Contemporary biosensing technologies and systems for music-based stress management

Natasha Yamane
Northeastern University, Boston, MA

ABSTRACT

In the last decade, researchers have explored leveraging biosensing technology to deliver music-based stress management interventions across laboratory and naturalistic contexts. From interactive music applications and affective music players to biofeedback devices and brain-computer interfaces, these technologies and systems are designed to offer users engaging and personalized experiences that enhance stress-related therapeutic outcomes. Drawing upon a range of systematic reviews and empirical research published in the last decade, this mapping review categorizes the current landscape of systems integrating biosensing technology and music for stress management. By mapping the current landscape, this review offers insights into emerging trends and existing gaps and guides research and development at the intersection of music, affective computing, and therapy.

---

1 Introduction

Stress, a ubiquitous aspect of human experience, is a departure from homeostasis provoked by a psychological, environmental, or physiological stressor [1]. According to the American Institute of Stress[1], 60 to 80 percent of individuals report work, financial, and health stress. Chronic exposure to stress can elevate the risk of depression, anxiety, cardiovascular disease, and weakened immune system functioning [2]. Recognizing and managing stress and addressing its underlying risk factors (e.g., trauma, sleep disturbance, poor diet, lack of exercise) are pivotal for promoting overall well-being and mitigating potential adverse outcomes [3].

Research on stress has utilized the circumplex model of affect [4, 5] to examine how stressors affect individuals' emotional experiences and physiological arousal levels. The circumplex model is a theoretical framework that proposes that affective states arise from two fundamental neurophysiological systems—one related to valence (a pleasure–displeasure continuum) and the other to arousal or alertness (**Figure 1**). Prior studies using ratings of affective states and

---

[1] https://www.stress.org

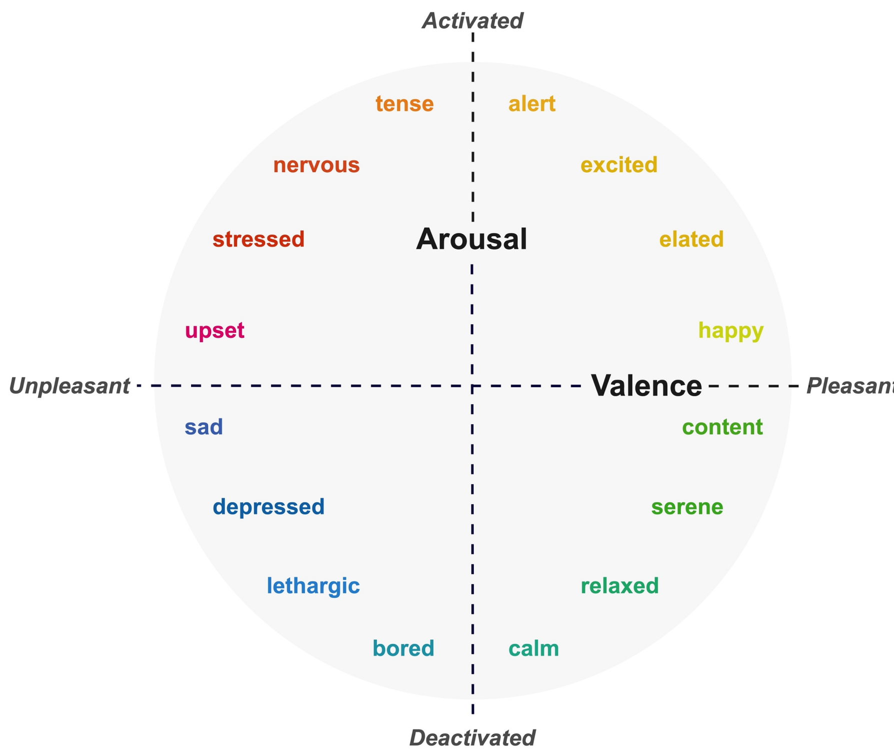

Figure 1. Circumplex model of affect. Adapted from Posner et al. [5].

physiological indices have consistently reproduced the two-dimensional structure of this model [6, 7]. By mapping individuals' responses onto a valence-arousal space, researchers have sought to investigate the interplay between emotional states (e.g., anxiety, frustration) and physiological changes in response to various stressors to explain higher-level processes such as emotional coping and stress management [8].

Thanks to advancements in mobile and ubiquitous computing, stress detection and management software have grown in number and complexity, seamlessly integrating computing capabilities into daily life [9–11]. Concurrently, consumer-grade wearable biosensing technology has become increasingly prevalent over the past decade, contributing real-time, continuous, and measurable indicators of the physiological mechanisms underlying changes in stress levels. The primary characteristics of wearables include their capacity to connect to other systems like smartphones via the Internet or Bluetooth for data transmission, logging, and analysis. As a result, digital tools designed to detect and manage stress leverage biosensors to enhance their effectiveness, incorporating physiological sensing, artificial intelligence, immersive experiences, or a combination of these approaches. This trend reflects a growing focus on precision health and individualized interventions in mental health [9]. By incorporating technologies such as electroencephalography (EEG), cardiovascular and respiration monitors, electrodermal activity sensors, or eye tracking devices, systems integrated with biosensors offer real-time monitoring of physiological indicators, enabling more tailored, adaptive therapeutic experiences based on users' unique biosignals [12]. When developed with adaptive biofeedback capability, these systems can provide visual, auditory, and haptic feedback to users who want to manage their stress proactively [13]. **Figure 2** depicts standard biosensing technologies used in stress management technologies.

Other stress management systems that do not harness biosensing technology are also available. Such tools may incorporate personalized goal setting and evidence-based techniques from cognitive behavioral therapy and positive psychology or leverage immersive platforms to reduce stress. For example, many non-biosensing mobile stress management applications integrate visual and auditory cues with cognitive restructuring or mindfulness practices to guide users through meditation exercises or identify stress-inducing thought patterns [14]. Virtual reality technologies can create immersive environments conducive to relaxation, such as natural scenes with greenery, animals, water, and rocks, among other elements [15]. Compared to systems integrated with biosensors, non-biosensing systems can be more cost-effective than those integrated with biosensors, as they eliminate the need for specialized sensors or wearables. However, such systems typically require self-awareness of individual stress levels and intentional engagement from the user, limiting accessibility for a larger user population and overall system usage.

Simultaneously, much research underscores music's therapeutic potential for stress management. Listening to music has been shown to decrease sympathetic activity [16–18]. This stress-relieving effect is attributed to two primary mechanisms. First, as a distraction from stressors, music can redirect attention [19], and second, by triggering the release of dopamine in the reward system, music can induce relaxation [20, 21]. These findings have spurred further investigations into stress reduction through music therapy (MT), music medicine (MM), and related interventions [22, 23]. A meta-study [23] investigating the application of MT for treating stress and anxiety revealed various noteworthy outcomes. These encompass psychological and physiological effects, distinctions between individual and group therapy settings, implementation of treatment protocols, and music's specific tempo and beat selections. However, MT and MM typically involve delivery by trained professionals. To date, no work has explored the integration of technology as an agent for administering MM or MT to patients and clients. Across music-based stress management systems, several elements of music, including rhythm, tempo, melodies, and tones, are leveraged to modulate stress. Thus, this review

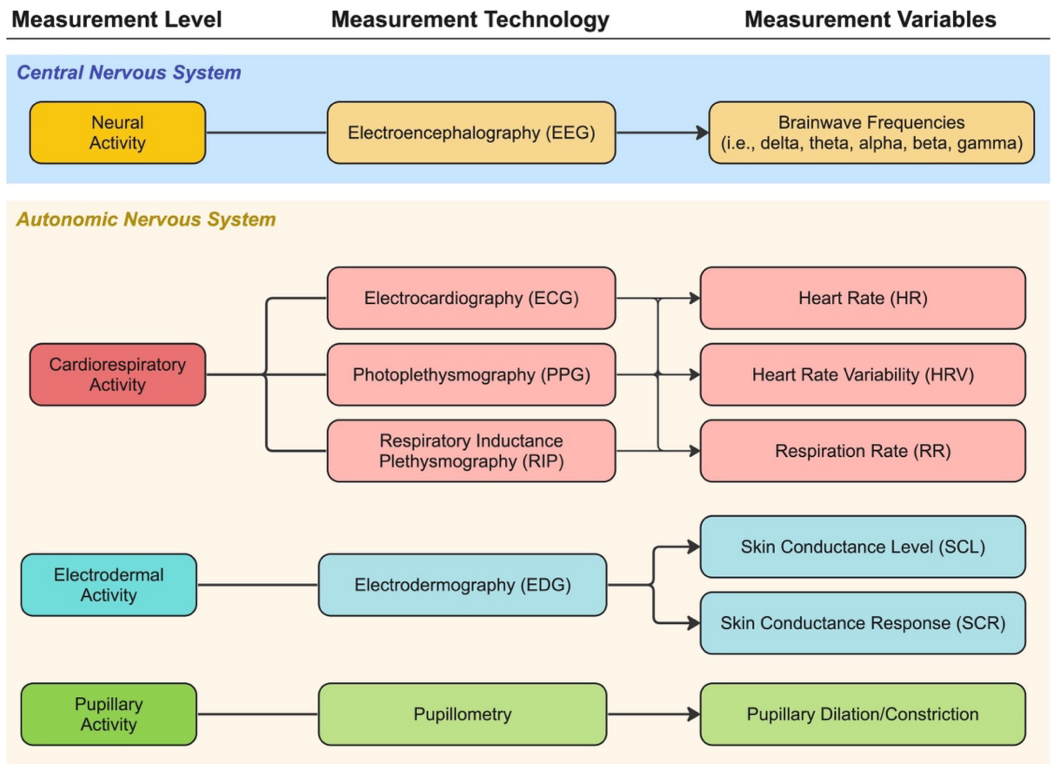

Figure 2. Biosensing technologies and their measurements in research and applications in stress management. While electrodermography is the measurement of skin conductance, "electrodermal activity" (EDA) and "galvanic skin response" (GSR) are more commonly used in the literature.

focuses on those systems that combine any element of music and biosensing technology to alleviate stress beyond MT and MM settings.

