# Mental Health Management Through Wearables and AI Innovation

Akshara Ajendla, Mahi Patel, Parthan Olikkal, and Ramana Vinjamuri

Vinjamuri Lab, Department of Computer Science and Electrical Engineering, University of Maryland Baltimore County, Baltimore, MD, USA

## Abstract

Mental health disorders, affecting nearly one billion people globally, pose a silent yet pervasive threat to well-being, reducing life expectancy and straining families, workplaces, and healthcare systems. Traditional management tools, clinical interviews, questionnaires, and infrequent check-ins fall short, hampered by subjective biases and their inability to capture the nature of conditions like anxiety and depression. This chapter explores how wearable technologies, powered by advanced sensors, artificial intelligence (AI), and machine learning (ML), are revolutionizing mental health care by enabling continuous, objective monitoring. Focusing on four approaches – physiological (e.g., heart rate variability via smartwatches), neurotechnological (e.g., Electroencephalography (EEG), Transcranial magnetic stimulation (TMS)), contactless (e.g., camera based vital sign detection), and multimodal (integrating multiple neurophysiological and behavioral signals) we analyze their mechanisms, applications, and transformative potential, supported by studies achieving up to 99.48% accuracy in detecting stress and anxiety. These innovations promise proactive care, early intervention, and greater accessibility, yet face challenges including privacy risks, standardization gaps, and the need for robust clinical validation. By integrating AI and refining device design, wearable technologies could redefine mental health management, empowering field, though their success hinges on overcoming technical and ethical hurdles.

## 1. Introduction

The landscape of mental health has reached a critical stage in the modern era, where disorders such as depression, anxiety, and stress related conditions have emerged as pervasive threats to human wellbeing across the globe. According to the World Health Organization (2022), nearly one in eight individuals, approximately one billion people, struggle with a mental health condition, a statistic that emphasizes the scale of this silent epidemic. These disorders not only diminish quality of life but also impose a staggering burden, reducing median life expectancy by about 10 years due to associated physical comorbidities, suicide risk, and socioeconomic hardship [Malik et al., 2024]. The ripple effects compound as families rupture under the strain, workplaces lose productivity as absenteeism and burnout rise, and healthcare systems buckle under escalating costs and unmet demand. In many regions, access to care remains a distant prospect, with stigma, resource shortages, and logistical barriers leaving millions untreated.

For decades, mental health management has leaned heavily on traditional tools: clinical interviews, standardized questionnaires, and periodic check-ins with professionals. These methods, while foundational, are plagued by inherent flaws. Self-reports hinge on patients' ability to accurately recall and articulate their experiences, a task complicated by memory biases, emotional suppression, or the stigma of disclosure. Clinical assessments, often scheduled weeks or months apart, capture mere snapshots of a patient's state, missing the ebb and flow of symptoms that characterize conditions like bipolar disorder or generalized anxiety. This disconnect between lived experience and clinical observation has fueled a growing demand for solutions that are continuous, objective, and responsive to the real time dynamics of mental health.

Wearable technologies have emerged as a beacon of hope in this context, leveraging cutting edge sensors, artificial intelligence (AI), and machine learning (ML) to redefine how we monitor and manage mental well-being. From smartwatches tracking heart rate variability (HRV) to neurotech devices measuring brainwaves, these innovations promise a shift from reactive to proactive care. They offer a window into physiological and neural markers, heart rhythms, skin conductance, sleep patterns, and more, that reflect mental states with unprecedented granularity. Fig. 1 shows the growth of publication data of research on mental health management using wearable devices from 2010 to 2024 on PubMed, National Library of Medicine.

This chapter provides an in-depth exploration of these advancements, focusing on four key approaches: physiological, neurotechnological, contactless, and multimodal. We examine their mechanisms, applications, strengths, and limitations, drawing on the latest research to inform their transformative

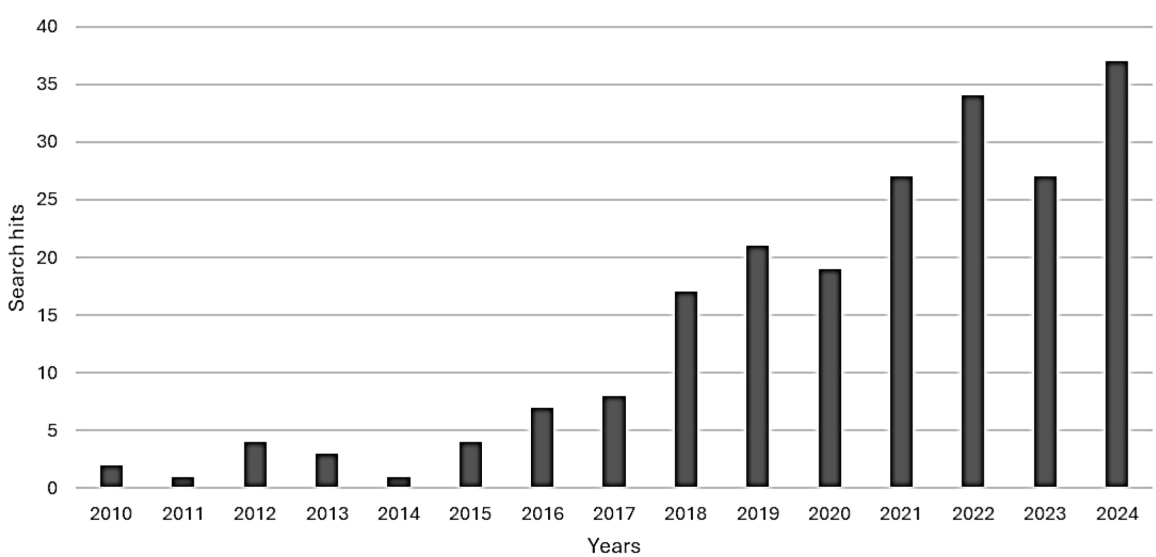


**Fig.1. Search results for "wearable devices in mental health management" on PubMed, National Library of Medicine, indicate a rapidly increasing interest in this field.**

potential, including recent studies like those by Can et al. (2019), Smirthy et al. (2023), and Khan et al. (2023), which highlight the efficacy of wearables and ML in stress detection across diverse scenarios. Beyond technical details, we consider the broader implications of how these tools integrate with AI, their advantages and challenges, and the future trajectories that could cement their role in mental health care. As we stand on the cusp of this technological revolution, wearable devices hold the promise of not just managing mental health, but reimagining it as a field rooted in precision, accessibility, and empowerment.

## 2. Emerging Technologies in Mental Health Management

This section explores how wearable technologies, powered by advanced sensors, artificial intelligence (AI), and machine learning (ML), are revolutionizing mental health care by enabling continuous, objective monitoring. Focusing on four approaches (Fig.2) – (1) physiological (e.g., heart rate variability via smartwatches), (2) neurotechnological, (3) contactless (e.g., camera based vital sign detection), and (4) multimodal (integrating multiple data streams) we analyze their mechanisms, applications, and transformative potential, supported by studies in detecting stress and anxiety.

