EEG-Based Assessment of Music Therapy: A Systematic Review of Neural Correlates and their Cognitive States, Artificial Intelligence Approaches, and Different DataSets

Shefali Gupta
shefaligupta91@gmail.com

NITTTR Bhopal

Systematic Review

Keywords: EEG, wellness music, meditation music, brain activity, relaxation, stress, neural biomarkers, functional connectivity, machine learning, deep learning

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Abstract

Premise. The increasing prevalence of stress, anxiety, cognitive fatigue, and other mental health challenges has intensified interest in non-pharmacological interventions. Wellness music including meditation music, ambient instrumental music, Indian classical music, Vedic chanting, devotional music, nature-inspired soundscapes, binaural beats, and therapeutic compositions has shown potential to influence emotional state, stress, attention, relaxation, and cognition. EEG, with its high temporal resolution, portability, and non-invasive nature, provides an effective tool for objectively investigating the neural effects of wellness music.

Objective. This systematic review examines 76 EEG-based research on wellness and therapeutic music published primarily between 2013 and 2026, focusing on EEG biomarkers and computational approaches for characterizing music-induced neural and psychological changes.

Methods. The literature is analyzed with respect to EEG biomarkers, experimental paradigms, musical stimuli, acquisition and preprocessing methods, statistical approaches, and computational techniques. Key measures include PSD, FAA, ABR, TAR, TBR, BAR, PRI, EI, functional connectivity, and machine-learning-based methods.

Observations. The reviewed studies commonly report increased alpha and theta activity, reduced high-beta activity, modulation of frontal hemispheric asymmetry, and enhanced functional synchronization during wellness music exposure. Increasingly, artificial intelligence, deep learning, graph-based methods, and wearable EEG systems are being used for automated classification of emotional and cognitive states. However, considerable methodological heterogeneity limits comparison and reproducibility across studies.

Significance. Future research should prioritize standardized EEG protocols and biomarkers, culturally diverse music paradigms, multimodal and longitudinal validation, and explainable AI. Greater investigation of Indian classical music, Vedic chanting, and other culturally specific wellness music may support the development of robust, interpretable, and personalized EEG-based systems for objectively characterizing the neurophysiological effects of wellness music.

Keywords: EEG, wellness music, meditation music, brain activity, relaxation, stress, neural biomarkers, functional connectivity, machine learning, deep learning.

1 Introduction

Mental health disorders, psychological stress, anxiety, cognitive fatigue, and reduced emotional well-being have become significant public health concerns worldwide. Consequently, there has been growing interest in non-pharmacological interventions capable of promoting relaxation, emotional regulation, cognitive restoration, and psychological well-being. Music is one of the most accessible and widely used interventions in this context. Its effects extend beyond subjective enjoyment and can influence autonomic activity, emotional processing, attention, memory, and large-scale neural dynamics [1], [2], [21]-[24].

Wellness music represents a broad category of auditory interventions intended to support psychological and physiological well-being. It includes meditation music, ambient instrumental music, nature-inspired soundscapes, Indian classical music, Vedic chanting, devotional music, binaural beats, Tibetan singing bowls, mindfulness music, personalized therapeutic compositions, and adaptive or AI-generated music [2], [3], [21], [22], [25]– [28]. These interventions differ considerably in their acoustic structure, cultural context, rhythmic organization, melodic complexity, and intended psychological effects. Nevertheless, many are designed to reduce stress, promote relaxation, enhance attention, regulate emotions, or facilitate meditative states.

The neurophysiological effects of music have traditionally been assessed using subjective questionnaires, behavioral performance, and physiological measurements such as heart rate and skin conductance. Although these measures provide valuable information, they do not directly characterize the temporal dynamics of cortical activity. Electroencephalography (EEG), therefore, has become an important method for investigating the neural effects of music because of its millisecond-level temporal resolution, portability, relatively low cost, and non-invasive nature [4], [5], [29], [30].

EEG enables researchers to quantify changes in oscillatory activity, hemispheric asymmetry, neural synchronization, functional connectivity, and cognitive engagement during music listening [5], [6]. Frequency-domain measures such as Power Spectral Density (PSD)[4], [15], [29], [31], [32] have been widely used to investigate changes in alpha, theta, beta, and gamma activity. In addition, derived indices such as Frontal Alpha Asymmetry (FAA) [5]-[7], Alpha-Beta Ratio (ABR), Theta-Alpha Ratio (TAR), Theta-Beta Ratio (TBR), Beta-Alpha Ratio (BAR), Power Ratio Index (PRI), and Engagement Index (EI) provide composite measures of relaxation, cognitive workload, arousal, fatigue, and attentional engagement [15], [16], [24], [31], [32], [34].

Recent advances have expanded EEG-based music research beyond traditional spectral analysis. Functional connectivity measures, including Phase Locking Value (PLV), coherence, Phase Lag Index (PLI), and Granger causality, have been used to examine communication among distributed cortical regions [8], [13], [35], [36]. Graph-theoretical methods have further enabled the investigation of network organization, modularity, efficiency, hub dynamics, and small-world properties during music perception. Concurrently, artificial intelligence and deep learning have provided new opportunities for automatically classifying emotional and cognitive states from EEG signals [15], [16], [29], [37], [38].

Despite rapid growth in this field, the literature remains fragmented. Studies vary substantially in the type of music used, experimental paradigms, EEG systems, preprocessing procedures, selected biomarkers, statistical approaches, and participant populations. Furthermore, although Western meditation music and general affective music have been widely investigated, culturally specific wellness traditions such as Indian classical music, Vedic chanting, and devotional music remain comparatively underrepresented in EEG research.

The objective of this systematic review is therefore to synthesize current EEG-based evidence on the neural effects of wellness music, identify commonly used neurophysiological biomarkers, evaluate emerging artificial intelligence approaches, address publicly available datasets, and highlight methodological gaps that must be addressed for the development of reliable EEG-based computational models for music-induced wellness assessment.

2 Review Objectives

This systematic review was conducted to address the following research questions:

1. What EEG biomarkers are most frequently used to evaluate the neural effects of wellness and therapeutic music?
2. How does wellness music influence oscillatory brain activity, hemispheric asymmetry, and neural connectivity?
3. Which EEG-derived indices are associated with relaxation, stress reduction, emotional regulation, attention, and cognitive engagement?
4. How are machine learning and deep learning approaches being used to classify music-induced cognitive and emotional states?
5. What are the major methodological limitations and research gaps in current EEG-based wellness music research?
6. How can future studies develop standardized and computationally robust frameworks for evaluating the neurophysiological effects of culturally specific wellness music?

