Psychological Medicine

cambridge.org/psm

Machine learning in mental health: a scoping review of methods and applications

Adrian B. R. Shatte[1,2], Delyse M. Hutchinson[2,3,4,5] and Samantha J. Teague[2]

[1]Federation University, School of Science, Engineering & Information Technology, Melbourne, Australia; [2]Deakin University, Centre for Social and Early Emotional Development, School of Psychology, Faculty of Health, Geelong, Australia; [3]Murdoch Children's Research Institute, Centre for Adolescent Health, Royal Children's Hospital, Melbourne, Australia; [4]Department of Paediatrics, University of Melbourne, Royal Children's Hospital, Melbourne, Australia and [5]University of New South Wales, National Drug and Alcohol Research Centre, Sydney, Australia

Review Article

Cite this article: Shatte ABR, Hutchinson DM, Teague SJ (2019). Machine learning in mental health: a scoping review of methods and applications. *Psychological Medicine* 1–23. https://doi.org/10.1017/S0033291719000151

Received: 22 July 2018
Revised: 11 December 2018
Accepted: 10 January 2019

Key words:
Big data; health informatics; machine learning; mental health

Author for correspondence:
Adrian B. R. Shatte, E-mail: a.shatte@federation.edu.au

Abstract

Background. This paper aims to synthesise the literature on machine learning (ML) and big data applications for mental health, highlighting current research and applications in practice.
Methods. We employed a scoping review methodology to rapidly map the field of ML in mental health. Eight health and information technology research databases were searched for papers covering this domain. Articles were assessed by two reviewers, and data were extracted on the article's mental health application, ML technique, data type, and study results. Articles were then synthesised via narrative review.
Results. Three hundred papers focusing on the application of ML to mental health were identified. Four main application domains emerged in the literature, including: (i) detection and diagnosis; (ii) prognosis, treatment and support; (iii) public health, and; (iv) research and clinical administration. The most common mental health conditions addressed included depression, schizophrenia, and Alzheimer's disease. ML techniques used included support vector machines, decision trees, neural networks, latent Dirichlet allocation, and clustering.
Conclusions. Overall, the application of ML to mental health has demonstrated a range of benefits across the areas of diagnosis, treatment and support, research, and clinical administration. With the majority of studies identified focusing on the detection and diagnosis of mental health conditions, it is evident that there is significant room for the application of ML to other areas of psychology and mental health. The challenges of using ML techniques are discussed, as well as opportunities to improve and advance the field.

Background and significance

Advances in technology, such as social media, smartphones, wearables and neuroimaging, have allowed mental health researchers and clinicians to collect a vast range of data at a rapidly growing rate (Chen *et al*., 2014). A robust technique that has emerged to analyse these data is machine learning (ML). ML involves the use of advanced statistical and probabilistic techniques to construct systems with an ability to automatically learn from data. This enables patterns in data to be more readily and accurately identified and more accurate predictions to be made from data sources (e.g. more accurate diagnosis and prognosis) (Jordan and Mitchell, 2015). ML has provided significant benefits to a range of fields, including artificial intelligence, computer vision, speech recognition, and natural language processing, allowing researchers and developers to extract vital information from datasets, provide personalised experiences, and develop intelligent systems (Jordan and Mitchell, 2015). Within health fields such as bioinformatics, ML has led to significant advances by enabling speedy and scalable analysis of complex data (Luo *et al*., 2016). Such analytic techniques are also being explored with mental health data, with the broad potential of both improving patient outcomes and enhancing understanding of psychological conditions and their management.

ML algorithms are broadly grouped into three categories: (i) *supervised*; (ii) *unsupervised*; and, (iii) *semi-supervised learning* (summarised in Table 1). In supervised learning, data with known labels are used to train a model that can predict the label for new data, for example classifying emails as spam based on previously labelled emails (El Naqa and Murphy, 2015). In contrast, unsupervised learning utilises mathematical techniques to cluster data in order to provide new insights, for example mapping topics of conversation in web forums (Teague and Shatte, 2018). Semi-supervised learning techniques develop models based on a combination of both labelled and unlabelled data (Zhu and Goldberg, 2009; Zhu, 2010). Such techniques are useful in enhancing supervised models through the use of unlabelled data, as labelled datasets may be scarce or expensive. Practitioners of ML should be aware that there is no single technique that works best for every problem, so it is recommended that a range of techniques are applied to determine which algorithm performs best for the particular dataset and task (Wolpert and Macready, 1997).

Table 1. Categories of ML algorithms, their definitions, frequently used models, and example applications within the health field

Category	Supervised learning	Unsupervised learning	Semi-supervised learning
Description	Learning from labelled data to predict the class label of unlabelled input data (El Naqa and Murphy, 2015)	Learning from unlabelled data to differentiate data into groups or to find patterns in a dataset (El Naqa and Murphy, 2015)	Learning from both labelled (usually a small subset of the total data) and unlabelled data to perform a supervised or unsupervised learning task (Zhu and Goldberg, 2009; Zhu, 2010)
Common models	SVM *k*-Nearest neighbours NB Regression techniques DT Random Forest	*k*-means clustering Hierarchical clustering Hidden Markov models LDA Neural networks	Self-training Mixture models Co-training and multiview learning Graph-based methods Semi-supervised SVM
Example application	Predicting risk of disease in patients with medical history data [e.g. see Khalilia *et al.* (2011), for application using random forests]	Extracting information about adverse drug reactions from unstructured social media posts [e.g. see Nikfarjam *et al.* (2015), for application using natural language processing techniques]	Identifying relevant information (e.g. diagnoses) from unstructured text in electronic health records [e.g. see Wang *et al.* (2012), for application generating a classifier with labelled examples]

A literature review of ML and big data research applications in mental health is pertinent and timely given the rapid developments in technology in recent years. Two reviews have explored this topic to date; yet neither review explored the breadth of research using ML in mental health applications. First, Luo *et al.* (2016) systematically investigated big data applications in the field of biomedical research and health care, finding many novel applications in bioinformatics, clinical informatics, imaging, and public health. Some examples and opportunities for ML in the mental health context were briefly discussed (specifically detecting depression using social media and predictive models for classifying psychological conditions), but were not explored in detail. A second article by Bone *et al.* (2017) described signal processing and ML for mental health research and clinical applications, concluding that the collaboration of clinicians with data scientists is leading to important scientific breakthroughs not previously possible. However, this article did not report any literature search techniques, thus it is unclear whether the article adequately reflects the scope of applications that exist.

This review aims to provide a concise snapshot of the literature investigating ML applications in mental health. Previous reviews have demonstrated ML techniques to be robust and scalable for mental health application, but no review to date has mapped the clinical applications within mental health research and practice. Such a review would inform practitioners in the methods and applications of mental health big data. It would also highlight the challenges of using ML techniques in this context, as well as identify gaps in the field and potential opportunities for further research. First, we outline the search strategies used to find relevant literature. Next, we conduct a synthesis of the literature, describing both the ML techniques and mental health applications of each article. Finally, we summarise the extant research and the implications for future work.

Method

A scoping review methodology was chosen to achieve this article's goal of mapping the state of the field of ML in mental health. A scoping review is defined by Arskey and O'Malley (2005) as a study that aims 'to map *rapidly* the key concepts underpinning a research area and the main sources and types of evidence available, and can be undertaken as stand-alone projects in their own right, especially where an area is complex or has not been reviewed comprehensively before'. As the field of ML is advancing exponentially, we chose to focus specifically on exploring broadly the nature of research activity, as per Arskey and O'Malley's (2005) first goal of scoping reviews.

Search strategy

The search strategy was adapted from Luo *et al.*'s (2016) similar review of big data applications in the biomedical literature. The searches were conducted to identify relevant literature using the main keywords 'big data', 'machine learning', and 'mental health'. As ML and mental health span interdisciplinary fields, the search was conducted in both health and Information Technology (IT) databases. First, a literature search was conducted through health-related research databases, including PsycInfo, the Cochrane Library, and PubMed. Next, IT databases IEEE Xplore and the ACM Digital Library were searched. Lastly, databases that index both fields including Springer, Scopus and ScienceDirect were

https://doi.org/10.1017/S0033291719000151

searched for the relevant literature. No specific date range was enforced in the search.

Study selection

Articles were included in the review if the following criteria were met: (i) the article reported on a method or application of ML to address mental health, with mental health conceptualised using the World Health Organisation's definition (World Health Organization, 2014); (ii) the article evaluated the performance of the ML or big data technique used; (iii) the article was published in a peer-reviewed publication; and, (iv) the article was available in English. Articles were excluded if the following criteria were met: (i) the article did not report an original contribution to ML applications in mental health (e.g. the paper commented on the future use of big data only, or reviewed other articles without contributing original research); (ii) the article did not focus on a mental health application; and, (iii) the full text of the article was not available (e.g. conference abstracts). Two reviewers independently reviewed all studies, reaching a consensus on all included studies.

Data extraction and analysis plan

For each article, data were extracted regarding: (i) the aim of research; (ii) area of mental health focus; (iii) data type; (iv) ML methods used; (v) results; (vi) the country of the author group; and, (vii) the discipline area of authors (e.g. health fields, data science fields, or both). To analyse the data, a narrative review synthesis method was selected to capture the large range of research investigating ML and big data for mental health. It should be noted that a meta-analysis was not appropriate for this review given the broad range of mental health conditions, ML techniques, and types of data used in the studies identified.

Results

Overview of article characteristics

The search strategies identified 1942 articles, with 300 of these articles meeting the criteria for inclusion in this review [see Fig. 1 for PRISMA flowchart (Moher *et al*., 2010)]. The mean publication year for articles was 2015 (s.d. = 2.2), with a range of 2004–2018. Most articles were authored by multidisciplinary teams ($n = 143$), including experts from both health (e.g. medicine, psychiatry, and/or psychology) and engineering fields (e.g. IT, computer science, and/or data science), with the remaining articles authored by either health ($n = 95$) or engineering ($n = 62$) experts only.

The ML techniques and mental health applications reported varied considerably. Most articles ($n = 170$) implemented one technique only, though some authors combined the use of classification, unsupervised learning, and other novel techniques. ML techniques included: supervised learning and classification approaches ($n = 267$) [e.g. support vector machines (SVM), naive Bayes (NB), decision trees (DT)]; unsupervised and clustering approaches ($n = 23$) (e.g. *k*-nearest neighbours (kNN), *k*-means clustering); text analysis ($n = 20$) [e.g. latent Dirichlet allocation (LDA), sentiment analysis]; and novel techniques ($n = 11$), including techniques based on deep learning and a range of custom ML methods devised for specific domains. ML applications were also evident across a range of mental health conditions, including depression ($n = 88$), Alzheimer's disease and other cognitive decline ($n = 46$), schizophrenia ($n = 37$), stress ($n = 30$), and suicide ($n = 20$). The data types used to develop ML models included imaging data ($n = 102$), survey data ($n = 40$), mobile and wearable sensor data ($n = 29$), and social media data ($n = 28$).

ML application domains in mental health

Through synthesis of the data, four domains of mental health applications were identified: (i) *detection and diagnosis* ($n = 190$); (ii) *prognosis, treatment and support* ($n = 67$); (iii) *public health* applications ($n = 26$); and, (iv) *research and clinical administration* ($n = 17$). *Detection and diagnosis* includes articles that aimed to identify or diagnose mental health conditions in individuals. *Prognosis, treatment and support* includes articles that aimed to predict the progression of mental health conditions, or explore treatment or support opportunities for such conditions. *Public health* articles used large epidemiological or public datasets (e.g. social media data) to monitor mental health conditions and estimate prevalence. *Research and clinical administration* includes articles that aimed to improve administrative processes in clinical work, mental health research, and health-care organisations. Articles were allocated into these categories based on consensus by the two article reviewers. The four categories are discussed in detail below.

Detection and diagnosis

Two themes emerged in the detection category: (i) the development of pre-diagnosis screening tools; and (ii) the development of risk models to identify an individual's predisposition for, or risk of, progressing to a mental health condition (see Table 2). For example, several papers focused on the use of supervised ML techniques with neuroimaging data to differentiate Alzheimer's disease from normal ageing (Sheela Kumari *et al*., 2014; Doan *et al*., 2017*a*), to improve early diagnosis of psychosis (Koutsouleris *et al*., 2012), and to predict vulnerability to depression (Sato *et al*., 2015). A novel approach identified for detection of conditions is the use of unstructured text with natural language processing techniques, including detection of suicide ideation from counselling transcripts (Oseguera *et al*., 2017), detection of schizophrenia from written texts (Strous *et al*., 2009), and analysis of social media data to detect depressive symptoms (Wu *et al*., 2012). Supervised ML has also been applied to wearable sensor data to assess general wellbeing (Sano *et al*., 2015), and to ambient sensors to detect psychiatric emergencies (Alam *et al*., 2016). Finally, speech data have been used with supervised ML techniques to detect underlying mental states indicative of schizophrenia and depression (Kliper *et al*., 2016), to assess the effects of drugs on mental state (Bedi *et al*., 2014), and to classify at-risk patients of Alzheimer's disease based on speech patterns (Fraser *et al*., 2016).

Two themes were identified in the diagnosis category: (i) predicting the diagnosis of a new patient based on a training dataset of prior diagnoses (e.g. Mohammadi *et al*., 2015; Skåtun *et al*., 2016; Dimitriadis *et al*., 2018); and (ii) differentiating between mental health conditions with similar symptomatology (e.g. Faedda *et al*., 2016; Bosl *et al*., 2017). The majority of studies considered neuroimaging data [e.g. magnetic resonance imaging (MRI), electroencephalography (EEG), and positron emission tomography]. For example, fMRI data have been used with supervised ML to improve the diagnosis of schizophrenia (Skåtun *et al*.,

https://doi.org/10.1017/S0033291719000151

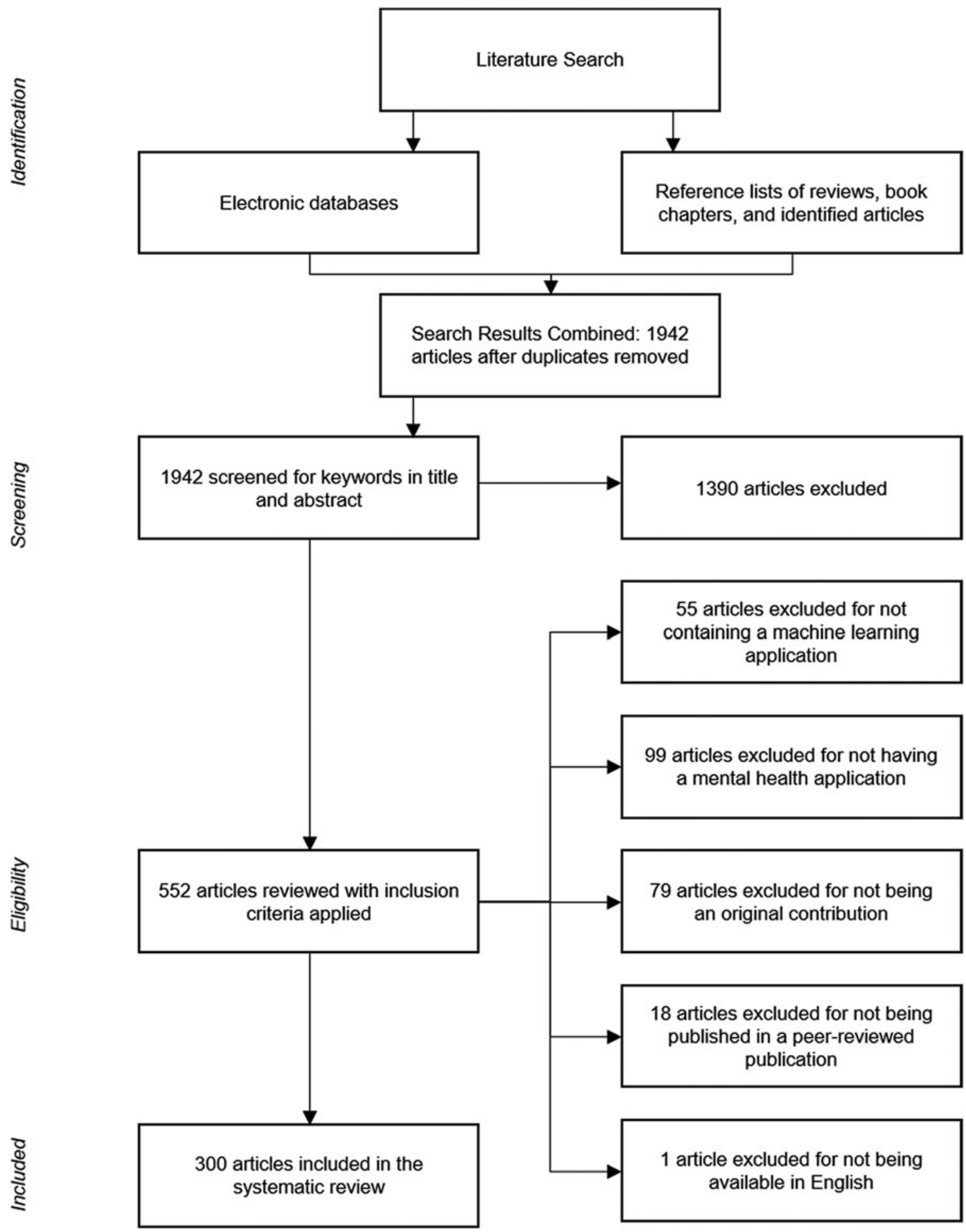

Fig. 1. PRISMA procedural flow chart.

2016). Further, MRI data were used with supervised ML to diagnose patients with Alzheimer's disease and cognitive impairment, achieving reasonable accuracy (Dimitriadis *et al.*, 2018). In addition, supervised ML has also been applied to the diagnosis of mental health conditions with similar symptomatology, for example differentiation of autism spectrum disorders and epilepsy using EEG data (Bosl *et al.*, 2017). Research has also investigated the application of ML techniques to sensor, speech and video data to improve diagnosis of Alzheimer's disease (König *et al.*, 2015), schizophrenia (Tron *et al.*, 2016), and suicide ideation (Pestian *et al.*, 2016), achieving high prediction accuracies with supervised techniques. Finally, supervised ML with wearable sensor data from actigraph monitors has been demonstrated to differentiate between children with ADHD and bipolar disorder (Faedda *et al.*, 2016). Overall, there has been a wide range of research published that focuses on diagnosis of mental health conditions using

https://doi.org/10.1017/S0033291719000151

Table 2. Summary of ML techniques and data types for the detection and diagnosis of mental health conditions

