

# From Jazz to EDM: What is the Mental Health Impact Associated with Someone's Music Choice?

## A Description Analysis of Music Listening Behaviors and Mental Health

Hope Tadsen, Kala Fajzo, Emmanuel Damas, Shola Able-Thomas

April 2026

Github Repo:

<https://github.com/UC-Berkeley-I-School/203-FinalProject-MusicandMentalHealth>

## Introduction

When discussing music, it is safe to assume that most of us have heard that, depending on the type of music someone prefers, it can have both positive and negative impacts on a person's mood or mental state. Empirical evidence has challenged these over simplifications. As said by Joachim-Ernst Berendt, "At the root of all power and motion, there is music and rhythm, the play of patterned frequencies against the matrix of time. We know that every particle in the physical universe takes its characteristics from the pitch and pattern and overtones of its particular frequencies, its singing. Before we make music, music makes us." Could it really be as simple as choosing a "happy" acoustic remix and changing your mood long term? Or maybe throwing on something a bit more "hardcore" to increase productivity?

Music's impact on mental health is a question that has been researched and reported on through many lenses. Some aim to gain a better understanding of the impact of an individual's preferences within the arts, while others seek to determine whether there are possible ways of influencing medical outcomes through non-medical pathways, such as music. An improved understanding of consumption patterns and preferences could prove impactful both socially and commercially. Industry reports from streaming platforms suggest a relationship between listening habits and self-reported well-being (Spotify, 2022). From a business perspective, this could lead to a wealth of marketing opportunities as well as partnerships to better serve their customer base.

In this study, we ask: **Are listening habits, genre preference, and song tempo associated with differences in anxiety, depression, insomnia, and OCD scores?** Using data collected in 2023 by a student at the University of Washington, we begin by identifying opportunities unique to the dataset and then apply the necessary transformations to enable regression modeling. We then evaluate whether there is a meaningful relationship between a person's age, chosen genre, beats per minute, hours listened to per day, and overall scores across four categories of mental health indicators.

## Data and Methods

### Data Decisions and Sample Construction

The data used for this study were collected through an online survey conducted in 2023 and posted across multiple online platforms, including Reddit, Discord, and other social media sites. The survey contained 736 responses and was not restricted by age or geography. The 33 questions ranged from categorical to scalar measures. Each question related either to listening habits, genre preferences, or variables representing mental health scores measuring severity across four common mental health conditions.

Following best practices, our team used a randomization formula to split the dataset into exploration (30%) and confirmation (70%) sets to allow for confirmation analysis after regression modeling. We then further restricted our sample by excluding variables that were deemed irrelevant to our study. The mental health variables included in the survey were anxiety, depression, insomnia, and OCD. To allow for a more direct analysis of the dependent and independent variables, our research team then chose to consolidate both the genre variables and the mental health variables, which will be discussed in detail in the following sections. Upon final inspection, the exploration dataset consisted of a total of eight variables and 219 responses, whilst our confirmation set consisted of 517 responses. Code specifications were constructed using the exploration set whilst regression results were reported using the validation set.

