Association of Different Genres of Music and Human Behaviour

Abhisek Chatterjee

University Roll No : C91/STS/191001

Department of Statistics

University of Calcutta

Supervisors : Dr. Bhaswati Ganguli

& Dr. Gaurangadeb Chattopadhyay

July, 2021

Contents

1 Introduction 3

2 Perceived Stress Scale 4

3 The PHQ-9 5

4 The Questionnaire 5

5 The Data 6

6 Analysis of Missing Values 8

7 Calculating The PSS & PHQ-9 Scores 9

8 Analysis 10

9 Conclusion 19

References & R Code Used 20

Abstract

This project is primarily based on the existence of any potential effect of different music genres and time spent listening to music on two of the most important mental health conditions, *stress* and *depression*. Secondarily, it also discusses any possible effect of the *second wave of Covid-19 pandemic* on the conditions. Data is collected through a questionnaire and response variables are formed with the help of two psychometric scales, *The Perceived Stress Scale* and *The PHQ-9*. Mainly nonparametric and parametric difference of central tendancy tests, a classification method and some categorical analyses are performed to establish some interesting and informative associations.
Keywords : PSS, perceived stress score, PHQ-9 score, severity of stress, severity of depression, music genre

1 Introduction

Prolonged experiences of stress are related to poor individual health and associated with substantial financial costs for the society. As a result, the development of cost effective stress prevention or stress management approaches has become an important endeavor of current research efforts. On the other hand, Depression is classified as a mood disorder. It may be described as feelings of sadness, loss, or anger that interfere with a person's everyday activities. Severe depression can also lead to other diseases and can even be fatal. Music has been shown to beneficially affect stress-related physiological, as well as cognitive, and emotional processes. Thus, the use of listening to music as an economic, non-invasive, and highly accepted intervention tool has received special interest in the management of stress and stress-related health issues. Listening to music can facilitate the non-verbal expression of emotion and allow people's inner feelings to be expressed without being threatened. Also, Music therapy seems to reduce depressive symptoms and anxiety, and helps to improve functioning (e.g., maintaining involvement in jobs, activities, and relationships). It is unclear whether music therapy is better than psychological therapy.

The experience of stress arises when an individual perceives the demands from the environment 'as taxing or exceeding her or his resources and endangering her or his well-being'. Accordingly, physiologic stress effects are regulated by top-down central nervous system processes (=cognitive stress component, e.g. 'I can't cope with the situation'), as well as by sub-cortical processes within the limbic system (=emotional stress component, e.g. 'anxiety'). Depression is considered a serious medical condition that can get worse without proper treatment. There are several possible causes of depression. They can range from biological to circumstantial. Trauma, alcohol misuse and recent adverse life events are generally the common causes.

However, It is widely believed that, the choice of music genres or the type of music and how it can potentially be associated with a person's mental health is very subjective. Here we try to investigate whether the general perception is completely true or not. We are also conducting our study just around the end of the second wave of the covid-19 pandemic. We may find some results regarding that also. Our primary objective is to investigate whether people who listen to different genres of music with different preferability, have different severity of stress or depression. We also investigate if the amount of time that an individual spends listening to music have any associations with severity of stress or depression.

2 Perceived Stress Scale

Psychological stress has been defined as the extent to which persons perceive (appraise) that their demands exceed their ability to cope. In *A Global Measure of Perceived Stress*, the authors presented evidence from three samples, two of college students and one of participants in a community smoking-cessation program, for the reliability and validity of a 14-item instrument, the Perceived Stress Scale (PSS), designed to measure the degree to which situations in one's life are appraised as stressful.

The PSS is a 14-item psychometric scale. There are seven positive and seven negative items in the set, each having 5 ordinal responses(0 to 4). PSS scores are obtained by reversing the scores on the seven positive items, e.g., 0=4, 1=3, 2=2, etc., and then summing across all 14 items. Items 4, 5, 6, 7, 9, 10, and 13 are the positively stated items. The PSS was designed for use with community samples with at least a junior high school education. The items are easy to understand and the response alternatives are simple to grasp. Moreover, the questions are quite general in nature and hence relatively free of content specific to any sub-population group.

Since perceived stress should generally increase with increases in objective cumulative stress levels, the PSS should be related to the number of life events. Moreover, these correlations should be higher when the life-event scores are based on the self-rated impact of the events, since impact scores reflect some of the same stressor appraisal measured by the PSS. The PSS showed adequate reliability and was correlated with life-event scores, depressive and physical symptomatology, utilization of health services, social anxiety, and smoking-reduction maintenance. In all comparisons, the PSS was a better predictor of the outcome in question than were life-event scores. When compared to a depressive symptomatology scale, the PSS was found to measure a different and independently predictive construct. The PSS is suggested for examining the role of nonspecific appraised stress in the etiology of disease and behavioral disorders and as an outcome measure of experienced levels of stress.

The PSS also differs from life-event scales in a number of ways. The main difference is, the PSS asks about a shorter period, one month as opposed to the usual six to 12 months covered by typical life-event scales. It is worth noting that with a subjective scale, the shorter period should be sufficient since perceived stress during the last month should reflect any objective events that are still affecting respondents' stress levels. In sum, the PSS is a brief and easy-to-administer measure of the degree to which situations in one's life are appraised as stressful. It has been proven to possess substantial reliability and validity; thus, it provides a potential tool for examining issues about the role of appraised stress levels in the etiology of disease and behavioral disorders.

3 The PHQ-9

The *Patient Health Questionnaire (PHQ)* is a self-administered version of the PRIME-MD diagnostic instrument for common mental disorders. The PHQ-9 is the depression module, which scores each of the nine DSM-IV criteria as "0" (not at all) to "3" (nearly every day). It has been validated for use in primary care.

The Patient Health Questionnaire (PHQ) is a 3-page questionnaire that can be entirely self-administered by the patient. The PHQ-9 is the 9-item depression module from the full PHQ. Major depression is diagnosed if 5 or more of the 9 depressive symptom criteria have been present at least "more than half the days" in the past few weeks, and 1 of the symptoms is depressed mood or anhedonia. As a severity measure, the PHQ-9 score can range from 0 to 27, since each of the 9 items can be scored from 0 (not at all) to 3 (nearly every day). An item was also added to the end of the diagnostic portion of the PHQ-9 asking patients who checked off any problems on the questionnaire: "How *difficult* have these problems made it for you to do your work, take care of things at home, or get along with other people?"

In the original analyses, the PHQ-9 score was divided into the following categories of increasing severity: 0-4, 5-9, 10-14, 15-19, and 20 or greater. These categories were chosen for several reasons. The first was pragmatic, in that the cut points of 5, 10, 15 and 20 are simple for clinicians to remember and apply. The second reason was empiric, in that using different cut points did not noticeably change the associations between increasing PHQ-9 severity and measures of construct validity.

The internal reliability of the PHQ-9 was excellent, with a Cronbach's α of 0.89 in the PHQ primary Care Study. Test-retest reliability of the PHQ-9 was also excellent. Correlation between the PHQ-9 completed by the patient in the clinic and that administered telephonically by the MHP (Mental Health Professional) within 48 hours was 0.84 and the mean scores were nearly identical. Data from the 2 studies totaling 6000 patients provide strong evidence for the validity of the PHQ-9 as a brief measure of depression severity.

4 The Questionnaire

The Population

For our study, we had to first think about the *population*, and the *sampling frame*. Now, as online questionnaires majorly attract the young population because they are generally distributed over social media, we at first knew that even if we didn't put an age barrier, we would actually get data only on young people. So, although, the questionnaire did not have any age barrier, our *sampling frame* was assumed to be the young-adult population. There were no other assumptions.

The Questions

Now, as per our objectives, we prepared the questionnaire. The questionnaire had a total of 43 questions. The first three questions were about personal information like *age*, *gender*, *occupation*. Then there were three sets of questions :

- 14 questions regarding music. One question about the amount of time per day an individual spends listening to music. 12 mainstream genres of music were chosen keeping in mind the potential sampling frame and population and respondents were asked to indicate how much they've listened to these 12 genres of music on a scale of 0 to 10. The choice of these 12 genres could not have been exhaustive anyway. So, another question was asked to know about the two genres that an individual listened to most frequently. Most of these questions had ordinal responses.

- The second set of 12 questions consisted the 9 questions for the 9 item *PHQ-9* scale, 1 additional question corresponding to the *PHQ-9* scale, one question enquiring whether an individual had previously been diagnosed with depression or not and a very important question about the severity of the negative effect of the *2nd wave of Covid-19 pandemic* on an individual's life. All of these questions had ordinal responses.
- The 3rd set of 14 questions were for the 14 item *Perceived Stress scale*. The questions had ordinal responses (0-4).

