The Influence of Daily Activities, Mood, and Sleep on Music Genre Selection: A Personal Data Analysis

Francheska L. Olympia
College of Computing and Information Technologies
National University - Manila
Manila, Philippines
olympiafl@students.national-u.edu.ph

***Abstract*—This study investigates the factors influencing music genre selection, focusing on daily activities, mood levels, and sleep duration, using a personally logged data collection over a three-month period with the dataset comprising of 588 listening sessions. Self-reported values such as music genre and daily activities were grouped for analysis. Descriptive statistics, data visualizations, ANOVA tests, Chi-square tests, and a Random Forest machine learning model were applied to examine the relationships between the factors and music choice. Results indicate that daily activity as the most influential factor, followed by mood levels, then sleep durations. Music listening also contributed to mood improvement, highlighting its role for emotional regulation. The combined analysis of the factors demonstrates how data science can reveal patterns in individual behavior and enhance understanding of personalized music preferences.**

***Index Terms*—Music Preferences, Music Genre, Mood before, Mood after, Daily activities, Sleep duration, Random Forest, ANOVA, Chi-square, Time-series analysis, Feature importance.**

I. Introduction

Music has played a very important role when it comes to people's everyday lives. Music, an integral part of our lives, which is not only a source of entertainment but plays an important role in mental well-being by impacting moods, emotions and other affective states [1]. Beyond the emotional and functional benefits, music also plays a significant role in decision-making, most especially how individuals select a specific music genre based on their current state. Overall, the relationship between music and the mind seems to depend on the task and the music [2]. It tends to influence the emotions, behaviors, and productivity of a person. People choose their preferred music taste depending on their mood and activities, whether they are engaging in physical, focused, or relax-related activities. In addition to mood and activity, sleep duration may also influence music selection, suggesting that these are factors that could contribute differently to an individual's choice of music genre.

This study focuses on identifying the most influential factor affecting music genre preferences, such as the mood levels, sleep duration, and daily activities using personal data collected over a three-month period. Listening to music is important as it helps on processing the emotions of a person, helps to improve their focus, and support their activities. Music preferences and listening strategies have been shown to be associated with the psychological well-being of listeners [1], due to these routines, identifying and understanding these patterns can help provide meaningful insights to the well-being and personal coping mechanisms.

Prior studies have shown that music preferences is strongly influenced by mood and daily activities. Listeners often choose a specific genre which matches their mood helps them to understand and process their feelings. It also helps listeners to improve their mood depending on their activity during that time. Another previous research mentioned that music helps improve sleep, most especially individuals who experience difficulty sleeping due to several factors. However, while these studies demonstrates meaningful relationships between music preferences and various factors, it is more focused on examining the variables rather than comparing their influences on music genre selection.

The gap or problem this project addresses lies on how the collection of data is done. It is self-recorded and is continuous per listening session in relation to the mood, sleep duration for the day, and daily activities. Previous research mostly relied on surveys and generalized trends and factors which focused on general understanding rather than individual understanding. Moreover, this project focuses on identifying which among mood, activity, or sleep serves as the dominant predictor of music genre choice, addressing a more detailed and individual-focused analysis of music genre preferences using continuous personal data.

The primary goal of this project is to determine which factor such as, daily activity, mood level, or sleep duration contributes the most to music genre selection. Specifically, the study aims to:

- Examine how music genre choice varies across different mood levels
- Analyze the relation between daily activities and preferred music genres
- Examine how sleep duration and mood relate to music genre choice

- Compare the strength of mood, activity, and sleep in influencing music genre choice
- Identify patterns in music genre preferences over an approximately three-month period

Together with the research objectives, the project is driven by the following questions:

- Which among the factors, such as daily activity, mood level, or sleep duration, has the strongest influence on music genre choice
- Which music genres are most related to specific daily activities?
- Does music genre choice vary with sleep duration?
- Do combined factors explain music genre choice more effectively than individual factors alone?

II. Literature Review

Music listening behavior of an individual is influenced by several factors, including their mood, sleep duration, and daily activities. In identifying patterns, Data Science plays a significant role in recognizing possible trends that can be understood on a deeper level. Previous studies shows that individuals tend to select their music preference based on their mood, on what they're doing, and also shows how music helps in relaxation and influencing sleep duration.

