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Review

A New Era in Stress Monitoring: A Review of Embedded Devices and Tools for Detecting Stress in the Workplace

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Abstract: Detection of stress and the development of innovative platforms for stress monitoring have attracted significant attention in recent years due to the growing awareness of the harmful effects of stress on mental and physical health. Stress is a widespread issue affecting individuals and often goes unnoticed as a health concern. It can lead to various negative physiological conditions, including anxiety, depression, cardiovascular diseases and cognitive impairments. The aim of this paper is to provide an overview of studies focusing on embedded devices for non-invasive stress detection, primarily in the form of a modified computer mouse or keyboard. This study not only fills a critical gap in the literature but also provides valuable insights into the design and implementation of hardware-based stress-detection methods. By focusing on embedded devices, specifically computer peripherals, this research highlights the potential for integrating stress monitoring into everyday workplace tools, thereby offering practical solutions for improving occupational health and well-being.

Keywords: computer peripherals; resource-limited embedded systems; machine learning; artificial intelligence

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1. Introduction

Stress detection has gained significant attention recently due to the growing recognition of its adverse effects on mental and physical health [1,2]. Stress affects everyone and is often a subtle health issue that can lead to severe conditions like depression, cardiovascular disease, structural changes and cognitive impairment [3]. Early and continuous monitoring of stress is essential for effective management and maintaining inner peace.

Historically, stress detection relied on subjective questionnaires, which can be unreliable [4]. Additionally, physiological markers such as heart rate variability and cortisol levels have been used [5], but these methods often lack real-time data and accuracy. Innovative stress detection utilizes recent advancements in technology, such as wearables, biosensors and machine learning, offering new opportunities for monitoring stress [6–8]. These devices can track a wide range of physiological and behavioral indicators, providing a more comprehensive view of an individual's stress levels.

The focus of this paper is on stress detection in the workplace, which is critical for several reasons. Chronic stress can lead to serious physical and mental health issues, including burnout and anxiety [9]. Early identification of stress enables employers to implement proactive measures to support their employees' well-being and prevent long-term adverse effects. Elevated or prolonged stress can affect cognitive function, concentration and decision-making skills. By effectively monitoring and managing workplace stress, employers can enhance employee performance and productivity. Employees experiencing lower stress levels are generally more focused, creative and efficient in their roles. Addressing stress in the work environment is vital for maintaining a healthy and high-performing workforce.

Stress detection and the development of new stress-monitoring platforms hold immense potential for transforming stress management. By incorporating advanced sensor technology and machine learning, these devices can provide a more precise and personalized approach to managing stress, ultimately aiding individuals in leading healthier and more fulfilling lives. However, achieving this potential will require collaboration among psychologists, physicians and engineers.

The workplace is a major source of stress due to the numerous demands and pressures faced by employees. Stress and health risks in the workplace can be categorized into two main areas: those related to the nature of the work itself and those linked to the social and organizational environment. Internal work-related factors include long working hours, excessive workloads, tight deadlines, challenging or complex tasks, insufficient breaks, lack of variety and poor physical working conditions (e.g., cramped spaces, uncomfortable temperatures and inadequate lighting) [10].

Ambiguous work tasks or conflicting responsibilities frequently contribute to stress, as does the challenge of supervising others. Career-advancement opportunities can act as a valuable buffer against stress, while issues such as lack of promotions, insufficient training and job instability tend to exacerbate stress levels. Furthermore, interpersonal relationships at work and the prevailing organizational culture significantly influence whether stress is heightened or mitigated.

Managers who are critical, demanding, or unsupportive can increase stress levels, whereas positive social dynamics and effective teamwork help reduce stress. Cultures that promote unpaid overtime tend to elevate stress, while those that encourage employee involvement in decision-making, maintain transparency in organizational matters and provide adequate equipment and recreational facilities help alleviate stress. Additionally, organizational changes, particularly those implemented without sufficient consultation, are significant stressors. Examples include mergers, relocations, restructuring, downsizing, adoption of individual contracts and layoffs [11].

Evaluating stress in the workplace is crucial across a variety of fields, including healthcare, aviation, finance, information technology, industry and transport [12–14]. Stress-detection technologies offer significant benefits by improving operational efficiency, safety and employee well-being. In healthcare, these tools help manage high-pressure situations and enhance patient care [15]. In aviation, they aid in maintaining flight safety by identifying stress early among pilots and air traffic controllers [16,17]. The finance sector benefits from stress monitoring by stabilizing performance and preventing costly errors. In information technology, these technologies support effective problem-solving and reduce system failures. In industry, stress detection improves productivity and safety in manufacturing, construction and logistics [18]. Lastly, in the transport sector, it ensures efficiency and reliability by monitoring stress levels among drivers and other personnel [19]. Overall, stress-detection technologies foster healthier work environments and enhance performance across these diverse domains.

The aim of this study is to analyze the current state of innovation in embedded stress-monitoring methods, identify key trends and evaluate their potential impact on occupational health. By examining data from 2014 to 2024, this research highlights the changing focus in stress-detection research and development, offering insights into emerging priorities and themes in the field.

The major contributions of this study are stated as follows:

- We present a review that contributes to this dynamic and growing field by providing a comprehensive synthesis, critically analyzing the state of the art and aiming to identify trends, challenges and emerging research areas in the use of PC peripherals for stress detection.
- We thoroughly examine the advantages of using PC peripherals for stress detection, their contributions and their limitations in stress-monitoring systems.

- With this contribution, we aim to guide future research and developments in the use of PC mice and keyboards for stress detection.

The structure of the rest of this paper is as follows: Section 2 presents a brief background about stress itself. Sections 3 and 4 provide explanations regarding the available biosignals for stress detection and the mechanisms behind stress. Sections 5 and 5.2 present a comprehensive comparison of the latest relevant studies. Section 6 engages in a detailed discussion about the findings. Section 7 concludes the research and suggests future directions.

Paper Selection Analysis

In order to systematically identify relevant published papers in this domain, literature research was performed from 1992 up to and including 2024. To acquire as many papers as possible, Web of Science, Scopus and Google Scholar were searched. The following keywords were chosen: computer mouse, sensors, stress detection, deep learning. Existing patents were not included. This review covers the field of biomedical engineering, artificial intelligence and sensors. A total of 73 papers were analyzed in this review. A graph showing the number of analyzed articles per year is shown in Figure 1.

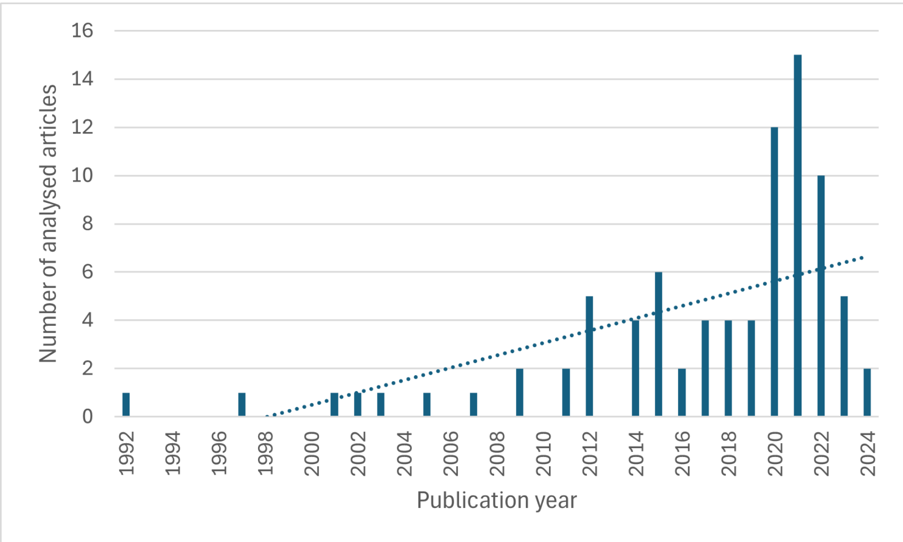

Figure 1. Graph showing the number of analyzed articles published over time.

As we can see, interest in this area has steadily increased each year since 1990. This review provides essential information on similar research in stress detection using embedded devices, computer mice and keyboards, alongside artificial intelligence techniques, highlighting recent advancements, methodologies and the effectiveness of these approaches in identifying and mitigating stress in real-time.

2. Physiological Stress

From a physiological perspective, stress is defined as a state of threatened homeostasis resulting from the action of external or internal adverse forces, known as stressors [20]. If stress mechanisms are activated unnecessarily and for prolonged periods, health risks can arise [21]. The action of stressors disrupts balance, swiftly mobilizing a range of physiological and behavioral responses as an adaptive reaction to stress. Attention heightens, and brain functions concentrate on, the perceived threat. These responses to stressors are typically transient and aim to maximize an individual's chances of survival, including [20]:

- An acceleration of cardiac output and an increase in blood pressure;
- Acceleration of breathing;
- Acceleration of catabolism;

- Redirection of blood flow, with a temporary increase in perfusion to endangered areas and the excited brain, heart and muscles.

An adaptive stress response can become maladaptive under chronic stimulation, leading to potentially harmful consequences. Neurochemical and physiological research has clarified how stress is regulated by two neuroendocrine systems [22]: the hypothalamic–pituitary–adrenal (HPA) axis and the sympathetic-adrenomedullary (SAM) system of the autonomic nervous system.

The HPA axis, shown in Figure 2, plays a crucial role in the organism's adaptation to stressful situations. Research has demonstrated a link between disorders induced by stressful stimuli (especially long-term) and depression, often due to HPA axis dysfunction. The HPA axis is vital for maintaining body homeostasis and managing the body's response to stress.

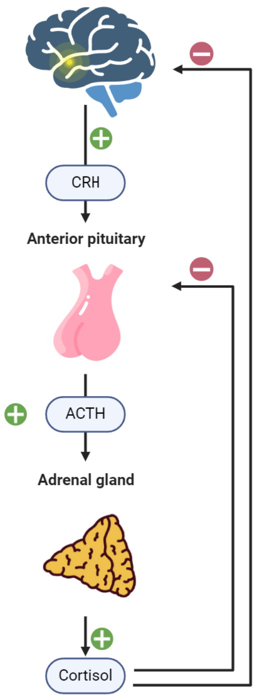

Figure 2. HPA axis.

Stress triggers the release of corticotropin-releasing hormone (CRH) from the hypothalamus. This signal is then sent to the anterior lobe of the pituitary gland, prompting the secretion of adrenocorticotropic hormone (ACTH). ACTH subsequently stimulates the adrenal cortex to release cortisol into the bloodstream. Elevated cortisol levels inhibit the secretion of CRH and ACTH through a negative feedback loop.

The importance of the HPA axis primarily lies in the action of cortisol. Cortisol is released during stressful situations as a defense mechanism, reducing inflammatory responses, stimulating gluconeogenesis and protecting the body against excessive immune reactions. The HPA axis is also activated in non-stressful situations, such as regulating circadian rhythms, with the highest cortisol levels observed in humans in the morning [23].

When a stressor is perceived, the brain processes this information and initiates the release of key hormones. Glucocorticoids are released via the HPA axis, while catecholamines, including adrenaline and noradrenaline, are released through the SAM axis. These hormones work together to elevate blood glucose levels by stimulating the liver to release glucose, which supports the "fight or flight" response. This response also involves increased cardiovascular output and the redirection of blood from the skin and gut to the skeletal muscles. Concurrently, the brain activates the ANS, triggering a rapid release of catecholamines, which enhances cardiac output and blood pressure, and further mobilizes glucose. At the same time, the HPA axis releases adrenal glucocorticoids—cortisol in humans and fish, and corticosterone in rodents. Elevated glucocorticoid levels improve the organism's ability to resist and adapt to stress, although the exact mechanisms of these effects are not yet fully understood. Glucocorticoids cooperate with adrenaline to increase blood glucose, ensuring the energy needed to effectively manage the stress response. The brain's central awareness and response to stress, anxiety and fear depend on extensive neural circuits, including the amygdala, thalamus, hypothalamus, neocortex, limbic cortex and brainstem nuclei like the locus coeruleus [22].

