From Sunrise to Sunset: Investigating Diurnal Rhythmic Patterns in Music Listening Habits in India

Geetika Arora, Keyur Choudhari, Ponnurangam Kumaraguru and Vinoo Alluri

International Institute of Information Technology Hyderabad, India
{geetika.arora@research, keyur.choudhari@students}.iiit.ac.in,
{pk.guru, vinoo.alluri}@iiit.ac.in

Abstract. Circadian rhythm is a 24-hour cycle of human physiology that governs various aspects of human behavior and cognition, including attention, mood, and performance. This suggests that daily physiological rhythms may influence an individual's musical preferences and listening habits. The objective of this study is to investigate how musical preferences vary throughout the day and across seasons among the Indian population. To this end, we examined music consumption of the participants in terms of audio features by analyzing their one-year Spotify listening history to identify distinct diurnal patterns in music choices. Unsupervised clustering of musical features suggests that preference can be divided into four distinct time blocks: morning, afternoon, evening, and night. Besides, we extended the analysis by incorporating demographic information of the individuals under study. We also conducted a seasonal analysis to investigate potential differences in music consumption patterns between winter and summer months. It was found that individuals prefer music with positive valence, low arousal, and high danceability post-midnight. Additionally, loudness was recorded as the highest (maximum value) around 12 noon. Gender-based differences were also observed, with females perceiving music as slightly less energetic and less positive in terms of emotional valence compared to males, but showing a preference for higher acousticness. Age-based differences revealed that older individuals prefer music that is less energetic, less danceable, less loud, and more acoustic. These findings suggest that music preferences and perceptions vary based on gender and age, and that diurnal patterns play a role in shaping musical choices and listening habits. The findings can have significant implications for the music industry, particularly in creating tailored playlists and curating music to suit different times of the day. Furthermore, the analyses provide a framework for understanding the role of music in other cultures as well, allowing for cross-cultural comparisons, thereby showing how diurnal patterns and other physiological factors may influence culture-specific musical traditions.

Keywords: Diurnal Variation, Musical Preferences, Online Streaming Platforms, Cultural Factors, Acoustic Features

1 Introduction

Chronobiologists have discovered that humans tend to perform activities according to the time of day, modulated by circadian rhythms. These rhythms are endogenously generated and persist without external cues such as light or temperature change. On the other hand, a diurnal pattern could be either a natural or man-made cyclic pattern of behavior, activity, or other phenomena occurring within a 24-hour period [19]. During the past few decades, it has also been demonstrated that cognitive and emotional states display regular diurnal rhythms [3]. For example, production of cortisol [10], also known as the stress hormone, also follows a diurnal pattern, with its level increasing to 50-60% after waking up and declining slowly for the rest of the day [11]. Cortisol levels tend to increase during a stressor; hence, it's often linked with higher negative affect characterized by feelings of psychological distress, such as nervousness and irritability. Consequently, it can be considered an indicator of psychological and physiological states.

Nowadays, there is a growing reliance on digital technologies for regulating moods, and music has emerged as the most common choice for many [16]. With the shift of music listening to the digital and online sphere, as evidenced by the 59.4 million users of paid music streaming in India in 2021 [18], music has taken on an increasingly prominent role in people's everyday lives. For instance, it is often used as background music while working or during physical activity. Interestingly, the emotional impact of music may also vary depending on the time of day, as seen in the strong association between time and each raga in Hindustani (Indian) music [2]. It has been observed that people may be more or less receptive to a particular raga during different parts of the day, indicating that the time of day could influence the emotional response to music. However, it remains to be determined whether this phenomenon also applies to popular music beyond Indian classical music. This trend presents an exciting opportunity to identify diurnal patterns in music usage and explore their potential association with psychological well-being. Previous research by Heggli et al. [6] quantified distinct diurnal patterns of musical preferences using the music streaming sessions dataset (MSSD), which contains over 2 billion music streaming events. As per their observation, the morning features higher loudness, valence, and energy, but lower tempo. Afternoon time saw a significant increase in tempo with beat strength and danceability reaching average values. Highest tempo along with peaks in beat strength and danceability were recorded in the evening, indicating tracks associated with dancing and partying. The limitation of the study is that the dataset was randomly sampled over an eight-week period for the analysis, and it does not include demographic or individual-level data.