A. Music Preference and Mood

It is universal that an individual could experience different kinds of mood that may change within seconds or hours, depending on the situation someone is experiencing. As music also became an important factor on a person's daily life, it helps them to express their emotions. Music has the potential to influence mood, feelings, and thoughts. It has the ability to change the emotional and physical status of people, whether they are in bad, good, or sad mood [3]. The relationship of music preference and mood could help on improving both the emotions and performance of an individual. It is said that people work much better after listening to music than those who sit in silence or with no music [3]. Moreover, music being used a tool for mood enhancement, leveraging the emotional power of music to boost motivation, reduce anxiety, or foster feelings of joy [4] of a person. These findings from previous studies emphasizes the strong connection between mood and music selection which supports the key role of music to an individual's emotional regulation.

B. Daily Activities, Productivity, and Music Listening

Research shows that music preferences can vary depending on the activity a person is performing, resulting to their productivity. Working with different activities, individuals often use music as their background completing different tasks to help maintain motivation and focus.

One study found that background music was shown to increase task-focus states compared to silence. Specifically, it was found that, while mind-wandering reports decreased, task-focus reports increased when music was playing in the background [5]. Previous studies also stated that music supports productivity when it comes to physical activities such as exercising, walking or other tasks that requires energetic music. In these contexts, music often serves as a stimulant and also a relaxant to get through tasks [6].In contrast, relaxation-oriented or leisure activities are also associated with music. Such as nature sounds and calming voices, which have demonstrated potential for stress relief [7], allowing an individual to be more comfortable when engaged with relax-related activities.

Overall, listening to music can make activities enjoyable and less stressful, therefore enhancing an individual's productivity across various tasks.

C. Music, Sleep, and Emotional Regulation

Sleep is an important factor in an individual's daily life and overall well-being. In today's fast-paced lifestyle, sleep problems have increased worldwide. Many people use self-help strategies, such as listening to music, to help fall asleep or to improve sleep quality [8]. Previous studies have found that music can act as therapy because it reduces activity disturbances, aggressiveness, and anxiety [9]. These findings suggest how sleep duration influences an individual's music choice, as people often listen to music that makes them more comfortable according to their sleep needs or mood.

D. Data Science and Music Preferences

With the progress of personal data tracking and easy access to music platforms, data science provides tools to easily analyze and predict music preferences. Studies show that features such as a person's mood, daily activities, and listening history can help data science to identify patterns and to provide predictions of music selection supporting personalized recommendations. Some studies used machine learning approaches because it can effectively handle large and complex data to bring more accurate and personalized results for music recommendation [10]. Algorithms such as Random Forests, Logistic Regression, Convolutional neural network (CNN), were one of the applied algorithms to predict music genre demonstrating a personalized music preference application.

Previous studies have examined the relationship of music preferences, mood, relaxation, daily activities, sleep, and productivity. The studies stated in gathering their data, surveys were conducted, observational tracking, experience sampling, and machine learning models applied to large datasets. Main findings indicate how mood and activity strongly influence an individual's choice of music. Allowing users to be more focused, productive, relaxed, and have an improved sleep quality. However, studies also contain limitations such as their laboratory-based settings, focus on single features, and short-term or session styled collection. In contrast, this project uses personal data over a four-month period with mood, sleep, and daily activities being categorized into physical, focus-related, and relaxation. By applying the chosen machine learning algorithm and data science techniques, the study aims to provide a personalized prediction of music genre preference.

III. METHODOLOGY

This chapter focuses on the processes used to examine how daily activities, mood levels, and sleep duration influence music genre selection. The study is based on personal data recorded per listening session over a period of nearly three months, from December to early February.

A. Participants

The study involved a single participant, the researcher, who served as the subject of the study. The participant mentioned is a 25-year-old fourth year university student pursuing a Bachelor of Science in Computer Science with a specialization in Machine Learning. She frequently listens to music throughout her daily activities and moods. The participant maintains a balanced lifestyle by being both outgoing and active, with habits of regular technology use, while spending time both indoors and outdoors.