5 The Data

The questionnaire was shared digitally over social media platforms and after a few days, we saw that 147 individuals responded to the questionnaire. Among them, 44.2% are male and 53.7% are female, 2% preferred not to tell their gender. We also observe that, a majority of the participants (76.9%) were students, followed by employees of private sector and researchers. Figure 1 and 2 represent the information about the participants who responded to the questionnaire.

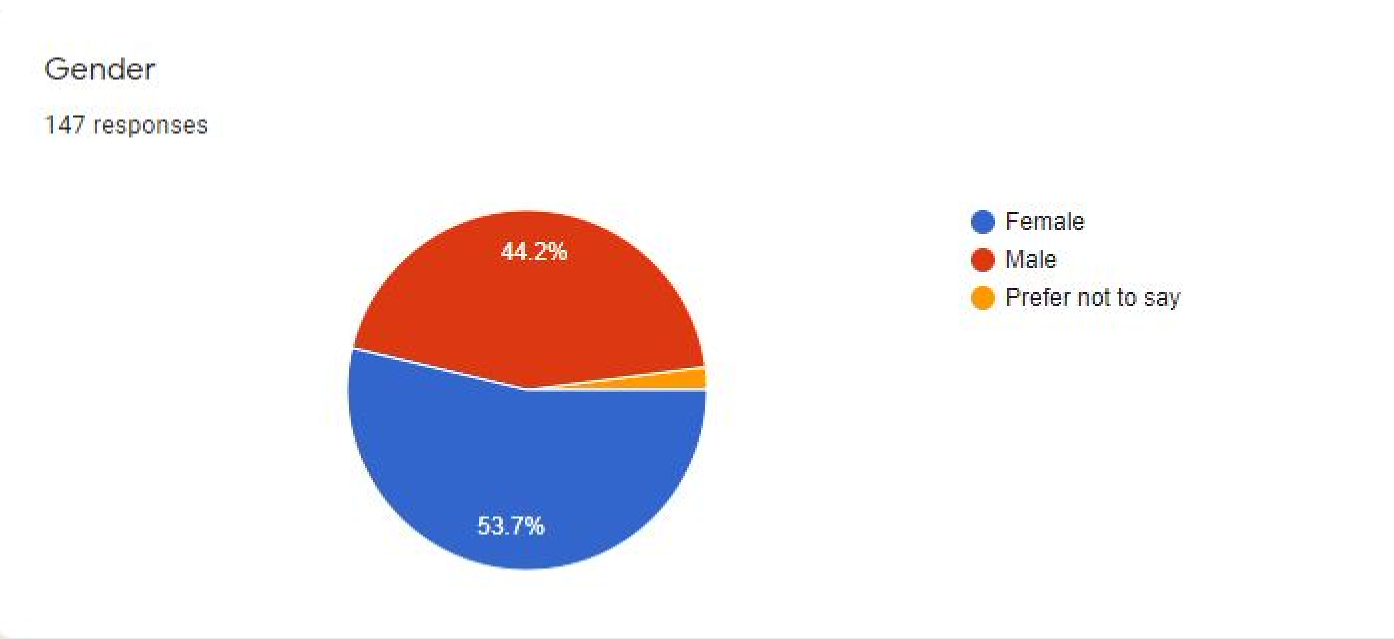


Figure 1: Details About the Respondents

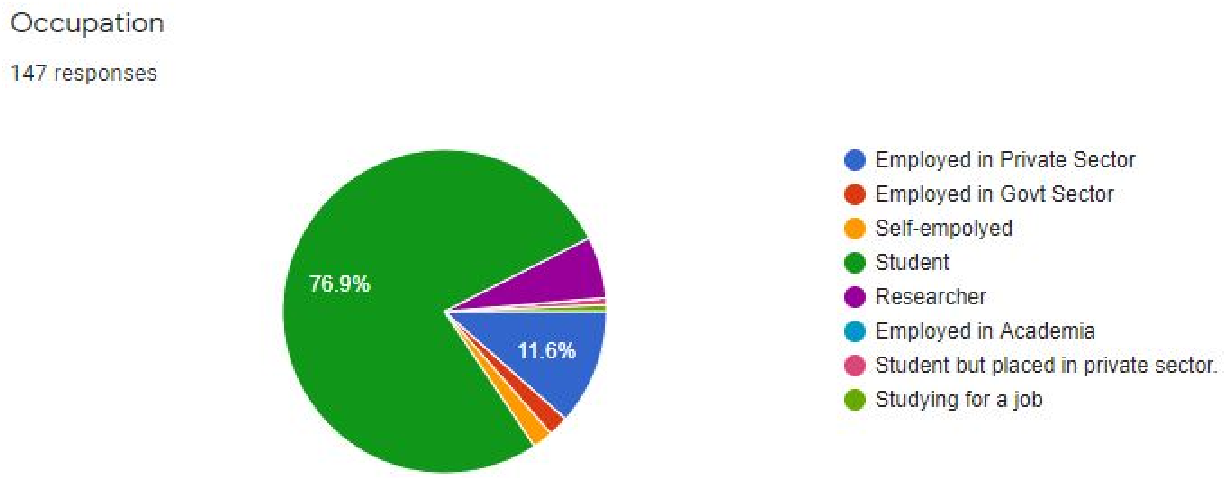
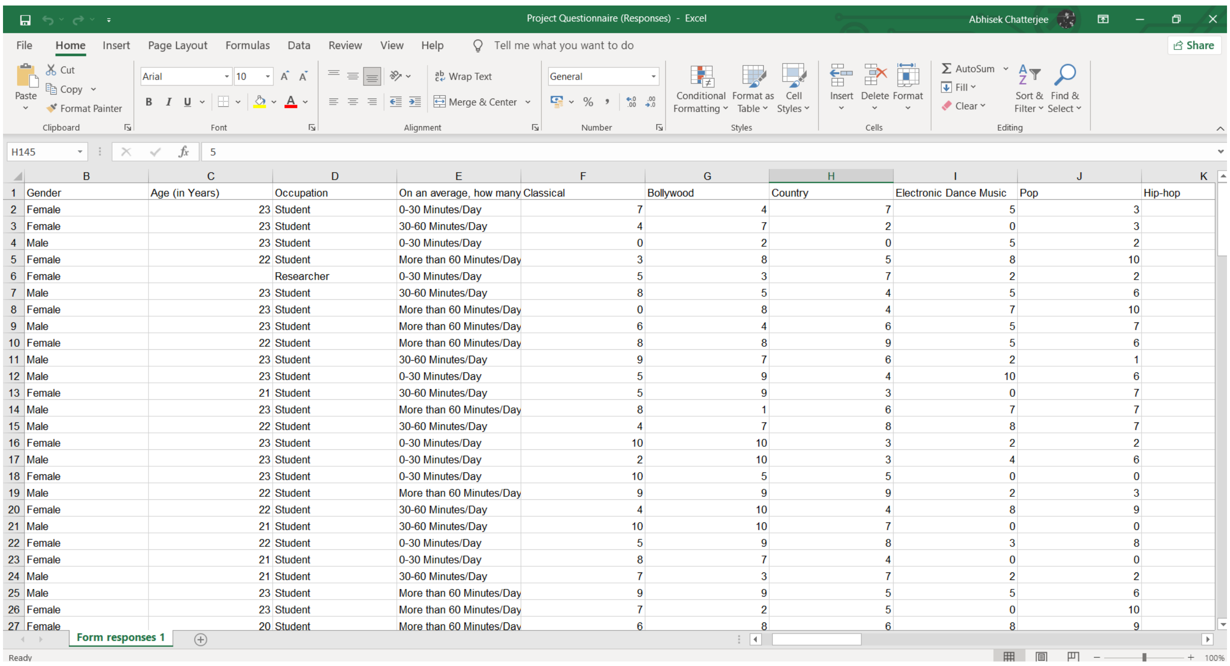


