Machine learning in mental health:

A systematic scoping review of methods and applications

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ABSTRACT

Objective

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.

Materials and Methods

Eight health and information technology research databases were searched using the terms “big data” or “machine learning” and “mental health”. Articles were assessed by two reviewers, and data were extracted on the article’s mental health application, ML technique, data type and size, 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.

Discussion and Conclusion

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 improve other areas of psychological functioning. 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 [1]. A robust technique that has emerged to analyse this data is machine learning (ML), which aims to construct systems that can automatically improve through experience using advanced statistical and probabilistic techniques [2]. 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 data, provide personalised experiences, and develop intelligent systems [2]. Within health fields such as bioinformatics, ML has led to significant advances by enabling speedy and scalable analysis of complex data [3]. 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 within the wider community.

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 been completed on this topic to date; yet neither review systematically assessed all published research using ML in mental health applications. First, Luo et al [3] investigated big data applications in the field of biomedical research and health care, finding many novel applications in bioinformatics, clinical informatics, imaging informatics, and public health informatics. However examples and opportunities for ML in the mental health context were only briefly discussed (specifically detecting depression using social media and predictive models for classifying psychological conditions), due to the broader aim of this study beyond mental health. A more recent review by Bone et al [4] investigated 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, as this review was not systematic in nature it did not cover the broad scope of applications that exist. Thus, we aim to broadly review the applications of ML to mental health data.

OBJECTIVE

This review aimed to provide a concise snapshot of the research to date investigating ML applications to mental health. Previous reviews have demonstrated ML techniques to be robust and scalable for mental health application, but no review has comprehensively mapped the clinical applications within mental health research and practice. Such a review would equip both data scientists and practitioners in the methods and applications of 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, the paper summarises the extant research and the implications for future work.

MATERIALS AND METHODS

Search strategy

A systematic review was performed adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [5]. Searches were conducted to identify relevant literature using the keywords “big data”, “machine learning”, and “mental health”. First, a literature search was conducted through health-related research databases, including PsycInfo, the Cochrane Library, and PubMed. Next, Information Technology databases IEEE Xplore and the ACM Digital Library were searched. Lastly, databases that index both fields including Springer, Scopus and ScienceDirect were searched for relevant literature.

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; (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 was extracted regarding: (i) the aim of research; (ii) area of mental health focus; (iii) data type; (iv) sample size; (v) ML methods used; (vi) results; (vii) the country of the author group; and, (viii) 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