Stress can have a devastating impact on both physical and emotional health. Numerous studies indicate that work stress is the primary source of stress for adults and has been steadily increasing over the past few decades. Excessive or chronic exposure to stressors can disrupt various fundamental physiological functions, including growth, metabolism, immune competence, reproduction, behavior and personality development [20]. It is linked to higher rates of heart attacks, addiction, hypertension, depression, obesity, anxiety and other disorders. Stress is a highly individual phenomenon, varying based on each person's vulnerability and resilience [22].

The impact of stress extends beyond the work environment and plays a crucial role in various mental disorders, including phobias, depression and bipolar disorder. Stress and anxiety can exacerbate schizophrenia, making it more challenging for individuals with this condition to manage daily life. Additionally, stress-inducing lifestyle changes can significantly burden mental health [22].

Stress is a non-specific reaction of the organism to any demand. It is important to recognize that an individual's ability to respond to stressors is influenced by a combination of developmental, genetic and environmental factors. These factors affect the effectiveness of adaptive responses and can partially predict susceptibility to chronic stress [20].

3. Generation of Biosignals

Physiological structures that indicate stress play a role in generating biosignals in humans [24]. To maximize the effectiveness of new platforms, it is essential to investigate the generation of biosignals [25], which serves as the primary focus of the section.

The human cell membrane is a thin, semi-permeable layer that envelops the cells of the human body. It is primarily composed of a phospholipid bilayer, within which various proteins are embedded. This dynamic mosaic structure is held together by hydrophobic interactions between phospholipid molecules. Due to the hydrophilic and hydrophobic orientation of these molecules, non-polar substances can enter the cell, while ions and polar molecules (e.g., water) cannot pass through the membrane unaided. The main function of the cell membrane is to regulate the exchange of chemical substances. Phospholipids allow access to non-polar hydrophobic molecules (e.g., hydrocarbons). However, the transfer of ions and polar molecules requires the assistance of integral proteins, such as ion channels and pumps or specific transport carriers. These proteins, known as ion channels, facilitate the transfer of certain polar molecules or ions. These channels enable the diffusion of ions from areas of higher concentration to lower concentration, driven by a specific ion concentration gradient, making this process passive in nature.

Conversely, another group of proteins, known as ion pumps, use energy to transport ions across a membrane against a potential and/or concentration gradient. The activity of these pumps and channels maintains the differences in ion concentrations between the intracellular and extracellular environments, thereby determining the cell's electrochemical properties. Consequently, a potential difference exists across the cell membrane in its resting state, unless disturbed. This phenomenon is the primary factor behind the creation of biosignals [25].

Bioelectric potentials (biopotentials) arise from the electrochemical activity of excitatory cells in nerve, muscle, or glandular tissues [26]. External or internal stimulation can cause excitatory cells, such as neurons, to alter their resting potential. This results in a sudden change in the permeability of ions like K^+ and Na^+. The shift in membrane permeability from a resting state to an excited state and back again generates an electrical phenomenon known as an action potential. The cell acts as an electrical source, generating a current that propagates throughout the human body (acting as a conductor).

An action potential occurs when Na^{+} ions suddenly pass through Na channels due to a sufficient stimulus that overcomes the threshold potential. The influx of Na^{+} ions reduces the polarized resting potential to a range of +30 to +40 mV, a phenomenon known as depolarization. At this point, potassium channels open, and the cell begins to repolarize towards its equilibrium potential due to the efflux of positive K^{+} ions. Because K channels remain open for a relatively long period, there can sometimes be an increase in the polarized resting potential, known as hyperpolarization. A typical nerve action potential, illustrating the different phases, is shown in Figure 3.

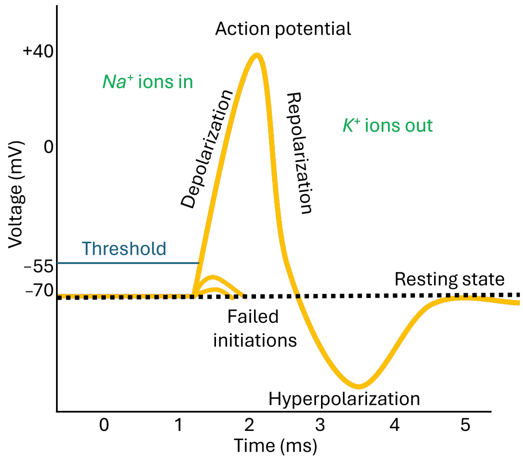

Figure 3. Schematic action potential.

The cell's ability to respond to a new stimulus and generate another action potential immediately after one is limited by a specific time interval known as the refractory period. This period is divided into two phases. The absolute refractory period occurs during the initial phase of the action potential, when it is entirely impossible to initiate another action potential, regardless of the stimulus intensity. Following this is the relative refractory period, during which another action potential can be triggered, but only by a stimulus that exceeds the threshold intensity.

An initial depolarization in one area of a neuron's membrane can trigger depolarization in an adjacent membrane area, provided the initial depolarization serves as an adequate stimulus. This process causes depolarization to propagate along the entire length of the cell membrane in a wave-like manner. Subsequently, depolarization that begins at the axon hillock travels along the axon to its terminus, where it transmits the action potential through a synaptic connection to a neighboring neuron or effector cell.

4. Biosignals for Stress Detection

Stress initiates a series of physiological reactions that can be monitored through various biosignals (Figure 4). Each signal captures different aspects of the body's autonomic nervous system, which controls stress responses. These signals, originating from physiological processes, offer real-time insights into how the body reacts to stress.

For stress detection, Sharma et al. recommend obtaining the following physiological signals [27]:

- Electroencephalogram (EEG);
- Electromyogram (EMG);
- Blood Volume Pulse (BVP);
- Heart Rate Variability (HRV);
- Galvanic Skin Response (GSR).

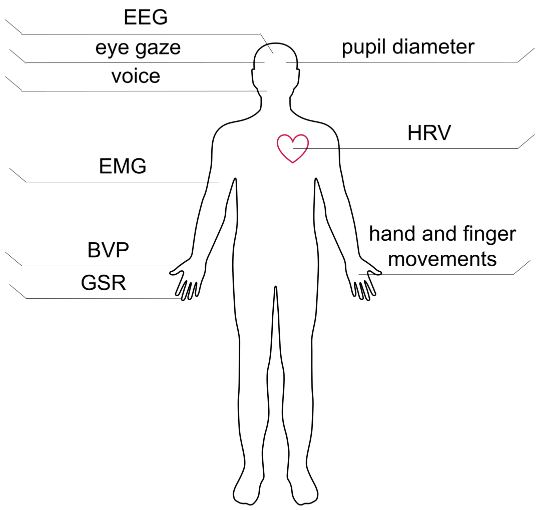

Figure 4. Common physical and physiological indicators for stress detection.

Other indicators of stress include various physiological signals and parameters, such as [25,28]:

- Electrocardiogram (EKG)—This records the electrical activity of the heart and is crucial for monitoring and diagnosing heart diseases [29,30]. Since the body acts as a volume conductor, the ECG can be captured through electrodes placed on the body surface. The ECG signal typically includes a P wave, QRS complex, T wave, as well as PR and ST segments [31]. These waves result from the propagation of the summation vector of action potentials within the heart structures relative to the electrodes.
- Recording of the electrical activity of the eyes—Eye monitoring is used to track eye movements and gaze patterns, typically employing cameras or electrodes for electrooculogram (EOG) measurement [32]. An electrooculogram measures the potential generated by eye movements. The human eye functions as a dipole, with the cornea at a positive potential relative to the retina, creating a potential difference between them. This corneal-retinal potential, ranging from 0.4 to 1.0 mV, varies with eye movement. Electrodes placed near the eyes record these potentials: the electrode closer to the cornea will detect a positive potential, while the one nearer to the retina will detect a negative potential. The potential difference between these electrodes, reflecting eye movement, is known as the EOG.
- Photoplethysmography (PPG)—This optical measurement technique detects changes in blood volume within the microvascular tissue bed. It has extensive clinical applications and is utilized in various commercially available medical devices, including pulse oximeters, vascular diagnostic tools and digital blood pressure monitors [33].
- Determination of blood oxygenation level—Non-invasive monitoring of blood oxygen saturation.
- EDA (Electrodermal Activity)—Monitoring of skin conductivity [34,35].
- Measuring body temperature—Elevated body temperature, as measured by an armpit thermometer, can be associated with psychological stress [36].

5. Comprehensive Overview of Related Studies and Their Key Contributions

This section provides an in-depth review of key studies related to the detection of stress using physiological signals (Section 5.1) and neural network-based techniques (Section 5.2). By analyzing the methodologies, hardware platforms and algorithms presented in the literature, we aim to highlight the significant advancements and contributions made by researchers in the field. The section also offers a comparative analysis of various approaches, focusing on their performance, accuracy and applicability in real-world scenarios, providing a comprehensive understanding of current trends and challenges in stress detection research.

5.1. Hardware Platforms for Stress Detection

Stress is a major health concern affecting both individuals and workplaces [37]. While traditional methods like questionnaires offer insights, they rely on personal reports, which can be unreliable. To address this, researchers have turned to physiological measurements using wearable sensors.

Wearable devices, such as smartwatches, can continuously track physical signs of stress [38,39]. This technology offers a more objective way to understand stress levels and can help people detect their stress effectively. In high-pressure jobs, these devices can even be crucial for maintaining performance and well-being. Building on this approach, researchers are exploring innovative integrations of stress-detection technology into everyday objects, such as computer peripherals [40–43]. This section presents the evolution of stress-detection technologies, highlighting the transition from traditional wearable sensors to the incorporation of stress-detection features into common devices like computer mice or keyboard.

An examination of various methods and devices used for stress detection reveals their technological foundations, applications and potential for future development. By understanding these tools, we can help address stress-management issues and improve the quality of life and productivity for individuals across different fields. A significant advancement in stress detection is the development of multi-sensor platforms, such as those by Rescio et al., which combine wearable and ambient sensors for remote and unobtrusive monitoring [44]. Mishra et al. further demonstrated the effectiveness of affordable heart rate monitors with advanced data processing for practical stress assessment [45]. The integration of stress-detection technology into everyday devices is exemplified by Valenti et al.'s ring probe, which combines PPG and GSR sensors for comprehensive physiological monitoring [46]. Lin et al. showcased the potential of embedding stress-detection technology into PC mice, achieving high accuracy in stress monitoring during regular use [47]. Androutsou et al. [48,49] enhanced this approach by incorporating a multi-sensor system into a standard optical mouse for occupational stress detection, while Chigira et al. introduced a mouse with PPG sensing surfaces for continuous data collection [50]. However, Freihaut et al. highlighted challenges in linking mouse movements to stress levels, indicating that while the technology holds promise, further research is needed to validate these connections [51]. Sun et al. [52] explored the use of common mouse operations to measure stress levels by capturing muscle stiffness during arm and hand movements. Vea et al. [53] focused on detecting emotional states like confusion and frustration in novice programmers by analyzing keyboard and mouse interactions. Silva et al. [54] introduced cost-effective methods to measure typing and mouse grip pressure using force-sensitive resistors. Tran et al. [37] developed a wireless PPG mouse for real-time monitoring of heart rate and variability during mouse use. Belk et al. [55,56] created "CogniMouse", a sensor-equipped mouse designed to assess stress levels in older adults at work, using grip force, heart rate and other physiological indicators through a probabilistic classification algorithm. Kaklauskas et al. [57] developed a biometric mouse system that assesses emotional states and productivity through real-time physiological, psychological and behavioral data, offering personalized stress-management recommendations. Leone et al. [58] proposed a framework for monitoring mental load in the workplace using wearable devices to measure heart rate, skin conductance and eye movements. Rescio et al. [59] developed an unsupervised learning framework for stress detection using wearable devices. Overall, these innovations reflect a significant leap in integrating stress-detection capabilities into everyday objects, offering new avenues for managing stress and improving well-being and productivity. All of these mentioned studies are detailed in the following text.

