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Review article

Stress monitoring using low-cost electroencephalogram devices: A systematic literature review

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ABSTRACT

Introduction: The use of low-cost, consumer-grade wearable health monitoring devices has become increasingly prevalent in mental health research, including stress studies. While cortisol response magnitude remains the gold standard for stress assessment, an expanding body of research employs low-cost EEG devices as primary tools for recording biomarker data, often combined with wrist and ring-based wearables. However, the technical variability among low-cost EEG devices, particularly in sensor count and placement according to the 10-20 Electrode Placement System, poses challenges for reproducibility in study outcomes.

Objective: This review aims to provide an overview of the growing application of low-cost EEG devices and machine learning techniques for assessing brain function, with a focus on stress detection. It also highlights the strengths and weaknesses of various machine learning methods commonly used in stress research, and evaluates the reproducibility of reported findings along with sensor count and placement importance.

Methods: A comprehensive review was conducted of published studies utilizing EEG devices for stress detection and their associated machine learning approaches. Searches were performed across databases including Scopus, Google Scholar, ScienceDirect, Nature, and PubMed, yielding 69 relevant articles for analysis. The selected studies were synthesized into four thematic categories: stress assessment using EEG, low-cost EEG devices, datasets for EEG-based stress measurement, and machine learning techniques for EEG-based stress analysis. For machine learning-focused studies, validation and reproducibility methods were critically assessed. Study quality was evaluated and scored using the IJMEDI checklist.

Results: The review identified several studies employing low-cost EEG devices to monitor brain activity during stress and relaxation phases, with many reporting high predictive accuracy using various machine learning validation techniques. However, only 54% of the studies included health screening prior to experimentation, and 58% were categorized as low-powered due to limited sample sizes. Additionally, few studies validated their results using an independent validation set or cortisol response as a correlating biomarker and there was a lack of consensus on data pre-processing and sensor placement as a key contributor to improving model generalization and accuracy.

Conclusion: Low-cost consumer-grade wearable devices, including EEG and wrist-based monitors, are increasingly utilized in stress-related research, offering promising avenues for non-invasive biomarker monitoring. However, significant gaps remain in standardizing EEG signal processing and sensor placement, both of which are critical for enhancing model generalization and accuracy. Furthermore, the limited use of independent validation sets and cortisol response as correlating biomarkers highlights the need for more robust validation methodologies. Future research should focus on addressing these limitations and establishing consensus on data pre-processing techniques and sensor configurations to improve the reliability and reproducibility of findings in this growing field.

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1. Introduction

Stress can be defined as any type of change that causes physical, emotional, or psychological strain. These changes in the environment can trigger a cascade of biological responses in the brain and body [1], known as the stress response, which helps the organism adapt to the dynamically changing external and internal environment. This adaptation is achieved through the mobilization of energy and its appropriate redistribution to organs that serve the adaptational response. While the stress response is adaptive and beneficial in the short term, long-term exposure to stress can have detrimental effects on the body, including an increased risk of developing metabolic, cardiovascular, and mental disorders, which can significantly compromise quality of life and shorten life expectancy [2].

The stress response is initiated by the brain as the different sensory cortical areas receive and process information from the changing environment and distribute them to a variety of cortical areas to initiate the appropriate response. Therefore, stress changes neuronal activity in the whole brain, which can be detected by measuring the electrical activation of the cerebral cortex by EEG [3].

EEG is a widely used technique to estimate changes in neurophysiological activity associated with external stimuli and/or with the performance of specific tasks [4]. This activity is measured via the electrical potential generated by the asynchronous firing of neurons [5] in the nervous system [6] using electrodes placed on the scalp according to the 10-20 international standard [7] (Fig. 1). The 10-20 system was first presented at the 1957 Brussels IV International EEG Congress by Herbert Jasper, to standardize the method of EEG placement. The numbers '10' and '20' refer to the distances between adjacent electrodes, which are either 10% or 20% of the total distance (front-back or right-left) of the skull.

The 10-20 system is based on the relationship between the location of an electrode and the underlying area of the cerebral cortex (Fig. 2). Each site has a letter (to identify the lobe) and a number or another letter to identify the hemisphere location. In 1985, an extension to the original 10-20 system was proposed involving an increase in the number of electrodes from 21 to 74 [8].

EEG waveforms may be characterized based on their location, amplitude, frequency, morphology, continuity (rhythmic, intermittent or continuous), synchrony, symmetry, and reactivity. However, the most frequently used method to classify EEG waveforms is by the frequency band, with the most commonly studied waveforms being delta (0.5 to 4 Hz), theta (4 to 7 Hz), alpha (8 to 12 Hz), sigma (12 to 16 Hz), beta (13 to 30 Hz) and gamma (> 30 Hz) [9]. Common brain states typically associated with different EEG waveform frequencies include concentration (gamma), anxiety dominant, active, external attention, relaxed (beta), very relaxed, passive attention (alpha), deeply relaxed, inward focused (theta) and sleep (delta) [10].

Prior studies [12–14] have utilized physiological measures including heart rate (HR), electrodermal activity (EDA) and salivary cortisol to assess the sympathetic nervous system and Hypothalamic-Pituitary-Adrenal (HPA) axis response to stress. These measures can be influenced by multiple factors including mental stress, and can further be affected by circadian rhythm and physical activity. Functional neuroimaging techniques including EEG have also previously been used to assess the brain's response to stress [4,15,16] by directly or indirectly measuring brain activity. EEG offers high temporal resolution, at the cost of requiring trained neurophysiologists to aid in the interpretation of results.

Although the assessment of cortisol response continues to be the primary indicator for evaluating stress [17], an increasing number of studies are now employing affordable, non-intrusive wearable health monitors and wireless EEG devices as the main tools for recording biomarker data [18–22] that may correlate with stress. This is likely driven by the increasing sophistication and miniaturization of device components at an ever reducing cost.

1.1. Related works

A number of previous survey articles have studied the topics of stress detection using EEG [4,15,16,23,24], and specifically using low-cost EEG or wearable devices [25,26]. Katmah et al. [15] reviewed existing EEG signal analysis methods for assessing mental stress, and concluded that variations in data analysis methods resulted in several contradictory results with regards to frequency band importance. These variations could be due to the study differences in experimental protocols, stressors employed, preprocessing of signals and choice of machine learning algorithms utilized. Newson et al. [23] reviewed 184 studies where EEG was used to study a varying number of mental disorders, and found differences in frequency bands in the resting state condition (eyes open and closed) across a spectrum of psychiatric disorders. They further cautioned against the interpretation of results that considered a single disorder in isolation when analyzing results. While their study focused on mental disorders, the question arises whether similar differences may be relevant to stress-related EEG studies. Hickey et al. [26] in their review on utilizing wearable devices including EEG focused on identifying those devices used to identify depression, anxiety, and stress, but did not analyze machine learning algorithms employed and sensor feature importance most likely to contribute to model generalization. Castro-García et al. [25] reviewed four wearable devices with a focus on analyzing signal quality and battery life.

None of the prior reviews specifically addressed EEG hardware and more specifically, the use of low-cost EEG devices for stress research. While Giannakakis et al. [4] reviewed sensor placement and relative importance, and Katmah et al. [15] addressed the use of machine learning algorithms and signal processing techniques, neither highlighted sensor placement or sensor limitations of low-cost EEG devices when used for stress research, and how this could potentially affect machine learning model performance and the reproducibility of the results reported in stress-related studies.

Towards addressing these questions, we first explore the current state of stress detection and measurement using EEG, with a focus on low-cost EEG devices. We further explore the available public datasets built using sensor data recorded from low-cost EEG devices that could enable future stress research. We review the machine learning approaches employed, and detection accuracy scores attained using low-cost EEG devices. Finally, we discuss the limitations of using such devices combined with machine learning techniques for stress-related studies and suggest several future research directions.

2. Methods

2.1. Research questions

The main aim of this work is to provide an overview of the use of EEG devices for stress detection and measurement when combined with machine learning techniques, with an emphasis on low-cost wearable EEG devices retailing for below USD1000.00. To assist in the assessment of the quality of the included literature, the IJMEDI checklist was utilized. Thus, our research questions can be formulated as follows:

- RQ1: Which low-cost EEG devices are predominantly being used for stress research, and what results are being reported?
- RQ2: Which scalp sensor locations and frequency bands are predominantly used for stress research, and are these physically supported by current low-cost EEG devices?
- RQ3: Which machine learning methods are being utilized in low-cost EEG studies for stress research, and how are the results from these studies validated?

