INVITED EDITORIAL

With data in mind: AI applications in depression, autism and dementia care

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Abstract

Mental health is essential for overall wellbeing, enabling individuals to cope with daily challenges and participate fully in society. Globally, nearly one billion people are affected by mental health conditions, including rising rates of depression, anxiety, autism, and dementia. In countries like Aotearoa New Zealand, approximately 26% of the population experiences poor mental wellbeing. However, traditional approaches to diagnosis and treatment often fall short due to limited resources and access to care, prompting a shift toward digital health solutions. This editorial explores how big data and artificial intelligence (AI) are transforming mental health research and care. These technologies offer new possibilities for early detection, scalable interventions, and personalised support addressing gaps in existing systems. We highlight key use cases across depression, autism, and dementia, where AI-driven tools are already showing promise in screening and supporting decision-making. We also examine AI applications in detecting depression, autism, and dementia, and the role of chatbot-based tools. The editorial also explores key challenges such as ethical concerns, data bias, and integration into healthcare systems, highlighting the need for responsible and inclusive AI development.

Article

Mental health is a crucial part of an individual's wellbeing. It enables people to function effectively, cope with life's challenges, and contribute meaningfully to their relationships and communities. The World Health Organization (WHO) reports that around one billion people globally are affected by mental health conditions.[1] A recent update by Statistics New Zealand indicates that 26% of the Aotearoa New Zealand population experience poor mental wellbeing, with prominent conditions including depression, anxiety, autism spectrum disorder, and dementia.[2] Moreover, according to the New Zealand Health Survey, 10.7% of adults had an unmet need for professional support for their mental health issues. Although there is a growing need for early detection and timely intervention to tackle the rise in mental health needs, the clinical approaches adopted are constrained by several limitations, including access to mental health services and a shortage of mental health professionals.[4,5]

The burden of mental illness is rising globally, and current diagnostic and treatment approaches are unable to keep pace. As a result, researchers and clinicians are adopting digital health solutions incorporating artificial intelligence (AI) to address this gap, particularly in the early detection of mental health disorders.[6] This editorial summarises how these technologies could potentially reshape the mental health field and explores relevant use cases in the detection of depression, autism, and dementia detection.

Mental health insights through big data and AI

Advancements in information technology and data management have positioned 'big data' as a transformative concept in research. It refers to large, complex datasets that exceed the capabilities of traditional data processing methods.[7] It is typically defined by the five Vs: volume (size), velocity (speed of generation), variety (types), veracity (trustworthiness), and value (quality). In digital mental health research, big data can be sourced from various domains, including electronic health records (EHRs), neuroimaging, genomic data, mobile sensor data, and social media platforms.[8,9]

The expansion of the use of wearable devices and mobile health applications has further enabled the collection of active (user-reported) and passive (sensor-based) data, supporting more ecologically valid and continuous mental health monitoring in real world settings.[10] Projects such as Remote Assessment of Disease and Relapse – Central Nervous System (RADAR-CNS) have demonstrated the clinical usage of these applications by collecting continuous data from individuals with major depressive disorder, epilepsy, and multiple sclerosis.[11] Social media and online forums have also become valuable data sources for mental health research. Researchers have demonstrated the correlations between the linguistic and sentiment patterns in posts shared on social media and depression severity or suicide risk.[12] Public data repositories such as the UK Biobank and ENIGMA Consortium offer extensive health, genetic, and imaging datasets that have significantly advanced health research, including mental health.[13,14,15] The Integrated Data Infrastructure (IDI) serves a similar function in Aotearoa New Zealand.[16] Administered by Statistics New Zealand, the IDI links anonymised data from health, education, justice, and social sectors, enabling cross-disciplinary mental health research tailored to the Aotearoa New Zealand context.

