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Research Article

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What is the Best Music for Neurofeedback Training?

Exploration into musical attributes that contribute to success in music neurofeedback

Abstract

The nucleus accumbens (NAc) is widely known for its role in reward seeking behavior which is heavily reliant on dopamine signaling. Dopamine plays an important role in reward seeking behavior and motivation and its dysregulation is shown to cause symptoms of depression such as apathy, a lack of motivation, and anhedonia, a loss of pleasure. Studying the NAc, specifically the ventral striatum in this case, is critical in understanding the underlying mechanisms of this dysregulation. Music neurofeedback is a biofeedback technique that provides feedback on brain activity through the audio quality of the music, with lower quality sounding more muffled. This study uses this technique to train participants to increase the activity of their ventral striatum in an attempt to upregulate the activity of the reward system.

This paper aims to investigate what the most effective music choices are in terms of genre, key, valence (positive or negative emotions) and energy (pertaining to levels of arousal) to maximize the improvement on neurofeedback training. These musical attributes were identified by the Spotify "Organize Your Music" categorization tool. Participants underwent six EEG music neurofeedback training sessions with individually tailored pleasurable music as the source of feedback. The participants either received real feedback in the neurofeedback group (NF) or sham feedback in the control group. The results of this study showed that neurofeedback performance was negatively correlated with valence whereby songs that led to the greatest performance, measured as increase in ventral striatum activity from baseline, were those low in valence. Participants that had the greatest improvement in their neurofeedback training selected songs that were in a minor key and belonged to the pop genre. Although this study is based on a small sample, it takes the first step towards the overarching goal of using music to manage dysregulation in the reward system.

Introduction

Music is a pleasurable stimulus that transcends age, gender and cultural differences. Previous studies have shown that listening to music activates many brain areas including the auditory cortex, amygdala and most notably the NAc. (14) The NAc regulates the release of dopamine and plays a crucial role in reward processing of both natural rewards like food as well as drugs, which has been studied previously in animals (Britt et al, 2012). The involvement of the NAc in music listening underscores the music-derived pleasure whereby the amount of enjoyment a participant experienced from listening to a certain song can be predicted by the increase in connectivity between the auditory cortex and the nucleus accumbens. (14) Reward system dysregulation has been heavily investigated in psychiatry. Anhedonia, the lack of pleasure, is a main symptom of depression as classified by the DSM V in 2013.

Studies have attributed this decreased feeling of pleasure to reduced activity in the NAc in response to reward. (13) Studies by Barch and colleagues in 2011 showed that this dysregulation in the reward system can start as early as three years of age for children with or at risk of depression as determined by parent reports and behavioral tests. Knowing that depression is a leading cause of disability worldwide (WHO, 2018) finding ways to alleviate it is crucial. This led to the search for techniques to upregulate the reward system in hopes of reducing the severity of anhedonia and apathy symptoms. (16)

In the past, techniques that aim to stimulate brain areas were not very convenient such as deep brain stimulation which is very invasive. (8) Therefore, a need for a non-invasive, volitional technique came about. Neurofeedback is a biofeedback technique that provides continuous neural feedback to the participant to help them regulate the activity of certain brain regions. Previous studies using visual imagery have confirmed that neurofeedback can be successful in training participants to upregulate the reward system. (7; 17). Combining these findings with our knowledge of the pleasurable nature of music, music neurofeedback can be utilized for this purpose in the form of music quality; clearer quality indicating greater activity in the region of interest. This paper uses EEG music neurofeedback as opposed to fMRI based on findings from Keynan and colleagues in 2016 that suggest that mesolimbic brain activity can be reliably recorded using EEG by establishing an electronic fingerprint (EFP) for the region of interest.

As music is such a complex stimulus, it is critical to identify the musical features that may be associated with neurofeedback success. When classifying music in the affective/emotional domain, the literature tends to follow a circumplex model of two attributes, valence and arousal (11), suggesting that happier, exciting music has positive valence and high arousal whereas sad, calm music has a negative valence and low arousal. Studies have found that participants that experienced musical chills, a physiological response related to feeling of pleasure from music (1), reported the song to have been both happy and sad (9) leaving a valence assignment to be desired.

The paper showed that compared to the physiological tears group, the chills group scored higher on measures of arousal and rated their self-selected music as significantly happier. (9) Extrapolating these results to musical attributes, this would suggest that higher valence, higher arousal music is associated with chills, an indication of pleasure from music. Two other musical attributes, key and energy were analyzed to extend the exploration beyond the typical model of valence and arousal.

