Research Article

Music, Mental Health, and Mood Regulation: A Data-Driven Approach to Understanding the Role of Music in Emotional Well-being

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ABSTRACT

Mental health disorders, such as anxiety, depression, and insomnia, have become increasingly prevalent. This paper explores the relationship between mental health conditions and music-related factors using a dataset which includes variables such as music genres and listening hours. The study employs two types of statistical models—ordinal logit regression and count regression—to investigate the impact of music genres, listening habits, and demographic variables on mental health and music consumption patterns. In the ordinal logit analysis, key predictors, including classical music preferences and favored genres, were positively associated with improvements in mental health, while listening to music while working and certain genres, such as R&B, negatively affected mental health outcomes. The count-oriented regression models, both negative binomial and Poisson models, used to assess the factors influencing daily music listening time, revealed that listening while working and being a composer were strongly associated with increased listening time, while being an instrumentalist decreased it. Psychological conditions like obsessive-compulsive disorder and insomnia were positively correlated with music listening hours, suggesting a potential coping mechanism for these conditions. Overall, this study provides valuable insights into how music preferences, mental health conditions, and listening behaviors interact, offering evidence-based recommendations for integrating music therapy into mental health treatments.

Keywords: Mental Health Disorders; Musical Therapies; Ordinal Logit; Negative Binomial; Poisson Models

INTRODUCTION

Mental health refers to a person's emotional, psychological, and social well-being. It encompasses how individuals think, feel, and behave, as well as their ability to handle stress, relate to others, and make decisions (1). Globally, mental health disorders have become increasingly prevalent, especially after the pandemic. The incidence of common conditions such as anxiety and depression surged by over 25% in the first year of the pandemic, contributing to the nearly one billion people already living with a mental disorder (2). The rise in mental health issues is attributed to increased life expectancy, weakened family and social support systems,

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civil unrest, and societal shifts toward technology and commercialization. These factors create environments that are often detrimental to mental health (3). Mental health issues can lead to significant emotional distress, impaired daily functioning, and deterioration in physical health. They also strain social relationships and can result in economic burdens and a decreased quality of life (4, 5).

Effective strategies for managing mental health involve a multifaceted approach. Seeking professional help through therapy or counseling, and medication, when necessary, can address underlying issues and provide targeted support (6). Self-care practices, including regular exercise, a balanced diet, and good sleep hygiene, are essential for maintaining overall well-being (7). Stress management techniques like mindfulness, meditation, and relaxation exercises can reduce stress and enhance emotional resilience (8). Additionally, building and nurturing supportive social connections and engaging in hobbies contribute to emotional stability and fulfillment (9). Educating oneself about mental health and working to reduce stigma also play a crucial role in fostering a supportive environment and improving overall mental wellness (10).

Music therapy is a therapeutic approach that uses music and musical elements to address the emotional, cognitive, physical, and social needs of individuals. This form of therapy is grounded in the belief that music has inherent healing properties and can facilitate personal growth and well-being. The practice involves various techniques such as listening to music, songwriting, performing, and improvisation, tailored to meet the specific needs and goals of each client (11). Music therapy has been shown to be effective in treating a range of conditions, including anxiety, depression, trauma, and neurological disorders. It provides a non-verbal outlet for expression, promotes relaxation, and enhances communication skills (12). Research supports its efficacy in improving mood, cognitive functioning, and overall quality of life, making it a valuable complementary treatment in both clinical and non-clinical settings (13).

Although music therapy is important, few methods utilize modeling strategies to explore the relationship between various music-related factors and different mental health issues. To address this research gap, this paper leverages a comprehensive dataset from Kaggle (14) to investigate these relationships, focusing on four mental health conditions: OCD, depression, insomnia, and anxiety. Music-related factors, such as BPM (beats per minute) and listening hours, are analyzed. To take full advantage of the data availability, two modeling approaches are employed: one that models the influence of various predictors on the mental health conditions using the ordinal logit model, and the other two belong to the count regression models that evaluate the music-playing hours per day. The expected results can provide enhanced insights into how music-related factors impact mental health conditions, leading to more effective and tailored music therapy interventions. They will also validate modeling strategies for analyzing these relationships, offering actionable, evidence-based recommendations for integrating music therapy into mental health treatments. Additionally, the findings will contribute valuable data to advance the field of music therapy.

