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Investigating Knowledge-Sharing Practices among Mental Health Practitioners for the Integration of Artificial Intelligence in Mental Health Care – A Qualitative Study

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Abstract

Artificial Intelligence (AI) has shown strong potential in medicine, particularly in oncology, dermatology, and radiology. However, its application in mental health care remains limited due to insufficient data availability. This research investigates knowledge-sharing practices among mental health practitioners to determine how data can be effectively captured and utilized for AI integration.

Using qualitative interviews and surveys with mental health professionals identifies barriers such as time constraints, digital skills gaps, resistance to change, and ethical concerns under GDPR, while also highlighting potential benefits of AI, including early detection of behavioural patterns, improved diagnosis, and enhanced patient independence. Nevertheless, respondents recognised AI's potential to support earlier detection of behavioural patterns, enhance communication, and improve patient independence.

By applying Nonaka's SECI model to mental health knowledge flows, this study proposes the Knowledge-Sharing AI Model (KSAI-Model). The model illustrates how tacit clinician insights can be externalised, combined within Electronic Patient Records (EPRs), analysed by AI, and reintegrated into practice under clinician oversight.

Findings demonstrate that effective knowledge-sharing is central to overcoming current limitations in the integration of AI in mental health.

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Introduction

Mental health disorders are a growing global concern, exacerbated by the COVID-19 pandemic [1]. Rising rates of depression, suicide, substance misuse, and social isolation have increased the demand for diagnosis and treatment [2]. Yet, the field continues to face resource constraints and heavy clinician workloads.

Artificial Intelligence (AI) has demonstrated significant value in areas such as oncology, radiology, and dermatology by leveraging structured datasets [3-5]. However, psychiatry presents unique challenges due to its reliance on subjective patient reports and complex behavioral data. AI's effectiveness in mental health depends on clinician knowledge-sharing practices that can transform tacit insights into structured data.

The research gap lies in limited studies exploring knowledge-sharing among mental health practitioners as a foundation for AI applications [6]. Without improved knowledge-sharing, AI will remain underutilised in psychiatry, constrained by data scarcity [7]. This study addresses that gap, proposing a framework for embedding AI into existing clinical practices in mental health domain.

Literature Review

Understanding Knowledge-Sharing Approaches

The success of knowledge management initiatives depends on effective knowledge sharing [8]. In healthcare, the exchange of expertise among professionals improves motivation, service effectiveness, and productivity [9]. Clinical practice guidelines are derived from structured knowledge representation, enabling consistent approaches to diagnosis and treatment [5].

Highlight the importance of tapping tacit knowledge — subjective insights, intuition, and ideals — to generate organisational competitiveness. In mental health care, the lack of structured knowledge-sharing has limited the availability of data needed to support AI applications [10-13].

Artificial Intelligence and Its Role in Mental Health

AI is defined as computational technology (hardware and software) that imitates human intelligence to perform tasks [14]. Current applications in medicine rely heavily on structured imaging data, but psychiatry requires a deeper integration of clinician– patient narratives and behavioural information [15]. Limited data availability is the major bottleneck for mental health AI [7].

The sensitive nature of mental health data requires careful management, since diagnosis often depends on self-reporting and subjective assessments [16].. Studies in oncology, radiology, and dermatology demonstrate that structured knowledge sharing has enabled AI to deliver value [3-4]. However, in psychiatry, progress is hindered by fragmented records, heavy clinician workload, and ethical constraints such as GDPR [6].

Relationship between Data, Information and Knowledge

Data are factual records, while information emerges from contextualised data, and knowledge represents interpreted, actionable understanding [17]. In psychiatry, clinician–patient interactions produce rich tacit knowledge, which must be externalised for AI to learn and provide reliable support. Without structured knowledge-sharing, AI in mental health will remain underdeveloped [15].

Knowledge-Sharing Theoretical Argument

The SECI model [10], remains one of the most widely recognised frameworks for explaining how knowledge is created and transformed within organisations. It conceptualises knowledge creation as a dynamic cycle of four stages: socialisation, externalisation, combination, and internalisation (SECI).