This paper aims to answer the question of what musical attributes are associated with the greatest improvement in neurofeedback training. Based on the previous literature, we would predict that songs with higher valence and energy levels should yield the greatest improvement in neurofeedback performance.

Methods

Participants

10 control and 10 test subjects ages 18-35 were recruited (9 male, 11 female, mean age = 21.1, standard deviation = 2.8). Eligibility criteria included no known medical diagnoses, including neurological or psychiatric disorders, hearing impairments. All participants were fluent English speakers. Participants provided written informed consent prior to experiment and were monetarily compensated upon finishing the experiment. All procedures were run in accordance with the Montreal Neurological Institute's research ethics office (REB) guidelines.

Two participants were excluded from the analysis: one participant was excluded from all analyses pertaining to performance because their first three sessions were sham (control) sessions although they were assigned to the test group. Another participant was excluded from all analyses pertaining to music because their songs could not be found by the Spotify organization tool. Two participants had one session each excluded when calculating their average improvement in maximal performances due to technical issues pertaining to those sessions.

EEG Recording

EEG measurements were acquired during the six music neurofeedback training sessions using a BrainAmp EEG amplifier. EEG activity was recorded from a 14 electrode channels EEG cap. The EEG was sampled at a rate of 250Hz and recorded from the following 14 channels: FP1, FP2, C4, F7, F8, T7, T8, P8, Fz, Cz, Pz, TP9, TP10, ECG. The data was recorded using the Brain Vision Recorder software (BrainProducts, GmbH, Germanny).

Music Neurofeedback Task

Participants completed six training sessions lasting 1.5-2 hours, over the course of two to three weeks. Each session consisted of a global baseline run, five training cycles and a transfer run (same instructions as the training cycle but without music/feedback). All runs required the participant to sit still with their eyes closed with earphones in while wearing an EEG cap. Each participant was asked to provide their top 10 favorite songs to be used during the neurofeedback training sessions.

The neurofeedback was produced using the NFM software, an in-house Graphical User Interface, which was implemented with the OpenViBE software for brain computer interface. For the global baseline period, the participant was asked to clear their mind so that their baseline neural activity level could be measured. The training cycles involved listening to music and were split up into a passive listening and training phase, lasting 2.5 and 2 minutes, respectively.

During the listening phase the music quality was extremely poor while during the training phase, the participant received continuous neurofeedback reflected in the music quality which was manipulated using filtering. Worse quality equated to lower neural activity in the electrical fingerprint (EFP) of the NAc and more frequency bands filtered. During the listening phase, the participant was simply prompted to passively listen to the music whereas during the training phase they were asked to regulate their brain activity using a suggested strategy (see below) or one of their choosing. Between every training cycle, the experimenter asked the participant questions regarding their general mood, how well they thought they did on a scale of 1-7, and what their chosen strategy was. In addition, they were shown a graph of the neural activity of the particular cycle which was indicative of performance. The participant was requested to adapt their strategies according to the feedback presented in order to determine the most effective one for them. Control participants underwent the exact same procedure except they received sham feedback which came from a different participant.

Strategies

The participant was prompted to explore the following four strategies throughout the training sessions and to evaluate their effectiveness in increasing neural activity and improving the quality of the music during the training phase:

1. *Imagination*: imagination centered around the song/piece or artist, usually involving a concert or imagination of the artists performing. Included imagination of singing or dancing along to the song.

2. *Memory*: recollection of happy memories. The memories did not have to be connected to the song at all but in some cases may be.

3. *Visual imagery*: imagination involving any visual images not directly related to the song or artists of the song/piece.

4. *Motor imagery*: imagination that involved motor movements specifically pertaining to playing instruments (typically related to the song/piece)

Data Analysis

Neurofeedback analysis:
Performance for every cycle was calculated by subtracting the average EFP at baseline from the average EFP during neurofeedback training. Improvement in maximal performance was calculated by subtracting the performance of the best cycle of the first session from the performance of the best cycle of each of the other sessions. These five values of improvement of maximal performance were then averaged to get one numeric measure of performance which is the average improvement in maximal performance with a greater value indicating better performance. Throughout the rest of the paper, the average improvement in maximal performance will simply be referred to as performance. Subgroups of good and bad performances in test and control groups were assigned using a median split whereby participants with performance greater than the median of the test group (median = 0.058) were categorized in the "good performer" category and those below the median belonged to the "bad performer" category.