### 2.1. Physiological Approaches

Physiological approaches to mental health monitoring harness wearable sensors to capture bodily signals that mirror psychological states, offering a noninvasive gateway to understanding conditions like stress, anxiety, and depression. These technologies rely on an array of sensors embedded in devices such as smartwatches, fitness trackers, and wristbands. Electrocardiogram (ECG) sensors measure the heart's electrical activity, providing data on heart rate (HR) and heart rate variability (HRV), both of which shift

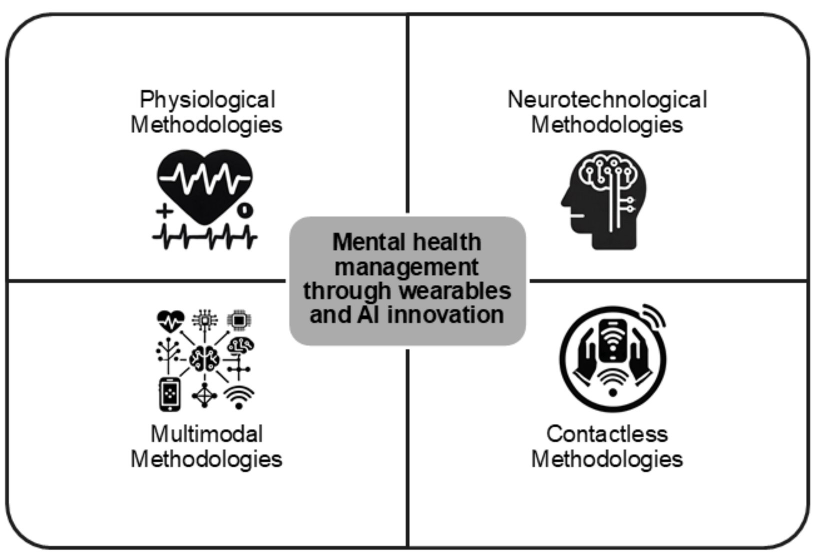


**Fig.2. Focusing on four approaches – (1) physiological (e.g., heart rate variability via smartwatches), (2) neurotechnological (e.g., EEG), (3) contactless (e.g., camera based vital sign detection), and (4) multimodal (integrating multiple data streams) we analyze their mechanisms, applications, and transformative potential, supported by studies in detecting stress and anxiety.**

under stress or emotional distress. Photoplethysmogram (PPG) sensors, commonly found in devices like the Apple Watch or Fitbit, use light to detect blood volume changes, offering a simpler alternative for HR monitoring. Galvanic skin response (GSR) or electrodermal activity (EDA) sensors track skin conductance, which rises with sweat production during emotional arousal, while respiratory sensors monitor breathing patterns that can signal tension or calm. Research underscores their efficacy: a 2021 study achieved a remarkable 96.25% accuracy in classifying stress during public speaking using ECG, GSR, and PPG data [Arsalan & Majid, 2021], and a 2023 systematic review of nine studies reported up to 99.48% accuracy in detecting anxiety with similar sensors [Gomes et al., 2023]. Additional studies reinforce this potential, with a 2018 study using bio-radar respiratory signals achieving 94.4% accuracy in binary stress detection [Fernández & Anishchenko, 2018], a 2019 study using PPG for multilevel stress detection reporting 94.33% accuracy [Zubair & Yoon, 2019], a 2023 ear-mounted PPG study achieving 96.02% accuracy [Barki & Chung, 2023], and a 2016 low cost ECG sensor study detecting stress with high precision [Salai et al., 2016].

Moreover, Shanmugasundaram et al. (2019) reviewed physiological stress detection, finding accuracies up to 85% with combined HR, GSR, and speech data, while Greene et al. (2017) noted GSR and PPG as noninvasive alternatives to ECG with high correlation (e.g., 93% for GSR). Further advancing this field, a 2023 study by Campanella et al. utilized the Empatica E4 bracelet to analyze PPG and EDA signals with machine learning techniques (Random Forest, SVM, Logistic Regression), achieving up to 76.5% accuracy in classifying stress versus no-stress states, though its small sample size and lab setting highlight limitations for real-world use [Campanella et al., 2023]. Similarly, a 2018 study by Attaran et al. designed low-power processors for personalized stress detection using HR and accelerometer data from a wearable Lifeshirt, achieving 96.7% accuracy with SVM in a shooting task context, suggesting potential for energy-efficient wearable solutions despite its task-specific focus [Attaran et al., 2018]. Mokhayeri et al. (2011) also contributed, using pupil diameter (PD), ECG, and PPG signals with genetic algorithms and fuzzy SVM, achieving 78.5% accuracy in a lab-based multimodal dataset, though real-world validation remains a gap [Mokhayeri et al., 2011]. These findings highlight the growing reliability of physiological wearables in real world applications.

The advantages of physiological approaches are manifold, rooted in their accessibility and real time capabilities. These sensors are increasingly ubiquitous, integrated into consumer devices that millions already own, such as the Samsung Galaxy Watch or Garmin trackers, requiring no specialized training or clinical oversight for basic use. This democratization of technology empowers individuals to monitor their mental health independently, potentially reducing reliance on overburdened healthcare systems. The continuous nature of the data collection, tracking HRV during a stressful meeting or sleep disruptions over weeks, offers a dynamic picture of mental states that static clinical visits cannot replicate. This granularity facilitates early detection, catching subtle shifts like elevated stress before they spiral into a full-blown crisis, a capability that could transform preventive care. Moreover, their noninvasive design ensures minimal disruption to daily life, blending seamlessly into routines without the stigma or discomfort of more intrusive methods, making them a practical choice for long term monitoring.

Despite these strengths, physiological approaches face notable disadvantages that temper their promise. Their dependence on indirect markers, HRV, skin conductance, or breathing, means they infer mental states rather than measure them directly, introducing a layer of ambiguity. For instance, an elevated heart rate might stem from physical exertion rather than anxiety, muddying the signal and necessitating careful contextual analysis. Environmental factors, such as temperature, humidity, or even caffeine consumption, can further distort readings, reducing reliability in uncontrolled settings like a bustling commute or a noisy home. The scope of these sensors is also limited; while they excel at detecting acute states like stress or panic, they struggle to capture the nuanced, long-term trajectories of disorders like depression or post-traumatic stress disorder (PTSD), which may not consistently manifest in physiological data. This limitation suggests that while powerful, these tools are best suited as complements to, rather than replacements for, deeper diagnostic methods, a point echoed by Can et al. (2019), who noted lower accuracies (e.g., 72%) in daily life settings due to noisy data and subjective ground truth. The Campanella et al. (2023) study further noted challenges like motion artifacts and unbalanced datasets, reinforcing the need for broader, real-world testing [Campanella et al., 2023].

The future direction of physiological approaches lies in overcoming these hurdles through technological refinement and broader integration. Researchers are exploring ways to enhance sensor robustness, developing algorithms that filter out noise from physical activity or environmental variables to ensure cleaner, more accurate data. Advances in miniaturization could lead to even less obtrusive devices, perhaps embedded in jewelry or clothing, further boosting user comfort and adoption. Pairing these sensors with AI holds immense potential; machine learning models could learn individual baselines, distinguishing between a workout induced heart rate spike and one tied to anxiety, thus personalizing insights, as demonstrated in personalized stress detection models achieving 92% accuracy in lab settings [Tervonen et al., 2020]. Expanding clinical trials to include diverse populations, across age groups, ethnicities, and socioeconomic backgrounds, will be crucial to validate their effectiveness universally, while integrating these tools into telehealth platforms could bridge the gap to professional care, creating a seamless ecosystem where data flows from wrist to clinician in real time. Khan et al. (2023) further suggest energy efficient designs and secure data transmission using lightweight physical-layer security (PLS) for real time monitoring in patients with communicable diseases, enhancing applicability in diverse health contexts. Similarly, Campanella et al. (2023) propose increasing sample diversity and testing multi-level stress tasks to improve real-world applicability, while Attaran et al. (2018) advocate for broader stress context optimization in wearable integration [Campanella et al., 2023; Attaran et al., 2018]. As these developments unfold, physiological wearables could evolve into a cornerstone of proactive mental health management.

