Artificial Intelligence–Enabled Stress Detection and Mental Well-Being Interventions: A Comprehensive Review

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Abstract

Stress and mental health issues have emerged as a pressing problem on work-places, educational institutions and hospital systems globally. The emergence of powerful AI/ML/DL, wearable sensing technologies, and digital mental health platforms have paved the way for continuous, personalized, and scalable systems for stress detection and intervention. In this paper, we provide a detailed survey of recent literature (2023–2025) in AI solutions for stress detection & monitoring and interventions that promote mental well-being. This review collects insights of systematic reviews, bibliometric analyses empirical studies and emerging frameworks for combining Internet of Things (IoT) devices and large language models (LLMs). Comparative analyses of datasets.

Keywords: Artificial Intelligence, Stress Detection, Mental Health, Machine Learning, Wearable Sensors, Digital Interventions.

I. INTRODUCTION

Stress is one of the most significant psychosocial problems of the twenty first century that affects people in different environments, such as the workplace, classroom, and medical institutions. The world has become a significant amount of stress due to the high rates of industrialization, digitalization, performance pressures, work insecurity, and breaking the borders between work and home [1], [2], [9]. Some of the adverse mental and physical health consequences that are highly attributed to the long-term exposure to stress include anxiety, depression, burnout, cardiovascular issues, cognitive impairment, and poor job safety [3], [10], and [14]. Thus, stress management and mental health are now put in the center of attention of corporations, legislators, and researchers.

Some demographic groups suffer stress especially. In the long-term bibliometric and empiric research, it was found that work-life imbalance, role conflict and expectations of society often lead to the accumulation of stress in women professionals [1], [2]. Similarly, the predisposition to high responsibility expectations, emotional labour, and compassion fatigue have an impact on healthcare workers, educators, mentors, and entrepreneurs, which decreases the level of psychological resilience and increases the possibility of burnout [7], [13], and [14]. Students of higher education are especially susceptible due to competitive environments and academic pressure and uncertainty [4], [12]. These results demonstrate the need to have stress monitoring and intervention systems, which are inclusive and sensitive to the context.

The traditional methods of assessing stress include self-report questionnaires, interviews, and routine examinations by the clinicians. Although these methods are very common, they have several limitations including subjectivity, biases regarding recollection, inability to capture the dynamics of stress in a temporal manner, and inability to capture real-time stress dynamics [15], [17]. Moreover, the conventional treatments are often resource-consuming, proactive, and difficult to expand to large groups of people. Such limitations have triggered the studies of active, technology-based mechanisms of continuous stress tracking and psychological support.

Recent advancements in artificial intelligence (AI), machine learning (ML), deep learning (DL), the Internet of Things (IoT), and wearable sensing technologies have made a paradigm change in stress and mental health management possible. To better measure the level of stress, AI-related systems will have an opportunity to analyze physiological measurements such as heart rate variability, electrodermal activity, electroencephalography, and behavioural patterns [15]-[18]. The ability to be robust in real-world scenarios has also been supplemented with the implementation of multimodal data sources and context-aware analytics [16], [18].

Concurrently, digital mental health applications and mobile-based applications have been demonstrated to be effective in offering scalable and low cost therapies of stress management [10], [14].

Large language models (LLMs) and conversational AI have become more recently, and they present fresh possibilities of personalized and adaptable mental health care. LLM-enabled systems are capable of enhancing user interaction and providing early intervention with the help of attaching natural language explanations, contextual information processing, and providing users with personalized coping strategies [3], [5].

In order to gain an understanding of existing trends, abilities, and constraints of AI-facilitated stress detection and mental disorders, it is essential to synthesize recent studies thoroughly. Having an focus on the AI-based approaches to stress detection, the digital intervention strategies, and the organizational implications, this article makes a critical analysis of the recent studies published in the period of 2023-2025. The paper proposes generic designs of intelligent stress management systems as well as provides comparative research of datasets, sensors and algorithms. The review will serve as an inclusive resource to scholars and professionals interested in obtaining ethical, human-centred, and scalable AI solutions to mental health.

II. LITERATURE SURVEY

The literature on stress and mental health has been developed quite significantly over the last several decades, and the aspect of applying digital technologies, machine learning, and artificial intelligence (AI) to detect and intervene with stress has gained more attention. In this segment, the researcher will provide an in-depth review of past studies grouped into key themes that are relevant to this study.

