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AI for Mental Health Risk Assessment in Occupational Therapy: Enhancing Clinical Insight While Managing Ethical and Safety Challenges

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Abstract

The increasing integration of artificial intelligence (AI) into healthcare systems is transforming the identification, monitoring, and management of mental health concerns. AI presents both significant opportunities and complex challenges for occupational therapy (OT) practitioners who use a client-centred, holistic approach. The use of AI-driven tools in mental health risk assessment is examined in this narrative review, focusing on early signs of suicide risk, cognitive decline, emotional dysregulation, and functional impairment. Drawing on current literature, this narrative review examines how AI technologies, such as wearable data monitoring, natural language processing, and predictive analytics, can assist occupational therapists in making more timely and informed clinical decisions. It does this by drawing on new findings from digital mental health and rehabilitation research. By spotting small behavioural patterns and changes in day-to-day functioning that could otherwise go unreported, these technologies have the potential to improve risk detection beyond conventional assessment techniques. A narrative review approach was employed to synthesis current evidence from healthcare, mental health, rehabilitation, and occupational therapy literature relating to AI-supported risk assessment and clinical decision-making. However, algorithmic bias, data privacy, and excessive dependence on automated systems are some of the serious clinical risk management issues raised by the / incorporation of AI into OT practice. The study addresses how these risks may disproportionately impact disadvantaged groups that occupational therapists frequently work with, including older people, those with severe mental illness, and people with neurodevelopmental disorders. It also emphasizes how crucial it is to preserve professional judgment, therapeutic thinking, and client autonomy in AI-supported practice. Furthermore, this article analyses the consequences for healthcare systems, emphasizing the need for clear governance frameworks, ethical principles, and targeted training to equip occupational therapists for AI-integrated environments. This article argues for a balanced strategy that uses technological innovation while protecting patient safety and dignity by placing AI within the fundamental principles of occupational therapy—meaningful occupation, engagement, and person-centred care. Ultimately, this study contributes to ongoing conversations on AI in medical security and clinical risk management by suggesting practical considerations for properly incorporating AI into mental health-focused occupational therapy practice.

Keywords: Artificial intelligence, Occupational therapy, Mental health risk assessment, Predictive analysis, Ethical AI .

1. Introduction

Artificial Intelligence (AI) is a technology that enables machines to perform tasks requiring human-like intelligence. Examples include facial recognition for identifying individuals and voice recognition used by virtual assistants like Alexa and Siri (1). AI uses advanced algorithms to learn patterns from large sets of healthcare data, applying these insights to improve clinical practice (2), It can also be equipped with knowledge and self-correcting abilities to enhance accuracy based on feedback. AI programs assist medical practitioners by providing up-to-date healthcare information from newspapers, journals, and professional guidelines, helping alert the appropriate treatment. Healthcare professionals can benefit from artificial intelligence in a number of duties, including clinical documentation, patient outreach, administrative work, image analysis, medical device administration, and patient monitoring. There is a lot of hope that the use of artificial intelligence (AI) will result in significant advancements in every aspect of healthcare, from diagnosis to therapy (3).

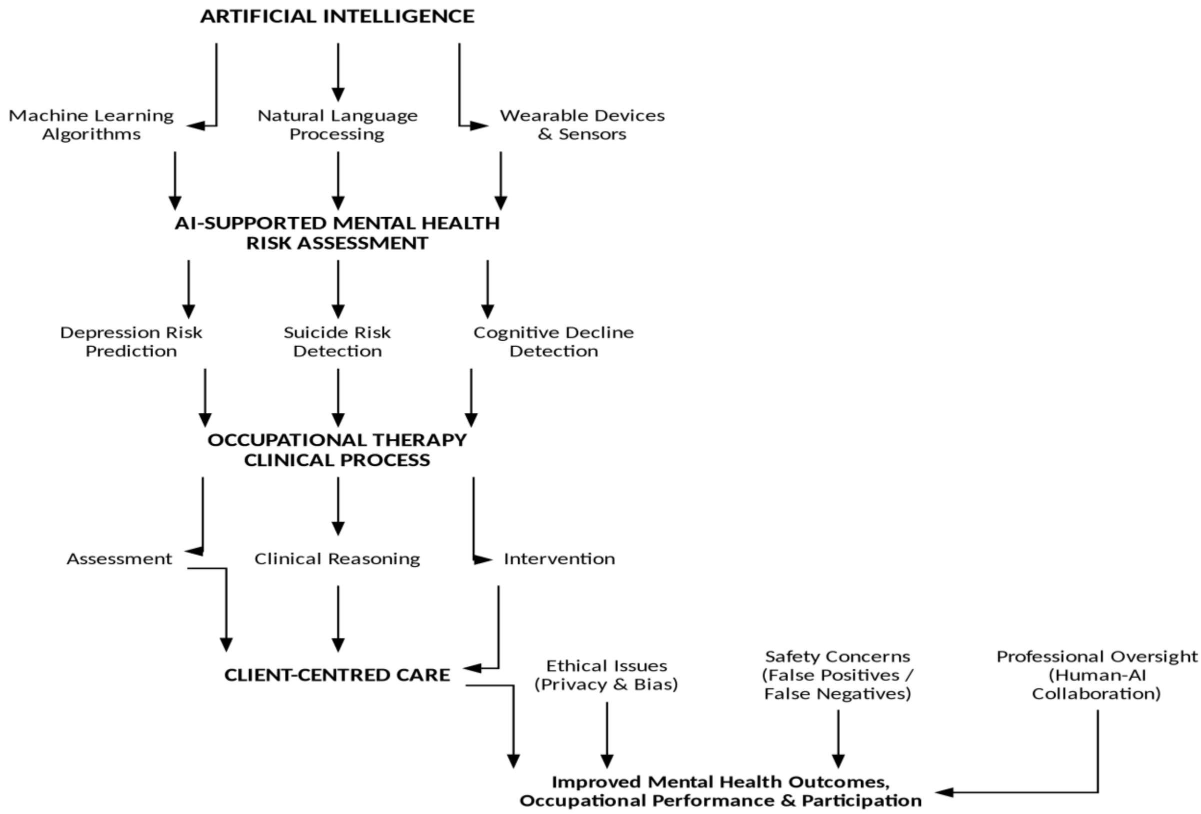
The World Health Organization (WHO) states that mental health conditions now significantly contribute to the world's illness burden, with depression alone being the primary cause of disability worldwide (4). The rise in mental health issues has put an unprecedented strain on healthcare systems, exposing the shortcomings of conventional mental health care approaches (5,6). The traditional method, which mostly depends on in-person consultations and therapies, is unable to meet the growing need for quickly available, reasonably priced, and services for expanding mental health (5). The field of mental healthcare is changing as a result of the integration of AI, this symbolises a revolution and progress in mental health (7). But while this change offers the possibility of broad access, early intervention, and therapeutic personalisation, it also raises ethical questions, creates regulatory obstacles, and necessitates continued study and development (8-10). With mental health problems accounting for over 16% of all diseases worldwide, the growing prevalence of mental health problems is nothing less than a global health crisis. The situation is made worse by the widespread stigma associated with mental health, which deprives many people of the assistance they need and feeds the cycle of abuse and misery (11).