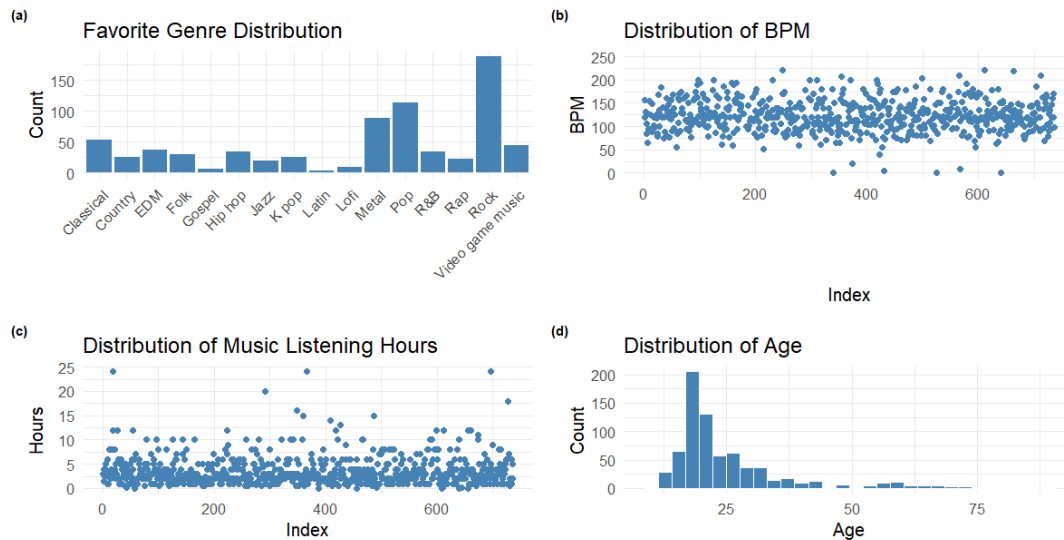
### Main Variables

Our analysis focused on several key predictors of mental health (X concept), related to both music listening behavior and demographics. The main variables included hours of music listened to per day, genre preference, BPM (tempo), and age. Genre was not used in its original high-dimensional form; instead, it was transformed into a single categorical variable representing genre clusters derived from

MCA and hierarchical clustering. This allowed us to capture broader listening patterns rather than individual genre frequencies.

The outcome variable (Y concept) was overall mental health, constructed as a composite score using Principal Component Analysis (PCA) on four measures: anxiety, depression, insomnia, and OCD. We used the first principal component (PC1) as a summary measure, which captured the general burden of mental health symptoms across individuals, while the second component (PC2) captured variation across specific symptom profiles.

## Data Summary



Respondents chose from 16 select genres (a), which included a favourite genre column and a frequency table that described listening habits using four categories — Never, Rarely, Sometimes, Very Frequently. BPM was a metric spanning a relatively arbitrary range, from 0 to infinity (b). Music Listening Hours ranged from 0 to 24 hours (c). Ages were distributed between 10 to 89 years (d). Anxiety, Depression, OCD and Insomnia were likert scales ranging from 0 to 10.

## PCA

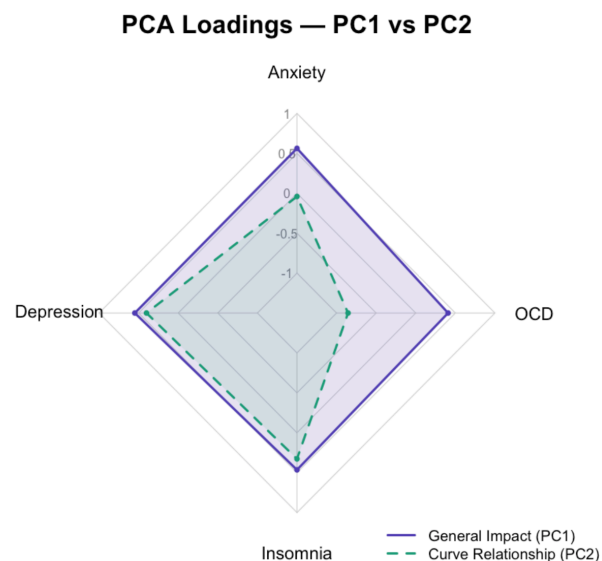
Measuring mental health as a single outcome presents a fundamental operationalization challenge. Our dataset contained four self-reported mental health variables — Anxiety, Depression, Insomnia, and OCD. Rather than treating these as four separate dependent variables which were independent from each other, or collapsing them into a simple average, we applied Principal Component Analysis to derive a single composite score that reflected the underlying shared structure across all four conditions.

- PCA works by identifying the directions of maximum variance in a dataset and projecting observations onto these new axes, called principal components. The first principal component, PC1, captured the single linear combination of variables that explained the most variance across the dataset. In our case, PC1 explained 50.03% of the total variance across the four mental health variables, with all four loading positively: Anxiety (0.56), Depression (0.55), Insomnia (0.46), and OCD (0.41).
- The second component, PC2, explained an additional 20.93% of variance and captured a contrasting pattern, primarily a tension between OCD (−0.85) and Depression and Insomnia (+0.40, +0.33 respectively). Together PC1 and PC2 accounted for 70.96% of the total variance.

A natural alternative to PCA would be to simply average the four mental health scores into a composite. While intuitive, this approach carries an implicit assumption that each condition contributes equally to overall mental health burden, which may not reflect reality. PCA derives weights empirically from the data itself. In our case, Anxiety and Depression received higher loadings than Insomnia and OCD, suggesting they were more strongly tied to the shared burden factor.