A. Work-Life Balance and Work Stress.

Work-life balance has also been identified to have a significant effect on occupational stress and mental health on numerous occasions. Baba et al. [1] used a method of the systematic literature review and bibliometric analysis over five decades, and identified some of the inherent gender differences in work-life balance especially in women professionals. Their results show that organizational culture, rigid work arrangements, and unequal care giving roles play a major role in chronic stress.

Chandrasekaran et al. [2] found that the key causes of stress among the working women in the Indian workforce in both the public and the private sectors were workload, role ambiguity, job instability, and the lack of managerial support. Such findings argue the need to have proactive stress monitoring systems over reactive ones and are aligned to more broad organizational stress models.

Corporate environments are not the only environments in which there is occupational stress. The studies of mentors, educators, and healthcare workers report high levels of emotional tiredness and compassion fatigue. Paleri et al. [7] conducted a systematic review of the literature on digital staff support interventions to support healthcare workers and pointed out the increased rate of burnout caused by emotional labour, excessive working hours, and shortage of personnel. Similarly, Lecanuel and San Jose [13] concluded that the psychological resilience of mentors was lower, highlighting the emotional toll of the long-term caring and mentoring duty.

B. Stress among maturing students and in Schools.

Academic stress has received increased attention due to the increased concerns by students regarding their mental health. In a study by Ovi et al. [4], the authors demonstrated the importance of using physiological data in conjunction with behavioural and environmental factors to identify stress in students, by means of a context-sensitive machine learning model. According to bibliometric analysis by Basha et al. [12], AI-based mental health research in the group of college students has quickly grown, particularly following the COVID-19 epidemic. All these studies present the need of continuous non-invasive stress monitoring systems in learning settings.

C. Stress Detection using AI and Machine Learning.

A sufficient amount of literature exists on the application of ML and DL algorithms to stress detection based on physiological cues. Lakshmanan et al. [15] conducted a systematic review and meta-analysis on ML- and DL based stress detection methods and in their study, the multimodal strategies, including heart rate variability, electrodermal activity, EEG, and breathing signals, outperformed single sensor system systems. The scientists did however, also mention problematic imbalanced datasets, lack of standardization as well as lack of external validation.

Liu et al. [17] studied the limitations and challenges of stressed monitoring with the help of physiological measurements in detail and investigated the issues of inter-individual differences, sensor noise, and overfitting. Kallio et al. [18] highlighted the importance of the context awareness and long term data collection in practical application of sensor based stress monitoring methods used in knowledge work environments in their comprehensive analysis of the topic.

D. Wearable Devices, IoT and Real-Time Monitoring.

With wearable technology and integration into IoT, it is now possible to constantly monitor stress beyond the laboratory environments. Paniagua-Gomez and Fernandez-Carmona [16] have outlined the role of edge computing and IoT architectures in the design of scalable and responsive systems in their overview of the prevailing trends in real-time stress detection and modulation. Amiri et al. [19] discussed the bigger concept of the Internet of Behaviours and demonstrated how, by adapting and providing feedback, ML-driven personal health apps could influence behaviour changes that are stress-related.

Although these have happened, wearable technology poses a challenge to the user acceptability, energy usage, and data privacy. These limitations manifest the need of privacy-saving analytics and lightweight models.

E. Large Language Models and Advanced AI to Mental Well-Being.

The application of large language models (LLM) to mental health-related applications has recently become a topic of study. As demonstrated by Hasan et al. [3], combining ML-based stress detection and LLM-driven analysis enhance early occupational stress and promote workplace safety. Neupane et al. [5] introduced a wearable-based LLM chatbot system, which provides customized stress therapy, which showed more user interaction with the support of conversations.

At the same time, ensemble and hybrid AI models have been proposed to forecast mental health. Ahmmed et al. [6] developed a stacked ensemble approach to depression prediction among professionals and proved the idea that it is possible to combine multiple classifiers to be more accurate and resilient.

F. AI-Assisted Digital Mental Health Interventions and Emotions.

Digital mental health therapies have proven to promise positive results in reducing stress and improving wellbeing. Freund et al. [10] conducted a randomized controlled experiment that revealed that a generalized digital intervention of stress management is effective and cost-effective to workers. A meta-analysis by Brinsley et al. [14] shows that digital lifestyle treatments can significantly reduce the symptoms of stress, anxiety, and depression in numerous groups of people.

To ensure that mental health care is provided in a structured and personalised way, emotional AI systems also including the cognitive behavioural therapy (CBT) concepts have become more popular. Pawar et al. [11] provided a comprehensive analysis of emotional AI solutions based on CBT and stressed that they could be more accessible and at the same time offer greater therapeutic rigor.

