Mental Health Commission of Canada
Commission de la santé mentale du Canada

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CADTH Health Technology Review

Artificial Intelligence and Machine Learning in Mental Health Services: An Environmental Scan

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Environmental Scan

Mental Health Commission of Canada
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CADTH

This environmental scan was commissioned by The Mental Health Commission of Canada to address the role of AI in mental health services. This report is a companion to a Rapid Response review on clinical effectiveness and guidelines for AI in mental health [Artificial Intelligence and Machine Learning in Mental Health Services: A Literature Review. Ottawa: Canadian Agency for Drugs and Technology in Health (CADTH), Mental Health Commission of Canada (MHCC); 2021 June.]

Authors: Charlotte Wells, Shannon Hill, Charlene Argaez

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Abbreviations

AI	artificial intelligence
A4I	App for Independence
CAT	computerized adaptive testing
CBT	cognitive behavioural therapy
COSC	combat and operational stress control
DSM	Diagnostic and Statistical Manual
fMRI	functional magnetic resonance imaging
LGBTQ2+	lesbian, gay, bisexual, transgender, queer or questioning, and two-spirited
MDD	major depression disorder
ML	machine learning
MRI	magnetic resonance imaging
NLP	natural language processing
PTSD	post-traumatic stress disorder
SVM	support vector machine
USC ICT	University of Southern California Institute for Creative Technologies

Summary

- There has been an increase in investment, funding, and interest in the use of artificial intelligence (AI) in the mental health area, especially over the past five years. The types of AI in use for mental health problems and illnesses include neural networks, support vector machines, logistic regression, linear discriminant analysis, and random forests.
- Currently, the use of AI for mental health is limited in a clinical environment. Consultations revealed that the majority of AI applications are in research and development and have not been expanded to clinical or patient use. The applications of AI in mental health include conversational agents, computerized adaptive testing, diagnosis of mental health conditions, prediction of behaviour, and prediction of prognostic outcomes in treatment.
- The professions currently using and researching AI are primarily researchers in the fields of psychology and computer science. There are limited AI applications available commercially, but some AI applications, such as chatbots, are available for the general public through mobile application stores such as Apple and Google Play.
- Four key domains of research and development in the use of AI for mental health are diagnosis, prognosis, public health, and clinical administration; most of the identified research is in the area of diagnosis.
- Research and development initiatives for mental health diagnosis using AI include the use of biomarkers, neuroimaging, genetics, metabolomic data and proteomic data to diagnose or detect mental illness, and new data collection methods such as smartphone-based data collection or wearable sensors paired with AI applications. Research initiatives for treatment include improvements in currently available chatbots, the creation of new AI chatbots, and research on whether individuals will respond to particular treatments based on their specific characteristics. Prognosis initiatives include predictions of mental health trajectories and potential future costs of illness.
- Trends in the development of AI for mental health include chatbots for mental health treatment, increased explainability of models, and an increase in wearable devices and smartphone-based sensors for data collection.
- In regard to specific life stages, there are some identified AI algorithms used in children and youth, including Kids' Help Phone's crisis text service, Bark's AI parental control application, and AI algorithms for the diagnosis of internalizing disorders and bipolar disorder. In older adults, there are several AI applications to combat loneliness in seniors using companion robots, and some AI specific to seniors for diagnosing depression.
- Policy and program initiatives in mental health–based AI include the translation of lab-based research initiatives into clinical applications. This translation may require careful planning to ensure that ethical standards are met, that assessments are carried out to determine the suitability of the AI for each aspect of mental health diagnosis and treatment, and that generalizable and culturally sensitive algorithms are created.

Context

Artificial intelligence (AI), or machine intelligence, is defined as a computer-based program that can learn autonomously from data to perform tasks such as problem-solving and pattern recognition. AI includes areas of computing such as machine learning (ML) and deep learning.[1] ML is generally defined as a methodology that learns from previous data to develop models capable of making predictions on unseen data,[2] and is a subset of AI. ML approaches to AI involve the creation of algorithms that can perform a variety of functions, including classification, regression, clustering, and normative modelling of data.[3] "Deep learning" is a type of ML based on artificial neural networks.[1] AI can also include predictive analytics, although not all predictive analytics models are AI-based. Predictive analytics are a branch of data analytics that attempt to make future predictions based on past data — a predictive analytics system with AI would include the ability to learn autonomously.[4] More detailed definitions are provided in Appendix 1.

AI is a field of study that has seen a large uptake of interest in the past five years.[5] The Government of Canada announced funding in 2017 of $125 million over five years for a Pan-Canadian Artificial Intelligence Strategy through the Canadian Institute for Advanced Research.[6] Canada is known to have a continued interest in AI and AI research, investing in the early years of AI, which has resulted in a number of advanced AI research labs in Canada.[1] Edmonton, Montreal, and Toronto are the main hubs of AI research in the country — with Edmonton being home to the Alberta Machine Intelligence Institute and the University of Alberta ranking fifth in the worldwide university rankings for AI and ML combined;[7] Montreal being home to the Institute for Data Valorization and the Montréal Institute for Learning Algorithms and having the highest concentration of researchers and students in AI; and Toronto being home to the Vector Institute, NextAI, and the Creative Destruction Lab, and having the highest concentration of AI start-ups in the world.[8]

ML and AI have been suggested to be major upcoming disrupters of medicine — through improving prognoses using thousands of predictor variables, potentially displacing the work of radiologists and pathologists, and through improvements in diagnostic accuracy of diseases.[9] In particular, AI and ML are potential innovations that can be used in the prevention, detection, diagnosis, and treatment of mental health conditions. The potential impact of these technologies is therefore large given that mental health illnesses are highly prevalent in Canada — one in five people in Canada will experience a mental health problem or illness in any given year.[10]

This Environmental Scan explores the types and trends of AI or ML that are emerging or currently in use for the prevention, diagnosis, or treatment of mental health problems and illnesses; identifies research and development initiatives; and discusses important policy and program directions for AI within the mental health field.

Previous CADTH work on AI and mental health includes a chapter in *Health Technology Update Issue 22*,[11] and *Issues in Emerging Health Technologies, Issue 174*.[12]

Objectives

The key objectives of this Environmental Scan are:

1. Report the types and trends of artificial intelligence or machine learning emerging or currently in use for the prevention, diagnosis, or treatment of mental health problems and illnesses; identify research and development initiatives, and important policy and program directions.
2. Report how artificial intelligence or machine learning are being used in the provision of mental health services and identify the types of artificial intelligence currently in use in mental health.
3. Report who the professional groups and organizations involved in the use or development of artificial intelligence or machine learning for mental health are; and outline the key players in research, academia, government, and industry across Canada and internationally.

This Environmental Scan does not include an assessment of the clinical or cost-effectiveness of the technology area; thus, conclusions or recommendations about the value of the technology or place in therapy are outside of the scope of this report. Additionally, this Environmental Scan does not endorse one form of AI or ML over others. A companion report, "*Artificial Intelligence and Machine Learning in Mental Health Services: A Literature Review,*"[13] provides more information on the clinical effectiveness and diagnostic accuracy of AI and ML for mental health.

For the purposes of this report, AI also encompasses ML and predictive analytics that have an AI component.

Methods

This Environmental Scan is based on information gathered through limited literature searches and targeted stakeholder consultations guided by three research questions.

Research Questions

The literature review and consultations attempted to address the following questions:

1. What are the types and trends of artificial intelligence or machine learning emerging or currently in use for the prevention, diagnosis, or treatment of mental health problems and illnesses?
2. How is artificial intelligence or machine learning being used in the provision of mental health services?
3. Who are the professional groups and organizations involved in the use or development of artificial intelligence or machine learning for mental health?

Literature Search

Methods for the literature search were identical to the literature search for the accompanying Rapid Response report, "*Artificial Intelligence and Machine Learning in Mental Health Services: A Review of Clinical Effectiveness and Guidelines*."[13]

A limited literature search was conducted by an information specialist on key resources including Medline (via OVID), PsycInfo (via OVID), the Cochrane Library, the University of York Centre for Reviews and Dissemination databases, the websites of Canadian and major international health technology agencies, as well as a focused internet search. The search strategy was comprised of both controlled vocabulary, such as the National Library of Medicine's MeSH (Medical Subject Headings), and keywords. The main search concepts were artificial intelligence and mental health. No filters were applied to limit the retrieval by study type. Grey literature was identified by searching relevant sections of the CADTH Grey Matters checklist (https://www.cadth.ca/grey-matters). Literature searches were limited to the past five years, with no filters applied for study design. Where possible, retrieval was limited to the human population. The search was also limited to English-language documents published between January 1, 2014, and September 5, 2019.

Screening and Study Selection

One author independently screened and retrieved citations. In the first level of screening, titles and abstracts were reviewed and potentially relevant articles were retrieved and assessed for inclusion. The final selection of full-text articles was based on the inclusion criteria presented in Table 1. Articles that were published in a language other than English or French or were published prior to January 1, 2014, were excluded. All publication types were eligible. Studies examining an algorithm that was not clearly an AI, ML, or AI-based predictive analytic algorithm were excluded.