Answering these research questions will aid in gaining a better understanding of the feasibility and potential of using lower-cost EEG devices

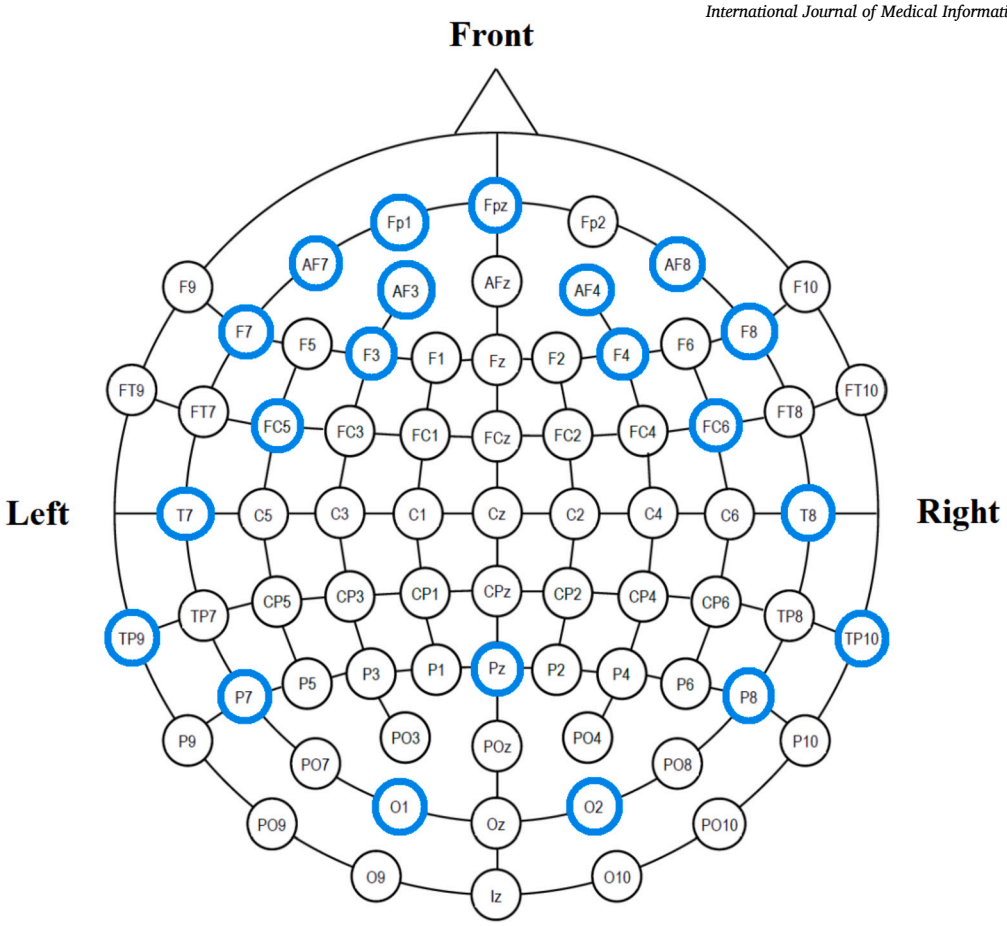

Fig. 1. The 10-20 international standard of EEG sensor placement, with sensor placements supported by devices included in this review indicated in blue. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

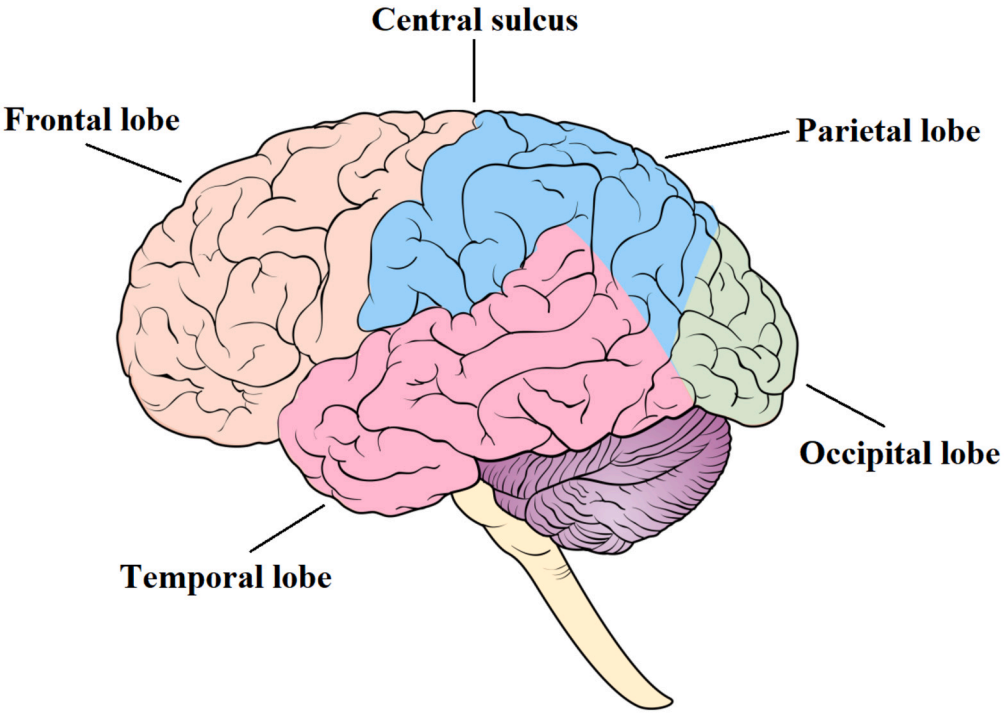

Fig. 2. Anatomy of the human brain [11].

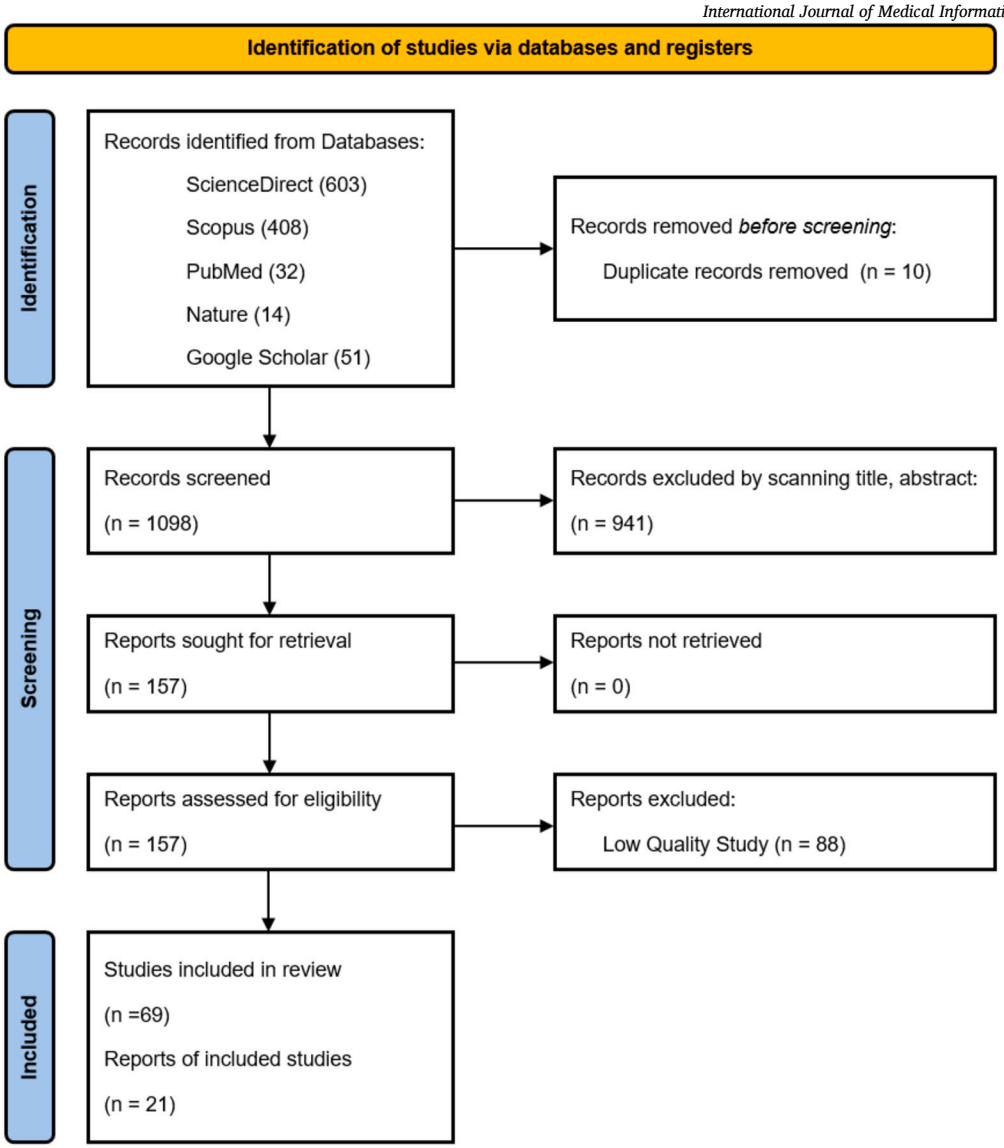

Fig. 3. Article screening process and the intermediate counts.

for stress monitoring, while providing guidance for the most appropriate machine learning algorithms to employ for stress prediction.

2.2. Search strategy

We reviewed key published works (Fig. 3) between 2013 and 2024 on acute stress assessment using EEG signals, and additionally, recorded using low-cost or consumer-oriented EEG devices. The electronic databases of Scopus, Google Scholar, ScienceDirect, Nature and PubMed were searched for relevant articles using the keywords *EEG AND stress AND (wearable OR machine learning)* in the title or abstract, and a total of 1108 papers were found. Duplicates were identified, and 10 were found and removed. Titles and abstracts were scanned and a further 941 irrelevant papers were excluded, including those in which the focus was stress in animals, or the main focus was mental health conditions other than acute stress. A quality review of the remaining papers was performed, with a further 88 removed due to low quality or lack of novelty. As a result, a total of 69 papers were chosen for the systematic review process, to assist in answering the aforementioned research questions.

The selected papers were then grouped by the high-level topics of: *RQ1: Stress Assessment Using EEG*, *RQ2: Low-Cost EEG Devices*, *RQ3: Available Datasets for EEG-based Stress Measurement* and *RQ3: Machine Learning Techniques for EEG-based Stress Measurement*. Table 1 lists, in chronological order, the papers included in this review. We further categorize these papers by study type, i.e. Original Research or Review, and domain, i.e. stress or other mental states. A single study [27] that predates the search criteria (2012) was included in this review due to its popular use as an open EEG dataset and high citation count. To answer the research questions systematically, we have structured our paper as shown in Fig. 4 to cover all the essential topics around utilizing low-cost EEG devices for stress detection using machine learning.