B. Data Collection Methods

The data collected were variables related to daily activities, mood levels, sleep duration, and music listening. Stated below are the whole dataset variables used in the project:

TABLE I
DATASET INFORMATION

Variable	Type	Unit	Frequency	Tool
id	Qualitative	ID	Per session	Primary key
date	Qualitative	Year–month–day	Daily	Phone clock / spreadsheet
timestamp	Qualitative	YYYY–MM–DD HH:MM	Per session	Phone clock / spreadsheet
music genre	Qualitative	Pop, Rock, EDM, OPM, R&B, etc.	Per session	Manual log
activity	Qualitative	Study, exercise, commute, rest, etc.	Per session	Manual log
mood before	Quantitative	Likert scale (1–5)	Per session	Manual log
mood after	Quantitative	Likert scale (1–5)	Per session	Manual log
sleep	Quantitative	Hours	Daily	Smartwatch / manual log
notes (optional)	Qualitative	Free text	Per session	Manual log

The dataset above consists of the following data variables: id, date, timestamp, music genre, activity, mood before, mood after, sleep, and notes. Among these, mood before, mood after, and sleep are classified as Quantitative types, while the remaining are Qualitative types. Each data variable has a defined unit or scale and frequency of collection done, with most data recorded is per listening session. The data were gathered using smartphones and their clocks, time logs, smartwatches, and manual logs with all records recorded and compiled in a spreadsheet for a more organized data tracking.

C. Operational Definitions

The data variables collected are used to examine the relationship between daily activities, mood, sleep duration, and music listening. Below are the defined variables:

- **id** - The unique identifier assigned to each log
- **timestamp** - Date and time of the music listening session
- **date** - The calendar date of the session
- **music genre** - The type of music listened during the session (e.g., Pop, Rock, EDM, Hip-Hop, Rap, Indie Pop, Soft Pop, Hip-Hop/Soul, R&B, OPM etc.)
- **activity** - The activity the individual is doing during the listening session (e.g., read, code, rest, commute, exercise, clean, work, shower, prepare, walk, play)
- **mood before** - The self reported mood before listening to music, measured on a 1-5 Likert Scale with 1 as very low and 5 as very high
- **mood after** - The self reported mood after listening to music, measured on a 1-5 Likert Scale with 1 as very low and 5 as very high
- **sleep** - Number of hours slept the previous night
- **notes** - An optional additional information free text for the listening session

The mood levels before and after listening were self-reported using a Likert scale to categorize easily the participant's mood state during each listening session, the scale ranges from 1 to 5. The descriptions were defined to ensure a uniform and consistent classification scale.

TABLE II
MOOD LEVEL RATING SCALE

Score	Label	Description
1	Very Negative	Sad, stressed, drained, anxious, low energy
2	Slightly Negative	Tired, unfocused, irritated, bored
3	Neutral	Okay, normal; neither clearly positive nor negative
4	Slightly Positive	Good mood, calm, productive, lightly happy
5	Very Positive	Very happy, excited, energetic, motivated, uplifted

For analytical purposes, both activities and music genres were grouped accordingly into categories for easier understanding and reduce redundancy.

Daily activities were grouped into four functional categories based on the intensity of the task done personally: Active, Focus, Routine, and Relax. The focus category includes cognitive and a more focused work. Routine includes repetitive activities that are done every single day. Active includes physically engaging activities that require more physical effort. And lastly, Relax includes leisure activities.

TABLE III
ACTIVITY GROUPING

Activity Grouping	Original Values
Focus	Study, Read, Code, Work
Routine	Commute, Prepare, Clean, Walk
Active	Exercise
Relax	Rest, Other leisure activities

On the other hand, music genres were grouped into three energy-based categories reflecting the intensity and tempo of the music. Mainstream group includes the common genres. The High-Energy group includes fast-paced music and intense genres. And lastly, Low-Energy group consists of slow and softer tempos.

TABLE IV
MUSIC GENRE GROUPING

Music Genre Group	Original Values
Mainstream	Pop, R&B, OPM, Hip-Hop/Soul
High-Energy	Rock, EDM, Rap, Hip-Hop, Pop-Rock variants
Low-Energy	Indie, Soft Pop, Indie Pop, Slow Pop

These groupings were applied after data cleaning to ensure appropriate sample sizes per category and to improve analysis and interpretation.

