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Dynamics of Popular Music Over a Decade: A Longitudinal Analysis of Spotify's Top Tracks and the Impact of the COVID-19 Pandemic

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ABSTRACT

The evolution of musical trends over time has been a topic of growing interest, particularly in understanding how technological advancements and global events, such as the COVID-19 pandemic, influence the soundscape of popular music. Despite this interest, few studies have quantitatively profiled the extent of these temporal changes. This study presents a comprehensive analysis of the top 1000 songs on Spotify from 2011 to 2023, using a range of statistical and machine learning techniques to explore changes in musical features. Key musical attributes annotated by Spotify, as well as advanced audio features extracted using the Librosa library, such as Mel-Frequency Cepstral Coefficients (MFCCs), were analyzed using Principal Component Analysis (PCA), trend analysis (including linear regression and the Mann-Kendall test), Change Point Analysis, and hierarchical clustering. Results indicated significant shifts in musical characteristics, with pre-pandemic years marked by increasing trends in energy and loudness, whereas the post-pandemic period showed an increase in introspective attributes such as acousticness and instrumentalness. The years 2020 and 2021, coinciding with the COVID-19 pandemic, emerged as periods of notable change, characterized by distinct shifts in spectral and rhythmic attributes. Clustering analysis highlighted the emergence of a distinct group of softer, acoustic-driven songs during the pandemic. Our findings underscore the dynamic nature of popular music, driven by both technological advancements and external events. By providing a framework for analyzing temporal shifts in musical attributes, this study offers valuable insights for artists, producers, and industry stakeholders seeking to understand and anticipate evolving music trends.

Introduction

Over the past decade, the music industry has experienced significant shifts, driven by technological advancements, changing consumer behavior, and global events that have impacted production and consumption patterns (Collins, 2022; Pasupuleti, 2024; Preston & Rogers, 2011; Sharakhina et al., 2020). The emergence of streaming platforms like Spotify has transformed how music is created, distributed, and consumed, leading to new trends in musical composition and production (Hracs & Webster, 2020; Pichl et al., 2016; Raffa, 2024). This study aims to explore these evolving trends by analyzing the musical features of the top songs on Spotify from 2011 to 2023.

The focus of this research is to understand how key musical features have changed over time, particularly in response to events like the COVID-19 pandemic. Beginning in 2020, the pandemic triggered widespread disruptions across industries, including music (Gloor, 2020; Khlystova et al., 2022). Lockdowns, social distancing measures, and shifts in consumer behavior likely influenced the types of music that gained popularity during this period (Denk et al., 2022; Giordano, 2023; Hu & Kim, 2022). By examining musical features extracted with the Librosa library—such as Mel-Frequency Cepstral Coefficients (MFCCs), Spectral Contrast, and Chroma—and combining these with attributes provided by Spotify, this study seeks to identify significant trends and shifts in popular music over this 12-year period.

Librosa, an open-source Python tool, is central to this analysis (McFee et al., 2015; Nirmaladevi et al., 2022). It offers an extensive toolkit for extracting a variety of features from audio signals, making it particularly useful for analyzing the underlying characteristics of music. Among these features, MFCCs are widely used in audio analysis for representing the timbral texture of sound, a critical aspect in distinguishing between different types of audio (Yang & Zhou, 2019). Spectral Contrast, another key feature from Librosa, measures the difference in amplitude between peaks and valleys in a sound spectrum, providing insight into harmonic content. Higher spectral contrast is often associated with clearer tonal qualities, common in specific instrument types or vocal performances. Chroma features, which correlate with the twelve pitch classes in Western music (C, C#, D, etc.), capture harmonic and melodic content, giving insight into the tonal structure—especially useful in genres with strong harmonic elements, like classical or jazz (Muller & Ewert, 2010).

In addition to the Librosa-extracted features, this study also incorporates attributes provided by Spotify, which are generated using proprietary algorithms that analyze the audio content of tracks (Otuokere et al., 2021). Key Spotify attributes include danceability, energy, loudness, speechiness, acousticness, and instrumentalness. By analyzing these Librosa and Spotify features together, this study aims to uncover how the musical landscape has evolved, particularly during the COVID-19 pandemic, and to identify the attributes that have driven changes in popular music trends. The combination of these feature sets provides a broad view of the technical, harmonic, and rhythmic characteristics of music, uncovering how these elements have shifted in response to external influences.

Previous studies have demonstrated that musical trends are not static but evolve in response to cultural, technological, and economic changes. However, there is limited research that quantitatively examines these trends over an extended period, especially in the context of global events like the pandemic. This study aims to bridge that gap by applying a comprehensive statistical analysis of how specific musical features have changed over time. Using Principal Component Analysis (PCA) to reduce data complexity, the study identifies key components driving changes in musical features. Linear regression and the Mann-Kendall trend tests reveal long-term trends, while comparative analyses across pre-pandemic, pandemic, and post-pandemic periods capture shifts tied to COVID-19's impact. Change Point Analysis highlights structural changes within the time series, further reflecting the influence of the pandemic. Finally, hierarchical clustering uncovers distinct groupings of songs based on feature profiles, providing insight into genre and style variations. By focusing on both the temporal dynamics of musical features and their relationship to global events, this study provides a comprehensive overview of how popular music has evolved over the past decade.

Methods

Data Collection and Preprocessing

The dataset used in this study consists of the top 1000 songs from Spotify for each year between 2011 and 2023. The selection of these songs was based on their annual popularity rankings, obtained directly through the Spotify API. Each song in the dataset includes various musical attributes provided by Spotify, including duration, tempo, danceability, energy, and loudness.

In addition to the Spotify-provided attributes, we extracted advanced audio features using the Librosa library, an open-source Python package for music and audio analysis. The extracted features include Mel-Frequency Cepstral Coefficients (MFCCs), Spectral Contrast, Chroma features, and Tonnetz. These features provide deeper insights into the tonal, rhythmic, and spectral characteristics of the music, which are critical for understanding the evolution of musical trends over time.

To ensure data quality and consistency, we performed several preprocessing steps. This included handling missing values, normalizing all features to ensure comparability, and segmenting the data into distinct periods: 2011-2013, 2014-2016, 2017-2019, and 2020-2023. The segmentation was informed by significant change points identified during preliminary analyses, allowing for a more focused examination of trends and shifts in musical features over time. Finally, the dataset was divided into Pre-COVID, During-COVID, and Post-COVID periods for further analysis. All features were standardized prior to clustering and analysis to facilitate accurate comparisons across the different time periods and song popularity levels.

Analytic Workflow and Computational Tools

All analyses were conducted using Python, which was implemented in Jupyter notebooks to facilitate an interactive and reproducible workflow. The notebooks were used to streamline the data preprocessing, feature extraction, statistical analyses, and machine learning modeling processes. Key Python libraries employed in the analysis included Pandas for data manipulation, NumPy for numerical operations, Matplotlib and Seaborn for data visualization, Scikit-learn for machine learning, and Librosa for audio feature extraction. Change point detection was implemented using the "ruptures" package to detect structural changes in the time series data, identifying specific years where significant shifts in musical features occurred. This analysis was crucial for understanding the dataset's temporal dynamics and pinpointing notable change periods.

Descriptive Statistics and Initial Feature Analysis

The initial examination of the dataset focused on descriptive statistics, highlighting key attributes across the 1000 most popular songs per year from 2011 to 2023. We started by examining the correlations among the key musical attributes annotated by both Spotify and the Librosa library. This was done to identify the relationships between different features and to understand how these attributes might influence the overall sound and popularity of songs over time.