Mental health application	ML technique(s)	Data type
Alzheimer's disease	Active learning (Qian *et al.*, 2015), BN (Labate *et al.*, 2014), Ensemble Learning (Labate *et al.*, 2014), Genetic Algorithm (Brasil Filho *et al.*, 2009; Johnson *et al.*, 2014), Regression (Westman *et al.*, 2013; Johnson *et al.*, 2014; Falahati *et al.*, 2016; Fraser *et al.*, 2016; Doan *et al.*, 2017*a*), kNN (Ertek *et al.*, 2014), SVM (Costafreda *et al.*, 2011*a*; Dyrba *et al.*, 2013, 2015; Burnham *et al.*, 2014; Ertek *et al.*, 2014; Besga *et al.*, 2015; König *et al.*, 2015; Souillard-Mandar *et al.*, 2016), DT (Ertek *et al.*, 2014; Besga *et al.*, 2015; Souillard-Mandar *et al.*, 2016), NN (Islam and Zhang, 2017), RF (Besga *et al.*, 2015; Souillard-Mandar *et al.*, 2016; Vigneron *et al.*, 2016; Dimitriadis *et al.*, 2018), Similarity Discriminative Dictionary Learning algorithm (Li *et al.*, 2017*a*), NB (Dyrba *et al.*, 2013)	Electronic Health Records (Qian *et al.*, 2015), Imaging (Costafreda *et al.*, 2011*a*; Dyrba *et al.*, 2013, 2015; Westman *et al.*, 2013; Burnham *et al.*, 2014; Labate *et al.*, 2014; Falahati *et al.*, 2016; Vigneron *et al.*, 2016; Dimitriadis *et al.*, 2018; Islam and Zhang, 2017; Doan *et al.*, 2017*a*; Li *et al.*, 2017*a*; Wang *et al.*, 2018), Clinical Assessment (Brasil Filho *et al.*, 2009; Ertek *et al.*, 2014; Johnson *et al.*, 2014; Besga *et al.*, 2015; Souillard-Mandar *et al.*, 2016), Survey (Johnson *et al.*, 2014), Audio (König *et al.*, 2015; Fraser *et al.*, 2016), Biological (Burnham *et al.*, 2014; Besga *et al.*, 2015)
Anxiety	DT (Carpenter *et al.*, 2016), Multivariate classification (Lueken *et al.*, 2015), NN (Tran and Kavuluru, 2017), Regression (Zhou *et al.*, 2015), SVM (Liu *et al.*, 2015*a*; Zhou *et al.*, 2015)	Clinical Assessment (Carpenter *et al.*, 2016), Imaging (Liu *et al.*, 2015*a*; Lueken *et al.*, 2015), Clinical Notes (Tran and Kavuluru, 2017), Video (Zhou *et al.*, 2015), Mobile/Wearable Sensors (Zhou *et al.*, 2015)
Attention deficit hyperactivity disorder	Genetic algorithm (Yaghoobi Karimu and Azadi, 2018), SVM (Iannaccone *et al.*, 2015; Yaghoobi Karimu and Azadi, 2018), Linear discriminant analysis (Zhu *et al.*, 2005), NN (Tran and Kavuluru, 2017; Zou *et al.*, 2017)	Imaging (Zhu *et al.*, 2005; Iannaccone *et al.*, 2015; Zou *et al.*, 2017; Yaghoobi Karimu and Azadi, 2018), Clinical Notes (Tran and Kavuluru, 2017)
Autism spectrum disorder	Authors developed their own classifier (Yahata *et al.*, 2016), DT (Jiao *et al.*, 2010; 2012; Alexeeff *et al.*, 2017; Bosl *et al.*, 2017), *k*-means clustering (Liu *et al.*, 2016), RF (Xiao *et al.*, 2017), SVM (Jiao *et al.*, 2010; Goch *et al.*, 2013; Bruining *et al.*, 2014; Plitt *et al.*, 2015; Bone *et al.*, 2016; Liu *et al.*, 2016; Bosl *et al.*, 2017; Oh *et al.*, 2017; Yuan *et al.*, 2017), kNN (Oh *et al.*, 2017), L2LR (Plitt *et al.*, 2015), NN (Jiao *et al.*, 2010)	Imaging (Jiao *et al.*, 2010; Goch *et al.*, 2013; Plitt *et al.*, 2015; Yahata *et al.*, 2016; Bosl *et al.*, 2017; Xiao *et al.*, 2017), Clinical Assessment (Bruining *et al.*, 2014; Bone *et al.*, 2016; Yuan *et al.*, 2017), Biological (Jiao *et al.*, 2012; Oh *et al.*, 2017), Electronic Health Records (Alexeeff *et al.*, 2017), Video/Photo (Liu *et al.*, 2016)
Behaviour and emotional problems	Gaussian Processes (Sato *et al.*, 2016), Regression (Sato *et al.*, 2016), NN (Sato *et al.*, 2018), DT (Sato *et al.*, 2018), RF (Sato *et al.*, 2018), SVM (Sato *et al.*, 2018), JRIP (Sato *et al.*, 2018), FURIA (Sato *et al.*, 2018)	Imaging (Sato *et al.*, 2016, 2018)
Borderline personality disorder	SVM (Koutsouleris *et al.*, 2014)	Imaging (Koutsouleris *et al.*, 2014)
Coping	NB (Golbeck, 2016)	Social Media (Golbeck, 2016), Survey (Golbeck, 2016)
Decision support system	Genetic Algorithm (Azar *et al.*, 2015), *k*-means clustering (Azar *et al.*, 2015)	Clinical Assessment (Azar *et al.*, 2015)
Dementia	BN (Chen and Herskovits, 2007), ensemble learning (Chen and Herskovits, 2007), JRIP (Bhagyashree *et al.*, 2018), NB (Bhagyashree *et al.*, 2018), RF (Bhagyashree *et al.*, 2018), DT (Bang *et al.*, 2017; Er *et al.*, 2017; Bhagyashree *et al.*, 2018), NN (Kumari *et al.*, 2013; Sheela Kumari *et al.*, 2014; Bang *et al.*, 2017), SVM (Diniz *et al.*, 2015; Klöppel *et al.*, 2015; Bang *et al.*, 2017; Er *et al.*, 2017), Regression (Er *et al.*, 2017)	Imaging (Chen and Herskovits, 2007; Kumari *et al.*, 2013; Sheela Kumari *et al.*, 2014; Diniz *et al.*, 2015; Klöppel *et al.*, 2015), Clinical Assessment (Bang *et al.*, 2017; Er *et al.*, 2017), Survey (Bhagyashree *et al.*, 2018), Biological (Diniz *et al.*, 2015)
Depression	AdaBoost (Liang *et al.*, 2018*a*), Bayes (Wang *et al.*, 2013), BN (Galiatsatos *et al.*, 2015; Ojeme and Mbogho, 2016*a*, 2016*b*), Classification (Hajek *et al.*, 2017), Clustering (Dipnall *et al.*, 2017*a*), Deep Learning (Kang *et al.*, 2017), DT (Wang *et al.*, 2013; Block *et al.*, 2014; Mitra *et al.*, 2014; Wardenaar *et al.*, 2014; Jin *et al.*, 2015; Ojeme and Mbogho, 2016*b*; Iliou *et al.*, 2017), epistasis network centrality analysis (Pandey *et al.*, 2012), Evaporative cooling feature selection (Pandey *et al.*, 2012), FURIA (Iliou *et al.*, 2017), Gaussian Processes (Mitra *et al.*, 2014; Hajek *et al.*, 2015; O'Halloran *et al.*, 2016), Genetic Algorithm (Mohammadi *et al.*, 2015; Kaufmann *et al.*, 2017), GLM (Zhao *et al.*, 2017*b*), Gradient Boosting (Ryu *et al.*, 2016; Ojeme and Mbogho, 2016*b*), hierarchical clustering (Dipnall *et al.*, 2016*b*), JRIP (Iliou *et al.*, 2017), *k*-means clustering (Wardenaar *et al.*, 2014; Ross *et al.*, 2015; Farhan *et al.*, 2016), kNN (Zhang *et al.*, 2013; Hou *et al.*, 2016; Ojeme and Mbogho, 2016*b*; Zhao *et al.*, 2017*b*), LDA (Yazdavar *et al.*, 2017), Linear discriminant analysis (Mohammadi *et al.*, 2015;	Audio (Mitra *et al.*, 2014; Kliper *et al.*, 2016; Zhao *et al.*, 2017*a*), Biological (Pandey *et al.*, 2012; Besga *et al.*, 2015; Diniz *et al.*, 2015, 2016; Dmitrzak-Weglarz *et al.*, 2015), Clinical Assessment (Besga *et al.*, 2015; Kliper *et al.*, 2016; Ojeme and Mbogho, 2016*a*; Liang *et al.*, 2018*a*, 2018*b*), Clinical Notes (Tran and Kavuluru, 2017), Electronic Health Records (Ross *et al.*, 2015; Ryu *et al.*, 2016; Ojeme and Mbogho, 2016*b*), Imaging (Costafreda *et al.*, 2011*b*; Lord *et al.*, 2012; Zhang *et al.*, 2013; Anticevic *et al.*, 2014; Cao *et al.*, 2014; Koutsouleris *et al.*, 2014; Diniz *et al.*, 2015, 2016; Fung *et al.*, 2015; Hajek *et al.*, 2015, 2017; Lueken *et al.*, 2015; Mohammadi *et al.*, 2015; Song *et al.*, 2015; Sato *et al.*, 2015; O'Halloran *et al.*, 2016; Ramasubbu *et al.*, 2016; Kaufmann *et al.*, 2017; Roberts *et al.*, 2017; Chen *et al.*, 2017*a*; Zhao *et al.*, 2017*b*; Bailey *et al.*, 2018; Deng *et al.*, 2018; Jie *et al.*, 2018), Mobile/Wearable Sensors (Zhou *et al.*, 2015; Farhan *et al.*, 2016; Cao *et al.*, 2017; Zhao *et al.*, 2017*b*), Social Media (Hao *et al.*, 2013; Shen *et al.*, 2013; Wang *et al.*, 2013; Chomutare, 2014; Hou *et al.*,

(*Continued*)

Table 2. (*Continued.*)

Mental health application	ML technique(s)	Data type
	Sato *et al.*, 2015; Kaufmann *et al.*, 2017), Multivariate classification (Lueken *et al.*, 2015), NB (Hao *et al.*, 2013; Hou *et al.*, 2016; Nguyen *et al.*, 2016*b*), NN (Zhang *et al.*, 2013; Dipnall *et al.*, 2016*b*; Iliou *et al.*, 2017; Pampouchidou *et al.*, 2017; Tran and Kavuluru, 2017; Zhao *et al.*, 2017*a*), PCA (Chen *et al.*, 2017*a*), Regression (Hao *et al.*, 2013; Mitra *et al.*, 2014; Wardenaar *et al.*, 2014; Dmitrzak-Weglarz *et al.*, 2015; Zhou *et al.*, 2015; Hou *et al.*, 2016; Dipnall *et al.*, 2016*b*, 2017*a*; Nguyen *et al.*, 2016*b*; Andrews *et al.*, 2017; Cao *et al.*, 2017; Reece and Danforth, 2017; Wu *et al.*, 2017; Almeida *et al.*, 2017*a*; Liang *et al.*, 2018*b*), RF (Jin *et al.*, 2015; Iliou *et al.*, 2017; Almeida *et al.*, 2017*a*), Searchlight (Chen *et al.*, 2017*a*), Semi-supervised Topic Modelling Over Time (Yazdavar *et al.*, 2017), Sentiment analysis (Wang *et al.*, 2013), SVM (Costafreda *et al.*, 2011*b*; Lord *et al.*, 2012; Shen *et al.*, 2013; Anticevic *et al.*, 2014; Cao *et al.*, 2014, 2017; Chomutare, 2014; Koutsouleris *et al.*, 2014; Besga *et al.*, 2015; Diniz *et al.*, 2015, 2016; Fung *et al.*, 2015; Hajek *et al.*, 2015; Jin *et al.*, 2015; Song *et al.*, 2015; Zhou *et al.*, 2015; Farhan *et al.*, 2016; Hou *et al.*, 2016; Kliper *et al.*, 2016; Ramasubbu *et al.*, 2016; Nguyen *et al.*, 2016*b*; Ojeme and Mbogho, 2016*b*; Iliou *et al.*, 2017; Roberts *et al.*, 2017; Almeida *et al.*, 2017*a*; Bailey *et al.*, 2018; Deng *et al.*, 2018; Jie *et al.*, 2018)	2016; Nguyen *et al.*, 2016*b*; Reece and Danforth, 2017; Yazdavar *et al.*, 2017; Almeida *et al.*, 2017*a*), Survey (Block *et al.*, 2014; Wardenaar *et al.*, 2014; Galiatsatos *et al.*, 2015; Jin *et al.*, 2015; Hou *et al.*, 2016; Dipnall *et al.*, 2016*b*, 2017*a*; Andrews *et al.*, 2017; Iliou *et al.*, 2017; Wu *et al.*, 2017), Video/Photo (Mitra *et al.*, 2014; Zhou *et al.*, 2015; Kang *et al.*, 2017; Pampouchidou *et al.*, 2017)
Epilepsy	DT (Besga *et al.*, 2015; Bosl *et al.*, 2017), RF (Besga *et al.*, 2015), SVM (Pedersen *et al.*, 2015; Bosl *et al.*, 2017)	Imaging (Pedersen *et al.*, 2015; Bosl *et al.*, 2017), Clinical Assessment (Besga *et al.*, 2015), Biological (Besga *et al.*, 2015)
Hyperactivity	SVM (Faedda *et al.*, 2016)	Mobile/Wearable Sensors (Faedda *et al.*, 2016)
Mania	NLP (Rentoumi *et al.*, 2017), NB (Rentoumi *et al.*, 2017), NN (Rentoumi *et al.*, 2017)	Letters (Rentoumi *et al.*, 2017)
Mild cognitive impairment	BN (Chen and Herskovits, 2007; Labate *et al.*, 2014), ensemble learning (Chen and Herskovits, 2007; Labate *et al.*, 2014), Regression (Westman *et al.*, 2013), RF (Dimitriadis *et al.*, 2018), Similarity Discriminative Dictionary Learning (SCDDL) algorithm (Li *et al.*, 2017*a*), SVM (König *et al.*, 2015)	Imaging (Chen and Herskovits, 2007; Westman *et al.*, 2013; Labate *et al.*, 2014; Dimitriadis *et al.*, 2018; Li *et al.*, 2017*a*), Audio (König *et al.*, 2015)
Obsessive compulsive disorder	NN (Erguzel *et al.*, 2015), kNN (Erguzel *et al.*, 2015), NB (Erguzel *et al.*, 2015), Searchlight Based Feature Extraction (SBFE) (Bleich-Cohen *et al.*, 2014), SLR algorithm (Takagi *et al.*, 2017), L1-SCCA algorithm (Takagi *et al.*, 2017), SVM (Parrado-Hernández *et al.*, 2012; Erguzel *et al.*, 2015)	Imaging (Parrado-Hernández *et al.*, 2012; Bleich-Cohen *et al.*, 2014; Erguzel *et al.*, 2015; Takagi *et al.*, 2017)
Parkinson's disease	SVM (Souillard-Mandar *et al.*, 2016), RF (Souillard-Mandar *et al.*, 2016), DT (Souillard-Mandar *et al.*, 2016), Regression (Souillard-Mandar *et al.*, 2016)	Clinical Assessment (Souillard-Mandar *et al.*, 2016)
Play therapy	Binary valence classification (Halfon *et al.*, 2016)	Clinical Assessment (Halfon *et al.*, 2016), Audio (Halfon *et al.*, 2016)
Post-traumatic stress disorder	*k*-means clustering (Ross *et al.*, 2015), Multivariate pattern analysis (Khondoker *et al.*, 2016), SVM (Karstoft *et al.*, 2015; Liu *et al.*, 2015*b*; Khondoker *et al.*, 2016; Jin *et al.*, 2017)	Electronic Health Records (Ross *et al.*, 2015), Imaging (Liu *et al.*, 2015*b*; Khondoker *et al.*, 2016; Jin *et al.*, 2017), Survey (Karstoft *et al.*, 2015)
Postnatal depression	NB (Jiménez-Serrano *et al.*, 2015), Regression (Jiménez-Serrano *et al.*, 2015), SVM (Jiménez-Serrano *et al.*, 2015), NN (Jiménez-Serrano *et al.*, 2015)	Clinical Assessment (Jiménez-Serrano *et al.*, 2015), Survey (Jiménez-Serrano *et al.*, 2015)
Psychiatric emergency	HMM (Alam *et al.*, 2016), Stochastic Variational Inference (Alam *et al.*, 2016)	Mobile/Wearable Sensors (Alam *et al.*, 2016), Clinical Notes (Alam *et al.*, 2016), Survey (Alam *et al.*, 2016)
Psychosis	Bayes Rule (Clark *et al.*, 2015), Gradient boosting (Perlini *et al.*, 2017), PCA (Rikandi *et al.*, 2017), DT (Rikandi *et al.*, 2017), Linear discriminant analysis (Rikandi *et al.*, 2017), Quadratic discriminant analysis (Rikandi *et al.*, 2017), RF (Maraş and Aydin, 2017), Regression (Maraş and Aydin, 2017; Rikandi *et al.*, 2017), NN (Maraş and Aydin, 2017), SVM (Koutsouleris *et al.*, 2009, 2012; Bendfeldt *et al.*, 2015; Squarcina *et al.*, 2015*b*; Rikandi *et al.*, 2017)	Clinical Assessment (Perlini *et al.*, 2017), Imaging (Koutsouleris *et al.*, 2009, 2012; Bendfeldt *et al.*, 2015; Clark *et al.*, 2015; Squarcina *et al.*, 2015*b*; Maraş and Aydin, 2017; Rikandi *et al.*, 2017)
Schizophrenia	AdaBoost (Liang *et al.*, 2018*a*), Classification (exact method not reported) (Hajek *et al.*, 2017), Gaussian Process (Taylor *et al.*, 2017), Genetic Algorithm (Kaufmann *et al.*, 2017),	Audio (Kliper *et al.*, 2016), Biological (Nicodemus *et al.*, 2010; Hess *et al.*, 2016), Clinical Assessment (Kliper *et al.*, 2016; Hettige *et al.*, 2017; Liang *et al.*, 2018*a*, 2018*b*), Imaging

	k-means clustering (Castellani *et al.*, 2009), Linear discriminant analysis (Kaufmann *et al.*, 2015; Skåtun *et al.*, 2016; Winterburn *et al.*, 2017), Multivariate analysis (Skåtun *et al.*, 2016), NN (Chakraborty *et al.*, 2017), PCA (Chen *et al.*, 2017*a*), Regression (Strous *et al.*, 2009; Nicodemus *et al.*, 2010; Hess *et al.*, 2016; Hettige *et al.*, 2017; Yong *et al.*, 2017; Liang *et al.*, 2018*b*), RF (Nicodemus *et al.*, 2010; Greenstein *et al.*, 2012; Hess *et al.*, 2016; Hettige *et al.*, 2017), Searchlight (Bleich-Cohen *et al.*, 2014; Chen *et al.*, 2017*a*), SVM (Castellani *et al.*, 2009, 2012; Strous *et al.*, 2009; Costafreda *et al.*, 2011*b*; Iwabuchi *et al.*, 2013; Yu *et al.*, 2013; Anticevic *et al.*, 2014; Guo *et al.*, 2014; Koutsouleris *et al.*, 2014; Hess *et al.*, 2016; Johannesen *et al.*, 2016; Kliper *et al.*, 2016; Mikolas *et al.*, 2016; Tron *et al.*, 2016; Chakraborty *et al.*, 2017; Hettige *et al.*, 2017; Iwabuchi and Palaniyappan, 2017; Rozycki *et al.*, 2018; Taylor *et al.*, 2017; Bae *et al.*, 2018*b*)	(Castellani *et al.*, 2009, 2012; Strous *et al.*, 2009; Nicodemus *et al.*, 2010; Costafreda *et al.*, 2011*b*; Greenstein *et al.*, 2012; Iwabuchi *et al.*, 2013; Yu *et al.*, 2013; Anticevic *et al.*, 2014; Bleich-Cohen *et al.*, 2014; Guo *et al.*, 2014; Koutsouleris *et al.*, 2014; Kaufmann *et al.*, 2015, 2017; Hess *et al.*, 2016; Johannesen *et al.*, 2016; Mikolas *et al.*, 2016; Skåtun *et al.*, 2016; Hajek *et al.*, 2017; Iwabuchi and Palaniyappan, 2017; Rozycki *et al.*, 2018; Taylor *et al.*, 2017; Winterburn *et al.*, 2017; Chen *et al.*, 2017*a*; Yong Yang *et al.*, 2017; Bae *et al.*, 2018*b*), Survey (Chakraborty *et al.*, 2017), Video/Photo (Tron *et al.*, 2016; Chakraborty *et al.*, 2017)
Stress	AdaBoost (Maxhuni *et al.*, 2016), BN (Smets *et al.*, 2016), Classification (exact method not reported) (Cvetković *et al.*, 2017), DT (Chiang *et al.*, 2013; Maxhuni *et al.*, 2016; Smets *et al.*, 2016), *k*-means clustering (Hagad *et al.*, 2014), kNN (Nakashima *et al.*, 2016), NB (Zhao *et al.*, 2011; Chiang *et al.*, 2013; Alharthi *et al.*, 2017), NN (Hagad *et al.*, 2014; Li *et al.*, 2017*b*), Regression (Stütz *et al.*, 2015; Smets *et al.*, 2016; Li *et al.*, 2017*b*), RF (Stütz *et al.*, 2015; Maxhuni *et al.*, 2016; Smets *et al.*, 2016), SVM (Chiang *et al.*, 2013; Hagad *et al.*, 2014; Sandulescu *et al.*, 2015; Gjoreski *et al.*, 2016; Maxhuni *et al.*, 2016; Nakashima *et al.*, 2016; Smets *et al.*, 2016)	Clinical Assessment (Gjoreski *et al.*, 2016; Alharthi *et al.*, 2017), Imaging (Zhao *et al.*, 2011), Mobile/Wearable Sensors (Chiang *et al.*, 2013; Sandulescu *et al.*, 2015; Stütz *et al.*, 2015; Gjoreski *et al.*, 2016; Maxhuni *et al.*, 2016; Smets *et al.*, 2016; Alharthi *et al.*, 2017; Cvetković *et al.*, 2017), Physiological Sensors (Hagad *et al.*, 2014; Nakashima *et al.*, 2016), Social Media (Li *et al.*, 2017*b*), Survey (Hagad *et al.*, 2014; Stütz *et al.*, 2015; Gjoreski *et al.*, 2016; Alharthi *et al.*, 2017)
Substance use	Regression (Whelan *et al.*, 2014; Squeglia *et al.*, 2017), SVM (Bedi *et al.*, 2014; Rakshith *et al.*, 2017; Squeglia *et al.*, 2017), RF (Squeglia *et al.*, 2017), DT (Squeglia *et al.*, 2017), Extreme Learning Machine (ELM) (Rakshith *et al.*, 2017)	Imaging (Whelan *et al.*, 2014; Rakshith *et al.*, 2017; Squeglia *et al.*, 2017), Survey (Squeglia *et al.*, 2017), Audio (Bedi *et al.*, 2014)
Suicide/self harm	AdaBoost (Pestian *et al.*, 2010), Conditional random fields (Moulahi *et al.*, 2017), DT (Pestian *et al.*, 2008, 2010; Oseguera *et al.*, 2017; Kessler *et al.*, 2017*a*), GLM (Tran *et al.*, 2013), HMM (Alam *et al.*, 2014), kNN (Tran *et al.*, 2013; Oseguera *et al.*, 2017), LDA (Zhang *et al.*, 2015*b*), Linear discriminant analysis (Oseguera *et al.*, 2017), LIWC (Zhang *et al.*, 2015*b*), NB (Oseguera *et al.*, 2017), NLP (Pestian *et al.*, 2010, 2016), Regression (Pestian *et al.*, 2008, 2010; Zhang *et al.*, 2015*b*; Zhou *et al.*, 2015; Hettige *et al.*, 2017; Oseguera *et al.*, 2017; Kessler *et al.*, 2017*a*), RF (Baca-García *et al.*, 2006; Hettige *et al.*, 2017), SVM (Baca-García *et al.*, 2006; Pestian *et al.*, 2008, 2010, 2016; Zhou *et al.*, 2015; Barros *et al.*, 2017; Hettige *et al.*, 2017; Kessler *et al.*, 2017*a*; Oseguera *et al.*, 2017)	Audio (Pestian *et al.*, 2016), Clinical Assessment (Baca-García *et al.*, 2006; Hettige *et al.*, 2017), Clinical Notes (Oseguera *et al.*, 2017), Electronic Health Records (Tran *et al.*, 2013; Kessler *et al.*, 2017*a*), Letters (Pestian *et al.*, 2008, 2010), Mobile/Wearable Sensors (Alam *et al.*, 2014; Zhou *et al.*, 2015), Social Media (Zhang *et al.*, 2015*b*; Moulahi *et al.*, 2017), Survey (Baca-García *et al.*, 2006; Barros *et al.*, 2017), Video (Zhou *et al.*, 2015)
Traumatic brain injury	DT (Karamzadeh *et al.*, 2016), Linear discriminant analysis (Karamzadeh *et al.*, 2016), RF (Stone *et al.*, 2016; Vakorin *et al.*, 2016), LogitBoost (Tremblay *et al.*, 2017), Regression (Tremblay *et al.*, 2017), SVM (Karamzadeh *et al.*, 2016; Vakorin *et al.*, 2016; Tremblay *et al.*, 2017)	Imaging (Karamzadeh *et al.*, 2016; Stone *et al.*, 2016; Vakorin *et al.*, 2016; Tremblay *et al.*, 2017), Biological (Tremblay *et al.*, 2017), Survey (Tremblay *et al.*, 2017)
Wellbeing	AdaBoost (Agarwal *et al.*, 2016), Fast Fourier Transform (FFT) (Sun *et al.*, 2017), Gaussian Processes (Sun *et al.*, 2017), HMM (Rabbi *et al.*, 2011), DT (Rabbi *et al.*, 2011), NB (Agarwal *et al.*, 2016), NN (Agarwal *et al.*, 2016), RF (Agarwal *et al.*, 2016; Kamdar and Wu, 2016), Regression (Kamdar and Wu, 2016; Sun *et al.*, 2017), kNN (Kamdar and Wu, 2016), SVM (Sano *et al.*, 2015; Agarwal *et al.*, 2016; Kamdar and Wu, 2016)	Survey (Sano *et al.*, 2015; Agarwal *et al.*, 2016; Sun *et al.*, 2017), Clinical Assessment (Sun *et al.*, 2017), Audio (Rabbi *et al.*, 2011), Mobile/Wearable Sensors (Rabbi *et al.*, 2011; Sano *et al.*, 2015; Kamdar and Wu, 2016)

RF, Random Forest; SVM, support vector machine; NB, Naive Bayes; NN, neural networks; LDA, latent Dirichlet allocation; kNN, *k*-nearest neighbours; HMM, hidden Markov model; BN, Bayesian network; ARM, association rule mining; PCA, principal component analysis.