Occupational therapy (OT) is a key component of rehabilitation, which aims to restore function and full participation in daily life for people with physical, cognitive, social, or psychiatric impairments (12,13). OT uses the lens of human occupation to analyse and categorise participation in daily routines. Through this approach, individuals are supported to achieve independence and social participation aligned with their goals.. Occupational therapists aim to maximise functional independence, restore confidence, and ultimately improve quality of life for those recovering from injury or living with a disability by emphasising meaningful activities, ranging from self-care and work to leisure (12,14,15). In order to assess a client's abilities and difficulties with activities of daily life, occupational therapy evaluations have historically relied on standardised instruments, clinical observations, and in-person interviews (16). These traditional techniques, such as questionnaires and performance-based assessments, offer crucial data for treatment planning. They do, however, have some significant drawbacks. A therapist's observation and subjective rating are frequently used in assessments, which may bring bias or inconsistencies. In therapeutic settings, many tools simply record a single moment in time, which may miss variations in an individual's daily functioning. In many situations, it is challenging to accurately connect perceived performance to underlying capacity due to the absence of objective measurement. This ambiguity may make doctors less confident in the outcomes of conventional assessments (17).

AI technologies can analyse large datasets to identify trends and forecast outcomes, improving assessment accuracy and facilitating the creation of customised rehabilitation programs (13,18,19,20). According to preliminary data, AI-driven methods can increase assessment accuracy and customise therapies to each person's needs (21). Human–computer interaction (HCI) is vital for these developments, improving user interfaces and facilitating the integration of AI tools into clinical settings (22). For example, AI platforms are now commonly used for scoring standardized assessments, providing gamified activities to boost patient involvement, and delivering immediate feedback for more adaptive treatment strategies (23,24). Additionally, AI-powered wearable devices allow for ongoing tracking of service users' progress, which supports more timely and evidence-based interventions. These developments improve therapists' capacity for comprehensive and precise evaluations, ultimately leading to better results.

The purpose of this narrative review is to explore the role of artificial intelligence (AI) in mental health risk assessment within occupational therapy practice. Specifically, the review aims to examine how AI-driven technologies, including predictive analytics, natural language processing, and wearable monitoring systems, can enhance clinical insight, support early identification of mental health risks, and improve clinical decision-making. Furthermore, the review critically evaluates the ethical, safety, and clinical risk management challenges associated with the integration of AI into occupational therapy, including issues related to algorithmic bias, data privacy, professional judgment, and patient autonomy. By synthesizing current evidence, the review seeks to provide a balanced understanding of the opportunities and limitations of AI in mental health-focused occupational therapy practice and to identify implications for future research, professional practice, and healthcare policy.

Figure 1 illustrates the conceptual framework of AI-supported mental health risk assessment in occupational therapy, demostrating how AI technologies contribute to clinical reasoning,



client-centred care, and improve occupational outcomes while highlighting the importance of ethical safeguarding and professional oversight.

Figure 1. Conceptual farmework illustrating the integration of artificial intelligence technologies into mental health risk assessment in occupational therapy, highlighting AI applications, the occupational therapy clinical process, client-centred care, improved outcomes, and the role of ethical and professional oversight.

2. Methodology

Review Design

This study employed a narrative review methodology to examine the role of artificial intelligence (AI) in mental health risk assessment within occupational therapy practice, with particular attention to clinical applications, ethical considerations, safety concerns, and implications for healthcare systems.

Search Strategy

Electronic databases such as PubMed, Scopus, CINAHL, Web of Science, Google Scholar, and ScienceDirect were used to do a thorough literature search. By manually searching the reference lists of chosen articles, more pertinent publications were found. Combinations of keywords and Boolean operators, including "artificial intelligence," "machine learning," "deep learning," "natural language processing," "mental health," "mental health risk assessment," "suicide prediction," "depression prediction," "cognitive decline detection," "behavioural monitoring," "occupational therapy", "rehabilitation", "clinical decision-making", "ethics", "patient-safety," and "clinical risk management," were used in the search.

Inclusion Criteria

The following criteria were used to guide the selection of literature for this review:

1. Peer-reviewed journal articles, systematic reviews, scoping reviews, narrative reviews, and policy papers.
2. Studies examining the use of artificial intelligence in mental healthcare, mental health risk assessment, rehabilitation, or occupational therapy practice.
3. Literature addressing ethical, safety, and clinical governance issues related to AI implementation.
4. Articles published between 2015 and 2026. Publications written in English. Studies involving adult or adolescent populations relevant to mental health assessment and intervention.

Exclusion Criteria

The following publications were excluded from the review:

1. Studies unrelated to healthcare or mental health applications of AI.
2. Articles focused solely on technical algorithm development without clinical relevance.
3. Conference abstracts, editorials, commentaries, and unpublished reports lacking sufficient methodological detail.
4. Non-English publications. Duplicate studies identified across databases.
5. Studies with insufficient information regarding clinical application or relevance to occupational therapy practice.

Data Synthesis

Relevant papers were assessed and thematically synthesised after the literature search. The identified evidence was categorised into the following major areas: (1) AI technologies used in mental healthcare; (2) AI applications in mental health risk assessment; (3) relevance to

occupational therapy practice; (4) ethical challenges; (5) safety and clinical risk management concerns; (6) implications for healthcare systems; and (7) future directions for research and practice.
As a narrative review, this study did not perform a formal quality appraisal or meta-analysis. Instead, the goal was to present a thorough and critical synthesis of recent research in order to make it easier to comprehend the advantages and disadvantages of incorporating AI into occupational therapy practice that is focused on mental health.

1. Overview of AI in Mental Health Care

Machine Learning

In a medical dataset there are two types of data, unstructured data and structured data. As a result, several approaches are employed to fulfil healthcare requirements. Neural network systems, machine learning techniques, and modern deep learning methods guarantee the analysis of structured data, including genetic and imaging data (25). Machine learning techniques in healthcare are used to cluster patient characteristics or estimate the likelihood of disease outcomes. As a result, machine learning determines the patient outcomes. Supervised learning is the most popular kind of machine learning in a healthcare context. It provides a more focused result by utilising a patient's physical characteristics with the use of a dataset containing medical data (26).

Predictive Analytics0

In recent years, there has been a lot of interest in the use of artificial intelligence (AI) in predictive analytics for mental health. Research has shown that AI can improve treatment adherence, early intervention, and overall mental health outcomes. Predictive models can be developed using diverse data sources, including social media activity, clinical assessments, and demographic information, to identify individuals who may benefit from early intervention (27). This proactive approach aligns with evidence suggesting that timely interventions can significantly reduce the severity of mental health conditions (28).