Figure 1 presents two correlation heatmaps that summarize the relationships between selected Spotify and Librosa attributes. The Spotify heatmap includes features such as popularity, danceability, energy, loudness, valence, and tempo, among others. Notably, strong positive correlations were observed between attributes such as loudness and energy, as well as danceability and energy, suggesting that songs with higher energy levels tend to be louder and more danceable. On the other hand, attributes like acousticness and energy displayed a negative correlation, indicating that more acoustic tracks tend to have lower energy levels. These relationships provide an initial understanding of how various musical elements interact and contribute to the overall character of popular music.

Feature Selection and Dimensionality Reduction

To reduce the complexity of the dataset and focus on the most relevant features, we employed a combination of statistical tests and machine learning techniques. Initially, we conducted exploratory data analysis (EDA) using descriptive statistics and visualizations such as histograms, box plots, and correlation heatmaps. This allowed us to identify potential outliers and understand the distribution of the data.

Subsequently, we applied t-tests and ANOVA to compare the means of each feature across different years and eras, identifying those with significant year-over-year changes. Features with p-values less than 0.05 were considered significant and selected for further analysis. We also utilized a Random Forest model to rank the features based on their importance in classifying the songs by year, further refining the selection of significant variables.

To address the multicollinearity issue and reduce the dataset's dimensionality, we performed Principal Component Analysis (PCA). PCA transforms the original features into a set of orthogonal components that capture the maximum variance in the data. We retained the first few principal components that explained the majority of the variance, ensuring that the most informative aspects of the dataset were preserved for subsequent analyses.

Trend Analysis

For trend analysis, we used linear regression and the Mann-Kendall trend test to identify long-term trends in the musical features across the study period. This allowed us to determine whether specific attributes were increasing or decreasing over time. To assess the impact of the COVID-19 pandemic on musical trends, we performed comparative analysis across three distinct periods: before (2011-2019), during (2020-2021), and after (2022-2023) the pandemic. Statistical tests, including t-tests and ANOVA, were used to compare the means of features across these periods, and post-hoc tests (Tukey's HSD and Dunn's test) were employed to identify specific periods with significant differences.

Clustering Analysis

Hierarchical clustering was performed using Ward's method, with the number of clusters set to six. The analysis was conducted separately for each period (Pre-COVID, During-COVID, and Post-COVID) to identify distinct groups of songs based on their feature profiles. The resulting dendrograms were color-coded to highlight the top five clusters in each period, facilitating the comparison of clustering patterns across different time frames.

Results

Descriptive Statistics and Initial Feature Analysis

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Figure 1A presents two correlation heatmaps that summarize the relationships between selected Spotify and Librosa attributes. The Spotify heatmap includes features such as popularity, danceability, energy, loudness, valence, and tempo, among others (Fig. 1A, top). Notably, strong positive correlations were observed between attributes such as loudness and energy, as well as danceability and energy, suggesting that songs with higher energy levels tend to be louder and more danceable. On the other hand, a negative correlation between acousticness and energy indicated that more acoustic tracks tend to have lower energy levels. These correlations provide an initial understanding of how various musical elements interact to shape the overall character of popular music.

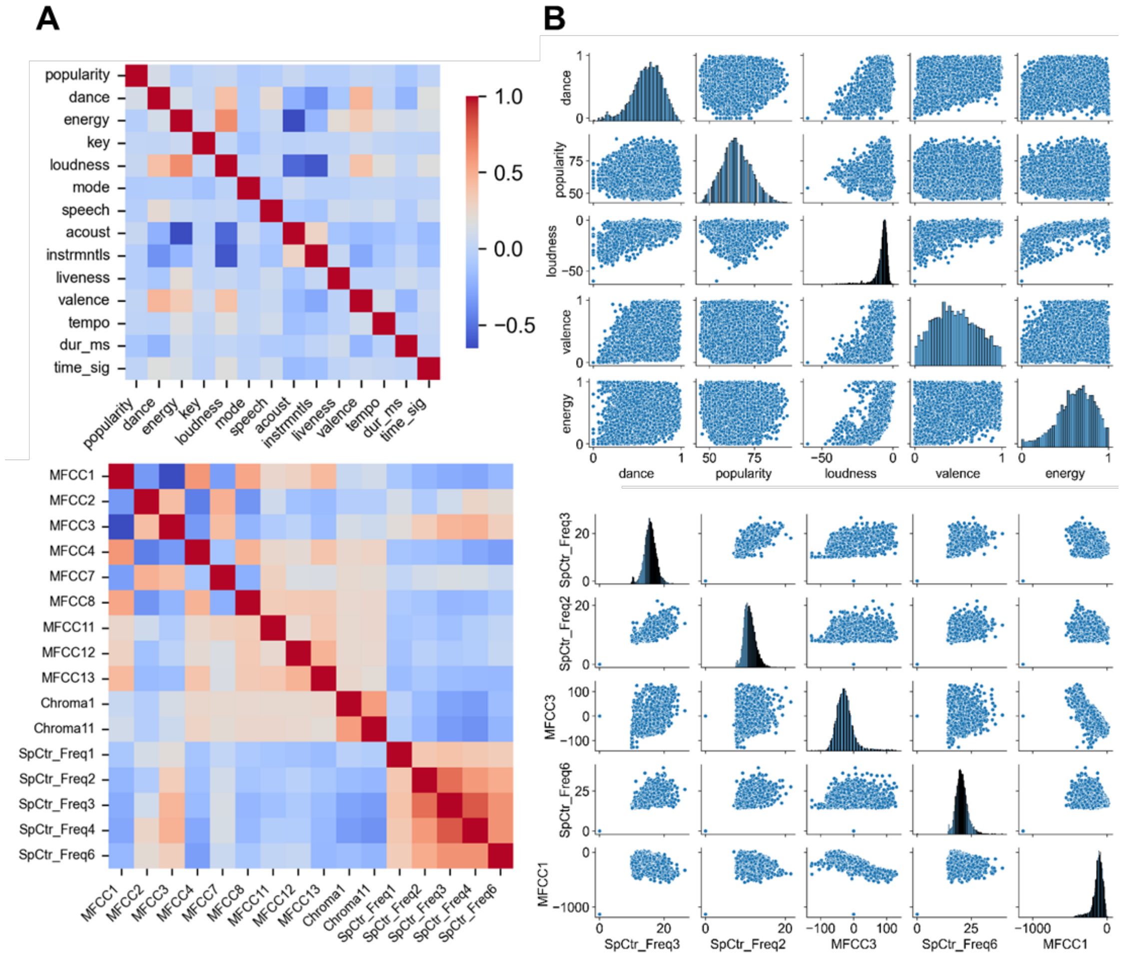


Figure 1. Distribution of song attribute data annotated by Spotify and Librosa. (A) The top figure presents a correlation heatmap of selected Spotify attributes, including popularity, danceability (dance), energy, loudness, valence, tempo, speechiness (speech), acousticness (acoust), instrumentalness (instrmntls), liveness, duration_ms (dur_ms), and time_signature (time_sig). Shown on the bottom is the correlation heatmap of selected Librosa audio features, such as MFCC1, MFCC2, Spectral Contrast Freq Band1 (SpCtr_Freq1), Chroma1, Chroma11, and other spectral and chroma-related attributes. The color gradient ranges from dark blue (negative correlation) to dark red (positive correlation), with white indicating no correlation. The strength of the correlation is depicted by the intensity of the color. (B) The pair plots visualize the relationships between the top 5 most correlated Spotify attributes (top) and Librosa audio features (bottom), which were determined by the highest absolute correlation values. Each scatter plot in the matrix shows the pairwise relationship between two variables, highlighting any underlying patterns, while the diagonal displays the distribution of individual attributes.