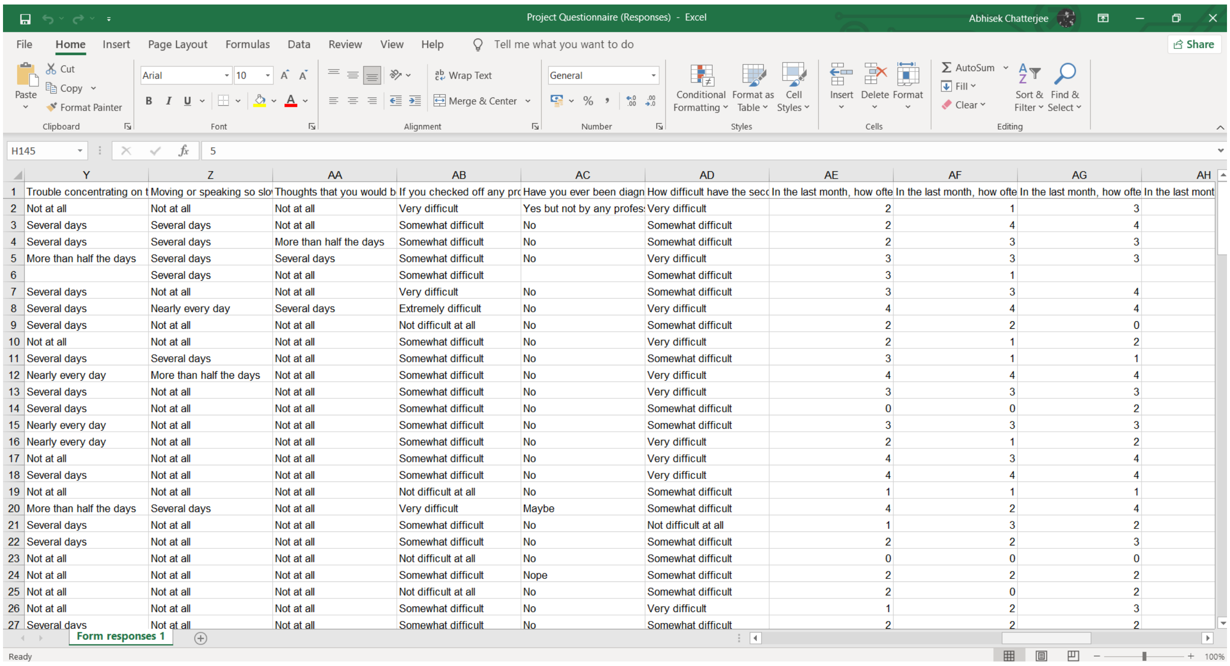
Figure 2: Details About the Respondents

Also, almost all of the individuals are in the age group 18-25 (142 responses) as we had expected. So, our dataset is a 147×44 dataframe (The timestamp column of responses and the 43 questions that we included in our questionnaire). Figure 3 and 4 shows how the collected dataset looks like. Now, before proceeding to any kind of analysis, we first look at the missing values.



	B	C	D	E	F	G	H	I	J	K
1	Gender	Age (in Years)	Occupation	On an average, how many	Classical	Bollywood	Country	Electronic Dance Music	Pop	Hip-hop
2	Female	23	Student	0-30 Minutes/Day	7	4	7	5	3	
3	Female	23	Student	30-60 Minutes/Day	4	7	2	0	3	
4	Male	23	Student	0-30 Minutes/Day	0	2	0	5	2	
5	Female	22	Student	More than 60 Minutes/Day	3	8	5	8	10	
6	Female		Researcher	0-30 Minutes/Day	5	3	7	2	2	
7	Male	23	Student	30-60 Minutes/Day	8	5	4	5	6	
8	Female	23	Student	More than 60 Minutes/Day	0	8	4	7	10	
9	Male	23	Student	More than 60 Minutes/Day	6	4	6	5	7	
10	Female	22	Student	More than 60 Minutes/Day	8	8	9	5	6	
11	Male	23	Student	30-60 Minutes/Day	9	7	6	2	1	
12	Male	23	Student	0-30 Minutes/Day	5	9	4	10	6	
13	Female	21	Student	30-60 Minutes/Day	5	9	3	0	7	
14	Male	23	Student	More than 60 Minutes/Day	8	1	6	7	7	
15	Male	22	Student	30-60 Minutes/Day	4	7	8	8	7	
16	Female	23	Student	0-30 Minutes/Day	10	10	3	2	2	
17	Male	23	Student	0-30 Minutes/Day	2	10	3	4	6	
18	Female	23	Student	0-30 Minutes/Day	10	5	5	0	0	
19	Male	22	Student	More than 60 Minutes/Day	9	9	9	2	3	
20	Female	22	Student	30-60 Minutes/Day	4	10	4	8	9	
21	Male	21	Student	30-60 Minutes/Day	10	10	7	0	0	
22	Female	22	Student	0-30 Minutes/Day	5	9	8	3	8	
23	Female	21	Student	0-30 Minutes/Day	8	7	4	0	0	
24	Male	21	Student	30-60 Minutes/Day	7	3	7	2	2	
25	Male	23	Student	More than 60 Minutes/Day	9	9	5	5	6	
26	Female	23	Student	More than 60 Minutes/Day	7	2	5	0	10	
27	Female	20	Student	More than 60 Minutes/Day	6	8	6	8	9	

Figure 3: Structure of The Collected Dataset



	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH
1	Trouble concentrating on t	Moving or speaking so slo	Thoughts that you would b	If you checked off any prc	Have you ever been diagn	How difficult have the secc	In the last month, how ofte	In the last month, how ofte	In the last month, how ofte	In the last mont
2	Not at all	Not at all	Not at all	Very difficult	Yes but not by any profes:	Very difficult	2	1	3	
3	Several days	Several days	Not at all	Somewhat difficult	No	Somewhat difficult	2	4	4	
4	Several days	Several days	More than half the days	Somewhat difficult	No	Somewhat difficult	2	3	3	
5	More than half the days	Several days	Several days	Somewhat difficult	No	Very difficult	3	3	3	
6		Several days	Not at all	Somewhat difficult		Somewhat difficult	3	1		
7	Several days	Not at all	Not at all	Very difficult	No	Somewhat difficult	3	3	4	
8	Several days	Nearly every day	Several days	Extremely difficult	No	Very difficult	4	4	4	
9	Several days	Not at all	Not at all	Not difficult at all	No	Somewhat difficult	2	2	0	
10	Not at all	Not at all	Not at all	Somewhat difficult	No	Very difficult	2	1	2	
11	Several days	Several days	Not at all	Somewhat difficult	No	Somewhat difficult	3	1	1	
12	Nearly every day	More than half the days	Not at all	Somewhat difficult	No	Very difficult	4	4	4	
13	Several days	Not at all	Not at all	Somewhat difficult	No	Very difficult	3	3	3	
14	Several days	Not at all	Not at all	Somewhat difficult	No	Somewhat difficult	0	0	2	
15	Nearly every day	Not at all	Not at all	Somewhat difficult	No	Somewhat difficult	3	3	3	
16	Nearly every day	Not at all	Not at all	Somewhat difficult	No	Very difficult	2	1	2	
17	Not at all	Not at all	Not at all	Somewhat difficult	No	Very difficult	4	3	4	
18	Several days	Not at all	Not at all	Somewhat difficult	No	Very difficult	4	4	4	
19	Not at all	Not at all	Not at all	Not difficult at all	No	Somewhat difficult	1	1	1	
20	More than half the days	Several days	Not at all	Very difficult	Maybe	Somewhat difficult	4	2	4	
21	Several days	Not at all	Not at all	Somewhat difficult	No	Not difficult at all	1	3	2	
22	Several days	Not at all	Not at all	Somewhat difficult	No	Somewhat difficult	2	2	3	
23	Not at all	Not at all	Not at all	Not difficult at all	No	Somewhat difficult	0	0	0	
24	Not at all	Not at all	Not at all	Somewhat difficult	Nope	Somewhat difficult	2	2	2	
25	Not at all	Not at all	Not at all	Not difficult at all	No	Somewhat difficult	2	0	2	
26	Not at all	Not at all	Not at all	Somewhat difficult	No	Very difficult	1	2	3	
27	Several days	Not at all	Not at all	Somewhat difficult	No	Somewhat difficult	2	2	2	

Figure 4: Structure of The Collected Dataset

6 Analysis of Missing Values

Now that we have a 147×44 dataframe, we look for missing values in the data. We see that 7 of the observations have more than 6 columns missing. A few of them have even more than 10 observations missing. As it's not a very good idea to impute these many columns for an observation, we omit these observations. However, we see that only 103 observations have zero missing values.

We then look for possible imputation ways. We see that the 9 and 14 columns that constitute our two response variables, have some missing values. Now, as these columns are not equivalent to a single variable, rather they are components of two variables, it makes sense to impute a few missing values amongst these. We also see that there are some missing values for some columns that were recorded for secondary analysis, and so we can ignore the missing values among them. However, we avoid imputing missing values for any covariate column, as each of them constitute a single variable, and as we'd see that we can proceed with a good proportion of observations without imputing the missing values among covariates. In this way, even if we don't impute the missing values among the covariates, we can still find patterns in the data precisely.

If we ignore missing values among variables that were recorded for secondary analysis purpose, we see that we have 116 observations. This is an improvement from the case where we'd have taken 103 observations that have zero columns missing, but we'd see that we can further get some more observations if we perform some imputation on the item columns. Even if we can increase the workable number of observations by 5%, we should perform imputation.

Hot-deck Imputation

Now, a suitable imputation technique could be the *Hot-deck imputation* method. In this method, we select an imputed value from an estimated distribution for each missing value. If we assume that we have a sample of n units that were selected from a population and m values of a variable/column C are recorded, where n, m and the population size are fixed, and for simplicity we assume that $C_1, C_2, ..C_m$ are observed, then for each of the unobserved $C_{m+1}, ..C_n$, we simply impute a value from the observed $C_1, C_2, ..C_m$ with some probability scheme.

