

mental-health-x-music

June 18, 2023

1 Correlation of Music to Mental Health

This notebook explores the intriguing relationship between music and mental health. This notebook aims to analyze and understand how music can impact our emotional well-being and potentially serve as a therapeutic tool for managing mental health conditions.

```
[1]: import pandas as pd

data = pd.read_csv('./data/mxmh_survey_results.csv')
data
```

```
[1]:
```

	Timestamp	Age	Primary streaming service	Hours per day	\
0	8/27/2022 19:29:02	18.0	Spotify	3.0	
1	8/27/2022 19:57:31	63.0	Pandora	1.5	
2	8/27/2022 21:28:18	18.0	Spotify	4.0	
3	8/27/2022 21:40:40	61.0	YouTube Music	2.5	
4	8/27/2022 21:54:47	18.0	Spotify	4.0	
..	
731	10/30/2022 14:37:28	17.0	Spotify	2.0	
732	11/1/2022 22:26:42	18.0	Spotify	1.0	
733	11/3/2022 23:24:38	19.0	Other streaming service	6.0	
734	11/4/2022 17:31:47	19.0	Spotify	5.0	
735	11/9/2022 1:55:20	29.0	YouTube Music	2.0	

	While working	Instrumentalist	Composer	Fav genre	Exploratory	\
0	Yes	Yes	Yes	Latin	Yes	
1	Yes	No	No	Rock	Yes	
2	No	No	No	Video game music	No	
3	Yes	No	Yes	Jazz	Yes	
4	Yes	No	No	R&B	Yes	
..	
731	Yes	Yes	No	Rock	Yes	
732	Yes	Yes	No	Pop	Yes	
733	Yes	No	Yes	Rap	Yes	
734	Yes	Yes	No	Classical	No	
735	Yes	No	No	Hip hop	Yes	

Foreign languages	...	Frequency [R&B]	Frequency [Rap]	Frequency [Rock]	\
-------------------	-----	-----------------	-----------------	------------------	---

0	Yes	...	Sometimes	Very frequently	Never
1	No	...	Sometimes	Rarely	Very frequently
2	Yes	...	Never	Rarely	Rarely
3	Yes	...	Sometimes	Never	Never
4	No	...	Very frequently	Very frequently	Never
..
731	Yes	...	Never	Rarely	Very frequently
732	Yes	...	Never	Never	Sometimes
733	No	...	Sometimes	Sometimes	Rarely
734	No	...	Never	Never	Never
735	Yes	...	Very frequently	Very frequently	Very frequently

	Frequency [Video game music]	Anxiety	Depression	Insomnia	OCD	\
0	Sometimes	3.0	0.0	1.0	0.0	
1	Rarely	7.0	2.0	2.0	1.0	
2	Very frequently	7.0	7.0	10.0	2.0	
3	Never	9.0	7.0	3.0	3.0	
4	Rarely	7.0	2.0	5.0	9.0	
..	
731	Never	7.0	6.0	0.0	9.0	
732	Sometimes	3.0	2.0	2.0	5.0	
733	Rarely	2.0	2.0	2.0	2.0	
734	Sometimes	2.0	3.0	2.0	1.0	
735	Rarely	2.0	2.0	2.0	5.0	

	Music effects	Permissions
0	NaN	I understand.
1	NaN	I understand.
2	No effect	I understand.
3	Improve	I understand.
4	Improve	I understand.
..
731	Improve	I understand.
732	Improve	I understand.
733	Improve	I understand.
734	Improve	I understand.
735	Improve	I understand.

[736 rows x 33 columns]

Now, show the data table head.

```
[2]: data.head()
```

```
[2]:      Timestamp  Age Primary streaming service  Hours per day  \
0  8/27/2022 19:29:02  18.0                      Spotify          3.0
1  8/27/2022 19:57:31  63.0                      Pandora          1.5
2  8/27/2022 21:28:18  18.0                      Spotify          4.0
```

3	8/27/2022	21:40:40	61.0	YouTube Music	2.5
4	8/27/2022	21:54:47	18.0	Spotify	4.0

	While working	Instrumentalist	Composer	Fav genre	Exploratory	\
0	Yes	Yes	Yes	Latin	Yes	
1	Yes	No	No	Rock	Yes	
2	No	No	No	Video game music	No	
3	Yes	No	Yes	Jazz	Yes	
4	Yes	No	No	R&B	Yes	

	Foreign languages	...	Frequency [R&B]	Frequency [Rap]	Frequency [Rock]	\
0	Yes	...	Sometimes	Very frequently	Never	
1	No	...	Sometimes	Rarely	Very frequently	
2	Yes	...	Never	Rarely	Rarely	
3	Yes	...	Sometimes	Never	Never	
4	No	...	Very frequently	Very frequently	Never	

	Frequency [Video game music]	Anxiety	Depression	Insomnia	OCD	Music effects	\
0	Sometimes	3.0	0.0	1.0	0.0	NaN	
1	Rarely	7.0	2.0	2.0	1.0	NaN	
2	Very frequently	7.0	7.0	10.0	2.0	No effect	
3	Never	9.0	7.0	3.0	3.0	Improve	
4	Rarely	7.0	2.0	5.0	9.0	Improve	

	Permissions
0	I understand.
1	I understand.
2	I understand.
3	I understand.
4	I understand.

[5 rows x 33 columns]

1.1 Data Shape

Showing the data's shape in this study correlating the mental health and music is essential for understanding data distribution, identifying outliers, assessing assumptions, communicating findings, and supporting the interpretation of results. It enhances the validity and reliability of the study and enables researchers to draw meaningful conclusions from the data analysis.

```
[3]: data.shape
```

```
[3]: (736, 33)
```

1.2 Data Overview

Using the `data.info()` method in your study on the correlation between mental health and music can provide valuable information about the dataset.

```
[4]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 736 entries, 0 to 735
Data columns (total 33 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Timestamp                             736 non-null    object
1   Age                                   735 non-null    float64
2   Primary streaming service             735 non-null    object
3   Hours per day                         736 non-null    float64
4   While working                         733 non-null    object
5   Instrumentalist                       732 non-null    object
6   Composer                             735 non-null    object
7   Fav genre                             736 non-null    object
8   Exploratory                           736 non-null    object
9   Foreign languages                     732 non-null    object
10  BPM                                   629 non-null    float64
11  Frequency [Classical]                 736 non-null    object
12  Frequency [Country]                   736 non-null    object
13  Frequency [EDM]                       736 non-null    object
14  Frequency [Folk]                      736 non-null    object
15  Frequency [Gospel]                   736 non-null    object
16  Frequency [Hip hop]                   736 non-null    object
17  Frequency [Jazz]                      736 non-null    object
18  Frequency [K pop]                     736 non-null    object
19  Frequency [Latin]                     736 non-null    object
20  Frequency [Lofi]                      736 non-null    object
21  Frequency [Metal]                     736 non-null    object
22  Frequency [Pop]                       736 non-null    object
23  Frequency [R&B]                       736 non-null    object
24  Frequency [Rap]                       736 non-null    object
25  Frequency [Rock]                      736 non-null    object
26  Frequency [Video game music]          736 non-null    object
27  Anxiety                              736 non-null    float64
28  Depression                            736 non-null    float64
29  Insomnia                             736 non-null    float64
30  OCD                                   736 non-null    float64
31  Music effects                         728 non-null    object
32  Permissions                           736 non-null    object
dtypes: float64(7), object(26)
memory usage: 189.9+ KB
```

```
[5]: data.dtypes
```

```
[5]: Timestamp                object
Age                          float64
Primary streaming service    object
```

```

Hours per day          float64
While working          object
Instrumentalist         object
Composer               object
Fav genre              object
Exploratory            object
Foreign languages      object
BPM                    float64
Frequency [Classical]  object
Frequency [Country]    object
Frequency [EDM]         object
Frequency [Folk]        object
Frequency [Gospel]     object
Frequency [Hip hop]     object
Frequency [Jazz]        object
Frequency [K pop]       object
Frequency [Latin]       object
Frequency [Lofi]        object
Frequency [Metal]       object
Frequency [Pop]         object
Frequency [R&B]         object
Frequency [Rap]         object
Frequency [Rock]        object
Frequency [Video game music] object
Anxiety                float64
Depression              float64
Insomnia                float64
OCD                     float64
Music effects           object
Permissions             object
dtype: object

```

```
[6]: data.describe().T
```

```

[6]:
      count      mean      std   min   25%   50%   75%  \
Age      735.0  2.520680e+01  1.205497e+01  10.0   18.0   21.0   28.0
Hours per day  736.0  3.572758e+00  3.028199e+00   0.0    2.0    3.0    5.0
BPM      629.0  1.589948e+06  3.987261e+07   0.0  100.0  120.0  144.0
Anxiety   736.0  5.837636e+00  2.793054e+00   0.0    4.0    6.0    8.0
Depression 736.0  4.796196e+00  3.028870e+00   0.0    2.0    5.0    7.0
Insomnia  736.0  3.738451e+00  3.088689e+00   0.0    1.0    3.0    6.0
OCD       736.0  2.637228e+00  2.842017e+00   0.0    0.0    2.0    5.0

      max
Age      89.0
Hours per day  24.0
BPM      999999999.0

```

Anxiety	10.0
Depression	10.0
Insomnia	10.0
OCD	10.0

As shown in the table above, the maximum hours per day listened to music is 24 hours (a whole day). Meanwhile, the youngest from the data is 10, and the oldest is 89.

```
[7]: data.describe(exclude='number').T
```

```
[7]:
```

	count	unique	top	freq
Timestamp	736	735	8/28/2022 16:15:08	2
Primary streaming service	735	6	Spotify	458
While working	733	2	Yes	579
Instrumentalist	732	2	No	497
Composer	735	2	No	609
Fav genre	736	16	Rock	188
Exploratory	736	2	Yes	525
Foreign languages	732	2	Yes	404
Frequency [Classical]	736	4	Rarely	259
Frequency [Country]	736	4	Never	343
Frequency [EDM]	736	4	Never	307
Frequency [Folk]	736	4	Never	292
Frequency [Gospel]	736	4	Never	535
Frequency [Hip hop]	736	4	Sometimes	218
Frequency [Jazz]	736	4	Never	261
Frequency [K pop]	736	4	Never	416
Frequency [Latin]	736	4	Never	443
Frequency [Lofi]	736	4	Never	280
Frequency [Metal]	736	4	Never	264
Frequency [Pop]	736	4	Very frequently	277
Frequency [R&B]	736	4	Never	225
Frequency [Rap]	736	4	Rarely	215
Frequency [Rock]	736	4	Very frequently	330
Frequency [Video game music]	736	4	Never	236
Music effects	728	3	Improve	542
Permissions	736	1	I understand.	736

The timestamp has the most unique counts because it contains different strings.

1.3 Cleaning up the data

```
[8]: data = data.drop(data[(data['Age'] > 60)].index, axis=0)
data = data.drop(data[data['Hours per day'] >= 15].index, axis=0)
```

The code above will drop all the listeners who are above 60 and the listeners who listens to music more than or equal 15 hours.

```
[9]: data.drop(['Timestamp', 'Permissions'], axis=1, inplace=True)
```

We have now omitted both the column timestamp and permission, because both are irrelevant. Now, let's remove all the missing value.

```
[10]: data.isnull().sum()

data['Age'] = data['Age'].fillna(round(data['Age'].mean(), 0))
data['Primary streaming service'] = data['Primary streaming service'].
    ↳fillna(data['Primary streaming service'].mode()[0])
data['While working'] = data['While working'].fillna(data['While working'].
    ↳mode()[0])
data['Instrumentalist'] = data['Instrumentalist'].
    ↳fillna(data['Instrumentalist'].mode()[0])
data['Composer'] = data['Composer'].fillna(data['Composer'].mode()[0])
data['Foreign languages'] = data['Foreign languages'].fillna(data['Foreign_
    ↳languages'].mode()[0])
data['Music effects'] = data['Music effects'].fillna(data['Music effects'].
    ↳mode()[0])
```

After cleaning up the data, we can now check the correlation.

```
[11]: correlation = data.corr()['Age']
correlation.sort_values()
```

```
[11]: Anxiety          -0.161227
Hours per day    -0.109664
OCD              -0.092071
Depression      -0.078018
BPM              -0.033482
Insomnia         0.039889
Age              1.000000
Name: Age, dtype: float64
```

Let's print all the rows with a missing BPM column.

```
[12]: data[data['BPM'].isnull() == True]
```

```
[12]:
```

	Age	Primary streaming service	Hours per day	While working	\
10	18.0	Spotify	3.0	Yes	
12	24.0	Spotify	3.0	Yes	
15	17.0	Spotify	2.0	No	
30	20.0	Apple Music	5.0	Yes	
32	19.0	Spotify	6.0	Yes	
..	
688	18.0	Spotify	4.0	Yes	
700	20.0	YouTube Music	1.0	Yes	
706	23.0	Spotify	1.0	Yes	
712	23.0	I do not use a streaming service.	3.0	Yes	
717	23.0	Spotify	2.0	No	

	Instrumentalist	Composer	Fav genre	Exploratory	Foreign languages	BPM	\
10	Yes	No	Country	Yes	No	NaN	
12	No	No	Hip hop	Yes	Yes	NaN	
15	No	No	Pop	Yes	Yes	NaN	
30	Yes	No	Rock	Yes	Yes	NaN	
32	Yes	No	Metal	Yes	Yes	NaN	
..	
688	No	No	R&B	No	No	NaN	
700	No	No	Pop	No	Yes	NaN	
706	Yes	No	Rock	Yes	Yes	NaN	
712	No	No	Rock	No	No	NaN	
717	No	No	Rock	Yes	Yes	NaN	

	Frequency [Pop]	Frequency [R&B]	Frequency [Rap]	Frequency [Rock]	\
10	Rarely	Rarely	Never	Rarely	
12	Sometimes	Sometimes	Rarely	Rarely	
15	Very frequently	Rarely	Sometimes	Sometimes	
30	Sometimes	Sometimes	Sometimes	Very frequently	
32	Sometimes	Never	Never	Sometimes	
..	
688	Sometimes	Very frequently	Sometimes	Never	
700	Very frequently	Rarely	Sometimes	Rarely	
706	Very frequently	Sometimes	Sometimes	Very frequently	
712	Sometimes	Rarely	Never	Very frequently	
717	Sometimes	Sometimes	Sometimes	Very frequently	

	Frequency [Video game music]	Anxiety	Depression	Insomnia	OCD	\
10	Never	7.0	7.0	4.0	7.0	
12	Never	9.0	3.0	2.0	7.0	
15	Rarely	7.0	5.0	4.0	1.0	
30	Rarely	7.0	7.0	2.0	0.0	
32	Sometimes	9.0	8.0	2.0	3.0	
..	
688	Never	8.0	0.0	0.0	2.0	
700	Very frequently	8.0	9.0	6.0	5.0	
706	Very frequently	8.0	6.0	1.0	4.0	
712	Never	10.0	5.0	2.0	0.0	
717	Never	5.0	7.0	10.0	2.0	

	Music effects
10	No effect
12	Improve
15	Worsen
30	Improve
32	Improve
..	...


```

688      No effect
700      Worsen
706      Improve
712      Improve
717      No effect

```

```
[101 rows x 31 columns]
```

```
[13]: sorted(data['Fav genre'].unique())
```

```

[13]: ['Classical',
      'Country',
      'EDM',
      'Folk',
      'Gospel',
      'Hip hop',
      'Jazz',
      'K pop',
      'Latin',
      'Lofi',
      'Metal',
      'Pop',
      'R&B',
      'Rap',
      'Rock',
      'Video game music']

```

The above array is the list of unique favorite genre of the listeners from our data.

```

[14]: for i in ['Classical', 'Country', 'EDM', 'Folk', 'Gospel', 'Hip hop', 'Jazz',
      ↪ 'K pop', 'Latin', 'Lofi', 'Metal', 'Pop', 'R&B', 'Rap', 'Rock', 'Video game
      ↪ music']:
      data['BPM'] = data['BPM'].fillna(round(data[data['Fav genre']== i ]['BPM'].
      ↪ mean(), 0))

