Understanding the Interrelation between Music and Mental Health

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Introduction

Mental health crisis is not a myth anymore. Almost 1 billion people are fighting with mental disorders, as World Health Organisation reports in June 2022. In the first year of the coronavirus pandemic, the cases of depression and anxiety have spiked by 25%.

At the time the growth in mental health cases forced healthcare facilities to reprioritise their preferences across the globe, this study aims to produce insights into how music can affect our mental wellbeing.

Music is an integral part of our everyday life and listening to the music of preference undoubtedly lifts up our mood (Clements-Cortes and Pascoe, 2020).

But our engagement with music is nothing new. The earlier date for using music for therapeutic purposes can be traced back to history. In his book De Anima, Aristotle (323–373 BCE), elaborated on the purifying effect of listening to a flute. Evidence shows physicians in Ancient Greece and Egypt used musical instruments to heal their patients.

Listening to music triggers an individual’s reward system. It helps manage emotional upsurges and boost positive feelings, such as motivation and pleasure (Chanda and Levitin, 2013).

The systematic and scientific study of the application of music in healing began at the end of the 19th century. Diogel of Salpetriere Hospital in Paris was the torchbearer. In his debut research paper, he showed case studies where music has uplifted cardiac performance (Meymadi, 2009).

This report will analyse if there is any truth in the claim that music boosts mood.

During analysing the explanatory questionnaire, we will dig deeper to fathom the relationship between the choice of music and the type of mental illness, too.

Research Questions

Exploratory:

• How old are the respondents?

• How do people listen to music?

• Do people listen to music at workplaces?

• How many of the respondents are expert musicians?

• What age group spend most of their time listening to music?

• What are the favourite genres across age groups?

Explanatory:

• Is mental health crisis a myth?

• In what kind of mental illness, what type of music is preferred the most?

• Does listening to music improve mental wellbeing?

Data collection / Survey design

This analysis has been comprised of two datasets.

The primary source of data (from now on, called: “Dataset 1”) has been collected by scrapping the website of Our World in Data using the Data Miner tool. The data was published by Institute for Health Metrics and Evaluation, Global Burden of Disease (2019).

Dataset 1 represents individuals of heterosexual gender identities and unrestricted age. The age was standardised during calculating the percentage of mental health issues.

The second dataset (from now on, called: “Dataset 2”) was generated by Catherine Rasgaitis, a student at the University of Washington. I have accessed the data from Kaggle, an online community platform for data analysis and machine learning enthusiasts.

Ms Rasgaitis conducted an open survey via a Google form. The form was circulated through social media platforms, Reddit forums and Discord servers. Advertisements were also displayed in libraries, parks, and other major public locations.

The survey was not restricted by age, gender, or location.

Though Dataset 1 has been sourced from the governmental outlet, the lack of explanation on standardising the age and gender across the entries turns it quite challenging to fathom the inherent biases.

In the dataset, the last column, titled— “Prevalence- Mental disorders- Sex: Both- Age: Age-standardized (Percent)” denotes that the data have been collected from two major gender identities which probably are ‘Male’ and ‘Female’. If that is the fact, the dataset obviously lacks the voice of the LGBTQ+ communities.

Dataset 2 has been collected by a university student through an open survey. The lack of plenty of demographic data makes it difficult to rationalise if a demographic bias is underlying or not.

Data overview and pre-processing

Dataset 1 is in CSV data format and spread across 6753 rows. The first row contains the titles of the key variables. The key variables and their nature are discussed below:

Field Name	Field Type	Remarks
Entity	Object	Name of the countries or geographic regions.
Code	Object	Contains a unique three-letter code for each country or region. Not useful for our analysis.
Year	Integer	From 1990 to 2019. Essential for the timeline plot.
Prevalence- Mental disorders- Sex: Both- Age: Age-standardized (Percent)	Float	Denotes the percentage of mental health issues across the years.

The dataset contained mental health data for countries which are not relevant to this analysis. To narrow down the choices, the specific_rows command was called before initiating further processing.

Dataset 2 is also in CSV format. It consists of 736 rows and 33 columns. Here, too, the first row contains titles of the key variables. The key variables and their nature are discussed below:

Field Name	Field Type	Remarks

Timestamp|Object|The time when individual survey entries were created. Not required for this analysis.| Age| Float|The age of the survey takers.| Primary streaming service|Object|Platforms used to listen to music.| Hours per day|Float|The amount of time music is consumed daily.| While working|Object|Listening to music in workplaces.| Instrumentalist|Object|Can a participant play an instrument?| Composer|Object|Does the respondent compose music?| Fav genre|Object|Respondent's favourite genre of music.| Exploratory|Object|Does the respondent actively explore new artists/genres?| Foreign languages|Object|Does the participant listen to music written in foreign languages?| BPM|Float|The tempo of the songs the participant commonly listens to.| Frequency [Classical]|Object|Genre of music.| Frequency [Country]|Object|Genre of music.| Frequency [EDM]|Object|Genre of music.| Frequency [Folk]|Object|Genre of music.| Frequency [Gospel]|Object|Genre of music.| Frequency [Hip hop]|Object|Genre of music.| Frequency [Jazz]|Object|Genre of music.| Frequency [K pop]|Object|Genre of music.| Frequency [Latin]|Object|Genre of music.| Frequency [Lofi]|Object|Genre of music.| Frequency [Metal]|Object|Genre of music.| Frequency [Pop]|Object|Genre of music.| Frequency [R&B]|Object|Genre of music.| Frequency [Rap]|Object|Genre of music.| Frequency [Rock]|Object|Genre of music.| Frequency [Video game music]| Object|Genre of music.| Anxiety|Float|Nature of mental health condition. Measured on a scale of 0 to 10.| Depression|Float|Nature of mental health condition. Measured on a scale of 0 to 10.| Insomnia|Float|Nature of mental health condition. Measured on a scale of 0 to 10.| OCD|Float|Nature of mental health condition. Measured on a scale of 0 to 10.| Music effects|Object|Nature of mental health conditions. Measured on a scale of 0 to 10.| Permissions|Object|Does the respondent agree to share the data? Not necessary for this analysis.|

The dataset was apparently in tidier formats with rare blank fields. It did not need any rigorous pre-processing. But during creating the visualisations, .value_counts(), usecols, nrows etc. filtering tools have been utilised.

Analysis and results

Exploratory:

How old are the respondents?

The survey conducted by Ms Rasgaitis was primarily participated by youngsters and young adults. Figure 1 shows, the majority of them were aged between 15 and 45 years. It also shows that 10 years of age is the earliest and almost 90 years of age is the oldest value recorded in the dataset (figure 1).