Computational approaches, such as machine learning (ML) and music information retrieval (MIR), play a pivotal role in the evolution of music-based stress management systems, driving innovations in music recommendation algorithms and more sophisticated and accurate emotion recognition models [24–26]. In MIR, researchers harness the properties of music by extracting and classifying elements such as tempo, rhythm, key, and melody to develop systems and methods that enhance how we interact with, recommend, and understand musical content. Together, ML and MIR techniques are pushing the area of music emotion recognition (MER) further in recognizing and understanding the emotional content of music. Music emotion recognition models leverage techniques such as feature extraction, with which relevant musical features are identified, and classification algorithms, like support vector machines (SVMs) or neural networks (NNs), to categorize affective states. By training on labeled datasets that associate musical features with specific emotions, these models can learn to generalize and accurately predict the emotional content of new music.

Moreover, exploring ML approaches in MER has spurred the design and development of automated emotionally intelligent interfaces and systems, offering personalized music recommendations for entertainment and mental health purposes [27, 28]. When integrated into music recommender systems for stress management, these approaches adapt musical selections to users' emotional states, creating more personalized therapeutic experiences.

The intersection of affective computing and MIR is evolving with an increasing array of tools for individuals to alleviate stress through music. Music recommender systems (MRS) can adapt preselected music to users' affective states. Simultaneously, the proliferation of passive biosensing technology enables non-intrusive and continuous stress monitoring and thus new avenues for designing and developing stress management tools. Given these rapidly growing research areas, this review aims to map the diverse landscape of systems and applications leveraging music and biosensing data for stress management. Drawing from a range of sources, including systematic reviews and empirical research studies published in peer-reviewed journals and conference proceedings, this review presents a comprehensive overview of the development and evaluation of these solutions. These include systems that harness biosensing technology that is further subcategorized according to the biosensing modality and interface type (e.g., mobile, ubiquitous) leveraged. Ultimately, this mapping review aims to understand better how technology and music intersect to measure stress and promote relaxation, paving the way for potential advancements, informed interventions, and improved user experiences.

2 Methodology

This mapping review thoroughly examines contemporary technologies and interfaces that utilize music for stress management. Unlike systematic reviews, this approach uses a more inductive and exploratory search strategy to explore a variety of studies [29] on digital tools and systems for music-based stress management. The solutions are presented regarding biosensing modality and discussed in terms of the platforms (e.g., desktop, mobile, immersive) and computational models (e.g., time-frequency analysis, machine learning, deep learning) leveraged. Finally, this review categorizes research studies and their respective systems according to other metadata variables, including technology type, study purpose, participant sample, and primary findings.

2.1 Search Strategy

The search strategy for the current review involved a purposive and iterative approach. Initial searches were conducted across multiple academic research databases, including Google Scholar, PubMed, IEEE Xplore, and ACM Digital Library, inputted with variations of the following search term strings: music* AND technolog* OR interface* OR system OR app* AND stress OR anxiety OR emotion* OR affect* OR relax*. Initial search results were screened by title and filtered to systematic reviews and empirical research studies. A snowballing technique was also employed, wherein references from identified articles were reviewed to discover additional relevant literature.

Given increased advancements in biosensing technology in the last decade, studies and articles included in this mapping review were limited to those published from 2013 to the present. Inclusion criteria involved empirical research papers focusing on music-based technologies and interfaces that use biosensors and their applications in stress management or affect regulation. Exclusion criteria encompassed studies not published in English, non-peer-reviewed publications, and studies unrelated to music-based stress management systems. Such unrelated systems included those using auditory stimuli that are not strictly considered or manipulated concerning musical elements (i.e., rhythm, tempo, melodies, tones), such as white noise. Systems developed with biosensing and affect classification or modulation capabilities for applications in areas other than mental health, stress management, or mood improvement (e.g., entertainment, artistic creation) were also excluded.

2.2 Data Extraction and Synthesis

A standardized data extraction form was used to collect relevant information from the selected studies systematically. Extracted data included: (1) author information; (2) publication year; (3) type of study conducted (i.e., technical feasibility and technology development or evaluation); (4) study purpose; (5) participant sample; and (6) study findings. This process aimed to provide an overview of the current research landscape on music-based technologies and systems for stress management.

Data synthesis involved organizing and categorizing the extracted information to identify relationships between different music-based technologies and interfaces for stress management based on the type of technology, biosensing modality, computational model(s), and types of music and interface (i.e., desktop, mobile, wearable, ubiquitous). These categories were chosen to support the aim of uncovering emerging themes and identifying research gaps in developing and evaluating digital music-based stress management tools.

3 Results

The results of this mapping review demonstrate the diverse landscape of contemporary music-based biosensing technologies and interfaces for stress management. A total of 29 studies describing systems evaluated on n = 674 user participants were identified for this review. Among the systems reviewed, 48.0% use cardiorespiratory sensors (17.0% ECG, 6.9% PPG, 24.0% RIP), 17.0% use EDA sensors, and 31.0% use EEG technology. Of these, 65.5% used wearable systems (e.g., Zephyr BioHarness, Empatica E4). While desktop-based interfaces accounted for 58.6% of the total systems, mobile interfaces constituted 20.7%, ubiquitous types made up 17.2%, and immersive (i.e., virtual reality) interfaces comprised only 3.4%. Additionally, 27.6% of the systems had a biofeedback mechanism, with most focusing on respiratory-based biofeedback. Finally, 62.1% of the identified systems used prerecorded musical stimuli, including user-selected or experimenter-selected material, and 37.9% relied on generated music (i.e., music created by automated music composition systems or manipulated by the experimenters). **Figure** 3 illustrates the distribution of biosensing modalities and types of interfaces and music across all systems reviewed.

Collectively, the studies reviewed suggest that the majority of music-based systems being developed for stress management show promise in inducing and modulating affective states. Overall, 65.5% of the systems, evaluated on n = 404 user participants, demonstrate the ability to modulate users' affective states, as validated by changes in physiological measures, including heart rate variability, electrodermal activity, respiratory rate, and alpha and theta brainwaves. The remainder of the systems were assessed for their technical feasibility, such as using or creating various acoustic stimuli and detecting user affective states.

The following subsections summarize the development and evaluation of digital music-based stress management tools by biosensing modality. Below, each modality-specific subsection encompasses systems that exclusively incorporate that particular biosensing modality, while multimodal systems are addressed separately in Section 3.4. Additionally, selected system features, such as types of interface and auditory stimuli or computational model(s) leveraged, are highlighted based on their identifiable prevalence across each modality. For reference, Table I summarizes each study based on the biosensing modality, interface, type of musical stimuli, and computational model leveraged with music to detect and regulate stress. The table also includes the study type (i.e., feasibility, development, or evaluation), purpose, participant sample, and relevant findings.

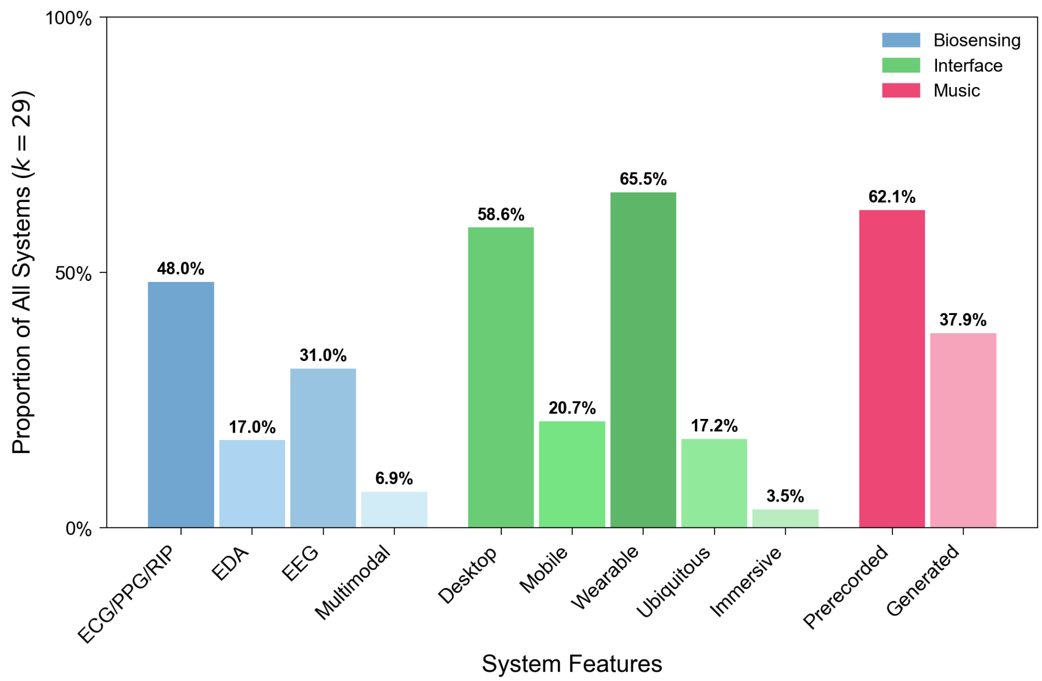

Figure 3. Distribution of features across all k = 29 biosensing systems for music-based stress detection and management reviewed.