Table 3. Summary of ML techniques and data types for the prognosis, treatment and support of mental health conditions

Mental health application	ML technique(s)	Data type
Alzheimer's disease	COMPASS (Zhu *et al.*, 2016), SVM (Chen *et al.*, 2015; Zhu *et al.*, 2016), DT (Zhu *et al.*, 2016), Genetic Algorithm (Vandewater *et al.*, 2015), NN (Chalmers *et al.*, 2016)	Imaging (Chen *et al.*, 2015; Zhu *et al.*, 2016), Biological (Vandewater *et al.*, 2015), Smart Meter (Chalmers *et al.*, 2016)
Anxiety	BN (Panagiotakopoulos *et al.*, 2010), ARM (Panagiotakopoulos *et al.*, 2010), DT (Bermejo *et al.*, 2013; Hoogendoorn *et al.*, 2017), Regression (Hoogendoorn *et al.*, 2017), RF (Hoogendoorn *et al.*, 2017), *k*-means clustering (Park *et al.*, 2018), NB (Xu *et al.*, 2011), SVM (Sundermann *et al.*, 2017)	Electronic Health Records (Panagiotakopoulos *et al.*, 2010), Survey (Xu *et al.*, 2011; Bermejo *et al.*, 2013), Letters (Hoogendoorn *et al.*, 2017), Social Media (Park *et al.*, 2018), Imaging (Bermejo *et al.*, 2013; Sundermann *et al.*, 2017)
Attention deficit hyperactivity disorder	Regression (Wong *et al.*, 2017)	Clinical Assessment (Wong *et al.*, 2017)
Autism spectrum disorder	Bayesian classification (Dao *et al.*, 2017), ConceptNet (Song *et al.*, 2011), DT (Thin *et al.*, 2017), NLP (Beykikhoshk *et al.*, 2015), NB (Beykikhoshk *et al.*, 2015; Thin *et al.*, 2017), RF (Thin *et al.*, 2017), Regression (Beykikhoshk *et al.*, 2015), Sentiment analysis (Nguyen *et al.*, 2014*a*), SVM (Song *et al.*, 2011; Thin *et al.*, 2017)	Social Media (Song *et al.*, 2011; Nguyen *et al.*, 2014*a*; Beykikhoshk *et al.*, 2015; Dao *et al.*, 2017; Thin *et al.*, 2017)
Cyberbullying	NB (Nandhini and Sheeba, 2015)	Social Media (Nandhini and Sheeba, 2015)
Dementia	SVM (Siang Fook *et al.*, 2009), BN (Siang Fook *et al.*, 2009), PCA (Siang Fook *et al.*, 2009)	Mobile/Wearable Sensors (Siang Fook *et al.*, 2009)
Depression	Bayesian classification (Dao *et al.*, 2017), Clustering (Xu and Zhang, 2016), DT (Burns *et al.*, 2011; Bermejo *et al.*, 2013; Erguzel and Tarhan, 2016; Kessler *et al.*, 2016; Yang *et al.*, 2017; Fabbri *et al.*, 2018), Gradient boosting (Fabbri *et al.*, 2018), *k*-means clustering (Park *et al.*, 2018), LDA (Dao *et al.*, 2014; Nguyen *et al.*, 2015, 2017), LIWC (Nguyen *et al.*, 2015), NB (Xu *et al.*, 2011; Perlis, 2013), NLP (Ma *et al.*, 2017), NN (Chalmers *et al.*, 2016; Erguzel and Tarhan, 2016; Fabbri *et al.*, 2018), Regression (Perlis, 2013; Dao *et al.*, 2014, 2016; Nguyen *et al.*, 2014*b*, 2015; Iniesta *et al.*, 2016; Kessler *et al.*, 2016; Fabbri *et al.*, 2018), RF (Perlis, 2013; van Breda *et al.*, 2016; Wahle *et al.*, 2016; Fabbri *et al.*, 2018), Semi-supervised Topic Modelling Over Time (Nguyen *et al.*, 2017), Sentiment analysis (Nguyen *et al.*, 2014*b*), SVM (Perlis, 2013; Guilloux *et al.*, 2015; Erguzel and Tarhan, 2016; van Breda *et al.*, 2016; Wahle *et al.*, 2016; Yang *et al.*, 2017)	Biological (Guilloux *et al.*, 2015; Fabbri *et al.*, 2018), Clinical Assessment (Perlis, 2013; Iniesta *et al.*, 2016), Imaging (Bermejo *et al.*, 2013; Erguzel and Tarhan, 2016), Mobile/Wearable Sensors (Burns *et al.*, 2011; Wahle *et al.*, 2016), Smart Meter (Chalmers *et al.*, 2016), Social Media (Dao *et al.*, 2014, 2016, 2017; Nguyen *et al.*, 2014*b*, 2015, 2017; Xu and Zhang, 2016; Ma *et al.*, 2017; Park *et al.*, 2018), Survey (Burns *et al.*, 2011; Xu *et al.*, 2011; Bermejo *et al.*, 2013; Kessler *et al.*, 2016; van Breda *et al.*, 2016; Yang *et al.*, 2017)
Gambling	DT (Auer and Griffiths, 2018)	Survey (Auer and Griffiths, 2018)
MH service usage	RF (Roysden and Wright, 2015), NLP (Roysden and Wright, 2015)	Electronic Health Records (Roysden and Wright, 2015)
Obsessive compulsive disorder	SVM (Lenhard *et al.*, 2018), Regression (Lenhard *et al.*, 2018), RF (Lenhard *et al.*, 2018)	Clinical Assessment (Lenhard *et al.*, 2018)
Parkinson's disease	SVM (Ye *et al.*, 2016)	Imaging (Ye *et al.*, 2016), Clinical Assessment (Ye *et al.*, 2016)
Post-traumatic stress disorder	*k*-means clustering (Park *et al.*, 2018), kNN (Broek *et al.*, 2013), NN (Broek *et al.*, 2013), NLP (Shiner *et al.*, 2013), RF (Saxe *et al.*, 2017), Regression (Saxe *et al.*, 2017), SVM (Broek *et al.*, 2013; Saxe *et al.*, 2017)	Audio (Broek *et al.*, 2013), Biological (Saxe *et al.*, 2017), Clinical Notes (Shiner *et al.*, 2013), Clinical Assessment (Saxe *et al.*, 2017), Social Media (Park *et al.*, 2018)
Psychosis	Gaussian Processes (Amminger *et al.*, 2015), SVM (Koutsouleris *et al.*, 2016; Mechelli *et al.*, 2017)	Biological (Amminger *et al.*, 2015), Clinical Assessment (Amminger *et al.*, 2015), Survey (Koutsouleris *et al.*, 2016; Mechelli *et al.*, 2017)
Schizophrenia	Reverse Engineering and Forward Simulation (REFS) (Anderson *et al.*, 2017), SVM (Bak *et al.*, 2017; Koutsouleris *et al.*, 2018)	Clinical Assessment (Anderson *et al.*, 2017; Bak *et al.*, 2017), Imaging (Bak *et al.*, 2017; Koutsouleris *et al.*, 2018)
Social support	Bayesian classification (Deetjen and Powell, 2016), LDA (Carron-Arthur *et al.*, 2016)	Social Media (Carron-Arthur *et al.*, 2016; Deetjen and Powell, 2016)
Stress	Gaussian Processes (Xue *et al.*, 2014), *k*-means clustering (Salafi and Kah, 2015), NB (Xue *et al.*, 2014; Doan *et al.*, 2017*b*), NN (Xue *et al.*, 2014), RF (Paredes *et al.*, 2014; Xue *et al.*, 2014), SVM (Xue *et al.*, 2014; Salafi and Kah, 2015; Doan *et al.*, 2017*b*)	Mobile/Wearable Sensors (Paredes *et al.*, 2014; Salafi and Kah, 2015), Social Media (Xue *et al.*, 2014; Doan *et al.*, 2017*b*), Survey (Paredes *et al.*, 2014)

Substance use	Regression (Harikumar *et al.*, 2016*a*, 2016*b*; Nguyen *et al.*, 2016*a*), RF (Harikumar *et al.*, 2016*a*)	Social Media (Harikumar *et al.*, 2016*a*, 2016*b*; Nguyen *et al.*, 2016*a*), Mobile/Wearable Sensors (Harikumar *et al.*, 2016*a*)
Suicide/Self-harm	NLP (Cook *et al.*, 2016), Regression (Cook *et al.*, 2016), SVM (Kavuluru *et al.*, 2016)	Survey (Cook *et al.*, 2016), Social Media (Kavuluru *et al.*, 2016)
Traumatic brain injury	NN (Dabek and Caban, 2015), Regression (Hellstrøm *et al.*, 2017)	Clinical Assessment (Dabek and Caban, 2015), Imaging (Hellstrøm *et al.*, 2017)
Wellbeing	AdaBoost (Chen *et al.*, 2017*b*), BN (Chen *et al.*, 2017*b*), Gaussian Mixture Models (Banos *et al.*, 2016), kNN (Chen *et al.*, 2017*b*), DT (Aguilar-Ruiz *et al.*, 2004; Chen *et al.*, 2017*b*), RF (Chen *et al.*, 2017*b*; DeMasi and Recht, 2017), Regression (Hao *et al.*, 2014; DeMasi and Recht, 2017; Chen *et al.*, 2017*b*), SVM (Banos *et al.*, 2016; DeMasi and Recht, 2017)	Interview (Aguilar-Ruiz *et al.*, 2004), Mobile/Wearable Sensors (Banos *et al.*, 2016; DeMasi and Recht, 2017), Social Media (Hao *et al.*, 2014), Survey (Chen *et al.*, 2017*b*)

RF, Random Forest; SVM, support vector machine; NB, Naive Bayes; NN, neural networks; LDA, latent Dirichlet allocation; kNN, *k*-nearest neighbours; HMM, hidden Markov model; BN, Bayesian network; ARM, association rule mining; PCA, principal component analysis.

ML techniques. Models developed using imaging data demonstrate promising results; however a major issue is the lack of consistency in accuracy of techniques and datasets used. More research is needed to synthesise results and provide standard techniques that can be adopted by mental health clinicians. In addition, the majority of studies investigating the detection and diagnosis of mental health conditions used neuroimaging data with supervised classification techniques. Yet diagnosis of mental health conditions is commonly made using standardised assessment tools (i.e. questionnaires) across both clinical and research settings. Future ML research should focus on improving diagnostic outcomes using a range of data types, especially for individuals who may not have access to imaging services. Further research is also required to ensure that the techniques proposed in a research context can be translated into diagnosis options for the public.

Prognosis, treatment and support

Research investigating mental health prognosis focused predominantly on the use of ML to predict long-term outcomes of a patient prior to, or after diagnosis (see Table 3). Conditions of focus include schizophrenia (Bak *et al.*, 2017), Alzheimer's disease (Chen *et al.*, 2015; Vandewater *et al.*, 2015; Zhu *et al.*, 2016), post-traumatic stress disorder (Saxe *et al.*, 2017), depression (Guilloux *et al.*, 2015; Erguzel and Tarhan, 2016; Iniesta *et al.*, 2016; Kessler *et al.*, 2016), and psychosis (Amminger *et al.*, 2015; Koutsouleris *et al.*, 2016; Mechelli *et al.*, 2017). For example, supervised ML using SVM was demonstrated to predict treatment responders and non-responders to a drug for Parkinson's disease, subsequently leading to improved treatment outcomes (Ye *et al.*, 2016). Further, natural language processing techniques have been used to predict suicide ideation and psychiatric symptoms amongst recently discharged patients, finding accurate results that could improve prognosis (Cook *et al.*, 2016). In addition, researchers have applied unsupervised ML techniques to social media and online communities to determine the individual and psycholinguistic features most predictive for successful alcohol abstinence (Harikumar *et al.*, 2016*a*) and smoking cessation (Nguyen *et al.*, 2016*a*).

Three themes were identified among studies examining treatment and support: (i) ML with mobile and sensor data to detect changes in behaviour indicative of mental health conditions (Salafi and Kah, 2015; Chalmers *et al.*, 2016); (ii) ML to provide personalised and timely treatment or interventions (Auer and Griffiths, 2018; Bae *et al.*, 2018*a*; Chen *et al.*, 2017*b*; Yang *et al.*, 2017); and, (iii) analysis of online support groups for mental health communities (Song *et al.*, 2011; Nguyen *et al.*, 2014*a*, 2014*b*; Deetjen and Powell, 2016; Kavuluru *et al.*, 2016; Thin *et al.*, 2017). The studies identified in this category demonstrate several benefits of ML for treatment and support. For example, ML has achieved positive results using smart meter data with neural networks to detect changes in sleep behaviour indicative of depression of Alzheimer's disease (Chalmers *et al.*, 2016), and with wearable sensor data (i.e. heart rate, galvanic skin response and temperature) and both supervised and unsupervised ML methods to predict stress (Salafi and Kah, 2015). Further, various supervised ML techniques were used with mobile sensor and survey data to provide personalised and timely intervention for depression (Yang *et al.*, 2017), gambling addiction (Auer and Griffiths, 2018) and alcohol use in young adults (Bae *et al.*, 2018*a*) with positive results. Additional benefits have been demonstrated when using supervised ML with data from online communities, such as matching patients to suitable support communities (Song *et al.*, 2011) and automatic

https://doi.org/10.1017/S0033291719000151

moderation of helpful comments in suicide and autism support groups (Kavuluru *et al.*, 2016; Thin *et al.*, 2017).

While the studies identified in this category demonstrate the potential for ML to improve outcomes for patients with mental health conditions, there are areas that require further investigation. First, the use of social media data for prognosis has to date only been applied to addiction research; such approaches have considerable potential for application to a range of other mental health conditions. Second, despite promising early results on sensor data for personalised and timely intervention, some studies have indicated that sensors such as GPS do not accurately predict behaviour (DeMasi and Recht, 2017). It is evident that more research on sensor data with ML is needed to improve the automatic classification of mental health conditions. Finally, much of the work on online community assessment has focused on behaviour and/or the characteristics of such communities; scant work to date has focused on providing direct benefit to participants through these online communities. Furthermore, many studies in this area are proof-of-concept studies; as such, these techniques warrant further investigation by both researchers and clinicians.

Public health

Public health applications included: assessing the mental health of both specific and broader populations (e.g. Liang *et al.*, 2015; Chary *et al.*, 2017); monitoring mental health following an event or disaster (e.g. Glasgow *et al.*, 2014; 2016); and creating models of risk to improve health system delivery e.g. Almeida *et al.*, 2017*b*; Kessler *et al.*, 2017*b*) (see Table 4). Public health applications typically used social media data ($n = 11$), electronic health records ($n = 6$), and clinical data (e.g. diagnostic surveys and tools; $n = 9$). Social media data were found to be a particularly useful epidemiological resource for natural language processing and classification, including assessments of the mental health status of over 60 000 college students in China (Liang *et al.*, 2015) and prescription opioid misuse in an estimated sample of over 1.3 million Twitter users (Chary *et al.*, 2017). Social media also enables researchers to assess the impact of an incident on population mental health (e.g. classifying stress levels of college students after experiencing gun violence using supervised ML techniques) (Saha and de Choudhury, 2017), and tracking public response to disaster situations to inform the allocation of support resources using classification and natural language processing techniques (Glasgow *et al.*, 2014, 2016; Almeida *et al.*, 2017*b*). Supervised ML applied to electronic health records was demonstrated to predict suicide risk with an accuracy similar to clinician assessment (Kessler *et al.*, 2017*b*; Metzger *et al.*, 2017), as well as predict dementia and its risk factors with high accuracy (Kim *et al.*, 2017). Research has also investigated the use of ML with clinical data to improve variable selection in epidemiological data analysis (Sidahmed *et al.*, 2016), and to better understand the relationship between complex risk factors for mental health conditions such as depression (Dipnall *et al.*, 2017*b*).

Overall, ML appears to be a promising tool for public health. Social media data and electronic health records are enabling researchers to monitor the wellbeing of large groups of people in a cost-efficient manner. Social media data in particular are providing an ecologically valid assessment of mental health in the population in real-time, enabling assessment of groups that have typically been challenging to monitor through traditional research methods [e.g. opioid misuse (Chary *et al.*, 2017)]. With only minimal research conducted in this area to date, there is considerable scope for future research to consider refinements of ML techniques and indicators in both social media and electronic health record data. To realise these benefits, researchers and health clinicians must consider sharing their datasets and improving data harmonisation techniques (Hutchinson *et al.*, 2015).

Research and clinical administration

Three themes were identified in the research and clinical administration category: (i) improving resource allocation methods [e.g. via patient risk status (Castillo *et al.*, 2014; Wang *et al.*, 2017)]; (ii) improving research methodologies [e.g. data sharing (Dluhoš *et al.*, 2017; Zhu *et al.*, 2017), participant selection (Geraci *et al.*, 2017), and analysis (Guan *et al.*, 2015; Squarcina *et al.*, 2015*a*; Khondoker *et al.*, 2016; Dipnall *et al.*, 2016*a*)]; and, (iii) extracting mental health symptoms from existing sources (e.g. research publications, clinical notes and databases [Ghafoor *et al.*, 2015; Hu and Terrazas, 2016; Caballero *et al.*, 2017; Posada *et al.*, 2017; Zhang *et al.*, 2017*b*; Karystianis *et al.*, 2018)] (see Table 5). The studies identified in this category demonstrate several benefits of ML for mental health administration. For example, predicting high-cost patients using supervised ML techniques can ensure that resources are allocated more efficiently (Wang *et al.*, 2017). Further, distributed supervised ML techniques that build predictive models using meta-analytic data have demonstrated improved predictive models while maintaining patient privacy (Dluhoš *et al.*, 2017; Zhu *et al.*, 2017). Additional benefits have been demonstrated for mental health researchers, including the use of supervised classification techniques to match research participants to studies to save time and money in recruitment (Geraci *et al.*, 2017).

While these studies demonstrate the potential for ML to improve mental health administration, it is clear that there is room for further research. In particular, the techniques used to predict high-cost patients may also provide benefits for researchers in improving retention by identifying participants at greatest risk of drop-out (Teague *et al.*, 2018). Finally, future research may also focus on using patient histories to improve triaging and tailored treatment plans.

Discussion

This paper aims to synthesise the literature on ML and big data applications for mental health, highlighting current research and applications in practice. Mental health applications for ML techniques were identified in four key domains: (i) detection and diagnosis of mental health conditions; (ii) prognosis, treatment and support; (iii) public health; and, (iv) research and clinical administration. Predominantly, research has focused on the benefits of ML to improve detection and diagnosis of mental health conditions including depression, Alzheimer's disease, and schizophrenia. There has also been growing interest in the application of ML to other areas of mental health research, including the use of ML to improve administration and research methods, treatment and support of mental health conditions, studies of public health trends, and investigations into the behaviours of support communities online. Overall, ML demonstrates the potential to improve the efficiency of clinical and research processes and to generate new insights into mental health and wellbeing.

