing, computer vision, robotics, and expert systems.

The basic principle behind developing AI is to create algorithms and programs that can mimic human intelligence and problem-solving capabilities. This is achieved through various techniques, including machine learning and deep learning methods, which enable AI systems to improve and adapt based on experience and feedback. Other principles include data-driven approaches, where algorithms are trained on large datasets to identify patterns and make predictions, as well as symbolic or knowledge-based approaches, which incorporate symbolic representations of domains and prior knowledge to enable more informed reasoning and decision-making.

An artificial intelligence system can contribute to new scientific understanding through three main avenues. First, by functioning as a "computational microscope", it can furnish insights unattainable through conventional experimental methods. Second, by acting as a "resource of inspiration", it can augment human imagination and innovation, thereby broadening the scope of scientific possibilities. The third dimension in which AI contributes to scientific understanding is its role as an "agent of understanding". By substituting humans in the process of generalizing observations and transferring these novel scientific concepts to different phenomena, and crucially, conveying these insights to human scientists, AI enables a deeper and broader comprehension of complex scientific matters [84].

3.2 AI-based methods classification

Some common primary methods include machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, robotics, and expert systems. Machine learning involves training algorithms on large datasets, enabling them to learn patterns and make predictions or decisions based on new data [85, 86]. Deep learning is a subset of machine learning that employs artificial neural networks, inspired by biological neurons, to learn patterns and make predictions [87, 88]. NLP focuses on understanding, generating, and interacting with human language [89–91], while computer vision deals with understanding and processing visual information [92, 93]. Robotics focuses on the development of autonomous robots [94, 95], while expert systems employ rule-based logic programming to mimic the decision-making capability of human experts [96, 97]. In artificial intelligence and machine learning, the Support Vector Machine (SVM) is a supervised learning model that can be used for classification and regression analysis [98–102]. The SVM algorithm essentially constructs a hyperplane or a set of hyperplanes in a high-dimensional space to identify the class labels of new instances or to map the input features into an N-dimensional space.

Brain functional connectivity (FC) [103] for AI refers to the analysis of interactions and relationships between different regions of a brain or neural network to understand how they work together. Specifically, it involves measuring changes in the synchronization or phase relationship of signals between regions to identify patterns and correlations between regions and their associated functions [104–107]. This technique has been used for AI