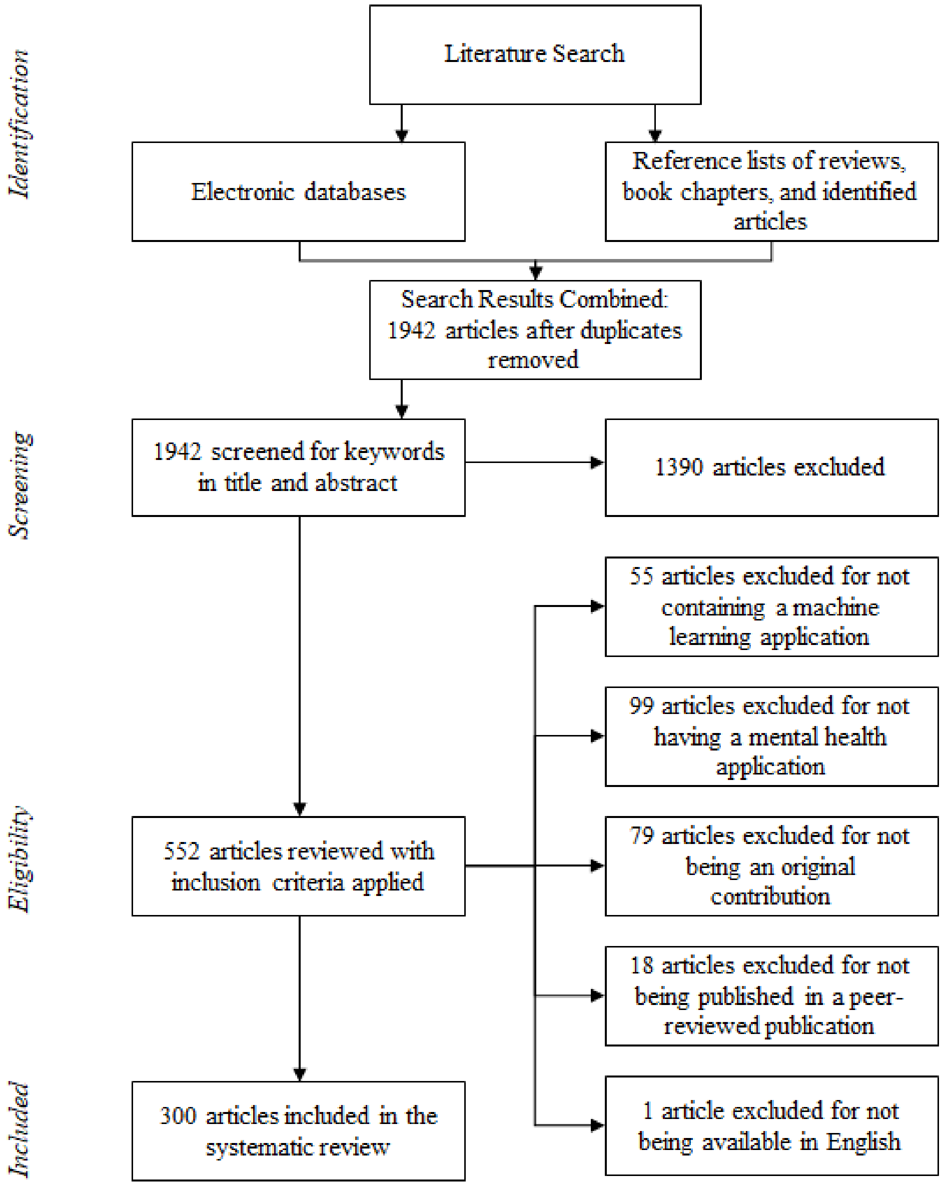
Overview of Article Characteristics

The search strategies identified 1,942 articles, with 300 of these articles meeting the criteria for inclusion in this review (see Figure 1). The mean publication year for articles was 2015 (SD=2.2), with a range of 2004 to 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., information technology, 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 neighbors (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), with a mean sample size of 28,754 (SD=174,426.91).

Figure 1

PRISMA procedural flow chart



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 1). For example, several papers focused on the use of ML with neuroimaging data to differentiate Alzheimer's disease from normal ageing [6,7], to improve early diagnosis of psychosis [8], and to predict vulnerability to depression [9]. A novel approach identified for detection of conditions is the use of unstructured text, including detection of suicide ideation from counselling transcripts [10], detection of schizophrenia from written texts [11], and analysis of social media data to detect depressive symptoms [12]. ML has also been applied to wearable sensor data to assess general wellbeing [13], and to ambient, in-home sensors to detect psychiatric emergencies [14]. Finally, speech data has been used with ML to detect underlying mental states indicative of schizophrenia and depression [15], to assess the effects of drugs on mental state [16], and to classify at-risk patients of Alzheimer's disease based on speech patterns [17].

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.[18–20]; and (ii) differentiating between mental health conditions with similar symptomatology, e.g.[21,22]. The majority of studies considered neuroimaging data (e.g., magnetic resonance imaging (MRI), electroencephalography (EEG), and positron emission tomography (PET)). For example, fMRI data has been used with ML to improve the diagnosis of schizophrenia [19]. Further, MRI data was used to diagnose patients with Alzheimer's disease and cognitive impairment, achieving reasonable accuracy [20]. In addition, 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 [21]. Research has also investigated the application of ML techniques to sensor, speech and video data to improve diagnosis of Alzheimer's disease [23], schizophrenia [24], and suicide ideation [25], achieving high accuracy. Finally, ML with wearable sensor data from actigraph monitors, has been demonstrated to differentiate between children with ADHD and bipolar disorder [22]. Overall, there has been a wide range of research published that focuses on diagnosis of MH conditions using 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. Yet diagnosis of mental health conditions are 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.