Data Description

The dataset used for this research on the relationship between music genre and mental health comprises a comprehensive collection of survey responses from 736 participants. This dataset includes a variety of features related to music listening habits, such as the primary streaming service used, hours of listening per day, preferred music genres, and frequency of listening to specific genres. Additionally, it captures data on mental health aspects including anxiety, depression, insomnia, and obsessive-compulsive disorder (OCD), with detailed frequency information on how often participants experience these issues. The dataset's extensive size and diverse range of variables are well-suited for exploring the connections between music-related factors and mental health outcomes. This analysis aims to provide insights that could benefit mental health professionals and inform strategies for using music as a therapeutic tool. The data is publicly accessible through Kaggle (14) and is supported by substantial engagement metrics, including numerous views and downloads. While Kaggle datasets offer valuable resources and convenience, it is important to note that they may lack the specificity and control of personally collected data. Nonetheless, the substantial sample size and comprehensive nature of the dataset align with the primary objectives of this study. Detailed information about the dataset is presented in Table 1.

Given the main purpose is to evaluate the impact of music genre on the mental health, some unrelated variables such as "Primary streaming service" and "Timestamp" were excluded from the analysis. The predictor "Permissions" is also deleted from the study as is has unique category only which would lead to the zero-variance issue.

Table 1. The List of Variables and The Associated Definition and Descriptive Statistics

Variable	Type	Definition	Descriptive Statistics
Timestamp	Date/Time	The date and time when the survey was completed.	Unique values: 735, Mode: 8/28/2022 16:15:08
Age	Numeric	The age of the respondent.	Mean: 25.21, SD: 12.05, Min: 10, Max: 89
Primary streaming service	Categorical	The streaming service primarily used by the respondent (e.g., Spotify, Apple Music).	Unique: 6, Mode: Spotify, Frequency: 458
Hours per day	Numeric	The number of hours per day the respondent listens to music.	Mean: 3.57, SD: 3.03, Min: 0, Max: 24
While_working	Binary	Whether the respondent listens to music while working (Yes/No).	Yes: 579, No: 154
Instrumentalist	Binary	Whether the respondent plays a musical instrument (Yes/No).	Yes: 235, No: 497
Composer	Binary	Whether the respondent composes music (Yes/No).	Yes: 126, No: 609
Fav genre	Categorical	The respondent's favorite music genre.	Unique: 16, Mode: Rock, Frequency: 188
Exploratory	Binary	Whether the respondent likes to explore new music genres (Yes/No).	Yes: 525, No: 211
Foreign languages	Binary	Whether the respondent listens to music in foreign languages (Yes/No).	Yes: 404, No: 328
BPM	Numeric	Preferred beats per minute in music.	Mean: 1.5899e+06, SD: 3.9873e+07, Min: 0, Max: 1.0e+09
F_Classical	Categorical	Frequency of listening to Classical music.	Unique: 4, Mode: Rarely, Frequency: 259
F_Country	Categorical	Frequency of listening to Country music.	Unique: 4, Mode: Never, Frequency: 343
F_EDM	Categorical	Frequency of listening to EDM.	Unique: 4, Mode: Never, Frequency: 307
F_Folk	Categorical	Frequency of listening to Folk music.	Unique: 4, Mode: Never, Frequency: 292
F_Gospel	Categorical	Frequency of listening to Gospel music.	Unique: 4, Mode: Never, Frequency: 535
F_Hip_hop	Categorical	Frequency of listening to Hip hop music.	Unique: 4, Mode: Sometimes, Frequency: 218
F_Jazz	Categorical	Frequency of listening to Jazz music.	Unique: 4, Mode: Never, Frequency: 261
F_K_pop	Categorical	Frequency of listening to K pop music.	Unique: 4, Mode: Never, Frequency: 416
F_Latin	Categorical	Frequency of listening to Latin music.	Unique: 4, Mode: Never, Frequency: 443
F_Lofi	Categorical	Frequency of listening to Lofi music.	Unique: 4, Mode: Never, Frequency: 280

