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Affective Brain-Computer Music Interface in Emotion Regulation and Neurofeedback: A Research Protocol

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Abstract

Introduction: Emotion regulation is an integral part of mental health, dynamically impacting brain function as one's emotions change continuously throughout the day. Impairments in emotion regulation are associated with a range of psychiatric disorders. Although the implications of emotion regulation are crucial to mental health, few studies have examined training emotion regulation strategies with respect to the brain. Thus, this manuscript will propose an affective brain-computer music interface (aBCMI) prototype for emotion regulation that continuously generates music by estimating emotions from real-time electroencephalography (EEG) signals.
Methods: In this proposal, we describe our prototype consisting of an emotion classifier that detects the expression of emotions from EEG signals, and a music generator that generates music reflective of those emotions. We evaluate the prototype in three separate studies. In study 1, the accuracy of the music generator is tested. In study 2, the accuracy of the emotion classifier is tested by assessing its correlation with real-time, self-reported emotions. In study 3, the generative music algorithm is assessed to explore emotion regulation strategies.
Discussion: The proposed BCMI is expected to accurately estimate emotions, provide musical feedback of participants' emotions, and enable users to intentionally modulate their emotions from musical feedback. This involves capturing the listener's emotions in real-time using EEG signals, providing the opportunity to regulate one's emotional state with musical feedback. Thus, in addition to enabling greater neurofeedback training of emotions, our prototype can enhance the understanding of affective computing and emotions with EEG and machine learning.
Conclusion: Clinical applications of this prototype may have a tremendous impact as a neurofeedback tool in music therapy for training emotion regulation. Future research may benefit from using the proposed BCMI as a neurofeedback treatment in mood disorders.

Keywords: affective brain-computer interface; brain-computer interface (BCI); neurofeedback; emotion regulation; non-invasive affective intervention; music therapy

Introduction

Emotional affect underlies much of our cognitive functioning such as attention, memory and perception [1]. Continued research highlights how affect can be systematically investigated in the neuroscience literature. Specifically, physiological data can reveal participants' emotional responses across several physiological measures [2], despite individuals with psychiatric disorders showing impaired functioning with emotion modulation, mood, and music [3]. While numerous studies have contributed to affective psychology, much less is known about the mechanisms that induce, regulate, predict, and modulate emotional activity. Thus, we propose an affective brain-computer music interface (aBCMI) that can be used to modulate emotion.

BCMIs are computer-based brain acquisition systems that interpret brain activity for control of an external musical device. BCMIs are typically used with three central goals:

extracting meaningful brain signals, designing generative music to improve livelihood, and coordinating its therapeutic benefits. Typically, this set-up involves transforming neuroelectric signals recorded by electroencephalography (EEG) into digital music signals such as Musical Instrument Digital Interface (MIDI). EEG enables users to control their brainwaves to generate music from band-power based features [4]. Furthermore, extracted features from EEG signals that correspond to one's affective states can be used to classify their ongoing arousal and valence [5]. This can be useful for therapeutic applications, in which an individual can modulate their emotions by moving from persistent, negative emotions (e.g., anger and sadness) to more desirable emotions (e.g., contentment and excitement).

Generative music techniques are often employed in BCMI research as a measure to control and respond to brain signals [6]. The conception of generative music in the BCMI literature can be traced to the extensive research in music psychology showing music can elicit emotional responses in listeners. Since the 1930s, empirical research has identified the relationship between specific musical parameters (e.g., tempo and rhythm) and the emotional responses of listeners [7]. The advent of emotion-based generative music algorithms can be attributed to the advancement of the circumplex model [8]. The circumplex model is a dynamic model that represents emotions with two distinct orthogonal dimensions. Valence (i.e., positive, or negative) is represented on one axis and arousal (i.e., activation or deactivation) is represented on a separate, intersecting axis. Any position on the circumplex model can be defined by musical parameters with a valence and arousal value typically between 0 and 1 (Figure 1). The emotional coordinates of arousal and valence can be mapped onto a generative music algorithm to create a closed-loop feedback system in which the participants' emotions are reflected in the music.

