Music & Mental Health: An Exploration into Music Therapy

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Introduction and Motivation

Through this report, our team studies the effects of music therapy on individuals to provide insights to firms to improve their therapy practices or new companies looking to break into the music therapy space. Music is a massive industry in today's world, with roughly 7.11 billion people indicating that they listen to music (HeadphonesAddict, n.d.). It can be impactful for some people, resulting in many people listening to or producing music as a method of relief. In fact, 57% of the American population uses music to relieve stress (Statista, n.d.). This has resulted in many firms offering music therapy, which comprises clinical & evidence-based use of music interventions to accomplish individualized goals. Although music therapy has been used for a long time, its prevalence in our society has only increased in the past 50 years.

Business Questions

Our team aims to solve the following business questions. Our reasonings for why we included these questions in our research will be provided as we talk about the experimental design of each of our business questions. All statistical analysis was done at the α = 0.05 significance level.

1. What are the distinct segments of patients in music therapy based on their personal information and music preferences?
2. Are there specific music genres that correlate with better or worse mental health scores?
3. How does the frequency of listening to music impact mental health? Are those who listen daily reporting better or worse mental health compared to occasional listeners?
4. Does listening to music of different tempos help or worsen mental health?
5. Does a listener who is a musician (defined as playing an instrument or composing music) show better signs of mental health improvement?
6. Does a listener actively exploring music get better mental health improvement?
7. Among those who listen while working, are there notable differences in stress-related mental health scores? How does listening during work affect stress levels compared to listening at other times?
8. Can we predict certain factors that may cause music therapy to be helpful for an individual?

Dataset Source

In 2022, Catherine Rasgaitis, a University of Washington computer science undergraduate, was curious about the effects of music on mental health conditions. As a result, she created a 33 question survey and posted on social media platforms, Discord channels, and Reddit forums. The survey results, converted to a dataset, contains 736 observations and was collected from August 27, 2022 to November 9, 2022.

The survey questions fall into three categories: Personal & Medical Information, Music Background & Listening Habits, and Music Genre Frequency. First, the survey asked respondents for their age, a self-reported score for certain mental health conditions (OCD, Insomnia, Anxiety, and Depression), and whether music improved their mental health. Next, it asked about respondents' music listening habits, including how many hours they listen to music per day, whether they listen while working, whether they are an instrumentalist or composer, their favorite genre, their interest in exploring different genres, whether they listen to music in a language other than their native language, and the tempo of their favorite genre. Lastly, the survey asked respondents to indicate how often they listen to 16 different music genres. We also created derived variables to help our research, and they are listed below:

Newly Derived Variables	
Youth	**21 and Under**: Respondents who are younger or equal to 21 years old. **Above 21**: Respondents who are older than 21.
Frequency Group	**Daily**: Respondents who listen to 3 hours or more of music a day. **Occasional**: Respondents who listen to less than 3 hours of music a day.
Variables Converted into Binary Variables (for future analysis)	
IoC	**1**: The respondent is an instrumentalist or a composer. **0**: The respondent is neither an instrumentalist nor a composer.
Exploratory Num	**1**: The respondent explores various genres of music. **0**: The respondent does not explore various genres of music.
Improve	**1**: The respondent experiences an improved in music effects **0**: The respondent experiences no effect or worsened music effects.

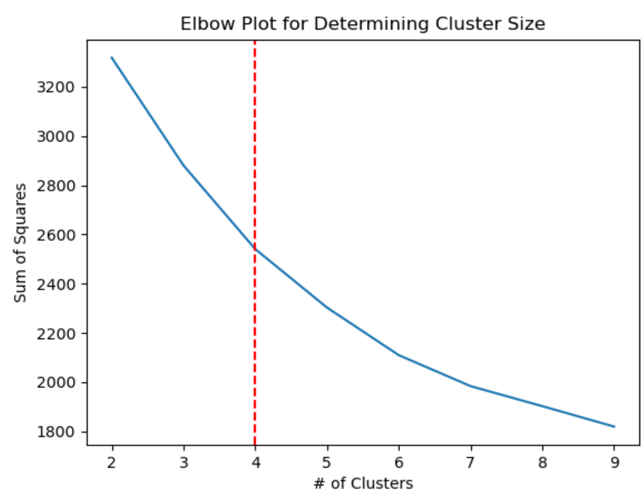
We believe that this survey data can help us understand the impacts of music therapy, with a few limitations which are described below.

Constraints

There are two main constraints in this dataset that impacted our results: the sampling method and the distribution channels of the survey. Survey data is subject to response bias, which occurs because individuals voluntarily choose to participate. This contrasts with observational data, where no participant interaction is required and a broader range of data points can be collected, offering a more comprehensive view of the effects of music therapy. Additionally, people tend to only reply to surveys they have an extreme opinion on. For example, an overwhelming number of users indicated that therapy improved their mental health compared to those who responded “No effect” or “Worsen”. Second, the platforms used to distribute the survey may have influenced the sample demographic. As detailed in the dataset source, the survey was primarily posted on social media platforms such as Discord and Reddit, where users tend to be younger than the global average. As a result of these constraints, our data may not fully represent the target population, and this limitation should be considered when interpreting the conclusions.