Continued Table 1. The List of Variables and The Associated Definition and Descriptive Statistics

Variable	Type	Definition	Descriptive Statistics
F_Metal	Categorical	Frequency of listening to Metal music.	Unique: 4, Mode: Never, Frequency: 264
F_Pop	Categorical	Frequency of listening to Pop music.	Unique: 4, Mode: Very frequently, Frequency: 277
F_R&B	Categorical	Frequency of listening to R&B music.	Unique: 4, Mode: Never, Frequency: 225
F_Rap	Categorical	Frequency of listening to Rap music.	Unique: 4, Mode: Rarely, Frequency: 215
F_Rock	Categorical	Frequency of listening to Rock music.	Unique: 4, Mode: Very frequently, Frequency: 330
F_Video_game_music	Categorical	Frequency of listening to Video game music.	Unique: 4, Mode: Never, Frequency: 236
Anxiety	Numeric	Anxiety levels of the respondent (scale from 1 to 10).	Mean: 5.84, SD: 2.79, Min: 0, Max: 10
Depression	Numeric	Depression levels of the respondent (scale from 1 to 10).	Mean: 4.80, SD: 3.03, Min: 0, Max: 10
Insomnia	Numeric	Insomnia levels of the respondent (scale from 1 to 10).	Mean: 3.74, SD: 3.09, Min: 0, Max: 10
OCD	Numeric	Obsessive-compulsive disorder levels of the respondent (scale from 1 to 10).	Mean: 2.64, SD: 2.84, Min: 0, Max: 10
Music effects	Categorical	Effects of music on the respondent's mental health (e.g., calming, energizing).	Unique: 3, Mode: Improve, Frequency: 542
Permissions	Binary	Whether the respondent gave permission for their data to be used in the study (Yes/No).	Mode: I understand, Frequency: 736

METHODS

Given the nature of the available dataset, two distinct modeling approaches were employed to capture the key relationships between music-related factors and mental health outcomes. The first approach utilizes ordinal logit regression models to assess the effects of music on mental health, given the ordered categorical nature of the outcome variable. The second approach involves count-based regression models to quantify the relationship between the number of hours spent listening to music per day and relevant predictors. The subsections below provide a detailed discussion of the methodology and rationale behind each modeling approach.

Ordinal Logit Regression Models

Ordinal logit regression models are designed to handle dependent variables with an inherent order, making them particularly suitable for analyzing outcomes like the perceived effects of music on mental health, which can be categorized into ordered levels (e.g., improve). The general form of the ordinal logit model is (15):

$$\log\left(\frac{P(Y \le j)}{P(Y > j)}\right) = \alpha_j - \beta_1 X_1 - \cdots - \beta_n X_n \qquad 1)$$

Where: P(Y≤j) is the cumulative probability of the response variable being at or below level j, are the cut-points (thresholds), and are the coefficients for predictors .

The primary advantage of ordinal logit models over multinomial logit models is their ability to leverage the ordinal nature of the dependent variable, which preserves the natural order of categories. This allows for more efficient parameter estimation since the ordinal logit model imposes fewer parameters compared to multinomial models, which treat each category as independent. As a result, ordinal models reduce overfitting and provide more interpretable results when working with ordered outcomes. For example, the "no effect" category of the dependent variable can be naturally placed between the "improve" and "worsen" categories, and ordinal logit models take this ranking into account, unlike multinomial models which disregard the ordering of categories.

One of the key assumptions of the ordinal logit model is the proportional odds assumption, also known as the parallel lines assumption. This assumption stipulates that the relationship between each pair of outcome categories is the same in terms of the predictors, meaning the effect of the predictors is constant across the different thresholds. In practical terms, it implies that the coefficients () for each predictor are identical across all levels of the response variable. This assumption simplifies the interpretation of the model and ensures that a single set of coefficients can describe the relationship between the predictors and the ordered outcome.