3 Methodology

3.1Search Strategy

A comprehensive literature search was conducted across multiple scientific databases and academic search platforms, including PubMed, Scopus, IEEE Xplore, Web of Science, and Google Scholar and other sources. The search aimed to identify peer-reviewed journal articles, conference proceedings, and relevant preprints investigating EEG-based assessment of wellness and therapeutic music.

The search strategy combined keywords related to EEG, wellness and therapeutic music, and neurophysiological outcomes. The principal search expression was:

> **("EEG" OR "Electroencephalography") AND ("Wellness Music" OR "Music Therapy" OR "Mindfulness Music" OR "Vedic Chanting") AND ("Brain Activity" OR "Emotion" OR "Stress" OR "Relaxation") AND ("EEG Biomarkers") AND ("AI Method" OR "AI approach") AND ("Music Datasets")**

The review primarily considered 76 studies published between 2013 and 2026. This period was selected because it encompasses substantial advances in wearable EEG systems, signal-processing techniques, machine learning, deep learning, and computational approaches for neurophysiological data analysis [15]– [20], [29]– [36].

The database search initially identified 1,120 records from electronic databases, including PubMed (n = 420), Scopus (n = 320), IEEE Xplore (n = 160), Web of Science (n = 150), and Google Scholar with other sources (n = 70). After removing 28 duplicate records, 1,092 studies remained for title and abstract screening. During the initial screening stage, 958 records were excluded because they were unrelated to wellness music or its neural effects (n = 712), did not involve human participants (n = 92), reported non-neurophysiological outcomes (n = 78), or were not freely accessible (n = 76). Consequently, 134 full-text articles were assessed for eligibility.Studies were included if they:

1. **Criteria 1 (C1):**Recorded neurophysiological signals, particularly EEG, while participants listened to wellness, therapeutic, meditative, relaxing, or culturally specific music (need to mention the points which were excluding from C2 and C3.. will talk on it;
2. **Criteria 2 (C2):** Reported quantitative neurophysiological biomarkers, including power spectral density (PSD), frontal alpha asymmetry (FAA), phase-locking value (PLV), coherence, event-related potentials (ERPs), spectral power, functional connectivity, or derived EEG indices; and evaluated the neural, emotional, cognitive, physiological, or well-being-related effects of music;
3. **Criteria 3 (C3):** Investigated emerging artificial intelligence (AI) or machine-learning approaches for analysing music-related neurophysiological responses; or
4. **Criteria 4 (C4):** Provided publicly available datasets, repositories, or sufficient information regarding data accessibility, EEG acquisition, preprocessing, feature extraction, and analytical methods.

A total of 58 full-text articles were excluded during the eligibility assessment. The major reasons for exclusion were the absence of reported neurophysiological biomarkers (n = 23), no AI or machine-learning component (n = 12), insufficient dataset description or limited data accessibility (n = 11), and a lack of specific focus on wellness or therapeutic music (n = 12). Following the eligibility assessment, 76 studies were included in the systematic review. These studies were categorized according to their primary contribution: neural effects of wellness music (n = 50), commonly used neurophysiological biomarkers (n = 9), emerging AI approaches (n = 13), and publicly available datasets and repositories (n = 4).

The selected literature encompassed a broad range of interventions, including meditation music, binaural beats, mindfulness music, Tibetan singing bowls, Indian ragas, Vedic chanting, devotional music, nature-based soundscapes, personalized therapeutic music, AI-generated adaptive music, soundscape therapy, and wearable neurofeedback systems [2], [3], [12], [21]– [28], [34]– [36]. The overall study-selection process is illustrated in Figure 1. using a PRISMA-style flow diagram.

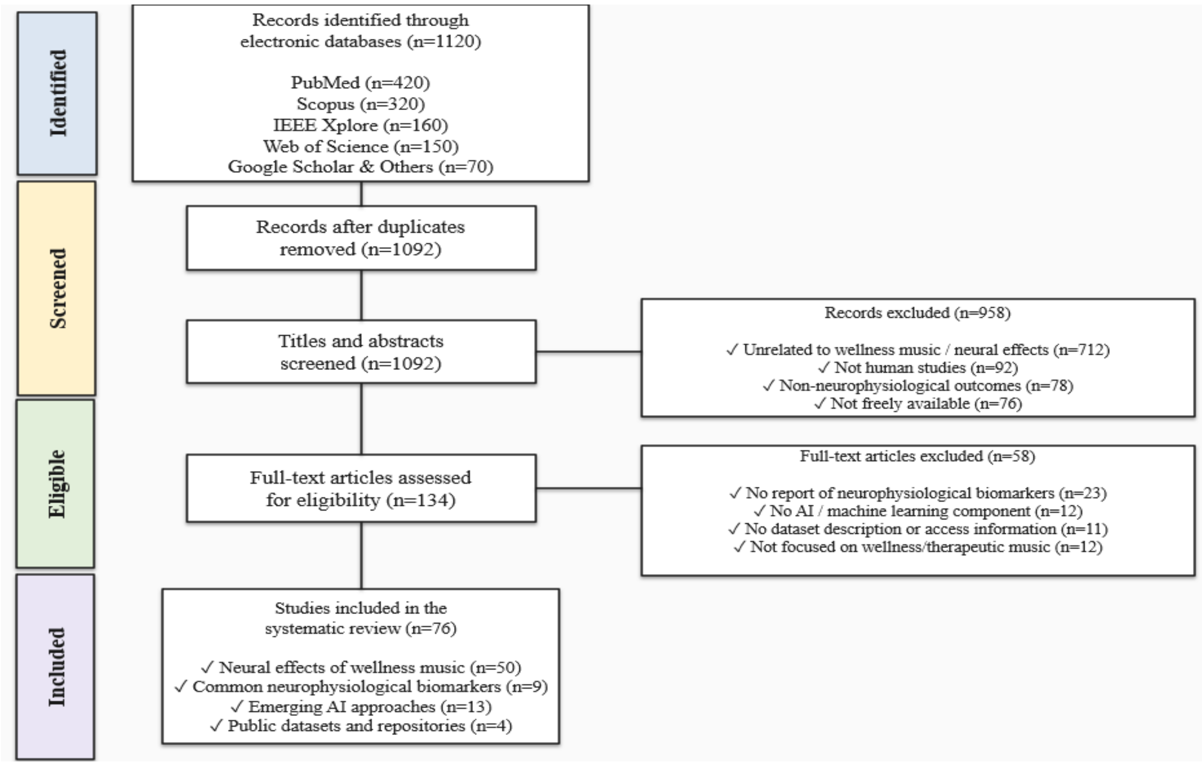

Figure 1: PRISMA chart of the systematic review on music therapy, commonly used neurophysiological biomarkers, emerging AI approaches, and publicly available datasets

The Figure 2 shows an overall increasing trend in publications on music therapy, neurophysiological biomarkers, AI-based approaches, and EEG datasets, with a notable rise from 2022 onward. The highest number of reviewed papers was observed in 2023 (13 papers), followed by 2024 (11) and 2025 (10), indicating growing research interest in this interdisciplinary field.