Experimental Design & Statistical Analysis

Customer Groups



First, we are interested in understanding the current segmentation of music therapy users. Our team used k-means clustering, which aims to classify similar data points into one cluster, to achieve this task due to its simplicity, efficiency, and effectiveness. In k-means clustering, we can only use continuous data; therefore, we used the respondents age, the number of hours per day they spend listening to music, and their mental health scores to cluster. Having this information can help current and future firms know the music therapy environment and make decisions in tuning their business model based on specific features.

We first need to determine how many clusters to use for our analysis. To do this, we created an elbow plot to determine how many clusters we need. Looking at the elbow plot, we determined that 4 clusters would be valuable, since 3 clusters was too small and 5 clusters provided too much information.

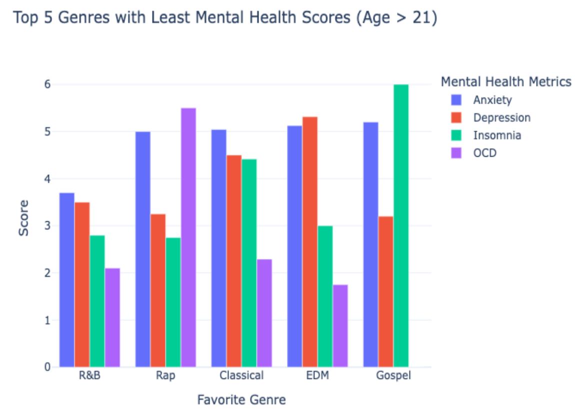
To do the clustering, we used the StandardScaler and KMeans classes to scale and cluster the data, and the summary of cluster groups are below. The first cluster is highlighted by higher mental health scores, especially with a larger insomnia score compared to the other groups, indicating a potential customer group firms can market to. The second group is significant due to being the youngest group and having the best mental health scores among all groups, indicating a market that might not be valuable. The third cluster calls into attention potential areas to market to older individuals, while the last cluster could thrive from solutions to resolve anxiety scores from those who listen to a lot of music per day. These results might be helpful for firms aiming to target younger audiences, but otherwise, they should be used sparingly due to the constraints mentioned earlier.

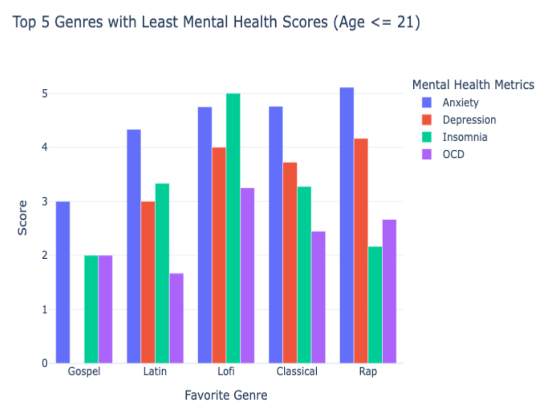
	Age	Hours per day	Anxiety	Depression	Insomnia	OCD
Cluster						
0	-0.202342	-0.023807	0.622152	0.668768	1.140262	0.519782
1	-0.342569	-0.136783	-0.814408	-0.648385	-0.524720	0.103261
2	1.148928	-0.110893	-0.037995	0.185274	-0.062186	-0.458368
3	-0.286140	0.240749	0.269551	-0.102901	-0.493886	-0.264376

Music Genre

Moving on, our team believes analyzing the frequency of listening to specific *music genres* and its impact on mental health outcomes (Anxiety, Depression, Insomnia, and OCD) is important. Here, we aim to answer three core questions: (1) whether listening frequency influences mental health scores across genres, (2) which genres show the strongest associations to these metrics, and (3) how such insights can inform therapeutic applications. The study's motivation arises from the growing recognition of music's role, specifically genre, in emotional regulation and mental well-being.

Listening frequency was label-encoded into two categories: frequent listeners (≥ 3 on a 1–5 scale) and non-frequent listeners (< 3). The analysis of the attached graphs reveals intriguing patterns in the relationship between favorite music genres and mental health metrics across two age groups. For individuals aged ≤ 21, genres like Gospel, Latin, Lofi, Classical, and Rap emerged as having the lowest mental health scores across Anxiety, Depression, Insomnia, and OCD. Notably, Gospel music showed the most significant positive impact on anxiety and insomnia scores, while Lofi and Classical music demonstrated balanced benefits across all metrics. For individuals aged > 21, the genres with the least mental health scores shifted slightly, highlighting R&B, Rap, Classical, EDM, and Gospel. R&B and Rap were strongly associated with reduced anxiety and depression, while Classical maintained its consistent benefits across both age groups. Interestingly, Gospel, while still beneficial, showed a slightly higher association with insomnia for older adults. These findings suggest a nuanced influence of music genres on mental well-being, with both shared and age-specific preferences contributing to emotional regulation and mental health support.





While the dataset supports robust statistical analysis, constraints include its subjective nature, possible biases, and underrepresentation of some genres. Additionally, the absence of contextual variables (e.g., purpose for listening) limits the exploration of underlying causes. Moreover, the methodology assumes linear relationships between listening frequency and mental health metrics, potentially oversimplifying complex interactions.