### 2.2. Neurotechnological Approaches

Neurotechnological (neurotech) approaches offer a direct interface to the brain, using devices like the electroencephalogram (EEG) to measure electrical activity and uncover mental health patterns that physiological sensors cannot access. EEG systems, ranging from clinical grade setups with dozens of electrodes to portable consumer devices like the Muse headband, record brainwave frequencies, alpha for relaxation, beta for alertness, theta for drowsiness, that shift with emotional states. Other emerging tools, such as functional near infrared spectroscopy (fNIRS), track cerebral blood flow, though EEG remains the dominant player due to its established use and portability. A 2023 review highlighted EEG's precision, achieving 98.13% accuracy in emotion recognition [Lin & Li, 2023], while a 2024 study praised its reliability for detecting cognitive health changes [M et al., 2024]. A 2024 study further demonstrated EEG's prowess in stress detection, achieving 98.1% accuracy in classifying stress types (social, mental) and 97.8% in stress levels using multimodal physiological signals including EEG, PPG, GSR, $SpO_2$, HR, and temperature, though its small sample of 11 healthy individuals (3 females, avg. age 24.7) in a controlled lab setting suggests caution for real-world variability [Pei et al., 2024]. Additionally, a 2018 study combining EEG and ECG signals achieved 79.54% accuracy in detecting early stress across four levels [Xia et al., 2018]. Greene et al. (2017) emphasized EEG as a gold standard alongside ECG, noting its utility in affective computing with accuracies up to 93% when paired with facial expression analysis (AFEA). Complementing these findings, a 2022 study by AlShorman et al. used real-time frontal lobe EEG analysis with Fast Fourier Transform (FFT) and machine learning (SVM and Naïve Bayes), achieving 98.21% accuracy in subject-wise stress classification, though its focus on a single gender and lobe limits generalizability [AlShorman et al., 2022]. Similarly, Priya et al. (2020) extracted EEG sub-band power ratios from a 19-channel system, achieving 99.42% accuracy with KNN on the Fp1 channel, highlighting EEG's precision in controlled settings despite reliance on a public dataset [Priya et al., 2020]. Liao et al. (2018) explored EEG via the NeuroSky MindWave Mobile, using deep learning to predict attention and meditation states under music influence, achieving 80.13% accuracy, though its small sample and binary classification suggest room for broader application [Liao et al., 2018]. These devices are increasingly applied beyond research labs, with applications in depression monitoring, anxiety classification, and stress management through biofeedback.

The advantages of neurotech approaches stem from their unparalleled directness and sensitivity. Unlike physiological methods that rely on downstream bodily signals, EEG captures the brain's electrical activity in real time, offering a primary source of data on mental states. This immediacy is invaluable for conditions with distinct neural signatures, depression's reduced alpha activity or anxiety's heightened beta waves, allowing for precise differentiation that indirect measures might miss. The biofeedback potential is another boon; devices like Muse provide users with live brainwave feedback, enabling them to actively regulate their mental state through techniques like mindfulness or breathing exercises, fostering a sense of agency over their well-being. This combination of diagnostic depth and therapeutic utility positions neurotech as a powerful tool for both clinical intervention and personal empowerment, bridging the gap between passive monitoring and active management.

Neurotech is not without its disadvantages, which largely revolve around practicality and complexity. Current EEG systems, even portable ones, remain more invasive than a smartwatch, requiring headsets with electrodes that can be uncomfortable or awkward for extended wear, especially in social settings. The cost is another barrier; while consumer devices like Muse are more affordable than clinical setups, they still exceed the price of mainstream wearables, limiting accessibility for lower income populations. Data interpretation poses a further challenge; EEG generates vast, intricate datasets that demand sophisticated analysis, often via AI, to distill meaningful insights, a process that can overwhelm non-experts and slow real-world adoption. Variability between individuals' brain signals adds another layer of difficulty, as models trained on one population may falter when applied to another, necessitating extensive calibration that complicates scalability, a concern also noted by Greene et al. (2017) regarding EMG localization and long-term stress studies. Studies like AlShorman et al. (2022) and Priya et al. (2020) further highlight small sample sizes and controlled settings as barriers to broader adoption [AlShorman et al., 2022; Priya et al., 2020].

The future direction of neurotech hinges on making it more practical, affordable, and insightful. Innovations in design could yield lightweight, discreet devices, perhaps resembling stylish headbands or caps, that blend into daily life without drawing attention, enhancing user compliance. Cost reduction through mass production and simplified sensor arrays might broaden access, particularly in developing nations where mental health resources are scarce [M et al., 2024]. Real-time AI analysis, running on device rather than requiring cloud processing, could streamline interpretation, delivering instant feedback without the need for specialized training. Combining EEG with other modalities, physiological sensors or contactless systems, offers a promising hybrid path, enriching neural data with contextual cues to improve accuracy and applicability, as suggested by Smirthy et al. (2023), who reported accuracies up to 98% with EEG and HRV in stress detection. Larger, longitudinal studies to map brainwave patterns across diverse populations will also be key, building a foundation for universal models that unlock neurotech's full potential in transforming mental health care. Expanding studies like the 2024 stress detection research [Pei et al., 2024] and earlier EEG-based efforts [Xia et al., 2018] with larger, more diverse samples and real-world applications could further refine these methodologies, aligning with Greene et al.'s (2017) call for integrating virtual reality (VR) and commercial wearables. AlShorman et al. (2022) and Priya et al. (2020) also recommend integrating additional physiological signals and testing real-time applications to enhance practical utility [AlShorman et al., 2022; Priya et al., 2020].

Furthering mental health management, neurostimulation holds promise for easing opioid tapering, reducing withdrawal symptoms, and lowering overdose risk. New drug approaches are looking to manage opioid use by targeting systems like the ghrelin system. One drug, PF-5190457, which blocks the GHS1αR receptor, has shown potential in lowering opioid use in rodents without affecting their pain sensitivity [Cunningham et al., 2023]. In addition to pharmacological strategies, researchers are also exploring non-drug approaches that directly target brain activity to help manage opioid use. Techniques like Deep Brain Stimulation (DBS), Repetitive Transcranial Magnetic Stimulation (rTMS), and Transcranial Direct Current Stimulation (tDCS) are being investigated for reducing opioid cravings and promoting abstinence, though larger trials are required to confirm efficacy and safety [MacLellan et al., 2022]. Additionally, auricular neural stimulation (ear-based nerve stimulation) is showing promise as a noninvasive treatment for opioid withdrawal, with the potential to be used alongside medications to reduce side effects and make it easier for people to stick to the treatment [Qureshi et al., 2020]. A systematic review revealed that neuromodulation therapies, particularly rTMS and tDCS, showed reductions in substance use and cravings, though deeper investigation into neural mechanisms, long-term outcomes, and accelerated treatment protocols is essential [Mehta et al., 2024]. These findings reinforce the role of neuromodulation as a multifaceted tool for addressing substance use disorders, combining both direct brain stimulation and targeted neuropharmacology to reshape treatment approaches.

**2.3. Contactless Approaches**

Contactless approaches mark a paradigm shift in mental health monitoring, employing technologies like cameras, radar, and microphones to assess well-being without physical contact. Cameras enable remote photoplethysmography (rPPG) to measure heart rate through subtle skin color changes or analyze facial expressions for emotional cues, as seen in software like FaceReader. Radar systems use electromagnetic waves to detect vital signs, respiration, heart rate, or even micro movements during sleep, offering a discreet alternative to wearables. Microphones capture voice characteristics, pitch, tempo, or hesitations, that signal stress or depression, a method validated in studies like the PSYCHE project [Javelot et al., 2014]. A 2022 review lauded these methods for linking noninvasive vital sign data to mental states, with promising detection performance [Nouman et al., 2021], positioning them as a scalable, user-friendly option. Further, a 2015 study using webcam-based PPG achieved 94.4% accuracy in binary stress detection [Maaoui et al., 2015], while a 2019 study combining smartphone PPG and thermal imaging reported 78.33% accuracy in detecting perceived stress [Cho et al., 2019], showcasing the potential of contactless methods. Additionally, a 2018 study by Aigrain et al. introduced person-specific behavioral features (body and facial) using video and depth data from Microsoft Kinect and HD cameras, achieving 77-80% accuracy with SVM in a mental arithmetic task, demonstrating how contactless visual analysis can enhance stress detection with normalization techniques [Aigrain et al., 2018].