Clinicians' capacity to act early can be improved by AI-driven predictive models, particularly for anxiety disorders, which are among the most prevalent mental health problems. Early identification of anxiety symptoms can result in more successful treatment outcomes (29). AI can provide real-time insights into a person's mental state by combining data from wearable technology with self-reporting methods, allowing physicians to proactively modify treatment programs.

A 30% reduction in mental health symptom severity has been associated with the use of AI-driven interventions, highlighting the potential of predictive analytics to facilitate earlier and more effective intervention. Despite these benefits, treatment adherence remains a significant challenge in mental healthcare (30).

Natural Language Processing

Natural language processing (NLP) increases and improves standardised medical data (2) by extracting information from unstructured data sources like clinical notes or medical literature. NLP techniques aim to transform texts into computer-readable, structured data that can be analysed through machine learning techniques. Human-computer interaction is the main use of natural language processing. Large volumes of scientific data may be effectively evaluated by NLP algorithms, which also assist in removing unwanted spam from datasets. NLP facilitates the analysis and organization of complex healthcare data. The integration of artificial intelligence with natural language processing enables healthcare systems to collect vital real-time information from reliable sources (31).

Wearable Technology

One technology used to identify and forecast depression is wearable technology. In order to gather and evaluate biomarkers or biosignals, such as heart rate, physical activity, sleep patterns and quality, blood oxygen, and respiratory rate, people typically wear wearable devices. There are many different types of wearable devices, including watches, bracelets, jewellery, shoes, and clothes (33). Over the previous few years, wearable use has grown significantly; in 2020, 21% of Americans reported using a fitness tracker or smartwatch, and this percentage is still rising (34). Up to 45% of people in some nations use wearables, according to reports (35). Numerous metrics gathered by wearable technology can be used to evaluate depressive symptoms. Artificial Intelligence (AI) has been used to wearable technology, creating what we refer to as "Wearable AI," in response to the need for autonomous, objective, effective, and real-time methods to identify or forecast depression. Wearable AI is the use of wearable technology in conjunction with AI to evaluate vast amounts of wearable data and offer tailored responses (36,37,38,39).

4. AI and Mental Health Risk Assessment

Depression prediction

With one-year global incidence rates ranging from 7 to 21%, depression is the most prevalent mental illness worldwide (40). A significant contributing factor to the hundreds of thousands of suicides that occur each year is depression (41,42). Beyond fleeting melancholy, depression significantly impairs day-to-day functioning, lowers quality of life, and is a major contributor to disability (44, 45). The World Health Organization underlines its disproportionate impact on women, underlining the urgent need for tailored interventions (44). Both diagnosis and therapy are made more difficult by the disorder's complicated symptomatology, which includes persistent sorrow, anhedonia, exhaustion, cognitive impairment, and somatic complaints (45). This calls for sophisticated diagnostic techniques and individualised therapeutic methods.

Early detection of depression is crucial to providing effective treatment and improving the quality of life for affected individuals. Therefore, by gathering and evaluating a variety of biomarkers or biosignals, including heart rate, physical activity, sleep patterns, blood oxygen, and respiration rate, wearable technology and artificial intelligence (AI) have been used in tandem to diagnose and predict depression. The use of machine learning in depression prediction is not limited to conventional clinical contexts. For instance, studies have demonstrated that machine learning can analyze social media data to identify markers of depression, showcasing the technology's ability to leverage unconventional data sources for mental health insights (46). Furthermore, by examining characteristics like heavy metal exposure or familial factors, prediction models have been created to evaluate depression risk in particular populations, such as college students or older persons(47,48).

The application of machine learning classifiers to depression prediction across various data modalities has advanced significantly in recent studies. In a thorough evaluation of machine learning techniques for social media depression detection, (46) emphasised the potential of text-based features for early detection. Research on wearable technology has demonstrated that sleep and activity patterns are accurate indicators of depression (49,50).

Suicide risk assessment

According to World Health Organization (WHO) suicide is the act of deliberately killing oneself. Report indicates that, the majority of purposeful injuries in developed nations are caused by suicide (51), and over the next few decades, suicide is expected to contribute even more to the worldwide burden of disease (52,53). The World Health Organization (WHO) reports that poverty, unemployment, and untreated mental health conditions are the main causes of Africa's highest suicide rate globally (55). Furthermore, men are four to five times more likely than women to commit suicide worldwide. The need for more focused prevention efforts across genders is highlighted by the fact that women report twice as many attempts (56). Clinicians can identify individuals who are at risk with the aid of psychometric tools, which offer systematic and validated measures. However, despite their therapeutic value, traditional psychometric techniques have a number of drawbacks, such as subjectivity in self-reporting, recall bias susceptibility, a lack of real-time monitoring, and difficulties in identifying sudden changes in mental state (57, 58). Furthermore, a lot of evaluations are carried out at predetermined intervals, which may miss dynamic changes in suicide thoughts in between therapeutic visits.

Through the introduction of real-time, continuous, and context-sensitive behavioural and emotional data analysis, artificial intelligence (AI) has become a complementary tool that improves psychometric tests (59, 60). AI models provide a dynamic substitute for static psychometric assessments by integrating multimodal inputs such linguistic patterns, physiological signs, and digital footprints (61,62,63).

Cognitive decline detection

Timely intervention and management of disorders like dementia and mild cognitive impairment depend on early detection of cognitive decline. Conventional screening techniques, however, can be expensive, time-consuming, and reliant on the availability of specialists. By analysing voice, language, and clinical data, AI provides prospects for more effective and accessible cognitive assessment (64). Recent studies have shown how well machine learning algorithms and LLMs may identify cognitive impairment by analysing natural conversations. By analysing linguistic characteristics … AI systems can detect subtle indicators of cognitive impairment that might otherwise go unnoticed including comprehension issues, memory-related mistakes, diminished awareness, and distractibility. These techniques offer scalable and non-invasive ways to evaluate cognitive function (64).

Another useful method for identifying cognitive deterioration is speech analysis. In order to find trends linked to neurological decline, machine learning models can assess speech fluency, word usage, pauses, and semantic coherence. According to research, speech-based AI systems may aid in the early diagnosis of dementia-related disorders and can successfully differentiate people with cognitive impairment from healthy controls (65).

AI systems have also been applied to healthcare documentation analysis. According to recent research, AI models that looked at doctor's notes were able to identify early cognitive issues with a high degree of agreement with clinicians. These systems could be useful screening tools that help medical practitioners identify people who need more assessment (66).

Despite positive results, there are still issues with dataset diversity, model generalisability, and the requirement for validation in various healthcare contexts (64).

