

Analysing Music and Mental Health Dataset Through Correspondence Analysis and Logistic Regression Models

Nurnabiha Syuhada Ibrahim¹, Norziha Che Him^{1,2,*}, Noor Azliza Abd Latif¹, Mohd Saifullah Rusiman¹

1 Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology, UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 86400 Pagoh, Muar, Johor, MALAYSIA.

2 Computational Intelligence and Data Science Focus Group (CIDaS), Faculty of Applied Sciences and Technology, UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 86400 Pagoh, Muar, Johor, MALAYSIA.

*Corresponding Author: norziha@uthm.edu.my

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Abstract

Mental Health problems are now very common in modern communities today, and music is often cited as an impactful tool for mental health improvement. Therefore, this study uses descriptive analysis, correspondence analysis (CA) and ordinal logistic regression to investigate the relationship between music and mental health preference. The aims of this study are to identify the most preferred music genre among respondents, uncover patterns between favourite music genre and mental health variables and investigating the association between music's effect and favourite music genre alongside with other factors. The dataset that has been used consists of age, primary streaming service, hours per day, while working, instrumentalist, composer, favourite genre, exploratory, foreign language, frequency of listening for each genre, anxiety depression, insomnia, obsessive-compulsive disorder (OCD) and music effect. Descriptive analysis indicates that Rock is the most favourite music genre based on the highest frequency of the respondents which is 188 respondents. The biplot of correspondence analysis reveals that respondents with Depression and OCD preferred Electronic Dance Music (EDM) genre, while Insomnia and Anxiety have an inconsistent genre either Metal or Classical for Insomnia and Rock or Pop for Anxiety. Based on ordinal logistic regression, Gospel and Lofi are the most consistent genres in the model, with odds ratios of 13100000 and 83500000, respectively, and both having p -values close to zero. Additionally, other factors, such as anxiety and listening to music while working, also show a significant association with p -values near zero. This study highlights the complex relationship between music preferences and mental health, suggesting that certain genres may align with particular mental health conditions. At some point, music can have potential for mental health support and therapy.

1. Introduction

Mental health is a priority in today's digital age for both young and old people. It needs early treatment to prevent severe effects, especially in critical cases. Various treatments are available to help people with mental health problems. Interestingly, music preferences can be related to mental health improvement. Listening to music helps people manage their emotion daily in spite of that, only a few have the knowledge about specific genre that could help people control their emotional mood [1]. Numerous studies in psychology have utilized statistical methods to explore this connection. To fully understand this issue, it is crucial to analyse the relationship between music and mental health [2].

In today's world, mental health is a critical issue for all generations, impacting physical well-being, including food intake, sleep, and relationships. Understanding the effectiveness of music treatment in handling mental health issues is essential. This knowledge can provide insights into how music can influence emotions and reduce psychological discomfort. This study aimed to underline the relationship between music preferences and mental health, highlighting the potential effectiveness of specific music genres in improving the mental well-being of individuals and also detecting mental health conditions among patients could have become easier if the analysis showed that specific music genres were related to certain types of mental health issues

Music can be enjoyed by everyone, even those with hearing loss. The excessive volume or beats can create calmness and excitement, while also affecting personal consciousness [3]. Music has been shown to have profound positive impacts on mental health, acting as a mood booster. The benefits include emotional regulation, stress reduction, and enhanced social connection. Certain genres of music have a positive association with college students' mental health [4]. A study conducted by [5] investigated the effects of music therapy on reducing anxiety among pregnant women in Changsha, China. By applying a randomized controlled trials method in medical statistics, the results revealed significant evidence that music therapy can relieve anxiety levels and improve physiological responses.

However, a notable gap in literature exists regarding the influence of respondents' diverse backgrounds, such as age, cultural context, gender, and socioeconomic status, on the relationship between music preferences and mental health. For instance, individuals from different cultural backgrounds may perceive the emotional effects of music genres differently due to varying cultural connotations associated with the music. [6] study on mental health literacy by using Multiblock Discriminant Correspondence Analysis and indicates that while age and gender interactions particularly females have a higher number of mental health literacy compared to males. [7] used Multiple Correspondence Analysis (MCA) and revealed that adolescents with the highest-level well-being and fewer symptoms less likely to face with behavioural disorder. [8] used CA and indicates that lower resilience levels have an association with symptoms of depressive and childbirth anxiety related but resilience and stress found no correlation with the pandemic.