In this study, we aim to analyze diurnal patterns of musical preferences in the Indian population. India is known for its incredibly diverse and rich culture, one of the oldest and most unique in the world due to its unparalleled diversity and richness, stemming from its ancient civilization and history that spans thousands of years. Additionally, India's diverse geography and climatic conditions give rise to multiple seasons, such as Spring, Autumn, Summer, Winter, and Monsoon [7]. Therefore, observing how musical preferences vary in a day in such a diverse culture and according to the different seasons would be worthwhile. To this end, we analyzed one year of Spotify listening history of Indian participants. We additionally examined differences in diurnal patterns in music

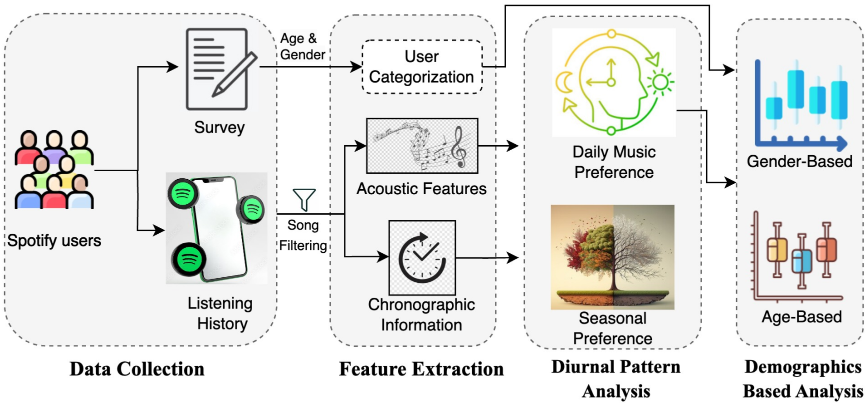

Fig. 1. The research methodology consists of four modules: Data Collection, Feature Extraction, Diurnal Pattern Analysis, and Demographics-Based Analysis. The process starts by collecting Spotify listening history from active users. The collected data is preprocessed by keeping only the songs that have been listened to for more than 45 seconds and extracting their audio features. Chronographic data such as date, time of the day, day of the week, and month are also extracted for each song. These features are utilized to examine diurnal and seasonal trends in the musical preferences of the Indian population. Diurnal patterns are also analyzed for different gender and age groups to find if they are a factor of influence in musical preferences on daily basis.

consumption specific to age and gender. We added unique dimension to our study by examining the effect of seasons on diurnal pattern in music listening to understand the interplay between seasonality and music preferences in Indian specific context. This analysis could offer unique insights into population-level musical preferences throughout the day. Inferences from the study have the potential to make a significant impact in the field of Music Information Retrieval (MIR), specifically in the areas of developing customized playlists and curating music to align with a culture at different times of the day. Moreover, understanding how these factors contribute to diurnal patterns in music can provide insights into the relationship between culture, geography, and musical preferences, with potential implications for the music industry.

2 Methodology

The methodology encompasses four modules: data collection, feature extraction, diurnal pattern analysis for the entire year and across seasons, and demographic-based analysis of daily diurnal patterns. A block diagram illustrating the proposed methodology is shown in Fig. 1. Each of these modules is elaborated upon in the subsequent subsections.

2.1 Data Collection

Hundred and one Indian citizens (mean age = 21 years, std = 2.44; 88 males) volunteered to participate in exchange for monetary compensation. For the study, a ‘call for participation' was disseminated through various social media platforms, including Instagram, LinkedIn, and Twitter, as well as email. Ethical approval was taken for the study from the Institute Review Board (IRB) of the affiliated institute before publishing the same. Eligible participants were required to be Indian citizens and residents, as well as active users of the music streaming service Spotify, for at least one year at the time of the call. Participants were requested to obtain and upload their listening history data from their Spotify accounts, which typically takes 3-5 days to be delivered by Spotify via email in the form of a JSON file. Participants were also asked to complete supplementary questionnaires, including the Kessler's psychological distress scale, Healthy Unhealthy Music Scale (HUMS), Highly Sensitive Person Scale (HSPS), and Inter-Personal Reactivity Index (IRI). However, these questionnaires are not utilized in the current analysis and can be used in the future for analyzing diurnal patterns in various categories of people.