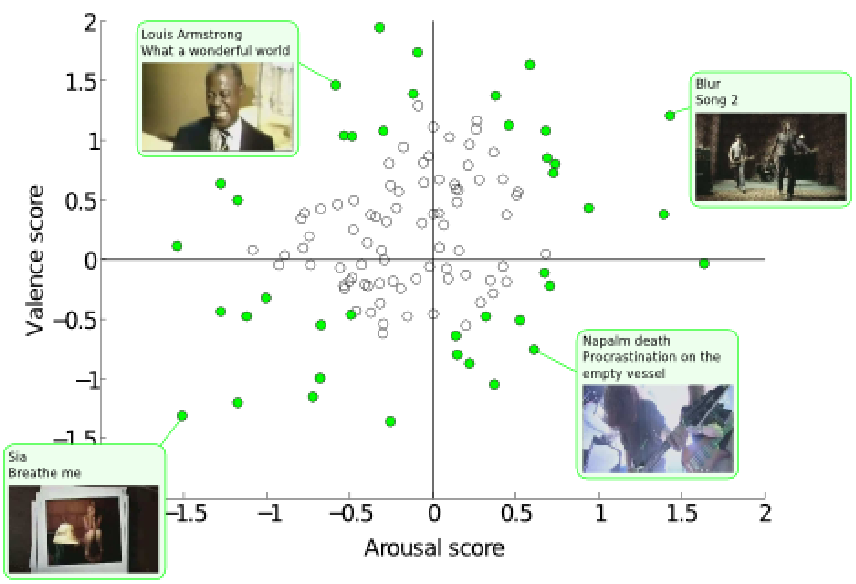

Figure 1. Illustration of songs in each quadrant of the circumplex model from the DEAP dataset. Positive values along the valence axis indicates positive valence (PV), and negative values indicate negative valence (NV). Positive values along the arousal axis indicate high activation (HA), and negative values indicate low activation (LA). Each quadrant corresponds to a combined arousal and valence score (i.e., PVHA, PVLA, NVHA, NVLA) (adapted from Koelstra et al. [9]).

The circumplex model has been employed in music therapy using neurofeedback and real-time EEG for emotion recognition. For example, Sourina et al. proposed a system to classify valence and arousal values based on EEG data collected from participants listening to songs chosen to elicit a specific emotional state [10]. However, the study didn't examine specific emotion regulation strategies to alter one's emotions with neurofeedback. Specifically, Gross' process model of emotion defines cognitive-based emotion regulation strategies as antecedent-focused [11]. Antecedent-focused emotion regulation strategies includes mental imagery [12,13] and mindfulness meditation [14]. Mental imagery is the process of eliciting an emotional memory to perform emotion modulation. Mindfulness meditation entails focused-breathwork, cognitive awareness, and following prompts from a trained mindfulness practitioner to reach a desired emotion state [12].

In order to validate subjective affective changes from emotion regulation, a self-assessment tool is necessary. One popular method of self-reporting emotions is the Self-Assessment Manikin (SAM), which provides information about emotions over discrete time points [15]. In contrast, FEELTRACE is an instrument that allows observers to continuously self-report emotions as they attend to stimuli.

It uses an emotion response space that enables participants to indicate their emotions in terms of valence and arousal [16]. The advantage of FEELTRACE is its ability to continuously track emotions. One study used an aBCMI design that involved providing emotion ratings with FEELTRACE. It was found that the aBCMI effectively assists in modulating affective states toward targeted emotions using music as feedback [5].