3.1 Cardiorespiratory Sensing

Cardiorespiratory activity is intricately linked to the stress response, as revealed by a meta-analysis by Kim and colleagues [30]. Stressors can trigger the release of stress hormones, such as cortisol and adrenaline, leading to increased heart rate, blood pressure, sweating, and breathing rate. These responses are involved in the adaptive mechanisms of the autonomic nervous system (ANS) when coping with perceived threats or challenges. Cardiorespiratory measures used to detect or corroborate the stress response by the systems under review include heart rate (HR), heart rate variability (HRV), blood volume pulse (BVP), and respiration rate (RR). They are commonly recorded using electrocardiography (ECG), photoplethysmography (PPG), and respiratory inductance plethysmography (RIP).

Technologies integrating ECG, PPG, and RIP encompass stationary systems and ambulatory devices tailored for various medical and personal healthcare applications. These devices range from medical-grade monitors used in clinical settings, such as Holter and wired event monitors, to consumer-grade wearables, such as smartwatches and chest belts. Using such biosensing technologies, researchers interested in music-based stress management can develop more complex systems designed with algorithms that can identify specific patterns of cardiorespiratory dynamics in the presence of a stressor. Studies have shown that low HRV conveys a monotonously regular HR and is associated with impaired regulatory and homeostatic ANS, which reduces the body's ability to cope with internal and external stressors [30]. In this vein, elevations in HR and RR values, along with a reduction in HRV, can be used in these systems to prompt the delivery of a stress-relief intervention.

Cardiorespiratory sensing technologies have been integrated with music and auditory stimuli in interactive music systems, biofeedback devices, and affective music generators to facilitate identifying and modulating an individual's affective state. Below, evidence of the development and testing of cardiorespiratory-based systems in the last decade is summarized across $k = 13$ studies with $n = 243$ user participants. Eight feasibility studies, three development studies, and two evaluation studies were identified. Two studies are highlighted regarding the biosensing technology, intervention, type of interface, and type of music leveraged.

3.1.1 Physiological Sensors

Of the 13 stress management systems employing heart rate or breathing, four exclusively utilize ECG [31–34], four use only PPG [35–38], three use RIP alone [39–41], one utilizes both ECG and RIP sensors [42], and one uses breathing data with an unspecified biosensing technology [43]. All ECG-integrated systems use data collected with wired electrodes or a chest belt such as the Zephyr BioHarness [32–34, 42], except one which relies on electromechanical film embedded in chair seats [31]. PPG- and RIP-integrated systems also leverage heart rate and breathing data collected with wireless chest belts [35–37, 39, 40–42], as well as finger-worn PPG sensors [38]. Most studies that created systems combining ECG and RIP through a chest belt opted for the well-validated Zephyr BioHarness [44].

3.1.2 Prerecorded and Generated Music

Auditory stimuli used by these systems vary from prerecorded music to generated music [33, 40, 41] or music manipulated in different ways (e.g., volume modulation, channel reduction, or noise addition [35, 38, 39]) to provide variations in auditory cues. While some systems incorporate various prerecorded music selections, the use of multiple pieces of music in designing and evaluating music-based intervention systems may introduce methodological challenges due to inconsistencies in emotional and structural characteristics across pieces. Such potential confounds can be more rigorously controlled by testing with only one song, as in the work by Harris et al. [35], for example, or using music generated by automated music composition systems.

Generated music, created with advanced artificial intelligence algorithms, may offer methodological advantages by providing standardized stimuli, allowing for precise control over variables. Idrobo-Ávila and colleagues [34] evaluated the feasibility of developing a biofeedback system based on generative adversarial networks (GANs) that could generate and alter sequences of harmonic musical intervals (HMIs), or chords, to elicit target HRV responses. The authors used two GANs (i.e., 'GAN-1' and 'GAN-2'), each formed by a generator and a discriminator. Each discriminator was trained to classify whether a given input sequence was a real or synthetic HMI or HRV data sequence generated by its respective generator. GAN-1's discriminator was trained with human-created HMIs and HMIs generated by its respective generator. It achieved an accuracy of 0.53 for accurate data and 0.52 for generated data, indicating that its generated HMIs are similar to human-created HMIs. Similarly, GAN-2's discriminator was trained with human HRV data and HRV data from audio data by its respective generator. The mean discrimination accuracy was 0.56 for real data and 0.51 for generated data, suggesting good performance in generating new HRV data. Due to study constraints, the system could not be piloted and evaluated on human participants to assess whether HRV data could be modulated using generated HMIs. However, their findings contribute to a potential working model to implement generated music in a biofeedback-based stress management system.

3.1.3 Biofeedback

Biofeedback-based stress management systems externalize an individual's internal physiological state, allowing users to monitor changes in HR or RR in real-time [45]. Most biofeedback systems use *closed-loop* architectures, in which real-time feedback is provided to the user based on their physiological data. On the other hand, *open-loop* systems do not provide immediate feedback to the user but may record data for later analysis or intervention planning.

Using biofeedback-based stress management systems, users can learn to consciously regulate their physiological stress responses, such as incorporating controlled breathing techniques to facilitate relaxation [46]. Eight of the 13 systems surveyed operate on respiratory-based biofeedback to regulate stress. In these systems, auditory feedback, in combination with other modalities (e.g., visual, haptic), is used to prompt mindful or slow breathing [33, 37–43]. Among these, all but one system by Marentakis et al. [40] employ a closed-loop architecture. The authors argued that compared to closed-loop architectures, open-loop implementations may be less vulnerable to specific challenges associated with data collection, such as interference with user activities and data privacy concerns. Therefore, they evaluated three types of generated auditory feedback stimuli for guided breathing in open-loop stress management systems. The auditory stimuli consisted of (1) a synthesized pseudo-breath sound, (2) a musical sequence of notes rising and falling in pitch, and (3) a combination of both the synthetic breath and musical sequence. Ten adult volunteers were recruited to evaluate the ability of each auditory feedback type to guide their breathing along two target respiration rates—one slow and one fast—while wearing a respiration belt. Participants underwent multiple testing phases, including regular and paced breathing sections, with each phase featuring different counterbalanced types of feedback (i.e., breath, music, compound) and respiration rates. Results showed that all three types of feedback effectively guided participants to match the target breathing rate, with more significant deviations observed during fast breathing. Music feedback resulted in a more significant average deviation from the target breathing rate than breath feedback. However, compared to breath feedback alone, compound feedback demonstrated significantly more minor errors and longer durations close to the target breathing rate, particularly under conditions of fast respiration rates.

3.2 Electrodermal Sensing

Electrodermal activity (EDA) or galvanic skin response (GSR) refers to the electrical conductance of the skin, which varies with changes in sweat gland activity driven by the ANS [47]. In the context of stress, EDA serves as a physiological indicator, reflecting sympathetic nervous system arousal associated with stress responses. Stress detection algorithms utilize EDA measurements to identify changes in patterns that may signal the onset or escalation of stress [48], enabling timely intervention and support. In stress management systems, EDA measurements can be incorporated into biofeedback processes to help individuals become more aware of their stress levels and apply stress reduction techniques.

Because EDA is a reliable and frequently used index of autonomic arousal, EDA data are often used to validate arousal ratings when developing and evaluating stress detection or management systems. Across all papers that met inclusion criteria, only k = 5 music-based stress detection and management systems exclusively integrating EDA sensing and evaluated with n = 196 user participants, were identified. Further, two studies on these systems focused on the feasibility of developing music generators for prospective stress management applications.

For example, Daly and colleagues [49] proposed and evaluated an affectively-driven music generator for brain-computer music interfaces (BCMIs) that might modulate users' affect to a target state. The music generator in this work is a generative system that creates new musical passages based on a 16-channel feedforward artificial neural network (ANN)[2]. The ANN is trained on 12 bars of polyphonic piano music in the key of C major, played at a tempo of 120 bpm. Musical elements—tempo, mode, pitch, timbre, and amplitude envelope—are mapped to different affective states via a Cartesian grid comprising valence and arousal, analogous to the circumplex model. For instance, a point with coordinates (1, 1) indicating low valence and low arousal would guide the generator to produce music with a slow tempo, minor chords, soft timbre, an amplitude envelope with considerable legato, and a narrow pitch range. The ability of the system to generate novel musical stimuli corresponding to 9 possible affective states was validated on EDA recordings from $n = 20$ listeners with the BrainAmp GSR sensor (Brain Products, Germany). Participants' music-induced and self-reported affect ratings were collected via the FEELTRACE [50] and the Self-Assessment Manikin (SAM) [51] and then analyzed with EDA peak amplitudes and affective states targeted by the generator. The study found that, relative to baseline, EDA peak amplitude increased with self-reported arousal and decreased with self-reported valence. Additionally, EDA peak amplitude significantly covaried with the targeted stress level of the music generation system. On average, FEELTRACE and SAM ratings were also moderately correlated with the generator's targeted affective states by valence ($r = 0.59$, $p < .01$) and arousal ($r = 0.54$, $p < .01$). Together, the findings of this study demonstrate that the music generator was able to induce a range of targeted emotions in its listeners, making it feasible for use in interfaces such as multimodal BCMIs or biofeedback-based systems for stress management.