```

1.4 Data Visualizations

This section focuses on the visual exploration and representation of data related to mental health and music. Through various plotting techniques and visualizations, this section aims to enhance the understanding of the correlation between mental health and musical factors. Furthermore, this also delves into the creation of more sophisticated visualizations specifically tailored to analyzing the mental health correlation to music.

```

[15]: import seaborn

seaborn.set(color_codes=True)

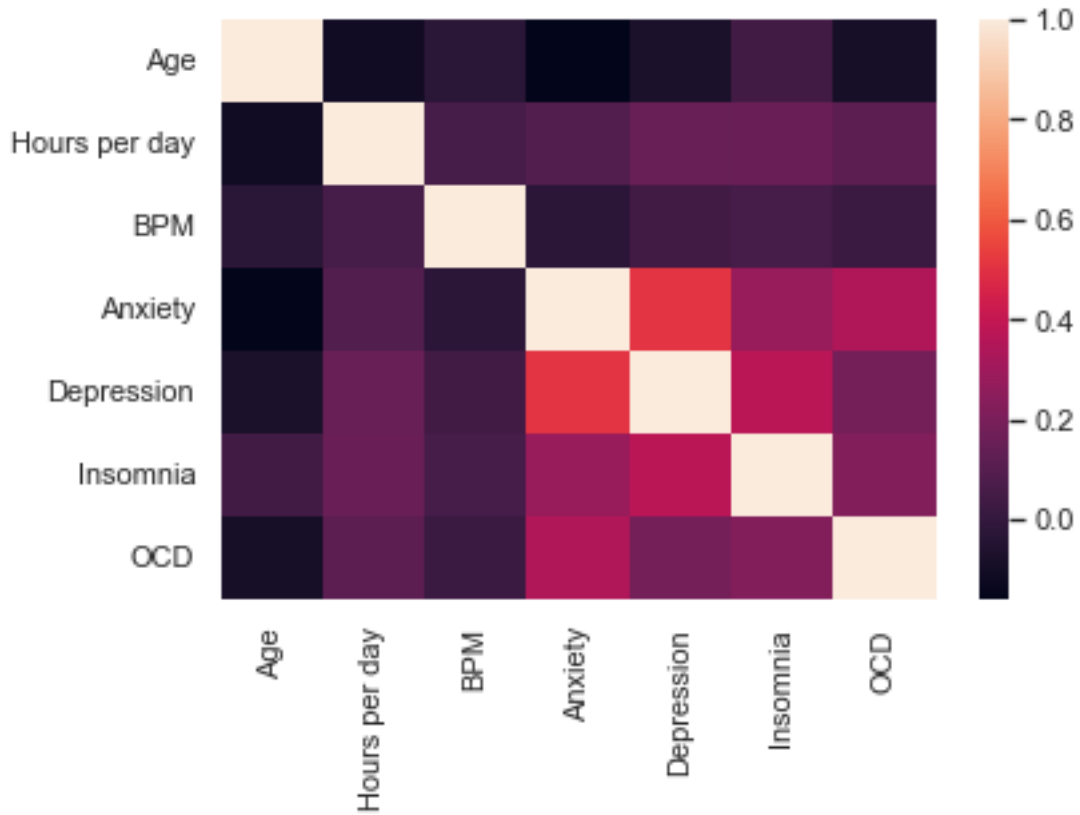
```

The interpretation of the seaborn `heatmap()` graph in the context of the study on the correlation between mental health and music depends on the specific data being visualized. Generally, a

heatmap() graph represents the strength or magnitude of the relationship between two variables using a color-coded grid.

```
[16]: seaborn.heatmap(data.corr())
```

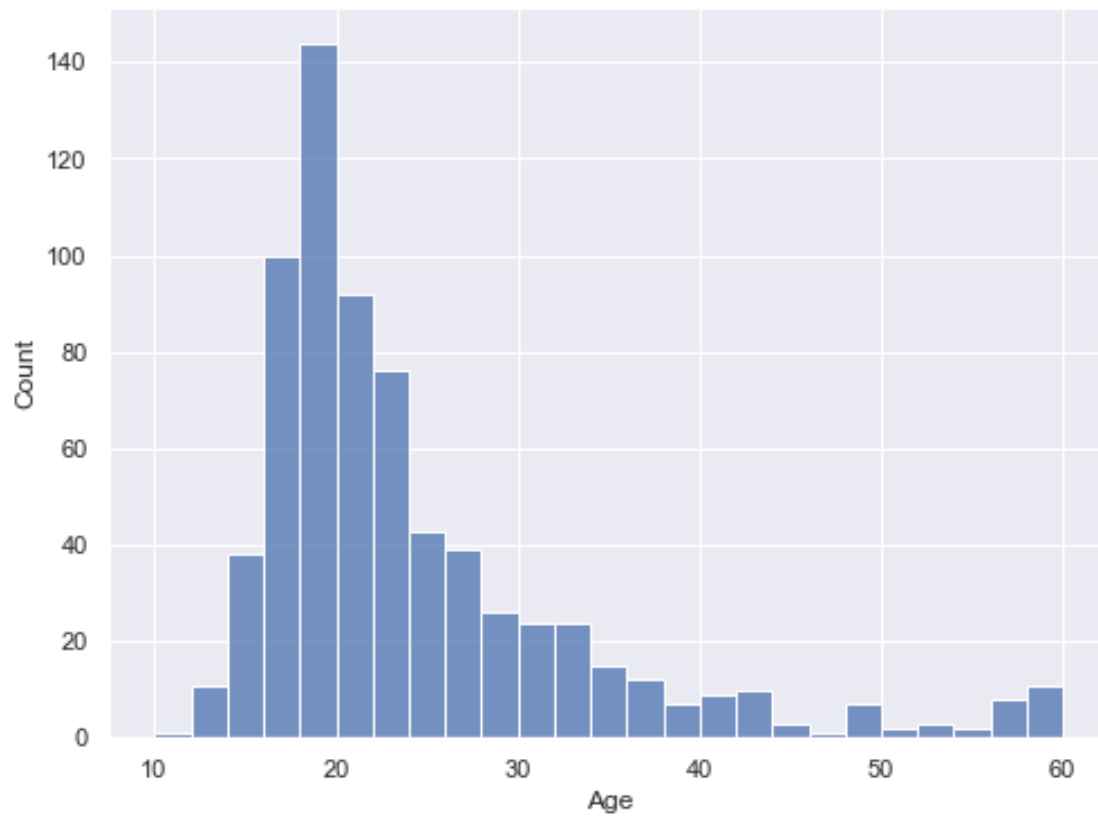
```
[16]: <AxesSubplot:>
```



```
[17]: import matplotlib.pyplot as plt
```

```
[18]: plt.figure(figsize=(8,6))
seaborn.histplot(data['Age'])
```

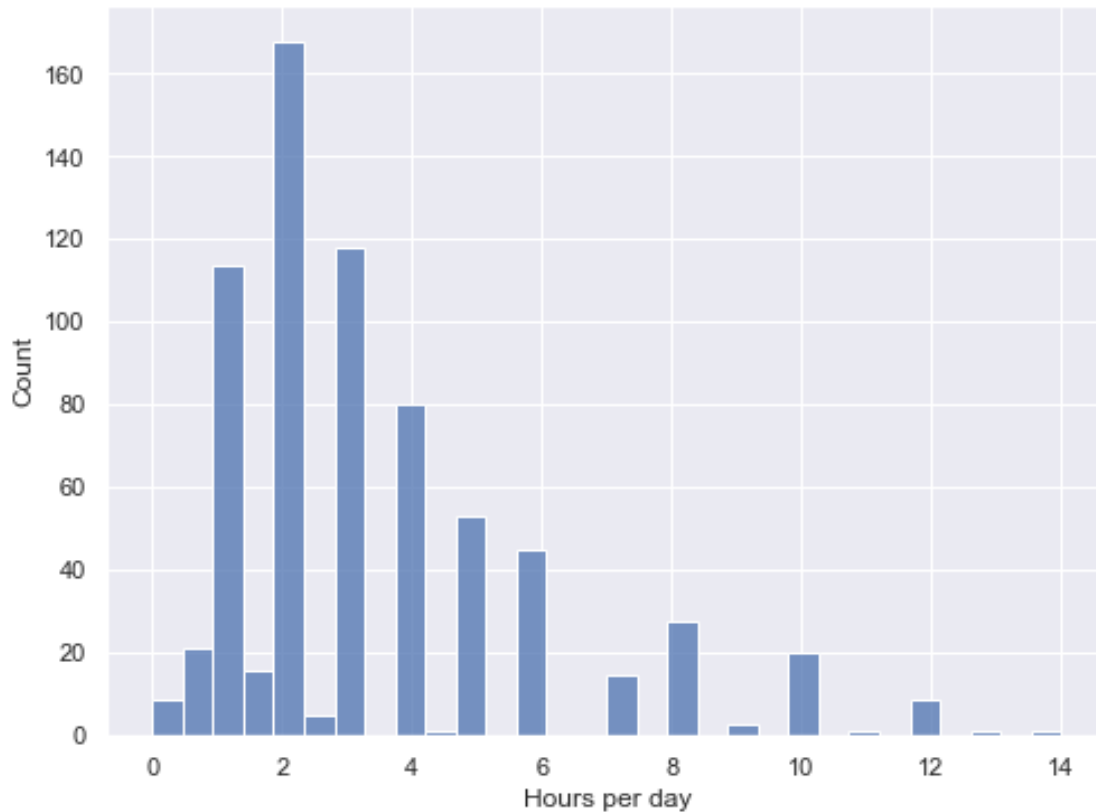
```
[18]: <AxesSubplot:xlabel='Age', ylabel='Count'>
```



In average, people from 15 to 24 are much more frequently listening to music.

```
[19]: plt.figure(figsize=(8,6))
      seaborn.histplot(data['Hours per day'])
```

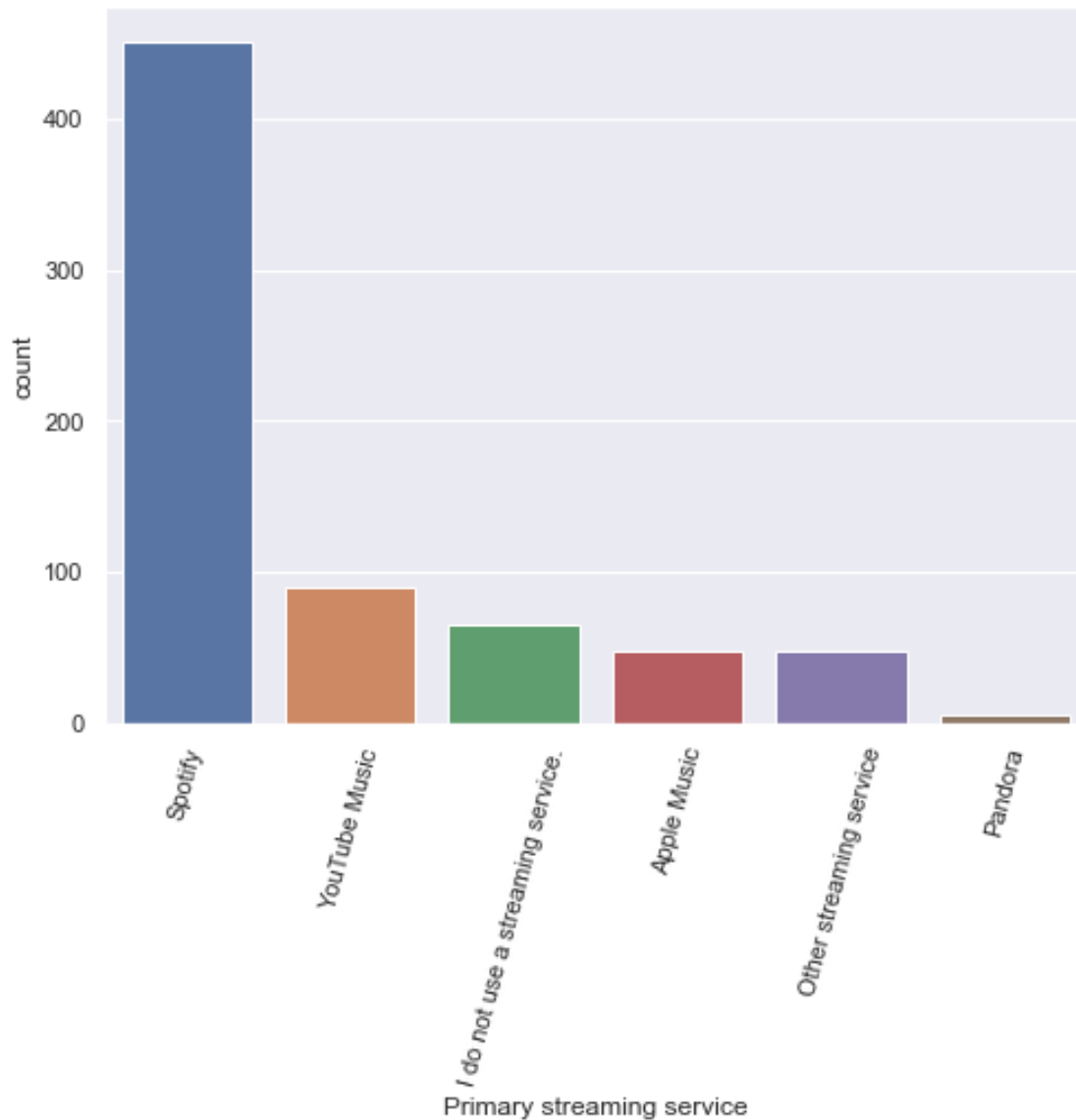
```
[19]: <AxesSubplot:xlabel='Hours per day', ylabel='Count'>
```



The people who are working more than 4 hours tend to listen less to music in comparison to those who work less than 4 hours.

```
[20]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Primary streaming service'])
      plt.xticks(rotation=75)
```

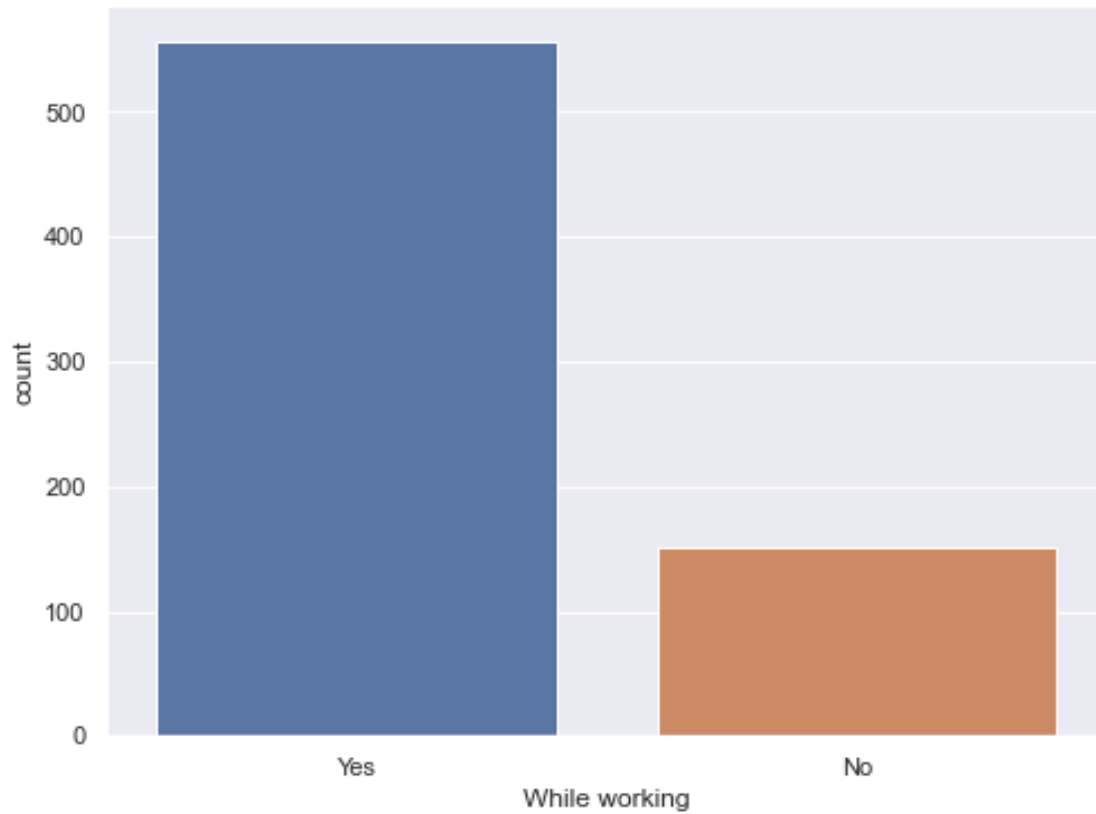
```
[20]: (array([0, 1, 2, 3, 4, 5]),
      [Text(0, 0, 'Spotify'),
       Text(1, 0, 'YouTube Music'),
       Text(2, 0, 'I do not use a streaming service.'),
       Text(3, 0, 'Apple Music'),
       Text(4, 0, 'Other streaming service'),
       Text(5, 0, 'Pandora')])
```