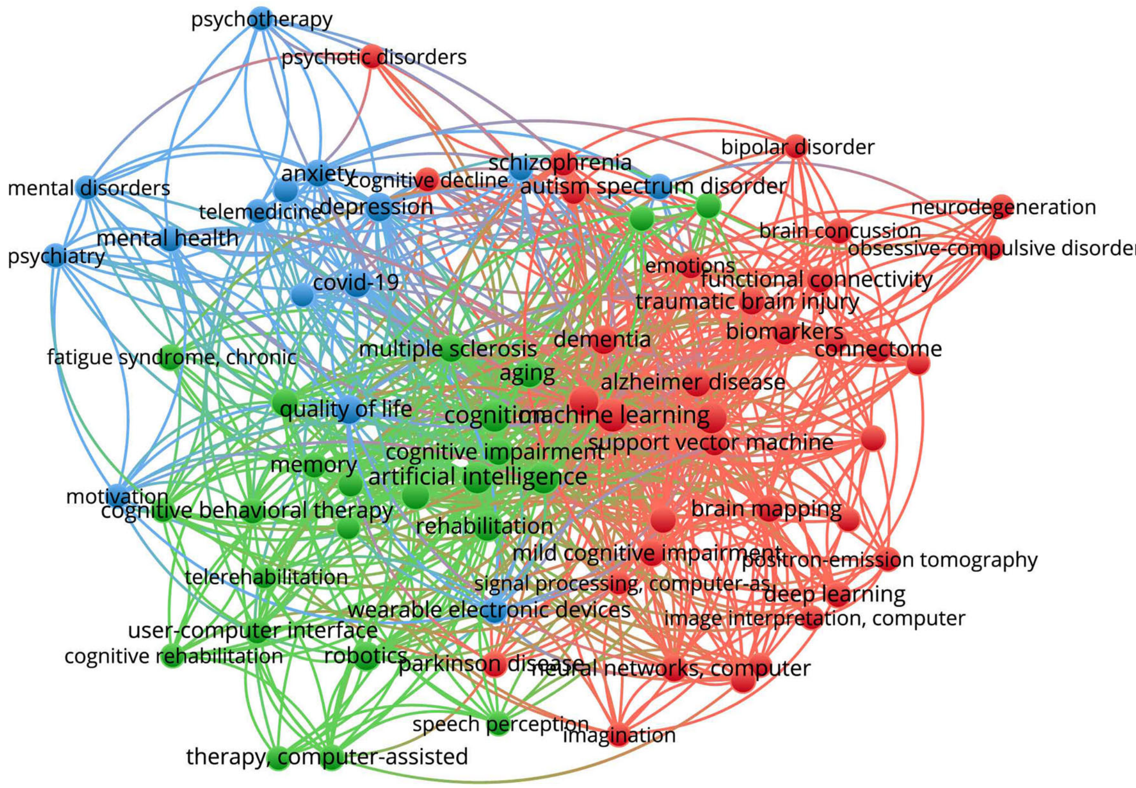


Fig. 2 The co-occurrence network constructed using VOSviewer. The sizes of the nodes are determined by the weight of the corresponding item that indicate the importance of the item, and the color is determined by the cluster to which the item belongs

applications in areas such as brain–computer interfaces (BCI) and predictive modeling of brain activity. The pinnacle of using AI in functional connectivity is the development of sophisticated models that can accurately identify patterns and correlations in brain activity, enabling breakthroughs in understanding how different regions of the brain interact to produce complex cognitive functions [108, 109].

Image interpretation in the context of AI refers to the process of analyzing and understanding visual information contained within an image [99, 110]. This includes extracting relevant features from the image, identifying patterns, and making predictions or decisions based on the information extracted. AI-based image interpretation systems use machine learning techniques, such as convolutional neural networks (CNNs) or deep learning models, to process images and recognize objects, scenes, or patterns within them. This technology has a wide range of applications, including medical imaging [111], BCI [112], brain mapping [113], object recognition, autonomous driving, and facial recognition [114].

Finally, AI chatbots and virtual assistants (CVA) have been explored in the field of rehabilitation for individuals with mental impairments [115–117]. These technologies can serve multiple purposes like providing emotional support, engaging users in meaningful conversations, and delivering therapeutic interventions. They can help maintain motivation, structure daily routines, and promote self-management skills. In addition, AI-based chatbots can monitor progress, provide feedback, and generate customized care plans based on user responses. These AI systems can reduce the burden on healthcare professionals and improve accessibility to rehabilitation services.

3.3 Results and findings

The VOSviewer identified three big (> 10 items) clusters, which can be easily interpreted based on the keywords they contain (Fig. 2). The first, largest cluster (red) is related to machine learning methods and also includes neurodegenerative diseases that require significant support, if not physical assistance. This seems to be a consequence of the high co-occurrence between terms involving methods and such specific disorders. The second cluster, green, is mainly related to AI and cognitive impairment, and this included various therapeutic and rehabilitative methods, as well as the memory, attention and aging nodes. The third cluster is blue, it covers abstract psychological and psychiatric terms and diseases, this includes motivation, quality of life, anxiety and depression.

