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

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Review Article

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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

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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.*,

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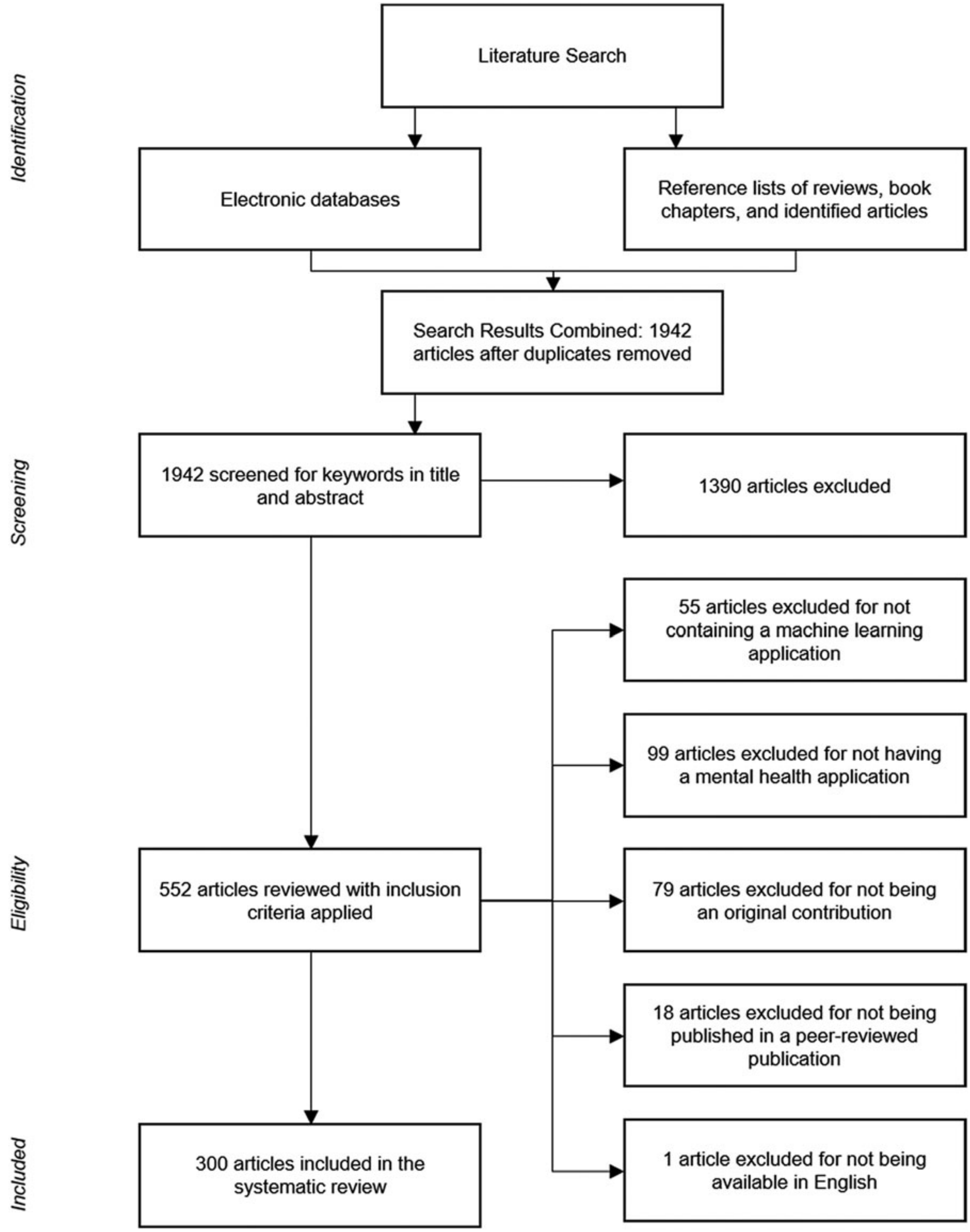

Fig. 1. PRISMA procedural flow chart.

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

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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

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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

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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.

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