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ARTIFICIAL INTELLIGENCE ADVANCEMENTS FOR PERSONALIZED PTSD RESEARCH

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ABSTRACT

Post-traumatic stress disorder (PTSD) research grapples with numerous challenges, including the wide variability in symptoms among individuals, the complexity of comorbidities, and the scarcity of predictive biomarkers. Integrating diverse data sources and translating research findings into clinical practice further compounds these challenges. These challenges prompted the exploration of machine learning, deep learning, and natural language processing techniques to enhance disorder classification, outcome prediction, and personalized treatment selection. A systematic review of 69 studies, drawn from a pool of 364 abstracts identified through PubMed, Embase, and Web of Science, revealed the diverse applications of machine learning, deep learning, and natural language processing in this domain. Studies predominantly utilized multiple data types to predict risk factors or early symptoms related to PTSD, while other artificial intelligence (AI) techniques aimed to differentiate symptoms of PTSD from those with other psychiatric disorders or controls. The findings highlight the suitability of artificial intelligence for addressing the heterogeneity of ASD/PTSD patients, with the future challenge lying in translating these advancements into practical clinical applications for individualized patient benefits.

Keywords: Machine learning, Deep learning, Natural language Processing, Electronic medical records, Post-traumatic stress disorder

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INTRODUCTION

Trauma-related disorders, including post-traumatic stress disorder (PTSD) and acute stress disorder (ASD), are recognized as debilitating conditions stemming from exposure to traumatic events such as war, mass violence, natural disasters, sexual assaults, and accidents [1]. The DSM-5 outlines 20 diagnostic criteria for PTSD across four symptom clusters: re-experiencing the traumatic event, avoidance, persistent negative thoughts or feelings, and trauma-related arousal and reactivity [2]. The World Mental Health Survey by the World Health Organization (WHO), conducted in 24 countries, reported a lifetime prevalence of any traumatic event at 70.4%, emphasizing the influence of constitutional and sociocultural factors in addition to the magnitude of trauma [3].

The prevalence of PTSD, with a lifetime occurrence of 11% in women and 5.5% in men, suggests a dose-response relationship between exposure to traumatic events and the subsequent development of the disorder [4]. Evidence-based, trauma-focused therapies, particularly cognitive- and exposure-based approaches like prolonged exposure and cognitive processing therapy, are considered effective [5]. Nevertheless, determining first-line psychotherapies can be intricate, considering patient burden and diverse profiles. Notably, statistically significant results from evidence-based medicine may not always translate to meaningful benefits for individual patients, especially given the clinical heterogeneity in PTSD.

Addressing these challenges, machine learning (ML), deep learning (DL) and natural language processing (NLP), which are different branches of artificial intelligence (AI), may offer a promising avenue. AI algorithms can analyze large and heterogeneous datasets, identifying patterns and associations to better understand PTSD risk, progression, and treatment response. By building predictive models, AI can predict PTSD outcomes and identify personalized treatment approaches tailored to individual patient characteristics. Furthermore, AI-driven biomarker discovery holds the potential to unveil reliable indicators for early detection and intervention. Ultimately, its capabilities in data analysis, predictive modeling, and personalized medicine can offer a pathway to overcome the challenges in PTSD research, paving the way for improved patient care and outcomes. The present study seeks to review data utilizing ML, DL and NLP techniques to assess PTSD and ASD, focusing on classification, prognostic, risk prediction and treatment selection studies.

METHODS

The methodology adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, with registration on the International Prospective Register of Systematic Reviews (PROSPERO) [6]. The search strategy covered PubMed, Embase, and Web of Science from December 2009 to October 2024, with no language restrictions.

The search, conducted, utilized a query crafted by O.M, L.W and L.K., encompassing keywords and related terms for PTSD, machine learning, deep learning, and natural language processing. Synonyms for PTSD such as PTSI, PTSS, post-traumatic, or stress disorder were explored, along with alternative terms for machine learning, like artificial intelligence, deep learning, computer-assisted, image classification, computer vision, or natural language processing. Papers with the keyword 'electronic medical records' were treated as synonymous with 'electronic health records.' We independently conducted the initial screening of the titles and abstracts for the identified articles. Subsequently, we procured and thoroughly read the full texts of the potential articles. In cases of disagreement, the final decision was made by L.W. Throughout both primary and secondary screening, all processes were overseen by L.W.

Data extraction from the articles encompassed information such as the year of study publication, the type of data utilized in the model (e.g., neuroimaging, biomarkers, social determinants of health, clinical and demographical characteristics, and big data), sample size, scales and diagnoses assessed, the machine learning/deep learning/natural language processing algorithm employed, and the statistical measure of performance (e.g., accuracy, sensitivity, specificity, F1 score, precision, recall and area under the curve [AUC]). Additionally, details regarding the use of controls in the sample, outcome assessment, the characteristics of the algorithm (e.g. description and metrics), utilization of the testing dataset, feature selection, use of hyperparameters, and handling of missing data were retrieved through a thorough quality evaluation of the studies. The interpretation of results was facilitated by the contributions of O.M., L.W. and L.K., and all authors collectively engaged in discussions to shape the final version of the manuscript.

RESULTS

In our review, we adhered to the PRISMA guidelines, meticulously analyzing a total of 364 studies as depicted in Figure 1, which illustrates the PRISMA flowchart detailing our study selection and review process. Efficient management of the study screening process was facilitated by Covidence, an online systematic review management system. Upon importing the 364 studies into Covidence, the system automatically eliminated duplicate articles across various databases, resulting in 360 unique studies. Subsequently, a thorough screening of titles and abstracts from these 360 studies was conducted, leading to the exclusion of 126 studies that fell outside the scope of our review. Following this initial screening, a full-text assessment of the remaining 234 studies was performed, resulting in the exclusion of 165 studies based on predefined inclusion and exclusion criteria outlined in Figure 1. Ultimately, our final selection comprised 69 studies, which included data extracted from a variety of sources such as brain images, clinical interviews, patient-reported