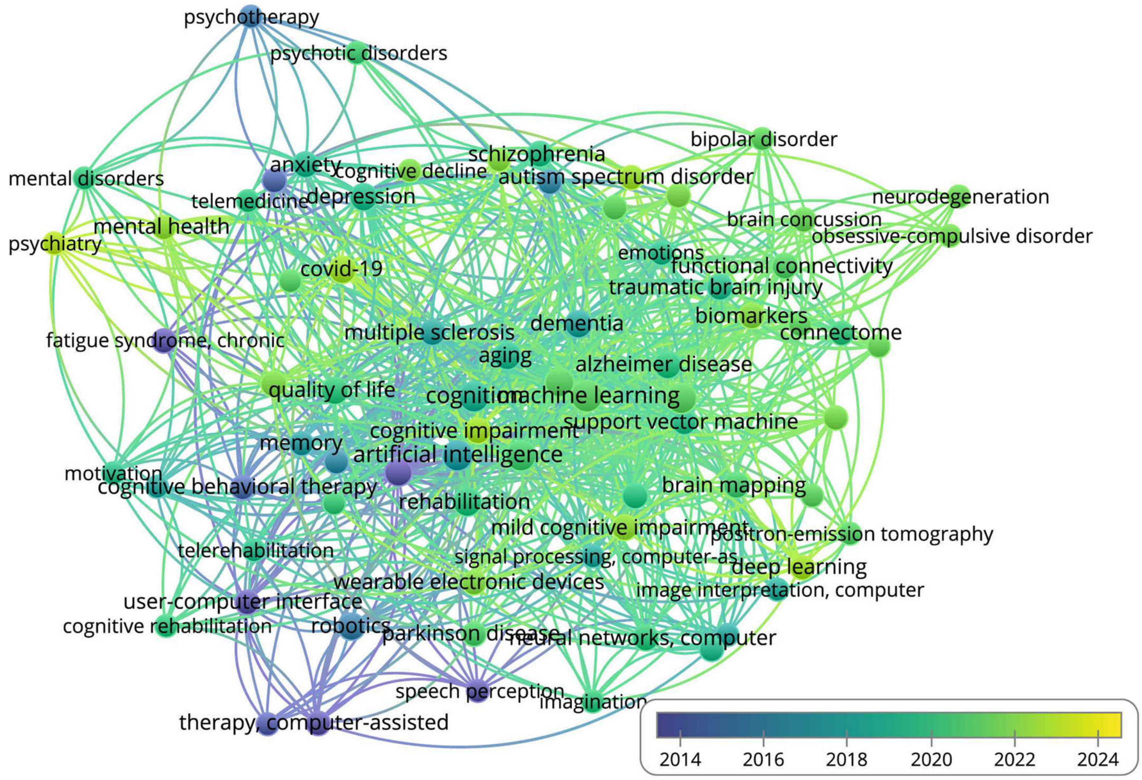
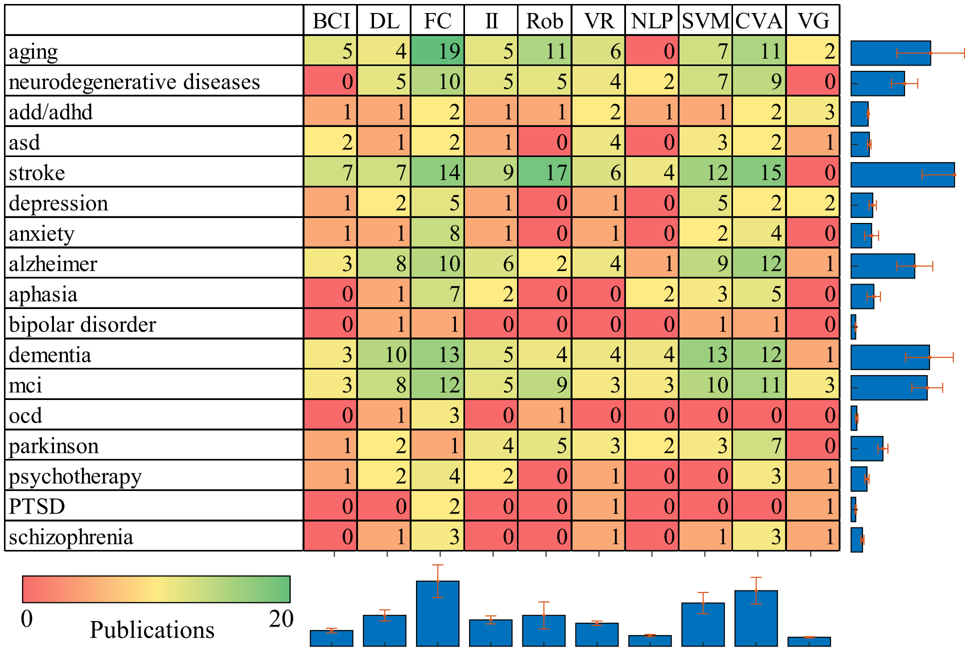


