Published in final edited form as:

Biol Psychiatry Cogn Neurosci Neuroimaging. 2021 September ; 6(9): 856–864. doi:10.1016/j.bpsc.2021.02.001.

Artificial Intelligence for Mental Healthcare: Clinical Applications, Barriers, Facilitators, and Artificial Wisdom

Ellen E. Lee, MD[1,2,3,*], **John Torous, MD**[4,*], **Munmun De Choudhury, PhD**[5], **Colin A. Depp, PhD**[1,2,3], **Sarah A. Graham, PhD**[1,2], **Ho-Cheol Kim, PhD**[6], **Martin P. Paulus, MD**[7], **John H. Krystal, MD**[8,**], **Dilip V. Jeste**[1,2,9,**]

[1]Department of Psychiatry, University of California San Diego, CA, USA

[2]Sam and Rose Stein Institute for Research on Aging, University of California San Diego, CA, USA

[3]VA San Diego Healthcare System, San Diego, CA, USA

[4]Department of Psychiatry, Beth Israel Deaconess Medical Center and Harvard University, Boston, MA, USA

[5]School of Interactive Computing, Georgia Institute of Technology, Atlanta, GA, USA

[6]AI and Cognitive Software, IBM Research-Almaden, San Jose, CA, US

[7]Laureate Institute for Brain Research, Tulsa, OK, USA

[8]Department of Psychiatry, Yale University, New Haven, CT, USA

[9]Department of Neurosciences, University of California San Diego, CA, USA

Abstract

Artificial intelligence (AI) is increasingly employed in healthcare fields such as oncology, radiology, and dermatology. However, the use of AI in mental healthcare and neurobiological research has been modest. Given the high morbidity and mortality in people with psychiatric disorders, coupled with a worsening shortage of mental healthcare providers, there is an urgent need for AI to help identify high-risk individuals and provide interventions to prevent and treat mental illnesses. While published research on AI in neuropsychiatry is rather limited, there is a growing number of successful examples of AI's use with electronic health records, brain imaging, sensor-based monitoring systems, and social media platforms to predict, classify, or subgroup mental illnesses as well as problems like suicidality. This article is the product of a Study Group held at the American College of Neuropsychopharmacology conference in 2019. It provides an overview of AI approaches in mental healthcare, seeking to help with clinical diagnosis, prognosis, and treatment, as well as clinical and technological challenges, focusing on multiple illustrative publications. While AI could help re-define mental illnesses more objectively, identify

Please address all correspondence to: Dilip V. Jeste, MD, Senior Associate Dean for Healthy Aging and Senior Care, Distinguished Professor of Psychiatry and Neurosciences, Estelle and Edgar Levi Chair in Aging, Director, Sam and Rose Stein Institute for Research on Aging, University of California San Diego, 9500 Gilman Drive #0664, La Jolla, CA 92093, USA. Phone: +(858) 534-4020; djeste@ucsd.edu.

*Co-First authors

**Co-Senior authors

them at a prodromal stage, personalize treatments, and empower patients in their own care, it must address issues of bias, privacy, transparency, and other ethical concerns. These aspirations reflect human wisdom, which is more strongly associated than intelligence with individual and societal well-being. Thus, the future AI or Artificial Wisdom (AW) could provide technology that enables more compassionate and ethically sound care to diverse groups of people.

Keywords

Machine learning; Compassion; Emotional regulation; Social media; Depression; Robot

The global burden of mental illnesses accounts for 32% of years lived with disability, making mental illnesses the first in global burden of disease (1). Moreover, mental health challenges have increased in recent decades with a rise in suicides, substance use, and loneliness (2), worsened by the Covid-19 pandemic (3). Mental healthcare is compounded by a shortage of nearly 4.5 million mental healthcare providers, including well over 100,000 psychiatrists in the US (4). Artificial Intelligence (AI) presents a potential solution to address this shortage, and is increasingly employed in healthcare fields like oncology, radiology, and dermatology (5–7). The global AI in healthcare market is expected to grow from $5 billion in 2020 to $45 billion by 2026 (8). Also, there are increasing numbers of large-scale databases like Electronic Health Records (EHRs) in various countries (9).

The use of AI in mental healthcare is, however, limited. The computational power harnessed by AI systems could be leveraged to reveal the complex pathophysiology of psychiatric disorders and thus better inform therapeutic applications (10). Mental healthcare relies on strong clinician-patient relationships that are often hindered by the limited interaction time allotted for clinical care. AI technologies offer a way to streamline tasks that do not require a “human touch” and thus provide complementary support that enables clinicians to focus on delivering more empathic care, thus “humanizing” medical practice (11). A recent survey of psychiatrists highlighted documenting/updating medical records and synthesizing information as two time-consuming tasks where AI could replace a human clinician (12). AI may further complement clinical intuition by enhancing diagnostic accuracy by supporting the clinical reasoning process (13) and advancing the mechanistic understanding of mental illnesses (14,15).

This article is the product of a Study Group held at the American College of Neuropsychopharmacology that included academic, clinical, and industry experts in mental health and AI in 2019. While there have been several excellent reviews of AI in psychiatric disorders, they have focused on specific conditions like autism (16) or bipolar disorder (17), or a specific goal such as genetic prediction (18). This article provides an overview of AI approaches in mental healthcare, to help with clinical diagnosis, prognosis, and treatment as well as clinical and technological challenges, and the future of AI (- i.e., Artificial Wisdom or AW), focusing on multiple illustrative examples.

AI Approaches: Machine Learning and Natural Language Processing

No FDA-approved or FDA-cleared AI applications currently exist in psychiatry (19). However, such applications have long been envisioned – e.g., the potential of expert systems and computerized therapy (20). Reasons for the delayed adoption of AI into routine psychiatric practice include the sensitive nature of data generated by mental health patient-clinician interactions (e.g., written clinical notes, conversations with patients) and multi-faceted diagnostic criteria in the DSM-5 (21,22). These types of data and clinical decision-making in psychiatry are far more complex than specific and objective tasks (e.g., tumor identification from an image) that are well-supported by current AI methods (23). AI technologies are also notoriously "data-hungry," and the field of mental healthcare has been limited in its access to large, high-quality datasets.

Machine Learning (ML):

This is the most commonly used subset of AI in healthcare. It employs data-driven algorithms to learn from data, estimating or predicting outcomes for new data and/or future events (13,24). ML differs from more traditional statistical approaches in several key ways: being more hypothesis-generating than hypothesis-driven; having minimal model assumptions rather than the strict assumptions required for statistical inference; and being focused more on predictions and pattern recognition than estimating parameters of interest (for details see (10,25)). Recommendations for using ML with mental health data are available. The International Society for Bipolar Disorders Big Data Task Force (17) has outlined the essential steps from acquiring patient data from multiple sources and biological levels to translating the knowledge to generate risk calculators. Similarly, Park, et al. (26) described clinical research strategies to systematically evaluate AI model performance in healthcare. Liu et al. (27) provided a guide on how to interpret ML-based publications and assess the appropriateness of the ML model for the size and type of input data.

