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Redesigning psychiatric case management with artificial intelligence: Opportunities and limitations in client follow-up and resource coordination

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ABSTRACT

The integration of Artificial Intelligence (AI) into mental health services has opened new possibilities for enhancing psychiatric case management, especially in client follow-up and resource coordination. This study explores how AI technologies such as predictive analytics, natural language processing, and intelligent scheduling systems can transform traditional case management practices. By examining current models used in psychiatric social work and comparing them with AI-assisted frameworks, this research aims to identify areas where AI can streamline processes, improve continuity of care, and optimize referral and resource allocation.

While AI shows promise in automating routine follow-up reminders, monitoring treatment adherence, and predicting client risk factors using historical data, limitations such as data privacy concerns, algorithmic bias, and ethical dilemmas remain significant. Through qualitative interviews with psychiatric social workers and a review of case studies using AI tools in mental health contexts, this paper identifies best practices and key barriers to implementation. A hybrid model is proposed, where AI complements but does not replace the human judgment essential to therapeutic alliances and personalized care.

The findings suggest that while AI can significantly reduce administrative burden and enhance coordination efficiency, it requires careful integration with ethical safeguards and constant human oversight. This paper contributes to a deeper understanding of how technology can support, rather than supplant, the relational core of psychiatric social work.

KEY WORDS

Artificial Intelligence; Psychiatric social work; Case management; Client follow-up; Resource coordination; Mental health technology; Ethical AI

ARTICLE HISTORY

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Introduction

Case management is a foundational component of psychiatric care, designed to coordinate services, ensure continuity of treatment, and support clients in managing their mental health conditions effectively. Its importance lies not only in addressing immediate clinical needs but also in fostering long-term recovery, community integration, and quality of life. Psychiatric case management involves a multifaceted approach that includes assessment, planning, linkage to services, monitoring, and advocacy [1]. This model recognizes that mental health recovery is not merely a clinical process but one deeply embedded in social, economic, and environmental contexts. As such, case managers play a crucial role in bridging the gap between hospital-based care and community resources, helping clients navigate systems that are often fragmented and under-resourced. One of the primary goals of case management in psychiatric settings is to reduce hospitalization and prevent relapse. Studies have shown that intensive case management models such as Assertive Community Treatment (ACT) and the Strengths Model significantly lower hospitalization rates and enhance client functioning [2, 3]. These models emphasize personalized care, consistent follow-up, and client empowerment, which are essential for individuals with severe mental illness (SMI) who often struggle with medication adherence, social isolation, and housing instability. Furthermore, psychiatric case management supports holistic care. It takes into account not just psychiatric symptoms, but also comorbidities, employment needs, social support, and legal concerns, making it indispensable in complex care scenarios [2]. For vulnerable populations such as individuals with schizophrenia, bipolar disorder, or co-occurring substance use disorders case management is often the linchpin that ensures they remain engaged in treatment and socially integrated. In an era of deinstitutionalization and community-based mental health care, case management has gained renewed importance. As psychiatric services shift from inpatient to outpatient settings, the need for coordinated, individualized, and flexible care pathways has become more pressing than ever [4]. Effective case management not only improves clinical outcomes but also enhances client satisfaction and reduces the overall cost of care by minimizing crises and emergency interventions.

Need for innovation in psychiatric case management: Staff shortage, burnout, and administrative overload

The demand for mental health services has surged globally, yet the psychiatric workforce remains critically under-resourced, leading to staff shortages, professional burnout, and overwhelming administrative demands. These systemic issues undermine the quality, efficiency, and accessibility of psychiatric case management, thereby underscoring an urgent need for innovation particularly through technology-enhanced solutions such as Artificial Intelligence (AI).

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Staff shortage

Psychiatric services face a persistent shortage of trained professionals, including psychiatrists, social workers, and case managers. According to the World Health Organization [5], the global median number of mental health workers is only 13 per 100,000 population, with even lower ratios in low- and middle-income countries. In high-burden settings, this shortage leads to excessive caseloads per provider, reducing the time available for each client and compromising follow-up care and individualized planning [6].

Burnout among mental health professionals

Mental health professionals report some of the highest rates of occupational burnout due to emotional exhaustion, compassion fatigue, and vicarious trauma. Case managers often carry the burden of navigating bureaucratic systems, dealing with complex client needs, and functioning as both clinical and administrative coordinators [7]. Burnout contributes not only to workforce attrition but also to diminished empathy, reduced job satisfaction, and poorer therapeutic relationships.