Beyond the averaging question, we also considered whether to use PC1 or PC2 as our primary outcome variable in the regression model. We selected PC1 for two reasons:

- First, PC1 explained 50.03% of total variance compared to PC2's 20.93%, making it the more informative single summary of mental health outcomes.
- Second, and more importantly, PC1 had a clear and interpretable meaning. It represented the general mental health burden with all four variables pointing in the same direction, meaning, a higher PC1 score could be interpreted directly as a lower general mental health state. PC2 by contrast represented a contrast between conditions rather than an overall level, making it harder to interpret in the context of a descriptive regression, being less aligned with our core research question of how music listening habits relate to overall mental health.
- That said, PC2 was not without value. Its ability to distinguish respondents with elevated OCD relative to their mood and sleep symptoms could be an area worth exploring in future work, particularly if the research question shifts toward understanding specific condition profiles rather than overall burden.



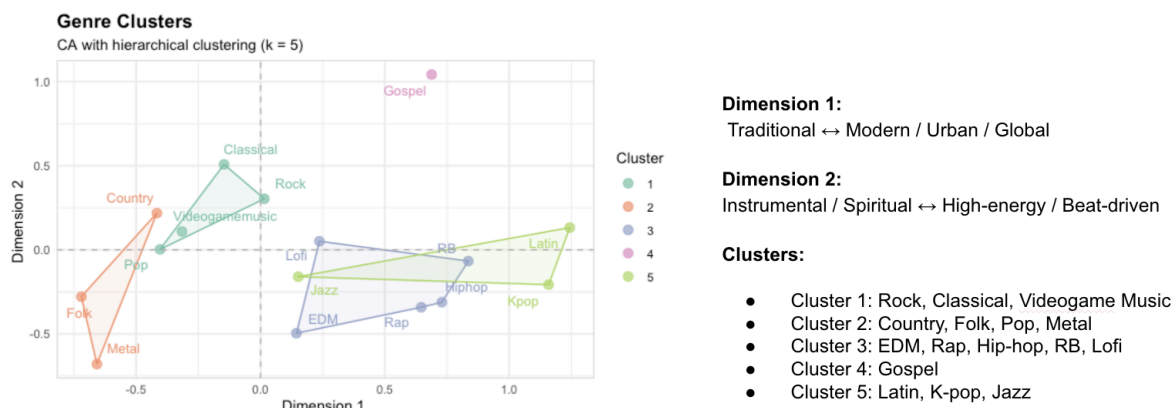
Importance of components:

|                        | PC1       | PC2         | PC3        | PC4        |
|------------------------|-----------|-------------|------------|------------|
| Standard deviation     | 1.4147    | 0.9150      | 0.8513     | 0.6609     |
| Proportion of Variance | 0.5003    | 0.2093      | 0.1812     | 0.1092     |
| Cumulative Proportion  | 0.5003    | 0.7096      | 0.8908     | 1.0000     |
|                        | PC1       | PC2         | PC3        | PC4        |
| Anxiety                | 0.5626858 | -0.04014875 | -0.4832837 | -0.6694846 |
| Depression             | 0.5483819 | 0.40102113  | -0.3137495 | 0.6633405  |
| Insomnia               | 0.4644146 | 0.32716813  | 0.7971058  | -0.2047009 |
| OCD                    | 0.4086331 | -0.85471115 | 0.1806115  | 0.2643243  |

## MCA

To better understand patterns in genre listening behavior, we applied Multiple Correspondence Analysis (MCA) to the genre frequency variables. The dataset included ordinal frequency-of-listening variables that created a high-dimensional space that was difficult to interpret. Since we could not assume equal spacing between levels, we converted these responses into an indicator matrix, and used MCA to identify underlying patterns in how genres were listened to. We further went to use Joint MCA in the post-hoc, which used a Burt matrix with Greenacre's correction to further understand how genres were clustered. This allowed us to think in terms of broader listening profiles rather than individual genres. We explored multiple dimensions, including up to five, but found that additional dimensions did not meaningfully improve interpretability or separation, so we focused on the first two dimensions for analysis and visualization.