As shown above, the least used platform is Pandora. While the most popular is the Spotify.

```
[21]: plt.figure(figsize=(8,6))  
      seaborn.countplot(x=data['While working'])
```

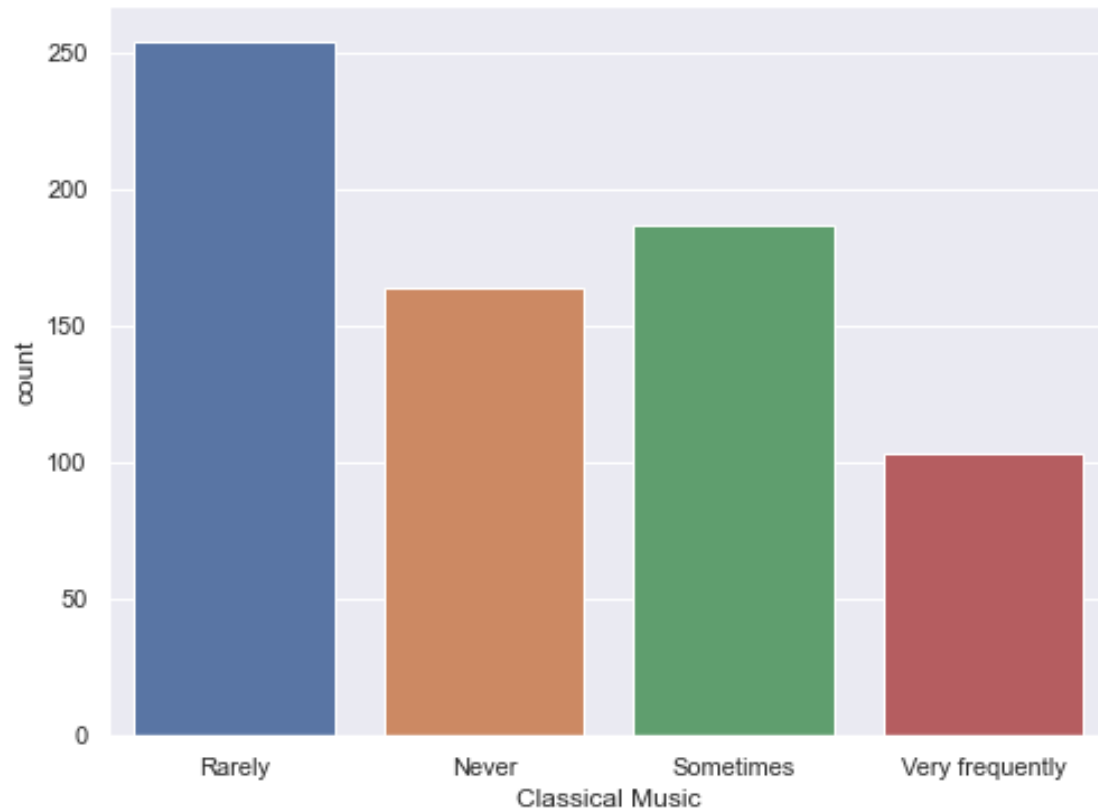
```
[21]: <AxesSubplot:xlabel='While working', ylabel='count'>
```



Almost 1/4 of the people doesn't like to listen to music while working.

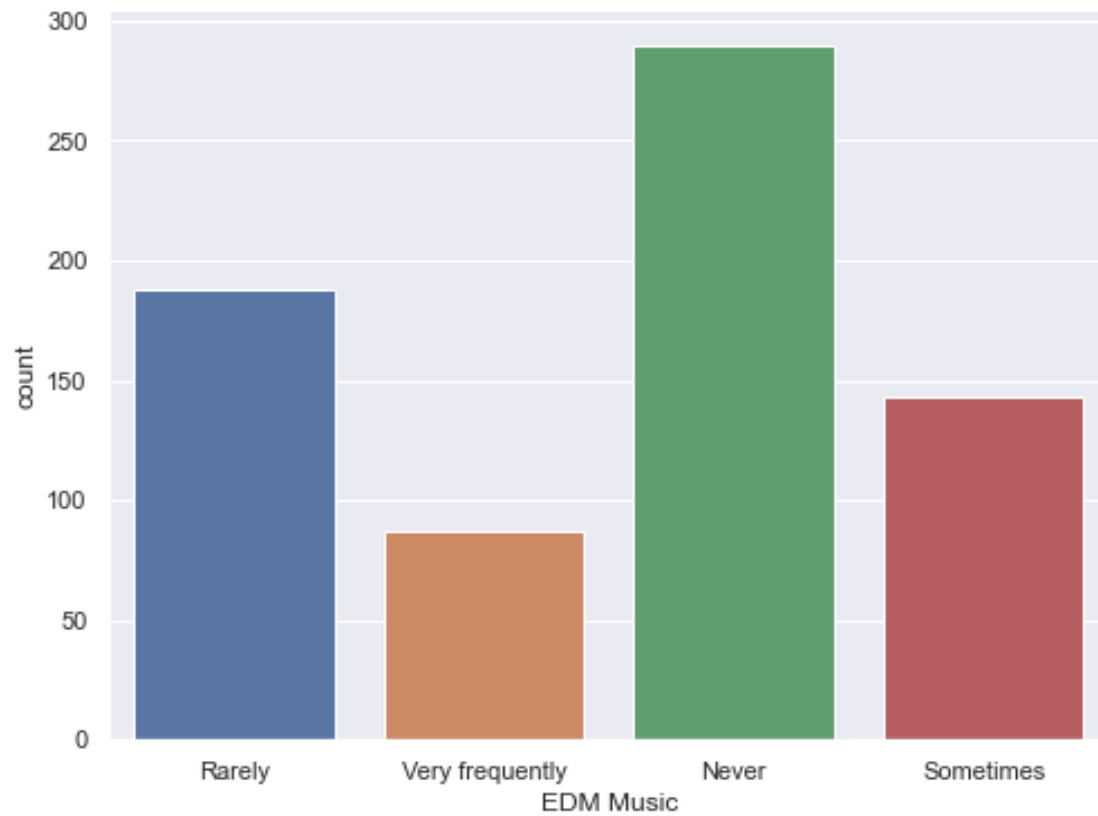
```
[22]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Classical]'])
      plt.xlabel('Classical Music')
```

```
[22]: Text(0.5, 0, 'Classical Music')
```



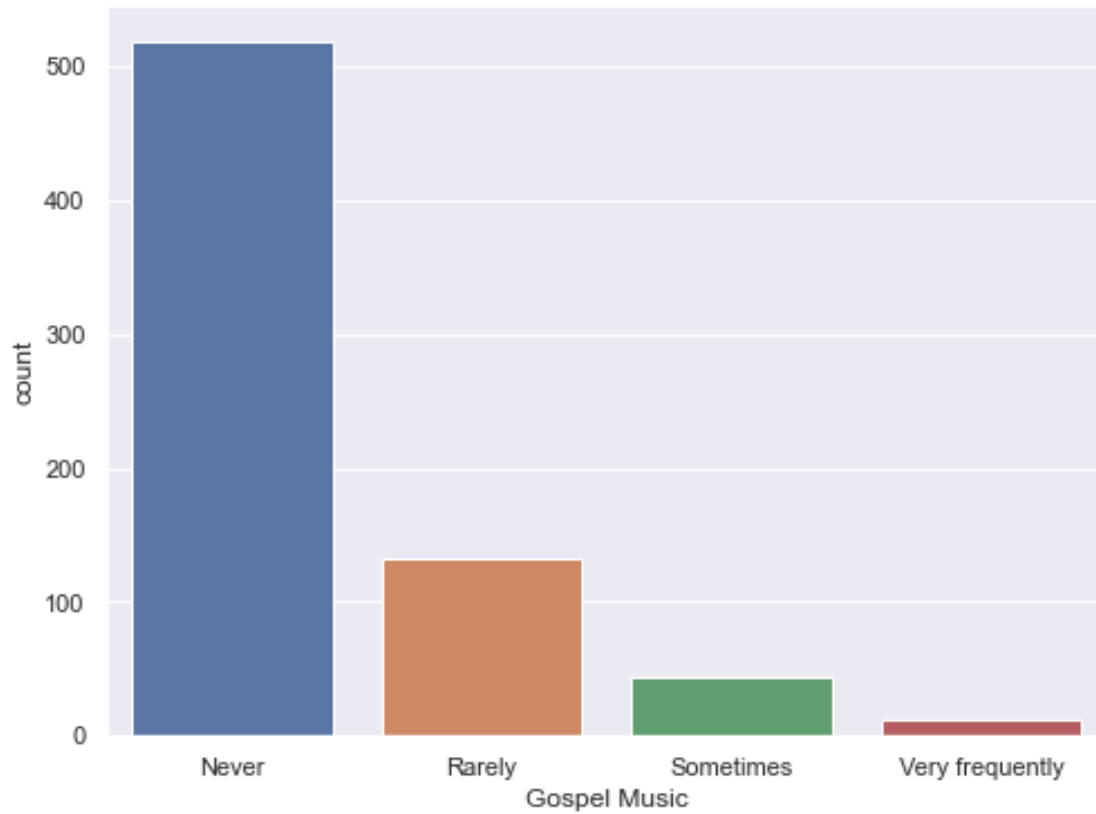
```
[23]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [EDM]'])
      plt.xlabel('EDM Music')
```

```
[23]: Text(0.5, 0, 'EDM Music')
```



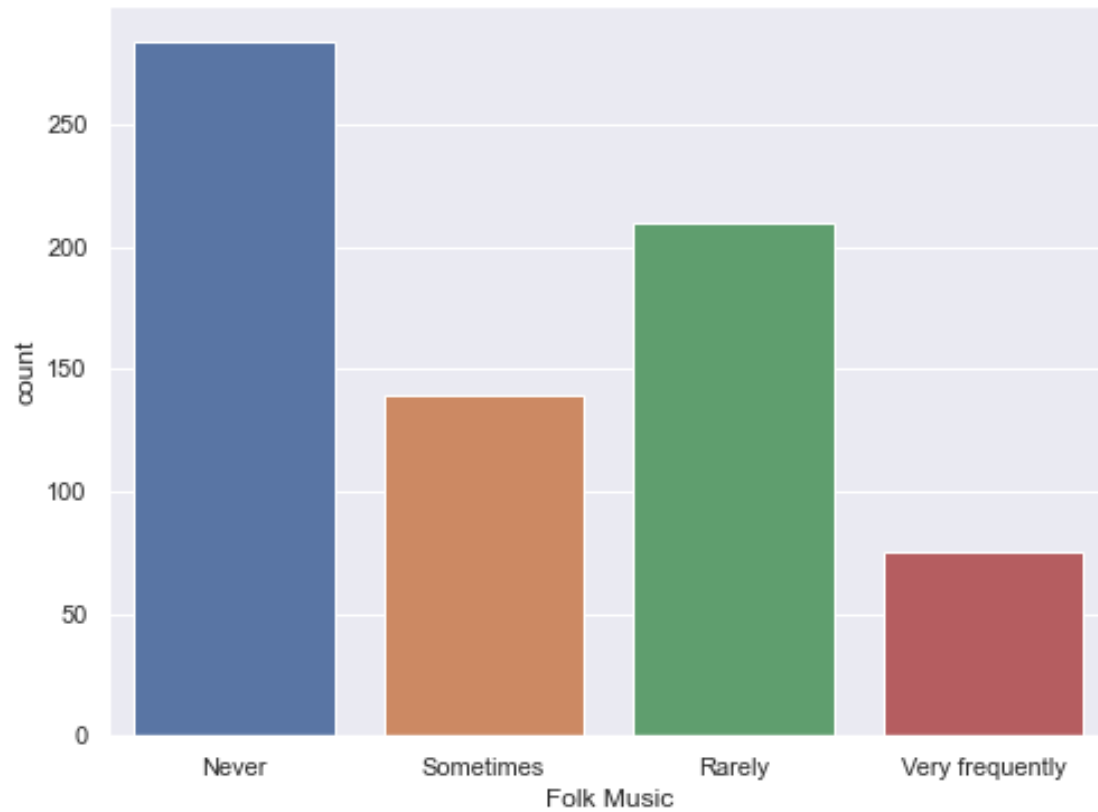
```
[24]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Gospel]'])
      plt.xlabel('Gospel Music')
```

```
[24]: Text(0.5, 0, 'Gospel Music')
```

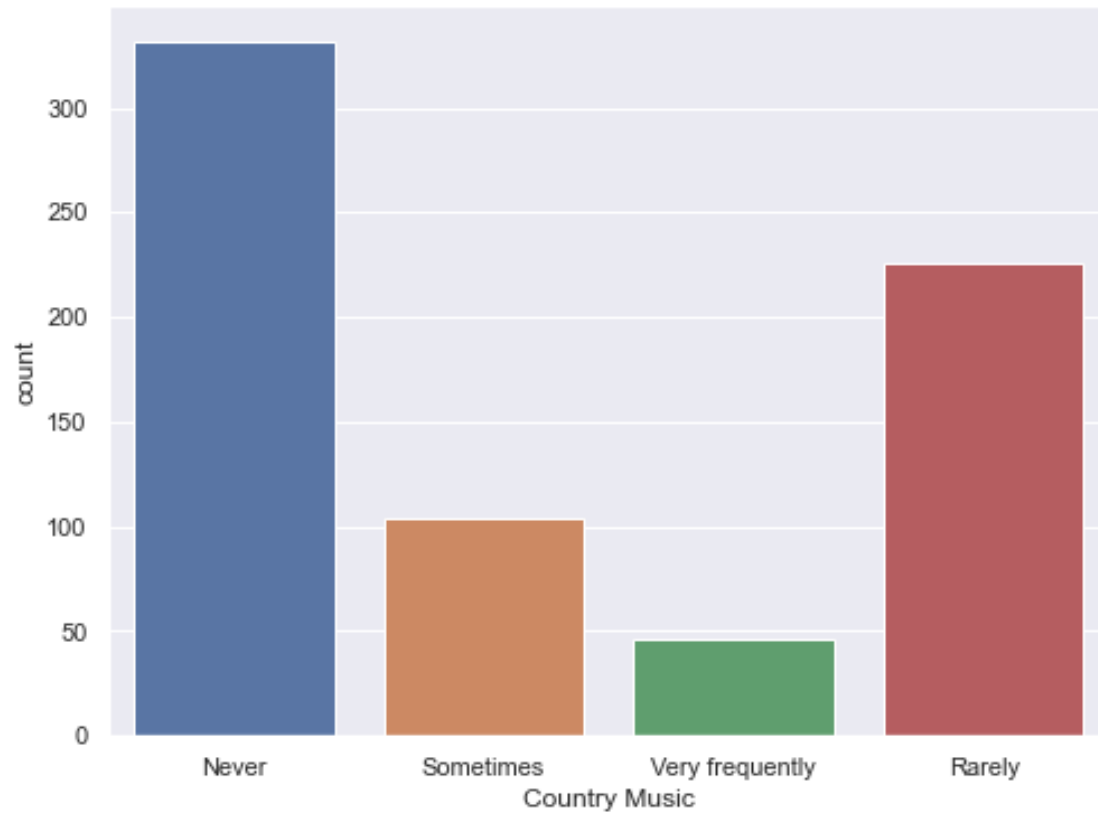
```
[25]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Folk]'])
      plt.xlabel('Folk Music')
```

```
[25]: Text(0.5, 0, 'Folk Music')
```



