SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(1), 604.
https://doi.org/10.62617/mcb604

Article

Analysis of the intrinsic biophysical and molecular process correlations between music activity and biosensor-monitored mental health status

Lisha He

School of Music, Shangqiu Normal University, Shangqiu 476000, China; helisha929929@sina.com

CITATION

He L. Analysis of the intrinsic biophysical and molecular process correlations between music activity and biosensor-monitored mental health status. Molecular & Cellular Biomechanics. 2025; 22(1): 604. https://doi.org/10.62617/mcb604

ARTICLE INFO

Received: 24 October 2024
Accepted: 18 November 2024
Available online: 10 January 2025

Abstract: Music activities, such as listening or performing music, have been linked to various mental health benefits, including stress reduction, emotional regulation, and overall well-being. However, from the perspective of cellular and molecular biomechanics, the underlying mechanisms linking music activity and mental health status, especially as monitored through biosensors, require further exploration. With advancements in biosensor technology, it is possible to observe physiological indicators such as heart rate, galvanic skin response, and brainwave activity that reflect mental health in real time during music-related activities. Changes in heart rate might be associated with the modulation of autonomic nervous system activity, which in turn can affect the release of neurotransmitters and intracellular signaling pathways at the cellular and molecular level. Brainwave activity alterations could reflect changes in neural cell excitability and synaptic transmission, involving complex molecular cascades. The study examines the relationship between music activities and mental health status utilizing biosensor data to measure physiological responses associated with mental health indicators. Data preprocessing included normalization to standardize physiological measurements and noise reduction to enhance signal quality. Feature extraction utilized Scale-Invariant Feature Transform (SIFT) to identify key features associated with physiological changes during music engagement. The study proposed a Golden Jackal Optimized Intelligent Extreme Gradient Boosting (GJO-IXGBoost) method, which was then applied to analyze the processed data, providing robust insights into the correlations between music activities and mental health. Statistical techniques, including correlation analysis and regression modeling, were used in this study. The proposed method is the performance of various evaluation metrics such as MSE (9.8%), RMSE (21.3%), MAE (13.2%), accuracy (92%), F1-score (90.2%), sensitivity (91%), MCC (85.6%) and specificity (93%). The results suggesting a positive impact of music activities, especially active participation, on mental health as monitored by biosensor data could potentially be due to the modulation of cellular and molecular processes. Applying the GJO-IXGBoost method helps in deciphering these complex cellular and molecular biomechanical correlates, contributing to the evidence base for the therapeutic potential of music in mental health interventions at the cellular and molecular level.

Keywords: music; mental health, biosensor; golden jackal optimized intelligent extreme gradient boosting (GJO-IXGBoost); cellular and molecular biomechanics

1. Introduction

Music has been one of the most productive resources used in the most profound influence on the human mind and body for years [1]. It was used by old civilizations and continues to the day in the service of therapeutic usage, forming social bonds, and showing emotions [2]. However, multidisciplinary research combining psychology, neuroscience, and technology has only recently examined the relationship between music and mental wellness [3]. Thus, because of the growing number of mental health issues worldwide, academics have been interested in how music might improve mood, reduce stress, and demonstrate mental well-being [4]. It is possible to monitor the effect of music on physiological response objectively through wearable technology and biosensors, which allows an approach to knowing music's impact on mental health in a more data-driven sense [5].

Music is filled with that special capacity to invoke feelings and cognitive procedures, thus carrying strong potential as a lever in mental health interventions [6]. It can create relaxation from one perspective and self-expression from another, depending upon the necessities of the individual and the type of music [7]. It has been proven that research can reduce the symptoms of anxiety, depression, and stress and even improve the quality of sleep, and cognitive functions of a person are improved [8]. There are multiple neural mechanisms correlated with the emotional impact of music. For instance, listening to music might stimulate the release of neurotransmitters, for example, dopamine and endorphin [9]. Apart from these, music may modulate the nervous system autonomic, including physiological changes such as, for example, lowered heart rates, lowered blood pressure, or even levels of the stress hormone cortisol [10].

Different genres of music may stimulate various emotional reactions. For instance, the impact of stress may decrease as a result of listening to classical music or one might feel relaxed when listening to it [11]. Conversely, more energetic genres such as pop or rock can heighten one's mood and energy levels [12]. Moreover, individual tastes and cultural influences will further determine how people would respond to music associated with mental health. Personalized music interventions therefore have a good potential to handle mental health issues connected to a particular unique, emotional, and psychological profile [13]. Wearable biosensors are revolutionizing the way to measure physiological states in real time, allowing scientists to analyze biometric signals, such as heart rate, skin response, body temperature, and brainwave activity [14].

Music activity and biosensors in monitoring mental health face challenges due to individual response variability, cultural backgrounds, and emotional states. Biosensors provide objective physiological data but cannot accurately represent the complexity of a person's psyche or emotional status. High costs and technical complexity may make biosensor technology less accessible, and long-term wear may cause user fatigue or discomfort, affecting data accuracy and reliability.

The study investigates the association between music activities and mental health state by employing biosensor data to evaluate physiological reactions linked to mental health markers, A Golden Jackal Optimized Intelligent Extreme Gradient Boosting (GJO-IXGBoost) technique was suggested in the study.

Key contributions

- Initially, a dataset is gathered. The data was preprocessed using min-max normalization to remove noise from the data. Then SIFT was used to extract the features from the preprocessed data.
- This study proposed a Jackal Optimized Intelligent Extreme Gradient Boosting (GJO-IXGBoost) technique for biosensor data to evaluate physiological reactions linked to mental health status.

- Statistical techniques, including correlation analysis and regression modeling, were used in this study.
- MSE, RMSE, MAE, accuracy, sensitivity, specificity, MCC, and F1-score parameters are used to assess the simulation outcomes.

This work is organized as follows: Part 2 discusses related work on employing biosensor data to evaluate physiological reactions linked to mental health markers. Part 3 details the methodology, starting with the collection of data, followed by data preprocessing and feature extraction, which are important to classification aimed at utilizing biosensor data to assess physiological reactions connected to mental health status. Statistical techniques, including correlation analysis and regression modeling, were used. Part 4 presents results, including comparison graphs (accuracy, sensitivity, specificity, MCC, F1-score), and error graphs (RMSE, MSE, MAE), illustrating classification performance. Part 5 concludes the study.

2. Related work

Disturbances in behavior regulation, emotional control, and cognition were brought about by mental illnesses examined in Wang et al. [15]. Nevertheless, there were not many clinical instruments accessible for early diagnosis and real-time assessment. For forecasting, evaluation, treatment, and prevention, biosensors possessing exceptional sensitivity, selectivity, and repeatability were essential.