The advantages of contactless approaches lie in their unobtrusiveness and versatility. By eliminating the need for wearable devices, they sidestep issues of discomfort or stigma, allowing users to engage in normal activities without the burden of straps, electrodes, or batteries. This makes them ideal for continuous monitoring over extended periods: imagine a camera tracking sleep patterns in a bedroom or a radar system assessing stress in an office without requiring active user effort. Their environmental integration is another strength; a single setup could monitor multiple individuals in shared spaces like classrooms or waiting rooms, offering a cost-effective solution for population level screening. This scalability, combined with their noninvasive appeal, could revolutionize mental health surveillance in public health contexts, catching trends like rising anxiety in a community before they escalate. These advantages come with significant disadvantages, primarily tied to environmental sensitivity and ethical concerns. Contactless systems are notoriously vulnerable to external variables; dim lighting can disrupt camera accuracy, background noise can garble microphone data, and furniture placement can interfere with radar signals, all of which erode reliability outside controlled settings. This fragility limits their use in dynamic, real-world environments like a busy household or urban street. Privacy is an even thornier issue; continuous monitoring via cameras or microphones risks capturing intimate moments or private conversations, personal habits, raising profound questions about consent, data ownership, and potential misuse. Moreover, their reliance on indirect indicators like facial expressions or breathing patterns can oversimplify complex mental states, missing the depth needed for conditions like bipolar disorder or PTSD, which demand richer data, a limitation also noted by Can et al. (2019) in daily life stress detection scenarios. The Aigrain et al. (2018) study further noted challenges with small sample sizes and less informative features, underscoring the need for broader validation [Aigrain et al., 2018].

The future direction of contactless approaches centers on enhancing robustness and trust. Algorithmic breakthroughs could mitigate environmental interference, think AI that adjusts for low light or filters out ambient noise, making these systems viable in diverse settings, from rural homes to bustling cities. Privacy solutions are equally critical; on-device processing, where data is analyzed locally rather than sent to the cloud, could minimize exposure, while transparent consent protocols might reassure users about how their information is handled [Boonstra et al., 2018]. Pairing contactless methods with wearables or neurotech in hybrid setups could deepen their insights, balancing noninvasive ease with comprehensive data collection. Expanding research into real world applications, like stress detection in drivers [Siam et al., 2023] or webcam-based monitoring [Maaoui et al., 2015] and addressing ethical frameworks will be essential to scale these technologies responsibly, ensuring they enhance mental health care without compromising personal autonomy. Singh et al. (2023) further suggest standardizing data collection to improve contactless system reliability, aligning with these future goals, while Aigrain et al. (2018) propose combining raw facial and normalized body features for improved accuracy [Aigrain et al., 2018].

**2.4. Multimodal Approaches**

Multimodal approaches synthesize physiological, neurotech, and contactless modalities into a unified framework, aiming to deliver a holistic assessment of mental health by leveraging the strengths of each method. A 2021 workplace study exemplified this, combining camera-based pulse wave data, microphone captured speech, and wearable EDA to quantify stress and well-being among office workers [Izumi et al., 2021]. A 2024 review of 184 studies further validated the approach, finding that multimodal passive sensing, enhanced by neural networks, significantly boosts detection accuracy for disorders like depression and anxiety [Khoo et al., 2024]. By integrating heart rate from a smartwatch, brainwaves from an EEG, and facial cues from a camera, these systems create a multidimensional profile that captures both the body's responses and the mind's activity. Additional studies in 2022 used chest-worn devices like RespiBAN Professional to detect stress, identifying EDA, body temperature, and accelerometer data as key biomarkers in 15 subjects (12 males, 3 females, avg. age 27.5) [Jambhale et al., 2022], while another 2022 study with RespiBAN and Empatica E4 wrist sensors confirmed these features' significance for stress classification in a similar cohort [Jambhale et al., 2022]. Further, a 2018 study combined phonocardiography (PCG) and ECG signals to achieve 93.14% accuracy in stress detection [Cheema & Singh, 2019], and a 2016 study integrating body, facial, and physiological data reported F1-scores up to 0.85 [Aigrain et al., 2016], illustrating the power of multimodal fusion. Can et al. (2019) also highlighted multimodal systems using smartphones (accelerometer, GPS) and wearables (EDA, HR), achieving accuracies up to 89% in lab settings, though lower (e.g., 72%) in daily life. Mokhayeri et al. (2011) added to this body of work, combining pupil diameter (PD), ECG, and PPG with genetic algorithms and fuzzy SVM, achieving 78.5% accuracy in a controlled setting, suggesting potential for multimodal integration despite its lab-based limitations [Mokhayeri et al., 2011]. Similarly, Attaran et al. (2018) utilized HR, accelerometer, respiratory rate, and $SpO_2$ from a wearable Lifeshirt, achieving 96.7% accuracy with SVM in a shooting task, highlighting multimodal wearable applications [Attaran et al., 2018]. Aigrain et al. (2018) further advanced contactless multimodal approaches, using video and depth data for behavioral features, boosting SVM accuracy to 77-80% with person-specific normalization [Aigrain et al., 2018].

The advantages of multimodal approaches lie in their comprehensive scope and resilience. By drawing on multiple data streams, they offer a richer, more reliable picture of mental health, cross-validating a stress spike in HRV with EEG beta wave increases or vocal tension, reducing the risk of false positives that single modality systems might produce. This redundancy also bolsters accuracy in noisy environments; if a camera fails due to poor lighting, a wearable sensor can pick up the slack, ensuring consistent monitoring. Personalization is a standout benefit, fusing physiological, neural, and behavioral data allows for tailored insights that reflect an individual's unique patterns, potentially improving the efficacy of interventions like therapy or medication adjustments. For clinicians, this breadth provides a robust dataset to inform diagnoses, while for users, it offers a nuanced tool for self-awareness and management.

However, the disadvantages of multimodal approaches are tied to their complexity and user burden. Integrating disparate sensors, each with its own data format, sampling rate, and noise profile, requires sophisticated software and computational power, driving up costs and limiting accessibility to well-funded settings like research labs or affluent healthcare systems. The multi-device nature of these systems can also overwhelm users; wearing a smartwatch, an EEG headset, and sitting under a camera might feel intrusive or exhausting, especially for those already struggling with mental health challenges. Data synchronization poses another hurdle: misaligned timestamps or incompatible platforms can skew results, demanding technical expertise that many lack. These factors collectively hinder scalability, confining multimodal approaches to niche applications rather than the mainstream adoption seen with simpler wearables, a challenge also noted by Khan et al. (2023) regarding on-device computation limits in secure frameworks.

The future direction of multimodal approaches involves simplifying their complexity while maximizing their reach. Developing all-in-one devices, perhaps a single wearable that combines ECG, EEG, and motion sensors, could streamline data collection, reducing both cost and user effort while preserving the benefits of multimodality. User-centered design will be pivotal; creating discreet, comfortable systems that integrate into daily life, think smart glasses with embedded sensors or furniture with built-in radar, might enhance acceptance and long-term use. Advances in AI-driven data fusion could automate the integration process, transforming raw signals into cohesive insights without requiring manual oversight, a leap that would democratize access. Scaling these technologies into clinical settings, with seamless links to electronic health records, and validating them through large, diverse trials will be key to unlocking their potential, positioning multimodal approaches as a gold standard in comprehensive mental health monitoring. Future studies building on the 2022 chest-worn sensor research [Jambhale et al., 2022; Jambhale et al., 2022] and earlier multimodal efforts [Aigrain et al., 2016; Cheema & Singh, 2019] could refine models for real world use and extend them to populations like individuals with substance use disorders (SUD), as suggested by Smirthy et al. (2023) for enhancing real life applicability. Mokhayeri et al. (2011) and Attaran et al. (2018) also suggest exploring additional signals and broader contexts to enhance multimodal systems [Mokhayeri et al., 2011; Attaran et al., 2018].