G. Organizational, Ethical and Societal Perspectives.

The use of AI in workplace well-being programs raises organizational and ethical issues. To measure the impact of AI on safety, health, and well-being of workers, Jetha et al. [8] recommended a living systematic review process, which implies the need to continue with the synthesis of evidence. During their presentation of the relevance of workforce empowerment in AI-driven situations, Zhang et al. [9] highlighted the importance of organizational support and co-skilling in reducing the job instabilities caused by AI.

As noted by Hart [20], a case-based perspective on the use of AI in healthcare retail contributes to the significance of workforce adaption, leadership, and transparency to the successful digital transformation. These studies combined show that both organizations need to be prepared and ethically governed to aid technical solutions.

III. AI-BASED STRESS DETECTION TECHNIQUES

A. Physiological Signal-Based Methods.

The physiological signals to which AI models are commonly applied are heart rate variability (HRV), electrodermal activity (EDA), electroencephalography (EEG), respiration, and skin temperature [15], [17], and [18]. Systematic reviews and meta-analyses [15], [16], and [18] indicate that multimodal signal fusion is more accurate than single-signal methods in categorizing stress. However, issues in inter-individual variability, noise as well as limited generalizability persist.

B. Wearable and IoT-Based Monitoring.

Wearable technology and IoT platforms help to maintain a constant level of stress monitoring in real-world environments [16], [18]. The correct identification of stress needs the analytics of the context and sensor fusion, especially in knowledge-intensive workplaces. Despite the advantages, wearable-based systems pose a problem in terms of consumer acceptability, energy consumption, and privacy of data.

Large Language Models (LLMs) will be incorporated within the platforms to enable students to utilize them with ease.Large Language Models integration. LLMs will be integrated into the platforms to allow students to easily use them.

IV. COMPARATIVE ANALYSIS

Table 1: Comparison of Stress Detection Datasets

Dataset Source	Data Type	Target Population	Application Context	Limitations
Wearable-generated datasets	HRV, EDA, Temperature	Employees	Occupational stress	Privacy, small samples
Student stress datasets	Physiological + Context	Students	Academic stress	Short-term data

Dataset Source	Data Type	Target Population	Application Context	Limitations
Healthcare staff datasets	Surveys, digitallogs	Healthcare workers	Burnout monitoring	Subjective bias
Laboratory datasets	EEG, ECG, EDA	General adults	Controlled experiments	Poor real-world generalization
IoT-based datasets	Multimodal sensors	Knowledge workers	Continuous monitoring	Noise, missing data

Table 2: Comparison of Sensors for Stress Monitoring

Sensor Type	Measured Signal	Stress Indicator	Advantages	Challenges
ECG / PPG	Heart rate, HRV	Autonomic response	High accuracy	Motion artefacts
EDA (GSR)	Skin conductance	Emotional arousal	Low cost	Environmental sensitivity
EEG	Brain activity	Cognitive stress	High resolution	Wearability issues
Skin temperature	Peripheral temperature	Stress-induced vasoconstriction	Low power	Low specificity
Accelerometer	Activity patterns	Behavioural stress	Context awareness	Indirect measurement

Table 3: Comparison of AI Algorithms for Stress Detection

Algorithm	Input Type	Strengths	Limitations
Support Vector Machine (SVM)	HRV, EDA	Robust, interpretable	Limited scalability
Random Forest	Multimodal features	Handles non-linearity	Feature dependency
Convolutional Neural Network (CNN)	Time-series signals	Automated feature learning	High data demand
Long Short-Term Memory (LSTM)	Sequential data	Temporal modeling	Training complexity
Ensemble models	Multimodal data	High accuracy	Computational cost
LLM-based models	Text and context	High personalization	Explainability issues

V. PROPOSED AI-BASED STRESS MANAGEMENT ARCHITECTURE

Figure 1: Conceptual AI-Based Stress Detection Framework

Physiological Sensors (ECG, EDA, EEG, Temperature)

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Data Acquisition Layer

↓

Signal Pre-processing Module
(Noise Removal, Normalization)

↓

Feature Extraction Layer
(Time & Frequency Features)

↓

AI-Based Classification
(ML / DL Algorithms)

↓

Stress Level Output
(Low / Medium / High)

