Can Binaural Beats Increase *Your* Focus? Exploring the Effects of Music in Participants' Conscious and Brain Activity Responses

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ABSTRACT

Music is a universal medium that can elicit strong emotion, and can significantly help us in gaining focus while doing specific tasks. However, it is unclear what types of music can help to improve focus while doing other activities. In this paper, we investigate the effects of six different music stimuli on participants' verbal and physiological responses while identifying genuine and acted emotions from video clips. Initial analysis was conducted on the comments participants made on the different stimuli in order to identify emerging patterns. Then, participants' verbal and EEG responses were collected, processed and analyzed to classify two types of emotion. Empirical analysis of the results show that binaural beats, which are believed to increase focus on tasks, can often cause discomfort and therefore hinder focus. On the other hand, music containing a sombre tone, or familiar popular music with high level valence can help improve focus. Identifying which music stimuli can improve focus can be highly beneficial in managing day-to-day tasks and activities. This study will also be useful in broadening the range of music stimuli used in affective computing studies.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**.

KEYWORDS

Binaural Beats, Music Stimuli, Physiological Signals, EEG, Affective Computing, Classification, Emotion Recognition

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1 INTRODUCTION

Music is a powerful medium that has a compelling influence on peoples' mood and emotion. It has also shown to help prolong attention and improve the level of concentration while doing different tasks [11]. Due to the ongoing global pandemic, many people have been forced to stay and work from home. This has caused a decrease of attention in daily life activities [10]. Listening to appropriate music can help regain focus in these activities. Peoples perception can be influenced by different music. For instance, the background music played during movie scenes has significant effects on how those scenes are perceived [26]. According to brain anatomy researchers, music acts as a nonverbal medium moving through the auditory cortex directly to the limbic system. This system plays an important role in the emotional response system [24]. Thus, music stimuli have been widely used by psychology and affective computing researchers. Music has been extensively used as a source of therapeutic interventions for stress and anxiety reduction, depression and other mental disorders [13, 32]. It has also been used in cognitive load measurement studies [18]. However, it is unclear which types of music stimuli can be beneficial to improve focus on different tasks. One type of audio stimulus is called binaural beats, which synchronizes brainwaves to enhance specific brainwave patterns. Different brainwaves serve different purposes in the human brain. For example, alpha waves promote relaxation, beta waves dictate active states and external attention, gamma waves facilitate concentration in information-rich task processing etc [1]. Understanding the effects of different music stimuli through human physiology can significantly enhance medical and affective computing research.

The use of physiological responses in emotion recognition gained popularity among researchers as these responses are involuntary and so cannot be faked. The electroencephalogram (EEG) is fast, non-invasive and one of the most commonly used means of measuring physiological signals in research. It enables understanding of brain activities associated with emotion processing by recording different brainwave patterns. These signals can reveal useful patterns related to different emotions [2]. Emotion recognition using physiological signals while listening to music such as using music videos [22], movie soundtracks [23], participant chosen music [19] etc have achieved some success in recent years. However, there has not been any analysis of what types of music can improve focus while doing other tasks, in our case related to emotion recognition. Another contribution of our work is that we take a computational approach to understand the effects of a broader range of music stimuli, which previous works in this area had not explored.

In this paper, we explore the effects of six different music stimuli on people's affective reasoning using their verbal and brain activity responses. We conducted a study where EEG signals from different brain regions are collected when participants listened to these stimuli and identified different emotions from video stimuli. These signals were then processed and analysed using statistical and machine learning techniques to classify the video stimuli emotions. In addition, comments on the different music stimuli are collected from the participants in order to understand how the music influenced their performance on their given task. The rest of the sections of this paper are organized as follows: Section 2 describes the experiment methodology and stimuli used in this study. Section 3 explains the results and discusses some patterns identified from the participants' comments on the stimuli. Finally, section 4 highlights some limitations and discusses future work.