D. Data Cleaning

The data cleaning process was conducted to ensure a consistent and complete dataset for the model and analysis. Since the study focuses on a Random Forest Machine Learning model, where the three factors were trained together. The data cleaning process consists of:

- **Removing Outliers** - No outlier removal was performed because all data points were considered relevant, all extreme values may represent meaningful behaviors rather than errors in the dataset.
- **Handling Missing Values** - Missing values were addressed at multiple checkpoints all throughout the processing. The "timestamp" and "date" columns were converted to standard datetime formats. When missing "date" field was encountered, the corresponding timestamp in the row was used. While the missing values in the "sleep" column were filled with the median.
- **Converting Text to Numeric** - With Machine Learning Model as a tool, it is known that models require numeric input. With that, all categorical features, such as activity were converted using one-hot encoding. This method generates a binary column for each category, to ensure all unique values are shown and handled. One-hot encoding was applied to all categorical features that needed conversion to ensure a consistent pre-processing of data to model.
- **Standardizing Units** - With Random Forest as the chosen Machine Learning Model tool, standardizing units is not needed. Numeric features were maintained in their original units. "date" and "timestamp" fields were standardized to datetime format to ensure consistency across observations. Optional free-text fields, such as "notes" were dropped to prevent unnecessary noise from the data and model.

E. Statistical Analysis

Upon analyzing the data, Inferential Statistics were used to understand and examine more the relationships of the factors. Chi-square is used to determine whether there is a relationship between two categorical variable. The formula is:

$$\chi^2 = \sum \frac{(O-E)^2}{E} \tag{1}$$

Where:

- O - is the observed frequency: the actual number of listening sessions recorded for each combination of activity group (Relax, Focus, Routine, Active) and genre group (Mainstream, High Energy, Low Energy)
- E - is the expected frequency: the frequency that would be expected if the activity group and genre group were independent (computed from row and column totals)

The chi-square test was selected because both daily activity and music genre values are categorical, and it is used to assess their independence.

Another inferential statistical tool used was Analysis of Variance or ANOVA to determine whether there were significant differences between the mean in mood levels and sleep duration across different music genres. Mood and sleep were quantitative variables while the music genre was an independent categorical variable. ANOVA assessed whether there are at least one genre that differed significantly in terms of the average of mood or sleep duration. The formula for ANOVA is:

$$F = \frac{\text{Variance between groups}}{\text{Variance within groups}} \tag{2}$$

Where:

- The numerator represents the variance between group means
- The denominator represents the variance within each group

For an easier understanding and analysis of the data, visualization tools were used:

- Bar charts were used to show the frequency of music genre selections per activity
- Stacked bar charts were used to compare the genre distributions across multiple activity category groups
- Box and whisker plots were used to visualize the differences in mood levels and sleep duration across grouped music genres

The ANOVA test was chosen for the sleep and mood level values because it allows for the comparison of mean values across multiple categorical groups.

As the dataset was collected from a single participant, the study may reflect self-reporting bias because every variable were recorded with personal assessment or interpretation of Likert Scales. Sleep duration on the other hand, was recorded using a mix of manual logging and a smartwatch which may show only minor inaccuracies. Manual logging of activity and music genre may also result in minor inconsistencies because of the possible mix-up of activity during a certain session, but it was ensured a same timestamp for multiple activities or multiple music genre listening sessions. These possible errors or biases were analyzed and considered during the analysis.

IV. Results

This chapter presents the results from the analysis of the dataset, examining the relationship between activities, mood levels, sleep duration, and music genre. The results are presented through descriptive statistics, data visualizations, and machine learning metrics.

1) Mean, Median, SD: After the data cleaning and preprocessing, the dataset consisted of 588 rows recorded over approximately three months. Music genres were grouped into three categories, Mainstream, Low-Energy, and High-Energy. Daily activities were grouped into Relax, Focus, Routine, and Active categories.

TABLE V
DESCRIPTIVE STATISTICS OF MOOD AND SLEEP VARIABLES

Variable	Mean	Median	Std. Dev.
Mood Before	2.79	3.00	1.06
Mood After	3.37	3.00	0.99
Sleep	6.68	7.00	1.68

The above table presents the mean, median, and standard deviation for the three numerical factors, mood before, mood after, and sleep duration. These statistical overviews show the central tendency and variability of the mood states and sleep duration throughout the recorded sessions.

2) Histogram: Histograms were used to examine how the values of numerical data, such as mood before listening, mood after listening, and sleep duration, are distributed across all the recorded sessions.