Logistic regression has been applied in psychological study to assess mental health outcomes. An analysis by [9] discovered that people with low awareness levels and those who spent more than 3 hours a day are more likely to experience high anxiety level while females, younger age and medical students experienced with higher level of depression. While another study by [10] used multivariable logistics regression to identify the factors affecting the prevalence of anxiety during exam, concluding that three factors that contribute to exam anxiety are excessive course load (AOR=2.22, 95% CI: 1.03-4.78), psychological stress (AOR=2.89, 95% CI: 1.51-5.48) and low self-esteem (AOR=8.15, 95% CI: 1.51-43.96).

These findings highlight the importance of considering demographic and cultural diversity in future studies on the relationship between music and mental health. Such an approach would enable a more nuanced understanding of how music can be effectively leveraged to improve mental well-being across different population groups.

2. Materials and Methods

2.1 Data Description

The dataset of the Music and Mental Health survey was conducted in the year 2022 by Catherine Rasgaitis, a Computer Science student at the University of Washington. The survey aimed to determine if there is a relationship between music taste and mental health and to explore intriguing insights about music in the human mind. The data was obtained using a survey form shared on various online platforms, including Reddit forums and Discord servers. One of the online websites used for sharing the survey was GitHub (https://crasgaitis.github.io/mental_music/). The survey was also advertised in libraries, parks, and other public locations to ensure a variety of respondents. The dataset contained 736 observations with 31 variables, excluding the timestamp of survey submission and respondents' permission to publish their responses and data. The dataset available in excel format with detailed questionnaires.

2.2 Descriptive Analysis

Descriptive analysis is a method of approaching and carrying out analysis to find the trends and variation in dataset besides providing answers to who, what, where, when and how much for research questions [11]. It is a crucial part of scientific study to reveal the fact of an indirectly connected to the issue [12]. It can also be stand-alone research for certain research projects which can offer a good assessment on an important aspect.

By classifying the respondents into groups based on their favourite music genre types and the highest scale of self-reported mental health, the frequency of respondents was calculated to create contingency tables for each category, determining which favourite music genre was potentially associated with the highest number of mental health issues. Furthermore, the contingency table revealed which music genre had the most fans and which specific mental health problem was most prevalent among the respondents.

2.3 Correspondence Analysis

The first step to implement CA is by representing the data into contingency tables which contained the frequencies of each variable with total of each row and column and the grand total. By reducing the dimensions of the matrix, CA simplifies the data and highlights major patterns, helping to visualize the categorical variables in lower dimensions, commonly two or three [13].

Illustration such as Biplots is one of the graphical visualizations that can be used to present the data effectively [14]. The strength of association or similarity is indicated by the proximity of the points in a biplot. The closer the points are to one another, the greater the correlation while the farther away the points, the weaker the relationship. Furthermore, categories with typical contributions are represented by points close to the graph's centre, whereas more specialized or unique patterns in the data are indicated by points distant from the centre.

2.4 Logistic Regression Model

An ordinal logistic regression model was used for the analysis, as the data contains ordinal variables related to favourite music genres and the effects of music. The response variable assumed to be ordinal, with categories that reflect different levels of music preference or effect. The general form of the ordinal logistic regression model can be expressed as equation (1);

$$\log\left(\frac{P(Y \leq j)}{P(Y > j)}\right) = \alpha_j - (\beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k) \quad (1)$$

where:

Y : Dependent variable with $j = 1, 2, \dots, J - 1$ levels.

X_k : Independent variable

$P(Y \leq j)$: Cumulative probability of Y being in category j or below.

α_j : Thresholds (cut-points) for the j^{th} category.

β_k : Coefficients for the k^{th} independent variable X_k .

The model assumption for ordinal logistic regression is that the ordinal scale of dependent variable is meaningful and thus, an appropriate analysis of level progression can be done. A very important assumption is the proportional odds where this ensures consistency in the relationship of predictors with the dependent variable across thresholds. In other words, the independent variable does not affect the different categories of dependent variable. Besides, it must be proportional odds where each independent variable (x) has the same influence at every level of ordinal dependent variable (y). In other words, the independent variable does not affect the different categories of the dependent variable. The proportional odds assumption was tested using the Brant test, which evaluates whether the relationship between each predictor and the dependent variable is consistent across thresholds.