The Librosa heatmap similarly illustrates the correlations among key audio features such as MFCCs, Spectral Contrast, and Chroma features (Fig. 1A, bottom). The analysis revealed strong positive correlations between various MFCCs, which are indicative of the timbral characteristics of the audio. For instance, MFCC1 showed a strong positive correlation with MFCC2, reflecting their shared ability to capture the spectral envelope of the music. Spectral Contrast features, which measure the difference in amplitude between peaks and valleys in the sound spectrum, also correlated with certain MFCCs, indicating a link between the harmonic content of the music and its timbral texture.

To further explore these relationships, pair plots were generated for the top five most correlated attribute pairs from both the Spotify and Librosa datasets (Fig. 1B). The pair plot of Spotify attributes highlights the relationships between loudness, energy, danceability, valence, and tempo, showing distinct clustering patterns and linear relationships (Fig. 1B, top). This visualization confirms the strong correlation between loudness and energy, as well as the connection between danceability and these energy-related attributes. The pair plot for Librosa features similarly shows relationships between among MFCCs and Spectral Contrast features, reinforcing the findings from the heatmap analysis (Fig. 1B, bottom). This initial feature correlation analysis provides a foundational understanding of the relationships between key musical attributes, setting the stage for more detailed examinations of how these musical features evolved across different periods.

PCA and Feature Importance Analysis Highlight Musical Trends Driving Evolution of Popular Music

Understanding how musical characteristics evolve over time and impact track popularity is key to identifying trends in music production and listener preferences. To capture this, we performed a two-tiered analysis: first, we employed PCA to reduce the dimensionality of our dataset and identify the primary components driving changes in musical features over time. Next, we evaluated the importance of individual features in predicting key outcomes, such as the year of release and the era (grouped years), using Random Forest classifiers. This combined approach allowed us to capture both general trends and specific attributes influencing temporal placement and commercial success.

Figure 2A presents a 3D PCA plot illustrating the distribution of Spotify song attributes across this period, with the first three principal components (PC1, PC2, and PC3) capturing the most significant variation in the data. The 3D PCA plot on the left shows the distribution of mean attribute values for each year, with distinct clustering patterns that highlight shifts in musical trends. Notably, data points for 2020 and 2021 separate from earlier years, suggesting that the COVID-19 pandemic may have impacted the musical landscape and led to divergent characteristics during this time. The 3D PCA plot on the right aggregates data by era, providing a broader view of temporal trends. The eras are defined as Era 4 (2011-2013), Era 3 (2014-2016), Era 2 (2017-2019), Era 1 (2020-2022), and the year 2023. Clear separations between eras, particularly between Era 4 and Era 1, reveal significant shifts in musical characteristics over the past decade. The clustering of data points within each era also suggests a degree of consistency in musical attributes during those periods, while the transitions between eras highlight the ongoing evolution of popular music.

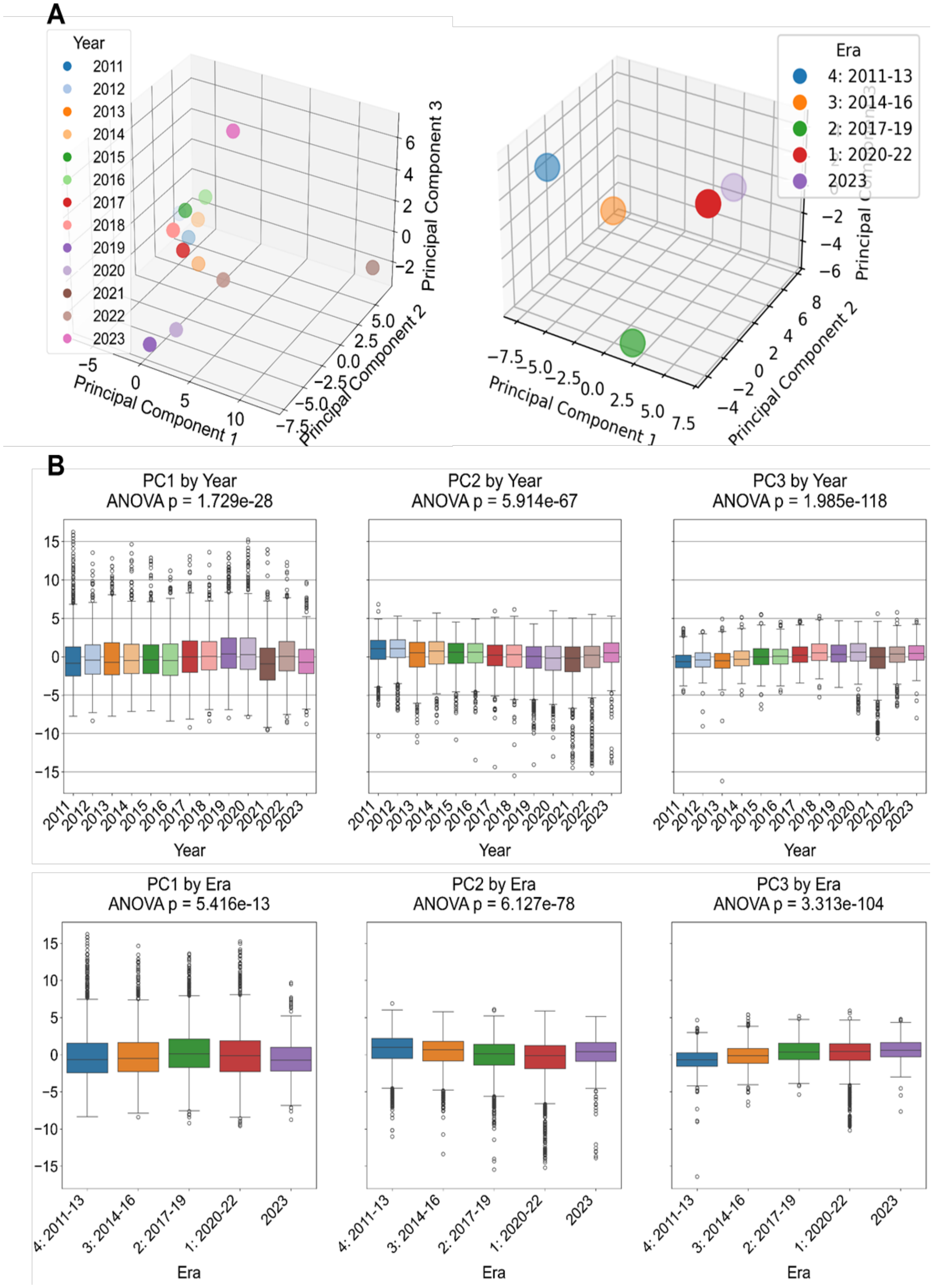


Figure 2. Principle Component Analysis of Spotify song attributes and temporal trends. (A) The 3D Principal Component Analysis (PCA) plot illustrates the distribution of Spotify song attributes for each year from 2011 to 2023 (left)

as well as for aggregated attribute data across different eras (right). The first three principal components (PC1, PC2, and PC3) are displayed, capturing the most significant variation in the data. Each data point represents the mean attribute values for a specific year or era, colored accordingly. For Era definitions: Era 4 (2011-2013), Era 3 (2014-2016), Era 2 (2017-2019), Era 1 (2020-2022), and 2023. (B) The box plots display the first three principal components (PC1, PC2, and PC3) for each year from 2011 to 2023 (top) or for segmented eras (bottom), highlighting the distribution of these components over time. The x-axis lists the years/era, while the y-axis shows the principal component scores. ANOVA results (p values) are provided for each principal component, indicating statistically significant differences across years/eras. These plots emphasize the year-to-year or era-to-era variations in musical attributes, with particular attention to shifts observed during the COVID-19 pandemic years (2019-2021).