AI is well-suited to handle "big data," granular, or digitized data (28). The potential of a subset of ML, deep learning (DL), in psychiatry is just beginning to be realized [see (29)]. DL has been used to support diagnostics, in particular for dementia, using the largest possible publicly available datasets (e.g., Alzheimer's Disease Neuroimaging Initiative, or ADNI) (30). EHRs, digital phenotyping data from mobile phones, and social media platforms represent additional sources of high-dimensional data that could provide the necessary inputs to fully harness the power of DL for mental health applications. Medical data sharing has become increasingly more important, as models trained on high-dimensional data with small samples (e.g., more features than participants) lead to poor generalizability (31).

One potential solution to address small samples is transfer learning, which enables use of pretrained AI algorithms, designed for different purposes, as a starting point for analysis of new data (32). For example, Wang et al. (33) used a pre-existing algorithm (with fine tuning) called AlexNet that was originally trained on the large visual database ImageNet to classify alcoholism vs. non-alcoholism. Another example is that of Banerjee et al. (34) who used knowledge from a large speech-recognition database called TIMIT to detect post-traumatic stress disorder (PTSD). These approaches work because of similarities in the structure of the different datasets. Transfer learning is an economical and efficient solution, avoiding the development of a new model from scratch and requiring less training data. Given the relative dearth of large psychiatric datasets, transfer learning could prove useful for AI in mental healthcare.

Natural Language Processing (NLP):

This includes techniques like speech recognition, sentiment, lexical, and semantic analysis, and optical character recognition to transfer text from unstructured to structured formats in order to enable subsequent analyses (35). NLP techniques are relevant for psychiatry because language and speech are the primary sources of information used to diagnose and treat mental disorders. Unstructured psychiatric evaluation records are readily available, inexpensive, and rich in information to help identify phenotypes and comorbidities (36,37). Relevant examples in mental health include applying NLP within the Clinical Record Interactive Search (CRIS) platform (38), and predicting the risk of suicide (39) and early psychiatric readmission (40), from hospital discharge notes within the EHR. NLP can also be applied more broadly to EHR or insurance claims data for automating chart reviews, clustering patients into particular phenotypes, and predicting patient-specific outcomes (41,42).

Assistance with Clinical Diagnosis, Prognosis, and Treatment

Clinical Diagnosis:

Today’s AI systems can help with differential diagnostic challenges in several key ways. First, AI approaches can bolster the ability to differentiate between diagnoses with similar initial clinical presentations but divergent treatment approaches (43) – e.g., identifying bipolar versus unipolar depression based on brain imaging features (44), or differentiating between types of dementia using structural MRI scans (45). Secondly, data-driven AI methods can help identify novel disease subtypes based on heterogeneity of presentations, demographic features, and environmental factors (43). Examples include neurocognitive profiles in bipolar disorder (46), genetic profiles in schizophrenia (47), biomarker profiles in psychoses (48), and neuroimaging subtypes in depression (49). Thirdly, AI approaches can build models from unusual/novel data sources and reconcile data from multiple heterogeneous data-streams, e.g., EHR, behavioral data from digital phenotyping and wearable sensors, speech, social media feeds, neurophysiology, imaging, and genetics (50), to coalesce explanatory and mechanistic models of mental illness across self-report to molecular assessments. Illustrations include Instagram photographs to predict risk of developing depression (51), speech data to predict psychosis onset in high-risk youth (52), and identifying individuals with PTSD (53). AI methodology can also incorporate both genetic and environmental risks (54), accounting for complex environment-gene interactions and psych-bio-social factors, particularly relevant in PTSD (55). Furthermore, AI methodologies are well-suited for deciphering patterns from longitudinal data (56), critical for honing the accuracy of diagnoses based on evolving psychiatric symptoms. Lastly, AI methods may have a growing role in gathering sensitive and accurate data from patients. One study found that individuals were more forthcoming disclosing sensitive information with a computer system than with a person (57).

Use of Non-Clinical Data:

The digital health movement is closely aligned with AI methods using data outside of typical physician-patients interactions (58). Day-to-day and longitudinal monitoring of sensors (59) and social media can enable early detection of symptoms or relapse, and shed light on helpful versus harmful behaviors (60,61). Multimodal-sensing including smartphones, wearable devices, physiological sensors (e.g., heart rate, electrodermal activity), and ambient sensors (e.g., motion, temperature, light) enables collection of real-world, continuous data concerning symptoms, treatment response, and behaviors, thoughts, and emotions (62,63). Platforms designed to enable multimodal data collection, like mindLAMP (64), AWARE (65), and CrossCheck (66) aid in continuous remote monitoring and identification of subjective and objective indicators of psychotic relapse. ML techniques can derive meaningful or novel features from inherently noisy signals generated by sensors (62). Behaviors like social withdrawal may be detected using smartphones and Fitbit data (67).

Social media platforms represent a new form of social communication, reflecting day-to-day functioning of many individuals (68), thus providing an unprecedented, unobtrusive “lens” into longitudinal behaviors and moods (69,70), especially for adolescents and young adults who are both the highest internet users and at the greatest risk for the emergence of mental disorders (71,72). Examining the content, language, and consumption patterns of social media provide novel insights into relationships and communication, as well as create new opportunities for seeking help (73,74). Web-based influences impact people’s knowledge of, and attitudes toward, healthcare practices like vaccination, at population and individual levels (75). Mental illnesses may be observable in online contexts, and social media data have been leveraged to predict diagnoses and relapses (51,72,76,77), with accuracies comparable to clinician assessments and screening surveys (78).

However, sensor data do not yet have clear usability in clinical mental health settings (79) due to lacking clinical validity and implementation challenges. Likewise, analyses of social media data need AI-based innovations, e.g., shared infrastructures for data collection and data donation. Furthermore, important privacy and ethical issues regarding social media data (80,81) as well as public distrust of data usage for sensitive purposes may hinder research and creation of large-scale data sets necessary for AI algorithms (82).

Prognosis:

AI methodologies applied to longitudinal data can bolster accurate prognoses for psychiatric patients (43). Studies have harnessed neuroimaging, EHR, genetic, and speech data to model trajectories of depression (83), suicide risk (84), future substance abuse (85), and functional outcomes (86). AI algorithms can also use data-driven approaches to build new clinical risk prediction models (87) without relying primarily on current theories of psychopathology. However, internal and external validation of an AI algorithm is essential for its clinical utility. Cross validation or split-sample validation are important steps for preliminary internal validation; though these steps do not ensure generalizability of the results. Temporal validation (newly recruited participants) and geographical validation (data from a different site) are more rigorous strategies to ensure clinical utility (see (87,88)).