Another important assumption is that of linearity between independent variables and log odds of dependent variable, which makes sure that the model captures proper relationships. This assumption was assessed using diagnostic plots, such as partial residual plots, to verify the linearity. Sufficient sample size is also vital to get reliable estimates of parameters when a large number of predictors or categories exist.

For model evaluation, Meanwhile, there are few types of evaluation metrics could be used to evaluate which are AIC and BIC. For AIC checking, the smaller value indicates that the model is better since AIC does not depend on the increasing of variables as it penalized the increasing number of coefficients in the models. AIC is more useful

for non-parametric regression while BIC is useful to choose the right model for forecasting [15]. Each criterion indicates that the model with lowest value is the better.

3. Results and Discussion

3.1 Demography Analysis

Table 1 The Demography of Respondent

Demography	Category	Frequency	Percentage(%)
Age	10-20	339	46.06
	21-30	247	33.56
	31-40	76	10.33
	41-50	26	3.53
	51-Above	48	6.52
Primary Streaming Service	YouTube	94	12.79
	Spotify	458	62.31
	Pandora	11	1.45
	Apple Music	51	6.94
	Other service	50	6.80
	Not use service	71	9.66
Hours Listening Per Day	0-6	649	88.18
	7-12	77	10.46
	13-18	6	0.82
	19-24	4	0.54
Background of Music (Yes)	While working/studying	579	78.6
	Instrumentalist	235	31.93
	Composer	126	17.12
	Exploratory	525	71.33
	Foreign languages	404	54.89

Table 1 summarizes the demographic information and music-related habits among respondents. Based on age distribution, the majority of respondents fall within the 10–20 age group (46.06%), followed by the 21–30 age group (33.56%), while the smallest group is 41–50 years (3.53%). For primary streaming services, Spotify is the most popular choice (62.31%), while other services such as YouTube (12.79%) and Apple Music (6.94%) are used by fewer respondents. Interestingly, 9.66% of respondents do not use any streaming service.

In terms of daily listening hours, the majority of respondents (88.18%) listen to music for 0–6 hours, with only a small percentage (10.46%) listening for 7–12 hours, and even fewer exceeding that duration. Based on the background of music preferences, 78.6% of participants listen to music while working or studying. There are 71.33% of respondents love to explore new music while 54.89% of the respondents love to listen music of other foreign languages. Instrumentalist and composer-related music account for 31.93% and 17.12%, respectively, indicating varied music preferences among respondents.

Music preferences influenced by the demographic factors such as age, preferred music, listening hours, and streaming provider. Younger people (10–20 and 21–30) dominate the sample, often using platforms like Spotify and exploring diverse genres. Older groups may have different preferences, favouring traditional formats or specific music types. Most respondents (88.18%) listen for 0–6 hours daily, often while studying or working, with younger people likely using music more for focus. The preference for foreign language and exploratory music shows cultural openness, especially among younger individuals. These factors shape how music is used for relaxation, focus, and emotional support.

3.2 Type of Music Genre preferred by Respondent

Table 2 The Frequency of Favourite Music Genre by Streaming Service

Favourite Genre	Apple Music	Not use service	Other service	Pandora	Spotify	YouTube Music	Total
Classical	3	10	3	2	25	10	53
Country	3	1	3	0	15	2	24
EDM	4	1	5	0	21	6	37
Folk	1	1	2	0	20	6	30
Gospel	0	1	0	2	2	1	6

Hip hop	2	0	1	1	28	3	35
Jazz	0	0	3	0	15	2	20
K pop	1	0	1	0	22	2	26
Latin	1	0	0	0	2	0	3
Lofi	1	0	1	0	8	0	10
Metal	5	8	3	0	61	11	88
Pop	11	11	5	1	68	18	114
R&B	4	2	3	2	23	1	35
Rap	4	0	4	0	12	2	22
Rock	10	23	12	3	118	22	188
Video game music	1	13	4	1	18	8	44

Table 2 presents the respondents' favourite music genres. Since one respondent deselect any streaming service, the total number of respondents is 735. Rock emerges as the most popular genre, with 188 respondents, followed by pop with 114 and metal with 88. Genres such as Classical, Video game music, EDM, Hip hop, and R&B attract a moderate number of listeners, ranging between 35 and 53 respondents. Meanwhile, the least preferred genres are Lofi, Gospel, and Latin, with only 10, 6, and 3 respondents, respectively.