2 METHODS

2.1 Music Stimuli

In this experiment, we used six different music stimuli which can broadly be divided into three categories. They are: binaural beats, classical music and pop music. The music stimuli are described in detail below:

- "Brain Energizer - Gamma Waves for Focus / Concentration / Memory - Binaural Beats - Focus" - This stimulus was chosen from a YouTube video [15] and it is said to increase gamma wave activity on the brain. According to the description of the video, this stimulus is highly beneficial for studying and improving focus during work.
- "Serotonin Release Music with Alpha Waves - Binaural Beats Relaxing Music, Happiness Frequency" - This binaural beat stimulus was also chosen from a YouTube video [3]. This is a relaxing piece which is said to boost alpha wave activity on the brain.
- "F. Chopin's 'Funeral March' from Sonata in B flat minor Op.35/2" - this is one of Chopin's most popular pieces and has a very sombre tone to it. The piece has been used in music therapy studies due to its long lasting periodicity [20].
- "J.S Bach's 'Air' from Suite for Orchestra No. 3 in D" - this is an orchestral music piece also showing long lasting periodicity [20]. It has a moderate intensity and can be considered a more relaxing piece.
- "Justin Bieber's 'Love Yourself' from the album Love Yourself" - This music piece was chosen as the top song in the 2017 Billboard Hot 100 year-end chart [6]. It is classified as an acoustic pop song, having a moderate valence level (Spotify valence score 0.515).
- "Ed Sheeran's 'Shape of You' from the album Divide" - This song was chosen as it was the top song according to the Billboard Hot 100 year-end chart of 2018 [6]. It is an upbeat and energetic song having a high valence level (Spotify valence score 0.931).

In this paper, we only considered the category of music for the computational analysis. We did not consider the valence score as this score was not known for some of the stimuli.

2.2 Video Stimuli

Video stimuli used in this experiment were taken from four different datasets. All of these datasets contain videos of people displaying different types of emotions in genuine or acted form. These are, AFEW [12], MAHNOB [27, 30], MMI [25] and the Anger dataset from [7]. A total of 48 video clips were used in this experiment, 24 of them labelled as genuine emotion, and 24 labelled as acted. The six types of basic emotions were represented in the videos. These emotions were contained in a blended manner in the videos to reflect the real world emotions [21]. The video clip lengths ranged from one second to four seconds. However, during analysis, all physiological signal recordings were cropped to the same length for comparison. All the clips were cropped to the same width, height and converted to grayscale. As one of the datasets contained only grayscale videos, we converted the other videos to eliminate any effects of video colour.

2.3 Participants

A total of 22 participants (9 female and 13 male) participated in this study. Their mean age was 20.8 with a standard deviation of 4.8. All participants were university students and they were recruited through the University's voluntary research participation scheme website. They were given participation credit after completion of the study.

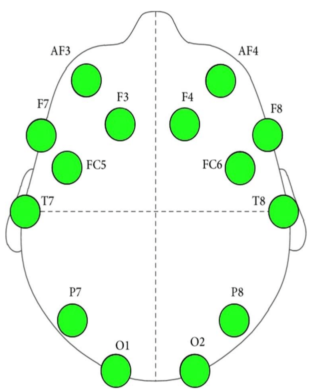
2.4 Experiment Design

The experiment was approved by the Australian National University's Human Research Ethics Committee. After arriving at their scheduled time, the participants were welcomed by the experimenter and were given a participation information sheet and consent form. They were briefed on the aim of the study and asked to read through the information sheet. Following their agreement to participate in the experiment (through the signed consent form), they were asked to sit in front of a monitor and asked to adjust the seat so that they had a comfortable view and easy access to the keyboard and mouse. Then the the EEG device was fitted. All the participants completed the experiment in the same experiment lab, and the room temperature, lighting were kept consistent for all of them. A photo taken during the experiment in shown in figure 1 (a).

EEG data was collected using the Emotiv EPOC [14] headset device. It is a 14-channel wireless headset that collects signals from the pre-frontal, frontal, temporal and occipital lobes of the brain. The electrode placement of the device follows the International 10-20 System of Electrode Placement. Figure 1(b) shows the channel names and locations of the headset. The headset also has a 9-axis motion sensors. In order to setup the device, the electrodes are first hydrated using a conductive gel and then fitted on the participants' head. After ensuring good connectivity between all the electrodes and the scalp, participants' baseline EEG values were collected.

This was done by asking participants to keep their eyes open for 15 seconds, then keep their eyes closed for 15 seconds. Raw data from the device was collected at a sampling rate of 128 Hz, while the band power data is collected at a sampling rate of 8 Hz. The data was recorded using the Emotiv Pro Software.

(a) Experimental setting



(b) Emotiv EPOC Channel Location and Names [5]

Figure 1: (a) shows a photo of the experimental setting. 1(b) shows an image of the head and the locations where electrodes are located are highlighted in green.

In the final step before starting the experiment, participants were asked to wear a pair of Bose QuietComfort® 20 Acoustic Noise Cancelling™ headphones to ensure participants were not affected by any outside noise. Participants' verbal responses and comments were collected through an interactive website. At the start of the experiment, participants were asked some pre-experiment demographic questions such as their age, gender, music preferences etc. They were also asked if they had experience in playing musical instruments.