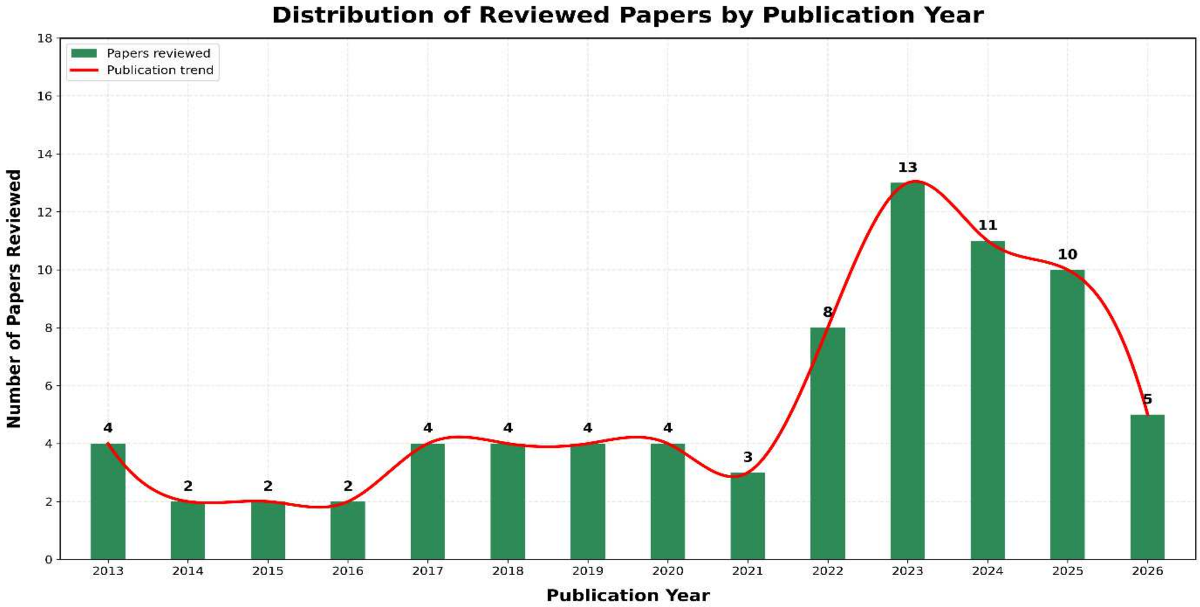

Figure 2: Papers reviewed on music therapy, commonly used neurophysiological biomarkers, emerging AI approaches, and publicly available datasets

3.2 Summary of Search Results

Existing research consistently demonstrates that wellness music induces measurable changes in neural activity associated with relaxation, emotional regulation, cognitive restoration, and stress reduction [1], [2], [12], [21]– [24], [27]. Across numerous experimental studies, calming and meditative music has been associated with increased alpha (approximately 8–13 Hz) and theta (approximately 4–8 Hz) activity. These oscillations are commonly associated with relaxation, internally directed attention, reduced cognitive effort, meditative states, and emotional regulation [1], [4], [10], [21], [22], [25], [31]. Recent EEG research further suggests that the neural effects of music are not limited to changes in absolute spectral power but may also involve alterations in functional connectivity, phase synchronization, cross-frequency coupling, and large-scale neural dynamics [41]– [45].

The relationship between music and neural oscillations appears to be influenced by both the acoustic characteristics of the stimulus and the listener's subjective emotional response. For example, the tempo of music can differentially modulate cortical activity, with slower musical tempos being associated with greater frontal theta and alpha activity, whereas faster tempos may increase beta and gamma activity linked to heightened arousal and emotional activation [41]. Similarly, music-induced emotional states have been associated with changes in theta-band activity and theta–beta coupling, suggesting that emotional processing during music listening may depend on interactions between multiple frequency bands rather than on isolated oscillatory changes [42]. Such findings are particularly relevant to wellness music, where the therapeutic or restorative effect may arise from the interaction between rhythm, tempo, familiarity, affective valence, and individual preference.

Conversely, reductions in high-beta activity, particularly within the 20–30 Hz range, have frequently been associated with decreased anxiety, reduced cognitive workload, and lower physiological arousal [7], [13]. However, the relationship between beta activity and relaxation is not uniform. For example, some studies examining ASMR and binaural-beat-based interventions have reported improvements in subjective stress and anxiety despite changes involving increased beta and high-beta activity, demonstrating that enhanced high-frequency activity does not invariably indicate a negative or stressful state [43]. Similarly, music-assisted relaxation in clinical populations has produced simultaneous changes across delta, theta, alpha, and beta bands, indicating that relaxation may involve a coordinated reorganization of multiple oscillatory systems rather than a simple increase in low-frequency activity [44].

Music may also influence neural activity through changes in functional organization and inter-regional communication. Studies of music-induced emotion have demonstrated that prefrontal EEG asymmetry can reflect affective responses associated with subcortical emotional networks, suggesting that EEG measures may provide indirect information about broader emotion-related neural systems [45]. Other research has reported increased alpha-band synchronization and phase-based connectivity during music listening, particularly during emotionally meaningful or autobiographical musical experiences [46]. These findings indicate that the neural effects of wellness music may be expressed not only through local changes in spectral power but also through enhanced coordination between distributed cortical regions.

The importance of stimulus characteristics is further supported by studies showing that familiarity and attentional state can substantially alter EEG responses to music. Familiar music may induce continuous changes in alpha and low-beta power, while the neural response to music also varies depending on whether the listener is actively attending to the music or passively exposed to it [47], [48]. Consequently, similar spectral changes may reflect different underlying psychological processes depending on whether the listener is engaged in focused auditory attention, emotional absorption, autobiographical memory retrieval, or passive relaxation. In addition, recent work on Indian classical music and raga-based interventions has reported increases in alpha activity and attention-related measures, supporting the potential relevance of culturally specific wellness music for modulating cognitive and affective states [49].

These findings suggest that wellness music may facilitate a transition from a state of heightened arousal toward a more relaxed cognitive state, but this transition should not be interpreted through a single universal EEG signature. Indeed, a systematic review and meta-analysis of music-based stress-recovery studies found that the effects of music were influenced by factors such as musical genre, tempo, music selection, and the specific outcome used to measure stress recovery [50]. This variability emphasizes the importance of considering individual differences, musical preference, familiarity, cultural background, and the purpose of listening when interpreting EEG responses to wellness music.