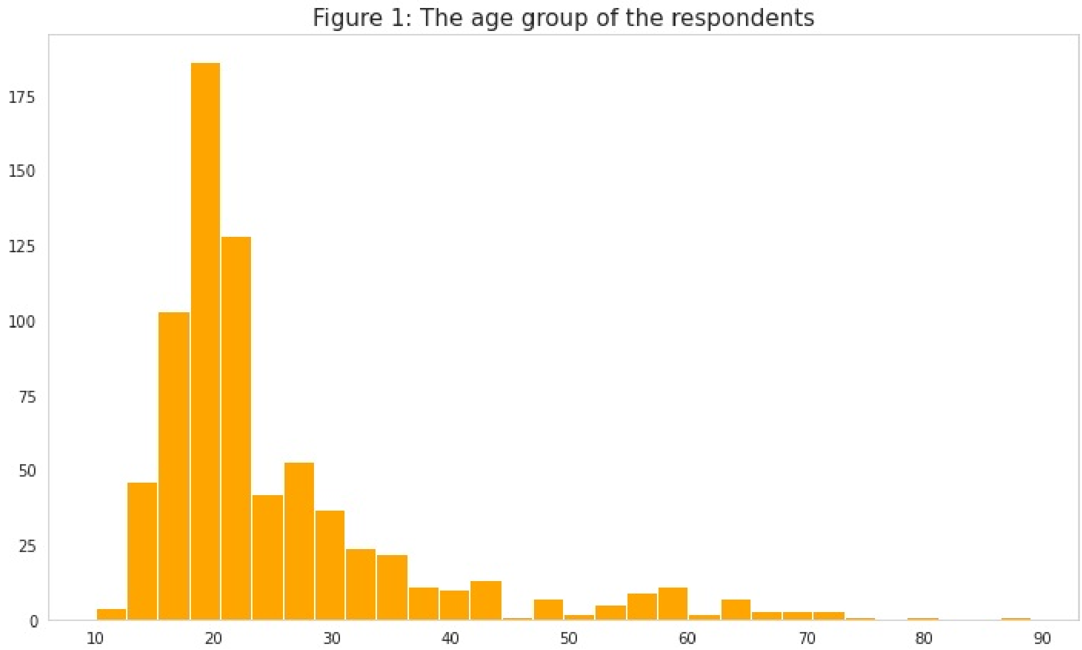

Figure 1: The age group of the respondents

How do people listen to music?

In our context of measuring the effectiveness of music listening in addressing mental health issues, the initial endeavour was taken to understand how people consume music in today's scenario.

Among the 735 individuals who participated in the survey conducted by Catherine Rasgaitis (Dataset 2), apparently, 90.34% used web-based platforms to access music e.g., Spotify, YouTube, Apple Music etc. Contrastingly, a minority of 9.66% still used traditional methods to listen to music (figure 2).

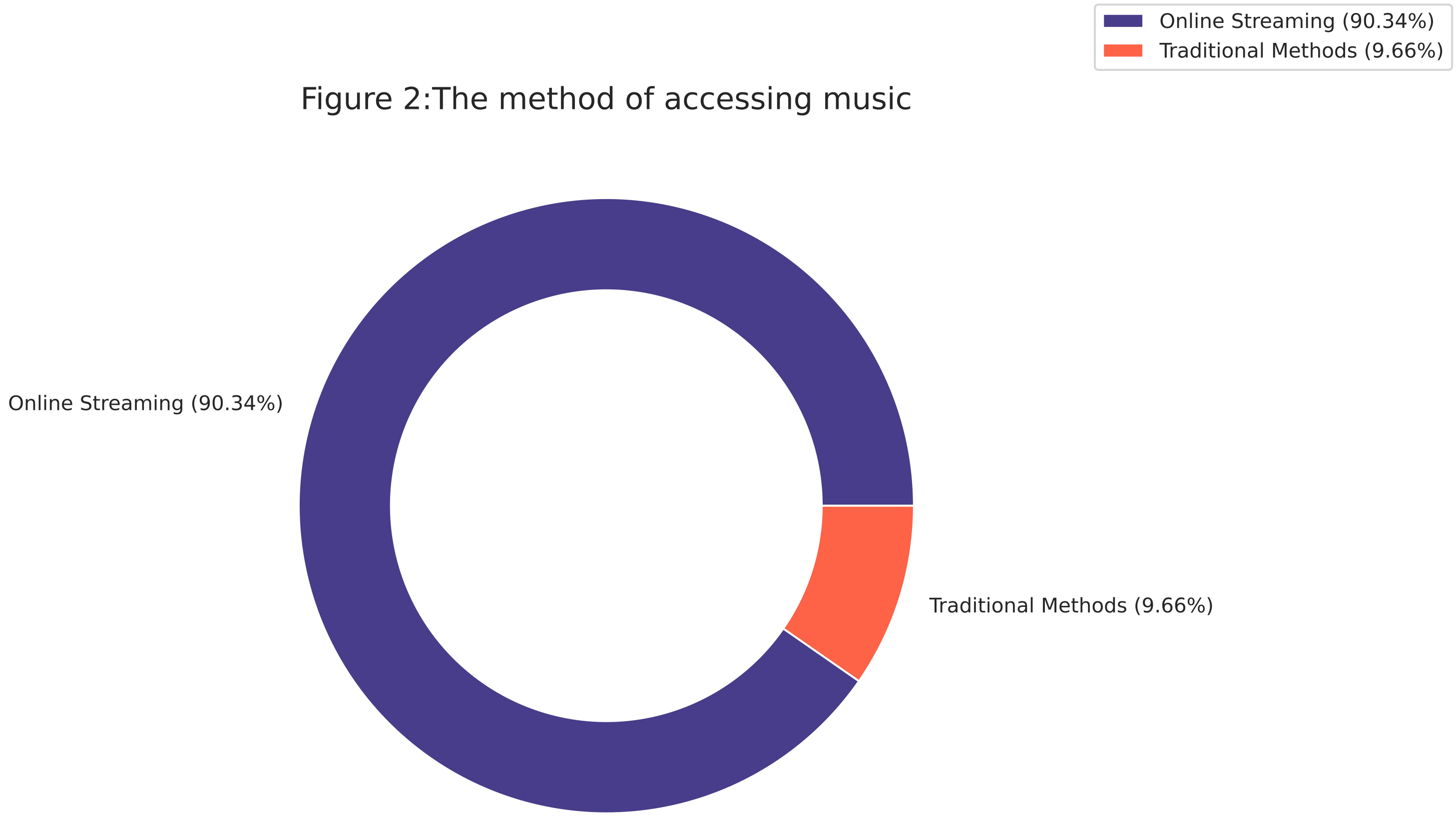

Figure 2: The method of accessing music

Across the sample, Spotify (62.31%) is the most preferred online music streaming platform. Its share is 4.87 times more than the nearest counterpart YouTube Music. Apple Music and Pandora are notable other stakeholders in this scenario (figure 3).