Imputing The Data

For our data we simply use *simple random sampling with replacement* as a probability scheme and impute some of the missing values of these 23 columns corresponding to the questions of the two psychometric scales, where each missing value is replaced with an observed response from a similar column. After imputation, we see that we have 128 observations that we can do further analysis on. It is an improvement from the cases where we'd have 103 observations (Observations with none of the 43 columns missing) or 116 observations (if we simply ignore missing values for variables that were recorded for secondary analysis and don't do any imputation). However, we avoid imputing for any observation that has more than 4 of these column values missing.

7 Calculating The PSS & PHQ-9 Scores

For the 128 observations that we have, we calculate the values of two response variables. We have seen how the 14 questions corresponding to the PSS, have responses 0 to 4. We point out the seven positive items in the PSS question set, reverse score them (by basically subtracting the score from 4) and then add the scores for the 14 columns to calculate the Perceived Stress score for each individual. For the set of PHQ-9 questions, we assign scores 0, 1, 2, 3 to ordered responses and add the scores to calculate the Depression severity score for each individual. So, Perceived Stress score for an individual ranges from 0 to 56 and Depression severity score of an individual ranges from 0 to 27, higher scores indicating higher severity of the condition.

We see some summary statistics of the data. We see that the median and mean Depression severity score is 8 and 8.938 respectively. The median and mean Perceived Stress score is 32.00 and 31.97 respectively. We can see the summaries from the table below.

Response Variable	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
PSS	4.00	26.00	32.00	31.97	39.00	52.00
PHQ-9	0.000	5.000	8.000	8.398	13.000	21.000

We also see that 1st and 3rd quartile of the stress scores is 26 and 39 respectively. We will use this information later in our analysis. We also observe that the average PSS and PHQ-9 scores are high.

8 Analysis

Location Testing

Now, we have two response variables. At first, we have to check whether they resemble the normal distribution. For PSS and PHQ-9, we perform *Shapiro–Wilk test* with the null hypothesis that the sample observations came from a normally distributed population.

We get p-values 0.4223 and 6.695×10^{-06} respectively. We have thus evidence that PSS resembles a normal distribution with statistical significance and PHQ-9 does not, as the p-values are less than 0.05. This level of significance i.e. 5% level of significance is also the general level of significance that we use throughout all our study, in every parametric and nonparametric test. Now, whenever we want to test for difference of locations of the PHQ-9 variable corresponding to different groups (grouped by conditions on any covariate(s)), we can use *Kruskal-Wallis test* based on the ranks where we test $H_0 : \theta_1 = \theta_2 = ... = \theta_k$ against all alternatives, $\theta_i, i = 1(1)k$ being the locations corresponding to different groups. When we have two groups instead, we can simply use *Wilcoxon rank-sum test* with a similar null hypothesis. Again, whenever we want to test for difference of locations of the PSS variable corresponding to different groups (grouped by conditions on any covariate(s)), we can use the parametric counterparts, i.e. *F-test using anova* for more than two groups and *two sample t-test* for two groups. At any case, we assume equal variablity among groups. We'll use the general *at least one of them are not equal* alternative hypothesis for Kruskal-Wallis test and F-test, and may use any one sided alternative hypothesis for pairwise wilcoxon rank sum tests and two sample t-tests.

Odds Ratios

As our objectives are to find any association of the two response variables with our covariates, we can't only rely on location testing. An odds ratio (OR) is a measure of association between variables, it basically quantifies the strength of the association. Odds ratios are generally used with contingency tables and we will use the *Cumulative odds ratio* several times in our study to conclude about any type of association. This type of odds ratios generally provide a comparison of pairs of levels of a covariate with respect to their entire conditional distribution on the response variable.

For $r \times c$ tables, odds ratios can use each pair of rows in combination with each pair of columns. For rows a and b and columns c and d, the odds ratio $n_{ac}n_{bd}/n_{bc}n_{ad}$ uses four cells falling in a rectangular pattern. All such odds ratios of this type are determined by a basic set of $(r - l)(c - 1)$ odds ratios. There are broadly three types of odds ratios for such tables : *Local*, *Global* and *Cumulative*.

A natural basic set of $(r - l)(c - 1)$ odds ratios for two odds ratios is the set of *Local* odds ratios, defined by $\hat{\theta}^L_{ij} = \frac{n_{ij}n_{i+1,j+1}}{n_{i,j+1}n_{i+1,j}}$. for $i = 1, ..., r - 1, j = 1, ..., c - 1$. These odds ratios use cells in adjacent rows and adjacent columns. Their values describe the relative magnitudes of associations in localized regions of the table.

A second natural family of odds ratios for ordinal variables is the set of *Global* odds ratios, defined by $\hat{\theta}^G_{ij} = \frac{(\sum_{a<=i}\sum_{b<=j} n_{ab})(\sum_{a>i}\sum_{b>j} n_{ab})}{(\sum_{a<=i}\sum_{b>j} n_{ab})(\sum_{a>i}\sum_{b<=j} n_{ab})}$. for $i = 1, ..., r - 1, j = 1, ..., c - 1$. These measures are the regular odds ratios computed for the 2x2 tables obtained from the $(r - l)(c - 1)$ ways of collapsing the row and column classifications into dichotomies. They describe associations that are global in both variables, in the sense that each odds ratio uses all categories of each variable instead of a localized region.

However, in our study we will majorly require comparing two adjacent ordinal categories of an ordinal covariate and all the categories of a response. The local and global odds ratios treat row and column variables alike. They are especially useful when both variables are response variables. A family of odds ratios that distinguishes between rows and columns is $\hat{\theta}^C_{ij} = \frac{(\sum_{b<=j} n_{ib})(\sum_{b>j} n_{i+1,b})}{(\sum_{b>j} n_{ib})(\sum_{b<=j} n_{i+1,b})}$. for $i = 1, ..., r-1, j = 1, ..., c-1$. These odds ratios are local in the row variable but global in the column variable. An equivalent definition for these odds ratios uses the sample conditional cumulative distribution functions of Y given x. We refer to them as *Cumulative* odds ratios. We will mainly use cumulative odds ratios, however we also may use local odds ratios sometimes.

Categorization of The Response Variables

Now for categorical analyses and any kind of model fitting, we decide to create two categorized versions of our two response variables. As discussed earlier, for the PHQ-9 scores, we use the same categorization as used in *The PHQ-9: Validity of a Brief Depression Severity Measure*. The PHQ-9 scores are divided into the following categories of increasing severity : 0-4 (No depression), 5-9 (Mild depression), 10-14 (Moderate depression), 15-19 (High depression) and 20-27 (Severe depression). However, we could not find such a categorization in *A Global Measure of Perceived Stress*. So, we use the sample distribution of the observed Perceived Stress scores for categorization. We observed that, the 1st and 3rd quartile for the Perceived Stress scores are 26 and 39 respectively. We use this fact and categorized the response variable into following categories of increasing severity : 0-26 (Mild to Moderate perceived stress), 27-39 (High perceived stress), 40-56 (Severe perceived stress). We observe that 92 of the 128 respondents had at least High perceived stress and 47 of the 128 respondents had at least Moderate depression.

Classification Tree

Our primary goal in our study is not to see how different genres are associated with Depression or Perceived Stress scores, but really is whether such association even exist. Now, as each of these covariates have 11 ordered responses, initially we look for any classification method that can help us establish an association between any music genre and the severity of depression or stress. Now, a suitable choice could be a classification tree, because, before further categorization of the 12 ordinal covariates, we can take advantage of the fact that each of these covariates have 11 ordinal values. As a classification tree uses recursive partitioning based on a set of questions on the covariates, the algorithm can have a large set of questions basis which it can find patterns in the data swiftly. We had a question in our dataset about the severity of the negative effect of the second wave of pandemic on our respondents' lives, the question having 4 ordered responses like "Not at all difficult", "Somewhat difficult", "Very Difficult", "Severely Difficult". We should try to get an idea about the effect of the second wave of pandemic on the depression and stress severity, as our data collection was performed around the end of the wave.

Now, we proceed towards growing two separate classification trees for the two response variables and taking the 12 music genre variables and the above mentioned variable as covariates. We first grow 2 large trees and then prune them using the *complexity parameter* and the lowest *cross-validation error*. From the trees we can get an idea about the probable covariates who may have associations with the response variables.

Figures 5 and 6 represent the plots corresponding to cross-validation and Figures 7 and 8 represent the pruned trees for the two response variables. We observe that the variable about the severity of the negative effect of the second wave of pandemic is not used in any splits of both the trees. However, we will later see whether it really has any association with the severity of depression and scores.