Rescio et al. [44] developed and tested a multi-sensor platform comprising a wearable system and an ambient sensor. The wearable system was designed to be minimally intrusive and comfortable for the user, while providing real-time data access and high accuracy for reliable stress detection. The platform incorporated an inexpensive and readily available RGB camera to assess eye blinking. This camera has proven effective for stress detection and can be easily used in the workplace. Additionally, non-wearable sensors were included to measure specific parameters or characteristics for remote stress evaluation without physical contact. These sensors can be categorized into physical and visual measurements.

The wearable system is designed to be minimally intrusive, focusing on detecting heart rate and EDA. It consists of a shoulder strap equipped with an electronic device. To reduce physical discomfort and enhance user experience, the authors selected optimal body locations, such as the shoulder and earlobe, for obtaining physiological data. They emphasized the strategic placement of sensors rather than the design of the straps, significantly improving the system's wearability. The platform functions as a support system for optimal worker management and well-being. Its performance was evaluated under controlled laboratory conditions to determine one or two levels of stress. Three deep learning algorithms were tested, with a 1D-convolutional neural network achieving the highest detection accuracy. Specifically, the accuracy values were approximately 96.88% for one stress level and 95.88% for two stress levels.

In another study, Mishra et al. [45] explored whether accessible and affordable wearable sensors could be used for stress monitoring and if commonly available devices could accurately detect stress. They demonstrated that a widely available heart rate-monitoring device (the commercial Polar H7 chest sensor) could measure stress in both controlled and free-living conditions.

The authors compared different data-processing methods and their impact on the accuracy of stress detection using a commodity sensor. They noted that some typical preprocessing steps used in previous studies were less effective for commodity devices. They provided recommendations on data-processing procedures for stress detection that are also applicable to custom-built sensors. The authors introduced a novel two-layer method for stress detection that accounts for both previous and current stress levels. They found that this approach significantly improves stress detection. In a laboratory study using only a consumer heart rate monitor, they achieved an F1 score of 0.87 for identifying stress periods. They also distinguished between three types of stress-inducing tasks with a maximum F1 score of 0.82. Adding a GSR sensor to the heart rate monitor increased the F1 score from 0.87 to 0.94. When using only heart rate data and GSR, the F1 scores were 0.66 and 0.72, respectively. The authors recommend future research focus on identifying not just "stressful" versus "non-stressful" periods, but also the specific type of stress a person is experiencing to enable early adaptive interventions.

Valenti et al. [46] have developed and implemented a wearable device that simultaneously collects data from PPG and GSR sensors, both positioned on the finger. Their prototype, designed as a ring probe, also measures SpO_2 levels. This helps in evaluating physiological stress and blood oxygen saturation. By placing the sensors in a single location, the device's overall footprint is minimized, enhancing user comfort during measurements. The device allows for the assessment of cardiovascular status, the analysis of sympathetic nervous system activity (via HRV and GSR) and the detection of low oxygen levels, which could pose health risks. To validate the ring probe's functionality, multiparametric data were collected from healthy subjects during periods of rest, stress tasks and breath-holding exercises.

Testing with the new ring-shaped probe confirmed the device's functionality and its capability for multi-parametric data acquisition to assess various physiological responses. Lower heart rate and GSR values during relaxation indicated parasympathetic dominance, while increases after exercise showed sympathetic activation. Stress induced consistent trends across all subjects, but breath-holding produced varied responses. SpO_2 monitoring revealed protocol-induced changes in oxygen saturation with individual differences. Overall, the results highlighted the potential of this synchronous biosignal acquisition device, which offers convenience, cost-effectiveness and high-quality signal collection.

The system's versatility makes it suitable for home monitoring, fitness and clinical applications, particularly for diagnosing cardiovascular disease. However, it has limitations, including insufficient detection of motion artifacts and potential inaccuracies in peak detection and filtering. Laboratory results demonstrate that the system can effectively monitor physiological states, assess emotional fluctuations and measure oxygen saturation.

Lin et al. [47] developed a user-friendly module for stable and accurate pulse detection, integrated into a PC mouse. Given that most people use a PC mouse daily, whether at work or home, their design incorporates multi-channel sensors to address issues like palm drift or misalignment. To evaluate the performance of the proposed mixed-signal algorithm, experiments were conducted in four phases involving six movements: rest, slow movement (both horizontal and vertical), fast movement (both horizontal and vertical) and a search phase. The accuracy of pulse rate detection was assessed by comparing PPG signals from the proposed device with reference ECG signals. During rest, the mixed signal achieved a sensitivity of 98.50% and a false detection rate (FDR) of 0.15%, indicating high accuracy. Even the least sensitive channel (channel 4) maintained a sensitivity of 93.05% and an FDR of 1.77%. The weighted mean method outperformed the median method in terms of higher sensitivity and lower FDR. Motion artifacts during slow and fast movements affected signal quality, but the weighted average method mitigated these effects more effectively than the median method. In the search phase, sensitivity decreased due to intermittent sensor contact during mouse movements and clicks. However, the proposed method improved signal clarity and reduced noise effects.

The study also addressed eye safety concerns when the palm was not in contact with the mouse by implementing an LED power-saving mode to reduce modulation frequency. Limitations include the need for continuous palm contact during measurement and the necessity to test the device across different demographic groups and conditions.

The study demonstrates that the proposed multi-sensor module and weighted average method effectively enhance the usability of detected PPG signals, thereby increasing the likelihood of successful signal detection from the palm. Due to its simplicity, user-friendliness, and cost-effectiveness, this device could be a valuable tool for collecting physiological signals and aiding early disease detection, particularly in low- and middle-income countries, thus addressing healthcare access barriers.

Androutsou et al. [48,49] introduced a user-friendly system for detecting occupational stress in office employees. This system uses a multisensor setup embedded in a computer mouse to analyze physiological signals and identify stress. To validate the system, the researchers designed and implemented an experimental protocol that simulates the stressful office work environment. According to the authors, no similar system combining a non-invasive, user-friendly design with wireless data transmission has been documented in the literature. They also highlight that validation procedures for comparable stress-detection devices have not been adequately detailed. The experimental protocols aim to replicate real workplace stressors.

The smart computer mouse developed by the researchers includes a PPG PulseSensor, a Grove—GSR sensor, and a development board with a microcontroller and a Wi-Fi module. All components are integrated into a commercially available wired optical mouse.

The system's objective was to determine users' stress levels by analyzing physiological parameters derived from signal processing. The GSR module includes a printed circuit board with two disk-shaped electrodes, which measure changes in skin resistance. These changes can be correlated with emotional variations.

During the experiment, PPG and GSR signals from all participants were recorded, resulting in 32 datasets. Analysis of these datasets provided physiological BPM and skin conductance (SC) values, allowing the investigation of occupational stress detection. It was observed that both BPM and SC values increase with stress. However, there were inter- and intra-subject variations in response to stress-inducing tasks. The physiological response's impact depends on the intensity of the stimulus and individual perception. Some subjects remained continuously alert during stress, while others exhibited brief reactions.

Statistical analysis of the calculated physiological parameters was conducted. The null hypothesis indicated no statistically significant difference between measurements taken during controlled and stressful phases for both tasks. However, SC values showed highly significant differences between control and stressful phases for both tasks. BPM values also showed significant differences between phases of the Mental Arithmetic Task, but not for the Stroop Color Word Task. The latter required longer and more abrupt mouse movements, and the use of a Kalman filter to remove motion artifacts may have affected the extraction of useful information from rapid or subtle changes in signals.

The system's effectiveness for automatic stress detection in an office environment was validated using stress-inducing tasks that mimic common workplace stressors. To address motion and noise artifacts, a Kalman filter and a moving average filter were employed, with the Kalman filter effectively preprocessing the PPG signal. Participants reported higher stress levels and decreased performance during stressful tasks. Statistical analysis showed significant differences between the different periods of the experimental protocol. The proposed system aims to offer a non-invasive, easily customizable and user-friendly solution for monitoring and automatically detecting the stress levels of office workers.

Chigira et al. [50] assessed that a conventional PPG sensor, being relatively small, requires the user to place their hand or fingertip precisely on the sensor point. To address this limitation, they introduced a mouse with PPG surfaces, allowing unobtrusive PPG sensing during regular use [60]. Up to 90% of the light from the diffusion plate can pass through the detection plate, and the light that reaches the fingertip is reflected back to the detection plate.

The study collected PPG waveform data from three different sensors—left, right and spot—each capturing 15 s of data from each subject. The results showed consistent patterns across all participants, indicating reliable data collection. Correlation analysis between surface sensor data and point sensor data revealed high correlation coefficients.

Specifically, the correlation coefficients were 0.97 for the left sensor and 0.99 for the right sensor. These high coefficients indicate a strong agreement between the data collected by the surface sensors and the point sensor, suggesting that the surface sensors capture physiological signals with similar accuracy. Overall, the study findings indicate that surface sensors are reliable for capturing PPG waveform data.

Freihaut et al. [51] explored the use of computer mouse movements to identify stress. They emphasized the potential advantages of this approach, which is completely non-invasive and unobtrusive compared to traditional methods. Participants were recruited through WisoPanel, an online panel representative of the German population. Invitations were sent to all 14,343 panel members, with 1941 (15.65%) opening the study link and 1091 completing it for a reward of 1 euro (retention rate: 56.21%). After excluding 97 participants due to careless responses or technical issues, the final sample included 994 participants (mean age = 54.4; standard deviation = 13.3; 515 female; 479 male). Participants were required to use a physical computer mouse, have a display resolution of at least 950 × 600, and use a modern web browser, with measures in place to filter out noncompliant users. The median duration of the study was 21 min.

The experiment used a between-subjects design with two phases. In the baseline phase, all participants practiced four mouse tasks to establish a baseline level. In the application phase, they were randomly assigned to high-stress or low-stress conditions and worked on the same tasks. The experiment was implemented as a web application. Stress was manipulated by presenting either a difficult (high-stress) or easy (low-stress) counting task before each mouse task. The high-stress counting task involved identifying squares among complex geometric shapes and distractors, making the task challenging yet manageable.

In the high-stress condition, participants were told the tasks were a performance test measuring intelligence, adding a social evaluation element. In the low-stress condition, participants were informed that the tasks aimed to improve computer skills. Both groups received feedback and were instructed to perform the tasks as quickly and accurately as possible. The framing of instructions was identical for both conditions.

The four mouse tasks were designed to capture various mouse actions: point and click, drag and release, press the scroll bar and follow the circle. These tasks remained consistent across both baseline and stress conditions to avoid confounding effects. Mouse-usage data were collected on the client side, recording mouse events at varying sampling rates. Participants' stress levels were measured after each task using the Self-Assessment Manikin and the German Multidimensional Mood Questionnaire, which assessed emotional states and stress levels to ensure the manipulation's effectiveness.