Table 1: Components for Literature Screening and Information Gathering

Population	Individuals at risk of mental health problems and illnesses (formal diagnosis not required) Individuals with mental health problems and illnesses (formal diagnosis not required) Subgroups of interest: • Life stage (children, adolescents, emerging adults, adults, older adults)a • Population (IRER, First Nations, Inuit, Métis, LGBTQ2+, male identifying individuals, female identifying individuals, those who speak foreign and Indigenous languages)
Intervention	Any artificial intelligence, machine learning, or predictive analytics used in a mental health–related capacity
Settings	Across Canada and internationally, in research, academia, government, or industry
Types of Information	RQ1: Information on the types of AI in use, or the types of AI in development or planning for use Information on trends for AI use within the mental health system (throughout prevention, diagnosis, or treatment) RQ2: Information on the use of AI in the provision of mental health services RQ3: Information on the individuals, groups, and professional organizations involved in the use or development of AI for mental health purposes

AI = artificial intelligence; IRER = immigrant, refugee, ethnocultural, and racialized; LGBTQ2+ = lesbian, gay, bisexual, transgender, queer or questioning, and two-spirited; RQ = research question.

[a] For the purposes of this report, age categories were based on definitions used in selected papers. In the absence of a definition, the following was used: Children, younger than 12 years old; adolescents, 13 to 17 years old; adults, 18 to 65 years old; and older adults, over 65 years old.

Data Extraction

Relevant information from the retrieved full-text citations was organized into a table with the objectives as headings by one reviewer. This information was then used to inform the current report. Data that were extracted included information on types of AI in use, types of AI in development or planning for use, trends for AI use within the mental health system (throughout prevention, diagnosis, or treatment), the use of AI in the provision of mental health services, and individuals, groups, professional organizations involved in the use or development of AI for mental health purposes. Any available information was used to inform the research questions and objectives in a narrative format.

Consultations

Targeted consultations were sought with stakeholders involved in AI and mental health, either through research, industry, or clinical practice, to validate findings and fill gaps in knowledge, and to provide both clinical and decision-maker perspectives. The occupations of relevant stakeholders included researchers, psychologists, industry professionals, mental health professionals, computer scientists, clinicians, policy-makers, ethicists, and others. Stakeholders contacted for this report were identified through CADTH's network of liaison officers situated across Canada, the Mental Health Commission of Canada, internet searching, or referred through other informants during consultations. Consultations were done with a convenience sampling method, with one researcher reaching out to stakeholders via email, and interviewing those willing or able to participate (i.e., key informants). One researcher conducted the consultation one-on-one with each key informant via phone using a semi-structured interview format or by email if telephone consultations were not possible. Interview questions were developed based on the research questions, and included questions related to how AI is being used in the provision of mental health services; the types and trends of AI in prevention, diagnosis, or treatment of mental health problems and illnesses; and the various professional group or organizations currently involved in the use, research, or development of AI technologies. Key informants involved in the consultations, and other relevant stakeholders, were also asked to provide feedback on the reports' contents and interpretation after completion of the first draft.

Synthesis Approach

Information from literature and consultations was analyzed by objective. Notes obtained through telephone consultations were hand-written, and then key points from these and from notes obtained through email consultation were sorted into relevant categories under the objectives of this Environmental Scan. Literature search results supplemented information provided by consultations and provided additional information relevant to the scan. After categorization by objective, data were then categorized by type or purpose of AI or mental health condition. Data were presented narratively, with additional details provided in appendices. Where possible, specific and separate reporting based on age (i.e., youth, emerging adults, adults, and seniors) and population (i.e., immigrant, refugee, ethnocultural and racialized; First Nations; Inuit; Métis; lesbian, gay, bisexual, transgender, queer or questioning, and two-spirited (LGBTQ2+); male identifying individuals, female identifying individuals, and those who speak minority languages) was provided.

Feedback

Feedback on the contents and interpretation of the report was solicited from stakeholders through targeted solicitation on November 20, 2019. Informants involved in the consultations were also asked to provide feedback. Stakeholder feedback was used to supplement the information gathered from the literature search and consultations.

Findings

The findings presented are based on literature searches and consultations received and collected by October 21st, 2019.

Twenty-nine stakeholders were contacted via email for consultation. Sixteen stakeholders responded to this call for consultations, with three refusing consultation (two felt they were not able to provide appropriate expertise on the subject, and one was out of office for the time period of consultations). Three individuals expressed interest in providing an interview but were unable to do so in the timelines provided. Ten consultations were completed (nine via phone and one via email) with individuals located in Ontario, Alberta, Nova Scotia, and British Columbia.

A total of 1,025 citations were identified in the literature search. Following the screening of titles and abstracts, 956 citations were excluded and 69 potentially relevant reports from the electronic search were retrieved for full-text review. Twenty-five potentially relevant publications were retrieved from the grey literature search for full-text review. Of these potentially relevant articles, 24 publications were excluded for various reasons, and 68 publications met the inclusion criteria and were included in this report.

Objectives 1 and 2: Report the types and trends of artificial intelligence or machine learning emerging or currently in use for the prevention, diagnosis, or treatment of mental health problems and illnesses; identify research and development initiatives, and important policy and program directions. Report how artificial intelligence or machine learning are being used in the provision of mental health services and identify the types of artificial intelligence currently in use in mental health.

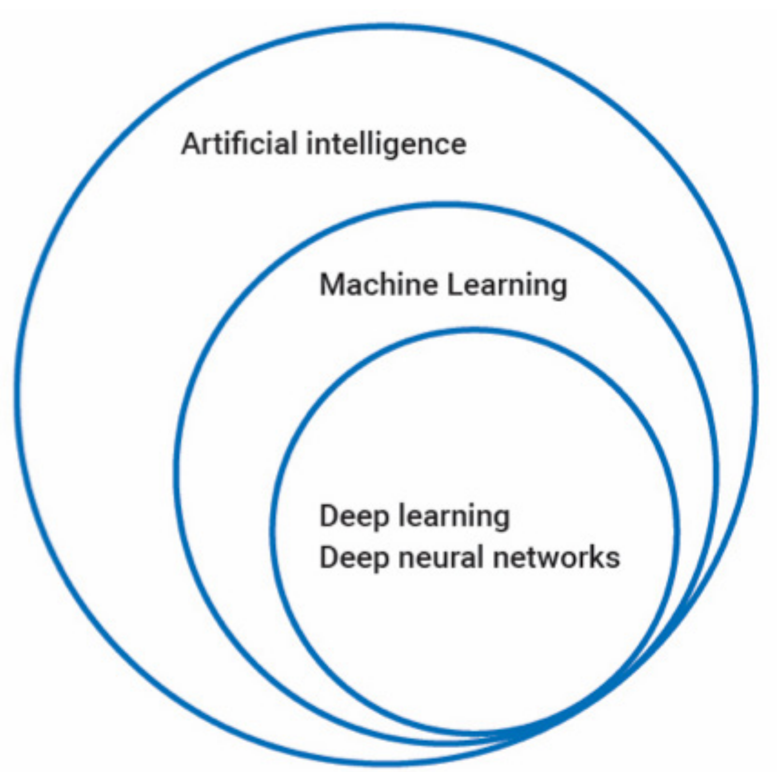
In this section, types of AI in use for mental health, current use of AI, and research and development initiatives are discussed.

Types of Artificial Intelligence in Use for Mental Health

Appendix 1 includes a glossary of terms used in AI and ML algorithms. In a simplified model shown in Figure 1, ML is a subset of AI, and deep learning is a subset of ML.

ML is a computer program that can autonomously learn from data, and can label new information or descriptions it receives. For example, you may have a picture and want to know whether the picture is or isn't of a cat. An average person could look at the picture and determine that it is or is not a cat through previous experiences of seeing cats in photos or in real life. In ML, if we want a computer program to do the same task, it is possible to train an algorithm using hundreds of example pictures that may or may not contain cats; the resultant algorithm should be able to classify an unseen photo as "cat" or "not cat." In ML, the data inputted into the model (e.g., magnetic resonance imaging [MRI] data, social media posts, pictures, or voice recordings) will determine what the output will be (e.g., diagnosis or treatment prediction). The algorithm is "trained" on data as more inputs are added to the model and the model changes or adapts to new information.

Figure 1: Simplified Venn Diagram of Artificial Intelligence, Machine Learning, and Deep Learning



Supervised Machine Learning and Unsupervised Machine Learning

Two common forms of ML are supervised and unsupervised learning. Supervised ML involves labelling the cases (e.g., diagnosis), training the model to map from data to these predefined labels, then use this mapping to make predictions about unseen and unlabelled data.[3] Unsupervised learning is when cases are unlabelled and the ML algorithm divides the sample in groups of related cases, with no assigned names for the outputs.[3] For example, similar to the cat or non-cat analogy used previously, if an algorithm is trying to determine whether a picture is of a dog or a cat, in supervised learning, the photos used to train the algorithm would have attached "dog" and "cat" labels, so the output of the algorithm would be either "dog" or "cat." In unsupervised learning, the dog and cat labels would not have been attached to the training data; therefore, the algorithm may differentiate between the two animals, but would not specifically label the output as a dog or cat. Table 2 illustrates the three common types of ML, including reinforcement learning.