Behavioural monitoring

The ongoing evaluation of a person's behaviours, activities, emotional states, and bodily reactions is known as behavioural monitoring (67). In order to detect changes linked to mental

health issues and cognitive problems, AI-powered behavioural monitoring systems can gather and examine data from wearable technology, cellphones, sensors, and digital platforms (68).
In this area, wearable biosensors have grown in significance. Physiological indications including heart rate variability, sleep quality, physical activity levels, and stress reactions can all be continuously monitored by these devices. In order to identify behavioural patterns linked to depression, anxiety, suicide risk, and other mental health problems, machine learning algorithms examine these data streams. This kind of ongoing observation makes it possible to spot early warning indicators before symptoms worsen clinically (69).

Ecological momentary assessment (EMA) systems have also been integrated with AI-driven behavioural monitoring. These devices gather data in real time regarding a person's emotions, actions, and surroundings. EMA data can offer personalised mental health therapies and dynamic risk forecasts when paired with machine learning models. This strategy has been very effective in tracking suicide risk and assisting with precision mental health care (70).

Furthermore, AI systems are also capable of analysing audiovisual behavioural cues, such as social interactions, body language, speech patterns, and facial emotions. When concerning behavioural changes are identified, these multimodal monitoring techniques may offer a more thorough picture of a person's psychological state and enable early intervention (71).

Although there are many clinical advantages to behavioural monitoring, responsible application requires careful consideration of ethical concerns pertaining to informed permission, privacy, data security, and algorithmic bias (68).

5. Relevance to Occupational Therapy

Functional assessment

A key element of occupational therapy practice is functional evaluation, which provides details about a client's skills, limitations, and engagement in fulfilling occupations. Occupational therapists have historically assessed functional performance using client interviews, clinical observations, and standardised tests. However, new possibilities to improve the impartiality, effectiveness, and accuracy of functional assessments have been presented by recent developments in artificial intelligence (AI). Large volumes of performance data from wearable sensors, motion-capture devices, digital assessment platforms, and computerised tasks can be analysed by AI-powered evaluation tools. These tools make it possible to find tiny patterns in cognition, movement, and task performance that can be challenging to find with just traditional observation.

In order to give occupational therapists more thorough data for clinical evaluation, AI-based assessment systems have shown promise in evaluating motor skills, handwriting performance, upper extremity function, and daily living activities. Additionally, machine learning algorithms can continually process client data to produce predictive insights about functional decline or rehabilitation progress, enabling more individualised treatment planning and earlier intervention (72).

By lowering observer variability and promoting evidence-based decision-making, integrating AI into functional evaluation may potentially increase assessment reliability. However, in order to guarantee the effective application of assessment results, occupational therapists must continue to interpret assessment results within the larger context of the client's professional duties, environmental demands, and personal aspirations (72).

Client-centered care

One of the fundamental tenets of occupational therapy is client-centered care. In order to establish meaningful goals, encourage autonomy, and facilitate involvement in occupations that are personally meaningful, this method places a strong emphasis on therapists and clients working together. The compatibility of AI technologies with client-centered practice has been a topic of discussion since their introduction. According to recent research, by facilitating more individualised interventions, AI can enhance rather than replace client-centered care. AI systems are able to create personalised suggestions and intervention techniques by analysing individual preferences, behavioural patterns, health histories, and performance data. AI-driven solutions have the ability to modify rehabilitation programs in accordance with the needs and preferences of specific clients, improving therapeutic relevance and engagement (73).

In a similar vein, (74) highlighted that client-centered occupational therapy interventions enhance stroke survivors' satisfaction and engagement results. When, properly included, AI technology can enhance this client-centered approach by giving therapists comprehensive data about client priorities, performance trends, and advancement toward occupational goals. AI may help therapists and clients collaborate more intelligently, allowing for collaborative decision-making and customised care planning, rather than weakening the therapeutic alliance (73).

Despite these benefits, there are still issues with relying too much on automated recommendations. Occupational therapists must make sure that client choices, values, cultural considerations, and lived experiences—all of which are still essential to occupational therapy practice—are not overshadowed by AI-generated recommendations (73).

Occupational performance

The ability of a person to successfully participate in responsibilities and activities in their daily life is referred to as occupational performance. Occupational therapy approaches in physical, cognitive, psychosocial, and community contexts continue to prioritise improving occupational performance. Intelligent rehabilitation systems, adaptive technologies, and performance-monitoring tools are some of the ways AI technologies are increasingly being used to achieve this goal.

Numerous AI applications intended to improve occupational performance were found in a scoping review by (75). Robotic rehabilitation systems, virtual reality platforms, intelligent assistive technologies, and machine learning-based monitoring systems are some examples of these uses. These technologies can enable the repetitive practice required for skill acquisition and functional recovery, give real-time feedback, and adjust task complexity based on client performance. By tailoring activities to each client's skills and objectives, AI-assisted treatments may help increase involvement in fulfilling occupations. In order to maintain an ideal degree of difficulty and encourage ongoing engagement, intelligent rehabilitation systems, for instance, can alter therapeutic tasks based on ongoing performance data (75). Furthermore, by improving accessibility and independence, AI-driven HCI solutions have been demonstrated to promote occupational engagement among people with neurological, cognitive, and physical disabilities (75). AI-powered monitoring systems may offer objective data on involvement in daily tasks, adherence to routines, and changes in functional performance for those with depression, anxiety, or severe mental illness. Occupational therapists can use these data to identify obstacles to occupational engagement and assess the long-term efficacy of interventions (68).

These developments imply that AI has a great deal of potential to improve occupational performance outcomes while assisting occupational therapists in creating customised, occupation-focused therapies.

Telehealth and remote care

Healthcare delivery has changed as a result of the growth of telehealth services, especially in the wake of the COVID-19 epidemic. In order to increase access to services for those who live in underserved, rural, or mobility-restricted areas, occupational therapy has been using telehealth models more and more. Through automated evaluation, intelligent rehabilitation systems, and remote monitoring, AI technologies are further improving telehealth capabilities. One of the occupational therapy applications of AI that is expanding the fastest is telerehabilitation, according to (75). Real-time data on client performance, physical activity, adherence to therapies, and interactions with the environment can be gathered by AI-enabled healthcare solutions. With the use of these devices, therapists can remotely assess patients' progress and modify treatment regimens in response to evolving client demands. An example of AI-supported remote assessment is the Walk4Me project, as detailed in a scoping review by (75). The system assesses community mobility performance and gait patterns outside of clinical settings using smartphone sensors and machine learning algorithms. These technologies assist more ecologically valid assessments and therapies by providing occupational therapists with objective information about functional mobility and engagement in real-world environments.

By promoting prompt intervention and early diagnosis of functional deterioration, remote monitoring technology may also enhance continuity of care. AI-supported telehealth systems can encourage continued engagement and support participation in meaningful occupations for clients with neurological impairments, mental health disorders, or chronic conditions while lowering barriers related to geographic distance and transportation (75).