Bhave et al. [16] described a non-intrusive, privacy-preserving technique that tracks potential behavior activations in plants near humans to measure human emotions. It involved the use of an electrical signal for predicting sentiments using a machine learning model and a basil plant as an activity and acoustic detector. Data was gathered from a 19-musician jazz music rehearsal session, as well as from wristwatch sensor data and CNNs for facial emotion identification.

Smith et al. [17] examined wearable health sensors' history, development, technology, ethics, and commercial prospects. Real-time environmental and health monitoring with wearable health sensors was redefining personalized healthcare. The devices had wireless connection modules, data disclosure, and signal processing circuits to offer more precise physiological indications due to developments in sensors and operational hardware systems technologies.

Government initiatives sought to increase awareness of the importance of mental health and to offer assistance. Caretakers and those with mental illnesses could benefit from technological advancements. Fareesha et al. [18] suggested an interactive artificial mood-tracking system employing sensors for biosensors to monitor brain chemical dopamine levels and other critical health metrics.

Hunt and Sims [19] investigated that skills could be developed in music therapy students through the use of course-based undergraduate research experiences, or CUREs. Data from three biosensors were used in the study, which revealed higher levels of interest, self-assurance, and individual connection. Pupils expressed an intention to pursue master's level study and a greater interest in upcoming research projects.

A new area of Erdem et al. [20] that allows for the sensitive, non-invasive measurement of a wide range of analytics was wearable biosensors. Real-time monitoring of biological signals, metabolic variables, and personal parameters was possible with these sensors. They were employed in the biomedical fields along with the sciences to evaluate accurate medical diagnoses.

An electronic skin that tracks three vital signs and six molecular indicators in human sweat non-invasively has been developed by Xu et al. [21] for stress reaction assessment. The devices employed a generic methodology for the fabrication of electrochemical sensors, depending on comparable composite materials to stabilize and preserve interfaces.

Clinical testing could shift from centralized labs to point-of-care (POC) applications due to the quick and affordable diagnostics provided by electrochemical biosensors in Khan et al. [22]. POC devices could benefit from the electrical, physical, chemical, and structural properties of carbon-based nanomaterials, such as carbon nanotubes, graphene, and graphene oxide.

Portable diagnostic instruments had been developed in Wasilewski et al. [23] due to developments in consumer electronics and microflow methods. These instruments were used in point-of-care testing and patient health monitoring. Artificial intelligence (AI) could gather real-time physiological and behavioral data from patients, which could help with diagnosis and therapy planning.

3. Methods

Initially, a dataset was gathered. In data pre-processing, cleaning, and normalization are used; SIFT is used for feature extraction. Jackal Optimized Intelligent Extreme Gradient Boosting (GJO-IXG Boost) technique for biosensor data to evaluate physiological reaction linked to mental health status. Then, statistical techniques, containing correlation analysis and regression modeling were used in this study. **Figure 1** illustrates the overall research flow.

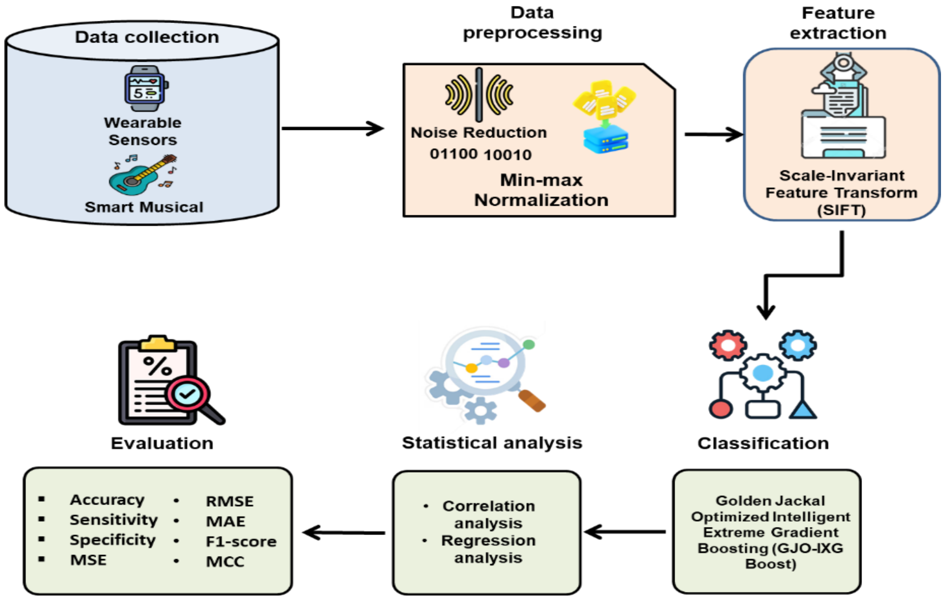

Figure 1. Overall research flow: A visual representation of the methodology from data collection to analysis and model evaluation.

3.1. Dataset

The experimental design aimed to investigate the effects of music activities on mental health by analyzing various physiological measurements. A total of 30 participants were involved in the study, evenly split between 15 males and 15 females, all aged between 18 and 35 years. This age range was selected to ensure that the participants were generally healthy adults, free from any serious mental or physical health conditions that could affect the study's results. The selection process likely focused on individuals who were willing and able to participate in both passive listening and active performance tasks, which required engagement with music stimuli and physiological data recording. The experimental design included two types of music sessions for each participant: passive listening and active performance. Passive listening involved participants listening to soothing music genres such as classical or ambient music, while active performance involved engaging with more stimulating music genres, such as rock or electronic. This design allowed for a comparison of physiological responses under different types of musical stimuli. Each participant underwent a total of 60 sessions: 30 sessions of passive listening and 30 sessions of active performance. The sessions were conducted in real-time, during which physiological data, including heart rate (HR) in beats per minute (BPM), galvanic skin response (GSR) in microsiemens (μS), and brainwave activity (EEG) in hertz (Hz) were recorded. These measurements were used to assess emotional and cognitive responses, with HR reflecting heart rate variability, GSR capturing arousal levels, and EEG data indicating mental states, particularly the alpha and beta brainwave activities associated with relaxation and active thought, respectively. The data collection process was highly controlled to ensure consistent measurements across all participants. Real-time recordings of physiological fluctuations were obtained while participants listened to the various musical stimulants, providing insights into the direct physiological impact of different music genres on mental health. **Table 1** demonstrates the sample datasets.

Table 1. Sample dataset.