Preparing the mouse data for analysis involved several steps for each task. First, all relevant data points were extracted for each specific task. Next, artifacts in the data, identified by consecutive points with the same timestamp or the same x and y coordinates, were removed. Visual inspection was then conducted to identify potential tracking problems. Participants who exhibited tracking issues or whose task duration exceeded three times the median were excluded from the analysis. Finally, mouse-movement data were interpolated into uniform 15 ms intervals to ensure consistent temporal resolution. These steps ensured reliable data preparation for subsequent analysis and allowed for a detailed investigation of mouse behavior across various tasks and experimental conditions.

In this study, the first step was to predict stress conditions (high vs. low) for each mouse task using features derived from mouse usage. Five-fold cross-validation assessed the prediction accuracy, which was statistically validated against the null distribution via permutation tests. The analysis standardized input functions and employed three common algorithms: logistic regression, support vector machine classification and Random Forest with default hyperparameters. Models were tested with and without baseline data, resulting in six models for each task.

Regression analysis then examined the relationship between mouse usage and subjective ratings of valence (qualitative emotional response) and emotional arousal. Despite these efforts, no significant correlations were found, suggesting that stress does not clearly affect mouse behavior as measured by self-reported affective states. An alternative approach involved generating images from raw mouse data to predict stress states and affective ratings using a convolutional neural network. However, the results were similar to those obtained using traditional features, with classification accuracy around chance level. While some models showed promising results, the variability between tasks and methodologies highlights the complexity of linking mouse usage to stress in a controlled experimental setting.

The study also outlined several challenges with this method. Changes in mouse movements can be influenced by various factors, not just stress. The authors acknowledge that this research is still in its early stages and that further studies are needed to identify specific patterns of mouse movements truly indicative of stress. Moreover, even if a link between mouse movements and stress is established, the accuracy of this method needs thorough evaluation. Can tracking mouse movements reliably distinguish between different stress levels? Is it sensitive enough to detect subtle stress differences? These questions require further investigation.

Computer mouse tracking is a simple and cost-effective method for collecting continuous behavioral data, with potential applications in various areas of psychological science. This study aimed to assess its ability to measure individual stress levels, but no clear correlation was found between stress and mouse usage. This suggests that using the computer mouse as a general tool for measuring stress may not be feasible. However, these results underscore the need for theoretical advances in understanding how stress affects sensorimotor behavior.

Sun et al. [52] investigated how common computer mouse operations can be used to measure stress levels. Their study highlights that muscle stiffness during arm and hand movements can be captured through typical mouse usage, employing a physiological model known as the Mass-Spring-Damper system. From this model, they derived two stress metrics based on mouse movements and developed a computational method for accurately estimating these parameters. A controlled study was conducted with 49 participants, collecting data on mouse activity, ECG readings and subjective stress ratings under both calm and stress-induced conditions.

The findings suggest that stress measures derived from mouse movements are highly reliable, surpassing traditional physiological methods in strength. Moreover, the study shows that stress detection is feasible, achieving 70% accuracy in identifying stress states using just 10 samples of mouse movements under controlled conditions. However, the model requires 100–200 training movements to establish a single-parameter model for each user.

To determine which mouse operations to analyse, the researchers noted that a few repetitive tasks account for most mouse interactions. These include pointing and clicking to perform actions (e.g., launching applications or sending messages), dragging and dropping to move or rearrange objects, and steering the cursor through constrained paths, such as navigating drop-down menus or highlighting text. These interactions were abstracted into three primary operations: point-and-click, drag-and-drop and steering. In the experiment, two conditioning tasks were used—one to induce stress and another to alleviate it.

The study aimed to evaluate individual-level stress classification by integrating multiple data types: subjective stress ratings (SSR), electrocardiogram data and mouse activity data. SSRs were recorded at various stages using an 11-point Likert scale, where participants rated their stress levels from 0 (no stress) to 10 (extreme stress). Continuous ECG data were captured using a 3-lead ECG setup, and analyzed with the Kubios HRV tool to extract heart rate variability indicators, while mouse activity was monitored through a high-resolution mouse and analyzed using a MSD model to compute stress-related metrics.

The study also investigated the effectiveness of a individual-level stress-classification approach. The process involved training a classifier with a subset of data points from each subject and testing it on the remaining unseen samples. A simple model-based classifier was employed, characterized by a staircase structure representing stress behavior based on target distance and size. The model used a fixed step magnitude for all subjects and varied step slopes for different tasks.

To classify stress, the model required only the distance of mouse movements, thus minimizing privacy concerns. A one-dimensional classifier was used to determine the best threshold for classification. This model was evaluated by measuring classification accuracy with varying numbers of samples for training and testing. The results indicated that the model with a maximum-accuracy threshold significantly improved classification accuracy compared to baseline models, reaching up to 71% accuracy with 30 samples. However, accuracy declined with more samples due to insufficient data for model training. Overall, the study demonstrated that around 10 mouse movements under a fixed stress state could achieve approximately 70% accuracy in stress classification.

The study by Vea et al. [53] aims to advance the development of formal models for recognizing the emotional states of novice programmers using common, low-cost, non-intrusive computer peripherals. The models or patterns identified for detecting negative emotional states may help computer scientists create computational systems that provide automatic feedback to educators and students. The researchers utilized a customized mouse-key logger and a webcam.

They then extracted relevant keystroke and mouse dynamic features, resulting in a CSV file with these features recorded at 15 s intervals. This file, referred to as the incomplete dataset, initially lacked affective labels. Video logs were similarly divided into 15 s segments matching those in the incomplete dataset. The researchers developed various affective models to detect confusion, frustration and boredom by training tree classifiers such as J48, Decision Tree and Random Forest using RapidMiner. They evaluated different feature sets, including keystroke verbosity features, keystroke time duration and latency, all keystroke features combined, mouse features alone and a combination of all keystroke and mouse features. Feature selection was based on the Gini index, and batch-X-validation was used to validate the models. The depth of the trees in each classifier was also explored to identify the model with the highest performance.

The study found that notable features for detecting negative affect include typing errors (e.g., backspace and delete key presses), idle time, typing variance, key events, mouse-movement distance and key press durations. Boredom was linked to minimal keyboard activity and slight mouse movement, while frustration also involved reduced keyboard use but with additional hand gestures. Confusion showed relationships with both keyboard and mouse behaviors. Feature stability varied over time: typing errors were significant in the early and middle stages, while idle time became more influential towards the end. Idle time was a major indicator of boredom, typing errors indicated confusion and a combination of both was needed for frustration. Combining mouse features, such as distance traveled along the x-axis, with keystroke dynamics enhanced the accuracy of detecting student affect compared to using either type of feature alone.

Silva's study [54] introduces two cost-effective methods for measuring typing and mouse grip pressure using readily available devices, incorporating force-sensitive resistors (FSRs) on keyboards and mice to detect pressure variations. To evaluate these designs, a user study was conducted where participants performed typical tasks, such as typing and answering multiple-choice questionnaires. Binary classifiers were trained to distinguish between stress and neutral states based on keystroke dynamics, mouse movements and pressure data. The results showed that combining keystroke and mouse dynamics with pressure features improved classification accuracy. In the study, software recorded typing pressure, mouse pressure, keystrokes and mouse events in the background. Two types of features were extracted from the keyboard data: keystroke dynamics and pressure measurements. Pressure data were only collected during keydown events, excluding inactive periods. The analysis revealed that the bottom-left sensor, located near the Z key, was the most sensitive due to its proximity to 60% of the alphabetical keys, so the analysis focused on data from this sensor. Similarly, mouse data provided two feature sets: mouse dynamics and pressure measurements, focusing on six key dynamics—travel distance, direction change, overall speed, moving speed, dwell duration and moving duration. The keyboard analysis involved 188 samples from four control and four experimental sessions per participant, where a random classifier would have achieved 50% accuracy. Mouse data, collected from 87 sessions, resulted in 174 samples. Trajectory features outperformed pressure features with accuracies of 70% and 61%, respectively. Combining both types into a single model boosted classification accuracy to 73%, a 3% improvement over using trajectory features alone.

Tran et al. [37] developed a device that transmits PPG signals to a PC via a wired connection. However, the use of infrared light instead of the typical red light resulted in weak output signals. To address this issue, the authors propose an alternative: a wireless PPG mouse. This device integrates a compact PPG sensor and Bluetooth module within a standard mouse, enabling real-time monitoring of PPG waveforms, heart rate and heart rate variability during normal mouse use. Detecting peaks and minimum points is crucial for analyzing PPG signals to estimate heart rate, heart rate variability, mental stress and blood pressure. The Adaptive Threshold Algorithm (ADT) algorithm is commonly used for peak detection, especially when baseline drift from respiration is present. However, ADT's reliance on two adaptive thresholds can lead to missed peak-valley pairs, affecting its accuracy. ADT sometimes fails to detect peak-valley pairs when the valley drops sharply. In contrast, the proposed Robust Peak Detection (RPD) algorithm consistently identifies these pairs. The RPD algorithm also performs well under challenging conditions, accurately detecting premature and delayed peaks while reducing error peaks. It corrected 103 peaks in the noisy 3rd reference dataset, compared to 22 by ADT and none by Local Maximum and Minimum Detection algorithm (LCM). Additionally, RPD achieved a false detection rate of just 2.3%, significantly lower than the 13.4% for LCM and 11.7% for ADT, demonstrating its superior performance in PPG peak detection using the PPG mouse.

Belk et al. [55,56] have focused on the seamless identification of psychological stress among older adults who remain active in the workplace by using sensors embedded in a computer mouse. They developed a custom mouse, known as CogniMouse, equipped with sensors to measure heart rate, skin conductance, temperature and grip force in real time. This device is part of the CogniWin project, which aims to assist and motivate older adults to remain active in their jobs. The CogniMouse integrates a classification algorithm based on probabilistic theory, designed to continuously assess the likelihood that a user is experiencing stress. This Bayesian-based approach, utilizing conditional probability distributions, is chosen for its flexibility in accommodating new variables. The classification inputs include: grip force, heart rate, skin conductance, hand temperature variations, hand trembling indicators from mouse motion and acceleration, and click stream frequency. CogniMouse is supported by two applications. The first is a background worker that parses and distributes incoming data messages to relevant applications. The second provides a visual interface for easy data verification. CogniMouse not only measures and analyzes physiological data but also delivers personalized feedback to users and caregivers, including insights into emotional states, task-related difficulties, frustration levels and signs of sleepiness.

Kaklauskas et al. [57] made significant advancements using the web-based biometric computer mouse advisory system. This system provides a thorough analysis of a user's emotional state and work productivity using three primary biometric techniques: physiological, psychological and behavioral. By integrating these methods, the system can evaluate eleven different states of being, including stress, work productivity, mood and interest, as well as seven specific emotions, such as self-control, happiness, anger, fear, sadness, surprise and anxiety, all within a practical time frame. To enhance accuracy and reliability, the system incorporates additional data from the Biometric Finger, which measures blood pressure and pulse rates, thus allowing for a more detailed physiological assessment. A standout feature of the system is its ability to generate personalized stress-management recommendations. Based on real-time biometric data and the user's needs, the system produces of potential recommendations derived from Maslow's Pyramid Tables, which are derived by survey data and global best practices. It then selects the most suitable recommendations for each user. These tables provide recommendations based on Maslow's hierarchy of needs, covering physiological, safety, social, esteem and self-actualization needs, to help users enhance work efficiency and reduce stress. The Model-base Management System and Model Base analyse correlations between user emotions, mood, productivity and biometric data, generating customized recommendations to boost both work productivity and emotional well-being. Moreover, the system offers real-time assessments of productivity and emotional state, providing users with immediate insights into their performance and well-being. The article includes a case study, and various scenarios used to test and validate the system, demonstrating its validity, efficiency and practical utility. The system is designed to analyse and improve user emotions and productivity through interconnected subsystems. It begins with e-Self-Assessment, where users complete a questionnaire to evaluate their mood, productivity, stress levels and emotions on a ten-point scale. This self-reported data are then compared against biometric parameters.