2.3. Assessment of the quality of the studies

Two reviewers (Vos and Rahimi Azghadi) used the IJMEDI checklist [85] to independently evaluate the included studies' quality. The IJMEDI checklist is a quality assessment tool for medical artificial intelligence studies proposed by the IJMEDI, which aims to distinguish high-quality machine learning studies from simple medical data-mining studies. Six dimensions are included as 30 questions in the checklist: problem and data understanding, data preparation, modeling, validation, and deployment. Each question can be answered as OK (adequately addressed), mR (sufficient but improvable), and MR (inadequately addressed). In high-priority items, OK, mR and MR were assigned scores of 2, 1, and 0, respectively, whereas, in low-priority items, the scores were

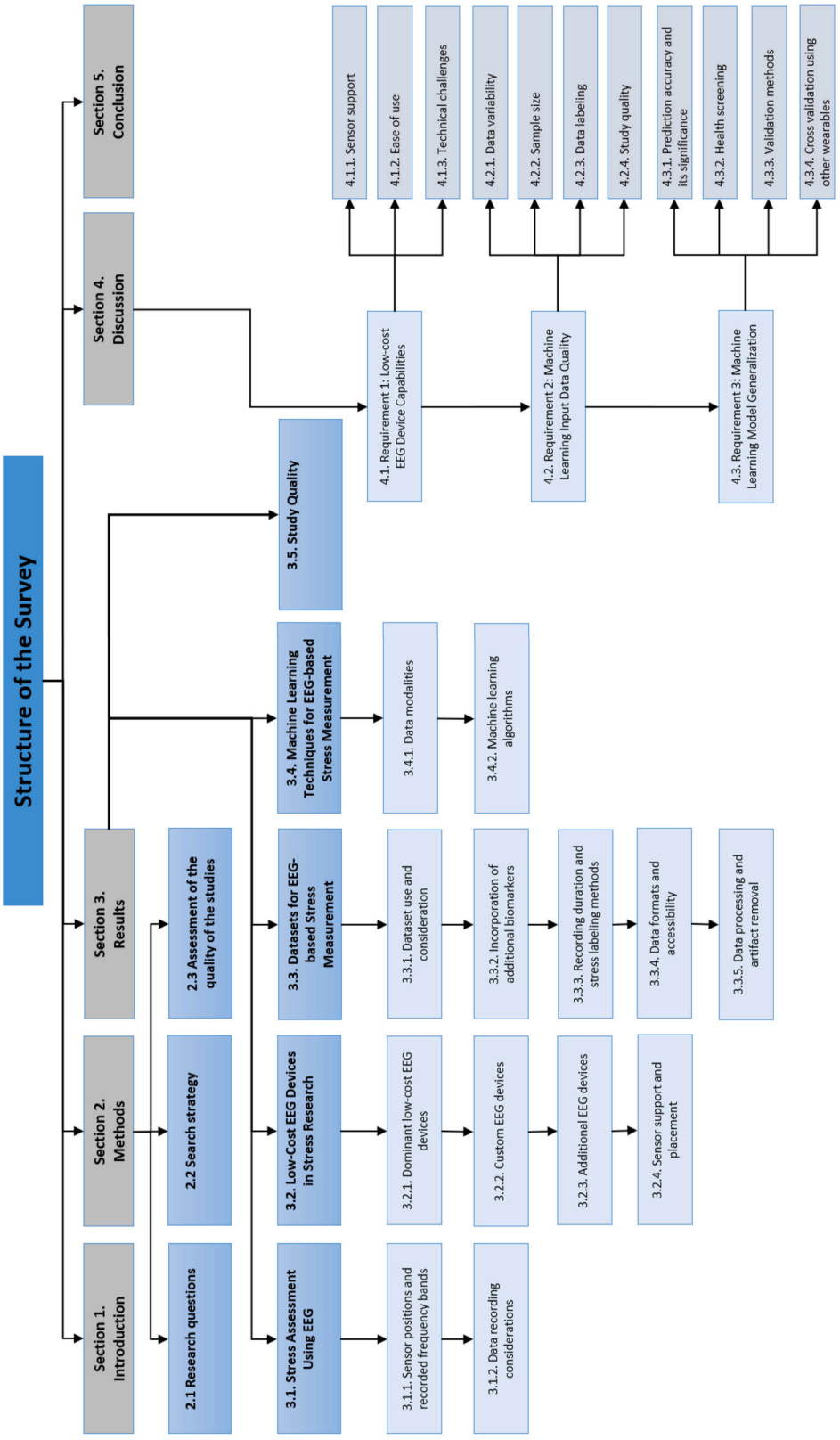

Fig. 4. Survey structure.

Table 1
Studies included in this review.

Paper	Year	Title	Study Type	Domain
[27]	2012	DEAP: A database for emotion analysis using physiological signals	Research	Emotion
[28]	2014	Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness	Research	Stress
[29]	2015	EEG based stress monitoring	Research	Stress
[30]	2015	Automated identification of abnormal adult EEGs	Research	Normal/Abnormal
[31]	2015	Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks	Research	Emotion
[32]	2015	Detection of stress/anxiety state from EEG features during video watching	Research	Stress
[33]	2016	Stress assessment by prefrontal relative gamma	Research	Stress
[34]	2018	Evaluation of an Integrated System of WearablePhysiological Sensors for Stress Monitoringin Working Environments by UsingBiological Markers	Research	Stress
[35]	2018	Selection of neural oscillatory features for human stress classification with single channel EEG headset	Research	Stress
[36]	2019	Multilevel assessment of mental stress via network physiology paradigm using consumer wearable devices	Research	Stress
[37]	2019	A mind-brain-body dataset of MRI, EEG, cognition, emotion, and peripheral physiology in young and old adults	Research	Emotion
[4]	2019	Review on psychological stress detection using biosignals	Review	Stress
[38]	2019	DASPS: A database for anxious states based on a psychological stimulation	Research	Anxiety
[23]	2019	EEG frequency bands in psychiatric disorders: A review of resting state studies	Review	Various
[39]	2019	A Novel wearable EEG and ECG recording system for stress assessment	Research	Stress
[40]	2019	Classification of perceived human stress using physiological signals	Research	Stress
[18]	2020	Stress monitoring using multimodal bio-sensing headset	Research	Stress
[19]	2020	K-EmoCon, a multimodal sensor dataset for continuous emotion recognition in naturalistic conversations	Research	Emotion
[41]	2020	EEG based classification of long-term stress using psychological labeling	Research	Stress
[42]	2020	Stress recognition using Electroencephalogram (EEG) signal	Research	Stress
[43]	2020	PASS: A multimodal database of physical activity and stress for mobile passive body/brain-computer interface research	Research	Stress
[44]	2020	Multivariate correlation measures reveal structure and strength of brain-body physiological networks at rest and during mental stress	Research	Stress
[45]	2020	Database for an emotion recognition system based on EEG signals and various computer games – GAMEEMO	Research	Emotion
[6]	2020	On identification of driving-induced stress using electroencephalogram signals: A framework based on wearable safety-critical scheme and machine learning	Research	Stress
[46]	2020	Detecting fatigue in car drivers and aircraft pilots by using non-invasive measures: The value of differentiation of sleepiness and mental fatigue	Review	Stress
[47]	2020	Dynamic cognitive workload assessment for fighter pilots in simulated fighter aircraft environment using EEG	Research	Stress
[48]	2020	A feasibility study of a complete low-cost consumer-grade brain-computer interface system	Review	Various
[49]	2020	Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review	Review	Emotion
[15]	2021	A review on mental stress assessment methods using EEG signals	Review	Stress
[50]	2021	Evaluating deep learning EEG-based mental stress classification in adolescents with autism for breathing entrainment BCI	Research	Stress
[51]	2021	Performance evaluation of EEG based mental stress assessment approaches for wearable devices	Research	Stress
[52]	2021	Enhancing EEG-based mental stress state recognition using an improved hybrid feature selection algorithm	Research	Stress
[53]	2021	Human stress classification during public speaking using physiological signals	Research	Stress
[54]	2021	Relationship between rework of engineering drawing tasks and stress level measured from physiological signals	Research	Stress
[55]	2021	Monitoring army drivers' workload during off-road missions: An experimental controlled field study	Research	Stress
[56]	2021	A LSTM based deep learning network for recognizing emotions using wireless brainwave driven system	Research	Emotion
[57]	2021	NeuroSense: Short-term emotion recognition and understanding based on spiking neural network modeling of spatio-temporal EEG patterns	Research	Emotion
[58]	2021	A review on transfer learning in EEG signal analysis	Review	Various
[59]	2021	Psychological and physiological effects of a green wall on occupants: A cross-over study in virtual reality	Research	Stress
[60]	2021	Exploring the effects of EEG signals on collision cases happening in the process of young drivers' braking	Research	Stress
[26]	2021	Smart Devices and Wearable Technologies to Detect and Monitor Mental Health Conditions and Stress: A Systematic Review	Review	Stress
[61]	2021	EEG-based multi-level stress classification with and without smoothing filter	Research	Stress
[25]	2022	Towards Human Stress and Activity Recognition: A Review and a First Approach Based on Low-Cost Wearables	Review	Stress
[20]	2022	Assessing electroencephalography as a stress indicator: A VR high-altitude scenario monitored through EEG and ECG	Research	Stress
[62]	2022	A multi-modal open dataset for mental-disorder analysisResearch	Various	
[63]	2022	A multimodal perceived stress classification framework using wearable physiological sensors	Research	Stress
[64]	2022	Evaluating the stressful commutes using physiological signals and machine learning	Research	Stress
[65]	2022	Frontal lobe real-time EEG analysis using machine learning techniques for mental stress detection	Research	Stress
[66]	2022	Stress classification using brain signals based on LSTM network	Research	Stress
[21]	2022	Development of an EEG headband for stress measurement on driving simulators	Research	Stress
[67]	2022	Genetic algorithm-based human mental stress detection and alerting in internet of things	Research	Stress
[68]	2022	Real-time stress analysis affecting nurse during elective spinal surgery using a wearable device	Research	Stress
[69]	2022	Emerging wearable biosensor technologies for stress monitoring and their real-world applications	Review	Stress
[70]	2022	Wavelet based machine learning models for classification of human emotions using EEG signal	Research	Emotion
[71]	2022	Fusion-based learning for stress recognition in smart home: An IoMT framework	Research	Stress
[16]	2022	The neural correlates of psychosocial stress: A systematic review and meta-analysis of spectral analysis EEG studies	Review	Stress
[72]	2023	Cheating detection in E-exams system using EEG signals	Research	Stress
[73]	2023	Automated detection of Alzheimer's disease and other neurophysiological applications based on EEG	Research	Various
[74]	2023	Deep learning framework for classification of mental stress from multimodal datasets	research	stress
[75]	2023	A deep learning approach for assessing stress levels in patients using electroencephalogram signals	Research	Stress
[76]	2023	Brain activity monitoring for stress analysis through EEG dataset using machine learning	Research	Stress
[77]	2023	Comparing online cognitive load on mobile versus PC-based devices	Research	Stress
[78]	2023	An innovative random-forest-based model to assess the health impacts of regular commuting using non-invasive wearable sensors	Research	Stress
[79]	2023	EEG emotion recognition using improved graph neural network with channel selection	Research	Emotion

