



## A Review on Machine Learning for Stress Management

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### Abstract

Stress represents a major global health concern, creating an urgent need for objective, scalable, and data-driven stress management solutions. This review provides a comprehensive and timely synthesis of machine learning (ML) approaches for stress detection, prediction, and management, highlighting their growing importance in healthcare, workplace well-being, and digital mental health systems. A total of fifteen recent peer-reviewed studies employing ML-based data analysis are examined as representative examples to illustrate current methodological trends and practical applications. The review consolidates diverse data sources, including physiological, behavioral, psychological, and multimodal signals, and critically compares traditional ML algorithms with modern deep learning architectures such as CNNs and LSTMs. Methodological aspects, including preprocessing, feature engineering, validation strategies, and evaluation metrics are systematically analyzed to assess rigor and comparability across studies. Beyond predictive performance, the review discusses key challenges related to interpretability, privacy, and ethical deployment. Consequently, this work serves as a pivotal reference, outlining current capabilities and guiding the development of robust, interpretable, and trustworthy ML-driven stress management systems.

**Keywords:** *stress detection, deep learning, psychological distress, healthcare analytics, smart healthcare*

### 1. Introduction

Stress has escalated into a critical global health challenge, driving the need for advanced healthcare management strategies beyond reactive treatment. Significantly, chronic stress impacts cognitive function and physiological health, yet traditional assessment methods, such as episodic clinical interviews and self-report questionnaires, lack the temporal resolution required for effective management (Kehadit et al., 2024; Kumar et al., 2020). This gap has catalyzed the integration of machine learning (ML) into healthcare technology, providing a robust framework for transforming raw sensor data into objective, actionable insights for both real-time stress monitoring and proactive management.

Recent advances in machine learning (ML) have fundamentally reshaped how stress is detected, quantified, and managed, enabling a transition from subjective assessments toward data-driven, continuous, and personalized solutions (Gedam et al., 2025; Giannakakis et al., 2025; Mohammadi et al., 2025; Prinzi et al., 2025; Tariq et al., 2025; Wang et al., 2025). Among the most widely adopted approaches, classification algorithms play a central role in categorizing physiological and behavioral states into discrete stress levels, such as low, moderate, or high stress. Traditional models, including Random Forests (RF) and Support Vector Machines (SVM), remain popular due to their robustness and interpretability, while deep learning architectures, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance when handling high-dimensional and multimodal data (Kanchapogu & Nandan Mohanty, 2025; Wang et al., 2025). These classification frameworks are especially valuable for real-time stress monitoring systems, where rapid detection can trigger just-in-time interventions, such as adaptive feedback or behavioral recommendations. Complementing classification-based approaches, regression models have gained increasing attention for their ability to estimate continuous stress scores rather than categorical labels.

[1]



Techniques such as Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) networks are particularly effective in modeling temporal dependencies and capturing dynamic changes in physiological signals over time. Continuous stress estimation provides a more nuanced representation of an individual's stress trajectory, supporting longitudinal monitoring and the early detection of chronic stress patterns (Ghoshe et al., 2024; Rashed et al., 2025; Simmachan et al., 2025; Wang et al., 2025). This capability is especially relevant in healthcare and occupational settings, where gradual changes in stress levels may precede adverse health outcomes. Beyond supervised learning, unsupervised clustering techniques have emerged as powerful tools for uncovering latent structures within stress-related data. By grouping individuals based on shared physiological, behavioral, or psychological characteristics, clustering methods enable the identification of distinct stress phenotypes or subpopulations. Such stratification supports a shift away from one-size-fits-all interventions toward precision stress management strategies tailored to individual risk profiles and contextual factors. This paradigm aligns closely with broader trends in personalized medicine and digital health. Despite these methodological advances, significant challenges hinder the translation of ML-based stress management from research prototypes to real-world deployment. Model interpretability remains a critical barrier, as clinicians, practitioners, and end users must understand the rationale behind model predictions to trust and act upon them. Black-box models, although accurate, often lack transparency, limiting their clinical acceptance. In parallel, ethical concerns surrounding data privacy, informed consent, and the secure handling of sensitive biometric and behavioral data are increasingly prominent. Addressing these challenges through eXplainable Artificial Intelligence (XAI), robust validation frameworks, and privacy-preserving data practices is essential for ensuring that ML-driven stress management systems are not only accurate but also trustworthy, ethical, and practically deployable.