Based on Table 2, Spotify is the most popular service, with Rock being the most frequently listened-to genre among its users, followed by Pop and Metal. YouTube ranks as the second most-used platform with 94 respondents where 22 of them listen to Rock, and 18 listen to Pop, while other genres have fewer listeners, ranging from 11 to none. Interestingly, 71 respondents disemploy any streaming service, yet 23 of them prefer Rock. This suggests they might use other alternative formats such as DVDs, radio, or other electronic devices to enjoy their favourite music. Apple Music and Other Streaming Services have similar patterns and number of respondents, with a majority of respondents also favouring Rock. Overall, Rock stands out as the most popular genre, especially among Spotify users, as indicated in Table 2. Pop is also highly popular, particularly among Spotify and YouTube users. In line with general trends in the music industry, Rock and Pop have maintained strong followings, likely due to their broad appeal and extensive availability on streaming platforms. In contrast, genres like Gospel, Latin, and Lofi are the least popular, which could indicate limited availability on major streaming services.

3.3 Correspondence Analysis

The dataset includes four types of mental health conditions: Anxiety, Depression, Insomnia, and OCD. Respondents rated the severity of each condition on a scale from 1 to 10. A contingency table is constructed to analyse the relationship between respondents' favourite music genres and their highest-rated mental health conditions, allowing to calculate the frequency of individuals experiencing these conditions based on their music preferences.

Table 3 The Contingency Table of Favourite Music Genre and Type of Mental Health

Music Genre	Anxiety	Depression	Insomnia	OCD	Total
Classical	18	12	16	4	50
Country	18	5	1	1	25
EDM	18	9	4	5	36
Folk	23	5	2	0	30
Gospel	4	0	2	0	6
Hip Hop	18	9	4	4	35
Jazz	13	2	3	2	20
K Pop	17	8	0	1	26
Latin	2	0	1	0	3
Lofi	2	5	2	1	10
Metal	46	20	15	5	86
Pop	77	15	14	7	113
R&B	21	7	5	2	35
Rap	13	3	2	3	21
Rock	100	41	31	14	186
Video Games Music	30	7	6	1	44
Total	420	148	108	50	726

Table 3 displays the mental health conditions, ranging from mild to severe, of 726 respondents. Anxiety had the highest number of respondents, with 420, followed by Depression with 148 respondents, Insomnia with 108, and OCD with 50. This indicates that only a few respondents are facing OCD conditions. Most respondents experiencing each mental health condition preferred Rock as their favourite music genre. Additionally, a significant number of respondents favoured Pop and Metal.

Table 4 The Eigenvalues of Each Dimensions

Dimension	Variance (eigenvalues)	Percentage of Variance	Cumulative Percentage of Variance
Dim 1	0.047996	57.1324	57.1324
Dim 2	0.024235	28.84877	85.98118
Dim 3	0.011777	14.01882	100

Table 4 shows the variance also known as eigenvalues for each dimension, indicating the contribution of each dimension to the data's variability. The variances are relatively low, suggesting that the data has lower variability and does not deviate much from the mean. However, the variance for Dimension 1 is higher, indicating that its data is more widely spread compared to Dimensions 2 and 3. Dimension 1 accounts for 57.13% of the total variation, Dimension 2 explains an additional 28.85%, and Dimension 3 contributes the remaining 14.02%. The cumulative percentage across all dimensions is 100%. According to the cumulative percentage column, the first two dimensions capture 85.98% of the variance, which is sufficient to explain the overall variation in the dataset.