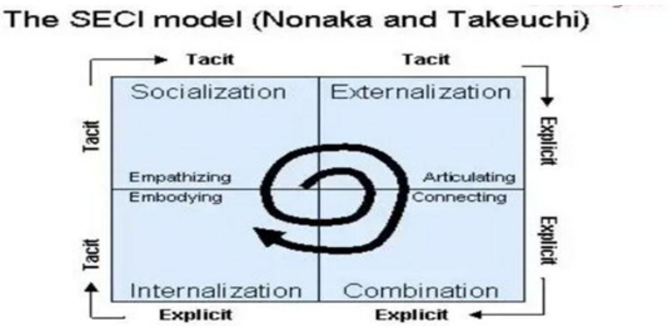

Figure 1: The SECI model (Nonaka and Takeuchi, 1GG5)

In the context of mental health care, these stages can be mapped as follows:

- **Socialisation:** Informal exchange of tacit insights among clinicians during ward rounds, clinical review meetings, or inter-professional discussions.
- **Externalisation:** Transformation of tacit insights into explicit documentation, such as structured clinical notes or patient records.
- **Combination:** Integration of these explicit records into broader systems such as Electronic Patient Records (EPRs) or shared databases, making knowledge available across disciplines.
- **Internalisation:** Re-absorption of explicit knowledge by practitioners, who apply stored insights in new cases, leading to refinement of practice.

While the SECI model was not specifically developed for healthcare — and even less so for mental health — its adaptability has enabled this research to use it as a lens for studying complex knowledge environments. What makes psychiatry distinctive is the highly tacit, context-dependent, and relational nature of its knowledge. Unlike imaging-based disciplines, where explicit data can be captured mechanically, mental health care depends on subjective dialogue and patient–clinician trust. This creates both challenges and opportunities for applying SECI.

This research extends Nonaka's theoretical foundation by showing how the SECI model can be operationalised in a setting where tacit knowledge dominates, but where AI can provide new possibilities for transformation. In particular, the externalisation and combination stages become crucial in psychiatry: converting clinicians' tacit observations into structured EPR entries and then aggregating these across practitioners and settings.

This creates the opening for the Knowledge-Sharing AI Model (KSAI-Model) proposed in this thesis. Whereas Nonaka described how knowledge cycles within organisations, the KSAI-Model integrates an additional layer: AI as both a knowledge-sharing facilitator and analytical partner. In effect, this study builds on SECI to demonstrate how tacit insights in mental health can move beyond individual clinical notes, through structured sharing, into a machine-augmented cycle of knowledge creation.

Thus, the relevance of Nonaka's framework lies not in its original design for mental health, but in its transferability and adaptability. By situating SECI within the psychiatric context, this research demonstrates how a classic organisational theory can underpin a novel, domain- specific model (the KSAI-Model) with practical implications for AI integration in mental health care.

Methodology

This study adopted a qualitative approach to explore how knowledge-sharing practices among mental health practitioners can enable data availability for AI integration. Both semi- structured interviews and surveys were conducted with five categories of professionals: psychiatrists, psychologists, care coordinators, occupational therapists, and mental health workers.

Participants

A total of 25 practitioners participated (five from each group). Participants were anonymised and coded (e.g., Psci-A1 for psychiatrists, Psco-A2 for psychologists).

Research Questions

- **RQ1:** What are the knowledge-sharing critical success factors for integrating AI into mental health care?
- **RQ2:** What are the challenges facing knowledge-sharing practices in mental health care?
- **RQ3:** Could AI contribute to the effectiveness of mental health care?

Data Collection

Interviews and surveys were designed to capture both tacit and explicit perspectives. Responses were categorized, coded, and analysed for recurring themes.

Data Analysis

Analysis revealed patterns in practitioners' responses to RQ1–RQ3.

Appendix A1: Tables

Table 1: Psychiatrist Responses (Q1–Q3)

ID	**Q1**	**Q2**	**Q3**
Psci-A1	70%	80%	45%
Psci-B1	60%	100%	60%
Psci-C1	70%	100%	55%
Psci-D1	60%	100%	60%
Psci-E1	55%	80%	40%

Table A2: Psychologist Responses (Q1–Q3)

ID	**Q1**	**Q2**	**Q3**
Psco-A2	65%	80%	60%
Psco-B2	45%	100%	50%
Psco-C2	60%	90%	55%
Psco-D2	40%	90%	60%
Psco-E2	65%	100%	40%