Analysing these data resources, however, poses challenges in terms of storage and processing. AI techniques, particularly machine learning (ML) and deep learning (DL), have been adopted in processing this data, enabling researchers to identify hidden and complex patterns. AI has also facilitated the development of digital phenotyping tools that combine speech, facial expressions, and physiological data to predict mental health status.[17] These multimodal systems provide a more holistic understanding of patients and enable predictive modelling for diagnosis and treatment outcomes.[18] For instance, behavioural indicators such as eye gaze, facial expressions, vocal tone, and language use are increasingly utilised in the diagnosis of autism. These indicators can be extracted from audio-visual and text-based data, including clinical notes, questionnaires, and caregiver reports.[19] Similarly, in dementia research, DL models have successfully detected early cognitive decline by analysing significant changes in language, memory recall, and speech patterns.[20]

Although different data sources are available, acquiring high-quality, balanced, and large labelled data (data scarcity) remains a critical bottleneck, particularly when building robust and generalisable AI models in mental health. As a result, AI researchers frequently rely on small or synthetic datasets, which may limit the clinical applicability of the developed models.[21] Additionally, these datasets often contain a higher proportion of positive cases than negative cases, leading to class imbalance and potential bias in model training and evaluation. Thus, researchers, including our team, have attempted to tackle these data issues, focusing on improving data quality, balancing data samples, data augmentation, and synthetic data generation. Together, big data and AI are not only reshaping how mental health is studied and understood, but also redefining how we detect, monitor, and ultimately care for individuals across a spectrum of psychiatric, neurodevelopmental, and neurodegenerative conditions.

Use cases

Our research builds on global efforts by developing novel AI tools for detecting mental health conditions. We specifically focus on depression, autism, and dementia and attempt to adopt different AI architectures to build the gap between technology and healthcare, while unveiling algorithmic biases, enhancing accessibility, efficiency, and generalisability in the mental health domain. Thus, our primary focus is on developing such systems to effectively manage limited data while achieving high early detection accuracy.

Use case 1: autism-AI

Worldwide, the diagnosis of autism is often delayed, despite symptoms typically appearing before the age of two.[22,23] Early diagnosis is critical, yet many individuals remain undiagnosed due to the absence of a standard diagnostic test.[24] Current clinical methods are time-consuming, subjective, and lack scalability.[25] In Aotearoa New Zealand, the average age of diagnosis is 6–7 years, with even greater delays and disparities affecting Māori and Pasifika children.[26,27] While AI holds promise for improving autism screening, it still faces challenges such as data scarcity, class imbalance, and algorithmic bias.[28,29] Datasets often contain more autistic than non-autistic samples, amplifying these issues. Addressing these challenges by integrating behavioural indicators from standardised assessment tools aims to overcome data scarcity and algorithmic bias by leveraging labelled and unlabelled data to develop a robust and scalable autism assessment tool. For example, the Autism AI dataset is one of the largest available, containing over 13,000 samples collected since 2018.[30] However, the dataset is imbalanced, with more autistic than non-autistic samples, and contains limited labelled data. Autism AI is a multi-stage screening tool designed to identify autistic traits in children as young as 18 months.[31] The system is designed to adapt and improve over time for different ages, genders, and cultural backgrounds. Using this dataset, we are developing an integrated ensemble model that combines insights from three AI modules: Screening AI, Diagnosis AI, and Correlation AI. Screening AI helps to screen for early signs of autism by scoring behavioural characteristics, replacing traditional scoring methods. It is built upon traditional tools, such as the AQ-10[32] and Q-CHAT10[33], developed by the University of Cambridge. Already available both online and on Android platforms, this module has successfully collected behavioural data from individuals aged 18 months and older. The second module, Diagnosis AI, builds on that information to make diagnostic suggestions. The third, Correlation AI, adopts AI approaches that learn from mathematical data similarity to further enhance early autism assessments. Correlation AI processes the unlabeled autism data samples through multiple DL algorithms, each generating distinct feature spaces and corresponding label sets.

After building the initial models, we will analyse the patterns to identify which behavioural aspects need adjustment. Based on this analysis, we will refine the screening questions capturing autistic characteristics to ensure they are inclusive and effective. By working closely with families, health professionals, and community members, we will ensure the system will be easy to use, culturally appropriate, and helpful. The system will provide accurate, data-informed autism screening for diverse users, and an open trial will follow to further assess its effectiveness. Integrating AI-powered autism screening into existing healthcare workflows can improve detection from as early as 18 months by optimising clinical resources and supporting both healthcare providers and families with AI-assisted assessment tools.

Use case 2: AI-powered depression detection

Depression can result in impaired social and occupational functioning or, in the worst-case scenario, suicide.[34,35] Furthermore, it has a major impact on the economy.[36] Thus, early detection becomes critical in helping to understand depression better and provide patients with better care.