Other exclusively EDA-based systems—affective music players and MER systems—with and without adaptive manipulation of music, were identified in studies assessing their affect modulation capabilities with EDA measures [52–54]. For instance, in work by Bartolomé-Tomás and colleagues [53], changes in arousal levels of older individuals were detected by a MER system using a variety of musical stimuli and EDA measures. Musical stimuli consisted of prerecorded pieces custom-composed in styles representing various genres for the experiment, and EDA measures were recorded with the wrist-worn Empatica E4. Their objective was to investigate how familiarity with different musical genres (i.e., rock/jazz, Cuban, Spanish folklore, and Flamenco) influences emotional responses, potentially guiding future intervention systems that use music to trigger emotional self-regulation processes in older adults. Employing methods involving EDA signal deconvolution, they conducted two studies. The first study identified differences across EDA data's temporal, morphological, statistical, and

[2] A feedforward neural network is a type of artificial neural network (ANN) in which nodes are connected circularly. Data input is processed in only one direction—from the input layer, through one or more hidden layers, to the output layer without any feedback loops—making this type of ANN suitable for classification and regression.

frequency features. The second evaluated machine learning techniques to explore correlations between EDA-based arousal detection and participants' subjective arousal responses. The first study revealed that Flamenco and Spanish Folklore music presented the highest number of statistically significant parameters. In the second study, the best-performing machine learning classifiers for arousal detection were SVMs, with 87% accuracy for Flamenco and 83.1% for Spanish Folklore, followed by KNN, with 81.4% and 81.5% for Flamenco and Spanish Folklore, respectively.

3.3 Neural Sensing

The complex neural activity related to stress involves interactions in brain regions such as the limbic system, hypothalamus, amygdala, and prefrontal cortex, orchestrating the stress response by balancing the ANS and the neuroendocrine system [55]. By interpreting neural signatures in such regions, brain-computer interfaces provide an approach for measuring and monitoring stress levels, facilitating potential applications in adaptive brain-based stress management interventions.

Brain-computer interfaces (BCI) are computational systems that capture electrical signals from the brain (most commonly with electroencephalography [EEG]), interpret them, and convert them into commands before transmitting them to output devices for the execution of predefined tasks [56]. Thus, BCIs provide a direct link between the brain and a computer or other external devices, allowing individuals to control machines or devices using their brain activity [57]. BCI systems generally comprise three components: (1) data acquisition and pre-processing, (2) feature extraction, and (3) classification.

Applications of BCI systems have been explored with music and other auditory stimuli to identify and mediate an individual's affective state. Such affective brain-computer music interfaces (aBCMI) detect neuro-correlates of a user's current affective state and attempt to modulate it by generating or selecting stress-reducing music [58]. Some researchers argue that aBCMIs have an advantage over conventional music therapy approaches in that aBCMIs are "able to directly monitor the users' emotional state via physiological indices of emotion, which have the potential to be more robust and objective measures of emotion than user reports or even the expertise of the music therapist" [59] (p. 201).

The past decade has witnessed a surge in publications on aBCMIs, simultaneously contributing to developing direct-to-consumer home applications of aBCMI technology [58]. The Mico system[3], a 2013 conceptual wearable device, offers personalized music choices through headphones and an iPhone application. By analyzing brainwaves, the sensor in the headphones categorizes users into "neural groups," selecting music from a database that matches the identified neural pattern. Imec's EEG headset aims to measure and influence emotions, learn users' musical preferences, and create real-time music to align with emotional states [60]. Neurosity's Crown™, a portable EEG device, is marketed as a productivity booster that detects brainwaves and plays focus-enhancing music from Spotify[4].

Within the scope of the current review, $k = 9$ studies on aBCMIs with $n = 195$ user participants were identified from the literature. The earliest and only feasibility study on an aBCMI found in the timeframe was published in 2013. Uma and Sridhar [61] evaluated the feasibility of developing an EEG-based BCI system to recognize and manage the stress level of a user based on the circumplex model of affect [5]. Three categories of musical stimuli (i.e., “soft/melody,” “devotional,” and “rock/fast beat”) were presented to participants while EEG waveforms were recorded using a 64-channel system. However, no ground truth data were obtained on participants’ affective states or stress levels, such as self-report or observational measures. The participants’ ages, personal preferences, and experiences with music were also not analyzed. The authors concluded that alpha, beta, and theta rhythms in the frontal regions could be reliably differentiated across music categories and used for future classifier development. However, other features valuable to the development of classification models, such as properties of each auditory stimulus (e.g., volume, tempo, timbre), were not accounted for.

3.3.1 Deployment Platforms

Among the nine studies, four proposed and evaluated aBCMIs with a mobile form factor, with the remainder focused on desktop-based aBCMIs. While desktop-based aBCMIs are deployed from either desktop or laptop computers, mobile aBCMIs integrate wearable EEG headsets and smartphone applications to deliver neurofeedback or musical stimuli to the user [62–65]. For example, Chen et al. [62] proposed the design of a mobile, EEG-based affective BCI aimed at delivering real-time personalized emotional feedback to users during interactions with various multimedia, including music. EEG data was collected using the NeuroSky Mindset. This reportedly portable and convenient single-channel EEG headset also outputs information on “Attention” and “Meditation” mental states of the user to an Android mobile application via Bluetooth

[3] https://www.neurowear.com/mico
[4] https://www.neurosity.co

technology. Real-time, personalized emotional feedback is delivered via voice- or text-based cues of NeuroSky's measures of user mental state. Although the proposed system does not provide a music-based stress-reduction intervention, it is a potentially valuable tool to collect EEG data conveniently in naturalistic contexts during exposure to music. However, a potential drawback of the system lies in using an EEG system that employs proprietary algorithms for extracting and classifying only two mental states per user, thereby restricting the exploration of other affective states and the development of different ML algorithms. In addition, using a single-channel instead of more common multi-channel configurations introduces further concerns about the quality, precision, and accuracy of EEG data being used to detect user states [66, 67].

3.3.2 Computational Models

In total, 11 different computational models were employed in the nine aBCMI studies identified in the literature to extract meaningful features from EEG data associated with music exposure and affective response [68]. Three of these studies explored the use of artificial intelligence models, with the remainder using system-proprietary or other computational models, including time-frequency analysis (e.g., wavelet transforms) [61, 63], and stream processing [69]. Artificial intelligence techniques included machine learning models such as SVMs and linear discriminant analysis (LDA), as well as deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). For example, Tiraboschi and colleagues [70] developed an aBCMI for real-time music generation using a 6-channel EEG system and the open-source environment OpenViBE for feature extraction. They evaluated the performance of supervised learning methods (i.e., SVM, LDA, and Naïve Bayes) in classifying affective valence and arousal using EEG data collected from 32 participants. Their study revealed that LDA performed best in valence ($F_1 = 0.61$) and arousal ($F_1 = 0.56$) classification across various electrode configurations, demonstrating the potential of aBCMIs using fewer EEG channels to classify affective valence and arousal effectively. This insight can potentially contribute to developing more cost-effective and less cumbersome aBCMIs.

3.4 Multimodal Sensing

Multimodal biosensing data, encompassing physiological signals such as heart rate, skin conductance, and brainwaves, offers a comprehensive approach to understanding the stress response. Several research studies using multimodal biosensing data have been conducted in the last decade to evaluate their potential for stress detection and management [71–73]. However, only $k = 2$ studies with $n = 52$ user participants incorporated a music-based stress detection or management model.

Following their work in [49], Daly et al. [74] developed and evaluated an aBCMI to detect and modulate a user's current affective state with a music generator and case-based reasoning approach. Their aBCMI system includes four separate processes: (1) multimodal physiological data acquisition, (2) affective state detection, (3) affective trajectory identification, and (4) music generation according to the affective trajectory. In the first process, data is collected with a 32-electrode EEG system, finger-worn EDA sensors, single-lead ECG electrodes on the wrists, and a respiration chest best, all connected to the BrainAmp ExG amplifier (Brain Products, Germany). In the second process, band-power-based EEG features and ECG, EDA, BVP, and respiration rate measures are employed in an SVM for affective state classification. Next, the case-based reasoning system identifies "affective trajectories" with which the music generator [49] can transition users between different affective states. These trajectories encompass values of valence and arousal estimated for all musical parameters in the generative model used to induce desired affective states. The multimodal aBCMI was evaluated for its ability to modulate the affective states of $n = 8$ participants. Results of the study revealed that the aBCMI could detect users' current affective states with classification accuracies of up to 65% (3 class, $p < .01$) and modulate its users' affective states significantly above chance level ($p < .05$).

Ayata, Yaslan, and Kamasak [75] proposed a music recommendation system based on user emotions detected multimodally with physiological data. The system uses a machine learning algorithm to predict emotions from PPG and EDA data. PPG and EDA sensor data are inputted, segmented, and then processed in feature extraction to yield mean, maximum, minimum, or variance statistics. Using 10-fold cross-validation and the DEAP dataset ($n = 32$) [76], the authors evaluated the performance of different classifiers, including SVM, random forest (RF), decision trees, and KNN, in predicting arousal and valence values. The RF classifier achieved the highest accuracy rates for both arousal and valence. Strong correlations were found between EDA and PPG signals with emotion recognition, with multimodal feature sets showing slightly improved accuracy rates compared to unimodal sets. For EDA, arousal and valence prediction accuracy rates were 71.53% and 71.04%, respectively, while for PPG, accuracy rates were 70.92% and 70.76%. By fusing EDA and PPG signals, the accuracy rates improved to 72.06% for arousal and 71.05% for valence prediction. Despite the modest improvement in accuracy with feature fusion, this system's model holds promise for enhancing music recommendation engines by incorporating multimodal emotion data.