4 Criterions based linear analysis

4.1 Segment on Criteria 1 (Base Music Therapy)

The studies show that music can modulate EEG activityand neural connectivity**.** The findings also indicate that music therapy can be used for mental health care [1], emotional states [2][5], anxiety reduction [36], enhancement of cognitive function [35], stress reduction [43][50], cognitive impairment [58], mental fatigue [59], insomnia [63], and many moreconditions and states.Music Therapy can be done through different kinds of music such as Hindustani Ragas[22]-[23][48] and Classical music [36], Mantra chants [25] [28], Binaural beats [43], etc. The proposed study covers aspects of music therapy for different cognitive medical conditions using different type of music.

Table1 summarizes 50 studies examining the effects of music and music therapy using EEG and related measures.

Table 1: Summary of articles that highlight the effect of music therapy using EEG.

Theme	Representative References	Methodology & EEG Measures	Major Findings
Music & Emotion	[2], [4], [5], [16], [20], [23], [24], [32], [33], [41], [47]	EEG, spectral power, frontal asymmetry, connectivity, nonlinear features, emotion-related EEG patterns	Music reliably modulates neural activity associated with emotional valence, arousal, familiarity, and affective processing.
Music, Stress, Anxiety & Relaxation	[10], [11], [18], [21], [22], [28], [37], [41]	EEG spectral analysis, alpha/theta activity, HRV, physiological and subjective measures	Music, particularly relaxing/Indian classical music, was associated with reduced stress/anxiety and enhanced relaxation, with effects depending on musical characteristics and context.
Music & Cognition / Mental Fatigue	[7], [17], [29], [30], [35], [46]	EEG power, connectivity, attention, memory, cognitive performance, fatigue measures	Music influenced attention, cognitive performance, mental fatigue, and EEG activity, although effects varied across tasks and protocols.
Music Therapy & Clinical Applications	[1], [8], [9], [31], [34], [42], [43], [49], [50]	EEG, neuropsychological measures, functional connectivity, behavioral and clinical outcomes	Music therapy showed potential for emotional regulation, cognitive rehabilitation, stress reduction, and clinical recovery across several conditions.
Functional	[3], [14], [15],	PLI, functional	Music altered functional

Connectivity & Brain Networks	[20], [36], [44], [47], [48]	connectivity, graph theory, network measures, directed connectivity	and directed connectivity, with changes suggesting modulation of network integration and organization.
Brain Dynamics & Nonlinear EEG	[13], [39], [40]	Jitter/shimmer, entropy, complexity, nonlinear dynamics, frequency-specific measures	Nonlinear EEG measures captured music-related changes in brain dynamics that were not fully represented by conventional spectral analysis.
EEG Microstates & Music	[27], [33], [43]	EEG microstate classes, duration, occurrence, coverage, transitions, GEV	Music altered microstate dynamics, suggesting changes in large-scale temporal organization of brain activity.
Indian Classical Music & Vedic Chanting	[11], [12], [14], [15], [27], [33]	EEG spectral power, connectivity, entropy, microstates	Indian classical music and chanting produced measurable changes in oscillatory activity, connectivity, and microstate organization, with several studies reporting relaxation- or emotion-related effects.
Music, Pain & Affective Processing	[24], [38]	EEG oscillations, nonlinear EEG features, pain ratings, emotional measures	Music influenced affective dimensions of pain and emotional processing, including reductions in pain unpleasantness.
Interbrain Synchronization & Social Interaction	[44], [45]	EEG hyperscanning, intra-/inter-brain connectivity and synchronization	Music therapy and improvisational interaction were associated with dynamic neural coupling within and between interacting individuals.

Across studies, music consistently modulates EEG activity and large-scale brain dynamics, particularly through changes in spectral power, functional connectivity, and temporal organization. These neural changes are generally associated with alterations in emotion, stress, relaxation, cognition, and affective processing, although the effects vary with musical characteristics and experimental context.

4.2 Segment on Criteria 2 (quantitative neurophysiological biomarkers)

The studies show that music can modulate different cognitive states like relaxation, attention, cognition, and stress**.** Common measures include PSD, frequency-band power, frontal asymmetry, connectivity, entropy, microstates, and nonlinear features**.** The findings also indicate that neural responses vary with music type, tempo, familiarity, listening condition, and individual characteristics, highlighting the need for multidimensional EEG biomarkers for assessing music-induced cognitive and emotional states.

The presented paper proposed framework integrates spectral, asymmetry, ratio-based, and connectivity biomarkers, including PSD, FAA, TAR, BAR, TBR, ABR, PLV, PRI, and EI, to provide a multidimensional assessment of music-induced relaxation, emotional response, cognitive engagement, arousal, and functional brain connectivity.PSD, FAA and connectivity measures are frequently used in music EEG studies, while ratio-based indices are more often borrowed from broader EEG workload, attention, engagement, and affective-computing research. Therefore, for this review, it is scientifically correct to describe TAR, BAR, TBR, ABR, PRI, and EI as composite biomarkers for wellness assessment, rather than claiming that all are already standardized music-specific biomarkers. Therefore, this section is divided according to the mentioned assessment.

4.2.1 Power Spectral Density

Power Spectral Density (PSD) remains the most widely used EEG measure for investigating music-induced changes in neural activity [4], [15], [29], [31], [32]. PSD quantifies the distribution of signal power across different frequency bands and enables researchers to determine whether specific musical interventions increase or decrease oscillatory activity. A considerable number of studies have reported increased alpha power over frontal, central, and parietal regions during relaxation and meditation music [9]– [11], [7], [13].

4.2.2 Frontal Alpha Asymmetry

Frontal Alpha Asymmetry (FAA) is one of the most extensively investigated EEG biomarkers of affective processing and emotional regulation. FAA is calculated from the difference in alpha-band activity between homologous left and right frontal electrodes [5].Because alpha power is generally considered inversely related to cortical activation, relatively lower alpha power over the left frontal cortex may indicate greater relative left-frontal activation. Greater left frontal activation has traditionally been associated with positive affect, approach-related behavior, motivation, and psychological resilience. In contrast, relatively greater right frontal activation has been associated with withdrawal-related emotions, negative affect, stress, and anxiety [5]-[7], [30], [33].Several studies have reported that resting-state FAA may predict individual differences in music preference and emotional responsiveness to affective musical stimuli [6], [7].