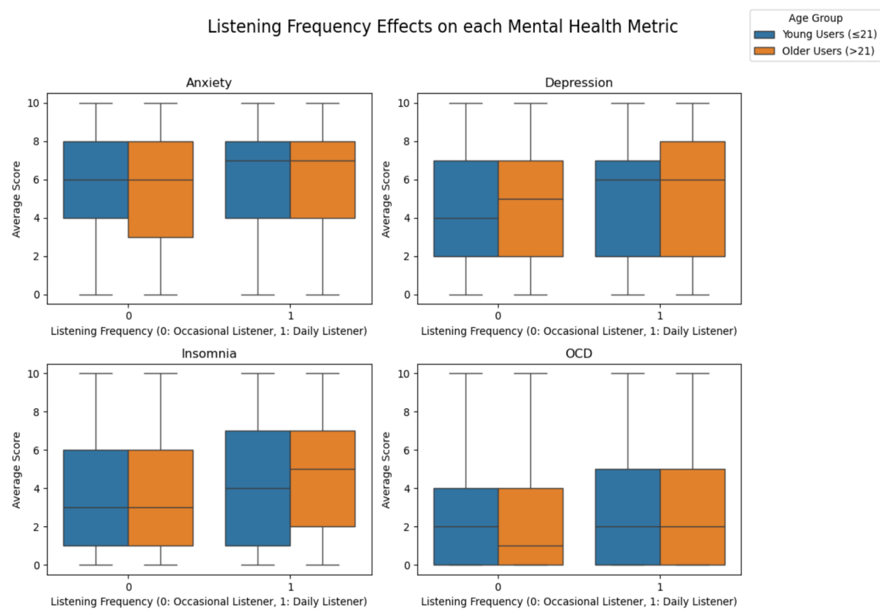
The analysis combined descriptive statistics and t-tests to evaluate genre-specific impacts. Descriptive results identified Gospel and Classical music with high mental health scores, signaling their potential emotional intensity. T-tests revealed significant associations, such as frequent Classical music listeners reporting higher insomnia scores and infrequent Country music listeners showing elevated depression scores, suggesting protective benefits of Country music. Genres like Metal (depression: T=4.095, p<0.0001) and Video Game Music (anxiety: T=3.171, p=0.002) exhibited pronounced distress among frequent listeners. These results align with theoretical expectations regarding the emotional and structural traits of these genres.

Genre	Mental Health Variable	T-Statistic	P-Value	Significant
Frequency [Classical]	Insomnia	1.982	0.047865	TRUE
Frequency [Country]	Depression	-2.009	0.045567	TRUE
Frequency [EDM]	OCD	2.100	0.036339	TRUE
Frequency [Folk]	Anxiety	2.022	0.04382	TRUE
Frequency [Folk]	Depression	2.599	0.009686	TRUE
Frequency [Lofi]	Anxiety	2.875	0.004209	TRUE
Frequency [Metal]	Depression	4.095	0.000048	TRUE
Frequency [Metal]	Insomnia	4.312	0.000019	TRUE
Frequency [Pop]	Anxiety	2.302	0.021995	TRUE
Frequency [Rap]	Depression	2.287	0.022516	TRUE
Frequency [Rock]	Anxiety	2.137	0.03333	TRUE
Frequency [Rock]	Depression	4.902	0.000002	TRUE
Frequency [Video Game]	Anxiety	3.171	0.001588	TRUE
Frequency [Video Game]	Depression	3.068	0.002246	TRUE
Frequency [Video Game]	Insomnia	2.908	0.003767	TRUE

The findings underscore nuanced relationships between music and mental health. Genres such as Gospel and Classical hold potential for therapeutic applications, while Metal and Video Game Music correlate with heightened distress. Anxiety consistently emerged as the most significant metric, reflecting its sensitivity to musical influences. Although the analysis addressed key business questions, further research incorporating demographic and contextual factors is essential to deepen understanding and refine music-based mental health interventions.

Listening Frequency

We also wanted to explore how listening frequency impacts mental health, specifically focusing on anxiety, depression, insomnia, and OCD. For this analysis, we defined daily listeners as individuals who listen to music for 3 or more hours a day, while occasional listeners are those who listen for less than 3 hours a day. This value (3) was decided because that is the median amount of hours respondents listened to music per day. We also categorized respondents into two age groups (as described in the dataset section). The motivation behind this analysis was to explore whether listening frequency, combined with age, affects mental health as frequent music listening might have different impacts depending on age.



To visualize the effects, we created side-by-side boxplots for each mental health metric separated by both listening frequency *and* age group. From this visualization, we noticed that the median mental health scores and overall distribution between *age groups* were not vastly different (specifically, median anxiety levels were the exact same), while 75% of the data fell within similar bounds between age groups. However (putting age aside), the median levels between frequent and occasional listernes are different; on average, daily listeners reported higher mental health scores across all mental health metrics indicating frequent listeners have worse mental health (frequent listening does not necessarily improve scores). Our team found this result interesting and noted that perhaps frequent listening could be a form of escapism to distract respondents from underlying mental health challenges. Or perhaps this result reflects correlation rather than causation if daily listeners are *already* struggling with mental health issues (their increased listening could simply be a coping mechanism). Regardless, the potential for reverse causation or confounding does present a shortcomings.