We went on to apply hierarchical clustering on the MCA coordinates to group similar genres, testing multiple values of  $k$  and ultimately selecting a five-cluster solution based on interpretability, despite relatively weak clustering structure. The post-hoc included a silhouette analysis which used a data-based approach to identify the optimal number of clusters. These clusters were used to assign each respondent to a dominant genre group, reducing many genre variables into a single consolidated feature for regression. Overall, the results suggest that genre preferences form overlapping patterns rather than clearly distinct groups, which helps explain why genre was not a strong predictor of mental health in our models.



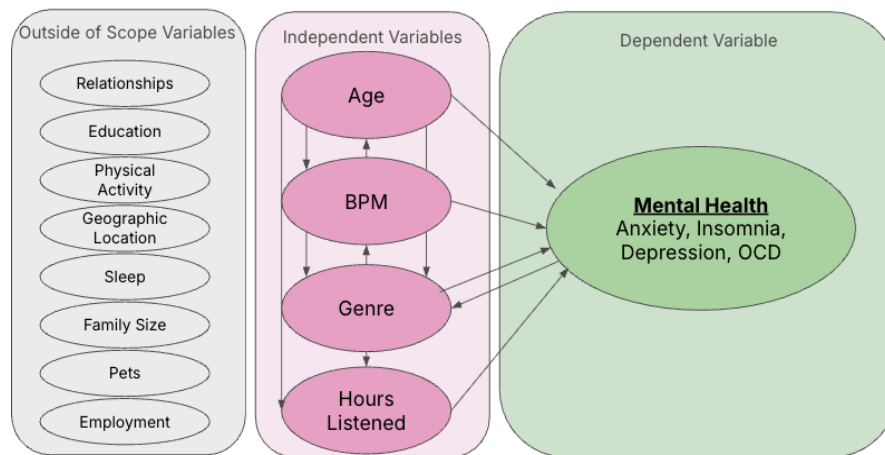
## OLS

Ordinary Least Squares (OLS) regression is a statistical method that estimates the linear relationship between one or more independent variables and a continuous outcome by minimizing the sum of the squared differences between observed and predicted values. In this study, we applied OLS regression to describe the relationship between music listening characteristics, specifically age, genre cluster and tempo (BPM), and our composite mental health impact score, PC1. Robust standard errors (HC3) were used throughout to account for heteroskedasticity in the self-reported data, confirmed using the Breusch-Pagan test, ensuring our inference remained valid even if the variance of residuals was not constant across observations.

## Model Assumptions

Equipped with a more thorough understanding of the variables and their distributions, we can begin to make assumptions that will build into and inform regression modeling. When discussing linear regression, a primary assumption is independence. Independence of the responses can be assumed due to each survey respondent having come from a unique person without replication or over-time response.

Another primary linear regression assumption is the linear relationship between the independent variables and mental health; we will be testing this assumption with homoskedasticity through our linear regression. Through choosing age, BPM and listening hours as the main explanatory variables we also assume no perfect collinearity due to the diverse nature of the variables. Assumptions related to the survey design are also high-priority factors. Due to self-reporting, we can assume a certain level of measurement error to be seen within the data set. This error may also be exacerbated by systematic bias, as respondents with certain genre preferences may be culturally more or less likely to self-report their mental health burdens (Sue et al., 2012). This begins to touch on a major set of assumptions relating to endogeneity. Examples of endogeneity within our data would be the relationship between a person's age and their mental health or the relationship between preferred genre and a person's age. This relationship makes us question whether listening habits determine mental health or mental health determines listening habits. There are also numerous unmeasured variables, like sleep or activity level, that have been proven to also impact a person's mental health but are not included within this research (see figure below). With these limitations and assumptions in mind, we continue toward determining the regression model for our research question.



## Results

### Simple Models

Simple OLS regression models were constructed to investigate the effect of singular independent variables on the outcome variable (Table 1). The first model evaluated the relationship between general mental health score (PC1), and hours spent listening to music (Hours per Day). An association was apparent. After confirming heteroskedasticity with the Breusch-Pagan test, robust standard errors were used to generate the F-statistic, which had a significant value ( $p < 0.001$ ). The model suggested that for every hour of music listened, PC1 scores increased by 0.079 ( $p < 0.001$ ).