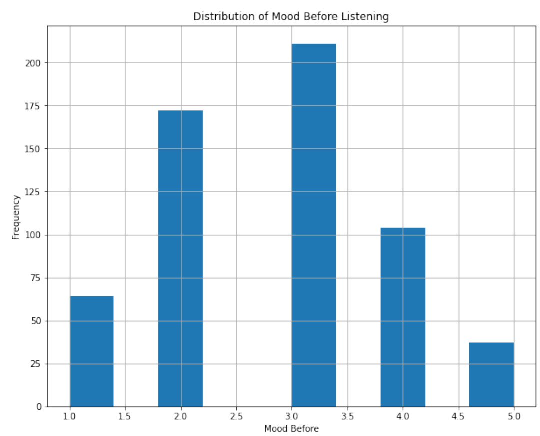

Fig. 1. Histogram Distribution of Mood Before Listening

Figure 1 presents the histogram for mood before listening to music across all sessions. Measured by a five-point Likert scale, the distribution shows that most records are primarily around the mid-range values, specifically in mood level 3. Extreme values occur less frequently, indicating moderate variability in the distribution across listening sessions.

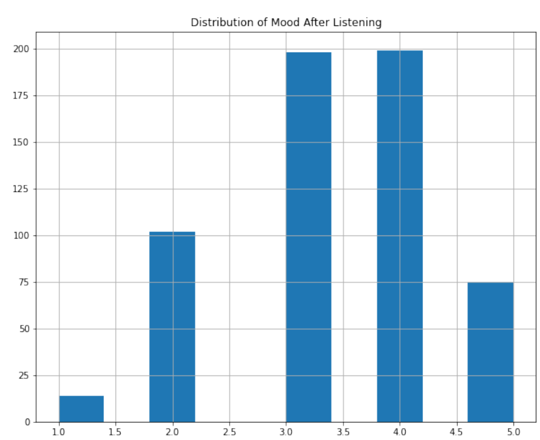

Fig. 2. Histogram Distribution of Mood After Listening

Figure 2 presents the histogram for mood after listening to music using the same five-point Likert scale. The distribution shows a higher concentration of values in the neutral to slightly positive range. The lower mood scales appear less frequently compared to the mood before listening. Overall, the variability remains moderate across listening sessions.

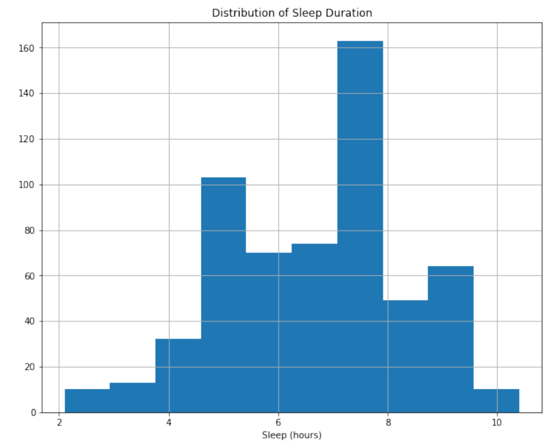

Fig. 3. Histogram Distribution of Sleep Duration

Figure 3 illustrates the distribution of sleep duration in hours. The graph showed that most durations fall within the range of approximately seven to eight hours, with few results and observations at very high or very low sleep durations.

3) Stacked Bar Charts : Qualitative values such as the activity factor was visualized using a stacked bar chart to understand and explore the association of daily activities to music genre selection.

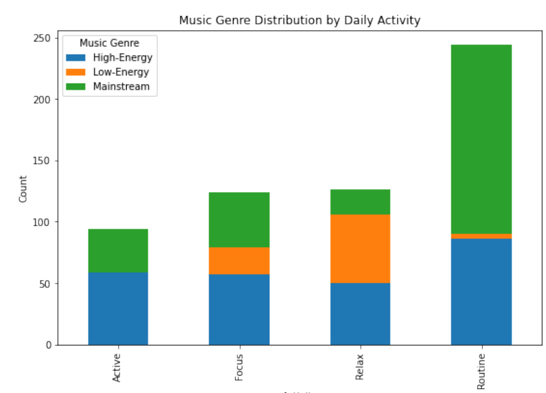

Fig. 4. Stacked Bar Chart for Daily Activities and Music Genre

Figure 4 shows the distribution of grouped music genres across different daily activity categories, the distribution indicates that certain genre groups appear within specific activity category, while other combinations occur less often.

4) Time-Series Trends: Time-series trends were used to visualize and explore how the data varied over time using their daily averages duration.