Fig. 3 The co-occurrence network constructed using VOSviewer. The sizes of the nodes are determined by the weight of the corresponding item that indicate the importance of the item, and the color is determined by the publishing activity per year (blue color denotes nodes with the majority of publications of 2014 year, and yellow denotes nodes where corresponding publications are from 2023 to 2024)

Looking at the current trends in the field, presented in the Fig. 3, we can see that among the clusters under consideration, there is a relatively even distribution of more and less recently popular terms. Nevertheless, we can clearly see that terms related to robotics, user-computer interface, speech perception, and among applications—chronic fatigue syndrome and psychological adaptation—are gradually losing popularity. Conversely, techniques related to deep learning, VR, virtual assistance are gaining popularity, and trending applications include autistic spectrum disorders, mild cognitive impairments, and psychiatry.

Main tables for the various keyword combinations is presented in the Fig. 4. As a first interesting observation from our review, we can note the varying popularity of different combinations of methods and applications. Of all the combinations considered, the following should be noted as the most popular: stroke and robotics [9, 118–124] or CVA [7, 63, 125–127], dementia and FC [128–134] or SVM [102, 135, 136], aging and FC [97, 137–140]. About one-third of the possible combinations have no publications, and of the remaining, about half are represented by only one or two publications. Among the most obvious trends is the prevalence of assistive or robotic techniques for stroke rehabilitation. In general, the most popular application areas are stroke, aging, Alzheimer's, dementia, and MCI. The least represented are works related to PTSD, OCD, bipolar disorder. In terms of solution options, FC, SVM, CVA are the most pronounced, NLP and video games the least, apparently due to the complexity and cost of development. Looking at BCI and robotic solutions, it can be seen that they are most prevalent in cases where the diseases are characterized by motor impairments and do not affect diseases of a purely psychiatric nature. At the same time, DL and FC methods are common in relatively equal measure for most applications. Image interpretation has a similar scope to BCI, except for the additional extension to neurodegenerative diseases. VR is ubiquitous except for OCD, bipolar disorder and aphasia. NLP is not a widespread technique, but does include applications against aphasia and neurodegenerative disorders. SVM has applications everywhere except OCD, PTSD, psychotherapy. CVA is the second most popular technique after FC, but also does not cover OCD, PTSD, instead it is presented for psychotherapy and schizophrenia. Video games one of the least common methods which, however, has a niche application against MCI and add/adhd.

Further, we highlight the most interesting developments for the found combinations.



	BCI	DL	FC	II	Rob	VR	NLP	SVM	CVA	VG
aging	5	4	19	5	11	6	0	7	11	2
neurodegenerative diseases	0	5	10	5	5	4	2	7	9	0
add/adhd	1	1	2	1	1	2	1	1	2	3
asd	2	1	2	1	0	4	0	3	2	1
stroke	7	7	14	9	17	6	4	12	15	0
depression	1	2	5	1	0	1	0	5	2	2
anxiety	1	1	8	1	0	1	0	2	4	0
alzheimer	3	8	10	6	2	4	1	9	12	1
aphasia	0	1	7	2	0	0	2	3	5	0
bipolar disorder	0	1	1	0	0	0	0	1	1	0
dementia	3	10	13	5	4	4	4	13	12	1
mci	3	8	12	5	9	3	3	10	11	3
ocd	0	1	3	0	1	0	0	0	0	0
parkinson	1	2	1	4	5	3	2	3	7	0
psychotherapy	1	2	4	2	0	1	0	0	3	1
PTSD	0	0	2	0	0	1	0	0	0	1
schizophrenia	0	1	3	0	0	1	0	1	3	1

Fig. 4 Amount of publications by application/data keywords. *BCI* brain–computer interface, *DL* deep learning, *FC* functional connectivity, *II* image interpretation, *ML* machine learning, *Rob* robotics, *VR* virtual reality, *NLP* natural language processing, *SVM* support vector machine, *CVA* computer/virtual assistant/chatbot, *VG* video games, *add/adhd* attention-deficit hyperactivity disorder, *ASD* autism spectrum disorder, *OCD* obsessive–compulsive disorder, *mci* mild cognitive impairments, *PTSD* post-traumatic stress disorder. The blue histograms provide an overview of the average ± SD number of publications related to each technique or application, respectively