Count-Based Regression Models

In addition to assessing the effects of music on mental health, the study also sought to explore factors influencing the number of hours individuals spend listening to music per day. Given that the dependent variable (music listening hours) is a count variable, two count-based regression models—Poisson regression (16) and negative binomial regression (17)—were employed. These models are well-suited for count data and allow for the estimation of how predictor variables influence the frequency of music listening.

The Poisson model is typically used when the mean and variance of the count variable are assumed to be equal. However, given the overdispersion observed in the dataset (where the variance exceeds the mean), the negative binomial regression model was used to account for this overdispersion. The general form of the negative binomial model is similar to that of the Poisson model, but it introduces an extra parameter to account for the variance exceeding the mean, thus providing a more flexible and accurate fit to the data:

$$log(E(Y_i)) = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n \qquad 2)$$

where E(Yi) represents the expected count of music listening hours for individual i, and $X_1, \ldots, X_n$ represent the predictor variables. The inclusion of this dispersion parameter allows the model to handle greater variability in the response variable, which is critical in this case, as music listening behaviors are likely to vary widely across individuals.

By employing both Poisson and negative binomial models, the study rigorously examines the key predictors of daily music listening time. The negative binomial model was ultimately preferred due to its ability to handle overdispersion, as indicated by the model fit statistics, such as the log-likelihood and AIC. This approach provides robust insights into the factors influencing music consumption patterns and offers a comprehensive understanding of how demographic variables, work habits, and mental health conditions shape music-listening behaviors.

RESULTS

Ordinal Logit Regression Results for Music Effects

The ordinal logit regression analysis was conducted to examine the impact of music genres and other predictors on mental health status, specifically the dependent variable "Music_effects," which was recoded into four categories: Unknown (0), Improve (1), No effect (2), and Worsen (3). A total of 726 observations were analyzed, with 695 degrees of freedom for residuals and 28 degrees of freedom for the model. As shown in Table 2, the model fit was evaluated using log-likelihood (-463.96), AIC (989.9), and BIC (1132), which provided a reasonable basis for model selection and interpretation. The results highlight several significant predictors related to music preferences and demographic variables that influence the mental health outcomes under study.

Among the predictors, age ($p = 0.755$) and several music genres such as Hip-hop ($p = 0.991$), Jazz ($p = 0.851$), K-pop ($p = 0.651$), and Latin ($p = 0.996$) were found to be non-significant, indicating that these variables do not have a measurable effect on the ordinal outcome of music effects on mental health. However, the variable "While_working" (coefficient = -0.863, $p < 0.001$) demonstrated a strong negative association with improved mental health, suggesting that listening to music while working may worsen or negatively influence the perceived effect of music on mental health. Similarly, genres such as R&B (coefficient = -0.272, $p = 0.020$) and exploratory music preferences (coefficient = -0.57, $p = 0.006$) were found to negatively impact the mental health status, supporting the idea that certain genre preferences might be linked to a perceived worsening in mental health.

Conversely, Classical music (coefficient = 0.251, $p = 0.016$) and favored genre (coefficient = 0.059, $p = 0.006$) were positively associated with improvements in mental health. These findings align with existing literature that suggests classical music is often used for relaxation and