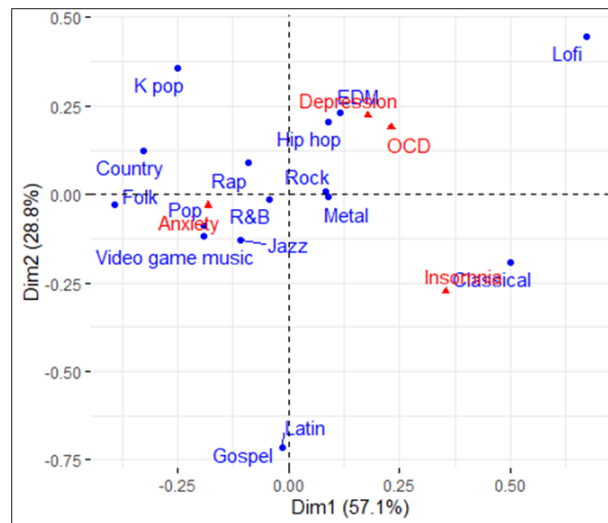


Fig. 1 Biplot of Favourite Music Genre and Mental Health Conditions

Fig. 1 presents the mental health conditions such as Depression and OCD that are close to EDM and Hip Hop, suggesting a relationship between these genres and the conditions. Respondents with Depression tend to favour EDM and Hip Hop, while those with OCD are also more likely to prefer these genres, as indicated by their proximity on the plot. Additionally, Anxiety is positioned near Pop, Jazz, and Music Video genres, highlighting a potential connection between these genres and respondents experiencing anxiety. Insomnia, on the other hand, is closer to Classical music, suggesting that respondents with Insomnia are more likely to favour the Classical genre.

Moreover, the close proximity of EDM and Hip Hop suggests that listeners of these genres may have similar mental health patterns. In contrast, R&B is located near the centre, indicating a neutral relationship with any specific mental health condition. Additionally, genres such as K-pop appear distant from any mental health conditions, suggesting a weaker association. Meanwhile, Gospel, Latin, and Lofi are positioned far from other genres, which might indicate that they are unique and do not strongly align with any specific mental health condition. To study further on the pattern, each of the Anxiety, Insomnia, Depression, and OCD distributed into four level which are healthy (0), mild (1-3), moderate (4-6) and extreme (7-10) based on respondent's answer. The analysis separated according to each mental health with the four-level mentioned. The step of analysis is similar with the correspondence analysis by the highest rated of mental health.