2.2 Feature Extraction

Data Filtering and Pre-processing. Data preprocessing step provided valuable temporal information that was used for further analysis and interpretation of the music listening patterns in our study. The JSON file obtained from Spotify contained track-level information, including attributes such as track name, artist name, endTime, and msPlayed, representing the song name, artist of the song, the chronological information, and the number of milliseconds for which the track was played, respectively. To facilitate further analysis, we converted this JSON file to a CSV format. We extracted the chronological components such as, date, hour, day of the week, and month, from the endTime information, which was in the format "yyyy-mm-dd hh:mm". The milliseconds information was utilized to filter out songs that were played for less than 45 seconds, indicating that they were skipped. The milliseconds information was utilized to filter out songs that were played for less than 45 seconds, as they were considered skipped tracks. On average, each participant listened to 510 songs in one year, with each one being listened to for more than 45 seconds.

Audio Features. To gather audio features of the songs, we utilized the Spotify Web API [17], which allows users to retrieve multiple audio features based on track names. These features include Valence, Energy, Acousticness, Danceability, Loudness, Tempo, and Instrumentalness, and are derived from advanced calculations using algorithms proposed by Echo Nest.[1] These audio features provide a comprehensive and multi-dimensional understanding of music content, capturing both basic and more nuanced aspects of the music. For each participant in our study, we computed an average of the considered audio features on an hourly basis. This resulted in an seven-dimensional feature vector representing the average audio feature values for each hour of the day for each participant. The obtained 24×8 feature vectors for each participant were then clustered to find optimal sub-divisions in the day, as explained in the next section.

[1] https://blog.echonest.com/

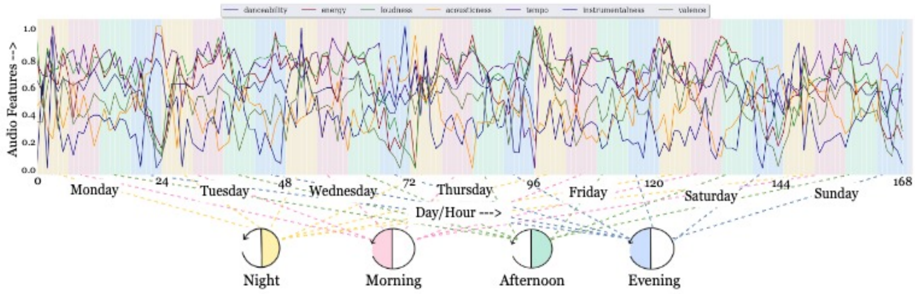

Fig. 2. Diurnal patterns in audio features mapped to four subdivisions of the day using k-means clustering. Normalized audio features are plotted across the entire week with optimal division into distinct clusters represented by colored overlays. Clusters label is based on descriptive terms for time of day.

2.3 Chronological Sub-divisions

K-means clustering [8] was utilized to identify recurring patterns in the data and to partition the data into k clusters with minimized within-cluster variance. Clustering was performed on normalized audio features data for a range of k values from 2 to 24 using the KMeans function from the sklearn library, with a maximum of 300 iterations per k. Varying the value of k in the k-means clustering algorithm and observing the resulting clusters, helps in identifying which value of k yields meaningful and interpretable clusters that align with diurnal patterns in music preferences. The “elbow knee method” is a common approach to determine the optimal value of k, where the inertia (i.e., within-cluster sum-of-squares) is plotted against various values of k and the point where the decrease in inertia flattens out, resembling an elbow or knee shape, is visually identified. This point indicates the optimal partitioning of the dataset into clusters and for our dataset, we could identify four clusters. Data normalization was performed using the MinMaxScaler [15] function from scikit-learn [13]. The MinMaxScaler function individually scales each feature to a given minimum and maximum value, with a default range of 0 and 1. Following selection of $k = 4$, we used an inverse transformation on the normalized cluster centroids to get the mean and standard deviation of audio features in each cluster.