Music analysis:
All information regarding the musical attributes of the songs were retrieved from a Spotify tool called "Organize Your Music" (http://organizeyourmusic.playlistmachinery.com/). The information used came from the measures of: valence, energy and genre. This Spotify tool operates according to algorithms that have been explained in depth by Jedmar et al (2015) which included analyzing lyrical and audio features extracted using the online music intelligence platform The Echo Nest and weighting them through statistical analyses. Information regarding song key was retrieved from https://tunebat.com/Analyzer. Analyses were run using attributes of all the NF songs as well as the song of the cycle that had the best performance overall, which will be referred to as the "best song" hereafter. This was done to observe any possible discrepancies between the general trends of the chosen songs as compared to the song with the best performance.

Statistics

To analyze the difference in performance between the control and test groups, a paired samples t-test was conducted using the coupling of neurofeedback received since every control participant received sham feedback from a specific NF participant. One-Way ANOVAS were conducted across groups for comparisons of song valence, % major and energy levels and Tukey's HSD post hoc comparisons were run when appropriate. A Shapiro-Wilks test was used to establish that the data was normally distributed. A Pearson correlation was used to assess the association between song valence and energy with performance. Correlations were collapsed across groups to compare the music attributes to performance regardless of the accuracy of neurofeedback received. Separate correlations were run exclusively for the NF group. Error bars on the graphs represent +/- standard error of the mean (SEM). The significance level was set to $p < 0.05$.

Results

Neurofeedback Performance

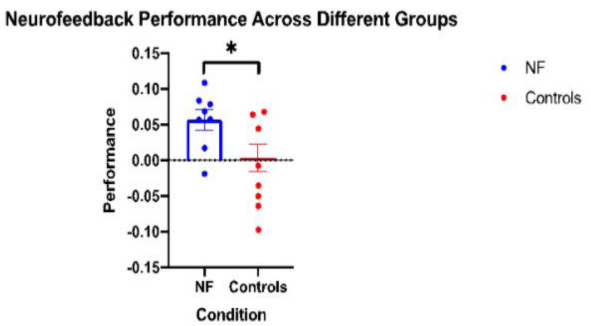


Figure 1. Neurofeedback performance across groups. (a) Difference in performance between control and NF groups. Error bars represent +/- SEM. Scattered data points represent individual performances. * indicates $p < 0.05$.

A paired samples t-test was conducted to analyze the data from neurofeedback performance across the control and NF groups (fig. 1). There was a significant difference in means of neurofeedback performance between groups ($t(7) = 3.692$, $p < 0.05$) suggesting that the NF group neurofeedback performed significantly better than the control group.

Valence

A one-way ANOVA was conducted to analyze the average valence of the neurofeedback training songs across the four subgroups (fig. 2a), which was not significant ($p > 0.05$). This indicates that there was no significant difference between the mean of average valences of the training songs across the groups, thus confirming that the observed group effects of training cannot be explained by a mere difference in the valence of the musical selection. A Pearson correlation was conducted for average valence of training songs vs performance across all groups (fig. 2b) which was also not significant ($p > 0.05$).

A one-way ANOVA was also conducted to analyze the data from the valence of the "best" song across the four subgroups (fig. 2c). The differences in means of best song valence across the four groups was not significant ($p > 0.05$). This indicates that there was no significant difference between the mean valence of best song across the groups. A Pearson correlation was conducted for valence of best song vs performance across all groups (fig. 2d). There was a significant negative correlation ($R = -0.468$, $p < 0.05$) indicating that performance improved as valence of the best song decreased across the entire sample.

Neurofeedback Performance

A one-way ANOVA was conducted to analyze the average energy level of the neurofeedback training songs across the four subgroups (fig. 3a). The differences in means of average training song energy across the four groups was not significant ($p > 0.05$) indicating that there was no significant difference between the mean of average energy of the training songs across the groups. A Pearson correlation was conducted for average energy of training songs vs performance across all groups (fig. 3b). There was a small positive correlation ($r = 0.2061$) however it was not significant ($p > 0.05$).