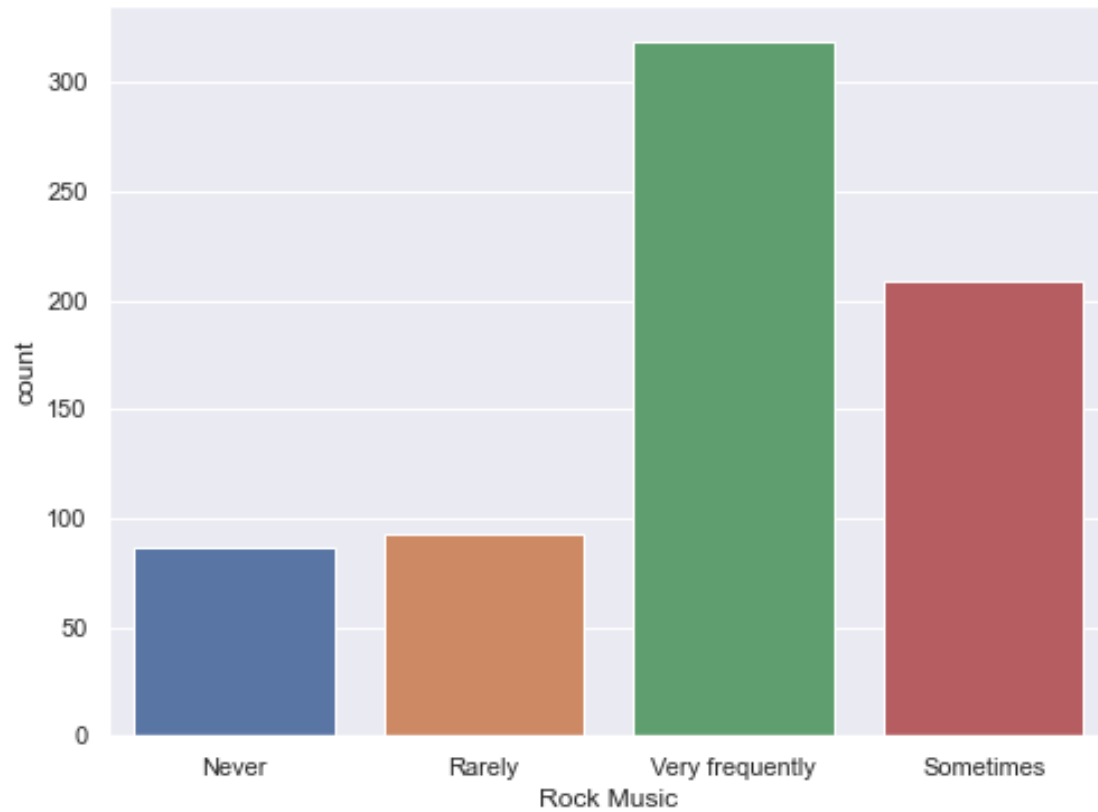
```
[26]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Country]'])
      plt.xlabel('Country Music')
```

```
[26]: Text(0.5, 0, 'Country Music')
```



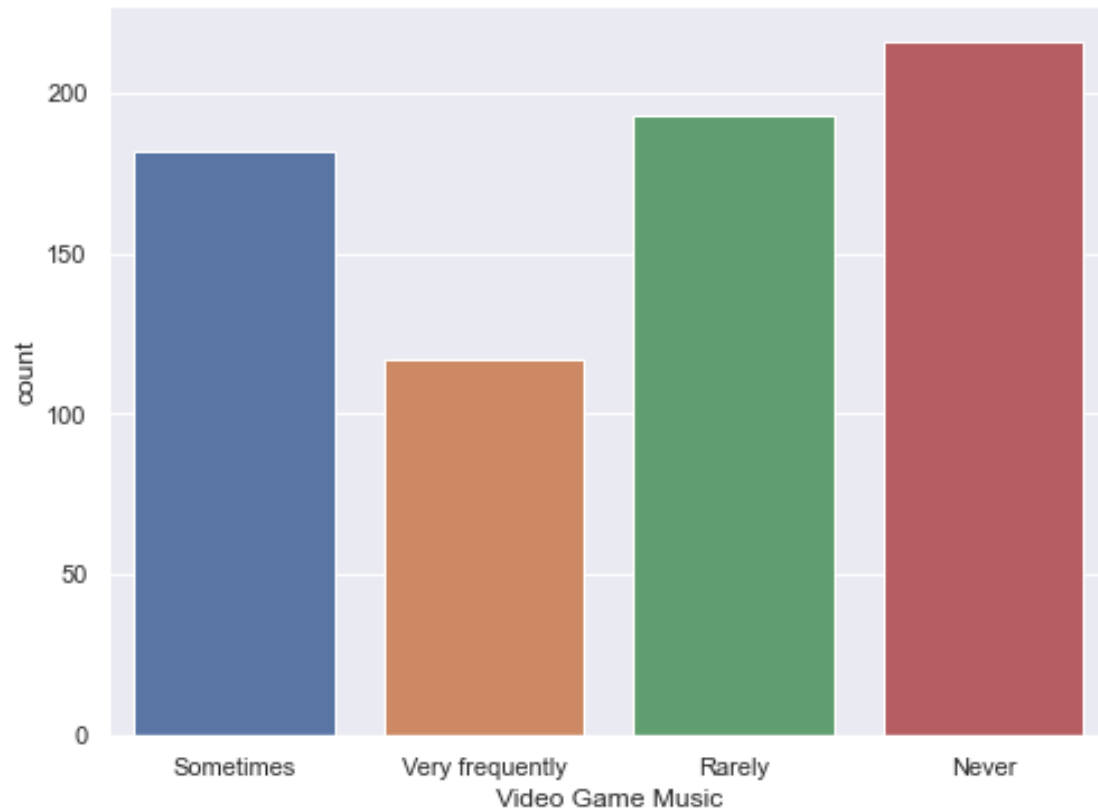
```
[27]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Rock]'])
      plt.xlabel('Rock Music')
```

```
[27]: Text(0.5, 0, 'Rock Music')
```



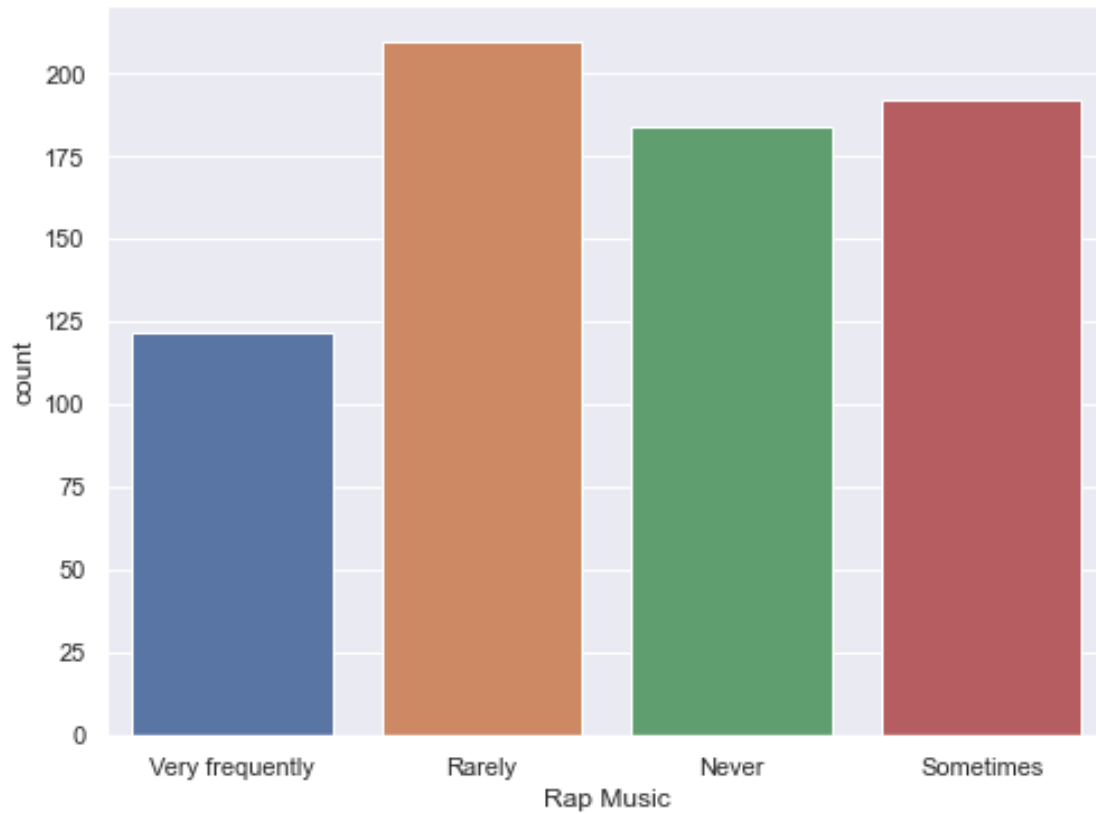
```
[28]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Video game music]'])
      plt.xlabel('Video Game Music')
```

```
[28]: Text(0.5, 0, 'Video Game Music')
```



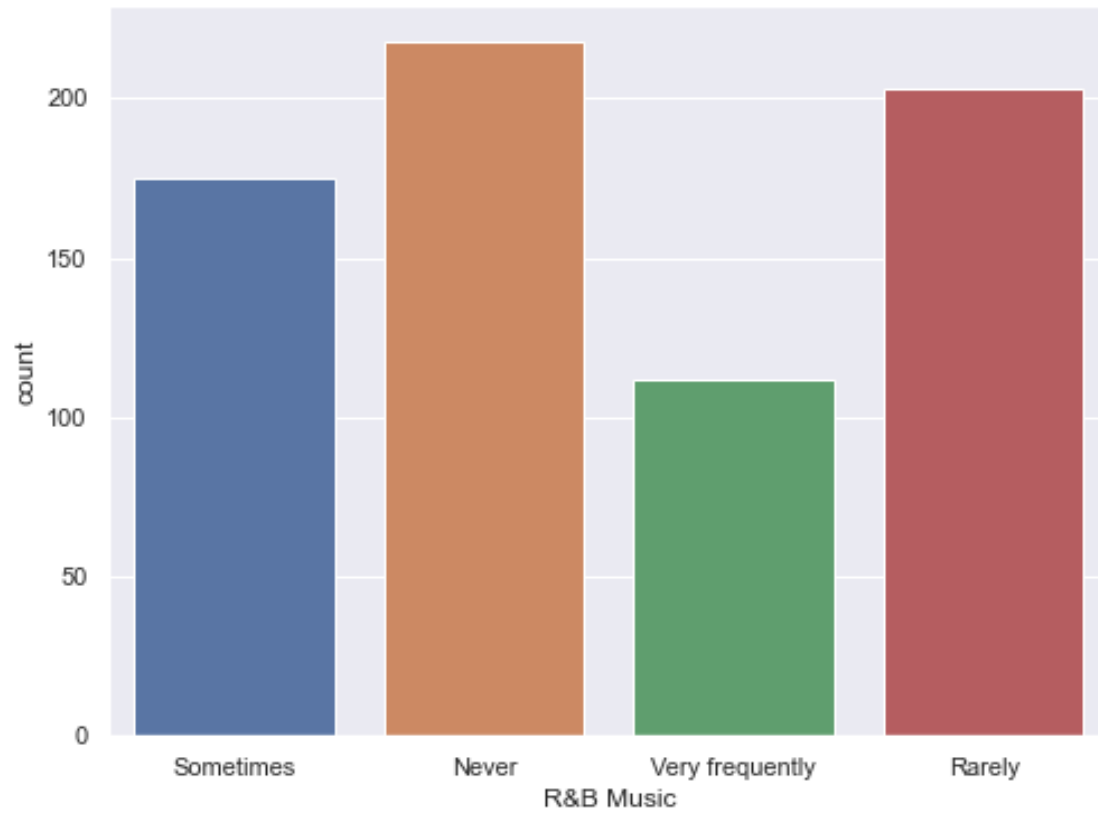
```
[29]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Rap]'])
      plt.xlabel('Rap Music')
```

```
[29]: Text(0.5, 0, 'Rap Music')
```



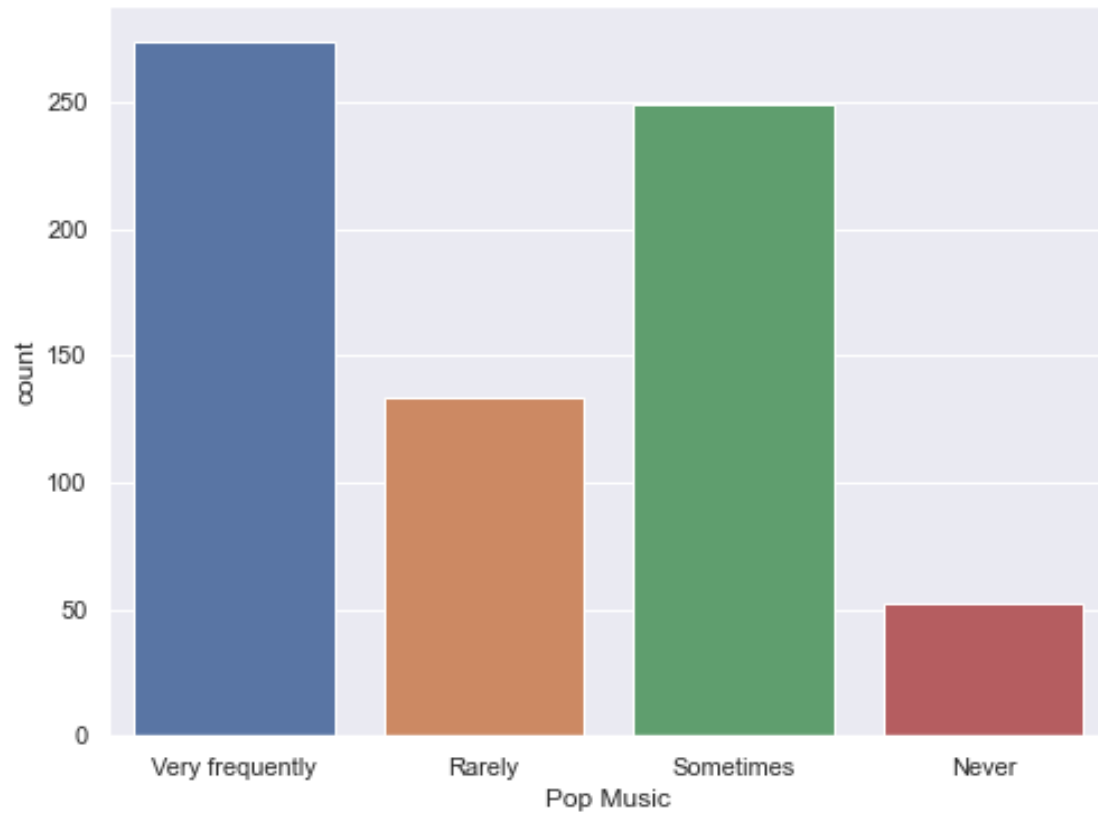
```
[30]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [R&B]'])
      plt.xlabel('R&B Music')
```

```
[30]: Text(0.5, 0, 'R&B Music')
```