Table 2: Types of Machine Learning

Supervised Machine Learning	Unsupervised Machine Learning	Reinforcement Learning
Definition		
A process that involves labelling the cases during the training of the dataset so that the outputs (classified groups) already have assigned names.[3] For example, if you are labelling a picture as "cat" or a "dog," when the model was initially trained, all of the data used in training the algorithm was labelled by humans as "cat" or "dog," to enable the algorithm to learn from it. When the algorithm is fed new data, it will determine if a picture is a "cat" or "dog."	When cases are unlabelled and the machine learning algorithm divides the sample in groups of related cases, with no assigned names for the outputs.[3] The data are categorized based on the properties of the data itself.[14] In the "cat" or "dog" picture example, this data are not already labelled as "cat" or "dog." If an algorithm was fed 50 pictures of cats and 50 pictures of dogs, it would cluster these pictures into "group A" and "group B" based on the properties of the pictures, with no specific guidance from a human during this phase.	Training of an algorithm through reward of "good" decisions and penalization of "bad" decisions.[14]
Examples of General Applications		
• Handwriting recognition (all letters are labelled for the algorithm during training) • Facial recognition software • Spam detection for emails (emails are labelled as "spam" or "not spam")	• Tracking purchase history and behaviours to find patterns in customer bases (e.g., customer segmentation; potentially for advertising purposes) • Anomaly detection, such as in fraudulent purchases on a credit card	• Self driving cars (negative reinforcement when collision occurs)

Some ML models use binary learning to generate an output. For example, in a supervised learning algorithm for diagnostics, binary outcomes may be used to label an individual as "with a mental health condition" or "without a mental health condition" (a binary yes or no output), using data inputted into the model (e.g., patient characteristics, symptoms, or writing), similar to how you could label pictures as "cat" or "not cat," or label emails as "spam" or "not spam." The pitfall of using binary classification comes when simplifying mental health conditions into a "yes or no" diagnosis, when in reality, many mental health conditions fall on a spectrum of severity, and not all individuals have one specific mental health diagnosis.[15]

Commonly Used Machine Learning Algorithms

Common methods of ML include logistic regression, support vector machine (SVM), artificial neural networks, linear discriminant analysis, random forest, and naive Bayes.[15] A previous CADTH report (An Overview of Clinical Applications of Artificial Intelligence)[12] provides some information on SVM, artificial neural networks, deep learning, and natural language processing (NLP).

SVMs are a commonly used ML algorithm. An SVM is, in simple terms, a method used in regression or classification of data. It can be used to segregate data into groups by defining a hyperplane that can divide the dataset. Essentially, an SVM can divide data into groups based on common features. Another ML algorithm in use is an artificial neural network. Neural networks are designed to resemble neurons in the brain, arranged in layers. The first layer is the input layer in which information is received, and the final layer is the output layer, which provides the answer to the question. The layers between the input and output layers are the "hidden layers" that use the information provided to create the output. Figures 2 and 3 show basic representations of neural networks and SVM, respectively.

Figure 2: Simplified Diagram of a Neural Network

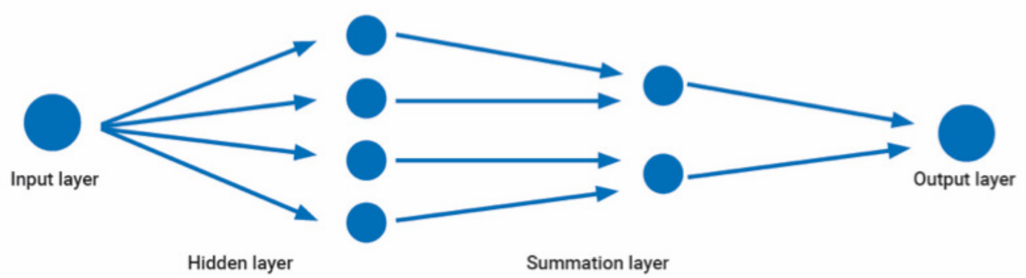
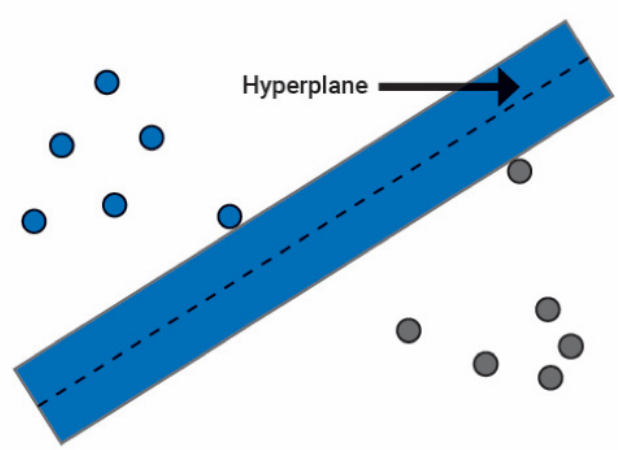


Figure 3: Simplified Diagram of a Support Vector Machine Classification



Conversational Chatbots or Agents

Conversational chatbots or agents are applications of ML and AI that mimic natural human-to-human conversations and can be used for both patients and clinicians. Conversational agents are a medium used to increase engagement of the user, as humans may respond more naturally to technologies that exhibit emotional and social dynamics similar to human peers.[16] Conversational chatbots can be text-based, or include an embodied agent (i.e., an avatar that incorporates body language, movement, and facial expression into the conversation).[17]

Conversational agents can be used as virtual therapists, delivering mental health content similarly to an in-person therapist, and can also be used to train clinicians to recognize specific behaviours (such as suicidal ideation) through virtual training scenarios.[17] However, not all conversational agents are based on AI technology — many chatbots have predefined responses to user input and do not "learn" from previous interactions with the user.[17] Conversational agents may be useful for patients who live in underserved areas and are not able to attend in-person therapies, and may help individuals overcome fear of self-disclosure.[18] Limitations exist with the technology, as well, including few properly designed studies examining effectiveness within a variety of contexts, potential for patient harms using the technology, privacy issues, and lack of current regulations for the technology.[18] Chatbots are also not meant to be a full replacement for in-person therapies, and are often designed to be an adjunct therapy.[16]

Examples of mental health chatbots include Woebot, Wysa, and SimCoach. These chatbots are further discussed in objective 2 and Appendix 4.

CADTH has previously published a newsletter chapter within *Health Technology Update — Issue 22* (2018) that discusses AI chatbots for mental health in more detail.[11]

Computerized Adaptive Testing

In traditional mental health scales such as the Patient Health Questionnaire-9 and Generalized Anxiety Disorder 7-item, identical items are provided to each participant, with a total score generated at the end that is used to aid in diagnosis of the patient. In these types of scales, each question is weighted equally (e.g., items that are related to suicide are weighted equally to questions about eating habits).[19] In contrast, in computerized adaptive testing (CAT), individuals receive different targeted items (questions) based on previous responses to questions, which can lower the number of questions received and reduce examinee burden. For example, the Computerized Adaptive Diagnostic Test for Major Depressive Disorder developed by Gibbons et al. uses random forests and decision trees (types of ML) to classify patients as having or not having major depressive disorder (MDD), and the CAT-ANX is a diagnostic test for anxiety.[19-21] Additionally, a CAT related to suicidality and CATs specific to youth (mental health conditions in children) have been developed.[22,23] According to Devine et al., as of 2016, eight mental health CATs or CAT systems have been developed and applied to real patients.[24] A list of CATs that have been used in real patients is provided in Appendix 2. One criticism of the CAT is an inability to discern between similar mental health conditions, which would have implications for treatment (e.g., in the CAT-ANX, the test labelled a particular patient as having a 99% chance of generalized anxiety disorder, but based on the Diagnostic and Statistical Manual of Mental Disorders (DSM), Fourth Edition, criteria, the patient was more likely to have a severe panic disorder).[25]

Detection of Affect

Affect is defined as the experience of emotion or feeling (ether positive or negative)[26] and is linked directly to many mental health conditions, including depression.[27] ML has been suggested as an option to detect affect or moods in individuals, either to assist in treatment plans or to determine current mood of individuals who do not have the capacity to verbalize their mood state.[27] The theory of automated mental state detection is that when an individual interacts with the world, this interaction creates hidden mental states. These mental states are not directly measurable, but some emotional changes occur that can be measured, either physiologically (e.g., heart rate, facial expression) or neurobiologically (e.g., changes in brain activity). The accurate mental state can then be inferred from these measurable factors.[27] For example, if a person felt happy, there is no tool that can directly measure happiness (besides directly asking the individual), but we can perhaps infer happiness through other signals, such as a smile, laughter, increased heart rate, or other measurable signs.

This type of analysis could be accomplished with webcams that detect changes in facial expression, microphones that detect pitch and amplitude from speech, or wearable sensors that detect heart rate.[27]

Current Use of Artificial Intelligence in Clinical Settings or Practice

Individuals consulted for this Environmental Scan did not report using AI or ML within the context of clinical practice. It was indicated that while this may be on the horizon, the use of AI in practice for mental health purposes was limited, especially for diagnostics. Information from the literature echoed this, stating that the use of ML for classification of depression is limited and has not been integrated into clinical applications.[2] Consultations did indicate a few projects in progress, including therapist-led Cancer Chat Canada (from the DeSouza Institute at the University Health Network and for individuals with cancer to receive psychosocial support in the form of online chat),[28] and integration of AI into A4I (i.e., App for Independence, a peer-to-peer patient-centric mobile app for patients with schizophrenia that uses ML to personalize algorithms and assess risk).[29] A4I was named one of ten start-ups changing health care by Scientific American in 2017.[30] Consultations stated that the vision for the A4I application is to be able to detect changes in the behaviour of a user, such as detection of hallucination episodes through sleep disturbances, continuous refreshing of the application, or content of posts to the application. A person with lived experience and patient advocate noted that they enjoyed the peer-to-peer aspect of the application, as support from others with the disorder is important.[31]

Kids' Help Phone uses AI (a neural network based on NLP) to triage users who initiate conservations with the crisis text line. As a user sends their first few messages, the program will determine if the user is at imminent risk of harming themselves, and will connect them sooner with a human crisis counsellor.[32] Future work on the crisis test line includes an improvement in waiting time as accuracy of the algorithm improves, a model that adjusts risk during the course of a conversation and not solely at the beginning, and expansion in other languages, including culturally specific and sensitive algorithms.[33-35] Currently, Kids' Help Phone is also in the process of creating a chatbot program for youth and for mental health support using data collected from the crisis text line.