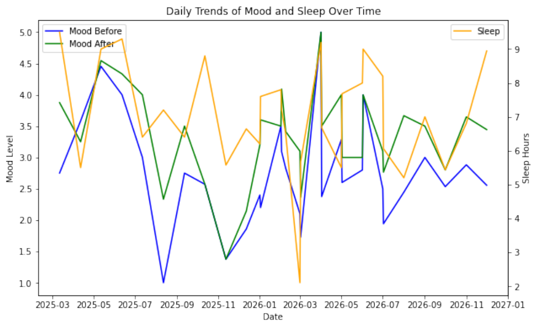

Fig. 5. Time-Series of Mood Before, Mood After, and Sleep

Figure 5 shows the daily averages of mood before, mood after, and sleep duration across the whole recording session. Two y-axes were created to easily understand the range levels of mood and sleep. Mood levels were measured on Likert scales, and sleep was measured in hours. Certain fluctuations were seen in the graph with peaks and dips of the values mostly the same.

5) Correlation Matrix: To understand and examine more the relationship of the three quantitative variables, correlation matrix was computed. Visualization of the correlation matrix can show how strong each variable to each other is.

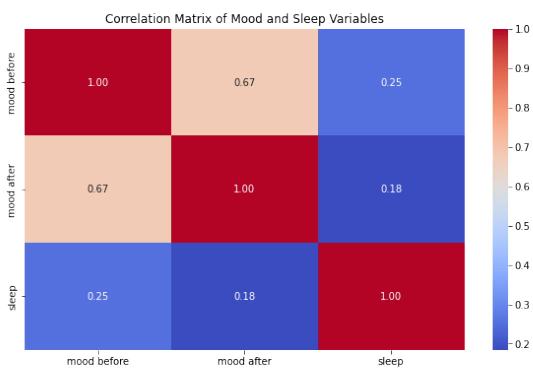

Fig. 6. Correlation Matrix of Mood Before, Mood After, and Sleep

Figure 6 heatmap shows correlations between mood before, mood after, and sleep duration. It is observed that mood before and after are positively correlated with a value of 0.67, while sleep duration shows weak correlations for both mood before and after with values 0.25 and 0.18, indicating a minimal association with moods in the dataset.

6) Results of Statistical Tests: In order to examine whether the factors of daily activity, mood level, and sleep duration influence music genre selection, inferential statistical tests were conducted. Specifically, One-way ANOVA and Chi-square tests were used. For a more effective testing, the null and alternative hypothesis are defined:

- Null Hypothesis H_0 - No factors significantly influence music genre selection
- Alternative Hypothesis H_1 - At least one of the factors significantly influences music genre selection

Examining numerical values was done using a one-way ANOVA test to determine whether mood levels and sleep are associated with music genre selection:

TABLE VI
ONE-WAY ANOVA RESULTS

Variable	F Statistic	p-value
Mood Before	3.87	0.021
Mood After	6.47	0.002
Sleep	2.99	0.051

The ANOVA results indicate that the null hypothesis can be rejected for both the mood before (F = 3.87, p = 0.021) and mood after (F = 6.47, p = 0.002), as their p-values are below the significant level of 0.05. This demonstrates that the mood levels differ significantly across the music genres. On the other hand, sleep duration (F = 2.99, p = 0.051) shows a marginal effect with the p-value slightly above 0.05, suggesting a weaker association with music genre selection.

To further examine the relationship between categorical values, a Chi-square test was conducted to determine whether daily activities and music genres are associated with each other:

TABLE VII
OBSERVED AND EXPECTED FREQUENCIES OF MUSIC GENRE BY DAILY ACTIVITY

Activity	Observed (O)			Expected (E)		
	High-E	Low-E	Mainstream	High-E	Low-E	Mainstream
Active	59	0	35	40.29	13.11	40.61
Focus	57	22	45	53.14	17.29	53.56
Relax	50	56	20	54.00	17.57	54.43
Routine	86	4	154	104.57	34.03	105.40

Chi-square test results: $\chi^2(6) = 183.83,\ p = 5.22 \times 10^{-37}$

The Chi-square test result, all expected counts exceeded the minimum requirement of 5, satisfying the assumptions in the test done. The results revealed that there is a statistically significant relationship between daily activity and music genre selection, with the χ^2 statistic = 183.83, the Degrees of freedom = 6 and p-value < 0.001. Therefore, rejecting the null hypothesis.