Table 1

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 [26], BN [27], Ensemble Learning [27], Genetic Algorithm [28,29], Regression [6,17,29–31], kNN [32], SVM [23,32–38], DT [32,37,38], NN [39], RF [20,37,38,40], Similarity Discriminative Dictionary Learning algorithm [41], NB [34]	Electronic Health Records [26], Imaging [6,20,27,30,31,33–36,39–42], Clinical Assessment [28,29,32,37,38], Survey [29], Audio [17,23], Biological [35,37]
Anxiety	DT [43], Multivariate classification [44], NN [45], Regression [46], SVM [46], SVM [47]	Clinical Assessment [43], Imaging [44,47], Clinical Notes [45], Video [46], Mobile/Wearable Sensors [46]
Attention Deficit Hyperactivity Disorder	Genetic algorithm [48], SVM [48,49], Linear discriminant analysis [50], NN [45,51]	Imaging [48–51], Clinical Notes [45]
Autism Spectrum Disorder	Authors developed their own classifier [52], DT [21,53–55], k-means [56], RF [57], SVM [21,53,56,58–63], kNN [63], L2LR [60], NN [53]	Imaging [21,52,53,57,58,60], Clinical Assessment [59,61,62], Biological [54,63], Electronic Health Records [55], Video/Photo [56]
Behaviour and Emotional Problems	Gaussian Processes [64], Regression [64], NN [65], DT [65], RF [65], SVM [65], JRIP [65], FURIA [65]	Imaging [64,65]
Borderline Personality Disorder	SVM [66]	Imaging [66]
Coping	NB [67]	Social Media [67], Survey [67]
Decision Support System	Genetic Algorithm [68], k-means clustering [68]	Clinical Assessment [68]

Dementia	BN [69], ensemble learning [69], Jrip [70], NB [70], RF [70], DT [70–72], NN [7,72,73], SVM [71,72,74,75], Regression [71]	Imaging [7,69,73–75], Clinical Assessment [71,72], Survey [70], Biological [75]
Depression	AdaBoost [76], Bayes [77], BN [78–80], Classification [81], Clustering [82], Deep Learning [83], DT [77,79,84–88], epistasis network centrality analysis [89], Evaporative cooling feature selection [89], FURIA [88], Gaussian Processes [86,90,91], Genetic Algorithm [18,92], GLM [93], Gradient Boosting [79,94], hierarchical clustering [95], JRIP [88], k-means clustering [85,96,97], kNN [79,93,98,99], LDA [100], Linear Discriminant Analysis [9,18,92], Multivariate classification [44], NB [99,101,102], NN [45,88,95,98,103,104], PCA [105], Regression [46,82,85,86,95,99,101,102,106–112], RF [87,88,111], Searchlight [105], Semi-supervised Topic Modeling Over Time [100], Sentiment analysis [77], SVM [15,37,46,66,75,79,87,88,90,97,99,102,107,111,113–126]	Audio [15,86,103], Biological [37,75,89,106,121], Clinical Assessment [15,37,76,80,112], Clinical Notes [45], Electronic Health Records [79,94,96], Imaging [9,18,44,66,75,81,90–93,98,105,113,114,117–126], Mobile/Wearable Sensors [46,93,97,107], Social Media [77,99–102,110,111,115,116], Survey [78,82,84,85,87,88,95,99,108,109], Video/Photo [46,83,86,104]
Epilepsy	DT [21,37], RF [37], SVM [21,127]	Imaging [21,127], Clinical Assessment [37], Biological [37]
Hyperactivity	SVM [22]	Mobile/Wearable Sensors [22]
Mania	NLP [128], NB [128], NN [128]	Letters [128]
Mild Cognitive Impairment	BN [27,69], ensemble learning [27,69], Regression [30], RF [20], Similarity Discriminative Dictionary Learning (SCDDL) algorithm [41], SVM [23]	Imaging [20,27,30,41,69], Audio [23]
Obsessive Compulsive Disorder	NN [129], kNN [129], NB [129], Searchlight Based Feature Extraction (SBFE) [130], SLR algorithm [131], L1-SCCA algorithm [131], SVM [129,132]	Imaging [129–132]
Parkinson's Disease	SVM [38], RF [38], DT [38], Regression [38]	Clinical Assessment [38]