The use of machine learning has been introduced in aBCMIs to classify emotions in terms of valence and arousal scores from EEG signals using Support Vector Machine (SVM), K-Nearest Neighbors (k-NN) and Random Forest classifiers [17,18]. The classification model we used relies on pre-recorded EEG data from the OpenBCI headset. It was trained on previous participants' valence and arousal ratings of auditory stimuli, which is suited for subsequent music generation [19]. In sum, our work requires testing the accuracy of emotion classification in machine learning to ensure that the BCMI can predict users' affective states.

The present paper presents an aBCMI which transforms EEG data into a SVM classification model to predict emotions (i.e., valence and arousal) from participants' brain activity and then produce music that reflects their emotions. Three studies were devised to first, validate perceived participant emotion associated with musical pieces produced by our generative music algorithm; second, test if continuous self-rated emotions are reflective of real-time EEG classification; and third, determine whether emotion regulation techniques are effective in altering the valence and arousal of participants using EEG. By classifying emotions from extracted EEG signals, generative music can then be controlled voluntarily by participants' by altering their EEG activity. Hence, a real-time aBCMI is used to employ emotion regulation strategies. This research could be used prospectively to enable clinical populations to consciously mediate their emotions by recognizing and managing undesirable emotions with assistance of this aBCMI. This can have a tremendous impact on our understanding of affect, emotion regulation, and rehabilitation of individuals with disorders of emotional regulation.

Methods

Participants

Thirty-two participants between 20 and 55 years of age with a balanced sex ratio will be recruited through a university research participant pool across studies 1, 2, and 3. Participants must indicate experience with prior musical training and will be excluded from the final analysis if years of musical training is found to significantly covary with emotion estimation. They must have no disorders of auditory processing (i.e., normal, or corrected-to-normal hearing), no concurrent diagnosis of neurological, psychiatric, or personality disorder, and report no symptoms of amusia that affect auditory processing. A mental health checklist pre-questionnaire will be performed prior to consenting to participate in the study.

Study 1: Musical Accuracy Study

Objective:

The purpose of Study 1 is to test a generative music algorithm to verify its ability to induce targeted emotions in a listener. The algorithm in the present study has been previously tested in a pilot study that induced emotions in listeners [20]. The generative music algorithm used in this study uses five musical parameters for either valence or arousal. Valence is represented by harmonic mode and pitch; arousal is represented by rhythmic roughness, loudness, and tempo. For example, when a song becomes louder and speeds up in tempo, one becomes more activated in arousal. Thus, when the value of an emotional dimension changes, it's given musical parameter will change in accordance, associated with a corresponding change in the participant's EEG activity. Figure 2 provides a detailed schematic of the generative algorithm.

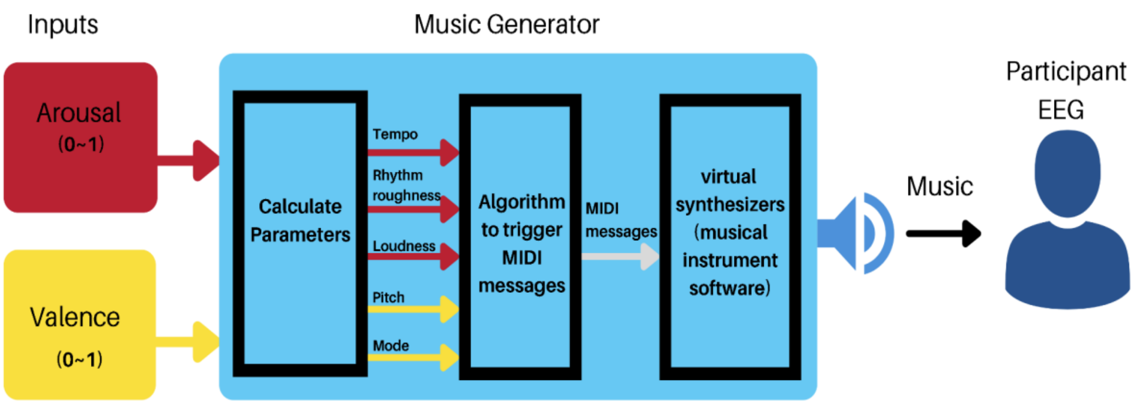

Figure 2. Music generator algorithm. First, the algorithm is fed information about the arousal and valence of the listener from the emotion classifier. Subsequently, the generative algorithm calculates parameters that corresponds to the valence and arousal of the listener. MIDI messages are relayed to a virtual synthesizer to play notes from the algorithm, which finally

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generates music to the listener. Red arrows denote arousal, and yellow arrows denote valence. This figure was created with Canva ™.