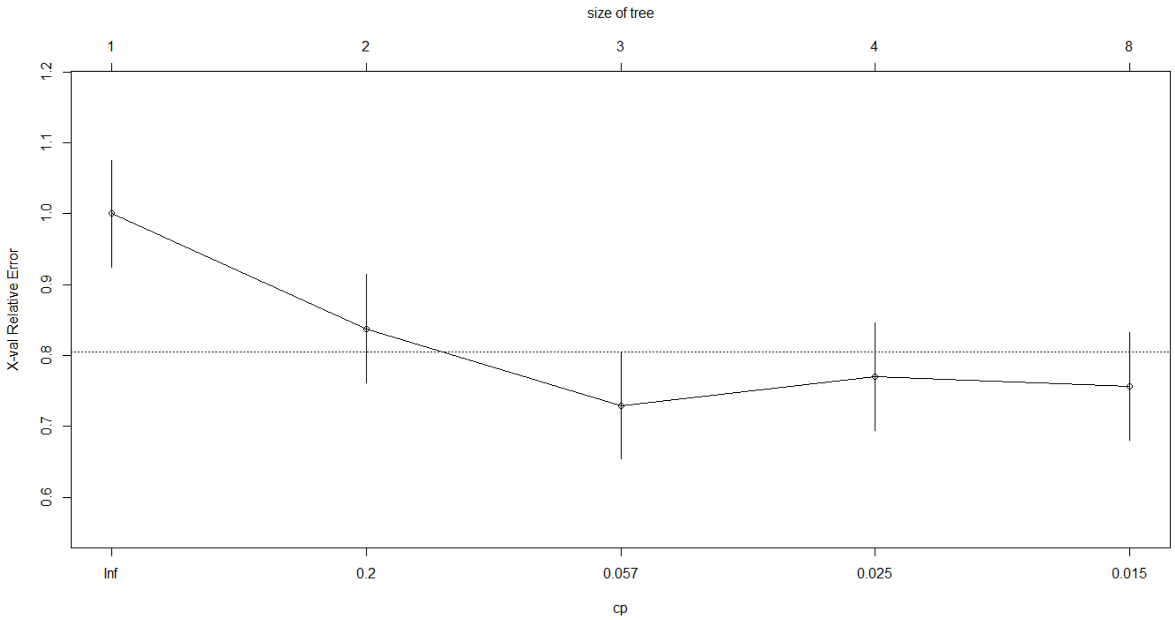


Figure 5: Complexity Parameter Against Cross-validation Error For PSS Tree

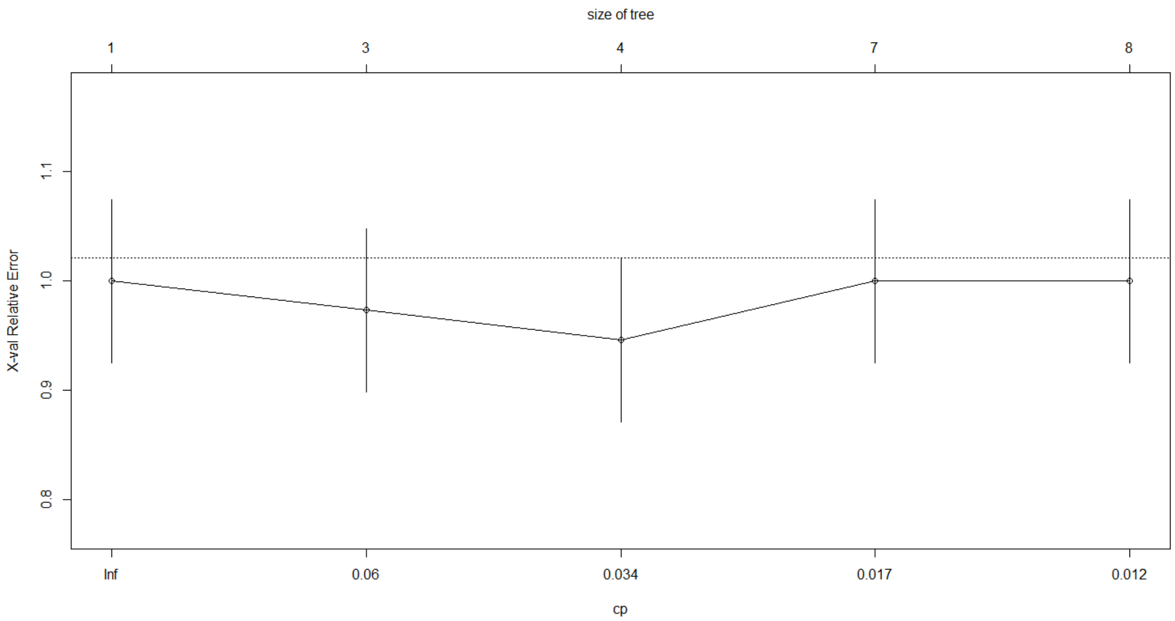


Figure 6: Complexity Parameter Against Cross-validation Error For PHQ-9 Tree

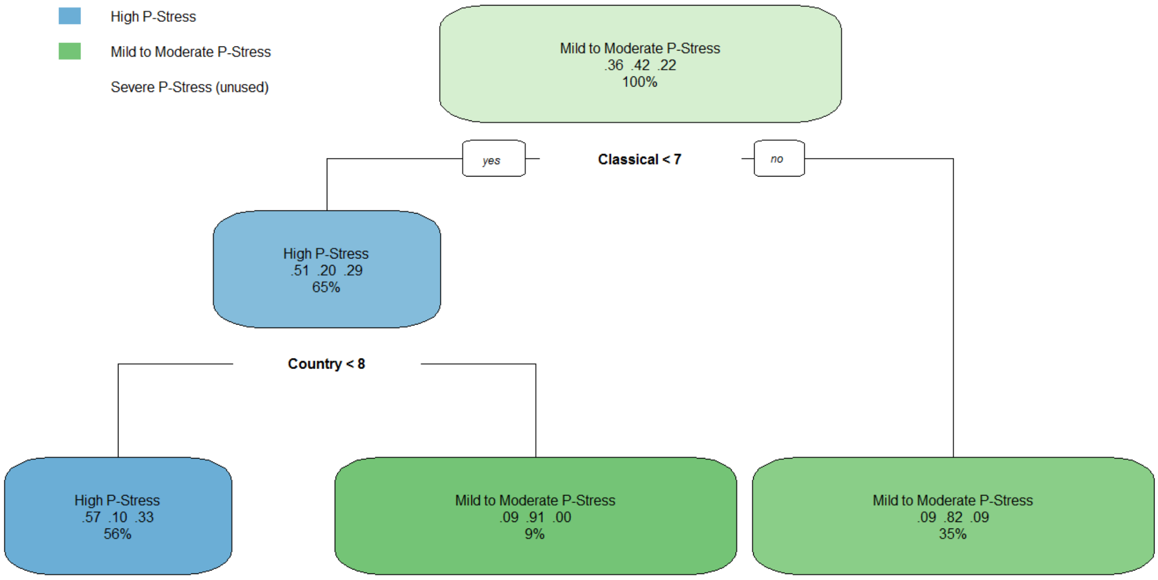


Figure 7: Pruned Tree For Severity of Perceived Stress

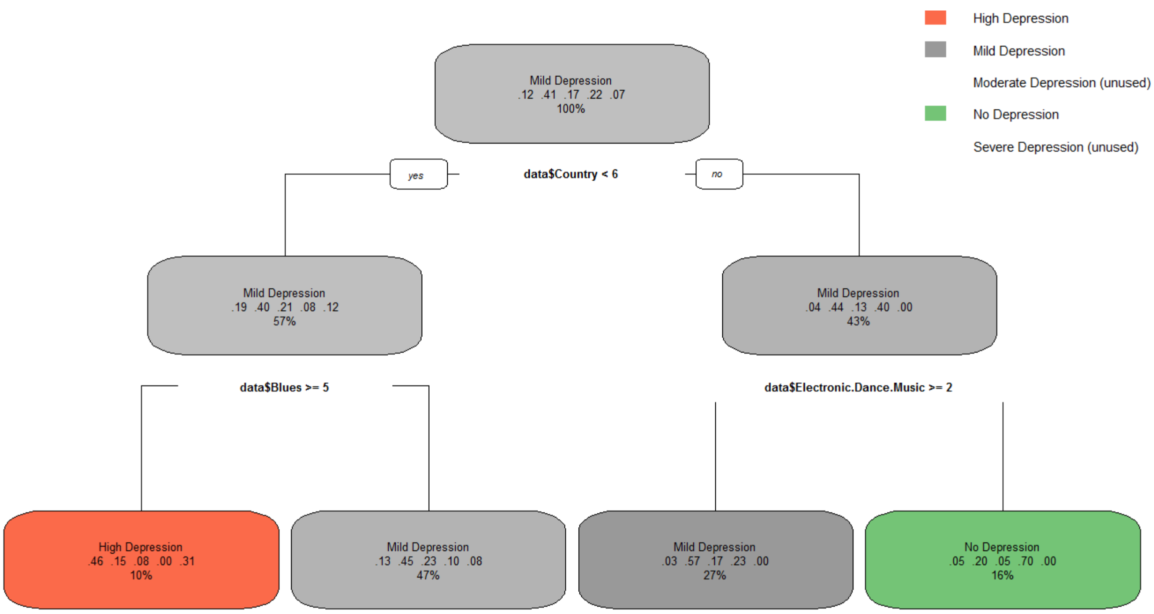


Figure 8: Pruned Tree For Severity of Depression

Looking at the trees, it seems, *Classical* and *Country* music need further inspection about any potential association with severity of perceived stress and *Country*, *Blues* and *Electronic Dance Music* need further inspection about any potential association with severity of depression.

