








THE DATA POWERING AI SOLUTIONS IN MENTAL HEALTH

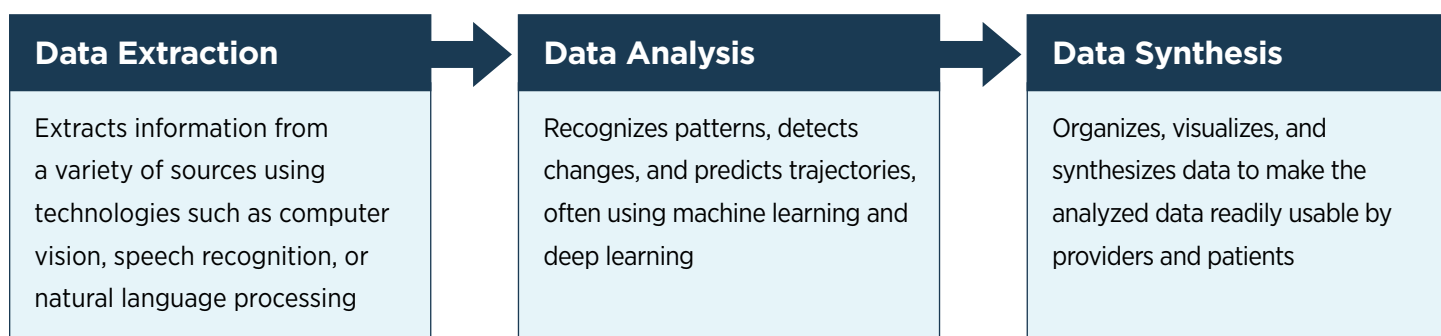
AI technologies hold the potential to transform many aspects of mental health care. Across use cases – from screening and diagnosis to monitoring and treatment – the transformative power of AI derives from its ability to leverage massive amounts of data from multiple sources and make it more actionable. In doing so, AI can identify meaningful patterns and generate insights to support better decision-making for clinicians and patients.^{1,2} This means earlier detection of mental illness, enhanced quality of care, better medication management, improvements in treatment adherence, improved care coordination, and ultimately, improved outcomes, reduced costs, and less suffering.

The Data Underpinning AI Tools in Mental Health Care

One of the most promising aspects of leveraging AI is the potential to create a more complete treatment picture by pulling in data from a variety of sources. AI technologies can analyze data from sources inside and outside the health care setting to generate meaningful insights, many of which are not currently being used, including:³

Source		Data Extracted
	Electronic health records	Data on prescriptions, refills, procedures, appointments, admissions, observations, patient reported symptom assessments, and laboratory results ⁴
	Wearables and smartphones	Multimodal sensing data (such as sleep patterns, physical activity, heart rate, and smartphone usage) to support real-world monitoring ⁵
	Audio, text, and video	Voice data to capture acoustic and speech patterns or facial expression data to analyze visible emotional cues and psychomotor indicators that may indicate psychiatric symptoms and symptom severity ^{6,7}
	Clinical notes and patient-generated text	Unstructured data (such as therapy notes, clinical observations, secure messaging, or patient journals) to detect changes in cognition, affect, or functioning and identify emerging risk signals ⁸
	ECG or heart rate monitor	Heart rhythm and electrical activity to assess physiological responses associated with stress, anxiety, and depression ⁹
	Brain images	Neurophysiological data to identify biomarkers and neurocognitive profiles of mental conditions ¹⁰
	Laboratory tests	Physiological data from laboratory tests to analyze biological markers (such as genetic expression and metabolic indicators) associated with mental health conditions ¹¹

AI uses multiple technologies to extract, analyze, and synthesize data from these sources, transforming raw data into meaningful insights and organizing them so clinicians and patients can easily put them into action.



While technologies and their evidence-bases are constantly evolving, the insights from these data can be employed across a range of mental health care settings to help identify, diagnose, monitor, and treat mental health conditions. By unlocking these new sources of data, mental health care has the potential to reach the level of precision already common in other areas of medicine, delivering more personalized care and better outcomes.¹²

Responsible Use Considerations for Data in AI Mental Health Technologies

The Meadows Institute supports the responsible use of AI in mental health care. While many safeguards and governance practices are necessary to ensure AI is used ethically and effectively, some considerations that are particularly important when evaluating the **data that underpin these technologies** include:

Datasets as the building blocks of AI: Ensuring that AI applications are developed and tested using robust, clinically grounded, high-quality datasets is foundational to developing effective and ethical tools. Datasets must be representative across care settings, mental health conditions, demographics, languages, and uses.¹³

Real-world application research: Although current evidence for AI’s performance in research settings is promising, additional longitudinal, real-world trials are needed to assess utility, sustainability, and fairness when new data streams (such as voice analysis and multimodal sensing) are used in routine clinical practice.¹⁴

Privacy and security: As with all health care technology, strong privacy and cybersecurity protections must be in place to safeguard sensitive information. Additional precautions are necessary when handling sensitive biometric data.¹⁵

¹Koutsouleris et al. (2022). [https://doi.org/10.1016/S2589-7500\(22\)00153-4](https://doi.org/10.1016/S2589-7500(22)00153-4). ²Stade et al. (2024). <https://doi.org/10.1038/s44184-024-00056-z>. ³Baydili et al. (2025). <https://doi.org/10.3390/diagnostics15040434>. ⁴Koutsouleris et al. (2022). [https://doi.org/10.1016/S2589-7500\(22\)00153-4](https://doi.org/10.1016/S2589-7500(22)00153-4). ⁵Hau et al. (2025). <https://doi.org/10.1016/j.schres.2025.05.019>. ⁶Muddaloor et al. (2025). <https://doi.org/10.3390/s25113424>. ⁷Ramanarayanan (2024). https://doi.org/10.1044/2024_JSLHR-24-00142. ⁸Kim et al. (2025). <https://doi.org/10.1007/s40501-025-00359-8>. ⁹Linardon & Torous. (2025). <https://doi.org/10.1002/eat.24468>. ¹⁰Lee et al. (2021). <https://doi.org/10.1016/j.bpsc.2021.02.001>. ¹¹Baydili et al. (2025). <https://doi.org/10.3390/diagnostics15040434>. ¹²Le Tourneau, and Bièche. (2018). <https://doi.org/10.2217/pme-2018-0036>. ¹³Mandal et al. (2025). <https://doi.org/10.48550/arXiv.2508.09809>. ¹⁴Nilsen et al. (2022). <https://doi.org/10.1177/26334895221112033>. ¹⁵Magee, M. & Farahany (2024). <https://doi.org/10.1016/j.neuron.2024.09.004>