To further investigate this, we conducted two-sample hypothesis tests with unequal variance for each mental health metric to determine whether the differences between the two groups were statistically significant. The null hypothesis was that there is no difference in the average scores between frequency and age group, while the alternative hypothesis was that there is a difference:

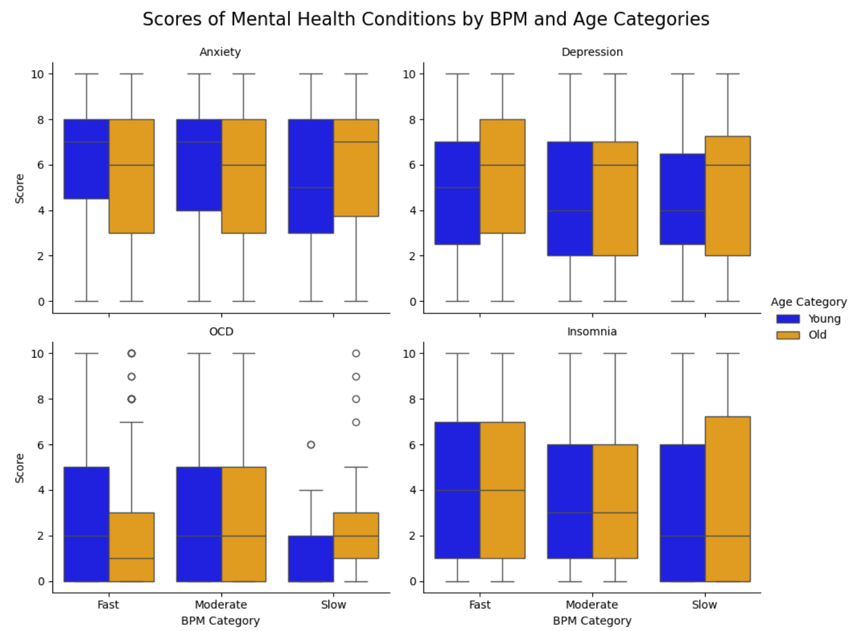
	Frequency Group			**Age Group**		
	T-Statistic	P-Value	Significant	T-Statistic	P-Value	Significant
Anxiety	-1.9450	0.0521	FALSE	0.6416	0.5213	FALSE
Depression	-2.9737	0.0030	TRUE	-1.6803	0.0933	FALSE
Insomnia	-3.0969	0.0020	TRUE	-1.2120	0.2259	FALSE
OCD	-3.3001	0.0010	TRUE	1.1180	0.2639	FALSE

The results revealed that depression, insomnia, and OCD had significant differences between the frequency groups (p-values < 0.05), while anxiety showed a borderline result (p-value = 0.052). This suggests that frequent listeners may experience more severe mental health symptoms. Further, age group analysis showed no significant differences in any of the mental health metrics. This suggests that age did not play a statistically significant role in mental health outcomes in this dataset, implying that the impact of listening frequency on mental health may be independent of the listener's age.

Music Tempo

Another metric we found interesting to explore is the effect of different music tempos on a listener's mental health. Recent studies show that fast, slow, and moderate tempos can affect the instantaneous mood of the listener (Liu, et. all, 2018). For example, slow-tempo music (<80 BPM) has been shown to lower the listener's heart rate, moderate-tempo (80-120 BPM) can enhance focus and concentration, and fast-tempo (120+ BPM) is believed to stimulate the release of dopamine.

For our project, we wanted to see if these effects could translate to long-term mental health benefits for various mental conditions. To visualize and assess this relationship we created a Facet Grid to understand the relationship between 'Fast', 'Slow', and 'Moderate' tempo music and mental health conditions such as Depression, Anxiety, Insomnia, and OCD. Additionally, we considered age to achieve more accurate results, classifying listeners under 21 years old as 'Young', and listeners above 21 as 'Old'.



Our Facet Grid showed us that tempo has no real effect on the mental conditions we analyzed in the long term, as each age group had similar results for most metrics. Our most significant findings, however, informed us that slow-tempo music can help with Insomnia and OCD. In contrast, music with faster tempos can lead to higher levels of Anxiety in listeners.

While we found these results interesting, it was clear that we were not getting the full story from our Facet Grid. This is why we decided to take our findings a step further and conduct a Chi-Square test. Our goal was to assess whether there is a statistically significant relationship between Music Tempo and Mental Health. We considered age in this test once again, categorizing listeners as either 'Young' or 'Old'.

```
Young vs Effects
Chi-Squared Statistic: 3.0662265723758324
P-Value: 0.5468043646191438
Degrees of Freedom: 4
Expected Frequencies:
 [[159.76363636  37.43636364   5.8       ]
 [120.41298701  28.21558442   4.37142857]
 [ 22.82337662   5.34805195   0.82857143]]
Music effects  Improve  No effect  Worsen
groupBeats
Fast               160         37       6
Moderate           123         27       3
Slow                20          7       2

Old vs Effects
Chi-Squared Statistic: 3.6154291154375375
P-Value: 0.4605454505214782
Degrees of Freedom: 4
Expected Frequencies:
 [[137.26822157  56.28571429   3.44606414]
 [ 81.52478134  33.42857143   2.04664723]
 [ 20.20699708   8.28571429   0.50728863]]
Music effects  Improve  No effect  Worsen
groupBeats
Fast               133         61       3
Moderate            82         32       3
Slow                24          5       0
```