After completing the pre-experiment questionnaire, the experiment began. All the participants listened to the six music pieces. Each music piece was played for two minutes. The music pieces were order balanced to reduce bias which may occur due to the presentation order. While each music piece was playing, participants watched short video clips showing people displaying different emotions. The videos were order balanced as well. Then they were asked the following question, "How does the expression presented in the video look to you?". This was a closed question where the two options below were given,

- ***Genuine Emotion*** means the dominating emotion this person experienced is genuine
- ***Acted Emotion*** means this person acted the emotion

They were further asked whether they had seen this video clip before. Most of the participants said that they had not watched the clip before. So their verbal and physiological responses can be considered to be free from prior bias on the videos. After each music stimuli finished playing, participants were asked an open ended question to provide comments on the music.

3 RESULTS AND DISCUSSION

3.1 Findings on Stimuli

We performed a qualitative analysis on the comments participants provided on the music stimuli by using a grounded theory approach [17]. We used NVivo 12 software to complete this analysis. Memos on NVivo were used for coding participants comments into higher level themes. The comments were divided based on how participants described what they felt while listening to the music. These codes were then divided into three categories: positive, neutral and negative. During the coding process, frequently appearing words that were considered negative were: 'dislike', 'depressing', 'irritating', 'disturbing'. Some of the comments highlighted as positive were: 'like', 'calm', 'relax', 'soothing'. The neutral comments mostly described some features about the music, or whether they heard the song or not, and the comments did not reflect participants' emotions. Some of the common words used for neutral comments were: 'slow', 'fast', 'know', 'familiar' etc. Table 1 shows the percentage of participants providing different types of comment on the stimuli.

All 22 participants provided comments on the six stimuli. So, a total of 132 comments were analyzed to extract some general themes that were prevalent. The analysis of participants' verbal and physiological response (described in section 3.2) aligns with the themes presented in section 3.1.1-3.1.3. These themes are described below. Participants are mentioned as P1, P2... etc.

3.1.1 Binaural beats inducing gamma waves causes discomfort and distraction. The stimulus Binaural Beats 1 (Brain Energizer) was designed to improve the level of concentration and focus of the brain. Thus our expectation was that it will help participants with the video emotion classification task. However, surprisingly, this stimulus received quite a few negative comments (45.5%) and said to cause discomfort among participants. One participant (P19) mentioned that they "*...disliked the continuous tone underlying, became quite irritating*". Another participant (P17) added, "*...Background droning noise was off-putting. Sounded sci-fi like*". This was unexpected and also resulted in a lower classification result, which is described in detail in section 3.2. Binaural Beats 2 (Serotonin Release Music with Alpha Waves) on the other hand received the expected reaction from the participants. It was meant to increase alpha waves on the brain and promote relaxation, it often made the participants too calm to focus on the given task. According to participant P14, "*...it*

Table 1: Type of Comments Provided by Participants on Each Music Stimuli

Stimuli	Negative Comments	Neutral Comments	Positive Comments
Binaural Beats 1	45.5%	22.7%	31.8%
Binaural Beats 2	18.2%	18.2%	63.6%
Classical 1	36.3%	22.7%	41%
Classical 2	18.2%	0%	81.8%
Pop 1	9.1%	13.6%	77.3%
Pop 2	13.6%	18.2%	68.2%

was a slow piece and made me feel sleepy and hindered with concentration". Another participant (P17) mentioned, "*I liked this piece, it was very calming. Sounded like mindfulness/meditation music*".

3.1.2 Classical music having a sombre tone helps increase focus and answer questions. The stimulus Classical 1 (Funeral March) is played in a minor key and has very slow recurring patterns and accents. Therefore, the stimulus in general should invoke sad emotions. This was aligned with the participants' comments on this stimulus. However, although some participants reported that the music stimuli made them feel sad and depressed, they also thought it had a calming effect and therefore helped them focus in identifying the emotions from the video stimuli. For instance, P20 commented about this stimuli by saying, "*...this piece is a bit sad, but it helps while answering questions*". P2 said, "*...feels heavy to listen but like*". This resulted in this stimuli receiving more positive comments than negative (36.3% negative comments, 41% positive comments), which was mildly surprising. This theme was also observed in the better classification results of participants' verbal and physiological responses using Classical 1 stimulus which is described in section 3.2. In comparison, Classical 2 (Air) mostly received positive comments and said to have a very relaxing effect. One participant (P7) mentioned, "*...the quiet piece playing in the background makes it nice and easy to hear*". Another one (P17) said, "*I loved this piece. The music was smooth and rich. The violin was beautiful and very inspiring*". Although this piece was generally liked by the participants (81.8%) and induced a relaxing effect, it did not contribute as much to the video emotion classification task compared to the previous stimulus, and had a similar effect as Binaural Beats 2 on the classification accuracy.