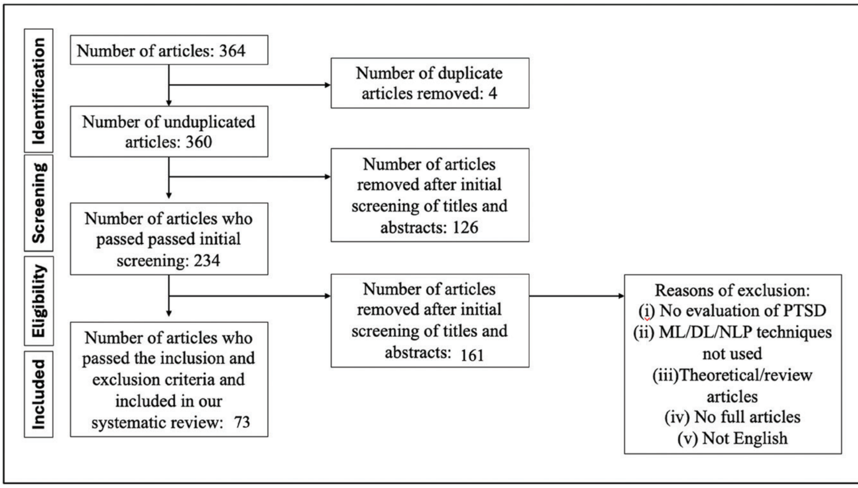

Figure 1. Flowchart of our selection process

Table 1. Aspects considered during the data collection process

Aspect	Description
Objective	The primary objective of the study
Data source	Description of data source
Sample size and distribution	Description of the patient population (including size and cases/controls)
Method	Which AI model was used
Results	Key findings
Validation	Validation procedure
Conclusion	Conclusion
Limitations and future directions	Inclusion of limitations and future directions

questionnaires, online surveys, audio recordings, facial features, social media, geospatial information, social determinants of health, clinical narratives, structured and unstructured EMRs. Across these studies, AI models were utilized to understand PTSD in diverse sample sets, including data collected from the general population, individuals who have experienced traumatic incidents, online databases, veterans, firefighters, healthcare providers and patients with other comorbidities.

*PTSD: post-traumatic stress disorder, ML: machine learning, DL: deep learning and NLP: natural language processing.

We extracted the information by following the guidelines mentioned in Table 1. If the articles had almost all of these aspects, those articles were included in our study.

We then divided the papers based on the types of data used. These strategies collectively aim to enhance understanding and contribute to more effective, personalized, and integrated treatment strategies for this complex comorbidity:

BRAIN IMAGES

We examined a total of 26 studies employing advanced neuroimaging techniques, including functional Magnetic Resonance Imaging (fMRI), Magnetoencephalography (MEG), Diffusion tensor imaging (DTI), and Electroencephalography (EEG), to automate PTSD diagnosis across diverse sample groups as seen in Table 2. Noteworthy findings emerged from various studies, shedding light on distinctive aspects of PTSD diagnosis. Nicholson et al. demonstrated the significance of heightened amygdala activation as a robust indicator of PTSD, achieving a remarkable balanced accuracy of 96.08% for PTSD patients [7]. Similarly, Harricharan et al. revealed enhanced connectivity patterns in healthy controls compared to PTSD cases, particularly in brain regions associated with environmental monitoring and emotion evaluation, showcasing an accuracy above 0.80 [8]. Zilcha-Mano et al. distinguished between PTSD and major depressive disorder (MDD) patients from healthy controls using rest-state functional connectivity biomarkers, achieving a notable accuracy of 70.6% [9]. Moreover, Saba et al. identified K-nearest neighbors (KNN) and support vector machine (SVM) with radial basis function kernel as top performers, showcasing high accuracy rates in PTSD diagnosis [10]. In studies focusing on trauma-exposed individuals, Gong et al. and Zhang et al. successfully differentiated PTSD from healthy controls using SVM classifiers, emphasizing the potential of MRI data analysis for accurate classification [11, 12]. Yang et al. achieved a diagnostic accuracy of 71.2% by employing brain function groups as predictors, highlighting the effectiveness of DL approaches in PTSD prediction [13]. Among veterans, Georgopoulos et al. and James et al. utilized MEG to differentiate PTSD from healthy controls with high accuracy, indicating the potential of brain functional connectivity as an objective marker of PTSD recovery [14, 15]. Shahzad et al. employed an artificial neural network (ANN) to identify PTSD using specific brain regions, reporting notable accuracy rates [16]. In EEG-based studies, various ML models predicted PTSD outcomes with high accuracy. Shim et al. and Kim et al. employed SVM classifiers and novel ML techniques, respectively, achieving significant accuracies [17, 18]. Terpou et al. integrated microstate-based segmentation with SVM classifiers, demonstrating promising results [19]. Li et al. and Tahmasian et al. utilized EEG signals to predict PTSD in firefighters, achieving high classification accuracy [20, 21]. Overall, SVM emerged as a preferred choice for feature classification in neuroimaging studies due to its ability to handle non-linear data effectively. While fMRI scans focus on key brain regions and fluctuations, MEG scans often outperform resting-state fMRI by studying features from various bands and synchronous neural

Table 2. Studies leveraging brain images and AI

Study	Techniques Used	Sample size	Brain regions studied	Key Findings
Nicholson et al.	fMRI	N = 181	Amygdala, dorsolateral prefrontal cortex (DLPFC), ventrolateral prefrontal cortex (VLPFC), rostral anterior cingulate cortex (rACC), insula, dorsomedial prefrontal cortex (DMPFC)	Heightened amygdala activation as a robust indicator of PTSD
Harricharan et al.	fMRI	N = 84	Periaqueductal gray (PAG), dorsolateral PAG (DL-PAG), ventrolateral PAG (VL-PAG), dorsal anterior cingulate cortex (dACC), anterior insula, temporoparietal junction (TPJ), rolandic operculum	Enhanced connectivity patterns in healthy controls compared to PTSD cases, particularly in brain regions associated with environmental monitoring and emotion evaluation
Zilcha-Mano et al.	Rest-state functional connectivity biomarkers	N = 179	Executive control network (ECN), prefrontal network, salience network and basal ganglia network	Distinguished between PTSD and major depressive disorder patients from healthy controls using rest-state functional connectivity biomarkers
Saba et al.	MEG	N = 28	Prefrontal cortex, amygdala, hippocampus, anterior cingulate cortex, insula, temporal cortex, parietal cortex, occipital cortex, striatum, and thalamus	Identified KNN and SVM with radial basis function kernel as top performers, showcasing high accuracy rates in PTSD diagnosis
Gong et al., Zhang et al.	MRI	N = 140, N = 57	Prefrontal regions, parietal regions, occipital regions, and fronto-limbic network	Successfully differentiated PTSD from healthy controls using SVM classifiers among trauma-exposed individuals.