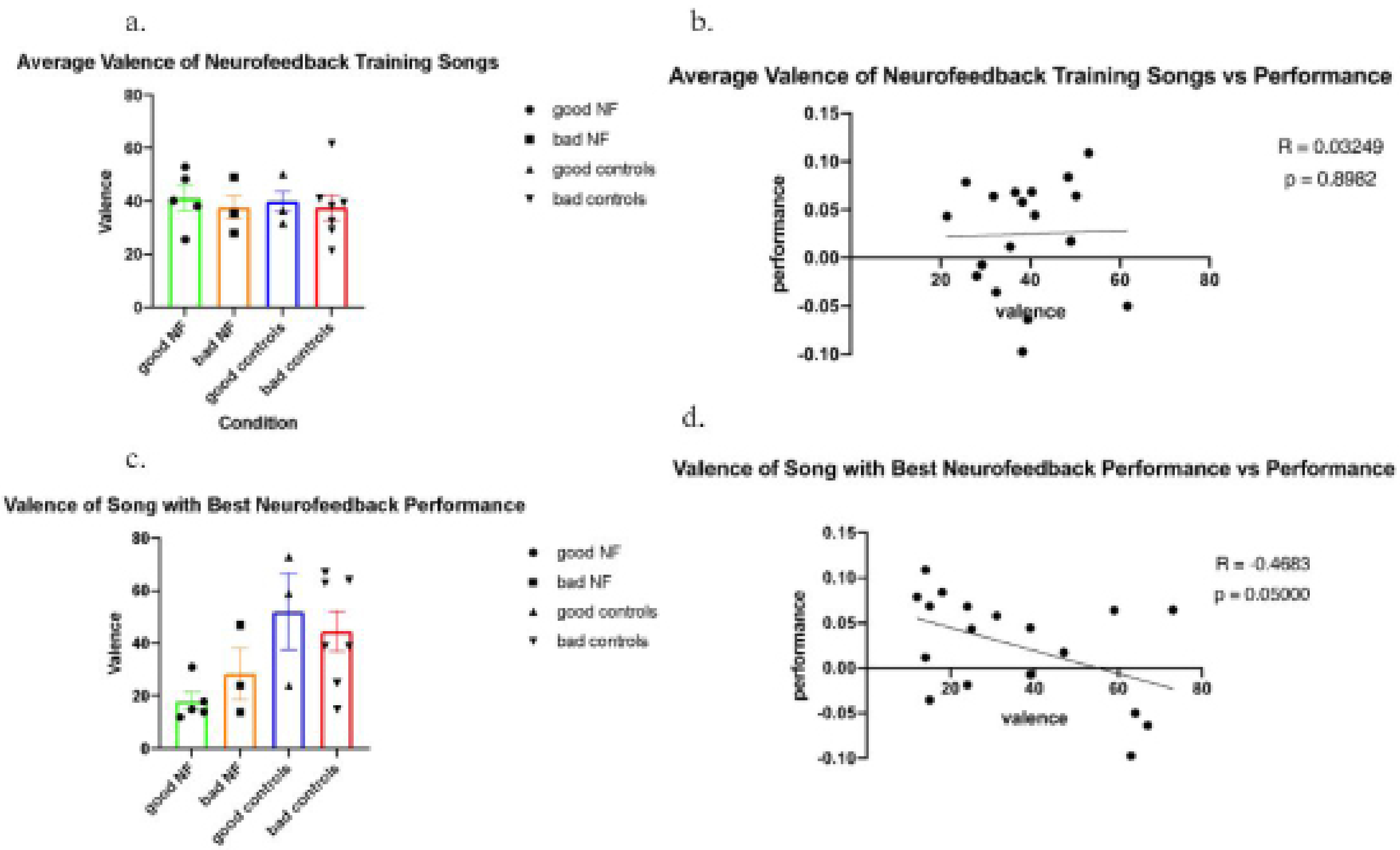
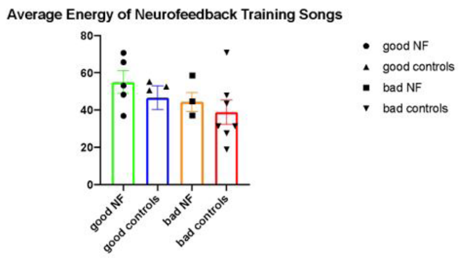


Figure 2. Song valence across subgroups. (a) Average valence of training songs across the four subgroups. (b) Correlation of the average valence of training songs with performance across all subgroups. (c) Valence of the best song across the four subgroups. (d) Correlation of the best song valence against performance across all subgroups. Error bars represent +/- SEM. Scattered data points represent individual performances. * indicates $p < 0.05$.