Participant ID	Gender	Age	Session Type	Passive/Active	Heart Rate (BPM)	GSR (μS)	EEG Alpha (Hz)	EEG Beta (Hz)
1	Male	23	Active Performance	Active	90	8.6	8.0	21.0
2	Male	24	Passive Listening	Passive	72	5.1	10.5	15.0
3	Female	29	Passive Listening	Passive	68	4.8	11.0	14.5
4	Male	27	Passive Listening	Passive	70	5.2	10.2	14.6
5	Female	25	Active Performance	Active	88	8.3	8.6	20.7
6	Male	28	Passive Listening	Passive	76	5.8	10.8	15.6
7	Female	23	Active Performance	Active	90	8.7	8.9	21.1
8	Male	22	Passive Listening	Passive	70	5.5	10.8	16.0
9	Male	26	Active Performance	Active	88	8.4	8.5	20.5
10	Female	27	Active Performance	Active	85	7.9	9.0	19.0

3.2. Data preprocessing using min-max normalization

Min-max normalization is one of the data preprocessing techniques applied in transforming features into a specified range, usually between 0 and 1. It transforms the variables such that each, though varying in scale, would have uniformity of transformation, which would be useful when seeking analysis in the areas of biosensor data because features such as heart rate, GSR, and EEG signals can vary greatly in their range. Min-Max normalization subtracts the minimum value of each feature from all data points to achieve an offset so that zero will appear in all data points. Dividing by the range gives a normalized dataset with enhanced performance of machine learning algorithms and reduced bias due to various scales.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

X is the feature's initial value (for example, a particular biosensor reading, like heart rate). X_{min} is the feature's lowest value inside the dataset. The feature's maximum value inside the dataset is called X_{man}. The feature's normalized value after Min-Max scaling is applied, which is denoted by X_{norm}.

3.3. Feature extraction using SIFT

SIFT extracts some relevant features from the preprocessed physiological data, and this measures key points from time-series data that are invariant to variations in scale and translation, hence capturing critical patterns of emotional states during music activities. This background leads SIFT to focus more on physiological change because it is linked to mental health for further study on how the degree of engagement with music by participants can have a relationship with their well-being.

The SIFT method remains unchanged by changes in brightness, scale, or rotation. Enormous feature data can be computed using the SIFT feature, which can then be combined with other feature-matching techniques. The SIFT algorithm is invariant to translations, rotations, and scaling alterations of the image and is used for image matching and recognition. Employing the deviation of the Gaussian (DOG) method, SIFT is used to determine the dimension of space extrema and then locates the key point localization for removing the low contrast points. Lastly, a key point-oriented assignment based on the gradient of the local image has been completed. Next, the amplitude and orientation of the image gradient were used to get the image descriptor for each key point. The target image is obtained, the dimension space extrema of the image is computed using the DOG function, the essential feature localization is found, and the image descriptor is computed. This is the SIFT method in action. For every critical point (a, b), in the SIFT method, local extrema helps find key points in an image that are important for matching and recognition. This involves comparing the difference between a smoothed version of the image and its scaled versions. By identifying these key points, the algorithm ensures they remain stable under changes in brightness, rotation, and scale. This makes it easier to match features across different images. Where Equations (2) and (3) are described as follows:

$$\frac{1}{2\pi\sigma^2} e^{-(a^2+b^2)/2} = H(a, b, \sigma) \tag{2}$$

$$(H(a, b, \sigma) \times J(a, b,) = K(a, b, \sigma) \tag{3}$$

where K (a, b, σ) is the Gaussian Softened image at the important position with σ, and σ is a scaling parameter. The coefficient interpolation for every key location is found using the Taylor-series extension of the DOG scale-space variable C (a, b, σ), which is provided by Equation (4),

$$C(a) = C + \frac{\lambda C^S}{\lambda a} a + \frac{1}{2} a^S \frac{\lambda^2 C}{\lambda a^2} a \tag{4}$$

To calculate the gradient magnitude θ (a, b) at a pixel, to assess the intensity differences between neighboring pixels both horizontally and vertically, then compute the square root of the sum of the squared differences. For the gradient orientation, the angle of the greatest intensity change is determined by taking the arctangent of the ratio of these intensity differences. These calculations help identify the strength and direction of features at each pixel in the image.

3.4. Golden jackal optimized intelligent extreme gradient boosting (GJO-IXGBoost)

The GJO algorithm directly applies to the greatest possible selection of key features for biosensor data like heart rate, GSR, and EEG readings during music activities. Much like the hunting strategies employed by the golden jackal, the GJO refines how well the model can capture any alterations in physiological changes associated with mental health status, thereby enhancing accuracy in real-time assessment of stress, relaxation, and emotional regulation. Improved XGBoost enhances the gradient boosting framework further by introducing more efficient gradient calculations that can better enable the handling of high-dimensional biosensor data. When used with music activities, this models the relationship between physiologic responses, such as heart rate variability, GSR, and EEG signals, about mental health outputs to robustly predict levels of stress or relaxation during different types of music engagement. The hybrid GJO-IXGBoost approach combines the optimization power of GJO with the predictive strength of the improved XGBoost. Thus, it produces a very efficient model for the interpretation of biosensor data. Initially, the GJO identifies the most relevant physiological features, and XGBoost accurately predicts mental health states against those features. The hybrid approach provides deeper insights into interactions between music activities and mental health indicators than simply using the linear model, thus better indicating types of music engagement and their effect on emotional and psychological well-being.

3.4.1. Intelligent XGBoost

Intelligent XGBoost enhances gradient calculations for high-dimensional biosensor data, showcasing physiological responses and mental health outcomes in music activities, and providing reliable stress or relaxation indicators.

A boosted tree model called XGBoost combines several tree models to create a strong classifier model. The XGBoost technique improves the gradient of the descending tree. The basic idea is to determine a score associated with each node based on sample attributes by learning a new function every single time to match the residuals of the previous prediction. The data set's prediction value is the total of all scores. Additionally, the gradient boosting decision tree (GBDT) technique is enhanced by the XGBoost model. While the traditional GBDT method only uses the first derivatives, XGBoost uses the second-order Taylor expansion of the loss function.