Table 1 (*continued*)

Paper	Year	Title	Study Type	Domain
[80]	2023	Use of portable devices to measure brain and heart activity during relaxation and comparative conditions: Electroencephalogram, heart rate variability, and correlations with self-report psychological measures	Research	Stress
[81]	2023	The utility of wearable headband electroencephalography and pulse photoplethysmography to assess cortical and physiological arousal in individuals with stress-related mental disorders	Research	Stress
[82]	2024	Contribution of EEG biosignals for Stress Detection	Research	Stress
[83]	2024	The Effect of Stress on a Personal Identification System Based on Electroencephalographic Signals	Research	Stress
[84]	2024	Cognitive Stress Detection during Physical Activity using Simultaneous, Mobile EEG and ECG signals	Research	Stress

halved. The maximum possible score was 50 points, with study quality divided into low (0–19.5), medium (20–34.5), and high (35–50).

3. Results

3.1. Stress assessment using EEG

The use of EEG in stress research relates to its purported sensitivity to localized brain activity in regions involved in the generation of the stress response, or activity associated with increased arousal or specific psycho-emotional states, with the majority of studies supporting the view that in a stressed state there is generally greater frontal right alpha activity in relation to the left alpha activity [4]. Cortisol response magnitude remains the gold standard indicator for stress assessment [17], as cortisol levels quantify the endocrine response to stress [86]. Seo et al. [86] reported a significant positive correlation between the cortisol level and relatively high beta power at both the anterior temporal lobes (Fig. 2), and a tendency toward a similar relationship at one of the occipital sites. Barzegar et al. [87] similarly found salivary cortisol levels increased significantly along with the relative delta band frequency, while the beta bands and, in less amount, the theta and gamma decreased, especially in the frontal region. These effects on the cortisol stress hormone generally peak after about 20–30 min [88].

3.1.1. Sensor positions and recorded frequency bands

Table 2 provides an overview of the studies incorporated in this review, explicitly detailing sensor positions and recorded frequency bands. Among these, five [6,33,44,53,72] focused on alpha waves, ten [20,35,41,53,54,63,65,72,76,78] investigated beta waves, two [43,75] explored delta waves, eight [6,20,33,35,41,43,65,76] examined gamma waves, and four [6,44,63,65] delved into theta frequency. Importantly, Newson et al. [23] in their review of EEG frequency bands in psychiatric disorders noted that it is not always obvious whether changes in particular frequency bands are specific to individual disorders, or whether overlap may exist, limiting clinical diagnosis potential. This finding is of further importance when machine learning classification models are utilized for diagnosis or prediction when such models are trained on datasets containing binary classes, for example, stressed/not-stressed.

3.1.2. Data recording considerations

Fifty-seven of the 69 studies included in this review provided in-depth descriptive detail of the data that were used during experimentation. Of these, 41 (59%) did not provide access to their study data, complicating the ability to easily reproduce study results. The remaining twenty-one studies either published their datasets or used datasets previously made public. Additionally, 46% of the total 69 studies reviewed did not explicitly note health screening before experimentation and data recording. A detailed health screening is of critical importance in order to build an accurate baseline dataset for training machine learning models, and as noted by Newson et al. [23], underlying or undiagnosed mental health conditions can compromise model training if the data from such subjects are erroneously introduced into the baseline dataset.

3.2. Low-cost EEG devices in stress research

Consumer-oriented EEG devices such as the Emotiv EPOC [89] have been present in the market since at least 2010 (Table 3). Most of these devices would be considered low-cost in terms of total cost of ownership, operation and interpretation, given that they are mostly re-usable with supporting software and platforms to assist with interpretation of results. For this review, the scope for low-cost device inclusion was limited to those retailing for less than USD 1,000.00. Typical pricing for the devices included at the time of writing ranged from USD249.99 for the InteraXon Muse 2 (5 sensors) [90], up to USD849 for the Emotiv EPOC (14 sensors). This range was chosen to be comparable to smartwatches with embedded health monitoring sensors that can be used for stress measurement [91].

3.2.1. Dominant low-cost EEG devices

Of the studies included in this review using a low-cost EEG device, 24 used either the Emotiv [6,29,36,38,41,44,45,54,59,77,83], InteraXon [43,53,56,63,66,72] or NeuroSky [19,34,35,42,76,78,80] range of devices [92] (Table 3). Two studies [48,50] utilized the OpenBCI [93] series of devices consisting of an 8-channel OpenBCI Cyton board [93], combined with a low-cost skull cap and electrodes. A lower cost Ganglion board with 4 channels is also available, retailing at USD499.00, compared to the Ganglion board which retails for USD999.00. OpenBCI introduced their EEG Headband Kit in 2022 which can be paired with either the Ganglion or Cyton board. The kit retails at USD279.99.

3.2.2. Custom EEG devices

Three studies included in this review used custom designed EEG devices, mostly built by hand. Lee et al. [18] designed a wearable in-and over-ear bio-metric sensing device that measured EEG and electrocardiogram (ECG) signals simultaneously. They further proposed a novel sensing electrode which is highly conductive, dry and flexible, and designed with portability and comfort in mind during long-term usage. Ahn et al. [39] designed a wearable, two-channel EEG and single channel ECG device that was lightweight and exhibited excellent noise management performance. Affanni et al. [21] designed a six-channel EEG wearable headband that transmits data over WiFi to a laptop, featuring a rechargeable battery with 10 hours of continuous transmission life.

3.2.3. Sensor support and placement

Given the wide range of frequency bands reportedly used for stress research, requiring multiple scalp sensors to cover multiple brain lobes (Table 2), it is important to consider sensor support and placement for low-cost devices. As shown in Table 3, the Emotiv EPOC series of devices provide the broadest range of sensors (14), while the OpenBCI provides the most flexibility in sensor configuration due to its ability to pair with any sensor configuration (up to 16 channels). The NeuroSky Mindwave Mobile 2 device provides a single sensor resting on the forehead above the eye (FP1 position) with a separate reference electrode that is clipped to the left ear. Prior studies have reported the FP1 position to be involved in cognition, working memory and perception [94].

In contrast, wrist and ring based wearable devices used for stress research typically offer a smaller, but more specialized range of sensors including for measuring heart or pulse rate, electrodermal activity, skin

Table 2
Reported sensor placement with frequency band for stress studies included in this review.

Paper	Year	Title	Frontal	Temporal	Central	Parietal	Occipital
[33]	2016	Stress assessment by prefrontal relative gamma	Alpha, Beta, Theta	Alpha	Alpha, Gamma	Alpha	
[35]	2018	Selection of neural oscillatory features for human stress classification with single channel EEG headset	Beta, Gamma				
[41]	2020	EEG based classification of long-term stress using psychological labeling	Beta, Gamma				
[43]	2020	PASS: A multimodal database of physical activity and stress for mobile passive body/ brain-computer interface research		Gamma, Delta		Gamma, Delta	
[44]	2020	Multivariate correlation measures reveal structure and strength of brain-body physiological networks at rest and during mental stress	Theta, Alpha				
[6]	2020	On identification of driving-induced stress using electroencephalogram signals: A framework based on wearable safety-critical scheme and machine learning	Alpha	Gamma		Theta, Alpha	Gamma
[53]	2021	Human stress classification during public speaking using physiological signals	Alpha, Beta				
[54]	2021	Relationship between rework of engineering drawing tasks and stress level measured from physiological signals	Beta	Beta			
[59]	2021	Psychological and physiological effects of a green wall on occupants: A cross-over study in virtual reality					
[20]	2022	Assessing electroencephalography as a stress indicator: A VR high-altitude scenario monitored through EEG and ECG	Beta	Gamma, Beta		Gamma, Beta	Gamma, Beta
[63]	2022	A Multimodal perceived stress classification framework using wearable physiological sensors		Theta, Beta		Theta, Beta	
[65]	2022	Frontal lobe real-time EEG analysis using machine learning techniques for mental stress detection	Theta, Beta, Gamma				
[72]	2023	Cheating detection in E-exams system using EEG signals	Alpha, Beta			Alpha, Beta	
[78]	2023	An innovative random-forest-based model to assess the health impacts of regular commuting using non-invasive wearable sensors	Beta				
[75]	2023	A deep learning approach for assessing stress levels in patients using electroencephalogram signals	Delta	Delta			
[76]	2023	Brain activity monitoring for stress analysis through EEG dataset using machine learning	Beta, Gamma				

Table 3
Low-cost EEG devices included in this review.