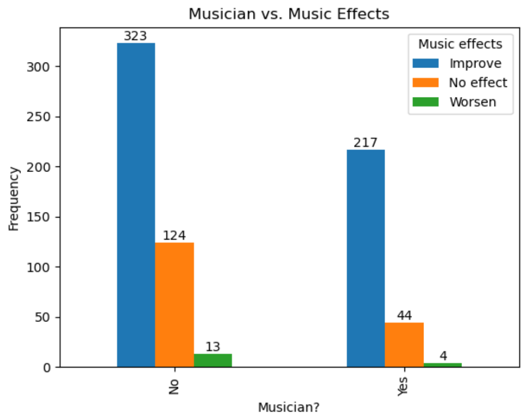
The Chi-Square test helped us understand that the relationship between Music Tempo/BPM and mental health was statistically insignificant. Since the p-value in both tests is greater than 0.05, we could not reject the null hypothesis. Thus, proving that the tempo of music a listener chooses to listen to does not affect their mental health or well-being in the long term.

From these analyses, we concluded that Music Tempo may have an effect on some listeners with Anxiety, Insomnia, or OCD. However, the relationship between mental health and tempo is too statistically insignificant to compare.

Musician Impact

We also wanted to study the impact of being a musician on an individual's mental health. Our team was curious about this since some musicians use music to relieve stress, while others interact with music so much that there might not be an effect on their mental health.

To evaluate this, we used the derived IoC variable and created a bar graph to compare music effects between musicians and non-musicians. In our data, we saw that non-musicians outnumber musicians by around a 1.73:1 ratio. However, we don't see this ratio between musicians and non-musicians. We see a 1.48:1 ratio between respondents who responded that music improved their mental health, but we see a 2.81:1 ratio between those who answered no effect and a ratio of 3.21:1 between those who answered



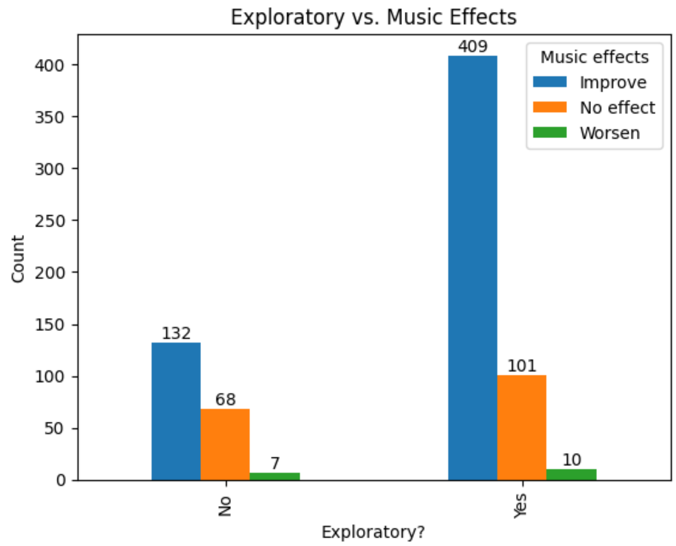
worsened. This indicates potential music effect differences between the two groups, and warranted further evaluation by our team.

To determine if music effects are different between musicians and non-musicians, we conducted a two-sample hypothesis test to determine whether the effects of music are different among musicians and non-musicians. To conduct this test, we used the derived numeric translation of whether music improved, worsened, or caused no effect on an individual, with 1 representing improvement, -1 indicating worsening, and 0 to represent no effect. We found the sample mean music effect scores for musicians and non-musicians to be 0.803 and 0.673, respectively, with variances of 0.188 and 0.276. The variance values indicated that we needed to use unequal variances in our hypothesis testing.

The null hypothesis is that there is no difference in the average music effect scores between musicians and non-musicians, while the alternative hypothesis is that there was a difference in the average music effect scores between the two groups. The test statistic was 3.582 with a p-value of 0.0003, indicating a significant difference between the average music effect scores between musicians and non-musicians. As a follow up on this, a hypothesis test to determine if average music effect scores between musicians is greater than non-musicians found average music effect scores of musicians to be greater than nonmusicians. Although the previously mentioned constraints apply here, we believe these constraints weren't significant, since the number of nonmusicians didn't dominate the number of musicians.