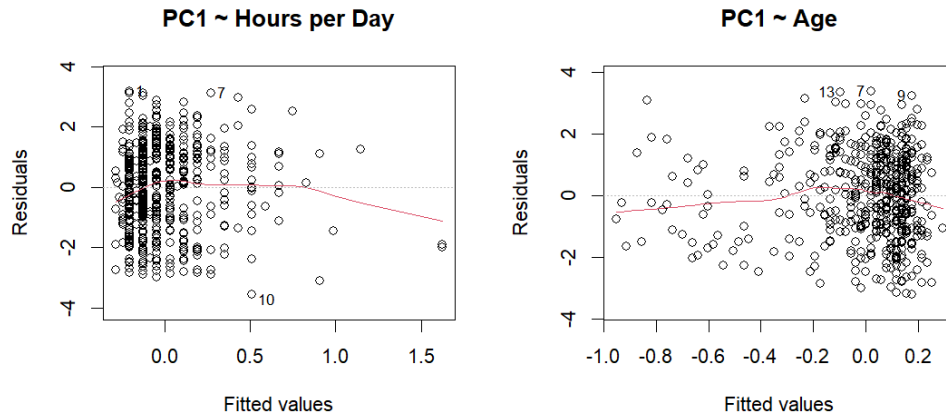
The second model looked at the effect of BPM on PC1 scores. No apparent relationship was observed. The third model looked at the relationship between Age and PC1 scores. A significant association was observed, with age possessing a negative coefficient in relation to PC1 scores. F-statistic was significant, thereby rejecting the null hypothesis. The model suggested that for a one year increase in Age, PC1 scores reduced by 0.019.

Table 1: Regression Results for Mental Health Scores

|                         | Dependent variable:       |                     |                         |
|-------------------------|---------------------------|---------------------|-------------------------|
|                         | Mental Health Score (PC1) |                     |                         |
|                         | (1)                       | (2)                 | (3)                     |
| Hours per Day           | 0.079***<br>(0.024)       |                     |                         |
| BPM                     |                           | 0.000<br>(0.001)    |                         |
| Age                     |                           |                     | -0.019***<br>(0.005)    |
| Constant                | -0.285**<br>(0.100)       | 0.021<br>(0.116)    | 0.488**<br>(0.149)      |
| Observations            | 517                       | 437                 | 517                     |
| R <sup>2</sup>          | 0.028                     | 0.001               | 0.025                   |
| Adjusted R <sup>2</sup> | 0.026                     | -0.001              | 0.023                   |
| Residual Std. Error     | 1.403 (df = 515)          | 1.435 (df = 435)    | 1.405 (df = 515)        |
| F Statistic             | 14.952*** (df = 1; 515)   | 0.437 (df = 1; 435) | 13.289*** (df = 1; 515) |

Note:

Significant at \*p &lt; 0.05, \*\*p &lt; 0.01, \*\*\*p &lt; 0.001



### Multivariate Models

Multivariate models added increasing complexity to the regression analysis (Table 2). Using the genre clusters derived from the MCA analysis, the regression investigated associations between PC1 scores and genre. Using the classical genre group as the reference variable, Model (1) found no relationship between PC1 scores and other genre groups. Models (2) and (3) yielded similar results, whilst emphasizing the relationship between PC1 scores, Age and Hours per Day. Model (4) suggested a negative relationship between the Country genre group and PC1 scores ( $p < 0.05$ ). Further analysis was conducted in the post-hoc to assess the validity of this relationship.

Table 2: Regression Results for Mental Health Scores

|                         | <i>Dependent variable:</i> |                       |                        |                        |
|-------------------------|----------------------------|-----------------------|------------------------|------------------------|
|                         | Mental Health Score (PC1)  |                       |                        |                        |
|                         | (1)                        | (2)                   | (3)                    | (4)                    |
| Country                 | −0.346<br>(0.193)          | −0.256<br>(0.191)     | −0.337<br>(0.190)      | −0.404*<br>(0.206)     |
| Rap/EDM/Kpop            | 0.024<br>(0.144)           | −0.038<br>(0.146)     | −0.118<br>(0.144)      | −0.067<br>(0.155)      |
| Gospel                  | −0.186<br>(0.348)          | −0.082<br>(0.351)     | −0.077<br>(0.357)      | −0.254<br>(0.422)      |
| Jazz/Latin              | 0.100<br>(0.285)           | 0.194<br>(0.274)      | 0.095<br>(0.277)       | 0.049<br>(0.305)       |
| Age                     |                            | −0.019**<br>(0.006)   | −0.017**<br>(0.006)    | −0.018**<br>(0.007)    |
| Hours per Day           |                            |                       | 0.077**<br>(0.024)     | 0.080**<br>(0.026)     |
| BPM                     |                            |                       |                        | 0.000<br>(0.0002)      |
| Constant                | 0.045<br>(0.093)           | 0.511**<br>(0.171)    | 0.232<br>(0.192)       | 0.257<br>(0.214)       |
| Observations            | 517                        | 517                   | 517                    | 437                    |
| R <sup>2</sup>          | 0.009                      | 0.031                 | 0.056                  | 0.070                  |
| Adjusted R <sup>2</sup> | 0.001                      | 0.021                 | 0.045                  | 0.055                  |
| Residual Std. Error     | 1.421 (df = 512)           | 1.407 (df = 511)      | 1.389 (df = 510)       | 1.394 (df = 429)       |
| F Statistic             | 1.134 (df = 4; 512)        | 3.241** (df = 5; 511) | 5.078*** (df = 6; 510) | 4.613*** (df = 7; 429) |