As an emerging field, there are understandably significant gaps for future research to address. The majority of papers reviewed focus on diagnosis and detection, particularly on depression, suicide risk and cognitive decline. There is significant scope to

https://doi.org/10.1017/S0033291719000151

Table 4. Summary of ML techniques and data types for public health of mental health conditions

Mental health application	ML technique(s)	Data type
Anxiety	SVM (Zhang *et al*., 2015*a*), Linear discriminant analysis (Zhang *et al*., 2015*a*), RF (Zhang *et al*., 2015*a*)	Electronic Health Records (Zhang *et al*., 2015*a*)
Cognitive distortions	DT (Simms *et al*., 2017), Regression (Simms *et al*., 2017), NB (Simms *et al*., 2019), NN (Simms *et al*., 2017), kNN (Simms *et al*., 2017), RELIEF (Simms *et al*., 2017)	Social Media (Simms *et al*., 2017)
Dementia	SVM (Kim *et al*., 2017)	Electronic Health Records (Kim *et al*., 2017)
Depression	DT (Peng *et al*., 2019), Gradient boosting (Ryu *et al*., 2015), kNN (Peng *et al*., 2019), LIWC (Saha *et al*., 2016), LDA (Saha *et al*., 2016), Linear discriminant analysis (Zhang *et al*., 2015*a*), NB (Peng *et al*., 2019), NN (Dipnall *et al*., 2017*b*), RF (Zhang *et al*., 2015*a*), Regression (Dipnall *et al*., 2017*b*), SVM (Zhang *et al*., 2015*a*; Peng *et al*., 2019)	Electronic Health Records (Zhang *et al*., 2015*a*), Social Media (Saha *et al*., 2016; Peng *et al*., 2019), Survey (Ryu *et al*., 2015; Dipnall *et al*., 2017*b*)
Grief	LIWC (Glasgow *et al*., 2014), SVM (Glasgow *et al*., 2014)	Social Media (Glasgow *et al*., 2014)
MH service usage	Regression (Sidahmed *et al*., 2016)	Survey (Sidahmed *et al*., 2016)
Post-traumatic stress disorder	DT (Rosellini *et al*., 2018), Regression (Kessler *et al*., 2014; Rosellini *et al*., 2018), RF (Kessler *et al*., 2014), Super Learner (Kessler *et al*., 2014), SVM (Rosellini *et al*., 2018)	Interview (Rosellini *et al*., 2018), Survey (Kessler *et al*., 2014)
Psychiatric emergency	BN (Almeida *et al*., 2017*b*), DT (Almeida *et al*., 2017*b*), SVM (Almeida *et al*., 2017*b*)	Social Media (Almeida *et al*., 2017*b*)
Psychiatric stressors	Named-entity recognition (Zhang *et al*., 2017*a*), NLP (Zhang *et al*., 2017*a*)	Clinical Notes (Zhang *et al*., 2017*a*)
Psychosis	Regression (Fusar-Poli *et al*., 2016), RF (Abou-Warda *et al*., 2017)	Clinical Assessment (Abou-Warda *et al*., 2017), Electronic Health Records (Fusar-Poli *et al*., 2016)
Social support	LIWC (Glasgow *et al*., 2016), SVM (Glasgow *et al*., 2016)	Social Media (Glasgow *et al*., 2016)
Stress	Cluster analysis (Meyer *et al*., 2015), Sentiment Analysis (Saha and de Choudhury, 2017), SVM (Saha and de Choudhury, 2017)	Clinical Assessment (Meyer *et al*., 2015), Social Media (Saha and de Choudhury, 2017)
Substance use	NLP (Chary *et al*., 2017), PCA (Chary *et al*., 2017), RF (Abou-Warda *et al*., 2017)	Clinical Assessment (Abou-Warda *et al*., 2017), Social Media (Chary *et al*., 2017)
Suicide/self-harm	ARM (Metzger *et al*., 2017), DT (Metzger *et al*., 2017), Genetic Algorithm (Poulin *et al*., 2014), NB (Kessler *et al*., 2017*b*; Metzger *et al*., 2017), RF (Kessler *et al*., 2017*b*; Metzger *et al*., 2017), Regression (Kessler *et al*., 2015, 2017*b*; O'Dea *et al*., 2015; Tran *et al*., 2015; Metzger *et al*., 2017), SVM (O'Dea *et al*., 2015; Metzger *et al*., 2017; Kessler *et al*., 2017*b*), TFIDF (O'Dea *et al*., 2015)	Clinical Notes (Poulin *et al*., 2014), Clinical Assessment (Tran *et al*., 2015), Electronic Health Records (Kessler *et al*., 2015, 2017*b*; Metzger *et al*., 2017), Social Media (O'Dea *et al*., 2015)
Wellbeing	Semantic analysis (Liang *et al*., 2015)	Social Media (Liang *et al*., 2015)

RF, Random Forest; SVM, support vector machine; NB, Naive Bayes; NN, neural networks; LDA, latent Dirichlet allocation; kNN, *k*-nearest neighbours; HMM, hidden Markov model; BN, Bayesian network; ARM, association rule mining; PCA, principal component analysis.

Table 5. Summary of ML techniques and data types for the research and clinical administration of mental health conditions

Mental health application	ML technique(s)	Data type
Alzheimer's disease	RF, SVM, Linear discriminant analysis, kNN (Khondoker *et al.*, 2016)	Imaging, Biological (Khondoker *et al.*, 2016)
Attention deficit hyperactivity disorder	RF, SVM, Linear discriminant analysis, kNN (Khondoker *et al.*, 2016)	Imaging, Biological (Khondoker *et al.*, 2016)
Children in care	Regression, NB (Castillo *et al.*, 2014)	Clinical Notes (Castillo *et al.*, 2014)
Decision support system	Deep Learning (Hu and Terrazas, 2016)	Research Articles (Hu and Terrazas, 2016)
Depression	DT (Ghafoor *et al.*, 2015), kNN (Guan *et al.*, 2015; Khondoker *et al.*, 2016), NN (Geraci *et al.*, 2017), Regression (Dipnall *et al.*, 2016*a*; Zhu *et al.*, 2017), RF (Khondoker *et al.*, 2016), SVM (Khondoker *et al.*, 2016), Linear discriminant analysis (Khondoker *et al.*, 2016)	Survey (Ghafoor *et al.*, 2015; Dipnall *et al.*, 2016*a*; Caballero *et al.*, 2017), Social Media (Guan *et al.*, 2015), Electronic Health Records (Geraci *et al.*, 2017), Imaging (Khondoker *et al.*, 2016; Zhu *et al.*, 2017), Biological (Dipnall *et al.*, 2016*a*; Khondoker *et al.*, 2016)
Healthy ageing	RF (Caballero *et al.*, 2017)	Survey (Caballero *et al.*, 2017)
Psychosis	SVM, Multiple Kernel Learning (Squarcina *et al.*, 2015*a*)	Imaging (Squarcina *et al.*, 2015*a*)
Schizophrenia	RF (Wang *et al.*, 2017), SVM (Dluhoš *et al.*, 2017; Wang *et al.*, 2017), Linear discriminant analysis (Wang *et al.*, 2017), kNN (Wang *et al.*, 2017)	Insurance (Wang *et al.*, 2017), Imaging (Dluhoš *et al.*, 2017)
Substance use	Topic modelling (Atkins *et al.*, 2014)	Interview (Atkins *et al.*, 2014)
Symptom severity	NN (Karystianis *et al.*, 2018)	Clinical Notes (Karystianis *et al.*, 2018)
Wellbeing	BN (Posada *et al.*, 2017), SVM (Posada *et al.*, 2017), Deep Learning (Zhang *et al.*, 2017*b*), NN (Liu *et al.*, 2017)	Clinical Notes (Posada *et al.*, 2017; Zhang *et al.*, 2017*b*), Research Articles (Zhang *et al.*, 2017*b*), Electronic Health Records (Liu *et al.*, 2017)

RF, Random Forest; SVM, support vector machine; NB, Naive Bayes; NN, neural networks; LDA, latent Dirichlet allocation; kNN, *k*-nearest neighbours; HMM, hidden Markov model; BN, Bayesian network; ARM, association rule mining; PCA, principal component analysis.

explore whether ML can have similar accuracy in the detection and diagnosis of other mental health conditions, such as anxiety disorders, eating disorders, and neurodevelopmental disorders. Comparatively less research has explored applications in domains such as public health, treatment and support, and research and clinical administration. Social media data and electronic health records both hold promise of innovating in these domains, particularly when leveraged by ML techniques. Across domains, very little research was identified that investigated ML techniques applied to positive mental health outcomes (e.g. resilience, identity formation, personal growth), perhaps partly reflective of a lack of available data in this area.

It is also clear that the majority of studies reviewed utilised supervised classification techniques rather than other ML techniques. This is perhaps indicative of the large focus on detection and diagnosis in the literature, which is typically designed using large, retrospective, labelled datasets ideal for classification tasks. Mental health researchers could consider the possibility of using less structured, prospective data for real-time ML analysis. Such analytic techniques, combined with supervised techniques, may allow researchers and clinicians to provide personalised and context-sensitive information for assessment and intervention. Organisations such as Netflix use recommendation algorithms to personalise user experiences (Gomez-Uribe and Hunt, 2015), which could be applied to personalised mental health assessment and intervention (Johansson *et al*., 2012; Nahum-Shani *et al*., 2017). While there were some studies identified that proposed ML to provide adaptive, just-in-time interventions (e.g. Nahum-Shani *et al*., 2017), these studies are limited and focused on a small subset of mental health conditions.

Finally, there are some challenges for consideration when using ML techniques in mental health applications. ML models are inevitably limited by the quality of the data used to develop a model. As such, ML does not replace other research or analytic approaches; rather, it has the potential to value-add to mental health research. Many ML techniques require access to training data sets, which may require greater collaboration between researchers and clinicians to share and harmonise data. Greater collaboration is also required between mental health and data science experts to maximise the usefulness of the models developed. Very little research was found that demonstrated the use of ML techniques in real-world settings, suggesting that further research is required to test clinical utility. While a model may appear promising in lab settings, deployment in real-world settings is likely to present new challenges, particularly if applied across different contexts. All of these challenges also raise important ethical issues, including the ethics of collecting, storing and sharing mental health data, as well as the level of autonomy and privacy afforded to ML systems.

This paper has two key limitations. First, restrictions in the search methodology may have resulted in relevant articles being missed, e.g. broad search terms and the exclusion of non-peer-reviewed literature. This is a common limitation reported in scoping review studies, attributable to the balance between achieving breadth and depth of analysis within a rapid time-frame (Pham *et al*., 2014). The current review was successfully able to map a broad cross-section of the literature and provide a useful synthesis for researchers and clinicians to understand the potential of ML in their respective fields. Although a more comprehensive review would provide greater clarity on gaps in the literature, such a review would be less feasible to complete and would quickly be out of date given the rapidly evolving nature of the field. Second, this paper did not examine the effectiveness of ML techniques within each mental health application. Such research questions would be suitable for future systematic reviews, guided by the framework outlined in our results tables, i.e. the effectiveness of specific ML techniques within specific data types for specific clinical applications. With the field advancing rapidly and the number of relevant publications increasing exponentially, such systematic reviews would benefit from the use of rapid review strategies to ensure they are timely and relevant.

Conclusion

To conclude, research in the field of ML for mental health has revealed exciting advances, particularly in recent years. Overall, it is clear that ML can significantly improve the detection and diagnosis of mental health conditions. Research into other applications of ML, including public health, treatment and support, and research and clinical administration, has demonstrated initial positive results. However, this work is currently limited and further research is required to identify additional benefits of ML to these areas. With ML tools becoming more accessible for researchers and clinicians, it is expected that the field will continue to grow and that novel applications for mental health will follow.

Author contributions

AS conceived the study, participated in its design and coordination, performed the search and data extraction, interpreted the data, and drafted the manuscript; DH assisted with the interpretation of the data, and helped to draft and revise the manuscript; ST conceived the study, participated in its design and coordination, contributed to the data extraction, contributed to the interpretation of the data, and helped to draft and revise the manuscript. All authors read and approved the final manuscript.

Author ORCIDs. Adrian B. R. Shatte, 0000-0002-6225-9697; Delyse M. Hutchinson, 0000-0003-3221-7143; Samantha J. Teague, 0000-0002-0487-7307

Financial support. This research received no specific grant from any funding agency, commercial or not-for-profit sectors.

Conflict of interest. None.

References

Abou-Warda H, Belal NA, El-Sonbaty Y and Darwish S (2017) A random forest model for mental disorders diagnostic systems. In Hassanien A, Shaalan K, Gaber T, Azar A and Tolba M (eds), *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2016. AISI 2016*. Advances in Intelligent Systems and Computing, vol 533. Cham: Springer, pp. 670–680.

Agarwal A, Baechle C, Behara RS and Rao V (2016) Multi-method approach to wellness predictive modeling. *Journal of Big Data* 3, 15.

Aguilar-Ruiz JS, Costa R and Divina F (2004) Knowledge discovery from doctor-patient relationship. In *Proceedings of the 2004 ACM Symposium on Applied Computing SAC '04*. New York, NY, USA: ACM, pp. 280–284.

Alam MGR, Cho EJ, Huh EN and Hong CS (2014) Cloud based mental state monitoring system for suicide risk reconnaissance using wearable biosensors. In *Proceedings of the 8th International Conference on Ubiquitous Information Management and Communication ICUIMC '14, Siem Reap, Cambodia*. New York, NY, USA: ACM, pp. 56:1–56:6.

Alam MGR, Abedin SF, Al Ameen M and Hong CS (2016) Web of objects based ambient assisted living framework for emergency psychiatric state prediction. *Sensors* **16**, 1431.

Alexeeff SE, Yau V, Qian Y, Davignon M, Lynch F, Crawford P, Davis R and Croen LA (2017) Medical conditions in the first years of life associated with

https://doi.org/10.1017/S0033291719000151

future diagnosis of ASD in children. *Journal of Autism and Developmental Disorders* **47**, 2067–2079.

Alharthi R, Alharthi R, Guthier B and El Saddik A (2017) CASP: context-aware stress prediction system. *Multimedia Tools and Applications* Available at https://doi.org/10.1007/s11042-017-5246-0.

Almeida H, Briand A and Meurs M-J (2017*a*) Detecting early risk of depression from social media user-generated content. In *Proceedings Conference and Labs of the Evaluation Forum (CLEF), Dublin, Ireland*.

Almeida H, Queudot M, Kosseim L and Meurs M-J (2017*b*) Supervised methods to support online scientific data triage. In Aïmeur E, Ruhi U and Weiss M (eds), *E-Technologies: Embracing the Internet of Things. MCETECH 2017*. Lecture Notes in Business Information Processing, vol 289. Cham: Springer, pp. 213–221.

Amminger GP, Mechelli A, Rice S, Kim S-W, Klier CM, McNamara RK, Berk M, McGorry PD and Schäfer MR (2015) Predictors of treatment response in young people at ultra-high risk for psychosis who received long-chain omega-3 fatty acids. *Translational Psychiatry* **5**, e495.

Anderson JP, Icten Z, Alas V, Benson C and Joshi K (2017) Comparison and predictors of treatment adherence and remission among patients with schizophrenia treated with paliperidone palmitate or atypical oral antipsychotics in community behavioral health organizations. *BMC Psychiatry* **17**, 346.

Andrews JA, Harrison RF, Brown LJE, MacLean LM, Hwang F, Smith T, Williams EA, Timon C, Adlam T, Khadra H and Astell AJ (2017) Using the NANA toolkit at home to predict older adults' future depression. *Journal of Affective Disorders* **213**, 187–190.

Anticevic A, Cole MW, Repovs G, Murray JD, Brumbaugh MS, Winkler AM, Savic A, Krystal JH, Pearlson GD and Glahn DC (2014) Characterizing thalamo-cortical disturbances in schizophrenia and bipolar illness. *Cerebral Cortex* **24**, 3116–3130.

Arksey H and O'Malley L (2005) Scoping studies: towards a methodological framework. *International Journal of Social Research Methodology* **8**, 19–32.

Atkins DC, Steyvers M, Imel ZE and Smyth P (2014) Scaling up the evaluation of psychotherapy: evaluating motivational interviewing fidelity via statistical text classification. *Implementation Science* **9**, 49.

Auer M and Griffiths MD (2018) Cognitive dissonance, personalized feedback, and online gambling behavior: an exploratory study using objective tracking data and subjective self-report. *International Journal of Mental Health and Addiction* **16**, 631–641.

Azar G, Gloster C, El-Bathy N, Yu S, Neela RH and Alothman I (2015) Intelligent data mining and machine learning for mental health diagnosis using genetic algorithm. In *2015 IEEE International Conference on Electro/Information Technology (*EIT*)*. IEEE, pp. 201–206.

Baca-García E, Perez-Rodriguez MM, Basurte-Villamor I, Saiz-Ruiz J, Leiva-Murillo JM, de Prado-Cumplido M, Santiago-Mozos R, Artés-Rodríguez A and de Leon J (2006) Using data mining to explore complex clinical decisions: a study of hospitalization after a suicide attempt. *The Journal of Clinical Psychiatry* **67**, 1124–1132.

Bae S, Chung T, Ferreira D, Dey AK and Suffoletto B (2018*a*) Mobile phone sensors and supervised machine learning to identify alcohol use events in young adults: implications for just-in-time adaptive interventions. *Addictive Behaviors* **83**, 42–47.

Bae Y, Kumarasamy K, Ali IM, Korfiatis P, Akkus Z and Erickson BJ (2018*b*) Differences between schizophrenic and normal subjects using network properties from fMRI. *Journal of Digital Imaging* **31**, 252–261.

Bailey NW, Hoy KE, Rogasch NC, Thomson RH, McQueen S, Elliot D, Sullivan CM, Fulcher BD, Daskalakis ZJ and Fitzgerald PB (2018) Responders to rTMS for depression show increased fronto-midline theta and theta connectivity compared to non-responders. *Brain Stimulation* **11**, 190–203.

Bak N, Ebdrup BH, Oranje B, Fagerlund B, Jensen MH, Düring SW, Nielsen MØ, Glenthøj BY and Hansen LK (2017) Two subgroups of antipsychotic-naive, first-episode schizophrenia patients identified with a Gaussian mixture model on cognition and electrophysiology. *Translational Psychiatry* **7**, e1087.

Bang S, Son S, Roh H, Lee J, Bae S, Lee K, Hong C and Shin H (2017) Quad-phased data mining modeling for dementia diagnosis. *BMC Medical Informatics and Decision Making* **17**, 60.

Banos O, Bilal Amin M, Ali Khan W, Afzal M, Hussain M, Kang BH and Lee S (2016) The Mining Minds digital health and wellness framework. *Biomedical Engineering Online* **15**(suppl. 1), 76.

Barros J, Morales S, Echávarri O, García A, Ortega J, Asahi T, Moya C, Fischman R, Maino MP and Núñez C (2017) Suicide detection in Chile: proposing a predictive model for suicide risk in a clinical sample of patients with mood disorders. *Revista Brasileira de Psiquiatria* **39**, 1–11.

Bedi G, Cecchi GA, Slezak DF, Carrillo F, Sigman M and de Wit H (2014) A window into the intoxicated mind? Speech as an index of psychoactive drug effects. *Neuropsychopharmacology* **39**, 2340–2348.

Bendfeldt K, Smieskova R, Koutsouleris N, Klöppel S, Schmidt A, Walter A, Harrisberger F, Wrege J, Simon A, Taschler B, Nichols T, Riecher-Rössler A, Lang UE, Radue E-W and Borgwardt S (2015) Classifying individuals at high-risk for psychosis based on functional brain activity during working memory processing. *NeuroImage. Clinical* **9**, 555–563.

Bermejo P, Lucas M, Rodríguez-Montes JA, Tárraga PJ, Lucas J, Gámez JA and Puerta JM (2013) Single- and multi-label prediction of burden on families of schizophrenia patients. In Peek N, Marín Morales R and Peleg M (eds), *Artificial Intelligence in Medicine. AIME 2013*. Lecture Notes in Computer Science, vol 7885. Berlin, Heidelberg: Springer, pp. 115–124.

Besga A, Gonzalez I, Echeburua E, Savio A, Ayerdi B, Chyzhyk D, Madrigal JLM, Leza JC, Graña M and Gonzalez-Pinto AM (2015) Discrimination between Alzheimer's disease and late onset bipolar disorder using multivariate analysis. *Frontiers in Aging Neuroscience* **7**, 231.

Beykikhoshk A, Arandjelovic O, Phung D, Venkatesh S and Caelli T (2015) Using Twitter to learn about the autism community. *Social Network Analysis and Mining* **5**, 22.

Bhagyashree SIR, Nagaraj K, Prince M, Fall CHD and Krishna M (2018) Diagnosis of dementia by machine learning methods in epidemiological studies: a pilot exploratory study from south India. *Social Psychiatry and Psychiatric Epidemiology* **53**, 77–86.

Bleich-Cohen M, Jamshy S, Sharon H, Weizman R, Intrator N, Poyurovsky M and Hendler T (2014) Machine learning fMRI classifier delineates subgroups of schizophrenia patients. *Schizophrenia Research* **160**, 196–200.

Block M, Stern DB, Raman K, Lee S, Carey J, Humphreys AA, Mulhern F, Calder B, Schultz D, Rudick CN, Blood AJ and Breiter HC (2014) The relationship between self-report of depression and media usage. *Frontiers in Human Neuroscience* **8**, 712.