4.2.3 Functional Connectivity

Music perception is inherently distributed and involves auditory, attentional, emotional, memory-related, and reward-related neural systems. Consequently, regional spectral activity alone may not fully explain the neural effects of wellness music.Functional connectivity methods have therefore emerged as important tools for investigating communication among brain regions. Measures such as Phase Locking Value (PLV), coherence, Phase Lag Index (PLI), and Granger causality have been used to investigate changes in synchronization and directional information flow during music listening [8], [13], [35], [36].Studies have reported enhanced synchronization among frontal, temporal, parietal, and occipital regions during emotionally positive and meditative music. These findings suggest that wellness music may influence large-scale neural networks rather than isolated cortical regions.

4.2.4 Composite Indices

Recent research has increasingly focused on derived EEG indices that combine information from multiple frequency bands. Unlike absolute or relative power measures, which describe activity within a single oscillatory band, composite indices quantify the relative relationship between two or more frequency components [4], [15], [29], [31], [32]. Composite EEG indices are particularly relevant for wellness music research because music-induced changes in relaxation, attention, emotional arousal, cognitive workload, and mental fatigue may occur simultaneously. The most commonly investigated composite EEG indices include the following.

Alpha–Beta Ratio (ABR): The Alpha–Beta Ratio is generally calculated as:

$$ABR = \frac{P_{alpha}}{P_{beta}}$$

where P_{alpha} represents alpha-band power and P_{beta} represents beta-band power. The ABR is commonly used to characterize the balance between relatively relaxed cortical activity and higher-frequency activity associated with active cognitive processing and arousal. An increase in ABR may occur when alpha power increases and/or beta power decreases. In wellness music studies, this pattern may be interpreted as a shift toward a more relaxed or less cognitively effortful state[51]. Particularly, ABR may be useful for comparing resting-state EEG with music-listening conditions.

Theta–Alpha Ratio (TAR): The Theta–Alpha Ratio is generally expressed as:

$$TAR = \frac{P_{theta}}{P_{alpha}}$$

where P_{theta} represents theta-band power, and P_{alpha} represents alpha-band power. TAR is used to characterize the relative contribution of slower theta activity compared with alpha activity. An increase in TAR may occur when theta power increases relative to alpha power. In some contexts, this pattern has been associated with mental fatigue, reduced alertness, drowsiness, or increased internal processing [52].In a music-based EEG paradigm, TAR may be particularly useful for investigating whether a musical stimulus induces cognitive restoration or mental fatigue.

Theta–Beta Ratio (TBR): The Theta–Beta Ratio is commonly calculated as:

$$TBR = \frac{P_{theta}}{P_{beta}}$$

where P_{theta} is theta-band power and P_{beta} is beta-band power. The TBR has been widely investigated as a measure related to attentional regulation, relaxation, cognitive control, and arousal [53]-[54].In wellness music research, TBR may be useful for evaluating whether music promotes a relative shift from high-frequency activation toward slower oscillatory activity. Nevertheless, TBR should not be considered a standalone biomarker of relaxation.

Beta–Alpha Ratio (BAR): The Beta–Alpha Ratio is the inverse relationship of the ABR and is commonly calculated as:

$$BAR = \frac{P_{beta}}{P_{alpha}}$$

The BAR represents the relative dominance of beta activity compared with alpha activity and is frequently used as an indicator of cortical arousal, cognitive activation, alertness, and mental effort [55].In a wellness music paradigm, a reduction in BAR during music listening compared with baseline may indicate a shift toward alpha-dominant activity and reduced relative arousal.

Power Ratio Index (PRI):The Power Ratio Index is a composite measure designed to integrate activity across multiple EEG frequency bands. Unlike simple two-band ratios, PRI may incorporate several frequency components to provide a broader estimate of the balance between slower and faster cortical oscillations. The exact mathematical formulation varies considerably across studies. A general formulation may be represented as:

$$PRI = \frac{P_{delta} + P_{theta} + P_{alpha}}{P_{beta} + P_{gamma}}$$

The primary advantage of PRI is that it may provide a more global representation of changes in brain activation. Music-induced changes may involve simultaneous increases in alpha and theta activity together with reductions in beta activity. A multidimensional ratio may capture this overall shift more effectively than a single-band measure [56].PRI may therefore be useful for comparing baseline and music-listening conditions, ranking different musical stimuli, and developing composite indicators of relaxation or cognitive activation. For example, a music stimulus that consistently increases lower-frequency activity while reducing higher-frequency activity may produce a systematic change in PRI.

Engagement Index (EI): The Engagement Index is generally used to estimate the degree of cognitive engagement or attentional involvement during a task or stimulus presentation [57]. A commonly used formulation is:

$$EI = \frac{P_{beta}}{P_{alpha} + P_{theta}}$$

The rationale behind EI is that increased beta activity relative to alpha and theta activity may indicate greater active cognitive processing, alertness, or attentional involvement. A higher EI may therefore reflect increased engagement with a musical stimulus, whereas a lower EI may indicate reduced cognitive effort, passive listening, relaxation, or decreased alertness.In wellness music studies, EI is particularly valuable because relaxation does not necessarily imply disengagement. A listener may be highly immersed in music while simultaneously experiencing low stress and emotional calm. Therefore, a reduction in stress accompanied by a moderate or increased EI may suggest attentive immersion rather than passive relaxation.

Table 2: Summary of articles that highlight commonly used neurophysiological biomarkers to understand the effect of music therapy on the brain.

Theme	Reference(s)	Main Parameters	Overall Observation
Spectral Activity	[93], [47], [48], [59]	PSD, delta, theta, alpha, beta, gamma, individual alpha peak	Music alters EEG spectral activity, with effects influenced by music, attention and cognitive state.
Connectivity & Brain Networks	[94], [95], [23]	Functional connectivity, phase synchronization, interregional correlation, network dynamics	Music modifies functional interactions and time-varying brain network organization.
Affective Processing	[76], [96], [97], [23]	FAA, alpha/theta activity, connectivity, emotional responses	Music characteristics and therapeutic interventions modulate affective, relaxation and emotional responses.
Stress, Arousal & Cognitive State	[51], [52], [53], [55]	ABR, TBR, alpha/beta/theta power	Spectral ratios can reflect stress, arousal and cognitive states, but their interpretation is context-dependent.
Attention & Mental Fatigue	[47], [48], [55], [59]	Alpha/beta activity, engagement measures, PSD	Music-related neural changes are associated with attention, engagement and mental-fatigue modulation.