Table A3: Care Coordinator Responses (Q1–Q3)

ID	**Q1**	**Q2**	**Q3**
CC-A3	45%	100%	60%
CC-B3	75%	100%	50%
CC-C3	65%	100%	45%
CC-D3	45%	90%	60%
CC-E3	50%	90%	55%

Table A4: Occupational Therapist Responses (Q1–Q3)

ID	**Q1**	**Q2**	**Q3**
OT-A4	60%	100%	55%
OT-B4	70%	90%	60%
OT-C4	60%	90%	55%
OT-D4	45%	90%	45%
OT-E4	55%	80%	70%

Table A5: Mental Health Worker Responses (Q1–Q3)

ID	Q1	Q2	Q3
MHW-A5	50%	70%	40%
MHW-B5	60%	70%	45%
MHW-C5	40%	85%	50%
MHW-D5	45%	80%	45%
MHW-E5	50%	75%	50%

Findings per Research Question

- RQ1 (Critical Success Factors): Limited practitioners' awareness of AI highlighted the need for training and awareness-building.
- RQ2 (Challenges): Four barriers were common: time constraints, digital barriers, resistance to change, and GDPR/legal concerns.
- RQ3 (AI Contributions): Participants agreed AI could enhance quality of life, improve communication, support independence, and enable earlier interventions if supported by structured clinician knowledge-sharing.

Findings and Discussion

Current Knowledge-Sharing Practices

Clinical review meetings remain the central mechanism for decision-making in mental health care. Practitioners share observations and determine treatment pathways by reviewing Electronic Patient Records (EPRs). However, the EPR system currently functions only as a repository of information rather than an intelligent support tool. Entries on medication, behavioural patterns, risk assessments, and treatment plans are logged manually and later reviewed during meetings.

Outside of these meetings, professionals often rely on email exchanges to share information, a method prone to fragmentation and delays. Consequently, communication lacks integration and timeliness, undermining opportunities for early intervention.

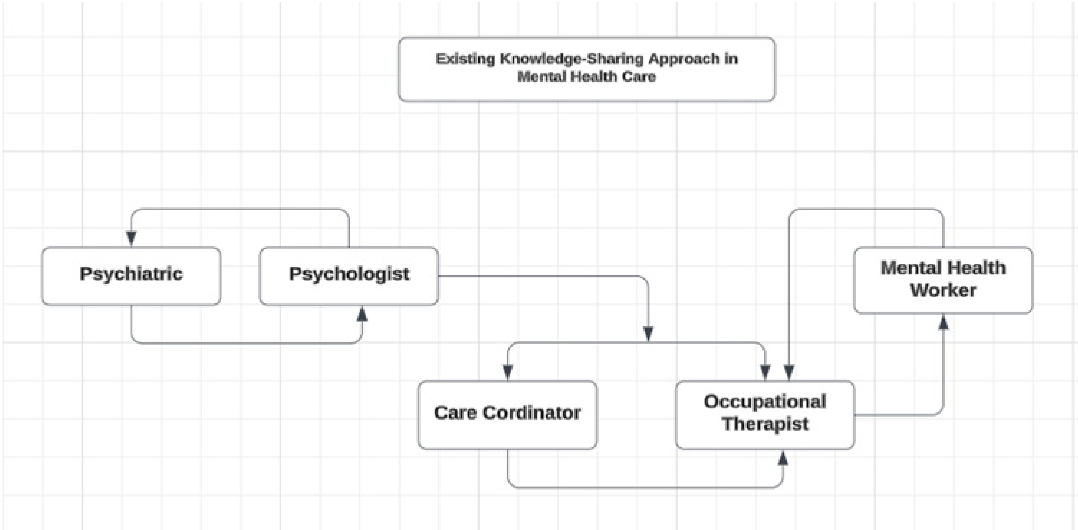

Figure 2: Existing Knowledge-Sharing Approach in Mental Health Care

[EPR entries + fragmented email communications → manual clinician review meetings → treatment decisions.]

These findings confirm existing literature, which notes that psychiatry is constrained by fragmented knowledge flows and inconsistent data structures [15,6]. Unlike radiology or oncology, where imaging data can be codified and shared easily, psychiatry relies heavily on tacit insights that remain underutilized when confined to clinician notes.