4 Discussion

Integrating biosensors in stress detection and management tools allows for a more personalized and adaptive approach, as these systems dynamically adjust therapeutic components such as visualizations or sounds based on the users' unique biosignals. Growing research in this area has spurred the development of direct-to-consumer applications and devices that claim to boost productivity and regulate mood. However, these devices still lack research-grade results. This limitation highlights the need for more rigorous validation and standardization in the field, as existing research employs diverse methodologies, leading to a broad range of results depending on their participants, datasets (e.g., auditory stimuli), recording protocols, emotion elicitation techniques, and computational models. In light of these factors, this mapping review takes an inductive approach to explore the diverse array of contemporary music-based stress management technologies and systems, while providing insights into future research directions and areas of improvement.

The results of this mapping review highlight the diversity and evolution of music-based biosensing technologies and interfaces for stress detection and management. A total of 29 systems with feasibility, development, and evaluation studies involving 674 participants across studies were identified. The systems reviewed encompass various biosensing modalities, with cardiorespiratory sensing being the most prevalent, followed by electrodermal and neural sensing. Various interfaces were employed across the systems, including desktop-based interfaces, mobile applications, wearable devices, ubiquitous systems, and incipient frameworks designed for immersive platforms. Wearable interfaces, particularly those integrating cardiorespiratory sensors, were found to be the predominant type.

Within each biosensing modality, distinct trends in system development and evaluation emerged. Cardiorespiratory sensing systems predominantly utilize ECG, PPG, and RIP technologies, often integrated into stationary and ambulatory devices. These systems frequently incorporate various forms of prerecorded and generated musical stimuli, the latter of which may present a methodological advantage in providing standardized stimuli for stress interventions. Additionally, biofeedback mechanisms, particularly those focusing on respiratory-based biofeedback, are prevalent in stress management systems focused on mindful breathing. The integration of auditory cues in biofeedback systems aimed at stress reduction through breathwork is gaining traction.

Electrodermal sensing systems rely on EDA measures in response to musical stimuli as input to detect affective states with machine and deep learning models. While machine learning algorithms like SVM and KNN can accurately predict arousal and valence based on EDA and PPG signals, the interpretation of their predictions remains complex. A meta-analysis of 202 studies examining ANS reactivity during induced emotions in non-clinical adults showed increased effect sizes for most ANS variables across emotion categories, but no clear differentiation between categories [77]. These findings suggest that ANS responses are context-specific and highly variable, and that researchers should exercise caution when developing and training machine learning models to predict emotion. Data fusion from multiple sensing modalities, which has shown promising results in enhancing emotion recognition accuracy [75], may be necessary to capture the variability of emotional experiences.

Neural sensing systems, predominantly EEG-based, offered innovative approaches to stress management through affective brain-computer music interfaces (aBCMIs). These interfaces leverage EEG data to detect and modulate users' affective states through personalized music interventions. While most aBCMIs are still desktop-based, aBCMIs with mobile form factors are emerging, highlighting the importance of increasing accessibility to real-time, on-the-go stress interventions [14]. Further, results from studies using machine and deep learning techniques demonstrate the feasibility of accurately classifying affective states from EEG data.

5 Future Directions

This mapping review underscores the wealth of music-based biosensing technologies and systems for stress detection and management in the last decade. Over half of the systems reviewed demonstrate the capability to induce changes in user affect, indicating potential in the area of stress management system development. However, while the studies reviewed may offer researchers and engineers valuable insight into refining existing systems to support mental health with biosensing and music, notable gaps in the research exist.

First, there is a need for more investigations into integrating multimodal biosensing approaches with music-based stress detection and reduction. In general stress research studies, the combination of data collected from multiple modalities has been shown to improve the performance of stress detection models [72, 73, 78, 79]. However, some researchers argue that instead of combining as many data sources as possible, selecting modalities for integration into a stress detection model should balance prediction accuracy and other crucial evaluation criteria [80]. This would require future investigations to identify the most effective combination of modalities concerning the accuracy of music-based stress detection models.

Future research could also uncover the mechanisms and specific musical elements and features contributing to music's therapeutic effects on stress. Several studies in this review used ambient, meditative, and soundscapes in their systems to induce relaxation. Techniques from the music information retrieval field may allow researchers to extract specific features of music from such genres for further testing and integration into music generators and their stress management models.

Finally, as systems increasingly rely on collecting and analyzing sensitive user health data, concerns about data privacy and protection become crucial. Some experts have argued for users' rights to mental privacy and integrity [81, 82]. Ensuring the confidentiality and security of this data is essential to gaining and maintaining usage and trust. This will require that the individual user be in control of what is recorded, how the recordings are stored, and what is revealed and shared by the system about their mental health data and classification results.

Table 1. **Music-Based Stress Management Systems with Biosensing Integration (*k* = 29 studies; *n* = 674 participants)**

Study	Study Type	Purpose	Type of Music	Biosensing Modality	Interface	Computational Model	Sample	Outcome
Uma and Sridhar (2013)	Feasibility	Assess the feasibility of developing a BCI system to recognize and control affective states using EEG brainwave frequencies and preselected music.	Prerecorded; Various	EEG	Desktop	Time-frequency analysis	$N = 4$	Alpha, beta, and theta rhythms in the frontal regions could be reliably differentiated during exposure to different music categories.
Van der Zwaag et al. (2013)	Feasibility	Validate whether an affective music player could direct the mood states (i.e., energized or calm).	Prerecorded; Various	EDA	Desktop	Probabilistic models	$N = 10$	Skin conductance and mood could be directed toward energized or calm states, which persisted for at least 30 minutes.
Harris et al. (2014)	Feasibility	Present and validate “Sonic Respiration,” an auditory biofeedback system to slow breathing rate for stress management using two forms of acoustic manipulation.	Prerecorded; “On the Line” by James May	RIP	Mobile; Wearable	Not described	$N = 6$	Both forms of acoustic manipulation (i.e., adding white noise, reducing channels in a multi-track song) are equally effective at slowing breathing.
Shin et al. (2014)	Evaluation	Evaluate a wearable, wireless PPG-based stress-relieving music recommendation system.	Prerecorded; Various songs	PPG	Mobile; Wearable	Time-frequency analysis (to compute the sympathovagal balance index [SVI])	$N = 20$	The system showed strong correlations between SVI values and users' music preferences, with increased sensitivity and specificity as music repetitions increase.

Bhandari et al. (2015)	Feasibility	Present and evaluate a music-based respiratory biofeedback intervention to regulate stress levels during a visually-demanding task.	Prerecorded; Various slow-tempo songs	RIP	Desktop; Wearable	Not described	*N* = 28	When compared to two non-biofeedback conditions, music biofeedback led to lower arousal levels across RR, HRV, and EDA measures.
Chen et al. (2015)	Development	Propose the development of a mobile aBCMI aimed at delivering real-time personalized emotional feedback to users.	Prerecorded; Various	EEG	Mobile; Wearable	Proprietary algorithm; Threshold-based affect scoring	Not described	The system can collect training data during exposure to various multimedia and output real-time data to users on their mental states.
Daly et al. (2015)	Evaluation	Evaluate an affectively-driven music generator for use in a BCMI to induce intended affective states in users.	Generated; Various	EDA*	Desktop	Artificial neural network	*N* = 20	There were moderate correlations between the generator's targeted affective states and self-report valence and arousal ratings, indicating that the generator can induce targeted emotions in listeners.
Liu and Rauterberg. (2015)	Development	Present a heart rate-controlled in-flight music recommendation system for stress reduction during air travel.	Prerecorded; Various user-selected songs	ECG (via electromech-anical film)	Ubiquitous	Content-based filtering	*N* = 12	A simulated long-haul flight experiment revealed that passengers' stress can be reduced through listening to music playlists preselected for decreasing, increasing, or maintaining user HR.

Tseng et al. (2015)	Evaluation	Develop and evaluate a BCI-based smart multimedia controller to analyze user EEG features and select music according to user state.	Prerecorded; Various	EEG	Mobile; Wearable	Time-frequency analysis	$N = 28$	The system was able to automatically select music based on the user's EEG features and demonstrated superior efficiency in evoking attention compared to random music selection.
Daly et al. (2016)	Evaluation	Develop and evaluate an aBCMI for modulating the affective states of its users.	Generated; Various	ECG; EDA; EEG; RIP	Desktop; Wearable	SVM	$N = 8$	The system can detect users' affective states with classification accuracies of up to 65% (3 class, $p < .01$) and modulate its user's affective states ($p < .05$).
Zhu et al. (2016)	Feasibility	Assess the efficacy of recognizing negative affect through HR data and whether tempo and personal familiarity with the music can reduce drivers' negative affect, and consequently improve driving performance.	Prerecorded; Various user-selected songs	ECG	Ubiquitous; Wearable	Fourier analysis	$N = 30$	In a simulated driving experiment, HR data could be used in the recognition of driver anger. Medium-tempo music led to faster alleviation of negative affect compared to fast-tempo music.
Tiwari and Tiwari (2017)	Development	Propose the development of a mobile aBCMI to prompt the user via text messaging to engage in relaxation methods with yoga or listening to preselected music.	Prerecorded; Various	EEG; EOG	Mobile; Wearable	Stream processing algorithm	$N = 50$	The system was able to detect user states of stressed, stressed and relaxed by music, and stressed and relaxed by yoga from all but 9 participants.