An enhanced XGBoost model is presented in this study to achieve multi-batch feature gathering and fusion predictions. A simultaneous learning mechanism is devised to extract features in distinct batches, and several local XGBoost feature extraction models are developed independently. Furthermore, the fusion forecasting method produces the multi-feature fusing result. Additionally, a regular term is added to the objective function to identify the most effective approach from the total and prevent overfitting, which lowers the gradient disappearance and the complexity of the model. The following are the main components of the suggested IXGBoost model:

Given *t* samples and *o* features wafer data sets, the wafer data set $C = \{(w_j, z_j)\}$ ($|C| = t$, $w_j \in Q$, $z_j \in Q$). The final result of the boosted tree model is the product of *L* iterations. The expected price for the *j-th* wafer sample, w_j, is $\hat{z}_j$, and it can be expressed as Equation (5):

$$\hat{z}_j = \phi(w_j) = \sum_{l=1}^{L} e_l(w_j) \tag{5}$$

The following calculations (6) and (7) demonstrate the loss function that was used to train the wafer forecasting framework:

$$Obj = \sum_j k(z_j, \hat{z}_j) + \sum_l \Omega(e_l) \tag{6}$$

$$\Omega(e_l) = \gamma S + \frac{1}{2}\lambda \left|\left|f_i\right|\right|^2 \tag{7}$$

The loss function is represented by $\sum_j k(z_j, \hat{z}_j)$, the regularization term is depicted $\sum_{by\ l} \Omega(e_l)$, the actual value of wafer yield is presented by z_j, and the forecast value is by $\hat{z}_j$. One regression tree is added to the model at a time using the gradient boosting technique, which is used to keep the current models in place during the training phase. Assume that $\hat{z}_j^{(s)}$is the expected outcome of the *j-th* wafer sample in the *s-th* iteration. The newly added regression tree, denoted as $e_s(w_j)$, was derived in the manner described below in Equation (8).

$$\begin{gathered}
\hat{z}_j^{(0)} = 0 \\
\hat{z}_j^{(1)} = e_1(w_j) = \hat{z}_j^{(0)} + e_1(w_j) \\
\hat{z}_j^{(2)} = e_1(w_j) + e_2(w_j) = \hat{z}_j^{(1)} + e_2(w_j) \\
\vdots \\
\hat{z}_j^{(s)} = \sum_{l=1}^{s} e_l(w_j) = \hat{z}_j^{(s-1)} + e_s(w_j)
\end{gathered} \tag{8}$$

Moreover, it changed to produce the subsequent Equation (9).

$$Obj^{(s)} = \sum_{j=1}^{t} k\left(z_j, \hat{z}_j^{(s-1)} + e_s(w_j)\right) + \Omega(e_l) + constant \tag{9}$$

Apply an expression frequently and do a second-order Taylor extension of the intended function.

$$Obj^{(s)} \cong \sum_{j=1}^{t}\left[h_j e_s(w_j) + \frac{1}{2} g_j e_s^2(w_j)\right] + \Omega(e_s) = \sum_{j=1}^{t}\left[h_j \theta_{r(w)} + \frac{1}{2} g_j \theta_{r(w)}^2\right] + \gamma S + \frac{1}{2}\lambda\left||\omega_i|\right|^2 \tag{10}$$

$$= \sum_{i=1}^{S}\left[\left(\sum_{j\epsilon J_i} h_j\right)\theta_i + \frac{1}{2}\left(\sum_{j\epsilon J_i} g_j + \lambda\right) f_i^2\right] + \gamma S \tag{11}$$

Especially in (12), $g_j = \partial^2 z_j^{(s-1)} k\left(z_j, z_j^{(s-1)}\right)$, $H_j = \sum_{j\in I_i} h_j$, $G_j = \sum_{j\in J_i} g_j$, define $h_j = \partial_{\hat{z}_j^{(s-1)}} k\left(z_j, z_j^{(s-1)}\right)$ and insert into Equation (12), it might be made simpler as follows:

$$Obj^{(s)} = \sum_{i=1}^{S}\left[H_j\theta_i + \frac{1}{2}(G_j + \lambda)\theta_i^2\right] + \gamma S \tag{12}$$

The value of the leaf nodes θ_i in Equations (13) is unclear. Consequently, the desired functional $Obj^{(s)}$ looks for the first derivative for θ_i, thus it is possible to solve for the ideal value of θ_i^* of leaf node *i*.

$$\theta_i^* = -\frac{H_j}{H_j + \lambda} \tag{13}$$

When θ_i^* is substituted into the goal operation, $Obj^{(s)}$ yields the lowest possible value.

$$Obj^{(s)} = -\frac{1}{2}\sum_{i=1}^{S}\frac{H_j}{H_j + \lambda} + \gamma S \tag{14}$$

3.4.2. Golden jackal optimization

In Algorithm 1, the GJO algorithm enhances biosensor data accuracy by identifying key physiological changes linked to mental health state, improving real-time stress, relaxation, and emotional regulation assessments, akin to golden jackal hunting tactics.

Algorithm 1 GJO-IXGBoost

```
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error
def IXGBoost(data, labels, num_iterations, learning_rate):
 model = initialize_model()
 for iteration in range(num_iterations):
  residuals = calculate_residuals(data, model, labels)
  for sample in data:
   score = calculate_score(sample, residuals)
   model = update_model(model, score, learning_rate)
 return model
def GJO(prey_positions, num_jackals, max_iterations):
 for iteration in range(max_iterations):
  for jackal in range(num_jackals):
   Z_N = get_male_jackal_position(jackal)
   Z_FM = get_female_jackal_position(jackal)
   F = calculate_prey_energy(iteration, max_iterations)
```

Algorithm 1 (*Continued*)

```
        rl = levy_flight_function()
        updated_position = update_jackal_position(Z_N, Z_FM, prey_positions, F, rl)
        prey_positions = update_prey_position(updated_position)
    return prey_positions
def GJO_IXGBoost(data, labels, num_iterations, learning_rate, num_jackals, max_iterations):
    model = IXGBoost(data, labels, num_iterations, learning_rate)
    prey_positions = initialize_prey_positions(data)
    optimized_prey_positions = GJO(prey_positions, num_jackals, max_iterations)
    final_model = enhance_model_with_prey_data(model, optimized_prey_positions)
    return final_model
```

Swarm intelligence algorithms like the golden jackal algorithm simulate how golden jackals hunt in the wild. Male and female golden jackals typically hunt together. The GJ's three phases of hunting are: (1) seeking out and approaching the prey; (2) encircling and agitating the prey until it stops moving; and (3) lunging in the direction of the prey. Equation (15) generates a randomized collection of prey position vectors during the initial phase.

$$\begin{bmatrix} Z_{1,1} & \cdots & Z_{1,i} & \cdots & Z_{1,m} \\ Z_{2,1} & \cdots & Z_{2,i} & \cdots & Z_{2,m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ Z_{M-1,1} & \cdots & Z_{M-1,i} & \cdots & Z_{M-1,m} \\ Z_{M,1} & \cdots & Z_{M,i} & \cdots & Z_{M,m} \end{bmatrix} \tag{15}$$

where m stands for measurements and M for the quantity of predator populations.