Bone D, Bishop SL, Black MP, Goodwin MS, Lord C and Narayanan SS (2016) Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion. *Journal of Child Psychology and Psychiatry, and Allied Disciplines* **57**, 927–937.

Bone D, Lee CC, Chaspari T, Gibson J and Narayanan S (2017) Processing and machine learning for mental health research and clinical applications. *IEEE Signal Processing Magazine [Perspectives]* **34**, 189–195.

Bosl WJ, Loddenkemper T and Nelson CA (2017) Nonlinear EEG biomarker profiles for autism and absence epilepsy. *Neuropsychiatric Electrophysiology* **3**, 1.

Brasil Filho AT, Pinheiro PR and Coelho A (2009) Towards the early diagnosis of Alzheimer's disease via a multicriteria classification model. In Ehrgott M, Fonseca CM, Gandibleux X, Hao JK and Sevaux M (eds), *Evolutionary Multi-Criterion Optimization. EMO 2009*. Lecture Notes in Computer Science, vol 5467. Berlin, Heidelberg: Springer.

Broek EL, Sluis F and Dijkstra T (2013) Cross-validation of bimodal health-related stress assessment. *Personal and Ubiquitous Computing* **17**, 215–227.

Bruining H, Eijkemans MJ, Kas MJ, Curran SR, Vorstman JA and Bolton PF (2014) Behavioral signatures related to genetic disorders in autism. *Molecular Autism* **5**, 11.

Burnham SC, Faux NG, Wilson W, Laws SM, Ames D, Bedo J, Bush AI, Doecke JD, Ellis KA, Head R, Jones G, Kiiveri H, Martins RN, Rembach A, Rowe CC, Salvado O, Macaulay SL, Masters CL, Villemagne VL and Alzheimer's Disease Neuroimaging Initiative, Australian Imaging, Biomarkers and Lifestyle Study Research Group (2014) A blood-based predictor for neocortical Aβ burden in Alzheimer's disease: results from the AIBL study. *Molecular Psychiatry* **19**, 519–526.

https://doi.org/10.1017/S0033291719000151

Burns MN, Begale M, Duffecy J, Gergle D, Karr CJ, Giangrande E and Mohr DC (2011) Harnessing context sensing to develop a mobile intervention for depression. *Journal of Medical Internet Research* **13**, e55.

Caballero FF, Soulis G, Engchuan W, Sánchez-Niubó A, Arndt H, Ayuso-Mateos JL, Haro JM, Chatterji S and Panagiotakos DB (2017) Advanced analytical methodologies for measuring healthy ageing and its determinants, using factor analysis and machine learning techniques: the ATHLOS project. *Scientific Reports* **7**, 43955.

Cao L, Guo S, Xue Z, Hu Y, Liu H, Mwansisya TE, Pu W, Yang B, Liu C, Feng J, Chen EYH and Liu Z (2014) Aberrant functional connectivity for diagnosis of major depressive disorder: a discriminant analysis. *Psychiatry and Clinical Neurosciences* **68**, 110–119.

Cao B, Zheng L, Zhang C, Yu PS, Piscitello A, Zulueta J, Ajilore O, Ryan K and Leow AD (2017) Deepmood: modeling mobile phone typing dynamics for mood detection. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. New York: ACM, pp. 747–755.

Carpenter KL, Sprechmann P, Calderbank R, Sapiro G and Egger HL (2016) Quantifying risk for anxiety disorders in preschool children: a machine learning approach. *PloS One* **11**, e0165524.

Carron-Arthur B, Reynolds J, Bennett K, Bennett A and Griffiths KM (2016) What's all the talk about? Topic modelling in a mental health Internet support group. *BMC Psychiatry* **16**, 367.

Castellani U, Rossato E, Murino V, Bellani M, Rambaldelli G, Tansella M and Brambilla P (2009) Local kernel for brains classification in schizophrenia. In Serra R and Cucchiara R (eds), *AI*IA 2009: Emergent Perspectives in Artificial Intelligence. AI*IA 2009*. Lecture Notes in Computer Science, vol 5883. Berlin, Heidelberg: Springer, pp. 112–121.

Castellani U, Rossato E, Murino V, Bellani M, Rambaldelli G, Perlini C, Tomelleri L, Tansella M and Brambilla P (2012) Classification of schizophrenia using feature-based morphometry. *Journal of Neural Transmission* **119**, 395–404.

Castillo A, Castellanos A and Tremblay MC (2014) Improving case management via statistical text mining in a foster care organization. In Tremblay MC, VanderMeer D, Rothenberger M, Gupta A and Yoon V (eds), *Advancing the Impact of Design Science: Moving From Theory to Practice. DESRIST 2014*. Lecture Notes in Computer Science, vol 8463. Cham: Springer, pp. 312–320.

Chakraborty D, Tahir Y, Yang Z, Maszczyk T, Dauwels J, Thalmann D, Thalmann NM, Tan B-L and Lee J (2017) Assessment and prediction of negative symptoms of schizophrenia from RGB+ D movement signals. In *2017 IEEE 19th International Workshop on Multimedia Signal Processing (MMSP)*. Luton, United Kingdom: IEEE, pp. 1–6.

Chalmers C, Hurst W, Mackay M and Fergus P (2016) A smart health monitoring technology. In Huang DS, Bevilacqua V and Premaratne P (eds), *Intelligent Computing Theories and Application. ICIC 2016*. Lecture Notes in Computer Science, vol 9771. Cham: Springer, pp. 832–842.

Chary M, Genes N, Giraud-Carrier C, Hanson C, Nelson LS and Manini AF (2017) Epidemiology from tweets: estimating misuse of prescription opioids in the USA from social Media. *Journal of Medical Toxicology* **13**, 278–286.

Chen M, Mao S and Liu Y (2014) Big data: a survey. *Mobile Networks and Applications* **19**, 171–209.

Chen R and Herskovits EH (2007) Clinical diagnosis based on Bayesian classification of functional magnetic-resonance data. *Neuroinformatics* **5**, 178–188.

Chen T, Zeng D and Wang Y (2015) Multiple kernel learning with random effects for predicting longitudinal outcomes and data integration. *Biometrics* **71**, 918–928.

Chen X, Liu C, He H, Chang X, Jiang Y, Li Y, Duan M, Li J, Luo C and Yao D (2017*a*) Transdiagnostic differences in the resting-state functional connectivity of the prefrontal cortex in depression and schizophrenia. *Journal of Affective Disorders* **217**, 118–124.

Chen Y, Yann ML-J, Davoudi H, Choi J, An A and Mei Z (2017*b*) Contrast pattern based collaborative behavior recommendation for life improvement. In Kim J, Shim K, Cao L, Lee JG, Lin X and Moon YS (eds), *Advances in Knowledge Discovery and Data Mining. PAKDD 2017*. Lecture Notes in Computer Science, vol 10235. Cham: Springer, pp. 106–118.

Chiang H-S, Liu L-C and Lai C-Y (2013) The diagnosis of mental stress by using data mining technologies. In Park J, Barolli L, Xhafa F and Jeong HY (eds), *Information Technology Convergence*. Lecture Notes in Electrical Engineering, vol 253. Dordrecht: Springer, pp. 761–769.

Chomutare T (2014) Text classification to automatically identify online patients vulnerable to depression. In Cipresso P, Matic A and Lopez G (eds), *Pervasive Computing Paradigms for Mental Health. MindCare 2014*. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 100. Cham: Springer, pp. 125–130.

Clark SR, Schubert KO and Baune BT (2015) Towards indicated prevention of psychosis: using probabilistic assessments of transition risk in psychosis prodrome. *Journal of Neural Transmission* **122**, 155–169.

Cook BL, Progovac AM, Chen P, Mullin B, Hou S and Baca-Garcia E (2016) Novel use of Natural Language Processing (NLP) to predict suicidal ideation and psychiatric symptoms in a text-based mental health intervention in Madrid. *Computational and Mathematical Methods in Medicine* **2016**, 8708434.

Costafreda SG, Dinov ID, Tu Z, Shi Y, Liu C-Y, Kloszewska I, Mecocci P, Soininen H, Tsolaki M, Vellas B, Wahlund L-O, Spenger C, Toga AW, Lovestone S and Simmons A (2011*a*) Automated hippocampal shape analysis predicts the onset of dementia in mild cognitive impairment. *NeuroImage* **56**, 212–219.

Costafreda SG, Fu CHY, Picchioni M, Toulopoulou T, McDonald C, Kravariti E, Walshe M, Prata D, Murray RM and McGuire PK (2011*b*) Pattern of neural responses to verbal fluency shows diagnostic specificity for schizophrenia and bipolar disorder. *BMC Psychiatry* **11**, 18.

Cvetković B, Gjoreski M, Šorn J, Maslov P and Luštrek M (2017) Monitoring physical activity and mental stress using wrist-worn device and a smartphone. In Altun Y *et al.* (eds), *Machine Learning and Knowledge Discovery in Databases. ECML PKDD 2017*. Lecture Notes in Computer Science, vol 10536. Cham: Springer, pp. 414–418.

Dabek F and Caban JJ (2015) A neural network based model for predicting psychological conditions. In Guo Y, Friston K, Aldo F, Hill S and Peng H (eds), *Brain Informatics and Health. BIH 2015*. Lecture Notes in Computer Science, vol 9250. Cham: Springer, pp. 252–261.

Dao B, Nguyen T, Phung D and Venkatesh S (2014) Effect of mood, social connectivity and age in online depression community via topic and linguistic analysis. In Benatallah B, Bestavros A, Manolopoulos Y, Vakali A and Zhang Y (eds), *Web Information Systems Engineering – WISE 2014. WISE 2014*. Lecture Notes in Computer Science, vol 8786. Cham: Springer, pp. 398–407.

Dao B, Nguyen T, Venkatesh S and Phung D (2016) Effect of social capital on emotion, language style and latent topics in online depression community. In *2016 IEEE RIVF International Conference on Computing Communication Technologies, Research, Innovation, and Vision for the Future (RIVF), Hanoi*, pp. 61–66.

Dao B, Nguyen T, Venkatesh S and Phung D (2017) Latent sentiment topic modelling and nonparametric discovery of online mental health-related communities. *International Journal of Data Science and Analytics* **4**, 209–231.

Deetjen U and Powell JA (2016) Informational and emotional elements in online support groups: a Bayesian approach to large-scale content analysis. *Journal of the American Medical Informatics Association: JAMIA* **23**, 508–513.

DeMasi O and Recht B (2017) A step towards quantifying when an algorithm can and cannot predict an individual's wellbeing. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers UbiComp '17*. New York, NY, USA: ACM, pp. 763–771.

Deng F, Wang Y, Huang H, Niu M, Zhong S, Zhao L, Qi Z, Wu X, Sun Y, Niu C, He Y, Huang L and Huang R (2018) Abnormal segments of right uncinate fasciculus and left anterior thalamic radiation in major and bipolar depression. *Progress in Neuro-Psychopharmacology & Biological Psychiatry* **81**, 340–349.

Dimitriadis SI, Liparas D, Tsolaki MN and Alzheimer's Disease Neuroimaging Initiative (2018) Random forest feature selection, fusion and ensemble strategy: combining multiple morphological MRI measures to discriminate among healthy elderly, MCI, cMCI and Alzheimer's disease patients: from the Alzheimer's disease neuroimaging initiative (ADNI) database. *Journal of Neuroscience Methods* **302**, 14–23.

Diniz BS, Sibille E, Ding Y, Tseng G, Aizenstein HJ, Lotrich F, Becker JT, Lopez OL, Lotze MT, Klunk WE, Reynolds CF and Butters MA (2015) Plasma biosignature and brain pathology related to persistent cognitive impairment in late-life depression. *Molecular Psychiatry* **20**, 594–601.

Diniz BS, Lin C-W, Sibille E, Tseng G, Lotrich F, Aizenstein HJ, Reynolds CF and Butters MA (2016) Circulating biosignatures of late-life depression (LLD): towards a comprehensive, data-driven approach to understanding LLD pathophysiology. *Journal of Psychiatric Research* **82**, 1–7.

Dipnall JF, Pasco JA, Berk M, Williams LJ, Dodd S, Jacka FN and Meyer D (2016*a*) Fusing data mining, machine learning and traditional statistics to detect biomarkers associated with depression. *PLoS One* **11**, e0148195.

Dipnall JF, Pasco JA, Berk M, Williams LJ, Dodd S, Jacka FN and Meyer D (2016*b*) Into the bowels of depression: unravelling medical symptoms associated with depression by applying machine-learning techniques to a community based population sample. *PLoS One* **11**, e0167055.

Dipnall JF, Pasco JA, Berk M, Williams LJ, Dodd S, Jacka FN and Meyer D (2017*a*) Getting RID of the blues: formulating a risk Index for depression (RID) using structural equation modeling. *The Australian and New Zealand Journal of Psychiatry* **51**, 1121–1133.

Dipnall JF, Pasco JA, Berk M, Williams LJ, Dodd S, Jacka FN and Meyer D (2017*b*) Why so GLUMM? Detecting depression clusters through graphing lifestyle-environs using machine-learning methods (GLUMM). *European Psychiatry: The Journal of the Association of European Psychiatrists* **39**, 40–50.

Dluhoš P, Schwarz D, Cahn W, van Haren N, Kahn R, Španiel F, Horáček J, Kašpárek T and Schnack H (2017) Multi-center machine learning in imaging psychiatry: a meta-model approach. *NeuroImage* **155**, 10–24.

Dmitrzak-Weglarz MP, Pawlak JM, Maciukiewicz M, Moczko J, Wilkosc M, Leszczynska-Rodziewicz A, Zaremba D and Hauser J (2015) Clock gene variants differentiate mood disorders. *Molecular Biology Reports* **42**, 277–288.

Doan NT, Engvig A, Zaske K, Persson K, Lund MJ, Kaufmann T, Cordova-Palomera A, Alnæs D, Moberget T, Brækhus A, Barca ML, Nordvik JE, Engedal K, Agartz I, Selbæk G, Andreassen OA, Westlye LT and Alzheimer's Disease Neuroimaging Initiative (2017*a*) Distinguishing early and late brain aging from the Alzheimer's disease spectrum: consistent morphological patterns across independent samples. *NeuroImage* **158**, 282–295.

Doan S, Ritchart A, Perry N, Chaparro JD and Conway M (2017*b*) How do you #relax when you're #stressed? A content analysis and infodemiology study of stress-related tweets. *JMIR Public Health and Surveillance* **3**, e35.

Dyrba M, Ewers M, Wegrzyn M, Kilimann I, Plant C, Oswald A, Meindl T, Pievani M, Bokde ALW, Fellgiebel A, Filippi M, Hampel H, Klöppel S, Hauenstein K, Kirste T, Teipel SJ and EDSD study group (2013) Robust automated detection of microstructural white matter degeneration in Alzheimer's disease using machine learning classification of multicenter DTI data. *PLoS One* **8**, e64925.

Dyrba M, Barkhof F, Fellgiebel A, Filippi M, Hausner L, Hauenstein K, Kirste T, Teipel SJ and EDSD study group (2015) Predicting prodromal Alzheimer's disease in subjects with mild cognitive impairment using machine learning classification of multimodal multicenter diffusion-tensor and magnetic resonance imaging data. *Journal of Neuroimaging* **25**, 738–747.

El Naqa I and Murphy MJ (2015) What is machine learning? In El Naqa I, Li R and Murphy M (eds), *Machine Learning in Radiation Oncology*. Cham: Springer, pp. 3–11.

Er F, Iscen P, Sahin S, Çinar N, Karsidag S and Goularas D (2017) Distinguishing age-related cognitive decline from dementias: a study based on machine learning algorithms. *Journal of Clinical Neuroscience* **42**, 186–192.

Erguzel TT and Tarhan N (2016) Machine learning approaches to predict repetitive transcranial magnetic stimulation treatment response in Major depressive disorder. In Bi Y, Kapoor S and Bhatia R (eds), *Proceedings of SAI Intelligent Systems Conference. (IntelliSys) 2016. IntelliSys 2016*. Lecture Notes in Networks and Systems, vol 16. Cham: Springer, pp. 391–401.

Erguzel TT, Ozekes S, Sayar GH, Tan O and Tarhan N (2015) A hybrid artificial intelligence method to classify trichotillomania and obsessive compulsive disorder. *Neurocomputing* **161**, 220–228.

Ertek G, Tokdil B and Günaydın İ (2014) Risk Factors and Identifiers for Alzheimer's Disease: A Data Mining Analysis. In Perner P (ed.), Advances in Data Mining. *Applications and Theoretical Aspects. ICDM 2014*. Lecture Notes in Computer Science, vol 8557. Cham: Springer.

Fabbri C, Corponi F, Albani D, Raimondi I, Forloni G, Schruers K, Kasper S, Kautzky A, Zohar J, Souery D, Montgomery S, Cristalli CP, Mantovani V, Mendlewicz J and Serretti A (2018) Pleiotropic genes in psychiatry: calcium channels and the stress-related FKBP5 gene in antidepressant resistance. *Progress in Neuro-Psychopharmacology & Biological Psychiatry* **81**, 203–210.

Faedda GL, Ohashi K, Hernandez M, McGreenery CE, Grant MC, Baroni A, Polcari A and Teicher MH (2016) Actigraph measures discriminate pediatric bipolar disorder from attention-deficit/hyperactivity disorder and typically developing controls. *Journal of Child Psychology and Psychiatry, and Allied Disciplines* **57**, 706–716.

Falahati F, Ferreira D, Soininen H, Mecocci P, Vellas B, Tsolaki M, Kłoszewska I, Lovestone S, Eriksdotter M, Wahlund L-O, Simmons A, Westman E and AddNeuroMed consortium and the Alzheimer's Disease Neuroimaging Initiative (2016) The effect of Age correction on multivariate classification in Alzheimer's disease, with a focus on the characteristics of incorrectly and correctly classified subjects. *Brain Topography* **29**, 296–307.

Farhan AA, Lu J, Bi J, Russell A, Wang B and Bamis A (2016) Multi-view bi-clustering to identify smartphone sensing features indicative of depression. In *2016 IEEE First International Conference on Connected Health: Applications, Systems and Engineering Technologies (*CHASE*)*, pp. 264–273.

Fraser KC, Meltzer JA and Rudzicz F (2016) Linguistic features identify Alzheimer's disease in narrative speech. *Journal of Alzheimer's Disease: JAD* **49**, 407–422.

Fung G, Deng Y, Zhao Q, Li Z, Qu M, Li K, Zeng Y-W, Jin Z, Ma Y-T, Yu X, Wang Z-R, Shum DHK and Chan RCK (2015) Distinguishing bipolar and major depressive disorders by brain structural morphometry: a pilot study. *BMC Psychiatry* **15**, 298.

Fusar-Poli P, Rutigliano G, Stahl D, Schmidt A, Ramella-Cravaro V, Hitesh S and McGuire P (2016) Deconstructing pretest risk enrichment to optimize prediction of psychosis in individuals at clinical high risk. *JAMA Psychiatry* **73**, 1260–1267.

Galiatsatos D, Konstantopoulou G, Anastassopoulos G, Nerantzaki M, Assimakopoulos K and Lymberopoulos D (2015) Classification of the most significant psychological symptoms in mental patients with depression using Bayesian network. In *Proceedings of the 16th International Conference on Engineering Applications of Neural Networks (*INNS*) EANN '15*. New York, NY, USA: ACM, pp. 15:1–15:8.

Geraci J, Wilansky P, de Luca V, Roy A, Kennedy JL and Strauss J (2017) Applying deep neural networks to unstructured text notes in electronic medical records for phenotyping youth depression. *Evidence-Based Mental Health* **20**, 83–87.

Ghafoor Y, Huang Y-P and Liu S-I (2015) An intelligent approach to discovering common symptoms among depressed patients. *Springer Soft Computing* **19**, 819–827.

Gjoreski M, Gjoreski H, Luštrek M and Gams M (2016) Continuous stress detection using a wrist device: in laboratory and real life. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct UbiComp '16*. New York, NY, USA: ACM, pp. 1185–1193.

Glasgow K, Fink C and Boyd-Graber JL (2014) 'Our Grief is Unspeakable': Automatically Measuring the Community Impact of a Tragedy. In *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media*, pp. 161–169.

Glasgow K, Vitak J, Tausczik Y and Fink C (2016) 'With your help… we begin to heal': social media expressions of gratitude in the aftermath of disaster. In Xu K, Reitter D, Lee D and Osgood N (eds), *Social, Cultural, and Behavioral Modeling. SBP-BRiMS 2016*. Lecture Notes in Computer Science, vol 9708. Cham: Springer, pp. 226–236.

Goch CJ, Oztan B, Stieltjes B, Henze R, Hering J, Poustka L, Meinzer H-P, Yener B and Maier-Hein KH (2013) Global changes in the connectome in autism Spectrum disorders. In Schultz T, Nedjati-Gilani G, Venkataraman A, O'Donnell L and Panagiotaki E (eds), *Computational Diffusion MRI and*

Brain Connectivity. Mathematics and Visualization. Cham: Springer, pp. 239–247.

Golbeck J (2016) Detecting coping style from twitter. In Spiro E and Ahn YY (eds), *Social Informatics. SocInfo 2016*. Lecture Notes in Computer Science, vol 10046. Cham: Springer, pp. 454–467.

Gomez-Uribe CA and Hunt N (2015) The Netflix recommender system: algorithms, business value, and innovation. *ACM Trans. Manage. Inf. Syst*. **6**, 13:1–13:19.

Greenstein D, Malley JD, Weisinger B, Clasen L and Gogtay N (2012) Using multivariate machine learning methods and structural MRI to classify childhood onset schizophrenia and healthy controls. *Frontiers in Psychiatry/ Frontiers Research Foundation* **3**, 53.