Treatment:

AI technologies have great potential to support clinical treatments in psychiatry in several ways. First, AI can be used to predict treatment response, potentially bypassing ineffective medication trials, invasive and expensive brain stimulation therapies, or time-consuming psychotherapies (43). Studies have predicted response to antidepressant medications using clinical questionnaire items (89) and EEG signals (90), response to antipsychotics based on EEG (91), response to electroconvulsive therapy (ECT) based on brain structure (44), response to CBT for anxiety based on brain fMRI (92), and response to brain stimulation based on MRI (93). Such studies can identify the target populations for various treatments (94), though not all studies are positive (95,96). Secondly, AI approaches can help predict serious side effects of treatments (97). One study used EHR data to predict development of renal insufficiency among patients treated with lithium (98). Thirdly, AI approaches can aid in building new theoretical models of disease pathophysiology. One study reported progressive divergence of neuroimaging abnormalities in bipolar patients (from non-psychiatric controls), supporting the hypothesis of bipolar disorder as a neuroprogressive disease (99). Similarly, characterizing the timing and course of brain changes during the conversion from psychosis prodrome to schizophrenia (100) can contribute to understanding risk and resilience factors during the prodromal phase. These approaches may also uncover novel opportunities for early intervention, through identifying the most heavily weighted risk factors for transitions to illnesses. Fourthly, ML approaches can help identify gene expression patterns characteristic of different psychiatric disorders (101). One study described a model that could accurately predict which individuals would develop PTSD based on pre-deployment blood transcriptome data (102), highlighting immune-related gene dysregulation as a risk factor for, and not just a consequence of, PTSD. Lastly, AI can aid directly in the discovery of new treatments (103). AI methods can aid in predicting the clinical action of drugs through simulation or data-driven approaches, thus discovering novel compounds with therapeutic potential (94) – e.g., pharmacodynamics of ketamine infusion through BOLD fMRI response to ketamine and other drugs (104).

Clinical Challenges

There are unique challenges to use of ML in psychiatry. Performance of supervised algorithms depends on the quality of the diagnostic labels used to train a model. Given the heterogeneity characteristic of mental illnesses, labels of disease states may not be specific enough to yield AI algorithms with high sensitivity and specificity. One possibility is to use ML algorithms to predict specific symptoms or functional consequences rather than diagnoses. Another opportunity lies in leveraging the strength of deep neural networks that can operate without human oversight to identify novel biomarkers for detecting specific diseases (29). However, a barrier to using ML algorithms is so-called “stealth science” which protects trade secrets though transparency and reproducible methods are necessary. Big data (e.g., EHR, clinical notes, sensor data, social media data) are inherently messy and require considerable transformation before they are usable (105). When the results of ML algorithms are published, they must include information regarding the quality of the data used to train the model as well as any potential biases in it, which is rarely done at present.

The major advantage of AI tools is their superior ability to handle large quantities of data quickly to guide clinical decision-making. However, there are still relatively few examples of adoption of ML into clinical psychiatry practice and little evidence of clinical or economic impact. Sendak et al. (105) have proposed four phases of translation necessary to bridge this gap: design and development of ML products that can support clinical decision-making and are actionable; evaluation and validation; diffusion and scaling across settings such that the tools are more widely applicable; and continued monitoring and maintenance to remain current with clinical practice needs. An exemplar is the ML product IDx-DR used to automatically diagnose diabetic retinopathy.

Healthcare systems face key challenges in adopting AI systems (106,107). One case study at Yale University involved implementation of AI-based decision support for improving selection of antidepressant treatments (108–110). The cost-benefit assessment conducted by the healthcare system considered both clinical benefits for patients and financial benefits to the healthcare system. The upfront cost of building a specialized IT infrastructure, skepticism of its utility, and concern for unintended consequences were key hurdles. In addition, enabling a larger pool of primary care physicians to treat poorly reimbursed psychiatric disorders might increase the burden on these physicians and reduce their overall productivity, thus affecting the hospital’s revenues. Both clinicians and patients expressed concern about the eventual regular utilization of these clinical tools. Thus, for AI-based clinical tools to become fixtures of hospital-based clinical practice, they must be incorporated into the culture of the healthcare setting.

Another example of the promise and challenges of AI implementation in psychiatric population health is the REACH VET program at the US Veterans Affairs (111,112). The VA has leveraged its immense and harmonized EHR system to investigate a new ML-based program that identifies high suicide risk individuals. Qualitative research indicated that Veterans were less concerned about the predictive origin of the outreach than the tone and clinical skill of the clinician providing outreach. The ongoing Yale and VA projects are experiments in how large clinical datasets can potentially lead to predictive interventions and integrated into patient-centered care systems.

Technological Challenges

A major challenge for AI in mental health is that the underlying biological processes of psychiatric disorders are still poorly understood (113). Therefore, AI models have to be bootstrapped from observations, rather than be derived from first principles. However, a major problem for data-based derivations of models is the statistical bias-variance trade-off (114). A complex model may overfit – i.e., fit the observed data well (minimizing statistical bias) but is unstable and highly dependent on the specific data used to fit it (maximizing variance). Conversely, a simple model may underfit the observed data and miss relevant structures. Good ML approaches seek to optimize the statistical bias-variance trade-off by finding the “sweet spot” for prediction. Predictive models evaluate how accurately a built model can forecast future outcomes and need well-defined metrics of individual-level model performance (115); explanatory disease models identify robust effects on understandable variables (116). Despite the clear trade-off between accuracy and explainability, explainable models are needed to ensure safety of the patients and establish trust in the AI models. Recent developments in AI include recurrent neural network (RNN) variant models that can control data inputs at various stages and self-evaluate which timepoints and data inputs are most predictive of the outcome, visualizing techniques, association rule mining (using biologically-based relationships between data elements), and functional validation of the results (117,119). In instances where the biological associations are not well-understood, e.g., in analyses of complex imaging and language data, the AI models may not be as clearly interpretable. However, future AI models must strive to improve transparency in order to establish their clinical utility.

Regulatory oversight of AI technologies is essential for reducing another type of bias – evaluative bias, i.e., particularly for continually evolving AI models (118). Ungoverned AI might perpetuate such bias through furthering social inequities or demonstrating prejudices by arriving at different conclusions for individuals (e.g., based on race or gender) without any rational basis [see (120)]. Non-diverse unrepresentative training data or data that reflects human biases (e.g., due to systemic racism that leads to unequal treatment of racial minorities) can lead to evaluative bias in healthcare applications. Training ML models on human biases may lead to pernicious propagation of inequity. EHR data (generated by humans) can be less in-depth for some segments of the population than others, leading to erroneous conclusions (121). If a feature is rare in a training set, then a model will be less prepared to detect similar occurrences. Undetected evaluative bias is obviously difficult to eliminate, however, there are tools to help detect and mitigate bias in AI models. For example, the Google What-If tool enables visualization of AI algorithm results and manual manipulation of datapoints to view effects of changing certain parameters. The IBM AI Fairness 360 is an open-source tool available on Git Hub to test for algorithmic bias. Beyond rigorously assessing algorithms for bias, ML offers an opportunity to advance health equity through ensuring equality in patient outcomes, performance, and resource allocation (122).

It is important to highlight a distinction between pragmatic and explanatory approaches (29,123). Pragmatic approaches using automated ML (124) aim to develop tools that can lead to robust and accurate predictions that are clinically useful; however, these optimization procedures are computationally expensive, and are limited by interpretability of how the various workflows' features contribute to the predictions – the black box. The explanatory models seek to establish relationships between variables that provide meaningful insights into how the system works. We need ML tools that provide pragmatic guidance and are explainable. More in-depth understanding of how to develop AI systems like DL to capture the complexity of patients is needed.