Identified Gaps

The data analysis revealed recurring themes in the challenges facing knowledge-sharing in mental health care:

- **Time Constraints:** Heavy workloads limit opportunities for thorough collaboration.
- **Digital Barriers:** Many practitioners struggle to keep pace with rapid technological changes.
- **Resistance to Change:** Some professionals remain sceptical of innovations that alter established workflows.
- **Ethical and Legal Concerns:** Fears of GDPR violations and confidentiality breaches discourage proactive data sharing.

These barriers confirm that while practitioners recognise AI's potential to enhance communication, independence, and early detection, current systems cannot deliver without more robust knowledge-sharing mechanisms.

Extending the SECI Framework to Psychiatry

To conceptualise a way forward, this study applied the SECI model [10], which describes knowledge creation through socialisation, externalisation, combination, and internalisation (SECI).

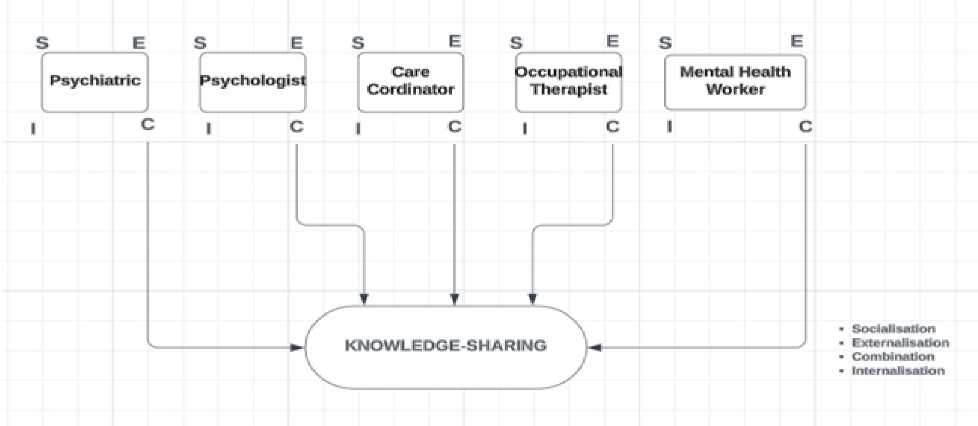

Figure 3: [Preliminary Knowledge-Sharing AI Model (KSAI-Model) from existing SECI-Model]

In psychiatry:

- Socialisation occurs when clinicians informally share tacit insights during case discussions.
- Externalisation involves documenting these insights in structured formats (e.g., EPR entries).
- Combination integrates these records across departments and disciplines.
- Internalisation allows clinicians to absorb new insights and apply them to future cases.

While not originally developed for healthcare, SECI provides a useful lens for understanding how tacit knowledge might flow into explicit data in psychiatry. Yet, psychiatry's reliance on subjective, relational knowledge exposes limitations in SECI's direct application.

Proposed Knowledge-Sharing AI Model (KSAI-Model)

The KSAI-Model builds on SECI while introducing AI analytics into the cycle of knowledge creation. Clinician insights (tacit) are externalised through structured EPR entries, aggregated across practitioners, and analysed by AI systems to detect behavioural patterns, flag risks, and recommend interventions. These outputs are then reintegrated into clinical practice under professional oversight.