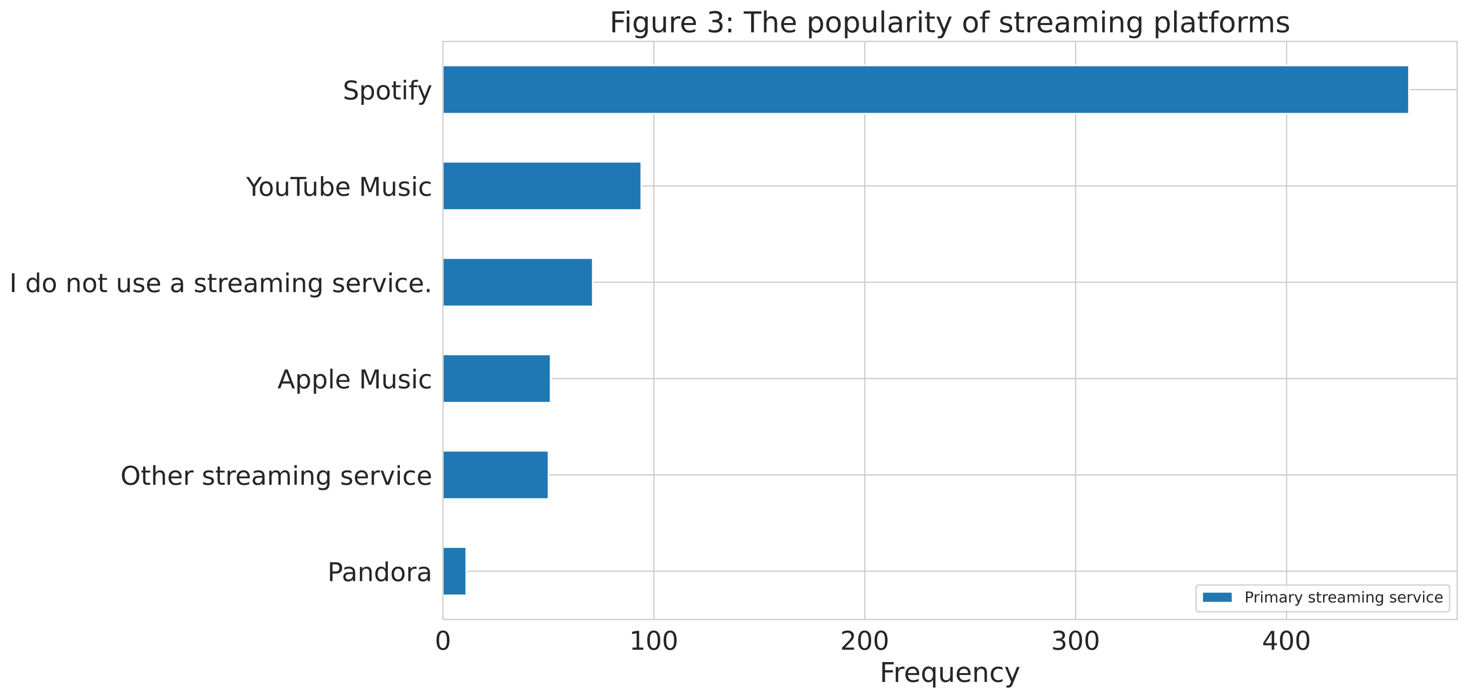

Figure 3: The popularity of streaming platforms

Do people listen to music at workplaces?

Listening to music while at work has been proven a staple for the majority (79%) of the participants in Rasgaitis' survey.

The remaining 21% do not play music while they are in workplaces, as figure 4 reflects.

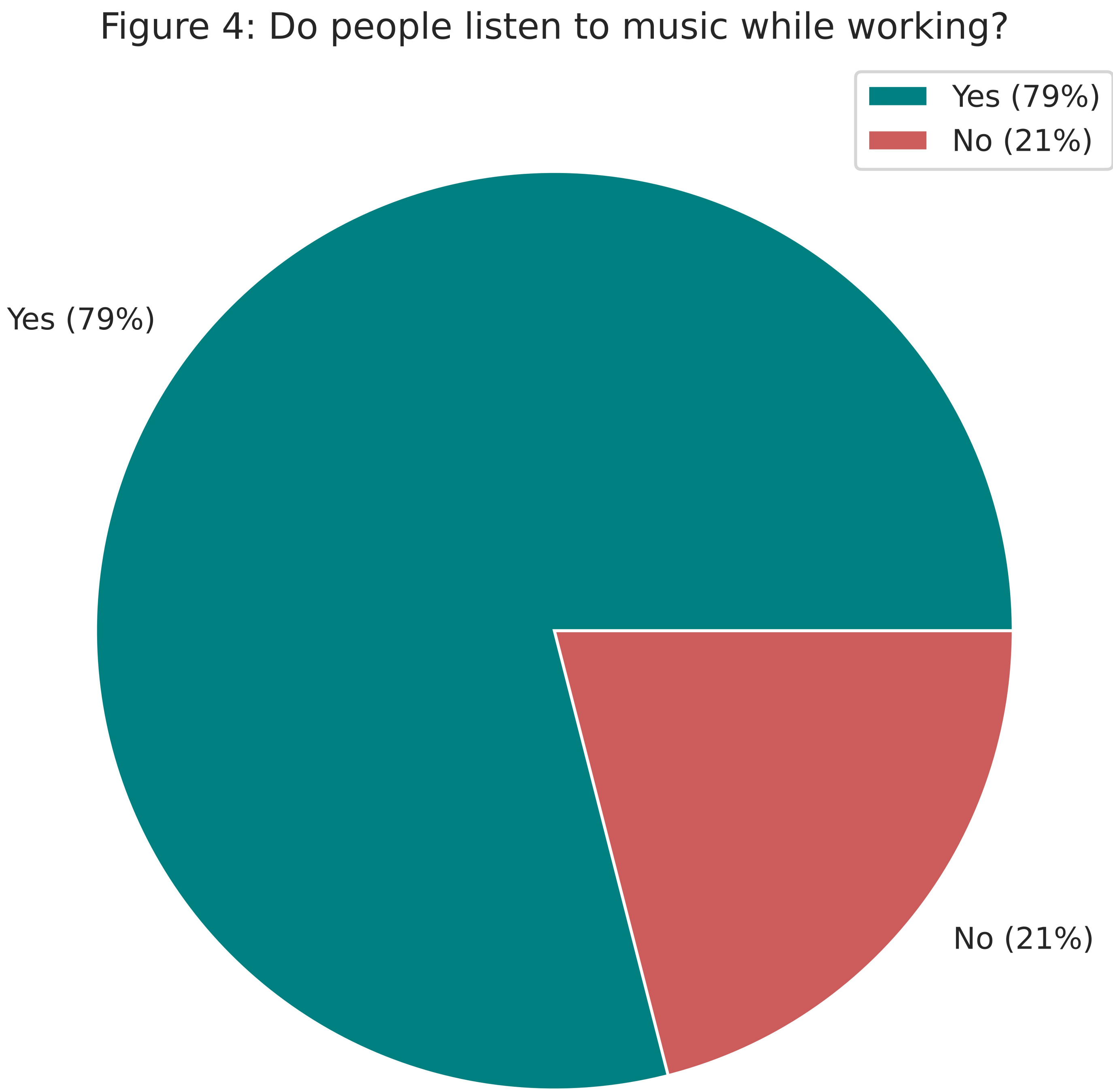

Figure 4: Do people listen to music while working?

How many of the respondents are expert musicians?