Leone et al. [58] proposed a workplace framework to monitor mental load and improve well-being using wearable devices that track heart rate, skin conductance and eye movements. The system uses two wearable devices: J!NS MEME glasses and the E4 wristband from Empatica. These devices send data to a computer or smartphone for processing, aiming to automate stress detection. The experimental part involved a series of LEGO brick-based tasks designed to simulate manufacturing activities like assembly and manual handling. Data collection started with a 2 min baseline period, followed by five tasks to induce cognitive load. Tasks included assembling LEGO robots and airplanes or filling and carrying a toolbox. After each task, participants had a 2 min recovery period, and errors were counted to help assess stress levels. A moderator recorded the task's start and end times and marked errors, as frequent mistakes may indicate higher stress. The collected EDA and EOG signals were filtered to isolate relevant components. For classification, a SSVM was used, testing various kernels like Linear, Polynomial, Gaussian radial basis function (RBF) and Sigmoid. In this initial study, a two-class classification distinguished between stress and no-stress states. The results showed that the Gaussian RBF kernel allowed the SVM to recognize stress with 93.6% accuracy and a classification accuracy of 92.7%. However, the study's limitation was the small number of participants. Future research aims to expand the participant pool, explore real-time stress detection and assess multiclass classification to detect varying stress levels.

Rescio et al. [59], along with another group, proposed a stress assessment system based on an unsupervised learning technique to monitor workers' mental load, aiming to improve well-being in the workplace. The system uses minimally invasive wearable devices that combine HR, EDA and EOG measurements to automate stress detection. To evaluate the framework's performance, traditional mental stress tests and simulations of manufacturing activities were conducted. The data collection was carried out under controlled, simulated conditions, involving 7 female and 4 male volunteers. During the experiment, participants wore the wearable devices and performed five tasks, each separated by a two-minute rest period. The tasks, which included manufacturing simulations using LEGO bricks and a toolbox, were designed to induce stress, with detailed procedures available in prior studies. In addition, a mental arithmetic test, a common method for inducing stress, was conducted. At the end of the experiments, participants were asked to assess the cognitive load caused by each task. The mental arithmetic tests and complex LEGO assembly tasks, performed without instructions, were unanimously rated as the most stressful. More than 90 stress events and 130 rest events were identified and labeled for performance evaluation. During the data collection, data from the wristband and chest strap devices were stored on integrated memory, while data from the glasses were transmitted to an embedded PC. All data were synchronized and analyzed offline using MathWorks MATLAB. An unsupervised k-means clustering approach was employed, yielding good results in terms of specificity, sensitivity and accuracy (around 80%), without the need for a training phase, which is often time-consuming and less accurate.

Comparative Analysis of Hardware Platforms for Stress Detection

The field of stress detection has advanced with the development of different hardware platforms, using various technologies and sensors to provide continuous and reliable stress monitoring. These systems range from wearable sensors to devices integrated into everyday objects, offering multiple ways to track physiological and behavioral signs of stress. As shown in Table 1, the various hardware platforms used for stress detection exhibit distinct capabilities in terms of sensing, data transmission and sampling rates. These features play a crucial role in determining the overall accuracy and efficiency of stress-detection systems.

- Multisensory Platform

In the study by Rescio et al. [44], the authors proposed a system that integrates both an ambient and a wearable device within a multisensory platform [61]. The wearable component is a sensorized backstrap integrated with a ShimmerGSR unit, a portable sensor system. The ShimmerGSR unit is attached to the backstrap and uses Bluetooth for real-time data transmission, making it convenient for wireless communication with external systems. It features a range of sensing capabilities, including the measurement of GSR, PPG and various motion parameters such as angular rate, orientation and acceleration. GSR is measured using Ag/AgCl electrodes placed on the shoulder, which offer stable signal acquisition compared to other electrode types, while heart rate is assessed via a PPG probe connected to the earlobe. Vital parameters were sampled at a frequency of 10 Hz and transmitted via Bluetooth to an embedded PC, where a stress-detection algorithm was executed. The Bluetooth protocol, known for its low battery consumption, enables continuous monitoring over an entire work shift (approximately 8 h). Additionally, Bluetooth allows data to be transferred to a nearby cellphone for further transmission to a server, facilitating subsequent processing on the embedded PC. Complementing the wearable device, the system also includes an ambient device, which is a consumer-grade RGB camera capable of capturing images with a minimum resolution of 320 × 240 pixels. The RGB camera is used to perform facial recognition to estimate stress based on visual cues, such as facial expressions. The integration of both physiological signals and visual data provides a multimodal approach to stress detection, making the system well-suited for research requiring comprehensive data collection.

- Polar H7 and Amulet Platform

The system presented in study by Mishra et al. [45] employs a more streamlined approach by utilizing commercially available hardware. The primary sensing device is the Polar H7 heart rate monitor, a chest-worn device capable of measuring both heart rate and R-R intervals. The Amulet wearable platform is used as a data hub to collect and store the data transmitted from the Polar H7. The Amulet is an open-source platform designed for energy- and memory-efficient sensing applications and includes various onboard sensors such as a three-axis accelerometer, light sensor and ambient air temperature sensor. Amulet system focuses on physiological and activity data, making it more portable and user-friendly. Data from the Polar H7 are transmitted via BLE at 1 Hz to the Amulet wearable platform, which acts as the data hub for collection and storage.

- Compact Ring-Based Sensor System

In the paper by Valenti et al. [46], the authors proposed a compact and lightweight system for stress monitoring, consisting of two main components: a ring-shaped sensor probe and a microcontroller-based processing unit. The system integrates both GSR and PPG sensors, which are used to monitor physiological signals related to stress. This configuration optimizes sensor contact with the skin, standardizing the pressure across different users. The GSR sensor in the system is composed of silver-chloride (Ag/AgCl) electrodes. These electrodes are connected to the Mikroe-2860 GSR-Click sensor, which utilizes a volt-amperometric method for skin conductance detection, a reliable technique for assessing electrodermal activity, commonly associated with stress responses. The PPG sensor is based on the MAX30102 chip, which operates in reflectance mode. This mode involves placing the photodetector and light-emitting diodes on the same side of the sensor, a design that reduces the dependency of the PPG signal on tissue volume. To manage the sensors and process the acquired data, the authors use an STM32F446RE Nucleo-64 development board, a microcontroller that operates in continuous sampling mode. A key aspect of the system is its low-power design, with an estimated total power consumption of approximately 205 mW. This energy efficiency makes the system suitable for long-term monitoring applications, where low power consumption is critical for extended wear and continuous data acquisition. The GSR data are transmitted directly to the 12-bit analog-to-digital converter of the microcontroller, while the PPG sensor communicates with the board via the Inter-Integrated Circuit (I2C) protocol, allowing for efficient and high-frequency data acquisition. The system supports a sampling rate of up to 1.6 kHz, but for the purposes of the study, a rate of 800 Hz was selected, which is sufficient for analyzing heart rate variability with a 17-bit ADC resolution

- Integrated PPG Sensor System Embedded in a PC Mouse

The system developed by Lin et al. [47] provides a hardware solution designed for precise pulse rate detection across a range of conditions. The system integrates a NUC120 microcontroller, a Bluetooth module and four PPG sensors from uPI Semiconductor, which operate at a wavelength of 850 nm. These sensors, equipped with an infrared LED and a photodiode, capture physiological signals. To enhance signal quality, the system incorporates band-pass filters and a PGA117 amplifier with programmable gain, which allows for real-time adjustments of signal amplification via the Serial Peripheral Interface (SPI). The Inter-Integrated Circuit is utilized to control the PPG sensors, while the SPI manages the PGA switching to adjust the gain across different PPG channels. The filtered and amplified PPG signals are then input into a built-in 12-bit analog-to-digital converter with a sampling rate of 200 Hz. The resulting output is transmitted to a personal computer via the Bluetooth module, where the waveform and evaluated pulse rate are displayed. The data are stored and can be analyzed using an application program. A notable feature of their system is its Cortex-M0 processor, which is embedded in a PC mouse. This processor controls the

PPG sensors and handles signal processing within the mouse's compact form factor. The PPG sensor module is mounted on the top surface of the mouse, with sensors numbered 1 through 4 positioned to capture signals from different channels. This innovative integration provides a unique approach to wearable monitoring.

- Multisensor System in a Computer Mouse

The system developed by Androutsou et al. [48,49] represents an approach to stress detection by embedding a multisensor setup within a commercially available wired optical mouse. This system integrates a PPG PulseSensor (Pulse Sensor by World Famous Electronics LLC, Brooklyn, NY, USA), a Grove-GSR sensor (by Seeed), and a Particle Photon development board with a 120 MHz ARM Cortex M3 microcontroller and an onboard Broadcom Wi-Fi chip. The PPG PulseSensor includes a reverse-mounted green LED and an ambient light sensor (Broadcom APDS-9008) to measure blood pulse by detecting light reflected from the skin. The signal is filtered, amplified and adjusted for processing by the microcontroller. The Grove-GSR sensor uses disc-shaped electrodes to detect changes in skin resistance due to sweat, which affect the sensor's output. The Particle Photon board processes these signals with its 12-bit ADC and facilitates wireless data transmission via its Wi-Fi module, allowing for remote data collection and updates without needing to disassemble the mouse or install additional software. It operates within a supply voltage range of 3.6–5.5 V, drawing power from the mouse's USB connection. The system's efficient integration of sensors and compact design makes it a user-friendly solution for stress monitoring.

- PPG Sensors in a Wired Optical Mouse

The study by Chigira et al. [50] presents a design featuring wide, thin sensing surfaces that are optimized for integration into everyday devices. It enhances a conventional PPG sensor by employing two thin optical plates, a diffusion plate and a detection plate, separated by a narrow air gap. These high-refractive-index acrylic plates act as a waveguide, directing light from an IR LED through the user's fingertip to a photodetector. Up to 90% of the light from the diffusion plate passes through the detection plate, with light reflected from the fingertip returning to the detection plate. The PPG sensors are installed on both sides of a standard wired mouse, where a single IR LED and photodetector with a peak wavelength of 940 nm are positioned at the plates' light entrance. The LEDs are powered by a 100 mA direct current. The captured signals are amplified, filtered with a 10 Hz low-pass filter, digitized and transmitted to a PC via a USB connection.

- ECG and mouse activity

For data collection and processing, Sun et al. [52] obtained three distinct stress measures from each participant: subjective stress ratings, continuous electrocardiogram data and mouse activity data. Continuous ECG data were captured through a 3-lead ECG setup, with electrodes placed on the chest. These data were analyzed using the Kubios HRV tool to extract heart rate variability indicators, which are established measures of emotional response, particularly in relation to stress. Any incorrectly detected heartbeats were corrected, and missing beats were added. Mouse activity data were gathered using a high-resolution gaming mouse with a spatial resolution of 5700 counts per inch. The system recorded raw mouse input events at a sub-pixel level using C++ and Microsoft Windows GDI+. To simulate the resolution of a regular mouse, the data were decimated to 400 CPI, which did not affect detection accuracy.

- Mouse-Key Logger and Webcam

The study by Vea et al. [53] used a mouse-key logger to capture mouse movements, clicks, scrolls and keystroke events, along with a webcam to record the students' facial expressions and body movements.