Play Therapy	Binary valence classification [133]	Clinical Assessment [133], Audio [133]
Post-traumatic Stress Disorder	k-means clustering [96], Multivariate pattern analysis [134], SVM [134–137]	Electronic Health Records [96], Imaging [134,136,137], Survey [135]
Postnatal Depression	NB [138], Regression [138], SVM [138], NN [138]	Clinical Assessment [138], Survey [138]
Psychiatric Emergency	HMM [14], Stochastic Variational Inference [14]	Mobile/Wearable Sensors [14], Clinical Notes [14], Survey [14]
Psychosis	Bayes Rule [139], Gradient boosting [140], PCA [141], DT [141], linear discriminant analysis [141], quadratic discriminant analysis [141], RF [142], Regression [141,142], NN [142], SVM [8,141,143–145]	Clinical Assessment [140], Imaging [8,139,141–145]
Schizophrenia	AdaBoost [76], Classification (exact method not reported) [81], Gaussian Process [146], Genetic Algorithm [92], k-means clustering [147], linear discriminant analysis [19,148,149], Multivariate analysis [19], NN [150], PCA [105], Regression [11,112,151–154], RF [151–153,155], Searchlight [105,130], SVM [11,15,24,66,113,117,146,147,150,152,153,156–164]	Audio [15], Biological [151,152], Clinical Assessment [15,76,112,153], Imaging [11,19,66,81,92,105,113,117,130,146–149,151,152,154–164], Survey [150], Video/Photo [24,150]
Stress	AdaBoost [165], BN [166], Classification (exact method not reported) [167], DT [165,166,168], k-means clustering [169], kNN [170], NB [168,171,172], NN [169,173], Regression [166,173,174], RF [165,166,174], SVM [165,166,168–170,175,176]	Clinical Assessment [172,176], Imaging [171], Mobile/Wearable Sensors [165–168,172,174–176], Physiological Sensors [169,170], Social Media [173], Survey [169,172,174,176]
Substance Use	Regression [177,178], SVM [16,178,179], RF [178], DT [178], Extreme Learning Machine (ELM) [179]	Imaging [177–179], Survey [178], Audio [16]

Suicide/Self Harm	AdaBoost [180], Conditional random fields [181], DT [10,180,182,183], GLM [184], HMM [185], kNN [10,184], LDA [186], linear discriminant analysis [10], LIWC [186], NB [10], NLP [25,180], Regression [10,46,153,180,182,183,186], RF [153,187], SVM [10,25,46,153,180,182,183,187,188]	Audio [25], Clinical Assessment [153,187], Clinical Notes [10], Electronic Health Records [183,184], Letters [180,182], Mobile/Wearable Sensors [46,185], Social Media [181,186], Survey [187,188], Video [46]
Traumatic Brain Injury	DT [189], Linear Discriminant Analysis [189], RF [190,191], LogitBoost [192], Regression [192], SVM [189,191,192]	Imaging [189–192], Biological [192], Survey [192]
Wellbeing	ADABoost [193], Fast Fourier Transform (FFT) [194], Gaussian Processes [194], HMM [195], DT [195], NB [193], NN [193], RF [193,196], Regression [194,196], kNN [196], SVM [13,193,196]	Survey [13,193,194], Clinical Assessment [194], Audio [195], Mobile/Wearable Sensors [13,195,196]

NOTES: RF=Random Forest; SVM = Support Vector Machine = SVM; NB = Naive Bayes; NN = Neural Networks; LDA = Latent Dirichlet Allocation; kNN = k-Nearest Neighbors; HMM = Hidden Markov Model; BN = Bayesian Network; ARM = Association Rule Mining, Principal Component Analysis = PCA