Treatment

Conversational Chatbots

Some Canadian organizations are exploring the use of AI-based treatment options, as indicated in the literature.[36] For example, at Saint Elizabeth Health Care (a home care and health care service provider located in Ottawa), Tess, a conversational chatbot developed by X2AI, was introduced to the "living lab" environment (a pilot test using employees who are family caregivers) over a 30-day period as part of their "IntelligentCare Platform." Tess is a customizable platform that can deliver cognitive behavioural therapy (CBT) or other related psychological treatment modalities.[36] The pilot results reported high adoption and engagement.[37] Saint Elizabeth is planning to incorporate Tess into an employee wellness program — Elizz's "Caregivers in the Workplace" (www.elizz.com) program.[37]

Other chatbots that exist for use in mental health include Woebot[16] and Wysa,[38] mental health chatbots that use the principles of CBT. Both of these technologies are available through Facebook Messenger and as their own mobile applications. The Woebot founder describes Woebot as being usable as "an early intervention," "a step down from higher care," or "used alongside therapy."[39]

Research and Development Initiatives

According to Hahn et al., there are three principal areas of clinical application for predictive analytics in mental health:

1. prediction of therapeutic response to assist in individualized treatment plans
2. support for differential diagnoses
3. prediction of risk for preventive medicine.[40]

One individual noted during the consultations that Edmonton is among the top three sites for AI globally — it was named one of the top three sites in Canada after the announcement of funding for the Pan-Canadian Artificial Intelligence Strategy. The Alberta Machine Intelligence Institute received a portion of funding from this initiative. This organization is involved with mental health research initiatives, including functional magnetic resonance imaging (fMRI)-based diagnosis and treatment.[41]

In addition to the Alberta Machine Intelligence Institute, groups such as DeepMind (owned by Alphabet, Google's parent company), the IBM Centre for Advanced study, Huawei (a Chinese telecommunications company), and AltaML were noted as players in AI research, including mental health research. More information on these projects can be found in Appendix 4.

According to the Canadian Institute of Health Research, the top three Canadian universities publishing in the field of AI in public health (not mental health specifically) are McGill University, the University of British Columbia, and Université Laval.[42] The Government of Canada has developed an Algorithmic Impact Assessment, an open source program designed to help individuals creating automated decision systems to mitigate risks and assess impacts of their program.[43] Similarly, the Canada Protocol provides an ethical checklist for consideration in mental health applications of AI. The checklist contains recommendations related to the description of the technology, privacy and transparency, security, health-related risks, and bias. More information on this checklist can be found in the Ethics section of this report.

A scoping review of methods and applications for ML in mental health found four key domains in research and development initiatives: diagnosis, prognosis, public health, and clinical administration.[5] The majority of research lies in the area of diagnosis and detection of mental health conditions.[5] This scoping review by Shatte et al. lists many ML techniques and data types under these categories, including over 300 studies related to ML and mental health.[5] This report focuses on diagnosis, prognosis, and treatment, but public health initiatives include monitoring of mental health after natural disasters or incidents, modelling risk factors in broad populations, and monitoring of social media. Clinical administrative initiatives include modelling allocation of resources based on patient risk factors, improvement in research methods, extraction of mental health information from clinical documents, and predicting high-cost patients.[5]

Prevention

Robot Companions

AIBO (artificial intelligence robots) are robotic pets developed by Sony that are intended to provide companionship. The use of this companion robot has been trialled in people with schizophrenia as an assisted-therapy.[44] In consultation, it was noted by an individual with lived experience that individuals may use AI robots or other options differently during their mental health journey. It was suggested that robots may appeal to individuals who fear judgment from "real" people such as therapists.

Loneliness is directly linked to mental well-being.[45] Feelings of loneliness have been linked to depression, Alzheimer disease, suicidal ideation, and alcoholism.[45] The Alberta Machine Intelligence Institute has created an prototype AI companion for elders to combat loneliness.[46] The Automated Nursing Agent (Ana) is a chatbot that is intended to fulfill social needs through conversation.[46] Other options for combatting loneliness include conversational agents such as Alexa (Amazon's AI virtual assistant).[47]

Other examples of social companion robots include MARIO (Kompai)[48] from the National University of Ireland Galway, part of the European Union Horizon 2020 research project, and CompanionAble,[49] a socially assistive home robot funded by the European Union.

Stress

Given that stress and mental health are closely related, ambulatory stress monitoring is an additional approach to mental health monitoring.[50] One such multimodal approach used the Affectiva Q-Sensor (electrodermal sensor and accelerometer), phone usage records, sleep, and location to categorize participants into high- and low-stress groups. Similarly, accurate predictions were made with only the smartphone data, so monitoring could theoretically be achieved without the wearable sensor. This approach would provide a low-cost option for monitoring patients' stress levels, and indirectly, their mental health.[27]

Diagnosis and Detection of Mental Health Conditions

ML may have clinical utility for differential diagnoses (i.e., when diagnosis is unclear and symptoms are similar to multiple potential diagnoses) or when assessments are costly or time consuming.[3] Diagnoses in mental health conditions often overlap with one another, and when combined with the subjective nature of physician diagnosis, it can be difficult to provide patients with a timely and accurate diagnosis.[2] Accurate diagnosis allows patients to receive timely and appropriate treatment.

A review of the literature found many publications looking at diagnostics in mental health using ML or AI techniques. Appendix 3 provides some examples of these publications. Eight systematic reviews were identified (within the past five years) that examined outcomes of accuracy of ML for mental health diagnoses.[2,51-57]

Types of markers used in ML for the diagnosis of mental health conditions include:

- neuroimaging (fMRI, structural MRI, electroencephalogram, diffusion tensor imaging)[51]
- blood biomarkers[51]
- genetic analysis[51]
- metabolomic and proteomic data.[3]

Diagnostic projects disclosed by consultations included an ML model (EMPaSchiz — Ensemble algorithm with Multiple Parcellations for Schizophrenia prediction) created by researchers at the University of Alberta for diagnosing schizophrenia from patient brain scans. EMPaSchiz was demonstrated to be accurate in diagnosing patients who had not undergone pharmacotherapy treatment when compared with clinical interviews and the Mini International Neuropsychiatric Interview Plus, so it may be useful in early diagnosis for at-risk patients.[58,59]

The University of Alberta's Computational Psychiatry Research Group emerged in 2014 as a collaboration of psychiatrists, psychologists, computing scientists, and neuroscientists who have links to the private sector. The group has an ongoing collaboration with IBM Centers for Advanced Studies. The goal of the group is to improve diagnosis and prognosis using advanced computational psychology to analyze patterns in large amounts of data.[60] Partners of this group include Harvard University; The National Institute of Mental Health and Neurosciences in Bengaluru, India; the Kangning Hospital Group in China; and Alberta Health Services. Consultations noted that the AI projects are a team activity that marry clinical and academic perspectives.

Mindstrong Health, a digital health company using digital phenotyping for mental health research, was mentioned during several consultations as a key player in the AI for mental health domain. Its company goal is to provide personalized treatments for mental health, provide precision therapies, and detect early mental illness or relapse.[61] Its team is currently working on a mobile phone application that passively analyzes data from the user and predicts mental health–related events. Mindstrong Health announced a partnership with Takeda (a Japanese pharmaceutical company) in 2018 for schizophrenia and depression research, and is partnering with BlackThorn Therapeutics (an AI technology company) for its research into BTRX-246040, a developing selective nociceptin receptor antagonist (an antidepressant targeting nociceptin receptors).[62]

The literature also revealed projects related to youth and children experiencing mental health conditions, including ML for pediatric bipolar disorder.[63] Additional studies on children included diagnosis of internalizing disorder through analysis of voice recordings of children (such as anxiety)[64] and analysis of wearable sensor data in a fear-based exercise.[65]

Challenges

Some research initiatives are in the form of responses to competitive challenges posed by organizations. For example, the Depression Recognition Sub-challenge was a challenge posed by the Audio/Visual Emotion Challenge and Workshop in 2019 to compare ML methods in audiovisual health and emotion analysis. The organization provided a test set of video and audio data and asked groups to submit a model to detect depression.[27] Another example of a competitive challenge was the Critical Assessment of Genome Interpretation bipolar disorder challenge, for which the objective was to show developments in computational methods, build a collaborative community, and show where progress can be made.[66] This challenge was won with a convolutional neural network-based AI (DeepBipolar).[67]

Prognosis

Treatment for mental health conditions is generally a personalized process as not all treatments work effectively for all individuals. Establishment of an effective treatment plan is usually done through a process of trial-and-error based on broader guidelines for treatment and may take several attempts.[3] In mental illness, this delay in finding appropriate treatment for the individual can be frustrating, and in some cases may lead to remission or worsening of the condition.[3] Therefore, predictions regarding prognosis of treatment or predictions of response to treatment may lead to fewer treatments being trialled on patients, and potentially quicker access to effective treatments for the individual. An example of ongoing research initiatives in treatment prediction is using fMRI to determine MDD neurophysical biotypes associated with clinical symptoms that may respond differently to different treatments.[2]

Current prognostic projects include work underway by CAN-BIND (https://www.canbind.ca/), which are a collective of projects (with a scope broader than only AI) that seek to assist in treatment planning by answering questions related to which populations will respond best to particular treatments (such as classes of antidepressants).[68] For example, one project discussed by a consulted stakeholder involves fMRI data compared with individuals' clinical responses to escitalopram (an antidepressant medication). The purpose of the project is to determine who would be good candidates for that treatment path, and whether different variables can guide treatment planning in depression.