3.1.3 Pop songs received positive feedback due to familiarity, but that can also be distracting. Both music stimuli in the pop category received mostly positive comments (Stimuli 1 and 2 received 77.3% and 68.2% positive comments respectively). In addition, both stimuli were familiar to the participants (21 out of 22 participants were familiar with at least one of the songs). This may have added certain bias from the stimuli or the artists, which may have affected their task performance. Commenting about Pop Song 1 (Love Yourself by Justin Bieber), one participant (P11) mentioned this piece as, "*...familiar and predictable*", while another (P17) said, "*I liked this piece because it was soothing and I listen to it frequently, it has a calming vibe*". Pop Song 2 (Shape of You by Ed Sheeran) generally received favourable comments such as "*I like this song, probably one of my favourites. It makes me somewhat dance to the beat*" (P1). Another participant (P14) said, "*...upbeat tune and heard a lot so made me feel comfortable*". However, the familiarity and biases may have caused some mixed outcomes in the classification tasks and therefore needs to be analyzed in greater detail.

3.2 Verbal and Physiological Data Analysis

The results from participants' verbal and EEG responses showed a strong correlation with the comments they gave on the music stimuli. We used the video labels provided by the original datasets as the ground truth and compared them with participants' verbal and physiological responses. For the preliminary analysis reported in this paper, out of the 14 channels of Emotiv EPOC, we chose data from two channels, F7 and F3. Both of these channels are located in the frontal lobe and they have been connected to emotion processing [29, 31] and decision making [8]. These channels have also been shown to contain the most useful features for classifying different types of music using participants' EEG signals [28]. We chose the alpha and gamma band power data as features. The data were first normalized using min-max normalization because these signals tend to vary in range i.e. being subject-dependent. We then segmented the data according to the length of videos. Finally, we applied baseline correction in order to remove environmental noise from the signals. These segments were then used to classify genuine and acted emotion labels using a one dimensional CNN (1D CNN) network. The 1D CNN has shown impressive results in analyzing physiological signals [4]. It also has the advantage of automatic feature extraction, which eliminates the process of handcrafted feature extraction and reduces computational complexity. Due to the size of data being very small, we opted for a simple architecture with two convolution layers, two maxpool layers, one dropout layer and two dense layers. We performed a 5-fold cross validation by randomly splitting 80 percent data for training and 20 percent data for testing. For evaluation measures, we report the classification accuracy and F1-score. F1-score is the harmonic mean of precision and recall, and it is considered to be a stronger measure than accuracy in revealing useful information in groups having different properties [16]. The results of participants' verbal and EEG response classifications are shown in figure 2 below:

From figure 2 it can be seen that the highest accuracy using participants' verbal and EEG response were 62.5% and 68.6% respectively and both were achieved when participants listened to the classical 1 stimulus. The F1-score using Classical 1 stimulus is 0.69, which is also the highest out of all conditions. This suggests that music stimuli that can invoke a sad emotion also help centering focus in identifying genuine and acted emotion from videos. The next best performance was achieved using Pop 2 stimuli, achieving

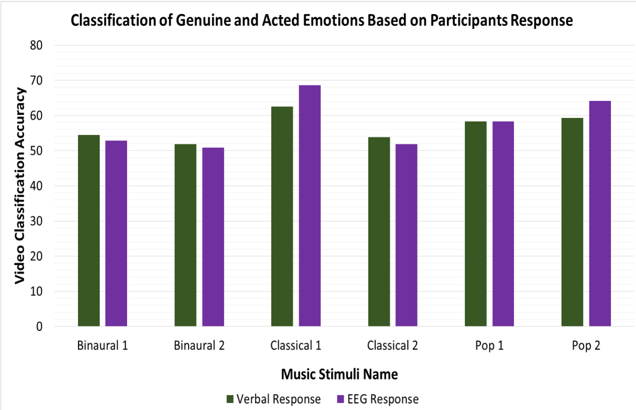


Figure 2: Classification Results Using Participants Verbal and Physiological Response

Figure 2 description Bar graphs showing the classification accuracy of genuine and acted emotions based on participants verbal and EEG response. Green colour bars indicate verbal response and purple colour bars indicate EEG response. X axis shows the six stimuli. Y axis shows the classification accuracy in percent.