- Pressure-Sensitive Keyboard and Mouse Using Force-Sensitive Resistors

Due to the absence of pressure-sensitive keyboards and mice on the market, Silva et al. [54] proposed a low-cost, simple design that can measure pressure using off-the-shelf keyboards and mice. The experimental setup incorporates FSRs to detect typing pressure. These FSRs are arranged in a voltage-divider configuration, with four sensors placed at the keyboard's underside corners. The sensors are connected to a microcontroller with data transmitted via an HC-06 Bluetooth module. A voltage divider was used to adjust the microcontroller's 5 V output to 3.3 V, suitable for the HC-06's input. The design utilizes a Dell KB212-B keyboard, chosen for its flat underside and convenient placement of its feet near the corners, making it ideal for sensor routing. In addition to the keyboard, the study explored measuring mouse grip pressure with FSRs. Early tests showed variability in grip patterns (palm, claw, tip), so the researchers opted for a vertical mouse (Anker Ergonomic) to encourage consistent grip pressure. After attaching FSRs and protecting them with duct tape, the final pressure-sensitive mouse was completed, with FSRs sampling at a rate of 100 Hz for both keyboard and mouse measurements.

- Wireless PPG Mouse Using Bluetooth Module

Tran et al. [37] developed a wireless PPG mouse by integrating a PPG sensor and a Bluetooth module into a standard USB 2.0 PC mouse (Samsung Co., Ltd., Suwon, Republic of Korea). The system features a red LED (APT1608SRCPRV) that provides a bright, wide-angle illumination with low power consumption of 20 mA and a peak wavelength of 660 nm. The accompanying photodetector (PDB-C160SM) has a large active area of 2.9 mm × 2.6 mm and a 120° viewing angle, allowing it to capture most of the reflected light from the LED. The proposed system includes a passive high-pass filter to eliminate baseline drift, a microcontroller with a 10-bit A/D converter for digitizing the PPG signal and a Bluetooth module for data transmission. With a total power consumption of 280 mW and the PC mouse consuming approximately 300 mW, the system operates well within the USB 2.0 standard's maximum power limit of 2500 mW, ensuring it does not interfere with normal PC operations. The PPG sensor is affixed to this window with silicon glue, while the Bluetooth board is mounted on the upper part of the mouse. The PPG system shares the PCB mouse's main power source via a wired connection. As the user operates the mouse, their thumb makes contact with the PPG sensor, allowing continuous, real-time monitoring of PPG signals. This non-invasive method enhances user comfort by avoiding the need for additional wearable devices. The system's sampling rate is set at 100 Hz to ensure accurate measurement of temporal parameters.

- CogniMouse

Belk et al. [56] developed the CogniMouse Architecture, a human interface device that connects to any computer via USB. This device is compatible with all major operating systems, thanks to a custom HID protocol that enables the transmission of 64 bytes of sensor data per packet. The design features a transparent GSR sensor embedded in the mouse button area to detect changes in the user's skin response. The prototype uses a commercial Microsoft Comfort Mouse 4500, which ensures user acceptance and familiarity. The current focus is on creating a classifier to assess user hesitation based on GSR sensor data and mouse motion patterns. A parser module processes the raw data from the sensors, which are then analyzed by the classifier algorithm.

- Biometric Computer Mouse and Finger System

The core of Kaklauskas et al.'s [57] system includes a Biometric Computer Mouse that measures various physical metrics such as hand temperature, skin conductance, touch intensity and heart rate. These biometric data are used to assess the user's emotional state and productivity. Additionally, the system captures mouse events, such as movements, clicks and idle times, storing this information in CSV format. It analyzes features like mouse speed, acceleration and tremble to evaluate work productivity and emotional well-being. The Biometric Finger subsystem complements this by providing further data on skin humidity, electrogalvanic skin conductance, skin temperature and heart rate. These additional data ensure a more comprehensive analysis.

- J!NS MEME ES_R Glasses and Empatica E4 Wristband

In the study by Leone et al. [58], two wearable devices, J!NS MEME ES_R glasses and the Empatica E4 wristband, send data to an embedded PC or smartphone for recording and processing. The J!NS MEME glasses continuously acquire real-time data using three-point electrooculography sensors placed on the nose pads, which measure vertical and horizontal EOG signals. Although the glasses also include an accelerometer and gyroscope to track head movements, this study focuses on the EOG sensor, which detects eye-blinks, a key factor in stress monitoring. The data are transmitted via a low-energy Bluetooth connection, and the rechargeable battery lasts about 16 h in streaming mode. The sample rate for this study is 50 Hz. The Empatica E4 wristband continuously collects data from four sensors: a PPG sensor to measure heart rate, an EDA sensor for tracking sympathetic nervous system arousal, an infrared thermopile for skin temperature and a tri-axial accelerometer to evaluate wrist movements. For this study, only the HR and EDA data were used due to their relevance in stress analysis. The sample rate is 1 Hz for HR and 4 Hz for EDA. Like the glasses, the wristband uses low-energy Bluetooth for data transmission and is paired with a mobile app for real-time data visualization and storage.

- J!NS MEME ES_R Glasses, Empatica E4 Wristband, and Bioharness 3.0 Chest Strap

In a study by Rescio et al. [59], an algorithmic framework was developed using three minimally invasive commercial wearable devices. Bioharness 3.0 Chest Strap—Produced by Zephyr, measures HR with built-in electrode sensors and an integrated electronic module. It can operate in streaming mode for real-time data viewing via low-energy Bluetooth or in recording mode using internal memory. Although the E4 wristband also measures HR, it was found to be less accurate compared to the Bioharness 3.0. As a result, Rescio et al. chose to use all three devices in their study to ensure better accuracy in data collection.

Table 1. Comparative overview of hardware platforms for stress detection.

Authors	Hardware Components	Sensing Capabilities	Data Transmission	Sampling Rate	Key Features
Rescio et al. (2024) [44]	ShimmerGSR unit integrated into a sensorized backstrap, Bluetooth module, RGB camera	GSR, PPG, heart rate, motion parameters (angular rate, orientation, acceleration), facial recognition	Bluetooth	10 Hz	Multisensory platform, combining wearable and ambient devices, continuous monitoring over 8 h, low battery consumption
Mishra et al. (2020) [45]	Polar H7 heart rate monitor, Amulet platform (with 3-axis accelerometer, light sensor, ambient temperature sensor)	Heart rate, R-R intervals, activity data (motion, ambient light, temperature)	Bluetooth Low Energy (BLE)	1 Hz	Commercially available hardware, energy- and memory-efficient sensing, portable and user-friendly
Valenti et al. (2023) [46]	Ring-shaped GSR and PPG sensors, Mikroe-2860 GSR-Click sensor, STM32F446RE Nucleo-64 development board	GSR (Ag/AgCl electrodes), PPG (MAX30102 chip in reflectance mode)	Direct ADC, I2C protocol	800 Hz	Compact, lightweight, low-power design (205 mW), optimized for skin contact, continuous sampling, high-frequency data acquisition

Table 1. *Cont.*

Authors	Hardware Components	Sensing Capabilities	Data Transmission	Sampling Rate	Key Features
Lin et al. (2017) [47]	Four PPG sensors (uPI Semiconductor), NUC120 microcontroller, PGA117 amplifier, Bluetooth module	PPG, pulse rate	Bluetooth	200 Hz	Embedded PPG sensors in a PC mouse, real-time signal amplification adjustment
Androutsou et al. (2023, 2021, 2022) [40,48,49]	PulseSensor (PPG), Grove-GSR sensor, Particle Photon development board (ARM Cortex M3, Wi-Fi chip)	PPG, GSR	Wi-Fi	-	Integrated sensors in a commercial optical mouse, remote data collection, compact and user-friendly design
Chigira et al. (2012, 2011) [50,60]	Two optical plates, IR LED, photodetector, USB connection	PPG (940 nm IR LED)	USB	-	Thin optical plates used in a wired optical mouse, high-refractive-index acrylic plate, digitized via USB
Freihaut et al. (2021) [51]	ECG with 3-lead electrodes, high-resolution gaming mouse	ECG (heart rate variability), mouse activity data	USB	-	Combination of ECG and high-resolution gaming mouse for detailed stress detection based on HRV and mouse activity
Sun et al. (2014) [52]	3-lead ECG, high-resolution gaming mouse	ECG, mouse acvtivity	USB	-	Combines ECG and high-resolution gaming mouse for stress detection, tracks mouse events and ECG data
Vea et al. (2017) [53]	Mouse-key logger, webcam	Mouse movements, clicks, scrolls, keystrokes, facial expressions	-	-	Combines mouse-key logger and webcam for stress detection based on user interaction
Silva et al. (2021) [54]	Dell KB212-B keyboard, Anker Ergonomic mouse, FSRs, HC-06 Bluetooth module	Typing and grip pressure	Bluetooth	100 Hz	Measures typing and grip pressure with FSRs, simple design, vertical mouse encourages consistent grip pressure

Table 1. *Cont.*

Authors	Hardware Components	Sensing Capabilities	Data Transmission	Sampling Rate	Key Features
Tran et al. (2020) [37]	PPG sensor (red LED, photodetector), Bluetooth module, USB PC mouse	PPG (660 nm red LED)	Bluetooth	100 Hz	Wireless PPG sensor integrated in a PC mouse, low power consumption, continuous real-time monitoring
Belk et al. (2016) [55]	Microsoft Comfort Mouse 4500, GSR sensor	GSR, mouse motion patterns	Bluetooth	-	Measures skin response, mouse motion, assesses hesitation and stress
Kaklauskas et al. (2011) [57]	Biometric computer mouse, Biometric finger system	Hand temperature, skin conductance, touch intensity, heart rate, skin humidity	-	-	Comprehensive physiological data, multiple biometric sensors for detailed emotional and productivity analysis
Leone et al. (2020) [58]	J!NS MEME ES_R glasses, wristband Empatica E4	3-point EOG)sensors (J!NS MEME), Accelerometer and Gyroscope (J!NS MEME), PPG sensor (Empatica), EDA sensor (Empatica), Infrared thermopile (Empatica), Tri-axial accelerometer (Empatica)	BLE	50 Hz (J!NS MEME) 1 Hz (HR) and 4 Hz (EDA) (Empatica)	Eye-blink detection and vertical/horizontal EOG tracking (J!NS MEME), HR and EDA data for stress analysis (Empatica), 16 h battery life (J!NS MEME), mbile app for real-time data visualization (Empatica)
Rescio et al. (2020) [59]	J!NS MEME ES_R Glasses, Empatica E4 Wristband, Bioharness 3.0 Chest Strap	EOG, EDA, HR	Low-energy Bluetooth/Internal memory	50 Hz (EOG), 4 Hz (EDA)	J!NS MEME ESR: Measures vertical and horizontal eye movements, 16 h battery life; Empatica E4: Assesses sympathetic nervous system arousal, includes mobile app for real-time visualization and storage, onboard memory; Bioharness 3.0: Measures heart rate with built-in sensors, operates in streaming or recording mode

This comparative analysis highlights a wide range of hardware platforms developed for stress detection and monitoring, each utilizing distinct technologies and sensor configurations.

Rescio et al.'s [44] multisensory platform combines physiological data from GSR, PPG and motion sensors with facial expression analysis, while Valenti et al.'s [46] compact ring-based sensor focuses on physiological data with a high sampling rate. Mishra et al.'s [45] Polar H7 and Amulet system prioritize portability and low energy consumption for heart rate and activity tracking. Lin et al. [47] integrate PPG sensors into a PC mouse for non-intrusive pulse monitoring, whereas Androutsou et al. [40,48,49] combine PPG and GSR sensors into a computer mouse for remote data collection. Chigira et al. [50,60] and Freihaut et al. [51] offer more basic but cost-effective PPG-based stress detection using a standard mouse. Sun et al.'s [52] system merges ECG and mouse activity data for a detailed physiological and behavioral analysis, while Vea et al. [53] add facial recognition and body movements to capture stress markers. Silva et al. [54] use force-sensitive resistors to measure typing and grip pressure in their low-cost design. Tran et al. [37] offer a wireless PPG mouse for continuous monitoring and Belk et al.'s [55] CogniMouse measures skin response to track user stress. Kaklauskas et al. [57] provide a biometric mouse and finger system that captures multiple physiological markers like heart rate, temperature and touch intensity. Leone et al. [58] focused on developing a framework for monitoring mental load and improving workplace well-being using wearable devices to track heart rate, skin conductance and eye movements for automated stress detection. Finally, Rescio [59] focused in another study on developing an unsupervised learning-based system to monitor workplace stress using wearable devices that measure heart rate, electrodermal activity and eye movements.