Device	Released	Sensors	Data Download?
Emotiv EPOC	2010	AF3, AF4, F3, F4, F7, F8, FC5, FC6, O1, O2, P7, P8, T7, T8	Y
NeuroSky MindWave	2011	FP1	Y
NeuroSky Mindwave Mobile	2012	FP1	Y
Emotiv EPOC+	2013	AF3, AF4, F3, F4, F7, F8, FC5, FC6, O1, O2, P7, P8, T7, T8	Y
InteraXon Muse	2014	AF7, AF8, Fpz, TP9, TP10	Y
Emotiv INSIGHT	2015	AF3, AF4, T7, T8, Pz	Y
InteraXon Muse 2	2018	AF7, AF8, Fpz, TP9, TP10	Y
NeuroSky MindWave Mobile II	2018	FP1	Y
OpenBCI EEG Headband Kit	2022	Up to 8, User-configurable	Y

temperature and a three-axis accelerometer. This leads to more restrictive but simpler device placement and more standardization of sensor types across devices, resulting in less pre-processing during data analysis. Additionally, due to the nature of the recorded biomarkers, data produced by these sensors are simpler to standardize across devices requiring less pre-processing for reproducing prior study results.

3.3. Datasets for EEG-based stress measurement

Datasets that are publicly available (or available upon request) provide researchers with pre-labeled EEG sensor data for experimentation and reproducibility of prior results. Eight publicly available datasets were included in this review (Table 4), of which three (PASS, BrainBodyStress, EDPMSC) [40,43,44] are specifically designed and labeled for stress. Four are labeled for emotion (DEAP, SEED, K-EmoCon, GAMEEMO) [19,27,31,45] and one dataset (DASPS) is labeled for anxiety [38]. Although labeled for emotion, the DEAP, SEED, K-Emocon and GAMEEMO datasets could potentially be utilized for stress research due to measuring states of arousal and valence which are known characteristics of emotional stress [95]. Among the datasets reviewed, the Emotiv EPOC EEG device was the most frequently used. The remaining datasets use a variety of other EEG devices.

The scarcity and limited availability of open-access EEG datasets for stress research (Table 4) sharply contrast with the abundance of datasets available for wrist- and ring-worn wearable devices. This disparity hinders both experimental exploration and the validation of findings. For instance, Aarts et al. [96] developed the Healthy Brain Study (HBS), which includes data from 1,000 participants, featuring biomarker recordings collected via wrist-worn wearables. This dataset emerged from an interdisciplinary, longitudinal cohort study employing multidimensional and dynamic assessments in both laboratory and real-world settings. Consequently, there is a pressing need for a large-scale EEG dataset comprising raw sensor data, annotated for both healthy controls and individuals with varying mental health conditions, including acute stress. Such a dataset would serve as a foundational resource for training machine learning models and advancing EEG-based research.

3.3.1. Dataset use and consideration

Some of the eight datasets included in this review are used more frequently. For instance, seven studies utilized the DEAP dataset [27,57,67,70,74,79,83] for experimentation, while only two used the SEED dataset [31,79]. Parent et al. [43] and Sadoun et al. [84] utilized the PASS stress dataset. Similarly, Alakus et al. [45] designed and utilized the GAMEEMO stress dataset, while Pernice et al. [44] developed the

Table 4
Datasets included in this review.

Paper	Year	Dataset	Device(s)	Biomarkers	Subjects	Gender	Age (Mean)	Health	Condition	Duration
[27]	2012	DEAP	Biosemi ActiveTwo	EEG, GSR, ECG	32	16 F, 16 M	26.9	Y	Emotion (SAM)	15 min
[31]	2015	SEED	NeuroScan	EEG	15	8 F, 7 M			Emotion	5 min
[38]	2019	DASPS	Emotiv EPOC	EEG	23	13 F, 10 M	30	Y	Anxiety (HAM-A, SAM)	3 min
[40]	2019	EDPMSC	InteraXon Muse	EEG	40	20 F, 20 M	24.85	Y	Stress	6 min
[43]	2020	PASS	InteraXon Muse, BioHarness 3, E4	EEG, ECG, EDA, TEMP	48			Y	Stress (NASA-TLX, BORG)	30 min
[19]	2020	K-EmoCon	NeuroSky MindWave, E4, Polar H7	EEG, HR, TEMP, IBI, BVP, EDA	32	12 F, 20 M	23.8		Emotion	10 min
[45]	2020	GAMEEMO	Emotiv EPOC+	EEG	28		23.5	Y	Emotion (SAM)	20 min
[44]	2020	BrainBodyStress	Emotiv EPOC+, Empatica E4	EEG, ECG, BVP	18	5 F, 13 M	25	Y	Stress	30 min

BrainBodyStress dataset. Arsalan et al. [40] collected and curated the EDPMSC dataset. The DEAP, DASPS, PASS, GAMEEMO, BrainBodyStress and EDPMSC datasets specifically noted employing a health screening protocol during dataset development.

3.3.2. Incorporation of additional biomarkers

Four datasets included additional biomarkers to enable extended experimentation (Table 4), including ECG, Galvanic Skin Response (GSR) [27,43,44], environmental Temperature (TEMP) [19,43], HR [19], Blood Volume Pulse (BVP) [19,44], Inter-Beat Interval (IBI) and EDA [19]. For non-EEG biomarkers, the device most commonly used for data recording was the Empatica E4 wrist-worn health monitor [97], commonly used in stress research [12,13,91,98].

3.3.3. Recording duration and stress labeling methods

The recording duration (Table 4) of the datasets included in this review varied from 3 minutes (DASPS dataset) to over 30 minutes (PASS and BrainBodyStress datasets). Stress is not a binary condition, further complicating clinical diagnosis when assessing EEG results. Researchers typically employ several different known methods for labeling or assessing biomarker data including the STROOP Color and Word Test [99,100], utilized in [29,75], the Perceived Stress Scale [101], utilized in [35,41,63], and the State-Trait Anxiety Inventory [102], utilized in [6,66]. Alternatively, researchers may label biomarker data according to relaxation periods and periods where stress is induced, as utilized in [43,44,72,80].

The DEAP dataset [27] recorded a 2-minute non-stressed baseline followed by a 1-minute display of a music video to assess arousal, valence, liking and dominance. This was repeated for 20 trials. The SEED dataset [31] provided a 5-second hint prior to displaying a movie for 4 minutes, followed by a 45-second period to allow for self-assessment via a questionnaire. This was followed by a 15-second rest period, repeated for a total of 15 trials. The DASPS datasets [38] performed a total of 6 trials consisting of a 5-minute baseline, 30-second stimuli, and a 4-minute post-stimuli period during which a self-assessment questionnaire was completed.

The PASS dataset [43] simulated a stressful event through the use of two video games, one being stressful while the other was considered non-stressful. Additionally, this dataset implemented a 2-minute baseline followed by 5 to 15 minutes of game-play, with a 5-minute break between sessions. Two datasets provided short, but well-balanced periods of baseline and stress conditions. The BrainBodyStress dataset [44] used a 12-minute relaxation baseline, followed by a 12-minute sustained attention task and a 7-minute mental arithmetic task, while the EDPMSC dataset [40] used a 3-minute relaxation baseline followed by 3 minutes of public speaking, and a 3-minute post-activity phase.

3.3.4. Data formats and accessibility

The datasets included in this review are provided in a wide range of file formats, including Comma-Separated Values (CSV), MATLAB [103], and the European Data Format (EDF) [104]. Researchers looking to utilize these datasets in their studies are therefore required to use statistical software capable of supporting these formats or develop external conversion scripts. A number of these datasets provided both raw and pre-processed filtered data. Providing raw EEG data, as is the case with the DEAP, K-EmoCon, PASS and GAMEEMO datasets (Table 4), allows researchers to experiment with various pre-processing and filtering techniques to match their experimental requirements.

3.3.5. Data processing and artifact removal

Low-cost, consumer-oriented health tracking and monitoring devices frequently provide a sophisticated software platform with built-in analytics to deliver insights directly to users, often as a paid subscription model. While this is of great benefit to consumers and other non-experts, for researchers this likely implies less control over data processing and artifact removal. The NeuroSky range of devices transmit processed data via a wireless Bluetooth connection to a computer, and offer a wide range of plug-in modules to extend the base software functionality of the device. NeuroSky devices apply a Fast Fourier Transform (FFT) to the raw EEG prior to transmission. For the Emotiv EPOC series devices, baseline removal is applied prior to finite impulse response (FIR) filtering, channel rejection and independent component analysis (ICA) for artifact removal. The InteraXon Muse devices can be configured to provide raw, unprocessed data, while the OpenBCI devices provide raw EEG signals by default.