Clinical decision-making

When creating intervention plans, occupational therapists must include assessment results, client preferences, professional skills, and evidence-based knowledge in the intricate process of clinical decision-making. With predictive analytics, pattern recognition, and data-driven suggestions, AI technologies are increasingly being suggested as tools to assist this process.

AI can produce clinically meaningful recommendations for assessment and intervention planning, according to research comparing occupational therapists and AI systems. According to (76), ChatGPT could generate recommendations for occupational therapy in a variety of clinical situations. Although AI-generated responses demonstrated a broad knowledge base, they frequently lacked the sophisticated comprehension of contextual, environmental, psychological, and occupational elements that define professional occupational therapy thinking. As a result, rather than taking the role of expert judgement, AI should thus be seen as a decision-support tool rather than a replacement for professional expert judgement. AI In order to combine computational efficiency with the comprehensive, client-centered approach that characterises occupational therapy practice, the most successful use of AI in occupational therapy is probably going to involve human expertise and intelligent technologies working together (76, 75). Table 1 summarises the major AI technologies used in mental health risk assessment, their relevance to occupational therapy practice, and the key challenges associated with their implementation

Table 1. Summary of Artificial Intelligence Applications in Mental Health Risk Assessment and Their Relevance to Occupational Therapy

AI Technology	Mental Health Application	Occupational Therapy Relevance	Key Challenges
Machine Learning	Depression and suicide risk prediction	Early identification of clients requiring intervention	Algorithmic bias
Natural Language Processing	Analysis of speech and clinical notes	Cognitive and behavioural assessment support	Reliability and transparency
Wearable Technology	Monitoring sleep, activity and physiological indicators	Functional assessment and behavioural monitoring	Privacy concerns
Predictive Analytics	Risk stratification and outcome prediction	Clinical decision support	False positives and false negatives
Telehealth AI Systems	Remote monitoring and rehabilitation	Community-based and home-based OT services	Data security
Generative AI	Clinical documentation and decision support	Information synthesis and treatment planning	Over-reliance and professional accountability

Critical Evaluation of Current Evidence

The application of artificial intelligence in mental health risk assessment shows great promise, however there are a number of limitations that should be noted. A large portion of the information that is currently available was produced through the use of retrospective datasets, strictly regulated study settings, or specific patient populations. As a result, it is yet unclear if many AI models can be used to everyday occupational therapy practice (81,82,83).

Additionally, a lot of research places more emphasis on algorithm performance indicators and prediction accuracy than on clinically significant results. Although AI systems may be able to recognise patterns linked to depression, suicide risk, cognitive decline, or behavioural changes, there is little proof that these predictions consistently result in better treatment adherence, functional independence, occupational participation, or quality of life (83,84,85).

The representativeness and quality of the data present another significant constraint. Datasets from particular healthcare systems, demographic groups, or geographic areas are used to train many predictive models. This could make them less applicable to people with different cultural backgrounds and raise the possibility of algorithmic bias (77,78,79).

Given environmental, social, cultural, and contextual elements have a significant impact on occupational engagement and performance, these issues are especially pertinent in

occupational therapy. Therefore, without proper professional interpretation and validation, AI systems might not be able to fully capture the complexity of occupation-centered practice (74,75,76).
Therefore, before general deployment can be advised, more validation studies, longitudinal studies, and occupational therapy-specific research are needed, even if AI technologies provide tremendous prospects to improve mental health risk assessment (72,75,76).

7. Ethical Challenges
The integration of artificial intelligence (AI) into healthcare and occupational therapy relies heavily on the collection, storage, and analysis of large volumes of personal health information. To produce clinical forecasts and recommendations, AI systems often use data from wearable sensors, digital interactions, speech recordings, behavioural monitoring data, and electronic health records. These features improve evaluation and intervention planning, but they also bring up serious privacy and confidentiality issues. Safeguarding private patient data is one of the main ethical issues. To reach acceptable accuracy levels, AI systems need access to large datasets, which raises the possibility of data breaches, unauthorised access, re-identification of anonymised data, and exploitation of personal health information.

Williamson and Prybutok (77) highlight tensions between patient rights protection and technological innovation as a result of the increasing reliance on large-scale healthcare databases. Advances in data analytics may allow re-identification of individuals by merging numerous data sources, jeopardising confidentiality even in cases where health information is anonymised.

Previous studies indicated by, (78) found that among the most commonly mentioned ethical issues in healthcare AI applications are privacy and confidentiality. Inadequate governance frameworks, ambiguous data ownership, and a lack of openness about data utilisation may erode patient trust in AI systems, according to their thorough scoping review. These issues are especially pertinent in the fields of occupational therapy and mental health, as practitioners frequently gather extremely private data about social engagement, daily routines, occupational functioning, and psychological well-being. Concerns about privacy are made worse by the rise of AI-powered behavioural monitoring technologies. Movement patterns, communication behaviours, emotional states, and social interactions can all be continuously monitored via smartphones, wearable technology, and healthcare platforms. These technologies raise ethical concerns about the scope of surveillance and the preservation of individual autonomy, even though they may aid in the early detection of mental health hazards (77).

Researchers recommend implementing strong cybersecurity measures, differential privacy techniques, encryption protocols, and transparent governance frameworks that prioritise patient confidentiality while preserving the clinical utility of AI systems in order to address these issues (77,79).

A fundamental ethical precept in occupational therapy and healthcare is informed consent. Before consenting to participate, people must comprehend the nature, goals, advantages, and possible hazards of an intervention. Since many AI algorithms function as extremely complex systems that may be difficult for patients or physicians to understand, the arrival of AI technology has complicated this process. Research has demonstrated (78), a significant ethical issue with the use of AI in healthcare is informed consent. The way AI systems collect data, make recommendations, or learn from continuing patient encounters is frequently not sufficiently explained by traditional consent models. As a result, patients may provide their

consent to data collecting without completely comprehending how it will be used, shared, or kept.
Research has shown that (77) further contend that increased openness about AI decision-making procedures and data governance standards is necessary for genuine informed consent. In addition to the clinical use of AI systems, patients should be made aware of data sharing policies, privacy issues, and algorithmic prediction limits.

In mental health and occupational therapy settings, where AI systems may continuously gather behavioural data over extended periods of time, the problem becomes very crucial. In these situations, consent should be seen as a continuous process that enables people to change their permissions, withdraw participation, or ask questions about how their data is used (79).

As a result, researchers have highlighted the necessity of dynamic consent models that support patient autonomy, comprehension, and active involvement in AI-related decision-making. These methods are in line with the client-centered philosophy of occupational therapy, which emphasises independence, teamwork, and well-informed decision-making (78).

When AI is used in healthcare, one of the biggest ethical issues is algorithmic bias. AI systems can replicate and magnify preexisting prejudices if they learn from historical records that contain errors, under-representation of particular groups, or institutional injustices.

