EAI Endorsed Transactions on Pervasive Health and Technology

Review Article **EAI.EU**

Exploring Diverse Features: A Through Survey for Anxiety Disorders

Rakhi Nagpal[1], Saravjeet Singh[1*] and Aditi Moudgil[1]

[1]Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab 140401, India

Abstract

INTRODUCTION: The prevalence of mental health issues, mainly anxiety disorders, has risen significantly in today's fast paced world. Thus, giving the imperative to confront the challenges associated in identifying these issues.
OBJECTIVE: The objective of this review paper is to signify the importance of different features or parameters (acoustic, prosodic, linguistic, facial, neuroimaging, psychological, and physiological) being extracted from different data modalities (audio, video, psychological, physiological, textual, and neuroimaging) that are being used to assess different kinds of mental disorders.
METHODS: Considering the systematic literature review technique, a total of 117 studies have been identified in the field of anxiety disorders and mental health issues spanning the years 2015 to 2024. By considering diverse features being used to diagnose different kinds of anxiety disorders, this paper provides a foundation for future research that will help researchers to design the new strategies and techniques to handle the anxiety disorder.
CONCLUSION: This comprehensive review paper outlines the details of diverse features extracted across various data modalities, contributing significantly to the prediction of a wide range of anxiety disorders.

Keywords: Anxiety Disorder, Mental illness, Acoustic features, Disorder Identification

Received on 20 March 2024, accepted on 23 May 2025, published on 06 June 2025

doi: 10.4108/eetpht.11.5475

*Corresponding author. Email: saravjeet.2009@gmail.com

1. Introduction

The incidents of mental health disorders are becoming widespread, presenting a considerable medical challenge that society faces nowadays. Several psychological issues like anxiety, stress, depression, and exhaustion are becoming prevalent. Mental illness is a term used to describe a wide range of conditions that affect a person's mood, thinking, behaviour, and overall well-being. Mental illness can be caused by a variety of factors, including genetics, environmental factors, and life experiences. Economically as well, the mental health disorders are highly significant as compared to other non-communicable diseases like heart diseases, asthma, cancer [1].
There are different types of mental disorders that can be found in almost one out of every three individuals worldwide [2]. Depression and anxiety are two common mental health disorders [3]. These disorders can affect a person's mood, behaviour, and overall well-being. While they are distinct conditions, they often occur together and share some common symptoms, such as feelings of sadness or worry, changes in sleep or appetite, and difficulty concentrating [4]. One of the studies has emphasized on the significance of natural language processing (NLP) in differentiating the emotions in depression and anxiety [5]. The coexistence between different anxiety disorders or between depressive disorders and anxiety, complicates the treatment process due to their high comorbidity [6]. Depression is characterized by persistent feelings of sadness, hopelessness, and a loss of interest in activities that used to be enjoyable. It can also cause physical symptoms, such as changes in sleep patterns, appetite, and energy levels. Anxiety, on the other hand, is a result of extreme tension and fear and is characterized by persistent feelings of worry, fear, or panic [7]. According to World Health Organization (WHO), "anxiety disorder is a result of extreme tension and fear" which further results into

abdominal pain, chest pain, headaches, increased blood pressure and increased heart rate as well. It can cause physical symptoms such as rapid heartbeat, sweating, and shaking, and can interfere with daily activities such as work or socializing. It can also start at early stage of life [8]. Depression and anxiety can both interfere with a person's sense of competence and ability to succeed academically as well. People with depression may struggle to focus or concentrate and lose interest in their academic pursuits as well. People with anxiety may struggle with test-taking or public speaking, experience excessive worry or perfectionism, and have difficulty managing their time or organizing their work. During pandemic context, few studies have explored the mediating role of maternal anxiety and sheds light on how it influences infant neurodevelopment, thus emphasizing the necessity of timely evaluations in monitoring early childhood development [9–11].

1.1 Types of Anxiety Disorders

Anxiety disorders have been categorised into different types (shown in figure 1) namely Generalized Anxiety Disorder (GAD), Social Anxiety Disorder (SAD), Post-Traumatic Stress Disorder (PTSD), and Panic Disorder (PD) [12].

Generalized Anxiety Disorder

Anxiety refers to the term “extreme nervousness” which in turns causes health problems in an individual. The common disorder that occurred due to this cause is Generalized Anxiety Disorder (GAD). Worry is one of the main reasons for mental illnesses, but has proved to be a major cause for Generalized Anxiety disorder [13]. An individual having generalized anxiety disorder feels stressful throughout his routine which may even lead to suicidal or negative thoughts. It is very difficult to predict GAD at an early stage. The main symptom of GAD is inconsistent tension and anxiety about daily life issues, which is uncontrollable [14]. Individuals having GAD can also have increased heart rate, rapid breathing, and lack of concentration in their daily life routine tasks [15].

Social Anxiety Disorder

An extreme dread of negative judgement as well as an inconsistent awkwardness in public areas are the traits of Social Anxiety Disorder [16]. Moreover, avoiding social gatherings or being unwilling to attend work or school are significant indicators of social anxiety disorder [17]. It is very normal for everyone to feel awkward while presenting them in public or to feel shy, so SAD cannot be predicted based on this factor only. According to research, the main cause of social phobia for young teenager is positively related to some kind of bullying (direct or indirect) and public [18]. An individual suffering from SAD avoids doing interaction with other people and going to public areas which in turns greatly impact one’s personal and social life [19]. Moreover, this can lead to substantial impairments in overall functioning of one’s life [20]. One of the studies concluded that the individuals having SAD usually takes more time in redirecting their gaze from the eye region as compared to healthy controls [21].

Post-Traumatic Stress Disorder

At any point in one’s life, any shocking or terrible event can trigger post-traumatic stress disorder. This disorder is one of the dangerous mental illnesses that one can face in their life, because, everybody in their life may experience such incidents. Moreover, the Coronavirus disease (COVID-19) pandemic has also proved to be a terrifying incident for most of the people. The major diagnostic criteria for post-traumatic stress disorder during the time of covid pandemic was extreme injuries and threatening deaths of people who were suffering from COVID-19. The major reason for this disorder in people who were suffering from COVID-19, was their disturbed state of mind, as they have survived from such a big traumatic incident of their life [22]. Moreover, the study has also stated that the care takers also went through the major stress while taking care of COVID-19 patients. In order to calculate the presence of PTSD, the researchers estimated the value of pooled prevalence. The level of PTSD was categorised into two parts, one was mild level and the other was moderate level. The cut off for both the levels was decided by the authors, according to clinical relevancy. The study stated, about 21.5% prevalence estimate for PTSD among COVID-19 health-care takers [23]. The symptoms of this mental illness may include recalling the incident, anxiety, annoying or disturbing behaviour just after the occurrence of incident etc.

Panic Disorder

PD: Panic disorder stands out as one of the prevalent anxiety disorders, marked by recurring and unforeseen episodes of panic attacks [24]. A person having panic disorder faces rapid increase in heart rate because of abrupt and uncontrollable feeling of worry or fear. The main causes of PD include genetic factors, excessing fear, addiction to drugs which may results into rapid growth of heart rate, twitching (sudden movements which are uncontrollable), shortness of breath (suffocation). Developmental and neurobiological factors unique to panic disorder differentiate it from other anxiety disorders [25]. One of the studies emphasized the significance of physiological features also while examining the abnormal changes among individuals suffering from PD [26].
Unlike PTSD, panic disorder does not trigger apparently, rather this disorder is unexpected and sudden. Moreover, during the time of COVID-19, the patients had breathing/respiratory problems which in turns cause asthma in few patients. One of the studied also stated that because of panic disorder, patients may have the problem of asthma as they suffer from respiratory issues [27]. But according to few studies the asthma and mental illness has no direct correlation between them, rather the patients having panic disorder and asthma both are facing more discomfort and pain than other patients who are suffering only from PD. Moreover, the level of PD is much more affected due to worse bodily indications rather than worse condition of asthma [28].

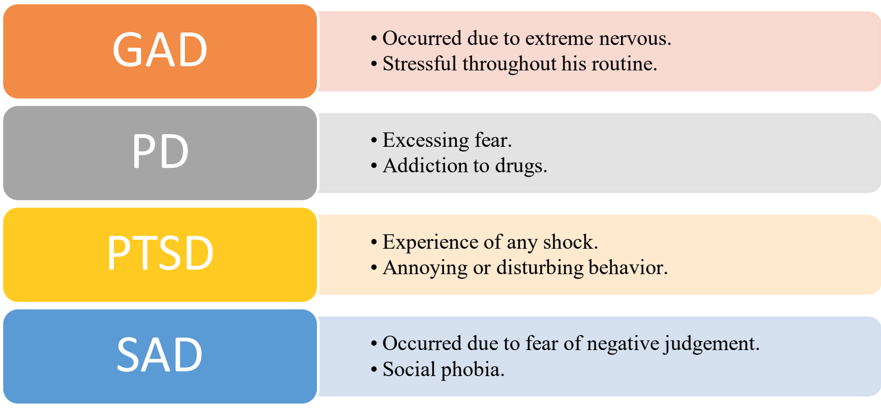

Figure 1. Types of Anxiety Disorders

A prevalent viewpoint in the media implies that there is a growing number of individuals experiencing anxiety disorders each year. Yet, obtaining reliable evidence to support a shift in the prevalence rates of anxiety disorders proves challenging [29]. Thus, the increasing significance of comprehending and resolving mental health issues in current society serves as the driving force for this review article. There is a need to evaluate and synthesise the current body of knowledge in this area by having better understanding of pertinent characteristics or parameters affecting anxiety disorders.

1.2 Objective of current study

The main purpose of this paper is to analyze different sets of features being used to assess anxiety disorders. The further categorization of features (acoustic, linguistic, facial, prosodic, psychological, neuro-imaging, and physiological) extracted from different data modalities (text, audio, and video) sheds light on relevance of these features with mental state of an individual. This study seeks to provide a thorough resource for researchers by analysing and aggregating the present state of research on diverse features used in investigating mental health concerns. The results of this evaluation will help researchers to have better knowledge of efficient approaches and equipment for mental health research, ultimately facilitating the creation of more precise diagnosis and therapeutic techniques.

2. Research Trends in the field of Mental Disorders

In today's world, mental disorders are very common among human beings. Due to the severity of these disorders, research has been carried out in this field by different researchers. In the initial phase of the research, many theoretical frameworks and studies were proposed to use technology for the detection and prevention of these disorders. However, with the advancement of technology, different studies based on machine learning, deep learning, and automation have been proposed to detect and prevent mental disorders. One of the research evaluated a theoretical framework for Generalized Anxiety Disorder (GAD), emphasizing its clinical implications. They collected data from 24 GAD patients and 20 non-clinical subjects, identifying key factors like cognitive avoidance, worry, intolerance, and deficient problem-solving. Intolerance of uncertainty played a vital role in distinguishing GAD patients with 82% accuracy.

Nowadays, depression is a common mental health issue affecting well-being. Depression's impact on mental and physical health led researchers to propose a multimodal depression scale prediction system combining audio and visual data. Using a Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) for dynamic temporal information, they leveraged emotion data and multi-task learning. On the AVEC2014 dataset, the system's dimensional emotion recognition, especially with multi-task learning, improved depression scale prediction. These studies advance our understanding of mental health assessment and treatment, offering insights into GAD and depression evaluation techniques. Studies have shown that one of the reasons for anxiety disorders could be aging as well. It has been shown that aging is directly proportionate to anxiety disorder [30].

The rising incidence of mental illness has increased the demand for healthcare services. [31] analysed textual features extracted from Reddit posts to classify them into 11 mental disorder themes. They employed several classifiers namely Convolutional Neural Network (CNN), Linear Regression (LR), Feed Forward (FF), and Support Vector Machine (SVM). CNN excelled, achieving 91.08% accuracy in distinguishing mental health-related posts from others. On the other hand, the use of social media is also contributing towards social anxiety. One of the studies explored such impact of social media on individuals by revealing the fact that the negative comparison with influencers results into increase in their anxiety level [32].