Pernice et al. [44] performed artifact removal using a high-pass filter (half power frequency of 1 Hz) and a low-pass filter (half power frequency of 20 Hz), followed by power spectral density (PSD) calculation for each EEG signal using a 2-second sliding window with 50% overlap. Hou et al. [29], Suryawanshi et al. [76] and AlShorman et al. [65] applied FFT to extract the mean power spectrum for EEG frequency bands (delta, theta, alpha, beta and gamma), while Majid et al. [63] applied FFT using a window size of 256 with an overlap of 90%. Before applying the FFT, AlShorman et al. [65] filtered the raw signal by using a band pass filter with a cut-off frequency of 0.1–30 Hz, while Suryawanshi et al. [76] applied a band-pass filter at 1 Hz, subsequently followed by a low-pass filter at 50 Hz for artifact removal, a standard practice in EEG signal processing [105].

While artifact removal and filtering techniques are common across all studies reviewed, and are a normal part of EEG analysis, slight differences in algorithmic application and sequence of implementation could potentially hinder the reproducibility of prior reported results [15,23,69,106]; more so when the EEG signals are recorded using different devices. Reproducibility would therefore require the exact step-by-step pre-processing techniques, statistical software, libraries and algorithms on the raw EEG sensor data.

Numerous factors can affect EEG measurement [69] including sensor type, placement, signal processing methods and artifact treatment and removal. In this review, a large and varied number of methods were found to be utilized showing a lack of standardization and no definitive approach to signal processing employed across the studies included in this review. Katmah et al. [15], Safayari et al. [106] and Newson et al.

Table 5
Machine Learning studies included in this review.

Paper	Year	Device(s)	Biomarkers	Algorithm(s)	Accuracy	Subjects	Validation
[29]	2015	Emotiv EPOC	EEG	SVM	85.71	9	5-Fold
[34]	2018	Neurosky Mindwave Mobile, BioHarness 3	EEG, HRV, EDA	SVM	86	15	5-Fold, Cortisol
[35]	2018	NeuroSky MindWave	EEG	SVM	78.57	28	10-Fold
[36]	2019	Emotiv Epoc Plus	EEG, ECG, PPG	SVM, LR, RF	84.3	17	LOSO
[6]	2020	Emotiv EPOC+	EEG	SVM, NN, RF	97.95 (ENS)	86	70/30
[43]	2020	InteraXon Muse, BioHarness 3, Empatica E4	EEG, ECG, EDA, TEMP	SVM	74	48	5-Fold, LOSO
[44]	2020	Emotiv EPOC+, Empatica E4	EEG, ECG, BVP	LR		18	Fisher F-test
[41]	2020	Emotiv INSIGHT	EEG	SVM, NB, KNN, LR, MLP	85.2 (SVM)	33	10-Fold
[61]	2021	RABio w8	EEG	LR, SCM, RF, KNN, MLP	90	20	5-Fold
[53]	2021	InteraXon Muse	EEG, GSR, PPG	KNN, DT, RF, MLP, SVM	96.25 (SVM)	40	LOSO
[50]	2021	OpenBCI	EEG	SVM, CNN, LTSM	93.27 (LSTM)	13	70/30
[65]	2022	Geodesic	EEG	SVM, NB	98 (SVM)	14	3-Fold CV
[63]	2022	InteraXon Muse Headband, Shimmer GSR	EEG, GSR, PPG	SVM, NB, MLP	95 (MLP)	40	LOSO
[66]	2022	InteraXon Muse Headband	EEG	MLP, LSTM	93.17 (LTSM)	40	10-Fold
[75]	2023		EEG	EEGNet	99.45	45	10-Fold
[72]	2023	InteraXon Muse 2	EEG	CNN	97.37	15	70/30
[78]	2023	NeuroSky Mindwave Mobile, MySignals	EEG, BP	RF, KNN, SVM, NB	91 (RF)	45	10-Fold
[76]	2023	NeuroSky Mindwave Mobile	EEG	SVM, KNN, NN	90 (SVM)		70/30
[82]	2024	Neuroelectrics Enobio, BIOPAC MP36	EEG, ECG, EDA	LGBM	86.77	30	5-Fold
[83]	2024	Emotiv Epoc	EEG	SVM	99.67	40	70/30
[84]	2024	Muse EEG, Empatica E4, BioHarness 3	EEG, PPG, TEMP, EDA	LGBM, RF	91	48	70/30

[23] noted critical differences reported with respect to model accuracy and input features between stress-related studies utilizing EEG and suggested the variation could be due to lack of standardization during data pre-processing, feature extraction and experimental setup and duration. Newson et al. [23] further noted differences in band ranges that define each frequency range due to either hardware configuration and limitations or pre-processing implementation during data analysis, ultimately leading to differences in results interpretation.

The absence of a standardized approach to EEG artifact removal, preprocessing, and feature engineering poses significant challenges for replicating studies across datasets and EEG devices, particularly for low-cost devices with limited sensor configurations. Although the MNE package [107] for the Python programming language provides some degree of standardization, studies often omit detailed technical descriptions, further compounded by the frequent lack of publicly available source code. In contrast, progress toward standardization has been more pronounced for non-EEG wearable devices, exemplified by the introduction of the Neurokit package [108] and the early development of the Wearables International [109] packages.

3.4. Machine learning techniques for EEG-based stress measurement

Of the studies included in this review, thirty-none applied machine learning techniques to predict or measure acute stress response. Of these, 21 utilized a low-cost EEG device to record brain activity, as shown in Table 5. The study by AlShorman et al. [65] where a 128-channel EEG device was used, and Bhatnagar et al. [75] study did not report their devices. Both of these studies reported the highest accuracy rates from the thirty studies reviewed and were therefore used as a baseline for comparison to low-cost EEG results reported.

3.4.1. Data modalities

Twelve of the twenty-one studies utilized only EEG data as input to their machine learning algorithms. Nine studies [34,36,43,44,53,63,78,82,84] implemented a multi-modal approach incorporating additional biomarker data from ECG or other health monitoring devices (EDA, GSR, TEMP, BP, PPG). Majid et al. [63] used a signal fusion approach to combine raw EEG from a Muse device with GSR and Photoplethysmography (PPG) signals from additional devices into a single feature set. Additionally, three studies [18,63,74] employed fusion-based architectures to combine the features from EEG with other health monitoring devices.

3.4.2. Machine learning algorithms

The most widely applied machine learning algorithm across the studies reviewed was the Support Vector Machine (SVM) [110] (Table 5). SVM is a linear model commonly used for classification and regression problems in machine learning studies and can solve both linear and non-linear problems by creating a line or a hyperplane to separate input data into separate classes. When applied to stress research, these classes would typically be one of stressed or non-stressed. A number of more advanced techniques were noted in the studies reviewed, however, these were not applied to data recorded from low-cost EEG devices. Bhatnagar et al. [75] utilized EEGNet, a compact convolutional neural network for EEG-based brain–computer interfaces first proposed by Lawhern et al. [111]. Also noted were the use of Spiking Neural Networks (SNN) [57], graph models [79] and the use of genetic algorithms [67].

As detailed in Table 5, twelve studies tested several different algorithms, with the best-performing algorithm shown in the *Accuracy* column. SVM outperformed other algorithms in all but four studies. Of those, two [50,66] utilized a dual-layer Long Short-Term Memory (LSTM) network [112]. The study by Sharif et al. [78] was the only one where a tree-based algorithm provided the highest accuracy of any combination. While Halim et al. [6] achieved their highest accuracy by combining the outputs of SVM, Random Forest (RF) and a Neural Network (NN) through an ensembling (ENS) approach, SVM outperformed both RF and NN before combining the predictions.

Eleven of the twenty-one studies [29,34,35,41,43,61,65,66,75,78,82] validated their results using a K-Fold cross-validation approach, while six [6,50,72,76,83,84] utilized a more traditional train-test split, where 70% of the data was used for training, and the predicted results validated against the remaining 30%.

Of the twenty-one studies listed in Table 5, seven reported the relative importance of the frequency bands used as algorithm input features. Three studies [6,44,75] reported the delta band to be the most important input feature, while alpha was reported by two [44,53], beta by two [53,78], gamma by two [6,43] and theta by a single study [63].

Fig. 5. Study quality assessment based on the IJMEDI checklist. Proportion of the different answers in the high- and low-priority items. OK = adequately addressed; mR = sufficient but improvable; MR = inadequately addressed.

Table 6
Quality assessment scores of the 20 ML-based studies according to the IJMEDI checklist.

	Problem Understanding (10)	Data Understanding (6)	Data Preparation (8)	Modeling (6)	Validation (12)	Deployment (8)	Total (50)
[65]	8	5	4	6	5	1	29
[53]	7	5	2	6	6	3	29
[75]	5	0	0	6	7	0.5	18.5
[6]	8	4	2	6	7.5	2.5	30
[29]	7	4	2	6	7	1	27
[63]	8	2	2	6	7	0	25
[72]	5	0	0	6	7	1	19
[43]	9	4	8	6	9	6.5	42.5
[66]	8	4	1	6	7	0	26
[35]	8	2	2	6	6	1	25
[41]	10	6	4	6	8	2	36
[78]	7.5	2	4	6	6	0	25.5
[50]	8	4	3	6	6	0	27
[76]	2	0	1	6	2	0	11
[83]	6	1	2	6	6	0	21
[34]	8	5	0	6	7	0	26
[82]	6	2	15	6	7	1	37
[61]	8	3	2	6	6.5	0.5	26
[84]	8	2	2	6	9	0	27
[36]	5.5	4	2	6	6	1	24.5

Frontal and temporal lobes were the most reported locations for sensor placement [43,44,75].