To quantify these temporal shifts, box plots for PC1, PC2, and PC3 scores were generated (Fig. 2B), showing distributions across each year from 2011 to 2023 and across the defined eras. The ANOVA results for each principal component indicate statistically significant differences across years and eras, with p-values of 1.729e-28, 5.914e-67, and 1.985e-118 for PC1, PC2, and PC3, respectively, when analyzed by year. Similar patterns were observed when the data were segmented by era, with significant p-values confirming the temporal shifts in musical attributes.

The heatmap in Figure 3A illustrates the significant correlations between the musical features and the first three principal components from PCA, each representing major variance dimensions. PC1 is primarily associated with spectral features such as spectral contrast frequency bands (SpCtr_Freq4, SpCtr_Freq6) and MFCCs. These attributes are key drivers of variance related to the timbral and spectral complexity of tracks. Conversely, PC1 shows negative correlations with acousticness and valence, highlighting a contrast between energetic, complex tracks and more acoustic, emotionally positive music. PC2 reflects variations in intensity and energy levels, with strong positive correlations with features like energy and loudness. This component likely captures the contrast between high-energy, loud tracks and those with more subtle, harmonic structures, as evidenced by the negative correlations with MFCC and Chroma features. PC3 captures variance related to rhythm and timbre, with positive correlations with speechiness and duration (dur_ms). This suggests that PC3 is influenced by the rhythmic and lyrical content of tracks, distinguishing between more vocal-centric and instrumental pieces.

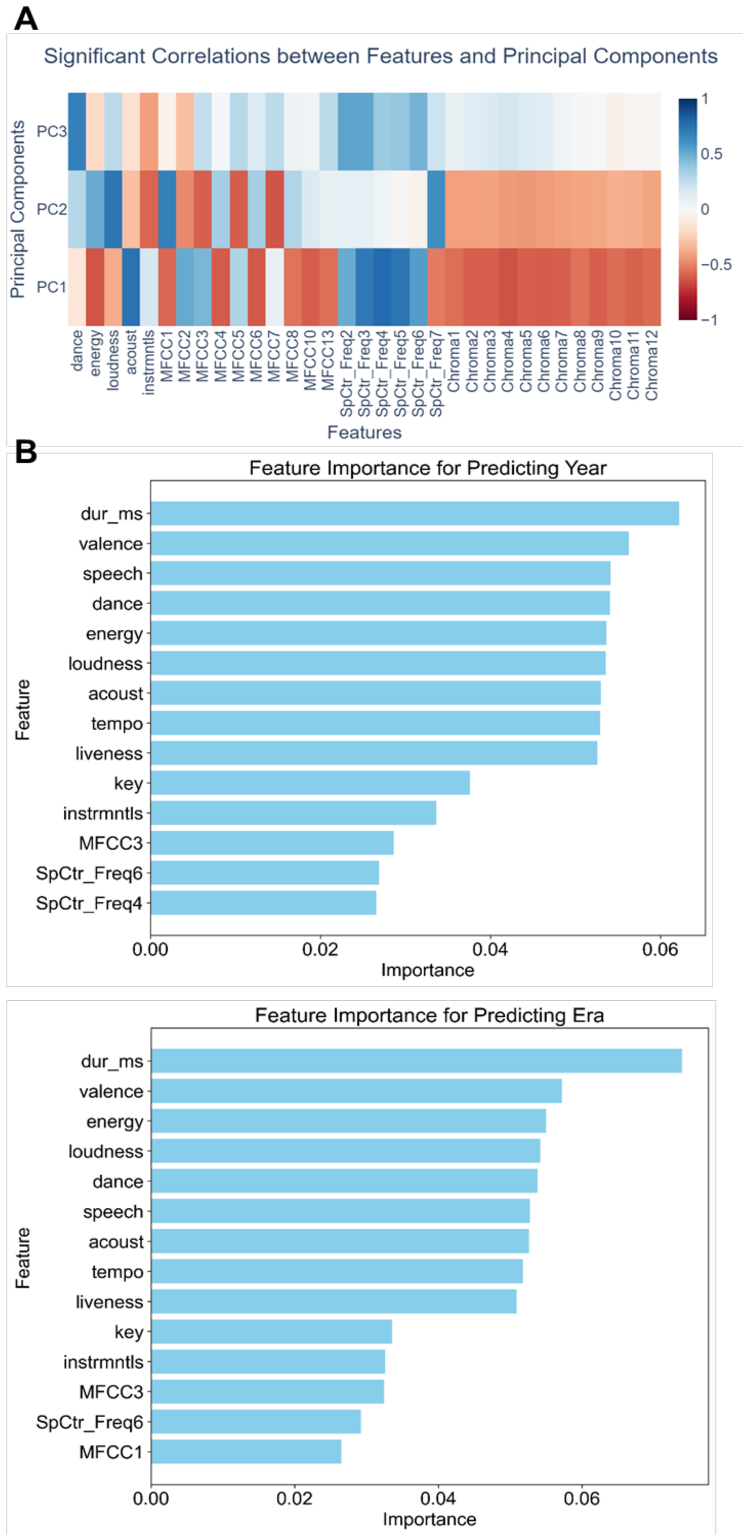


Figure 3. Analysis of underlying factors driving musical trends over time. (A) A heatmap is used to highlight the specific song attributes that contribute most strongly to each principal component. It illustrates the correlation coefficients between the original song attributes and the first three principal components (PC1, PC2, and PC3) derived from PCA. The y-axis represents the principal components, while the x-axis lists the song attributes. The color scale

indicates the strength and direction of correlations, with blue hues representing positive correlations and red hues representing negative correlations. Correlations with an absolute value greater than 0.5 were considered significant. (B) Feature importance analysis for predicting the year (top) or era (bottom) of song release. The top 14 most important features for each prediction are displayed, ranked by their importance as determined by a Random Forest classifier.

Feature importance analysis using Random Forest classifiers further explored the role of these features in determining key outcomes (Fig. 3B, top). For predicting the year of release, top features included track duration (dur_ms), valence, speechiness, and danceability, reflecting evolving trends in music, such as changes in the average length of songs and the emotional tone conveyed by the music. For era prediction, track duration again emerged as a significant feature, along with valence, energy, and loudness, indicative of broader trends across different music periods (Fig. 3B, bottom).

These results emphasize the dynamic nature of popular music, especially during the pandemic years (2019-2021). The clear separations between different eras and the statistically significant year-to-year variations suggest that global events, including the pandemic, have played a crucial role in shaping musical trends over the last decade. Moreover, the central role of specific musical attributes, as highlighted by PCA and feature importance analysis, underscores their significance in defining the temporal and commercial characteristics of tracks.