Table 2. Ordinal Logit Regression Model Results

Variables	Coef.	Std_err	z	P>|z|	[0.025	0.975]
Age	-0.003	0.009	-0.312	0.755	-0.020	0.014
While_working	-0.863	0.219	-3.942	0.000	-1.292	-0.434
Instrumentalist	-0.432	0.234	-1.850	0.064	-0.890	0.026
Composer	-0.324	0.283	-1.146	0.252	-0.878	0.230
Fav_genre	0.059	0.022	2.724	0.006	0.017	0.101
Exploratory	-0.57	0.208	-2.746	0.006	-0.976	-0.163
Foreign_languages	0.125	0.200	0.626	0.532	-0.266	0.516
F_Classical	0.251	0.104	2.409	0.016	0.047	0.454
F_Country	-0.15	0.111	-1.354	0.176	-0.367	0.067
F_EDM	0.035	0.096	0.368	0.713	-0.153	0.224
F_Folk	0.065	0.104	0.627	0.531	-0.138	0.268
F_Gospel	-0.233	0.153	-1.523	0.128	-0.532	0.067
F_Hip_hop	0.002	0.151	0.012	0.991	-0.294	0.297
F_Jazz	0.021	0.114	0.187	0.851	-0.202	0.244
F_K_pop	-0.05	0.111	-0.453	0.651	-0.267	0.167
F_Latin	0.001	0.123	0.005	0.996	-0.240	0.241
F_Lofi	-0.028	0.104	-0.272	0.786	-0.231	0.175
F_Metal	0.025	0.098	0.256	0.798	-0.166	0.216
F_Pop	-0.001	0.112	-0.009	0.993	-0.220	0.218
F_R&B	-0.272	0.117	-2.327	0.020	-0.501	-0.043
F_Rap	0.111	0.143	0.776	0.438	-0.169	0.391
F_Rock	0.006	0.113	0.053	0.958	-0.216	0.228
F_Video_game_music	-0.042	0.100	-0.420	0.674	-0.238	0.154
Anxiety	-0.134	0.040	-3.386	0.001	-0.211	-0.056
Depression	0.049	0.036	1.354	0.176	-0.022	0.121
Insomnia	0.017	0.032	0.531	0.595	-0.045	0.079
OCD	0.026	0.034	0.764	0.445	-0.041	0.092
0/1	-6.188	0.779	-7.948	0.000	-7.714	-4.662
1/2	1.820	0.065	28.027	0.000	1.692	1.947
2/3	1.031	0.087	11.869	0.000	0.861	1.202
Other Model Output:						
No. Observations: 726; D.f. Residuals: 695; D.f. Model: 28						
Log-Likelihood: -463.96; AIC: 989.9; BIC: 1132						

Note: See Table 1 for detailed definition of variables.

mental well-being. The positive influence of favored genres suggests that individuals who prefer certain music genres may experience enhanced mental health effects, reinforcing the importance of musical preference in emotional regulation and mental health management.

Lastly, anxiety (coefficient = -0.134, p = 0.001) was a significant negative predictor, implying that individuals with higher anxiety levels are less likely to report improvements in mental health due to music. This result points to the complex relationship between mental health conditions and the perceived impact of music. The recoding of the dependent variable into ordinal categories, coupled with the application of ordinal logit regression, provided valuable insights into how various factors, including music preferences and psychological conditions, interact to influence mental health perceptions in this study population.

Modelling Analysis for Influential Factors of Music Playing Hours Per Day

In addition to the evaluation of music effects and its associated predictors, the present study also takes advantage of the avaible data to investigate the influence of variables on the amount of music playing time per day. For modeling purpose, the predictors indicating the frequency of playing of various music genres are excluded as they overlap with the dependent variable of music hours per day. Two popular models were used, one is Poisson model, and the other is Negative Binomial Regression model. The negative binomial regression model results are shown in Table 3. The model accommodates the overdispersion in the data, which is reflected in the large difference between the log-likelihood of the fitted model (-1559.9) and the null model (-1634.4), supporting the appropriateness of this modeling approach. The results reveal significant associations between several key predictors and the frequency of daily music listening time.

The variable "While_working" (coefficient = 0.687, p < 0.001) demonstrated a strong positive relationship with the amount of music played per day, suggesting that individuals who listen to music while working tend to spend significantly more time listening to music. This is consistent with existing research indicating that background music during work or study may increase