Procedure:

First, participants will be provided a survey to test musical preferences and demographic data to control for receptiveness to the generative music algorithm. Then, participants will be played a sample musical excerpt from the generative music. Finally, participants will be presented the experimental stimuli – consisting of 12 pre-recorded musical excerpts generated by the generative music algorithm. Each excerpt will consist of an evenly distributed position across each of the four quadrants in the circumplex model (i.e., high arousal, high valence; low arousal, low valence; high arousal, low valence; low arousal, high valence). Thus, a total of three musical excerpts will be used for each quadrant to capture a range of emotions. Each excerpt will be played for a duration of 30 seconds in a pseudo-randomized order. During each musical excerpt, participants will be prompted to rate the excerpt using FEELTRACE. The FEETRACE instrument displays a wheel with particular emotions from each quadrant, which can be selected by participants using a mouse-click. Participants will be given all 30 seconds of the excerpt to select their emotions with the FEELTRACE pointer.

Study 2: Emotion Classification Study

Objective:

The objective of Study 2 is to test if self-rated emotions over continuous time points are reflective of the real-time EEG classifier. Participants will provide personal emotion ratings to determine if the classifier accurately reflects the self-reported emotions of the participants. To control for the potential impact the music may have on participants' emotions, this study will evaluate two participant groups separately: one that is exposed to music, and one that is not.

Procedure:

To collect brain electrical activity, a 4-channel EEG (OpenBCI Ganglion) will be mounted on the participant's head. Participants will be separated into two groups: feedback group or a no-feedback group as a control, with similar age and sex distribution for each group. During testing, the feedback (experimental) group will hear audio-feedback from the generative algorithm to evoke changes in their emotional state reflected in EEG signals. The no-feedback (control) group will receive no feedback to account for the influence music may have on participants' emotions. The FEELTRACE instrument will be used by participants during the experiment to rate their emotions in terms of arousal and valence. In the feedback group, participants will be situated in front of a computer screen, in which the FEELTRACE pointer will appear during their EEG recording. Participants will be exposed to four blocks of musical stimuli representing each quadrant in the circumplex model (e.g., HAPV: happy, HANV: scared, LANV: sad, LAPV: calm) in a randomized order. Participant EEG activity will be tracked by a pre-trained EEG classifier. The pre-trained classifier is not recorded in real-time, so to account for this, we will record each participants' brain activity, and retrain the classifier in real-time. Self-reported emotions ratings from FEELTRACE will be fed to the classifier in real-time. Finally, a correlation analysis will be made to assess the accuracy of the classifier compared to the participants' self-reported ratings of emotions.

Study 3: Emotion Regulation Study

Objective:

Study 3 will examine (1) cognitive strategies deploying mental imagery and mindfulness meditation for emotion modulation and (2) the conjunctive role of music in emotion modulation with these cognitive strategies. We expect an increased valence and arousal output in the generative music – reflective of self-reported emotion – to arise out of mental imagery and meditation instruction in the music feedback group compared to the no music feedback group.

Procedure:

Participants will be trained on mental imagery and mindfulness meditation trials prior to testing. In mental imagery trials, participants will be asked to visualize a specific past event to modulate their emotional states toward a targeted emotion with the following prompt: "remember a time that you felt either angry, excited, content, or sad". In mindfulness meditation trials, trained breathwork techniques will be used to direct affect to targeted emotions. The FEELTRACE instrument will be used to record participants' emotions with a mouse click.