Federal and Private Funding Support

Driving the field forward will need careful navigation and long-term support from government and industry, such as the National Institute of Mental Health (NIMH) which emphasizes support of explainable AI in mental health. The National Science Foundation (NSF) and other federal agencies are funding AI Research Institutes, although they do not focus on mental health challenges. Spring Health, an AI-based company to match patients with mental health providers, was born from academic research at Yale University. In the private sector, AI companies have collaborated with mental health startups and universities – e.g., a collaboration between Microsoft and Silvercloud Health, a digital platform for mental healthcare. Microsoft's AI for Accessibility program funds industry-academic partnerships to improve mental healthcare. In one such project, Northwestern University, University of Toronto, and Mental Health America are co-developing a text message-based psychotherapeutic intervention. Amazon is partnering with University of Pittsburgh and Carnegie Mellon University to build sensors for speech and facial expression data and identify changes associated with depression. Georgia Tech University and Befrienders India are co-developing an AI-based system to match crisis-line callers with peer support specialists from similar sociodemographic, cultural, and lived experiences (coauthor MDC is a PI). Another academic-industry partnership example is the UC San Diego and IBM Research's Center on AI for Healthy Living (Investigators include coauthors EEL, CAD, SAG, HCK, DVJ), which is conducting a longitudinal study of older adults residing within a continuing care senior housing community. The researchers assess the participants using wearable sensors, clinical, neuropsychological, and physical functioning measures, and microbiome-based biomarkers, with the ultimate goal of identifying the earliest predictors of cognitive and functional decline (10,36,125).

Future of AI: Artificial Wisdom (AW)

AI is modeled after human intelligence and today's AI can accomplish various concrete tasks far more quickly than a human, through replicating discrete human intelligence skills like processing speed, memory, quantitative reasoning, visuospatial ability, auditory processing, and comprehension-knowledge. AI will continue to improve and develop into super-intelligence. Yet, it does not have the ability to make compassionate, fair, and equitable decisions. AI cannot self-reflect or self-correct or consider diversity among people and perspectives, ethics, and morality. Reframing such future AI for what it really is – i.e., Artificial Wisdom (AW) – highlights the limitations of today's AI and the need for wisdom it should offer in the future.

Human wisdom is a multi-component personality trait that includes pro-social behaviors like empathy and compassion, emotional regulation, self-reflection (with self-correction), acceptance of uncertainty and diversity of perspectives, social decision making, and perhaps spirituality (126). Wisdom, rather than intelligence, is associated with greater individual and societal well-being. In all likelihood, only humans can be truly wise, as uniquely human characteristics including consciousness, autonomy, and will are key to cultivating wisdom. The notion of creating AI that shares our societal values and could be considered to be wise is a relatively new area of exploration (127–129). The future AI will need to have some aspect of emotional intelligence (130), morality (131), and empathy (132). Paiva et al. (133) defined "empathic agents" as "agents that have the capacity to place themselves into the position of a user's or another agent's emotional situation and respond appropriately." It is improbable that human wisdom could be fully programmed into a robot, but partial examples exist in the form of robotic social workers and physical therapists deployed in nursing homes (134,135), social robots for loneliness, and those providing cognitive assistance to older adults (36). These tools illustrate the efforts to develop computers that can perform actions which employ wise principles and result in wise acts.

Author Manuscript

Author Manuscript

Author Manuscript

Ethical and wise AI – i.e., AW, will help promote individual and societal well-being (136–138). As noted above, freedom from bias is essential for widespread practical use. Evolution of AW will require active collaboration between computer scientists, engineers, psychiatrists, psychologists, neuroscientists, and ethicists.

Common concerns about AI today often focus on the "four horsemen of the AI apocalypse": loss of jobs for humans, unethical decision-making, hostile robot-led takeovers, and uninterpretable "black box" decision-making (139). These are countered by the hope for developing behavior-based digital biomarkers; re-defining diagnoses; facilitating earlier detection of mental illnesses; continuous learning systems that can assess patients in context; tools to help patients and clinicians better understand an illness and themselves; personalized approaches to diagnosis and treatment; and built-in computational models that make mental healthcare safer, more efficient, and personalized. This dichotomy between fears and aspirations can be reframed by considering ways to develop AW to support mental healthcare. The path to achieve sustainability, implementation, and clinician and patient acceptance will require transparency, trust, and wisdom.

Funding Support:

This study was supported, in part, by the National Institute of Mental Health [NIMH T32 Geriatric Mental Health Program MH019934 (PI: Dilip V. Jeste), and NIMH K23MH119375-01 (PI: Ellen E. Lee), NIMH K23MH116130-03 (PI: John Torous), NIGMS R01GM112697 (PI: De Choudhury), NIMH R01MH117172 (PI: De Choudhury), NARSAD Young Investigator grant from the Brain and Behavior Research Foundation (PI: Ellen E. Lee, MD), by the VA San Diego Healthcare System, by the Stein Institute for Research on Aging (Director: Dilip V. Jeste, MD) at the University of California San Diego, and by IBM Research AI through the AI Horizons Network. Dr. Krystal was supported by NIAAA (P50AA012870), NCATS (*UL1* TR0018630), and the National Center for PTSD (Department of Veterans Affairs).

References

1. Vigo D, Thornicroft G, Atun R (2016): Estimating the true global burden of mental illness. The Lancet Psychiatry 3: 171–178. [PubMed: 26851330]
2. Jeste DV, Lee EE, Cacioppo S (2020): Battling the modern behavioral epidemic of loneliness: Suggestions for research and interventions. JAMA psychiatry 77: 553–554. [PubMed: 32129811]
3. Iob E, Frank P, Steptoe A, Fancourt D (2020): Levels of severity of depressive symptoms among at-risk groups in the UK during the COVID-19 pandemic. JAMA Netw open 3: e2026064–-e2026064. [PubMed: 33104209]
4. (SAMSHA) Substance Abuse and Mental Health Services Administration (n.d.): Behavioral Health Workforce Report. Retrieved from https://www.samhsa.gov/sites/default/files/behavioral-health-workforce-report.pdf
5. Bi WL, Hosny A, Schabath MB, Giger ML, Birkbak NJ, Mehrtash A, et al. (2019): Artificial intelligence in cancer imaging: clinical challenges and applications. CA Cancer J Clin 69: 127–157. [PubMed: 30720861]
6. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL (2018): Artificial intelligence in radiology. Nat Rev Cancer 18: 500–510. [PubMed: 29777175]
7. Zakhem GA, Fakhoury JW, Motosko CC, Ho RS (2020): Characterizing the role of dermatologists in developing artificial intelligence for assessment of skin cancer: A systematic review. J Am Acad Dermatol.
8. Mahajan S (2020): Artificial Intelligence In Healthcare Market-Global Industry Analysis, Size and Growth Report, 2026.
9. Evans RS (2016): Electronic health records: then, now, and in the future. Yearb Med Inform S48. [PubMed: 27199197]