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Study	Techniques Used	Sample size	Brain regions studied	Key Findings
Yang et al.	fMRI	N = 33	Broca's area, Wernicke's area, the primary auditory cortex, the superior temporal gyrus, the hippocampus, the prefrontal cortex, left hemisphere language regions, memory and learning regions, auditory processing regions, language-related regions, a coherent multi-path brain network, effective connectivity, and functional connectivity networks	Achieved a diagnostic accuracy of 71.2% by employing brain function groups as predictors, highlighting the effectiveness of deep learning approaches in PTSD prediction
Georgopoulos et al., James et al.	MEG	N = 18, N = 121	Prefrontal cortex, amygdala, hippocampus, anterior cingulate cortex, insula, default mode network (DMN), salience network, executive control network, sensory processing regions, limbic system, thalamus, parietal cortex, temporal cortex, orbitofrontal cortex, and hippocampal formation	Utilized MEG to differentiate PTSD from healthy controls among veterans with high accuracy, indicating the potential of brain functional connectivity as an objective marker of PTSD recovery
Shahzad et al.	MRI	N = 28	Amygdala, hippocampus, and prefrontal cortex	Employed ANN to identify PTSD using specific brain regions, reporting notable accuracy rates
Shim et al., Kim et al., Terpou et al.	EEG	N = 135, N = NA and N = 122	Centro-posterior regions, frontal cortex, parietal cortex, temporal cortex, and occipital cortex	Various ML models predicted PTSD outcomes with high accuracy in EEG-based studies, including SVM classifiers and novel ML techniques
Li et al., Tahmasian et al.	EEG	N = 1107 and N = 64	No particular brain regions mentioned	Utilized EEG signals to predict PTSD in firefighters, achieving high classification accuracy

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Study	Techniques Used	Sample size	Brain regions studied	Key Findings
Bartal et al., Salminen et al.	Cortical and subcortical imaging	N = 995 and N = 976	Right posterior cingulate, cortical thickness, surface area, subcortical brain volumes, and intracranial volume	Employed cortical and subcortical imaging to classify war veterans with early life stress exposure, achieving a modest accuracy for PTSD diagnosis
Rangaprakash et al.	fMRI, DTI	N = 87	Hyperconnected brain regions, particularly the hippocampus-striatum connectivity	Integrated fMRI and DTI data to pinpoint areas associated with PTSD, unveiling a link between hippocampal-striatal hyperconnectivity and PTSD
Liu et al.	fMRI	N = 40	Limbic structure, prefrontal cortex, regional amplitude of low-frequency fluctuations, temporal functional connectivity, and spatial functional connectivity	Analyzed fMRI findings to distinguish between vehicle accident victims with PTSD and healthy controls, achieving remarkable accuracy
Zhu et al.	Structural MRI (s-MRI), Resting state fMRI (rs-fMRI), Diffusion MRI (d-MRI), Denoising Variational Autoencoder (DVAE)	3,477 (s-MRI), 2,495 (rs-fMRI), 1,952 (d-MRI)	NA	Traditional machine learning methods and DVAE used to classify PTSD vs. controls. Lower AUCs (~60%) across modalities for multi-site data, but increased to 75% AUC when controls had no trauma history. DVAE showed better generalizability across sites than traditional ML models. Results indicate DVAE framework's potential in neuroimaging-based PTSD diagnosis due to greater generalizability across multi-site data

*fMRI: Functional Magnetic Resonance Imaging, PAG: Periaqueductal Gray, DL-PAG: Dorsolateral Periaqueductal Gray, VL-PAG: Ventrolateral Periaqueductal Gray, dACC: Dorsal Anterior Cingulate Cortex, TPJ: Temporoparietal Junction, KNN: K-Nearest Neighbors, SVM: Support Vector Machine, ECN: Executive Control Network, MEG: Magnetoencephalography, ANN: Artificial Neural Network, EEG: Electroencephalography, DTI: Diffusion Tensor Imaging, DMN: Default Mode Network interactions. EEG measures, correlating strongly with psychiatric states, are suited for simpler ML models like SVM, facilitating accurate PTSD classification. In addition, specific studies were highlighted to illustrate distinct contributions to the field. Zandvakili et al. employed electroencephalographic studies to forecast the response to transmagnetic stimulation treatment, achieving notable predictive accuracy [22]. Nicholson et al. investigated the predictive power of resting-state fMRI in associating PTSD with depressive symptoms, achieving impressive accuracy levels [23]. Yuan et al., Im et al., Jin et al., Li et al., Wang et al., and Cisler et al. each contributed valuable insights into predicting PTSD diagnosis, recovery, and associated structural changes using various neuroimaging techniques [24–29]. Machine learning models were leveraged to identify and categorize cortical regions implicated in the diagnosis of PTSD. Salminen et al. employed cortical and subcortical imaging to classify war veterans with early life stress exposure, achieving a modest accuracy of 68% for PTSD diagnosis [30]. Rangaprakash et al. integrated fMRI and DTI data to pinpoint areas associated with PTSD, unveiling a link between hippocampal-striatal hyperconnectivity and PTSD with an accuracy of 83.59% [31]. Liu et al. analyzed fMRI findings from vehicle accident victims with PTSD and healthy controls, achieving a remarkable accuracy of 92.5% (with an AUC of 0.91) in distinguishing between the groups [32]. Discriminant features were predominantly located in the limbic system and prefrontal cortex. Zhu et al. classified PTSD versus controls using large, heterogeneous neuroimaging datasets from the Enhancing NeuroImaging Genetics through Meta-Analysis (ENIGMA) Psychiatric Genomics Consortium (PGC) PTSD Working Group. They used the denoising variational autoencoder (DVAE) framework, improved classification by reducing feature dimensions and demonstrated better generalizability [33]. These studies collectively highlight the presence of diverse neuroimaging techniques and predictive models utilized in current PTSD research.