Guan Z, Li A and Zhu T (2015) Local regression transfer learning with applications to users' psychological characteristics prediction. *Springer Brain Informatics* **2**, 145–153.

Guilloux J-P, Bassi S, Ding Y, Walsh C, Turecki G, Tseng G, Cyranowski JM and Sibille E (2015) Testing the predictive value of peripheral gene expression for nonremission following citalopram treatment for major depression. *Neuropsychopharmacology* **40**, 701–710.

Guo S, Palaniyappan L, Yang B, Liu Z, Xue Z and Feng J (2014) Anatomical distance affects functional connectivity in patients with schizophrenia and their siblings. *Schizophrenia Bulletin* **40**, 449–459.

Hagad JL, Moriyama K, Fukui K and Numao M (2014) Modeling work stress using heart rate and stress coping profiles. In Baldoni M *et al.* (eds), *Principles and Practice of Multi-Agent Systems. CMNA 2015, IWEC 2015, IWEC 2014*. Lecture Notes in Computer Science, vol 9935. Cham: Springer, pp. 108–118.

Hajek T, Cooke C, Kopecek M, Novak T, Hoschl C and Alda M (2015) Using structural MRI to identify individuals at genetic risk for bipolar disorders: a 2-cohort, machine learning study. *Journal of Psychiatry & Neuroscience: JPN* **40**, 316–324.

Hajek T, Franke K, Kolenic M, Capkova J, Matejka M, Propper L, Uher R, Stopkova P, Novak T, Paus T, Kopecek M, Spaniel F and Alda M (2017) Brain age in early stages of bipolar disorders or schizophrenia. *Schizophrenia Bulletin* **45**, 190–198.

Halfon S, Aydın Oktay E and Salah AA (2016) Assessing affective dimensions of play in psychodynamic child psychotherapy via text analysis. In Chetouani M, Cohn J and Salah A (eds), *Human Behavior Understanding. HBU 2016*. Lecture Notes in Computer Science, vol 9997. Cham: Springer, pp. 15–34.

Hao B, Li L, Li A and Zhu T (2013) Predicting mental health status on social media. In Rau PLP (ed.), *Cross-Cultural Design. Cultural Differences in Everyday Life. CCD 2013*. Lecture Notes in Computer Science, vol 8024. Berlin, Heidelberg: Springer, pp. 101–110.

Hao B, Li L, Gao R, Li A and Zhu T (2014) Sensing Subjective Well-being from Social Media. In Ślęzak D, Schaefer G, Vuong ST and Kim YS (eds), *Active Media Technology. AMT 2014*. Lecture Notes in Computer Science, vol 8610. Cham: Springer.

Harikumar H, Nguyen T, Gupta S, Rana S, Kaimal R and Venkatesh S (2016*a*) Understanding behavioral differences between short and long-term drinking abstainers from social media. In Li J, Li X, Wang S, Li J and Sheng Q (eds), *Advanced Data Mining and Applications. ADMA 2016*. Lecture Notes in Computer Science, vol 10086. Cham: Springer, pp. 520–533.

Harikumar H, Nguyen T, Rana S, Gupta S, Kaimal R and Venkatesh S (2016*b*) Extracting key challenges in achieving sobriety through shared subspace learning. In Li J, Li X, Wang S, Li J and Sheng Q (eds), *Advanced Data Mining and Applications. ADMA 2016*. Lecture Notes in Computer Science, vol 10086. Cham: Springer, pp. 420–433.

Hellstrøm T, Kaufmann T, Andelic N, Soberg HL, Sigurdardottir S, Helseth E, Andreassen OA and Westlye LT (2017) Predicting outcome 12 months after mild traumatic brain injury in patients admitted to a neurosurgery service. *Frontiers in Neurology* **8**, 125.

Hess JL, Tylee DS, Barve R, de Jong S, Ophoff RA, Kumarasinghe N, Tooney P, Schall U, Gardiner E, Beveridge NJ, Scott RJ, Yasawardene S, Perera A, Mendis J, Carr V, Kelly B, Cairns M, Neurobehavioural Genetics Unit, Tsuang MT and Glatt SJ (2016) Transcriptome-wide mega-analyses reveal joint dysregulation of immunologic genes and transcription regulators in brain and blood in schizophrenia. Schizophrenia Research 176, 114–124.

Hettige NC, Nguyen TB, Yuan C, Rajakulendran T, Baddour J, Bhagwat N, Bani-Fatemi A, Voineskos AN, Mallar Chakravarty M and De Luca V (2017) Classification of suicide attempters in schizophrenia using sociocultural and clinical features: a machine learning approach. *General Hospital Psychiatry* **47**, 20–28.

Hoogendoorn M, Berger T, Schulz A, Stolz T and Szolovits P (2017) Predicting social anxiety treatment outcome based on therapeutic email conversations. *IEEE Journal of Biomedical and Health Informatics* **21**, 1449–1459.

Hou Y, Xu J, Huang Y and Ma X (2016) A big data application to predict depression in the university based on the reading habits. In *2016 3rd International Conference on Systems and Informatics. (ICSAI), Shanghai*, pp. 1085–1089.

Hu B and Terrazas BV (2016) Building a mental health knowledge model to facilitate decision support. In Ohwada H and Yoshida K (eds), *Knowledge Management and Acquisition for Intelligent Systems. PKAW 2016*. Lecture Notes in Computer Science, vol 9806. Cham: Springer, pp. 198–212.

Hutchinson DM, Silins E, Mattick RP, Patton GC, Fergusson DM, Hayatbakhsh R, Toumbourou JW, Olsson CA, Najman JM, Spry E, Tait RJ, Degenhardt L, Swift W, Butterworth P, Horwood LJ and Cannabis Cohorts Research Consortium (2015) How can data harmonisation benefit mental health research? An example of the cannabis cohorts research consortium. *The Australian and New Zealand Journal of Psychiatry* **49**, 317–323.

Iannaccone R, Hauser TU, Ball J, Brandeis D, Walitza S and Brem S (2015) Classifying adolescent attention-deficit/hyperactivity disorder (ADHD) based on functional and structural imaging. *European Child & Adolescent Psychiatry* **24**, 1279–1289.

Iliou T, Konstantopoulou G, Ntekouli M, Lymperopoulou C, Assimakopoulos K, Galiatsatos D and Anastassopoulos G (2017) ILIOU machine learning preprocessing method for depression type prediction. *Evolving Systems* **475**, 53–60.

Iniesta R, Malki K, Maier W, Rietschel M, Mors O, Hauser J, Henigsberg N, Dernovsek MZ, Souery D, Stahl D, Dobson R, Aitchison KJ, Farmer A, Lewis CM, McGuffin P and Uher R (2016) Combining clinical variables to optimize prediction of antidepressant treatment outcomes. *Journal of Psychiatric Research* **78**, 94–102.

Islam J and Zhang Y (2017) A novel deep learning based multi-class classification method for Alzheimer's disease detection using brain MRI data. In Zeng Y *et al.* (eds), *Brain Informatics. BI 2017*. Lecture Notes in Computer Science, vol 10654. Cham: Springer, pp. 213–222.

Iwabuchi SJ and Palaniyappan L (2017) Abnormalities in the effective connectivity of visuothalamic circuitry in schizophrenia. *Psychological Medicine* **47**, 1300–1310.

Iwabuchi SJ, Liddle PF and Palaniyappan L (2013) Clinical utility of machine-learning approaches in schizophrenia: improving diagnostic confidence for translational neuroimaging. *Frontiers in Psychiatry/Frontiers Research Foundation* **4**, 95.

Jiao Y, Chen R, Ke X, Chu K, Lu Z and Herskovits EH (2010) Predictive models of autism spectrum disorder based on brain regional cortical thickness. *NeuroImage* **50**, 589–599.

Jiao Y, Chen R, Ke X, Cheng L, Chu K, Lu Z and Herskovits EH (2012) Single nucleotide polymorphisms predict symptom severity of autism spectrum disorder. *Journal of Autism and Developmental Disorders* **42**, 971–983.

Jie N-F, Osuch EA, Zhu M-H, Wammes M, Ma X-Y, Jiang T-Z, Sui J and Calhoun VD (2018) Discriminating bipolar disorder from major depression using whole-brain functional connectivity: a feature selection analysis with SVM-FoBa algorithm. *Journal of Signal Processing Systems* **90**, 259–271.

Jiménez-Serrano S, Tortajada S and García-Gómez JM (2015) A mobile health application to predict postpartum depression based on machine learning. *Telemedicine Journal and e-Health* **21**, 567–574.

Jin H, Wu S and Di Capua P (2015) Development of a clinical forecasting model to predict comorbid depression among diabetes patients and an application in depression screening policy making. *Preventing Chronic Disease* **12**, E142.

Jin C, Jia H, Lanka P, Rangaprakash D, Li L, Liu T, Hu X and Deshpande G (2017) Dynamic brain connectivity is a better predictor of PTSD than static connectivity. *Human Brain Mapping* **38**, 4479–4496.

Johannesen JK, Bi J, Jiang R, Kenney JG and Chen C-MA (2016) Machine learning identification of EEG features predicting working memory performance in schizophrenia and healthy adults. *Neuropsychiatric Electrophysiology* **2**, 3.

Johansson R, Sjöberg E, Sjögren M, Johnsson E, Carlbring P, Andersson T, Rousseau A and Andersson G (2012) Tailored vs. Standardized internet-based cognitive behavior therapy for depression and comorbid symptoms: a randomized controlled trial. *PLoS One* **7**, e36905.

Johnson P, Vandewater L, Wilson W, Maruff P, Savage G, Graham P, Macaulay LS, Ellis KA, Szoeke C, Martins RN, Rowe CC, Masters CL, Ames D and Zhang P (2014) Genetic algorithm with logistic regression for prediction of progression to Alzheimer's disease. *BMC Bioinformatics* **15**(suppl. 16), S11.

Jordan MI and Mitchell TM (2015) Machine learning: trends, perspectives, and prospects. *Science* **349**, 255–260.

Kamdar MR and Wu MJ (2016) PRISM: a data-driven platform for monitoring mental health. *Pacific Symposium on Biocomputing* **21**, 333–344.

Kang Y, Jiang X, Yin Y, Shang Y and Zhou X (2017) Deep transformation learning for depression diagnosis from facial images. In Zhou J *et al.* (eds), *Biometric Recognition. CCBR 2017*. Lecture Notes in Computer Science, vol 10568. Cham: Springer, pp. 13–22.

Karamzadeh N, Amyot F, Kenney K, Anderson A, Chowdhry F, Dashtestani H, Wassermann EM, Chernomordik V, Boccara C, Wegman E, Diaz-Arrastia R and Gandjbakhche AH (2016) A machine learning approach to identify functional biomarkers in human prefrontal cortex for individuals with traumatic brain injury using functional near-infrared spectroscopy. *Brain and Behavior* **6**, e00541.

Karstoft K-I, Statnikov A, Andersen SB, Madsen T and Galatzer-Levy IR (2015) Early identification of posttraumatic stress following military deployment: application of machine learning methods to a prospective study of Danish soldiers. *Journal of Affective Disorders* **184**, 170–175.

Karystianis G, Nevado AJ, Kim C-H, Dehghan A, Keane JA and Nenadic G (2018) Automatic mining of symptom severity from psychiatric evaluation notes. *International Journal of Methods in Psychiatric Research* **27**, e1602.

Kaufmann T, Alnæs D, Brandt CL, Doan NT, Kauppi K, Bettella F, Lagerberg TV, Berg AO, Djurovic S, Agartz I, Melle IS, Ueland T, Andreassen OA and Westlye LT (2017) Task modulations and clinical manifestations in the brain functional connectome in 1615 fMRI datasets. *NeuroImage* **147**, 243–252.

Kaufmann T, Skåtun KC, Alnæs D, Doan NT, Duff EP, Tønnesen S, Roussos E, Ueland T, Aminoff SR, Lagerberg TV, Agartz I, Melle IS, Smith SM, Andreassen OA and Westlye LT (2015) Disintegration of sensorimotor brain networks in schizophrenia. *Schizophrenia Bulletin* **41**, 1326–1335.

Kavuluru R, Williams AG, Ramos-Morales M, Haye L, Holaday T and Cerel J (2016) Classification of helpful comments on online suicide watch forums. *ACM Conference on Bioinformatics, Computational Biology and Biomedicine* **2016**, 32–40.

Kessler RC, Rose S, Koenen KC, Karam EG, Stang PE, Stein DJ, Heeringa SG, Hill ED, Liberzon I, McLaughlin KA, McLean SA, Pennell BE, Petukhova M, Rosellini AJ, Ruscio AM, Shahly V, Shalev AY, Silove D, Zaslavsky AM, Angermeyer MC, Bromet EJ, de Almeida JMC, de Girolamo G, de Jonge P, Demyttenaere K, Florescu SE, Gureje O, Haro JM, Hinkov H, Kawakami N, Kovess-Masfety V, Lee S, Medina-Mora ME, Murphy SD, Navarro-Mateu F, Piazza M, Posada-Villa J, Scott K, Torres Y and Carmen Viana M (2014) How well can post-traumatic stress disorder be predicted from pre-trauma risk factors? An exploratory study in the WHO World Mental Health Surveys. *World Psychiatry* **13**, 265–274.

Kessler RC, Warner CH, Ivany C, Petukhova MV, Rose S, Bromet EJ, Brown III M, Cai T, Colpe LJ, Cox KL, Fullerton CS, Gilman SE, Gruber MJ, Heeringa SG, Lewandowski-Romps L, Li J, Millikan-Bell AM, Naifeh JA, Nock MK, Rosellini AJ, Sampson NA, Schoenbaum M, Stein MB, Wessely S, Zaslavsky AM, Ursano RJ and Army STARRS Collaborators (2015) Predicting suicides after psychiatric hospitalization in US Army soldiers: the Army Study To Assess Risk and rEsilience in Servicemembers (Army STARRS). *JAMA Psychiatry* **72**, 49–57.

Kessler RC, van Loo HM, Wardenaar KJ, Bossarte RM, Brenner LA, Cai T, Ebert DD, Hwang I, Li J, de Jonge P, Nierenberg AA, Petukhova MV, Rosellini AJ, Sampson NA, Schoevers RA, Wilcox MA and Zaslavsky AM (2016) Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports. *Molecular Psychiatry* **21**, 1366–1371.

Kessler RC, Hwang I, Hoffmire CA, McCarthy JF, Petukhova MV, Rosellini AJ, Sampson NA, Schneider AL, Bradley PA, Katz IR, Thompson C and Bossarte RM (2017*a*) Developing a practical suicide risk prediction model for targeting high-risk patients in the Veterans health Administration. *International Journal of Methods in Psychiatric Research* **26**, e1575.

Kessler RC, Stein MB, Petukhova MV, Bliese P, Bossarte RM, Bromet EJ, Fullerton CS, Gilman SE, Ivany C, Lewandowski-Romps L, Millikan Bell A, Naifeh JA, Nock MK, Reis BY, Rosellini AJ, Sampson NA, Zaslavsky AM, Ursano RJ and Army STARRS Collaborators (2017*b*) Predicting suicides after outpatient mental health visits in the Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS). *Molecular Psychiatry* **22**, 544–551.

Khalilia M, Chakraborty S and Popescu M (2011) Predicting disease risks from highly imbalanced data using random forest. *BMC Medical Informatics and Decision Making* **11**, 51.

Khondoker M, Dobson R, Skirrow C, Simmons A and Stahl D (2016) A comparison of machine learning methods for classification using simulation with multiple real data examples from mental health studies. *Statistical Methods in Medical Research* **25**, 1804–1823.

Kim H, Chun H-W, Kim S, Coh B-Y, Kwon O-J and Moon Y-H (2017) Longitudinal study-based dementia prediction for public health. *International Journal of Environmental Research and Public Health* **14**, 983.

Kliper R, Portuguese S and Weinshall D (2016) Prosodic analysis of speech and the underlying mental state. In Serino S, Matic A, Giakoumis D, Lopez G and Cipresso P (eds), *Pervasive Computing Paradigms for Mental Health. MindCare 2015*. Communications in Computer and Information Science, vol 604. Cham: Springer, pp. 52–62.

Klöppel S, Peter J, Ludl A, Pilatus A, Maier S, Mader I, Heimbach B, Frings L, Egger K, Dukart J, Schroeter ML, Perneczky R, Häussermann P, Vach W, Urbach H, Teipel S, Hüll M, Abdulkadir A and Alzheimer's Disease Neuroimaging Initiative (2015) Applying automated MR-based diagnostic methods to the memory clinic: a prospective study. *Journal of Alzheimer's Disease: JAD* **47**, 939–954.

König A, Satt A, Sorin A, Hoory R, Toledo-Ronen O, Derreumaux A, Manera V, Verhey F, Aalten P, Robert PH and David R (2015) Automatic speech analysis for the assessment of patients with predementia and Alzheimer's disease. *Alzheimer's & Dementia: The Journal of the Alzheimer's Association* **1**, 112–124.

Koutsouleris N, Meisenzahl EM, Davatzikos C, Bottlender R, Frodl T, Scheuerecker J, Schmitt G, Zetzsche T, Decker P, Reiser M, Möller H-J and Gaser C (2009) Use of neuroanatomical pattern classification to identify subjects in at-risk mental states of psychosis and predict disease transition. *Archives of General Psychiatry* **66**, 700–712.

Koutsouleris N, Borgwardt S, Meisenzahl EM, Bottlender R, Möller H-J and Riecher-Rössler A (2012) Disease prediction in the at-risk mental state for psychosis using neuroanatomical biomarkers: results from the FePsy study. *Schizophrenia Bulletin* **38**, 1234–1246.

Koutsouleris N, Davatzikos C, Borgwardt S, Gaser C, Bottlender R, Frodl T, Falkai P, Riecher-Rössler A, Möller H-J, Reiser M, Pantelis C and Meisenzahl E (2014) Accelerated brain aging in schizophrenia and beyond: a neuroanatomical marker of psychiatric disorders. *Schizophrenia Bulletin* **40**, 1140–1153.

Koutsouleris N, Kahn RS, Chekroud AM, Leucht S, Falkai P, Wobrock T, Derks EM, Fleischhacker WW and Hasan A (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.

Koutsouleris N, Wobrock T, Guse B, Langguth B, Landgrebe M, Eichhammer P, Frank E, Cordes J, Wölwer W, Musso F, Winterer G, Gaebel W, Hajak G, Ohmann C, Verde PE, Rietschel M, Ahmed R, Honer WG, Dwyer D, Ghaseminejad F, Dechent P, Malchow B, Kreuzer PM, Poeppl TB, Schneider-Axmann T, Falkai P and Hasan A

https://doi.org/10.1017/S0033291719000151

(2018) Predicting response to repetitive transcranial magnetic stimulation in patients with schizophrenia using structural magnetic resonance imaging: a multisite machine learning analysis. *Schizophrenia Bulletin* **44**, 1021–1034.

Kumari RS, Sheela Kumari R, Varghese T, Kesavadas C, Albert Singh N and Mathuranath PS (2013) A genetic algorithm optimized artificial neural network for the segmentation of MR images in frontotemporal dementia. In Panigrahi BK, Suganthan PN, Das S and Dash SS (eds), *Swarm, Evolutionary, and Memetic Computing. SEMCCO 2013*. Lecture Notes in Computer Science, vol 8298. Cham: Springer, pp. 268–276.

Labate D, La Foresta F, Palamara I and Morabito G (2014) EEG complexity modifications and altered compressibility in mild cognitive impairment and Alzheimer's disease. In Bassis S, Esposito A and Morabito F (eds), *Recent Advances of Neural Network Models and Applications*. Smart Innovation, Systems and Technologies, vol 26. Cham: Springer, pp. 163-173.

Lenhard F, Sauer S, Andersson E, Månsson KN, Mataix-Cols D, Rück C and Serlachius E (2018) Prediction of outcome in internet-delivered cognitive behaviour therapy for paediatric obsessive-compulsive disorder: a machine learning approach. *International Journal of Methods in Psychiatric Research* **27**, e1576

Li Q, Wu X, Xu L, Chen K, Yao L and Li R (2017*a*) Multi-modal discriminative dictionary learning for Alzheimer's disease and mild cognitive impairment. *Computer Methods and Programs in Biomedicine* **150**, 1–8.

Li Q, Zhao L, Xue Y, Jin L and Feng L (2017*b*) Exploring the impact of co-experiencing stressor events for teens stress forecasting. In Bouguettaya A *et al*. (eds), *Web Information Systems Engineering – WISE 2017. WISE 2017*. Lecture Notes in Computer Science, vol 10570. Cham: Springer, pp. 313–328.

Liang X, Gu S, Deng J, Gao Z, Zhang Z and Shen D (2015) Investigation of college students' mental health status via semantic analysis of Sina microblog. *Wuhan University Journal of Natural Sciences* **20**, 159–164.

Liang S, Brown MRG, Deng W, Wang Q, Ma X, Li M, Hu X, Juhas M, Li X, Greiner R, Greenshaw AJ and Li T (2018*a*) Convergence and divergence of neurocognitive patterns in schizophrenia and depression. *Schizophrenia Research* **192**, 327–334.

Liang S, Vega R, Kong X, Deng W, Wang Q, Ma X, Li M, Hu X, Greenshaw AJ, Greiner R and Li T (2018*b*) Neurocognitive graphs of first-episode schizophrenia and major depression based on cognitive features. *Neuroscience Bulletin* **34**, 312–320.