3.3.1 AI interpretation techniques and functional connectivity

Better understanding means better prognosis and treatment. The process of identifying different subtypes of neurodegenerative diseases and analyzing the distinct stages of each subtype's progression is crucial. By studying the underlying mechanisms and identifying specific biomarkers, researchers can better understand the course and trajectory of these diseases, leading to improved diagnostic methods and targeted therapies [141]. Functional connectivity of the brain at rest after the stroke emerges as a crucial predictor of responsiveness to treatment, demonstrating its importance, both individually and in combination with other patient-related aspects [142]. One innovative approach is Neuropsychological Assessment of Patients with Acquired Brain Injury: A Cluster Analysis Approach to Tackle Heterogeneity in Web-Based Cognitive Rehabilitation [143]. This study used cluster analysis to group individuals with acquired brain injury into different subgroups based on their neuropsychological profiles and utilized web-based cognitive rehabilitation tailored to the specific needs of each subgroup. This approach aimed to improve the efficacy of cognitive rehabilitation programs by addressing individual differences and improving treatment outcomes.

3.3.2 Natural language processing

The application of conversational agents equipped with unconstrained natural language input capabilities for health-related purposes is an emerging area of research. However, the few studies published in this field mostly employed quasi-experimental designs and rarely examined efficacy or safety. To advance the field, future studies would benefit from more robust experimental designs and standardized reporting [91, 144]. Using machine learning models, the authors one of the works compared the performance of features to detect dementia, overall and during time periods relative to dementia case ascertainment in health administrative database. They managed to identified dementia-related features by applying published lists, clinician input, and NLP with word embeddings to free-text progress and consult notes and organized features into thematic groups [145].

3.3.3 Machine learning and support vector machines

Research has revealed that while behavioral factors, multimodal neuroimaging data, and demographic information collectively contribute important information in predicting responses to rehabilitation for chronic aphasia following a stroke [142]. One research [14] presented the implementation of a human-in-the-loop machine learning framework applied to an automated story recall assessment model. The evaluation of human verbal memory is a crucial aspect in determining neurocognitive function in psychiatry, and there are similarities to the anamnesis process, which involves gathering information about a patient history. A scoping review was conducted to summarize the range of existing evidence on how participation is captured and operationalized in pediatric re/habilitation research using AI-based assessment approaches [146]. A narrative review explored the applications of machine learning models in stroke rehabilitation, focusing on models such as random forest, logistic regression, and deep neural networks [63].

3.3.4 BCI and neurofeedback

One of the works proposed a game-based neurofeedback training system designed to improve cognitive performance in healthy elderly individuals and those suffering from amnestic mild cognitive impairment [147]. Specific focus should be given to combined approaches, such as bolstering the effects of non-invasive neuromodulation and closed-loop methodologies. By search of multimodal biomarkers and electric field modeling it is possible to guide targeting and quantify dosages of treatment with the power of machine learning algorithms to integrate data gathered, ultimately pinpointing clinical outcomes [148]. Interactive games with the biofeedback were successfully used for the rehabilitation tasks [123, 149, 150]. Studies have demonstrated that it is possible to enhance artificial agents' ability to anticipate human decisions in situations involving coordination issues through the integration of well-known solutions referred to as focal points into machine learning algorithms [151].

3.3.5 Chatbots and virtual assistants

A more innovative trend is the utilization of CVA powered by sophisticated artificial intelligence. A randomized controlled trial examined the effects of an entirely automated conversational agent that reinforced cognitive behavioral therapy (CBT) techniques through a text-message format, comparing it to an information-only control [25, 152–154]. The study found a significantly greater reduction in depressive symptoms among individuals in the intervention group [155]. Noteworthy uses of CVA include predicting lithium treatment effectiveness in individuals experiencing their first manic episode and customizing treatment plans for bipolar disorder by targeting neuroimaging-based treatment markers [156]. The quantitative analysis measured the CVA impact by comparing the average improvement in symptoms of depression between more and less active CVA service users. The qualitative analysis measured the app engagement and experience by analyzing in-app user feedback and evaluated the performance of a machine learning classifier to detect user objections during conversations [157]. Utilizing the mimicking of body movements by a virtual agent, it is possible to enhance synchronization behavior and rapport in individuals suffering from schizophrenia [158].