2.4 Age and Gender-Based Analysis

We further delved deeper to identify if there are potential differences in diurnal music listening patterns based on gender and age. Initially, we assess whether the variables under investigation follow a normal distribution using the Shapiro–Wilk test [14]. This evaluation helps us determine whether to employ parametric or non-parametric statistical tests in our subsequent analyses. For the variables which do not exhibit a normal distribution, we apply the Box-Cox transformation technique [1], which aims to convert non-normal variables into normal ones. We then perform the Shapiro–Wilk test again to verify if the transformation has achieved normality, as it is not always guaranteed.

The variables under consideration were following a normal distribution and thus, for each chronological subdivision obtained through k-means clustering, we conducted a two-way repeated measures analysis of variance (RM-ANOVA) for the considered features to assess if there were significant differences because of the sources of variation, including gender, time of the day, and the interaction between gender and time of the day. Additionally, we employed a similar approach to examine differences based on three age groups (i.e., 18-20, 21-25, and > 25 years) with 55, 39, and 7 participants, respectively.

2.5 Seasonal Patterns

Inspired by previous research by Part et al. [12], we conducted a seasonal analysis to investigate potential differences in music consumption patterns between winter and summer months. We selected two months from each season, specifically December and January for winter and April and May for summer, which represent the respective seasons in the Indian region. Using a similar approach as our diurnal analysis, we analyzed the variations in music listening patterns by conducting an in-depth analysis of the acoustic features for each sub-division during different times of the day in both winter and summer months.

3 Results

3.1 Diurnal Patterns: Chronological Sub-Divisions

The k-means clustering algorithm identified four sub-divisions in a day. The cluster labels of the audio features for each hour of the week exhibited a sequence over 168 hours, in which a recurring cycle was found to occur on a 24-hour day. The first sub-division ‘Night’ covers the duration from midnight (denoted by 00 hours) to 6 a.m., followed by ‘Morning’ (6 a.m. to 12 noon), ‘Afternoon’ (12 noon to 6 p.m.), and ‘Evening’ (6 p.m. to 12 midnight). This differed from what was obtained in the previous study on the MSSD dataset [6], which reported five sub-divisions in the day- morning (6a.m. - noon), afternoon (noon - 8 p.m.), evening (8p.m. - 11 p.m.), night (11p.m. - 4 a.m.), and early morning (4a.m. - 6 a.m.). Fig. 2 illustrates the diurnal pattern exhibited by normalized audio features across these four sub-divisions of the day and across the days of the week.

The diurnal pattern of music listening behavior, as revealed through song-level analysis, showed a peak in the number of songs being listened to during the afternoon (33.48%), followed by the morning (30.98%) and evening (20.03%) periods with slightly lower percentages, and the lowest percentage during the night (15.51%). This pattern may be influenced by various factors such as daily routines, activities, and energy levels. For instance, during the afternoon and morning, people may be engaged in work, study, or other activities that are conducive to listening to music using streaming platforms. Specifically, since our sample was predominantly university students, listening to music at these hours is indeed predictable. Interestingly, the diurnal pattern in music listening behavior was found to be consistent when analyzing streams for weekdays and weekends separately, suggesting that it is a stable feature of music

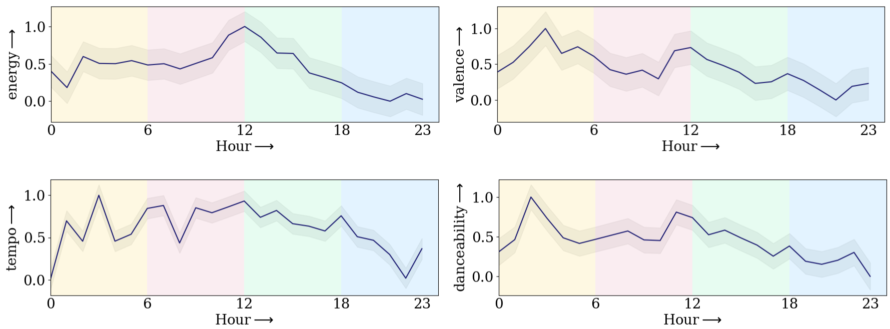

Fig. 3. Plots demonstrating diurnal patterns exhibited by the selected four audio features across a day, from 12 midnight to 2359 hours. The shaded area indicates the standard deviation of the considered acoustic feature.

preferences among the Indian population and not influenced by external factors such as work schedules or other obligations.

