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# SPOTIFY USER BEHAVIOR ANALYSIS USING POWER BI

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*A Data Visualization and Insight Generation Project*

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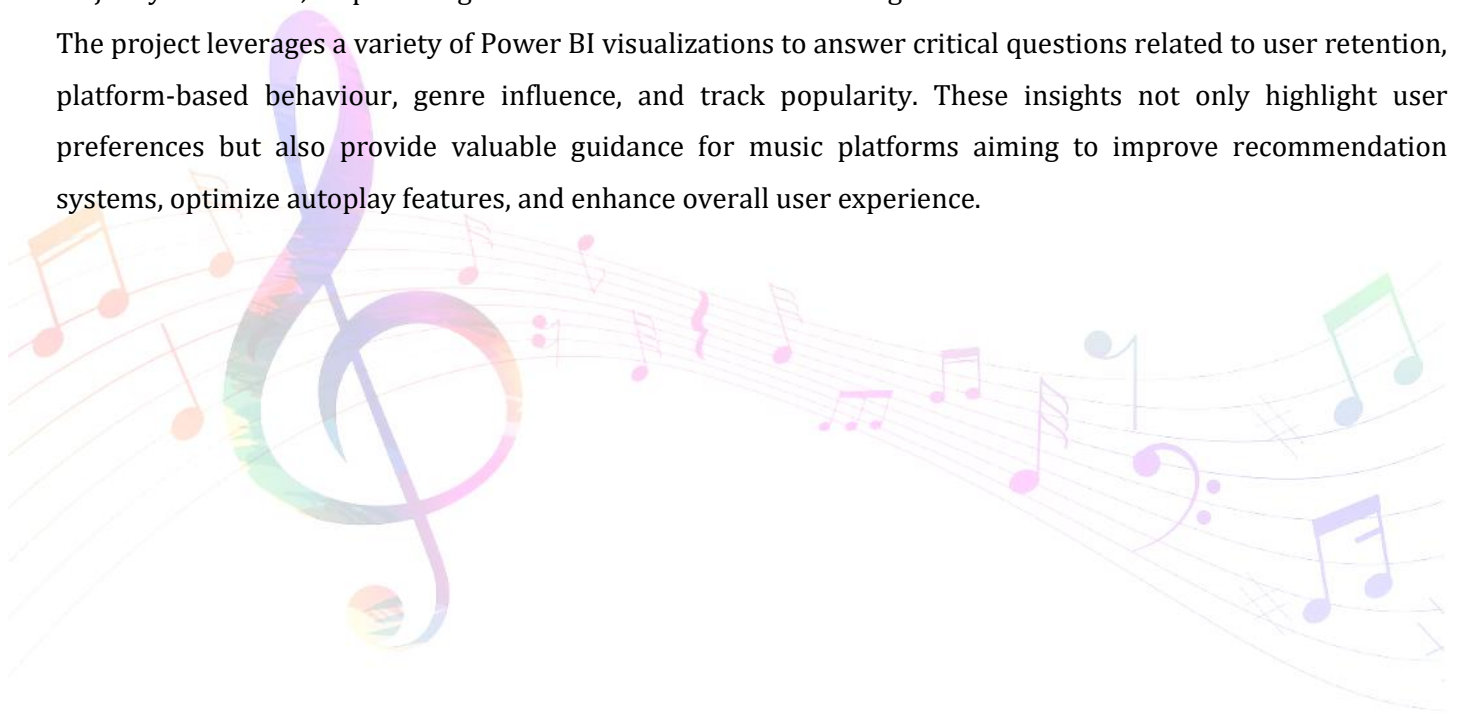
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## 2. Abstract:

This Power BI project presents an in-depth analysis of user engagement and listening behaviour using a dummy Spotify dataset sourced from Kaggle. The primary objective is to uncover actionable insights into how users interact with music content—focusing on artist popularity, skip rates, retention, listening patterns, and platform usage.

Key findings reveal that classic rock and alternative artists like The Beatles and The Killers dominate both play counts and total listening time. Users demonstrate a strong preference for manual song selection over autoplay, which directly correlates with lower skip rates and higher retention. Peak engagement occurs during morning and evening hours, especially mid-week, while Android devices account for the overwhelming majority of streams, emphasizing the dominance of mobile listening.