In addition to predicting responses to treatment, ML techniques have been tested for determining a patient's prognostic outcomes for various mental health conditions. For example, ML in depression research has been used to categorize depression trajectories over two years.[3] Other research in depression trajectories has attempted to classify patients based on suicide risk, illness course, and future substance use.[3] Research in prognosis of psychosis is also ongoing.[3]

Electronic health records may be a valuable public health tool for ML to predict future health status of individuals.[3,9] For example, ML can be used to determine who may be at a higher likelihood for use of health care resources or who may be more likely to require more in-depth care.[9] One identified study in the literature attempted to predict future high-cost schizophrenia patients using payer administrative data in order to guide health organizations to provide more targeted and coordinated services.[69]

Mood, Speech, Facial Expression, and Tone

Individuals with depression often have reduced pitch and range, are slower speaking, and have higher numbers of articulation errors (problems with pronunciation and enunciation) than individuals who are not depressed.[70] These differences have been a target for AI and ML techniques in diagnosis of MDD when compared with people without MDD.

As previously mentioned, affect is a potential characteristic that ML can use to detect mental health conditions. For example, an SVM classifier used facial and physiological features from a recording of participants describing events that were happy, sad, made them angry, or were neutral to classify the emotion of the participants.[27] Results found the ML algorithm to be substantially more accurate than human judges in classifying basic emotions.[27] Another study examined non-basic emotions such as boredom, confusion, delight, engagement, and frustration within a noisy classroom environment.[27] The ML methods could discriminate affective states with an accuracy of 62% to 83%.[27] Another preliminary focus of ML for detecting mood is in the detection of mind wandering using eye trackers, as mind wandering (attentional lapses and mindfulness) may be associated with mental health.[27]

Virtual reality is another potential application of AI to mental health — the creation of environments that can simulate real-life environments, and the creation of human representations (avatars) that can interact believably with individuals.[71] Proposed options for virtual reality include virtual coaches, phobia desensitization, or for the conduct of initial clinical interviews. According to Rizzo et al., these technologies exist within the lab as production prototypes.[71] One prototype (SimCoach) was originally proposed for veteran populations (and their families) to seek anonymous text-based support through a virtual human avatar.[71] SimSensei, an offshoot of the SimCoach technology, which has facial recognition technology (Multisense), speech recognition, and tone recognition built into the program, is a prototype at the University of Southern California Institute for Creative Technologies (USC ICT) that is designed as support for mental health care. These projects were initially part of the Detection and Computational Analysis of Psychological Signals project at USC ICT.[72] These projects have not been tested clinically or compared with a trained psychiatrist.[73]

Prediction of Specific Behaviours

Prediction of Violent Behaviours

A previously completed project mentioned by consultations included an NLP-type ML intended to predict potential violent behaviour of individuals with mental health issues toward health care professionals.[74] It was a collaborative effort between IBM (IBM Content Analytics) and Ontario Shores, and was envisioned as a collaboration between the clinical world and the world of industry. The project was not considered successful as the ML algorithms did not perform better than the current measures of risk, and it was unclear what value the ML component added. There were also concerns regarding accuracy as there were many false-negatives in the model. There were also a lack of dynamic variables provided by the model to act on (i.e., what could the hospital do to help lower risk of violent behaviour) and the black box style of the AI model used in the project did not provide insight into this, as black box AI is not interpretable.[74]

Prediction of Suicide-Related Behaviours

Prediction of suicidal ideation or behaviours is important as prediction of future behaviours may lead to early intervention that could prevent deaths by suicide. On average, more than ten Canadians die by suicide every day, and for each death, seven to ten survivors are affected by the loss.[75] Predictions using surrogate markers of suicide attempts, suicidal planning, suicidal ideation, and self-injury have been limited through the restricted numbers of variables that can be added to traditional statistical methods.[52] AI applications within the field of prediction of suicide and self-harm was named as one of the "Top 12 Innovations Disrupting Healthcare by 2020" by the Disruptive Dozen panel at the World Medical Innovation Forum.[76]

Suicidal behaviour may also be predicted post-discharge from the hospital setting using AI. One study examined if NLP could predict suicidal ideation through a series of therapeutic reminders delivered through text messages to the patient. The reminders asked questions that were open ended (such as "how are you feeling today?") and examined responses through NLP.[77]

Concerns regarding the use of AI for suicide-related crises include whether the AI will respond appropriately to an individual expressing self-harming or violent intentions, and whether the AI will react appropriately (e.g., providing a number to call for help or providing resources).[39] In a 2016 study of AI smartphone assistants, the assistants reacted inconsistently to phrases such as "I want to commit suicide."[18] Consistency and accuracy in response to suicidal ideation or intent to die by suicide is an important factor in preventive efforts, and effective responses would require improvement in current performance.[18]

Military Populations

Veterans represent a specific population that may be at risk for mental health conditions, especially related to post-traumatic stress disorder (PTSD) and suicidality.[78] Combat and operational stress control (COSC) may therefore be a target for predictive analytics.[79] Using decision tree analysis, planning for COSC could occur through analysis of combat experiences and identifying those at a higher risk for PTSD.[79] This information could then be used to plan future resource allocation for COSC programs. Another program that is being developed specifically for veterans includes a collaboration between the Lawrence Berkeley National Laboratory (Berkeley Lab), the Department of Veterans Affairs, and the Department of Energy in the US; the program is looking at deep learning and genomics to address suicide risk.[80]

Consultations also noted a project by the University of Alberta in collaboration with the IBM Centre for Advanced Study that uses NLP to assist in early symptom identification and early diagnosis in Canadian military populations. The mental illness in focus for this project is PTSD.

Social Media and Artificial Intelligence: "Infoveillance" and Public Health Applications

Language analysis is a large initiative in ML and mental health — primarily through NLP (analysis of language) — and social media can provide large public (or accessible) datasets of self-disclosed, autobiographical information that may reveal insights into an individual's thoughts and feelings.[81] Social media can provide additional information in addition to the semantic content of the posts themselves, including when and where the posts were made and who interacted with the posts.[81] Passive monitoring of social media posts may be useful in identifying at-risk individuals and improving screening and monitoring.[81] Monitoring using NLP may also assist in flagging words and concepts that are associated with the risk of harming oneself or others.[76]

Random forests can also be used for social media analysis in early detection of MDD, as demonstrated in a study by Cacheda et al.[82] This study attempted to characterize behaviour based on textual spreading (how long the posts are), time gap (how long between writing posts), and time span (time of day of posts) in posts from Reddit.[82] Social media has been used to attempt to diagnose schizophrenia,[83,84] through Twitter, bulletin boards, and Weibo,[84] or to diagnose anxiety through Twitter.[85]

Other groups — such as the World Well-Being Project — aim to predict depression through Facebook posts. The results showed that when using electronic health records of depression in comparison with social media posts, researchers could potentially identify depression up to three months prior to a formal diagnosis.[86,87] The World Well-Being Project also analyzes the effect of psychosocial factors on heart disease mortality using Twitter.[87] Other projects underway include a collaborative project between Microsoft Research and Georgia Tech using social media platforms to monitor public health and identify individual risk factors. Projects include research on identification of postpartum depression through analysis of tweets prior to and after announcements of childbirth.[87]

International Perspectives

Along with Canadian projects and research initiatives, there are many international initiatives in the sphere of AI and mental health, both in academic and commercial enterprises. The US has AI -based chatbot programs (e.g., Woebot, Wysa, and SimCoach) for treatment, as well as initiatives for treatment planning, such as MindStrong, Ginger, and Spring Health. There are a number of diagnosis initiatives, including diagnosis using wearable sensors, speech recognition, electronic health records, daily routines, sleep tracking; more information on some of these initiatives can be found in Appendix 4.

Trends in Research and Use of Artificial Intelligence in Mental Health

Four main domains of ML applications are common in the literature, including detection and diagnosis, prognosis and treatment, public health, and research and administration.[5] Research in all of these domains has increased in studies of depression, and in 2018 the top research topics (by volume of literature) were pattern recognition, neuro-morphometrics, neuroimaging, and electroencephalogram-based diagnosis.[88] The volume of literature examining AI and depression has grown substantially over the past five years, from 27 studies published in 2014 to 117 studies in 2019.[88] In social media research, it was predicted that the novel trends would be algorithms with more technical analysis such as image analysis (e.g., filter use) and social networks (e.g., study of the individuals' friends and interactions with others).[57]

Trends noted in the consultations were the influx of new wearable devices that could record real-time data, and how this data could feed into an AI-based application that can either notify the patients or notify the patients' counsellor of their progress. Some companies are already moving toward wearable sensors, such as UK-based BioBeats, a company that uses a real-time sensor to detect stress levels.[89] Patient-focused AI applications were also mentioned as a trend in AI research and development, including more mobile applications and e-health applications geared toward patient use.

Another trend mentioned in the consultations was the increasing emphasis on explainability or interpretability of models in exchange for accuracy. Explainability is the ability to explain the steps involved in black box neural networks (i.e., why the model works as it does) and interpretability is the use of methods that are interpretable (i.e., able to predict what the model will do with varying inputs).[90] Despite the desire for increased explainability and interpretability, Wongkoblap et al. predicts that fewer interpretable methods such as deep learning will be used in social media research in the future as it is useful and has a higher performance for large datasets.[57]

Policy and Program Directions

Consultation also revealed limitations to the use of AI in the clinical setting. For instance, it was suggested that in attempting to oversimplify AI or to rush the projects, we may potentially be over-hyping the value that AI can provide for mental health services, at least in the short-term (similar to IBM's AI solution, Watson for Oncology[91]). It was mentioned that for some projects, rhetoric had potentially got further than the actual research. Additionally, adding AI into the care pathway requires planning and organization. If AI is added to already over-burdened clinicians as an "extra" task needed to complete, it may fall by the way-side and not add the value that was intended.