Overall, composite EEG biomarkers provide a promising framework for characterizing the multidimensional effects of wellness music. By integrating information across multiple oscillatory bands, these indices may improve sensitivity to changes in cognitive workload, attentional engagement, emotional arousal, mental fatigue, relaxation, and immersive listening [15], [16], [24], [25], [31], [32], [34]. Nevertheless, their usefulness depends on careful methodological standardization and context-sensitive interpretation. Rather than treating any individual ratio as a definitive biomarker of a specific psychological state, future studies should combine multiple complementary indices and evaluate their relationship with subjective experience, behavioral outcomes, and autonomic physiological responses.

4.3 Segment on Criteria 3 (Emerging AI Approaches)

The integration of artificial intelligence has significantly expanded the capabilities of EEG-based music research. Traditional machine-learning algorithms, including Support Vector Machines (SVM), Random Forests, Decision Trees, and k-Nearest Neighbors (k-NN), have been used to classify emotional states, stress levels, relaxation, and cognitive conditions from EEG data [15], [16].

These models typically use engineered features derived from:

- Frequency-domain power;
- Time-domain statistics;

- Spectral entropy;
- Band-power ratios;
- Functional connectivity;
- Frontal asymmetry;
- Hjorth parameters; and
- Nonlinear EEG measures.

More recently, deep-learning approaches have demonstrated the ability to learn hierarchical representations directly from EEG signals. Convolutional Neural Networks (CNNs) can learn spatial and spectral representations, while Long Short-Term Memory (LSTM) networks are suitable for modelling temporal dependencies. Graph Neural Networks (GNNs) can represent EEG electrodes as nodes connected through functional or structural relationships. Transformer architectures and self-supervised learning methods have further introduced new approaches for learning generalizable representations from large-scale EEG datasets [15], [16], [29], [37], [38].

Table no. 3: Summary of articles that highlight the recent evaluation of emerging artificial intelligence approaches to understand the effect of music therapy on the brain.

AI Theme	Reference(s)	Major Techniques / Features	Overall Findings
EEG Emotion Recognition	[80], [81], [85], [92]	CNN, EEGNet, attention networks; spectral, temporal and spatial EEG features	DL-based approaches improve emotion recognition, but generalization and interpretability remain challenges.
Multimodal EEG–Music Fusion	[82], [83], [87]	EEG + acoustic/music features; fusion and domain adaptation	Multimodal learning improves emotion assessment and robustness across participants.
Connectivity & Graph Learning	[84], [86]	Functional/dynamic connectivity, coherence, GNN, temporal attention	Connectivity-aware models capture inter-channel relationships and improve affective-state modeling.
Personalized Music Therapy	[88], [89], [91]	ML/DL with clinical, behavioral and EEG features	AI enables prediction of therapeutic response and supports adaptive/personalized interventions.
Neurofeedback & Closed-Loop AI	[90]	EEG rhythms, neurofeedback and adaptive feedback mapping	Supports closed-loop music therapy, but requires greater standardization and clinical validation.

Recent AI-based approaches have enhanced the analysis of music-induced EEG responses through deep learning, multimodal fusion, connectivity modeling, and personalized prediction. However, limited datasets, inter-subject variability, lack of interpretability, and insufficient clinical validation remain key challenges for reliable and generalized music-therapy applications.

4.4 Segment on Criteria 4 (publicly available datasets)

Publicly available datasets such as DEAP[18], DREAMER[19], SEED[37], AMIGOS[39], and MAHNOB-HCI have significantly accelerated the development and benchmarking of computational models for EEG-based affective computing However, the application of these datasets to wellness music research presents several limitations. Many publicly available datasets were designed primarily for emotion recognition rather than wellness assessment. Furthermore, the musical stimuli may not represent meditation music, Indian classical music, Vedic chanting, or therapeutic compositions. Consequently, models trained on conventional emotional EEG datasets may not generalize effectively to culturally specific wellness interventions.

Table no. 4: The following table summarizes representative EEG dataset papers involving music listening, music-induced emotion, or music therapy. The studies are relevant to spectral analysis, EEG-based emotion recognition, functional connectivity, and machine-learning applications:

Theme	Reference(s)	Major Data / Features	Overall Findings
Naturalistic Music EEG	[99]	High-density EEG, PSD, frequency bands, familiarity, enjoyment	Supports naturalistic analysis of music responses and listener-specific variability.
Clinical & Multimodal Music EEG	[100], [44]	EEG, ECG, EMG, PSD, physiological measures	Provides clinically relevant rest/music comparisons and multimodal assessment of therapeutic responses.
Context-Dependent Music EEG	[101]	Multichannel EEG, spectral and temporal features	Enables investigation of the influence of presentation and immersive listening conditions.
AI-Based Music Emotion EEG	[86]	Valence/arousal, entropy, temporal features, connectivity and graph features	Shows the potential of graph-based and temporal deep learning for music-induced emotion recognition.

Existing datasets cover naturalistic listening, clinical therapy, immersive contexts, and AI-based emotion recognition, but they remain heterogeneous in recording systems, participant populations, modalities, and experimental paradigms. This indicates a need for standardized, multimodal, and clinically relevant music-therapy EEG datasets for robust biomarker discovery and AI-based analysis.

5 Cross Criterions Analysis

5.1 Various Psychological/Cognitive States addressed by surveyed papers

EEG markers associated with wellness music can be organized according to the psychological states they may reflect. However, these associations are context-dependent, and no single EEG measure can be considered a definitive biomarker of a specific psychological state.

Mental Relaxation: Mental Relaxation is commonly associated with increased alpha and theta activity, reflecting reduced cortical arousal and internally directed attention. An increased Alpha–Beta Ratio (ABR), reduced Beta–Alpha Ratio (BAR) and decreased high-beta activity may further indicate a shift toward a relatively relaxed state [55].

Stress and Anxiety Reduction: Reduced stress and anxiety may be reflected by decreased beta activity and increased alpha activity. Changes in Frontal Alpha Asymmetry (FAA) [33] may indicate altered emotional processing, while increased heart-rate variability (HRV) and reduced skin conductance provide complementary evidence of improved autonomic regulation.

Cognitive Engagement and Attention: Cognitive engagement is commonly associated with increased beta activity, higher Engagement Index (EI) [57], alpha suppression, and changes in the Theta–Beta Ratio (TBR) [54]. Changes in functional connectivity may further indicate enhanced communication between brain regions during attentive or immersive music listening.

Mental Fatigue: Mental fatigue is frequently associated with increased theta activity, elevated Theta–Alpha Ratio (TAR) [52], reduced beta activity, and decreased EI [57]. Changes in alpha activity may also occur, although the direction of these changes depends on the experimental task and fatigue level.

Emotional Arousal and Valence: Music-induced emotional responses may involve changes in FAA [33], beta and gamma activity, and functional connectivity. These measures may reflect variations in emotional valence, arousal, and engagement. However, their interpretation should be supported by subjective emotional ratings because EEG responses can vary considerably across individuals and musical stimuli.