Overall, this review synthesizes the state of the art in supervised ML-based stress management by examining the complementary roles of classification for detection and regression for continuous scoring, thereby supporting the development of proactive healthcare technologies that address the complex nature of human stress.

## 2. Objectives

The objectives of the study are listed as follows:

- 1) To synthesize the data sources, sensing technologies, and feature modalities commonly used in ML research on stress detection and management.
- 2) To review and compare ML models and analytical strategies applied in stress-related studies, including traditional algorithms and modern deep learning approaches.
- 3) To evaluate preprocessing methods, validation protocols, and performance metrics, identifying the methodological strengths and limitations in the existing literature.
- 4) To examine issues of interpretability, privacy, and ethical considerations in ML-based stress management, and to propose future directions for developing scalable and personalized solutions.

## 3. Methodology

The review followed a structured, multi-stage process to ensure methodological rigor and consistency. First, the scope and objectives were defined by specifying a focus on ML applications in stress detection, prediction, and management. Second, a comprehensive search strategy was developed using combinations of keywords related to stress, physiological and behavioral data, and ML; searches were conducted across major databases, including Scopus, PubMed, Web of Science, IEEE Xplore, and Google Scholar. Third, all retrieved records were imported into a reference manager, and duplicates were removed before proceeding to screening. Fourth, titles and abstracts were systematically screened based on predefined inclusion and exclusion criteria, as presented in Table 1, followed by a full-text assessment of eligible studies. Fifth, data from the final set of studies were extracted using a structured form aligned with the review objectives, covering data characteristics, ML models, preprocessing procedures, validation strategies, and evaluation metrics. Sixth, the included studies were synthesized using a narrative approach due to

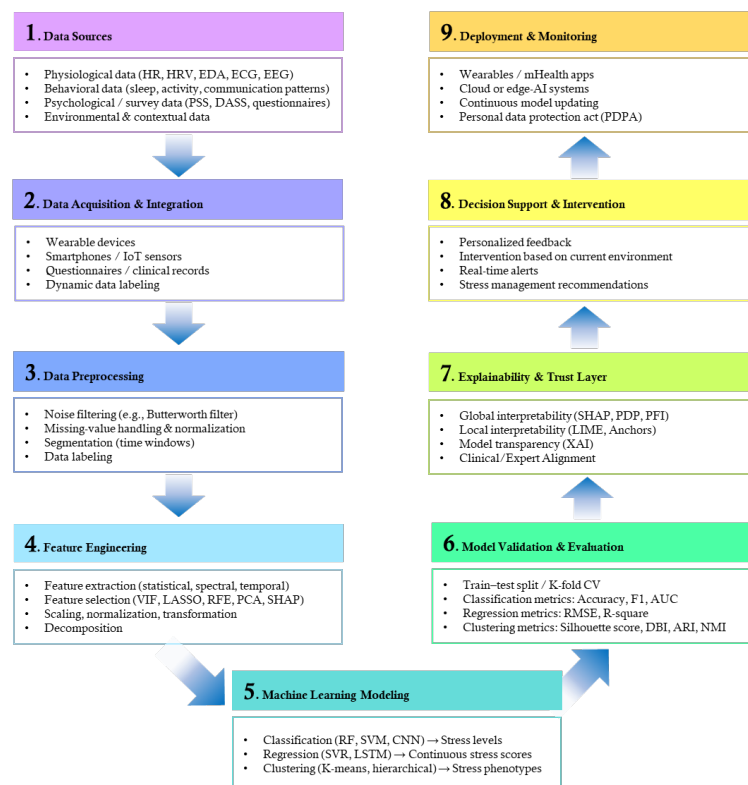
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heterogeneity in data modalities and analytical methods, allowing comparison across sensing technologies, model types, and methodological implementations. Finally, methodological strengths, limitations, and emerging research gaps were identified to inform future directions for developing robust, interpretable, and ethically grounded ML-based frameworks for stress management.