Although effective screening is critical for improving the outcomes of people with depression, it remains challenging due to the social stigma, the limited access to mental health services, and the shortage of medical practitioners to meet the demand.[37,38] Therefore, it is important to have a system that can potentially fill this gap while providing efficient, easily accessible, privacy-protected, and scalable detection of depression. AI-based early depression detection tools associated with smartphones and telehealth platforms are easily accessible and can help screen individuals actively and passively, reducing the limitations as mentioned above. By providing a private, accessible entry point to mental health support, such technologies have the potential to overcome the shortage of medical practitioners and individual stigma. Accordingly, AI-based systems enable early detection before symptoms become more severe.

Privacy concerns lead to limitations in sensitive data collection, making it difficult to gather large, diverse datasets with annotated labels for depression detection. This is reflected in the imbalance of data, even in widely used datasets such as DAIC-WOZ[39] and Extended Distress Analysis Interview Corpus (E-DAIC),[21] which contain a comparatively high number of non-depressed participants compared to depressed. Furthermore, while speech data can be relatively easy to capture, it can also easily be impacted by environmental noise. This significantly hinders the accuracy of depression detection systems.

To address this data challenge, we developed an advanced AI-based depression detection system leveraging limited data. This approach utilised speech data focusing on both linguistic and acoustic cues associated with depression for enhanced detection. Our research leverages two datasets, the E-DAIC and the MoodAI dataset, to evaluate the applicability of AI-based systems in depression detection with limited data.[21,40,41] We collected the MoodAI dataset as a part of a longitudinal observational study designed to analyse mood variations in healthy and depressed individuals in the Aotearoa New Zealand context.[42] The data collection process is still ongoing with the study. However, preliminary experiments were conducted with the E-DAIC dataset to develop a robust speech-based model by addressing data size, quality, and imbalance challenges. The developed depression detection system based on the E-DAIC dataset achieved promising results in depression detection with limited data, showcasing the potential applicability in the area. Future experiments will focus mainly on adopting our MoodAI dataset in the developed depression detection system while enhancing generalisability.

Use case 3: AI-powered dementia detection

Dementia is a growing challenge for individuals, families, and healthcare systems worldwide.[43] Early and timely diagnosis has emerged as a critical step in managing the condition more effectively. Detecting dementia at earlier stages could delay disease progression, improve quality of life, and reduce healthcare costs. Despite these benefits, many individuals receive late diagnosis due to limited access to specialists and the complexity of current diagnostic tools. This is where AI-based tools provide promising support in detecting early cognitive decline using speech-based ML models, however; large, high-quality datasets that are not always available in dementia research for these systems to be effective. Data sensitivity and privacy issues often limit the availability of large-scale audio corpora for model training.

Our research in AI-powered early identification of dementia leverages Pitt Corpus speech data available through the DementiaBank repository.[44] While this corpus is among the most widely used datasets for speech-based dementia detection, it remains relatively small in scale, comprising 388 samples and approximately 643 minutes of transcribed speech from participants diagnosed as Alzheimer's disease (AD), mild cognitive impairment (MCI), and healthy control (HC). MCI is an early stage of dementia, characterised by cognitive decline, particularly in memory and language. However, this decline is greater than expected for age but not severe enough to significantly impair daily functioning. Additionally, the dataset contains inherent imbalances across diagnostic categories, complicating model training and generalisability.

To address these limitations, standard data augmentation techniques can be applied during data preprocessing. Generating variations in speech samples by changes made in frequency and time, while ensuring the linguistic and contextual integrity is preserved, can help augment the limited data.[45] This can lead to an increase in the diversity of training data and improve the model's robustness to real-world variations.

Building on this enhanced dataset, we are designing a multimodal dementia detection framework that integrates audio and text modalities.[46] Transcripts of participant speech are used alongside audio features to capture linguistic and acoustic cues. This combination allows the AI algorithm to maintain strong performance while remaining well-suited to data-scarce dementia detection tasks.

This approach allows us to create a reliable and flexible system for detecting dementia, even when labelled data is scarce. Most importantly, by using speech data, our work helps make dementia screening more accessible.

