

Music and Mental Health

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Abstract

This study considers the correlational relationship between music listening and mental health, investigating whether listening frequency, genre, and music therapy practices provide associations with anxiety, depression, insomnia, and OCD. We utilized survey data from the MxMH Music Therapy dataset (n=629), collected through online surveys on public forums in 2022, alongside lyrical sentiment analysis from the Million Song Dataset. Using Ordinary Least Squares regression models and genre-specific comparative analysis, we analyzed relationships between music listening and self-reported mental health conditions. Our analysis proved modest but significant associations between specific genre listening frequencies and mental health outcomes (R-squared values: 0.056-0.092), with Metal and Rock correlating with higher depression scores while Country displayed the opposite, and higher daily music consumption positively predicting insomnia and OCD diagnoses. These findings suggest genre specific relationships between music consumption and mental health that cannot be reduced to simple frameworks of “more music is better” or “upbeat genres are healthier”. This research contributes to understanding music’s role in mental health and may inform evidence-based listening practices and therapy innovations. Future research should explore causal mechanisms and longitudinal effects of music consumption on human psychological well-being.

Keywords

Music, Wellness, Genre, Mental Health

1 Introduction

Throughout human history, music has served as a cornerstone of human social interaction and

storytelling, conveying emotions ranging from joy and triumph to pain and melancholy. Given music’s profound role in emotional expression, this study examines the relationship between music consumption and mental health outcomes, and how that relationship influences listening behaviors.

Our research seeks to identify correlational links between music listening habits and mental health status. Understanding these connections can inform more conscious listening practices and contribute to broader discussions about our cultural relationship with music. We build upon prior research by Rebecchini ("Music, mental health, and immunity"), Baker and Bor ("Can Music Preference Indicate Mental Health Status in Young People?"), and Golden et al. ("The Use of Music in the Treatment and Management of Serious Mental Illness: A Global Scoping Review of the Literature").

Based on this literature, we developed three hypotheses. First, increased frequency of music listening correlates with improved mental health outcomes. Second, listening to calm or upbeat genres (e.g., classical, pop, jazz) correlates with positive mental health indicators. Third, music therapy demonstrates statistically significant efficacy as a mental health intervention.

2 Data

Our preliminary analysis was conducted with data from the "MxMH" Music Therapy dataset compiled by Catherine Rasgaitis at the University of Washington. This dataset was compiled in 2022 through google form survey data posted in assorted online forums, as well as posted physically throughout locations in or near Washington University. The form was brief so that respondents would be more likely to finish the survey. This preliminary data consisted of 33 columns, and we only included the significant features of: Age, Hours Per Day, Favorite Genre,

Genre Frequency, and Mental Health Diagnosis. Two types of categorical variables were converted to numerical formats to enable quantitative analysis. The 'While working' variable, indicating whether respondents listen to music while working, was converted to a binary format where 'Yes' was mapped to 1 and 'No' (including NaN values) was mapped to 0. Additionally, all 'Frequency [Genre]' columns (e.g., 'Frequency [Classical]', 'Frequency [Country]', 'Frequency [EDM]') were transformed from categorical text responses to a numerical scale: 'Never' = 0, 'Rarely' = 1, 'Sometimes' = 2, and 'Very frequently' = 3. For our alternative analysis, we utilized the **Million Songs Dataset**. This dataset is a collection of one million songs from 2000-2012 with annotated features from **The Echo Nest**, a music intelligence and data platform. This data set was modified to include the significant features of: Genre, Lyrics. This was acquired online through the official Million Song Dataset website.

3 Materials & Methods

To examine the relationships between music listening habits and mental health outcomes, Ordinary Least Squares (OLS) regression models were constructed for each mental health aspect. The dependent variables were Anxiety, Depression, Insomnia, and OCD, each analyzed independently. Independent variables included numerical features ('Age', 'Hours per day', 'BPM') and the converted categorical features representing listening frequency for different genres. A constant term was added to each model to account for the intercept. The regressions were performed using the statsmodels.api.OLS function, and statistical outputs including coefficients, p-values, R-squared values, and diagnostic statistics were generated using results.summary() method. Genre-specific analysis was performed using average scores for each genre for respondents who reported listening to that genre 'Very frequently' (numerical value of 3 in the transformed dataset). These averages were compiled into a DataFrame (mhBarGraph) and visualized using bar charts with genres on the x-axis and average mental health scores on the y-axis. To quantify how each genre's mental health profile deviated from the overall population, compound scores were calculated for each mental health variable. First, the overall average score across the entire dataset was determined. Then, for each genre, the population average was subtracted from the genre-specific average. Positive compound scores indicated that frequent listeners of a particular genre tended to report