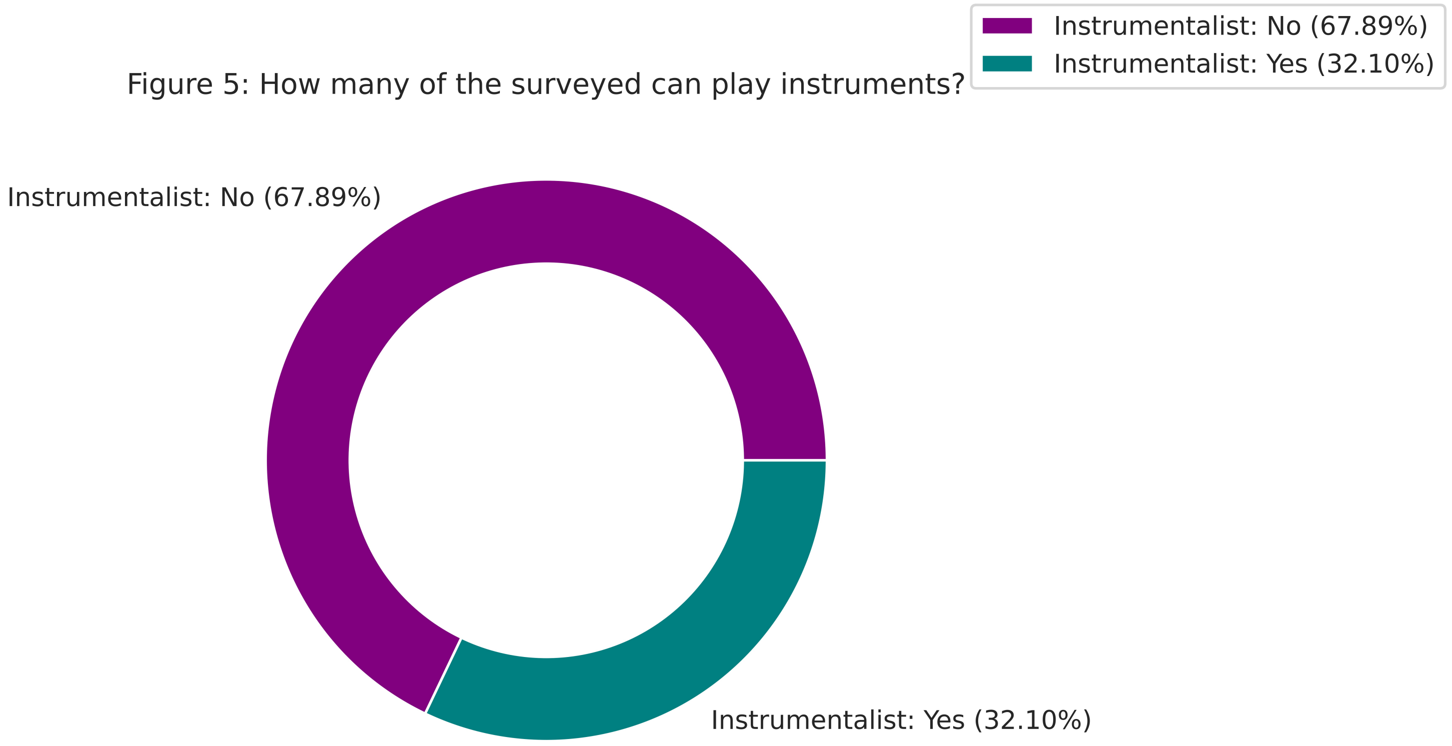

Figure 5: How many of the surveyed can play instruments?

Astonishingly, the demography that took part in the survey is not mere listeners. A good number (32.10%) of them can play musical instruments (figure 5) and another comparatively lower but still, a considerable number (17.14%) of respondents can compose original music, too (figure 6).

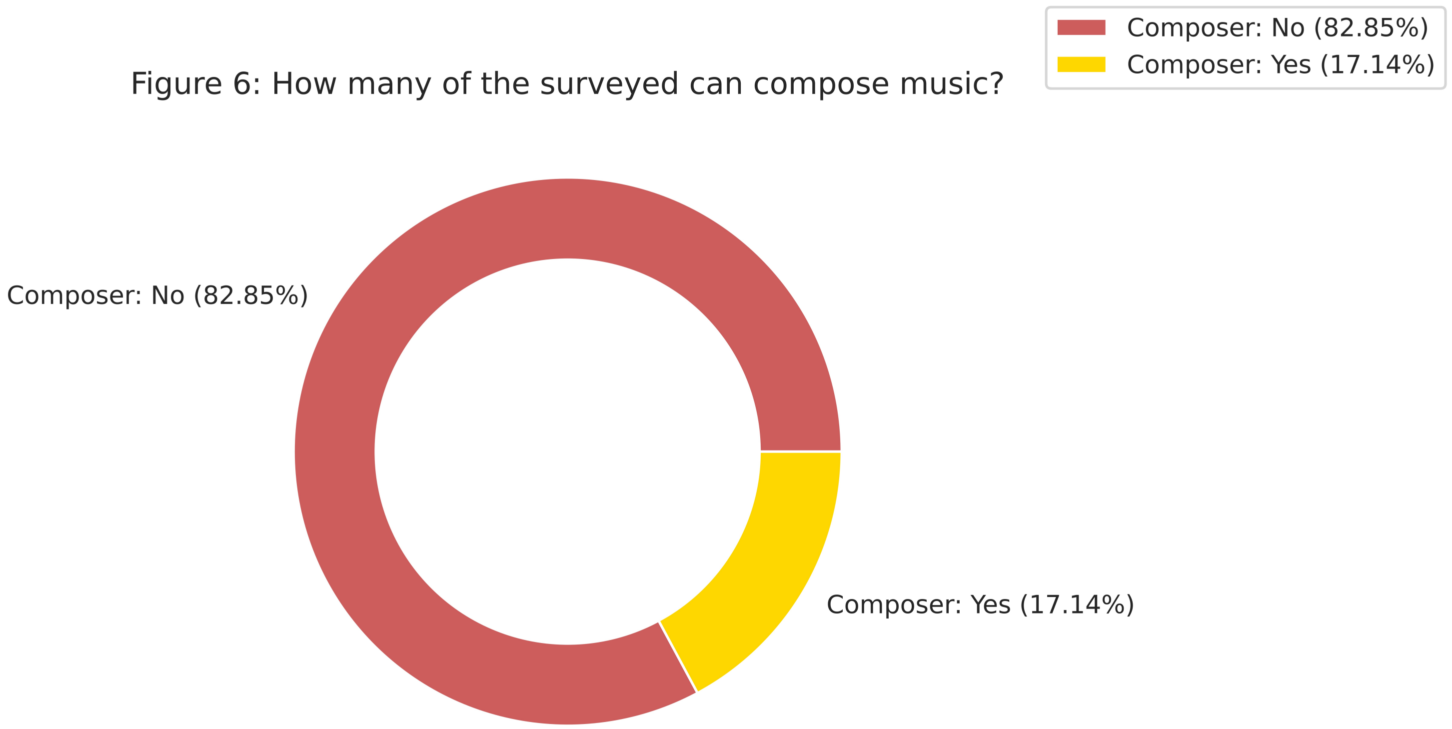

Figure 6: How many of the surveyed can compose music?

What age group spend most of their time listening to music?

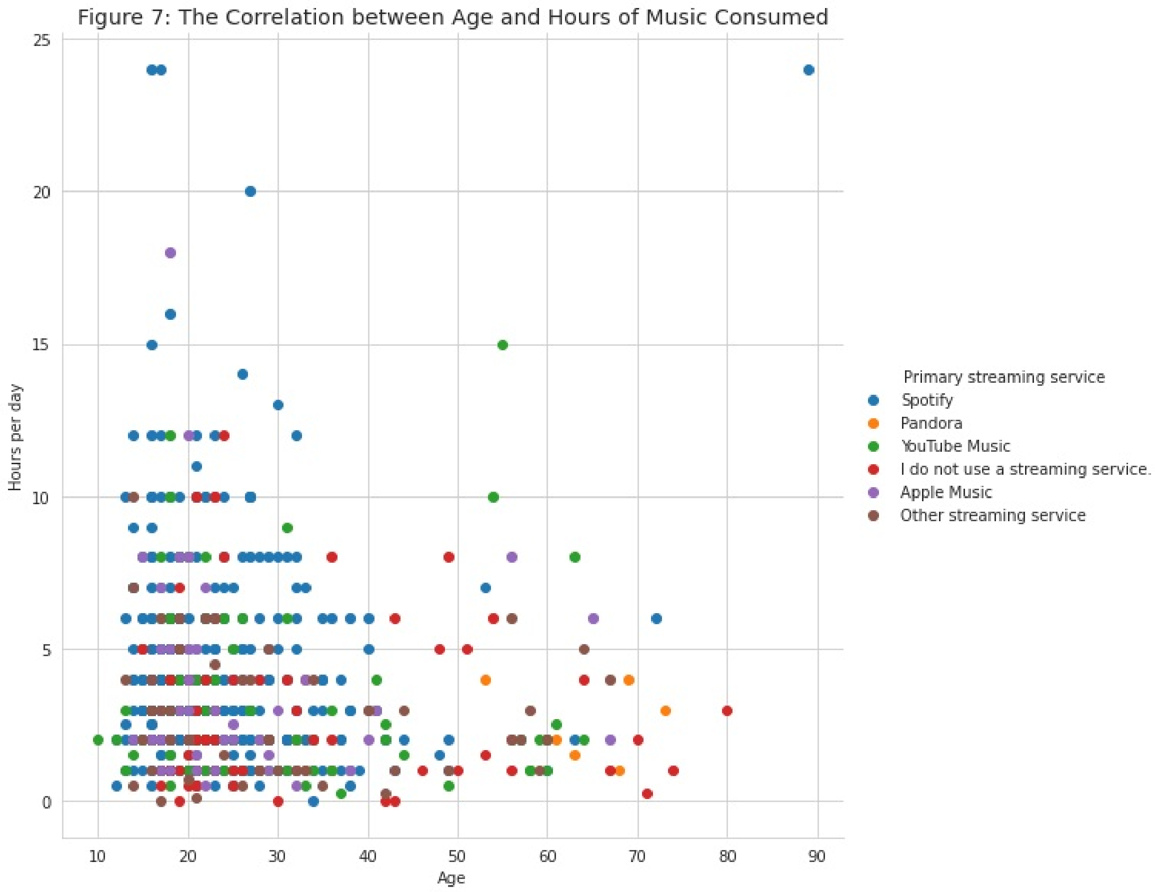

Figure 7: The Correlation between Age and Hours of Music Consumed

According to figure 7, respondents aged between 10 and 40 typically spend five hours or less daily consuming music. Few of them tend to listen to music for up to twelve hours daily.