Liu F, Guo W, Fouche J-P, Wang Y, Wang W, Ding J, Zeng L, Qiu C, Gong Q, Zhang W and Chen H (2015*a*) Multivariate classification of social anxiety disorder using whole brain functional connectivity. *Brain Structure & Function* **220**, 101–115.

Liu F, Xie B, Wang Y, Guo W, Fouche J-P, Long Z, Wang W, Chen H, Li M, Duan X, Zhang J, Qiu M and Chen H (2015*b*) Characterization of post-traumatic stress disorder using resting-state fMRI with a multi-level parametric classification approach. *Brain Topography* **28**, 221–237.

Liu W, Li M and Yi L (2016) Identifying children with autism spectrum disorder based on their face processing abnormality: a machine learning framework. *Autism Research* **9**, 888–898.

Liu Z, Tang B, Wang X and Chen Q (2017) De-identification of clinical notes via recurrent neural network and conditional random field. *Journal of Biomedical Informatics* **75S**, S34–S42.

Lord A, Horn D, Breakspear M and Walter M (2012) Changes in community structure of resting state functional connectivity in unipolar depression. *PLoS One* **7**, e41282.

Lueken U, Straube B, Yang Y, Hahn T, Beesdo-Baum K, Wittchen H-U, Konrad C, Ströhle A, Wittmann A, Gerlach AL, Pfleiderer B, Arolt V and Kircher T (2015) Separating depressive comorbidity from panic disorder: a combined functional magnetic resonance imaging and machine learning approach. *Journal of Affective Disorders* **184**, 182–192.

Luo J, Wu M, Gopukumar D and Zhao Y (2016) Big data application in biomedical research and health care: a literature review. *Biomedical Informatics Insights* **8**, 1–10.

Ma L, Wang Z and Zhang Y (2017) Extracting depression symptoms from social networks and web blogs via text mining. In Cai Z, Daescu O and Li M (eds), *Bioinformatics Research and Applications. ISBRA 2017*. Lecture Notes in Computer Science, vol 10330. Cham: Springer, pp. 325–330.

Maraş A and Aydin S (2017) Discrimination of psychotic symptoms from controls through data mining methods based on emotional principle components. In *CMBEBIH 2017*. Singapore: Springer, pp. 26–30.

Maxhuni A, Hernandez-Leal P, Morales EF, Enrique Sucar L, Osmani V, Muńoz-Meléndez A and Mayora O (2016) Using intermediate models and knowledge learning to improve stress prediction. In Sucar E, Mayora O, Munoz de Cote E (eds), *Applications for Future Internet*. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 179. Cham: Springer, pp. 140–151.

Mechelli A, Lin A, Wood S, McGorry P, Amminger P, Tognin S, McGuire P, Young J, Nelson B and Yung A (2017) Using clinical information to make individualized prognostic predictions in people at ultra high risk for psychosis. *Schizophrenia Research* **184**, 32–38.

Metzger M-H, Tvardik N, Gicquel Q, Bouvry C, Poulet E and Potinet-Pagliaroli V (2017) Use of emergency department electronic medical records for automated epidemiological surveillance of suicide attempts: a French pilot study. *International Journal of Methods in Psychiatric Research* **26**, e1522.

Meyer D, Abbott J-AM and Nedejkovic M (2015) Big data study for coping with stress. In *Proceedings of the Scientific Stream at Big Data in Health Analytics 2015 (BigData 2015), Sydney, Australia*.

Mikolas P, Melicher T, Skoch A, Matejka M, Slovakova A, Bakstein E, Hajek T and Spaniel F (2016) Connectivity of the anterior insula differentiates participants with first-episode schizophrenia spectrum disorders from controls: a machine-learning study. *Psychological Medicine* **46**, 2695–2704.

Mitra V, Shriberg E, McLaren M, Kathol A, Richey C, Vergyri D and Graciarena M (2014) The SRI AVEC-2014 evaluation system. In *Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge AVEC '14*. New York, NY, USA: ACM, pp. 93–101.

Mohammadi M, Al-Azab F, Raahemi B, Richards G, Jaworska N, Smith D, de la Salle S, Blier P and Knott V (2015) Data mining EEG signals in depression for their diagnostic value. *BMC Medical Informatics and Decision Making* **15**, 108.

Moher D, Liberati A, Tetzlaff J, Altman DG and PRISMA Group (2010) Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *International Journal of Surgery* **8**, 336–341.

Moulahi B, Azé J and Bringay S (2017) DARE to care: a context-aware framework to track suicidal ideation on social media. In *Bouguettaya A et al. (eds), Web Information Systems Engineering – WISE 2017. WISE 2017*. Lecture Notes in Computer Science, vol 10570. Cham: Springer, pp. 346–353.

Nahum-Shani I, Smith SN, Spring BJ, Collins LM, Witkiewitz K, Tewari A and Murphy SA (2017) Just-in-Time Adaptive Interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine* **52**, 446–462.

Nakashima Y, Kim J, Flutura S, Seiderer A and André E (2016) Stress recognition in daily work. In Serino S, Matic A, Giakoumis D, Lopez G and Cipresso P (eds), *Pervasive Computing Paradigms for Mental Health. MindCare 2015*. Communications in Computer and Information Science, vol 604. Cham: Springer, pp. 23–33.

Nandhini BS and Sheeba JI (2015) Cyberbullying detection and classification using information retrieval algorithm. In *Proceedings of the 2015 International Conference on Advanced Research in Computer Science Engineering & Technology (*ICARCSET 2015*) ICARCSET '15*. New York, NY, USA: ACM, pp. 20:1–20:5.

Nguyen T, Duong T, Phung D and Venkatesh S (2014*a*) Affective, linguistic and topic patterns in online autism communities. In Benatallah B, Bestavros A, Manolopoulos Y, Vakali A and Zhang Y (eds), *Web Information Systems Engineering – WISE 2014. WISE 2014*. Lecture Notes in Computer Science, vol 8787. Cham: Springer, pp. 474–488.

Nguyen T, Phung D, Dao B, Venkatesh S and Berk M (2014*b*) Affective and content analysis of online depression communities. *IEEE Transactions on Affective Computing* **5**, 217–226.

Nguyen T, O'Dea B, Larsen M, Phung D, Venkatesh S and Christensen H (2015) Differentiating sub-groups of online depression-related communities using textual cues. In Wang J *et al.* (eds), *Web Information Systems Engineering – WISE 2015. WISE 2015*. Lecture Notes in Computer Science, vol 9419. Cham: Springer, pp. 216–224.

Nguyen T, Borland R, Yearwood J, Yong H-H, Venkatesh S and Phung D (2016*a*) Discriminative cues for different stages of smoking cessation in

https://doi.org/10.1017/S0033291719000151

online community. In Cellary W, Mokbel M, Wang J, Wang H, Zhou R and Zhang Y (eds), *Web Information Systems Engineering – WISE 2016. WISE 2016*. Lecture Notes in Computer Science, vol 10042. Cham: Springer, pp. 146–153.

Nguyen T, Venkatesh S and Phung D (2016*b*) Textual cues for online depression in community and personal settings. In Li J, Li X, Wang S, Li J and Sheng Q (eds), *Advanced Data Mining and Applications. ADMA 2016*. Lecture Notes in Computer Science, vol 10086. Cham: Springer, pp. 19–34.

Nguyen T, O'Dea B, Larsen M, Phung D, Venkatesh S and Christensen H (2017) Using linguistic and topic analysis to classify sub-groups of online depression communities. *Multimedia Tools and Applications* **76**, 10653–10676.

Nicodemus KK, Callicott JH, Higier RG, Luna A, Nixon DC, Lipska BK, Vakkalanka R, Giegling I, Rujescu D, St Clair D, Muglia P, Shugart YY and Weinberger DR (2010) Evidence of statistical epistasis between DISC1, CIT and NDEL1 impacting risk for schizophrenia: biological validation with functional neuroimaging. *Human Genetics* **127**, 441–452.

Nikfarjam A, Sarker A, O'Connor K, Ginn R and Gonzalez G (2015) Pharmacovigilance from social media: mining adverse drug reaction mentions using sequence labeling with word embedding cluster features. *Journal of the American Medical Informatics Association: JAMIA* **22**, 671–681.

O'Dea B, Wan S, Batterham PJ, Calear AL, Paris C and Christensen H (2015) Detecting suicidality on Twitter. *Internet Interventions* **2**, 183–188.

O'Halloran R, Kopell BH, Sprooten E, Goodman WK and Frangou S (2016) Multimodal neuroimaging-informed clinical applications in neuropsychiatric disorders. *Frontiers in Psychiatry/Frontiers Research Foundation* **7**, 63.

Oh DH, Kim IB, Kim SH and Ahn DH (2017) Predicting autism spectrum disorder using blood-based gene expression signatures and machine learning. *Clinical Psychopharmacology and Neuroscience* **15**, 47–52.

Ojeme B and Mbogho A (2016*a*) Predictive strength of Bayesian networks for diagnosis of depressive disorders. In Czarnowski I, Caballero A, Howlett R and Jain L (eds), *Intelligent Decision Technologies 2016. IDT 2016*. Smart Innovation, Systems and Technologies, vol 56. Cham: Springer, pp. 373–382.

Ojeme B and Mbogho A (2016*b*) Selecting learning algorithms for simultaneous identification of depression and comorbid disorders. *Procedia Computer Science* **96**, 1294–1303.

Oseguera O, Rinaldi A, Tuazon J and Cruz AC (2017) Automatic quantification of the veracity of suicidal ideation in counseling transcripts. In Stephanidis C (ed.), *HCI International 2017 – Posters' Extended Abstracts. HCI 2017*. Communications in Computer and Information Science, vol 713. Cham: Springer, pp. 473–479.

Pampouchidou A, Pediaditis M, Maridaki A, Awais M, Vazakopoulou C-M, Sfakianakis S, Tsiknakis M, Simos P, Marias K, Yang F and Meriaudeau F (2017) Quantitative comparison of motion history image variants for video-based depression assessment. *EURASIP Journal on Image and Video Processing* **2017**, 64.

Panagiotakopoulos TC, Lyras DP, Livaditis M, Sgarbas KN, Anastassopoulos GC and Lymberopoulos DK (2010) A contextual data mining approach toward assisting the treatment of anxiety disorders. *IEEE Transactions on Information Technology in Biomedicine* **14**, 567–581.

Pandey A, Davis NA, White BC, Pajewski NM, Savitz J, Drevets WC and McKinney BA (2012) Epistasis network centrality analysis yields pathway replication across two GWAS cohorts for bipolar disorder. *Translational Psychiatry* **2**, e154.

Paredes P, Gilad-Bachrach R, Czerwinski M, Roseway A, Rowan K and Hernandez J (2014) Poptherapy: coping with stress through pop-culture. In *Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare PervasiveHealth '14*. Brussels, Belgium, Belgium: ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), pp. 109–117.

Park A, Conway M and Chen AT (2018) Examining thematic similarity, difference, and membership in three online mental health communities from Reddit: a text mining and visualization approach. *Computers in Human Behavior* **78**, 98–112.

Parrado-Hernández E, Gómez-Verdejo V, Martinez-Ramon M, Alonso P, Pujol J, Menchón JM, Cardoner N and Soriano-Mas C (2012) Identification of OCD-relevant brain areas through multivariate feature selection. In Langs G, Rish I, Grosse-Wentrup M and Murphy B (eds), *Machine Learning and Interpretation in Neuroimaging*. Lecture Notes in Computer Science, vol 7263. Berlin, Heidelberg: Springer, pp. 60–67.

Pedersen M, Curwood EK, Archer JS, Abbott DF and Jackson GD (2015) Brain regions with abnormal network properties in severe epilepsy of Lennox-Gastaut phenotype: multivariate analysis of task-free fMRI. *Epilepsia* **56**, 1767–1773.

Peng Z, Hu Q and Dang J (2019) Multi-kernel SVM based depression recognition using social media data. *International Journal of Machine Learning and Cybernetics* **10**, 43–57.

Perlini C, Bellani M, Finos L, Lasalvia A, Bonetto C, Scocco P, D'Agostino A, Torresani S, Imbesi M, Bellini F, Konze A, Veronese A, Ruggeri M, Brambilla P and GET UP Group (2017) Non literal language comprehension in a large sample of first episode psychosis patients in adulthood. *Psychiatry Research* **260**, 78–89.

Perlis RH (2013) A clinical risk stratification tool for predicting treatment resistance in major depressive disorder. *Biological Psychiatry* **74**, 7–14.

Pestian JP, Matykiewicz P and Grupp-Phelan J (2008) Using natural language processing to classify suicide notes. In *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing BioNLP '08*. Stroudsburg, PA, USA: Association for Computational Linguistics, pp. 96–97.

Pestian J, Nasrallah H, Matykiewicz P, Bennett A and Leenaars A (2010) Suicide note classification using natural language processing: a content analysis. *Biomedical Informatics Insights* **2010**, 19–28.

Pestian JP, Grupp-Phelan J, Bretonnel Cohen K, Meyers G, Richey LA, Matykiewicz P and Sorter MT (2016) A controlled trial using natural language processing to examine the language of suicidal adolescents in the emergency department. *Suicide & Life-Threatening Behavior* **46**, 154–159.

Pham MT, Rajić A, Greig JD, Sargeant JM, Papadopoulos A and McEwen SA (2014) A scoping review of scoping reviews: advancing the approach and enhancing the consistency. *Research Synthesis Methods* **5**, 371–385.

Plitt M, Barnes KA and Martin A (2015) Functional connectivity classification of autism identifies highly predictive brain features but falls short of biomarker standards. *NeuroImage. Clinical* **7**, 359–366.

Posada JD, Barda AJ, Shi L, Xue D, Ruiz V, Kuan P-H, Ryan ND and Tsui FR (2017) Predictive modeling for classification of positive valence system symptom severity from initial psychiatric evaluation records. *Journal of Biomedical Informatics* **75S**, S94–S104.

Poulin C, Shiner B, Thompson P, Vepstas L, Young-Xu Y, Goertzel B, Watts B, Flashman L and McAllister T (2014) Predicting the risk of suicide by analyzing the text of clinical notes. *PLoS One* **9**, e85733.

Qian B, Wang X, Cao N, Li H and Jiang Y-G (2015) A relative similarity based method for interactive patient risk prediction. *Data Mining and Knowledge Discovery* **29**, 1070–1093.

Rabbi M, Ali S, Choudhury T and Berke E (2011) Passive and In-situ assessment of mental and physical well-being using mobile sensors. In *Proceedings of the 13th International Conference on Ubiquitous Computing UbiComp '11*. New York, NY, USA: ACM, pp. 385–394.

Rakshith V, Apoorv V, Akarsh NK, Arjun K, Krupa BN, Pratima M and Vedamurthachar A (2017) A novel approach for the identification of chronic alcohol users from ECG signals. In *TENCON 2017–2017 IEEE Region 10 Conference, IEEE Penang*. pp. 1321–1326.

Ramasubbu R, Brown MRG, Cortese F, Gaxiola I, Goodyear B, Greenshaw AJ, Dursun SM and Greiner R (2016) Accuracy of automated classification of major depressive disorder as a function of symptom severity. *NeuroImage: Clinical* **12**, 320–331.

Reece AG and Danforth CM (2017) Instagram photos reveal predictive markers of depression. *EPJ Data Science* **6**, 15.

Rentoumi V, Peters T, Conlin J and Garrard P (2017) The acute mania of King George III: a computational linguistic analysis. *PLoS One* **12**, e0171626.

Rikandi E, Pamilo S, Mäntylä T, Suvisaari J, Kieseppä T, Hari R, Seppä M and Raij TT (2017) Precuneus functioning differentiates first-episode psychosis patients during the fantasy movie Alice in Wonderland. *Psychological Medicine* **47**, 495–506.

Roberts G, Lord A, Frankland A, Wright A, Lau P, Levy F, Lenroot RK, Mitchell PB and Breakspear M (2017) Functional dysconnection of the inferior frontal gyrus in young people with bipolar disorder or at genetic high risk. *Biological Psychiatry* **81**, 718–727.

Rosellini AJ, Dussaillant F, Zubizarreta JR, Kessler RC and Rose S (2018) Predicting posttraumatic stress disorder following a natural disaster. *Journal of Psychiatric Research* **96**, 15–22.

Ross J, Neylan T, Weiner M, Chao L, Samuelson K and Sim I (2015) Towards constructing a new taxonomy for psychiatry using self-reported symptoms. *Studies in Health Technology and Informatics* **216**, 736–740.

Roysden N and Wright A (2015) Predicting health care utilization after behavioral health referral using natural language processing and machine learning. *Annual Symposium Proceedings/AMIA Symposium. AMIA Symposium* **2015**, 2063–2072.

Rozycki M, Satterthwaite TD, Koutsouleris N, Erus G, Doshi J, Wolf DH, Fan Y, Gur RE, Gur RC, Meisenzahl EM, Zhuo C, Ying H, Yan H, Yue W, Zhang D and Davatzikos C (2018) Multisite machine learning analysis provides a robust structural imaging signature of schizophrenia detectable across diverse patient populations and within individuals. *Schizophrenia Bulletin* **44**, 1035–1044.

Ryu E, Takahashi PY, Olson JE, Hathcock MA, Novotny PJ, Pathak J, Bielinski SJ, Cerhan JR and Sloan JA (2015) Quantifying the importance of disease burden on perceived general health and depressive symptoms in patients within the Mayo Clinic Biobank. *Health and Quality of Life Outcomes* **13**, 95.

Ryu E, Chamberlain AM, Pendegraft RS, Petterson TM, Bobo WV and Pathak J (2016) Quantifying the impact of chronic conditions on a diagnosis of major depressive disorder in adults: a cohort study using linked electronic medical records. *BMC Psychiatry* **16**, 114.

Saha K and de Choudhury M (2017) Modeling stress with social media around incidents of gun violence on college campuses. *Proceedings of the ACM on Human-Computer Interaction (CSCW)* **1**, 92, 1–27.

Saha B, Nguyen T, Phung D and Venkatesh S (2016) A framework for classifying online mental health-related communities with an interest in depression. *IEEE Journal of Biomedical and Health Informatics* **20**, 1008–1015.

Salafi T and Kah JCY (2015) Design of unobtrusive wearable mental stress monitoring device using physiological sensor. In Goh J and Lim C (eds), *7th WACBE World Congress on Bioengineering 2015*. IFMBE Proceedings, vol 52. Cham: Springer, pp. 11–14.

Sandulescu V, Andrews S, Ellis D, Bellotto N and Mozos OM (2015) Stress detection using wearable physiological sensors. In Ferrández Vicente J, Álvarez-Sánchez J, de la Paz López F, Toledo-Moreo F and Adeli H (eds), *Artificial Computation in Biology and Medicine. IWINAC 2015*. Lecture Notes in Computer Science, vol 9107. Cham: Springer, pp. 526–532.

Sano A, Phillips AJ, Yu AZ, McHill AW, Taylor S, Jaques N, Czeisler CA, Klerman EB and Picard RW (2015) Recognizing Academic Performance, Sleep Quality, Stress Level, and Mental Health using Personality Traits, Wearable Sensors and Mobile Phones. ieeexplore.ieee.org … *International Conference on Wearable and Implantable Body Sensor Networks. International Conference on Wearable and Implantable Body Sensor Networks* 2015.

Sato JR, Moll J, Green S, Deakin JFW, Thomaz CE and Zahn R (2015) Machine learning algorithm accurately detects fMRI signature of vulnerability to major depression. *Psychiatry Research* **233**, 289–291.

Sato JR, Salum GA, Gadelha A, Crossley N, Vieira G, Manfro GG, Zugman A, Picon FA, Pan PM, Hoexter MQ, Anés M, Moura LM, Del'Aquilla MAG, Amaro Jr E, McGuire P, Lacerda ALT, Rohde LA, Miguel EC, Jackowski AP and Bressan RA (2016) Default mode network maturation and psychopathology in children and adolescents. *Journal of Child Psychology and Psychiatry, and Allied Disciplines* **57**, 55–64.

Sato JR, Biazoli CE, Salum GA, Gadelha A, Crossley N, Vieira G, Zugman A, Picon FA, Pan PM, Hoexter MQ, Amaro E, Anés M, Moura LM, Del'Aquilla MAG, Mcguire P, Rohde LA, Miguel EC, Jackowski AP and Bressan RA (2018) Association between abnormal brain functional connectivity in children and psychopathology: a study based on graph theory and machine learning. *The World Journal of Biological Psychiatry* **19**, 119–129.

Saxe GN, Ma S, Ren J and Aliferis C (2017) Machine learning methods to predict child posttraumatic stress: a proof of concept study. *BMC Psychiatry* **17**, 223.

Sheela Kumari R, Varghese T, Kesavadas C, Albert Singh N and Mathuranath PS (2014) Longitudinal evaluation of structural changes in frontotemporal dementia using artificial neural networks. In Satapathy S, Udgata S and Biswal B (eds), *Proceedings of the International Conference on Frontiers of Intelligent Computing: Theory and Applications (*FICTA*)* 2013. Advances in Intelligent Systems and Computing, vol 247. Cham: Springer, pp. 165–172.

Shen Y-C, Kuo T-T, Yeh I-N, Chen T-T and Lin S-D (2013) Exploiting temporal information in a Two-stage classification framework for content-based depression detection. In Pei J, Tseng VS, Cao L, Motoda H and Xu G (eds), *Advances in Knowledge Discovery and Data Mining. PAKDD 2013*. Lecture Notes in Computer Science, vol 7818. Berlin, Heidelberg: Springer, pp. 276–288.