STRUCTURED CLINICAL INTERVIEWS

Six studies employed interview data to diagnose PTSD, each utilizing different AI approaches tailored to speech and textual analysis as seen in Table 3. Schultebrauck et al. developed a deep learning-fused model to discern PTSD among trauma-exposed individuals, achieving strong performance metrics, including a 0.90 AUC, 0.84 precision, 0.84 recall, and 0.83 F1 score, by analyzing visual, acoustic, and semantic features extracted from clinical interviews [34]. Banerjee et al. employed a deep belief network model (DBN) and transfer learning approach on the TIMIT Speech Corpus, demonstrating significant potential for small datasets with a 74.99% accuracy [35]. Gupta et al. explored extreme gradient boosting (XGB) on TIMIT and FEMH datasets, yielding impressive accuracies of 97.5% and 96.29%, respectively, for early PTSD diagnosis [36]. Additionally, Sawalha et al. employed a random forest

Table 3. Studies leveraging structured clinical interviews and AI

Study	AI Approach	Sample Size	Key Research Area of Interest	Commentary
Schultebrauck et al.	Deep learning-fused model	N = 81	Facial features of emotion and their intensity, movement parameters, speech prosody, and natural language content	Analyzed visual, acoustic, and semantic features from clinical interviews to discern PTSD among trauma-exposed individuals
Banerjee et al.	Deep belief network model	N = 26	Speech signal features, facial emotion recognition and intensity, movement parameters, speech prosody, and natural language content	Demonstrated potential for small dataset analysis
Gupta et al.	Extreme gradient boosting	TIMIT dataset (N = 630) and PEMH dataset (N = NA)	Speech signal features	Yielded impressive accuracies for early PTSD diagnosis
Sawalha et al.	Random forest classifier	N = 275	Emotional content both audio and visual data	Utilized random forest classifier with a Vader semantic analyzer on semantic features from the AVEC-19 corpus
Tu et al.	Large Language Models (LLMs) - GPT-4 and Llama-2	N = 411 clinician-administered diagnostic interviews	Clinical interviews	Developed a framework to automate PTSD diagnostic assessments. LLMs demonstrated strong potential in assisting clinicians with diagnostic validation, marking the first AI system to fully automate mental illness assessment based on clinical interviews
Quillivic et al.	Psychiatry, Linguistics, NLP, Machine Learning, Deep Learning	N = 148 individuals exposed to the Paris attacks	Clinical interviews	Developed a three-step methodology to diagnose PTSD based on language analysis. Achieved an AUC of 0.72 with a psychiatrist, 0.69 with machine learning, and 0.64 with deep learning. Highlights language as a potential diagnostic biomarker for PTSD.

PTSD: Post-traumatic stress disorder, Vader: Valence Aware Dictionary and Sentiment Reasoner, AVEC-19: Audio/Visual Emotion Challenge 2019, NLP: Natural Language Processing, TIMIT dataset: Texas Instruments/Massachusetts Institute of Technology (TI/MIT) dataset and PEMH: Publicly Available Electronic Mental Health dataset.

classifier with a Vader semantic analyzer on semantic features from the Audio/Visual Emotion Challenge and Workshop (AVEC-19) corpus, achieving an accuracy of 80.4% and a 0.80 AUC [37]. Ma et al. developed a clinical decision support system for early trauma by utilizing questionnaires from phone calls and clinical interviews. They identified three outcome categories (non-remitting, slow remitting, rapid remitting) with sensitivities ranging from 0.616 to 0.667 and specificities from 0.697 to 0.726 [38]. Speech features served as the primary predictors in these clinical interview models, encompassing acoustic, prosodic, and physical characteristics of speech. Transcript analysis and semantic feature extraction techniques, such as bag-of-words, were also utilized. Unlike neuroimaging features, speech and textual features are more abstract, necessitating substantial feature engineering. Consequently, deep learning techniques, preferred for their ability to handle sequential data, were employed in most studies. A 2024 study integrated a customized large language model (LLM) into the PTSD Diagnostics workflow. They collected 411 clinician-administered diagnostic interviews, creating a robust dataset to support model training. They used GPT-4 and Llama-2, they developed a novel framework to automate PTSD assessments from interview data. These results indicate that these LLMs hold significant potential to assists clinicians in diagnostic validation, representing the first fully automated AI system for mental health assessments based on clinician-led interviews. This framework not only enhances PTSD diagnostics but also opens avenues for broader clinical applications in mental healthcare [39]. Another study investigated language as a diagnostic biomarker for PTSD, analyzing a cohort of 148 individuals exposed to the Paris terrorist attacks. They implemented a three-step interdisciplinary approach combining psychiatry, linguistics, and NLP to examine how language correlates with PTSD. They compared the AUCs between a clinical psychiatrist, machine learning algorithm and a deep learning model and found they were comparable to the gold standard AUC. Overall, their findings highlight language's potential as a biomarker [40]. Researchers leveraged transfer learning to enhance classifier performance, highlighting the potential of advanced AI approaches in diagnosing PTSD from interview data.

PATIENT-REPORTED QUESTIONARIES AND CLINICAL NARRATIVES

Our review studied 21 studies focusing on self-report questionnaires, clinical notes and online surveys, emphasizing semantic features as seen in Table 4. He et al. pioneered the use of NLP and text mining to create an automated PTSD screening tool, achieving an impressive accuracy of 82% and an AUC of 0.94 [41]. Kessler et al. employed an ensemble ML model, super learner, on data from the World Health Organization's world mental health survey, achieving a notable AUC of 0.98 [42]. In the realm of research surrounding trauma-exposed individuals, Orovas et al. utilized a multi-layer perceptron (MLP) classifier on

Table 4. Studies leveraging patient reported questionnaires and clinical narratives and AI

Study	AI Approach	Sample Size	Commentary
He et al.	NLP, Text Mining	N = 300	Pioneered the use of NLP and text mining to create an automated PTSD screening tool, achieving impressive accuracy and AUC values
Kessler et al.	Ensemble ML (SuperLearner)	N = 47,466	Employed an ensemble ML model, SuperLearner, on data from the World Health Organization's world mental health survey, achieving a notable AUC value
Orovas et al.	MLP Classifier	N = 469 women	Utilized a multi-layer perceptron classifier on self-report questionnaire data, reporting high accuracy for the PTSD group
Bartal et al.	NLP Model (Transformer)	N = 1127 women	Investigated the predictive power of written childbirth narratives using an NLP model transformer, reporting respectable AUC and F1 score values
Galovski et al.	Latent Class Growth Analysis	N = 69	Employed latent class growth analysis to discern change patterns during cognitive behavioral therapy, identifying three distinct responder groups
Karstoft et al.	SVM Classifier	N = 561	Utilized a SVM classifier to identify pre- and post-deployment PTSD in Danish soldiers, achieving commendable AUC values
Portugal et al.	Regression Model	N = 437	Developed a regression model to predict depression and PTSD severity in healthcare workers, demonstrating promising performance metrics
Kim et al.	SVM Classifiers	N = NA	Predicted PTSD prevalence among firefighters using SVM classifiers, yielding robust performance metrics
Rosellini et al.	SuperLearner	N = 7,048 assessed for 1 month, N = 7,081 assessed for 3 months	Employed a SuperLearner algorithm to identify risk factors for PTSD among earthquake survivors, achieving an impressive AUC value
Reece et al.	Random Forest	N = 204 Depressed N = 174 PTSD	Utilized random forest on Twitter posts to predict PTSD and depression, achieving a notable AUC value
Leightley et al.	Random Forest	N = 13,690	Analyzed data from military personnel, achieving high accuracy in predicting PTSD using a random forest approach
Gradus et al.	Random Forest	N = 2,244	Developed a mail survey to predict suicidal ideation in war veterans, where probable PTSD diagnosis emerged as a crucial variable