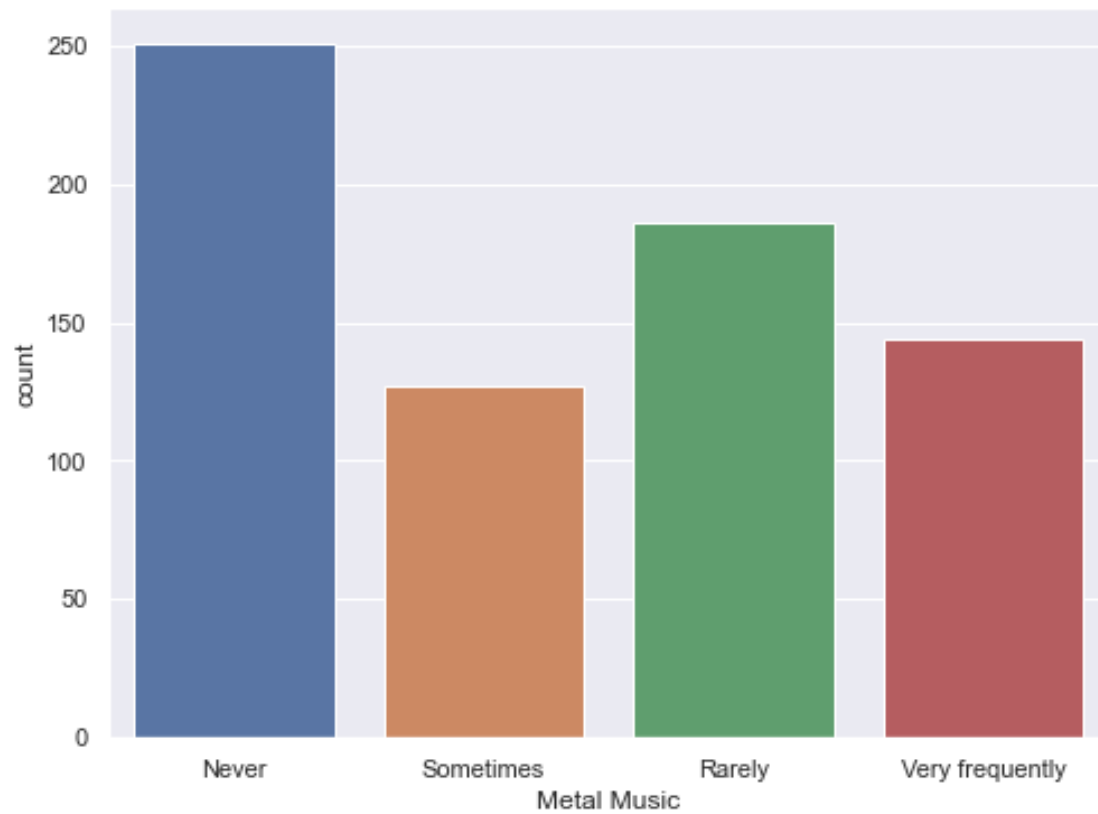
```
[31]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Pop]'])
      plt.xlabel('Pop Music')
```

```
[31]: Text(0.5, 0, 'Pop Music')
```



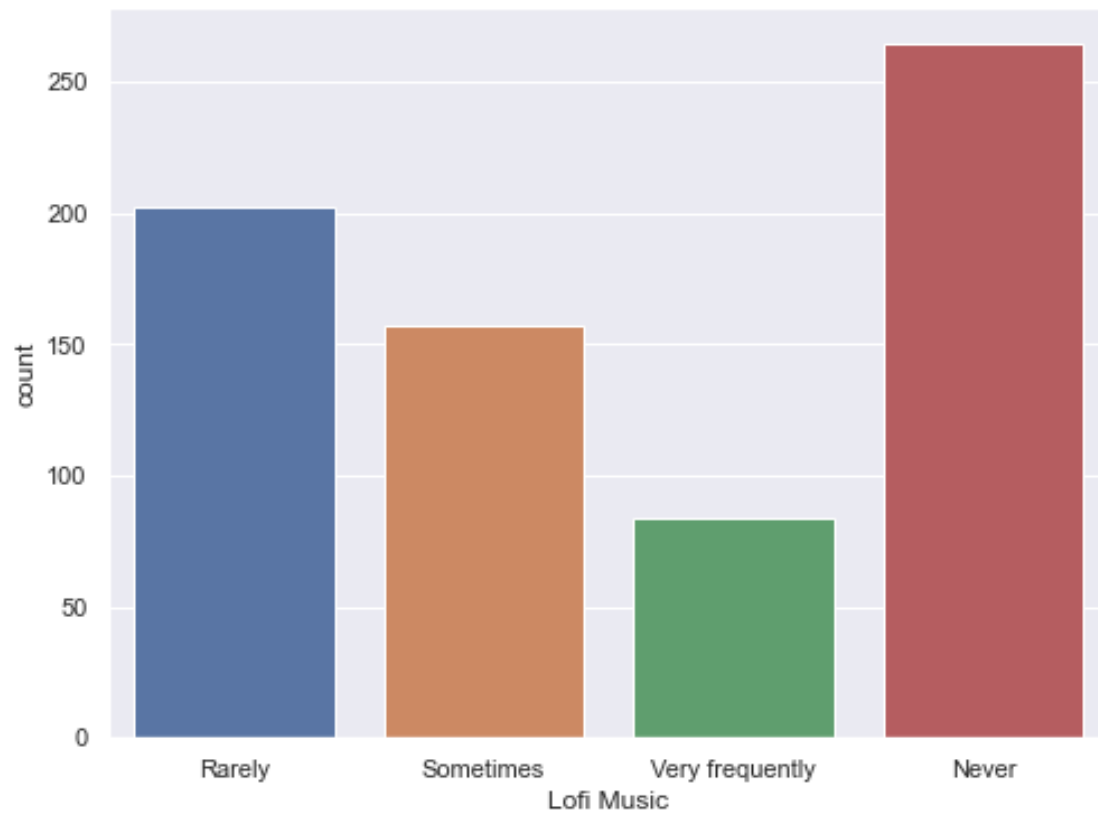
```
[32]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Metal]'])
      plt.xlabel('Metal Music')
```

```
[32]: Text(0.5, 0, 'Metal Music')
```

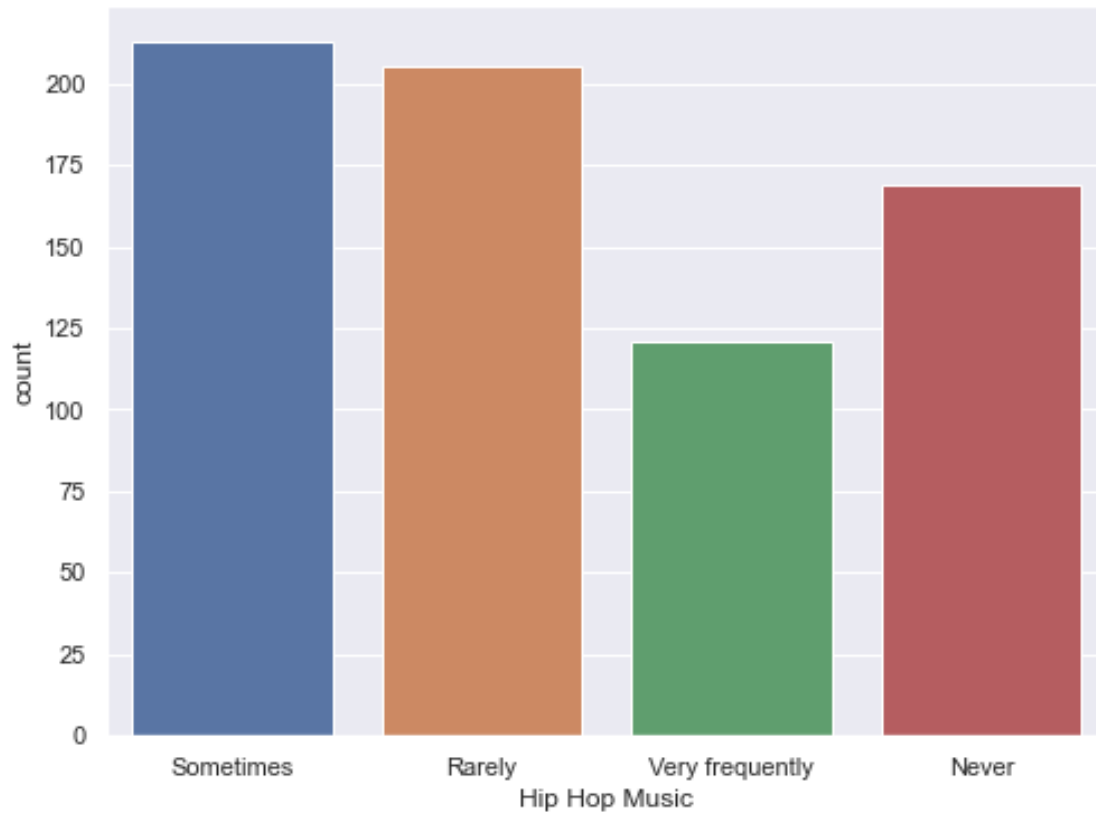
```
[33]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Lofi]'])
      plt.xlabel('Lofi Music')
```

```
[33]: Text(0.5, 0, 'Lofi Music')
```



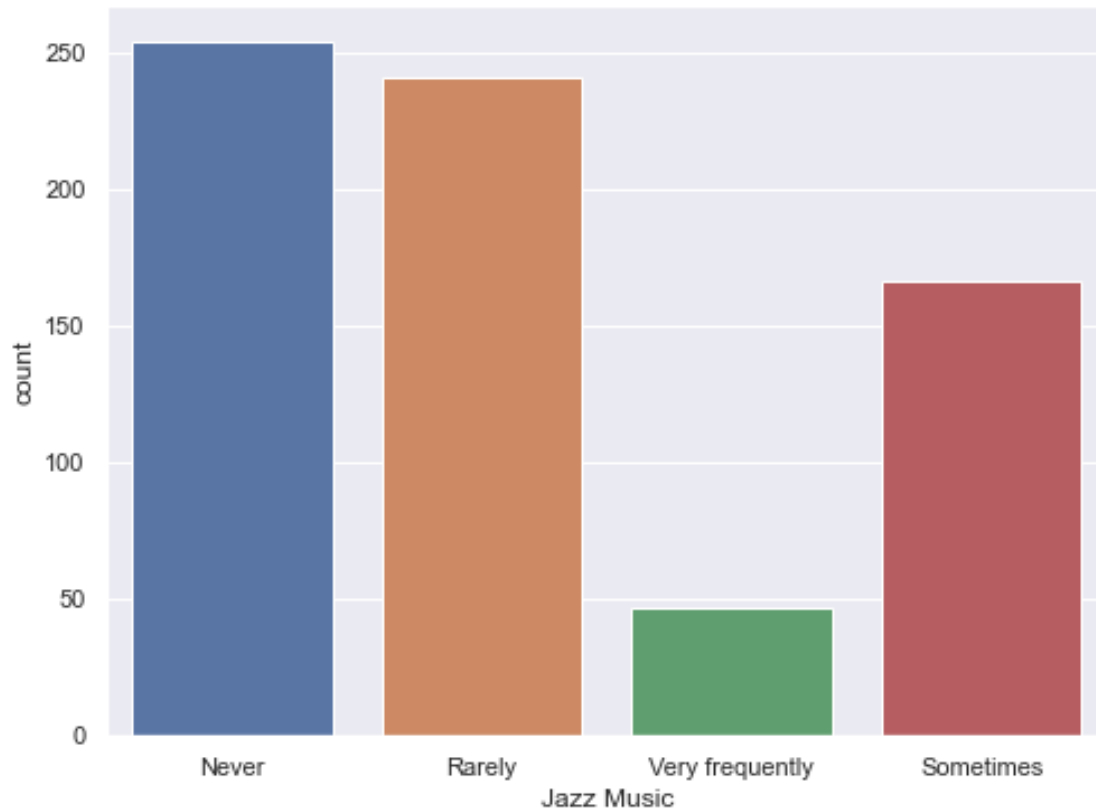
```
[34]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Hip hop]'])
      plt.xlabel('Hip Hop Music')
```

```
[34]: Text(0.5, 0, 'Hip Hop Music')
```



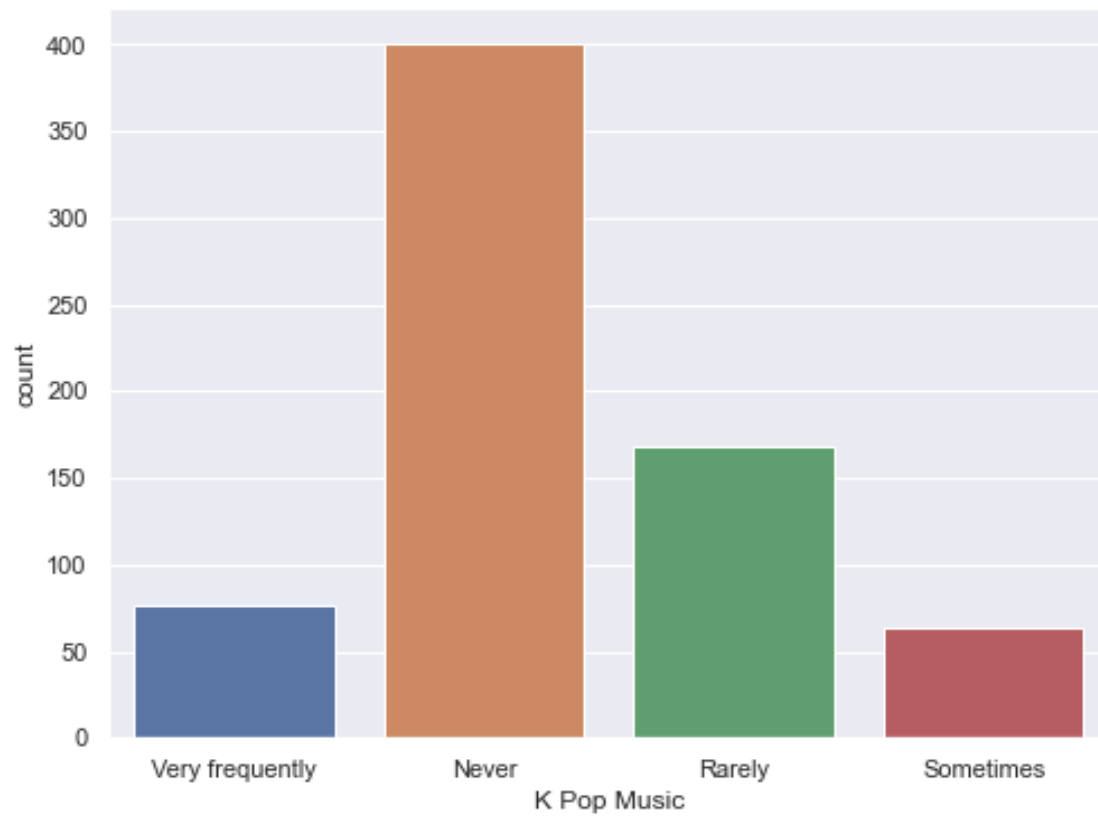
```
[35]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Jazz]'])
      plt.xlabel('Jazz Music')
```

```
[35]: Text(0.5, 0, 'Jazz Music')
```



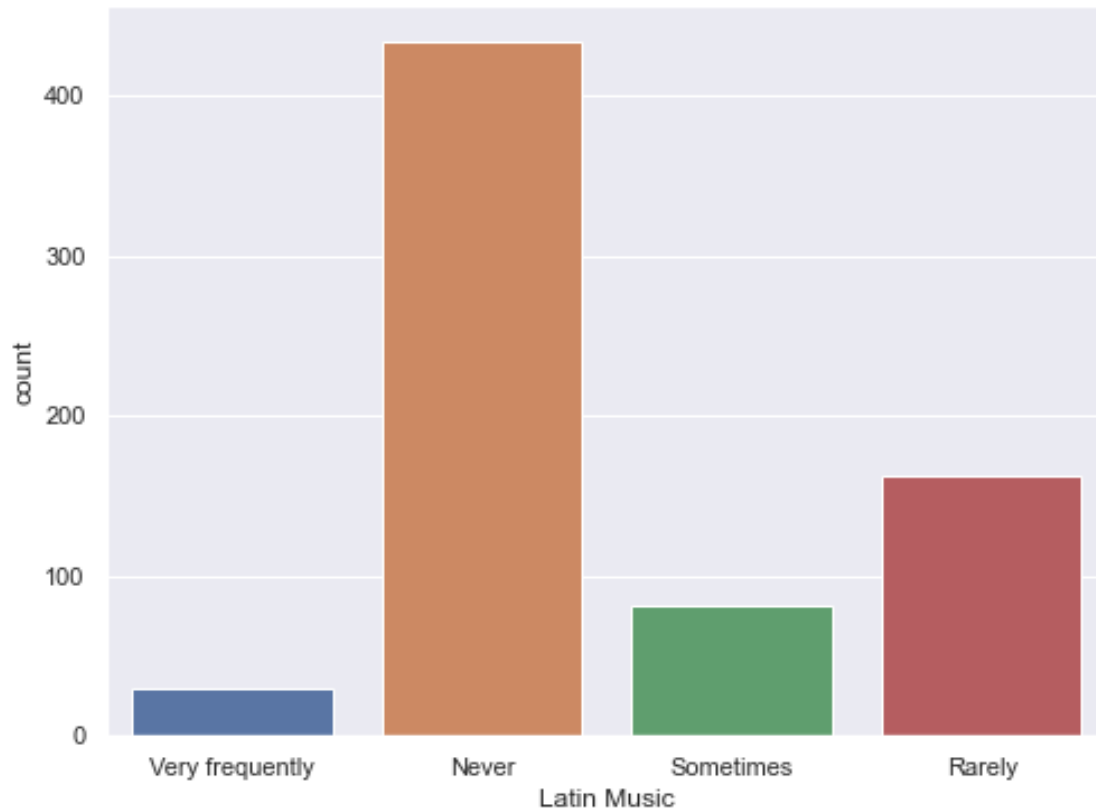
```
[36]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [K pop]'])
      plt.xlabel('K Pop Music')
```

```
[36]: Text(0.5, 0, 'K Pop Music')
```



```
[37]: plt.figure(figsize=(8,6))
      seaborn.countplot(x=data['Frequency [Latin]'])
      plt.xlabel('Latin Music')
```

```
[37]: Text(0.5, 0, 'Latin Music')
```