These platforms present a balance of multimodal, sensor-rich systems and simpler, cost-effective devices, each with varying levels of data complexity, user comfort and integration challenges. Their applications depend on specific research goals and practical use cases.

5.2. Advanced Techniques in Neural Network-Based Stress Detection

In an era of rapid technological progress and increased mental health awareness, developing effective stress-detection methods is crucial. Neural networks, particularly deep learning models, have emerged as powerful tools for continuous and precise stress monitoring. This section delves into various approaches leveraging neural networks for stress detection, emphasizing the contributions of several key studies. Li et al. explored the use of deep learning techniques, including one-dimensional convolutional neural networks (CNNs) and multilayer perceptron (MLP) networks, for analyzing physiological signals, achieving notable accuracy in stress and emotion classification [62]. Similarly, Song et al. proposed a stress-classification model based on a Deep Belief Network (DBN), which bridged supervised and unsupervised learning. Their model demonstrated superior performance compared to traditional classifiers, indicating its effectiveness for stress detection. Zanetti et al. extended the concept of Network Physiology, utilizing consumer-grade wearable devices and sophisticated data-synchronization techniques to differentiate between levels of psychological stress [21]. Han et al. applied Random Forest to optimize symptom combinations for improving stress-classification performance [63], while Pepa et al. developed a method based on keystroke and mouse dynamics to infer stress levels in real-world settings [64]. Additionally, Gil-Martin et al. proposed a deep learning architecture using CNNs to analyze physiological signals, achieving high accuracy in stress detection [65]. Meanwhile, Lawanont et al. employed unsupervised learning techniques, such as k-means and hierarchical clustering, to analyze stress levels in a workplace setting [66]. They utilized various sensors to collect data related to behavior and the work environment, providing insights into stress-related behaviors. Akhonda et al. [67] used a three-layer Back Propagation Neural Network to detect stress by analyzing EEG alpha waves and other physiological signals during computer use. Lv et al. [68] employed the

Common Spatial Pattern (CSP) algorithm and an SVM model to develop an accurate EOG-based eye gesture recognition system, enhancing detection capabilities for both saccadic movements and complex gestures.

Collectively, these studies highlight the effectiveness and versatility of neural networks in advancing stress-detection technologies and their potential for practical applications in stress monitoring. All of these mentioned studies are detailed in the following text.

Li et al. proposed the use of deep learning techniques, specifically a one-dimensional (1D) CNN and a multilayer perceptron neural network, for stress detection and emotion classification [62]. They transformed physiological signals into vectors and inputted them directly into the neural network. The models were trained and tested using a dataset from Schmidt et al. [69]. A deep convolutional neural network typically includes filtering layers, activation functions, pooling layers and fully connected layers.

For their study, Li et al. utilized two datasets collected from sensors placed on the participants' bodies. The first dataset was acquired with sensors positioned on the chest, monitoring ECG, EDA, electromyogram, skin temperature, respiration rate and a tri-axial accelerometer. In the second dataset, sensors embedded in a wrist-worn device captured the signals. This device included an accelerometer and measured pulse blood volume and EDA. The results for three-class emotion classification and binary stress detection indicated that deep neural networks consistently outperformed traditional machine learning algorithms. Specifically, the deep 1D convolutional neural network, applied to data from chest-worn sensors, achieved an accuracy of 99.55% for all physiological signals and 97.48% when excluding accelerometer-derived signals for emotion classification. Similarly, the deep multilayer perceptron neural network, applied to wrist-worn sensors, achieved accuracy rates of 98.38% and 93.64% under the same conditions.

For binary stress detection, the deep 1D convolutional neural network, using chest-worn sensors, attained accuracy rates of 99.80% and 99.14% for all physiological signals and accelerometer-excluded signals, respectively. The deep multilayer perceptron neural network, using wrist-worn sensors, achieved accuracy rates of 99.65% and 97.62% under similar conditions. These findings demonstrate that both deep neural networks significantly outperformed traditional machine learning methods, highlighting their effectiveness for stress detection and emotion classification.

In a separate study, Zanetti et al. aimed to develop a model to distinguish between three different levels of psychological stress, conducting measurements on 17 participants [21]. Their novel approach employs a stress-detection method known as Network Physiology, developed by Bashan et al. [70]. Bashan conceptualized each organ system as a node in a complex network of dynamic physiological interactions. Zanetti extends this idea by analyzing the interactions among multiple systems and examining the relationships between their output signals. They use information theory to quantify these physiological interactions and differentiate between various levels of psychological stress.

Physiological signals were acquired using non-invasive, consumer-grade wearable devices. A sensor trio from Smartex measured ECG and respiratory signals at sampling rates of 250 Hz and 25 Hz, respectively, with respiratory waveforms recorded by a piezoresistive sensor positioned on the rib cage. An Empatica2 bracelet captured BVP signals at 64 Hz. EEG signals were collected using a 14-channel wireless head-mounted device, the Emotiv EPOC PLUS, with sensors placed according to the international 10–20 system and a sampling rate of 256 Hz for each channel.

Zanetti et al. emphasize the importance of accurate electronic clock generation to prevent time shifts and desynchronization in recorded data, which can complicate the analysis of signal interactions critical for network physiology. To address this issue, they developed a synchronization method utilizing variables from all available devices. The process involves:

1. Identifying the primary motion directions for each device,
2. Securing the devices with industrial Velcro fasteners to ensure stability,

3. Creating a non-uniform acceleration pattern by moving the fixed support (with sensors) along a sinusoidal path,
4. Synchronizing the collected, low-pass filtered and accelerated signals with a reference signal.

The last two steps mentioned are conducted both at the start and end of the signal recording to account for any factors that might affect the timeline. Synchronization is achieved through linear time warping relative to the reference signal.

To differentiate among three psychological stress states, recordings from ECG, BVP, EEG and respiration were collected using wearable devices. Information-theoretic measurements were utilized to train various classification algorithms. The best performance was achieved by Logistic Regression (LR) and Random Forest (RF) classifiers, with an accuracy of 84.6%. RF, when using only cardiac and respiratory signals, achieved an accuracy of 76.5%.

The authors demonstrated the efficacy of applying the Network Physiology approach with signals from low-invasive, consumer-grade wearable devices to identify different levels of psychological stress. Their findings are promising and suggest that using inter-subject models with these parameters is feasible.

In related work, Lawanont et al. explored stress levels in the workplace [66]. They developed a monitoring device for subjects and applied unsupervised learning to the data. By using the Perceived Stress Scale (PSS) [71], they identified relationships between data clusters and stress levels, with the PSS assessing how stressful individuals perceive various life situations to be.

Their system gathered various attributes related to behavior and the work environment [66]. These attributes contributed to clustering results and can be used to provide employees with insights into their stress-related behaviors. The authors also developed a data-acquisition device using Arduino, Raspberry Pi and multiple sensors. A force measurement sensor integrated into the seat cushion tracked how frequently the subject shifted between sitting and standing positions, while a sensor embedded in the mouse pad recorded the force of mouse movements. By analyzing the force data from these sensors, they linked it to individual stress levels. Additionally, humidity, temperature and ambient light sensors collected data on the working environment's attributes.

Instead of using PSS-based classification, the study employed unsupervised learning techniques, specifically k-means clustering and hierarchical clustering. The experiment involved seven participants who worked continuously at their workstation for five hours without breaks. Initially, participants completed a PSS questionnaire. The researchers compared the clustering results with the PSS scores of the subjects, using the number of instances from each subject within each cluster to represent stress levels. Each cluster was associated with high or low stress based on the number of instances and their PSS values, thereby determining the stress levels in the work environment.

Song et al. developed a stress-classification model based on a Deep Belief Network (DBN) [72]. DBN is a sophisticated machine learning method that bridges supervised and unsupervised learning and is widely used in medical fields due to its effectiveness. They utilized data from the Korea National Health and Nutrition Examination Survey (2013–2015) and employed two approaches. First, they assessed stress by comparing physical activity and lifestyle data (such as sleep duration, blood pressure, body mass index, alcohol and cigarette use) among individuals under 19 and over 80, relative to their stress levels. Second, they applied a DBN classification model to this data, performing statistical analysis to identify significant variables for stress detection. The results showed that the DBN model achieved an accuracy of 66.23%, outperforming other classification models like Support Vector Machine, Naive Bayes and Random Forest, proving its effectiveness for stress detection.

Gil-Martin et al. proposed a deep learning architecture using CNNs for stress detection [65]. Their architecture includes three convolutional layers for extracting features from inertial and physiological signals. They investigated several signal-processing techniques, such as Fourier transform, third root transformation and Constant Q Transform (CQT), to prepare the data for the deep learning model. Using the WESAD dataset [69], they examined different classification tasks: two classes (stress vs. no stress), three classes (stress, baseline and fun) and five classes (stress, baseline, fun, meditation and recovery).

Signals from wearable devices, sampled at different frequencies and containing information in various frequency ranges, were segmented into 60 s windows with a 0.25 s overlap. Classification was performed at the window level, with preprocessing including fast Fourier transform and averaging the spectra of subwindows. The input to the CNN consisted of the frequency range and spectrum coefficients. They tested two preprocessing options: calculating the third root of the spectra before averaging and applying CQT after Fourier transformation. The CNN, featuring three convolutional layers, two max-pooling layers and three fully connected layers with dropout, learned relevant features from the signal spectra. Accuracy and F1 scores were used for evaluation, with the third root transformation significantly improving the results.

The low-frequency components were emphasized, revealing a more distinct harmonic structure, though the Constant Q Transform (CQT) did not offer additional improvements. Comparing these results to previous studies, accuracy improved from 93.1% to 96.6% in classifying stressed versus non-stressed states. Similarly, the accuracy for distinguishing stress and enjoyment from a baseline increased from 80.3% to 85.1%. The authors suggested exploring the use of physiological signal measurement devices on other body areas to avoid potential interference, such as during professional flights, thereby enhancing practical stress monitoring.

Han et al. utilized Random Forest to determine the optimal combination of symptoms for improving classifier performance [63]. They evaluated four different classifiers to achieve the best results. Given the absence of a universally accepted definition of stress and standardized databases, their study examined work-related stress from multiple perspectives. The first perspective combined psychological and psychosocial stress factors to simulate stressful work conditions. In another approach, they aimed to identify three levels of stress (none, moderate and high). Data were collected using a wearable device that measured ECG and respiratory signals, providing continuous stress level monitoring. Random Forest was used to identify the best feature combinations to enhance classifier performance.

The study involved 39 healthy participants who underwent the Montreal Imaging Stress Task (MIST), designed to assess the effects of psychological stress on physiology and brain activity. The data, segmented into one-minute intervals, included ECG and respiratory signals. Random Forest ranked the significance of these symptoms to select the most relevant ones for training and testing classifiers.