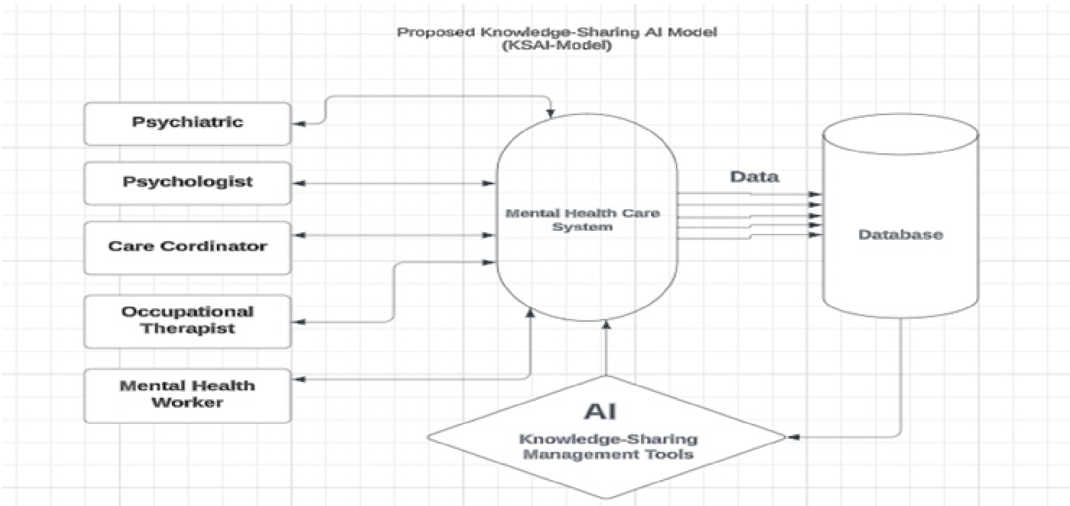

Figure 4: (Proposed) Knowledge-Sharing AI Model (KSAI-Model)

[Tacit clinician knowledge → externalised in EPR → aggregated database → AI analytics → recommendations → clinician validation → reintegration into practice.]

By embedding AI into the knowledge-sharing process, the KSAI-Model addresses the gaps of fragmented communication and underutilised tacit insights. It demonstrates how psychiatry can evolve towards precision care without compromising ethical standards or human expertise.

Table 1: Comparison of SECI Model and KSAI-Model in Mental Health Care

Dimension	Nonaka's SECI Model (1995)	Proposed KSAI-Model (this research)
Origin/ Purpose	Developed for knowledge creation in organisations, primarily in business and manufacturing.	Adapted to mental health care to support AI integration through structured knowledge-sharing.
Knowledge Type	Focuses on tacit and explicit knowledge transformation	Emphasises tacit clinical insights (patient–clinician narratives) externalised into structured datasets usable by AI.
Knowledge Type	Tacit-to-tacit sharing through informal interaction.	Clinician collaboration in clinical reviews, ward discussions, and multidisciplinary team meetings.
Externalisation	Tntegration of explicit knowledge across departments or databases.	Clinician observations documented in Electronic Patient Records (EPRs), structured for consistency.
Combination	Integration of explicit knowledge across departments or databases.	Aggregation of structured EPR data across practitioners, enhanced with AI analytics for pattern detection
Internalisation	Explicit knowledge absorbed back into tacit knowledge through practice.	AI-supported recommendations reabsorbed into clinical judgment; practitioners validate and apply insights in new cases.
Role of Technology	Technology provides storage and communication but is not central.	AI acts as a co-creator of knowledge: analysing aggregated data, flagging patterns, and enhancing decision-making.
Outcome	Continuous cycle of knowledge creation within organisations.	A hybrid human–machine cycle that enables early detection, personalized enables early detection, personalised

Expanding SECI into KSAI

The comparison highlights how this research extends Nonaka's framework. Whereas SECI provides a conceptual entry point, the KSAI-Model operationalises it in a domain where tacit, context-rich knowledge is dominant and ethically sensitive.

The KSAI-Model advances SECI in four ways:

- **Domain-specific adaptation:** Demonstrates SECI's relevance in psychiatry by formalising tacit insights into structured data.
- **AI as active partner:** Recasts "combination" as a human–machine interaction, where AI analyses aggregated clinician data.

- **Bridging gaps:** Addresses the challenge that codification alone cannot solve fragmentation; AI provides cross-case synthesis.
- **Ethical safeguards:** Keeps clinicians as ultimate decision-makers, ensuring AI supports rather than replaces human judgment.

Thus, the KSAI-Model is not a departure from SECI but a contextual expansion. It introduces AI into the knowledge creation cycle, creating a hybrid model of human and machine intelligence that is both theoretically grounded and practically applicable to psychiatry.

Contribution to Knowledge

This research contributes to both theory and practice in three keyways:

Theoretical Advancement

- Extends [10] into a domain where knowledge is predominantly tacit, subjective, and ethically sensitive.
- Demonstrates that the SECI cycle can be enriched by integrating Artificial Intelligence as an active partner in knowledge creation, transforming "combination" into a human–machine collaboration.