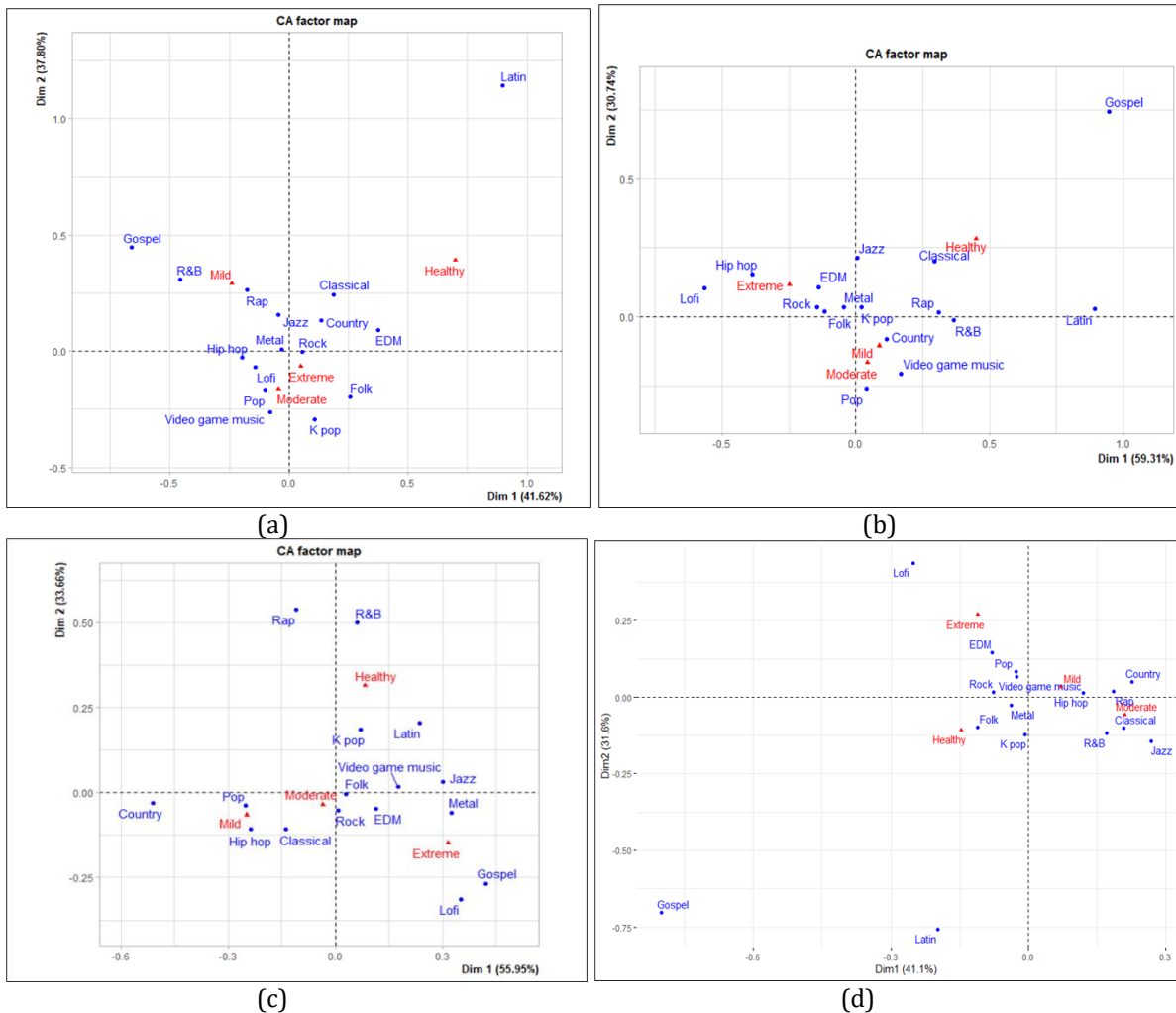


Fig. 2 (a) Biplot of Anxiety; (b) Biplot of Depression; (c) Biplot of Insomnia; (d) Biplot of OCD

Fig. 2 shows the biplot for each of the mental health problem. Firstly, Fig. 2(a) shows the extreme level of anxiety is positioned close to Rock, indicating a strong association between this anxiety level and the preference for Rock music. The moderate anxiety level is located near Pop, suggesting that individuals with moderate anxiety tend to favour this kind of genre. Similarly, the mild anxiety level is positioned near Rap, implying a link between mild anxiety and a preference for Rap music. On the other hand, the "Healthy" group does not appear to show any affection toward any music genre, indicating no clear association between being free of anxiety and a specific genre preference.

Meanwhile, Fig. 2(b) displays that most of respondents who are healthy would favour Classical genre as they located close to each other, indicating a strong preference for this genre among individuals without depression. Extreme levels situated close to EDM and Rock genre, explaining that both genres mostly listen by respondents with extreme depression. While Mild closer to country which highlighting a preference for Country music within this group and moderate close to Pop which indicating that Pop music is most preferred by individuals with moderate levels of depression.

The structure of respondents based on their level of insomnia and music preferences is shown clearly in Fig. 2(c). The healthy group is positioned further away from all music genres, suggesting that individuals in this group do not have a strong preference for any particular genre. The moderate insomnia group is located closer to Rock, indicating a tendency for respondents with moderate insomnia to favour this genre. The extreme insomnia group is situated near Metal, highlighting a preference for Metal music among individuals with extreme insomnia. Meanwhile, the mild insomnia group is positioned closer to Pop, suggesting that Pop music is more popular among those with mild insomnia.

Based on the Fig. 2(d), the extreme level of OCD is located close to EDM genre which implying that there is a strong relationship between this level and Rock. For the moderate level of OCD, it is situated close to classical and rap, indicating an association between moderate OCD with both genre preference. Hence, Mild located close to Hip Hop genre which can highlight that respondents with a mild OCD prefer Hip Hop genre. As for Healthy group of

respondents, it is located close to genre of Folk, showing that respondent who are not facing with OCD problem favour Folk genre.

The biplots of Fig. 2 show clear links between mental health conditions and music preferences. For anxiety, extreme levels are associated with Rock, moderate levels with Pop, and mild levels with Rap, reflecting the emotional and comforting qualities of these genres. For depression, healthy individuals prefer calming Classical music, while extreme levels favour the intensity of EDM and Rock. Moderate depression aligns with Pop for its uplifting nature, and mild depression with Country for its relatable themes. For insomnia, the healthy group shows no strong preference, but moderate insomnia leans toward Rock, and extreme insomnia is linked to Metal, both likely for their energetic and cathartic qualities. Mild insomnia prefers Pop for its soothing tones. For OCD, extreme levels favour the structured beats of EDM, moderate levels are linked to Classical and Rap, and mild levels prefer Hip Hop, while healthy individuals lean toward the calming simplicity of Folk music. These patterns highlight how music preferences connect to emotional states and can guide personalized music therapy.