For the age group of 40 to 80, the typical spending limits lie within ten hours on a daily basis.

Two outlier values have been found in the age group of 10 to 20, where the respondents spent almost twenty-four hours of a day listening to music.

Interestingly, only one participant has been found in the 80+ age group but the person, too, had spent all the hours of a day consuming music.

No specific trend, here, has been observed in terms of the use of the streaming platform, age, and the hours of music listening.

What are the favourite genres across age groups?

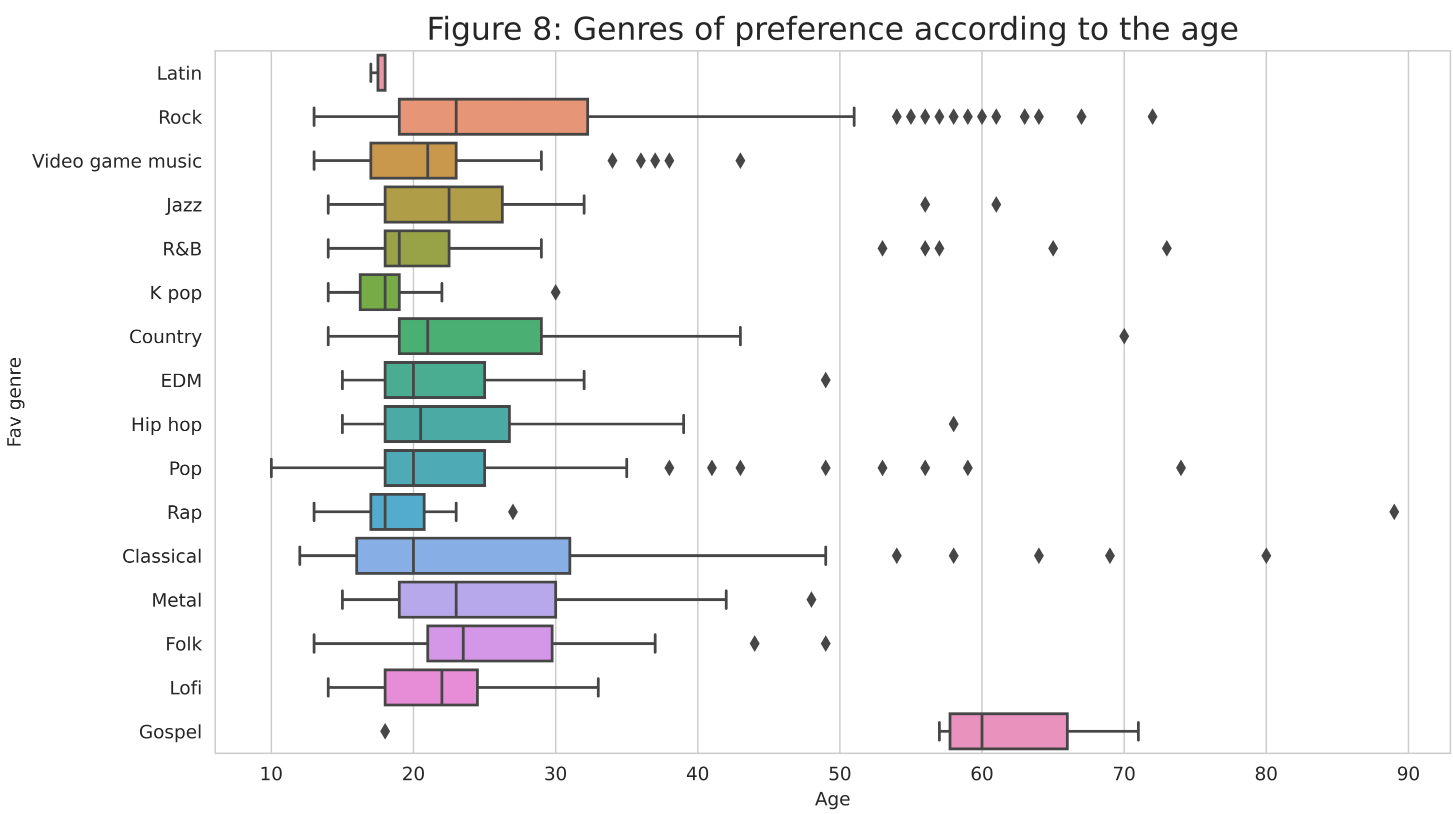

Figure 8: Genres of preference according to age

As figure 8 reflects, Classical is the most widely listened to genre of music among the surveyed populace. Though people from almost age 10 to 50 listen to this kind of music, the concentration of listeners lies between the age group of 20 and 30. The oldest listener of Classical music is 80 years old.

Rock comes second. The earliest age of listeners of this genre starts a bit late than the Classical one. Interestingly, compared to the mentioned genre, slightly more older people (aged 50+ years) also the preferers to Rock music.

Video game music, Jazz, R&B, K pop and Rap were mostly streamed by youngsters aged roughly between 15 and 25.

The oldest user across the dataset listened to Rap music though it is mostly preferred by young adults.

EDM, Hip hop, Pop, Metal, Lofi and Folk genres are enjoyed the most by the generation aged between 15 and 35. Users over 40 years of age are also regular listeners of EDM and Metal music.

Among the 16 types of music discussed, Gospel is the only kind that is dominantly preferred by senior citizens. Its audience lies between the age group of 55-70. A young adult is an exception on the list.

In our dataset, Latin is the least preferred musical genre. A few under-twenty music lovers listened to it.

Explanatory:

Is Mental Health Crisis a Myth?

Mental health disorder is not a negligible phenomenon.

Figure 9 shows, in the United States alone, 16.93% of the population, irrespective of age and gender, suffered from mental health disorders in 2019. A decade earlier, in 2009, the figure was 17.41%. If the study is pushed a decade more, in 1999, 17.84% of American citizens were suffering from psychological illness.

The data, measured over a course of 30 years, opens at 15.56% in 1990 and runs till 2019 to conclude at 16.93%. In the covered period, the number touched the highest peak in 2000 when 18% of residents of the country were challenged mentally. In 2015 and 2016, the figure dropped to the lowest point of 16.47%.

Thus, it can be observed that a variation of only 1.53% between the highest and lowest values has been recorded. It proves mental health issues are not temporary happenings but chronic issue that needs to be addressed.

As discussed in the introduction, it should further be considered that the survey ended before the coronavirus pandemic, which hit in 2020, caused a steep rise of 25% in the number of cases of mental illness worldwide.