A one-way ANOVA was also conducted to analyze the data from the valence of the "best" song across the four subgroups (fig. 2c). The differences in means of best song valence across the four groups was not significant ($p > 0.05$). This indicates that there was no significant difference between the mean valence of best song across the groups. A Pearson correlation was conducted for valence of best song vs performance across all groups (fig. 2d). There was a significant negative correlation ($R= -0.468$, $p<0.05$) indicating that performance improved as valence of the best song decreased across the entire sample.

Energy

a.



b.

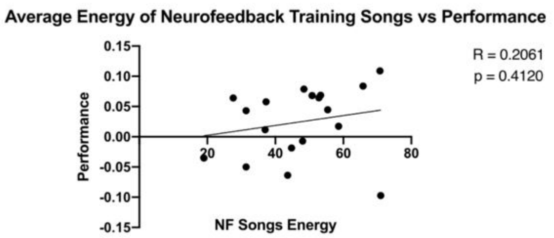
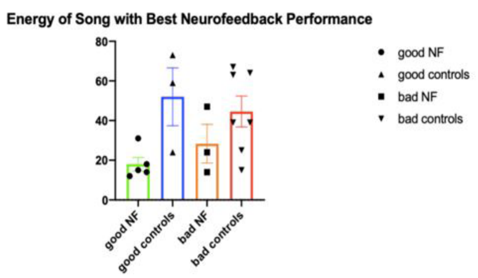
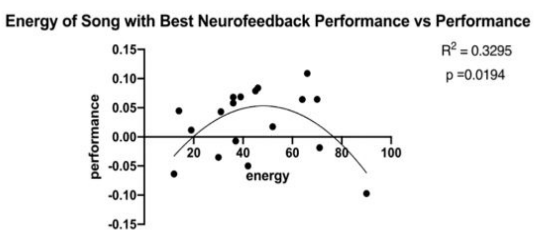


Figure 3. Song energy across subgroups. (a) Average energy of training songs across the four subgroups. (b) Correlation of the average energy of training songs with performance across all subgroups. (c) Energy of the best song across the four subgroups. (d) Correlation of the best song energy against performance across all subgroups. Error bars represent +/- SEM. Scattered data points represent individual performances. * indicates $p < 0.05$.

c.



d.

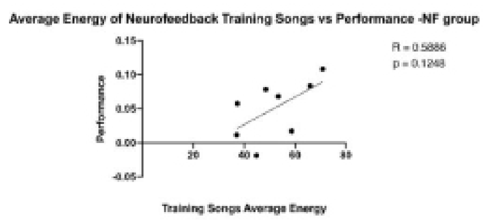


A one-way ANOVA was conducted to analyze the average energy level of the neurofeedback training songs across the four subgroups (fig. 3a). The differences in means of average training song energy across the four groups was not significant ($p > 0.05$) indicating that there was no significant difference between the mean of average energy of the training songs across the groups. A Pearson correlation was conducted for average energy of training songs vs performance across all groups (fig. 3b). There was a small positive correlation ($r = 0.2061$) however it was not significant ($p>0.05$).A one-way ANOVA was conducted to analyze the data from the energy of the best song across the four subgroups (fig. 3c). The differences in means of best song energy across the four groups was not significant ($p > 0.05$). This indicates that there was no significant difference between the mean energy of best song across the groups. A second order polynomial was fit to the distribution of best song song vs performance across all groups (fig. 3d). A nonlinear regression analysis was conducted yielding ($R2 =0.3295$, $F(1,15) = 6.859$, $p = 0.0194$) which suggests that the second order polynomial was a good model for the distribution of best song energy across performance levels and 33% of the variation in performance can be attributed to the energy level of the best song.

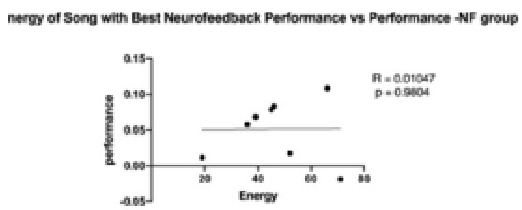
NF Group Correlations:

Four Pearson correlations were run for valence and performance and energy and performance specifically for the NF group (fig. 4a-d). All four correlations were not significant. That being said, a trend of positive correlation was found for average energy against performance ($r =0.59$, $p =0.12$) and average valence against performance ($r =0.44$, $p =0.27$). A negative correlation was found between the valence of the best song and performance ($r = -0.44$, $p = 0.27$).