One concern regarding AI and predictive analytic research is the ability to effectively move research findings from a lab-based setting to a clinical practice setting. This will require expert knowledge and data integration technology. Predictive analytics require strategic choices, suggested by Hahn et al., such as guidelines for predictive analytics projects and fostering a greater discussion and discourse among researchers, clinicians, funding bodies, and other stakeholders.[40] Examples of resources, such as the Patient-Centered Outcomes Research Network (www.PCORnet.org), exist for connecting resources and establishing partnerships in clinical research.[40] Wongkoblap et al. echoed these recommendations for research in social media, stating that there needs to be methodology created that assists in translating this research into practice, and that there needs to be efforts that complement the diagnostics aspects of the research, such as offered health services, real-time interventions, and CBT.[57]

Other directions and future research may be focused on the suitability of this type of technology for mental health interventions, such as whether they should be used as a screening tool, are a suitable replacement for human therapists, or should solely be an adjunct intervention alongside other interventions.[92] Consultations noted that these stakeholders must also include individuals with lived experience of mental illness, and include asking them about why they use AI, and what they use it for. One writer with lived experience expressed the concern that using an objective measure such as AI will undermine an individuals' lived experiences, and lead health care providers to view individuals as data instead of human beings.[93] Consultations also noted that AI has not always shown a strong efficacy in other fields, so many are wary of their current effectiveness of AI for mental health. And some individuals with mental disorders may not currently trust medicine due to previous bad experiences with treatment.[93]

Ethical Implications

The Canada Protocol details ethical considerations for mental health and AI.[94] AI should be well described, including the project objectives, techniques used, funding sources, and target population; it should also have justified, evidence-based performance.[94]

Bias in the creation and implementation of AI is a key ethical issue for the field. Race and ethnicity play a major factor in medical treatment receipt and in equity of service.[93] A 2016 survey by the University of Virginia found that medical students may have misconceptions about black individuals in comparison with individuals of other races — these biases may find their way into the created algorithms for treatment and diagnosis of mental health conditions.[93] Despite the inherent objectivity of a machine-based algorithm, if the inputs provided to the algorithm are biased, outputs that the algorithm provides will also be, by definition, biased. Bias in algorithms can occur through the initial creation of the algorithm (e.g., which tools are used to collect data) or if there are biases inherent in the training dataset. For example, women are more likely to be prescribed psychotropic drugs for mental health conditions, and biases such as this may be pulled into the creation of AI algorithms.[93] The introduction of potential biases into AI algorithms should be explained to individuals fully.[95] The Canada Protocol recommends biases be explained to potential users — such as potential exclusion or discrimination, stigmatization, detection errors (false-positives, false-negatives), and how the data would be used and transformed.[94]

Consultations noted the need for culturally sensitive AI algorithms that are generalizable to the diverse populations in Canada. How technologies like AI take into account other groups, such as multicultural or LGBTQ2+ groups, is yet to be seen.[39] Other concerns include the inability of AI to correctly "read" the facial expressions and speech patterns of neurodiverse individuals.[39]

Privacy is also an ethical issue that surrounds AI and technology-based mental health interventions. Mental health data are sensitive data, and must comply with federal and international laws regarding usage and collection.[39] The Canada Protocol suggests that creators of AI algorithms should detail what data are collected, who has access to the data, what the data will be used for, and whether an individual has a right to remove their information.[94] Consultation with people with lived experience noted that people with lived experiences want control over their data and how it is used. Concerns about "wellness apps" geared toward mental health that circumvent privacy policies such as the Health Insurance Portability and Accountability Act (HIPAA) could extend to AI-based mental health applications, as well.[96] Individuals who were consulted had mixed opinions on the collection of individuals' private data for research — with some cautioning participants about entering data into mobile applications (especially after recent controversies regarding the selling of personal data to third parties),[96] but a different perspective regarding privacy was that if it is too strict, it won't be possible to gather enough data to properly research and create useful AI-based interventions. It has been suggested that traditional concepts of privacy may not be adequate or apply to AI-driven technologies, given that the technology requires such vast amounts of data.[1]

Consent is another issue surrounding new technologies such as AI. Professor Thombs, the chair of the Canadian Task Force on Preventive Health Care, has stated that AI should be treated equally to other medical screening procedures regarding consent and benefits.[97] According to Professor Thombs, screening has not (so far) been shown to help individuals with mental health conditions, as being identified does not necessary directly lead to improvement in mental health.[97] With AI potentially identifying more cases of mental illness, there is a possibility of false-positives, leading individuals to potentially seek treatment unnecessarily.[97] Consultations echoed this concern, stating that it may not be ethical to intervene if someone with mental health concerns is identified, especially if consent was not given to analyse their data (such as in social media screening).

Although current research is often published from a publicly funded academic context where data are freely shared, private companies may wish to use data predictions to make decisions regarding reimbursement or hiring, or to target advertisements to individuals.[40] Thus, policies and public consensus regarding fair use of, and access to, information are needed.[40] It is not clear how open the public is to the use of their personal health data, either for commercial or research purposes.[98] Despite this, marrying academic or publicly funded projects with industry may be a promising avenue for AI research and development to flourish. Academic projects may bring the clinical expertise needed for research or have access to specific clinical populations.[98] Industry-funded projects often do not have the limitations that academia may have — there is no requirement to wait for the proposed idea to receive funding, companies are frequently product focused, and industry may have access to large-scale population data that smaller-scale academic institutions do not.[98] However, partnerships between academia and industry are still important.[98] In other words, both basic research and product development have a place in the emerging field of AI and mental health.[98] Users of commercially produced applications may require guidance when identifying applications that are evidence based, and should provide informed consent for use of their data. For example, mobile applications available for download by anyone may not be evidence based, or not be intended for patient use (e.g., for clinician diagnosis). Ethically, it may be important to ensure that the efficacy of the AI interventions provided to individuals outweigh the commercial interests of the provider.[37] Embodied AI that is available outside of a professional mental health setting should have a demonstrated risk pathway assessment, and should refer users to appropriate treatment options and services.[95] Transparency has been noted to be important in ethical considerations — especially with embodied AI — and should respect patient autonomy, and limit manipulation or coercion.[95] For example, an elderly person or a intellectually disabled person who does not understand how a robot works may be at risk for coercion, privacy concerns, or manipulation.[95] People may be more compliant when asked to do a task by a robot than when asked to do the same task by a human, which is an issue that may come into play with AI-driven therapies.[95] The Canada Protocol recommends that it should be made clear whether a patient is interacting with a machine or a human.[94]

Ethics in Social Media Research

There are similar ethical implications in social media related research, including implications based on user expectations and privacy. Largely related to social media, there is the ethical dilemma that if data are publicly available (as in, through social media), that may not also mean that it is fair to use the data freely for research purposes.[87] The controversies with research performed by Facebook and Cornell University that used data without the option for participants to opt out highlights some of these issues — research by academia in the US requires an opt-out option for participants, but this rule does not apply to private companies.[57] This fair use ethical dilemma is especially prevalent in sensitive issues such as mental health.[87] It has been suggested that current ethical principles may not be sufficient for guidance in social media research.[83]

Gaps in Literature and Limitations of Artificial Intelligence

Mental illnesses are extremely complex in etiology and symptomology. The complicated nature of the conditions does not lend itself well to strict classification and algorithms may be less reliable than intended. For example, differentiating between an individual with depression and an individual with bipolar disorder who has not experienced a manic episode may be difficult.[40] ML may be of use to increase accuracy of labels in predictive analytics. Currently, the definitions of mental illnesses in the *DSM, Fifth Edition or International Statistical Classification of Diseases and Related Health Problems, 10th revision*, are heterogenous in themselves, which increases the complexity of the models needed for classification. There is no single measurement that can be used to explain variance in psychiatric disorders.[40] Additionally, whereas in other diagnostic endeavours such as biopsy for cancer detection, it is possible to discern whether a sample is malignant or not, in mental health conditions there is no definitive "biopsy" for a patient.[93]

There is also no "one-size-fits-all" approach for ML in mental health research. No algorithm is superior for every available problem; therefore, the "best" algorithm or combination of algorithms must be determined on a case-by-case basis, which may take time and resources.[40] Additionally, it may be more beneficial to take a pragmatic approach to predictive analytics in mental health, as a highly accurate model based on very expensive data collection (e.g., MRI) might not be as widely efficient or useful to clinicians in daily practice as a less accurate model that can use less expensive data (e.g., smartphone data).[40] Consultations echoed these challenges — research in AI requires massive amounts of data, which can be difficult to obtain, and it can be difficult to guarantee high-quality, complete, and relevant features for analysis. The Computational Psychiatry Group Data Strategy is a strategy noted by the consultations that aims to increase data access for applied AI work, including international large population datasets for real-world evidence.

A common pitfall of ML in the classification of psychiatric disorders is "peeking" or "double dipping." This occurs when the algorithm's training set of data and testing set of data are not kept independent from one another. Not separating these groups can overestimate the accuracy of an algorithm.[15] However, many ML studies for psychiatric disorders have small sample sizes, therefore limiting the amount of data for training and testing. Small samples sizes can lead to overfitting of the data and skewed accuracy measurements.[2] The lack of usable data was also mentioned during many consultations. One consultation mentioned that although data are limited in many areas, this should not stop us from making predictive models, but we should be aware of the limitations of these models.