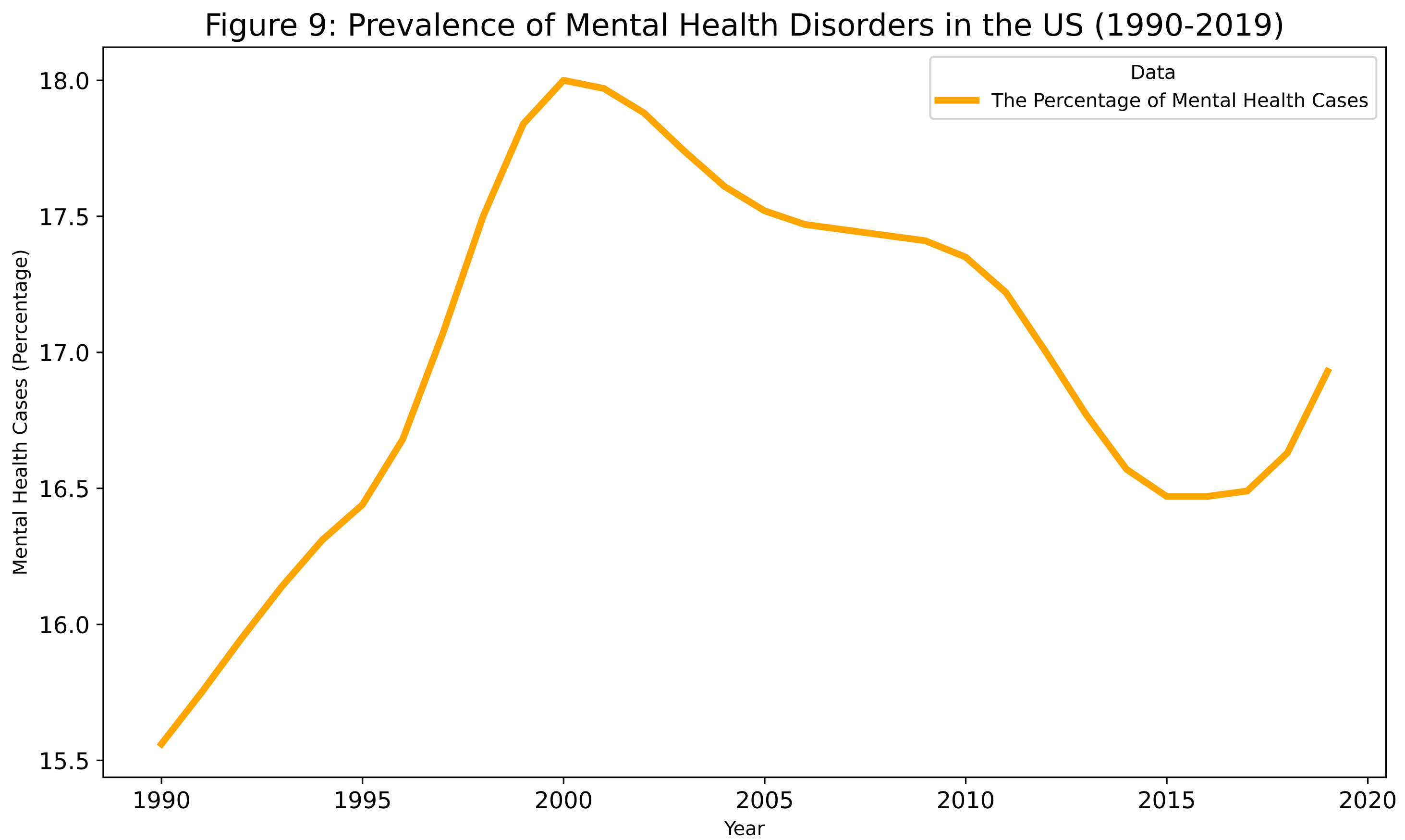

Figure 9: Prevalence of Mental Health Disorders

In what kind of mental illness, what type of music is preferred the most

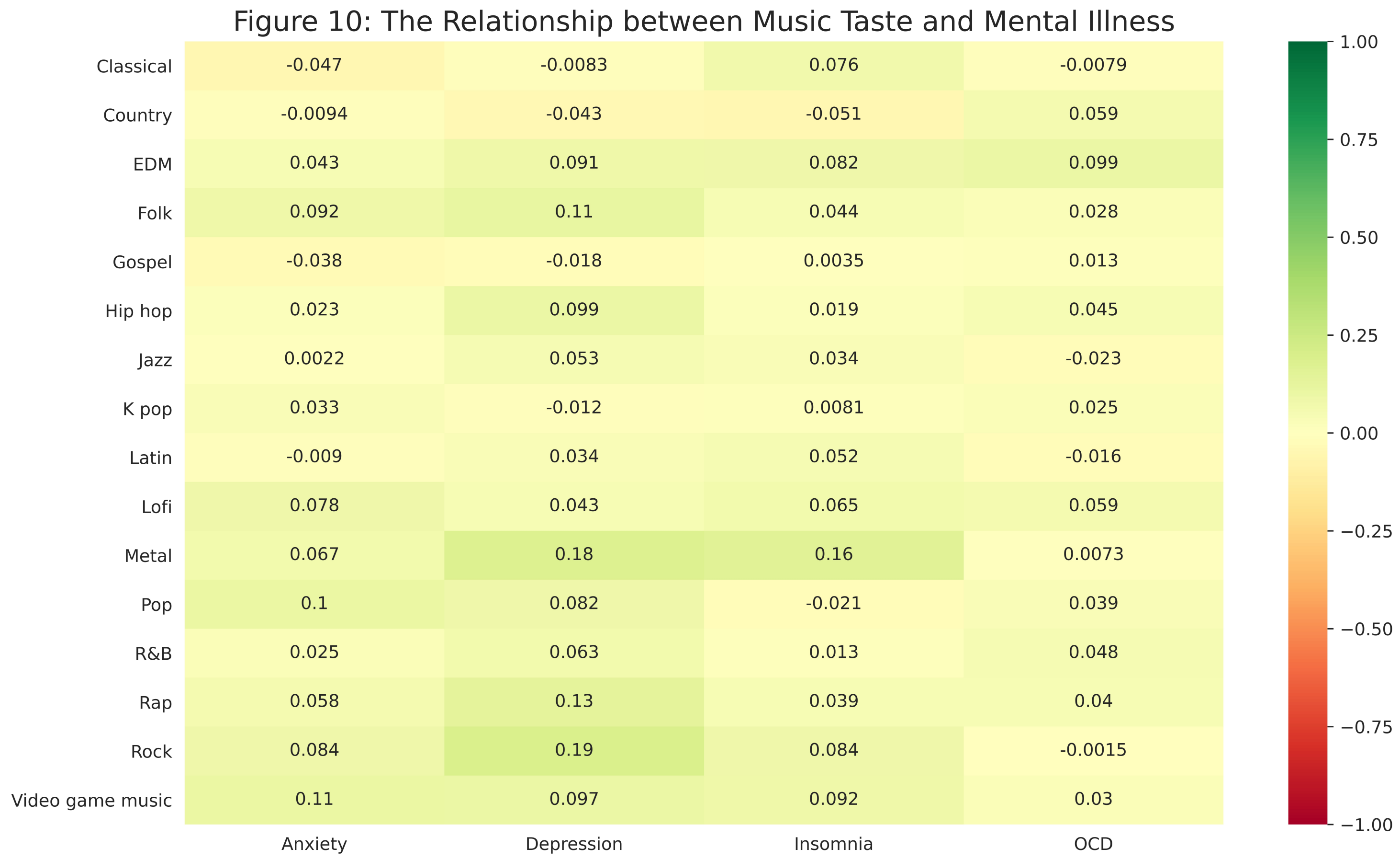

Figure 10: The Relationship between music taste and mental illness

The sufferer of anxiety likes to listen to Pop music (0.10) the most, followed by Folk (0.092) and Lofi (0.078) songs, as figure 6 shows. Classical (-0.047), Country (-0.0094), and Latin (-0.009) genres are avoided by them.