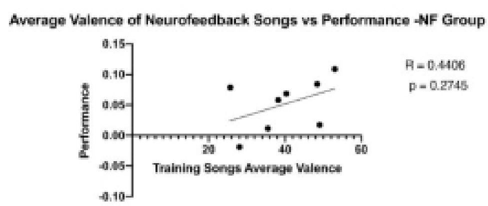
a.



b.



c.



d.

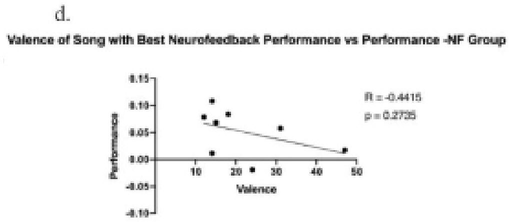


Figure 4. Energy and valence correlations exclusively for the NF groups. (a) Correlation of average energy of training songs vs performance. (b) Correlation of best song energy vs performance. (c) Correlation of average valence of training songs vs performance. (d) Correlation of best song valence vs performance. Error bars represent +/- SEM. Scattered data points represent individual performances. * indicates $p < 0.05$.

Genre and Key Breakdown

The pie charts (fig. 5a-h) show that the most common genre for the best song across all four subgroups is pop and that the most common key for all the subgroups except the bad controls is minor.

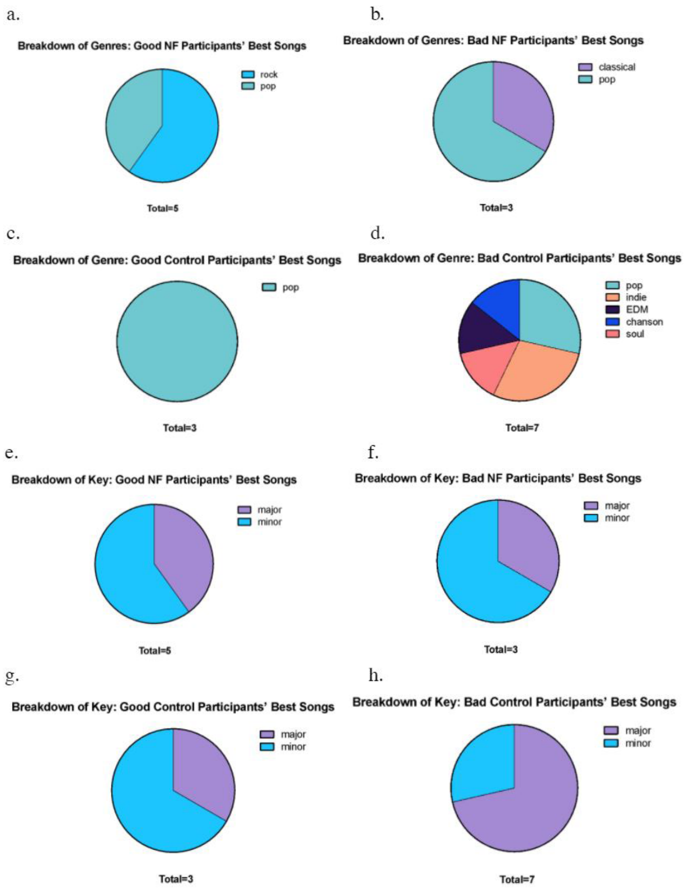
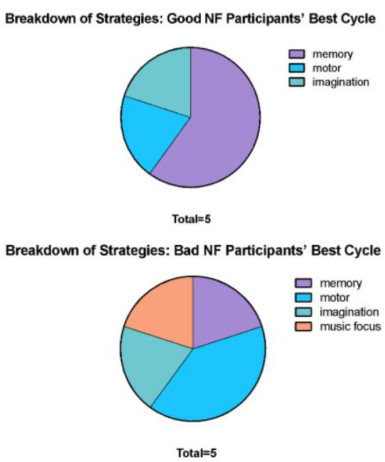


Figure 5. Genre and key of best song breakdown across the four subgroups. (a) Best song genres of good NF group. (b) Best song genres of bad NF group. (c) Best song genres of good control group. (d) Best song genres of bad control group. (e) Best song key of good NF group. (f) Best song key of bad NF group. (g) Best song key of good control group. (h) Best song key of bad control group.

Strategies of Best Cycle Breakdown

The pie charts (fig. 6a-d) show that the most common strategy used during the best cycle is memory across all four subgroups.