more severe symptoms than the overall average, while negative scores suggested less severe symptoms. These compound scores and the 'Very frequently' listeners per genre were stored in a separate DataFrame (compBarGraph) and visualized using bar charts. The lyrics data was extracted from the SQLite database through a processing pipeline. A connection to the database was established, and a SQL query (SELECT * FROM lyrics;) was executed to retrieve the lyrical data. The data was then processed to aggregate words associated with each unique track identifier. All individual words for a given track were collapsed into a single string, representing the complete lyrics for each song. This was done for enabling sentiment analysis on entire songs rather than on individual words or fragments. The collapsed lyrics data, containing track id and full song lyrics, was subsequently merged with genre classification information sourced from MSDGenre.txt. This text file provided mappings between track identifiers and their corresponding musical genres, allowing each song's lyrics to be associated with its genre category. Finally, the merged dataset was grouped by genre, and separate CSV files were generated for each musical genre.

4 Results

4.1 OLS Regression Analysis

Initial OLS regressions for each mental health category were run on listening frequency across genre, age, total listening hours per day, listening while working, and BPM returned statistically insignificant results. The R-squared value was between 0.05 and 0.10 for all mental health categories (anxiety = 0.056, depression = 0.092, insomnia = 0.063, OCD = 0.057). The only significant finding from these regressions was a two-tailed p value of 0.001 for age in the OCD regression, indicating a significant correlation between age and self reported OCD symptoms.

4.2 Genre-Specific Mental Health Scores

By plotting the average mental health indicator of the top listeners in each genre, it is seen that – across music genres – there is very little deviation in mental health scores. Along with this, Figure 1 shows that Latin music and video game music had some of the highest (worst) scores across mental health categories, however it is difficult to draw any specific conclusions. By calculating the compound score (taking the sum of differences between average of each men-

tal health feature) for each genre, differences in mental health scores become clearer. Figure 2 shows that listeners of classical, country, gospel, lofi, and metal have below average anxiety scores, while the rest have above average anxiety scores. Listeners of country, classical, gospel, K-pop, and lofi music have below average depression scores, while the rest are above average. Listeners of country, gospel, Latin, and pop music have below average insomnia scores, while the rest are above average. Listeners of classical, country, folk, gospel, and metal music have below average OCD scores, while the rest are above average. One thing worth noting is that the most drastic scores have the least amount of samples, indicating a potential sampling gap.

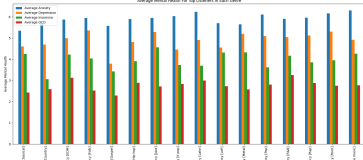


Figure 1: Average anxiety, depression, insomnia, and OCD per top listener in a genre.

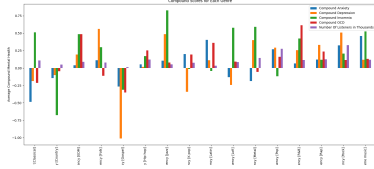


Figure 2: Compound scores for each genre and mental health indicator, with listeners (in thousands).

4.3 Lyric Sentiment Analysis

VADER was used to run sentiment analyses on genre specific ratings, giving each genre a sentiment score and polarity label. Figure 3 shows this sentiment analysis across genres. It indicates positive sentiment for a majority of genres, including, blues, classical, country, folk, jazz, religious, RnB, and vocal. The most positive genre was country, with an average sentiment score of nearly 0.500. Rap is the most negative genre, with a sentiment score of "-0.270"; contradictory to this, pop_rock had the most neutral sentiment score of 0.057. All other genres are weakly positive, neutral, or weakly negative. Overlaying the sentiment data per genre with mental health data, Figure 4 indicates some correlation between sentiment and mental health. Correlation between positive sentiment and lower mental health as well as negative sentiment and

higher mental health is seen on the graph. Note that this is displayed as inversely directed mental health and sentiment bars.

Genre	Average Sentiment	Sentiment Label
Blues	0.3710580189	Overall Blues Sentiment: Positive
Classical	0.3353989796	Overall Classical Sentiment: Positive
Country	0.4993536335	Overall Country Sentiment: Positive
Electronic	0.1281494757	Overall Electronic Sentiment: Neutral
Folk	0.3358103423	Overall Folk Sentiment: Positive
Jazz	0.4330972973	Overall Jazz Sentiment: Positive
Pop_Rock	0.05704142681	Overall Pop_Rock Sentiment: Neutral
Rap	-0.2717232848	Overall Rap Sentiment: Weakly Negative
Reggae	0.2281306365	Overall Reggae Sentiment: Weakly Positive
Religious	0.4694851471	Overall Religious Sentiment: Positive
RnB	0.4963929196	Overall RnB Sentiment: Positive
Vocal	0.4599808283	Overall Vocal Sentiment: Positive

Figure 3: Sentiment score and category per genre. Less than -0.3 = Negative, between -0.3 and -0.15 = Weakly Negative, -0.15 to 0.15 = neutral, 0.15 to 0.3 = Weakly Positive, greater than 0.3 = Positive.