Figure 10 aims to correlate the relationship between the taste of music and mental health illness on a scale of -1.0 to 1.0. The positive values reflect the inclination towards a particular type of music while the negative ones signify the opposite.

The experience of music listening for people with depression comes primarily from Rock, Metal, Rap, Folk, and EDM genres. The populace is not fond of Classical, Country, Gospel, and K Pop music.

In contrast to others, patients with obsessive-compulsive disorder (OCD) listen to Country music in moderation (0.059). Their taste in music spreads well across the genres but electronic dance music (EDM) tops (0.099) on the list.

Though classical music is not fondly chosen by all of the above, it is moderately (0.076) picked out by the folk experiencing sleeping challenges (insomnia). It comes third after Metal (0.16) and EDM (0.082). They never incline towards the Country (-0.051) and Pop (-0.021) music.

While Classical and Country music are disliked mainly by patients with mental illness— EDM, Folk, Hip Hop, Lofi, Metal, R&B, and Rap— are quite often accessed by them.

Does listening to music improve mental wellbeing?

Among the mentally challenged population, a majority of 74.45% have experienced an improvement in their mental wellbeing.

23.21% of others stated, they could not notice a change in mood after listening to music.

A minority of the remaining 2.33% have alleged that music has contributed towards worsening their state of mind.

Figure 11 portrays the above argument on a waffle plot where the dominance of an opinion can be determined by the volume of area that has occupied.

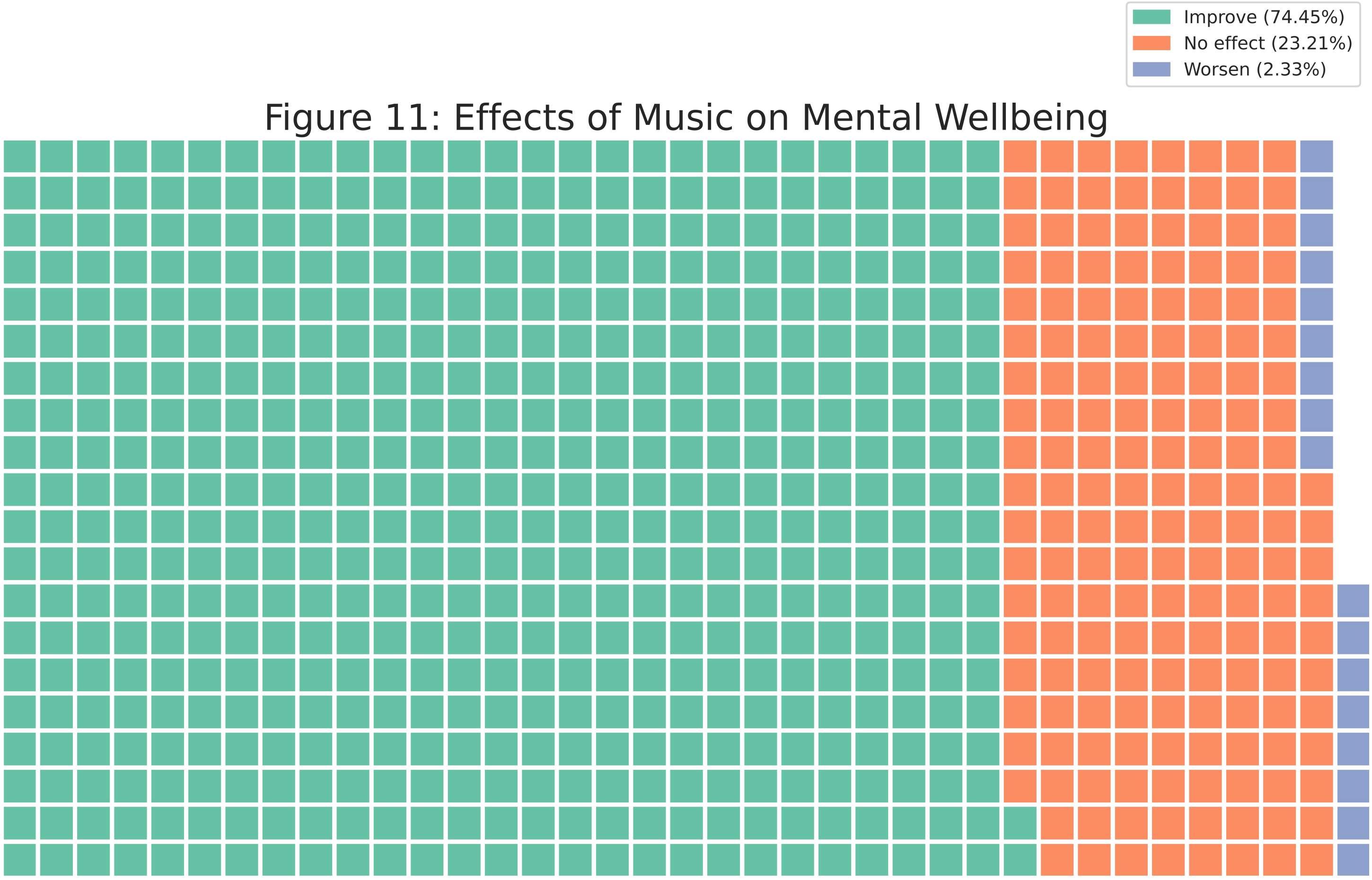

Figure 11: Effects of Music on Mental Wellbeing

To yield a deeper understanding of the effects of music on mood, it has further been considered how specific genres influence the mental health of people across different age groups.

In figure 12, Gospel and Lofi are the most benign types of music that improve the mood of all the listeners. The uplifting effect of the Gospel is far-reaching. It is the only type of music that evidently helps the golden agers.

Latin music is popular among young adults who have reported its zero negative effects.

Rock, Jazz, R&B, Country, K Pop, EDM, Hip Hop, Metal, and Folk are also genres with absolutely no negative impacts. The audience for these kinds of music is comparatively more mature than the listeners of Latin music. Interestingly, the ineffectiveness of these types of music has increased in accordance with the progression of age.

Video game music is the only type which majorly affects people's mental wellbeing, and its negative influence outweighs the positive and neutral ones. The consumers of video game music are more prone to experience its adverse effects when they are more than twenty years old.

In addition to the above observation, most of the participants across the Dataset 2 have been found young and less than forty years old. The only exception is the senior listeners of the Gospel.