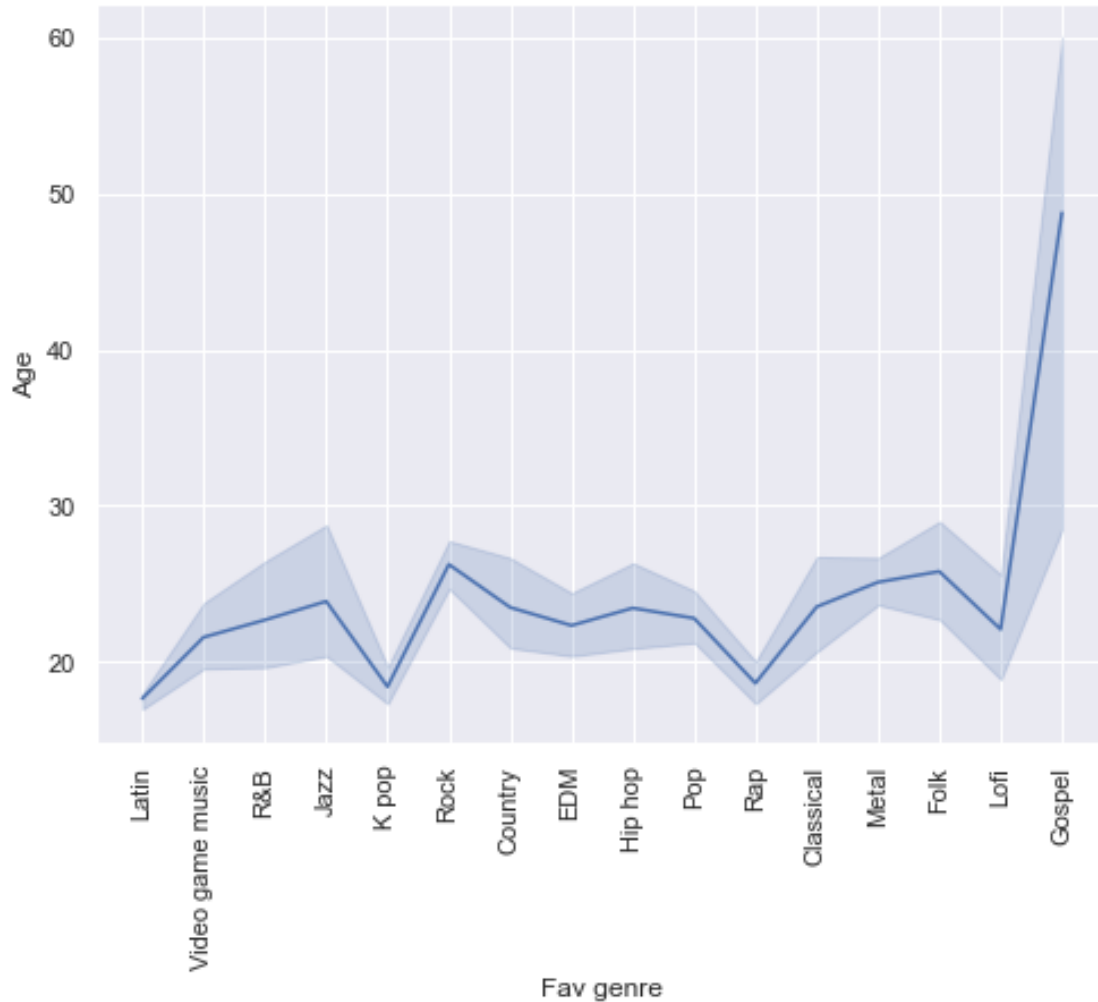
1.5 Bivariate Analysis

The bivariate analysis aims to uncover any potential correlations or associations between the mental health and the music someone is listening to.

```
[38]: plt.figure(figsize=(8,6))
      seaborn.lineplot(x=data['Fav genre'], y=data['Age'])
      plt.xticks(rotation=90)
```

```
[38]: ([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15],
      [Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, ''),
       Text(0, 0, '')])
```

```
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, '')[0]]
```



Individuals in their twenties tend to show a keen interest in *Latin*, *K-pop*, and *Rap* music genres, while *Gospel* music tends to be more popular among individuals aged 50 and above. Additionally, the aforementioned genres are commonly enjoyed by people ranging from 20 to 30 years old.

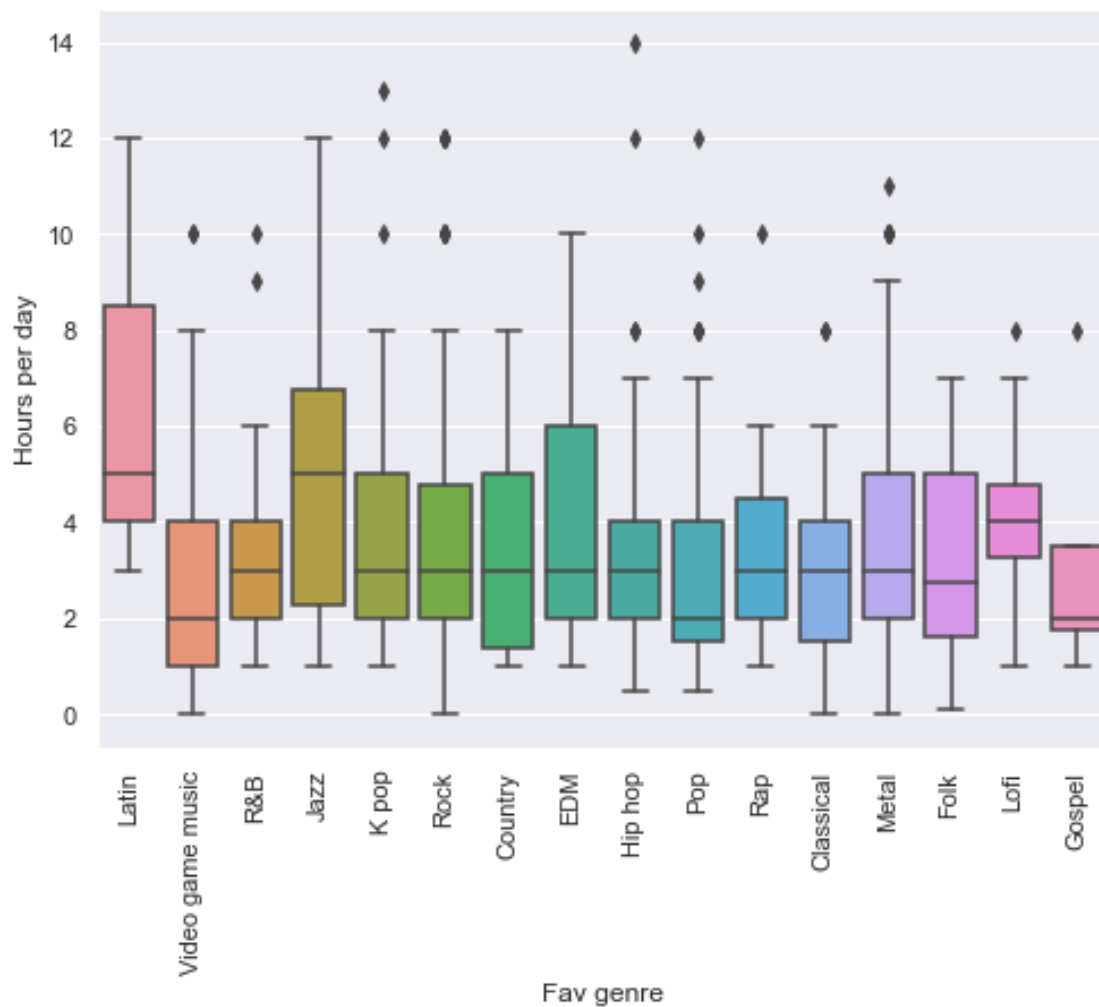
```
[39]: plt.figure(figsize=(8,6))
      seaborn.boxplot(x=data['Fav genre'], y=data['Hours per day'])
      plt.xticks(rotation=90)
```

```
[39]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
      [Text(0, 0, 'Latin'),
```

```

Text(1, 0, 'Video game music'),
Text(2, 0, 'R&B'),
Text(3, 0, 'Jazz'),
Text(4, 0, 'K pop'),
Text(5, 0, 'Rock'),
Text(6, 0, 'Country'),
Text(7, 0, 'EDM'),
Text(8, 0, 'Hip hop'),
Text(9, 0, 'Pop'),
Text(10, 0, 'Rap'),
Text(11, 0, 'Classical'),
Text(12, 0, 'Metal'),
Text(13, 0, 'Folk'),
Text(14, 0, 'Lofi'),
Text(15, 0, 'Gospel'])])

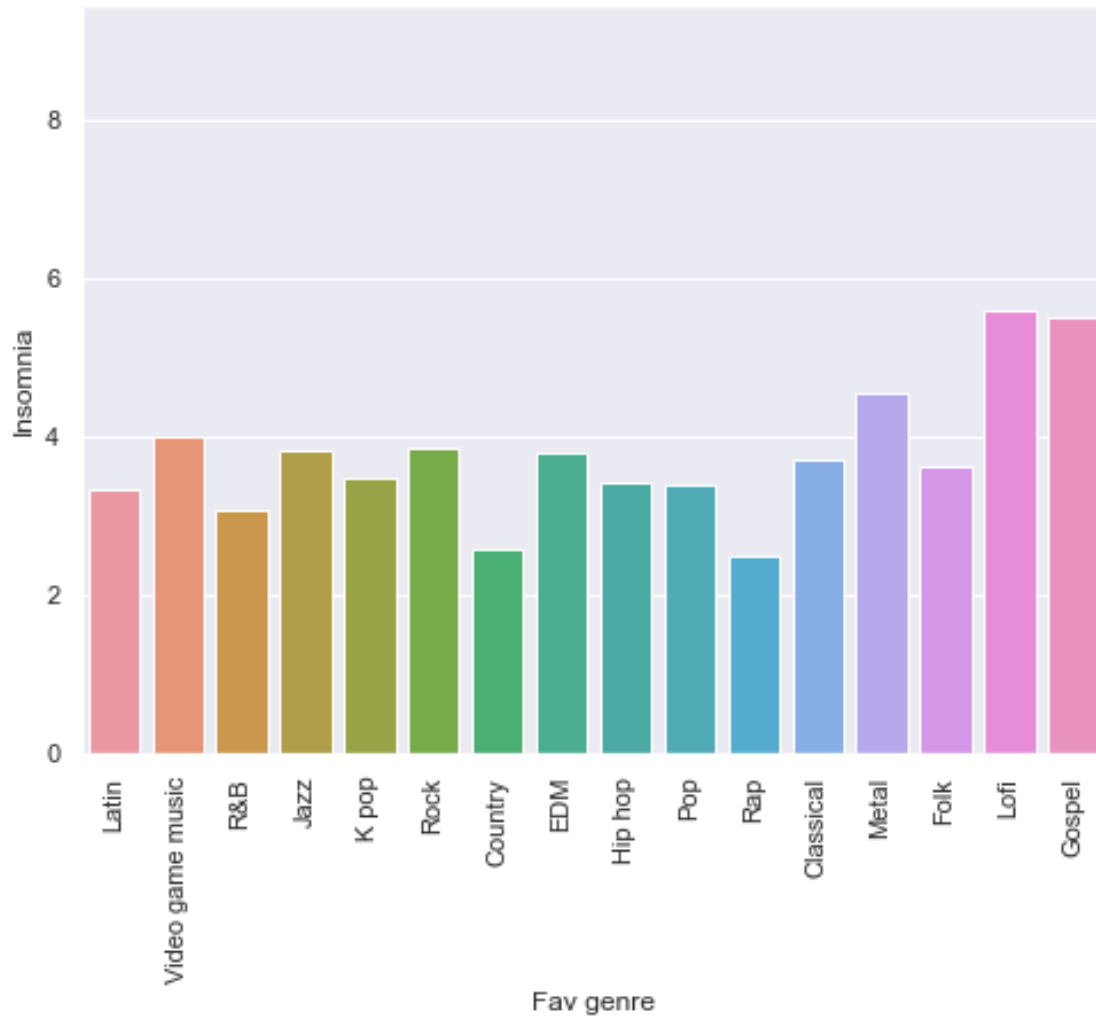
```



Individuals who engage in 12-hour workdays tend to exhibit a higher inclination towards listening to *Latin* and *Jazz* music genres. Conversely, individuals who prefer *Gospel* music genres typically work fewer hours compared to others.

```
[40]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Insomnia'], errwidth=0)
      plt.xticks(rotation=90)
```

```
[40]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
      [Text(0, 0, 'Latin'),
       Text(1, 0, 'Video game music'),
       Text(2, 0, 'R&B'),
       Text(3, 0, 'Jazz'),
       Text(4, 0, 'K pop'),
       Text(5, 0, 'Rock'),
       Text(6, 0, 'Country'),
       Text(7, 0, 'EDM'),
       Text(8, 0, 'Hip hop'),
       Text(9, 0, 'Pop'),
       Text(10, 0, 'Rap'),
       Text(11, 0, 'Classical'),
       Text(12, 0, 'Metal'),
       Text(13, 0, 'Folk'),
       Text(14, 0, 'Lofi'),
       Text(15, 0, 'Gospel')])
```

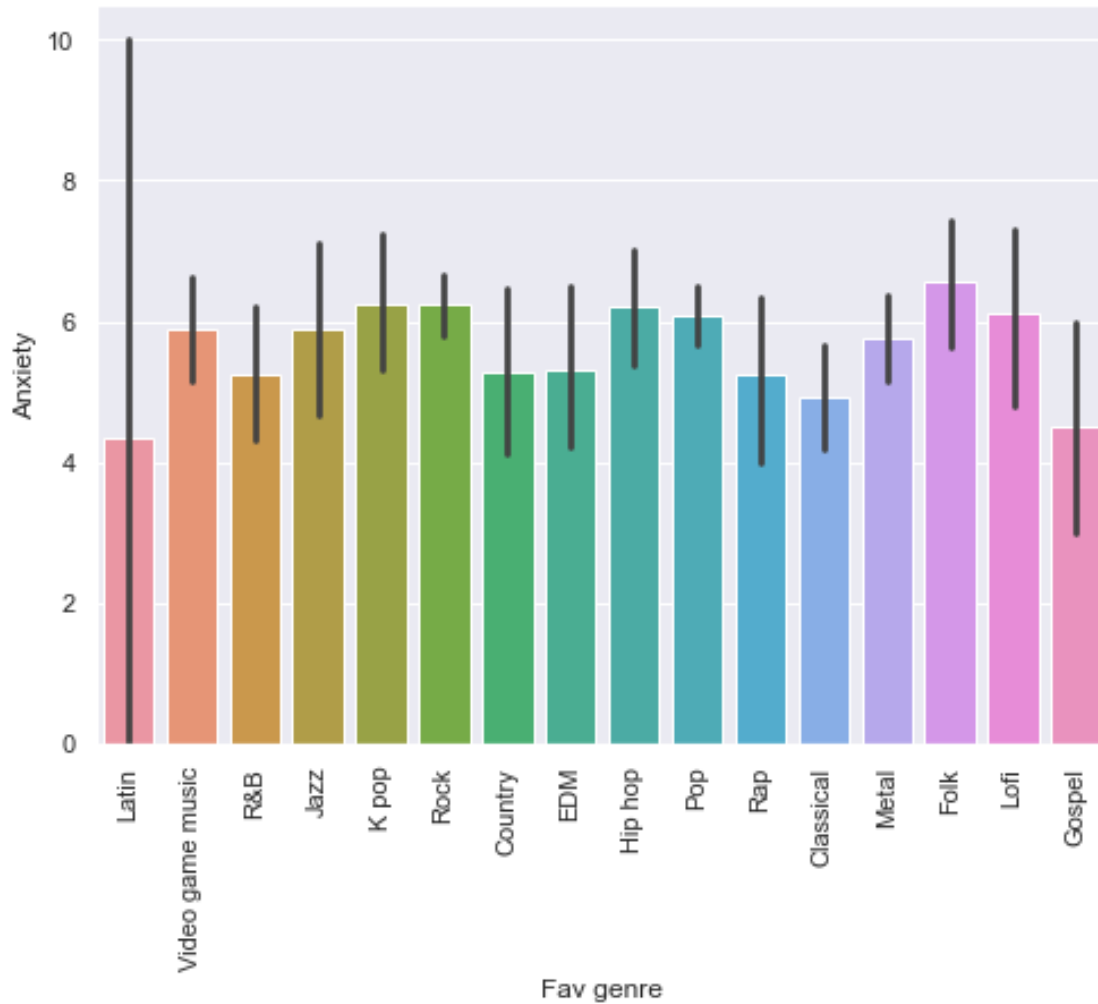


With the exception of *Metal*, *Lofi*, and *Gospel* genres, every listener typically has an insomnia level below 4.

```
[41]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Anxiety'])
      plt.xticks(rotation=90)
```

```
[41]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
      [Text(0, 0, 'Latin'),
       Text(1, 0, 'Video game music'),
       Text(2, 0, 'R&B'),
       Text(3, 0, 'Jazz'),
       Text(4, 0, 'K pop'),
       Text(5, 0, 'Rock'),
       Text(6, 0, 'Country'),
```