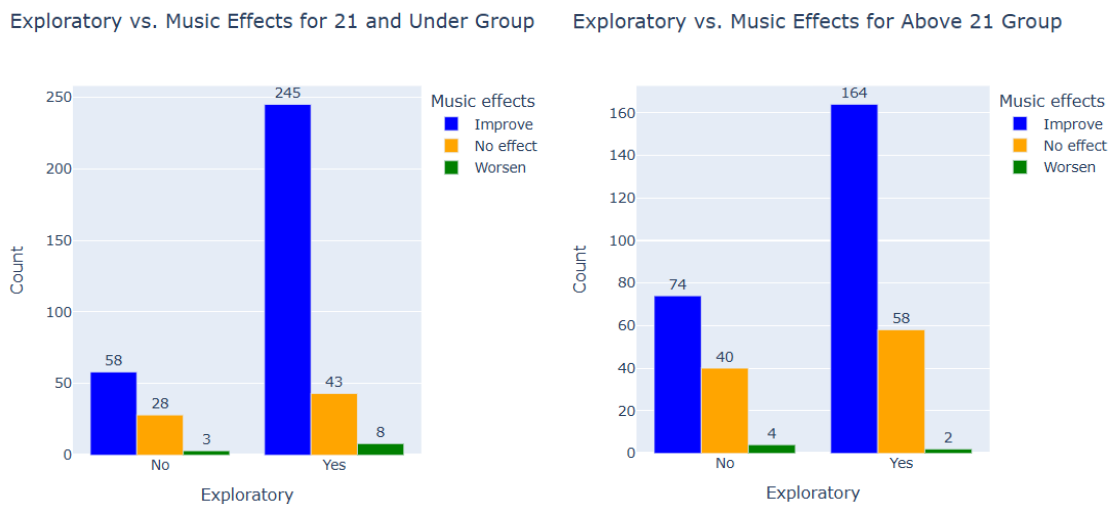
Explorance of Music

Next, we aimed to determine if actively exploring new artists or genres has a more positive effect on mental health and if so the impact will be different within different groups. We hypothesized that the motive or process of exploring something new might be beneficial for mental health.



To address this, we conducted data visualization and a two-sample hypothesis test. We first created a bar graph to compare the effects of music on respondents who actively explore new music versus those who do not. The ratio of the exploratory group to the non-exploratory group in our data is 7:3. However, when it comes to mental improvement, the ratios differ. The improvement ratio for the exploratory group reaches 4:1, while around 33% of respondents in the non-exploratory group report an improvement in mental health. It seems that the exploratory behavior possibly has an effect on mental health.

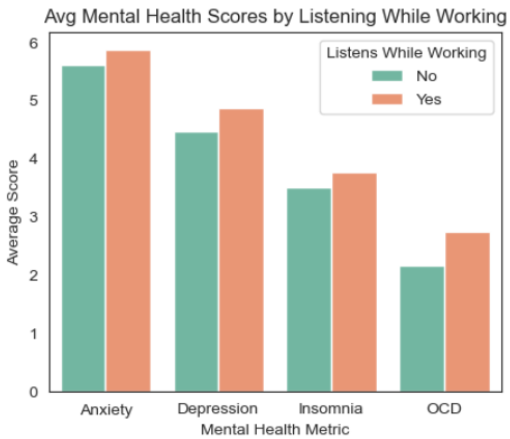
Subsequently, we added an age group (as described in the dataset section) to conduct an extra layer of analysis distinguishing between “young” and “old” respondents (around 1.1:1 ratio). In each age group, 70% of younger respondents will explore new music while only 60% of the older respondents will do so. In the bar chart below, we see that actively exploring new music is associated with a more positive effect on mental health across both age groups. Contrary, the majority of respondents who do not explore new music tend to report either no effect or a lower improvement rate.



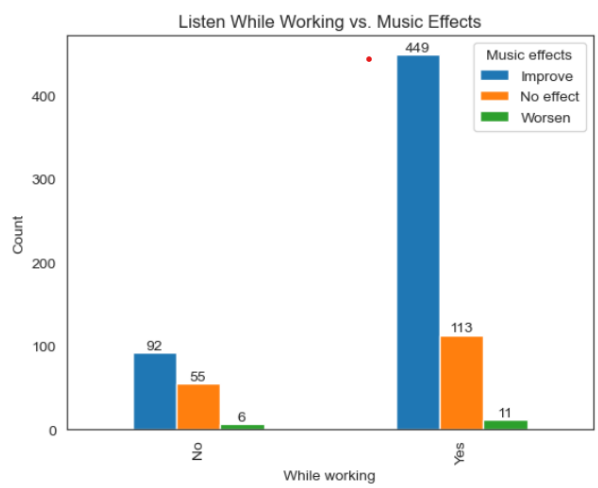
In a two-sample hypothesis test, we used the same derived numeric translation of the music effect. The sample means and variances of music effect scores for the two age groups are 0.758 and 0.678, and 0.24 and 0.225, respectively, indicating that we should account for unequal variances in our hypothesis testing. The null hypothesis for this test was that there is no difference in the average music effect scores between the two age groups, while the alternative hypothesis was that a difference exists. The t-statistic for the younger age group was 3.113 with a p-value of 0.0004, indicating a significant difference in the average music effect across respondents prone to exploring music. For the older age group, the t-test statistic was 2.28 with a p-value of 0.023, also indicating a significant difference (though less pronounced than in the younger group). In conclusion, exploratory behavior is associated with a higher likelihood of a positive effect from music, with the impact being more significant in the younger age group compared to the older age group.

Work Environment

Another focus is investigating whether listening to music while working impacts mental health scores, and how listening during work affects stress levels compared to listening at other times. We hypothesized that individuals who listen to music during work are more likely to experience improvements in mental health compared to those who do not. Additionally, we examined whether this effect differs across age groups.