**Table 1** Eligibility criteria for manuscript selection in the review

Inclusion criteria	Exclusion criteria
(1) ML/ DL applied to stress detection, prediction, or management.	(1) Focuses exclusively on non-stress mental health outcomes.
(2) Uses physiological, behavioral, psychological, or multimodal data.	(2) Uses non-ML or only descriptive studies.
(3) Reports data preprocessing, model training, and validation procedures.	(3) Articles lacking essential information on data sources, model development, validation procedures, or performance evaluation, preventing meaningful comparison.
(4) Published as a peer-reviewed journal article or full conference paper in English.	(4) Review papers, editorials, short abstracts, theses, patents, and non-peer-reviewed reports.



**Figure 1** ML framework for stress management

#### 4. ML-Driven Approaches for Stress Management

ML models have emerged as powerful analytical frameworks for stress management, enabling objective detection, prediction, and personalized intervention across diverse contexts. This section reviews key ML approaches applied to stress-related data, encompassing traditional algorithms and advanced deep learning models. Emphasis is placed on data sources, feature engineering strategies, model training, validation procedures, and evaluation metrics. By synthesizing representative studies, methodological trends, practical applications, and current challenges are highlighted in ML-driven stress management systems.

[3]



#### 4.1 Overview

ML is a powerful tool for personalized stress management, leveraging data analysis for timely detection and intervention across various settings. The core function is stress detection and prediction, achieved by analyzing physiological and behavioral indicators (Abd Al-Alim et al., 2024; Al-Atawi et al., 2023; Jandachot et al., 2024). As shown in Figure 1, models utilize data from sources such as heart rate, skin conductivity, and sleep patterns, along with behavioral metrics such as work hours and emails sent. Crucially, ML systems support real-time monitoring via wearables, enabling immediate feedback and timely interventions upon detecting stress spikes (Gedam et al., 2025; Rashed et al., 2025). In workplace stress management, ML models are vital for assessing employee well-being, proactively identifying employees in need of support, thereby helping to maintain a healthy and productive environment. This leads to customized interventions, in which ML systems, sometimes integrated with emotional intelligence algorithms, recommend personalized coping strategies and counseling (Srikanteswara et al., 2024). The technology is also transformative in healthcare and mental health. ML techniques are widely used for mental health monitoring, predicting and facilitating early intervention for conditions like anxiety and depression by analyzing complex data, including speech patterns and activity levels. Research indicates that using hybrid models combining algorithms such as logistic regression, RF, and SVM enhances overall stress detection accuracy (Al-Atawi et al., 2023; Ganai et al., 2024; Kumar et al., 2020).

#### 4.2 Literature Review

The development of effective ML models for stress management follows a structured pipeline, beginning with data acquisition and culminating in real-world deployment. This review examines fifteen recent studies, systematically summarizing their modeling approaches, data sources, validation strategies, and interpretability methods in Table 2 to support transparent comparison and reproducibility. The key methodological components of these studies are discussed below in alignment with this pipeline.

##### 4.2.1 Data Collection

Data collection is a critical initial stage in developing reliable ML models for stress management, relying on a diverse set of sources and methodologies. Primary data collection methods focus on direct, objective physiological and behavioral monitoring. These include physiological measurements captured by wearable sensors, which gather vital signals like heart rate, pulse rate (PPG), galvanic skin response (GSR), and biopotential signals (EEG, ECG, EMG) (Abd Al-Alim et al., 2024; Ghoshe et al., 2024; Rashed et al., 2025). Concurrently, behavioral and motion sensors such as accelerometers, gyroscopes, and magnetometers, embedded in smart devices, track physical movement and stress-related behaviors. Essential subjective ground truth is collected through questionnaire-based assessments, most notably the Perceived Stress Scale (PSS) (Ganai et al., 2024; Kumar et al., 2020), which provides self-reported stress levels crucial for labeling data (Ahmed et al., 2024; Al-Atawi et al., 2023). Additionally, secondary data collection methods significantly aid model robustness. Researchers leverage public datasets like WESAD and MAUS datasets, which offer comprehensive, high-resolution multimodal data for comparative testing (Al-Atawi et al., 2023).