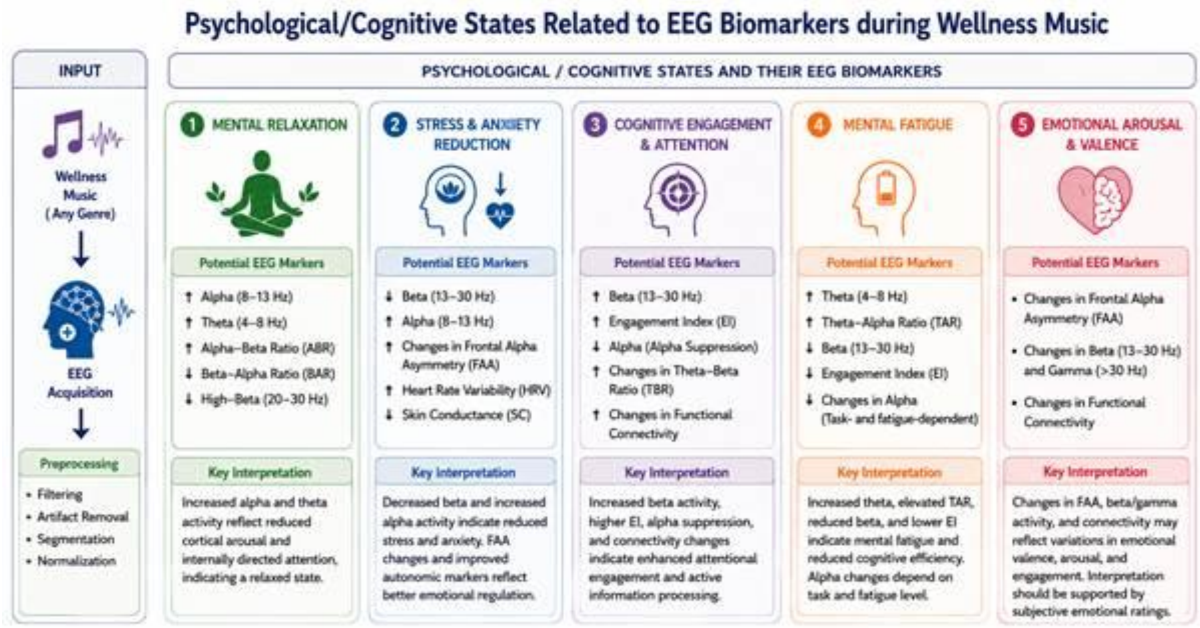

Figure 3: Relation between EEG Biomarkers and Cognitive States in response to wellness music study

5.2 Different Design paradigms & data collection methodologies

The reviewed studies employed different various experimental design paradigms and data collection methodologies, including resting-state EEG, music-listening experiments, active and passive listening conditions, randomized controlled trials, clinical interventions, and music-evoked emotion paradigms [34]– [36]. Data were collected using both conventional and high-density EEG systems, with some studies incorporating EEG hyperscanning, physiological measures such as HRV, behavioral assessments, and subjective questionnaires. Different musical stimuli, including classical music, Indian ragas, Vedic chanting, binaural beats, familiar music, and music with varying tempos or moods, were used to investigate neural, emotional, cognitive, and therapeutic responses [21]– [28].

May discuss some common practices to be mentioned sampling frequency, electrodes, clinical/ research grade, number of participants

5.3 Evaluation metrics

The reviewed studies used a diverse set of evaluation metrics to quantify music-induced neural, cognitive, emotional, and therapeutic effects. Common EEG-based measures included EEG spectral, asymmetry, connectivity, complexity, and cognitive–emotional measures. The commonly reported parameters included PSD and frequency-band power (delta, theta, alpha, beta, and gamma), FAA, functional connectivity/PLV, entropy, microstate characteristics, and nonlinear features such as signal complexity, jitter, and shimmer. Several studies also incorporated HRV, subjective stress/emotion ratings, cognitive performance, and clinical outcomes. Overall, the surveyed parameters suggest that combining measures such as PSD, FAA, PLV, entropy, microstates, along with derived indices such as ABR, TAR, TBR, BAR, PRI, and EI, can provide a more comprehensive evaluation of music-induced relaxation, emotional state, attention, engagement, and cognitive workload.

5.4 Influence of Musical and Individual Factors

The neural response to music is influenced by both the characteristics of the musical stimulus and individual listener differences. Tempo can modulate arousal, with slower music generally associated with relaxation and faster music with increased activation. Musical preference and familiarity also influence EEG responses, as preferred and familiar music may evoke stronger emotional engagement, memory retrieval, and autobiographical processing than unfamiliar or disliked music. Cultural background is particularly important when examining Indian classical music, ragas, Vedic chanting, and devotional music, as cultural familiarity may influence emotional interpretation and neural responses [21]-[28]. In addition, individual factors such as age, musical training, personality, baseline anxiety, and meditation experience can substantially affect music-induced EEG activity. Therefore, these factors should be considered when comparing neural responses across participants and interpreting the effects of wellness music.

6 Research Gaps and Future Directions

Despite the growing interest in EEG-based wellness music research, several methodological and data-related gaps remain. Large, diverse, and standardized EEG datasets are limited, while most publicly available datasets are primarily designed for emotion recognition and may not include wellness-specific outcomes or culturally relevant musical stimuli, such as meditation music, Indian classical music, Vedic chanting, and therapeutic compositions. Consequently, models trained on conventional emotion-based EEG datasets may not generalize effectively to culturally specific wellness interventions. Furthermore, the lack of standardized composite EEG indices integrating relaxation, arousal, attention, cognitive workload, and functional connectivity limit the comprehensive assessment of music-induced well-being.

Significant gaps remain in understanding how cultural familiarity, musical traditions, and individual preferences influence neural responses to wellness music. Most existing studies focus on limited musical traditions and do not adequately examine whether EEG-based findings generalize across cultures and diverse listener populations. Furthermore, most studies investigating the neural effects of wellness music rely primarily on EEG as the sole neurophysiological modality, with relatively few integrating complementary physiological signals such as electrocardiography (ECG), heart rate variability (HRV), electrodermal activity (EDA), photoplethysmography (PPG), electrooculography (EOG), respiration, or electromyography (EMG) [102]-[105]. This restricts the comprehensive assessment of the emotional, cognitive, and autonomic effects of music.