### 2.5. Machine Learning and AI

Machine learning (ML) and artificial intelligence (AI) serve as the intellectual engine behind wearable and contactless mental health technologies, processing vast datasets to extract patterns and predictions that human analysis alone cannot achieve. Techniques like Support Vector Machines (SVMs) have demonstrated high precision, classifying stress with 96.25% accuracy using EEG and physiological signals [Arsalan & Majid, 2021], while random forests excel at identifying key features across multimodal inputs. Neural networks, particularly deep learning models, shine in fusing diverse data streams, as evidenced by a 2024 review praising their performance in mental health detection [Khoo et al., 2024]. A 2024 study leveraged ML classifiers to achieve 98.1% accuracy in stress-type classification and 97.8% in stress-level classification using EEG and peripheral signals (PPG, GSR, $SpO_2$, HR, temperature) from 11 subjects [Pei et al., 2024], while 2022 studies using chest-worn sensors (RespiBAN) and wrist-worn devices (Empatica E4) identified EDA, temperature, and accelerometer data as top stress biomarkers, with XGBoost outperforming other classifiers in a cohort of 15 subjects [Jambhale et al., 2022; Jambhale et al., 2022]. Additional research highlights AI's versatility: a 2018 study used multilayer perceptrons for 94.4% accuracy with bioradar signals [Fernández & Anishchenko, 2018], a 2020 study employed self-organizing maps for 92% lab accuracy in personalized stress detection [Tervonen et al., 2020], and a 2019 study achieved 98.6% accuracy with ECG signals using SVMs [Rizwan et al., 2019]. Ahuja and Banga (2019) applied SVM to PASS data from 206 students, achieving 85.71% accuracy in stress detection, while Singh et al. (2023) reported Random Forest at 89% accuracy with HRV and skin conductance. Smirthy et al. (2023) noted SVM as the most used algorithm, with accuracies up to 98% in wearable based stress detection. Campanella et al. (2023) used Random Forest, SVM, and Logistic Regression on Empatica E4 data, achieving 76.5% accuracy, with RF outperforming others [Campanella et al., 2023]. AlShorman et al. (2022) achieved 98.21% accuracy with SVM and Naïve Bayes on EEG data, while Priya et al. (2020) reached 99.42% with KNN on EEG power ratios [AlShorman et al., 2022; Priya et al., 2020]. Mokhayeri et al. (2011) employed fuzzy SVM with genetic algorithms, achieving 78.5% accuracy [Mokhayeri et al., 2011], and Attaran et al. (2018) reported 96.7% with SVM on multimodal wearable data [Attaran et al., 2018]. Liao et al. (2018) used deep learning on EEG signals, achieving 80.13% accuracy [Liao et al., 2018].

Aigrain et al. (2018) boosted SVM accuracy to 77-80% with person-specific normalization on behavioral features [Aigrain et al., 2018].

These tools not only diagnose current states but also forecast future risks, enabling interventions tailored to individual needs. The advantages of ML and AI lie in their scalability and adaptability. They can sift through terabytes of sensor data, heartbeats, brainwaves, voice inflections, in seconds, uncovering subtle correlations that might elude clinicians, such as a link between sleep disruption and impending depression. Their ability to learn and refine over time means they grow more accurate with each user interaction, adapting to personal quirks like a unique stress response or cultural speech patterns. This personalization is a gamechanger, offering bespoke insights that generic models cannot match. For healthcare providers, AI automates tedious analysis, freeing them to focus on patient care, while for individuals, it powers apps that deliver real-time feedback, say, a smartwatch prompting a breathing exercise when stress spikes, enhancing self-management.

The disadvantages of ML and AI are significant, rooted in data and transparency issues. Overfitting remains a persistent risk; models trained on small or homogenous datasets may falter when applied to new populations, reducing generalizability, a concern echoed in studies noting poor cross-subject performance [Malik et al., 2024]. The opacity of deep learning often frustrates clinicians who need to understand why a diagnosis was made, eroding trust in critical settings. Data quality is another issue: noise from sensors, missing readings, or inconsistent collection can skew results, demanding robust preprocessing that adds complexity. Ethical concerns, like bias in training data reflecting historical inequities, further complicate their deployment, risking unfair outcomes for marginalized groups, as highlighted by Singh et al. (2023) regarding lack of transparency in ML predictions. Studies like Campanella et al. (2023) and AlShorman et al. (2022) also note small sample sizes and lab-based constraints as limiting factors [Campanella et al., 2023; AlShorman et al., 2022].

The future direction of ML and AI in mental health technology involves refining their precision and broadening their impact. Cross-subject models that generalize across diverse populations, rather than requiring individual tuning, could scale these tools for global use, while explainable AI techniques, like visualizing feature importance, might demystify decision making, aligning with clinical needs. Edge computing, processing data on-device, promises faster, more private analysis, sidestepping cloud reliance and addressing privacy fears [Nouman et al., 2021]. Integrating AI with real-world systems, like driver assistance technologies for stress detection [Siam et al., 2023] or biosignal based systems [Rizwan et al., 2019], could extend its reach beyond healthcare into daily life. Addressing bias through inclusive datasets and ethical oversight will be crucial, ensuring AI amplifies equity rather than disparity, and cementing its role as the linchpin of next generation mental health solutions. Khan et al. (2023) propose federated learning for privacy and efficient computing frameworks, aligning with these goals. Expanding on studies like those in 2024 and 2022 [Pei et al., 2024; Jambhale et al., 2022; Jambhale et al., 2022] with larger samples, real-world validation, and personalized models could further enhance AI's transformative potential, as suggested by Campanella et al. (2023) and Priya et al. (2020) for real-time and diverse applications [Campanella et al., 2023; Priya et al., 2020].

Below is a table (Table 1) summarizing the major findings of this chapter. The table is organized with rows representing the key approaches (Physiological, Neurotech, Contactless, Multimodal) and columns detailing the papers reviewed and highlights from those papers.

**Table 1: Methodologies for Mental Health Management**

| **Approach** | **Papers Reviewed** | **Highlights from the Papers** |
|---|---|---|
| **Physiological methods** | - Arsalan & Majid (2021) - Gomes et al. (2023) - Fernández & Anishchenko (2018) - Zubair & Yoon (2019) - Barki & Chung (2023) - Salai et al. (2016) - Shanmugasundaram et al. (2019) - Greene et al. (2017) - Campanella et al. (2023) - Attaran et al. (2018) - Mokhayeri et al. (2011) | - 96.25% accuracy in stress classification using ECG, GSR, PPG (Arsalan & Majid, 2021). - Up to 99.48% accuracy in anxiety detection (Gomes et al., 2023). - 94.4% accuracy with bioradar respiratory signals (Fernández & Anishchenko, 2018). - 94.33% accuracy in multilevel stress detection with PPG (Zubair & Yoon, 2019). - 96.02% accuracy with near PPG (Barki & Chung, 2023). - High precision with low-cost ECG (Salai et al., 2016). - 85% accuracy with HR, GSR, speech (Shanmugasundaram et al., 2019). - 93% correlation for GSR vs. ECG (Greene et al., 2017). - 76.5% accuracy with Empatica E4 and ML (Campanella et al., 2023). - 96.7% accuracy with HR and accelerometer data (Attaran et al., 2018). - 78.5% accuracy with PD, ECG, PPG, and fuzzy SVM (Mokhayeri et al., 2011). |
| **Neurotech methods** | - Lin & Li (2023) - M et al. (2024) - Pei et al. (2024) - Xia et al. (2018) - Greene et al. (2017) - AlShorman et al. (2022) - Priya et al. (2020) - Liao et al. (2018) | - 98.13% accuracy in emotion recognition with EEG (Lin & Li, 2023). - Reliable cognitive health change detection with EEG (M et al., 2024). - 98.1% accuracy in stress type classification, 97.8% in stress levels with EEG and multimodal signals (Pei et al., 2024). - 79.54% accuracy in early stress detection with EEG and ECG (Xia et al., 2018). - 93% accuracy with EEG and facial expression analysis (Greene et al., 2017). - 98.21% accuracy with frontal lobe EEG and ML (AlShorman et al., 2022). - 99.42% accuracy with EEG sub-band power ratios (Priya et al., 2020). - 80.13% accuracy |