These issues have also increased the rate of suicides worldwide. Keeping in mind the need to predict the risk of suicidal behaviours in advance, [33] used demographic and clinical information by collecting electronic health record data from 1998 to 2012. They used a Naïve Bayes classifier to assess the risk of suicidal deaths for both men and women separately. The study identified high-risk patients based on positive risk scores and found that 1.2% of patients had a high risk of suicidal behaviors. Importantly, the study highlighted the significance of clinical features in predicting suicidal deaths 3-5 years in advance with 90% specificity.

Anxiety disorders are very prominent mental health issues and totally depend upon the daily prevailing conditions and environment. [34] in their research studied how sociodemographic and clinical features vary in OCD patients having GAD and OCD patients without suffering from GAD. Moreover, stress and anxiety are commonly related to each other and affects physiological state of diverse age groups. Several studies have shown the impact of parental stress on children's physiological state and at the same time the academic stress is influencing mental health in medical students and social workers as well. Studies have proved that in order to improve one's mental state, the timely management of stress is very important [35–37]. One of the studies focuses on visual features in order to detect anxiety and stress level in individuals. The authors have mainly worked on mouth and eye activities, head movements, and heart activities. Results have shown that the facial cues play a prominent role in detecting one's stress and anxiety level [38]. The authors [39] used video data to detect stress in individuals. They trained the CNN model on a dataset of video clips, recorded from 122 participants watching relaxed and stressful content. The study aimed to assess stress levels by tracking facial expressions and actions, forming the Two-level Stress Detection Network (TSDNet). Results showed that combining both facial expressions and actions achieved the best performance (accuracy 85.42%, F1 score 85.28%, recall 85.53%, precision 85.32%) compared to considering either factor alone. [40] have used neuro-imaging features (electroencephalography (EEG)) and physiological features (Effective Connectivity) to investigate neural connectivity biomarkers for SAD. They assessed different SAD severity levels with CNN, LSTM, and a CNN-LSTM combination. Their dataset included 88 respondents categorized into Healthy Controls (HC), mild, moderate, and severe SAD. Results indicated that the CNN-LSTM hybrid approach achieved the highest accuracy, specificity, and sensitivity among the deep learning models. One of other studies emphasized the use of physiological measures while monitoring stress and anxiety level [41]. This study revealed that the 62.5% of the studies focused on such objective measures and 48% of those studies used decision tree analysis method to detect anxiety and stress level. Another study developed an ECG-based classification framework for anxiety detection by collecting electrocardiography (ECG) data of 19 participants using wearable sensing device [42].

In recent years, mood disorders have become a significant and widespread psychiatric concern around the world. Any individual having this disorder may suffer from wither unipolar depression or bipolar disorder. To identify this, [43] in their study aims to experiment with triggering emotional responses in the subjects by exposing them to six different emotional video clips having emotions of surprise, sadness, happiness, disgust, anger, and fear. This experiment was based on the data of 39 individuals and eNTERFACE dataset. SVM and LSTM classifiers to detect the mood disorders, and from result is has been observed that LSTM classifier provide an accuracy of 76.92% for mood disorder detection. The author [44] developed a model to detect mood disorders using both audio and video data through a fusion approach. They employed a hierarchical clustering algorithm, SVM, and cell-coupled LSTM with L-skip fusion to combine facial and audio features, obtain emotion profiles, and capture time-based information for 1170 responses collected from 39 individuals. The authors used LSTM, SVM, and DAE, with HSC-DAE for feature extraction. Their proposed model, the cell-coupled LSTM with fusion, outperformed unimodal methods with a 41% increase in MS and 69.2% in EP. LSTM achieved high accuracy (97.42%) when HSC-DAE was used, compared to when it wasn't. [45] have addressed the prevalent and crucial medical condition of addressed Major Depressive Disorder (MDD) by proposing an approach to detect and predict depression severity using acoustic voice features, primarily MFCC. They utilized three datasets, including DAIC-WOZ (189 audio recordings categorized by depression), implemented transfer learning from RAVDESS (1440 audio samples expressing different emotions), and assessed their model's performance with the Avi-D dataset, achieving 76.27% accuracy with an RMSE of 0.4. Despite suicide being a significant global concern, there are substantial challenges in comprehending, predicting, and preventing suicidal behavior. [46] introduced a robust audio dataset and baseline models to predict anxiety and depression severity. They collected 2674 audio samples from US and Canadian residents via Amazon Mechanical Turk (mTurk), having participants describe pictures while providing demographic information. Spectral, voicing, linguistic, generic, and acoustic features were extracted from the audio. The authors trained Random Forest, Support Vector Regressor, and Linear Regression models separately on demographic, acoustic, and linguistic features. Mean Absolute Error and Root Mean Square Error were used as performance metrics. Support Vector Regressor (SVR) performed best with demographic features, while positive fluency excelled with task-specific linguistic features.

The traditional way of screening for detecting depression and anxiety may not be effective enough in managing and treating the mental health problems. Recent strides in natural language processing and speech analysis facilitate enhanced detection by fusing textual, acoustic, and hand-crafted features. [47] introduced a multi-model system to detect mental health issues utilizing the DEPAC dataset, merging manually created and deep-learned auditory traits. Results demonstrated F1 scores of 0.54 and 0.58 for anxiety and depression with manual traits. Integrating deep-learned and manual traits raised F1 scores to 0.57 for anxiety and 0.63 for depression. Digital markers hold potential for upcoming depression and anxiety screening.

The studies have shown the importance of diverse features in assessing different kinds of mental health issues. However, the increasing prevalence of anxiety disorders have influenced the researchers to study more about these features in order to evaluate the association between mental illnesses and these features. The following table 1 summarizes the studied literature.

3. Methodological Approach

This review paper seeks to explore the features utilized by researchers in the prediction of anxiety disorders. By consolidating the existing body of literature, we aim to classify and assess a vast range of features utilized in diverse domains, encompassing acoustic, linguistic, physiological, facial, psychological, and neuroimaging features. The related work presented in this review elaborates the research studied which have used different kinds of features in context of mental health issues over a period of 2015 to 2024, describes the methodology opted for the review, provides the review based on the answer corresponding to designed research questions and the major findings of this review followed by an insight of future direction and conclusion.

3.1. Framing the research questions

What are different kinds of features being used by researchers to assess different kinds of anxiety disorders.

3.2. Data Sources

Several data sources have been used in order to extract the research papers for this study. In order to assess the diverse range of academic publications, the IEEE Digital Library (https://www.ieee.org/), ACM Digital Library (https://dl.acm.org), ProQuest (https://www.proquest.com/), and PubMed (https://pubmed.ncbi.nlm.nih.gov/) were explored. Additionally, ResearchGate (https://www.researchgate.net/) and Google Scholar (https://scholar.google.com/) were also utilized as valuable resources to conduct a thorough literature survey. By incorporating these resources, the current study guarantees the thorough investigation of conference papers, journal articles, proceedings and other academic resources that align with current research topic.

3.3. Keywords

According to designed inclusion and exclusion criteria, research studies from 2007 to 2024 are considered in this review. Several keywords have been used in order to retrieve a good number of research studies that focus on prediction of mental health issues at an early stage. In order to perform a good database search, query strings were designed using the keywords associated with this current literature and AND/OR operators. Query string being used to enhance the search quality are as follows: Anxiety disorder, Anxiety and speech, Anxiety AND video data, Anxiety AND physiological, Anxiety AND speech, Anxiety AND EEG, Mental Health issues OR Anxiety AND acoustic features, Anxiety disorder AND linguistic features, Social Anxiety, Generalized Anxiety Disorder, Panic Disorder, Anxiety OR Social Anxiety OR Generalized anxiety disorder OR Panic disorder AND prosodic features, Anxiety OR Social Anxiety OR Generalized anxiety disorder OR Panic disorder AND acoustic features, Anxiety Disorder AND brain connectivity, panic disorder AND deep learning. Anxiety AND disorder AND deep AND learning, anxiety AND deep AND learning AND speech, anxiety AND deep AND learning AND audio, anxiety AND deep AND learning AND facial, mental AND issues AND deep AND learning, anxiety OR mental AND disorder AND machine AND learning.

Table 1. Summary of studied literature

Year	References	Problem	Features	Results
2015	[48]	Social Anxiety Disorder	Neuro-imaging features	In order to predict treatment response in SAD patients, brain connectomics outperformed clinical measures with 81% accuracy.
2016	[43]	Mood disorder	Speech features	Accuracy: SVM-0.4983, MLP-0.4197, LSTM-0.7692
2017	[31]	Mental Health Issues	Text-Based features	Classified posts into 11 different disorder themes including non-mental health as well.
2017	[33]	Suicidal behaviour	Clinical features	1.2% of the patients were found to be having high risk of suicidal behaviour with 90 to 95% of specificity.
2017	[38]	Anxiety	Visual features	Results have shown that the facial cues like head movement, eye and mouth activities are highly associated with anxiety.
2018	[49]	Social Anxiety and Depression	Speech features	NN2Vec features extracted from audio words outperformed the baselines with f1-score of 90.1% and 85.44% for detection of social anxiety and depression respectively.
2019	[44]	Mood disorder	Acoustic features	Highest accuracy of 97.42 % achieved by using LSTM

2020	[39]	Stress	Facial expression and action movements	For TSDNet: accuracy 85.42% and F1-Score 85.28
2021	[40]	Social Anxiety Disorder	Neuro-imaging features	CNN+LSTM Outperform other models
2021	[34]	GAD	clinical and sociodemographic features.	Comorbid GAD associated with heightened clinical severity, featuring increased avoidant behaviours and diagnostic markers in OCD.
2022	[46]	Anxiety and Depression	Hand-curated acoustic and linguistic features	Designed a rich audio dataset and baseline models for detection of depression severity.
2022	[45]	Depression	MFCC voice feature	Proposed MFCC-based RNN outperforms other with an accuracy of 76.27% and RMSE value of 0.4
2022	[47]	Anxiety and Depression	Acoustic, hand-crafted, and textual features.	Combination of deep learned + hand crafted gives high F1 score for depression and anxiety as compared to only hand crafted.
2023	[50]	Anxiety Disorders	Neuro-imaging features	Despite the sample size and methods limitations, the use of neuro-imaging (functional magnetic resonance imaging (fMRI)) features achieved up to 90% of the accuracy for the detection of anxiety disorders.
2023	[51]	Depression and Anxiety Disorders	Text-Based features	Multi-class models (LSTM, GRU) and hybrid models (CNN-Bi-GRU, CNN+LSTM) are more efficient in detecting depression and anxiety disorders as compared to binary-class models.
2024	[52]	Depression, Anxiety, and Stress	Acoustic features	1D CNN model is more reliable for predicting the severity level of several mental disorders like depression, anxiety, and stress,
2024	[53]	Anxious depression	Neuro-imaging features	Random Forest classifier distinguish anxious subjects with an accuracy of 80.2% and stated that anxious subjects have more dysregulated brain regions as compared to non-anxious subjects.

3.4. Inclusion Exclusion Criteria

This comprehensive review has followed systematic literature review (SLR) process and adheres to the guidelines recommended by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). To conduct this comprehensive review, a total of 117 studies which assesses the different kinds of anxiety disorders using acoustic, linguistic, facial, psychological, neuroimaging, and physiological features were considered. This study includes all the relevant documents like dissertations, conference papers, book sections, journal articles and review reports. The studies which didn't include any mental health disorder, didn't use any of the feature to assess anxiety disorders, not written in English language, not completely accessible were excluded from this evaluation. The total of 1231 studies (2015 to 2024) from different sources mainly Scopus, WoS, PubMed, and other databases were collected to conduct this comprehensive review analysis. The detailed overview of the selection process for this review has been shown in figure 2. Figure 3 shows the number of papers reviewed during the year 2015 to 2024 with 2024 having the most papers.