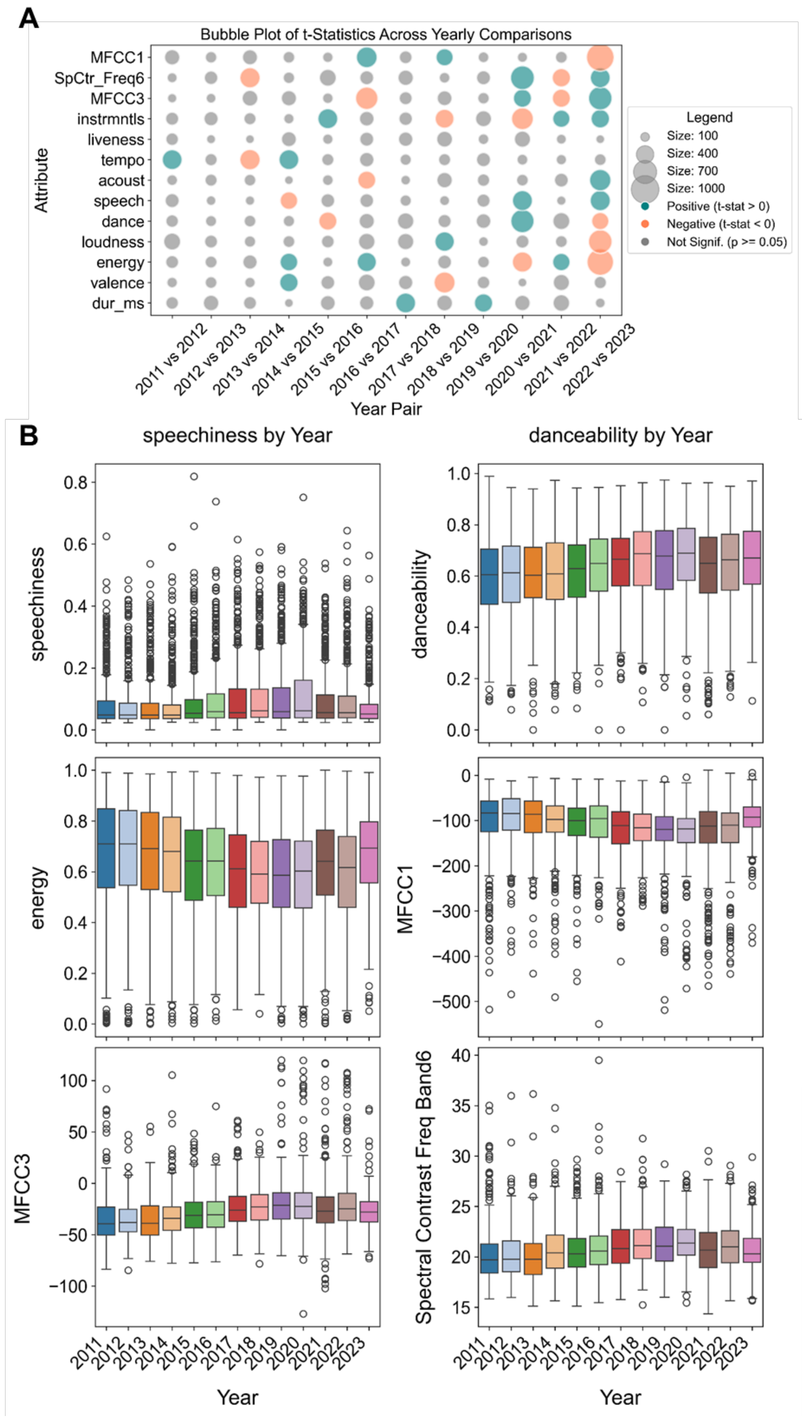
Trend and Impact Analysis Reveals Temporal Shifts in Key Musical Attributes

In the preceding analysis, PCA captured significant shifts in musical attributes across years, illustrating evolving composition and production styles in popular music. Building on these findings, a detailed trend and impact analysis was conducted to dissect specific musical attributes over time, focusing on significant changes that may correlate with external factors such as the rise of streaming services, shifts in listener preferences, or global events like the COVID-19 pandemic. Several analytical approaches were employed to gain a deeper understanding of these temporal dynamics (Table 1). The Mann-Kendall Trend Test and Linear Regression were applied to identify significant trends over time in attributes such as energy, loudness, and duration. This analysis revealed a marked decrease in duration (duration_ms) and energy, suggesting a shift toward shorter, possibly less intense tracks in recent years. In contrast, danceability and speechiness showed upward trends, indicating a gradual move toward more rhythmically engaging and lyrically focused music. These results likely reflect broader industry trends influenced by streaming-era listener behaviors and the effects of global events such as the pandemic.

Table 1. Summary of statistical tests for key musical attributes.

Attribute	Mann-Kendall			Linear Regression		
	Statistic/Tau	p-Value	Trend	Statistic/Slope	p-Value	R-squared
acousticness	0.054	0.000000108	Increasing	0.00279	0.0169	0.0013
danceability	0.104	0	Increasing	0.00626	1.45E-21	0.021
duration_ms	-0.194	0	Decreasing	-3835.03	4.98E-58	0.058
energy	-0.057	0.000000014	Decreasing	-0.00345	0.000047	0.0038
MFCC1	-0.093	0	Decreasing	-1.534	1.8E-09	0.0083
MFCC3	0.15	0	Increasing	1.257	3.97E-40	0.0396
SpCtr_Freq6	0.107	0	Increasing	0.07854	1.14E-14	0.0136
speechiness	0.058	1.08E-08	Increasing	0.00167	0.000012	0.0044

Pairwise t-tests were also performed to assess year-on-year differences in key attributes, with the results visualized in a bubble plot (Fig. 4). Significant year-to-year changes were most prominently observed in attributes such as MFCC1, MFCC3, and Spectral Contrast Frequency Band 6 (SpCtr_Freq6). The bubble plot illustrates that these features experienced notable shifts, particularly around the years 2020-2021, which correspond with the COVID-19 pandemic (Fig. 4A). The large red bubbles in the plot indicate significant differences in these years, suggesting that the pandemic may have had a considerable impact on the production and reception of music, leading to changes in the timbral and rhythmic characteristics of popular tracks.



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Journal of Student Research

Figure 4. Longitudinal variations in key musical features from 2011 to 2023. The bubble plot represents the t-statistics derived from pairwise t-tests comparing key musical attributes across consecutive years. Each bubble's size corresponds to the magnitude of the t-statistic, with larger bubbles indicating greater differences between years. The bubbles are color-coded based on statistical significance: teal for positive t-stat, coral for negative t-stat, and grey for non-significant comparisons ($p \geq 0.05$). The attributes analyzed are as labeled. This visualization highlights the temporal variations in these musical features from 2011 to 2023. (B) The box plots illustrate the distribution of six key musical attributes across years from 2011 to 2023. Each box plot shows the median, interquartile range, and outliers for the respective attribute in each year. These plots provide insight into how the distribution of these musical features has evolved over time, with potential shifts and trends visible through the variations in box heights and the spread of data points.