10. Graham S, Depp C, Lee E, Nebeker C, Tu X, Kim H, Jeste D (2019): Artificial Intelligence for Mental Health and Mental Illnesses: An Overview. Curr Psychiatry Rep 11;21(11):1–8. [PubMed: 30637488]
11. Topol E (2019): Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again, 1st Editio. New York, NY: Basic Books.
12. Doraiswamy PM, Blease C, Bodner K (2020): Artificial intelligence and the future of psychiatry: Insights from a global physician survey. Artif Intell Med 102: 101753. [PubMed: 31980092]
13. Bzdok D, Meyer-Lindenberg A (2018): Machine Learning for Precision Psychiatry: Opportunities and Challenges. Biol Psychiatry Cogn Neurosci Neuroimaging 3: 223–230. [PubMed: 29486863]
14. Braun U, Schaefer A, Betzel RF, Tost H, Meyer-Lindenberg A, Bassett DS (2018): From maps to multi-dimensional network mechanisms of mental disorders. Neuron 97: 14–31. [PubMed: 29301099]
15. Insel TR, Cuthbert BN (2015): Brain disorders? precisely. Science (80-) 348: 499–500.
16. Washington P, Park N, Srivastava P, Voss C, Kline A, Varma M, et al. (2019): Data-driven diagnostics and the potential of mobile artificial intelligence for digital therapeutic phenotyping in computational psychiatry. Biol Psychiatry Cogn Neurosci Neuroimaging 5(8): 759–769 [PubMed: 32085921]
17. Passos IC, Ballester PL, Barros RC, Librenza-Garcia D, Mwangi B, Birmaher B, et al. (2019): Machine learning and big data analytics in bipolar disorder: A position paper from the International Society for Bipolar Disorders Big Data Task Force. Bipolar Disord 21: 582–594. [PubMed: 31465619]
18. Bracher-Smith M, Crawford K, Escott-Price V (2020): Machine learning for genetic prediction of psychiatric disorders: a systematic review. Mol Psychiatry 1–10.
19. Benjamens S, Dhunnoo P, Meskó B (2020): The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database. NPJ Digit Med 3: 1–8. [PubMed: 31934645]
20. Servan-Schreiber D (1986): Artificial Intelligence and Psychiatry. Journal of Nervous & Mental Disease. 4.
21. Gabbard GO, Crisp-Han H (2017): The Early Career Psychiatrist and the Psychotherapeutic Identity. Acad Psychiatry 41: 30–34. [PubMed: 27882522]
22. Association AP (2013): Diagnostic and Statistical Manual of Mental Disorders, 5th Edition: DSM-5, 5th ed. Arlington: American Psychiatric Association.
23. Maddox TM, Rumsfeld JS, Payne PRO (2019): Questions for artificial intelligence in health care. Jama 321: 31–32. [PubMed: 30535130]
24. Jordan MI, Mitchell TM (2015): Machine learning: Trends, perspectives, and prospects. Sci Mag 349: 255–260.
25. Bzdok D, Altman N, Krzywinski M (2018): Statistics versus machine learning. Nat Methods 15: 233–234. [PubMed: 30100822]
26. Park JH, Cho HE, Kim JH, Wall M (2019): Electronic Health Records Based Prediction of Future Incidence of Alzheimer ‘ s Disease Using Machine Learning. bioRxiv (2019): 625582
27. Liu Y, Chen P-HC, Krause J, Peng L (2019): How to read articles that use machine learning: users’ guides to the medical literature. Jama 322: 1806–1816. [PubMed: 31714992]
28. Bzdok D, Yeo BTT (2017): Inference in the age of big data: Future perspectives on neuroscience. Neuroimage 155: 549–564. [PubMed: 28456584]
29. Durstewitz D, Koppe G, Meyer-Lindenberg A (2019): Deep neural networks in psychiatry. Mol Psychiatry 11;24(11):1583–98.. [PubMed: 30770893]
30. Vieira S, Pinaya WHL, Mechelli A (2017): Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. Neurosci Biobehav Rev 74: 58–75. [PubMed: 28087243]
31. Wiens J, Saria S, Sendak M, Ghassemi M, Liu VX, Doshi-Velez F, et al. (2019): Do no harm: a roadmap for responsible machine learning for health care. Nat Med 25: 1337–1340. [PubMed: 31427808]

32. Zhuang F, Qi Z, Duan K, Xi D, Zhu Y, Zhu H, et al. (2020): A comprehensive survey on transfer learning. Proc IEEE 7 7;109(1):43–76.
33. Wang S-H, Xie S, Chen X, Guttery DS, Tang C, Sun J, Zhang Y-D (2019): Alcoholism identification based on an AlexNet transfer learning model. Front psychiatry 10: 205. [PubMed: 31031657]
34. Banerjee D, Islam K, Xue K, Mei G, Xiao L, Zhang G, et al. (2019): A deep transfer learning approach for improved post-traumatic stress disorder diagnosis. Knowl Inf Syst 60: 1693–1724.
35. Sheikhalishahi S, Miotto R, Dudley JT, Lavelli A, Rinaldi F, Osmani V (2019): Natural language processing of clinical notes on chronic diseases: systematic review. JMIR Med informatics 7: e12239.
36. Graham SA, Lee EE, Jeste DV, Van Patten R, Twamley EW, Nebeker C, et al. (2020): Artificial intelligence approaches to predicting and detecting cognitive decline in older adults: A conceptual review. Psychiatry Res 284: 112732. [PubMed: 31978628]
37. Koleck TA, Dreisbach C, Bourne PE, Bakken S (2019): Natural language processing of symptoms documented in free-text narratives of electronic health records: a systematic review. J Am Med Informatics Assoc 26: 364–379.
38. Stewart R, Velupillai S (2020): Applied natural language processing in mental health big data. Neuropsychopharmacology 46: 252.
39. McCoy TH Jr, Pellegrini AM, Perlis RH (2019): Research Domain Criteria scores estimated through natural language processing are associated with risk for suicide and accidental death. Depress Anxiety 36: 392–399. [PubMed: 30710497]
40. Rumshisky A, Ghassemi M, Naumann T, Szolovits P, Castro VM, McCoy TH, Perlis RH (2016): Predicting early psychiatric readmission with natural language processing of narrative discharge summaries. Transl Psychiatry 6: e921–-e921. [PubMed: 27754482]
41. Juhn Y, Liu H (2020): Artificial intelligence approaches using natural language processing to advance EHR-based clinical research. J Allergy Clin Immunol 145: 463–469. [PubMed: 31883846]
42. Pradier MF, McCoy TH Jr, Hughes M, Perlis RH, Doshi-Velez F (2020): Predicting treatment dropout after antidepressant initiation. Transl Psychiatry 10: 1–8. [PubMed: 32066695]
43. Dwyer DB, Falkai P, Koutsouleris N (2018): Machine learning approaches for clinical psychology and psychiatry. Annu Rev Clin Psychol 14: 91–118. [PubMed: 29401044]
44. Redlich R, Almeida JR, Grotegerd D, Opel N, Kugel H, Heindel W, et al. (2014): Brain morphometric biomarkers distinguishing unipolar and bipolar depression: a voxel-based morphometry--pattern classification approach. JAMA psychiatry 71: 1222–1230. [PubMed: 25188810]
45. Klöppel S, Stonnington CM, Barnes J, Chen F, Chu C, Good CD, et al. (2008): Accuracy of dementia diagnosis—a direct comparison between radiologists and a computerized method. Brain 131: 2969–2974. [PubMed: 18835868]
46. Wu M-J, Passos IC, Bauer IE, Lavagnino L, Cao B, Zunta-Soares GB, et al. (2016): Individualized identification of euthymic bipolar disorder using the Cambridge Neuropsychological Test Automated Battery (CANTAB) and machine learning. J Affect Disord 192: 219–225. [PubMed: 26748737]
47. Arnedo J, Svrakic DM, Del Val C, Romero-Zaliz R, Hernández-Cuervo H, Fanous AH, et al. (2015): Uncovering the hidden risk architecture of the schizophrenias: confirmation in three independent genome-wide association studies. Am J Psychiatry 172(2): 139–153. [PubMed: 25219520]
48. Clementz BA, Sweeney JA, Hamm JP, Ivleva EI, Ethridge LE, Pearlson GD, et al. (2016): Identification of distinct psychosis biotypes using brain-based biomarkers. Am J Psychiatry 173: 373–384. [PubMed: 26651391]
49. Drysdale AT, Grosenick L, Downar J, Dunlop K, Mansouri F, Meng Y, et al. (2017): Erratum: Resting-state connectivity biomarkers define neurophysiological subtypes of depression. Nat Med 23: 264.