7) Machine Learning Classification Result: A machine learning model was used as a tool to support the main objective of the project, which is to determine which factor contributes the most to music genre selection. The model achieved a mean cross-validation accuracy of 61% across folds, with individual scores of [0.72, 0.62, 0.58, 0.56, 0.57]. An overall classification report shows the performance among the music genre categories:

TABLE VIII
RANDOM FOREST CLASSIFICATION REPORT

Genre	**Precision**	**Recall**	**F1-score**	**Support**
High-Energy	0.62	0.56	0.59	54
Low-Energy	0.73	0.38	0.50	21
Mainstream	0.54	0.74	0.63	43
Accuracy	-	-	0.59	118
Macro Avg	0.63	0.56	0.57	118
Weighted Avg	0.61	0.59	0.59	118

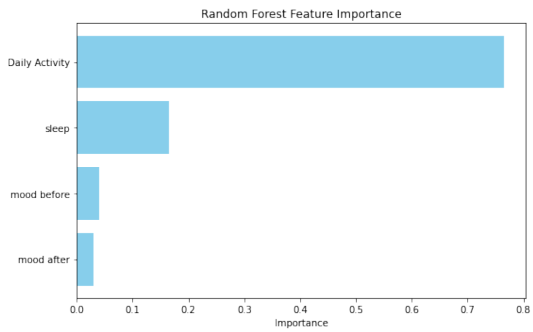

Fig. 7. Feature Importance of Trained Random Forest Factors

Figure 7 illustrates the feature importance of the factors after being trained with the model. The results shows that daily activity leads the highest influence on model predictions, followed by sleep, then mood before and after.

V. DISCUSSIONS

This chapter focuses on interpreting the results gathered in chapter 4. Exploring the relationships between activities, mood levels, sleep duration, and music genre selection, this chapter intends to explain why certain patterns emerged from the data gathered by personal logging. Additionally, this chapter discusses the limitations of the study and offers recommendations for future work.

A. Interpretation of Results

The results of the study provided insights on how daily activities, mood levels, and sleep duration, listed below are the gathered interpretation from the overall process:

1) ***Influence of Daily Activities on Music Genre:*** Among the three examined factors, daily activities emerged as the strongest contributor to music genre selection. The Chi-square test confirmed a significant association between daily activity and music genre selection ($\chi^2(6) = 183.83, p < 0.001$), supporting the observation that activity strongly influences music choice. With the help of stacked bar chart analysis and feature importance results from the trained Random Forest model, the activity factor shows the highest rank than the mood and sleep.

This pattern suggest that music preferences depend on the activity that the participant is performing. For example, mainstream genres such as POP, OPM, and R&B were more frequently associated with routine tasks like preparing, showering, cleaning, or commuting. On the other hand, low-energy genres appear more on relaxing tasks to help the participant feel more tranquil with the help of music. While high-energy are usually associated with active, focus, and routine activities too. This supports the idea of how music is often chosen to enhance the task engagement.

2) ***Relationship between Mood Levels and Music Genres:*** One-way ANOVA testing was used to see the significant differences of mood before and mood after across music genre groups. Results indicated that both mood before (F = 3.87, p = 0.021) and mood after (F = 6.47, p = 0.002) vary significantly across music genres, supporting rejection of the null hypothesis. This suggests that mood plays an important role in music selection as well.

Additionally, histograms were used to show that mood after listening tended to be higher than mood before listening, this indicates that music listening functions as a mood-regulator to the participant, where certain genres are chosen to improve, maintain, or dwell to the emotion feeling at that listening session.

The Correlation Matrix of the mood before and after shows a moderate to positive result indicating consistency in emotional states allowing for mood changes caused by music preferences.

3) ***Sleep Duration and Its Relationship to Music Genre:*** Sleep duration shows a weak correlation matrix on mood before and mood after, while the ANOVA results indicated that small differences in sleep duration across music genres. Suggesting that, within the recorded dateset of the participant, sleep had a less direct influence on music preferences compared to the other two factors.

Possible reasons for this result is the lack of variability of the sleep factor, as most recorded values were within the 6-8 hours of sleep range. This lack may result to the seen impact of sleep on music choice. Even so, the Random Forest model results indicated that sleep still contributed to music genre prediction, ranking higher than mood but lower than activity, suggesting that sleep is not dominant but acts as an support for the influence of other factors that affect music choice.