Prognosis, Treatment and Support

Research investigating mental health prognosis focused predominantly on the use of ML to make predictions about the long term outcomes of a patient with a condition or prior to diagnosis (see Table 2). Conditions that researchers have focused on include schizophrenia [197], Alzheimer's disease [198–200], posttraumatic stress disorder [201], depression [202–205], and psychosis [206–208]. For example, ML was demonstrated to identify treatment responders and non-responders to a drug for Parkinson's disease, subsequently leading to improved treatment outcomes [209]. Further, natural language processing and text analysis techniques have been used to predict suicide ideation and psychiatric symptoms amongst recently discharged patients, finding that accurate results that could improve prognosis [210]. In addition, researchers have applied ML to social media and online community data to determine the individual and psycholinguistic features most predictive for successful alcohol abstinence [211] and smoking cessation [212].

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 [213,214]; (ii) ML to provide personalised and timely treatment or interventions [215–218]; and, (iii) analysis of online support groups for mental health communities [219–224]. 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 to detect changes in sleep behaviour indicative of depression of Alzheimer's disease [214], and with wearable sensors (i.e., heart rate, galvanic skin response and temperature) to predict stress [213]. Further, ML techniques were used with mobile sensor and survey data to provide personalised and timely intervention for depression [216], gambling addiction [217] and alcohol dependency [218] with positive results. Additional benefits have been demonstrated when using ML with data from online communities, such as matching patients to suitable support communities [219] and automatic moderation of helpful comments in suicide and autism support groups [223,224].

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 [225]. 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 pilot or proof-of-concept studies; as such, these techniques warrant further investigation by both researchers and clinicians.

Table 2

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 [200], SVM [198,200], DT [200], Genetic Algorithm [199], NN [214]	Imaging [198,200], Biological [199], Smart Meter [214]
Anxiety	BN [226], ARM [226], DT [227,228], Regression [228], RF [228], k-means clustering [229], NB [230], SVM [231]	Electronic Health Records [226], Survey [227,230], Letters [228], Social Media [229], Imaging [227,231]
Attention Deficit Hyperactivity Disorder	Regression [232]	Clinical Assessment [232]
Autism Spectrum Disorder	Bayesian classification [233], ConceptNet [219], DT [224], NLP [234], NB [224,234], RF [224], Regression [234], Sentiment analysis [221], SVM [219,224]	Social Media [219,221,224,233,234]
Cyberbullying	NB [235]	Social Media [235]
Dementia	SVM [236], BN [236], PCA [236]	Mobile/Wearable Sensors [236]
Depression	Bayesian classification [233], Clustering [237], DT [203,205,216,227,238,239], Gradient boosting [239], k-means clustering [229], LDA [240–242], LIWC [241], NB [230,243], NLP [244], NN [205,214,239], Regression [203,204,220,239–241,243,245], RF [239,243,246,247], Semi-supervised Topic Modeling Over Time (ssToT) [242], Sentiment analysis [220], SVM [202,205,216,243,246,247]	Biological [202,239], Clinical Assessment [204,243], Imaging [205,227], Mobile/Wearable Sensors [238,246], Smart Meter [214], Social Media [220,229,233,237,240–242,244,245], Survey [203,216,227,230,238,247]
Gambling	DT [217]	Survey [217]

Mental Health Service Usage	RF [248], NLP [248]	Electronic Health Records [248]
Obsessive Compulsive Disorder	SVM [249], Regression [249], RF [249]	Clinical Assessment [249]
Parkinson's Disease	SVM [209]	Imaging [209], Clinical Assessment [209]
Post-traumatic Stress Disorder	k-means clustering [229], kNN [250], NN [250], NLP [251], RF [201], Regression [201], SVM [201,250]	Audio [250], Biological [201], Clinical Notes [251], Clinical Assessment [201], Social Media [229]
Psychosis	Gaussian Processes [206], SVM [207,208]	Biological [206], Clinical Assessment [206], Survey [207,208]
Schizophrenia	Reverse Engineering and Forward Simulation (REFS) [252], SVM [197,253]	Clinical Assessment [197,252], Imaging [197,253]
Social Support	Bayesian classification [222], LDA [254]	Social Media [222,254]
Stress	NB [255], SVM [255], NB [256], SVM [256], NN [256], RF [256], Gaussian Processes [256], RF [257], SVM [213], k-means clustering [213]	Mobile/Wearable Sensors [213,257], Social Media [255,256], Survey [257]
Substance Use	Regression [211,212,258], RF [211]	Social Media [211,212,258], Mobile/Wearable Sensors [211]
Suicide/Self-Harm	NLP [210], Regression [210], SVM [223]	Survey [210], Social Media [223]
Traumatic Brain Injury	NN [259], Regression [260]	Clinical Assessment [259], Imaging [260]
Wellbeing	AdaBoost [215], BN [215], Gaussian Mixture Models [261], kNN [215], DT [215,262], RF [215,225], Regression [215,225,263], SVM [225,261]	Interview [262], Mobile/Wearable Sensors [225,261], Social Media [263], Survey [215]