Feature selection improved classification accuracy from 78% to 84% when using the Support Vector Machine (SVM) classifier. The SVM classifier achieved 94% accuracy in distinguishing between resting and stressed conditions. It also outperformed other classifiers, such as Linear Discriminant Analysis (LDA), Adaboost and K-Nearest Neighbors (KNN), with an accuracy of 84% in classifying three stress levels. Combining ECG and respiratory signal features enhanced the classification model's performance. The authors integrate both psychological and psychosocial stress factors to simulate realistic office conditions.

Pepa et al. address stress classification by developing a method based on keystroke and mouse dynamics (K&MD) [64]. Their approach uses real data collected in unsupervised settings that resemble traditional office or remote work environments. They infer stress levels from PC tasks performed on a custom web application, utilizing various K&MD features for detection and validate their algorithm's robustness through inter-subject analysis.

The study, conducted during the COVID-19 pandemic, involved 62 participants aged 18 and older, primarily working remotely. Participants used their own devices to complete four progressively challenging tasks designed to induce cognitive load and anxiety. These tasks included text writing, the Tower of Hanoi puzzle, the Simon Speaks game and the Four Quadrant Test. Data collected included self-rated stress levels, keyboard data and mouse data. Participants rated their stress on a scale from 1 to 10 after each task. The keyboard data detailed each keystroke, including the character typed, event type, keystroke duration and timestamp.

Features were extracted from the keyboard and mouse data using a 5 s scrolling window, generating metrics such as maximum, minimum, mean, standard deviation and point-to-point deviation. A total of 15 features were calculated. The data were categorized into low (1–3), medium (4–7), or high (8–10) stress levels. After min-max normalization, feature selection was conducted using Neighborhood Component Analysis (NCA). The RF classifier performed the best and was further enhanced with Multiple Instance Learning (MIL) to address inaccuracies in labeling. MIL involves learning from labeled ensembles of multiple samples, with RF extending this approach.

Subject-independent 5-fold cross-validation tested both classifiers, with 80% of participants used for training and 20% for testing. The dataset contained 429 points (120 low, 222 medium and 87 high stress). The mouse classifiers achieved 63% accuracy, while the keyboard classifiers reached 76% accuracy.

Akhonda et al. [67] explored the relationship between EEG alpha wave amplitude and concentration, noting that higher alpha wave activity is linked to increased concentration, while stress is often inversely related. Alpha waves peak when the eyes are closed and are lowest when open. The goal of the study was to analyze physical and mental performance variations during prolonged computer use to determine stress levels. Using ECG, EMG, EOG and EEG signals, the research aimed to accurately detect these changes. Physiological signals were collected, leading to the extraction of 14 key features, with an expectation of significant correlations between them due to their shared physiological origin. To enhance stress detection and classification, a three-layer Back Propagation Neural Network was employed. Data from 12 participants performing various computer tasks in an office-like setting revealed that both intense eye work and mental stress were major contributors to stress, though other factors such as mental state and lack of sleep may also have an impact. The neural network was trained using data from 8 subjects, each contributing two datasets (Resting State and Stress State), for a total of 16 datasets, with 14 features extracted from the signals. The network was then tested on data from 4 subjects not involved in the training process. Although the exact accuracy of the neural network is not provided as a percentage, its effectiveness can be inferred from the test results. The network demonstrated its ability to classify subjects into resting state (RS) and stress state (SS) with considerable precision. For instance, in the case of Subject 3, the neural network correctly identified a resting state at the start of the session and a stress state by the fourth hour. Similarly, when the network was used to distinguish between stress due to eye strain (StES) and mental stress (MSt), it was able to highlight which type of stress was more dominant for each subject. For example, for Subject 1, the neural network output in the fourth hour indicated that eye strain contributed more to stress (StES: 0.5023) than mental stress (MSt: 0.4105). This consistency between the network's predictions and the actual self-reports of stress levels suggests that the neural network was highly effective at detecting and classifying stress conditions, even though an explicit numerical measure of accuracy was not reported.

Lv et al. [68] presented a feature extraction method based on the CSP algorithm to improve the accuracy of EOG-based saccadic detection. By using CSP to calculate spatial information from eye-movement sources, the method effectively distinguished predefined saccadic tasks, such as directional eye movements. Building on this, they developed an 8-class eye gesture recognition system to detect complex gestures like vertical, horizontal, diamond, "Z" shape and squares by analyzing consecutive saccadic signals. The system achieved high accuracy, with 96.8% for saccadic signals and 95.0% for eye gestures. The research aimed to create a precise EOG-based eye-movement-detection algorithm to complement video-based methods, particularly for individuals with motor disabilities. The CSP method enhanced the recognition of EOG signals by projecting them through a spatial filter bank and using an SVM model for classification. Future work will focus on improving saccadic detection through optimized sampling and noise reduction, and incorporating additional features like micro-saccades.

Comparative Analysis of Advanced Techniques in Neural Network-Based Stress Detection

Neural networks have become an effective tool for stress detection, enabling precise analysis of complex physiological data to assess stress levels accurately. This section provides a comparative analysis of various neural network techniques used in stress detection. Table 2 provides a comparative overview of the neural network techniques used for stress detection, highlighting the differences in physiological data utilized and the accuracy achieved by each method.

The compared studies demonstrate the growing potential of neural networks, especially deep learning models, to develop accurate, real-time stress-detection systems. These techniques have been applied to a range of physiological signals, including ECG, EDA, EEG and behavioral data such as keystroke dynamics.

Table 2. Comparative overview of neural network techniques for stress detection.

Authors	Neural Network Technique	Data Used	Accuracy
Li et al. (2020) [62]	1D CNN, MLP	ECG, EDA, EMG, skin temp, respiration, accelerometer (chest/wrist)	CNN: 99.55% (emotion), 99.80% (stress); MLP: 98.38% (emotion), 99.65% (stress)
Song et al. (2017) [72]	DBN	Physical activity, lifestyle data (sleep, BMI, etc.)	66.23% accuracy (DBN outperformed SVM, Naive Bayes and RF)
Zanetti et al. (2021) [21]	Logistic Regression, RF	ECG, BVP, EEG, respiration	RF: 76.5% accuracy (cardiac/respiratory signals); overall: 84.6%
Gil-Martin et al. (2022) [65]	CNN	Inertial and physiological signals (WESAD dataset [69])	CNN: 96.6% (stress vs. non-stress); 85.1% (stress, fun, baseline)
Han et al. (2017) [63]	RF	ECG, respiration (MIST stress task)	SVM with selected features: 94% accuracy (stress detection); RF: 84% (three stress levels)
Pepa et al. (2020) [64]	RF with Multiple Instance Learning	Keystroke and mouse dynamics	Mouse: 63%; Keyboard: 76% accuracy
Akhonda et al. (2014) [67]	Back Propagation Neural Network	EEG, ECG, EMG, EOG (alpha waves)	Accuracy not explicitly provided as a percentage but demonstrated through precise classification of stress states and corresponding neural network outputs.
Lv et al. (2018) [68]	SVM, CSP for feature extraction	EOG signals (eye movements)	96.8% (saccadic detection); 95.0% (eye gestures)

The exploration of advanced neural network techniques for stress detection reveals a rapidly evolving field with significant potential for enhancing mental health monitoring. Neural networks, particularly deep learning models, have demonstrated remarkable efficacy in analyzing physiological signals and inferring stress levels with high accuracy. The studies reviewed provide a comprehensive overview of various approaches, each contributing unique methodologies and insights into stress detection. Collectively, these studies illustrate the diverse and innovative approaches being developed in the field of neural network-based stress detection. The integration of deep learning models with physiological data analysis holds promise for creating more effective, personalized and real-time stress-monitoring systems. As the technology advances, future research will likely continue to refine these methods, enhance their accuracy and expand their practical applications, ultimately contributing to better mental health management and stress reduction.

6. Discussion

The study makes significant contributions to the field of stress detection by exploring a diverse range of technologies and methods. By exploring the potential of integrating stress-detection features into everyday objects like PC mice or keyboard, it opens up new possibilities for continuous and unobtrusive stress monitoring. The research highlights various innovative approaches and devices, demonstrating how these technologies can enhance stress detection, leading to improved well-being for each employee, which in turn increases their productivity.

Monitoring stress through PC peripherals, such as keyboards and mice, presents a range of advantages and disadvantages. On the positive side, these peripherals are already integrated into users' daily routines, allowing for seamless and continuous stress monitoring without requiring additional devices or altering existing workflows. This non-intrusive approach ensures that stress assessment occurs in the background, thereby enhancing user comfort and acceptance. Moreover, utilizing existing peripherals for stress monitoring can be more cost-effective compared to developing separate, specialized wearable devices, making the technology more accessible and scalable. Continuous data collection through these devices can provide real-time feedback, potentially allowing users to manage stress proactively and improve their overall well-being and productivity.

Implementing stress-monitoring systems using computer mice, keyboards (or even smartphone keyboard [73]) can greatly benefit employers by fostering a more reliable and productive workforce. These systems provide continuous, real-time assessments of employee well-being, helping to identify stress levels that could impact performance and reliability. This proactive approach enables the implementation of timely interventions, such as offering support or adjusting workloads, which can also enhance overall productivity and job satisfaction. Furthermore, accurate tracking of stress levels also offers insights into patterns and triggers affecting employee performance and decision-making, facilitating better management of potentially risky situations and leading to improved problem-solving and decision-making.

However, there are significant drawbacks to consider. The accuracy of stress detection can be influenced by the sensitivity and placement of sensors within the peripherals, as well as interference from other activities, potentially leading to unreliable stress assessments. Additionally, the scope of monitoring may be limited to certain physiological signals or behavioral patterns, potentially missing other crucial indicators of stress. Motion artifacts from normal keyboard and mouse usage can complicate data interpretation, requiring additional processing to ensure accuracy. Individual variability in typing patterns, mouse usage and stress responses may also impact the effectiveness of the monitoring systems, requiring customization or calibration for different users. Lastly, the effectiveness of stress monitoring depends on the continuous use of these peripherals. Gaps in usage, such as switching devices or taking breaks, can result in incomplete data and reduce the reliability of stress assessments.

Overall, while stress monitoring using PC peripherals presents promising opportunities for improving employee well-being and productivity, it also comes with limitations that need to be addressed to maximize its effectiveness and reliability.

7. Conclusions

In recent years, the importance of detecting and monitoring stress has become increasingly evident due to its significant impact on both mental and physical health. Stress is known to contribute to a range of issues, including anxiety, depression, cardiovascular disease and cognitive impairment. As such, early detection and ongoing monitoring are crucial for effective stress detection. Our review highlights the potential of innovative devices to transform how we interact with technology by integrating advanced sensors and tools for detecting stress.

Smart PC peripherals offer a range of functionalities beyond traditional input devices, including the monitoring of physiological metrics such as stress levels, hand movements and overall ergonomic impact. By leveraging technologies such as biosensors, machine learning algorithms and real-time data analysis, these devices might provide valuable insights into user well-being and performance.

The ability to monitor stress and other physiological signals through a smart PC mouse opens new routes for improving workplace health and productivity. Real-time feedback allows for timely interventions, potentially reducing the risk of stress-related issues and enhancing overall job satisfaction. Furthermore, the integration of these devices into everyday work routines offers a practical approach to ergonomics, helping users optimize their working conditions and prevent strain or discomfort.

As the technology continues to evolve, future developments in smart PC perpiherals could offer even more sophisticated features, including enhanced accuracy in physiological measurements and more intuitive user interfaces. Continued research and innovation will be crucial in refining these devices and expanding their applications, ultimately contributing to healthier and more efficient work environments.

In summary, smart PC perpiherals represent a promising intersection of technology and health monitoring, providing both immediate and long-term benefits for users. By addressing the challenges of modern work environments and offering actionable insights, these devices have the potential to significantly enhance both user experience and productivity.

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