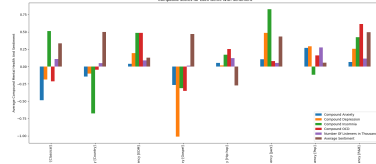


Figure 4: Compound mental health scores with sentiment analysis.

5 Discussion

Our initial OLS regression was run to try to find correlation between the raw mental health data and listening habits. While the results of these regressions did not indicate a statistically significant correlation between these variables, it showed that further and more in depth analysis was needed to provide meaningful findings. The regression for OCD did provide insight that age is correlated with OCD symptoms, meaning as people get older they feel more OCD. The main limitation of this dataset is that it is derived from self reported survey results, which could account for difficulty in finding correlated variables. The dataset also might be too small to find extremely significant results, as it only contains around 750 entries.

By plotting average mental health statistics of top listeners, we were hoping to find differences across genres. Figure 1 shows very little change across genres making it hard to interpret any meaningful results. Figure 2 describes the differences from the average of each mental health category across genres, creating more readable results. More low energy genres, such as gospel and country do indicate below average mental health statistics for top listeners of those genres. In addition, high energy genres

such as metal, pop, and rap show above average mental health statistics which are both consistent with our hypothesis. However, sample sizes for the most significant findings are very low, with the sample size for the furthest below average scores – depression for gospel listeners – having only 14 samples. This limitation makes it difficult to verify results for the most drastic examples. An immediately noticeable aspect of Figure 2 is that most mental health scores are either entirely positive or entirely negative, with those that are not having relatively neutral scores overall. This indicates that compound scores are not random, and specific genres do change people’s mental health in different ways than other genres. A larger sample size, and more robust reporting would be needed to verify exactly how each genre affects anxiety, depression, insomnia, and OCD.

To overlay mental health with genre based sentiment, we first gave each genre within our song lyric database a sentiment score using VADER. The results mostly support our hypothesis that upbeat genres have a more positive sentiment. With country, religious, and RnB genres having the highest sentiment, while rap has the lowest. Interestingly, pop_rock has the most neutral sentiment, which we expected to be higher. This could be due to a limitation of our lyric dataset, where the pop_rock genre contained around 95,000 lyrics, while other genres all contains less than 10,000.

Our final figure (Figure 4) overlays genre sentiment with average mental health scores. Both country and gospel have significantly below average mental health scores, while having high sentiment scores. This supports our hypothesis that happy, upbeat music (with high sentiment) would be better for mental health, indicated by the lower scores. Hip-hop shows higher than average mental health scores, while having negative sentiment, supporting the inverse hypothesis that sad or low sentiment songs decrease mental health, indicated by higher scores. Jazz, pop, and RnB all show higher mental health scores, while also having higher sentiment, making it difficult to conclude that our hypothesis is true.

Conclusions

All in all, this project examined the complex relationships between music consumption, genre preference, and self-reported mental health scores using both survey-based data and lyrical sentiment analysis. Though an initial OLS regression model produced low, largely insignificant explanatory powers, it was able to suggest

that music’s relationship to mental health cannot be explained by simple variables like listening frequency or environment alone. Instead, our later results explain that genre-specific patterns alongside side mental health scores – particularly ones that are a compounded mental health score – are able to offer a more nuanced picture of potential relationships.

Lyrical sentiment analysis further contextualized these findings. While many genres displayed generally positive or neutral lyrical sentiment, some genres such as rap negative sentiment at above average rates. When put side-by-side with mental health indicators, associations between negative sentiment and worse mental health as well as positive sentiment and better mental health could be seen. These correlative patterns highlight the potential importance of lyrical content in shaping listeners’ emotional states, however they exist short of significant causal relationships.

Future work should incorporate larger, more diverse datasets and more precise measures of mental well-being, and more experimental designs could potentially clarify causal relationships at play, explaining whether certain genres truly exert measurable effects on mental health over time. Despite its limitations, this project contributes to the ongoing discussions of the psychological aspects of music engagement and underscores the need for more precise, evidence-based approaches to wellness-oriented listening practices.

Code Availability

All code available for this project can be found on Github at this link: <https://github.com/miazjeffries/Final-Project—Music-and-Mental-Health-Research>

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