The golden jackal's hunt mathematical framework indicates such ($|F| > 1$):

$$Z_1(s) = Z_N(s) - F|Z_N(s) - rl.Prey(s)| \tag{16}$$

$$Z_2(s) = Z_{FM}(s) - F|Z_{FM}(s) - rl.Prey(s)| \tag{17}$$

where s is the current repetition, $Prey\ (s)$ is the prey's position vector, $Z_N\ (s)$represent the location of the male GJ, and $Z_{FM}\ (s)$ show the position of the female. The male and female GJ revised positions are denoted by $Z_1\ (s)$ and $Z_2\ (s)$. F, or the prey's avoiding energy, is computed using Equations (18) and (19):

$$F = F_1.F_0 \tag{18}$$

$$E_1 = d_1.\left(1 - \left(\frac{s}{S}\right)\right) \tag{19}$$

where S is the greatest number of repetitions, d_1 is the standard variable specified as 1.5, F_0 is a random integer in a range of [−1, 1], representing the prey's beginning energy, and F_1 is the prey's decreasing energy. The vector consisting of random numbers, represented by "rl" is determined by the Levy flight function, and the distance between the GJ and its prey is indicated by $|Z_N(s) - rl.Prey(s)|$ in Equations (20) and (21).

$$rl = 0.05.LF(z) \tag{20}$$

$$LF(z) = 0.01 \times \frac{\mu \times \sigma}{\left(u^{\left(\frac{1}{\beta}\right)}\right)} \quad \sigma = \left\{\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times (2^{\beta-1})}\right\}^{\frac{1}{\beta}} \tag{21}$$

where β is the default predictable, set at 1.5, and μ and u are random numbers in (0, 1).

$$Z(s+1) = \frac{Z_1(s) + Z_2(s)}{2} \tag{22}$$

where Z (s + 1) represents the prey's revised position depending on the locations of the GJ, male and female. The GJ harassment of their victim reduces the dodging energy. The following is a mathematical illustration ($|F| \leq 1$) of the GJ encircling and consuming their prey:

$$Z_1(s) = Z_N(s) - F.\,|rl.\,Z_N(s) - Prey(s)| \tag{23}$$

$$Z_2(s) = Z_{FM}(s) - F|rl.\,Z_{FM}(s) - rl.\,Prey(s)| \tag{24}$$

4. Results

4.1. Statistical analysis

A statistical analysis is conducted to measure the strength and direction of the relationship between different music activities (passive listening and active performance) and changes in physiological indicators.

4.1.1. Correlation analysis

Correlation analysis is used on the dataset to analyze the connections between different physiological indicators such as heart rate (BPM), galvanic skin response (GSR), brain-wave activity, EEG alpha and beta frequencies, and the types of music activities that participants perform through listening passively or performing actively. The rationale for correlation is that such analyses could help to determine the significance of correlations between physiological responses with the different types of engagement with music in that it communicates how each type of session affects feelings and cognitive states. By examining the strength and direction of these relations using Pearson's correlation, it is possible to determine which of the variables-heart rate, GSR, or brainwave activity more significantly associated with either passive or active participation in music. The correlational output between the various activities and mental and physiological well-being will serve as proof of the therapeutic function of music in reducing stress and managing emotions with the use of real-time biosensor data. **Table 2** and **Figure 2** show the results of correlation analysis.

Table 2. Values of correlation analysis.

physiological indicators	Session Type	Heart Rate (BPM)	GSR (μS)	EEG Alpha (Hz)	EEG Beta (Hz)
Session Type	1	0.76	0.85	−0.82	0.79
Heart Rate (BPM)	0.76	1	0.62	−0.68	0.71
GSR (μS)	0.85	0.62	1	−0.74	0.81
EEG Alpha (Hz)	−0.82	−0.68	−0.74	1	−0.63
EEG Beta (Hz)	0.79	0.71	0.81	−0.63	1

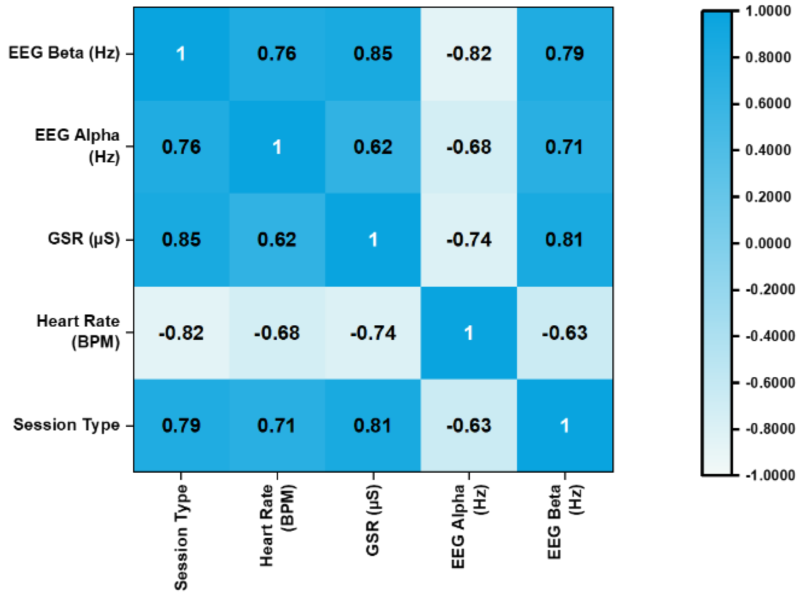

Figure 2. Pearson's correlation analysis of physiological measures and music participation.

A study examining the relationship between session type and various physiological and cognitive measures found notable correlations. Specifically, heart rate and GSR showed strong positive correlations (0.76 and 0.85, respectively) during active performance sessions compared to passive listening, indicating increased physiological arousal. Conversely, alpha brainwave activity demonstrated a negative correlation of −0.82, suggesting participants were less relaxed during active sessions, while beta activity positively correlated (0.79), indicating heightened cognitive engagement or stress. Furthermore, moderate positive correlations were observed between heart rate and GSR, as well as between heart rate and EEG beta, reinforcing the idea that increased physiological arousal accompanies higher cognitive activity during active performance. In contrast, passive listening resulted in higher EEG alpha activity and lower heart rate and GSR, signifying a more relaxing experience. Overall, active performance sessions correlate with increased heart rate, GSR, and EEG beta activity, highlighting greater physiological and cognitive arousal, while passive sessions are associated with relaxation.

4.1.2. Regression analysis

Regression analysis is the statistical method that describes the relationship of the variables. In the case of this dataset, the physiological indicators, such as heart rate, GSR, EEG alpha, and EEG beta, as predicting either active performance or being a passive listener to the music were explored. Critical regression coefficients, such as beta (β) values, standard errors, t-values, and p-values, are also examined to establish the statistical significance of each predictor. The R^2 and adjusted R^2 measure the efficiency of fit of the model; the latter is defined as to which extent the variables explain the variance variable. **Figure 3** and **Table 3** show the regression analysis.

Table 3. Values of regression analysis.