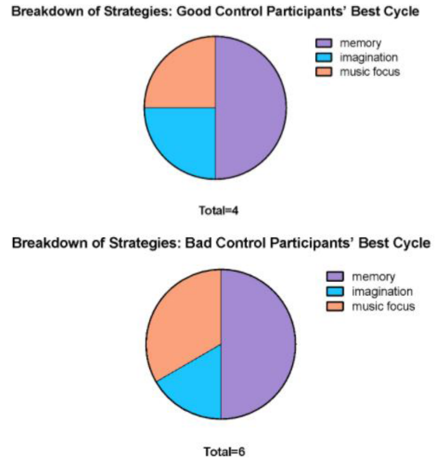


Figure 6| Best cycle strategy breakdown across the four subgroups. (a) Best cycle strategies of good NF group. (b) Best cycle strategies of bad NF group. (c) Best cycle strategies of good control group. (d) Best cycle strategies of bad control group.

Discussion

This paper aimed to investigate what music attributes were linked to best music neurofeedback performance. The musical attributes investigated were: valence, energy (arousal), key and genre. Participants were split into NF and control groups. Results compared groups and subgroups as well as collapsing the data across the entire sample and observing trends. We hypothesized that songs with higher valence and energy levels would be associated with the greatest improvement in neurofeedback performance. However, our data showed that songs with lower valence, medium energy levels, minor keys and within the pop genre were related to neurofeedback success.

Valence and Performance link: best song valence negatively correlated with performance

The valence of songs was extracted using the Spotify organizational tool as an indication of how happy or sad the song felt. Following work from previous studies, we hypothesized that songs with a more positive valence would be correlated with greater performance (9) however our data does not support this. Valence was correlated against performance in two ways. The first was the average valence of the songs used during the neurofeedback training. The second was the valence of the song of the cycle with the best neurofeedback performance. Average valence did not show significant correlation across the entire sample, nor within the NF group. For the NF group, although insignificant, here seemed to be a trend for the NF group whereby greater average valence was linked with greater performance. These results suggest that on average, music that subjects find pleasurable is highly variable in terms of valence which aligns with research regarding participants finding their own self-selected music pleasurable. (1)

The valence of best song showed a more interesting result. Across the entire sample, a strong negative correlation was found between best song valence and performance ($r = -0.468$, $p = 0.05$). This correlation maintained in the correlation of the NF group only however it was not significant ($r = -0.44$, $p > 0.05$). This finding suggests that songs with a negative valence are linked to increased performance regardless of whether the neurofeedback received is accurate (NF group), or not (control group). Studies have found that music can induce a sad affective state depending on the personality of listeners (18) however, people continue to listen to, and in fact enjoy sad music. (19) A systematic review suggests that sad music is found pleasurable "when it is perceived as non-threatening, aesthetically pleasing and produces psychological benefits such as mood regulation." (12) These studies may help explain why participants seemed to have increased pleasure levels with the more negative valence songs, contrary to what had been hypothesized.

Energy and Performance link: medium energy for best song optimizes performance

The energy of songs was extracted using the Spotify organizational tool as an indication of arousal levels. We hypothesized that songs with higher energy levels would correlate with greater performance based on literature that suggested participants who experienced musical chills rated their songs as high in arousal (9) however our findings do not fully support this. The average energy of neurofeedback training songs did not correlate significantly with performance across the entire sample or across the NF group alone. However, there seemed to be a trend that was more defined in the NF group correlation, whereby a greater average energy score correlated with greater performance ($r = 0.59$, $p = 0.12$). Once again this is probably due to the large variation in energy levels in song preferences even within the same participant. The energy of the best song across the sample seemed to follow an inverted u-shape curve when correlated against performance and fit nicely to a second order polynomial function ($F(1,15) = 6.859$, $p = 0.0194$). This finding suggests that songs with the best performance fell in a medium energy score of around 50. A possible explanation for this could be that songs that had high energy levels were overpowering the participant's focus which led to decreased performance. In 2010, Sandstrom & Russo showed that higher arousal music was not as effective at helping a participant recover from an acute stressor so perhaps the same logic applies here, however more extensive research is needed to properly assess and understand this relationship.