Preliminary research studies showcased a digital behavioral aid that gathers and reports quantitative data. This system comprises customizable smartglasses that deliver personalized coaching experiences via gamified augmented-reality applications powered by artificial intelligence for autism spectrum disorder. These applications offer coaching in areas such as emotion recognition, facing gaze, eye contact, and behavioral self-regulation, benefiting both children and adults [159, 160].

Loneliness is increasingly recognized as a significant public health issue that increases the risk of morbidity and mortality. Artificial agents, such as robots, conversational agents, and chatbots, represent an innovative approach in healthcare delivery and have been shown to alleviate patient loneliness by providing social support [161, 162]. Nevertheless, similar to doctor-patient relationships, the quality of the connection an individual has with an artificial agent can considerably influence its support efficacy and involvement in care provision [163].

3.3.6 Virtual reality

A review article [61] examines the application of virtual reality (VR) technology for cognitive rehabilitation, focusing on individuals with neurological conditions like stroke, traumatic brain injury, and neurodegenerative diseases. The review evaluates the effectiveness of VR-based interventions in improving cognitive functions, such as attention, memory, and problem-solving skills, in these populations. Acknowledging the presence of neuromuscular impairments, strategies such as kinetic guidance, combined with the use of virtual reality (VR) and augmented reality (AR) in interactive exercise programs, have been effectively implemented during gait training to enhance rehabilitation outcomes [164]. There is known experimental works involved a simple, target-directed reaching task, which focused on using sensory prediction errors rather than relying on cognitive strategies [165]. Virtual reality-based therapies hold significant potential to enhance both motor and functional skills in diverse age groups, particularly in cases of multiple sclerosis and other impairments, through promoting cortex reorganization and activating multiple neuronal connections [56, 166]. A narrative review was performed on the rehabilitation of acquired cognitive disorders, examining the current state of research and various approaches used in this field [61].

3.3.7 Deep learning

Deep learning is a subset of machine learning that uses artificial neural networks to model and analyze complex patterns and relationships in data. It is inspired by the structure and function of the brain, with multiple layers of interconnected nodes or neurons. Among the reported advances, there is a system which employed advanced machine learning and signal processing techniques to identify clinical sense from digital footprints, leveraging smartphone's native sensors in order to recognize suicide risk [167]. The systematic review on the broader scale [168] included 4 full-scale randomized controlled trials, along with feasibility, and quasi-experimental studies. The interventions employed various designs and targeted different mental health issues while utilizing a variety of therapeutic approaches. All included studies reported reductions in psychological distress postintervention. A positive effect was observed from using wearable digital AI intervention to improve socialization skills in children diagnosed with autism spectrum disorder [169]. Employing digital treatment as a therapeutic approach has shown promising outcomes in improving the executive functions, particularly inhibitory control and visuospatial working memory, in individuals with ADHD [170]. One study proposed a cognitive prosthesis device designed for addressing face memory impairment as a proof-of-concept for developing domain-specific cognitive prosthetic [171]. Among more simplified approaches: an artificial intelligence algorithm runs on a smartwatch and recognizes minutes of social interaction based on vocal features extracted from ambient audio samples, without relying on natural language processing [172]. A perspective review was conducted to explore neurotechnological solutions for addressing post-traumatic stress disorder (PTSD) [173]. Note also that DL may find application in reconstructing FC in various diseases of the nervous system and aging [174–176]