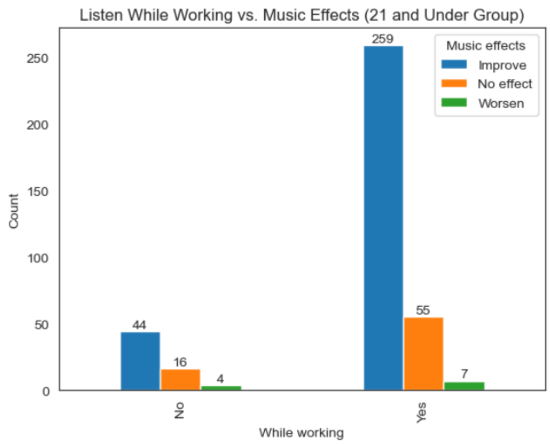


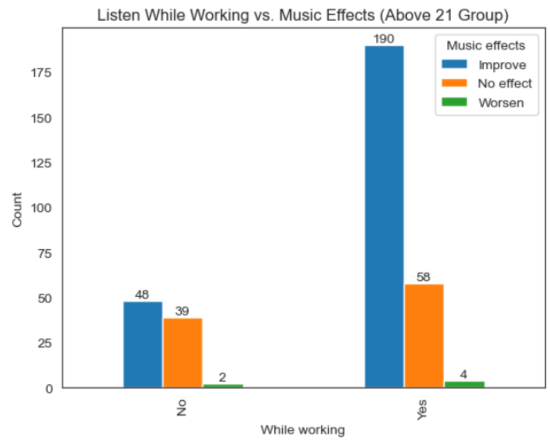
The analysis first focused on mental health scores between listeners and non-listeners during work. We analyzed average scores for the mental health metrics in our datasets. The bar chart shows that listeners consistently reported slightly higher scores across all metrics. However, hypothesis testing revealed no significant difference for anxiety, depression or insomnia, with p-values of 0.3013, 0.1302, 0.3467, respectively. However, a significant difference was observed for OCD, with a t-statistic of 2.23 and a p-value of 0.0258. These findings suggest that while listening to music may not strongly affect conditions such as anxiety or depression, it plays a more meaningful role in OCD symptoms, providing a valuable direction for workplace wellness programs.



Next, we focused on the *overall* music effects between listeners and nonlisteners during work. The ratio of the listener group to the non-listeners group in our data is 8:2. Among nonlisteners, 61% reported improvement. In contrast, among the listeners, 78% reported improvement. This result indicates that listening to music while working may have positive effects on mental health so our team did more evaluation to explore. We conducted a two-sample t-test to confirm this difference, using the derived "Improve" variable. We found a t-statistic of 4.032 and a p-value of essentially 0, indicating a significant difference between average music effect scores between listening to music while working.

Further, the impact of listening to music while working was analyzed across different age groups. For younger respondents, 81% of listeners reported improvement, and for older respondents, 76% of listeners reported improvement. From the bar chart, we discovered that respondents who listen to music while working tend to have a positive effect on mental health.





We used the same derived numerical music effect variable for a two-sample hypothesis test to test two age groups. For the younger group, the t-statistic is 2.006 with a p-value of 0.048, while for the older group, the t-statistic was 3.396 with a p-value of 0.0008. These findings suggest that listening to music while working is associated with a higher likelihood of mental health improvement, with the effect being more pronounced in the older age group.

In conclusion, listening to music while working has a significant impact on OCD health scores and positive improvement for stress-related mental health, with the impact being more significant in the younger age group compared to the older age group.

Logistic Regression

To further enhance our analysis, our team decided to perform a logistic regression analysis to examine the relationship between a binary dependent outcome, the self-reported mental health improvement (1 for improvement, 0 for no improvement), and a set of independent predictor variables. We wanted to explore how factors like listening frequency, mental health metrics (e.g., anxiety and depression), etc. contribute to the *likelihood* of improvement; thus, our primary motivation for this regression is its ability to model probabilities and strengthen our results. Unlike linear regression, which is not suitable for binary outcomes, logistic regression maps the predicted values onto a probability scale between 0 and 1, making it ideal for classification; this helps us interpret the model in terms of the odds of an event occurring. Additionally, logistic regression accounts for the non-linear relationship between independent variables and the log-odds of the outcome, which is important when dealing with complex datasets.

In our experiment, we selected several key indicators: Age, Frequency of Listening, Instrumentalist of Composer (IoC), Exploratory Behavior (Exploratory_num), Genres, and mental health metrics (Anxiety, Depression, Insomnia, OCD) to which we converted to binary values. Each of these variables theoretically has a relationship with the outcome; below is the result:

Logit Regression Results

Dep. Variable:	Improve	No. Observations:	727
Model:	Logit	Df Residuals:	703
Method:	MLE	Df Model:	23
Date:	Sun, 08 Dec 2024	Pseudo R-squ.:	0.08561
Time:	15:18:38	Log-Likelihood:	-378.03
converged:	False	LL-Null:	-413.42
Covariance Type:	nonrobust	LLR p-value:	9.179e-07