*Note:*

Significant at \*p &lt; 0.05, \*\*p &lt; 0.01, \*\*\*p &lt; 0.001

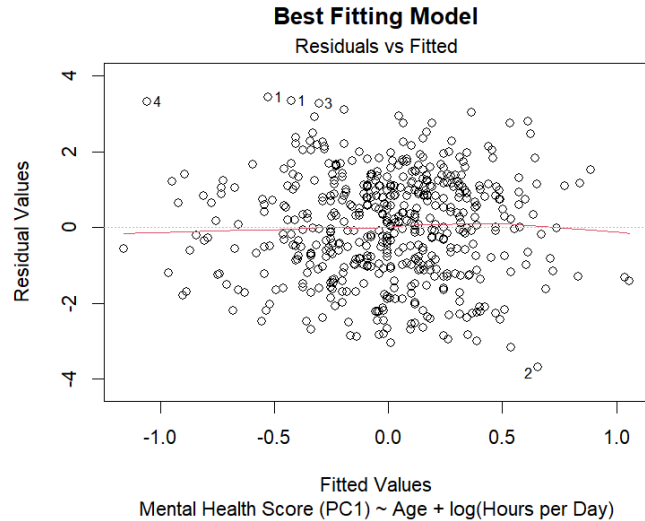
**Best Fitting Model**

To evaluate the best fitting model, we regressed PC1 scores against Age whilst transforming the Hours per Day variable by taking both its square root and logarithm. To avoid taking the logarithm of 0 hours, a scalar (1) was added to the Hours per Day variable. The results show that the logarithm model produced an F-statistic with the highest significance ( $p < 0.0001$ ), and an adjusted R<sup>2</sup> value of 0.056. The model with the square root of Hours per Day performed similarly well, ranking second in best fitting models.

Table 3: Regression Results for Mental Health Scores

|                                | <i>Dependent variable:</i> |                     |
|--------------------------------|----------------------------|---------------------|
|                                | Mental Health Score (PC1)  |                     |
|                                | (1)                        | (2)                 |
| Age                            | -0.017*<br>(0.006)         | -0.017*<br>(0.006)  |
| $\sqrt{\text{Hours per Day}}$  | 0.369***<br>(0.092)        |                     |
| $\log(\text{Hours per Day})$   |                            | 0.484***<br>(0.114) |
| Constant                       | -0.217<br>(0.228)          | -0.230<br>(0.223)   |
| Observations                   | 517                        | 517                 |
| R <sup>2</sup>                 | 0.058                      | 0.060               |
| Adjusted R <sup>2</sup>        | 0.054                      | 0.056               |
| Residual Std. Error (df = 514) | 1.383                      | 1.381               |
| F Statistic (df = 2; 514)      | 15.764***                  | 16.400***           |

Note: Significant at \*p < 0.01, \*\*p < 0.001, \*\*\*p < 0.0001



### Post-Hoc Analysis

To investigate the clustering of genres further, we went on to perform a post-hoc analysis which analyzed the entire dataset whilst incorporating some additional techniques. A Joint MCA was performed on the genre listening-frequency variables, using a Burt matrix with Greenacre's correction. To assess the right number of cluster groups formed from the JMCA analysis, a silhouette analysis was performed, resulting in a  $k$  value of 7. Genre groups were regressed against the PC1 scores, however no apparent association was found. The post-hoc analysis further confirmed the findings of the validation dataset.