| | | |
|---|---|---|
| | | in attention/meditation prediction with EEG and deep learning (Liao et al., 2018). |
| **Contactless methods** | - Nouman et al. (2021) - Maaoui et al. (2015) - Cho et al. (2019) - Aigrain et al. (2018) | - Promising detection performance linking vital signs to mental states (Nouman et al., 2021). - 94.4% accuracy in binary stress detection with webcam PPG (Maaoui et al., 2015). - 78.33% accuracy with smartphone PPG and thermal imaging (Cho et al., 2019). - 77-80% accuracy with person-specific behavioral features from video/depth data (Aigrain et al., 2018). |
| **Multimodal methods** | - Izumi et al. (2021) - Khoo et al. (2024) - Jambhale et al. (2022) (two studies) - Cheema & Singh (2019) - Aigrain et al. (2016) - Can et al. (2019) - Mokhayeri et al. (2011) - Attaran et al. (2018) - Aigrain et al. (2018) | - Quantified stress/wellbeing with camera pulse, speech, EDA (Izumi et al., 2021). - Significant accuracy boost with multimodal sensing and neural networks (Khoo et al., 2024). - Identified EDA, temperature, and accelerometer as key stress biomarkers (Jambhale et al., 2022). - 93.14% accuracy with PCG and ECG (Cheema & Singh, 2019). - F1 scores up to 0.85 with body, facial, physiological data (Aigrain et al., 2016). - 89% lab accuracy, 72% daily life with smartphones/wearables (Can et al., 2019). - 78.5% accuracy with PD, ECG, PPG, and fuzzy SVM (Mokhayeri et al., 2011). - 96.7% accuracy with HR, accelerometer, respiratory rate, $SpO_2$ (Attaran et al., 2018). - 77-80% accuracy with video/depth behavioral features (Aigrain et al., 2018). |

# 3. Discussion

### 3.1. Potential of Wearable Technologies for Mental Health

Wearable technologies for mental health management herald a seismic shift, offering continuous, objective monitoring that could reshape how we understand and address disorders like anxiety, depression, and stress. Their ability to track in real-time, capturing a racing heart during a panic attack or disrupted sleep before a depressive episode, promises earlier interventions, potentially halting escalation before it begins. This immediacy, paired with quantifiable data, reduces the guesswork of subjective reports, giving clinicians a reliable foundation for diagnosis and treatment planning. Personalization stands out as a transformative edge; by tailoring insights to an individual's physiological or neural profile, these tools can guide precise interventions, from medication tweaks to lifestyle adjustments. Their accessibility, through consumer devices like smartwatches or apps, further amplifies their reach, offering hope to underserved populations where traditional care is scarce [Lal, 2019]. Studies like those using wearable sensors for pain and stress detection underscore their broad applicability across diverse conditions [Chen et al., 2021], with Can et al.

(2019) and Smirthy et al. (2023) reinforcing their potential in daily life and clinical settings with accuracies up to 98%.

### 3.2. Challenges in Implementation

However, these advancements are shadowed by substantial challenges that must be navigated to realize their full potential. Privacy remains a towering concern, continuous monitoring, especially via contactless cameras or microphones, risks exposing intimate details of users' lives, from private conversations to daily routines, necessitating ironclad security measures to maintain trust [Boonstra et al., 2018]. Standardization lags behind innovation; with no universal protocols for data collection or analysis, integrating findings into healthcare systems or comparing studies becomes a logistical nightmare, stunting progress [M et al., 2024]. User acceptance varies widely, while a sleek Fitbit might appeal to tech savvy individuals, an EEG headset or radar system might feel intrusive or alienating, particularly for those with mental health related sensitivities. Clinical validation is another weak point; many studies, like those with small lab-based cohorts [Hickey et al., 2021], lack the scale and diversity to prove real world efficacy, leaving questions about their readiness for broad deployment. Singh et al. (2023) and Can et al. (2019) further highlight challenges like noisy data, small sample sizes, and limited daily life studies.

### 3.4. Pathways to Advancement

The future of these technologies demands a concerted effort across multiple fronts. Large-scale, longitudinal trials, spanning continents, cultures, and conditions, must establish their effectiveness and safety, building an evidence base that can withstand scrutiny from regulators and clinicians alike. Integration with healthcare infrastructure, such as linking wearable data to electronic health records or tele-health platforms, will streamline their use in routine practice, ensuring they enhance rather than disrupt existing workflows [Areàn et al., 2016]. Ethical frameworks must evolve in lockstep, tackling privacy, consent, and data equity with transparent policies that empower users rather than exploit them. AI's role will be pivotal in pushing these tools toward prevention, by predicting mental health shifts and offering tailored strategies, like a smartwatch suggesting a mindfulness break before stress peaks. Khan et al. (2023) and Smirthy et al. (2023) suggest secure frameworks and real-life applicability enhancements as critical steps forward.

### 3.5. Future Directions

Looking ahead, the evolution of wearable technologies for mental health management hinges on pushing beyond current capabilities toward greater precision and accessibility. Advances in sensor technology could enable detection of more nuanced biomarkers, such as cortisol levels or subtle neural shifts, enhancing the depth of mental state assessments. Collaborative efforts between technologists, clinicians, and patients could refine device design, creating unobtrusive, user-friendly tools that integrate seamlessly into daily life, such as smart clothing or jewelry. AI development should focus on predictive analytics, leveraging multimodal data to forecast mental health crises weeks in advance, empowering users with preemptive strategies. Scaling these technologies globally, particularly in low resource settings, through cost effective manufacturing and open-source platforms, could address disparities in mental health care access, aligning with global health equity goals. Comprehensive reviews suggest integrating these advancements with real-time systems for broader impact [Shanmugasundaram et al., 2019], while Can et al. (2019) advocate for context aware systems and unsupervised methods, and Khan et al. (2023) propose federated learning for privacy preserving analytics.

### 3.6. Challenges and Opportunities

The road to widespread adoption presents a dual landscape of obstacles and potential breakthroughs. Privacy concerns loom large, as data breaches could undermine user trust; however, this challenge opens avenues for innovative security solutions like blockchain or on-device processing, setting new benchmarks for data protection. The lack of standardization complicates integration, yet it also invites international collaboration to establish unified protocols, fostering a cohesive global research and application framework. User resistance, especially among those wary of intrusive devices, poses a hurdle, but it simultaneously encourages user centered design innovations that prioritize comfort and cultural sensitivity. Clinical validation remains limited by small scale studies, yet large, diverse trials offer the opportunity to build a robust evidence base, accelerating regulatory approval and clinical adoption. Navigating these challenges with strategic innovation could transform wearable technologies into a cornerstone of proactive mental health care, as evidenced by early multimodal efforts [Aigrain et al., 2016] and recent calls for standardization and ethical focus [Singh et al., 2023].