Further Analyses

Severity of Perceived Stress

From the first classification tree (Figure 7), we observe that the two genres *Classical* and *Country* may have associations with severity of perceived stress. From the summary of the grown tree, we see that these two covariates combined had almost 90% of the variable importance. We do some further analysis for strengthening our interpretation. First, we further categorize the genre variables into 3 ordered categories : 7 to 10 (very often listened to), 4 to 6 (listened to sometimes) and 0 to 3 (rarely listened to). Similarly, observing the second classification tree (Figure 8), we categorize *Blues* and *Electronic Dance Music* in a similar way. As we had created two separate categorised versions of our two response variables, we can use both pairs of variables in further analyses.

First, we look at the genre classical. Testing for difference of mean PSS scores among the three categories of this genre with the help of F test provides a p-value 4.048×10^{-08}, that indicates the mean PSS scores for different categories of this genre differ significantly. To see how they differ, we perform pairwise two-sample t tests. The p-values are very low indicating a statistical significance in difference of mean perceived stress scores. For example, the mean perceived stress scores corresponding to the respondents who listened to classical music "Very often" are significantly lower than the mean perceived stress scores corresponding to the respondents who listened to classical music "Sometimes" (p-value is 1.818×10^{-05}). The same is true for "Sometimes" and "Rarely" categories (p-value is 0.03746). For the genre country, again testing for difference of mean PSS scores among the three categories of this genre with the help of F test provides a p-value 1.528×10^{-10}, that indicates the mean PSS scores for different categories of this genre differ significantly. Pairwise two-sample t tests provide p-values 6.5×10^{-08} and 0.01213. So again, we get evidence that the mean perceived stress scores corresponding to the respondents who listened to country music "Very often" are significantly lower than the mean perceived stress scores corresponding to the respondents who listened to country music "Sometimes". The same is true for the next ordered pair.

We look at the covariate "time spent listening to music" that has three categories "less than 30 minutes per day", "30 to 60 minutes per day" and "more than 60 minutes per day". We perform F test to see if mean perceived stress scores differ for these categories and get a p-value 0.2786. So, we don't need to perform further pairwise tests as we have enough statistical evidence that the mean perceived stress scores do not differ significantly among these categories. Now, we do similar for the severity of the negative effect of the second wave of pandemic variable. Here however, we get a p-value of 3.257×10^{-07} for the F test. We further perform pairwise two-sample t-tests. Participants who answered "Extremely difficult" to the question had a significantly higher mean perceived stress score than participants who answered "Very difficult" (p-value is 0.01969). Again, participants who answered "Very difficult" to the question had a significantly higher mean perceived stress score than participants who answered "Somewhat difficult" (p-value is 0.0001827).

Finally, we create contingency tables and calculate odds ratios for the 4 covariates that we inspected. The contingency tables are shown below.

Severity of Perceived Stress				
Classical Music	**Mild to Moderate**	**High**	**Severe**	**Total**
Very often	26	15	4	45
Sometimes	8	27	13	48
Rarely	2	22	11	35
Total	36	64	28	**128**

Severity of Perceived Stress				
Country Music	**Mild to Moderate**	**High**	**Severe**	**Total**
Very often	21	10	2	33
Sometimes	12	37	13	62
Rarely	3	17	13	33
Total	36	64	28	**128**

Severity of Perceived Stress				
Time Spent	**Mild to Moderate**	**High**	**Severe**	**Total**
0-30 Minutes	14	22	13	49
30-60 Minutes	6	15	8	29
More than 60 Minutes	16	27	7	50
Total	36	64	28	**128**

Severity of Perceived Stress				
2nd Wave of Covid-19	**Severe**	**High**	**Mild to Moderate**	**Total**
Extremely difficult	6	7	0	13
Very difficult	12	18	6	36
Somewhat difficult	9	36	22	67
Not difficult at all	1	3	8	12
Total	28	64	36	**128**

From the first contingency table involving classical music, we calculate two odds ratios $\hat{\theta}_{11} = 8$ and $\hat{\theta}_{21} = 3.3$. The first cumulative odds ratio implies that the estimated odds of having mild to moderate perceived stress rather than high or severe perceived stress for individuals listening to classical music "Very often" is 8 times the corresponding estimated odds for those who listened to classical music "Sometimes". The second cumulative odds ratio implies that the estimated odds of having mild to moderate perceived stress rather than high or severe perceived stress for individuals listening to classical music "Sometimes" is 3.3 times the corresponding estimated odds for those who listened to classical music "Rarely". Both the odds ratios are far larger than 1. Again, from the second contingency table involving country music and get $\hat{\theta}_{11} = 7.29$ and $\hat{\theta}_{21} = 2.4$. The implications here are similar to the case of classical music and both the odds ratios are far larger than 1. So, from the cumulative odds ratios, we finally conclude that frequent listening to Classical music or Country music is positively associated with lower levels of Perceived stress (or equivalently, negatively associated with severity of Perceived stress).

From the third contingency table involving time spent listening to music, we calculate two odds ratios $\hat{\theta}_{11} = 2.2$ and $\hat{\theta}_{21} = 0.38$. Although these are interpretable, but do not indicate any direction of association as the first odds ratio is larger than 1 but the second one is not. Even if we observe two local odds ratios for the second column, there is no direction of association. For the severity categories of the negative effect of the second wave, we have created the fourth contingency table with the perceived stress severity categories in a different order keeping in mind the results of the two-sample t-tests. Here, we find $\hat{\theta}_{11} = 1.71$, $\hat{\theta}_{21} = 3.22$ and $\hat{\theta}_{31} = 1.71$. As all of these three odds ratios are larger than 1. So, we conclude finally, that the time that an individual spends per day listening to music is not significantly associated with her/his perceived stress levels. We also conclude that the 2nd wave of pandemic significantly effected the perceived stress levels of our respondents in a negative way (i.e. increased perceived stress levels).

Severity of Depression

From the second classification tree (Figure 6), we observe that the three genres *Country*, *Blues* and *Electronic Dance Music* may have associations with severity of depression. We again do some further analysis for strengthening our interpretation. We know that the PHQ-9 scores do not resemble a normal distribution. So, we will use the nonparametric location tests that we mentioned before. We have categorized *Country*, *Blues* and *Electronic Dance Music* as we've mentioned. As we had created two separate categorised versions of our two response variables, we can use both pair of variables in further analyses.

First, we look at the genre country. Testing for difference of median PHQ-9 scores among the three categories of this genre with the help of Kruskal-Wallis test provides a p-value 3.805×10^{-05}, that indicates the median PHQ-9 scores for different categories of this genre differ significantly. To see how they differ, we perform pairwise wilcoxon rank sum tests. We see, that the median PHQ-9 scores corresponding to the respondents who listened to country music "Very often" are significantly lower than the median PHQ-9 scores corresponding to the respondents who listened to country music "Sometimes" (p-value is 0.0001201). However, the same is not true for "Sometimes" and "Rarely" categories (p-value is 0.2031). For the genres blues and EDM, again testing for difference of median PHQ-9 scores among the three categories of these genres provide p-values 0.6813 and 0.1398 respectively, the large p-values indicate the median PHQ-9 scores for different categories of these genres do not differ significantly.

We again look at the covariate "time spent listening to music" that has three categories "less than 30 minutes per day", "30 to 60 minutes per day" and "more than 60 minutes per day". We perform Kruskal-Wallis test to see if median PHQ-9 scores differ for these categories and get a p-value 0.4337. So, we don't need to perform further pairwise tests as we have enough statistical evidence that the median PHQ-9 scores do not differ significantly among these categories. Now, we do similar for the severity of the negative effect of the second wave of pandemic variable. Here however, we get a p-value of 5.434×10^{-06} for the Kruskal-Wallis test. We further perform pairwise Wilcoxon rank sum tests. Participants who answered "Extremely difficult" to the question had a significantly higher median PHQ-9 score than participants who answered "Very difficult" (p-value is 0.004944). Again, participants who answered "Very difficult" to the question had a significantly higher median PHQ-9 score than participants who answered "Somewhat difficult" (p-value is 0.004546).

Finally, we create contingency tables and calculate odds ratios for the covariates that we inspected. For the two genres blues and edm, we get very large p-values. So we decide that we don't need to inspect them any further. The contingency tables are shown below.