3.4 Ordinal Logistic Regression

Table 5 Summary of Ordinal Logistic Regression Model

Variables	Coefficients	Std. Error	t-value	p-value
Worsen No effect (intercept)	-2.350	0.543	-4.320	0.000
No effect Improve (intercept)	0.487	0.500	0.975	0.330
Age	0.000	0.008	-0.003	0.998
Hours.per.day	-0.016	0.032	-0.500	0.617
While.workingYes	0.835	0.216	3.870	0.000
InstrumentalistYes	0.395	0.230	1.720	0.086
ComposerYes	0.397	0.293	1.350	0.176
Fav.genreCountry	0.461	0.624	0.739	0.460
Fav.genreEDM	0.834	0.575	1.450	0.147
Fav.genreFolk	0.278	0.583	0.478	0.633
Fav.genreGospel	16.400	0.000	172000000.000	0.000
Fav.genreHip Hop	1.190	0.649	1.830	0.067
Fav.genreJazz	0.206	0.674	0.305	0.760
Fav.genreK pop	0.480	0.671	0.716	0.474
Fav.genreLatin	-1.210	1.450	-0.836	0.403
Fav.genreLofi	18.200	0.000	695000000.000	0.000
Fav.genreMetal	0.274	0.428	0.640	0.522
Fav.genrePop	0.082	0.406	0.202	0.840
Fav.genreR&B	0.297	0.529	0.561	0.575
Fav.genreRap	0.372	0.632	0.589	0.556
Fav.genreRock	-0.210	0.376	-0.558	0.577
Fav.genreVideo game music	-0.661	0.462	-1.430	0.152
ExploratoryYes	0.614	0.197	3.120	0.002
Foreign.languagesYes	-0.260	0.193	-1.340	0.179
Anxiety	0.141	0.040	3.550	0.000
Depression	-0.055	0.037	-1.500	0.135
Insomnia	-0.026	0.032	-0.805	0.421
OCD	-0.011	0.035	-0.310	0.756

The coefficient, standard error, t-value and p-value for each predictor variable and intercept of response variables shown in the Table 5. The model's residual deviance is 858.73 and the Akaike Information Criterion (AIC) value is 914.73, indicating the model goodness of fit. Specifically, logits are modelled for the thresholds Worsen|No effect and No effect|Improve. The estimated model construct would be such equation (2) and the logit for each cumulative probability is defined as equation (3), where for Worsen|No effect and for No effect|Improve.

$$\text{Logit}[\hat{P}(Y \leq j)] = \theta_j - (\beta_1 a + \beta_2 b + \beta_3 c + \dots + \beta_{12} l) \quad (2)$$

$$\text{Logit}[P(Y \leq j)] = \theta_j - (-0.016 \text{Hours per day} + 0.835 \text{While working} + \dots - 0.011 \text{OCD}) \quad (3)$$

Table 6 Odds Ratio for Each Variable

Variables	Odds Ratio
Age	1.00
Hours.per.day	0.98
While.workingYes	2.31
InstrumentalistYes	1.48
ComposerYes	1.49
Fav.genreCountry	1.59
Fav.genreEDM	2.30
Fav.genreFolk	1.32
Fav.genreGospel	13100000.00
Fav.genreHip hop	3.29
Fav.genreJazz	1.23
Fav.genreKpop	1.62
Fav.genreLatin	0.30
Fav.genreLofi	83500000.00
Fav.genreMetal	1.31
Fav.genrePop	1.09
Fav.genreR&B	1.35
Fav.genreRap	1.45
Fav.genreRock	0.81
Fav.genreVideo game music	0.52
ExploratoryYes	1.85
Foreign.languagesYes	0.77
Anxiety	1.15
Depression	0.95
Insomnia	0.97
OCD	0.99

The odds ratio in Table 6 represents the positive effect of music based on the predictors variable's characteristics where the odd ratio more than 1 increase the odd while odd ratio less than one decreased the odd. For age, one unit increase has no effect on the odds of the music effect as the odds ratio is approximately 1.

For each additional hour spent per day, the odds of experiencing a positive music effect decrease by approximately 0.984. On the other hand, listening to music while working significantly boosts the odds of a positive music effect by 2.31 times. Likewise, being an instrumentalist increased the odds of a positive music effect by 48%, while engaging in exploratory behaviour further increases the odds by 85% more. On the other hand, the knowledge of foreign languages is associated with a decrease in odds of a positive music effect by 22.9%, whereas the composition of music increases the likelihood of a positive music effect by 49%.