## 4. Conclusion

Wearable technologies, encompassing physiological sensors, neurotech devices, contactless systems, and multimodal approaches, are poised to revolutionize mental health management. By offering continuous, objective, and personalized insights, they challenge the limitations of traditional care, promising earlier detection, better outcomes, and broader access. Yet, their journey is far from complete; privacy concerns, standardization gaps, user barriers, and validation needs stand as formidable obstacles. As research accelerates and solutions emerge, driven by AI, user-centered design, and ethical innovation, these tools could transform mental health into a field that anticipates crises rather than merely responds to them, delivering precise, empowering care to a world in need, with contributions from multiple studies paving the way for real-time, secure, and accessible mental health solutions.

## 5. Acknowledgement

This research was funded by the National Science Foundation (NSF) CAREER Award, grant number IIS-2053498 and NSF IUCRC Phase II UMBC: BRAIN, grant number CNS-2333292.

## 6. References

1. Ahuja, R., & Banga, A. (2019). Mental Stress Detection in University Students using Machine Learning Algorithms. *Procedia Computer Science*, 152, 349–353. https://doi.org/10.1016/j.procs.2019.05.007
2. Aigrain, J., Dubuisson, S., Detyniecki, M., & Chetouani, M. (2015). Person-specific behavioural features for automatic stress detection. *IEEE*. https://doi.org/10.1109/fg.2015.7284844
3. Aigrain, J., Spodenkiewicz, M., Dubuisson, S., Detyniecki, M., Cohen, D., & Chetouani, M. (2016). Multimodal Stress Detection from Multiple Assessments. *IEEE Transactions on Affective Computing*, 9(4), 491–506. https://doi.org/10.1109/taffc.2016.2631594
4. AlShorman, O., Masadeh, M., Heyat, M. B. B., Akhtar, F., Almahasneh, H., Ashraf, G. M., & Alexiou, A. (2022). Frontal lobe real-time EEG analysis using machine learning techniques for mental stress detection. *Journal of Integrative Neuroscience*, 21(1). https://doi.org/10.31083/j.jin2101020
5. Areàn, P. A., Ly, K. H., & Andersson, G. (2016). Mobile technology for mental health assessment. *Dialogues in Clinical Neuroscience*, 18(2), 163–169. https://doi.org/10.31887/dcns.2016.18.2/parean
6. Arsalan, A., & Majid, M. (2021). Human stress classification during public speaking using physiological signals. *Computers in Biology and Medicine*, 133, 104377. https://doi.org/10.1016/j.compbiomed.2021.104377
7. Attaran, N., Puranik, A., Brooks, J., & Mohsenin, T. (2018). Embedded Low-Power processor for personalized stress detection. *IEEE Transactions on Circuits & Systems II Express Briefs*, 65(12), 2032–2036. https://doi.org/10.1109/tcsii.2018.2799821
8. Barki, H., & Chung, W. (2023). Mental stress detection using a wearable InEar plethysmography. *Biosensors*, 13(3), 397. https://doi.org/10.3390/bios13030397
9. Boonstra, T. W., Nicholas, J., Wong, Q. J., Shaw, F., Townsend, S., & Christensen, H. (2018). Using mobile phone sensor technology for mental health research: Integrated analysis to identify hidden challenges and potential solutions. *Journal of Medical Internet Research*, 20(7), e10131. https://doi.org/10.2196/10131

10. Campanella, S., Altaleb, A., Belli, A., Pierleoni, P., & Palma, L. (2023). A method for stress detection using Empatica E4 bracelet and Machine-Learning techniques. *Sensors*, 23(7), 3565. https://doi.org/10.3390/s23073565
11. Can, Y. S., Arnrich, B., & Ersoy, C. (2019). Stress detection in daily life scenarios using smartphones and wearable sensors: A survey. *Journal of Biomedical Informatics*, 92, 103139. https://doi.org/10.1016/j.jbi.2019.103139
12. Cheema, A., & Singh, M. (2019). Psychological stress detection using phonocardiography signal: An empirical mode decomposition approach. *Biomedical Signal Processing and Control*, 49, 493–505. https://doi.org/10.1016/j.bspc.2018.12.028
13. Chen, J., Abbod, M., & Shieh, J. (2021). Pain and Stress Detection Using Wearable Sensors and Devices, A Review. *Sensors*, 21(4), 1030. https://doi.org/10.3390/s21041030
14. Cheung, H. C., De Louche, C., & Komorowski, M. (2023). Artificial intelligence applications in space medicine. *Aerospace Medicine and Human Performance*, 94(8), 610–622. https://doi.org/10.3357/amhp.6178.2023
15. Cho, Y., Julier, S. J., & BianchiBerthouze, N. (2018). Instant stress: Detection of perceived mental stress through smartphone photoplethysmography and thermal imaging. *JMIR Mental Health*, 6(4), e10140. https://doi.org/10.2196/10140
16. Cunningham, K., et al. (2023). Mining neuropharmacology within neuromodulation frameworks for pain and opioid use disorder. *Brain Stimulation: Basic, Translational, and Clinical Research in Neuromodulation, 16*(1), 215–216. https://doi.org/10.1016/j.brs.2022.11.377
17. Fernández, J. R. M., & Anishchenko, L. (2018). Mental stress detection using bioradar respiratory signals. *Biomedical Signal Processing and Control*, 43, 244–249. https://doi.org/10.1016/j.bspc.2018.03.006
18. Gomes, N., Pato, M., Lourenço, A. R., & Datia, N. (2023). A survey on wearable sensors for mental health monitoring. *Sensors*, 23(3), 1330. https://doi.org/10.3390/s23031330
19. Greene, S., Thapliyal, H., & CabanHolt, A. (2016). A Survey of Affective Computing for Stress Detection: Evaluating technologies in stress detection for better health. *IEEE Consumer Electronics Magazine*, 5(4), 44–56. https://doi.org/10.1109/mce.2016.2590178
20. Hickey, B. A., Chalmers, T., Newton, P., Lin, C., Sibbritt, D., McLachlan, C. S., CliftonBligh, R., Morley, J., & Lal, S. (2021). Smart devices and wearable technologies to detect and monitor mental health conditions and stress: A systematic review. *Sensors*, 21(10), 3461. https://doi.org/10.3390/s21103461
21. Izumi, K., Minato, K., Shiga, K., Sugio, T., Hanashiro, S., Cortright, K., Kudo, S., Fujita, T., Sado, M., Maeno, T., Takebayashi, T., Mimura, M., & Kishimoto, T. (2021). Unobtrusive

sensing technology for quantifying stress and wellbeing using pulse, speech, body motion, and electrodermal data in a workplace setting: Study concept and design. *Frontiers in Psychiatry*, 12. https://doi.org/10.3389/fpsyt.2021.611243