##### 4.2.2 Data Preprocessing

Data preprocessing is a crucial stage in the ML pipeline for stress management, ensuring data quality and preparing it for modeling. The process begins with data cleaning, where handling missing values is performed through techniques such as row deletion or imputation (using mean, median, or mode). This also involves essential noise removal and outlier handling to prevent degradation of model performance. Next, data transformation standardizes the data; normalization scales numerical values to a consistent range, which is vital for algorithms sensitive to feature magnitude, and encoding, such as one-hot encoding, converts categorical variables into numerical formats. The final phase, bridging preprocessing and modeling, is initial feature engineering (Rajeswari, 2025).



**Table 2** Recent prior studies on the application of ML models for stress management

No.	Research Articles	Study Objectives	Samples	Features (X)	Response (Y)	Feature Engineering	Models Used	Validation	Evaluation	Interpret
1.	Kumar et al. (2020)	To assess and classify the severity of mental health issues; To compare various ML algorithms	39,776	DASS-21/42 score	5-level stress severity	Data transformation; Rule-based scoring	Naive Bayes, Bayes Net, J48, Tree/C4.5, OneR, PART, ZeroR, RF	10-fold CV	Acc, ROC, MAE	N/A
2.	Nijhawan et al. (2022)	To detect stress of individuals from posts and comments on social networks	90,000	Contextual embeddings; TF-IDF vectors; Topic	3-level stress severity	Text preprocessing; Topic modeling	BERT, LDA, NB, SVM, RF	80/20	Acc, Pre, Rec, F1, AUC	N/A
3.	Al-Atawi et al. (2023)	To introduce IoT and ML-based system to monitor human stress levels in real-time via wearable devices	2,001	Body temperature; Sweat/humidity level; Step count	3-level stress severity	Rate conversion; Activity context	RF, DT, XGBoost, SVM, KNN	80/20	Acc, Pre, Rec, F1, AUC	N/A
4.	Mahayossanunt et al. (2023)	To detect depression via video-based facial features to prevent Major Depressive Disorder	474	Head pose; Eye gaze angles; Facial action units	Depression (Y/N)	Extraction, Feature fusion, Label smoothing	Transformer, LSTM, Fusion	80/10/10	Pre, Rec, F1	Gradient explanation
5.	Abd Al-Alim et al. (2024)	To create a stress detection ML model for individual with chronic	240	ECG; HRV; EDA; Respiration; Body	2/3-level stress severity from work	Extraction, Power spectral density, Segmentation;	KNN, SVC, DTs, RF, XGBoost	5-fold CV, 70/15/15	Acc, Pre, Rec, F1	N/A
6.	Ghoshe et al. (2024)	To detect stress using supervised ML analysis of HRV from ECG and PPG signals	22	ECG, PPG, Pix-art PPG, GSR	Mental workload level (NASA-TLX score)	Butterworth bandpass filter; Extraction; Notch filter; Low-pass butterworth	RF, DT, LR, Linear Naive Bayes, KNN	70/30, 80/20	Acc, Pre, Rec	N/A
7.	Ganai et al. (2024)	To develop a low-cost, automatic, and high-performing mental stress detection model	200	ECG, GSR, Skin temp.	Stress (Y/N)	Normalization, Label encoding	KNN, SVM, DTs, RF, AdaBoost, Gradient Boosting, XGBoost	10-fold CV	Various acc.	N/A
8.	Giannakakis et al. (2025)	To develop a non-invasive stress detection system using facial video	58	Facial action units	Stress (Y/N)	Extraction, Parewise transformation, Encoding, Normalization, Synthetic approx..	KNN, NVB, LDA, ODA, SVMs, DTs, XGBoost, CNN	10-fold CV	Acc, Sen, Spe	SHAP
9.	Kanchapogu & Nandan Mohanty (2025)	To detect depression and determine the bipolar status using behavioral and demographic data.	1,000	Demographic; Education; Lifestyle; Health	Bipolar (Y/N)	Normalization, Label encoding	Bagging, Boosting, Naive Bayes, SVM, RF	80/20, 3-fold CV, 5-fold CV	Acc, Pre, Rec, AUC	SHAP, Grad-CAM
10.	Mohammadi et al. (2025)	To identify key risk factors of mental health in adult males	400	Dietary; Demographics; Lifestyle; Clinical	Mental health status: Norma/ Disorder	Normalization, Label encoding	Naive Bayes, SVM, RF	70/30	Acc, Spe, AUC	N/A
11.	Prinzi et al. (2025)	To predict DASS severity via explainable ML models based on handwriting and drawing analysis.	200	Time/velocity, Ductus, Space, Pen inclination	Mental health status: Norma/ Disorder	N/A	XGBoost	10-fold CV	Acc, Sen, Spe, AUC, PPV, NVP	e-LEN, SHAP
12.	Rashed et al. (2025)	To build a low-cost, single-PPG stress detector that extracts respiration without extra sensors.	32	PPG signal; Heart rate; Respiratory rate	Stress (Y/N)	Butterworth bandpass filter; Segmentation; Extraction; Labeling	Naive Bayes, AdaBoost, SVM, KNN, GBC	75/25	Acc, Sen, F1, MSE, RMSE	N/A
13.	Simmachan et al. (2025)	To predict psoriasis DLQI using clinical and stress factors via advanced ML and penalized	149	Demo, Clin; Stress	DLQI continuous score	Penalized regression	MLR, Penalized Regression Models, RF, SVR	70/30	R-square, RMSE, MAPE	SHAP
14.	Tariq et al. (2025)	To build a low-cost, explainable stress classifier for students based on surveys.	1,100	Psychol, Physio, Social, Envi, Academic	2/3-level stress severity	Normalization, VIF	Logistic Regression, SVM, DTs, RF, Gradient Boosting, XGBoost	5-fold CV	Acc, Pre, Rec, F1	SHAP, XAI
15.	Wang et al. (2025)	To propose PhysioFormer for accurate, explainable affective state prediction using multimodal signals and symbolic regression.	15	BVP, EDA, EMG, ECG, RESP, Body temp	3-level stress severity	Denosing, Segmentation, Extraction	RF, SVM, KNN, AdaBoost, DTs, LDA, CNN, RNN, LSTM, PhysioFormer	Leave-one-out	Acc, Pre, Rec, F1, Sen, Spe, MSE	Symbolic regression