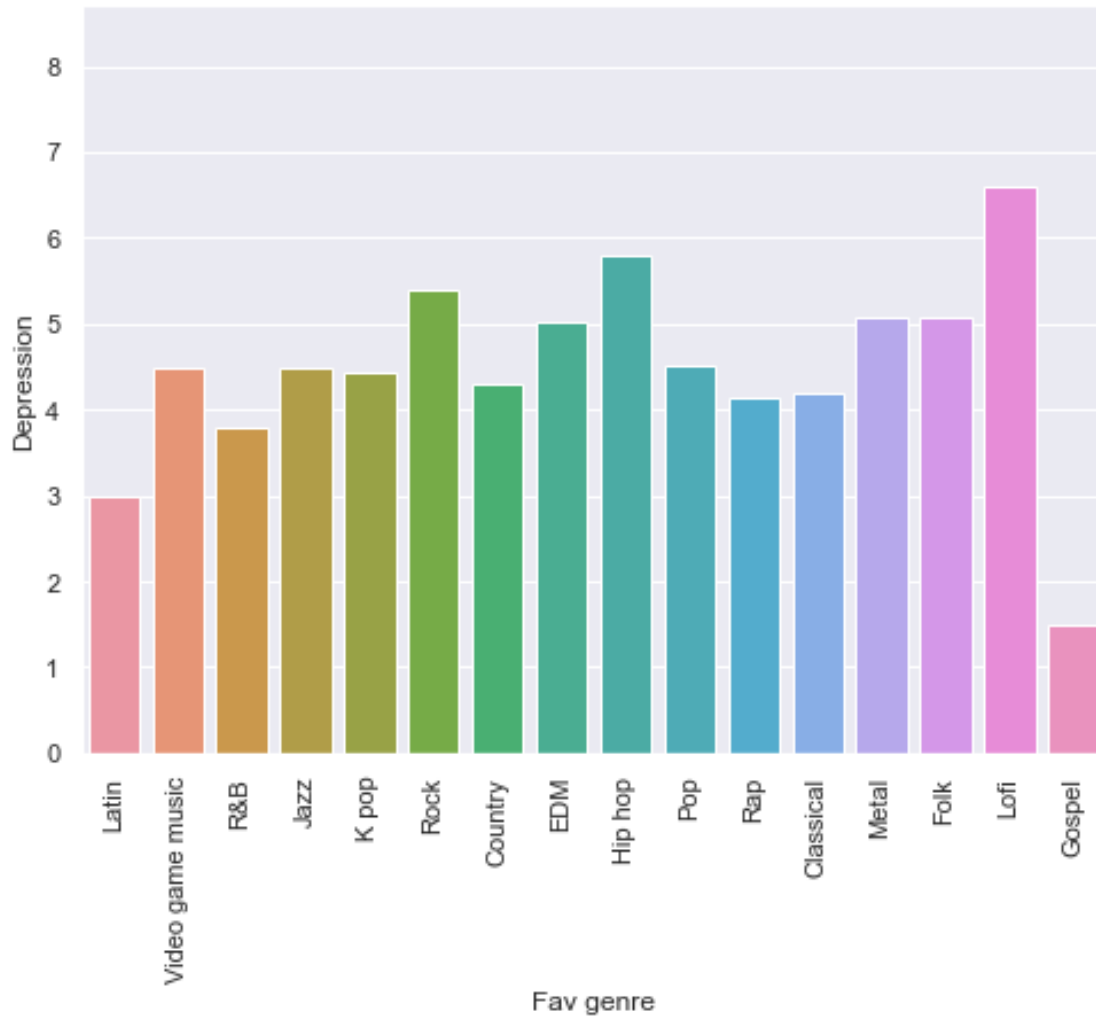
```
Text(7, 0, 'EDM'),
Text(8, 0, 'Hip hop'),
Text(9, 0, 'Pop'),
Text(10, 0, 'Rap'),
Text(11, 0, 'Classical'),
Text(12, 0, 'Metal'),
Text(13, 0, 'Folk'),
Text(14, 0, 'Lofi'),
Text(15, 0, 'Gospel']])
```



With the exception of *Rock*, *Jazz*, *K-pop*, *Hip hop*, *Pop*, and *Folk* music listeners, every listener generally has an anxiety level above 4. However, those who prefer the aforementioned genres tend to have anxiety levels above 6.

```
[42]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Depression'], errwidth=0)
      plt.xticks(rotation=90)
```

```
[42]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
      [Text(0, 0, 'Latin'),
       Text(1, 0, 'Video game music'),
       Text(2, 0, 'R&B'),
       Text(3, 0, 'Jazz'),
       Text(4, 0, 'K pop'),
       Text(5, 0, 'Rock'),
       Text(6, 0, 'Country'),
       Text(7, 0, 'EDM'),
       Text(8, 0, 'Hip hop'),
       Text(9, 0, 'Pop'),
       Text(10, 0, 'Rap'),
       Text(11, 0, 'Classical'),
       Text(12, 0, 'Metal'),
       Text(13, 0, 'Folk'),
       Text(14, 0, 'Lofi'),
       Text(15, 0, 'Gospel')])
```

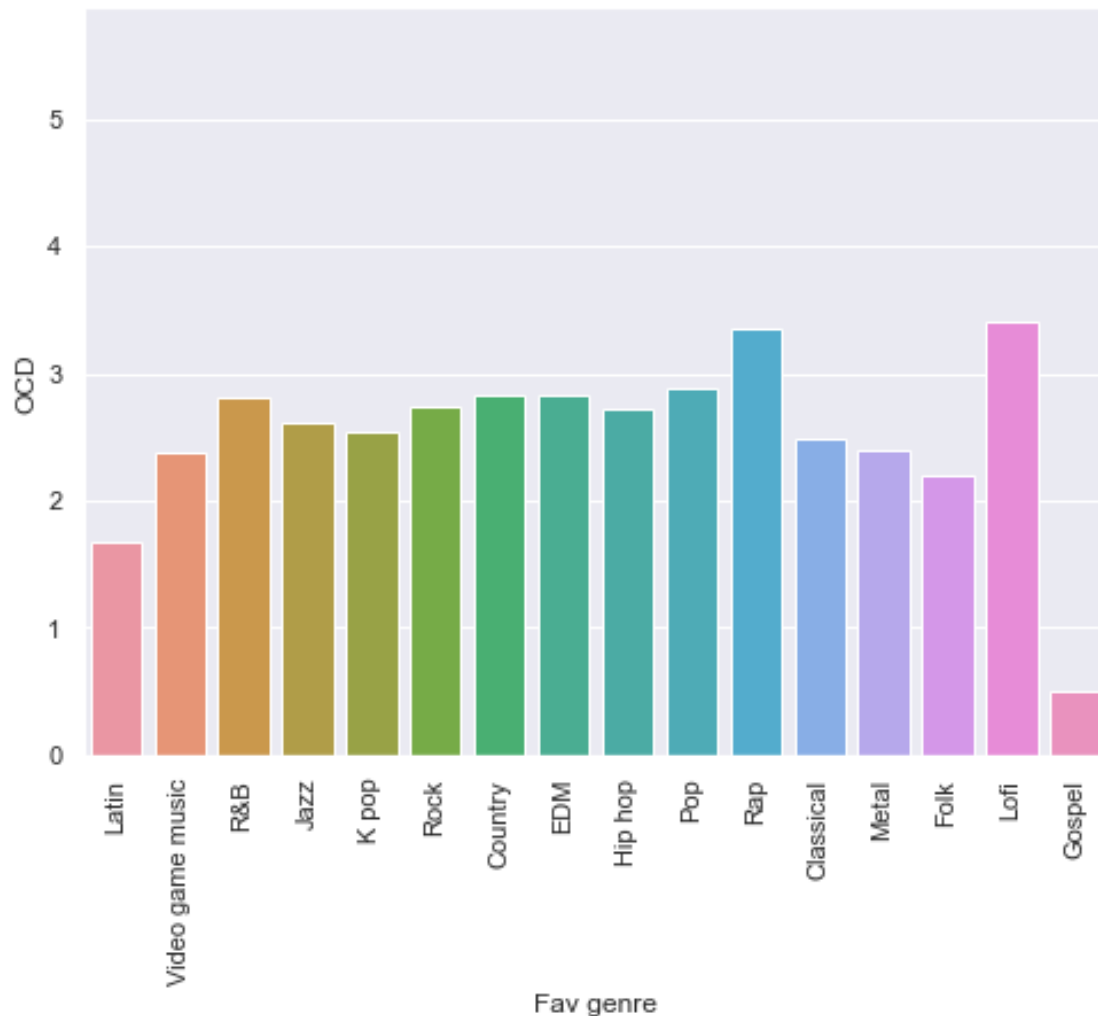


While every listener tends to have a depression level above 3, *Lofi*, *Hip hop*, and *Rock* music listeners specifically exhibit higher levels of depression, surpassing 5 on average.

```
[43]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['OCD'], errwidth=0)
      plt.xticks(rotation=90)
```

```
[43]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
      [Text(0, 0, 'Latin'),
       Text(1, 0, 'Video game music'),
       Text(2, 0, 'R&B'),
       Text(3, 0, 'Jazz'),
       Text(4, 0, 'K pop'),
       Text(5, 0, 'Rock'),
       Text(6, 0, 'Country'),
```

```
Text(7, 0, 'EDM'),
Text(8, 0, 'Hip hop'),
Text(9, 0, 'Pop'),
Text(10, 0, 'Rap'),
Text(11, 0, 'Classical'),
Text(12, 0, 'Metal'),
Text(13, 0, 'Folk'),
Text(14, 0, 'Lofi'),
Text(15, 0, 'Gospel']])
```

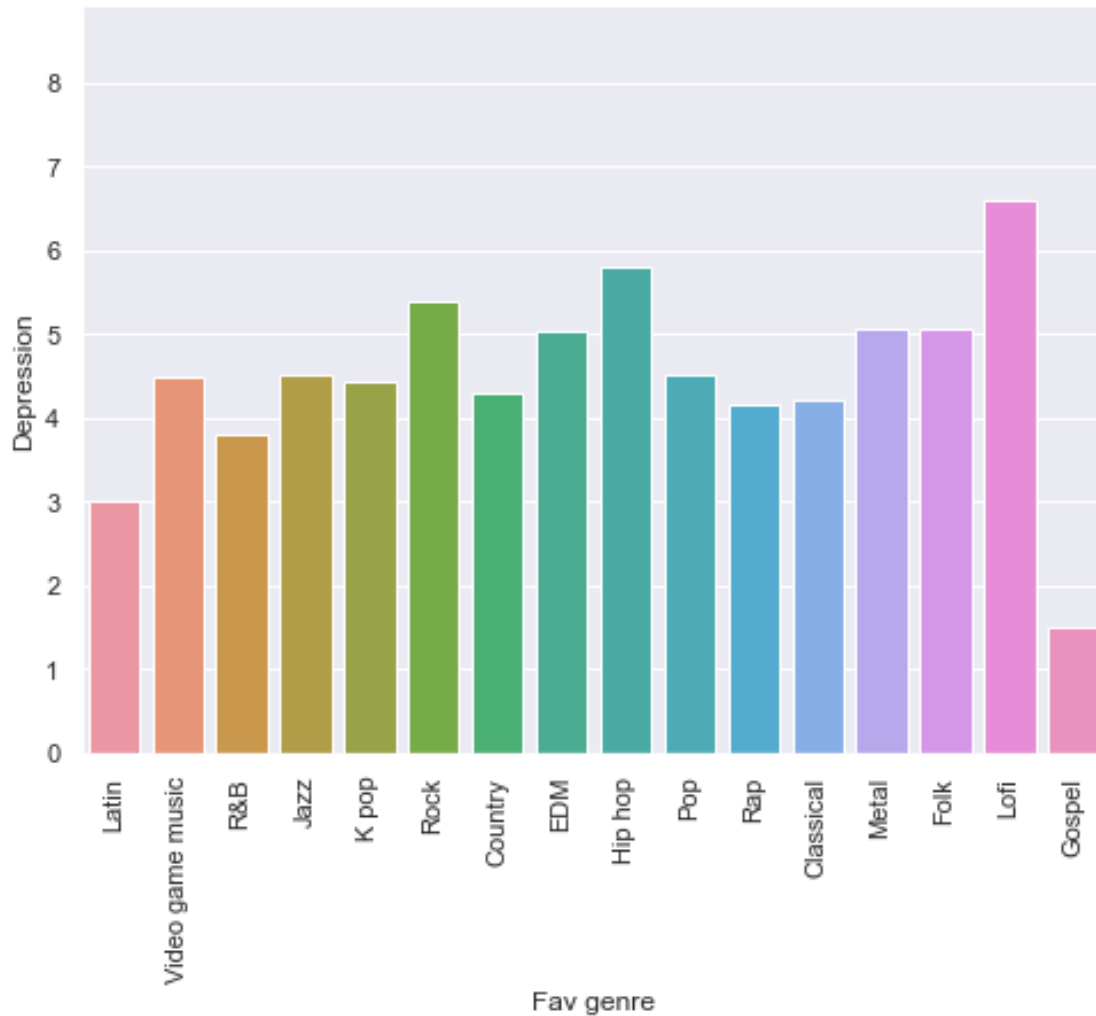


Rap and *Lofi* music listeners typically exhibit OCD levels above 3, indicating a higher prevalence of **obsessive-compulsive tendencies** in these groups.

```
[44]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Depression'], errwidth=0)
```

```
plt.xticks(rotation=90)
```