Severity of Depression						
Country Music	**No**	**Mild**	**Moderate**	**High**	**Severe**	**Total**
Very often	14	14	5	0	0	33
Sometimes	11	24	10	11	6	62
Rarely	3	15	7	5	3	33
Total	28	53	22	16	9	**128**

Severity of Depression						
Time Spent	**No**	**Mild**	**Moderate**	**High**	**Severe**	**Total**
0-30 Minutes	12	19	10	4	4	49
30-60 Minutes	2	14	8	4	1	29
More than 60 Minutes	14	20	4	8	4	50
Total	28	53	22	16	9	**128**

Severity of Depression						
2nd Wave of Covid-19	**Severe**	**High**	**Moderate**	**Mild**	**No**	**Total**
Extremely difficult	4	2	5	2	0	13
Very difficult	4	7	7	15	3	36
Somewhat difficult	1	7	8	32	19	67
Not difficult at all	0	0	2	4	6	12
Total	28	53	22	16	9	**128**

From the first contingency table involving country music, we calculate two odds ratios $\hat{\theta}_{11} = 3.41$ and $\hat{\theta}_{21} = 2.15$. The first cumulative odds ratio implies that the estimated odds of having no depression rather than mild, moderate, high or severe depression for individuals listening to country music "Very often" is 3.41 times the corresponding estimated odds for those who listened to country music "Sometimes". The second cumulative odds ratio implies that the estimated odds of having no depression rather than mild, moderate, high or severe depression for individuals listening to country music "Sometimes" is 2.15 times the corresponding estimated odds for those who listened to country music "Rarely". Both the odds ratios are far larger than 1. Even, if we merge the two lower categories of severity of depression "No" and "Mild", we get the two odds ratios $\hat{\theta}_{11} = 4.32$ and $\hat{\theta}_{21} = 1.08$. So, from the cumulative odds ratios, we finally conclude that frequent listening to Country music is positively associated with lower levels of depression (or equivalently, negatively associated with severity of depression).

From the second contingency table involving time spent listening to music, we calculate two odds ratios $\hat{\theta}_{11} = 4.37$ and $\hat{\theta}_{21} = 0.19$. Although these are interpretable, but do not indicate any direction of association as the first odds ratio is larger than 1 but the second one is not. Even if we merge the two lower categories as we did before, the odds ratios are $\hat{\theta}_{11} = 1.4$ and $\hat{\theta}_{21} = 0.58$, so we don't find any direction of association. For the severity categories of the negative effect of the second wave, we have created the third contingency table with the depression severity categories in a different order keeping in mind the results of the pairwise Wilcoxon tests. Here, we find $\hat{\theta}_{11} = 3.55$, $\hat{\theta}_{21} = 4.28$ and we can't calculate $\hat{\theta}_{31}$, as there are no participants who experienced severe depression and had "Not difficult at all" response the said question. If we merge the "Severe" and "High" depressin categories, we get the odds ratios $\hat{\theta}_{11} = 3.55$, $\hat{\theta}_{21} = 4.28$ and again we fail to calculate $\hat{\theta}_{31}$, as there are no participants who experienced high depression and had "Not difficult at all" response the said question . So, we conclude finally, that the time that an individual spends per day listening to music is not significantly associated with her/his depression severity. As all of those calculated odds ratios of the third table are larger than 1, we also conclude that the 2nd wave of pandemic significantly effected the depression of our respondents in a negative way (i.e. increased severity of depression).

Gender

Finally we look at the gender of the participants and see if we can find anything regarding severity of perceived stress or depression. A two-sample t-test for testing difference of means of males and females regarding the PSS score provides a p-value 0.009619 for the alternative hypothesis that mean PSS score for females is greater than that of males, and so we have evidence that mean PSS score for females is significantly greater than that of males. With a similar one-sided alternative hypothesis, for the PHQ-9 variable, a wilcoxon rank sum test provides a p-value 0.0295, and so we get evidence that median PHQ-9 scores for females is also significantly greater than median PHQ-9 scores for males. Now, we again construct two contingency tables taking gender as a covariate. From the first contingency table, we get the first cumulative odds ratio $\hat{\theta}_{11} = 2.35$ and the local odds ratio $\hat{\theta}_{12} = 2.11$. We see that the estimated odds of females having severe perceived stress rather than high or mild to moderate perceived stress is 2.35 times the corresponding estimated odds for males. Also, the estimated odds of females having high perceived stress rather than mild to moderate perceived stress is 2.11 times the corresponding estimated odds for males.

Severity of Perceived Stress				
Gender	**Severe**	**High**	**Mild to Moderate**	**Total**
Female	12	33	18	63
Male	23	30	9	62
Total	35	63	27	**125**

Severity of Depression						
Gender	**Severe**	**High**	**Moderate**	**Mild**	**No**	**Total**
Female	4	12	13	24	10	63
Male	4	4	8	29	17	62
Total	28	53	22	16	9	**125**

From the second contingency table, we get the first cumulative odds ratio $\hat{\theta}_{11} \simeq 1$ and if we combine the two categories "Severe" and "High", then $\hat{\theta}_{11}$ becomes 2.29. Further, combining the three categories "Severe", "High" and "Moderate", we get $\hat{\theta}_{11} = 2.45$. We can see a direction of association here, as two of these three odds ratios are far greater than 1. So, from the odds ratios obtained from the two tables, we conclude that during the period, females experienced higher levels of perceived stress and also were prone to higher severity of depression than males.

9 Conclusion

So, in this study, we tried to infer about any association with different genres of music and severity of depression and perceived stress. We further used classification trees not to conclude about any association of music genres and severity of depression or perceived stress, but to get an idea about potential associations. We later used nonparametric and parametric location tests and finally odds ratios to establish some associations.

We observed that, frequent listening to classical music or country music makes a person less prone to higher levels of perceived stress and frequent listening to country music makes a person less prone to higher levels of depression. However, we also, observed that, the amount of time a person spends listening to music is not significantly associated with her/his mental health and the second wave of covid-19 pandemic effected the mental health of the respondents significantly. We also observed that female participants experienced higher levels of perceived stress and depression than male participants.

However, as association do not imply causation and there are certainly far more factors other than music that can influence a person's mental health, we cannot say anything more than what we've concluded. However, a broader study of a similar concept with a much larger sample of participants from a more heterogeneous population can tell more stories regarding types of music and human behaviour.

Acknowledgement

I sincerely thank Prof. Bhaswati Ganguli and Prof. Gaurangadeb Chattopadhyay for their immense guidance and thoughtful suggestions throughout this study. I would also like to thank all the respondents of the questionnaire and my friends for helping me complete this study.

References

[1] Cohen, Sheldon, et al. *A Global Measure of Perceived Stress.* Journal of Health and Social Behavior, vol. 24, no. 4, 1983, pp. 385–396. JSTOR, www.jstor.org/stable/2136404. Accessed 27 July 2021.

[2] Kroenke K, Spitzer RL, Williams JB. *The PHQ-9: validity of a brief depression severity measure.* J Gen Intern Med. 2001 Sep;16(9):606-13. doi: 10.1046/j.1525-1497.2001.016009606.x. PMID: 11556941; PMCID: PMC1495268.

[3] Thoma, Myriam V et al. *The effect of music on the human stress response.* PloS one vol. 8,8 e70156. 5 Aug. 2013, doi:10.1371/journal.pone.0070156

[4] Olshen R.,Breiman L.,Friedman J.,Stone C.J.(1993).*Classification and Regression Trees.* United Kingdom:Taylor & Francis.

[5] Agresti, Alan. *Analysis of Ordinal Categorical Data.*

[6] James G., Witten D., Hastie T., Tibshirani R. *An Introduction to Statistical Learning with Applications in R.*