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Study	AI Approach	Sample Size	Commentary
Kobach et al.	Random forest regression with conditional inference trees	N = 368	Analyzed male ex-combatants to identify predictive factors of PTSD, achieving high accuracy in predicting PTSD in war veterans
Augsburger and Elbert	Predictive modeling	N = 56	Predicted risk behaviors among refugees using predictive modeling
Conrad et al.	Random Forest	N = 441	Demonstrated the higher accuracy of random forest in predicting PTSD in survivors of civil war compared to other methods
Breen et al.	Integrative SVM	N = 60	Concentrated on sleep disturbances and biochemical markers of hyperarousal to classify individuals with PTSD from controls, achieving high accuracy
Omurca and Ekinci	Naive Bayes	N = NA	Identified features pertinent to PTSD diagnosis using Naive Bayes model, achieving high accuracy
Bartels et al.	Network Analysis	N = 475 reports from children and adolescents and N = 424 reports from caregivers	Compared children and adolescents with PTSD to their caregivers to pinpoint core symptoms of the disorder using network analysis
Fried et al.	Network Analysis	N = 2,782	Investigated correlations among PTSD symptoms in a large sample using network analysis
Miranda et al.	NLP (Transformer-based)	N = 5.67 million notes from 38,807 PTSD patients	Leveraged NLP to extract RDoC from EMRs of PTSD patients, achieving high F1 scores across all domains

*NLP: Natural Language Processing, ML: Machine Learning, AUC: Area Under the Curve, MLP: Multi-Layer Perceptron, SVM: Support Vector Machine, SuperLearner: An ensemble machine learning approach, Naive Bayes: A probabilistic classifier based on Bayes' theorem, RDoC: Research Domain Criteria self-report questionnaire data, reporting a high accuracy of 92.9% for the PTSD group [43]. Bartal et al. investigated the predictive power of written childbirth narratives, employing an NLP model transformer, and reporting respectable AUC and F1 score values [44]. Galovski et al. employed a latent class growth analysis, a machine learning method identifying clusters that evolve, to discern change patterns during cognitive behavioral therapy. Their analysis delineated three distinct groups: partial responders, consistent responders, and initial responders [45]. Among high-risk professionals, Karstoft et al. utilized an SVM classifier to identify pre- and post-deployment PTSD in Danish soldiers, achieving commendable AUC values [46]. Portugal et al. developed a regression model to predict depression and PTSD severity in healthcare workers, demonstrating promising performance metrics [47]. Similarly, Kim et al. predicted PTSD prevalence among firefighters using SVM classifiers, yielding robust accuracy, precision, recall, and F1 score values [48]. In a study involving war veterans, Mitchell et al. identified the six most central PTSD symptoms in their sample and correlated them with PTSD checklist for the Diagnostic Statistical Manual of mental disorders-5 (PCL)-5 scores. The top six symptoms exhibited a correlation coefficient of R2 = 0.404, surpassing the International Classification of Diseases (ICD)-11 criteria (R2 = 0.379) [49]. Despite the prevalence of self-reported questionnaire data, SVM classifiers were often favored over deep learning models. Demographics, personal violence experiences, mental health conditions, PTSD symptoms, and traumatic experiences were the most commonly used features. SVM proved adept at classifying these well-engineered features, highlighting its effectiveness in analyzing survey-derived data. In addition to self-report methods, our review included studies focusing on predictive factors from various traumatic experiences. Rosellini et al. employed a SuperLearner algorithm, achieving an impressive AUC of 0.79 in identifying risk factors for PTSD among earthquake survivors [50]. Reece et al. utilized random forest on Twitter posts to predict PTSD and depression, achieving an AUC of 0.89 for PTSD [51]. Leightley et al. analyzed data from military personnel, achieving a 97% accuracy in predicting PTSD using a random forest approach [52]. Similarly, Gradus et al. developed a mail survey to predict suicidal ideation in war veterans, where a probable PTSD diagnosis emerged as a crucial variable [53]. Karstoft et al. observed risk factors in soldiers from combat missions, achieving notable AUC values [54]. Kobach et al. analyzed male ex-combatants to identify predictive factors of PTSD, achieving an accuracy of 80.39% in predicting PTSD in war veterans [55]. In studies involving war and refugee victims, Augsburger and Elbert predicted risk behaviors among refugees [56], while Conrad et al. demonstrated the higher accuracy of random forest in predicting PTSD in survivors of civil war compared to other methods [57]. Breen et al. concentrated on sleep disturbances and biochemical markers of hyperarousal to classify individuals with PTSD from controls, achieving an accuracy of 80% (AUC 0.80) by combining memory, sleep, and biological markers [58]. Omurca and Ekinci endeavored to identify features pertinent to PTSD diagnosis [59]. Utilizing three different feature selection strategies, they identified seven critical features from an original dataset of 39, achieving an accuracy of 78.9% with a Naive Bayes model. In the realm of network analysis, Bartels et al. compared children and adolescents with PTSD to their caregivers to pinpoint core symptoms of the disorder. Negative trauma-related cognitions and persistent negative emotional states emerged as the most central symptoms in their study [60]. Fried et al. investigated correlations among 16 PTSD symptoms in a large sample from four different centers using network analysis. They found network correlations ranging from 0.62 to 0.74 when comparing the four centers [61]. Miranda et al leveraged NLP to extract Research Domain Criteria (RDoC) from EMRs of PTSD patients [62]. The pre-trained sentence transformer-based NLP model achieved at least an 80% F1 score across all RDoC domains. The study offered insights into RDoC functioning across different populations and disease trajectories from extensive clinical notes. Collectively offering new avenues for understanding and identifying PTSD, complementing traditional diagnostic techniques and potentially enhancing patient care and research outcomes.