3.3.8 Robotics

A recent systematic review examined the efficacy and effectiveness of robotic rehabilitation in improving cognitive functioning [177]. Useful intellectual interaction system is founded on a foundation of cognitive psychology principles. With an understanding of educational robots and their features, it integrates traditional teaching activities synergistically. To achieve this, a robot-assisted talent training mode is designed, blending the strengths of educational robots with conventional teaching methodologies to optimize learning outcomes [178]. A robot-assisted visuomotor wrist training regiment leads to improvements in proprioceptive acuity and movement accuracy in the opposite wrist [179]. Robot-assisted somatosensory-based training involving progressively precise active wrist movements enhances both proprioceptive sensitivity and motor function in individuals experiencing strokes [118]. There are known reviews for current knowledge about social and service robots for elderly care [139, 180, 181]. Machine learning tools for identifying different types of motor activity, both real and imagined, of patients from video signals [182], myography [183], MEG- [184, 185], EEG- [186–188] and fNIRS-registration [189–191] of brain activity are of great importance here for diagnostics and rehabilitation [192–194].

3.3.9 Video games

In the realm of video games, a notable approach is the personalized Web-based cognitive rehabilitation for patients with ischemic stroke, where customized digital interventions are employed to enhance cognitive abilities and recovery in those affected by ischemic stroke or cognitive impairments [195–199]. An AI-based training game has been developed that can adjust the difficulty level automatically based on an individual's performance in order to improve their voluntary engagement and ultimately affect clinical outcomes [139, 200]. A scoping review on the role of AI in serious games and gamification for health is also published very recently [201].

4 Discussion

The field of AI in mental rehabilitation seems to have its own research traditions that define its strengths and weaknesses.

The modularity observed in the topic clusters Fig. 2 is likely due to the different focuses and subtopics within the broader field of mental rehabilitation using AI. The first cluster focuses on the technical aspects of AI, specifically machine learning methods, and their application in neurodegenerative diseases that require significant support. The second cluster highlights AI's role in cognitive impairments and rehabilitative methods, such as memory enhancement and attention training. The third cluster encompasses psychological and psychiatric factors, such as motivation, quality of life, anxiety, and depression, which can significantly impact mental rehabilitation.

These factors can significantly impact the effectiveness of mental health and rehabilitation interventions. Interestingly, one study [202] mentioned an interesting and valid point about using AI to understand human language in the context of psychoactive substances. From a scientific standpoint, drug effects on human mental states have been investigated through two primary approaches. The initial approach involves retrospective descriptive reports, which may be impacted by inaccurate recollections. These reports are typically non-standardized, making them more easily analyzed qualitatively, an analytic approach that can be time-consuming and lack generalizability. The application of AI for this type of analysis provides significant benefits. Another approach is automated speech-based technique to characterize clinically relevant alterations to mental state [203].

Computer-assisted cognitive rehabilitation systems and games for health are becoming increasingly common. To guarantee continuous, efficient, and long-term patient rehabilitation, these systems will need to be implemented within the home environment. However, current home systems often lack the presence of a therapist, which poses two major challenges. First, they require sensors and actuators that compensate for the absence of the therapist's eyes and hands. Second, these systems need to capture and utilize the therapist's expertise effectively [125].

On the other hand, robots equipped with machine learning capabilities have the advantage of being able to adapt their behavior and response mechanisms based on user input. This capability is particularly valuable when it comes to maximizing task performance and facilitating seamless social engagements. In the study [95], a robot directly asks a human user about their grasp of a learning objective, and adaptively adjusts the level of assistance it provides based on the response. Interestingly, the authors found that when the robot frequently queries the user for "learning-sensitive" information during every task-related question, users reported feeling more likely to rely on the robot's guidance.

In mental health, conversational AI has demonstrated both the potential to facilitate and inhibit the disclosure of information across various contexts. For instance, individuals have been found to be more open about reporting mental health symptoms when interacting with a conversational AI compared to a human listener, and these systems have successfully been implemented in treating persecutory delusions among individuals with psychosis [153, 204, 205].

Automated bots are currently unable to recreate the richness of a face-to-face interaction with a mental health professional, even with their efforts to mirror real-life interactions. Although some level of personalization is present (e.g., different tips or strategies are offered for individuals experiencing symptoms of depression vs. anxiety), the support provided remains generic and may be more akin to that of a self-help book at this stage [115].