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.3175	0.485	-0.655	0.512	-1.267	0.632
Age	0.0008	0.008	0.107	0.915	-0.014	0.016
Frequency Group	0.3151	0.195	1.613	0.107	-0.068	0.698
IoC	0.7543	0.209	3.607	0.000	0.344	1.164
Exploratory_num	0.6227	0.195	3.188	0.001	0.240	1.006
Anxiety	0.1360	0.040	3.403	0.001	0.058	0.214
Depression	-0.0387	0.036	-1.062	0.288	-0.110	0.033
Insomnia	-0.0355	0.032	-1.105	0.269	-0.099	0.027
OCD	0.0008	0.035	0.022	0.983	-0.068	0.069
Genre_Country	0.5438	0.624	0.871	0.384	-0.679	1.767
Genre_EDM	0.7478	0.572	1.308	0.191	-0.373	1.869
Genre_Folk	0.2722	0.583	0.467	0.640	-0.870	1.415
Genre_Gospel	11.6566	174.652	0.067	0.947	-330.655	353.968
Genre_Hip hop	1.1539	0.648	1.779	0.075	-0.117	2.425
Genre_Jazz	0.0290	0.666	0.044	0.965	-1.276	1.334
Genre_K pop	0.4065	0.664	0.612	0.540	-0.895	1.708
Genre_Latin	-1.7368	1.568	-1.108	0.268	-4.809	1.336
Genre_Lofi	24.1943	9.24e+04	0.000	1.000	-1.81e+05	1.81e+05
Genre_Metal	0.1776	0.427	0.416	0.677	-0.659	1.014
Genre_Pop	0.2032	0.410	0.496	0.620	-0.599	1.006
Genre_R&B	0.3166	0.531	0.597	0.551	-0.723	1.356
Genre_Rap	0.2126	0.625	0.340	0.734	-1.012	1.437
Genre_Rock	-0.1832	0.379	-0.483	0.629	-0.926	0.559
Genre_Video game music	-0.5400	0.462	-1.169	0.242	-1.446	0.366

The logistic regression results indicate that several factors are statistically significant predictors of the likelihood of improvement, with IoC, Exploratory number, and Anxiety showing strong positive relationships with the outcome, all having p-values less than 0.05. This suggests that higher involvement in playing an instrument/composing, greater music exploration, and higher levels of anxiety increase the likelihood of improvement by their respective coefficient. On the other hand, Depression, Insomnia, and OCD did not show significant effects, with p-values greater than 0.05, indicating these factors do not significantly contribute to the model's prediction of improvement. The model also reveals mixed results for genre-related variables, with some genres like Hip hop showing a borderline significant positive association, while others, like Gospel and Lofi, yielded results that are not meaningful due to large standard errors or lack of significance. Overall, the model's *weak* pseudo R-squared value of 0.08561 validates many of our findings such that many music attributes we tested are *not* necessarily significant in terms of mental improvement.

Conclusions

Our analysis underscores the potential of music as a powerful tool for improving mental health, with significant implications for firms considering investments in music therapy. By leveraging clustering analysis, genre-specific insights, and the exploration of behavioral patterns, this study reveals actionable strategies for tailoring music therapy to meet user needs. Below, we synthesize our key insights and their implications for businesses:

1. Clustering Analysis identified clear user groups with varying needs, particularly individuals experiencing insomnia or anxiety. Firms can capitalize on these segments by offering specialized solutions, such as relaxation-focused music playlists for insomnia or anxiety-reducing genres targeted at younger audiences. Genres like Folk and Rock showed promising results in reducing anxiety symptoms.
2. Genres such as Gospel, Classical, and Country music emerged as effective for mental health improvement. These genres present an opportunity for firms to design genre-specific interventions, maximizing therapeutic outcomes.
3. Participants who engaged in discovering new music consistently reported improved mental health outcomes across all age groups. Firms should consider promoting platforms that encourage music exploration.
4. Musicians reported greater mental health benefits compared to nonmusicians. This insight suggests opportunities for firms to develop programs that encourage users to learn or play music, potentially combining therapy with education.
5. Frequent listeners may use music as a coping mechanism, presenting a unique segment for tailored mental health solutions. Firms could explore subscription-based models or curated

playlists aimed at supporting specific mental health goals, such as stress reduction or mood enhancement.

6. Participants who listen to music while working often experience more significant improvement in stress-related mental health issues. This finding highlights an opportunity for firms to incorporate music-based initiatives into workplace wellness programs to support employees' mental health and reduce stress levels.

That is all to say, there are several limitations that should be acknowledged. The reliance on self-reported mental health outcomes may introduce biases, affecting the reliability of the results. Additionally, the relationship between music and mental health is non-linear and influenced by contextual factors, such as environment and individual preferences, which were not fully captured in this analysis.

Overall, the study demonstrates significant potential of music therapy to mental health improvement. Firms have the opportunity to tap into these insights and design targeted solutions (such as programs encouraging active musical engagement). While further research is necessary, our findings strongly support the adoption of music therapy as a strategic tool for enhancing mental well-being.

References

HeadphonesAddict. (n.d.). *Listening to music statistics*. Retrieved December 9, 2024, from **https://headphonesaddict.com/listening-to-music-statistics/#:~:text=Roughly%207.11%20billion%20people%20listen%20to%20music.&text=Listening%20to%20music%20reduces%20pain,sleep%2C%20alertness%2C%20and%20memory.**

Statista. (n.d.). *Popular ways to use media to manage stress U.S. 2020*. Retrieved December 9, 2024, from **https://www.statista.com/statistics/1186558/popular-media-activities-to-manage-stress-us/#:~:text%3DPopular%2520ways%2520to%2520use%2520media%2520to%2520manage%2520stress%2520U.S.%25202020%26text%3DA%2520survey%2520from%2520September%25202020,music%2520to%2520manage%2520stressful%2520situations**

Liu, Y., Liu, G., Wei, D., Li, Q., Yuan, G., Wu, S., Wang, G., & Zhao, X. (2018). Effects of Musical Tempo on Musicians' and Non-musicians' Emotional Experience When Listening to Music. *Frontiers in Psychology*, *9*, 2118. https://doi.org/10.3389/fpsyg.2018.02118