Table 3. Negative Binomial Regression Model Results

Variables	Coef.	Std_err	z	P>|z|	[0.025	0.975]
const	0.363	0.156	2.318	0.020	0.056	0.669
Age	0.000	0.002	-0.176	0.860	-0.005	0.004
While_working	0.687	0.076	9.058	0.000	0.538	0.836
Instrumentalist	-0.203	0.063	-3.233	0.001	-0.327	-0.080
Composer	0.335	0.073	4.571	0.000	0.191	0.478
Fav_genre	-0.001	0.006	-0.193	0.847	-0.012	0.010
Exploratory	0.156	0.063	2.497	0.013	0.034	0.279
Foreign_languages	0.072	0.054	1.333	0.183	-0.034	0.178
Anxiety	-0.011	0.012	-0.883	0.377	-0.034	0.013
Depression	0.013	0.011	1.182	0.237	-0.008	0.033
Insomnia	0.022	0.009	2.393	0.017	0.004	0.040
OCD	0.020	0.010	2.037	0.042	0.001	0.039
Music_effects	0.043	0.054	0.793	0.428	-0.063	0.149
alpha	0.193	0.023	8.356	0.000	0.147	0.238
Other Model Output:						
No. Observations: 726; D.f. Residuals: 713; D.f. Model: 12						
Pseudo R-squ: 0.045; Log-Likelihood: -1559.9; LL-Null: -1634.4; LLR p-value: 9.3e-26						

Note: See Table 1 for detailed definition of variables.

overall music exposure, even when it is not the primary activity. Similarly, being a composer (coefficient = 0.335, $p < 0.001$) is positively associated with increased music listening time, which may reflect composers' tendency to engage with music more frequently for inspiration or creative purposes.

In contrast, being an instrumentalist (coefficient = -0.203, p = 0.001) is associated with a decrease in the number of hours spent listening to music. This finding suggests that instrumentalists, who often spend considerable time practicing their instruments, may have less available time for passive music listening. The result aligns with the notion that musicians who actively create or perform music may engage with music differently than non-musicians.

Other variables such as exploratory music preferences (coefficient = 0.156, p = 0.013) and psychological conditions like insomnia (coefficient = 0.022, p = 0.017) and OCD (coefficient = 0.020, p = 0.042) were also significant predictors of music listening time. Individuals with exploratory preferences may spend more time discovering new music, thus increasing their daily music exposure. Furthermore, mental health variables like insomnia and OCD may be linked to increased music listening, possibly as a coping mechanism for stress or as a way to manage symptoms. However, other variables, including anxiety (p = 0.377) and depression (p = 0.237), did not show significant effects on music listening hours, suggesting that the influence of mental health on music listening habits may be complex and context-dependent.

Overall, this model highlights the multifaceted relationships between individual characteristics, music habits, and daily listening time. The significant predictors, particularly related to work habits, mental health, and creative engagement with music, offer valuable insights for understanding music consumption patterns in different demographic groups. The use of negative binomial regression provides a robust method for accounting for the variability in music listening time and underscores the importance of examining diverse factors influencing musical behavior.

The Poisson regression model was also employed alongside the negative binomial model to further assess the relationship between key predictors and the dependent variable, "music hours per day." The results of the Poisson model (Table 4) reveal several significant relationships

Table 4. Negative Binomial Regression Model Results

Variables	Coef.	std err	z	P>|z|	[0.025	0.975]
const	0.378	0.122	3.094	0.002	0.138	0.617
Age	0.000	0.002	-0.218	0.828	-0.004	0.003
While_working	0.687	0.063	10.842	0.000	0.563	0.812
Instrumentalist	-0.211	0.048	-4.371	0.000	-0.305	-0.116
Composer	0.328	0.054	6.045	0.000	0.221	0.434
Fav_genre	-0.002	0.004	-0.485	0.628	-0.010	0.006
Exploratory	0.155	0.049	3.184	0.001	0.060	0.250
Foreign_languages	0.074	0.041	1.802	0.072	-0.007	0.155
Anxiety	-0.012	0.009	-1.320	0.187	-0.030	0.006
Depression	0.012	0.008	1.515	0.130	-0.004	0.028
Insomnia	0.024	0.007	3.430	0.001	0.010	0.037
OCD	0.022	0.007	2.935	0.003	0.007	0.036
Music_effects	0.039	0.041	0.949	0.343	-0.041	0.118
Other Model Output:						
No. Observations: 726; D.f. Residuals: 713; D.f. Model: 12						
Pseudo R-squ: 0.075; Log-Likelihood: -1644.4; LL-Null: -1777.9; LLR p-value: 4.1e-50						

Note: See Table 1 for detailed definition of variables.

that align with findings from the negative binomial model, providing additional validation and insights into how individual characteristics and behaviors influence music listening habits. The log-likelihood of the Poisson model (-1644.4) was slightly higher than that of the negative binomial model (-1559.9), reflecting a more restrictive assumption of equal mean and variance, which may not fully account for the overdispersion in the data.