4. Data Modalities

For mental health assessment, the utilization of diverse data modalities has become a potential indicator for gaining a comprehensive understanding of anxiety disorders. Researchers have used different kinds of data modalities such as textual data, video data, audio data, physiological data, psychological data, and neuro-imaging data to assess the different aspects of mental well-being of individuals. Textual data, extracted from sources like online communities, and social media, provides insights into individuals' linguistic patterns, while video data captures non-verbal cues and expressions. Audio data, encompassing speech features such as prosodic, linguistic, and acoustic offers valuable auditory information. Physiological data, including heart rate variability (HRV), skin conductance, biological signals, and electrodermal activity, provides a physiological perspective. Psychological data delves into self-reported measures and behavioral indicators, adding a subjective layer to the assessment. Finally, neuro-imaging data allows researchers to explore the functioning of brain activity using different neuroimaging techniques such as MRI, fMRI, and PET. This comprehensive approach enriches the scope of mental health research, offering an insightful understanding of different kinds of mental disorders. The following table 2 synthesizes studies employing these diverse data modalities for comprehensive examination of mental health issues.

The different data modalities play an important role in developing the models for the prediction of different mental health issues as well. Using these data modalities, researchers extract different categories of features as shown in figure 4 in order to assess the mental disorders. One of the studies signifies the relevance of different data streams like smartphone sensor data, social media data, neuroimaging data, and EHR data in developing the models for the psychiatric issues prediction [54]

5. Features and Parameters

Anxiety disorders are a common type of mental illness that affect millions of people worldwide. To allow early intervention, individualised therapy, and improved patient outcomes, it is essential to precisely anticipate and detect these illnesses. Researchers have recently begun looking at several approaches to predict anxiety disorders, using a range of features collected from multiple modalities. These characteristics provide insightful data on the acoustic, linguistic, environmental, cognitive, behavioural, and physiological components of anxiety. This section will provide the detail of diverse features or parameters that can be used to identify the anxiety and related mental disorders.

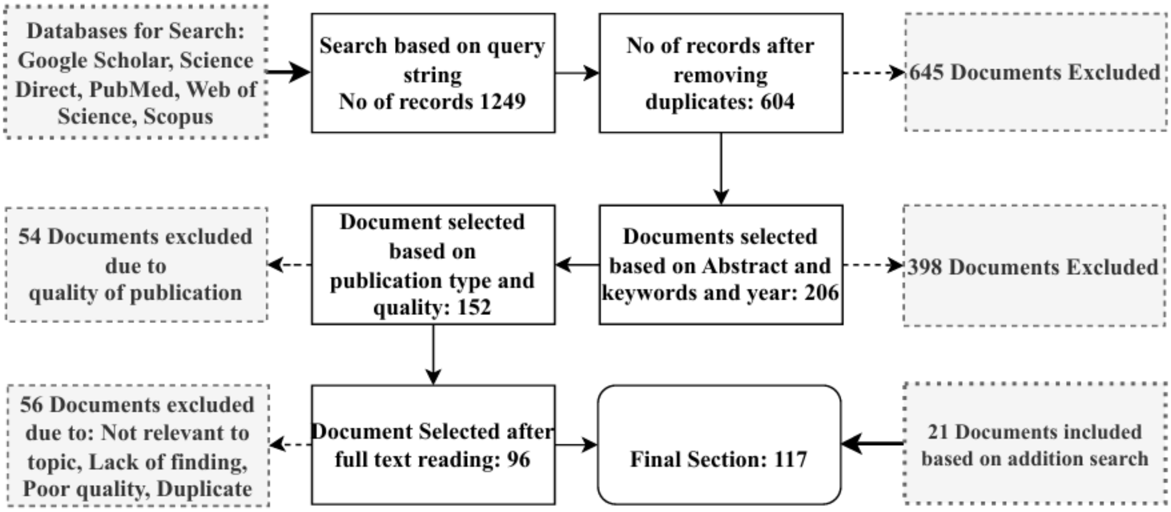

Figure 2. Research paper selection process for the proposed review study using SLR.

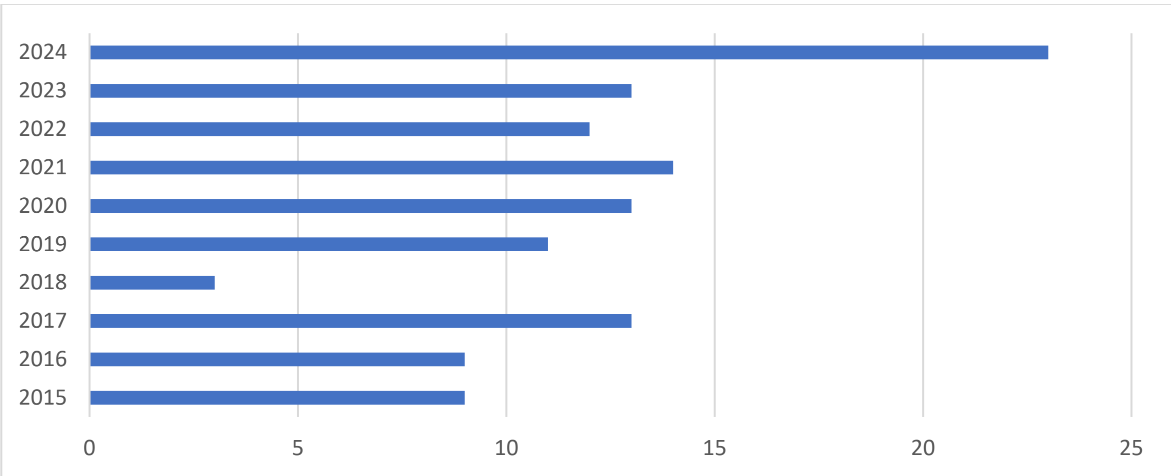

Figure 3. Number of reviewed articles by year with 2024 having the most papers

Table 2: Studies using different kinds of features from different data modalities

Data Modality	Reference	Disorder type	Objective of Study
Physiological	[55]	Anxiety	Automatically identifying anxiety in college students using deep features extracted from EEG data and finally performed

Data			classification of features using Takagi-Sugeno-Kang (TSK) fuzzy system
	[56]	SAD	The study aims at enhancing the EEG classification performance for better disorder classification.
	[57]	GAD, SAD, and depression	This study aims to assess the feasibility of automated screening for GAD, SAD, and depression using physiological data collected from an android app.
	[58]	ASD	The objective of this study is to develop a dynamic anxiety detection model using EEG signals.
	[59]	Anxiety	This study aims at improving the anxiety detection accuracy by comparing conventional approaches with ensemble learning strategies.
Audio Data	[49]	SAD and Depression	This study aims at differentiating depressed speakers from healthy control using acoustic features extracted from long audio clips.
	[60]	Speech Anxiety (Social Phobia)	To utilize VR for speech anxiety detection using acoustic features of an individual.
	[61]	SAD	This study examines the correlation between social anxiety symptoms, emotion recognition, and changes in heart rate using prosodic features (tone and pitch) as well as HRV.
	[62]	Anxiety disorder, depression, and bipolar disorder	To predict disorders like anxiety, bipolar and depression using acoustic features (MFCC) by performing voice analysis on audio data.
	[63]	Anxiety and Depression	To develop an effective audio-based model for anxiety and depression detection.
Video Data	[64]	Depression and Anxiety	The study aims at enhancing the automatic prediction of anxiety and depression using the facial features (head pose, eye gaze. And facial action units).
	[65]	Depression and Anxiety	This study developed a computational methodology to precisely identify depression and anxiety through dynamic facial expressions descriptors.
	[66]	State anxiety	To visualize the impact of state anxiety in SAD patients vs healthy controls by analyzing their gaze behaviour.
Neuro-Imaging Data	[48]	SAD	To investigate whether the brain connectomics surpass the clinical measures in predicting treatments response for SAD.
	[67]	PD	To investigate how comorbid depression influences neural substrates during fear conditioning and evaluate machine learning's capacity to predict comorbidity status based on neural characteristics in panic disorder with Agoraphobia.
	[68]	GAD	This study aims at examining the relationship between amygdala functional connectivity, emotion regulation, and the evolution of GAD symptomatology over the span of a year.
	[69]	Anxiety-related disorders	This study aims to explore how inflammatory stimuli in anxiety-related disorders affect brain, focussing neuroimaging.
	[70]	GAD	To predict GAD using neuro-imaging biomarkers along with machine learning techniques.
	[71]	GAD and Depressing Disorder (DD)	To classify GAD, DD, and healthy controls by analyzing their brain mechanisms using EEG signals.
Text-based Data	[72]	Anxiety	To explore anxiety disorders using social media (reddit posts)
	[73]	Depression and PTSD	To identify depression and PTSD in individuals by collecting data from social media (twitter posts).
	[74]	Depression and Anxiety	This study used Twitter posts in order to identify depression and anxiety and introduces a dataset for binary tweet classification.
	[75]	Anxiety, depression, bipolar	To categorize the individuals in different groups having different mental disorders using the textual based data collected from their Reddit posts.

	[51]	Depression and Anxiety	To develop a multimodal approach to identify mental disorders like anxiety and depression using twitter data.
	[76]	Generalized Anxiety Disorder	To detect Multi-Aspect GAD using textual data from social media.

The primary objective of this section is to play a constructive role in enhancing the diagnosis of different kinds of anxiety disorders by consolidating the present understanding on features-based prediction. Several features used by different researchers in order to diagnose the mental health issues are acoustic features, linguistic features, facial features, prosodic features, psychological features, physiological features, and neuro-imaging features.

5.1. Acoustic Features

These features play an important role in the diagnosis process of anxiety disorders as these features can be measured and analysed efficiently. Acoustic features are usually extracted from the sound comprises of pitch, voice quality, speech rate, prosody, and pause duration. [77] in their study illustrated the use of acoustic features for the diagnosis of social anxiety disorder. Having a verbal communication with control and SAD patients, acoustic features were examined which results into longer communication duration with SAD patients (avg. duration of 1913 seconds for 6 questions) as compared to control participants with avg. duration of 1012 seconds as they took more pauses and inter pausal units. Acoustic features have been widely used along with other data modalities by several other studies for SAD [78,79]. Moreover, the association of voice acoustic measures of speech with mild symptoms of depression and anxiety has also been done by [80]

5.2. Linguistic Features

Leveraging linguistic indicators from natural speech offers promising solutions, enabling the creation of a digital phenotype for different kinds of mental health assessment [81–83]. Linguistic indicators encompass diverse attributes related to the language used by any individual which mainly includes word count, linguistic inquiry, speech pattern, sentence formation etc. Social media posts have proven to be a potential source for collecting text-based data for the assessment of different kinds of mental disorders. Researchers have already worked in order to evaluate the association between data collected from different social media posts and mental disorders like depression and anxiety [84]. [85] in their study made use of twitter posts in order to diagnose the individuals with different levels of anxiety.

One of the studies examined both the acoustic and linguistic features and predicts the presence of GAD using logistic regression and random model [86]. In order to capture the linguistic features, the authors have used the linguistic inquiry and word count (LIWC) as a primary attribute in their study. With the use LIWC, the authors narrowed down to 80 pertinent features excluding certain punctuation and informal language. [87] contribute to research in linguistic analysis by examining the linguistic features in online reddit posts. The main objective of his study was to facilitate the online intervention and provide insights into patients' mental health condition.

5.3. Facial Features

An essential component for understanding the emotions of individuals in order to diagnose the mental health issue can be efficiently done with the use of one's facial expressions. Facial features are proved to be a potential indicator of mental health and emotional state of any individual. One of the studies had analyzed facial expressions of the individuals having SAD in comorbid with schizophrenia (SZ) and healthy controls [88].