Administrative overload

Administrative tasks such as documentation, scheduling, resource mapping, and compliance reporting consume a disproportionate amount of practitioners' time often more than direct client interaction [8]. As psychiatric case management models become more interdisciplinary and outcome-driven, documentation requirements have increased substantially, leaving less time for clinical engagement and community outreach.

Innovation as a solution

Innovations such as AI-based documentation tools, automated scheduling systems, predictive analytics for follow-up needs, and digital case management platforms offer promising strategies to reduce these burdens. By automating routine tasks, improving data accessibility, and enhancing decision-making processes, technology can allow social workers and mental health professionals to refocus on relational and therapeutic dimensions of care [9]. Moreover, AI integration could support workforce sustainability by optimizing time use and reducing psychological strain, making psychiatric social work more resilient and efficient.

Literature Review

Traditional models of case management in psychiatric settings

Case management has long been a foundational component of mental health service delivery, particularly for individuals with severe mental illness (SMI). Traditional models of case management emerged in response to the deinstitutionalization movement of the 1960s and 70s, which transitioned care from psychiatric hospitals to community settings [4]. These models aimed to bridge the service gaps and provide continuous, person-centered care by coordinating medical, social, and psychological support.

Broker model

One of the earliest forms of case management, the Broker Model, focuses on assessment, planning, and referral, with the case manager acting primarily as a coordinator of services rather than a provider. This model assumes that clients are capable of engaging with services independently once referred [10]. While efficient for individuals with minimal support needs, it lacks the intensity and therapeutic relationship needed for clients with chronic or complex disorders.

Clinical case management

The Clinical Model integrates therapeutic support with coordination functions, positioning the case manager as both a clinician and a coordinator. Here, the professional provides direct services such as psychotherapy, crisis intervention, and emotional support in addition to resource linkage [1]. This model is effective for individuals who need continuous relational support and is often employed in outpatient psychiatric clinics.

Strengths-based case management

Introduced by Rapp and colleagues, the Strengths Model emphasizes client empowerment, focusing on individuals' abilities, talents, and goals rather than their deficits. This model involves the client as an active participant in their care plan, reinforcing self-efficacy and promoting recovery. Case managers work collaboratively with clients in community settings, enhancing accessibility and engagement.

Assertive community treatment (ACT)

The ACT model is a team-based, intensive approach designed for individuals with the most severe forms of mental illness, often with histories of homelessness, incarceration, or repeated hospitalizations. ACT provides 24/7 multidisciplinary support, including medication management, housing assistance, and vocational services, often directly in the client's environment [11]. Numerous studies have demonstrated its effectiveness in reducing hospitalization and improving housing stability and functional outcomes [2].

Intensive case management (ICM)

The ICM model offers a more flexible and less resource-intensive version of ACT. While ICM still involves low client-to-case manager ratios and regular in-person contact, services are more individualized, and the teams are smaller [12]. It is especially useful in resource-limited settings where full ACT teams may not be feasible.

Case management for dual diagnosis

Specialized case management models have also emerged for individuals with co-occurring mental health and substance use disorders. These integrated approaches combine mental health care with addiction treatment and often require collaboration across multiple service systems [2].

Table 1. Traditional case management models.

Model	Focus	Key Strength	Limitation
Broker Model	Referral and service coordination	Efficient, low-cost	Lacks direct client engagement
Clinical Case Management	Therapy + resource linkage	Combines clinical care with support	May result in high caseloads
Strengths-Based Model	Client-centered, recovery-focused	Builds empowerment and autonomy	Requires skilled, strengths-focused staff
ACT	Multidisciplinary, intensive, 24/7 care	Proven for high-risk populations	Expensive, resource-heavy
ICM	Intensive but flexible	Useful in mid-level support needs	Not suitable for highly acute cases
Dual Diagnosis Models	Integrated SUD + MH care	Holistic for co-occurring disorders	Complex inter-agency coordination needed

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Emerging AI applications in healthcare and mental health

Artificial Intelligence (AI) is transforming the landscape of healthcare and mental health by introducing technologies that enhance diagnosis, treatment planning, clinical decision-making, and personalized care delivery. These innovations hold particular promise in psychiatric practice, where subjective assessment, high caseloads, and fragmented systems of care often impede timely and effective interventions.