The project leverages a variety of Power BI visualizations to answer critical questions related to user retention, platform-based behaviour, genre influence, and track popularity. These insights not only highlight user preferences but also provide valuable guidance for music platforms aiming to improve recommendation systems, optimize autoplay features, and enhance overall user experience.



### 3. Table of Contents

1. Title Page & Cover	
2. Abstract .....	1
3. Table of Contents .....	2
4. Introduction .....	5
4.1 Project Overview .....	5
4.2 Objectives .....	5
5. Data Description .....	6
5.1 Dataset Source & Acquisition .....	6
5.2 Dataset Characteristic .....	6
6. Methodology .....	7
6.1 Data Import and Cleaning .....	7
6.2 Data Modelling .....	7
6.3 Exploratory Data Analysis (EDA) .....	7
6.4 Dashboard Design and Visualization .....	8
6.5 Insight Derivation .....	8
7. From Data to Discovery: Visualizing the Hidden Layers of Listener Behavior .....	9
7.1 Track Information .....	9
7.2 Playback Details .....	9
7.3 Platform & Device Data .....	10
7.4 Temporal Dimension .....	10
7.5 Engagement Metrics .....	10
8. User Engagement case study for “Spotify” platform .....	11
8.1 User Engagement Insights: Top Artists & Peak Listening Time .....	11
8.1.1 Which Artists Keep Listeners Engaged the Longest? .....	11
8.1.2 When Do People Listen to Music the Most? .....	12
8.2 Decoding Spotify Listening Patterns: Track Popularity, Skip Rates & Music Eras .....	13

8.2.1 Ranking the Most Popular Tracks .....	13
8.2.2 The Science Behind Skips .....	14
8.2.3 What Decades Dominate Listening Habits? .....	15
8.3 Understanding Track Skipping & Retention Across Platforms .....	17
8.3.1 Do Some Platforms Encourage More Skipping? .....	17
8.3.2 The Impact of Autoplay vs. Manual Selection .....	18
8.3.3 How Many Tracks Are Fully Played? .....	18
8.4 The Influence of Autoplay vs. Manual Selection on Track Retention .....	21
8.4.1: Does Autoplay Keep Listeners Engaged? .....	21
8.4.2: How Does Manual Selection Affect Retention? .....	22
8.5 The Evolution of Music Consumption: A Deep Dive into Track Playback Trends .....	24
8.5.1 The Reign of Mobile Streaming .....	24
8.5.2 The Power of Tracks and Artists .....	24
8.6 Decoding Music Popularity: Artists, Albums, and Tracks .....	27
8.6.1 The Most Popular Artists .....	27
8.6.2 The Albums That Define Listening Habits .....	28
8.6.3 The Songs That Keep Playing .....	29
8.7 Music Streaming Analysis: Skips, Platforms & Listening Behavior .....	30
8.7.1 The Skip Phenomenon .....	30
8.7.2 Where Are People Listening? .....	31
8.7.3 Tracking Listening Behavior Over Time .....	32
8.7.4 How Many Artists Are in the Mix? .....	33
8.8 Music Streaming Analysis: Play Duration, Artist Popularity & Listening Trends .....	34
8.8.1 How Long Do Users Listen? .....	34
8.8.2 Which Artists Get the Most Playtime? .....	35
8.8.3 Listening Trends Over Time .....	36
8.8.4 Why Do Tracks End? .....	37
8.9 Music Listening Behavior: Skipping, Shuffle, Usage & Track Lengths .....	38
8.9.1: Do Users Skip Tracks? .....	38
8.9.2 How Many Songs Were Played on Shuffle? .....	39
8.9.3 How Long Are the Played Tracks? .....	40

8.10 Music Listening Behavior: Artists & Skipping Trends .....	41
8.10.1 Who Are the Most Played Artists? .....	41
8.10.2 How Many Tracks Were Skipped? .....	42
8.10.3 How Has Skipping Behavior Changed Over Time? .....	43
9. Discussion .....	44
9.1 Interpretation of Findings .....	44
9.1.1 Listener Preferences Are Artist-Driven but Genre-Inclusive .....	44
9.1.2 Manual Selection Increases Engagement .....	44
9.1.3 Peak Listening Times Reflect Daily Routines .....	44
9.1.4 Platform Usage Influences Behaviour .....	44
9.1.5 Skip Behaviour Indicates Selective Listening .....	44
9.1.6 Shuffle Mode and Long Tracks Still Engage Users .....	44
10. Future Work / Potential .....	46
10.1 Incorporating User Demographics .....	46
10.2 Sentiment Analysis on Lyrics or User Feedback .....	46
10.3 Predictive Modelling .....	46
10.4 Real-Time Data Integration .....	46
10.5 Enhanced Genre & Mood Analysis .....	47
10.6 Cross-Platform Behaviour Analysis .....	47
10.7 Integration with Subscription and Ad Interaction Data .....	47
11. Conclusion .....	48
12. Analyst Profile .....	49