5.4. Prosodic Features

Prosodic features subcategory of acoustic features are the aspect of speech only, but these features are more related to expressive and emotional quality of speech like variation in pitch, tone, rhythm, loudness, etc[89] in their study made use of prosodic features along with facial expressions in order to analyze how SAD patients can understand the emotions. Further studies have tracked the advancements of speech therapy in SAD patients by incorporating audio and video data modalities thus providing a framework for feature extraction [90]. This study has extracted several prosodic features (rhythm, timing, and intonation) form the individual's speech for the interpretation of results. Moreover, the importance of prosody along with other acoustic features like MFCC, and Zero Crossing Rate (ZCR) has also proved to be an effective measure for anxiety screening [91].

5.5. Psychological Features

In the assessment of mental health issues like anxiety, depression, and mood disorders, psychological features are also of great significance because they can provide subjective measures that gives valuable insights into an individual's mental state.

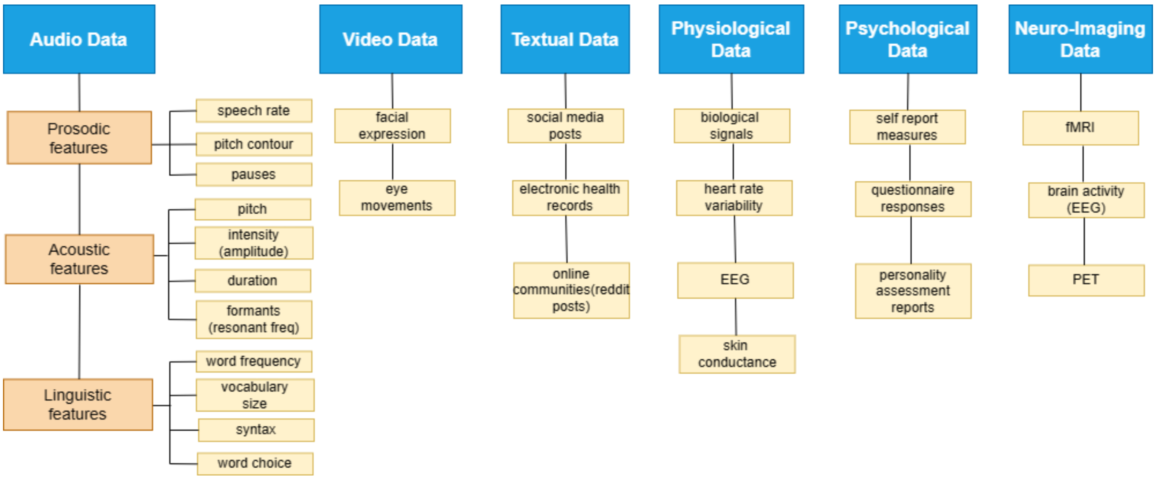

Figure 4. Overview of different data modalities used for assessment of mental disorders.

One of the studies used the smartphone data along with the Generalized Anxiety Disorder-7 (GAD-7) self-assessment report collected from 229 participants over a period of 14 days in order to assess and differentiate the GAD patients from HC [92]. The authors in their study collected psychological data along with machine learning techniques (gradient boost and regression modelling) and stated that gradient boost outperforms the regression modelling with an accuracy of 76%.

5.6. Neuro-imaging Features

Significant advancements in neuroimaging data have been achieved in pinpointing the neural foundation of anxiety disorders [93]. Thus, the use of neuro-imaging features (primarily related to brain activity) for the evaluation of anxiety disorders represents an advanced approach that provides valuable information about the neural processes behind anxiety, thereby improving the diagnosis and treatment procedures. Several neural biomarkers used by different researchers have been commonly discovered through neuroimaging methods like fMRI and EEG. Several studies have been done which have used the neural wearable sensors as well in order to assess the anxiety symptoms in individuals. [94] in their studies predicted the treatment responses of SAD patients with the use of different categories of data (genetic, demographic, clinical, and neuro-imaging). The results have shown that prediction outcomes obtained from the neural activities outperforms other variables.
[95] in their studies made use of different electronical biomarkers like EEG, brain connectivity, and ERP (neuro-imaging features) for the prediction of social anxiety disorder. This study also stated that a combination of these predictors along with MRI and fMRI can give better results. One of another studies [96] aims to explore unique brain network connectivity patterns in individuals with GAD and healthy controls, with the potential to function as diagnostic indicators. Analysing resting-state functional MRI data from 20 GAD patients and matched controls, scientists identified nine consistent connectivity patterns that exhibited significant distinctions between the two groups. The study also assessed effective connectivity among these brain regions, revealing reduced connectivity in individuals with GAD. The application of these neural connectivity metrics to a classification model achieved an accuracy of 87.5%, underscoring their potential as robust biomarkers for GAD. Signifies the importance of fMRI features along with machine learning technologies in distinguishing the anxiety disorder patients form healthy controls [50].
[92] introduced a novel approach in order recognize anxiety and depression by integrating deep learning with neuroimaging technique on the basis of EEG data.

5.7. Physiological Features

The physiological features like skin conductance, HRV, respiratory rate plays a crucial role in analyzing the mental state of any individual. Several studies revealed that the physiological features play a vital role in providing objective measures for one's psychiatric state and stated that skin conductance is one of most important objective measures for detecting one's anxiety level [97,98]. The researchers in their study [99] used skin conductance response in order to gauge the psychological arousal linked to recollection of extinction and fear conditioning in patients of anxiety disorders.
Several studies have used these features in order to track, predict, and assess the symptoms of different kinds of anxiety disorders. [100] in their study measured how HRV fluctuates in individuals having anxiety disorders and one's without anxiety disorders by collecting data through wristband sensors. One of the studies made use of smartphone sensors in order to predict the change in anxiety symptoms in future [101]. Using smartphone application, the data of 32 participants like their location, social interaction, light exposure, and physiological information has been gathered. The results have shown that the smartphone sensors along with customized deep learning techniques has accounted for

74.8% of the total variation in anxiety symptoms which is considered as a high degree of predictability.
Another study aimed at forecasting the long-term progression of anxiety symptoms in patients having GAD and PD by using actigraphy data (behavioral/physiological signals) to record daily movements and sleeping pattern at day and night respectively extracted from wearable sensors [102]. [103] in their study created an automated recognition system for three-level anxiety identification using physiological data (vasoconstriction, HRV) and virtual environments. [104] in their research emphasized the significance of physiological data like sleep data and activity tracking in screening anxiety and depression. Moreover, respiratory signals are also being used by researchers in order to develop anxiety detection systems [105].

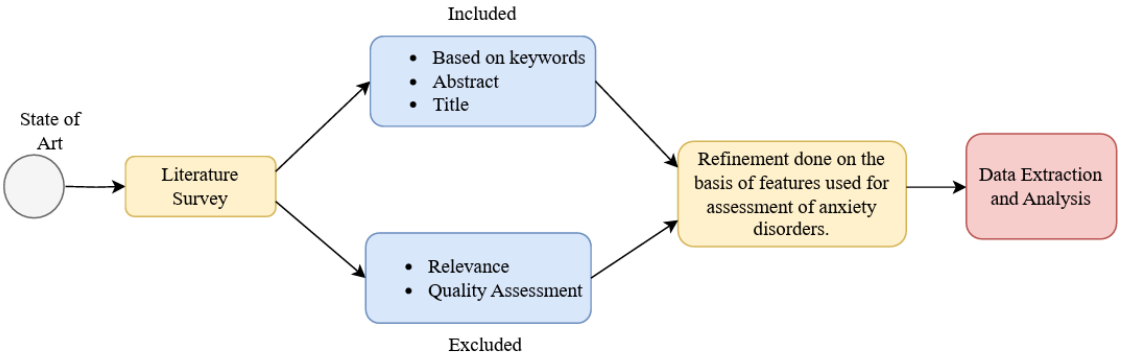

Figure 5. Flow chart of data collection of studies using diverse range of features for different disorders.

In context of assessing the mental state of any individual, these features play a vital role and are proved to be a potential indicator. Moreover, the integration of these features can enhance automated detection of mental disorders like depression and anxiety disorders in individuals [106]. One of the studies aims to enhance comprehension of the multimodal expression of social stress in adolescents with ASD compared to neurotypically developing (TD) peers by fusing the different categories of features mainly speech (acoustic-prosodic) and physiological (heart rate) [107]. [108] in their study, extracted informative characteristics of self-rated mental health issues (depression, anxiety and other psychiatric disorders) through the analysis of multimodal features (vocal, facial, and linguistic) extracted from remote interviews.

The outlined flow chart as shown in figure 5 illustrates the step-by-step procedure for systematically collecting the data related to the use of these features for different kinds of anxiety disorders. A comprehensive analysis has been done by doing the detailed literature survey followed by inclusion and exclusion criteria. In order to enhance the data quality, additional refinement has been done in which only those studies were included which made use of specific kinds of features (acoustic, linguistic, facial, prosodic, psychological, neuro-imaging, and physiological features). Several researchers have widely used these features in their studies in order to predict and assess different kinds of mental health issues.

Table 3 Studies using different kinds of features for assessing and predicting the anxiety disorders

Study	Features						
	Acoustic	**Linguistic**	**Facial**	**Prosodic**	**Psychological**	**Neuro-imaging**	**Physiological**
[109]	✓	×	×	×	×	×	×
[77]	✓	×	×	×	×	×	×
[110]	×	×	✓	×	×	×	×
[111]	×	×	×	×	×	✓	×
[89]	×	×	✓	✓	×	×	×
[112]	×	×	×	×	✓	×	×
[113]	×	×	×	×	×	×	✓
[114]	×	×	✓	×	×	×	×
[115]	×	×	×	✓	×	×	×
[116]	×	×	×	×	×	×	✓
[117]	✓	×	×	×	×	×	×
[88]	×	×	✓	×	×	×	×
[95]	×	×	×	×	×	✓	✓
[118]	✓	×	×	×	×	×	✓

[61]	×	×	×	✓	×	×	✓
[119]	✓	✓	×	✓	×	×	×
[86]	✓	✓	×	×	×	×	×
[120]	✓	×	×	×	×	×	×
[121]	×	×	×	×	✓	×	×
[101]	×	×	×	×	×	×	✓
[122]	✓	×	×	×	×	×	×
[123]	×	×	×	×	×	✓	×
[124]	×	×	×	×	×	×	✓
[125]	✓	×	✓	×	×	×	✓

As shown in table 3, the researchers have used different kinds of features like linguistic, facial, prosodic, psychological, and acoustic extracted from text, audios, and videos of the participants in order to assess and predict the severity of different kinds of anxiety disorders. This study shows that the features from different modalities have the potential to successfully diagnose the mental health issues. In this comprehensive review, the use of different data modalities over five distinct time period ranges 2015-2016, 2017-2018, 2019-2020, 2021-2022, and 2023-2024 have also been analysed as shown in figure 6.

From the given figure, we can clearly analyse the patterns that indicate a significant rise in research efforts involving different data modalities throughout the years. In context of speech data, there is a noticeable increase in the studies moving from 4 during 2015-2016 to 21 within the 2023-2024 timespan which signifies a growing preference for using speech data modality for anxiety prediction [126,127] The use of physiological features in different studies has also demonstrated significant relevance in the context of anxiety prediction evidenced by a noticeable upswing, with the number of studies increasing from 8 to 25 in the given timespan [95,128–131]. Moreover, across the years, there has been an increasing emphasis on incorporating text, video, psychological, and neuroimaging modalities in anxiety prediction research as well [38].

6. Discussion and Implications

As per the literature studied for detection of anxiety disorders, the researchers have used different kinds of data modalities from which the multiple set of features have been extracted like acoustic, linguistic, facial, prosodic, psychological, neuro-imaging, and physiological features. This review aims to summarize the use of different features sets across the years span of 2015-2024 trying to find the maximum used feature set in the field of anxiety disorder detection. The below given figure 7 answers the research question which clearly demonstrates the use of diverse features used by different studies across time period 2015 to 2024.