3.2 Hourly Diurnal Patterns: Granular Analysis of Audio Features

The analysis of audio features revealed distinct diurnal patterns, showcasing how various musical elements change over the course of the day with a high level of granularity. Figure 3 provides a detailed representation of how the emotional content of music may vary throughout different times of the day, ranging from morning to evening, and how people's listening preferences may reflect these changes. Among the seven features analyzed, four of them, that is, energy, valence, tempo and danceability can be seen in the figure. The remaining features were found to be highly correlated with these four. Specifically, we observed a strong positive correlation of loudness with energy and danceability, while instrumentalness and acousticness were highly but negatively correlated with the energy of the song.

Peak energy levels were observed during late morning to early afternoon, which could be due to people seeking an energy boost during those times to stay alert and focused, or to match their activities. On the other hand, the gradual dip in energy levels for the reminder of the day could be deemed indicative of their need to counteract the evening fatigue or stress. Peak valence was observed during late night/early hours followed by a gradual decrease. Variations in danceability values have been observed throughout the day which could be reflective of people's activities and preferences, with increased danceability during late-night hours possibly indicating preferences for more upbeat and danceable music during parties or social events, and a shift towards more relaxed music during the late-night and daytime hours as people wind down or engage in different activities. Loudness shows an overall upward trend during the night. This could be attributed to preferences for stimulating or energetic music during the night for studying. Potential spikes are reported during daytime hours which possibly reflects a desire for stimulating music during daytime hours. However, after 12 noon, loudness values start to decrease rapidly until midnight, which could indicate a shift towards

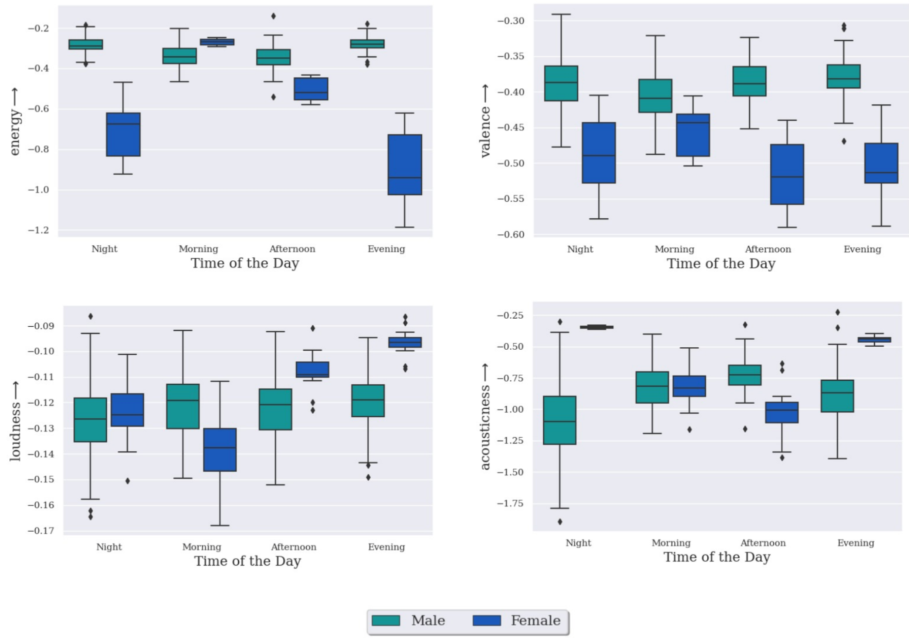

Fig. 4. Box plots showing the distribution of energy, valence, loudness, and acousticness for male and female participants across the four proposed sub-divisions of the day.

more mellow or relaxing genres as the day progresses. Tempo remains almost constant throughout most of the day, with a peak at 3 a.m. and a dip at 4 a.m., which could be reflective of people's preferences for more upbeat music before shifting to more relaxed music to wind down.