Use case 4: chatbots and interventions

Some people may be more comfortable communicating openly with a machine than with a human, because they are less afraid of being judged and less worried about making a good impression.[47] Chatbots are an emerging technology that engages in human-like conversations. Chatbots have a history tied to psychology, with ELIZA (1966) being the first notable example of a therapist.[48] Modern therapeutic chatbots, like Woebot, Wysa, Tess, Voice-based Conversational Agents for Autism, and A-CONECT help manage conditions such as depression, autism, and dementia, and studies have shown positive user satisfaction and preliminary efficacy.[49,50,51,52,53]

These chatbots provide benefits such as 24/7 availability, reduced stigma, and scalability for those lacking access to mental health services; however, they are not intended to replace human therapists. Moreover, the recent development of large language models (LLMs), which researchers trained on vast datasets sourced from the internet, has significantly expanded the capabilities and scope of chatbots. LLMs have enhanced these systems' conversational abilities, contextual understanding, and knowledge base, making them more promising in mental health support contexts.

ChatGPT is one of the most popular chatbots currently, and researchers have begun exploring it in mental health contexts. Studies have shown that ChatGPT has an excellent "theory of mind," which is the origin of cognitive empathy and performs well in sentiment analysis.[54,55] However, its usage in clinical mental health support remains a research area in progress. Although conversational agents like ChatGPT provide a potential support as a good listener, ongoing research and evaluation are needed to determine their safe and appropriate roles in mental healthcare.

As such, these systems are not yet ready to perform in the clinical context but can be used to support individuals with mild symptoms by serving as empathetic listeners. This approach enables individuals to have a 24/7 available support system, which traditional approaches with limited resources find hard to provide. Mental health professionals envision the safest operational mode where they supervise using AI systems as assistants in providing patient care.

Challenges and future directions

Despite the potential effectiveness of these tools, other challenges still exist in addition to challenges related to data availability and bias. For example, explainability is the ability of AI systems to provide transparent, interpretable reasoning behind their predictions or classifications.[56] The ability to explain how AI predicts or assesses individuals can be very useful, especially in mental health, where diagnostic decisions can result in personal and clinical consequences. Using unclear, "black box" models may damage trust among clinicians, patients, and policymakers, leading to hesitation in clinical adoption.

Moreover, deploying AI-based systems in such sensitive domains raises pressing concerns about ethical responsibility. The consent issues, bias in training data, unequal model performance across demographic groups, and the risk of unintended harm are concerns needing careful consideration. Ethical frameworks and guidelines for responsible AI use is necessary to ensure that these technologies enhance equity and safety in mental healthcare.[57]

Regulations can also be overly restrictive. There seems to be a bias against AI due to the lack of knowledge of what AI is and how it operates. This bias can influence policymakers, leading to unnecessarily restrictive regulations and policies for AI development and adoption. Unrealistic standards and expectations can drive away AI scientists, engineers, and investors, which is a significant risk for Aotearoa New Zealand. The current international trend seems to be excessive regulations compared to other technologies.

Moreover, healthcare regulatory bodies may not include experts with cutting-edge, practical AI expertise who can distinguish between what is realistic about AI and its risks. While regulation for AI, especially when it is used in the mental health domain, is vital to ensure AI development and usage are ethical and responsible, overly restrictive policies could hinder the development of beneficial AI systems. To avoid these outcomes, policymakers must strike a balance, encouraging the growth of good AI while preventing harmful developments.

Conclusion

AI and Big Data are revolutionising mental healthcare by offering opportunities for early detection, personalised treatment, and continuous monitoring. These technologies enable more effective and scalable mental health solutions by utilising diverse data sources. Despite available data sources, mental healthcare still faces data scarcity due to its sensitive nature, highlighting the need for ethical, robust AI systems that can effectively leverage limited data.

The use cases described here contribute to this growing field by developing practical, AI-driven tools for detecting conditions such as depression, autism, and dementia by specifically addressing data scarcity issues. Combining different aspects of speech and behavioural data, these models aim to support clinicians with more accurate and timely insights, especially in digital or remote care settings.

These advancements are particularly valuable in resource-constrained or underserved environments where traditional mental health services remain difficult to access. In such contexts, digital mental health innovations can be scalable, cost-effective tools for existing care pathways. However, using these technologies must be balanced with ethical, transparent, and inclusive design. Challenges such as algorithmic bias, explainability, and data sovereignty must be addressed through meaningful interdisciplinary collaboration. Thus, future research must focus on developing AI-based systems that are safe, effective, ethically responsible, accessible, equitable, cost-effective, and contextually appropriate for application within the mental health domain.

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