Zhu et al. (2017)	Development	Develop and test the feasibility of a physical digital mindfulness prototype for stress reduction.	Generated; Meditation music	ECG	Ubiquitous; Wearable	Time-frequency analysis	*N* = 25	The prototype, incorporating vapor, light, and sonification, was effective in promoting mindful breathing and reducing stress levels, as indicated by both subjecttive self-assessment and HRV measures.
Ayata, Yaslan, and Kamasak (2018)	Feasibility	Propose an emotion-based music recommendation framework that learns user emotions based on EDA and PPG data.	Not described	EDA; PPG	Desktop; Wearable	Decision tree; KNN; Random forest; SVM	*N* = 32	Feature fusion with a multimodal sensor dataset increased the SVM classifier's accuracy rate compared to single modality.
Yu et al. (2018)	Evaluation	Evaluate "Unwind," a musical interface for a HRV biofeedback system that facilitates breathing regulation and relaxation.	Generated; Sedative music with nature sounds	PPG	Desktop; Wearable	Not described	*N* = 40	There was a significant interaction effect between music and biofeedback on the improvement of heart rate variability.
Duncan et al. (2019)	Feasibility	Assess the feasibility of a generative music system to creating emotionally congruent music for applications in entertainment and mindfulness.	Generated	EDA*	Desktop; Wearable	Hidden Markov Models	*N* = 53	The two types of music (i.e., tense–scary, calm–not scary) elicited emotional responses that matched participants' questionnaire descriptions with their EDA measures.

Ehrlich et al. (2019)	Evaluation	Develop and evaluate a BCI prototype that can feedback a user's affective state in a closed-loop interaction between EEG and musical stimuli.	Generated; Various	EEG	Desktop; Wearable (wireless Emotiv Epoc+)	Rule-based probablistic model	<u>Study 1</u>: *N* = 11 <u>Study 2</u>: *N* = 5	In *Study 1*, there was a good match between users' perceptual ratings of affect and music generation settings, although there was high variance across subjects. In *Study 2*, participants were able to intentionally modulate the musical feedback by self-inducing emotions (e.g., recalling emotional memories).
Leslie et al. (2019)	Feasibility	Evaluate the feasibility of an interactive music system in influencing a user's breathing rate to induce a relaxation response across three interaction designs.	Generated; Ambient music with shifts in loudness	RIP	Desktop; Wearable	Breathing-based amplitude modulation	*N* = 19	The interactive music system effectively reduced breathing rates and physiological arousal, with the “personalized tempo” design having the largest effect.
Bartolomé-Tomás et al. (2020)	Feasibility	Assess the feasibility of detecting changes in arousal using musical stimuli and EDA measures of older individuals.	Prerecorded; Custom compositions in styles of four genres	EDA	Desktop; Wearable	Time-frequency analysis; Logistic regression; LDA; Naïve Bayes; Decision trees; KNN; SVM	*N* = 40	Flamenco and Spanish Folklore yielded the most number of significant EDA parameters. SVM and KNN showed the highest accuracies in arousal detection (> 80% for these genres).

Qin et al. (2020)	Feasibility	Evaluate the feasibility of using 3D music to modulate EDA responses in VR-based therapy for stress and anxiety.	Prerecorded; Electronic	EDA	Immersive; Wearable	Not described	$N = 73$	EDA can serve as an indicator of ANS activity and emotional arousal level, with 3D music significantly reducing EDA compared to other musical elements like tempo.
Jayaraj, Ghazali, and Ghaber (2021)	Development	Propose the design of a mobile aBCMI application to reduce stress among college students using human-computer interaction design principles.	Prerecorded; Solfeggio frequency; Binaural beats	EEG	Mobile	Not described	$N = 11$ (initial user needs survey); $N = 6$ (feasibility); $N = 10$ (usability)	Usability testing of the mobile BCI prototype revealed that the app showed good overall usability, with some inconsistencies noted. Most of the participants preferred the Solfeggio Frequency approach over binaural beats in reducing stress levels.
Kimmatkar and Babu (2021)	Feasibility	Detect emotional state by processing EEG signals and test the effect of meditation music therapy to stabilize mental state.	Prerecorded; Meditation music	EEG	Desktop; Wearable (wireless Emotiv Epoc+)	CNN; DNN; k-NN; RNN	$N = 22$	The k-NN classifier showed highest accuracy in classifying emotions. 15 out of 20 EEG signals from participants successfully transformed from the "annoying" state to the "relaxed" state.
Marentakis et al. (2021)	Feasibility	Compare three synthetic auditory feedback stimuli (i.e., breath, music, and compound) for guided breathing in an open-loop biofeedback system.	Generated; Various melodies and sounds	RIP	Desktop; Wearable	Not described	$N = 10$	Compound auditory feedback stimuli (i.e., synthetic breath and musical stimuli combined) show a stronger effect on breath entrainment to a target breathing rate.

Shor et al. (2021)	Feasibility	Explore the potential role of haptics as part of the "Resonance Pod," an enclosed hanging chair using lights, music, and vibrations to combat stress through breathing entrainment.	Prerecorded; Custom composition for the system	Unknown sensor type; RR	Ubiquitous	Not described	$N = 5$	Qualitative user feedback on four 3-minute breathing rhythm sequences suggests that the Resonance Pod creates a pleasant and calming multisensory breathing entrainment experience.
Tiraboschi, Avanzini, and Boccignone (2021)	Evaluation	Explore strategies for real-time music generation applications using biosensor data and evaluate the performance of supervised learning methods on classification of affective valence and arousal.	Generated; Various	EEG	Desktop	Linear discriminant analysis; Naïve Bayes; SVM	$N = 32$	The pipeline can generate affectively driven music using EEG data. A reduced number of EEG channels can still be used for binary classification of affective valence and arousal.
Zepf et al. (2021)	Development	Present a closed-loop system that monitors breathing in real-time and provides rhythmical feedback (i.e., acoustic, haptic, and mixed) to support slow breathing and relaxation.	Prerecorded; Ambient music[a]	ECG; RIP	Ubiquitous; Wearable	Breathing-based feedback rate adaptation	$N = 12$	Acoustic and mixed feedback can slow breathing without affecting focus, suggesting that subtle rhythmic feedback can be an effective stimuli type in biofeedback systems.
Idrobo-Ávila et al. (2022)	Feasibility	Propose a HRV-based biofeedback system that can generate harmonic musical intervals to moderate HRV responses.	Generated; Harmonic music intervals (HMIs)	ECG	Desktop	Generative adversarial network (GAN)	$N = 26$	Using HRV data from human subjects, the GAN achieved comparable accuracy in generating HMIs to human-created HMIs, suggesting the potential use of HRV data to generate HMIs.

Sun (2022)	Evaluation	Propose and evaluate a feedback-based aBCMI for depression.	Prerecorded; Various	EEG	Desktop	CNN	$N = 16$ (4 controls, 8 depression, 4 feedback training)	Participants receiving neurofeedback training with the aBCMI showed lower self-reported depression ratings.
Sato et al. (2023)	Feasibility	Explore the potential of cyclic melodies to individualize the phasic relationship between sound and respiration (PRSR).	Western classical-style music	RIP	Desktop	Not described	$N = 10$	Respiration intervals can be changed by controlling the PRSR, suggesting that for biofeedback devices for daily use, the PRSR could be considered when melody is presented as a stimulus.

Note. Technologies: aBCMI = affective brain-computer music interface; BCI = brain-computer interface. Biosensing modalities: ECG = electrocardiography; EEG = electroencephalography; EOG = electrooculography (eye blinks); HR = heart rate; HRV = heart rate variability; RIP = respiratory inductance plethysmography; RR = respiration rate. Computational models: CNN = convolutional neural network; DNN = deep neural network; k-NN = k-nearest neighbor; RNN = recurrent neural network; SVM = support vector machine.

[a] The selected ambient music can be found at: https://www.youtube.com/watch?v=n0svuurLibQ

* EDA measures were used to validate arousal ratings in system evaluation and not strictly recorded by the system for its intended purpose.

References

[1] G. P. Chrousos and P. W. Gold, "The concepts of stress and stress system disorders: Overview of physical and behavioral homeostasis," *JAMA*, vol. 267, no. 9, pp. 1244–1252, Mar. 1992.

[2] A. Mariotti, "The effects of chronic stress on health: New insights into the molecular mechanisms of brain–body communication," *Future Sci OA*, vol. 1, no. 3, pp. 1–6, Nov. 2015.

[3] B. L. Seaward, *Managing stress: Principles and strategies for health and well-being*, 9th ed. Burlington, MA: Jones & Bartlett Learning, 2017.

[4] J. A. Russell, "A circumplex model of affect," *Journal of Personality and Social Psychology*, vol. 39, no. 6, pp. 1161–1178, 1980.

[5] J. Posner, J. A. Russell, and B. S. Peterson, "The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology," *Development and Psychopathology*, vol. 17, no. 3, pp. 715–734, 2005.

[6] P. J. Lang, M. K. Greenwald, M. M. Bradley, and A. O. Hamm, "Looking at pictures: affective, facial, visceral, and behavioral reactions," *Psychophysiology*, vol. 30, no. 3, pp. 261–273, May 1993.