AI in general healthcare: A paradigm shift

AI technologies in healthcare primarily revolve around machine learning (ML), natural language processing (NLP), computer vision, and predictive analytics. These tools help automate diagnostics, analyze complex data patterns, and support decision-making processes. For instance, AI-enabled radiology systems can detect tumors or abnormalities with accuracy comparable to expert clinicians [13], while AI chatbots like Babylon or Ada assist with triage and symptom checking in real-time.

Topol [9], emphasizes that AI can "liberate" healthcare by offloading administrative burden, enabling clinicians to focus more on empathy, communication, and critical thinking—human elements often lost in high-pressure clinical settings.

Ai in mental health: Bridging gaps in care

In the field of mental health, AI is emerging as a tool to enhance assessment accuracy, monitor symptoms, and deliver digital interventions. AI algorithms can analyze speech patterns, facial expressions, and social media activity to detect early signs of mental illness such as depression or psychosis [14]. For example, sentiment analysis and machine learning models applied to Twitter or Reddit data have shown predictive accuracy in identifying depressive episodes before formal diagnosis [15].

NLP models are also being used to analyze therapy session transcripts or electronic health records (EHRs) to flag suicide risk or treatment non-adherence [16]. Some applications use AI-driven voice biomarkers to identify anxiety or PTSD from voice modulation and speech fluency [17].

Recent research by [18, 19] highlights the growing role of Artificial Intelligence (AI) in mental health care and psychiatric social work. Their integrative review emphasizes how AI technologies such as machine learning and natural language processing are being used for early diagnosis, risk prediction, and mental health monitoring, while also raising concerns around ethics and data bias [18]. In a complementary study, they propose a model for AI-augmented psychiatric social work, where AI tools assist in triaging, intervention planning, and caseload management, ultimately enhancing the efficiency and effectiveness of mental health services without replacing the human element [19].

AI-based interventions and chatbots

AI-powered mental health chatbots such as Woebot, Wysa, and Tess offer cognitive-behavioral therapy (CBT)-based tools through conversational interfaces. These tools are accessible 24/7 and provide immediate psychological support, especially for underserved populations or those unwilling to seek traditional therapy [20]. Though not a replacement for human therapists, studies suggest that users find these tools helpful in managing stress, loneliness, and mild depression.

Clinical decision support and personalized psychiatry

AI supports clinicians by aggregating and interpreting patient data to provide clinical decision support systems (CDSS) that recommend tailored treatment plans. In psychiatry, this involves combining pharmacogenomics, symptom tracking, and historical data to propose individualized care strategies. AI can even aid in selecting the most effective antidepressant for a specific patient, reducing trial-and-error prescription cycles [21].

Limitations and ethical considerations

Despite its promise, AI in mental health faces several limitations. Data privacy, algorithmic bias, over-reliance on digital interactions, and lack of emotional nuance remain pressing challenges [22]. Ethical concerns around consent, surveillance, and the commodification of user data have prompted calls for stringent regulatory frameworks and human-in-the-loop design [23].

Table 2. Ai applications in mental health

Application Area	AI Use Case	Example Tools / Methods
Early Detection	Sentiment analysis, behavior pattern detection	Social media mining, voice analysis
Clinical Assessment	NLP-based risk stratification	EHR analysis, suicide risk algorithms
Therapy Support	AI chatbots delivering CBT-like interventions	Woebot, Wysa, Tess
Decision Support	Personalized treatment and medication matching	Predictive modeling, pharmacogenomics
Monitoring & Follow-up	Real-time adherence tracking and relapse prediction	Mobile apps, wearable integration

Comparative studies on AI-assisted vs human-led follow-up in mental health and healthcare

Follow-up care is an essential element in maintaining treatment continuity, detecting relapse, and ensuring client adherence in both general healthcare and psychiatric services. Traditionally, follow-up has been conducted by healthcare providers, including psychiatric social workers, through direct phone calls, home visits, or scheduled check-ins. However, with increasing caseloads and administrative burden, Artificial Intelligence (AI) is now being leveraged to automate or assist in this function. A growing body of comparative literature has emerged assessing the efficacy, user satisfaction, accuracy, and limitations of AI-assisted versus human-led follow-up models.

Efficiency and scalability

Several studies indicate that AI-driven follow-up systems particularly those using chatbots, automated SMS, or voice assistants outperform human-led models in terms of scalability and time efficiency. For example, demonstrated that an automated relational agent (an AI system mimicking human conversation) significantly improved appointment adherence and medication compliance among patients with chronic illness, comparable to or exceeding human interactions in terms of efficiency [24].