3.5. Study quality

The *Supplementary File* details the results of the IJMEDI quality assessment. Table 6 summarizes the scores of each dimension and the total score of each study. The average score of the included studies was 26.6 (range: 11–42.5). Most of the studies were of medium quality, while three [41,43,82] were of high quality.

The majority of the studies lacked quality in the data preparation, validation and deployment dimensions. Fig. 5 shows the proportion of the different answers in the high and low priority items. Importantly, high-priority items were generally well addressed, with clear problem understanding and a very strong focus on machine learning modeling techniques and implementation.

4. Discussion

In order to build a robust machine learning model capable of accurately measuring stress via low-cost EEG sensors, we consider three important requirements. These include (i) EEG devices need to be technically capable of reading signals that correlate with acute stress response; (ii) For classifying stress through machine learning, high-quality training data needs to be available to properly train a classification algorithm; (iii) The resulting trained machine learning model should generalize by accurately predicting for new, unseen data. The discussion of this review is therefore focused on those three key requirements.

4.1. Requirement 1: low-cost EEG device capabilities

Low-cost, wireless EEG devices are generally limited in terms of sensor placement and count (Table 3). Hence, experiments utilizing these devices would be naturally biased towards reporting positive outcomes concerning these scalp locations. The majority of the studies included in this review focused on the frontal, parietal and temporal regions (Fig. 6), likely due to limited device sensor support (Table 3) for central and occipital sites.

4.1.1. Sensor support

Based on the findings of these aforementioned studies, these devices do appear to offer sufficient sensor support for measuring stress. Seo et al. [86] reports close relationships among EEG, ECG, and salivary cortisol indicative of acute stress, with chronic stress particularly associated with high levels of relative beta power, albeit at anterior temporal sites.

4.1.2. Ease of use

Of further importance to researchers when opting to use low-cost, wireless EEG devices are ease of use [6,35,63,72] and acquisition and operational costs [66,72]. A number of studies included in this review noted the mobility and affordability of EEG headsets as a key requirement for their specific study requirements [6,35,63,72,78]. Halim et

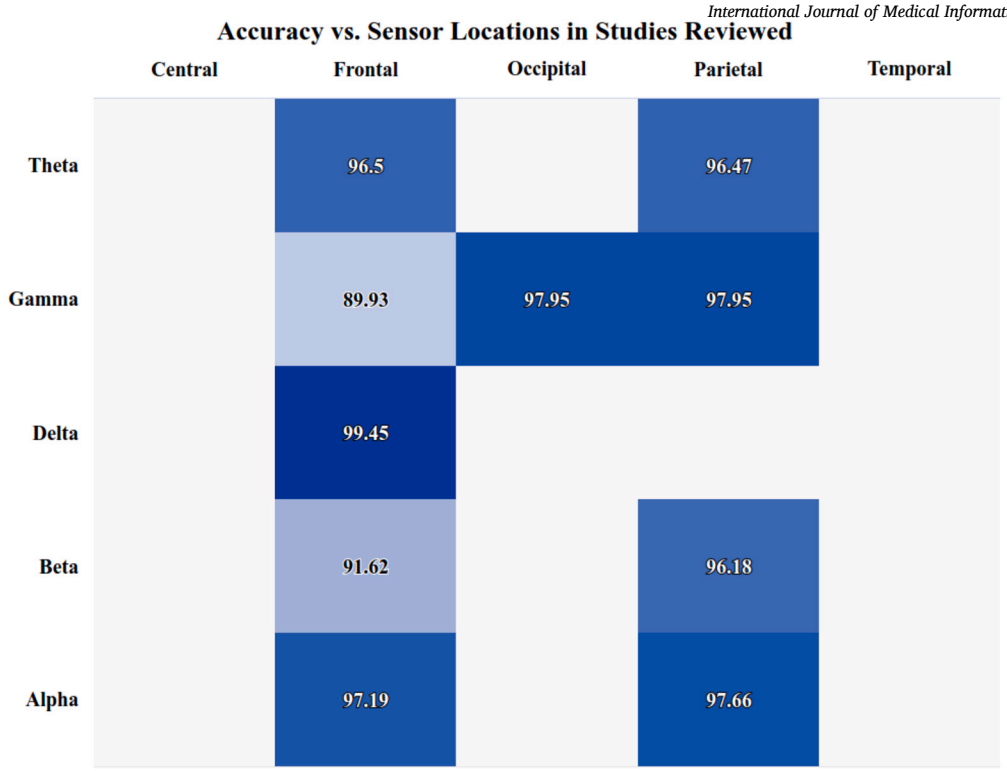

Fig. 6. Frequency band utilization and sensor locations of the low-cost EEG devices reviewed in this study.

al. [6] performed a study to evaluate the feasibility of detecting stress while subjects were driving motor vehicles, while Arsalan et al. [53] performed a study on measuring stress during public speaking. A mobile EEG device was therefore a technical necessity for both studies. However, very few studies have investigated stress detection and measurement in the presence of varying levels of physical activity [43].

4.1.3. Technical challenges

None of the studies included in this review reported any technical challenges, device failure or significant signal quality issues that required additional care or action during experimentation. While there are numerous benefits in using these lower cost EEG devices, researchers need to be acutely aware of any limitations when using such devices. For example, Pernice et al. [44] noted in their study that EEG devices with dry electrode, scalp level connectivity, such as those reviewed in this study, do not permit a perfectly reliable interpretation of interacting brain areas, as they can be corrupted by volume conduction effects or confounding factors.

4.2. Requirement 2: machine learning input data quality

Robust machine learning models require high-quality training data, and a number of datasets are publicly available containing EEG data for experimentation and/or model validation (Table 4). Three of these datasets are specifically labeled for stress, of which the PASS dataset contains the largest sample size and includes additional biomarkers (ECG, EDA, TEMP) that have previously been shown to be useful features for building machine learning models capable of detecting and measuring stress [33,86,91].

4.2.1. Data variability

A key challenge in utilizing these datasets for validation of trained models would be adjustment for differences in device brand and sensor availability. Variation in signal quality or sensor type could hinder a direct data comparison when using both datasets as training and or validation pairs [69], while differentiation in experimental recording protocol could introduce noise into the data [69]. In their review, Katmah et al. [15] highlighted critical differences between research findings and argued that variations in the data analysis methods contributed to several contradictory results.

4.2.2. Sample size

Of the datasets included in this review, most contained data for a small sample size of test subjects, recorded using a number of different EEG devices. Campos-Ugaz et al. [113] noted that almost all EEG studies have small sample sizes, which considerably reduces the generalizability of their findings.

Fig. 7 presents a time-series analysis of accuracy scores reported for machine learning models trained using data from both research-grade and low-cost EEG devices. The accuracy scores are shown as a function of the training sample size. Notably, the highest accuracy of 97.95% when using a low-cost EEG device (Emotiv EPOC+) was achieved using a sample size of 86 participants [6]. However, this study performed internal validation only using a 70%/30% train/test split, without further cross-validation or validation on an external, unseen dataset, raising concerns with regards to model generalization.

4.2.3. Data labeling

Finally, a critical aspect when performing supervised classification using machine learning approaches is accurate data labeling. This refers to the process of marking segments of data to correspond with the expected class, for example stressed or non-stressed. The datasets included in this review all included a baseline period labeled as non-stressed, with an experimental period marked as stressed. The duration of both baseline and experimental periods differed notably across the datasets, with the baseline period often being short, resulting in a class imbalance that researchers will need to adjust for when using these datasets for classification tasks.

4.2.4. Study quality

Having scored the machine learning studies included in this review using the IJMEDI checklist, we found three [41,43,82] of high quality,

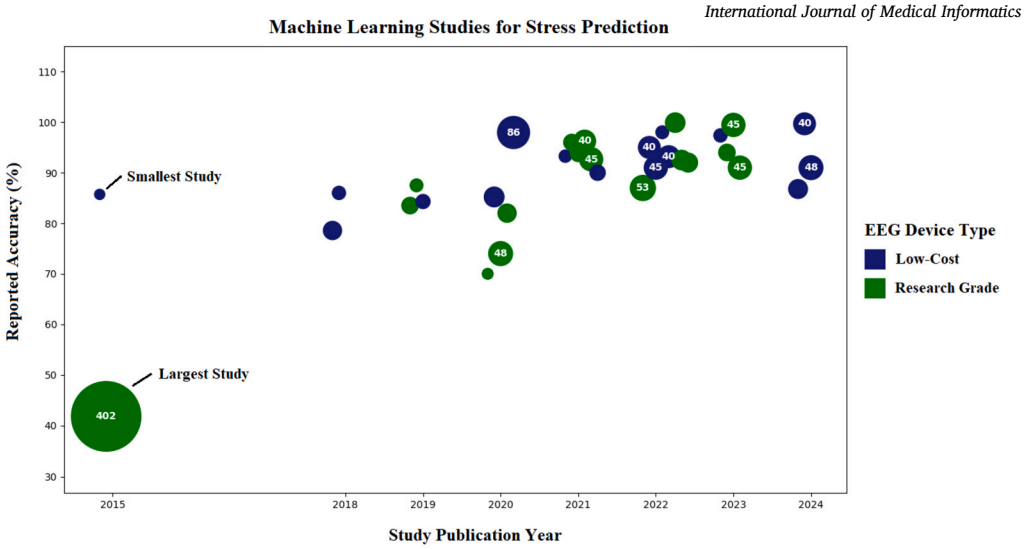

Fig. 7. Reported accuracy scores from machine learning stress studies over time with sample size (bubble size and text).

with fourteen studies being of medium quality [6,29,34–36,50,53,61,63,65,66,78,83,84], and three studies being of low quality [72,75,76]. Most studies scored well in problem, validation and modeling dimensions. Data preparation and deployment scores were notably low, with little focus on the deployment of models in real-life scenarios, including factors pertaining to sustainability, model bias and ethics. For data preparation scoring, the IJMEDI checklist focuses on four key areas including outlier detection and treatment, class balancing, missing-value identification and management and data pre-processing, and lower scores indicate that these items are not described or described in sufficient detail. The highest overall quality score was attained by Parent et al. [43] (42.5), with high scores across all dimensions.