Hahn et al. proposed several questions to ask regarding predictive analytics in mental health research. These include questions relating to the size and scope of the model, which predictors to use, how to make models efficient, which ML approach to use, how a validated model would be implemented and available for clinicians, and how to ensure future validity of the model.[40] Dr. Wesley Jackson posited some concerns regarding AI for heart rhythm applications that may be similar for mental health — how accurate will the technology be when used "in the wild," whether it will it trigger individuals prone to worrying about their health, and how the individual should react when given an "abnormal" reading.[99] Despite many studies testing ML and AI algorithms in an enclosed laboratory context, there are comparatively fewer studies examining the effectiveness of these algorithms in a real-world setting.

Gaps in the literature as noted by Ackerman et al. and Shatte et al. include the long-term impacts of digital health applications;[37] research into eating disorders, anxiety, and public health; and using prospective, real-time data for diagnosis.[5] There were also limited data on subgroups of interest, including varying life stages and population groups. The limited data available for these groups limits the generalizability of algorithms to these different groups.

Objective 3: Report who the professional groups and organizations involved in the use or development of artificial intelligence or machine learning for mental health are; and outline the key players in research, academia, government, and industry across Canada and internationally.

Appendix 4 details some professional groups and their programs. This list is not exhaustive of all professional groups and organizations involved in AI and will not be updated on an ongoing basis. At present, groups in a Canadian setting include the University of Alberta, McGill University, Université de Montréal, Saint Elizabeth Health Care, Krembil Centre for Neuroinformatics, and Strongest Families. Internationally, groups using conversational agents include Woebot labs, Wysa Inc., USC ICT, and Textpert. Diagnostic; prognostic AI companies include Mindstrong Health, Computer Science and Artificial Intelligence Laboratory, New York University, University of Vermont, University of Michigan, and Facebook.

The Government of Canada hosts a list of suppliers of AI products on their website. None of these providers appear to be specific to mental health.

Limitations

The findings in this Environmental Scan are based on a limited literature review (in which screening and data extraction were performed by a single author) and a limited number of targeted consultations. Therefore, it may not be a fully comprehensive overview of all AI applications and programs in mental health. Additionally, there was no critical appraisal of literature, so the quality of the evidence from the studies identified by the literature search is uncertain.

Limited information regarding mental health conditions such as PTSD, postpartum depression, and anxiety was obtained. The majority of current research has been performed on conditions such as bipolar disorder, schizophrenia, and MDD. As suggested by consultations, this may be due to the relative severity of these conditions and therefore, the more “obvious” mood changes, brain changes, and symptomology. Additionally, the literature was more often related to *DSM, Fifth Edition* diagnosed mental health conditions and was not focused on more mild mental health issues, transient mental health issues, or undiagnosed mental health conditions. No data specific to subgroups of interest were identified, including population groups such as LGBTQ2+ and Indigenous peoples. Limited information was found for varying life stages, with a small number of AI applications identified for youth and for seniors.

The consultations represented individuals from Ontario, Alberta, Nova Scotia, and British Columbia; therefore, there was no representation from other provinces and territories that may have perspectives that differ from the ten stakeholders that were involved in the present report. Additionally, all individuals who provided an interview were part of the research and development of AI, and were not using AI in clinical practice; therefore, this specific perspective may be lacking from this report.

Conclusions and Implications for Decision- or Policy-Making

Interest in AI and ML applications is steadily growing in Canada, including in the mental health sphere, with continuing investments in research and development. Applications of AI in mental health include conversational agents, CAT, diagnosis of mental health conditions, predictions and risk of behaviour, and prediction of prognostic outcomes in treatment. These applications are primarily research initiatives, and not currently clinically applied. Current AI applications include chatbots through mobile applications and applications for schizophrenia that provide personalized algorithms. There are some identified AI algorithms used in children and youth, including Kids' Help Phone's crisis text service. In older adults, there are several AI applications to combat loneliness in seniors through companion robots.

Key domains of research and development in AI for mental health include diagnosis and prognosis, with most of the research occurring in the diagnostic field — including the use of neuroimaging, blood biomarkers, genetic analysis, metabolomic, and proteomic data. Other diagnostic projects include using data from social media, individual speech, tone, facial expressions, and wearable sensors.

Trends in the development of AI for mental health include larger numbers of AI-based chatbots for use in treatment, greater emphasis on explainability and interpretability, and increasing numbers of wearable sensors and smartphone-based data collection. Translation of AI from the lab to clinical practice is a future policy and program direction and will require consideration of implementation issues, suitability of AI for mental health, and ethical concerns. Ethical concerns include addressing bias in the algorithms, creating generalizable and culturally sensitive AI interventions, privacy, consent, and the balance of commercial interests and effectiveness. Limitations of AI also need to be addressed, including the multimodal nature of mental illnesses, avoiding overfitting of the data, and the costliness of some data collection methods.

Professional groups involved in the research, development, and use of AI for mental health in Canada include the University of Alberta, McGill University, Université de Montréal, Saint Elizabeth Health Care, Krembil Centre for Neuroinformatics, and Strongest Families. Internationally, groups include USC ICT, Mindstrong Health, Woebot Labs, Wysa Inc., and Facebook.

The findings in this Environmental Scan were based on a limited literature search and stakeholder consultations. There was limited representation from some Canadian jurisdictions and limited representation from clinicians applying AI in practice. The present review also does not comment on the effectiveness or accuracy of AI or ML models. A Rapid Response report pertaining to clinical effectiveness and guidelines for AI in mental health was also conducted as a complement to this Environmental Scan.[13]

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Appendix 1: Glossary of Artificial Intelligence Terms

Artificial intelligence	The reproduction of human cognition (i.e., reasoning, thinking, understanding) through an artificial means such as a computer.[1]
Artificial neural network	A form of AI designed with neural "layers" — one input layer of neurons, multiple "hidden" layers of neurons, and a final output layer.[14]
Chatbot	AI-driven conversational agent programs that have the ability to "talk" with participants.[55] Examples of chatbots include customer service chatbots (e.g., "LiveChat," Facebook Messenger–based chatbots)
Computerized adaptive testing	An adaptive testing method that is targeted to the particular individual taking the test. The test gauges the estimate of whatever the targeted output is based on the previous answers to questions and adapts the test to provide more informative questions.[19]
Conversational agent	A system that mimics human conversation through text or spoken language.[55] These conversational agents include chatbots and "assistants" such as Siri, Alexa, and Google Home.
Convolutional neural network	An artificial neural network originally designed for images, with an input and output layer as well as a convolutional layer, pooling layer, and fully-connected layer.[100]
Deep learning	The layers within a neural network.[14]
Machine learning	Algorithms that "learn" from data to generate outputs rather than those that are programmed to deliver a fixed solution.[2]
Natural language processing	A machine learning technique in which inferences are made from text or speech about the speaker's thoughts, feelings, and motivations.[101]
Random forest	An ensemble learning method of multiple independent decision trees. Each tree casts a vote for a particular output, the output with the majority of votes is the final determined output.[102] This is similar to casting a vote in an election in which whatever had the majority of votes is the "winning" output.
Support vector machines	A linear classification method in which a hyperplane is draw between two classes based on the maximal distance from two support vectors (data points).[15] Kernels can be used to transform data to further discriminate the two classes.[103]

Appendix 2: List of Computerized Adaptive Tests Used in Real Patients as of 2016

Table 3: Computerized Adaptive Tests Used in Real Patients[24]

Type of CAT	Year Created	Content
German Language		
D-CAT	2005 2009	Depression
A-CAT	2008	Anxiety
Stress-CAT	2009	Stress levels and reaction
English Language		
CAT-MASS	2008	Mood, panic-agoraphobia and social phobia, OCD
CAT-DI	2012	Depression severity
PROMIS CATs	2011 2014	Anxiety, depression, anger
CAT-ANX	2014	Anxiety
Spanish Language		
CAT health instrument	2009 2010	HRQ

CAT = Computerized adaptive test; HRQoL = health-related quality of life; OCD = obsessive compulsive disorder.

Appendix 3: Sample Publications on the Topic of Using Artificial Intelligence for Mental Health Diagnosis

Sample Publications Using Artificial Intelligence for Mental Health Diagnosis

Schizophrenia

1. Deng Y, Hung KSY, Lui SSY, et al. Tractography-based classification in distinguishing patients with first-episode schizophrenia from healthy individuals. *Prog Neuropsychopharmacol Biol Psychiatry*. 2019;88:66-73.
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Appendix 4: Current and Future Artificial Intelligence and Machine Learning Applications in Mental Health

Table 4: Organizations Involved in Artificial Intelligence and Machine Learning in Mental Health

Organization	Type of AI	Professions or Users Involved	Name of Product	Purpose of Project
Canada				
A4I (App for Independence)	AI application	Researchers	A4I	A joint partnership with Memotext to create an application for patients with schizophrenia and psychosis.
AIFred Health	Deep learning	Researchers; physicians		Treatment prediction and patient data tracking for physicians.[104]
Alberta Machine Intelligence Institute	AI and ML	Researchers	Ana	Ana is a project from Alberta Machine Intelligence Institute (loneliness robot) that uses AI in a chatbot form for elderly patients to prevent loneliness.
AltaML	ML	Researchers	No product name	An Edmonton software company in partnership with Oliver Primary Care Network and Boehringer Ingelheim Canada Ltd. seeking to develop a frailty index to predict conditions such as mental health conditions. A partnership with Jeremiah technologies (Kangning group collaboration — more information under Kangning group) and Wenzhou Medical University to potentially commercialize a chatbot service that supports multiple stakeholders.
Asia Pacific Economic Cooperation Digital Hub for Mental Health	AI and ML	Researchers	No product name	A partnership of University of Alberta, University of British Columbia, Mood Disorders Society of Canada, and CANMAT to develop of a digital hub for mental health for the Asia Pacific Economic Cooperation, plans include e-mental health and AI. One of these projects is the Asia Pacific Economic Cooperation Global Alliance for Chronic Diseases Enhanced Measurement-Based Care Effectiveness for Depression project, a joint China and Canada project regarding implementation of evidence-based approaches to mental health (mood disorders) interventions in the Shanghai region.[105]
MindBeacon Software Inc.	AI	Employers; patients	BEACON	Digital CBT, moving into further AI capabilities.