This step involves Feature Selection, where techniques like recursive feature elimination (RFE) and LASSO identify the most relevant subset of features to reduce complexity and boost accuracy (Maurya et al., 2023; Simmachan et al., 2025; Srikanteswara et al., 2024). Simultaneously, feature extraction creates new, more predictive variables from existing data, enhancing the model's ability to learn stress patterns effectively.

#### 4.2.3 Feature Engineering and Selection

Feature engineering and selection are critical processes in developing effective ML models for stress management, primarily serving to improve model performance and interpretability. Their importance stems from the need for dimensionality reduction, which mitigates overfitting and decreases computational cost by eliminating redundant features, and for Improved Model Accuracy in stress classification. Furthermore, transforming raw data into meaningful features enhances model Interpretability (Giannakakis et al., 2025; Prinzi et al., 2025), crucial for designing effective interventions. Various techniques are employed, including Filter-Based Methods like Information Gain and Mutual Information for ranking feature relevance. Wrapper-Based Methods include iterative Recursive Feature Elimination (RFE) and Greedy Stepwise Search, which optimize the feature subset using a classifier. Embedding-Based Methods utilize techniques such as Principal Component Analysis (PCA) for dimensionality reduction (Maurya et al., 2023; Asemi et al., 2026) or leverage Convolutional Neural Networks (CNNs) (Mahayossanunt et al., 2023; Wang et al., 2025) for combined feature selection in complex datasets. Finally, Ensemble Methods like High-Level Ensemble Feature Selection (HLE-FS) combine multiple approaches for greater robustness. These methods are directly applied to enhance Stress Classification accuracy and provide valuable insights for Mental Health Assessment.