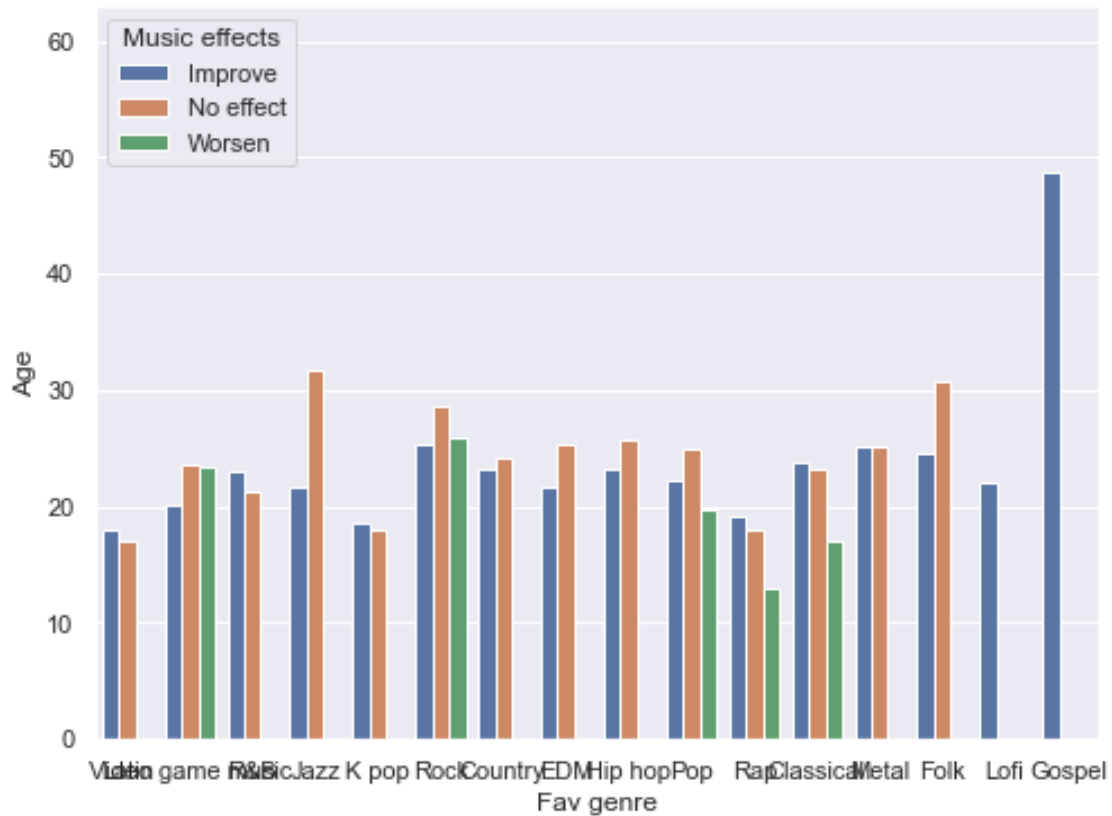
```
[44]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15]),
      [Text(0, 0, 'Latin'),
       Text(1, 0, 'Video game music'),
       Text(2, 0, 'R&B'),
       Text(3, 0, 'Jazz'),
       Text(4, 0, 'K pop'),
       Text(5, 0, 'Rock'),
       Text(6, 0, 'Country'),
       Text(7, 0, 'EDM'),
       Text(8, 0, 'Hip hop'),
       Text(9, 0, 'Pop'),
       Text(10, 0, 'Rap'),
       Text(11, 0, 'Classical'),
       Text(12, 0, 'Metal'),
       Text(13, 0, 'Folk'),
       Text(14, 0, 'Lofi'),
       Text(15, 0, 'Gospel')])
```



The *Lofi*, *Rock*, and *Hip Hop* listeners have Depression level above 5. While the rest are level 4 or below.

```
[45]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Age'], hue=data['Music effects'],
                      errwidth=0)
```

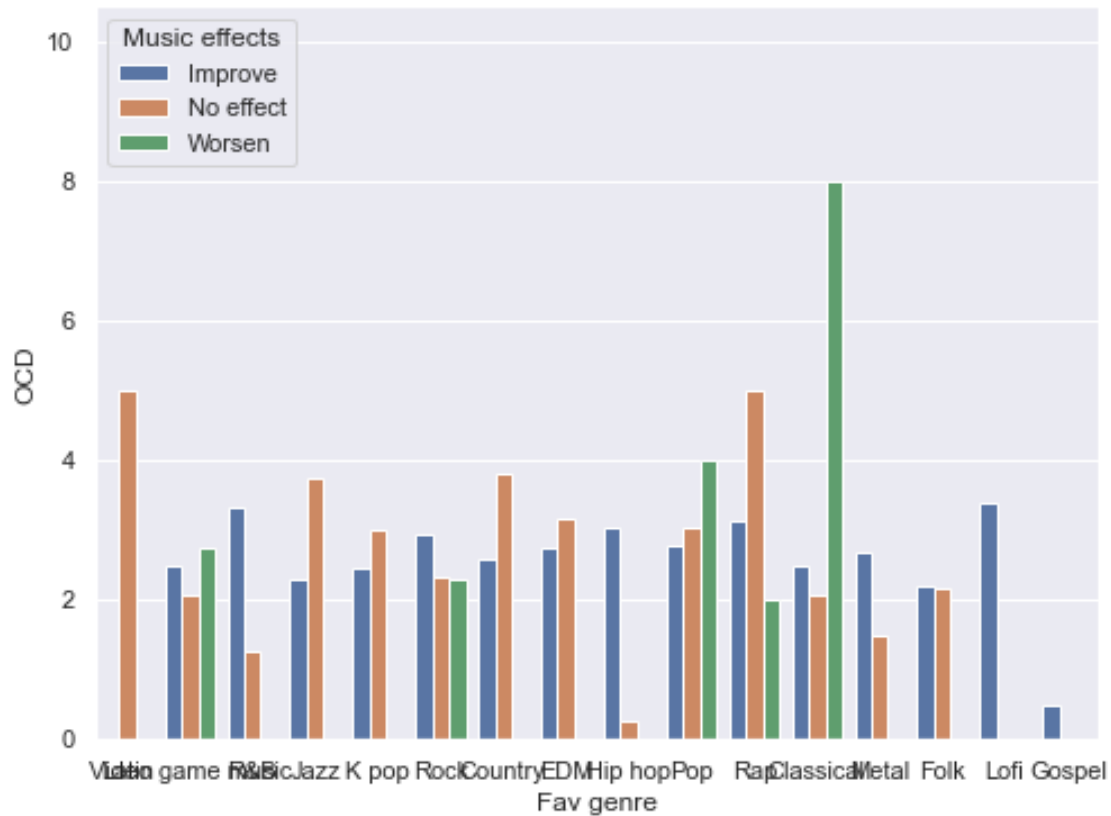
```
[45]: <AxesSubplot:xlabel='Fav genre', ylabel='Age'>
```

Rock, video game music, pop, rap, and classical music have worsened conditions, but listeners to music of all ages are improving in some way.

```
[46]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['OCD'], hue=data['Music effects'],
                      errwidth=0)
```

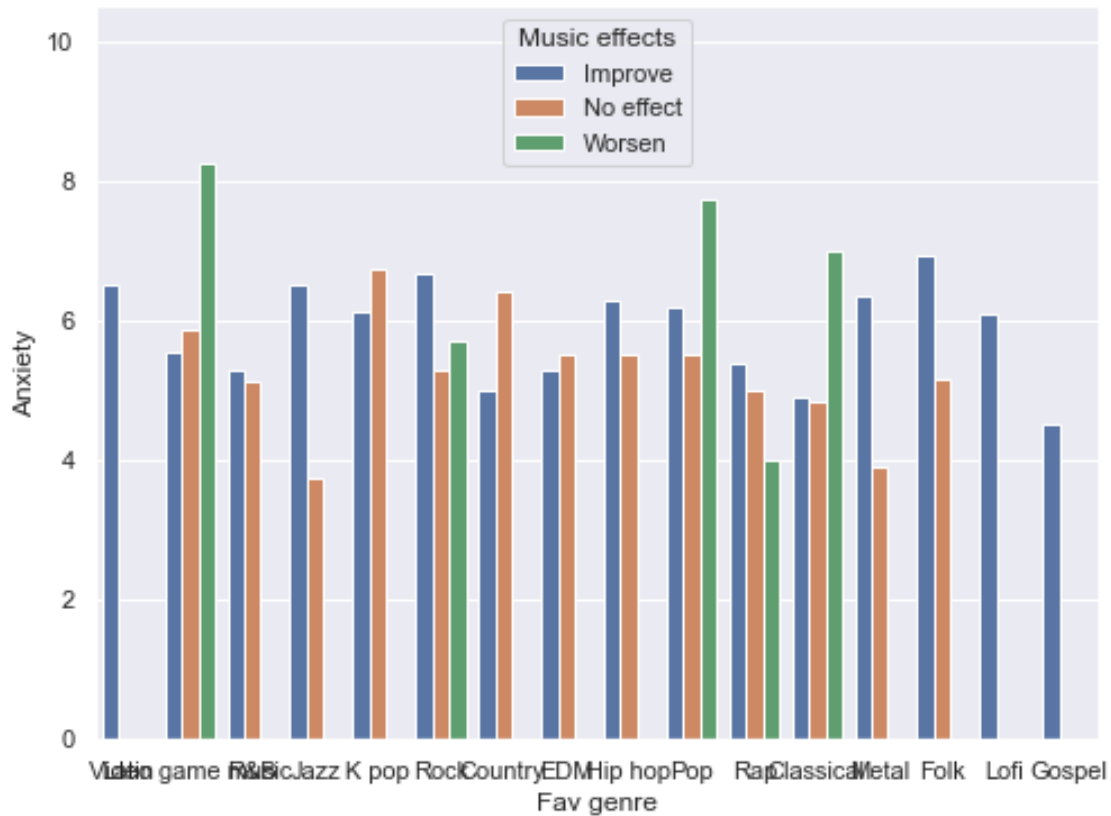
```
[46]: <AxesSubplot:xlabel='Fav genre', ylabel='OCD'>
```



People who listen to classical music have the greatest levels of **OCD**, followed by those who listen to *rock*, *video game music*, *pop*, *rap*, and other genres.

```
[47]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Anxiety'], hue=data['Music_
      ↪effects'], errwidth=0)
```

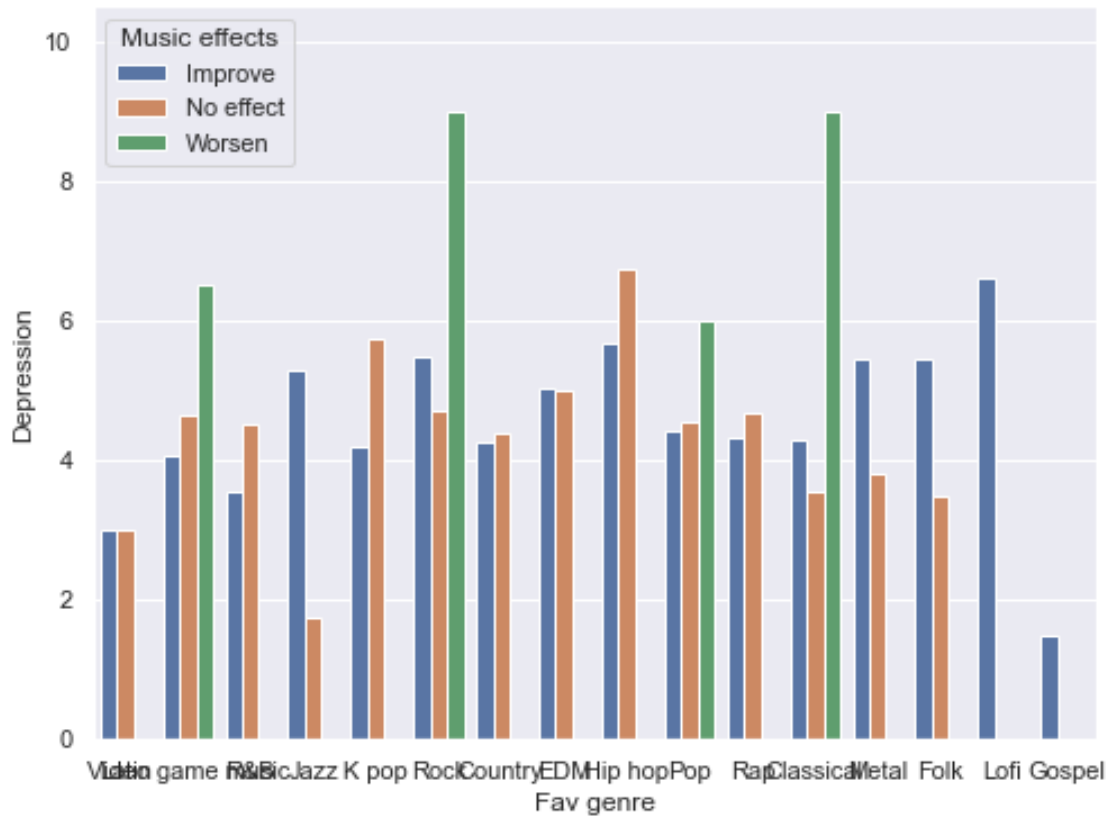
```
[47]: <AxesSubplot:xlabel='Fav genre', ylabel='Anxiety'>
```



Moreover, people who listen to *rock*, *video game music*, *pop*, *rap*, and *classical music* are generally anxious, while people who listen to *video game music* are the most anxious.

```
[48]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Depression'], hue=data['Music_
      ↪effects'], errwidth=0)
```

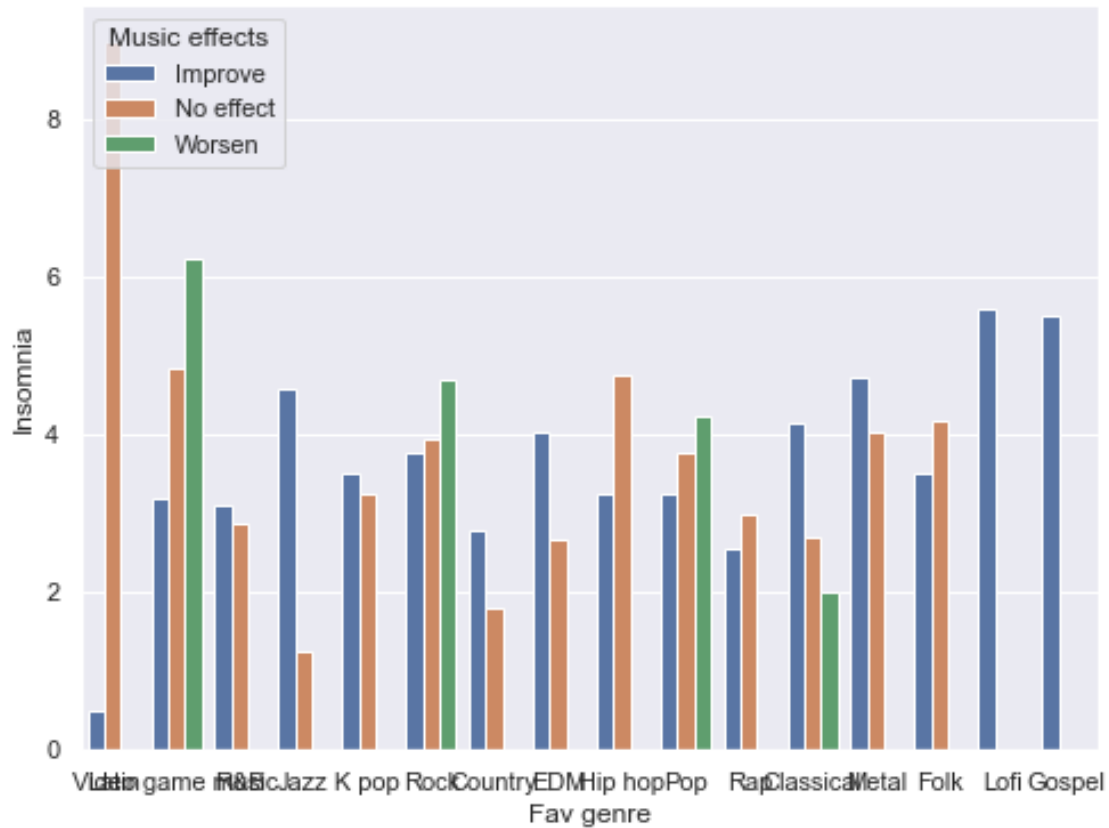
```
[48]: <AxesSubplot:xlabel='Fav genre', ylabel='Depression'>
```



Clearly, people who listen to *rock*, *video game music*, *pop*, and *classical music* are more depressed.

```
[49]: plt.figure(figsize=(8,6))
      seaborn.barplot(x=data['Fav genre'], y=data['Insomnia'], hue=data['Music_
      ↳effects'], errwidth=0)
```

```
[49]: <AxesSubplot:xlabel='Fav genre', ylabel='Insomnia'>
```



Rock, video game music, pop, and classical music listeners all experience some degree of **insomnia**, but **anxiety** is higher among *video game music* listeners.

1.6 Para terminar

This demonstrates the multiple qualities of music. Although it sometimes makes things worse, it could benefits our mental health.