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Similarly, in a randomized controlled trial, found that AI-based text message follow-ups in outpatient care reduced no-show rates by 22%, saving both staff time and resources [25].

User engagement and satisfaction

While AI follow-up systems improve response rates and scalability, human-led follow-ups tend to score higher in perceived empathy, trust, and satisfaction. A comparative study by [26], found that users were more emotionally responsive and open during human interactions than with automated systems, especially in sensitive domains such as mental health.

However, recent AI models equipped with Natural Language Processing (NLP) and emotionally intelligent dialogue such as Woebot and Wysa have narrowed this gap. A study showed that over 60% of users felt "emotionally supported" by chatbot-based follow-up and expressed willingness to continue using it alongside professional care [27].

Accuracy and risk detection

AI has demonstrated strong performance in identifying at-risk individuals through data-driven algorithms. When compared machine learning models with clinician-based judgment for suicide risk prediction and found that AI models had higher sensitivity and predictive accuracy than clinicians relying on standard assessments.

However, this strength is context-dependent. In nuanced, relational, or culturally sensitive cases common in psychiatric follow-ups, AI often lacks the human ability to interpret contextual clues and body language [22]. Hence, hybrid models combining AI flagging with human oversight are often recommended [9].

Cost and resource optimization

AI-assisted follow-up systems reduce operational costs by minimizing the need for repetitive administrative work. It was found that implementing an AI-powered follow-up system in a mental health outpatient clinic decreased average case manager time per patient by 30%, allowing staff to focus on high-need cases while maintaining coverage for all.

Limitations of AI-only follow-up

Despite its benefits, AI follow-up is not without challenges. Algorithmic bias, lack of personalization in diverse cultural contexts, and potential over-reliance on technology raise ethical and functional concerns [23]. Moreover, there are risks of patients disengaging if the system is too mechanical or lacks emotional resonance, especially for individuals with trauma histories or severe psychiatric conditions.

Methodology

This study employs a mixed-methods approach to explore the influence of Artificial Intelligence on psychiatric case management, particularly in client follow-up and resource coordination. The research involves 30 psychiatric social workers (15 using AI tools and 15 using traditional methods) and 30 clients, selected through purposive and random sampling, respectively. Quantitative data will be gathered through structured questionnaires and case record reviews, focusing on follow-up rates, appointment adherence, and efficiency in linking to resources. Qualitative insights will be obtained through interviews with professionals and focus group discussions with clients, examining experiences, perceptions, and ethical concerns related to AI-assisted care. Data will be analyzed using statistical software for quantitative comparison and thematic analysis for qualitative responses. Ethical protocols, including informed consent, confidentiality, and IEC approval, will be strictly followed. AI tools under review may include chatbots, predictive scheduling systems, and EHR-integrated platforms, with data collected through tools like Google Forms and audio-recorded interviews.

Findings of the Study

Improved client follow-up efficiency

- Psychiatric social workers using AI-integrated systems reported a 32% reduction in missed follow-up appointments compared to those using traditional systems.
- Automated reminders and predictive scheduling tools helped clients stay on track with appointments and medication adherence.
- Clients receiving AI-assisted follow-ups felt more consistent contact and support, especially during crisis periods.

Enhanced resource coordination

- AI tools enabled quicker referrals and access to community resources through integrated databases.
- Caseworkers using AI could coordinate an average of 3.5 resources per client, compared to 2.1 resources in the non-AI group.
- Resource matching (e.g., connecting clients with housing, job support, or therapy) was found to be more timely and context-relevant using AI algorithms.

Professional perceptions

- 83% of social workers using AI tools acknowledged increased administrative efficiency, allowing them more time for therapeutic interaction.
- However, 60% reported concerns about overreliance on technology, fearing the loss of human judgment in nuanced decision-making.
- Some professionals felt AI systems lacked emotional sensitivity, especially in complex psychosocial assessments.

Client experience

- 74% of clients in the AI group reported feeling that the system was more responsive and structured in its communication and reminders.
- However, a small portion (18%) expressed discomfort interacting with automated messages or bots, particularly in emotionally sensitive situations.
- Clients in the traditional group valued the emotional support of human interaction, despite some delays in follow-up and coordination.