[7] L. Barrett and T. Fossum, "Mental representations of affect knowledge," *Cognition and Emotion*, vol. 15, pp. 333–364, May 2001.

[8] K. Stanisławski, "The coping circumplex model: An integrative model of the structure of coping with stress," *Frontiers in Psychology*, vol. 10, pp. 1–23, Apr. 2019.

[9] Y. S. Can, B. Arnrich, and C. Ersoy, "Stress detection in daily life scenarios using smart phones and wearable sensors: A survey," *Journal of Biomedical Informatics*, vol. 92, p. 103139, Apr. 2019.

[10] M. Luštrek, J. Lukan, L. Bolliger, E. Lauwerier, and E. Clays, "Designing an intervention against occupational stress based on ubiquitous stress and context detection," in *Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing*, in UbiComp/ISWC '23 Adjunct. New York, NY, USA: Association for Computing Machinery, Oct. 2023, pp. 606–610.

[11] A. Alberdi, A. Aztiria, and A. Basarab, "Towards an automatic early stress recognition system for office environments based on multimodal measurements: A review," *Journal of Biomedical Informatics*, vol. 59, pp. 49–75, Feb. 2016.

[12] B. A. Hickey *et al.*, "Smart devices and wearable technologies to detect and monitor mental health conditions and stress: A systematic review," *Sensors*, vol. 21, no. 10, Art. no. 10, Jan. 2021.

[13] B. Yu, M. Funk, J. Hu, Q. Wang, and L. Feijs, "Biofeedback for everyday stress management: A systematic review," *Frontiers in ICT*, vol. 5, pp. 1–22, 2018.

[14] S. M. Coulon, C. M. Monroe, and D. S. West, “A systematic, multi-domain review of mobile smartphone apps for evidence-based stress management,” *American Journal of Preventive Medicine*, vol. 51, no. 1, pp. 95–105, Jul. 2016.

[15] S. Riches, L. Azevedo, L. Bird, S. Pisani, and L. Valmaggia, “Virtual reality relaxation for the general population: A systematic review,” *Soc Psychiatry Psychiatr Epidemiol*, vol. 56, no. 10, pp. 1707–1727, Oct. 2021.

[16] D. L. Bartlett, “Physiological responses to music and sound stimuli,” in *Handbook of Music Psychology*, 2nd ed., D. A. Hodges, Ed., San Antonio, TX: IMR Press, 1996, pp. 343–385.

[17] A. Linnemann, J. Strahler, and U. M. Nater, “Assessing the effects of music listening on psychobiological stress in daily life,” *JoVE (Journal of Visualized Experiments)*, no. 120, pp. 1–9, Feb. 2017.

[18] J. D. Halbert *et al.*, “Low frequency music slows heart rate and decreases sympathetic activity,” *Music and Medicine*, vol. 10, no. 4, Art. no. 4, Oct. 2018.

[19] L. Kiss and K. J. Linnell, “The effect of preferred background music on task-focus in sustained attention,” *Psychological Research*, vol. 85, no. 6, pp. 2313–2325, Sep. 2021.

[20] V. Salimpoor *et al.*, “The rewarding aspects of music listening involve the dopaminergic striatal reward systems of the brain: An investigation with [C11]Raclopride PET and fMRI,” *NeuroImage*, vol. 47, p. S160, Jul. 2009.

[21] A. M. Belfi and P. Loui, “Musical anhedonia and rewards of music listening: current advances and a proposed model,” *Annals of the New York Academy of Sciences*, vol. 1464, no. 1, pp. 99–114, 2020.

[22] M. de Witte, A. Spruit, S. van Hooren, X. Moonen, and G.-J. Stams, “Effects of music interventions on stress-related outcomes: A systematic review and two meta-analyses,” *Health Psychology Review*, vol. 14, no. 2, pp. 294–324, Jun. 2020.

[23] M. de Witte, A. da S. Pinho, G.-J. Stams, X. Moonen, A. E. R. Bos, and S. van Hooren, “Music therapy for stress reduction: A systematic review and meta-analysis,” *Health Psychology Review*, vol. 16, no. 1, pp. 134–159, Jan. 2022.

[24] W. C. Chiang, J. S. Wang, and Y. L. Hsu, “A music emotion recognition algorithm with hierarchical SVM based classifiers,” in *2014 International Symposium on Computer, Consumer and Control*, Jun. 2014, pp. 1249–1252.

[25] A. S. Shinde, V. V. Patil, K. R. Khadse, N. Jadhav, S. Joglekar, and M. Hatwalne, “ML based speech emotion recognition framework for music therapy suggestion system,” in *2022 6th International Conference On Computing, Communication, Control And Automation (ICCUBEA)*, Aug. 2022, pp. 1–5.

[26] A. Asif, M. Majid, and S. M. Anwar, “Human stress classification using EEG signals in response to music tracks,” *Computers in Biology and Medicine*, vol. 107, pp. 182–196, Apr. 2019.

[27] J. He, “Algorithm composition and emotion recognition based on machine learning,” *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–10, Jun. 2022.

[28] C. Ceccato, E. Pruss, A. Vrins, J. Prinsen, and M. Alimardani, “BrainiBeats: A dual brain-computer interface for musical composition using inter-brain synchrony and emotional valence,” in *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, in CHI EA ’23. New York, NY, USA: Association for Computing Machinery, Apr. 2023, pp. 1–7.

[29] M. J. Grant and A. Booth, “A typology of reviews: An analysis of 14 review types and associated methodologies,” *Health Information and Libraries Journal*, vol. 26, no. 2, pp. 91–108, Jun. 2009.

[30] H.-G. Kim, E.-J. Cheon, D.-S. Bai, Y. H. Lee, and B.-H. Koo, “Stress and heart rate variability: A meta-analysis and review of the literature,” *Psychiatry Investig*, vol. 15, no. 3, pp. 235–245, Mar. 2018.

[31] H. Liu, J. Hu, and M. Rauterberg, “Follow your heart: Heart rate controlled music recommendation for low stress air travel,” *IS*, vol. 16, no. 2, pp. 303–339, Nov. 2015.

[32] Y. Zhu, Y. Wang, G. Li, and X. Guo, “Recognizing and releasing drivers’ negative emotions by using music: Evidence from driver anger,” in *Adjunct Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, in AutomotiveUI ’16 Adjunct. New York, NY, USA: Association for Computing Machinery, Oct. 2016, pp. 173–178.

[33] B. Zhu, A. Hedman, S. Feng, H. Li, and W. Osika, “Designing, prototyping and evaluating digital mindfulness applications: A case study of mindful breathing for stress reduction,” *Journal of Medical Internet Research*, vol. 19, no. 6, p. e6955, Jun. 2017.

[34] E. Idrobo-Ávila, H. Loaiza-Correa, F. Muñoz-Bolaños, L. van Noorden, and R. Vargas-Cañas, “Development of a biofeedback system using harmonic musical intervals to control heart rate variability with a generative adversarial network,” *Biomedical Signal Processing and Control*, vol. 71, p. 103095, Jan. 2022.

[35] J. Harris, S. Vance, O. Fernandes, A. Parnandi, and R. Gutierrez-Osuna, “Sonic respiration: Controlling respiration rate through auditory biofeedback,” in *CHI ’14 Extended Abstracts on Human Factors in Computing Systems*, in CHI EA ’14. New York, NY, USA: Association for Computing Machinery, Apr. 2014, pp. 2383–2388.

[36] I.-H. Shin *et al.*, “Automatic stress-relieving music recommendation system based on photoplethysmography-derived heart rate variability analysis,” *Annu Int Conf IEEE Eng Med Biol Soc*, vol. 2014, pp. 6402–6405, 2014.

[37] R. Bhandari, A. Parnandi, E. Shipp, B. Ahmed, and R. Gutierrez-Osuna, “Music-based respiratory biofeedback in visually-demanding tasks,” in *Proceedings of the International Conference on New Interfaces for Musical Expression*, Baton Rouge, LA, Jun. 2015, pp. 78–82.

[38] B. Yu, M. Funk, J. Hu, and L. Feijs, “Unwind: A musical biofeedback for relaxation assistance,” *Behaviour & Information Technology*, vol. 37, no. 8, pp. 800–814, Aug. 2018.

[39] G. Leslie, A. Ghandeharioun, D. Zhou, and R. W. Picard, "Engineering music to slow breathing and invite relaxed physiology," in *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*, Sep. 2019, pp. 1–7.

[40] G. Marentakis, D. Borthakur, P. Batchelor, J. P. Andersen, and V. Grace, "Using breath-like cues for guided breathing," in *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, Yokohama Japan: ACM, May 2021.

[41] T. G. Sato, Y. Ooishi, M. Fujino, and T. Moriya, "Device for controlling the phasic relationship between melodic sound and respiration and its effect on the change in respiration rate," *Behaviour & Information Technology*, vol. 0, no. 0, pp. 1–13, 2023.

[42] S. Zepf, P.-W. Kao, J.-P. Krämer, and P. Scholl, "Breath-triggered haptic and acoustic guides to support effortless calm breathing," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Nov. 2021, pp. 1796–1800.

[43] D. Shor, Y. Ruitenburg, W. Boere, J. D. Lomas, and G. Huisman, "The Resonance Pod: Applying haptics in a multi-sensory experience to promote relaxation through breathing entrainment," in *2021 IEEE World Haptics Conference (WHC)*, Montreal, QC, Canada: IEEE, Jul. 2021, pp. 1143–1143.