Another important gap is the limited interpretability of AI-based EEG models. Many advanced machine learning and deep learning approaches function as “black-box” systems, providing limited insight into the EEG features, brain regions, and neural patterns underlying their predictions. In addition, EEG foundation models remain underexplored in wellness music research, particularly for large-scale pretraining, transfer learning, and cross-dataset generalization. The limited understanding of individual neural responses also constrains the development of personalized music recommendation systems tailored to specific wellness goals.

Finally, most current EEG-based music studies are conducted in offline and controlled settings, with limited development and validation of real-time adaptive systems. The potential of closed-loop systems that continuously monitor neural activity and dynamically modify musical features, such as tempo, rhythm, intensity, or complexity, remains largely unexplored. Addressing these gaps is essential for developing personalized, interpretable, and real-time EEG-based music interventions for relaxation, attention enhancement, stress reduction, and cognitive well-being. Consequently, there is a significant need for future research to develop multimodal wearable frameworks that combine EEG with complementary physiological biomarkers and leverage explainable artificial intelligence (XAI) for personalized, real-time, and adaptive music-based interventions, digital therapeutics, and brain–computer interface applications.

Future research should move beyond EEG-only paradigms toward multimodal wearable sensing, integrating EEG with ECG, HRV, EDA, PPG, EOG, respiration, EMG, and other physiological biomarkers. Such multimodal approaches, combined with portable wearable devices and explainable AI, can enable continuous, personalized, and real-time assessment of the neural, emotional, cognitive, and autonomic effects of wellness music, facilitating the development of adaptive music-based digital therapeutics and brain-computer interfaces.

7 Proposed Framework for Music Assessment

The framework begins with wellness music and participant profiling, incorporating cultural background, musical familiarity, and individual preferences. EEG will be recordedalongside physiological signals such as electrocardiography (ECG), heart rate variability (HRV), electrodermal activity (EDA), photoplethysmography (PPG), electrooculography (EOG), respiration, or electromyography (EMG) to capture neural, emotional, cognitive, and autonomic responses. After standardized preprocessing, multidimensional EEG features will be extracted and integrated into validated composite wellness indices representing relaxation, emotional state, attention, cognitive workload, and functional connectivity.

These features will be analyzed using subject-independent AI models and EEG foundation models, while explainable AI identifies the neural and physiological patterns underlying model predictions. The resulting wellness profile supports personalized music recommendations. In the final stage, a real-time closed-loop system continuously monitors the listener's state and adaptively modifies musical properties to optimize relaxation, attention, stress reduction, and overall cognitive well-being. Based on the reviewed literature, a comprehensive EEG-based wellness music assessment framework can be organized as shown in Figure 4.

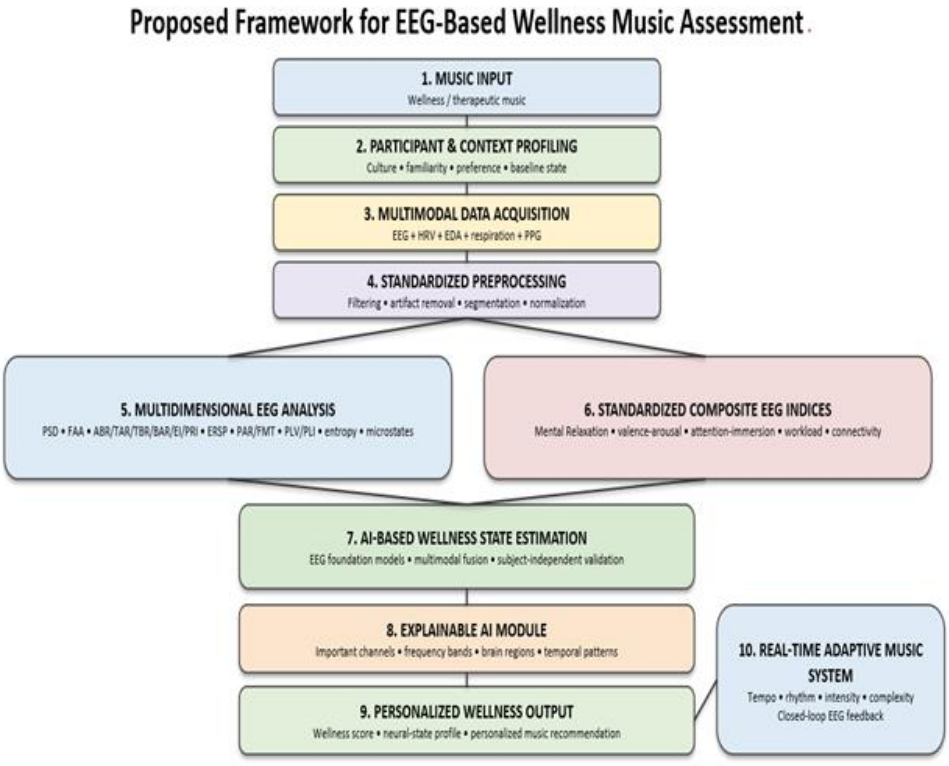

Figure 4: Closed-loop framework integrating standardized EEG analysis, multimodal sensing, explainable AI, personalization, and adaptive music.

8 Conclusion

This systematic review demonstrates that EEG has become an important tool for objectively investigating the neural effects of wellness and therapeutic music. Across the existing literature, music-based interventions have been associated with changes in oscillatory brain activity, particularly increased alpha and theta activity and reductions in high-beta activity. Frontal Alpha Asymmetry provides a potential marker of affective and motivational changes, while composite spectral indices may improve the sensitivity of EEG-based wellness assessment.

Functional connectivity and graph-theoretical methods further demonstrate that wellness music influences distributed neural networks involved in auditory perception, attention, emotion, memory, and cognitive regulation. Recent developments in artificial intelligence have expanded the field by enabling automated classification of emotional and cognitive states from EEG signals.

Nevertheless, substantial methodological challenges remain. Differences in musical stimuli, participant populations, EEG acquisition protocols, preprocessing pipelines, biomarker definitions, and statistical procedures limit the comparability and reproducibility of existing findings. In addition, culturally specific wellness music, particularly Indian classical music and Vedic chanting, remains insufficiently investigated using standardized EEG methodologies.

Future research should therefore focus on multimodal and longitudinal studies, standardized EEG protocols, culturally diverse music datasets, advanced connectivity analysis, explainable artificial intelligence, and personalized adaptive systems. The integration of EEG neuroscience with machine learning may ultimately enable the development of objective computational models capable of predicting and optimizing the neurophysiological effects of wellness music. Such systems could contribute to personalized stress management, cognitive well-being, meditation support, and non-pharmacological approaches to mental health.

Overall, the emerging convergence of EEG, music neuroscience, network neuroscience, and artificial intelligence represents a promising direction for understanding and quantifying how music influences the human brain and psychological well-being.

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