### Discussion

While genre groups showed a weak association with the general mental health score, age and hours listened to music were found to be more reliable predictors. The post-hoc analysis further reinforced this finding, as even with an expanded clustering approach using Joint MCA and a silhouette-based  $k$

selection ( $k = 7$ ), no meaningful relationship between genre groupings and PC1 scores was observed. This suggests that the lack of significance for genre is not simply due to how genres were clustered, but rather reflects a broader limitation of genre as a predictor of mental health within this dataset.

In the simple models, we found that though an association between age and PC1 scores was present, the residual plot showed evidence of model misspecification due to a curving smoother, meaning age alone could not reliably predict mental health scores. The same was found for music listening hours, as the residual plot indicated a non-linear relationship. Linearity was best satisfied in the  $PC1 \sim \text{Age} + \log(\text{Hours per Day})$  model, with residuals spread more evenly above and below zero. This suggests a diminishing effect of listening hours on mental health, where increases in listening are associated with higher mental health burden, but at a decreasing rate.

Importantly, even as model complexity increased, the overall explanatory power remained low, and multivariate models did not yield statistically significant results. This indicates that while age and listening behavior may have some association with mental health, they do not meaningfully explain variation in outcomes when considered together with other variables such as genre and BPM. The post-hoc results further support this conclusion, highlighting the difficulty of capturing mental health outcomes using music-related variables alone.

The results suggest that individuals experiencing poorer mental health may engage more heavily in music listening, potentially as a coping mechanism rather than as a causal driver of improved outcomes. For streaming platforms, this highlights an opportunity to explore more supportive, context-aware personalization strategies, while avoiding causal claims about music improving or harming mental health. At the same time, these findings emphasize the need to consider broader behavioral, psychological, and environmental factors when attempting to understand mental health variation.

### **Limitations (2–3 items)**

The study identifies association, not causation, with strong potential for reverse causality. Mental health and music variables are self-reported and may suffer from recall or social desirability bias. Dimensionality reduction (PCA and MCA) improves tractability but complicates direct interpretation of individual conditions or genres.

Several limitations should be considered when interpreting the findings of this study:

- First, the data is entirely self-reported, meaning that all mental health scores and music listening habits reflect respondents' own perceptions rather than clinically validated measurements.
- Second, the sample of 736 respondents, while sufficient for exploratory analysis, was recruited through an open online survey, raising concerns about selection bias and whether the sample is truly representative of the broader population.
- Third, our genre operationalization relied on MCA-based clustering of listening frequency responses, which while data-driven, produces genre groups that are not directly interpretable without careful inspection of their composition.
- Fourth, the cross-sectional nature of the data means we are observing a single snapshot in time for each respondent, making it impossible to assess whether mental health outcomes change as a function of changing music habits over time.
- Finally, as a purely descriptive study, we cannot make any causal claims. The relationships identified between music listening behavior and mental health impact may reflect unmeasured confounding variables such as socioeconomic status, prior mental health history, or life circumstances that drive both music preferences and mental health outcomes simultaneously.

## Future Work

Future work could expand this analysis in several key ways. First, incorporating longitudinal or clinical data would allow for a better understanding of causality, helping to disentangle whether music listening behavior influences mental health or vice versa. Second, enriching the music features used in the analysis, such as lyrical content, mood, or instrumentation, could provide a more nuanced view of how different aspects of music relate to mental health outcomes. In particular, further exploration of genre is important, as genre classifications are inherently broad and may mask significant variation in listening behavior and emotional impact.

Additionally, future work could explore alternative ways of measuring mental health, drawing on clinical frameworks or validated assessment tools rather than relying solely on self-reported survey responses. Finally, experimental or quasi-experimental designs, such as testing personalized playlist interventions, could help more directly evaluate the impact of music on mental health.

## Citations

Rasgaitis, C. (2022). *Music & Mental Health Survey Results (MxMH)* [Dataset]. Kaggle.  
<https://www.kaggle.com/datasets/catherinerasgaitis/mxmh-survey-results>

Sue, S., Cheng, J. K. Y., Saad, C. S., & Chu, J. P. (2012). Asian American mental health: A call to action. *American Psychologist*, 67(7), 532-544.

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). Springer.

Husson, F., Lê, S., & Pagès, J. (2011). *Exploratory Multivariate Analysis by Example Using R*. CRC Press.