Variables	Beta (β)	SD	t-value	p-value	R^2	Adjusted R^2
Heart Rate (BPM)	0.58	0.08	7.25	< 0.001	0.42	0.41
GSR (μS)	0.63	0.07	9.00	< 0.001	0.50	0.49
EEG Alpha (Hz)	−0.70	0.06	−11.67	< 0.001	0.55	0.54
EEG Beta (Hz)	0.65	0.05	13.00	< 0.001	0.57	0.56

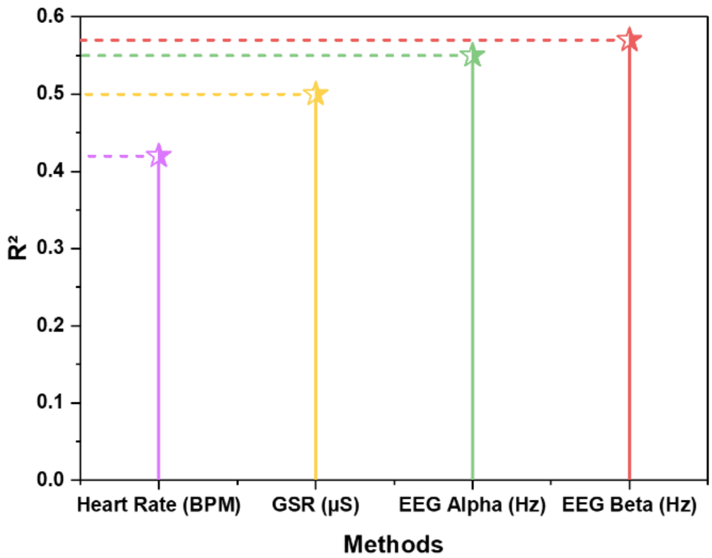

Figure 3. Regression analysis of physiological indicators predicting music participation.

The regression analysis reveals that physiological factors significantly predict music activity type (passive vs. active), with all variables heart rate, GSR, EEG alpha, and EEG beta having statistically significant beta coefficients ($p < 0.001$). Higher heart rates ($\beta = 0.58$) and GSR ($\beta = 0.63$) are positively associated with active performance, while increased EEG alpha activity ($\beta = -0.70$) predicts passive listening. In contrast, higher EEG beta activity ($\beta = 0.65$) correlates with active engagement. The models explain 42% to 57% of the variance in music activity type, indicating a strong fit and suggesting that physiological responses are key predictors of engagement level in music activities.

4.2. Simulation setup

The setup will utilize Python libraries, NumPy, SciPy, and Scikit-learn for the processing and analysis. The GJO-IXG Boost model can also be applied through either TensorFlow or XGBoost. A system that would have at least 16 GB of RAM and 20

GB of minimum storage would be good enough for handling large sets of data from biosensors. It combines a capability for real-time physiological monitoring with advanced machine learning techniques.

This study examined the existing RNN [24] approach using measures such as accuracy, sensitivity, specificity, MCC, MAE, MSE, RMSE, and F1-score.

- Accuracy

Accuracy refers to the general correctness of the model by calculating the number of correct classifications, both positive and negative, against all classification attempts. It shows how successfully the model classifies passive as well as active music activities. The suggested GJO-IXGBoost model has an accuracy of 92%, and thus it performed better than the RNN with an accuracy of 88.6%. This shows that the suggested approach is more capable of predicting music activity types based on data from physiological signals.

- Sensitivity

Sensitivity processes the strength of the framework in properly predicting true positive cases, which is an active music performance. In other words, how well the model can detect activity. The suggested model achieves a sensitivity of 91% where the RNN shows only 82.3%, with an indication that GJO-IXGBoost is a much better model for the detection of active music participation, reducing false negatives.

- Specificity

Specificity measures the number of negatives the model classifies precisely, for example, active music listening or passive music listening. It gives importance to the model's ability to produce fewer false positives while accentuating the correct labeling of non-active activities. The GJO-IXGBoost model surpasses the RNN (90.1%) at 93% specificity with its enhanced ability to classify passive music activities appropriately and thus reduce false positives. A comparison of the accuracy, sensitivity, and specificity, between the suggested and traditional procedures is shown in **Figure 4**.

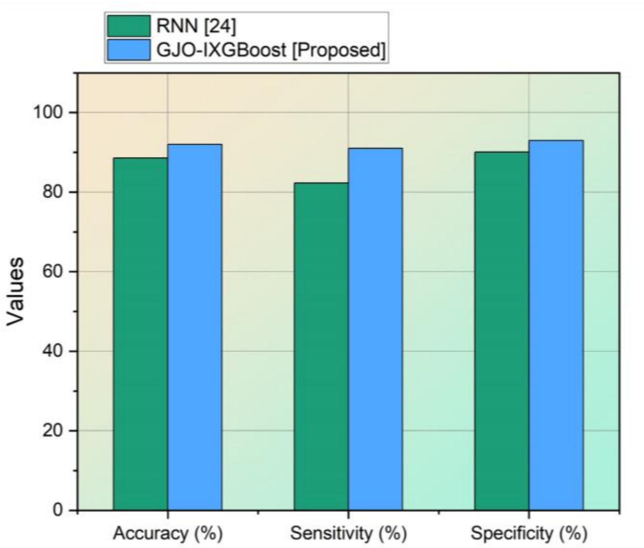

Figure 4. Comparison of performance between existing and suggested methods.

- MSE

MSE measures the regression metric by giving the average adjusted variance among anticipated and actual values. The lower the MSE will be, the closer the predictions will come to the actual values with fewer large errors. A smaller value of MSE means closer predictions from the model to the real values. For the present comparison, the value of MSE obtained for GJO-IXGB is 9.8, whereas, for the RNN model, it is 10.6, which also shows the superiority of the suggested model in terms of correctness.

- MAE

MAE is the average unconditional variance of predictions from actual values. It gives a direct, intuitive measure of the error of prediction. The lower it is, the better the predictions. The GJO-IXGB model with an MAE of 13.2 is substantially smaller than that by RNN at 26.1, meaning the GJO-IXGB model is more accurate.

- RMSE

RMSE is MSE to power one-half. It gives an understandable measure of error magnitude. Therefore, it helps understand the overall error in the predictions. Low RMSE values indicate less large deviation errors and more accurate predictions for the physiological responses. The RMSE value of 21.3 for the GJO-IXGB model is much better than its counterpart value of 32.1 obtained by the RNN, thus indicating the higher accuracy of the suggested model in predicting responses in the physiological domain. **Figure 5** depicts MAE, RMSE, and MSE comparisons of the recommended and conventional methods.