Shiner B, D'Avolio LW, Nguyen TM, Zayed MH, Young-Xu Y, Desai RA, Schnurr PP, Fiore LD and Watts BV (2013) Measuring use of evidence based psychotherapy for posttraumatic stress disorder. *Administration and Policy in Mental Health* **40**, 311–318.

Siang Fook VF, Jayachandran M, Phyo Wai AA, Tolstikov A, Biswas J and Lin Kiat PY (2009) iCOPE: intelligent context-aware patient management systems for elderly with cognitive and functional impairment. In McClean S, Millard P, El-Darzi E and Nugent C (eds), *Intelligent Patient Management*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 259–278.

Sidahmed H, Prokofyeva E and Blaschko MB (2016) Discovering predictors of mental health service utilization with k-support regularized logistic regression. *Information Sciences* **329**, 937–949.

Simms T, Ramstedt C, Rich M, Richards M, Martinez T and Giraud-Carrier C (2017) Detecting cognitive distortions through machine learning text analytics. In *2017 IEEE International Conference on Healthcare Informatics (ICHI), Park City, UT*, pp. 508–512.

Skåtun KC, Kaufmann T, Doan NT and Alnæs D (2016) Consistent functional connectivity alterations in schizophrenia spectrum disorder: a multisite study. *Schizophrenia* **43**, 914–924.

Smets E, Casale P, Großekathöfer U, Lamichhane B, De Raedt W, Bogaerts K, Van Diest I and Van Hoof C (2016) Comparison of machine learning techniques for psychophysiological stress detection. In Serino S, Matic A, Giakoumis D, Lopez G and Cipresso P (eds), *Pervasive Computing Paradigms for Mental Health. MindCare 2015*. Communications in Computer and Information Science, vol 604. Cham: Springer, pp. 13–22.

Song H, Du W and Zhao Q (2015) Automatic depression discrimination on FNIRS by using FastICA/WPD and SVM. In *Proceedings of the 2015 Chinese Intelligent Automation Conference*. Berlin, Heidelberg: Springer, pp. 257–265.

Song I, Dillon D, Goh TJ and Sung M (2011) A health social network recommender system. In *Agents in Principle, Agents in Practice*. Berlin, Heidelberg: Springer, pp. 361–372.

Souillard-Mandar W, Davis R, Rudin C, Au R, Libon DJ, Swenson R, Price CC, Lamar M and Penney DL (2016) Learning classification models of cognitive conditions from subtle behaviors in the digital clock drawing test. *Machine Learning* **102**, 393–441.

Squarcina L, Perlini C, Bellani M, Lasalvia A, Ruggeri M, Brambilla P and Castellani U (2015*a*) Learning with heterogeneous data for longitudinal studies. In Navab N, Hornegger J, Wells W and Frangi A (eds), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015*. Lecture Notes in Computer Science, vol 9351. Cham: Springer, pp. 535–542.

Squarcina L, Perlini C, Peruzzo D, Castellani U, Marinelli V, Bellani M, Rambaldelli G, Lasalvia A, Tosato S, De Santi K, Spagnolli F, Cerini R, Ruggeri M, Brambilla P and PICOS-Veneto Group (2015*b*) The use of dynamic susceptibility contrast (DSC) MRI to automatically classify patients with first episode psychosis. *Schizophrenia Research* **165**, 38–44.

Squeglia LM, Ball TM, Jacobus J, Brumback T, McKenna BS, Nguyen-Louie TT, Sorg SF, Paulus MP and Tapert SF (2017) Neural predictors of initiating alcohol use during adolescence. *The American Journal of Psychiatry* **174**, 172–185.

Stone JR, Wilde EA, Taylor BA, Tate DF, Levin H, Bigler ED, Scheibel RS, Newsome MR, Mayer AR, Abildskov T, Black GM, Lennon MJ, York GE,

Agarwal R, DeVillasante J, Ritter JL, Walker PB, Ahlers ST and Tustison NJ (2016) Supervised learning technique for the automated identification of white matter hyperintensities in traumatic brain injury. *Brain Injury* **30**, 1458–1468.

Strous RD, Koppel M, Fine J, Nachliel S, Shaked G and Zivotofsky AZ (2009) Automated characterization and identification of schizophrenia in writing. *The Journal of Nervous and Mental Disease* **197**, 585–588.

Stütz T, Kowar T, Kager M, Tiefengrabner M, Stuppner M, Blechert J, Wilhelm FH and Ginzinger S (2015) Smartphone based stress prediction. In Ricci F, Bontcheva K, Conlan O and Lawless S (eds), *User Modeling, Adaptation and Personalization. UMAP 2015*. Lecture Notes in Computer Science, vol 9146. Cham: Springer, pp. 240–251.

Sun B, Zhang Z, Liu X, Hu B and Zhu T (2017) Self-esteem recognition based on gait pattern using Kinect. *Gait & Posture* **58**, 428–432.

Sundermann B, Bode J, Lueken U, Westphal D, Gerlach AL, Straube B, Wittchen H-U, Ströhle A, Wittmann A, Konrad C, Kircher T, Arolt V and Pfleiderer B (2017) Support vector machine analysis of functional magnetic resonance imaging of interoception does not reliably predict individual outcomes of cognitive behavioral therapy in panic disorder with agoraphobia. *Frontiers in Psychiatry/Frontiers Research Foundation* **8**, 99.

Takagi Y, Sakai Y, Lisi G, Yahata N, Abe Y, Nishida S, Nakamae T, Morimoto J, Kawato M, Narumoto J and Tanaka SC (2017) A neural marker of obsessive-compulsive disorder from whole-brain functional connectivity. *Scientific Reports* **7**, 7538.

Taylor JA, Matthews N, Michie PT, Rosa MJ and Garrido MI (2017) Auditory prediction errors as individual biomarkers of schizophrenia. *NeuroImage. Clinical* **15**, 264–273.

Teague SJ and Shatte ABR (2018) Exploring the transition to fatherhood: feasibility study using social media and machine learning. *JMIR Pediatrics and Parenting* **1**, e12371.

Teague S, Youssef GJ, Macdonald JA, Sciberras E, Shatte A, Fuller-Tyszkiewicz M, Greenwood C, McIntosh J, Olsson CA, Hutchinson D and SEED Lifecourse Sciences Theme (2018) Retention strategies in longitudinal cohort studies: a systematic review and meta-analysis. *BMC Medical Research Methodology* **18**, 151.

Thin N, Hung N, Venkatesh S and Phung D (2017) Estimating support scores of autism communities in large-scale web information systems. In Bouguettaya A *et al.* (eds), *Web Information Systems Engineering – WISE 2017. WISE 2017*. Lecture Notes in Computer Science, vol 10569. Cham: Springer, pp. 347–355.

Tran T and Kavuluru R (2017) Predicting mental conditions based on 'history of present illness' in psychiatric notes with deep neural networks. *Journal of Biomedical Informatics* **75S**, S138–S148.

Tran T, Phung D, Luo W, Harvey R, Berk M and Venkatesh S (2013) An integrated framework for suicide risk prediction. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining KDD '13*. New York, NY, USA: ACM, pp. 1410–1418.

Tran T, Phung D, Luo W and Venkatesh S (2015) Stabilized sparse ordinal regression for medical risk stratification. *Knowledge & Information Systems* **43**, 555–582.

Tremblay S, Iturria-Medina Y, Mateos-Pérez JM, Evans AC and De Beaumont L (2017) Defining a multimodal signature of remote sports concussions. *The European Journal of Neuroscience* **46**, 1956–1967.

Tron T, Peled A, Grinsphoon A and Weinshall D (2016) Automated facial expressions analysis in schizophrenia: a continuous dynamic approach. In Serino S, Matic A, Giakoumis D, Lopez G and Cipresso P (eds), *Pervasive Computing Paradigms for Mental Health. MindCare 2015*. Communications in Computer and Information Science, vol 604. Cham: Springer, pp. 72–81.

Vakorin VA, Doesburg SM, da Costa L, Jetly R, Pang EW and Taylor MJ (2016) Detecting mild traumatic brain injury using resting state magnetoencephalographic connectivity. *PLoS Computational Biology* **12**, e1004914.

van Breda W, Pastor J, Hoogendoorn M, Ruwaard J, Asselbergs J and Riper H (2016) Exploring and comparing machine learning approaches for predicting mood over time. In Chen YW, Tanaka S, Howlett R and Jain L (eds), *Innovation in Medicine and Healthcare 2016. InMed 2016*. Smart Innovation, Systems and Technologies, vol 60. Cham: Springer, pp. 37–47.

Vandewater L, Brusic V, Wilson W, Macaulay L and Zhang P (2015) An adaptive genetic algorithm for selection of blood-based biomarkers for prediction of Alzheimer's disease progression. *BMC Bioinformatics* **16**(suppl. 18), S1.

Vigneron V, Kodewitz A, Tome AM, Lelandais S and Lang E (2016) Alzheimer's disease brain areas: the machine learning support for blind localization. *Current Alzheimer Research* **13**, 498–508.

Wahle F, Kowatsch T, Fleisch E and Rufer M (2016) Mobile sensing and support for people with depression: a pilot trial in the wild. *JMIR mHealth and uHealth* **4**, e111.

Wang S-H, Zhang Y, Li Y-J, Jia W-J, Liu F-Y, Yang M-M and Zhang Y-D (2018) Single slice based detection for Alzheimer's disease via wavelet entropy and multilayer perceptron trained by biogeography-based optimization. *Multimedia Tools and Applications* **77**, 10393–10417.

Wang Z, Shah AD, Tate AR, Denaxas S, Shawe-Taylor J and Hemingway H (2012) Extracting diagnoses and investigation results from unstructured text in electronic health records by semi-supervised machine learning. *PLoS One* **7**, e30412.

Wang X, Zhang C, Ji Y, Sun L, Wu L and Bao Z (2013) A depression detection model based on sentiment analysis in micro-blog social network. In Li J *et al.* (eds), *Trends and Applications in Knowledge Discovery and Data Mining. PAKDD 2013*. Lecture Notes in Computer Science, vol 7867. Berlin, Heidelberg: Springer, pp. 201–213.

Wang Y, Iyengar V, Hu J, Kho D, Falconer E, Docherty JP and Yuen GY (2017) Predicting future high-cost schizophrenia patients using high-dimensional administrative data. *Frontiers in Psychiatry/Frontiers Research Foundation* **8**, 114.

Wardenaar KJ, van Loo HM, Cai T, Fava M, Gruber MJ, Li J, de Jonge P, Nierenberg AA, Petukhova MV, Rose S, Sampson NA, Schoevers RA, Wilcox MA, Alonso J, Bromet EJ, Bunting B, Florescu SE, Fukao A, Gureje O, Hu C, Huang YQ, Karam AN, Levinson D, Medina Mora ME, Posada-Villa J, Scott KM, Taib NI, Viana MC, Xavier M, Zarkov Z and Kessler RC (2014) The effects of co-morbidity in defining major depression subtypes associated with long-term course and severity. *Psychological Medicine* **44**, 3289–3302.

Westman E, Aguilar C, Muehlboeck J-S and Simmons A (2013) Regional magnetic resonance imaging measures for multivariate analysis in Alzheimer's disease and mild cognitive impairment. *Brain Topography* **26**, 9–23.

Whelan R, Watts R, Orr CA, Althoff RR, Artiges E, Banaschewski T, Barker GJ, Bokde ALW, Büchel C, Carvalho FM, Conrod PJ, Flor H, Fauth-Bühler M, Frouin V, Gallinat J, Gan G, Gowland P, Heinz A, Ittermann B, Lawrence C, Mann K, Martinot J-L, Nees F, Ortiz N, Paillère-Martinot M-L, Paus T, Pausova Z, Rietschel M, Robbins TW, Smolka MN, Ströhle A, Schumann G, Garavan H and the IMAGEN Consortium (2014) Neuropsychosocial profiles of current and future adolescent alcohol misusers. *Nature* **512**, 185.

Winterburn JL, Voineskos AN, Devenyi GA, Plitman E, de la Fuente-Sandoval C, Bhagwat N, Graff-Guerrero A, Knight J and Chakravarty MM (2017) Can we accurately classify schizophrenia patients from healthy controls using magnetic resonance imaging and machine learning? A multi-method and multi-dataset study. *Schizophrenia Research*. ePub ahead of print.

Wolpert DH and Macready WG (1997) No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation* **1**, 67–82.

Wong HK, Tiffin PA, Chappell MJ, Nichols TE, Welsh PR, Doyle OM, Lopez-Kolkovska BC, Inglis SK, Coghill D, Shen Y and Tiño P (2017) Personalized medication response prediction for attention-deficit hyperactivity disorder: learning in the model space vs. learning in the data space. *Frontiers in Physiology* **8**, 199.

World Health Organization (2014) *Mental Health: A State of Well-Being*. Available at https://www.who.int/features/factfiles/mental_health/en/ (accessed 30 January 2019).

Wu J-L, Yu L-C and Chang P-C (2012) Detecting causality from online psychiatric texts using inter-sentential language patterns. *BMC Medical Informatics and Decision Making* **12**, 72.

Wu M-J, Mwangi B, Passos IC, Bauer IE, Cao B, Frazier TW, Zunta-Soares GB and Soares JC (2017) Prediction of vulnerability to bipolar disorder using multivariate neurocognitive patterns: a pilot study. *International Journal of Bipolar Disorders* **5**, 32.

Xiao X, Fang H, Wu J, Xiao C, Xiao T, Qian L, Liang F, Xiao Z, Chu KK and Ke X (2017) Diagnostic model generated by MRI-derived brain features in toddlers with autism spectrum disorder. *Autism Research* **10**, 620–630.

Xu R and Zhang Q (2016) Social dynamics of the online health communities for mental health. In Zheng X, Zeng D, Chen H and Leischow S (eds), *Smart Health. ICSH 2015*. Lecture Notes in Computer Science, vol 9545. Cham: Springer, pp. 267–277.

Xu X, Zhu T, Zhang R, Li L, Li A, Kang W, Fang Z, Ning Y and Wang Y (2011) Pervasive mental health self-help based on cognitive-behavior therapy and machine learning. In *6th International Conference on Pervasive Computing and Applications (ICPCA)*, pp. 212–219.

Xue Y, Li Q, Jin L, Feng L, Clifton DA and Clifford GD (2014) Detecting adolescent psychological pressures from micro-blog. In Zhang Y, Yao G, He J, Wang L, Smalheiser NR and Yin X (eds), *Health Information Science. HIS 2014*. Lecture Notes in Computer Science, vol 8423. Cham: Springer, pp. 83–94.

Yaghoobi Karimu R and Azadi S (2018) Diagnosing the ADHD using a mixture of expert fuzzy models. *International Journal of Fuzzy Systems* **20**, 1282–1296.

Yahata N, Morimoto J, Hashimoto R, Lisi G, Shibata K, Kawakubo Y, Kuwabara H, Kuroda M, Yamada T, Megumi F, Imamizu H, Náñez Sr JE, Takahashi H, Okamoto Y, Kasai K, Kato N, Sasaki Y, Watanabe T and Kawato M (2016) A small number of abnormal brain connections predicts adult autism spectrum disorder. *Nature Communications* **7**, 11254.

Yang S, Zhou P, Duan K, Hossain MS and Alhamid MF (2017) Emhealth: towards emotion health through depression prediction and intelligent health recommender system. *Mobile Networks and Applications* **23**, 216–226.

Yazdavar AH, Al-Olimat HS, Ebrahimi M, Bajaj G, Banerjee T, Thirunarayan K, Pathak J and Sheth A (2017) Semi-supervised approach to monitoring clinical depressive symptoms in social media. *Proceedings of the IEEE/ACM International Conference on Advances in Social Network Analysis and Mining* **2017**, 1191–1198.

Ye Z, Rae CL, Nombela C, Ham T, Rittman T, Jones PS, Rodríguez PV, Coyle-Gilchrist I, Regenthal R, Altena E, Housden CR, Maxwell H, Sahakian BJ, Barker RA, Robbins TW and Rowe JB (2016) Predicting beneficial effects of atomoxetine and citalopram on response inhibition in Parkinson's disease with clinical and neuroimaging measures. *Wiley Online Library Human Brain Mapping* **37**, 1026–1037.

Yong Y, Yang Y, Cui Y, Xu K, Liu B, Song M, Chen J, Wang H, Chen Y, Guo H, Li P, Lu L, Lv L, Wan P, Wang H, Yan H, Yan J, Zhang H, Zhang D and Jiang T (2017) Distributed functional connectivity impairment in schizophrenia: a multi-site study. In *2nd IET International Conference on Biomedical Image and Signal Processing (ICBISP 2017), Wuhan, China*.

Yu Y, Shen H, Zhang H, Zeng L-L, Xue Z and Hu D (2013) Functional connectivity-based signatures of schizophrenia revealed by multiclass pattern analysis of resting-state fMRI from schizophrenic patients and their healthy siblings. *Biomedical Engineering Online* **12**, 10.

Yuan J, Holtz C, Smith T and Luo J (2017) Autism spectrum disorder detection from semi-structured and unstructured medical data. *EURASIP Journal on Bioinformatics & Systems Biology* **2017**, 3.

Zhang X, Hu B, Zhou L, Moore P and Chen J (2013) An EEG based pervasive depression detection for females. In Zu Q, Hu B and Elçi A (eds), *Pervasive Computing and the Networked World. ICPCA/SWS 2012*. Lecture Notes in Computer Science, vol 7719. Berlin, Heidelberg: Springer, pp. 848–861.

Zhang J, Xiong H, Huang Y, Wu H, Leach K and Barnes LE (2015*a*) M-SEQ: early detection of anxiety and depression via temporal orders of diagnoses in electronic health data. In *2015 IEEE International Conference on Big Data (Big Data), Santa Clara, CA*, pp. 2569–2577.

Zhang L, Huang X, Liu T, Li A, Chen Z and Zhu T (2015*b*) Using linguistic features to estimate suicide probability of Chinese microblog users. In Zu Q, Hu B, Gu N and Seng S (eds), *Human Centered Computing. HCC 2014*. Lecture Notes in Computer Science, vol 8944. Cham: Springer, pp. 549–559.

Zhang OR, Zhang Y, Xu J, Roberts K, Zhang XY and Xu H (2017*a*) Interweaving domain knowledge and unsupervised learning for psychiatric stressor extraction from clinical notes. In Benferhat S, Tabia K and Ali M (eds), *Advances in Artificial Intelligence: From Theory to Practice. IEA/AIE 2017*. Lecture Notes in Computer Science, vol 10351. Cham: Springer, pp. 396–406.

Zhang Y, Zhang O, Wu Y, Lee H-J, Xu J, Xu H and Roberts K (2017*b*) Psychiatric symptom recognition without labeled data using distributional representations of phrases and on-line knowledge. *Journal of Biomedical Informatics* **75S**, S129–S137.

Zhao W, Liu L, Zheng F, Fan D, Chen X, Yang Y and Cai Q (2011) Investigation into stress of mothers with mental retardation children based on EEG (Electroencephalography) and psychology instruments. In Hu B, Liu J, Chen L and Zhong N (eds), *Brain Informatics. BI 2011*. Lecture Notes in Computer Science, vol 6889. Berlin, Heidelberg: Springer, pp. 238–249.

Zhao J, Su W, Jia J, Zhang C and Lu T (2017*a*) Research on depression detection algorithm combine acoustic rhythm with sparse face recognition. *Cluster Computing*, pp. 1–12.

Zhao S, Zhao Q, Zhang X, Peng H, Yao Z, Shen J, Yao Y, Jiang H and Hu B (2017*b*) Wearable EEG-based real-time system for depression monitoring. In Zeng Y *et al.* (eds), *Brain Informatics. BI 2017*. Lecture Notes in Computer Science, vol 10654. Cham: Springer, pp. 190–201.

Zhou D, Luo J, Silenzio V, Zhou Y, Hu J and Currier G (2015) Tackling mental health by integrating unobtrusive multimodal sensing. In *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI 2015)*. AAAI Press, pp. 1401–1408.

Zhu X (2010) Semi-Supervised learning. In Sammut C and Webb G (eds), *Encyclopedia of Machine Learning*. Boston, MA: Springer US, pp. 892–897.

Zhu X and Goldberg AB (2009) Introduction to semi-supervised learning. *Synthesis Lectures on Artificial Intelligence and Machine Learning* **3**, 1–130.

Zhu CZ, Zang YF, Liang M, Tian LX, He Y, Li XB, Sui MQ, Wang YF and Jiang TZ (2005) Discriminative analysis of brain function at resting-state for attention-deficit/hyperactivity disorder. *Medical Image Computing and Computer-Assisted Intervention* **8**, 468–475.

Zhu F, Panwar B, Dodge HH, Li H, Hampstead BM, Albin RL, Paulson HL and Guan Y (2016) COMPASS: a computational model to predict changes in MMSE scores 24-months after initial assessment of Alzheimer's disease. *Scientific Reports* **6**, 34567.

Zhu D, Riedel BC, Jahanshad N, Groenewold NA, Stein DJ, Gotlib IH, Sacchet MD, Dima D, Cole JH, Fu CHY, Walter H, Veer IM, Frodl T, Schmaal L, Veltman DJ and Thompson PM (2017) Classification of major depressive disorder via multi-site weighted LASSO model. In *Medical Image Computing and Computer-Assisted Intervention* –MICCAI 2017. Springer International Publishing, pp. 159–167.

Zou L, Zheng J, Miao C, Mckeown MJ and Wang ZJ (2017) 3D CNN based automatic diagnosis of attention deficit hyperactivity disorder using functional and structural MRI. *IEEE Access* **5**, 23626–23636.