Organization	Type of AI	Professions or Users Involved	Name of Product	Purpose of Project
Computational Brain Anatomy (CoBrA) Laboratory at the Cerebral Imaging Centre at the Douglas Mental Health University Institute	AI	Researchers	No product name	A group studying brain anatomy through neurodegenerative disease and mental health disorders such as schizophrenia.
Cychiatry Lab — Lab for Computational and Digital Psychiatry	AI and ML	Researchers	No product name	Led by Bo Cao, the lab looks at computational psychiatry and precision medicine for mental health. Examples of projects include using AI to predict outcomes of mental illness through electronic health records.
DeepMind	AI	Scientists; engineers; machine learning experts	No product name	A UK-based AI company with an office located in Alberta.
DeSouza Institute	AI	Researchers; health care professionals	Cancer Chat Canada	A tool for individuals with cancer to receive psychosocial support in the form of online chat.
IBM Centre for Advanced Study	AI	Researchers	No product name	Based at the University of Alberta, a collaboration with the Alberta Computational Psychiatry group. Current project includes NLP for post-traumatic stress disorder in early symptom diagnosis in military personnel.
Kids' Help Phone	NLP	Health care providers; researchers	Crisis Text Line	An AI-based triaging service that triages users who initiate conservations with the crisis text line into immediate crisis or less immediate crisis.
Memotext	ML	Researchers; patients; health care providers	A4I	A digital engagement engine that uses ML Mental Health Applications including A4I.
Saint Elizabeth Health Care in Partnership With X2AI (San Francisco)	Chatbot	Health care providers	Tess[37]	A chatbot designed by X2AI for mental health therapy.
Strongest Families	Neural network	Researchers; health care providers	IRIS[106]	A platform to increasing the amount of AI (neural network designs) for guided care and predictive analysis. Planning to add more eCoaching and virtual coaching using AI.
The Centre for Addiction and Mental Health — Krembil Centre for Neuroinformatics	Big data AI	Researchers	No product name	Various projects in AI and ML to analyze, categorize, and predict genetic, epigenetic, diffusor tensor imaging, magnetic resonance imaging, functional magnetic resonance imaging, and clinical data.[107]

Organization	Type of AI	Professions or Users Involved	Name of Product	Purpose of Project
University of Alberta The University of Alberta includes the Alberta Machine Intelligence Institute and the University of Alberta Computational Psychiatry Group	ML models	Researchers	EMPaSchiz (fMRI for schizophrenia)	A tool to recognize the speech qualities of people with depression. The goal is to create a smartphone application.[97] Use of fMRI to diagnose schizophrenia.[14]
		International		
7 Cups of Tea	Chatbot	Researchers; patients; therapists; volunteers	Noni	A "digital intake coordinator" that connects individuals with their human therapists.[92] It offers standard screening tests and triages participants.[108]
Alan Turing Institute	ML	Researchers	No product name	A machine learning algorithm to determine who is at high or low risk of mental health illness. Work has been done on dementia so far.[109]
Bark	AI	Researchers; parents and caregivers; health care providers	Bark	A parental control application to monitor children's text messages, social media activity, and email, and flag for risks. It can flag risks for suicide, depression, and bullying.[110]
BioBeats	AI wearable devices	Researchers; patients	BioBase	An application (BioBase) that tracks sleep duration and quality, activity, heart rate variability, mood, and brain function.[89]
Carnegie Mellon University and the University of Pittsburgh	ML	Researchers	No product name	A product to detect of suicide ideation.[111]
Cogniant	AI	Researchers; clinicians; social workers; caregivers; patients	Cogniant	A collection of data on a patient's daily routine to monitor behaviour[112]
Cognoa	AI	Researchers; patients and parents; health care providers	Cognoa	An assessment of childhood development (mostly related to autism spectrum disorders).[113]
Computer Science and Artificial Intelligence Laboratory, Massachusetts Institute of Technology	Neural network	Researchers	No product name	A product to detect depression through modelling of interactions between a human and virtual agent.[114]
Dartmouth University	ML	Researchers ; clinicians	Durkheim Project	A public health initiative that uses veteran's social media posts to determine risk for suicide in real time.[115]
EU Seventh Framework Programme	Social assistance robot	Clinicians; nursing home workers	CompanionAble "Hector"	An autonomous companion robots for assistive living.[49]
Facebook	ML	Researchers	No product name	AI that scans posts and flags users at risk of suicide for human review.[14]

Organization	Type of AI	Professions or Users Involved	Name of Product	Purpose of Project
Fralin Biomedical Research Institute at Virginia Tech Carilion	ML	Researchers	No product name	A product that uses fMRI and sMRI to diagnose mental health conditions, specifically depression and addiction.[93]
Ginger.io	ML	Researchers; patients; health care providers	Ginger	An algorithm that learns from patient historical mobile phone usage data, and personalizes treatment to them (e.g., connecting with therapists), or detects deviations in behaviour that may indicate distress.[116]
Harvard University	ML	Researchers	No product name	A collaboration with the University of Alberta Computational Psychiatry Group that created a multi-centre imaging and clinical variable dataset for mental health–related ML.
Kangning Hospital Group	AI and e-health	Researchers	No product name	A collaboration with the University of Alberta Computational Psychiatry group, which established an "Academician Work Station." The team is planning to implement AI-based e-health tools in a clinical setting.
Lawrence Berkeley National Laboratory (Berkeley Lab) and Department of Veterans Affairs and Department of Energy	Deep learning	Researchers	No product name	Using the EHR database and Million Veteran Program to pull out factors that may predict suicide.[80]
Limbic AI	AI	Researchers; clinicians	Limbic	A mobile-based application (patient reporting tool) for clinicians to track progress of patients using wearable technology.[117]
Lyra Health	Big data AI	Researchers; patients; health care providers	Lyra	A tool that connects companies and employees with mental health devices using ML.[118]
meQuilibrium	Big data AI	Researchers; patients; health care providers	meQuilibrium	A platform to boost employee resilience.[119]
Mindstrong Health	AI	Researchers	No product name	Digital phenotyping gathered from smartphone data to detect early dementia and mental illness.[98]
National University of Ireland Galway	Social assistance robot	Clinicians; nursing home workers	MARIO (Kompai)	Social assistive robots to combat loneliness in seniors.[48]
Neurotrack	AI	Researchers; patients; health care providers	Neurotrack	A product that measures cognition and maintaining cognitive health through assessments.[120]
New York University	ML program	Researchers	No product name	A product that distinguishes the voices of individuals with post-traumatic stress disorder.[97]

Organization	Type of AI	Professions or Users Involved	Name of Product	Purpose of Project
Quartet Health	ML	Researchers	Quartet	A product that uses machine learning to identify patients seeing a doctor for a physical ailment who may also have a potential mental health condition, and to match them to appropriate behavioural specialists.[116]
Spring Health	Predictive modelling	Researchers; patients; health care providers	Spring Health	A product for diagnosis and matching to appropriate treatment.[121]
Talkspace	AI	Researchers; health care providers; patients	Talkspace	A mobile-based therapy application. Expanding into AI capabilities.[122]
Textpert (AiME)	Mental health ECA	Researchers; health care providers	AiME	A product that asks users interactive questions, observes their responses, and then determines their risk for depression, anxiety, and addiction through analyzing users' speech content, vocal tonality, and facial expressions.[39,123]
The National Institute of Mental Health and Neurosciences	ML	Researchers	No product name	A collaboration with the Alberta Machine Intelligence Institute on a project related to schizophrenia, fMRI, and ML for schizophrenia
University of Southern California Institute for Creative Technologies	ECA	Researchers; patients	SimCoach; SimSensei	SimCoach and SimSensei, ECAs for treatment and diagnosis.[71,73]
University of Vermont and the University of Michigan	ML	Researchers	No product name	A product to identify anxiety and depression in young children through patterns of their speech.[97]
Huawei	AI	Researchers	No product name	A Chinese telecommunications company that opened an Edmonton office recently — one project is a collaboration with the University of Alberta computational psychiatry group related to remote sensing and diagnostics using AI.
Woebot Labs (San Francisco)	AI chatbot	Researchers; health care providers	Woebot	A CBT chatbot.[16]
World Well-Being Project; the Penn Positive Psychology Center and the Stony Brook Human Language Analysis Lab	ML	Researchers	No product name	A measurement of psychological well-being through social media analysis.[124]
Wysa Inc.	AI chatbot	Researchers; health care providers	Wysa	A CBT chatbot.[38]

A4I = App for Independence; AI = artificial intelligence; AiME = artificial intelligence mental evaluation; CANMAT = Canadian Network for Mood and Anxiety Treatments; CBT = cognitive behavioural therapy; ECA = embodied conversational agent; EHR = electronic health record; EU = European Union; fMRI = functional magnetic resonance imaging; ML = machine learning; NLP = natural language processing; sMRI = structural magnetic resonance imaging.