In line with the previous study done on MSSD dataset[6], the peaks in energy, loudness, danceability, and tempo were observed around the same time of the day (i.e., 12 noon, 2 a.m. and 3 a.m. respectively). However, they observed that the peak in valence starts around noon and remains fairly constant throughout the day while we observe the peak around 3 a.m.

To summarise, the acoustic features exhibit distinct patterns of fluctuation over the course of a day. Valence and energy tend to be higher at night and lower during the day, with energy slightly increasing in the morning. Loudness increases until noon and then decreases rapidly until midnight. Danceability shows a peak in the night and then decreases until early morning, after which it decreases till midnight. Tempo shows a generally consistent trend throughout the day, with some fluctuations, but it tends to decrease in the evening before increasing again after 11 p.m.

3.3 Gender Based Analysis

RM-Anova revealed significant main effects of gender and time of the day and demonstrated significant interactions (all $p < .001$) on the audio features. The F-statics and

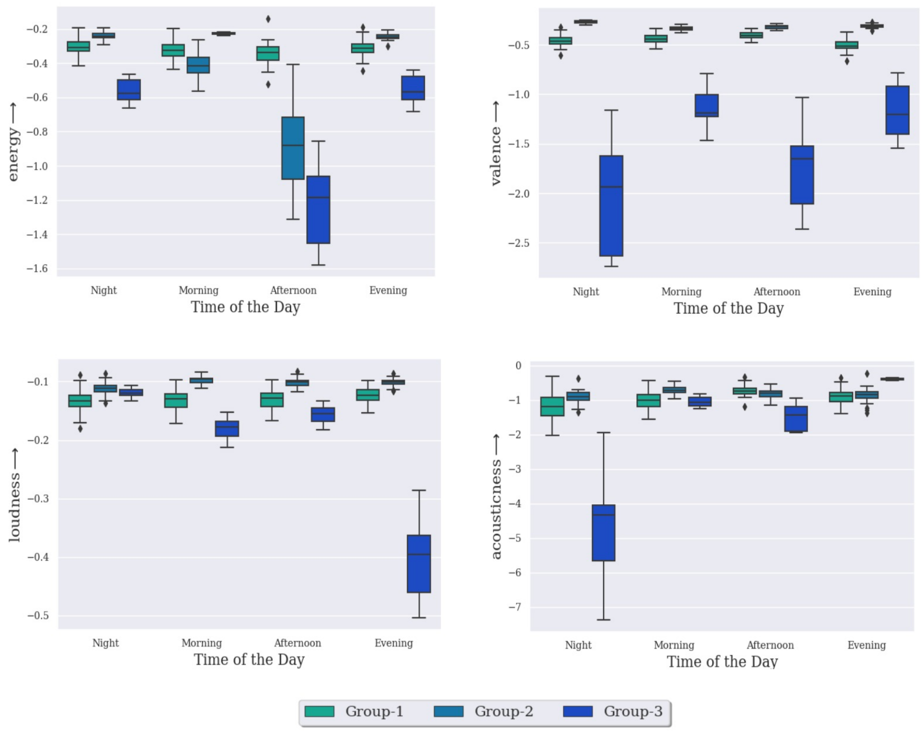

Fig. 5. Box plots showing the distribution of energy, valence, loudness, and acousticness for three age group participants (below 20 years, 21- 25 years and more than 25 years) across the four proposed sub-divisions of the day.

partial eta squared values for the variables are reported in Table 1. This suggests that the effect of the time of day on the kind of music consumed, represented here by audio features depend demonstrates gender-specific patterns. Highest effect was observed for energy, danceability, and valence as demonstrated by the partial eta square (ηp^2).

Fig. 4 shows box plots to depict differences in the four audio features for male and female participants at different times of the day. As can be seen, on average, females prefer music that is less energetic and negatively valenced when compared to males. On the contrary, the preference for higher acousticness was observed in females in the Indian population. The findings of this study are in line with Greenberg's research on the relationship between music preferences and the Empathizing-Systemizing (ES) theory [5]. According to the ES theory, females tend to be empathizers and thus have a preference for music that is mellow and has a negative valence. In contrast, males tend to be systemizers and prefer music that is more upbeat and positive in valence. These gender-based differences in music preferences observed in our study support the ES theory.