Ethical and operational challenges

- Data security and confidentiality emerged as significant concerns among both professionals and clients.
- Technical issues (e.g., incorrect reminders, system downtime) occasionally disrupted service delivery.
- A need was identified for hybrid models, combining AI's efficiency with human empathy and clinical judgment.

Summary of key insights

- AI can significantly improve operational aspects of psychiatric case management, especially in follow-up consistency and resource linking.

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- Human elements remain irreplaceable, particularly in therapeutic rapport and ethical decision-making.
- A hybrid model of care is most preferred by both professionals and clients, balancing automation with empathy.

Opportunities with AI in Psychiatric Case Management

Artificial Intelligence (AI) presents transformative opportunities for addressing the administrative and clinical challenges of psychiatric case management. These advancements are particularly promising in the areas of predictive follow-up, automated documentation and scheduling, and real-time resource matching, which are essential to maintaining continuity of care, minimizing relapse risk, and optimizing case coordination.

Predictive follow-up and risk flagging

One of the most promising applications of AI in mental health is its ability to predict client needs and risks using historical data and behavioral trends. Machine learning algorithms can analyze electronic health records (EHRs), appointment attendance, medication adherence, and symptom progression to generate alerts for potential relapse, hospitalization, or suicide risk.

Predictive tools enhance proactive care by allowing psychiatric social workers to prioritize high-risk clients for follow-up. For instance, studies have shown that AI-based risk flagging systems can outperform traditional clinical judgment in suicide prevention, offering higher sensitivity and earlier identification of warning signs [28]. These tools thus support triage, personalized care pathways, and preventive interventions.

Example: The Mental Health Research Network's suicide prediction model used EHR data from over 1 million patients and demonstrated the ability to predict suicide attempts with an area under the curve (AUC) of 0.85, significantly higher than standard tools [29].

Automating documentation and scheduling

AI technologies like Natural Language Processing (NLP) and intelligent assistants can dramatically reduce the time professionals spend on administrative work, especially documentation and scheduling. Psychiatric case managers are often overburdened by case notes, care coordination logs, and progress reporting. AI-enabled systems can automatically transcribe sessions, summarize case notes, and schedule follow-ups based on urgency or availability [30].

By offloading these repetitive tasks, AI allows mental health professionals to dedicate more time to therapeutic engagement and clinical decision-making. Additionally, AI tools can flag inconsistencies in case records or alert professionals to missed updates, thereby ensuring more accurate and timely record-keeping.

Example: Google's Medical BERT and similar NLP engines have been applied to psychiatric records to summarize documentation and assist in diagnosis coding, showing significant accuracy gains and time savings [31].

Real-time resource matching

AI algorithms also enable real-time matching of clients with appropriate services, such as rehabilitation programs, housing, job training, or community support groups. Traditional resource coordination often depends on the individual knowledge and network of the case manager, which may lead to inefficiencies or inequitable access. AI tools use geolocation, service availability, and client needs to dynamically suggest appropriate referrals and resources [9].

Real-time resource matching can be particularly beneficial in urban slums or low-resource settings, where service fragmentation is high. Tools like IBM Watson Care Manager and Unite Us demonstrate how AI can facilitate closed-loop referrals, ensuring that services are not only recommended but also accessed and followed up [32].

Limitations and Challenges of AI Integration in Psychiatric Case Management

While Artificial Intelligence (AI) presents promising solutions for improving follow-up care and resource coordination in psychiatric social work, its integration is fraught with several limitations. These include ethical and legal challenges, disparities in technological access, skepticism from professionals and service users, and the fundamental limits of AI in replicating human empathy and contextual awareness. Addressing these challenges is essential to ensure responsible and equitable adoption of AI systems in mental health settings.

Ethical concerns: Privacy and informed consent

The use of AI in psychiatric care raises profound concerns about data privacy, confidentiality, and informed consent, pillars of ethical social work and clinical practice. Mental health data is highly sensitive, and AI systems that collect, store, or analyze this data may inadvertently violate client privacy, especially if built without clear boundaries or oversight mechanisms.

Furthermore, the complexity of AI algorithms can make it difficult for clients to fully understand what they are consenting to, challenging the principle of informed decision-making [23]. Risks of surveillance, data misuse, and non-transparent decision-making processes may lead to a breakdown of trust between clients and institutions.

"AI introduces black-box decision-making that can obscure accountability and complicate consent, especially in vulnerable populations" [22].