#### 4.2.4 Model Training and Hyperparameter Tuning

Training a model is a multi-step process for stress management that involves fitting data to various ML algorithms, commonly including Random Forest, Support Vector Machines (SVM), Decision Trees, Gradient Boosting, and XGBoost (Ganai et al., 2024; Srikanteswara et al., 2024), to classify stress levels effectively. Following the initial training, hyperparameter tuning becomes a critical optimization phase to select the best unlearned parameters, significantly enhancing model accuracy and performance metrics. Tuning techniques range from the simple but computationally expensive Grid Search and the more efficient Random Search to advanced methods like Bayesian Optimization, Genetic Algorithms, and Particle Swarm Optimization (PSO) (Gedam et al., 2025; Rajeswari, 2025), which intelligently explore the parameter space. These optimized models are applied extensively in stress management: for student stress classification based on factors like sleep quality, and in mental health monitoring using SVM and physiological data from wearables for real-time detection. Furthermore, tuning improves predictive accuracy in healthcare applications, such as cardiovascular disease prediction. The effectiveness of this tuning is rigorously evaluated using standard performance metrics, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC, to ensure the model robustly distinguishes between stress states.

#### 4.2.5 Model Evaluation and Deployment

Evaluation metrics ensure the accuracy, reliability, and real-world applicability of stress management models. Performance is assessed using key metrics like accuracy, precision, recall, and F1-score, with models like Gradient Boosting demonstrating strong performance. To guarantee robustness and generalizability, cross-validation is widely utilized (Ganai et al., 2024). Evaluation also involves comparing algorithms like RF, SVM, and Gradient Boosting, and confirming that effective feature selection and engineering (using RFE or Boruta) were performed, as combining features like ECG and PPG has demonstrably improved accuracy. Regarding Table 2, the majority of the research focuses on classification models, with only a small number of studies utilizing regression to analyze continuous outcomes. For classification, the GBM achieved the highest performance metrics, with an accuracy and an F1-score of 99.77% (Rashed et al., 2025). Other notable high-performing classification models include the RF by Al-Atawi et al. (2023) and the PhysioFormer by Wang et al. (2025), both of which reported accuracy and F1 reaching 99%. In regression-based studies, performance is typically measured through variance explained;

[6]



for instance, the RF model by Ganai et al. (2024) reported  $R^2$  values of 0.65 for stress and depression. Similarly, Simmachan et al. (2025) employed an RF regression model that yielded an  $R^2$  value of 0.53, reflecting the different evaluative approach required for non-categorical data. Model deployment focuses on making these models practical for real-world use. This involves integration with wearable devices for real-time stress monitoring and leveraging cloud computing for real-time processing and enhanced scalability, crucial for timely intervention (Ramzan et al., 2024; Rashed et al., 2025). SHapley Additive exPlanations (SHAP) and eXplainable Artificial Intelligence (XAI) are crucial for stress management because they provide transparent, interpretable predictions, enabling clinicians and users to understand stress drivers, build trust, and support ethical, personalized interventions (Boonkrong et al., 2025; Yang et al., 2025). Successful deployment also necessitates user-friendly interface and effective feedback mechanisms to deliver actionable, personalized stress management strategies. Finally, strict attention must be paid to ensuring that sensitive health data is handled securely and transparently (Liu et al., 2024). In an ML-driven stress management system, the model's role is to detect and alert, but it cannot replace clinical diagnosis. Knowing when to step away from the app and seek a professional (healthcare provider or psychologist) is a critical part of the feedback loop.