50. Janssen RJ, Mourão-Miranda J, Schnack HG (2018): Making individual prognoses in psychiatry using neuroimaging and machine learning. Biol Psychiatry Cogn Neurosci Neuroimaging 3: 798–808. [PubMed: 29789268]
51. Reece AG, Danforth CM (2017): Instagram photos reveal predictive markers of depression. EPJ Data Sci 6: 1–12. [PubMed: 32355601]
52. Corcoran CM, Carrillo F, Fernández-Slezak D, Bedi G, Klim C, Javitt DC, et al. (2018): Prediction of psychosis across protocols and risk cohorts using automated language analysis. World Psychiatry 17: 67–75. [PubMed: 29352548]
53. Marmar CR, Brown AD, Qian M, Laska E, Siegel C, Li M, et al. (2019): Speech-based markers for posttraumatic stress disorder in US veterans. Depress Anxiety 36: 607–616. [PubMed: 31006959]
54. Menke A (2018): Precision pharmacotherapy: psychiatry's future direction in preventing, diagnosing, and treating mental disorders. Pharmgenomics Pers Med 11: 211. [PubMed: 30510440]
55. Schultebraucks K, Galatzer-Levy IR (2019): Machine learning for prediction of posttraumatic stress and resilience following trauma: an overview of basic concepts and recent advances. J Trauma Stress 32: 215–225. [PubMed: 30892723]
56. Florio T, Einfeld S, Levy F (1994): Neural networks and psychiatry: candidate applications in clinical decision making. Aust N Z J Psychiatry 28: 651–666. [PubMed: 7794209]
57. Lucas GM, Gratch J, King A, Morency L-P (2014): It's only a computer: Virtual humans increase willingness to disclose. Comput Human Behav 37: 94–100.
58. Torkamani A, Andersen KG, Steinhubl SR, Topol EJ (2017): High-definition medicine. Cell 170: 828–843. [PubMed: 28841416]
59. Torous J, Keshavan M, Gutheil T (2014): Promise and perils of digital psychiatry. Asian J Psychiatr 10: 120. [PubMed: 25042968]
60. Ben-Zeev D, Scherer EA, Wang R, Xie H, Campbell AT (2015): Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. Psychiatr Rehabil J 38: 218. [PubMed: 25844912]
61. Linggonegoro DW, Torous J (2020): Expanding Technology for Engagement in Dementia While Ensuring Equity, Interoperability, and Privacy. Int Psychogeriatrics 8;32(8):893–5.
62. Garcia-Ceja E, Riegler M, Nordgreen T, Jakobsen P, Oedegaard KJ, Tørresen J (2018): Mental health monitoring with multimodal sensing and machine learning: A survey. Pervasive Mob Comput 51: 1–26.
63. Mohr D, Zhang M, Schueller SM (2017): Personal Sensing: Understanding Mental Health Using Ubiquitous Sensors and Machine Learning. Annu Rev Clin Psychol 13: 23–47. [PubMed: 28375728]
64. Torous J, Wisniewski H, Bird B, Carpenter E, David G, Elejalde E, et al. (2019): Creating a digital health smartphone app and digital phenotyping platform for mental health and diverse healthcare needs: an interdisciplinary and collaborative approach. J Technol Behav Sci 4: 73–85.
65. Torous J, Walker R (2019): Leveraging digital health and machine learning toward reducing suicide—from panacea to practical tool. Jama Psychiatry 76: 999–1000. [PubMed: 31290952]
66. Ben-Zeev D, Brian R, Wang R, Wang W, Campbell AT, Aung MSH, et al. (2017): CrossCheck: Integrating self-report, behavioral sensing, and smartphone use to identify digital indicators of psychotic relapse. Psychiatr Rehabil J 40: 266. [PubMed: 28368138]
67. Doryab A, Villalba DK, Chikersal P, Dutcher JM, Tumminia M, Liu X, et al. (2019): Identifying behavioral phenotypes of loneliness and social isolation with passive sensing: statistical analysis, data mining and machine learning of smartphone and fitbit data. JMIR mHealth uHealth 7: e13209. [PubMed: 31342903]
68. Kapoor KK, Tamilmani K, Rana NP, Patil P, Dwivedi YK, Nerur S (2018): Advances in social media research: Past, present and future. Inf Syst Front 20: 531–558.
69. De Choudhury M, Counts S, Gamon M (2012): Not All Moods are Created Equal. Explor Hum Emot States Soc Media Accept Present ICWSM 5 20 (Vol. 6, No. 1).
70. De M, Michael C, Counts GS (2012): Happy, nervous or surprised? classification of human affective states in social media 5 20 (Vol. 6, No. 1).