Variable→	gender	g_tod	gender*g_tod	age	a_tod	age*a_tod
Energy						
F-statistics	1005.200	8.090	286.540	204.200	280.010	157.140
$\eta \mathbf{p}^2$	0.720	0.060	0.690	0.510	0.680	0.710
Valence						
F-statistics	367.250	5.280	13.400	1358.310	3.230	58.170
$\eta \mathbf{p}^2$	0.480	0.040	0.090	0.880	0.020	0.470
Loudness						
F-statistics	8.340	9.420	19.960	526.430	14.730	197.790
$\eta \mathbf{p}^2$	0.020	0.070	0.130	0.730	0.100	0.750
Tempo						
F-statistics	84.030	58.720	14.590	265.380	32.850	217.260
$\eta \mathbf{p}^2$	0.180	0.310	0.100	0.580	0.200	0.770
Danceability						
F-statistics	856.970	65.220	536.690	254.690	35.860	235.730
$\eta \mathbf{p}^2$	0.690	0.330	0.800	0.570	0.220	0.780
Acousticness						
F-statistics	48.320	22.770	52.070	138.790	57.100	110.670
$\eta \mathbf{p}^2$	0.110	0.150	0.280	0.420	0.310	0.630

Table 1. RM-ANOVA results (F-statics and partial eta-squared (ηp^2) for energy, valence, loudness, tempo, danceability, and acousticness by gender, time of day (g_tod) and their interaction (gender*g_tod) and age, time of day (a_tod) and their interaction (age*a_tod).

3.4 Age Based Analysis

The RM-Anova analysis showed that there were statistically significant differences in all the audio features among different age groups for four specific time periods of the day. The F-statics and partial eta squared values for the variables are reported in Table 1. This suggests that the effect of the time of day on the kind of music consumed, represented here by audio features, depend demonstrates age-specific patterns. Highest effect was observed for valence, loudness, and tempo as demonstrated by the partial eta square (ηp^2).

As shown in Fig. 5), individuals in Group 3, who were over 25 years of age, tend to prefer music with lower valence, energy, danceability, loudness, and acousticness. There could be several reasons for the observed preferences. One possible explanation is that music is becoming more danceable and louder [4], which implies that the older group would indeed gravitate towards music that aligns with their past musical experiences. While previous studies have demonstrated that sentiments in lyrics of English songs are decreasing in valence over time [9], this does not seem to hold in the Indian context where people engage in music in various Indian languages too.

3.5 Seasonal Analysis

Analysis of audio features in relation to winter and summer months, as well as different times of day, revealed potential differences in musical preferences. During winter nights, mornings, and afternoons, lower valence values but higher energy values were observed, suggesting a preference for more energetic and stimulating music with potentially introspective or reflective moods. In contrast, during winter evenings, lower energy and valence values were observed, indicating a preference for more calming and relaxing music to wind down after a day of activities.

Furthermore, higher loudness values were observed during winter months, except for evenings, indicating a preference for potentially energizing and stimulating music. Danceability values were generally lower during winter months, suggesting a preference for less physically active music. Higher tempo values during winter months indicated a potential preference for faster-paced and more lively music, while lower acousticness values in nights, mornings, and afternoons could indicate a preference for more electronic or synthesized sounds. In contrast, higher acousticness values in evenings could suggest a preference for more natural or organic music.

Overall, these findings suggest that during winter months, people may prefer music that is more energetic and potentially introspective or reflective in the night, morning, and afternoon, while seeking more calming and relaxing music in the evenings to wind down after a day of activities. Further research is needed to better understand the underlying factors driving these seasonal differences in musical preferences.