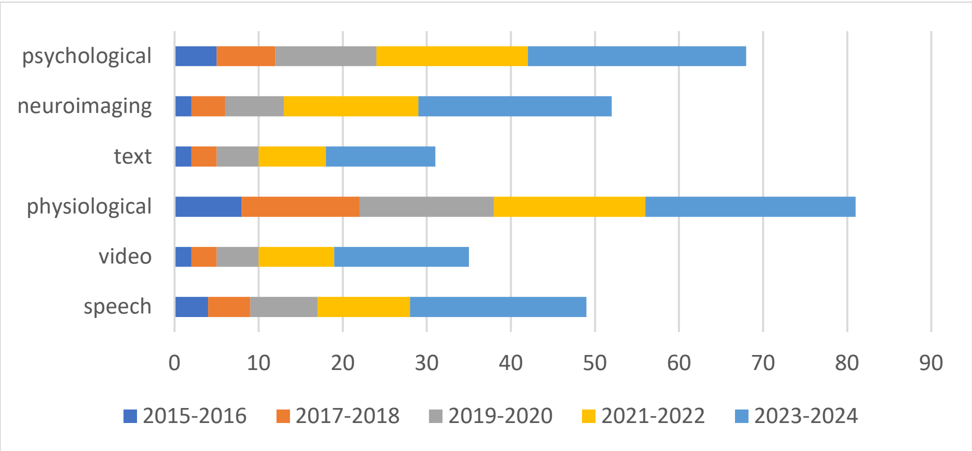

Figure 6. Distribution of studies using different data modalities across Time Periods (2015-2016, 2017-2018, 2019-2020, 2021-2022, 2023-2024) on the basis of search queries

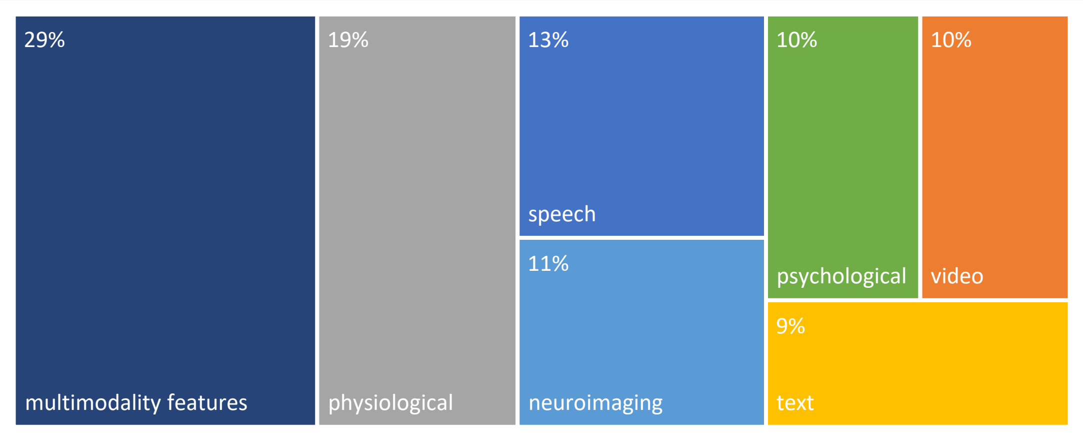

Figure 7. Distribution of studies using different features across Time Period (2015-2024)

From this figure, we can clearly see that after multimodality features, 19% of the total studies used physiological features in order to predict anxiety and thus its proved to be a significant potential biomarker for anxiety assessment. These studies have used HRV, EEG, skin conductance, and other biological signals in order to assess one's mental state. On the other hand, 13% of the studies used speech as a potential biomarker for anxiety assessment. Several different

categories of speech features have been extracted from the audio samples of individuals such as prosodic, acoustic, and linguistic. Prosodic features have been used by the studies to assess segmental characteristics of one's speech which includes speech rate, number of pauses, and pitch contour. Acoustic features have been used to refer physical properties of the speech which includes frequency (f_0), amplitude (intensity), resonant frequency, ZCR, MFCC, and duration. On the other hand, several studies have extracted linguistic features which refer to the content of the audio samples being collected and include word frequency, word choice, syntax, and vocabulary size. This evaluation clearly shows that 11% of the latest studies have used neuro-imaging features which helps in understanding the brain activity patterns of individuals which in turn gives intense information about one's mental state. The studies have used several different techniques like fMRI, EEG, and Positron Emission Tomography (PET) in order to capture brain activity patterns of individuals.

Other features like psychological and video have been used by 10% of the studies. Earlier studies used questionnaire and survey report in order to assess one's mental health. Several different scales like GAD-7, State-Trait Anxiety Inventory (STAI), Hamilton Anxiety Rating Scale (HAM-A), and Beck Anxiety Inventory (BAI) have been used by studies in order to capture the information regarding their mental health. Whereas video features like visual behaviour, and eye movement being extracted from one's video recording have been widely used by several latest studies. Textual features also play a vital role in capturing one's emotional state. Nowadays, social media and other online communities are being widely utilized by the individuals, where they share their daily routine activities. Studies are using such social media posts in order to analyze one's emotional state. For example, the use of stressful expressions, use of recurrent negative words are a linguistic indicator of anxiety.

These results clearly show the implication of multimodality features which are combination of one or two different kinds of features. 29% of the studies have used the multimodality features, because the use of diverse set of features helps practitioners to assess anxiety from several different perspective by focusing more on one's physiological state. The combination of several features like textual, acoustic, and visual or textual and acoustic, or psychological and speech, and so on provides more accurate assessment of anxiety by delving deeper into one's mental state.

7. Conclusion

This review paper has provided the details of different features extracted from different categories of data modalities which further helps in predicting various kinds of anxiety disorders. To conduct the comprehensive review, in this paper 117 research studies were considered in the field of anxiety disorder using different categories of features. For the identification of various anxiety disorders like SAD, GAD, PD, and ASD, all kinds of data modalities along with deep learning classifiers have shown encouraging results in terms of accuracy, specificity, and sensitivity. In addition, this review paper accentuates the importance for timely evaluation of anxiety disorders, recognizing their early emergence and enduring consequences on individuals' daily functioning using different categories of features such as prosody, linguistic, acoustic, facial, psychological, neuroimaging, and physiological. By employing neuroimaging biomarkers, researchers have gained valuable insights into daily fluctuations of anxiety levels.

8. Limitations and Future Work

This review paper highlights some limitations;(1) more focus on individual data modalities, partially overlooking the fusion of diverse data modalities;(2) temporal scope spanning from 2015 to 2024 may overlook the advancement in data modalities resulting into the heterogeneity of the including studies. Despite the promise exhibited by these modalities in assessing the various anxiety disorders, there is still abundant space for additional research and advancements. Future studies in the field of mental health assessment may explore a variety of avenues. To begin with, creating multi-model approach that use several data modalities might help improve prediction accuracy of anxiety disorder.

Author contributions:

Rakhi Nagpal performed the study, designed the research methodology, collected the data and drafted the initial version of manuscript. Saravjeet Singh visualized the research study, designed the methodology, reviewed and refined daft, performed the data analysis and interpretation of the findings. Aditi Moudgil reviewed and analysed the results.

Funding Details: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data Availability Statement: The authors confirm that the data supporting the finding of this research are available within the article.

Acknowledgments: NA.

Conflict of Interests: The authors declare no conflict of interest.

References

[1] Trautmann S, Rehm J, Wittchen H. The economic costs of mental disorders. EMBO Rep 2016;17:1245–9. https://doi.org/10.15252/EMBR.201642951.

[2] Christensen MK, Lim CCW, Saha S, Plana-Ripoll O, Cannon D, Momen NC, Whiteford HA, Iburg KM, McGrath JJ. The cost of mental disorders: a systematic review. Epidemiol Psychiatr Sci 2020;29:e161. https://doi.org/10.1017/S204579602000075X.

[3] Ahmed A, Sultana R, Ullas MTR, Begom M, Rahi MMI, Alam MA. A Machine Learning Approach to detect Depression and Anxiety using Supervised Learning. 2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering, CSDE 2020, Institute of Electrical and Electronics Engineers Inc.; 2020, p. 1–6. https://doi.org/10.1109/CSDE50874.2020.9411642.

[4] Craske MG, Stein MB. Anxiety. The Lancet 2016;388:3048–59. https://doi.org/10.1016/S0140-6736(16)30381-6.

[5] Malgaroli M, Hull TD, Calderon A, Simon NM. Linguistic markers of anxiety and depression in Somatic Symptom and Related Disorders: Observational study of a digital intervention. J Affect Disord 2024;352:133–7. https://doi.org/10.1016/J.JAD.2024.02.012.

[6] Thibaut F. Anxiety disorders: a review of current literature. Https://DoiOrg/1031887/DCNS2017192/Fthibaut 2022;19:87–8. https://doi.org/10.31887/DCNS.2017.19.2/FTHIBAUT.

[7] Pediaditis M, Giannakakis G, Chiarugi F, Manousos D, Pampouchidou A, Christinaki E, Iatraki G, Kazantzaki E, Simos PG, Marias K, Tsiknakis M. Extraction of facial features as indicators of stress and anxiety. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2015:3711–4. https://doi.org/10.1109/EMBC.2015.7319199.

[8] Arif M, Basri A, Melibari G, Sindi T, Alghamdi N, Altalhi N, Arif M. Classification of anxiety disorders using machine learning methods: a literature review. PdfsSemanticscholarOrg 2020. https://doi.org/10.36959/584/455.

[9] López-Morales H, Canet-Juric L, del-Valle MV, Sosa JM, López MC, Urquijo S. Prenatal anxiety during the pandemic context is related to neurodevelopment of 6-month-old babies. Eur J Pediatr 2023;182:4213–26. https://doi.org/10.1007/S00431-023-05112-Y/METRICS.

[10] McDonald AJ, Mew EJ, Hawley NL, Lowe SR. Anticipating the long-term neurodevelopmental impact of the COVID-19 pandemic on newborns and infants: A call for research and preventive policy. J Affect Disord Rep 2021;6:100213. https://doi.org/10.1016/J.JADR.2021.100213.

[11] Davenport MH, McCurdy AP, Mottola MF, Skow RJ, Meah VL, Poitras VJ, Jaramillo Garcia A, Gray CE, Barrowman N, Riske L, Sobierajski F, James M, Nagpal T, Marchand AA, Nuspl M, Slater LG, Barakat R, Adamo KB, Davies GA, Ruchat SM. Impact of prenatal exercise on both prenatal and postnatal anxiety and depressive symptoms: a systematic review and meta-analysis. Br J Sports Med 2018;52:1376–85. https://doi.org/10.1136/BJSPORTS-2018-099697.

[12] Martin P. The epidemiology of anxiety disorders: a review. Dialogues Clin Neurosci 2022;5:281–98. https://doi.org/10.31887/DCNS.2003.5.3/PMARTIN.

[13] Goodwin H, Yiend J, Hirsch CR. Generalized Anxiety Disorder, worry and attention to threat: A systematic review. Clin Psychol Rev 2017;54:107–22. https://doi.org/10.1016/J.CPR.2017.03.006.

[14] Madonna D, Delvecchio G, Soares JC, Brambilla P. Structural and functional neuroimaging studies in generalized anxiety disorder: a systematic review. Brazilian Journal of Psychiatry 2019;41:336. https://doi.org/10.1590/1516-4446-2018-0108.

[15] Priya A, Garg S, Tigga NP. Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms. Procedia Comput Sci 2020;167:1258–67. https://doi.org/10.1016/J.PROCS.2020.03.442.

[16] Emmelkamp PMG, Meyerbröker K, Morina N. Virtual Reality Therapy in Social Anxiety Disorder. Curr Psychiatry Rep 2020;22:1–9. https://doi.org/10.1007/S11920-020-01156-1/METRICS.

[17] Sharma A, Verbeke WJMI. Understanding importance of clinical biomarkers for diagnosis of anxiety disorders using machine learning models. PLoS One 2021;16:e0251365. https://doi.org/10.1371/JOURNAL.PONE.0251365.