To explore these trends further, box plots were generated for six key musical attributes: speechiness, danceability, energy, MFCC1, MFCC3, and Spectral Contrast Freq Band 6 (Fig. 4B). The distribution of these attributes over time revealed several noteworthy shifts. For instance, speechiness showed a broadening distribution in the years following 2015, indicating an increase in vocal emphasis in popular tracks, likely driven by the growing popularity of genres that emphasize lyrical content. Similarly, danceability demonstrated an upward trend in its median values, supporting earlier findings that suggest a shift towards more rhythmically engaging music. Conversely, MFCC1 and MFCC3 showed greater spread in recent years, reflecting diversity in the timbral qualities of popular music, possibly due to experimental production techniques and influences from varied genres.

These results underscore the dynamic nature of popular music, shaped by both industry innovation and external events. The observed trends in track duration and energy suggest that shorter, more accessible tracks are increasingly favored, a trend that may be amplified by the preferences of streaming platform users. Meanwhile, the increase in danceability and speechiness highlights a growing preference for rhythmically and lyrically engaging content, reflecting broader cultural shifts towards more interactive and socially-driven music consumption.

Significant Change Points in Key Musical Features Pinpoint Moments of Notable Shifts

Expanding upon the previous trend and impact analyses that revealed significant temporal changes in key musical attributes, a change point analysis was conducted to identify specific moments where these shifts occurred. Pinpointing these change points provides deeper insight into the evolution of music production styles and industry trends, potentially in response to external influences such as technological advancements, shifts in listener preferences, or global events like the COVID-19 pandemic. To capture these dynamics, a kernel-based change point detection method was applied to several critical musical features, including speechiness, danceability, energy, MFCC1, MFCC3, and Spectral Contrast Frequency Band 6. This approach is particularly effective for detecting non-linear patterns and abrupt changes in complex datasets, making it suitable for analyzing the diverse nature of musical evolution.

Figure 5 presents the results of this analysis, pinpointing periods of significant shifts across these attributes. MFCC1, for instance, showed notable change points around 2011, 2016, and 2022 (Fig. 5, top). These shifts likely reflect important changes in the spectral characteristics and timbral qualities of popular music. The change in 2011 may correspond with the early adoption of new digital production techniques and the increasing influence of electronic music. The 2016 shift could reflect the mainstream integration of diverse genres and experimentation with sound textures, while the 2022 change point may signal emerging post-pandemic trends as artists adapt to new modes of music consumption and production. MFCC3 showed multiple change points, especially concentrated between 2016 and 2022 (Fig. 5, bottom). This clustering underscores a period of substantial transformation in the tonal aspects of music. Changes around 2019-2021 align with the global impact of the COVID-19 pandemic, a time when artists and producers faced unique challenges, possibly leading to new recording techniques and sound exploration that impacted MFCC3 values.

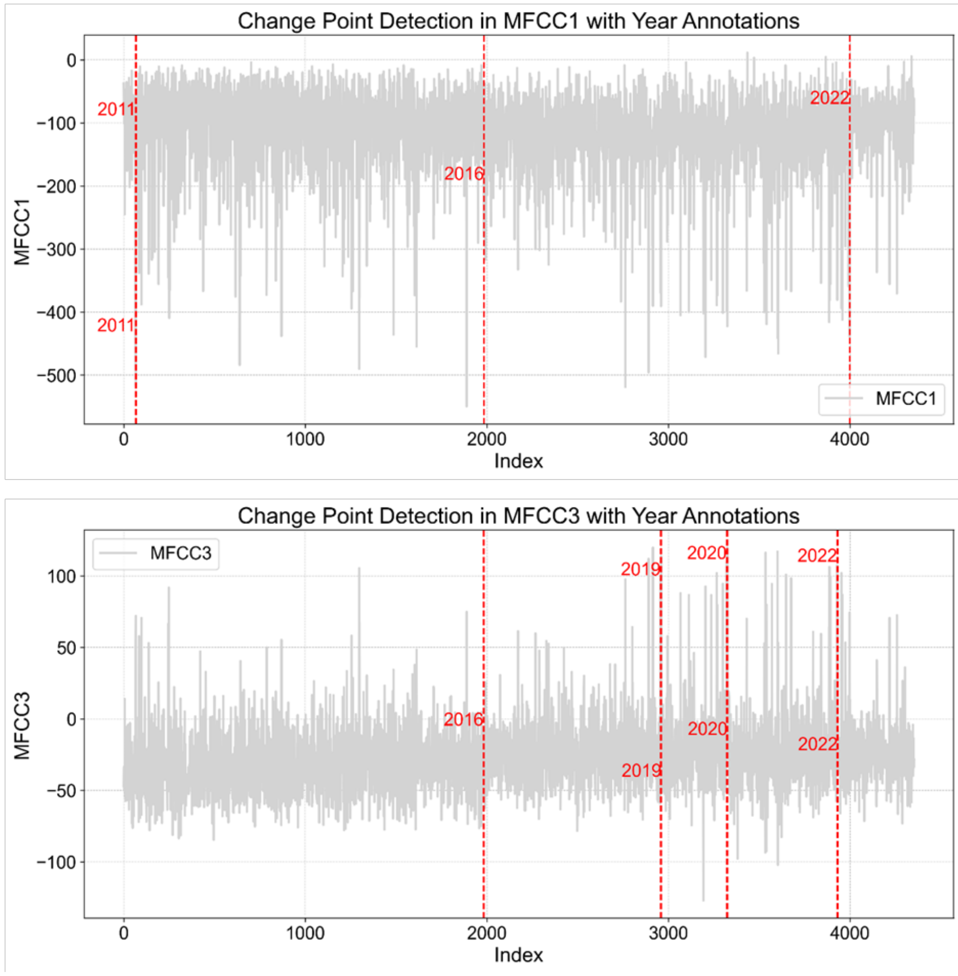

Figure 5. Change Point Detection in Song Shifts Using Spectral Attributes. This figure presents the change point analysis for the MFCC1 (top) and MFCC3 (bottom) features, key spectral characteristics in audio analysis, across the dataset. The plot shows the attribute values over time, with vertical red dashed lines indicating the detected change points. Each change point is annotated with the corresponding year, highlighting significant shifts in the spectral profile of popular music around the years 2016 and 2022. These change points suggest periods where notable alterations in music production or style occurred, possibly reflecting industry-wide changes or external influences.

In contrast, speechiness, danceability, energy, and Spectral Contrast Frequency Band 6 remained relatively stable with no significant change points under the conditions tested. This stability suggests that these attributes have evolved more gradually over time or have maintained consistent levels, possibly due to enduring listener preferences or foundational aspects of popular music production that persist despite external influences. Together with previous PCA and trend analyses, these findings offer a comprehensive view of the dynamic yet stable elements shaping popular music, highlighting both persistent traits and transformative shifts within contemporary music trends.

Segmented Analysis of Audio Features Across COVID-19 Periods

Following our analysis of overall trends in audio features from 2011 to 2023, it became evident that the COVID-19 pandemic (2020-2021) marked a distinct period of change in music. This observation led us to further investigate how musical attributes evolved across specific pandemic-related periods. To this end, we segmented the data into three distinct periods: Pre-COVID (2018-2019), During COVID (2020-2021), and Post-COVID (2022-2023), and analyzed these segments across different popularity levels, specifically focusing on the Top 500 and Bottom 500 songs. This segmented approach aimed to uncover whether the global disruptions of the pandemic drove unique shifts in music production and listener preferences, especially within different popularity strata. To capture the direction and magnitude of these changes, we used t-tests to compare audio features across the periods, visualized in a bubble plot (Figure 6). The t-statistics were categorized to highlight positive and negative shifts in these audio features.