The generalized AI-based stress detection pipeline with the physiological signals has been visualized in figure 1. The structure starts with biological indicators in the form of physiological sensors like ECG, EDA, EEG and skin temperature sensors which are constantly recording biological reactions with regard to stress. These signals are sent to the data acquisition layer which provides adequate sampling, synchronization, and integrity of data. IN in the effort to enhance signal quality, particularly when motion and ambient noise is frequent, signal pre-processing module performs key operations like noise reduction, artefact correction, normalization and segmentation. The feature extraction layer extracts meaningful time-domain, frequency-domain, and non-linear feature, which reflect the activity of the autonomic nervous system and emotional arousal. The extracted information is then processed by the AI-based classification module, which employs machine learning or deep learning algorithms, i.e. Support Vector Machines, Random Forests, Convolutional Neural Networks or Long Short-Term Memory networks. The last output of the system is stress level estimation which may be used to monitor and intervene in real-time, most commonly characterized as low, medium, and high.

Figure 2: Wearable and LLM-Assisted Stress Management Architecture

Wearable Sensors Contextual Data
(HRV, EDA, ACC) → (Workload, Time, Location)

Stress Detection Engine
(ML / DL Models)

LLM-Based Conversational Agent
(Stress Explanation & Guidance)

Personalized Intervention Module
(CBT, Alerts, Relaxation Techniques)

The figure 2 shows an end-to-end architecture of AI-based stress management that combines wearable sensing, contextual information, machine learning models and large language models (LLMs) to facilitate personal mental well-being support. Wearable sensors monitor physiological and behavioural cues, including heart rate variability, electrodermal activity, and physical activities, and contextual data, including workload, time, and location, give the situational awareness. These multimodal inputs are then fed into the stress detection engine, which then interprets the results of this engine using ML or DL models to infer whether one is stressed or not. When the stress levels are determined to be high, an LLM-based conversational agent will be activated. It then applies natural language interaction in order to interact with users, analyze stress patterns and provide human friendly explanations. This layer enhances transparency, user trust and interaction. Suggestions that rely on cognitive behavioural therapy (CBT), relaxation methods, mindfulness cues, and timely alarms are adaptive coping methods, which are offered through the customized intervention module. Our architecture enables proactive, context-aware and custom stress management whilst reducing user load.

Figure 3: Organizational Deployment of AI-Based Mental Well-Being System

Employees / Students / Healthcare Staff

AI Mental Well-Being Platform

Management / HR Mental Health Experts
(Policy & Support) (Clinical Oversight)

Figure 3 presents the implementation of an AI-driven mental well-being system in an organizational ecosystem that involves a number of stakeholders. The final users are the employees, students, and healthcare professionals, which will use the system via wearable gadgets or digital devices linked to the AI mental well-being platform. The platform will be a central hub of data integration and intervention service and stress detection. The aggregate and anonymised insights are delivered to management or HR teams to assist with optimization of workload and policy development and organizational well-being initiatives. Mental health practitioners are able to get clinically relevant insights in order to offer professional supervision, counselling, and escalation to high-risk stress patients.

This deployment plan ensures that AI-driven insights are used to supplement professional mental health care and organizational support systems by focusing on ethical governance, privacy protection, and human-in-the-loop decisions.

VI. CONCLUSION

It features machine learning, deep learning, wearable sensing technologies, Internet of Things designs, and big language models, which assists in making sure that every recent phenomenon in artificial intelligence-driven stress detection and mental health therapies is included in this review. The review of literature demonstrates that AI-based systems possess a high advantage over traditional stress assessment tools due to their ability to provide not only objective and constant but also context-sensitive stress detection in the real world in case of advanced AI models. The scalability and real-time monitoring become feasible through the wearable and IoT-enabled technologies, and the digital mental health interventions, specifically, the ones, that apply the principles of the cognitive behavioural therapy, are very likely to lessen the stress levels and improve the psychological well-being. This leads to even more personalization and user interaction since big language models are being built with conversational, explainable, and adaptive interventions added to it.These are positive developments that have had their share of challenges that are yet to be overcome. The data quality problems, the generalisability of the models, their explainability, ethical governance, privacy protection, long-term clinical validation all have remained barriers to widespread adoption. It needs workforce acceptability, open AI governance and relationship with the human centered support systems to be effectively implemented in organization context. Overall, the review shows that AI-based stress management solutions can substantially improve mental health when created and implemented well. The explicable and fair AI models should be made the main topic of further research, as well as hybrid human-AI systems that can offer the possibility of balancing between automation and professional mental health assistance. These challenges will need to be ironed out so as to achieve the full potential of AI in the management of mental health in a holistic and sustainable manner.

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