[18] Pontillo M, Tata MC, Averna R, Demaria F, Gargiullo P, Guerrera S, Pucciarini ML, Santonastaso O, Vicari S. Peer Victimization and Onset of Social Anxiety Disorder in Children and Adolescents. Brain Sciences

2019, Vol 9, Page 132 2019;9:132. https://doi.org/10.3390/BRAINSCI9060132.

[19] Koyuncu A, İnce E, Ertekin E, Tükel R. Comorbidity in social anxiety disorder: diagnostic and therapeutic challenges. Drugs Context 2019;8. https://doi.org/10.7573/DIC.212573.

[20] Felmingham KL, Stewart LF, Kemp AH, Carr AR. The impact of high trait social anxiety on neural processing of facial emotion expressions in females. Biol Psychol 2016;117:179–86. https://doi.org/10.1016/J.BIOPSYCHO.2016.04.001.

[21] Kleberg JL, Högström J, Sundström K, Frick A, Serlachius E. Delayed gaze shifts away from others' eyes in children and adolescents with social anxiety disorder. J Affect Disord 2021;278:280–7. https://doi.org/10.1016/J.JAD.2020.09.022.

[22] Kaseda ET, Levine AJ. Post-traumatic stress disorder: A differential diagnostic consideration for COVID-19 survivors. Https://DoiOrg/101080/1385404620201811894 2020;34:1498–514. https://doi.org/10.1080/13854046.2020.1811894.

[23] Li Y, Scherer N, Felix L, Kuper H. Prevalence of depression, anxiety and post-traumatic stress disorder in health care workers during the COVID-19 pandemic: A systematic review and meta-analysis. PLoS One 2021;16:e0246454. https://doi.org/10.1371/JOURNAL.PONE.0246454.

[24] de Jonge P, Roest AM, Lim CCW, Florescu SE, Bromet EJ, Stein DJ, Harris M, Nakov V, Caldas-de-Almeida JM, Levinson D, Al-Hamzawi AO, Haro JM, Viana MC, Borges G, O'Neill S, de Girolamo G, Demyttenaere K, Gureje O, Iwata N, Lee S, Hu C, Karam A, Moskalewicz J, Kovess-Masfety V, Navarro-Mateu F, Browne MO, Piazza M, Posada-Villa J, Torres Y, ten Have ML, Kessler RC, Scott KM. Cross-national epidemiology of panic disorder and panic attacks in the world mental health surveys. Depress Anxiety 2016;33:1155–77. https://doi.org/10.1002/DA.22572.

[25] Na KS, Cho SE, Cho SJ. Machine learning-based discrimination of panic disorder from other anxiety disorders. J Affect Disord 2021;278:1–4. https://doi.org/10.1016/J.JAD.2020.09.027.

[26] Jang EH, Choi KW, Kim AY, Yu HY, Jeon HJ, Byun S. Automated detection of panic disorder based on multimodal physiological signals using machine learning. ETRI Journal 2023;45:105–18. https://doi.org/10.4218/ETRIJ.2021-0299.

[27] Javelot H, Weiner L. Panic and pandemic: Narrative review of the literature on the links and risks of panic disorder as a consequence of the SARS-CoV-2 pandemic. Encephale 2021;47:38–42. https://doi.org/10.1016/J.ENCEP.2020.08.001.

[28] Boudreau M, Lavoie KL, Cartier A, Trutshnigg B, Morizio A, Lemière C, Bacon SL. Do asthma patients with panic disorder really have worse asthma? A comparison of physiological and psychological responses to a methacholine challenge. Respir Med 2015;109:1250–6. https://doi.org/10.1016/J.RMED.2015.09.002.

[29] Bandelow B, Michaelis S. Epidemiology of anxiety disorders in the 21st century. Dialogues Clin Neurosci 2015;17:327–35. https://doi.org/10.31887/DCNS.2015.17.3/BBANDELOW.

[30] Perna G, Iannone G, Alciati A, Caldirola D. Are anxiety disorders associated with accelerated aging? A focus on neuroprogression. Neural Plast 2016;2016. https://doi.org/10.1155/2016/8457612.

[31] Gkotsis G, Oellrich A, Velupillai S, reports ML-S, 2017 undefined. Characterisation of mental health conditions in social media using Informed Deep Learning. NatureCom 2017;7:45141.

[32] Mundel J, Wan A, Yang J. Processes underlying social comparison with influencers and subsequent impulsive buying: The roles of social anxiety and social media addiction. Journal of Marketing Communications 2024;30:834–51. https://doi.org/10.1080/13527266.2023.2183426.

[33] Barak-Corren Y, Castro VM, Javitt S, Hoffnagle AG, Dai Y, Perlis RH, Nock MK, Smoller JW, Reis BY. Predicting suicidal behavior from longitudinal electronic health records. American Journal of Psychiatry 2017;174:154–62. https://doi.org/10.1176/APPI.AJP.2016.16010077/ASSET/IMAGES/LARGE/APPI.AJP.2016.16010077F2.JPEG.

[34] Sharma P, Rosário MC, Ferrão YA, Albertella L, Miguel EC, Fontenelle LF. The impact of generalized anxiety disorder in obsessive-compulsive disorder patients. Psychiatry Res 2021;300:113898. https://doi.org/10.1016/J.PSYCHRES.2021.113898.

[35] Ebrahim OS, Sayed HA, Rabei S, Hegazy N. Perceived stress and anxiety among medical students at Helwan University: A cross-sectional study. J Public Health Res 2024;13:22799036241227892. https://doi.org/10.1177/22799036241227891/ASSET/IMAGES/LARGE/10.1177_22799036241227891-FIG2.JPEG.

[36] Maddock A. The Relationships between Stress, Burnout, Mental Health and Well-Being in Social Workers. The British Journal of Social Work 2024;54:668–86. https://doi.org/10.1093/BJSW/BCAD232.

[37] Robinson LR, Bitsko RH, O'Masta B, Holbrook JR, Ko J, Barry CM, Maher B, Cerles A, Saadeh K, MacMillan L, Mahmooth Z, Bloomfield J, Rush M, Kaminski JW. A Systematic Review and Meta-analysis of Parental Depression, Antidepressant Usage, Antisocial Personality Disorder, and Stress and Anxiety as Risk Factors for Attention-Deficit/Hyperactivity Disorder (ADHD) in Children. Prevention Science 2024;25:272–90. https://doi.org/10.1007/S11121-022-01383-3/METRICS.

[38] Giannakakis G, Pediaditis M, Manousos D, Kazantzaki E, Chiarugi F, Simos PG, Marias K, Tsiknakis M. Stress and anxiety detection using facial cues from videos. Biomed Signal Process Control 2017;31:89–101. https://doi.org/10.1016/J.BSPC.2016.06.020.

[39] Zhang H, Feng L, Li N, Jin Z, Cao L. Video-Based Stress Detection through Deep Learning. Sensors 2020;20:5552. https://doi.org/10.3390/S20195552.

[40] Al-Ezzi A, Yahya N, Kamel N, Faye I, Alsaih K, Gunaseli E. Severity Assessment of Social Anxiety Disorder Using Deep Learning Models on Brain Effective Connectivity. IEEE Access 2021;9:86899–913. https://doi.org/10.1109/ACCESS.2021.3089358.

[41] Paula L dos S, Pfeiffer Salomão Dias L, Francisco R, Barbosa JLV. Analysing IoT Data for Anxiety and

Stress Monitoring: A Systematic Mapping Study and Taxonomy. Int J Hum Comput Interact 2024;40:1174–94. https://doi.org/10.1080/10447318.2022.2132361.
[42] Baygin M, Barua PD, Dogan S, Tuncer T, Hong TJ, March S, Tan RS, Molinari F, Acharya UR. Automated anxiety detection using probabilistic binary pattern with ECG signals. Comput Methods Programs Biomed 2024;247:108076. https://doi.org/10.1016/J.CMPB.2024.108076.
[43] Yang T, Wu C, Huang K, Su M. Detection of mood disorder using speech emotion profiles and LSTM. 10th International Symposium on Chinese Spoken Language Processing (ISCSLP), IEEE; 2016, p. 1–5.
[44] Su MH, Wu CH, Huang KY, Yang TH. Cell-Coupled Long Short-Term Memory with L-Skip Fusion Mechanism for Mood Disorder Detection through Elicited Audiovisual Features. IEEE Trans Neural Netw Learn Syst 2020;31:124–35. https://doi.org/10.1109/TNNLS.2019.2899884.
[45] Rejaibi E, Komaty A, Meriaudeau F, Agrebi S, Othmani A. MFCC-based Recurrent Neural Network for automatic clinical depression recognition and assessment from speech. Biomed Signal Process Control 2022;71:103107. https://doi.org/10.1016/J.BSPC.2021.103107.
[46] Tasnim M, Ehghaghi M, … BD-P of the E, 2022 undefined. Depac: a corpus for depression and anxiety detection from speech. AclanthologyOrg 2022:1–16.
[47] Diep B, Stanojevic M, Novikova J. Multi-modal deep learning system for depression and anxiety detection 2022.
[48] Whitfield-Gabrieli S, Ghosh SS, Nieto-Castanon A, Saygin Z, Doehrmann O, Chai XJ, Reynolds GO, Hofmann SG, Pollack MH, Gabrieli JDE. Brain connectomics predict response to treatment in social anxiety disorder. Mol Psychiatry 2015;21:680–5. https://doi.org/10.1038/mp.2015.109.
[49] Salekin A, Eberle JW, Glenn JJ, Teachman BA, Stankovic JA. A Weakly Supervised Learning Framework for Detecting Social Anxiety and Depression. Proc ACM Interact Mob Wearable Ubiquitous Technol 2018;2:1–26. https://doi.org/10.1145/3214284.
[50] Rezaei S, Gharepapagh E, Rashidi F, Cattarinussi G, Sanjari Moghaddam H, Di Camillo F, Schiena G, Sambataro F, Brambilla P, Delvecchio G. Machine learning applied to functional magnetic resonance imaging in anxiety disorders. J Affect Disord 2023;342:54–62. https://doi.org/10.1016/J.JAD.2023.09.006.
[51] Bendebane L, Laboudi Z, Saighi A, Al-Tarawneh H, Ouannas A, Grassi G. A Multi-Class Deep Learning Approach for Early Detection of Depressive and Anxiety Disorders Using Twitter Data. Algorithms 2023;16:543. https://doi.org/10.3390/a16120543.
[52] Tasnim M, Ramos RD, Stroulia E, Trejo LA. A Machine-Learning Model for Detecting Depression, Anxiety, and Stress from Speech. ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE; 2024, p. 7085–9. https://doi.org/10.1109/ICASSP48485.2024.10446567.
[53] Zhou E, Wang W, Ma S, Xie X, Kang L, Xu S, Deng Z, Gong Q, Nie Z, Yao L, Bu L, Wang F, Liu Z. Prediction of anxious depression using multimodal neuroimaging and machine learning. Neuroimage 2024;285:120499. https://doi.org/10.1016/J.NEUROIMAGE.2023.120499.
[54] Chekroud AM, Bondar J, Delgadillo J, Doherty G, Wasil A, Fokkema M, Cohen Z, Belgrave D, DeRubeis R, Iniesta R, Dwyer D, Choi K. The promise of machine learning in predicting treatment outcomes in psychiatry. World Psychiatry 2021;20:154–70. https://doi.org/10.1002/WPS.20882.
[55] Meng X, Zhang J. Anxiety Recognition of College Students Using a Takagi-Sugeno-Kang Fuzzy System Modeling Method and Deep Features. IEEE Access 2020;8:159897–905. https://doi.org/10.1109/ACCESS.2020.3021092.
[56] Mokatren LS, Ansari R, Cetin AE, Leow AD, Ajilore OA, Klumpp H, Yarman Vural FT. EEG Classification by Factoring in Sensor Spatial Configuration. IEEE Access 2021;9:19053–65. https://doi.org/10.1109/ACCESS.2021.3054670.
[57] Di Matteo D, Fotinos K, Lokuge S, Mason G, Sternat T, Katzman MA, Rose J. Automated screening for social anxiety, generalized anxiety, and depression from objective smartphone-collected data: Cross-sectional study. J Med Internet Res 2021;23:e28918. https://doi.org/10.2196/28918.
[58] Tushar Umrani A, Harshavardhanan P. Hybrid feature-based anxiety detection in autism using hybrid optimization tuned artificial neural network. Biomed Signal Process Control 2022;76:103699. https://doi.org/10.1016/J.BSPC.2022.103699.
[59] Aldayel M, Al-Nafjan A. A comprehensive exploration of machine learning techniques for EEG-based anxiety detection. PeerJ Comput Sci 2024;10:e1829. https://doi.org/10.7717/PEERJ-CS.1829/SUPP-2.
[60] Aljabri A, Rashwan D, Qasem R, Fakeeh R, Albeladi R, Sassi N. Overcoming Speech Anxiety Using Virtual Reality with Voice and Heart Rate Analysis. Proceedings - International Conference on Developments in eSystems Engineering, DeSE, vol. 2020- December, Institute of Electrical and Electronics Engineers Inc.; 2020, p. 311–6. https://doi.org/10.1109/DESE51703.2020.9450783.
[61] Madison A, Vasey M, Emery CF, Kiecolt-Glaser JK. Social anxiety symptoms, heart rate variability, and vocal emotion recognition in women: evidence for parasympathetically-mediated positivity bias. Anxiety Stress Coping 2021;34:243–57. https://doi.org/10.1080/10615806.2020.1839733/SUPPL_FILE/GASC_A_1839733_SM9662.DOCX.
[62] Olatinwo DD, Abu-Mahfouz A, Hancke G, Myburgh H. IoT-Enabled WBAN and Machine Learning for Speech Emotion Recognition in Patients. Sensors 2023;23:2948. https://doi.org/10.3390/S23062948.
[63] Brueckner R, Kwon N, Subramanian V, Blaylock N, O'Connell H. Audio-Based Detection of Anxiety and Depression via Vocal Biomarkers. Lecture Notes in Networks and Systems, vol. 919 LNNS, Springer, Cham; 2024, p. 124–41. https://doi.org/10.1007/978-3-031-53960-2_9.
[64] Jaiswal S, Song S, Valstar M. Automatic prediction of Depression and Anxiety from behaviour and personality attributes. 2019 8th International