Participants will be split into two groups: music feedback, and no music feedback, as a control (see figure 3). In the feedback group, emotional induction through music (EIM) will expose participants to music from each quadrant of the circumplex model at least once. In the no-music feedback group, participants will sit in silence for 10 minutes while using the FEELTRACE to select their emotions with a mouse click. The no feedback group will serve as a control to compare its effectiveness relative to emotion modulation with the aBCMI.

Trials will begin by playing music associated with anger, excitement, contentment, or sadness. The FEELTRACE instrument will record participant's emotions with mouse clicks, while receiving instructions on regulating emotions toward targeted emotions using feedback from the generative music. For example, a participant with induced anger (high activation, negative

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valence) may be instructed to regulate their emotion toward contentment (low activation, positive valence). Self-regulation periods using the FEELTRACE instrument will last three minutes.

Then, instructions will be provided to aim to a new targeted emotion. Each trial will follow with participants using only one of the cognitive strategies (i.e., mental imagery or mindfulness meditation) to modulate their emotion from one point on the circumplex model to another. This will last for a total of 3 minutes to record changes in the targeted emotion with FEELTRACE.

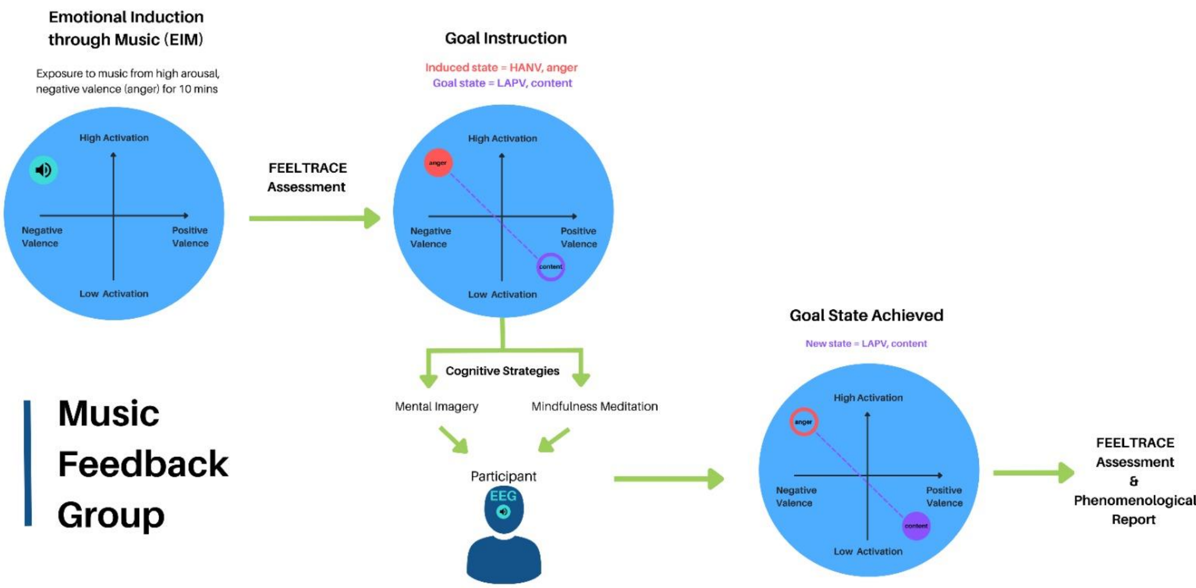

Figure 3. In the music feedback group, participants will be exposed to music for 10 minutes as an initial emotion prompt. Then, instructions will be provided to reach a target emotion (goal state) using either mental imagery or mindfulness meditation for emotion regulation. Participants will rate their emotions using the FEELTRACE assessment throughout the session. In the no music feedback group, participants will sit quietly in silence for 10 minutes and regulate their emotions toward a target emotion using either mental imagery or mindfulness meditation. Participants will rate their emotions using the FEELTRACE assessment throughout the session. This figure was created with Canva ™.