71. Birnbaum ML, Rizvi AF, Correll CU, Kane JM, Confino J (2017): Role of social media and the I nternet in pathways to care for adolescents and young adults with psychotic disorders and non-psychotic mood disorders. Early Interv Psychiatry 11: 290–295. [PubMed: 25808317]
72. Birnbaum ML, Ernala SK, Rizvi AF, Arenare E, Van Meter AR, De Choudhury M, Kane JM (2019): Detecting relapse in youth with psychotic disorders utilizing patient-generated and patient-contributed digital data from Facebook. npj Schizophr 5: 1–9. [PubMed: 30643138]
73. De Choudhury M, De S (2014): Mental health discourse on reddit: Self-disclosure, social support, and anonymity. Eighth International AAAI Conference on Weblogs and Social Media 5 16 (Vol. 8, No. 1).
74. De Choudhury M, Morris MR, White RW (2014): Seeking and sharing health information online: comparing search engines and social media. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems 1365–1376.
75. Glanz JM, Wagner NM, Narwaney KJ, Kraus CR, Shoup JA, Xu S, et al. (2017): Web-based social media intervention to increase vaccine acceptance: a randomized controlled trial. Pediatrics 140: e20171117. [PubMed: 29109107]
76. Coppersmith G, Leary R, Crutchley P, Fine A (2018): Natural language processing of social media as screening for suicide risk. Biomed Inform Insights 10: 1178222618792860.
77. De Choudhury M, Gamon M, Counts S, Horvitz E (2013): Predicting depression via social media. Icwsm 13: 1–10.
78. Chancellor S, De Choudhury M (2020): Methods in predictive techniques for mental health status on social media: a critical review. NPJ Digit Med 3: 1–11. [PubMed: 31934645]
79. Seppälä J, De Vita I, Jämsä T, Miettunen J, Isohanni M, Rubinstein K, et al. (2019): Mobile phone and wearable sensor-based mHealth approaches for psychiatric disorders and symptoms: systematic review. JMIR Ment Heal 6: e9819.
80. Arigo D, Pagoto S, Carter-Harris L, Lillie SE, Nebeker C (2018): Using social media for health research: Methodological and ethical considerations for recruitment and intervention delivery. Digit Heal 4: 2055207618771757.
81. Chancellor S, Birnbaum ML, Caine ED, Silenzio VMB, De Choudhury M (2019): A taxonomy of ethical tensions in inferring mental health states from social media. Proceedings of the Conference on Fairness, Accountability, and Transparency 79–88.
82. Ford E, Curlewis K, Wongkoblap A, Curcin V (2019): Public Opinions on Using Social Media Content to Identify Users With Depression and Target Mental Health Care Advertising: Mixed Methods Survey. JMIR Ment Heal 6: e12942.
83. Schmaal L, Marquand AF, Rhebergen D, van Tol M-J, Ruhé HG, van der Wee NJA, et al. (2015): Predicting the naturalistic course of major depressive disorder using clinical and multimodal neuroimaging information: a multivariate pattern recognition study. Biol Psychiatry 78: 278–286. [PubMed: 25702259]
84. Tran T, Luo W, Phung D, Harvey R, Berk M, Kennedy RL, Venkatesh S (2014): Risk stratification using data from electronic medical records better predicts suicide risks than clinician assessments. BMC Psychiatry 14: 76. [PubMed: 24628849]
85. Whelan R, Watts R, Orr CA, Althoff RR, Artiges E, Banaschewski T, et al. (2014): Neuropsychosocial profiles of current and future adolescent alcohol misusers. Nature 512: 185–189. [PubMed: 25043041]
86. Koutsouleris N, Kahn RS, Chekroud AM, Leucht S, Falkai P, Wobrock T, et al. (2016): Multisite prediction of 4-week and 52-week treatment outcomes in patients with first-episode psychosis: a machine learning approach. The Lancet Psychiatry 3: 935–946. [PubMed: 27569526]
87. Fusar-Poli P, Hijazi Z, Stahl D, Steyerberg EW (2018): The science of prognosis in psychiatry: a review. JAMA psychiatry 75: 1289–1297. [PubMed: 30347013]
88. Park SH, Han K (2018): Methodologic Guide for Evaluating Clinical Performance and Effect of Artificial Intelligence Technology for Medical Diagnosis. Radiology 286: 800–809. [PubMed: 29309734]
89. Etkin A, Patenaude B, Song YJC, Usherwood T, Rekshan W, Schatzberg AF, et al. (2015): A cognitive--emotional biomarker for predicting remission with antidepressant medications: a report from the iSPOT-D trial. Neuropsychopharmacology 40: 1332–1342. [PubMed: 25547711]

90. Khodayari-Rostamabad A, Reilly JP, Hasey GM, de Bruin H, MacCrimmon DJ (2013): A machine learning approach using EEG data to predict response to SSRI treatment for major depressive disorder. Clin Neurophysiol 124: 1975–1985. [PubMed: 23684127]

91. Iosifescu DV (2011): Electroencephalography-derived biomarkers of antidepressant response. Harv Rev Psychiatry 19: 144–154. [PubMed: 21631160]

92. Ball TM, Stein MB, Ramsawh HJ, Campbell-Sills L, Paulus MP (2014): Single-subject anxiety treatment outcome prediction using functional neuroimaging. Neuropsychopharmacology 39: 1254–1261. [PubMed: 24270731]

93. Hasan A, Wobrock T, Guse B, Langguth B, Landgrebe M, Eichhammer P, et al. (2017): Structural brain changes are associated with response of negative symptoms to prefrontal repetitive transcranial magnetic stimulation in patients with schizophrenia. Mol Psychiatry 22: 857–864. [PubMed: 27725655]

94. Doyle OM, Mehta MA, Brammer MJ (2015): The role of machine learning in neuroimaging for drug discovery and development. Psychopharmacology (Berl) 232: 4179–4189. [PubMed: 26014110]

95. He T, Kong R, Holmes AJ, Nguyen M, Sabuncu MR, Eickhoff SB, et al. (2020): Deep neural networks and kernel regression achieve comparable accuracies for functional connectivity prediction of behavior and demographics. Neuroimage 206: 116276. [PubMed: 31610298]

96. Schulz M-A, Yeo BTT, Vogelstein JT, Mourao-Miranada J, Kather JN, Kording K, et al. (2020): Different scaling of linear models and deep learning in UKBiobank brain images versus machine-learning datasets. Nat Commun 11: 1–15. [PubMed: 31911652]

97. Passos IC, Mwangi B (2018): Machine learning-guided intervention trials to predict treatment response at an individual patient level: an important second step following randomized clinical trials. Mol Psychiatry.

98. Castro VM, Roberson AM, McCoy TH, Wiste A, Cagan A, Smoller JW, et al. (2016): Stratifying risk for renal insufficiency among lithium-treated patients: an electronic health record study. Neuropsychopharmacology 41: 1138–1143. [PubMed: 26294109]

99. Mwangi B, Wu M-J, Cao B, Passos IC, Lavagnino L, Keser Z, et al. (2016): Individualized prediction and clinical staging of bipolar disorders using neuroanatomical biomarkers. Biol psychiatry Cogn Neurosci neuroimaging 1: 186–194. [PubMed: 27047994]

100. Chung Y, Cannon TD (2015): Brain imaging during the transition from psychosis prodrome to schizophrenia. J Nerv Ment Dis 203: 336. [PubMed: 25900551]

101. Tsuang MT, Nossova N, Yager T, Tsuang M-M, Guo S-C, Shyu KG, et al. (2005): Assessing the validity of blood-based gene expression profiles for the classification of schizophrenia and bipolar disorder: a preliminary report. Am J Med Genet Part B Neuropsychiatr Genet 133: 1–5.

102. Glatt SJ, Tylee DS, Chandler SD, Pazol J, Nievergelt CM, Woelk CH, et al. (2013): Blood-based gene-expression predictors of PTSD risk and resilience among deployed marines: A pilot study. Am J Med Genet Part B Neuropsychiatr Genet 162: 313–326.

103. Tai AMY, Albuquerque A, Carmona NE, Subramanieapillai M, Cha DS, Sheko M, et al. (2019): Machine learning and big data: Implications for disease modeling and therapeutic discovery in psychiatry. Artif Intell Med 99: 101704. [PubMed: 31606109]

104. Doyle OM, Mehta MA, Brammer MJ, Schwarz AJ, De Simoni S, Marquand AF (2012): Data-driven modeling of BOLD drug response curves using Gaussian process learning. Machine Learning and Interpretation in Neuroimaging. Springer, pp 210–217.

105. Sendak MP, D'Arcy J, Kashyap S, Gao M, Nichols M, Corey K, et al. (2020): A path for translation of machine learning products into healthcare delivery. EMJ Innov 10: 19–172.