Conference on Affective Computing and Intelligent Interaction, ACII 2019, Institute of Electrical and Electronics Engineers Inc.; 2019, p. 454–60. https://doi.org/10.1109/ACII.2019.8925456.
[65] Pampouchidou A, Pediaditis M, Kazantzaki E, Sfakianakis S, Apostoloki IA, Argyraki K, Manousos D, Meriaudeau F, Marias K, Yang F, Tsiknakis M, Basta M, Vgontzas AN, Simos P. Automated facial video-based recognition of depression and anxiety symptom severity: cross-corpus validation. Mach Vis Appl 2020;31:1–19. https://doi.org/10.1007/S00138-020-01080-7/METRICS.
[66] Lidle LR, Schmitz J. Assessing Visual Avoidance of Faces During Real-Life Social Stress in Children with Social Anxiety Disorder: A Mobile Eye-Tracking Study. Child Psychiatry Hum Dev 2024;55:24–35. https://doi.org/10.1007/S10578-022-01383-Y/TABLES/5.
[67] Lueken U, Straube B, Yang Y, Hahn T, Beesdo-Baum K, Wittchen HU, Konrad C, Ströhle A, Wittmann A, Gerlach AL, Pfleiderer B, Arolt V, Kircher T. Separating depressive comorbidity from panic disorder: A combined functional magnetic resonance imaging and machine learning approach. J Affect Disord 2015;184:182–92. https://doi.org/10.1016/J.JAD.2015.05.052.
[68] Makovac E, Watson DR, Meeten F, Garfinkel SN, Cercignani M, Critchley HD, Ottaviani C. Amygdala functional connectivity as a longitudinal biomarker of symptom changes in generalized anxiety. Soc Cogn Affect Neurosci 2016;11:1719–28. https://doi.org/10.1093/SCAN/NSW091.
[69] Felger JC. Imaging the Role of Inflammation in Mood and Anxiety-related Disorders. Curr Neuropharmacol 2017;16:533–58. https://doi.org/10.2174/1570159X15666171123201142.
[70] Boeke EA, Holmes AJ, Phelps EA. Toward Robust Anxiety Biomarkers: A Machine Learning Approach in a Large-Scale Sample. Biol Psychiatry Cogn Neurosci Neuroimaging 2020;5:799–807. https://doi.org/10.1016/J.BPSC.2019.05.018.
[71] Fang J, Li G, Xu W, Liu W, Chen G, Zhu Y, Luo Y, Luo X, Zhou B. Exploring Abnormal Brain Functional Connectivity in Healthy Adults, Depressive Disorder, and Generalized Anxiety Disorder through EEG Signals: A Machine Learning Approach for Triple Classification. Brain Sci 2024;14:245. https://doi.org/10.3390/BRAINSCI14030245.
[72] Shen JH, Rudzicz F. Detecting Anxiety through Reddit. Proceedings of the Fourth Workshop on Computational Linguistics and Clinical Psychology—From Linguistic Signal to Clinical Reality, Stroudsburg, PA, USA: Association for Computational Linguistics; 2017, p. 58–65. https://doi.org/10.18653/V1/W17-3107.
[73] Thorstad R, Wolff P. Predicting future mental illness from social media: A big-data approach. Behav Res Methods 2019;51:1586–600. https://doi.org/10.3758/S13428-019-01235-Z/TABLES/4.
[74] Owen D, Collados JC, Espinosa-Anke L. Towards Preemptive Detection of Depression and Anxiety in Twitter. ArXiv 2020:82–9.
[75] Kim J, Lee J, Park E, Han J. A deep learning model for detecting mental illness from user content on social media. Sci Rep 2020;10:1–6. https://doi.org/10.1038/s41598-020-68764-y.
[76] Alshanketi F. Revolutionizing Generalized Anxiety Disorder Detection using a Deep Learning Approach with MGADHF Architecture on Social Media. International Journal of Advanced Computer Science and Applications 2024;15:918–26. https://doi.org/10.14569/IJACSA.2024.0150192.
[77] Silber-Varod V, Levi-Belz Y, Amir N, Kreiner H, Lovett R. Do social anxiety individuals hesitate more? The prosodic profile of hesitation disfluencies in Social Anxiety Disorder individuals. Speech Prosody 2016 2016:1211–5. https://doi.org/10.21437/SpeechProsody.2016-249.
[78] Sahu NK, Yadav M, Lone HR. Unveiling Social Anxiety: Analyzing Acoustic and Linguistic Traits in Impromptu Speech within a Controlled Study. ACM Journal on Computing and Sustainable Societies 2024;2:1–19. https://doi.org/10.1145/3657245.
[79] Zheng C, Zhang T, Chen X, Zhang H, Wan J, Wu B. Assessing learners' English public speaking anxiety with multimodal deep learning technologies. Comput Assist Lang Learn 2024:1–29. https://doi.org/10.1080/09588221.2024.2351129.
[80] Albuquerque L, Valente ARS, Teixeira A, Figueiredo D, Sa-Couto P, Oliveira C. Association between acoustic speech features and non-severe levels of anxiety and depression symptoms across lifespan. PLoS One 2021;16:e0248842. https://doi.org/10.1371/JOURNAL.PONE.0248842.
[81] Jain SH, Powers BW, Hawkins JB, Brownstein JS. The digital phenotype. Nat Biotechnol 2015;33:462–3. https://doi.org/10.1038/nbt.3223.
[82] Insel TR. Digital Phenotyping: Technology for a New Science of Behavior. JAMA 2017;318:1215–6. https://doi.org/10.1001/JAMA.2017.11295.
[83] Elvevåg B, Cohen AS, Wolters MK, Whalley HC, Gountouna VE, Kuznetsova KA, Watson AR, Nicodemus KK. An examination of the language construct in NIMH's research domain criteria: Time for reconceptualization! American Journal of Medical Genetics Part B: Neuropsychiatric Genetics 2016;171:904–19. https://doi.org/10.1002/AJMG.B.32438.
[84] Guntuku SC, Preotiuc-Pietro D, Eichstaedt JC, Ungar LH. What Twitter Profile and Posted Images Reveal about Depression and Anxiety. Proceedings of the International AAAI Conference on Web and Social Media, vol. 13, Association for the Advancement of Artificial Intelligence; 2019, p. 236–46. https://doi.org/10.1609/ICWSM.V13I01.3225.
[85] Zarate D, Ball M, Prokofieva M, Kostakos V, Stavropoulos V. Identifying self-disclosed anxiety on Twitter: A natural language processing approach. Psychiatry Res 2023;330:115579. https://doi.org/10.1016/J.PSYCHRES.2023.115579.
[86] Teferra BG, Borwein S, DeSouza DD, Rose J. Screening for Generalized Anxiety Disorder From Acoustic and Linguistic Features of Impromptu Speech: Prediction Model Evaluation Study. JMIR Form Res 2022;6:e39998. https://doi.org/10.2196/39998.
[87] Kim S, Cha J, Kim D, Park E. Understanding Mental Health Issues in Different Subdomains of Social