AUDIO AND OTHER CLINICAL RECORDS

Several studies have explored the utilization of hospital records and clinical data for predicting PTSD as seen in Table 5 Van Der Broek et al. compared stress elicitation methods using audio recordings from female PTSD patients, with SVM and KNN achieving identical accuracies of 89.74%, followed by SVM at 82.37%, in distinguishing between the studies. Identifying suicide risk in PTSD patients is crucial for prevention efforts [63]. Harrington et al. introduced an algorithm leveraging electronic medical records to forecast the likelihood of PTSD, achieving an impressive AUC of 0.95 [64]. Similarly, Papini et al. developed a model utilizing clinical data, localization variables, and psychological questionnaires to predict PTSD following emergency room hospitalization, achieving an accuracy of 78% with an AUC of 0.85 [65]. In a proof-of-concept study by Saxe et al., 105 risk factors extracted from hospitalization data were employed to develop a prediction model for childhood PTSD [66]. The resulting model, incorporating various factors including demographics, stress levels, and neuroendocrine response, achieved an AUC of 0.79 with ten variables. Hu et al analyzed speech patterns in 76 individuals with PTSD and 60 healthy controls to identify potential diagnostic biomarkers. Using the openSmile framework for feature extraction and a random forest (RF) algorithm for feature selection, 18 acoustic features were identified. The RF model demonstrated high accuracy (0.975) and an AUC of 1.0 for binary classification. Additionally, the regression model effectively predicted PTSD severity with a significant correlation ($r = 0.33$, $p < 0.01$) between predicted and actual PCL-5 scores. Findings support speech patterns as distinguishing

Table 5. Studies leveraging audio and clinical records and AI

Study	AI Approach	Sample Size	Commentary
Van Der Broek et al.	SVM, KNN	N = 25	Compared stress elicitation methods using audio recordings from female PTSD patients, achieving accuracies of 89.74% with SVM and KNN, and 82.37% with SVM
Harrington et al.	Algorithm leveraging EMRs	N = 5700 charts	Developed an algorithm leveraging electronic medical records to forecast the likelihood of PTSD, achieving an impressive AUC of 0.95
Papini et al.	Model utilizing clinical data	N = 271	Developed a model utilizing clinical data, localization variables, and psychological questionnaires to predict PTSD following emergency room hospitalization
Saxe et al.	Algorithm leveraging EMRs	N = 163	Employed 105 risk factors extracted from hospitalization data to develop a prediction model for childhood PTSD, achieving an AUC of 0.79 with ten variables
Dabek and Caban	Neural network model	N = NA	Utilized clinical records of mild traumatic brain injury victims to develop a neural network model predicting psychological conditions, with high accuracy for PTSD
Galatzer-Levy et al.	Linear SVM model	N = 957	Focused on forecasting non-remitting PTSD using data collected within ten days of a traumatic event, achieving a strong predictive capability with a linear SVM model
Hu et al.	Acoustic Feature Extraction (openSmile), Random Forest for Feature Selection, Classification and Regression Models	N = 76 individuals with PTSD, N = 60 healthy controls	Achieved high diagnostic accuracy for PTSD with classification models, particularly the random forest model (AUC = 1.0, accuracy = 0.975). Regression model showed moderate prediction for PTSD severity based on PCL-5 scores.

*SVM: Support Vector Machine, KNN: K-Nearest Neighbors, AUC: Area Under the Curve, EMRs: Electronic Medical Records, PCL: Posttraumatic Stress Disorder Checklist for DSM-5 markers for PTSD, although further validation is needed [67]. Dabek and Caban utilized clinical records of mild traumatic brain injury victims to develop a neural network model predicting psychological conditions, reporting an overall accuracy of 82.35% and 83.82% for PTSD specifically [68]. Galatzer-Levy et al. focused on forecasting non-remitting PTSD using data collected within ten days of a traumatic event. Their linear SVM model achieved an AUC of 0.82, indicating strong predictive capability [69]. Additionally, from ASD symptoms alone, they achieved an AUC of 0.60. Furthermore, three studies explored machine learning techniques in analyzing audio recordings for PTSD prediction. Marmar et al. identified speech-based markers from clinical interviews, achieving an accuracy of 89.1% in predicting PTSD [70]. Wortwein and Scherer analyzed audio and video recordings from patient interviews, identifying key nonverbal behaviors indicative of PTSD symptoms with an F1 score of 0.748 [71]. Vergyri et al. studied audio recordings from war veterans, employing various machine learning models to achieve a prediction accuracy of 77% for PTSD [72]. Miranda et al developed DeepBiomarker, a deep-learning model, to predict suicide-related events (SREs) by analyzing lab tests, medication use, and diagnoses from EMR data of 38,807 PTSD patients [73]. DeepBiomarker achieved an AUC score of 0.930 for predicting SREs within 3 months. Through contribution analysis, they identified key lab tests associated with suicide risk, suggesting the involvement of immune, respiratory, cardiovascular, and gut microbiome regulation in promoting depression and suicidal tendencies and novel medications that could be repurposed and used to decrease the risk of developing worse adverse events including suicide, opioid use disorder, depression, alcohol, and substance use disorder. Collectively these findings may potentially guide treatment strategies.

SOCIAL DETERMINANTS OF HEALTH

We found 6 studies as seen in Table 6 leveraging social determinants of health that could be beneficial to include as a multimodal parameter to study its impact on a PTSD patient. Sullivan et al. employed network analysis to elucidate the connections and strengths among PTSD symptoms in victims of mass violence. Their findings indicated that intrusive thoughts exerted the strongest influence on other symptoms, while anger exhibited the shortest path (stronger connections) to all other symptoms [74]. Gagnon-Sanschagrin et al. identified individuals with undiagnosed PTSD using an random forest classifier based on various medical and physiological indicators, reporting a notable AUC value [75]. Gavrilescu et al. introduced a Facial Action Coding System to extract facial expression features from recordings for PTSD diagnosis, achieving an accuracy of 90.2% with an SVM classifier [76]. Dynamic topic modeling (DTM) captures changes in topic over time. A study done by Levis et al, employed DTM on EMR psychotherapy notes to distinguish patients who died by suicide from closely matched controls [77]. The cohort consists of US

Table 6. Studies leveraging social determinants of health and AI

Study	AI Approach	Sample Size	Commentary
Sullivan et al.	Network analysis	N = 4,639	Employed network analysis to elucidate connections and strengths among PTSD symptoms in victims of mass violence
Gagnon-Sanschagrin et al.	Random forest classifier	N = 44,342 (Actual positive PTSD cohort), N = 5,683 (Likely PTSD cohort) and N = 2,074,471 patients (Without PTSD cohort)	Identified individuals with undiagnosed PTSD using a random forest classifier based on various medical and physiological indicators
Gavrilescu et al.	SVM classifier	N = 128	Introduced a Facial Action Coding System to extract facial expression features from recordings for PTSD diagnosis
Levis et al.	Dynamic topic modeling	N = 5029 (Cases) and N = 20,145 (Control)	Employed dynamic topic modeling on EMR psychotherapy notes to distinguish patients who died by suicide from closely matched controls
Lekkas et al.	GPS data analysis	N = 185	Explored the use of GPS data from smartphones to detect PTSD among high-risk women, suggesting GPS data could serve as a digital biomarker for PTSD
Miranda et al.	Deep learning and NLP	N = 5,565	Developed DeepBiomarker2 to analyze EMR data including lab tests, medication, diagnoses, and multiple social determinants of health for outcome prediction