Key predictors such as "While_working" (coefficient = 0.687, $p < 0.001$) and "Composer" (coefficient = 0.328, $p < 0.001$) showed strong, positive associations with music hours per day in both models, reinforcing the conclusion that individuals who compose music or listen while working tend to spend more time listening to music. These significant predictors are consistent across both models, suggesting that work-related listening and creative engagement with music are robust factors influencing music consumption patterns.

The variable "Instrumentalist" (coefficient = -0.211, $p < 0.001$) maintained a strong negative association with music listening time in the Poisson model, similar to the negative binomial model. This suggests that instrumentalists are less likely to spend large amounts of time passively listening to music, potentially because they dedicate more time to active music creation and practice. Additionally, "Exploratory" preferences (coefficient = 0.155, $p = 0.001$) were also significant in both models, further emphasizing that individuals who enjoy discovering new music tend to spend more time engaging with music daily.

Interestingly, psychological variables such as "Insomnia" (coefficient = 0.024, $p = 0.001$) and "OCD" (coefficient = 0.022, $p = 0.003$) were significant positive predictors in the Poisson model, consistent with the negative binomial results. This suggests that individuals suffering from insomnia or obsessive-compulsive tendencies may use music as a coping mechanism, resulting in more frequent listening. However, variables such as "Anxiety" ($p = 0.187$) and "Depression" ($p = 0.130$) were not significant in either model, indicating that the relationship between mental health conditions and music listening habits might be more nuanced than previously thought.

A comparison of the two models highlights subtle but important differences. While both the Poisson and negative binomial models identified similar significant predictors, the Poisson model assumes that the variance of the dependent variable is equal to the mean, which may not be realistic given the overdispersion typically present in count data such as music listening hours. The negative binomial model, by allowing for greater variance, provides a better fit as indicated by the lower log-likelihood and pseudo R-squared values. This suggests that the negative binomial model may be more appropriate for modeling music listening time, as it accounts for the observed variability more effectively than the Poisson model.

In conclusion, the use of both the Poisson and negative binomial models provides a comprehensive understanding of the factors influencing music listening time. Significant predictors such as listening while working, being a composer, and mental health variables like insomnia and OCD offer valuable insights into how different behaviors and psychological conditions shape music consumption patterns. However, given the overdispersion in the data, the negative binomial model may be more reliable for future analyses of similar data sets.

CONCLUSION

The current study examined the relationship between various music-related factors and mental health conditions, including how these variables influence daily music listening time. By employing both ordinal logit regression and count models such as Poisson and negative binomial regression, the research provides valuable insights into the multifaceted dynamics of music consumption and its implications for mental well-being.

The ordinal logit regression analysis highlighted the complex relationship between music preferences and their perceived effects on mental health. While some variables, such as age and music genres like Hip-hop, Jazz, and K-pop, did not exhibit significant relationships with mental health outcomes, others like Classical music and R&B emerged as influential factors. Classical music, often associated with relaxation and well-being, was positively correlated with improved mental health, while R&B and exploratory music preferences were linked to a perceived worsening in mental health. Additionally, individuals who listened to music while working reported adverse effects on mental health, suggesting that background music in work settings may not always yield positive outcomes. This highlights the need for more targeted research into how and when music consumption can optimally contribute to mental wellness.

In addition to the analysis of music effects on mental health, the study used two count models—Poisson regression and negative binomial regression—to explore the impact of various predictors on daily music listening hours. Both models produced consistent results, revealing that factors like listening to music while working, being a composer, and having exploratory music preferences were positively associated with an increased number of music hours per day. Conversely, instrumentalists reported lower music listening times, likely due to the time they devote to actively practicing their instruments. Mental health conditions such as insomnia and OCD were also positively associated with music listening time, suggesting that individuals may turn to music as a coping mechanism for these conditions. However, anxiety and depression did not significantly influence music hours in either model, pointing to the complexity of the relationship between mental health and music consumption.