64.1% accuracy and 0.64 F1-score using participants' EEG response. This stimulus was also liked by participants due to its familiarity and liking for the artist. It is also worth noting that this stimuli has a high valence score (mentioned in section 2.1). In contrast, Binaural Beats 1 achieved low accuracy of 52.8% and 0.53 F1-score in detecting genuine and posed emotions. This result is contrary to what have been suggested in some papers in the literature about gamma music helping with focus [9]. Binaural beats 2 which induces alpha waves in the brain showed the expected outcome as participants performed poorly when listening to this piece (51.9% and 50.9% accuracy using verbal and EEG response respectively). Other stimuli which also promoted high levels of relaxation such as Classical music 2 also achieved low accuracy (53.8% and 51.8% accuracy using verbal and EEG response respectively). This is expected as these stimuli were meant to promote relaxation and therefore mostly used for mediation, sleep studies etc [33].

A further observation from the results is that, in three out of the six cases, participants' EEG response performed better than their verbal response in classifying between genuine and acted emotion. Although physiological response did not perform better in all cases, this aligns with previous studies which showed participants' physiological response performs better than their self-reports in recognizing emotions from videos [30]. It should be noted that two out of the three stimuli where participants EEG response resulted in lower accuracy were Classical 2 and Binaural Beats 2. Both of them had a relaxing effect on the participants, which hindered their task performance. The other stimuli was Binaural Beats 1, which caused discomfort in many participants, resulting in poor task performance. Our results suggest that three stimuli, Classical 1, Pop 1 and Pop 2, helped participants keep their focus during their task, and this was reflected better through their EEG response. We also performed a one-way ANOVA test among all the cross-validation results across the six stimuli. The result shows high statistical significance ($p < 0.01$). We also conducted paired sample t-test for all pairs of stimuli results. The pairs that were not statistically significant were Classical 2 - Instrumental 1; Classical 2 - Instrumental 2; Classical 2 - Pop 1 and Instrumental 1 - Instrumental 2. The other pairs were significant. This gives us motivation to explore this study in greater detail to understand and identify the effects of different music stimuli in participants' physiological response in detecting different type of emotions.

4 CONCLUSION AND FUTURE WORK

In this paper, we conducted a study to identify what types of music stimuli are beneficial to help improve concentration while identifying genuine and acted emotions from short video clips. Participants' EEG and verbal response were collected and analyzed using different approaches. A grounded theory approach was applied on participants' comments in order to understand their emotional reaction to the music stimuli. Then participants' performance in the experiment task of identifying emotions from videos were analyzed and compared using their verbal and EEG response. We further compared the outcomes of the grounded theory approach on participants' verbal comments to their performance in the experiment tasks. Our preliminary results show that classical music possessing a sombre tone increases concentration on the brain and helps participants identify different emotions from video clips. Familiar and popular music with high valence also help improving participants' focus. The study also reveals a crucial outcome related to binuaral beats which are believed to improve focus in the brain. Our results showed that certain binaural beats can also cause discomfort to participants, which results in disrupting focus in participants and thus achieving lower accuracy in detecting emotion veracity. Our study further shows that participants' EEG response perform better than their verbal response in identifying emotion from videos, when incorporated with a music stimuli that increases their focus on the task.

There are some limitations to this study. Due to the limited number of participants, the dataset is quite small and therefore the collected signals were not sufficient to train a suitably deep network. Future work will involve collecting more data to build a more robust model. It should also be noted that the study results are specific for the task of identifying genuine and acted emotions. This task can be important in for example judging the veracity of politicians' emotions while background music is playing in an election video. For tasks that require a high level of concentration, e.g. mathematical tasks, sudoku solving etc, the results may be different. More analysis will be done based on different tasks in the future. Future work will also involve considering the valence and arousal level of the music stimuli and do a broader comparison with other machine learning techniques, handcrafted features etc. Nevertheless, the results are promising and shows the usefulness of different types of music stimuli facilitating emotion recognition tasks. The use of binaural beats, specifically gamma inducing beats deviated from the expected outcome. This demands a further investigation into similar types of music stimuli and the use of physiological signals to identify which music stimuli are truly beneficial to improve concentration on various kinds of tasks, rather than just assumed to be.

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