*SVM: Support Vector Machine, EMR: Electronic Medical Record, NLP: Natural Language Processing, GPS: Global Positioning System

department veteran affairs patients diagnosed with PTSD who received psychotherapy for more than 9 months after diagnosis. The results revealed that population- specific themes like PTSD, psychotherapy, medication, communication, and relationships changed over time highlighting differences in engagement, expressivity, and therapeutic alliance compared to controls. Overall, laying the groundwork for deriving population-specific, psychosocial, and time-sensitive suicide risk variables. Detecting PTSD outside traditional clinical settings is challenging due to its complex symptomology. However, advancements in mobile technology offer promising avenues for research. Lekkas et al explored the use of Global Positioning System (GPS) data from smartphones to detect PTSD among high-risk women. By analyzing daily time spent away and maximum distance traveled from home, the model accurately predicted diagnostic status with high performance (AUC = 0.816, balanced sensitivity = 0.743, balanced specificity = 0.8, balanced accuracy = 0.771). These findings suggested that GPS data could serve as a digital biomarker for PTSD [78]. Predicting high-risk events in mental health patients is crucial for tailored interventions. Miranda et al (2024) developed DeepBiomarker2, combining deep learning and natural language processing, to analyze EMR data including lab tests, medication, diagnoses, and multiple social determinants of health for outcome prediction. The results showed an AUC of 0.93 and average F1 score, precision, and recall of 0.880, 0.895, and 0.866 respectively. They found social determinants of health such as access to psychotherapy may reduce alcohol and substance use disorder risk, while active veteran status and income segregation increased risk [79–81]. Thus suggesting, AI can offer valuable insights for personalized interventions and risk reduction strategies.

DISCUSSION

AI has emerged as a pivotal tool in advancing person-centered medicine, revolutionizing the way healthcare is delivered and personalized to individual patients. One significant contribution of AI lies in its ability to analyze vast amounts of patient data, ranging from EMR to genetic information, and extract actionable insights in real-time. By leveraging algorithms, AI can identify patterns and trends within this data, allowing healthcare providers to tailor treatment plans and interventions to meet the unique needs and preferences of each patient, especially in the mental healthcare space. Additionally, AI-powered predictive analytics enable early detection of potential mental health risks and prognostic indicators, enabling proactive and preventive care strategies. Furthermore, AI-driven decision support systems assist clinicians in making evidence-based decisions, optimizing clinical workflows, and reducing diagnostic errors. AI may empower healthcare practitioners to deliver more personalized, effective, and patient-centric care through these capabilities, ultimately improving mental health outcomes and enhancing the overall healthcare experience for these individuals. This, in turn, may help in the improvement of person-centered medicine with a special emphasis on collaboration between patients and healthcare providers, prioritizing the individual's needs, preferences, values, and goals throughout the care process.

Our review examined 69 studies utilizing AI for PTSD research. SVM, KNN, DL and NLP were the most common AI models, with SVM, DL, and combined models showing superior performance. SVM remains favored for its efficacy with small to moderate-sized datasets and low computational requirements, especially when predictive features are well-known. DL models, like CNN and RNN, gained popularity with larger datasets, requiring less feature engineering. Sample sizes varied widely from 24 to 5.67 million, with neuroimaging and clinical interviews often having small samples due to cost constraints. Despite this, their precise data aids in better PTSD diagnosis. Conversely, self-report questionnaires and online methods yield larger samples but pose challenges in extracting PTSD-specific features due to heterogeneity and data imbalance.

However, EMR data offer numerous advantages, including quick and efficient accessibility for authorized healthcare professionals, comprehensive patient information consolidation, integration of data from various sources, clinical decision support features, and remote access capabilities. However, EMRs also present challenges, such as privacy and security concerns, interoperability issues, potential inaccuracies and incompleteness in data, legal and regulatory compliance requirements, and workflow disruptions during implementation or updates. Despite these challenges, EMR data play a crucial role in enhancing healthcare tab, efficiency, and patient outcomes, driving ongoing advancements in healthcare data analysis. Five factors impact ML model performance for PTSD: limited sample size, comorbidity, lack of generalizability, insufficient controls, and imbalanced data distribution. Overfitting due to small samples decreases model accuracy, while comorbidities and unaddressed biases affect precision. Generalizability suffered when sample groups were not representative, and data imbalance can under-represent minority populations. Transformer-based models, such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformers (GPT), offer a promising approach to tackling the challenges in ML model performance for PTSD research. DL transformer-based models trained on longitudinal EMRs have excelled in predicting clinical outcomes. Pretraining on large datasets enhances their performance when fine-tuned with limited data. A study done by Yang et al (2023) leveraged TransformEHR, a novel encoder-decoder model pretrained to predict future patient outcomes based on past visits. TransformEHR achieves state-of-the-art performance, improving precision-recall curves for pancreatic cancer onset by 2% ($p < 0.001$) and for intentional self-harm in PTSD patients by 24% ($p = 0.007$) [82]. Its success highlights its potential for effective clinical intervention systems, and its generalizability allows for easy adaptation to tasks with limited data. Leveraging their capabilities in NLP, these models can effectively handle limited sample sizes by fine-tuning on available data and mitigate overfitting risks. They excel in identifying and accounting for comorbidities, biases, and insufficient controls by analyzing diverse textual data sources, leading to improved precision and robustness in model predictions. Additionally, transformer-based models exhibit strong generalizability by learning patterns from large datasets representing diverse populations, while also addressing imbalanced data distribution through specialized training techniques.

Through our review of AI-driven mental healthcare, we find that several dimensions of the Person-centered Care Index (PCI) are closely aligned with our findings. Firstly, our use of AI respects ethical commitment by providing personalized treatment recommendations that honor patient dignity, autonomy, and empowerment. Additionally, through NLP and EMR data analysis, we address cultural sensitivity by considering cultural and personal preferences, thus enhancing the relevance and effectiveness of care. These models also support a holistic scope by integrating diverse healthcare data to address both health problems and positive aspects like resilience. In terms of relational focus, our predictive analytics and decision support systems foster collaboration between clinicians and patients, promoting trust and effective communication. We emphasize individualized care by leveraging AI to analyze individual patient data, offering tailored care that aligns with each patient's unique needs. AI models contribute to common ground for diagnosis and care by providing accurate insights that aid in collaborative diagnosis and care planning. Our approach enhances people-centered systems of Care by optimizing care coordination and responsiveness to community needs through comprehensive data analysis and predictive capabilities. Finally, contributing to person-centered education and research and influencing educational practices. These alignments demonstrate how AI can significantly enhance person-centered care by integrating the PCI dimensions into the development and application of advanced predictive models [83].