[44] G. Nazari, P. Bobos, J. C. MacDermid, K. E. Sinden, J. Richardson, and A. Tang, "Psychometric properties of the Zephyr bioharness device: A systematic review," *BMC Sports Sci Med Rehabil*, vol. 10, no. 1, pp. 1–8, Feb. 2018.

[45] M. S. Schwartz, "A new improved universally accepted official definition of biofeedback: Where did it come from? Why? Who did it? Who is it for? What's next?," *Biofeedback*, vol. 38, no. 3, pp. 88–90, Sep. 2010.

[46] G. W. Fincham, C. Strauss, J. Montero-Marin, and K. Cavanagh, "Effect of breathwork on stress and mental health: A meta-analysis of randomised-controlled trials," *Sci Rep*, vol. 13, no. 1, Art. no. 1, Jan. 2023.

[47] W. Boucsein, *Electrodermal activity*, 2nd ed. Berlin, Germany: Springer Science+Business Media, 2012.

[48] Y. Liu and S. Du, "Psychological stress level detection based on electrodermal activity," *Behavioural Brain Research*, vol. 341, pp. 50–53, Apr. 2018.

[49] I. Daly *et al.*, "Towards human-computer music interaction: Evaluation of an affectively-driven music generator via galvanic skin response measures," in *2015 7th Computer Science and Electronic Engineering Conference (CEEC)*, Sep. 2015, pp. 87–92.

[50] R. Cowie, E. Douglas-Cowie, S. Savvidou, E. McMahon, M. Sawey, and M. Schroder, "'FEELTRACE': An instrument for recording perceived emotion in real time," presented at the Proceedings of the ISCA Workshop on Speech and Emotion, Jan. 2000.

[51] M. M. Bradley and P. J. Lang, “Measuring emotion: The self-assessment manikin and the semantic differential,” *Journal of Behavior Therapy and Experimental Psychiatry*, vol. 25, no. 1, pp. 49–59, Mar. 1994.

[52] M. D. van der Zwaag, J. H. Janssen, and J. H. D. M. Westerink, “Directing physiology and mood through music: Validation of an affective music player,” *IEEE Transactions on Affective Computing*, vol. 4, no. 1, pp. 57–68, Jan. 2013.

[53] A. Bartolomé-Tomás, R. Sánchez-Reolid, A. Fernández-Sotos, J. M. Latorre, and A. Fernández-Caballero, “Arousal detection in elderly people from electrodermal activity using musical stimuli,” *Sensors*, vol. 20, no. 17, Art. no. 17, Jan. 2020.

[54] Y. Qin, H. Zhang, Y. Wang, M. Mao, and F. Chen, “3D music impact on autonomic nervous system response and its therapeutic potential,” in *2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR)*, Aug. 2020, pp. 364–369.

[55] R. M. Buijs and C. G. Van Eden, “The integration of stress by the hypothalamus, amygdala and prefrontal cortex: Balance between the autonomic nervous system and the neuroendocrine system,” in *Progress in Brain Research*, vol. 126, in Cognition, emotion and autonomic responses: The integrative role of the prefrontal cortex and limbic structures, vol. 126. , Elsevier, 2000, pp. 117–132.

[56] J. J. Shih, D. J. Krusienski, and J. R. Wolpaw, “Brain-computer interfaces in medicine,” *Mayo Clin Proc*, vol. 87, no. 3, pp. 268–279, Mar. 2012.

[57] S. Saha *et al.*, “Progress in brain computer interface: challenges and opportunities,” *Frontiers in Systems Neuroscience*, vol. 15, pp. 1–20, 2021.

[58] E. Hildt, “Affective brain-computer music interfaces—drivers and implications,” *Frontiers in Human Neuroscience*, vol. 15, pp. 1–4, 2021.

[59] D. A. H. Williams and E. R. Miranda, “BCI for music making: Then, now, and next,” in *Brain–Computer Interfaces Handbook*, C. S. Nam, A. Nijholt, and F. Lotte, Eds., Boca Raton, FL: CRC Press, 2018, pp. 193–206.

[60] Imec, “Wearable EEG solutions.” Accessed: Jan. 03, 2024. [Online]. Available: https://www.imec-int.com/drupal/sites/default/files/2019-01/EEG_Headset_digital.pdf

[61] M. Uma and S. S. Sridhar, “A feasibility study for developing an emotional control system through brain computer interface,” in *2013 International Conference on Human Computer Interactions (ICHCI)*, Aug. 2013, pp. 1–6.

[62] H.-M. Chen, S.-Y. Chen, T.-J. Jheng, and S.-C. Chang, “Design of a mobile brain-computer interface system with personalized emotional feedback,” in *Future Information Technology - II*, J. J. (Jong H. Park, Y. Pan, C. Kim, and Y. Yang, Eds., in Lecture Notes in Electrical Engineering. Dordrecht: Springer Netherlands, 2015, pp. 87–95.

[63] K. C. Tseng, B.-S. Lin, A. M.-K. Wong, and B.-S. Lin, “Design of a mobile brain computer interface-based smart multimedia controller,” *Sensors*, vol. 15, no. 3, Art. no. 3, Mar. 2015.

[64] A. Tiwari and R. Tiwari, “Design and implementation of a brain computer interface for stress management using LabVIEW,” in *2017 International Conference on Computer, Communications and Electronics (Comptelix)*, Jul. 2017, pp. 152–157.

[65] P. J. Jayaraj, M. Ghazali, and A. Gaber, “Relax app: Designing mobile brain-computer interface app to reduce stress among students,” *International Journal of Innovative Computing*, vol. 11, no. 2, Art. no. 2, Oct. 2021.

[66] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, “Optimizing the channel selection and classification accuracy in EEG-based BCI,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 6, pp. 1865–1873, Jun. 2011.

[67] L. Troy M., G. Joseph T., and F. Daniel P., “How many electrodes are really needed for EEG-based mobile brain imaging?,” *Journal of Behavioral and Brain Science*, vol. 2012, Aug. 2012.

[68] S. Panwar, P. Rad, K.-K. R. Choo, and M. Roopaei, “Are you emotional or depressed? Learning about your emotional state from your music using machine learning,” *J. Supercomput.*, vol. 75, no. 6, pp. 2986–3009, Jun. 2019.

[69] S. K. Ehrlich, K. R. Agres, C. Guan, and G. Cheng, “A closed-loop, music-based brain-computer interface for emotion mediation,” *PLoS ONE*, vol. 14, no. 3, pp. 1–24, Mar. 2019.

[70] M. Tiraboschi, F. Avanzini, and G. Boccignone, “Listen to your mind’s (he)art: A system for affective music generation via brain-computer interface,” in *Proceedings of the 18th Sound and Music Computing Conference*, in 146–153. Virtual: Zenodo, Jul. 2021.

[71] V.-R. Xefteris *et al.*, “A multimodal late fusion framework for physiological sensor and audio-signal-based stress detection: An experimental study and public dataset,” *Electronics*, vol. 12, no. 23, Art. no. 23, Jan. 2023.

[72] G. Pinto, J. M. Carvalho, F. Barros, S. C. Soares, A. J. Pinho, and S. Brás, “Multimodal emotion evaluation: A physiological model for cost-effective emotion classification,” *Sensors*, vol. 20, no. 12, Art. no. 12, Jan. 2020.

[73] S. Lee, T. Lee, T. Yang, C. Yoon, and S.-P. Kim, “Detection of drivers’ anxiety invoked by driving situations using multimodal biosignals,” *Processes*, vol. 8, no. 2, Art. no. 2, Feb. 2020.

[74] I. Daly *et al.*, “Affective brain–computer music interfacing,” *Journal of Neural Engineering*, vol. 13, no. 4, pp. 1–14, Jul. 2016.

[75] D. Ayata, Y. Yaslan, and M. E. Kamasak, “Emotion based music recommendation system using wearable physiological sensors,” *IEEE Transactions on Consumer Electronics*, vol. 64, no. 2, pp. 196–203, May 2018.

[76] S. Koelstra *et al.*, “DEAP: A database for emotion analysis using physiological signals,” *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18–31, Jan. 2012.

[77] E. H. Siegel *et al.*, "Emotion fingerprints or emotion populations? A meta-analytic investigation of autonomic features of emotion categories," *Psychol Bull*, vol. 144, no. 4, pp. 343–393, Apr. 2018.

[78] M. Smith, R. Withnall, S. Anastasova, B. Gil-Rosa, J. Blackadder-Coward, and N. Taylor, "Developing a multimodal biosensor for remote physiological monitoring," *BMJ Mil Health*, vol. 169, no. 2, pp. 170–175, Apr. 2023.

[79] H. Zhang, L. Cao, L. Feng, and M. Yang, "Multi-modal interactive fusion method for detecting teenagers' psychological stress," *Journal of Biomedical Informatics*, vol. 106, p. 103427, Jun. 2020.

[80] M. Naegelin *et al.*, "An interpretable machine learning approach to multimodal stress detection in a simulated office environment," *Journal of Biomedical Informatics*, vol. 139, p. 104299, Mar. 2023.

[81] A. Lavazza, "Freedom of thought and mental integrity: The moral requirements for any neural prosthesis," *Front Neurosci*, vol. 12, p. 82, Feb. 2018.

[82] M. Ienca and R. Andorno, "Towards new human rights in the age of neuroscience and neurotechnology," *Life Sciences, Society and Policy*, vol. 13, no. 1, p. 5, Apr. 2017.