The comparison of the Poisson and negative binomial models demonstrated that while both identified similar significant predictors, the negative binomial model provided a better fit for the data due to its ability to account for overdispersion. This makes the negative binomial model a more reliable tool for future analyses, especially when modeling variables like music listening time, where variance is likely to be greater than the mean. The findings suggest that adopting flexible modeling strategies that account for the characteristics of the data can lead to more accurate and meaningful results, particularly when exploring complex behaviors such as music consumption.

Based on the study's findings, several recommendations can be made for future research and practical applications in the field of music therapy and mental health interventions:

1. **Targeted Music Therapy Interventions:** The results demonstrate that certain genres, particularly Classical music, have a positive impact on mental health, while others like R&B and exploratory music preferences are associated with negative effects. This suggests that music therapy interventions should be tailored to the individual's music preferences and mental health condition. Therapists and mental health practitioners could consider using Classical music or other calming genres as part of their treatment plans for anxiety, stress, and emotional regulation. On the other hand, caution should be exercised when using genres like R&B, which may exacerbate negative emotions in some individuals.
2. **Optimizing Music for Work and Study Environments:** The strong negative relationship between listening to music while working and mental health improvements calls for further exploration into the role of background music in professional or academic settings. While music can enhance productivity for some, it may have adverse effects on others. Future research should aim to identify the conditions under which music can positively or negatively impact mental health in the workplace. For instance, investigating the type of work or tasks performed, the volume of the music, and the genre can provide deeper insights into how background music affects focus, stress levels, and overall mental well-being.

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REFERENCES

1. Organization A. Mental health: A report of the Surgeon General. U.S. Department of Health and Human Services. 2001.
2. M., J. Global mental health impact of the pandemic. World Health Organization Report. 2022.
3. H., L. Societal impacts on mental health. Mental Health Review. 2000; 5 (2): 17-25.
4. Moussavi S. The burden of mental disorders. The Lancet. 2007; 370 (9590): 851-859. https://doi.org/10.1016/S0140-6736(07)61415-9
5. Moussavi S. Health implications of mental disorders. Journal of Mental Health. 2007; 16 (3): 187-199.
6. Association A. Guidelines for mental health treatment. American Psychological Association. 2019.
7. Craft LL. Self-care practices and mental health. Journal of Clinical Psychology. 2004; 60 (2): 167-183.
8. Cohen J. Stress management techniques. Journal of Behavioral Medicine. 1985; 8 (1): 1-22.
9. Seligman M. Building emotional stability and fulfillment. Positive Psychology Journal. 2011; 2 (1): 45-52.
10. Corrigan PW. Educating about mental health and reducing stigma. Community Mental Health Journal. 2004; 40 (4): 339-352. https://doi.org/10.1023/B:COMH.0000035226.19939.76
11. Bruscia K. Introduction to music therapy. Barcelona Publishers. 2014.
12. Bradt J. Music therapy for mental health conditions. Journal of Music Therapy. 2014; 51 (4): 422-434.
13. Särkämö T. Efficacy of music therapy. Music and Medicine. 2008; 1 (1): 13-20.
14. Rasgaitis G. Comprehensive dataset for predicting diabetes. Kaggle. Retrieved from https://www.kaggle.com/dataset. 2022.
15. Harrell Jr, FE & Harrell FE. Ordinal logistic regression. Regression modeling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis. 2015; 311-325. https://doi.org/10.1007/978-3-319-19425-7_13

16. Hayat MJ & Higgins M. Understanding poisson regression. Journal of Nursing Education. 2014; 53 (4): 207-215. https://doi.org/10.3928/01484834-20140325-04
17. Wapp C, Biver E, Ferrari S, Zysset P & Zwahlen M. Development of a personalized fall rate prediction model in community-dwelling older adults: a negative binomial regression modelling approach. BMC geriatrics. 2023; 23 (1): 200. https://doi.org/10.1186/s12877-023-03922-1