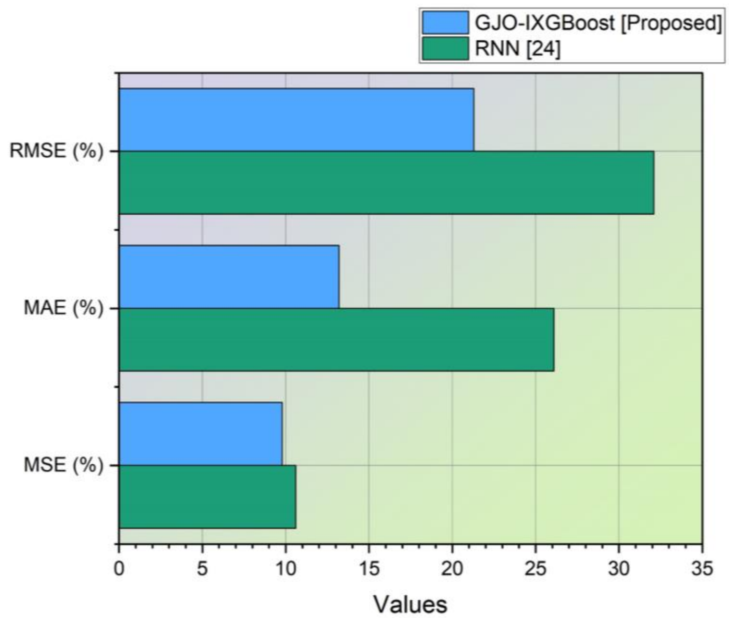

Figure 5. Performance comparison of MAE, RMSE, and MSE values.

- F1-score

The F1-score balances recall and precision so as to understand how well this model detects its active performances while minimizing false positives. **Figure 6** depicts the outcome of the F1-score. In the GJO-IXGB model, it obtains an F1-score of 90.2 compared to an RNN of 84.1. This is evidence that the proposed model outperforms in deference to a proper balance between precision and recall of active and passive music activities.

- Matthews Correlation Coefficient (MCC)

MCC is another balanced measure that considers TP, TN, FP, and FN. MCC can explain the integrated measure of the performance achieved by the model in terms of classification. The MCC of GJO-IXGB comes in at 85.6 compared to that of the RNN at 72.4. It demonstrated an impression that the proposed model outperformed better when classifying both active and passive music activities, but balanced performance in all categories was achieved. **Figure 6** displays an MCC and F1-score comparison of the recommended and conventional methods. **Table 4** shows the values of suggested and existing methods.

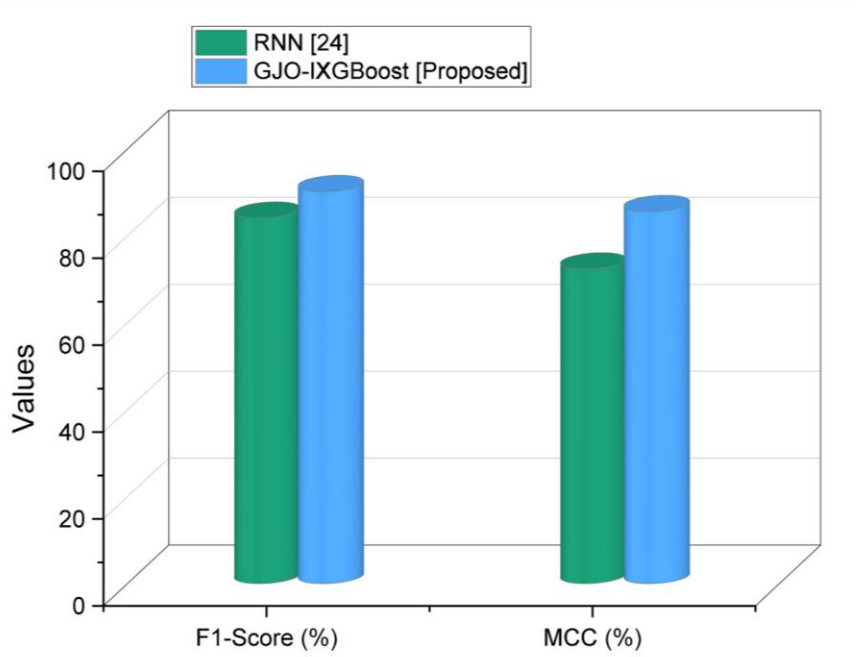

Figure 6. Comparison of MCC and F1-score for model performance.

Table 4. Values of suggested and existing method.

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)	MSE	MAE	RMSE	F1-score (%)	MCC (%)
RNN	88.6%	82.3%	90.1%	10.6	26.1	32.1	84.1%	72.4%
GJO-IXGBoost [Proposed]	92%	91%	93%	9.8	13.2	21.3	90.2%	85.6%

4.3. Discussion

Engaging with music in whichever form is linked with many benefits on mental health, with examples including alleviating stress, controlling feelings, and enhancements of overall health. These effects are familiar to anyone who is involved in psychological research that treats music as a kind of remedy. However, there is a noticeable absence in literature to systematically look at the extent to which music listening impacts mental health, especially when evaluated with biosensors. Biosignals such as heart rate, electroencephalogram, and other related signs are captured by biosensors and offer an immediate method of experimental evaluation of music on mental health. While several works have explored this link with traditional recorded data, a surprisingly limited number of papers can be found focusing on this link by using biosensor data. Another issue that needs to be addressed while analyzing the data from the biosensors for music listening is the fact that it is challenging to model the connection between these two factors. The Recurrent Neural Networks (RNNs) which are a kind of machine learning model typically used for sequential data such as time-series signals are typically used in this kind of context. Despite its advancement, RNNs have high challenges of not being able to memorize the long-term dependencies that may be found within physiological data and this includes the pattern of variation of the rate of heartbeat, and brain wave pattern when music is being played among others. These models tend to suffer from what is generally referred to as the vanishing gradient problem where the effect of the inputs that are early in the sequence is gradually washed out as the sequence proceeds. This keeps RNNs from easily tracking the physiological reactions to music over minutes or even hours, a given physical body may exhibit. In addition, RNNs are computationally expensive and take much time in the training phase hence are not very appropriate for real-time continuous monitoring of mental health status. To overcome these challenges, the model of Golden Jackal Optimized Intelligent Extreme Gradient Boosting (GJO-IXG Boost) presents a viable approach. Unless RNN, the data has temporal aspects or dependencies by ‘looping in’ previous outputs, as GJO-IXG Boost is a hybrid system that incorporates gradient boosting with an optimized feature selection approach. Considering GJO-IXG allows for a combination of fast gradient boosting and focus on the best features which enables more short and long dependencies in physiologic signals. Furthermore, this particular model is also scalable in computation thereby making it possible to run in processing bigger datasets more efficiently and also allows for real-time processing therefore this becomes a better option for biosensor data monitoring mental health. With the challenge of implementing RNNs for this kind of analysis, GJO-IXG Boost can provide a suitable and insightful solution for monitoring the effects of music on the well-being of individuals allowing for advanced mental health monitoring that is accurate, scalable, and in real-time.