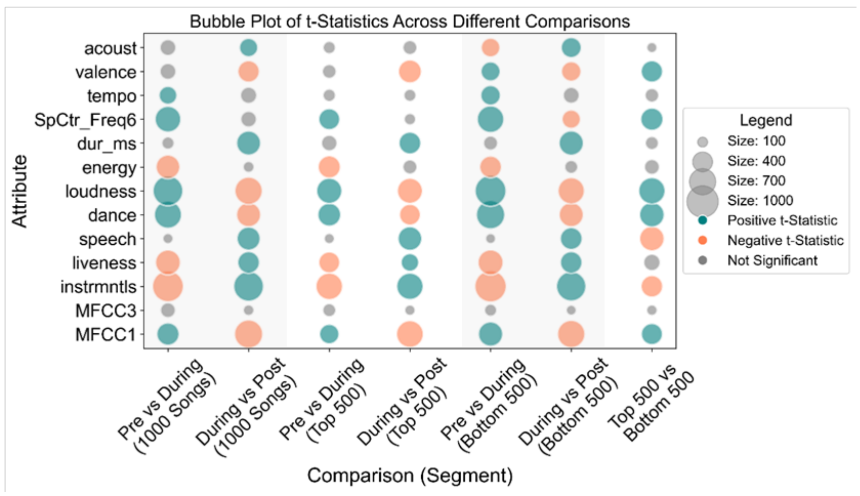

Figure 6. Segmented analysis of key musical attributes through the COVID period. The bubble plot illustrates the results of t-tests performed on selected audio features across different COVID-19 periods and popularity segments. Only selected years were included in the analysis and segmented into Pre-COVID (2018~19), During-COVID (2020~21), and Post-COVID (2022~23). The comparisons include Pre-COVID vs. During COVID, During COVID vs. Post-COVID for the entire dataset (1000 songs) or segmented by the top 500 and bottom 500 songs. Each bubble represents the t-statistic for a given feature comparison, with the size of the bubble corresponding to the magnitude of the t-statistic. The color of the bubbles indicates the direction of the change: teal for positive t-statistics (indicating an increase in the feature value), coral for negative t-statistics (indicating a decrease), and grey for non-significant results (p-value ≥ 0.05).

When comparing the Pre-COVID period to the During COVID period, significant changes were noted in features such as MFCC1, Spectral Contrast Freq Band 6, instrumentalness, liveness, danceability, loudness, and energy (Fig. 6). Positive t-statistics for MFCC1, Spectral Contrast Freq Band 6, and instrumentalness point to an increase in these attributes during the pandemic, indicating a shift towards more ambient or introspective music—a reflection of the global mood of uncertainty and introspection. Conversely, decreases in energy and loudness align with a more subdued, less dynamic musical style, mirroring the introspective atmosphere prevalent during this time. The transition from the pandemic to the post-pandemic period revealed further significant shifts in MFCC1, instrumentalness, loudness, danceability, speechiness, and duration_ms. Notably, the increase in loudness and danceability in the post-pandemic period suggests a shift towards more energetic and socially engaging music as societies began to recover from the impacts of the pandemic. This contrasts with the decline in instrumentalness and liveness, reflecting a movement away from the ambient and introspective styles that had characterized music during the pandemic.

Analyzing the data within specific popularity segments also revealed noteworthy patterns (Fig. 6). The top 500 songs exhibited similar trends in changes to the overall top 1000 songs. The fewer deviations in these more popular tracks suggest that they were representative of the broader societal shifts during the pandemic. On the other hand, several features show popularity-associated changes across the COVID periods. For example, when comparing the Top 500 and Bottom 500 songs across all periods, distinct variations emerged in features such as acousticness, valence, and tempo. Positive t-statistics for valence and tempo in the Bottom 500 songs suggest that these tracks were characterized by musical positiveness and speed, reflecting unique listener preferences. Conversely, the negative t-statistics for acousticness for the Bottom 500 songs indicate a tendency towards less instrumental styles in the less popular tracks.

Distinct Clustering Patterns During the COVID-19 Pandemic Reveal a Marked Shift Towards Softer, More Introspective Music

To expand upon the segmented analysis that highlighted significant shifts in musical attributes across different COVID-19 periods, we further investigated by applying hierarchical clustering to songs from the Pre-COVID, During-COVID, and Post-COVID phases. This approach aimed to identify distinct groupings that could provide additional insights into how musical attributes evolved during the pandemic and its aftermath. Hierarchical clustering was conducted using Ward's method on standardized features, allowing us to identify patterns and clusters that signify meaningful changes in music over time. We set the number of clusters to six and color-coded the top five clusters in each dendrogram to facilitate comparison across the periods (Fig. 7).