Algorithmic bias is a recurrent ethical problem in healthcare AI applications, according to (78). During data collection, model building, algorithm training, or implementation, bias may surface. As a result, people from socioeconomically challenged communities, minority populations, or culturally varied groups may receive forecasts from AI systems that are less accurate. According to (77), biased algorithms could lead to differences in diagnosis, treatment recommendations, and healthcare access. Biased prediction models may exaggerate or underestimate risk among specific demographic groups in mental health risk assessment, which could result in unsuitable interventions or missed care opportunities.

Similarly, (79) highlight that bias remains a major barrier to the equitable implementation of AI. The authors draw attention to the fact that many AI systems now in use were trained on datasets that don't fairly represent a range of populations. As a result, algorithmic results may consistently penalise those whose characteristics differ from those represented in the training data.
In occupational therapy, because occupational performance and participation are impacted by cultural, environmental, social, and contextual factors, algorithmic bias poses unique issues. AI systems may generate recommendations that are at odds with the requirements, values, and lived experiences of its clients if they neglect to take these things into consideration. Thus, to guarantee justice and equity in AI-assisted occupational therapy practice, continuous assessment, bias auditing, dataset diversity, and open reporting procedures are crucial (77,79).

Although AI technologies provide significant advantages in terms of efficiency, accuracy, and scalability, there have been worries expressed about the possible decrease in human involvement in the provision of healthcare. Therapeutic relationships, cooperative problem-solving, empathy, and client-centered treatment are the cornerstones of occupational therapy. Over-reliance on AI technologies could jeopardise these crucial practice components. According to (77), there are concerns that growing automation would change the conventional dynamic between patients and healthcare professionals. AI systems can offer important clinical

insights, but they are unable to completely replace human empathy, emotional intelligence, moral judgement, or therapeutic rapport.
Similarly, (80) contended that the extensive use of AI technology may change the roles of patients and healthcare providers in ways that call into question essential elements of healthcare delivery. The authors contend that although AI can improve decision-making, an excessive dependence on automated systems runs the danger of diminishing chances for personalised care and interpersonal interaction.

The necessity of preserving human oversight has also been highlighted in recent assessments of generative AI and massive language models in healthcare. AI systems may produce incorrect recommendations, misinterpret contextual factors, or fail to recognise the emotional aspects of healthcare interactions, even though they can help with information analysis, documentation, and clinical decision support (81,82).

The therapeutic use of self continues to be a key element of intervention in occupational therapy. Understanding clients' values, goals, occupational identities, and life experiences is essential to effective practice. Algorithmic analysis is insufficient to completely capture these elements. AI should therefore be seen as a tool that enhances rather than replaces interactions between therapists and their clients. To uphold the fundamental principles of the profession and guarantee the moral application of AI technologies, it is crucial to strike a balance between technical advancement and human-centered care (74,76,78,82).

8. Safety and Clinical Risk Management
The dependability and consistency of AI-generated outputs are critical to the successful integration of AI in occupational therapy and healthcare. The ability of an AI system to generate precise, repeatable, and clinically significant outcomes across many populations, environments, and situations is referred to as reliability. Although AI technologies have shown great promise in fields including clinical decision assistance, mental health risk assessment, and rehabilitation planning, questions about their reliability in actual clinical practice still exist. The fact that AI systems heavily rely on the calibre and representativeness of the data utilised for training is a significant obstacle. When applied to a variety of patient populations, models that were trained on incomplete, skewed, out-of-date, or non-representative datasets may perform badly. Evidence suggests (81), there are concerns regarding repeatability and dependability in healthcare applications since generative AI systems and big language models may generate inconsistent outputs depending on the input supplied. Additionally, these systems may produce "hallucinations," or plausible but factually wrong information, which, if not properly recognised and addressed, can jeopardise clinical decision-making.

Similarly, (82) highlighted that it might be challenging for medical experts to confirm the validity of recommendations because large language models frequently lack clarity regarding how conclusions are derived. The authors contend that many AI systems' opacity makes it difficult for clinicians to comprehend the reasoning behind algorithmic outputs, raising doubts about the systems' clinical reliability.

Topol (83) further emphasise that despite remarkable progress in predictive analytics, AI systems are still prone to mistakes brought on by inconsistent data, shifting clinical circumstances, and model design constraints. Therefore, to guarantee that performance stays accurate and clinically relevant over time, strict validation, ongoing monitoring, and frequent updates of AI systems are required. Reliability issues highlight the significance of critically assessing AI outputs rather than accepting them without question for occupational therapists using AI-supported assessment and intervention tools.

The incidence of false positive and false negative predictions is a major safety problem related to AI-driven mental health risk assessment. False negatives happen when a person who is actually at danger is not recognised by the system, whereas false positives happen when someone is mistakenly labelled as being at risk. Significant clinical ramifications may result from either kind of inaccuracy.

False positive predictions in suicide risk assessment can result in needless interventions, higher medical expenses, psychological distress, stigmatisation, and the improper use of scarce professional resources. On the other hand, for people who are truly at danger of suicide, false negatives could lead to missed opportunities for intervention, postponed treatment, and possibly disastrous consequences (68).

An analysis of suicide prediction models by Belsher et al. (84) found that while many algorithms achieve statistically significant prediction accuracy, their positive predictive value is limited. The authors contended that when applied to low-frequency events like suicide attempts and fatalities, even extremely accurate models may produce a significant percentage of false positive outcomes. Instead than depending only on algorithmic classifications, this discovery emphasises the significance of interpreting prediction outputs within larger clinical contexts.

Research has demonstrated (85), machine learning algorithms for suicide prevention frequently struggle to strike a balance between sensitivity and specificity. Increasing sensitivity can lead to an increase in false positive rates even while it may help identify high-risk individuals. On the other hand, attempts to lower false positives could unintentionally raise false negatives, thus ignoring people who need help right away. Therefore, rather than taking the place of thorough clinical examination, AI-based risk assessment systems should be seen as supplementary tools.

Within occupational therapy and mental health practice, these restrictions highlight the necessity of continuing evaluation, clinical judgement, and interdisciplinary cooperation when interpreting risk forecasts produced by AI. For contextualising findings, confirming outcomes, and choosing suitable intervention tactics, human physicians are still crucial.

Over-reliance on algorithmic recommendations poses serious clinical hazards, even though AI technology can improve productivity and assist evidence-based practice. Over-reliance on AI, also known as automation bias, is when medical personnel minimise their own critical analysis of data and place an excessive amount of trust in algorithmic results.

Even in cases when there is conflicting data, (86) argue that algorithmic decision-making systems may inadvertently encourage physicians to follow machine-generated recommendations. This tendency raises the possibility of therapeutic errors and compromises professional judgement. Despite the reality that algorithms themselves are prone to limits, biases, and mistakes, healthcare professionals may believe that AI-generated outputs are intrinsically superior or objective.