4 Conclusion

This study on circadian rhythms and music preferences among the Indian population sheds light on how daily physiological rhythms may influence listening habits. The analysis of audio features revealed distinct diurnal patterns in music choices, with variations in audio features depending on the time of day. The k-means clustering algorithm identified four sub-divisions in a day, in contrast to the previous study [6] that reported five sub-divisions. While similarities were observed in the arousal dimension represented by energy in addition to loudness and tempo, valence on the other hand, demonstrated distinct peak at a different time of the day. Furthermore, we identified significant gender-based and age-related differences in music preferences, with females perceiving music as slightly less energetic and less positive in valence compared to males, and older individuals showing preferences for music with lower valence, energy, danceability, loudness, and acousticness. Our findings also highlight potential seasonal differences in music choices, with preferences for different types of music during winter and summer months. These demographic differences emphasize the need to consider psychological, social, and cultural factors in understanding music preferences. Our findings not only have practical implications for the music industry in terms of tailoring music recommendations to a specific time of day and season but also contribute to our understanding of the role of music in different cultures. Further research in this area could deepen the understanding of the complex relationship between music, physiology, culture, and human behavior.

References

1. George EP Box and David R Cox. An analysis of transformations. *Journal of the Royal Statistical Society: Series B (Methodological)*, 26(2):211–243, 1964.

2. Olivier Brabant and Petri Toiviainen. Diurnal changes in the perception of emotions in music: Does the time of day matter? *Musicae Scientiae*, 18(3):256–274, 2014.
3. Mary L Forsling. Diurnal rhythms in neurohypophysial function. *Experimental physiology*, 85(s1):179s–186s, 2000.
4. Elena Georgieva and Blair Kaneshiro. Using spotify audio features to study the evolution of pop music.
5. David M Greenberg, Simon Baron-Cohen, David J Stillwell, Michal Kosinski, and Peter J Rentfrow. Musical preferences are linked to cognitive styles. *PloS one*, 10(7):e0131151, 2015.
6. Ole Adrian Heggli, Jan Stupacher, and Peter Vuust. Diurnal fluctuations in musical preference. *Royal Society open science*, 8(11):210885, 2021.
7. Alban Kuriqi, Rawshan Ali, Quoc Bao Pham, Julio Montenegro Gambini, Vivek Gupta, Anurag Malik, Nguyen Thi Thuy Linh, Yogesh Joshi, Duong Tran Anh, Van Thai Nam, et al. Seasonality shift and streamflow flow variability trends in central india. *Acta Geophysica*, 68:1461–1475, 2020.
8. Aristidis Likas, Nikos Vlassis, and Jakob J Verbeek. The global k-means clustering algorithm. *Pattern recognition*, 36(2):451–461, 2003.
9. Kathleen Napier and Lior Shamir. Quantitative sentiment analysis of lyrics in popular music. *Journal of Popular Music Studies*, 30(4):161–176, 2018.
10. Margit C Ockenfels, Laura Porter, Joshua Smyth, Clemens Kirschbaum, Dirk H Hellhammer, and Arthur A Stone. Effect of chronic stress associated with unemployment on salivary cortisol: overall cortisol levels, diurnal rhythm, and acute stress reactivity. *Psychosomatic medicine*, 57(5):460–467, 1995.
11. Lisa R Otto, Nancy L Sin, David M Almeida, and Richard P Sloan. Trait emotion regulation strategies and diurnal cortisol profiles in healthy adults. *Health Psychology*, 37(3):301, 2018.
12. Minsu Park, Jennifer Thom, Sarah Mennicken, Henriette Cramer, and Michael Macy. Global music streaming data reveal diurnal and seasonal patterns of affective preference. *Nature human behaviour*, 3(3):230–236, 2019.
13. Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830, 2011.
14. Patrick Royston. Approximating the shapiro-wilk w-test for non-normality. *Statistics and computing*, 2:117–119, 1992.
15. C Saranya and G Manikandan. A study on normalization techniques for privacy preserving data mining. *International Journal of Engineering and Technology (IJET)*, 5(3):2701–2704, 2013.
16. Wally Smith, Greg Wadley, Sarah Webber, Benjamin Tag, Vassilis Kostakos, Peter Koval, and James J Gross. Digital emotion regulation in everyday life. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, pages 1–15, 2022.
17. Spotify. Spotify for Developers. `https://developer.spotify.com/`. [Online; accessed 2022].
18. Statista. Statista- music users statistics in India. `https://www.statista.com/outlook/dmo/digital-media/digital-music/music-streaming/india`, 2023. [Online; accessed 24-March-2023].
19. Anna Wirz-Justice. Diurnal variation of depressive symptoms. *Dialogues in clinical neuroscience*, 2022.