HIGH SCHOOL EDITION
Journal of Student Research

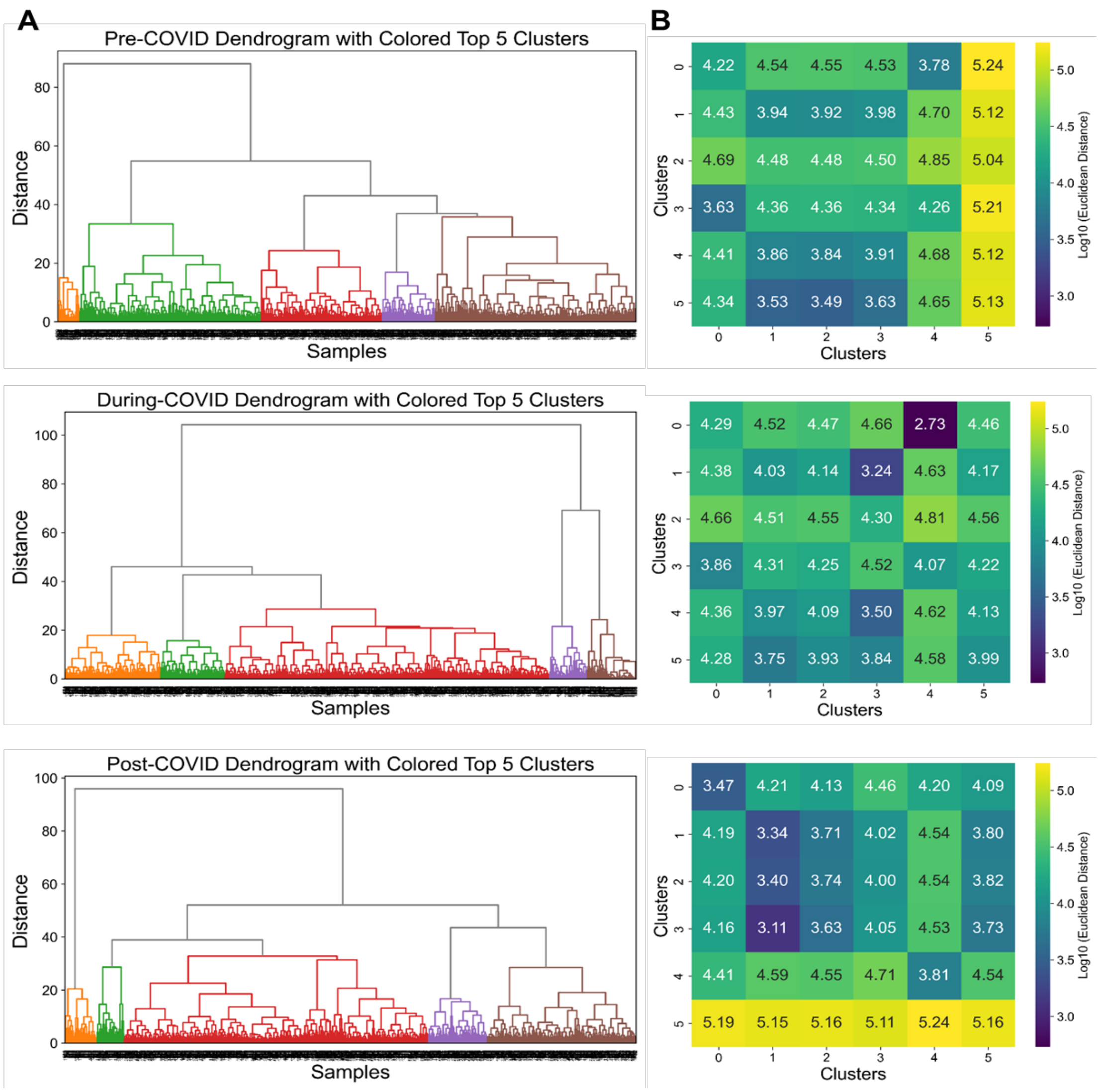

Figure 7. Transitional shifts in key musical attributes through the COVID period. Hierarchical clustering dendrograms and heatmaps of cluster distances for Pre-COVID, During-COVID, and Post-COVID periods. (A) The dendrograms display the hierarchical relationships between clusters, with the top five clusters color-coded for clarity. (B) Cluster compositions were compared between Pre-COVID vs. During-COVID (top), Pre-COVID vs. Post-COVID (middle), and During-COVID vs. Post-COVID (bottom). The accompanying heatmaps show the log10-transformed Euclidean distances between the centroids of the clusters, highlighting the distinctiveness of Cluster 5 during the COVID period.

The dendrograms (Fig. 7A) and corresponding heatmaps (Fig. 7B) of cluster distances reveal several key differences between the During-COVID period and the other two periods (Pre-COVID and Post-COVID). Most notably, Cluster 5 from the During-COVID period stands out as markedly different from other clusters, with significantly larger distances observed in the heatmap, especially when compared to clusters from the Pre-COVID and Post-COVID periods (Fig. 7B). This distinctive clustering pattern suggests that songs within Cluster 5 during the COVID period displayed unique characteristics not shared by songs in other periods. A detailed feature analysis of Cluster 5 during the COVID period shows substantial deviations from overall mean values at the time: MFCC1 (-227.59), MFCC3 (75.42), Instrumentalness (0.69), Liveness (-0.05), Speechiness (-0.05), Danceability (-0.40), Loudness (-20.50 dB), Energy (-0.47), Duration (ms) (-46,693.75), Spectral Contrast Freq Band6 (-1.54), Tempo (-18.10 BPM), Valence (-

0.33), and Acousticness (0.58). These results indicate that Cluster 5 songs during the COVID period was characterized by significantly lower levels of loudness, energy, tempo, and duration, alongside increased instrumentalness and acousticness. This pattern suggests a considerable shift towards a softer, more acoustic, and less energetic musical style during the pandemic.

Discussion

This study presents a comprehensive analysis of the evolution of musical attributes in popular songs from 2011 to 2023, using a dataset of the top 1000 songs per year on Spotify. By employing a range of statistical and machine learning techniques, including Principal Component Analysis (PCA), Change Point Analysis, and clustering methods, we were able to track temporal shifts in key audio features in music trends. The analysis revealed significant changes in features such as energy, loudness, duration, and MFCCs, indicating a shift in production and composition styles in popular music over the years.

One of the key findings was the increasing prominence of features related to intensity, such as energy and loudness, particularly in the pre-pandemic years. Conversely, the post-pandemic period was marked by an increase in introspective features like acousticness and instrumentalness, suggesting a shift in listener preferences during the pandemic years. Furthermore, significant deviations were identified in musical characteristics around 2020 and 2021, pointing to the influence of the COVID-19 pandemic on music production and consumption.

The findings of this study underscore the dynamic nature of popular music, which not only reflects artistic trends but also responds to external cultural and global events. The years 2020-2021, aligning with the onset and progression of the COVID-19 pandemic, showed significant deviations in musical characteristics across all three principal components. These years, particularly 2021, may be considered outliers or periods of distinct musical evolution. The marked decrease in loudness, energy, tempo, and duration during the pandemic reflects a shift towards more introspective and ambient music, likely driven by the global atmosphere of uncertainty and introspection.

The pandemic appeared to influence both the production and consumption of music, with listeners gravitating toward more subdued, reflective tracks. The clustering analysis particularly highlighted the emergence of a distinct cluster (Cluster 5) during the pandemic period, characterized by softer, more acoustic-driven sounds. Conversely, the post-pandemic increase in danceability and loudness in 2022 and 2023 suggests a cultural resurgence towards more energetic and socially engaging music as societies began to recover from the impacts of the pandemic.

From a broader perspective, PCA revealed that spectral features, particularly MFCC1 and MFCC3, played a central role in driving changes in music over time. These features, associated with the complexity of timbre and sound textures, highlight the evolving production techniques and experimentation in modern music. On a technical level, this shift may be influenced by advancements in production technology and the increased creative exploration facilitated by digital tools. The change point analysis identified specific years—such as 2016 and 2020—where abrupt changes occurred in these spectral features, offering insights into the pivotal moments of musical transformation. On the contrary, the consistency of features like danceability and energy, which showed fewer significant change points, suggests their enduring importance in maintaining the appeal of popular music across different eras.

Looking ahead, several avenues for future research are possible. One promising direction is the integration of lyrical content analysis. Natural language processing (NLP) techniques could provide valuable insights into how the themes, emotions, and stories conveyed in lyrics evolve alongside musical attributes (Betti et al., 2023; Martinez et al., 2024), particularly in response to global events like the COVID-19 pandemic. This integration could further clarify the connection between lyrical content and listener engagement during periods of societal upheaval. Finally, longitudinal studies extending beyond 2023 will be essential to understand the long-term implications of the trends identified in this study. Given the relatively short timeframe of the COVID-19 pandemic, it remains to be seen whether the changes observed during these years will have lasting effects or if the industry will revert to pre-pandemic norms. As streaming platforms continue to shape listening behaviors and global events continue to influence artistic output, ongoing research will be crucial to keep pace with these changes and understand their impact on the musical landscape.

Conclusion

This study explores how musical trends on Spotify evolved from 2011 to 2023, revealing significant shifts in response to technological advancements and the COVID-19 pandemic. Pre-pandemic music was characterized by high energy and loudness, whereas the pandemic years (2020-2021) saw a trend toward more introspective, acoustic sounds, mirroring a global atmosphere of reflection. Post-pandemic, there was a resurgence in danceability and loudness, suggesting a return to socially engaging music. The clustering analysis even highlighted a unique group of softer, acoustic songs during the pandemic, emphasizing music's responsiveness to societal events. Key features like MFCCs and spectral contrast drove these shifts, reflecting evolving production methods. This analysis offers valuable insights for artists and industry players, helping anticipate future trends in popular music.

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