R Code

```
rm(list = ls())

library(readxl)

data <- read_excel("Project Questionnaire (Responses).xlsx")

#Loading required libraries

library(rpart)

library(rpart.plot)

library(hot.deck)

#Checking Missing Values

n = dim(data)[1]

mo = numeric(n)

for (i in 1:n) {

  mo[i] = sum(is.na(data[i,]))

}

mo1 = numeric(44)

for (i in 1:44) {

  mo1[i] = sum(is.na(data[,i]))

}


data = data.frame(data)


#Checking the Missing value distribution

library(mice)

md.pattern(data)

#Removing the missing observations at first

#Two genres that people listened to the most have a lot of missing values

mo = numeric(n)

for (i in 1:n) {

  mo[i] = sum(is.na(data[i,-c(18:44)]))
```

```
}
data$mo = mo
#Observation 5,92,99,113,119,141,147 should be removed
data = data[-c(5,92,99,113,119,141,147),]

#Doing imputation
set.seed(123)
data2 = hot.deck(data[,c(19:27,31:44)], m = 1,method = "p.draw", impContinuous = "HD")
data[,19:27] = data2$data[[1]][,1:9]
data[,31:44] = data2$data[[1]][,10:23]
n = dim(data)[1]
mo = numeric(n)
for (i in 1:n) {
  mo[i] = sum(is.na(data[i,-c(18:44)]))
}
data$mo = mo
mo1 = numeric(44)
for (i in 1:44) {
  mo1[i] = sum(is.na(data[,i]))
}

data = data[which(data$mo ==0),] #Dataset with 128 observations

#Calculating PHQ9 Scores
data$PHQSC = numeric(nrow(data))
for (i in 19:27) {
data[,i] = factor(data[,i],
         levels = c("Not at all" , "Several days", "More than half the days",
               "Nearly every day"),
         labels = c(0, 1, 2, 3))
```

```
data[,i] = as.numeric(as.character(data[,i]))
data$PHQSC = data$PHQSC + data[,i]
}

#Calculating PSS Scores
#Fixing the scores of the positive items
for (i in c(34,35,36,37,39,40,43)) {
  data[,i] = 4 - data[,i]
}

data$PSS = numeric(nrow(data))
for (i in 31:44) {
  data[,i] = as.numeric(data[,i])
  data$PSS = data$PSS + data[,i]
}
#Testing Normality for the two response variables
shapiro.test(data$PSS)
shapiro.test(data$PHQSC)
#Some summary of the two response variables
summary(data$PHQSC)
sum(data$PHQSC>4)
sum(data$PHQSC>9)
sum(data$PHQSC>14)
sum(data$PHQSC>19)

summary(data$PSS)
sum(data$PSS<27)
sum(data$PSS>39)

#Checking the average Depression score of different time groups
```

```
data$time = data$On.an.average..how.many.minutes.per.day..have.you.listened.to.music.in.the.last.month.

unique(data[,5])

dataT1 = data[which(data$time=="0-30 Minutes/Day"),]

dataT2 = data[which(data$time=="30-60 Minutes/Day"),]

dataT3 = data[which(data$time=="More than 60 Minutes/Day"),]

summary(dataT1$PHQSC)

summary(dataT2$PHQSC)

summary(dataT3$PHQSC)


#Checking the average Perceived Stress score of different time groups

summary(dataT1$PSS)

summary(dataT2$PSS)

summary(dataT3$PSS)


#Categorizing the Scores

data$PSSC = ifelse(data$PSS<27,"Mild to Moderate P-Stress",

         ifelse(data$PSS <40,"High P-Stress","Severe P-Stress"))

data$PHQSCC = ifelse(data$PHQSC<5,"No Depression",

          ifelse(data$PHQSC <10,"Mild Depression",

             ifelse(data$PHQSC <15,"Moderate Depression",

                ifelse(data$PHQSC <20,"High Depression","Severe Depression"))))


#Converting the covid variable to an ordinal one for model building

data$covid =
data$How.difficult.have.the.second.wave.of.pandemic.made.it.for.you.to.do.your.work...take.care.of.things.at.h
ome.or.get.along.with.other.people.

data$covidord = ifelse(data$covid == "Not difficult at all",0,

           ifelse(data$covid == "Somewhat difficult",1,

              ifelse(data$covid == "Very difficult",2,3)))


#Fitting Classification Tree
```

```
ct =
rpart(PSSC~Classical+Bollywood+Country+Electronic.Dance.Music+Pop+Hip.hop+Jazz+Rock+Metal+Blues+Instrumental.Film.or.TV.Series.Scores+Bengali.Music+covidord, data = data, method = 'class')

rpart.plot(ct)

ctd =
rpart(data$PHQSCC~data$Classical+data$Bollywood+data$Country+data$Electronic.Dance.Music+data$Pop+data$Hip.hop+data$Jazz+data$Rock+data$Metal+data$Blues+data$Instrumental.Film.or.TV.Series.Scores+data$Bengali.Music+covidord, data = data, method = 'class')

rpart.plot(ctd)


#Cross Validation

printcp(ct)

printcp(ctd)

plotcp(ct)

plotcp(ctd)


#Pruning the trees

ctsf = prune(ct, cp=   ct$cptable[which.min(ct$cptable[,"xerror"]),"CP"])

rpart.plot(ctsf)

ctdf = prune(ctd, cp=   ctd$cptable[which.min(ctd$cptable[,"xerror"]),"CP"])

rpart.plot(ctdf)

printcp(ctsf)

printcp(ctdf)

summary(ctsf)

summary(ctdf)

#We can see some association of PHQ9 and PSS Scores with the genres Classical and Country

#We perform further non-parametric test

#Fist we split the data into two groups based on classical music

uclsc = data[which(data$Classical >6),]

lclsc = data[which(data$Classical <7),]

summary(uclsc$PSS)

summary(lclsc$PSS)
```

```r
wilcox.test(uclsc$PSS,lclsc$PSS, alternative = "two.sided")

#If we separately split the data in three groups based on classical music and country music
uclsc = data[which(data$Classical >6),]
mclsc = data[which(data$Classical <7 & data$Classical >3),]
lclsc = data[which(data$Classical <4),]

uctr = data[which(data$Country >6),]
mctr = data[which(data$Country <7 & data$Country >3),]
lctr = data[which(data$Country <4),]

data$ClassicalC = ifelse(data$Classical>6,"Very often listened",
                  ifelse(data$Classical>3,"Sometimes listened","Rarely listened"))

data$CountryC = ifelse(data$Country>6,"Very often listened",
                  ifelse(data$Country>3,"Sometimes listened","Rarely listened"))

#Running tests on PSS Scores
#For Classical Music Categories
anova(aov(data$PSS~data$ClassicalC))
t.test(mclsc$PSS,uclsc$PSS, alternative = "greater")
t.test(lclsc$PSS,mclsc$PSS, alternative = "greater")

#For country music categories
anova(aov(data$PSS~data$CountryC))
t.test(mctr$PSS,uctr$PSS, alternative = "greater")
t.test(lctr$PSS,mctr$PSS, alternative = "greater")

#For time spent listening to music categories
anova(aov(data$PSS~data$time))
```

```
#For the severity of 2nd wave of pandemic categories
anova(aov(data$PSS~data$covid))
t.test(data[which(data$covidord == 3),]$PSS,data[which(data$covidord == 2),]$PSS, alternative = "greater")
t.test(data[which(data$covidord == 2),]$PSS,data[which(data$covidord == 1),]$PSS, alternative = "greater")
t.test(data[which(data$covidord == 1),]$PSS,data[which(data$covidord == 0),]$PSS, alternative = "greater")

#We now look at the odds ratios, by creating contingency tables
table(data$ClassicalC, data$PSSC)
table(data$CountryC, data$PSSC)
table(data$time, data$PSSC)
table(data$covid, data$PSSC)

#Now we do the tests to the PHQ9 Variable
kruskal.test(list(lctr$PHQSC, mctr$PHQSC, uctr$PHQSC))
wilcox.test(mctr$PHQSC,uctr$PHQSC, alternative = "greater")
wilcox.test(lctr$PHQSC,mctr$PHQSC, alternative = "greater")

#Further we check importance of Country, Blues and EDM for Depression scores
ublues = data[which(data$Blues >6),]
mblues = data[which(data$Blues <7 & data$Blues >3),]
lblues = data[which(data$Blues <4),]

uedm = data[which(data$Electronic.Dance.Music >6),]
medm = data[which(data$Electronic.Dance.Music <7 & data$Electronic.Dance.Music >3),]
ledm = data[which(data$Electronic.Dance.Music <4),]

#Performing Non-parametric test
kruskal.test(list(lblues$PHQSC, mblues$PHQSC, ublues$PHQSC))
kruskal.test(list(ledm$PHQSC, medm$PHQSC, uedm$PHQSC))
```

```
kruskal.test(list(dataT1$PHQSC, dataT2$PHQSC, dataT3$PHQSC))

kruskal.test(list(data[which(data$covidord == 3),]$PHQSC,

               data[which(data$covidord == 2),]$PHQSC,

               data[which(data$covidord == 1),]$PHQSC,

               data[which(data$covidord == 0),]$PHQSC))

wilcox.test(data[which(data$covidord == 3),]$PHQSC,data[which(data$covidord == 2),]$PHQSC, alternative = "greater")

wilcox.test(data[which(data$covidord == 2),]$PHQSC,data[which(data$covidord == 1),]$PHQSC, alternative = "greater")

wilcox.test(data[which(data$covidord == 1),]$PHQSC,data[which(data$covidord == 0),]$PHQSC, alternative = "greater")


#Contingency tables for odds ratios for different covariates

table(data$CountryC, data$PHQSCC)

table(data$time, data$PHQSCC)

table(data$covid, data$PHQSCC)

table(data$Gender, data$PSSC)

table(data$Gender, data$PHQSCC)

t.test(data[which(data$Gender == "Female"),]$PSS,

      data[which(data$Gender == "Male"),]$PSS, alternative = "greater")

wilcox.test(data[which(data$Gender == "Female"),]$PHQSC,

           data[which(data$Gender == "Male"),]$PHQSC, alternative = "greater")
```