Networking Services: Computational Analysis of Text-Based Reddit Posts. J Med Internet Res 2023;25:e49074. https://doi.org/10.2196/49074.
[88] Faghel-Soubeyrand S, Lecomte T, Bravo MA, Lepage M, Potvin S, Abdel-Baki A, Villeneuve M, Gosselin F. Abnormal visual representations associated with confusion of perceived facial expression in schizophrenia with social anxiety disorder. NPJ Schizophr 2020;6:1–9. https://doi.org/10.1038/s41537-020-00116-1.
[89] Tseng HH, Huang YL, Chen JT, Liang KY, Lin CC, Chen SH. Facial and prosodic emotion recognition in social anxiety disorder. Cogn Neuropsychiatry 2017;22:331–45. https://doi.org/10.1080/13546805.2017.1330190.
[90] Weise T, Pérez-Toro PA, Deitermann A, Hoffmann B, Demir K can, Straetz T, Nöth E, Maier A, Kallert T, Yang SH. Multi-modal Biomarker Extraction Framework for Therapy Monitoring of Social Anxiety and Depression Using Audio and Video. Workshop on Machine Learning for Multimodal Healthcare Data, vol. 14315, Springer; 2023, p. 26–42. https://doi.org/10.1007/978-3-031-47679-2_3/COVER.
[91] Mo H, Li Y, Han P, Liao X, Zhang W, Ding S. SFF-DA: Spatiotemporal Feature Fusion for Nonintrusively Detecting Anxiety. IEEE Trans Instrum Meas 2024;73:1–13. https://doi.org/10.1109/TIM.2023.3341132.
[92] Xie Y, Yang B, Lu X, Zheng M, Fan C, Bi X, Zhou S, Li Y. Anxiety and Depression Diagnosis Method Based on Brain Networks and Convolutional Neural Networks. 2020 42nd Annual International Conference of the IEEE Engineering in Medicine \& Biology Society (EMBC), vol. 2020, Institute of Electrical and Electronics Engineers Inc.; 2020, p. 1503–6. https://doi.org/10.1109/EMBC44109.2020.9176471.
[93] Hahn T, Kircher T, Straube B, Wittchen HU, Konrad C, Ströhle A, Wittmann A, Pfleiderer B, Reif A, Arolt V, Lueken U. Predicting Treatment Response to Cognitive Behavioral Therapy in Panic Disorder With Agoraphobia by Integrating Local Neural Information. JAMA Psychiatry 2015;72:68–74. https://doi.org/10.1001/JAMAPSYCHIATRY.2014.1741.
[94] Frick A, Engman J, Alaie I, Björkstrand J, Gingnell M, Larsson EM, Eriksson E, Wahlstedt K, Fredrikson M, Furmark T. Neuroimaging, genetic, clinical, and demographic predictors of treatment response in patients with social anxiety disorder. J Affect Disord 2020;261:230–7. https://doi.org/10.1016/J.JAD.2019.10.027.
[95] Al-Ezzi A, Kamel N, Faye I, Gunaseli E. Review of EEG, ERP, and Brain Connectivity Estimators as Predictive Biomarkers of Social Anxiety Disorder. Front Psychol 2020;11:517065. https://doi.org/10.3389/FPSYG.2020.00730/BIBTE.
[96] Qiao J, Li A, Cao C, Wang Z, Sun J, Xu G. Aberrant functional network connectivity as a biomarker of generalized anxiety disorder. Front Hum Neurosci 2017;11:626. https://doi.org/10.3389/FNHUM.2017.00626/BIBTEX.
[97] Ko K, Jones A, Francis D, Robidoux S, McArthur G. Physiological correlates of anxiety in childhood and adolescence: A systematic review and meta-analysis. Stress and Health 2024;40:e3388. https://doi.org/10.1002/SMI.3388.
[98] Low DM, Bentley KH, Ghosh SS. Automated assessment of psychiatric disorders using speech: A systematic review. Laryngoscope Investig Otolaryngol 2020;5:96–116. https://doi.org/10.1002/LIO2.354.
[99] Marin MF, Zsido RG, Song H, Lasko NB, Killgore WDS, Rauch SL, Simon NM, Milad MR. Skin Conductance Responses and Neural Activations During Fear Conditioning and Extinction Recall Across Anxiety Disorders. JAMA Psychiatry 2017;74:622–31. https://doi.org/10.1001/JAMAPSYCHIATRY.2017.0329.
[100] Tomasi J, Zai CC, Zai G, Herbert D, Richter MA, Mohiuddin AG, Tiwari AK, Kennedy JL. Investigating the association of anxiety disorders with heart rate variability measured using a wearable device. J Affect Disord 2024;351:569–78. https://doi.org/10.1016/J.JAD.2024.01.137.
[101] Jacobson NC, Bhattacharya S. Digital biomarkers of anxiety disorder symptom changes: Personalized deep learning models using smartphone sensors accurately predict anxiety symptoms from ecological momentary assessments. Behaviour Research and Therapy 2022;149:104013. https://doi.org/10.1016/J.BRAT.2021.104013.
[102] Jacobson NC, Lekkas D, Huang R, Thomas N. Deep learning paired with wearable passive sensing data predicts deterioration in anxiety disorder symptoms across 17–18 years. J Affect Disord 2021;282:104–11. https://doi.org/10.1016/J.JAD.2020.12.086.
[103] Handouzi W, Maaoui C, Pruski A. Virtual reality exposure aided-diagnosis system for anxiety disorders: Long short-term memory architecture for three levels of anxiety recognition. Biomed Mater Eng 2023;34:491–502. https://doi.org/10.3233/BME-222542.
[104] Lee TR, Kim GH, Choi MT. Geriatric depression and anxiety screening via deep learning using activity tracking and sleep data. Int J Geriatr Psychiatry 2024;39:e6071. https://doi.org/10.1002/GPS.6071.
[105] Haritha H, Negi S, Menon RS, Kumar AA, Kumar CS. Automating anxiety detection using respiratory signal analysis. 2017 - IEEE International Symposium on Technologies for Smart Cities, IEEE; 2017, p. 1–5. https://doi.org/10.1109/TENCONSPRING.2017.8069995.
[106] Barua PD, Vicnesh J, Lih OS, Palmer EE, Yamakawa T, Kobayashi M, Acharya UR. Artificial intelligence assisted tools for the detection of anxiety and depression leading to suicidal ideation in adolescents: a review. Cogn Neurodyn 2022;18:1–22. https://doi.org/10.1007/S11571-022-09904-0/FIGURES/1.
[107] Bone D, Mertens J, Zane E, Lee S, Narayanan S, Grossman R. Acoustic-Prosodic and Physiological Response to Stressful Interactions in Children with Autism Spectrum Disorder. Interspeech, 2017, p. 147–51. https://doi.org/10.21437/Interspeech.2017-179.
[108] Jiang Z, Seyedi S, Griner E, Abbasi A, Rad AB, Kwon H, Cotes RO, Clifford GD. Multimodal Mental Health Digital Biomarker Analysis from Remote Interviews

using Facial, Vocal, Linguistic, and Cardiovascular Patterns. IEEE J Biomed Health Inform 2024. https://doi.org/10.1109/JBHI.2024.3352075.
[109]Weeks JW, Srivastav A, Howell AN, Menatti AR. “Speaking more than words”: Classifying men with social anxiety disorder via vocal acoustic analyses of diagnostic interviews. J Psychopathol Behav Assess 2016;38:30–41. https://doi.org/10.1007/S10862-015-9495-9/METRICS.
[110]Binelli C, Muñiz A, Subira S, Navines R, Blanco-Hinojo L, Perez-Garcia D, Crippa J, Farré M, Pérez-Jurado L, Pujol J, Martin-Santos R. Facial emotion processing in patients with social anxiety disorder and Williams–Beuren syndrome: an fMRI study. Journal of Psychiatry and Neuroscience 2016;41:182–91. https://doi.org/10.1503/JPN.140384.
[111]Liu F, Guo W, Fouche JP, Wang Y, Wang W, Ding J, Zeng L, Qiu C, Gong Q, Zhang W, Chen H. Multivariate classification of social anxiety disorder using whole brain functional connectivity. Brain Struct Funct 2015;220:101–15. https://doi.org/10.1007/S00429-013-0641-4/METRICS.
[112]Capozzi F, Manti F, Di Trani M, Romani M, Vigliante M, Sogos C. Children’s and parent’s psychological profiles in selective mutism and generalized anxiety disorder: a clinical study. Eur Child Adolesc Psychiatry 2018;27:775–83. https://doi.org/10.1007/S00787-017-1075-Y/METRICS.
[113]Mokatren LS, Ansari R, Cetin AE, Leow AD, Ajilore O, Klumpp H, Vural FTY. EEG Classification based on Image Configuration in Social Anxiety Disorder. 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER), vol. 2019- March, IEEE Computer Society; 2019, p. 577–80. https://doi.org/10.1109/NER.2019.8717152.
[114]Gavrilescu M, Vizireanu N. Predicting Depression, Anxiety, and Stress Levels from Videos Using the Facial Action Coding System. Sensors 2019;19:3693. https://doi.org/10.3390/S19173693.
[115]Ochi K, Ono N, Owada K, Kojima M, Kuroda M, Sagayama S, Yamasue H. Quantification of speech and synchrony in the conversation of adults with autism spectrum disorder. PLoS One 2019;14:e0225377. https://doi.org/10.1371/JOURNAL.PONE.0225377.
[116]Elgendi M, Menon C. Assessing Anxiety Disorders Using Wearable Devices: Challenges and Future Directions. Brain Sci 2019;9:50. https://doi.org/10.3390/BRAINSCI9030050.
[117]Rammohan RA, Medikonda J, Pothiyil DI. Speech Signal-Based Modelling of Basic Emotions to Analyse Compound Emotion: Anxiety. 2020 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics, DISCOVER 2020 - Proceedings, Institute of Electrical and Electronics Engineers Inc.; 2020, p. 218–23. https://doi.org/10.1109/DISCOVER50404.2020.9278094.
[118]Nirjhar EH, Behzadan AH, Chaspari T, Chaspari T 2021. Knowledge-and Data-Driven Models of Multimodal Trajectories of Public Speaking Anxiety in Real and Virtual Settings. Proceedings of the 2021 International Conference on Multimodal Interaction, New York, NY, USA: ACM; 2021, p. 712–6. https://doi.org/10.1145/3462244.
[119]Kwon N, Hossain S, Blaylock N, O’connell H, Hachen N, Gwin J. Detecting Anxiety and Depression from Phone Conversations using x-vectors. InProc. Workshop on Speech, Music and Mind, 2022, p. 1–5. https://doi.org/10.21437/SMM.2022-1.
[120]Wanderley Espinola C, Gomes JC, Mônica Silva Pereira J, dos Santos WP. Detection of major depressive disorder, bipolar disorder, schizophrenia and generalized anxiety disorder using vocal acoustic analysis and machine learning: an exploratory study. Research on Biomedical Engineering 2022;38:813–29. https://doi.org/10.1007/S42600-022-00222-2/METRICS.
[121]Choudhary S, Thomas N, Alshamrani S, Srinivasan G, Ellenberger J, Nawaz U, Cohen R. A Machine Learning Approach for Continuous Mining of Nonidentifiable Smartphone Data to Create a Novel Digital Biomarker Detecting Generalized Anxiety Disorder: Prospective Cohort Study. JMIR Med Inform 2022;10:e38943. https://doi.org/10.2196/38943.
[122]Zeghari R, Gindt M, König A, Nachon O, Lindsay H, Robert P, Fernandez A, Askenazy F. Study protocol: how does parental stress measured by clinical scales and voice acoustic stress markers predict children’s response to PTSD trauma-focused therapies? BMJ Open 2023;13:e068026. https://doi.org/10.1136/BMJOPEN-2022-068026.
[123]Jyothi S, Sneha S, Preetha P, Priyanka S, Taskeen R. A Deep Convolutional Neural Network Based Prediction System For Autism Spectrum Disorder In Facial Images. International Journal of Research in Engineering and Science 2023;11:319–24.
[124]Rao S, Shi H. EFFECTS OF PSYCHOLOGICAL STRESS AND ANXIETY ON PERFORMANCE AND COPING STRATEGIES IN ATHLETES. Revista Multidisciplinar de Las Ciencias Del Deporte 2024;24. https://doi.org/10.15366/RIMCAFD2024.94.030.
[125]Wang Y, Chen B, Liu H, Hu Z. Understanding Flow Experience in Video Learning by Multimodal Data. Int J Hum Comput Interact 2024;40:3144–58. https://doi.org/10.1080/10447318.2023.2181878.
[126]Laukka P, Linnman C, Åhs F, Pissiota A, Frans Ö, Faria V, Michelgård Å, Appel L, Fredrikson M, Furmark T. In a nervous voice: Acoustic analysis and perception of anxiety in social phobics’ speech. J Nonverbal Behav 2008;32:195–214. https://doi.org/10.1007/S10919-008-0055-9/METRICS.
[127]Sauter DA, Eisner F, Calder AJ, Scott SK. Perceptual Cues in Nonverbal Vocal Expressions of Emotion. Quarterly Journal of Experimental Psychology 2010;63:2251–72. https://doi.org/10.1080/17470211003721642.
[128]Billeci L, Varanini M, Tonacci A, Vaz M, Summavielle T, Sebastião R, Ribeiro RP. Multimodal Classification of Anxiety Based on Physiological Signals. Applied Science 2023;13:6368. https://doi.org/10.3390/app13116368.
[129]Baghdadi A, Aribi Y, Fourati R, Halouani N, Siarry P, Alimi A. Psychological stimulation for anxious states detection based on EEG-related features. J Ambient Intell Humaniz Comput 2021;12:8519–33.

https://doi.org/10.1007/S12652-020-02586-8/METRICS.

[130] Šalkevicius J, Damaševičius R, Maskeliunas R, Laukienė I. Anxiety Level Recognition for Virtual Reality Therapy System Using Physiological Signals. Electronics (Basel) 2019;8:1039. https://doi.org/10.3390/ELECTRONICS8091039.

[131] Giannakakis G, Grigoriadis D, Tsiknakis M. Detection of stress/anxiety state from EEG features during video watching. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Institute of Electrical and Electronics Engineers Inc.; 2015, p. 6034–7. https://doi.org/10.1109/EMBC.2015.7319767.