106. Habli I, Lawton T, Porter Z (2020): Artificial intelligence in health care: accountability and safety. Bull World Health Organ 98: 251. [PubMed: 32284648]

107. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D (2019): Key challenges for delivering clinical impact with artificial intelligence. BMC Med 17: 195. [PubMed: 31665002]

108. Chekroud AM, Krystal JH (2015): Personalised pharmacotherapy: an interim solution for antidepressant treatment? BMJ Br Med J 350.

109. Chekroud AM, Zotti RJ, Shehzad Z, Gueorguieva R, Johnson MK, Trivedi MH, et al. (2016): Cross-trial prediction of treatment outcome in depression: a machine learning approach. The Lancet Psychiatry 3: 243–250. [PubMed: 26803397]

110. Chekroud AM, Gueorguieva R, Krumholz HM, Trivedi MH, Krystal JH, McCarthy G (2017): Reevaluating the Efficacy and Predictability of Antidepressant Treatments A Symptom Clustering Approach. JAMA Psychiatry 74: 370–378. [PubMed: 28241180]

111. Reger GM, McClure M Lou, Ruskin D, Carter SP, Reger MA (2019): Integrating predictive modeling into mental health care: an example in suicide prevention. Psychiatr Serv 70: 71–74. [PubMed: 30301448]

112. Reger MA, Ammerman BA, Carter SP, Gebhardt HM, Rojas SM, Lee JM, Buchholz J (2020): Patient feedback on the use of predictive analytics for suicide prevention. Psychiatr Serv appi-–ps.

113. Monteggia LM, Heimer H, Nestler EJ (2018): Meeting report: can we make animal models of human mental illness? Biol Psychiatry 84: 542–545. [PubMed: 29606372]

114. Fortmann-Roe S (2012): Understanding the bias-variance tradeoff. URL http://scottfortmann-roecom/docs/BiasVariance.html (hämtad 2019-03-27).

115. Dinga R, Penninx BWJH, Veltman DJ, Schmaal L, Marquand AF (2019): Beyond accuracy: measures for assessing machine learning models, pitfalls and guidelines. bioRxiv 743138.

116. Bzdok D, Ioannidis JPA (2019): Exploration, inference, and prediction in neuroscience and biomedicine. Trends Neurosci 42: 251–262. [PubMed: 30808574]

117. Anguita-Ruiz A, Segura-Delgado A, Alcalá R, Aguilera CM, Alcalá-Fdez J (2020): eXplainable Artificial Intelligence (XAI) for the identification of biologically relevant gene expression patterns in longitudinal human studies, insights from obesity research. PLoS Comput Biol 16: e1007792. [PubMed: 32275707]

118. DeCamp M, Lindvall C (2020): Latent bias and the implementation of artificial intelligence in medicine. J Am Med Informatics Assoc 27: 2020–2023.

119. Lauritsen SM, Kristensen M, Olsen MV, Larsen MS, Lauritsen KM, Jørgensen MJ, et al. (2020): Explainable artificial intelligence model to predict acute critical illness from electronic health records. Nat Commun 11: 1–11. [PubMed: 31911652]

120. Cirillo D, Catuara-Solarz S, Morey C, Guney E, Subirats L, Mellino S, et al. (2020): Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare. NPJ Digit Med 3: 1–11. [PubMed: 31934645]

121. Gianfrancesco MA, Tamang S, Yazdany J, Schmajuk G (2018): Potential biases in machine learning algorithms using electronic health record data. JAMA Intern Med 178: 1544–1547. [PubMed: 30128552]

122. Rajkomar A, Hardt M, Howell MD, Corrado G, Chin MH (2018): Ensuring fairness in machine learning to advance health equity. Ann Intern Med 169: 866–872. [PubMed: 30508424]

123. Paulus MP, Thompson WK (2019): The challenges and opportunities of small effects: The new normal in academic psychiatry. JAMA psychiatry 76: 353–354. [PubMed: 30810720]

124. Balaji A, Allen A (2018): Benchmarking automatic machine learning frameworks. arXiv Prepr arXiv180806492.

125. Jeste DV., Glorioso D, Lee EE, Daly R, Graham S, Liu J, et al. (2019): Study of Independent Living Residents of a Continuing Care Senior Housing Community: Sociodemographic and Clinical Associations of Cognitive, Physical, and Mental Health. Am J Geriatr Psychiatry. 10.1016/j.jagp.2019.04.002

126. Jeste DV, Lee EE (2019): Emerging empirical science of wisdom: definition, measurement, neurobiology, longevity, and interventions. Harv Rev Psychiatry 27: 127. [PubMed: 31082991]

127. Jeste DV, Graham SA, Nguyen TT, Depp CA, Lee EE, Kim H-C (2020): Beyond artificial intelligence: exploring artificial wisdom. Int Psychogeriatrics 1–9.

128. Sevilla DC (2013): The quest for artificial wisdom. AI Soc 28: 199–207.

129. Tsai C (2020): Artificial wisdom: a philosophical framework. AI Soc 1–8.

130. Fan L, Scheutz M, Lohani M, McCoy M, Stokes C (2017): Do we need emotionally intelligent artificial agents? First results of human perceptions of emotional intelligence in humans compared to robots. International Conference on Intelligent Virtual Agents 129–141.

131. Conitzer V, Sinnott-Armstrong W, Borg JS, Deng Y, Kramer M (2017): Moral decision making frameworks for artificial intelligence. Proceedings of the AAAI Conference on Artificial Intelligence, vol. 31 31.
132. Banerjee S (2020): A framework for designing compassionate and ethical artificial intelligence and artificial consciousness. Interdiscip Descr Complex Syst INDECS 18: 85–95.
133. Paiva A, Leite I, Boukricha H, Wachsmuth I (2017): Empathy in virtual agents and robots: a survey. ACM Trans Interact Intell Syst 7: 1–40.
134. Šabanović S, Chang W-L, Bennett CC, Piatt JA, Hakken D (2015): A robot of my own: participatory design of socially assistive robots for independently living older adults diagnosed with depression. International Conference on Human Aspects of It for the Aged Population 104–114.
135. Hebesberger D, Koertner T, Gisinger C, Pripfl J, Dondrup C (2016): Lessons learned from the deployment of a long-term autonomous robot as companion in physical therapy for older adults with dementia a mixed methods study. 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI) 27–34.
136. Torous J, Larsen ME, Depp C, Cosco TD, Barnett I, Nock MK, Firth J (2018): Smartphones, sensors, and machine learning to advance real-time prediction and interventions for suicide prevention: a review of current progress and next steps. Curr Psychiatry Rep 20: 51. [PubMed: 29956120]
137. Torous J, Firth J (2018): Bridging the Dichotomy of actual versus aspirational digital health. World Psychiatry 17: 107–108. [PubMed: 29352561]
138. Nebeker C, Torous J, Ellis RJB (2019): Building the case for actionable ethics in digital health research supported by artificial intelligence. BMC Med 17: 137. [PubMed: 31311535]
139. Matheny M, Israni ST, Ahmed M, Whicher D (2020): Artificial intelligence in health care: The hope, the hype, the promise, the peril. Natl Acad Med 94–97.