4.3. Requirement 3: machine learning model generalization

When training a machine learning model, researchers need to select the appropriate learning method based on the desired outcome. This outcome could be binary (stressed or non-stressed) or contiguous (level of stress being experienced). All studies reviewed developed a binary model.

4.3.1. Prediction accuracy and its significance

Ten of the twenty-one studies (48%) reported predictive accuracy of more than 90% [6,50,53,63,65,66,72,75,76,78], with the frontal and parietal regions providing the most consistent results across the gamma, alpha and beta frequency bands. However, Newson's et al. [23] analysis of EEG frequency bands in psychiatric disorders emphasized the challenges in determining whether alterations in specific frequency bands are distinct to individual disorders or reflect overlapping patterns. These challenges may limit the utility of EEG frequency analysis for clinical diagnostic purposes.

Fig. 8 illustrates the mean predictive accuracy scores (the number in the bubble) of the 21 machine learning studies reviewed, all of which employed low-cost EEG devices for data acquisition. The marker size represents the number of studies highlighting the significance of specific brain regions and frequency bands. Notably, the beta frequency band in the frontal region was identified as the most commonly reported important feature for machine learning models, followed by the alpha and gamma bands in the same region. These findings may inform future research by guiding the selection of EEG devices with optimal sensor placement for these regions and enabling the engineering of features within these frequency bands.

4.3.2. Health screening

Of the datasets included in this review, three [19,31,40] did not provide extensive detail on health screening of subjects included in their datasets, while a further three noted that subjects were healthy [27,44,45]. Two datasets [38,43] specifically noted that test subjects were health screened specifically for neurological and psychological disorders. The lack of consistent health screening and detailed information on the screening process could potentially affect study reproducibility, and bring into question the high accuracy results reported should undiagnosed mental health conditions be present in the data.

4.3.3. Validation methods

A number of methods were employed for results validation in the studies reviewed (Table 5), including self-scoring questionnaires used as correlation measures against the predicted stress level reported by the machine learning algorithm. Saeed et al. [35,41] used the Perceived Stress Score, while Halim et al. [6] reported using the Self-Assessment Manikins, devised by Bradley et al. [114]. Phutela et al. [66] used the State Trait Anxiety Inventory. Statistical methods were also reported, with Parent et al. [43] validating their findings using a two-way ANOVA test, while Pernice et al. [44] used the Fisher F-Test.

4.3.4. Cross validation using other wearables

Three studies that incorporated signals from external devices to augment their input features [53,63,78] noted a significant correlation between heart rate and the predicted level of stress. Seo et al. [86] specifically reported a correlation between HRV and high beta activity at anterior temporal sites, opening the possibility of combining EEG with other wearable devices such as the Empatica range to cross-validate stress measurement between these devices.

4.4. Summary

The significant observations from this review are:

- Low-cost EEG devices are increasingly being used for mental health related studies, including stress. However, sensor availability and placement differ widely across devices, potentially limiting the reproducibility of results reported from machine learning studies utilizing these devices.
- A small number of datasets are publicly available for researchers to use in stress related studies, including for results validation. However, most studies included in this review did not validate their findings and results on an independent, unseen dataset.

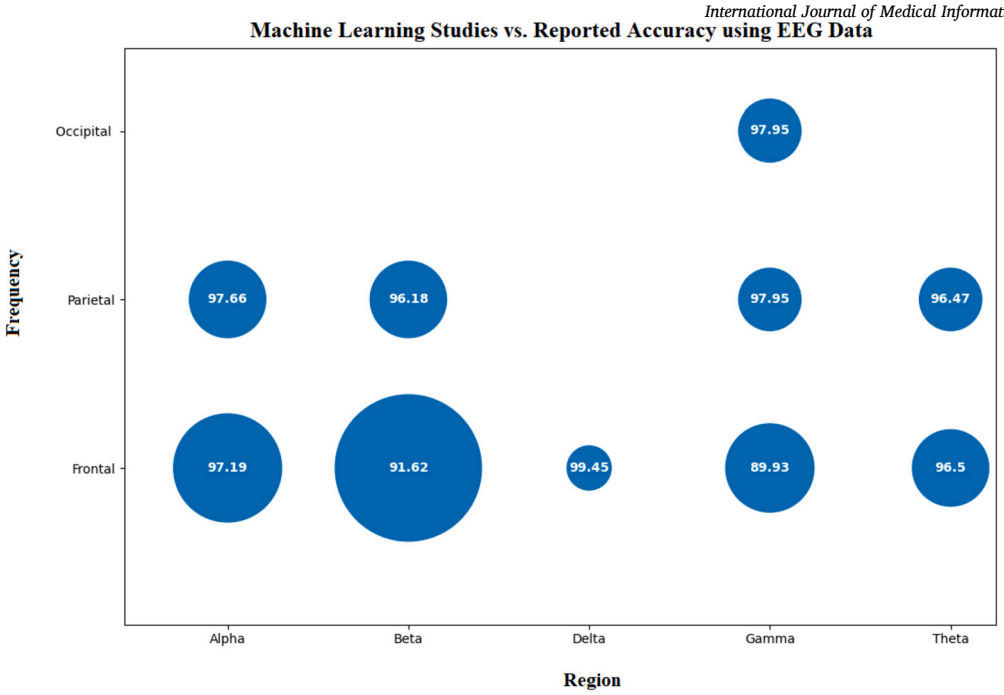

Fig. 8. Machine learning study count (bubble size) vs. reported accuracy (bubble text) per brain region and frequency band.

- None of the studies included in this review sufficiently considered the impact of underlying, undiagnosed mental health conditions on model predictive accuracy. This is especially important when considering the small size of study groups within the studies included in this review.

4.5. Study limitations

This review highlights two primary limitations that may influence its comprehensiveness:

- Firstly, the rapid evolution of low-cost EEG devices and the market for such devices is highly dynamic, with new models and upgraded versions being introduced regularly. As a result, this review could only include devices that were widely used in published studies up to 2024. While this approach ensures the inclusion of devices with established reliability and user adoption, it may inadvertently exclude emerging devices that could offer innovative features or improved performance. Consequently, the findings and recommendations of this review might not fully encompass the latest advancements in low-cost EEG technology.
- Secondly, a notable limitation pertains to the reproducibility of machine learning applications reported in the reviewed studies. None of the studies included in this review provided access to the source code or detailed implementation details of their machine learning models. This lack of transparency hinders the ability of other researchers to replicate the findings or validate the results.

4.6. Challenges and future research directions

To achieve robust and reliable machine learning models suitable for real-world monitoring of stress using low-cost EEG devices, future research should address three formidable challenges:

- The pre-processing of EEG data needs to be standardized to enable cross-device studies with the same machine learning models. Future research can develop a standard framework for dealing with data produced by low-cost EEG devices.
- While several EEG datasets recorded using low-cost devices have been made public, future work can provide larger datasets containing more significant and high-quality baseline (non-stressed) periods along with stressed periods to reduce data imbalance and assist researchers with model training and validation.
- A limited number of the studies reviewed utilized additional biomarkers recorded with non-EEG wearable devices. The use of other wearable devices that record biomarkers including heart rate and galvanic skin response could be further explored in two different ways. One is as a mechanism for validating the findings from stress-related studies, where EEG signals are the primary data-providing mechanism. Another is in a multi-modal approach, where both EEG and wearable biomarkers are used for stress prediction.

5. Conclusion

The main objective in algorithmic stress detection and measurement is to develop a robust, highly accurate model that can provide reproducible results. Low-cost EEG devices can potentially facilitate the development of machine learning models that produce accurate stress measurements and are reproducible across studies, irrespective of the study group or study setting. These devices also hold significant promise for use in disadvantaged or rural communities, where access to sophisticated and expensive EEG systems may be limited, enabling stress detection and management technologies to reach under-served populations. Nonetheless, several important factors should be taken into account. The review presented here synthesized the literature and discussed these essential factors in previous studies. In particular, we reviewed and analyzed the devices available, and their use in stress-related studies using machine learning techniques, while including their advantages, limitations and experimental quality. We also summarized our point of view on the challenges and opportunities in this emerging domain. We believe this review will advance knowledge in the general area of machine learning for stress detection using low-cost EEG devices, helping the research efforts move one step closer to realizing effective stress detection and management technology.

CRediT authorship contribution statement

Gideon Vos: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Maryam Ebrahimpour:** Writing – review & editing. **Liza van Eijk:** Writing – review & editing, Supervision. **Zoltan Sarnyai:** Writing – review & editing, Supervision. **Mostafa Rahimi Azghadi:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors, Gideon Vos, Maryam Ebrahimpour, Liza van Eijk, Zoltan Sarnyai, and Mostafa Rahimi Azghadi, declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijmedinf.2025.105859.

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