#### 4.3 Benefits of ML in Stress Management

ML offers significant advantages in stress management by focusing on individualized and timely care. A primary benefit is personalization, where ML models analyze individual-specific data to provide tailored stress management solutions, thereby enhancing the overall effectiveness of interventions. Coupled with this, ML enables a proactive approach to mental health (Lotfi et al., 2025; Tariq et al., 2025). By facilitating the early detection of stress, these systems allow for timely interventions, preventing the escalation of acute stress into more serious mental health issues. Furthermore, the use of advanced ML algorithms and sophisticated hybrid models directly contributes to enhanced accuracy in stress detection and prediction, ensuring that the personalized and proactive interventions are based on reliable and precise data analyses (Ganai et al., 2024a; Kumar et al., 2020). Deep learning (DL) architectures, particularly CNNs and LSTMs, demonstrate superior performance by autonomously learning hierarchical representations from raw, high-dimensional multimodal signals (Kanchapogu & Nandan Mohanty, 2025; Krishna et al., 2026; Wang et al., 2025). By leveraging backpropagation, these models identify non-linear spatio-temporal correlations that traditional methods may overlook. However, their deployment is often hindered by high inference latency and large memory footprints, posing challenges for real-time processing on resource-constrained wearable hardware. Conversely, classical machine learning algorithms, e.g., SVM and RF, offer distinct advantages in energy efficiency and interpretability. Consequently, while DL excels at capturing complex temporal dependencies, classical ML remains indispensable for edge-computing applications where resource optimization and physiological grounding are critical.

#### 4.4 Challenges

Despite its promise, implementing ML for stress management faces several challenges. High-quality physiological and behavioral data are required, yet individuals often produce noisy, incomplete, or inconsistent data due to device limitations or irregular usage. Ethical concerns, particularly privacy, consent, and the secure handling of sensitive mental health information, must also be carefully addressed. Model generalizability poses another constraint; stress responses vary widely across individuals, cultures, and contexts, making it difficult for a single model to perform equally well for everyone. Resource constraints, such as limited battery life and computational power on wearable devices, further restrict real-time processing. To make ML solutions feasible and suitable, hybrid approaches using edge computing, federated learning, and lightweight models can balance accuracy and efficiency. Using validated wearables, standardized data collection protocols, and interpretable ML methods can also improve trust and adoption. Collaboration among clinicians, data scientists, and technology developers is essential to ensure practical, safe, and user-centered implementation.



#### 4.5 Opportunities

ML offers significant opportunities to transform stress management by enabling personalized, real-time, and data-driven interventions. ML models can analyze diverse physiological and behavioral signals, e.g., heart rate variability, sleep patterns, physical activity, voice tone, and smartphone usage, to detect early signs of stress with high accuracy. These insights allow for tailored recommendations, ranging from breathing exercises to lifestyle adjustments. The integrating ML with wearable technologies, such as smartwatches, biosensors, and EEG headbands, enhances continuous monitoring and enables adaptive response systems. Mobile health (mHealth) applications equipped with ML-powered chatbots can deliver instant coping strategies, mood tracking, and cognitive-behavioral support (Ramzan et al., 2024). Cloud computing and edge AI technologies make it feasible to process large-scale data securely and efficiently. Furthermore, virtual reality (VR) and augmented reality (AR) platforms can incorporate ML to provide immersive stress-reduction environments customized to individual stress profiles. Together, these technologies offer a powerful ecosystem for proactive and personalized stress management.

#### 5. Conclusion

This review demonstrates that ML models hold substantial promise for advancing stress management through early detection, continuous prediction, and personalized intervention. By synthesizing evidence from fourteen recent peer-reviewed studies exemplifying ML-based data analysis, the review highlights how stress can be effectively modeled using a combination of physiological indicators (e.g., heart rate variability, skin conductance) and behavioral or contextual data (e.g., sleep patterns, work activity, communication behavior). Across these studies, traditional algorithms such as RF and SVM, as well as modern deep learning models, have consistently shown strong performance in stress classification and prediction tasks. Applications of ML for stress management span multiple domains. In workplace settings, ML models support organizational decision-making by identifying stress-related risk factors and vulnerable employee groups. In educational contexts, predictive models help detect student stress early, enabling targeted and timely interventions. In healthcare, ML contributes to the prediction of stress-related conditions and supports preventive and personalized care pathways. Despite these advances, challenges remain, particularly regarding data quality, heterogeneity, and the integration of multimodal data sources. Future research should prioritize robust multimodal frameworks, combining physiological, psychological, behavioral, and environmental data. Equally important is the adoption of XAI techniques, such as SHAP, to enhance transparency, trust, and clinical interpretability. Continued progress in real-time monitoring and ethical deployment will be essential for translating ML-based stress management from research into practice.

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