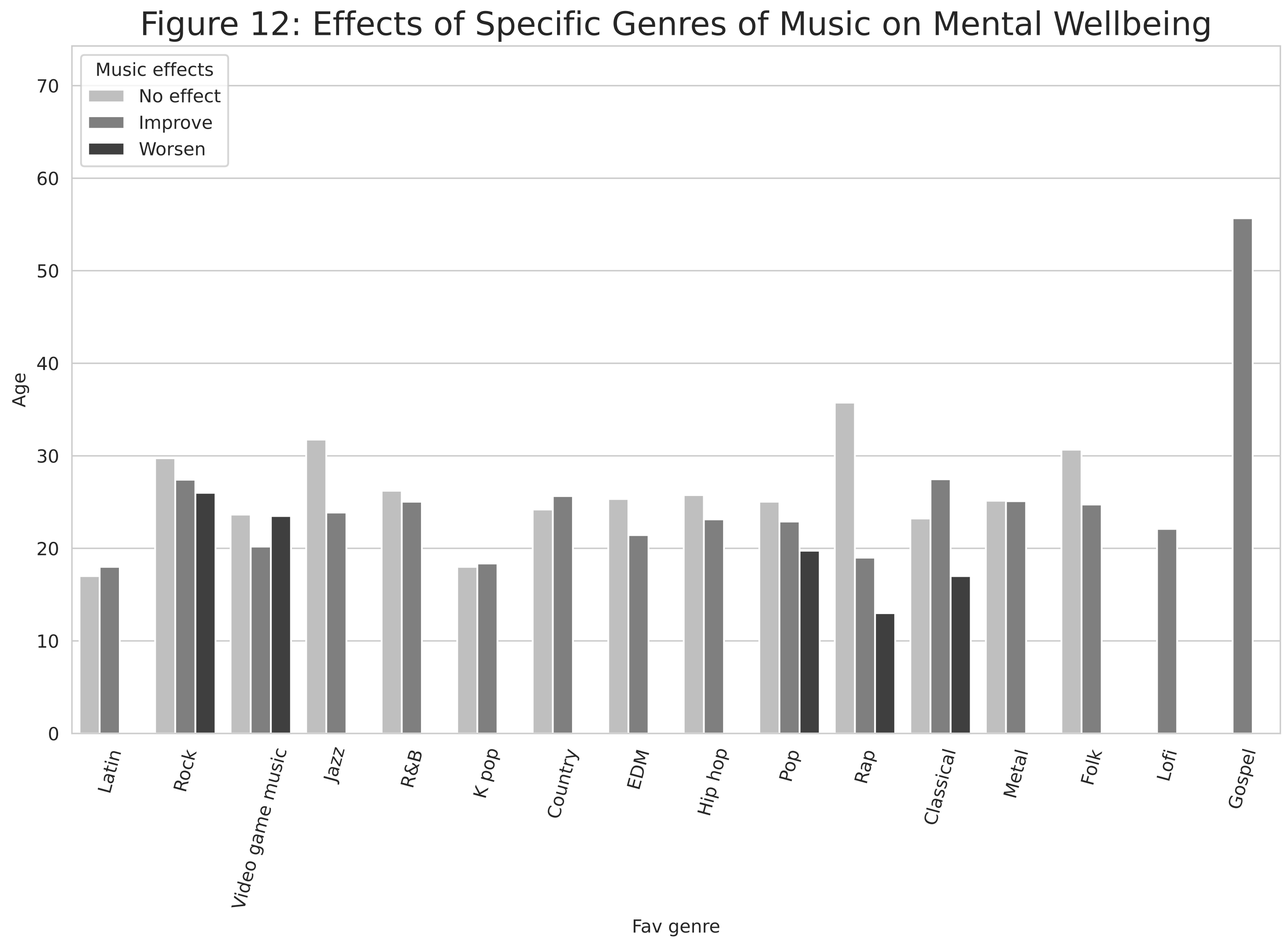

Figure 12: Effects of Specific Genres of Music on Mental Wellbeing

Conclusions

Thus, it can be concluded that listening to music has definitely a positive impact on the majority of the population. Only 2.33% of the population experienced a worsening of their mental state after listening to music but as further research showed, the effect of music also varies according to age and genre.

Neither mental illness nor music is a nondimensional phenomenon. People with a certain kind of mental issue prefer to listen to the music of a particular genre more. The wrong choice of music degrades their situation.

Overall, as data showed, a substantial amount of society is suffering from mental disorders, and the application of music in managing emotional upsurges must be promoted.

But as the analysis revealed, Music Therapy is a sensitive tool that must be administered by trained professionals only after assessing the individual needs of the sufferers.

Evaluation

As coming from a humanities background, initially it was difficult for me to navigate through the required coding skills to analyse this report.

But the topic I have chosen was close to my heart and helped me stick to the rigorous job of cleaning, sorting, and parsing the datasets.

Initially, I started working with Dataset 2 but subsequently realised the necessity of showing the percentage of the United States' population suffering from the mental health crisis. Working with another set of data justified why it is needed to put attention to the issue, right now.

Overall, the assignment was cognitively demanding but after all, aided me to push the boundary. I had put extra effort to use at least one of all the kinds of visualisation methods shown in the class and relevant to this analysis but could not apply advanced machine learning e.g., using Sci-Kit Learn for producing a Parallel Co-ordinate Plot. In the future, my endeavour would be to learn more resources on the same and to be a more effective data storyteller.

References

• https://www.who.int/publications/i/item/9789240049338 (https://www.who.int/publications/i/item/9789240049338)

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• Meymandi A. Music, medicine, healing, and the genome project. Psychiatry (Edgmont). 2009 Sep;6(9):43-5. PMID: 19855860; PMCID: PMC2766288.

Appendices

• Web link for Dataset 1: https://ourworldindata.org/grapher/share-with-mental-and-substance-disorders?tab=chart (https://ourworldindata.org/grapher/share-with-mental-and-substance-disorders?tab=chart)

• Web link for Dataset 2: https://www.kaggle.com/datasets/catherinerasgaitis/mxmh-survey-results (https://www.kaggle.com/datasets/catherinerasgaitis/mxmh-survey-results)

• Web link for Coding: Dataset 1: https://jupyter.doc.gold.ac.uk/user/smitr001/notebooks/Dataset2%3D%20Music%20%26%20Mental%20Health%20Survey%20Results.ipynb (https://jupyter.doc.gold.ac.uk/user/smitr001/notebooks/Dataset2%3D%20Music%20%26%20Mental%20Health%20Survey%20Results.ipynb)

• Web link for Coding: Dataset 2: https://jupyter.doc.gold.ac.uk/user/smitr001/notebooks/Dataset1%3D%20share-with-mental-and-substance-disorders.ipynb (https://jupyter.doc.gold.ac.uk/user/smitr001/notebooks/Dataset1%3D%20share-with-mental-and-substance-disorders.ipynb)

• Web link for Markdown Coding: Coursework Template: https://jupyter.doc.gold.ac.uk/user/smitr001/notebooks/Data%20Visualisation%20Coursework%20Template.ipynb#References (https://jupyter.doc.gold.ac.uk/user/smitr001/notebooks/Data%20Visualisation%20Coursework%20Template.ipynb#References)

Word Count

The following code will count the number of words in Markdown cells. Code cells are not included.

- `Main word count` is the number of words in the main body of the text, *excluding* references or appendices.
- `References and appendices word count` is the number of words in any references or appendices.

Only `Main word count` relates to the assignment word limit. There is no limit to the number of words that can be included in references or appendices. Please note that appendices should only be used to provide context or supporting information. *No marks will be directly awarded for material submitted in appendices*.

Important:

- Please do not modify the word count code!
- To exclude references from your word count **you must** have a cell that starts with the text `## References`. Everything below this cell will not count towards the main word count.
- If you are submitting additional material as appendices **you must** have a cell that starts with the text `## Appendices`. Everything below this cell will not count towards the main word count. If you do not have any appendices you can delete the `## Appendices` cell.
- Code comments should only be used to explain details of the implementation, not for discussing your findings. All analysis commentary **must** be written in Markdown cells. *No marks will be awarded for analysis discussion submitted as comments in code cells*.

In [1]:

```
%%js

// Run this cell to update your word count.

function wordcount() {
    let wordCount = 0
    let extraCount = 0
    let mainBody = true

    let cells = Jupyter.notebook.get_cells()
    cells.forEach((cell) => {
        if (cell.cell_type == 'markdown') {
            let text = cell.get_text()
            // Stop counting as main body when get to References or Appendices.
            if (text.startsWith('## References') ||
                text.startsWith('## Appendices')) {
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            }
            if (text.startsWith('## Word Count')) {
                text = ''
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            if (text) {
                let words = text.toLowerCase().match(/\b[a-z\d]+\b/g)
                if (words) {
                    let cellCount = words.length
                    if (mainBody) {
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                    } else {
                        extraCount += cellCount
                    }
                }
            }
        }
    })
    return [wordCount, extraCount]
}

let wc = wordcount()
element.append(`Main word count: ${wc[0]} (References and appendices word count: ${wc[1]})`)
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