NOTES: RF=Random Forest; SVM = Support Vector Machine = SVM; NB = Naive Bayes; NN = Neural Networks; LDA = Latent Dirichlet Allocation; kNN = k-Nearest Neighbors; HMM = Hidden Markov Model; BN = Bayesian Network; ARM = Association Rule Mining, PCA = Principal Component Analysis

Public Health

Public health applications included: assessing the mental health of both specific and broader populations (e.g.[264,265]); monitoring mental health following an event or disaster (e.g.[266,267]); and creating models of risk to improve health system delivery (e.g.[268,269]) (see Table 3). 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 was found to be a particularly useful epidemiological resource, with examples including assessments of the mental health status of over 60,000 college students in China [264] and prescription opioid misuse in an estimated sample of over 1.3 million Twitter users [265]. Social media data also enables researchers to assess the impact of an incident on population mental health (e.g., stress levels of college students after experiencing gun violence [270]), and to track public response to disaster situations to inform the allocation of support resources [266,267,269]. ML applied to electronic health records was demonstrated to predict suicide risk with an accuracy similar to clinician assessment [268,271], as well as predict dementia and its risk factors with high accuracy [272]. Research has also investigated the use of ML with clinical data to improve variable selection in epidemiological data analysis [273], and to better understand the relationship between complex risk factors for mental health conditions such as depression [274].

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 is 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 [265]). 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 [275].

Table 3

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

Mental Health Application	**ML Technique(s)**	**Data Type**
Anxiety	SVM [276], Linear discriminant analysis [276], RF [276]	Electronic Health Records [276]
Cognitive Distortions	DT [277], Regression [277], NB [277], NN [277], kNN [277], RELIEF [277]	Social Media [277]
Dementia	SVM [272]	Electronic Health Records [272]
Depression	DT [278], Gradient boosting [279], kNN [278], LIWC [280], LDA [280], Linear discriminant analysis [276], NB [278], NN [274], RF [276], Regression [274], SVM [276,278]	Electronic Health Records [276], Social Media [278,280], Survey [274,279]
Grief	LIWC [266], SVM [266]	Social Media [266]
Mental Health Service Usage	Regression [273]	Survey [273]
Post-traumatic Stress Disorder	Regression [281,282], DT [282], SVM [282], RF [281], Super Learner [281]	Interview [282], Survey [281]
Psychiatric Emergency	BN [269], DT [269], SVM [269]	Social Media [269]
Psychiatric Stressors	NLP [283], Named-entity recognition [283]	Clinical Notes [283]
Psychosis	Regression [284], RF [285]	Clinical Assessment [285], Electronic Health Records [284]
Social Support	LIWC [267], SVM [267]	Social Media [267]
Stress	Cluster analysis [286], Sentiment Analysis [270], SVM [270]	Clinical Assessment [286], Social Media [270]
Substance Use	PCA [265], NLP [265], RF [285]	Social Media [265], Clinical Assessment [285]

Suicide/Self-Harm	ARM [271], DT [271], Genetic Algorithm [287], NB [268,271], RF [268,271], Regression [268,271,288–290], SVM [268,271,289], TFIDF [289]	Clinical Notes [287], Clinical Assessment [288], Electronic Health Records [268,271,290], Social Media [289]
Wellbeing	Semantic analysis [264]	Social Media [264]