5. Conclusion

Leveraging biosensor data to track the physiological markers linked to mental health, in this study, the correlation between music activities and mental health was investigated, and biosensors were used to monitor the physical signs. The data was preprocessed by normalization and removing high-frequency noises and then fed into Scale-Invariant Feature Transform (SIFT) for key-point extraction. The experiment conducted with the proposed method GJO-IXG Boost demonstrated high efficiency, with the evaluation of varying metrics such as MSE 9.8, RMSE 21.3, MAE 13.2, MCC 85.6%, Accuracy being 92%, F1-score 90.2%, Sensitivity 91% and Specificity 93%. According to the given results, it is possible to state that music activities independency of the type have a positive impact on the concept of mental health supported by biosensors. The GJO-IXG Boost method, which has been applied to high-quality biosensor data in the present study, was able to identify the physiological conditions that result from music engagement to enhance the credibility of biosensor data, therefore it has even more possibility in the direction of introducing the biosensor into mental health research and methods of intervention.

Limitations and future scope

The GJO-IXGBoost method, based on high-quality biosensor data, may not accurately represent the emotional and psychological aspects of music's impact on mental health. Future research should use advanced biosensor technologies, larger samples, deep learning techniques, real-time data processing, and psychological and contextual factors to improve model robustness and enhance understanding of music's therapeutic effects.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

References

1. Alam A, and Mohanty A. Music and Its Effect on Mathematical and Reading Abilities of Students: Pedagogy for Twenty-First Century Schools. In Interdisciplinary Perspectives on Sustainable Development (pp. 342-346). 2023; CRC Press.
2. Koirala NR, Paudel A, Upadhyay S, and Koirala A. Music and mental health. Journal of Psychiatrists' Association of Nepal. 2024; 13(1), pp.37-43.
3. Ghanai K. The Neuroscience of Music: An Interdisciplinary Study of the Effects of Music on the Brain. 2023.
4. Tervaniemi M. The neuroscience of music–towards ecological validity. Trends in Neurosciences. 2023; 46(5), pp.355-364.
5. Bonde LO, Stensæth K, and Ruud E. Music and Health. A Comprehensive Model. Department of Communication and Psychology, Aalborg University, Denmark. 2023.
6. Poli A. Measurement and processing of multimodal physiological signals in response to external stimuli by wearable devices and evaluation of parameters influencing data acquisition. 2023.
7. Ma C. The Influence of College Physical Education Teaching on Students' Mental Health and Skill Improvement under the embodied cognition Theory. Revista de Psicología del Deporte (Journal of Sport Psychology). 2024; 33(2), pp.366-375.
8. Сулаймонова Д. An analysis of the importance of music therapy in an inclusive education. Зарубежнаялингвистика и лингводидактика. 2024; 2(1/S), pp.318-326.
9. Jianxin Z, Wenhong L, Yuli L, and Ruihong X. Understanding Aesthetic Principles in Music and its Effect on Contemporary Music Composition: An Educational Psychology Perspective. Journal of Psychology and Behavior Studies. 2024; 4(2), pp.08-30.
10. Cordero Jr DA. Music for Healing: A Careful Application of Music Therapy for the Sick. Journal of Pain & Palliative Care Pharmacotherapy. 2024; pp.1-2.
11. Trost W, Trevor C, Fernandez N, Steiner F, and Frühholz S. Live music stimulates the affective brain and emotionally entrains listeners in real time. Proceedings of the National Academy of Sciences. 2024; 121(10), p.e2316306121.
12. Smalley AJ, White MP, Sandiford R, Desai N, Watson C, Smalley N, Tuppen J, Sakka L, and Fleming LE. Soundscapes, music, and memories: Exploring the factors that influence emotional responses to virtual nature content. Journal of Environmental Psychology. 2023; 89, p.102060.
13. Musgrave G. Music and wellbeing vs. musicians' wellbeing: examining the paradox of music-making positively impacting wellbeing, but musicians suffering from poor mental health. Cultural Trends. 2023; 32(3), pp.280-295.
14. Chen S, Zheng L, and Chen Y. Mental Health and Therapeutic Music: An Interdisciplinary Exploration. In Interdisciplinary Research on Healthcare and Social Service: Chinese and Cross-Cultural Perspectives (pp. 221-231). Cham: Springer Nature Switzerland. 2024.
15. Wang L, Hu Y, Jiang N., and Yetisen AK. Biosensors for psychiatric biomarkers in mental health monitoring. Biosensors and Bioelectronics. 2024; p.116242.
16. Bhave A, Renold FK, and Gloor PA. Using plants as biosensors to measure the emotions of jazz musicians. In Handbook of Social Computing (pp. 173-188). Edward Elgar Publishing. 2024.

17. Smith AA, Li R, and Tse ZTH. Reshaping healthcare with wearable biosensors. Scientific Reports. 2023; 13(1), p.4998.
18. Fareesha F, Chandanashree YK, Gowthami V, Jayachandran R, and Kalathil S. February. Real-Time Artificial Mood-tracking and Health-monitoring System (RAMAHS) for people with mental illness and their Caregivers. In 2023 International Conference on Recent Trends in Electronics and Communication (ICRTEC) (pp. 1-6). IEEE. 2023.
19. Hunt AM, and Sims F. Integrating Physiological Measures within a Music Therapy Research Course: Program Description and Initial Evaluation. Dialogues in Music Therapy Education. 2024.
20. Erdem A, Eksin E, Senturk H, Yildiz E, and Maral M. Recent developments in wearable biosensors for healthcare and biomedical applications. TrAC Trends in Analytical Chemistry. 2023; p.117510.
21. Xu C, Song Y, Sempionatto JR, Solomon SA, Yu Y, Nyein HY, Tay RY, Li J, Heng W, Min J, and Lao A. A physicochemical-sensing electronic skin for stress response monitoring. Nature Electronics. 2024; 7(2), pp.168-179.
22. Khan A, DeVoe E, and Andreescu S. Carbon-based electrochemical biosensors as diagnostic platforms for connected decentralized healthcare. Sensors & Diagnostics. 2023; 2(3), pp.529-558.
23. Wasilewski T, Kamysz W, and Gębicki J. AI-Assisted Detection of Biomarkers by Sensors and Biosensors for Early Diagnosis and Monitoring. Biosensors. 2024; 14(7).
24. Jia Y. Impact of Music Teaching on Student Mental Health Using IoT, Recurrent Neural Networks, and Big Data Analytics. Mobile Networks and Applications. 2024; pp.1-20.