22. Jambhale, K., Mahajan, S., Rieland, B., Banerjee, N., Dutt, A., Kadiyala, S. P., & Vinjamuri, R. (2022). Identifying biomarkers for accurate detection of stress. *Sensors*, 22(22), 8703. https://doi.org/10.3390/s22228703
23. Jambhale, K., Rieland, B., Mahajan, S., Narsay, P., Banerjee, N., Dutt, A., & Vinjamuri, R. (2022). Selection of optimal physiological features for accurate detection of stress. *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. https://doi.org/10.1109/embc48229.2022.9871067
24. Javelot, H., Spadazzi, A., Weiner, L., Garcia, S., Gentili, C., Kosel, M., & Bertschy, G. (2014). Telemonitoring with respect to mood disorders and information and communication technologies: Overview and presentation of the PSYCHE project. *BioMed Research International*, 2014, 1–12. https://doi.org/10.1155/2014/104658
25. Khan, H. A., Nguyen, T. N., Shafiq, G., Mirza, J., & Javed, M. A. (2022). A secure wearable framework for stress detection in patients affected by communicable diseases. *IEEE Sensors Journal*, 23(2), 981–988. https://doi.org/10.1109/jsen.2022.3204586
26. Khoo, L. S., Lim, M. K., Chong, C. Y., & McNaney, R. (2024). Machine learning for multimodal mental health detection: A systematic review of passive sensing approaches. *Sensors*, 24(2), 348. https://doi.org/10.3390/s24020348
27. Kurniawan, H., Maslov, A. V., & Pechenizkiy, M. (2013). Stress detection from speech and Galvanic Skin Response signals. *IEEE*, 209–214. https://doi.org/10.1109/cbms.2013.6627790
28. Lal, S. (2019). Emental health: Promising advancements in policy, research, and practice. *Healthcare Management Forum*, 32(2), 56–62. https://doi.org/10.1177/0840470418818583
29. Liao, C., Chen, R., & Tai, S. (2018). Emotion stress detection using EEG signal and deep learning technologies. *2018 IEEE International Conference on Applied System Invention (ICASI)*, 90–93. https://doi.org/10.1109/icasi.2018.8394414
30. Lin, W., & Li, C. (2023). Review of studies on emotion recognition and judgment based on physiological signals. *Applied Sciences*, 13(4), 2573. https://doi.org/10.3390/app13042573
31. M, V. R., Gnk, G., D, R., T, V. P., & Rao, G. N. (2024). Neuro receptor signal detecting and monitoring smart devices for biological changes in cognitive health conditions. *Annals of Neurosciences*, 31(3), 225–233. https://doi.org/10.1177/09727531231206888

32. Maaoui, C., Bousefsaf, F., & Pruski, A. (2015). Automatic human stress detection based on webcam photoplethysmographic signals. *Journal of Mechanics in Medicine and Biology*, 16(04), 1650039. https://doi.org/10.1142/s0219519416500391
33. MacLellan A, Easton A, Pickett G. P.167 Documented growth of a de novo intracranial capillary hemangioma: a case report. *Canadian Journal of Neurological Sciences / Journal Canadien des Sciences Neurologiques*. 2022;49(s1):S51-S51. doi:10.1017/cjn.2022.249
34. Mehta, D. D., Praecht, A., Ward, H. B., et al. (2024). A systematic review and meta-analysis of neuromodulation therapies for substance use disorders. *Neuropsychopharmacology, 49*, 649–680. https://doi.org/10.1038/s41386-023-01776-0
35. Malik, A. S., Hussain, M., & Chaudhary, S. U. (2024). Editorial: From assessment to intervention: Role of consumer technology and neurotech in preventive mental health. *Frontiers in Psychology*, 15. https://doi.org/10.3389/fpsyg.2024.1372708
36. Mokhayeri, F., Akbarzadeh-T, M., & Toosizadeh, S. (2011). Mental stress detection using physiological signals based on soft computing techniques. *IEEE*, 232–237. https://doi.org/10.1109/icbme.2011.6168563
37. Neuropsychopharmacology. (2023). A systematic review and meta-analysis of neuromodulation therapies for substance use disorders. *Neuropsychopharmacology*, 48 (7), 1283–1299
38. Nouman, M., Khoo, S. Y., Mahmud, M. a. P., & Kouzani, A. Z. (2021). Recent advances in contactless sensing technologies for mental health monitoring. *IEEE Internet of Things Journal*, 9(1), 274–297. https://doi.org/10.1109/jiot.2021.3097801
39. Pei, D., Tirumala, S., Tun, K. T., Ajendla, A., & Vinjamuri, R. (2024). Identifying neuroph7ysiological correlates of stress. *Frontiers in Medical Engineering*, 2. https://doi.org/10.3389/fmede.2024.1434753
40. Priya, T. H., Mahalakshmi, P., Naidu, V., & Srinivas, M. (2020). Stress detection from EEG using power ratio. *2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)*, 1–6. https://doi.org/10.1109/ic-etite47903.2020.401
41. Qureshi IS, Datta-Chaudhuri T, Tracey KJ, Pavlov VA, Chen ACH (2020). *Auricular neural stimulation as a new non-invasive treatment for opioid detoxification*. Bioelectron Med. 2020 Mar 30;6:7. doi: 10.1186/s42234-020-00044-6.
42. Rizwan, M. F., Farhad, R., Mashuk, F., Islam, F., & Imam, M. H. (2019). Design of a biosignal based stress detection system using machine learning techniques. *2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, 364–368. https://doi.org/10.1109/icrest.2019.8644259

43. Robinson, T., Condell, J., Ramsey, E., & Leavey, G. (2023). Selfmanagement of subclinical common mental health disorders (anxiety, depression and sleep disorders) using wearable devices. *International Journal of Environmental Research and Public Health*, 20(3), 2636. https://doi.org/10.3390/ijerph20032636
44. Salai, M., Vassányi, I., & Kósa, I. (2016). Stress detection using low-cost heart rate sensors. *Journal of Healthcare Engineering*, 2016, 1–13. https://doi.org/10.1155/2016/5136705
45. Shanmugasundaram, G., Yazhini, S., Hemapratha, E., & Nithya, S. (2019). A comprehensive review on stress detection techniques. *2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN)*, 1–6. https://doi.org/10.1109/icscan.2019.8878795
46. Siam, A. I., Gamel, S. A., & Talaat, F. M. (2023). Automatic stress detection in car drivers based on noninvasive physiological signals using machine learning techniques. *Neural Computing and Applications*, 35(17), 12891–12904. https://doi.org/10.1007/s0052102308428w
47. Singh, K., Chawla, S. K., Singh, G., & Soni, P. (2023). Stress Detection using Machine Learning Techniques: A review. *IEEE*, 255–260. https://doi.org/10.1109/icac3n60023.2023.10541696
48. Smirthy, M., Dhanushree, M., & Ashisha, G. R. (2023). Investigation of Machine Learning Techniques and Sensing Devices for Mental Stress Detection. *IEEE*. https://doi.org/10.1109/icspc57692.2023.10125951
49. Tervonen, J., Puttonen, S., Sillanpää, M. J., Hopsu, L., Homorodi, Z., Keränen, J., Pajukanta, J., Tolonen, A., Lämsä, A., & Mäntyjärvi, J. (2020). Personalized mental stress detection with self-organizing map: From laboratory to the field. *Computers in Biology and Medicine*, 124, 103935. https://doi.org/10.1016/j.compbiomed.2020.103935
50. Wijsman, J., Grundlehner, B., Liu, N. H., Hermens, H., & Penders, J. (2011). Towards mental stress detection using wearable physiological sensors. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1798–1801. https://doi.org/10.1109/iembs.2011.6090512
51. Xia, L., Malik, A. S., & Subhani, A. R. (2018). A physiological signal-based method for early mental stress detection. *Biomedical Signal Processing and Control*, 46, 18–32. https://doi.org/10.1016/j.bspc.2018.06.004
52. Zubair, M., & Yoon, C. (2019). Multilevel mental stress detection using ultrashort pulse rate variability series. *Biomedical Signal Processing and Control*, 57, 101736. https://doi.org/10.1016/j.bspc.2019.101736
53. A review on mental stress detection using wearable sensors and machine learning techniques. (2021). *IEEE Journals & Magazine | IEEE Xplore*. https://ieeexplore.ieee.org/document/9445082

54. World Health Organization. (2022). *Mental health atlas 2021*. World Health Organization. https://www.who.int/publications/i/item/9789240036703