NOTES: RF=Random Forest; SVM = Support Vector Machine = SVM; NB = Naive Bayes; NN = Neural Networks; LDA = Latent Dirichlet Allocation; kNN = k-Nearest Neighbors; HMM = Hidden Markov Model; BN = Bayesian Network; ARM = Association Rule Mining, PCA = Principal Component Analysis

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 [291,292]); (ii) improving research methodologies (e.g., data sharing [293,294], participant selection [295], and analysis [134,296–298]); and, (iii) extracting mental health symptoms from existing sources (e.g., research publications, clinical notes and databases [299–304]) (see Table 4). The studies identified in this category demonstrate several benefits of ML for mental health administration. For example, predicting future, high-cost patients using ML can ensure that resources are allocated more efficiently to cope with the need [291]. Further, distributed ML techniques that build models using meta-analytic data have demonstrated improved predictive models while maintaining patient privacy [293,294]. Additional benefits have been demonstrated for mental health researchers, including the use of ML techniques to match research participants to studies which can save time and money in recruitment [295].

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 [305]. Finally, future research may also focus on using patient histories to improve triaging and tailored treatment plans.

Table 4

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 [134]	Imaging, Biological [134]
Attention Deficit Hyperactivity Disorder	RF, SVM, Linear Discriminant Analysis, kNN [134]	Imaging, Biological [134]
Children in Care	Regression, NB [292]	Clinical Notes [292]
Decision Support System	Deep Learning (word2vec) [299]	Research Articles [299]
Depression	DT [303], kNN [134,298], NN [295], Regression [294,296], RF [134], SVM [134], Linear Discriminant Analysis [134]	Survey [296,303,304], Social Media [298], Electronic Health Records [295], Imaging [134,294], Biological [134,296]
Healthy Ageing	RF [304]	Survey [304]
Psychosis	SVM, Multiple Kernel Learning [297]	Imaging [297]
Schizophrenia	RF [291], SVM [291,293], Linear Discriminant Analysis [291], kNN [291]	Insurance [291], Imaging [293]
Substance Use	Topic modelling [306]	Interview [306]
Symptom Severity	NN [301]	Clinical Notes [301]
Wellbeing	BN [302], SVM [302], Deep Learning (paragraph2vec) [300], NN [307]	Clinical Notes [300,302], Research Articles [300], Electronic Health Records [307]

NOTES: RF=Random Forest; SVM = Support Vector Machine = SVM; NB = Naive Bayes; NN = Neural

Networks; LDA = Latent Dirichlet Allocation; kNN = k-Nearest Neighbors; HMM = Hidden Markov Model; BN = Bayesian Network; ARM = Association Rule Mining, PCA = Principal Component Analysis

DISCUSSION

This paper aimed 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 a 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 online communities and support groups. Overall, ML demonstrates the potential to improve the efficiency of mental health clinical and research processes and to assist in generating new insights into health and wellbeing.

As an emerging field, there are understandably significant gaps for future research to address. It is evident that the majority of papers focus on diagnosis and detection, particularly on depression, suicide risk and cognitive decline. There is significant scope to explore whether ML can have similar accuracy in the detection and diagnosis of other mental health conditions, such as anxiety disorders, eating disorders, personality disorders, and neurodevelopmental disorders. Comparatively less research has explored applications in domains such as public health, treatment and support, and within 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 identified in the literature 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 similar recommendation algorithms to tailor and personalise user experiences [308], which could perhaps be applied to personalised mental health assessment and intervention [309,310]. While there were some studies identified that proposed ML to provide adaptive, just-in-time interventions (e.g., [310]), these studies are limited and have only 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 any given model. As such, ML does not replace other research or analytic approaches; rather, it has the potential to value-add to the toolkit for 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 the clinical utility of such models. While a tool may appear promising in lab settings, deploying tools into mental health 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 and the level of autonomy and privacy afforded to ML systems.

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.

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The authors declare that they have no conflict of interest.

Contributions of Authors:

AS conceived of 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 of 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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