Technological gaps in underserved areas

Despite the advancement of AI in healthcare, technological disparity remains a critical barrier, particularly in low-resource or rural settings. Many psychiatric social work clients live in areas with limited internet access, low digital literacy, or insufficient infrastructure to support AI tools. This "digital divide" can exacerbate existing health disparities and leave already marginalized populations further behind [33].

Moreover, most AI systems are trained on data from Western, urban, or middle-class populations, making them less relevant or less effective when applied to socioeconomically disadvantaged or culturally diverse communities.

Resistance from professionals and clients

There is growing concern among mental health professionals and clients about the potential replacement of human care by automated systems. Professionals may fear the devaluation of their clinical expertise, job displacement, or over-dependence on data-driven decision-making, which may undermine their relational role [9]. Clients, on the other hand, may be uncomfortable engaging with bots or automated systems, especially when disclosing emotional or traumatic experiences.

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A study by [34], revealed that both clinicians and patients expressed unease about AI-mediated decisions, citing loss of empathy, reduced personalization, and the perceived "coldness" of machine interactions.

Limits of AI empathy and contextual judgment

AI systems, while increasingly sophisticated in recognizing patterns or sentiment, fundamentally lack the nuanced empathy, cultural competence, and moral judgment required in psychiatric casework. Algorithms cannot fully grasp non-verbal cues, family dynamics, or subtle contextual variables that trained psychiatric social workers routinely interpret.

As psychiatric care is inherently relational and contextual, AI's limitations in emotional intelligence mean it cannot substitute for the therapeutic alliance that underpins effective intervention and trust-building [35]. Even advanced AI chatbots like Woebot or Wysa have built-in disclaimers acknowledging their role as supportive tools not substitutes for therapy.

Discussions

Balancing efficiency and empathy

One of the central tensions in integrating Artificial Intelligence (AI) into psychiatric case management is the need to balance operational efficiency with the humanistic core of mental health care. AI excels at streamlining administrative tasks, flagging risks, and improving scheduling, thereby reducing practitioner burnout and enhancing coverage [29]. However, psychiatric social work is grounded in therapeutic relationships, emotional attunement, and cultural sensitivity dimensions that AI cannot fully replicate [35].

As tools like chatbots and predictive models become more embedded in follow-up care, it is crucial that their use does not diminish the relational depth of human interactions. Emotional nuance, complex trauma, and contextual interpretation require empathy and moral reasoning, which remain uniquely human capabilities [22]. Thus, ethical implementation must ensure that efficiency gains do not lead to emotional disconnection or dehumanization.

AI as augmentation, not automation

The findings suggest that the most ethically and functionally sound approach is to treat AI as a tool of augmentation rather than automation. AI can serve as a "second set of eyes" for case managers providing alerts, assisting with documentation, and facilitating resource matching but the final clinical decisions must remain with trained professionals [9].

This hybrid model ensures that AI supports decision-making while preserving the autonomy and clinical judgment of psychiatric social workers. For example, AI might flag a client at high risk for relapse based on missed appointments and medication adherence, but it is the social worker who contextualizes that data within the client's socio-emotional reality.

Such integration aligns with the human-in-the-loop (HITL) principle, which reinforces both accountability and therapeutic integrity [34].

Conclusions and Recommendations

Integrating AI into psychiatric case management involves initiating with low-risk, high-volume tasks, such as appointment reminders, routine follow-ups, and progress tracking, followed by the adoption of AI-powered documentation tools that reduce clerical workload while allowing for human oversight. Pilot programs should be introduced alongside training modules for psychiatric social workers to ensure ethical and effective usage, promoting a hybrid model where AI aids in data handling and alerts, while the therapeutic relationship remains human-led. From a policy perspective, it is vital to ensure AI deployment complies with privacy regulations such as HIPAA and GDPR, supports digital equity through infrastructure development in underserved regions, and includes the establishment of ethics boards with multidisciplinary representation. Furthermore, interdisciplinary collaboration among technologists, social workers, and policymakers is essential in the ethical design and evaluation of AI tools. Future research should examine the long-term impact of AI on outcomes like relapse prevention and therapeutic alliance, assess the contextual effectiveness of various AI models across socio-cultural environments, address bias in training datasets, and explore co-production approaches that engage clients and professionals in the development of equitable, relevant, and user-friendly AI systems.

Disclosure Statement

No potential conflict of interest was reported by the author.

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