Genre and Key Breakdown: successful participants selected minor songs and pop genre

Genre and key breakdowns provide more insight into the stimuli being used during the NF training sessions, particularly during a participant's best cycle. It was hypothesized that happier, higher energy songs would be linked to greater performance. Often, happy songs are characterized by a major key whereas more sad songs are characterized by a minor key. (2) So according to the hypothesis, we expected to see a greater number of major songs in the best song category which pertained to increased neurofeedback performance. However, consistent with the rest of our findings, the majority of the best songs had a minor key, which links back to the concept of sad songs generally being in a minor key. This data serves as a confirmation of the valence classification from the Spotify tool against the more traditional approach of categorizing music whereby major and minor keys were used to classify positive and negative valences respectively. (2)

The genre breakdown showed that the most common genre in the best song category across the entire sample was pop, however, this alone does not explain much. Possibly due to our age demographics, pop was the most selected genre across all song selections for the sample, so conclusions from the genre breakdown alone are not reliable. Having the genre information available may shed some light in later stages of the research when investigating interaction effects between genre, energy and valence for example. The strategy breakdown was also included for the same reason. Although the most common strategy for the best cycles was memory, it was also the most frequently chosen strategy overall, so conclusions regarding that cannot be drawn yet and require more extensive research.

Limitations of study

The biggest limitation of this study is the small sample size ($N=20$ although some participants were excluded in certain analyses) which leads to a decrease in statistical power. As such, we are less likely to detect effects if they are indeed evident. This small sample size also leads to an inability to generalize our findings past our sample, especially considering that it comes from a biased undergraduate sample. Nevertheless, this paper provides a necessary first step into the investigation of aspects of music that lead to greater improvement in music neurofeedback training but more research is required to solidify these findings and generalize them beyond the sample.

Another limitation of this study comes from the subgroup split design. In order to classify participants into better and worse performing groups, they were split using the median of NF participants. This allowed for a clearer definition of what "good" performance was regardless of whether it was in the control group or NF group. However, due to the control group split being dependent on the NF median, subgroup comparisons (for example good NF vs good controls) could not be reliably conducted. In future studies, splitting the groups according to each of their own medians instead would allow for these subgroup comparisons.

An additional limitation was regarding the variability of the music. The fact that measures of average valence and average energy both did not vary significantly with performance implies that the large variation in energy and valence across the sample was too heterogeneous to establish a clear correlation. This could be corrected for by using experimenter-selected music instead of participants to self-select their own music however that would compromise the increased pleasure that comes specifically from one's own music. Another aspect of variability that was not controlled for in this design was personality. Studies have shown that enjoyment of different types of music varies with personality traits. (19) In future studies therefore, it would be worth trying to focus on individuals that score high on a certain personality trait such as withdrawal (10) for example to reduce this variation. Finally, it is important to acknowledge that the statistical analyses conducted were correlational and causation cannot be implied from these findings as a result and it could be that there is an interaction effect between valence and energy, or other variables that contribute to neurofeedback performance.

Future Experiments

A finding that prompted future investigation ideas was that the significant correlations in best song energy and valence levels that were found were across the entire sample. This suggested that the effects of valence and energy on performance were evident regardless of whether or not the feedback the participant received was accurate. This motivates the question of whether highly pleasurable music can be just as effective at upregulating the NAc activity as neurofeedback. According to our findings, to answer this question, music that exhibits medium energy levels and low valence levels should be used.

Additionally, an expansion that was touched upon the discussion above was the need to separate the effects of energy and valence on performance. A suggestion for doing so would be to give participants music with a constant energy level and varying valences and vice versa to establish a more concrete effect of each by reducing the possible interaction. Additionally, an interaction effect could be investigated by giving participants music high in valence and arousal, low in valence and arousal or high in one and low in another and observe the effects that has on performance.

Further expansions from our data could include a more extensive analysis of genre and key. This could be executed by assigning participants music of a specific genre or key and observing its effect on their performance. This data could also be triangulated with the valence and energy data to try and establish a specific sub-genre that might be most effective at enhancing neurofeedback performance.

Finally, a component that this paper briefly touched upon is the use of mental strategies during the music neurofeedback training. In order to study strategies according to their effectiveness, independently of their frequency, success using a strategy should be characterized by dividing the number of best cycles using that strategy by the number of total cycles the participant used the strategy. This gives us a measure of percent success rate. This would mitigate the effect of having the most frequent strategy also be the one used on the most successful trials which was observed in our data. Additionally, a strategy-music interaction study can be proposed. This study would look at whether certain strategies are coupled with songs of a particular valence or energy. Within our discussions between training cycles, some participants mentioned that they have specific strategies for specific songs which would motivate this suggested interaction study. Overall, this paper is meant to be seen as a stepping stone in the much larger realm of investigating the effects of different aspects of music on neurofeedback training.

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