Preferences for different genres of music have different impacts on the odds of a positive music effect. Country, EDM, folk, hip-hop, K-pop, metal, R&B, and rap all raise the odds to various extents, whereas EDM and hip-hop increase it especially strongly at 2.30 and 3.29 times higher, respectively. Gospel and Lofi music had extremely high odds, showing extremely strong associations. In contrast, the preferences for Latin, rock, and video game music decrease the odds, with the preference for Latin music showing the most significant drop of 70.1%. The remaining genres, jazz and pop, have smaller positive effects on the odds, increasing them by 23% and 9%, respectively. Mental health factors exert their influence on the odds of a positive music effect in different ways. While higher anxiety levels increase the odds by 15%, indicating a remarkable positive effect, higher levels of depression, insomnia, and OCD are associated with slight decreases in the odds, reducing them by 5.3%, 2.6%, and 1.1%, respectively. These findings highlight the nuanced relationships between mental health conditions and the effects of music.

Overall, the associations between music preferences, listening habits, and mental health highlight the complex ways music influences emotional well-being. Genres like Gospel and Lofi with their calming and uplifting qualities show strong positive effects, while energetic genres like EDM and hip-hop may boost mood and motivation. Conversely, Latin music's significant negative effect might stem from cultural or emotional disconnects with the study population. Besides, Anxiety shows a 15% increase in positive effects, suggesting music's role as a coping mechanism, while slight reductions for depression, insomnia, and OCD indicate that these conditions may complicate music's therapeutic potential.

4. Conclusions

This study successfully explored the relationship between respondents' music-related backgrounds and four types of mental health conditions: Depression, Anxiety, Insomnia, and OCD. Using Correspondence Analysis (CA) and Logistic Regression, valuable insights were derived, highlighting patterns of mental and favourite music genre and associations of music preferences towards music effect.

The first objective indicated that the most preferred music by the respondents is Rock followed by Pop, particularly because the respondents are among those under 30 years old. Additionally, most of respondents chose Spotify service to listen to their music. Founded in 2006, Spotify has been gaining popularity since 2011. This preference aligns with the widespread popularity of Spotify, as the majority of the respondents listen to their music by using the platform service.

The second objective discovered that Rock and Pop music genre are preferred by Anxiety patients, EDM and Rock music genre are preferred by Depression patients, Metal and Classical music genre are preferred by Insomnia patients, while EDM music genre is preferred by OCD patients. The discovery is based on two approaches used in the Correspondence Analysis method which are by the highest ranking of mental health level and the extreme level of each mental health. The similar result from both is the Depression and OCD which preferring EDM genres.

The third objectives identified the most associated variables that can influence music effect variables. Based on odds ratio, variables such as listening to music while working (2.31), Gospel (13100000) and Lofi (83500000) music genre and exploratory music behaviour (1.85) have a strong positive association. Conversely, variables such as Rock (0.811), Latin (0.299) and Music Video Game (0.516) are revealed as weak and negative associations. Moreover, mental health variables such as Anxiety (1.15) have a positive effect, Depression (0.947), OCD (0.989) and Insomnia (0.974) have a slightly positive effect, indicating that these mental health patients are more likely to transition from worsen to no effect and no effect to improve.

Overall, based on p -value, individuals who listen to music while working showed a significant positive effect and associate the music effect with the p -value near zero. Anxiety level also shows a significant effect with similar low p -value. Additionally, Gospel also shows a statistically significance for the model with an almost zero p -value, hence making it the most consistent variables for both analytical approaches.

To conclude, these findings highlight the need for deeper analysis to fully understand the underlying pattern of the music effect model. Further analysis is required to examine the relationships between variables and validate the robustness of the model. Based on these insights, healthcare providers and music therapists are encouraged to use music genres like Gospel, Lofi, and EDM in therapeutic settings, particularly for patients with anxiety, depression, insomnia, and OCD. Incorporating music into daily activities, such as listening while working, and promoting exploratory music behaviour may enhance its therapeutic benefits. Additionally, cultural and age preferences should be considered when recommending specific genres or platforms like Spotify to maximize the effectiveness of music therapy.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: **study conception and design:** Nurnabiha Syuhada Ibrahim, Norziha Che Him; **analysis and interpretation of results:** Nurnabiha Syuhada Ibrahim, Norziha Che Him; **draft manuscript preparation:** Nurnabiha Syuhada Ibrahim, Norziha Che Him, Noor Azliza Abd Latif, Mohd Saifullah Rusiman. All authors reviewed the results and approved the final version of the manuscript.

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