A comparison of the effectiveness between artificial intelligence and human coaching in achieving goals was made in one of the other pieces of research. Research has demonstrated that AI can effectively replace human coaches who utilize simplistic, model-based coaching approaches. However, at the moment, AI lacks empathy and emotional intelligence, which are important aspects when it comes to effective coaching interventions [206]. Although most recent work claim that CVA outperforms humans in emotional awareness evaluations [207, 208].

One of the more perspective directions of development is the Explainable Artificial Intelligence (XAI). It represents a novel array of methodologies aimed at enhancing understanding and transparency in AI decision-making. In the context of neurostimulation, XAI holds significant value for both basic scientific research and therapeutic applications [71, 209–212].

In its current state, artificial intelligence does not possess the same level of intelligence as humans. Consequently, AI is unlikely to experience genuine mental illnesses as we understand them. Nevertheless, some experts posit that certain mental health concerns may emerge as computers become more advanced and interact more closely with humans. Potential problems AI may encounter encompass:

- Mental health issues: AI can function as a mirror to users, potentially becoming a source of stress, anxiety, and depression due to its interactions with them;
- Cognitive biases: AI may learn from and replicate human biases, including bigotry, prejudice, and discrimination [213].

One of the strengths of the reviewed experimental works in our study lies in their clear and comprehensive descriptions of the research procedures involved. Even studies with slightly flawed methodologies frequently offer detailed descriptions of their methodologies or cite previously published protocols as references for their methods. This clarity and transparency are crucial for understanding the research process and its inner workings, as well as for facilitating both replication and evaluation of the results.

A significant weakness in the field of research in the field of AI is the preponderance of pilot studies [117, 127, 200, 214–220]. While these initial studies play a crucial role in paving the way for future research, the majority of data generated from such studies is often not replicable or confirmable, leading to an overall decrease in research quality within the field. Small-scale studies are instrumental in the early stages of developing a technology or protocol, as they provide vital insights and data that can be utilized to refine the overall design. The absence of a control group in a study makes it challenging, if not impossible, to effectively control for any influence factors unrelated to the particular treatment being tested. This weakens the overall rigor and reliability of the study, making it difficult to accurately attribute any observed changes or effects solely to the intervention in question.

Another weakness is that AI system could be designed or trained poorly, or if it is given inaccurate or incomplete data, it may produce less accurate or reliable results. However, the development of AI systems requires a combination of technical expertise, knowledge of algorithms and machine learning techniques, as well as access to large datasets and computing resources. Quality of markup on the train data should be improved for the better development in AI field.

It is essential to emphasize that our research has certain limitations. First, we acknowledge that we were unable to carry out a thorough assessment of each paper in relation to its respective field of interest, given the large sample size obtained from the PubMed database. Due to the sheer number of papers involved, it was impractical to manually review each one individually. While we made every effort to ensure thoroughness and accuracy in our review, some elements may have been overlooked. We attempted to address this challenge by applying several filters and inclusion criteria to generate relevant keywords for use in our search. While this method does not guarantee the complete exclusion of unsuitable papers from the final sample, there is a possibility that a few irrelevant articles may have been included. However, we can confidently state that the number of such papers is likely to be relatively small, and their inclusion did not significantly impact our overall results as a consequence of the rigorous screening process and the utilization of stringent filters and inclusion criteria.

5 Conclusions

Artificial intelligence has been effectively utilized for several years in aiding patients and healthcare professionals during rehabilitation processes. This article provides an examination of the current applications of AI methodologies within the field of mental rehabilitation. Functional connectivity analysis and virtual assistants are the most widely adopted form, yet new technologies are under investigation for their potential as diagnostic tools. Although the evidence supporting the utilization of AI in rehabilitation is encouraging, there is a paucity of systematic reviews that encompass a substantial body of work focusing on this topic. In addition, there is a necessity for extensive studies and systematic reviews examining various applications in diverse clinical populations.

This paper features a well-organized and straightforward way of presenting information, making it especially beneficial for specialists in the fields of AI, methods, and connected medical disciplines. It offers a clear overview of the various options available, detailing their advantages and drawbacks, thus serving as an informative guide or reference material for professionals seeking to utilize and apply distinct methods and techniques in their professional work.

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