Discussion

The purpose of this proposal is to use a BCMI that can accurately detect emotions and produce music with emotion modulation. There are several components that comprise the proposed BCMI design including EEG data acquisition and preprocessing, emotion classification, generative music, and auditory feedback. Firstly, the EEG data is acquired from a four-channel OpenBCI device, which is relayed into a trained model for emotion recognition [19]. The model can classify participants' valence and arousal. This model is relayed to a generative music algorithm pipeline – producing music reflective of participants' emotions. Finally, the participant will be given neurofeedback strategies to modulate their emotions.

In this design, emotion classification is essential for accurately capturing participants' emotions. EEG recordings from the OpenBCI will be used to classify arousal and valence. Similarly, one study used OpenBCI with k-means clustering to classify emotions from film ratings. This produced arousal scores of 68.47%, and valence of 72.35% [19]. In another study, participants rated emotions of music videos from the DEAP database while EEG was recorded. After applying feature selection to the models, it produced an accuracy of 98% relative to participant self-ratings [18]. In the current design, four electrodes are used to continuously measure valence and arousal scores in real-time. Subsequently, the accuracy will be assessed by real-time participant ratings using FEELTRACE [16]. In contrast to other emotion classification studies, our study aims to further validate participants' self-reported emotions in real-time. This allows participants to rate their emotions from a previously trained classifier. In sum, accurate emotion classification depends crucially on real-time, self-reported emotion ratings.

Additionally, participants' emotions should be reflected in the generative music. Similar to prior studies [20,21] we use musical parameters that correspond to arousal and valence. The generative music will be played in real-time to reflect participants' changing emotional state. This will employ EEG and emotion classification models previously discussed. The outcome will be a generative music algorithm that adjusts musical parameters based on participant' emotions (e.g., if a participant is happy, the generative algorithm will play happy music). While preliminary results for the algorithm have been previously demonstrated, our study validates it further. The original study that used the generative music algorithm consisted of only 11 participants [20]; therefore, a larger sample size was needed to give a clear indication of its accuracy. Additionally, the algorithm in our study was translated from MATLAB to Python, thus more testing was required to ensure no errors were made in replicating the original code.

Once participants are given feedback from the music generator, they will be trained to modulate their emotions. In a typical neurofeedback setting, participants learn to consciously control their brain waves withs EEG signals – often fed back visually or auditorily [22]. Prior literature has examined neurofeedback as a suitable tool for emotion regulation [23]. In our design, the music generator can be used as a means of neurofeedback for emotion regulation. First, participants are induced with distinct emotions from each quadrant of the music generator. Specific modulation strategies, including mental imagery and mindfulness meditation, in conjunction with auditory feedback from the generative music may allow participants to successfully control their emotions toward more desirable states. This protocol may be useful in therapeutic interventions for psychiatric patients who struggle with emotion regulation.

Due to the nature of the novelty and complexity of BCMIs, our design is impacted by several foreseeable limitations. First, the participant pool we chose will be screened as healthy and without difficulties in emotion regulation as assessed by instruments such as the difficulties in emotion regulation scale (DERS) [24]. However, our future work may benefit from recruiting psychiatric populations for therapeutic applications. Second, despite screening for disorders of emotional regulation, healthy adult participants may still struggle with self-regulating their emotions. Emotions fluctuate throughout our daily lives – making emotion regulation difficult to control. Third, the EEG headset we chose has few electrodes (i.e., four channels), therefore it is constrained by spatial resolution. Nonetheless, we found that FP1, FP2, T3 and T4 electrodes were sufficient for producing the highest accuracy in valence and arousal. We chose the OpenBCI, because it is feature-rich in programming options for designing BCMIs, despite the limited electrodes. Finally, the generative music algorithm proposed by these series of studies is constrained by Western musical features (e.g., instruments, scales, timbre). Western music was primarily employed due to technical constraints in producing non-Western musical generative algorithms. Future work may benefit from the use of non-Western music.