Similarly, (82) warn that large language models could produce convincing answers that seem authoritative even while they contain errors or conclusions that lack evidence. Clinicians may

unintentionally include false information in evaluation and intervention plans if proper verification is not done.
It has been suggested that (78) have noted concerns that an over-reliance on AI could reduce clinical skill and professional autonomy. The integration of assessment results, client preferences, environmental circumstances, occupational goals, cultural considerations, and therapeutic connections is known as professional reasoning in occupational therapy. Algorithmic analysis is insufficient to properly mimic these intricate aspects of practice.
Moreover, over-reliance on AI may contribute to the erosion of reflective practice, reducing opportunities for therapists to develop and refine critical thinking skills. Therefore, maintaining an appropriate balance between technological assistance and professional judgment is essential to ensuring safe and effective occupational therapy services.

One of the most crucial protections for the secure application of AI in healthcare is generally acknowledged to be professional monitoring. The environmental, emotional, ethical, and vocational factors that affect healthcare decision-making cannot be fully accounted for by AI systems, despite their ability to absorb massive amounts of data quickly and recognise patterns that are beyond human cognitive ability.

Topol (83) advocates for a human-AI collaboration approach where AI serves as a tool for decision-making rather than making decisions on its own. This viewpoint holds that AI should improve clinicians' skills by giving them more data and predicted insights while still letting humans make the final judgements. This strategy keeps healthcare workers accountable for patient care while enabling them to take advantage of technological improvements.

Similarly, (81) stress that human monitoring is crucial for spotting mistakes, assessing algorithmic suggestions, and guaranteeing that AI-generated results conform to accepted clinical standards. The authors suggest that personnel with the necessary training and expertise to decipher algorithmic results and spot possible errors should constantly supervise AI systems.
Occupational therapy evidence also bolsters the significance of expert supervision. AI-generated occupational therapy suggestions and those made by licensed occupational therapists were contrasted by (76). Although AI showed promise in producing pertinent evaluation and intervention recommendations, it often failed to take into account contextual, psychological, environmental, and client-centered elements that are essential to occupational therapy practice. The study came to the conclusion that while AI can assist professional reasoning, it cannot take the place of skilled occupational therapists' nuanced judgement and comprehensive viewpoint.
Although therapeutic judgements frequently involve complicated ethical issues, uncertainty, and individualised treatment planning, professional oversight is especially crucial for mental health risk assessment. AI forecasts must be evaluated by human physicians in conjunction with patient narratives, employment histories, psychological circumstances, and treatment objectives. Therefore, incorporating AI technology into collaborative models of care where professional competence continues to be the ultimate authority in clinical decision-making is the safest and most successful method.

Overall, expert supervision is an essential defence against issues with dependability, algorithmic mistakes, incorrect forecasts, and automation bias. Healthcare practitioners may optimise the advantages of AI while reducing possible dangers to patient safety and treatment quality by fusing AI-supported analytics with human experience.

9. Implications for Healthcare Systems

Training and AI literacy

A significant investment in workforce education and AI literacy is necessary for the effective integration of artificial intelligence (AI) into healthcare systems. Even though AI technologies have shown great promise for improving clinical assessment, risk prediction, decision support, and rehabilitation planning, healthcare practitioners need to have the knowledge and abilities needed to comprehend, assess, and use AI-generated outputs. Clinicians may find it difficult to spot algorithmic constraints, spot mistakes, or evaluate AI recommendations without sufficient training, which raises the possibility of making poor clinical decisions.

The literature indicates that (81), healthcare workers need to possess skills that go beyond simple technological know-how. Concepts like algorithm development, data quality, model validation, bias detection, explainability, and ethical AI use must be understood by clinicians. Healthcare professionals may assess the advantages and disadvantages of AI systems and determine whether algorithmic recommendations are appropriate in specific clinical settings through their professional expertise.

Similarly, (83) highlights that in order for the future healthcare workers to effectively work with AI technologies, they will need new forms of digital literacy. AI is anticipated to change professional responsibilities rather than replace physicians, necessitating practitioners to combine technological insights with clinical knowledge and human judgement. This change calls for continued education and professional development programs that cover the ethical and technological facets of implementing AI.

As occupational therapists often work in complicated situations where occupational performance is influenced by physical, psychological, social, cultural, and environmental aspects, AI literacy is especially crucial in this field. While AI systems can offer helpful assessment and intervention recommendations, (76) showed that they frequently lack the contextual awareness that distinguishes occupational therapy professional reasoning. As a result, occupational therapists need to be sufficiently trained to evaluate AI outputs critically while upholding client-centered treatment standards.

Therefore, it is the duty of healthcare organisations to create training frameworks that encourage physicians, administrators, educators, and students to be AI competent. While lowering the dangers of automation bias and improper dependence on algorithmic recommendations, incorporating AI literacy into professional curriculum and continuing education programs may improve safe deployment (81,83).

Policy and Regulation

Adequate legislative and regulatory frameworks are necessary to guarantee patient safety, moral behaviour, and accountability as AI technologies are further incorporated into the provision of healthcare. The issues around algorithmic decision-making, continuous learning systems, data governance, and AI-assisted clinical care may not be sufficiently addressed by current healthcare legislation, which were mostly created before to the advent of sophisticated AI systems.

Research has demonstrated that (78), one of the main obstacles to implementing AI in healthcare is regulatory ambiguity. The authors contend that many jurisdictions lack precise regulations pertaining to quality control, responsibility, liability, and transparency for healthcare services backed by AI. When AI systems lead to unfavourable health results, this ambiguity may make it difficult to determine who is at fault.

Previous research (77) has emphasized the importance of laws addressing patient rights, cybersecurity, data ownership, and privacy protection. Healthcare organisations need to put up governance frameworks that guarantee responsible data management while upholding public trust because AI technologies frequently rely on large health datasets.

Demands for more stringent regulatory monitoring have increased with the rise of generative AI and large language models. Standardised evaluation frameworks that evaluate AI systems for safety, dependability, fairness, transparency, and clinical efficacy prior to deployment are recommended by (81). These frameworks could assist guarantee that AI systems adhere to suitable quality standards and reduce patient hazards.

Policy development for occupational therapy and mental health services should also take into account concerns about clinical oversight, informed consent, professional accountability, and prejudice mitigation. To maintain professional accountability for patient care, regulatory frameworks should make it clear that AI serves as a decision-support tool rather than an independent clinical authority (78,81).

In order to ensure that AI technologies favourably impact healthcare delivery while reducing ethical and safety hazards, appropriate policy and regulation are ultimately required to strike a balance between innovation and patient protection.