4) ***Combined Influence of Factors on Music Genre Selection:*** The Random Forest model results indicate that combined factors explain music genre choice more effectively than any single factor alone. The ANOVA and Chi-square results provide evidence that multiple factors influence music selection, highlighting the value of examining these factors together rather than individually. The model also integrates the three factors simultaneously and achieves good to moderate classification accuracy.

5) ***Patterns Across the Nearly Three-Month Period:*** The time-series analysis showed observable fluctuations between sleep duration and mood states over time. While there are no extreme long-term shifts of data were present, it shows peaks in sleep duration corresponds to mood levels as well. These patterns suggest that mood resilience is sensitive to the sleep variance. The consistent gap between "mood before" and "mood after" implies a positive effect of how music listening on improving the mood after.

B. Comparison to Related Work

The findings gathered by this project are generally consistent with the prior researches discussed. Emphasizing on the role of mood level and daily activities to music preferences. The results show that music genre selection varies across mood levels, supporting the idea that music is commonly used for emotional regulation and mood enhancement.

The strong influence of daily activity on music genre aligns with previous research, indicating that individuals select music to support different activity categories. In contrast, previous studies suggest that music is frequently used to support sleep, the results of the current data indicate it as a weak dependent factor, it should be applied together with other factor to show a better influence on music preferences.

C. Limitations

Several limitations were considered upon interpreting the results of this study:

- Small Sample size (n = 1) - As the study is based on a single participant, findings cannot be generalized to a wider population.
- Self-Report Bias - Mood levels and activity were manually recorded, groupings were done according to self categorizations, which may introduce to subjectivity and inconsistency.
- Missing Entries - sessions lack complete information, resulting to the imbalance of records and affecting statistical accuracy.
- Short Data Collection Window - A nearly three-month duration may not capture long-term patterns which may lead to incomplete analysis.

D. Recommendations and Future Work

To improve and provide a better analysis and findings of this study, several improvements are recommended for future researchers:

- Increase the participant count to allow a population-level analysis and provide a stronger statistical validity
- Extend the duration of data collection to capture long-term patterns
- Include additional variables that may explain the music selection more specific
- Explore the machine learning model more to improve its accuracy and provide a recommendation system that integrates the mood, activity, and sleep to suggest music to listen to

Future researchers may take note of these improvements to provide a deeper and more specific understanding on how these factors affects music preferences and vice versa.

VI. Conclusion

The main objective of the study is to determine which factor contributes the most to music genre selection using personally logged data collected for over three months. By applying data analysis, statistical testing, visualization, and machine learning techniques, the study examined how music preferences vary across different factors as well as how these factors interact.

A. Key Findings

The findings indicate that daily activity is the most influential factor in music genre selection. Statistical tests conducted using chi-square, Exploratory Data Analysis, and Random Forest Model results showed that the type of activity being performed strongly guides the music choice of the participant. Mood level on the other hand was also found as a significant factor, with ANOVA tests confirming the differences in mood before and after listening to different music genres.

Sleep duration demonstrated a weak influence on selection. With the limited variability in sleep records, it impacted the results compared to activity and mood. However, the machine learning model results suggested that sleep still contributes to genre prediction when it is combined to other factors, implying that sleep serves as an independent value that helps other factors achieve more accurate results when combined.

B. Personal Insights

Analyzing the personal data provided valuable insights on how music listening adapts to daily routines and mood states personally. Understanding how music helps complete tasks supporting concentration, relaxation, and enhancement of mood. The consistent improvement results in mood before and mood after also showed how music helps encourage emotional states personally. This self-analysis increased the awareness of how music plays an important role on daily life personally.

C. Real Application Findings

The insights provided from this study can be applied in everyday situations where music can be used to support the emotional well-being and productivity. Understanding which music genres align with specific activity categories can help optimize focus, relaxation, and sustain the energy throughout the day. These findings with the help of Random Forest feature can also create a personal recommendation system that not only considers listening history but also other factors such as activity, mood, and sleep.

In conclusion, this study demonstrates that music genre selection is influenced by a combination of factors, with daily activity as the dominant factor, followed by mood and sleep. While each factor contributes differently, when combined, it provides a more accurate and comprehensive understanding of music preferences. Through personal data analysis, analyzing personal data encourages self-reflection and shows how data science can be applied to gain meaningful insights into everyday lives.

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