Conclusions

In the present proposal, we empirically evaluate an aBCMI prototype that can assist in emotion regulation. This prototype consists of a threefold design. Firstly, a generative music algorithm is tested to determine if the music is reflective of the participant's emotions. Secondly, we test the accuracy of an emotion classifier at recognizing participant's emotions in real-time using advanced machine learning and EEG. Finally, participants will be trained to use emotion regulation strategies to attain desired emotions in terms of valence and arousal. This BCMI introduces novel advances in the affective computing literature. While similar aBCMI designs have been tested [5], the literature on BCMIs is still in its infancy [6]. To the best of our knowledge, no literature to date has used an aBCMI with real-time EEG and continuous music generation for neurofeedback. This allows for greater sampling of the immediate changes to emotions that is reflective of emotions in real world.

The aim of neurofeedback in this design is to improve participants' voluntary control of their emotions. We have implemented emotion regulation strategies such as mental imagery and mindfulness meditation to assist in emotion regulation. Eventually, one future direction for this research is to train participants to consciously learn to regulate their valence and arousal values (e.g., become happier) and reduce undesirable emotions. In other words, we expect that participants will associate hearing more pleasant music high in positive valence with more desirable emotions. This has potential value for treating clinical populations such as those with depression, anxiety, or bipolar disorder, which are commonly associated with impairments in emotion regulation. Future work may additionally benefit from evaluating this system as a means of music therapy for treating affective disorders.

List of Abbreviations Used

EEG: electroencephalograph
BCMI: brain-computer interface
MIDI: musical instrument digital interface
DEAP: database for emotion analysis, using physiological signals
SAM: self-assessment manikin
HAPV: high arousal, positive valence
HANV: high arousal, negative valence
LANV: low arousal, negative valence
LAPV: low arousal, positive valence
EIM: emotion induction through music
SVM: support vector machine
KNN: k-nearest neighbors
DERS: difficulties in emotion regulation scale

Conflicts of Interest

The authors declare that they have no conflict of interests.

Ethics Approval and/or Participant Consent

All participants across Studies 1, 2, and 3 will be given informed consent for their participation in this design. They will be provided with explicit instructions about the procedures involved in the experiment. Once they agree to participate, documentation will be provided with the purpose of the study, the potential risks involved and their right to withdraw from the study at any time. Personal information from the consent forms will be stored anonymously and locked in a file cabinet only accessible to the researchers. All information for data analysis will remain anonymized throughout the remainder of the experiment, and only non-identifiable information will be collected from the participants. Only the researchers involved in the experiment will have access to participant's personal information and will not be shared with external parties.

Written consent forms will inform participants of the purpose of Studies 1, 2 and 3: to provide a non-invasive EEG with a small behavioral task that involves listening to samples of audio clips and inducing emotions. They will be informed that there are no known adverse effects to the study. Participants have the right to withdraw from the study at any time and refuse to provide sensitive information (e.g., age, gender, ethnicity etc.). Once the study is finished, participants will be given a full debriefing as to the purpose of the experiment.

Authors' Contributions

HG: made substantial contributions to drafting and revising the manuscript critically, performing the literature review, conceptualizing the study design and planning, and gave final approval of the version to be published.
DW: contributed to the study design protocol and planning, the drafting of the manuscript, and gave final approval of the version to be published.
NJ: made contributions to the design of the study, drafted and revised the manuscript critically, and gave final approval of the version to be published.
MS: contributed to study design and planning, assisted with the collection of the data, as well as interpretation and analysis of data, and gave final approval of the version to be published.
DL: made contributions to the design of the study, revised the manuscript critically, and gave final approval of the version to be published.

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