Interdisciplinary Collaboration

A variety of professional groups, including clinicians, occupational therapists, psychologists, psychiatrists, data scientists, software engineers, ethicists, legislators, and healthcare administrators, must work together to integrate AI in healthcare. No one profession has all the knowledge required to guarantee the safe and efficient use of AI systems because they function at the nexus of technology, healthcare, ethics, and legislation.

Ning et al. (81) argue that the future of healthcare will increasingly depend on collaborative partnerships between human expertise and technological innovation. Effective AI implementation requires clinicians to contribute domain-specific knowledge, while data scientists and engineers provide technical expertise related to algorithm development, validation, and maintenance.

Similarly Karimian et al, (78)stress the importance of interdisciplinary cooperation in resolving ethical issues related to the application of AI. To guarantee that technological advancements are in line with professional standards and social values, ethical concerns like prejudice, transparency, responsibility, privacy, and informed consent require participation from a variety of stakeholders.

As several aspects of health and welfare have an impact on occupational performance, multidisciplinary teamwork is especially crucial in occupational therapy. Information from psychology, psychiatry, occupational therapy, nursing, social work, and rehabilitation sciences may be incorporated into AI-supported mental health risk assessment systems. By ensuring that risk evaluations are taken into account within larger psychosocial and occupational contexts, collaborative interpretation of AI-generated findings might enhance therapeutic decision-making.

Interdisciplinary teams are also crucial for assessing AI performance, spotting unforeseen repercussions, and creating plans to increase system fairness and dependability. The development of AI systems that better reflect clinical reality and enable client-centered treatment can be facilitated by ongoing collaboration between technology developers and healthcare professionals (81).

Fostering interdisciplinary alliances will be essential to optimising clinical benefits while reducing ethical, safety, and implementation problems as healthcare institutions continue to incorporate AI technologies. This kind of cooperation facilitates the creation of ethical, just, and therapeutically significant AI applications that complement human knowledge rather than replace it.

10. Gaps in Literature and Future Directions

Despite the growing body of research examining artificial intelligence (AI) in mental healthcare, several important gaps remain, particularly in relation to occupational therapy practice. Relatively little research has examined AI-supported mental health risk assessment from an occupational therapy perspective, whereas the majority of current studies concentrate on general medical, psychiatric, or psychological uses of AI. Because of this, there is no data on how AI technologies can especially assist occupational therapists in assessing functional outcomes, occupational performance, and involvement among people with mental health issues. The absence of validation studies tailored to occupational therapy is a significant drawback in the existing research. Numerous AI algorithms have been created and evaluated utilising datasets from digital health platforms, mental evaluations, and medical records. Few research, however, have assessed how well these systems capture the occupational dimensions of health that are essential to the practice of occupational therapy. Therefore, validation research is required to ascertain the clinical utility, sensitivity, and reliability of AI-assisted assessment tools across a variety of occupational therapy populations, such as those with severe mental illness, neurodevelopmental disorders, cognitive impairments, and community-based rehabilitation needs.

The generalisability of AI systems across many cultural, social, and healthcare contexts is another important gap. Concerns have been raised about the prediction models' suitability for populations in low- and middle-income countries because many of them were created using datasets from high-income nations. Cultural variations in social engagement, job responsibilities, communication styles, and health-seeking behaviours may affect how accurate AI-generated forecasts are. To reduce algorithmic bias and enhance fairness in healthcare delivery, future research should place a higher priority on creating more representative datasets and assessing AI performance across a range of demographics.

Additionally, ethical research is still underdeveloped. Although algorithmic bias, privacy, informed consent, and transparency have all been extensively covered in theoretical literature, there is little empirical data analysing how these ethical issues impact patients and medical professionals in actual practice. The impact of AI technology on therapeutic interactions and client autonomy, service users' opinions of AI-supported mental health evaluation, and their willingness to contribute personal behavioural data all need further investigation.

Furthermore, longitudinal studies assessing the long-term efficacy of risk assessment systems and AI-assisted therapies are also necessary. Rather than long-term clinical results, the majority of current research focuses on algorithm development and short-term predicted accuracy.

Future research should look into whether AI-assisted decision-making enhances quality of life, treatment compliance, mental health outcomes, occupational engagement, and involvement in fulfilling careers over time.
Future studies should also improve interdisciplinary cooperation. To develop, validate, and deploy AI systems that represent both technology capabilities and person-centred healthcare concepts, occupational therapists, psychiatrists, psychologists, data scientists, ethicists, and legislators must collaborate. This kind of cooperation will help guarantee that AI technologies continue to be ethically sound, clinically applicable, and consistent with occupational therapy's holistic philosophy.

In conclusion, studies should concentrate on developing clinically significant, morally sound, and occupational reapplications of AI that improve mental health risk assessment while maintaining human-centered care rather than just showcasing technological capacity.

11. Conclusion

Artificial intelligence has the potential to significantly enhance mental health risk assessment in occupational therapy practice, and it is quickly changing the healthcare industry. AI can help with the early detection of mental health problems, such as depression, suicide risk, cognitive decline, and behavioural changes, through technologies including machine learning algorithms, wearable monitoring devices, natural language processing, and predictive analytics. More prompt interventions, more clinical understanding, better functional assessment, and more individualised care approaches are all made possible by these technologies.

Despite these benefits, there are significant ethical, safety, and clinical risk management issues with integrating AI into occupational therapy. The reliability of AI-generated outputs, algorithmic bias, false positive and false negative predictions, over-reliance on automated systems. Privacy and confidentiality, informed consent, and the possible loss of human interaction are all issues that need to be carefully considered. These difficulties could jeopardise patient safety, professional responsibility, and the client-centered principles that guide occupational therapy_practice in the absence of suitable safeguards.

According to the examined research, AI should be seen as a decision-support tool that enhances professional knowledge rather than as a substitute for occupational therapists. Effective mental health care still requires human professional reasoning, therapeutic self-use, ethical judgement, and knowledge of the patient's occupational context. For AI-generated data to be properly understood and included into comprehensive clinical decision-making, professional oversight is therefore essential.

Additionally, healthcare systems must invest in workforce training, AI literacy, regulatory frameworks, ethical governance structures, and interdisciplinary collaboration in order to get prepared for the expanding usage of AI. These measures will be required to optimise AI's advantages while lowering any possible risks related to its application.

In conclusion, AI presents encouraging prospects for improving occupational therapy's clinical decision-making and mental health risk assessment. However, for it to be successfully adopted, a responsible and balanced strategy that incorporates person-centred care, professional oversight, ethical practice, and technology innovation is needed. Occupational therapists can benefit from AI while preserving patient safety, autonomy, dignity, and meaningful engagement in daily life by maintaining this balance.

The development of clear, understandable, and ethically acceptable AI systems that assist occupational therapists in providing safe, equitable, and person-centred care should be the top priority for future developments. To guarantee that technological progress strengthens rather than lessens the human aspects of occupational therapy practice, further research, professional development, and interdisciplinary cooperation will be necessary.

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