LIMITATIONS

AI applications for PTSD face the following challenges, including limited data availability, biased outcomes, and the need for transparency. Privacy concerns are crucial, with the need for data security and compliance with ethical guidelines. Regulatory hurdles and unresolved liability issues hinder AI adoption. ML model selection depends on a combination of data suitability and resource availability, with SVM and ensemble models recommended for neuroimaging data, DL models for complex features like speech and textual data, and transformer-based models showing promise in NLP tasks. Multi-modality AI models integrate multiple forms of data (e.g. visual, audio, and semantic data) for comprehensive analysis. Predictive features may vary across diagnostic methods, with neuroimaging revealing important brain regions like the amygdala and prefrontal cortex as predictive. Data sample size and quality are paramount in AI, with strategies like data augmentation and transfer learning mitigating limitations. Data imbalance can be addressed through resampling and ensemble methods. Model validation, with cross-validation and permutation tests, ensures the reliability of the model. However, our review's limitations, including article selection and variability in performance metrics, warrant further research. Despite advancements, barriers to clinical adoption of AI in PTSD research persist, necessitating ethical considerations and standardized regulations.

FUTURE STUDY

Utilizing different types of multimodal data for future research endeavors is crucial for advancing our understanding and management of PTSD. We can implement the following considerations while building/leveraging AI: (i) building predictive models to identify PTSD patients at risk of developing multiple comorbidities, (ii) analyzing treatment response patterns to provide insights into medication effectiveness with/without psychological interventions, (iii) leveraging NLP to accurately identify and quantify symptoms, (iv) explore temporal relationships between PTSD and other comorbidities such as poly-substance use, (v) identifying subtypes within the comorbid population to elucidate heterogeneity, (vi) integrating of multiple social determinants of health to consider patients' contexts for patient-centered care delivery, (vii) addition of geospatial analysis to study regional disparities in access to care for equitable healthcare delivery, (viii) identifying predictors of treatment dropout to enhance treatment engagement and adherence and (ix) evaluating the impact of integrated care models on mental health related outcomes. Collectively, these research endeavors may hold promise for advancing our understanding of PTSD and improving existing clinical care practices.

CONCLUSION

In summary, the varied methodologies employed across studies and the absence of raw data pose limitations on our ability to conduct a meta-analysis. Nonetheless, we have conducted a comprehensive synthesis and examination of 69 studies pertaining to understanding PTSD using AI techniques. As the demand grows for more cost-effective, dependable, and efficient methods for diagnosing PTSD, predicting risk, examining symptoms and phenotypes, AI emerges as a promising solution to address this pressing challenge, particularly for individuals encountering obstacles in accessing quality care or facing stigma associated with seeking psychotherapy and pharmacotherapy. The studies included in our review highlight the potential of AI in enhancing PTSD diagnostic approaches. To facilitate future endeavors in PTSD research, we have proposed future guidelines encompassing model selection, feature selection, data acquisition, validation methods and inclusion of multimodal data. However, despite advancements in feature engineering and model selection, the practical implementation of these systems in real-world scenarios necessitates further refinement. Significant hurdles impeding the widespread clinical adoption include ethical and privacy considerations, as well as the absence of standardized regulations for AI in the healthcare space.

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Supplementary Table 1. Information on description of methods

Method	Description
Artificial intelligence	A branch of computer science that focuses on the development of intelligent systems capable of performing tasks that typically require human intelligence, such as learning from data, making decisions, and solving problems.
Deep Learning	A subset of machine learning that involves neural networks with multiple layers, enabling the model to learn hierarchical representations of data.
Machine Learning	A branch of artificial intelligence focused on the development of algorithms that allow computers to learn from and make predictions or decisions based on data.
Natural Language Processing	A field of artificial intelligence that focuses on the interaction between computers and humans through natural language.
Magnetic Resonance Imaging (fMRI)	A medical imaging technique used to visualize brain activity by detecting changes in blood flow.
Magnetoencephalography (MEG)	A non-invasive neuroimaging technique used to measure the magnetic fields produced by electrical activity in the brain.
Diffusion Tensor Imaging (DTI)	A type of MRI technique that measures the diffusion of water molecules in brain tissue, allowing for the visualization of white matter tracts.
Electroencephalography (EEG)	A non-invasive neuroimaging technique used to record electrical activity in the brain through electrodes placed on the scalp.
K-nearest neighbors (KNN)	A simple and commonly used algorithm for classification and regression tasks that predicts the class of a data point based on the majority class of its k nearest neighbors.
Support Vector Machine (SVM)	A supervised learning algorithm used for classification and regression tasks that finds the optimal hyperplane to separate different classes in the data.
Artificial Neural Network (ANN)	A computational model inspired by the structure and function of the human brain, consisting of interconnected nodes organized into layers.
Deep Belief Network Model (DBN)	A type of deep learning model composed of multiple layers of stochastic, latent variables that can learn hierarchical representations of data.
Transfer Learning Approach	A machine learning technique where a model trained on one task is reused or adapted for a different but related task.
Extreme Gradient Boosting (XGB)	An ensemble learning technique that builds a series of decision trees sequentially, with each tree correcting the errors of the previous one.
Random Forest Classifier	An ensemble learning method that constructs multiple decision trees during training and outputs the class that is the mode of the classes of the individual trees.
Ensemble ML Model	A machine learning model that combines the predictions of multiple individual models to improve performance.
Multi-layer Perceptron (MLP)	A type of feedforward artificial neural network composed of multiple layers of nodes, including an input layer, one or more hidden layers, and an output layer.

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Method	Description
Bidirectional Encoder Representations from Transformers (BERT)	A pre-trained natural language processing model developed by Google that has achieved state-of-the-art results on various NLP tasks.
Generative Pre-trained Transformers (GPT)	A series of natural language processing models developed by OpenAI that are trained to predict the next word in a sentence, achieving impressive results in language generation tasks.
Sentence Transformer model	A natural language processing model that converts input sentences into fixed-dimensional vectors, capturing semantic information and contextual relationships within the sentence.