Practical Innovation

- Proposes the Knowledge-Sharing AI Model (KSAI-Model) as a structured framework for embedding AI into psychiatric practice without displacing clinician expertise.
- Provides a roadmap for capturing tacit clinician insights, externalising them through structured EPR systems, and leveraging AI analytics for early diagnosis and personalised care.

Policy and Organisational Implications:

- Highlights the barriers (time constraints, digital gaps, resistance to change, and GDPR concerns) that must be addressed for AI adoption in psychiatry.
- Offers evidence-based recommendations for designing systems that enhance knowledge-sharing while safeguarding patient confidentiality and professional judgment.

Through these contributions, the study establishes a bridge between knowledge management theory and mental health practice, creating new opportunities for AI-enabled care while maintaining ethical and human-centred principles.

Recommendations

Based on the findings of this research, several recommendations are proposed for practitioners, organisations, and policymakers to enable effective integration of Artificial Intelligence in mental health care through strengthened knowledge-sharing practices:

Enhance Clinician Training and Awareness

- Provide targeted training programmes to increase practitioners' understanding of AI and its role in psychiatry.
- Raise awareness of how tacit knowledge, when externalised and structured, can become valuable data for AI systems.

Standardise Documentation Practices

- Develop consistent templates and protocols for Electronic Patient Records (EPRs) to facilitate the transformation of tacit insights into explicit, analysable formats.
- Encourage multidisciplinary teams to adopt uniform documentation standards, reducing fragmentation across services.

Invest in AI-Enabled Knowledge Systems

- Upgrade current EPR platforms to incorporate AI functionalities capable of detecting behavioural patterns, generating alerts, and supporting personalised treatment pathways.
- Ensure interoperability across healthcare systems to enable seamless aggregation of mental health data.

Foster a Culture of Knowledge-Sharing

- Create organisational incentives for collaboration, such as protected time for multidisciplinary review meetings.
- Encourage open dialogue between practitioners, reducing resistance to change and highlighting the value of shared learning.

Address Ethical and Legal Concerns

- Implement strict data governance policies to comply with GDPR and safeguard patient confidentiality.
- Design AI systems that enhance transparency, allowing clinicians to trace how recommendations are generated.

Embed Human Oversight as Standard

- Maintain clinicians as the final arbiters of treatment decisions, ensuring AI remains a supportive tool rather than a replacement for professional judgment.
- Position AI outputs as aids to reflection and decision-making, rather than as prescriptive directives.

By adopting these recommendations, mental health care systems can overcome current barriers to knowledge-sharing, strengthen data foundations, and safely harness the transformative potential of AI while protecting patient trust and clinician expertise.

Conclusion

Artificial Intelligence has shown transformative potential in several areas of healthcare, particularly those with well-structured datasets such as oncology, radiology, and dermatology. Psychiatry, however, has lagged behind because of its dependence on tacit knowledge, subjective reporting, and complex patient–clinician interactions.

This research confirms that limited knowledge-sharing among mental health practitioners has constrained data availability, leaving AI underutilised in psychiatry. By applying [10] as a theoretical lens, this study demonstrates that tacit insights in psychiatry can be externalised, combined, and reinternalised in ways that make them usable for AI systems. Yet, while SECI provides a useful conceptual framework, it was not designed for domains like psychiatry where knowledge is deeply contextual, relational, and ethically sensitive.

The originality of this research lies in its development of the Knowledge-Sharing AI Model (KSAI-Model). Building on SECI, the KSAI-Model introduces AI as an active participant in the knowledge cycle: aggregating clinician inputs, detecting patterns, and generating recommendations, while clinicians retain the ultimate authority to validate or reject AI outputs. This represents a domain-specific expansion of SECI, bridging knowledge management theory with practical challenges in mental health care.

The study concludes that effective AI integration in psychiatry requires three conditions:

- Strengthened knowledge-sharing practices among practitioners to make tacit knowledge more explicit.
- AI-enabled aggregation and analysis, addressing data fragmentation and unlocking new insights.
- Human-centred oversight, ensuring that ethical, legal, and relational concerns remain at the forefront.

In doing so, the KSAI-Model provides a theoretical contribution by adapting the SECI framework to the unique challenges of psychiatry, where tacit knowledge dominates and ethical constraints limit data sharing.

At the same time, it offers a practical roadmap for the safe and effective adoption of AI in mental health care.

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