## 4. Introduction

### 4.1 Project Overview

In the age of digital streaming, understanding user behaviour is crucial for enhancing platform engagement and delivering personalized experiences. This project utilizes Power BI to uncover patterns in music consumption, user engagement, and platform-specific behaviours through a series of interactive dashboards and data visualizations.

By leveraging Power BI's data modelling and DAX capabilities, the analysis covers a broad range of listener activities, including track skipping, retention rates, popular artists and albums, listening trends over time, platform usage, and the impact of autoplay versus manual selection. The findings offer a comprehensive view of how users interact with music streaming platforms and what factors contribute to deeper engagement or track abandonment.

### 4.2 Objectives

The main objectives of this project are as follows:

- To analyse **user listening behaviour** based on time of day, day of the week, and platform used.
- To identify **top-performing artists, albums, and tracks** based on play duration and frequency.
- To examine **skip rates and retention trends** in relation to how a track was initiated (autoplay vs. manual).
- To assess the influence of **platforms (Android, iOS, Windows, etc.)** on user engagement and skip behaviour.
- To explore **genre and decade preferences**, determining which types of music resonate most with users.
- To draw meaningful insights that can help music platforms **optimize recommendations, reduce skip rates**, and enhance the overall user experience.



## 5. Data Description

### 5.1 Dataset Source & Acquisition

The dataset used in this project was downloaded from **Kaggle.com**, where it was published by **Malinga Rajapaksha**. This dataset simulates Spotify streaming activity and includes detailed logs of track plays, user interactions, and playback characteristics. It was selected for its richness in behavioural attributes and its suitability for exploring user engagement patterns within a music streaming context.

### 5.2 Dataset Characteristics

The dataset comprises multiple fields that capture user interaction with the streaming platform. Key attributes include:

- **Track Metadata:** Track name, artist name, album name, release date, and genre.
- **User Interaction Metrics:** Milliseconds played, reason for track start, reason for track end, skip status, and shuffle status.
- **Playback Context:** Platform used (e.g., Android, iOS, Windows), device type, and whether the track was manually selected or autplayed.
- **Temporal Data:** Timestamps indicating when each track was played, enabling time-based analysis of listening habits.
- **Engagement Indicators:** Retention rates, skip frequency, average play duration, and track rankings.

Together, these variables allow for a comprehensive analysis of listening behavior, platform preferences, content engagement, and skip patterns. The dataset's granularity and diversity make it ideal for constructing meaningful Power BI dashboards aimed at uncovering actionable insights into user behavior on streaming platforms.

## 6. Methodology

The methodology followed in this project is designed to transform raw streaming data into insightful, interactive dashboards using Power BI. The process involves multiple stages, including data acquisition, preprocessing, data modelling, and visualization. Each step is structured to extract meaningful patterns and answer specific analytical questions about user behaviour and music consumption.

### 6.1 Data Import and Cleaning

- The dataset was first imported into Power BI Desktop.
- Data types were reviewed and corrected where necessary (e.g., datetime formatting, numeric conversions).
- Missing or inconsistent values were identified and handled to ensure data integrity.
- Unnecessary columns were removed to streamline the analysis and improve performance.

### 6.2 Data Modelling

- Relationships were established between tables using primary and foreign keys.
- A star schema model was used where appropriate to maintain simplicity and efficiency.
- New calculated columns and measures were created using **DAX (Data Analysis Expressions)** for custom metrics like:
  - Average Play Duration
  - Skip Rate
  - Retention Rate
  - Rank of Tracks, Artists, and Albums
  - Categorization of music by decade and track length

### 6.3 Exploratory Data Analysis (EDA)

- EDA was performed through card visuals, bar charts, matrices, tables, and line graphs to uncover:
  - Listening trends over time
  - Popularity of tracks and artists
  - Platform usage patterns
  - Skip behaviour and retention
  - Preferred times and days for listening

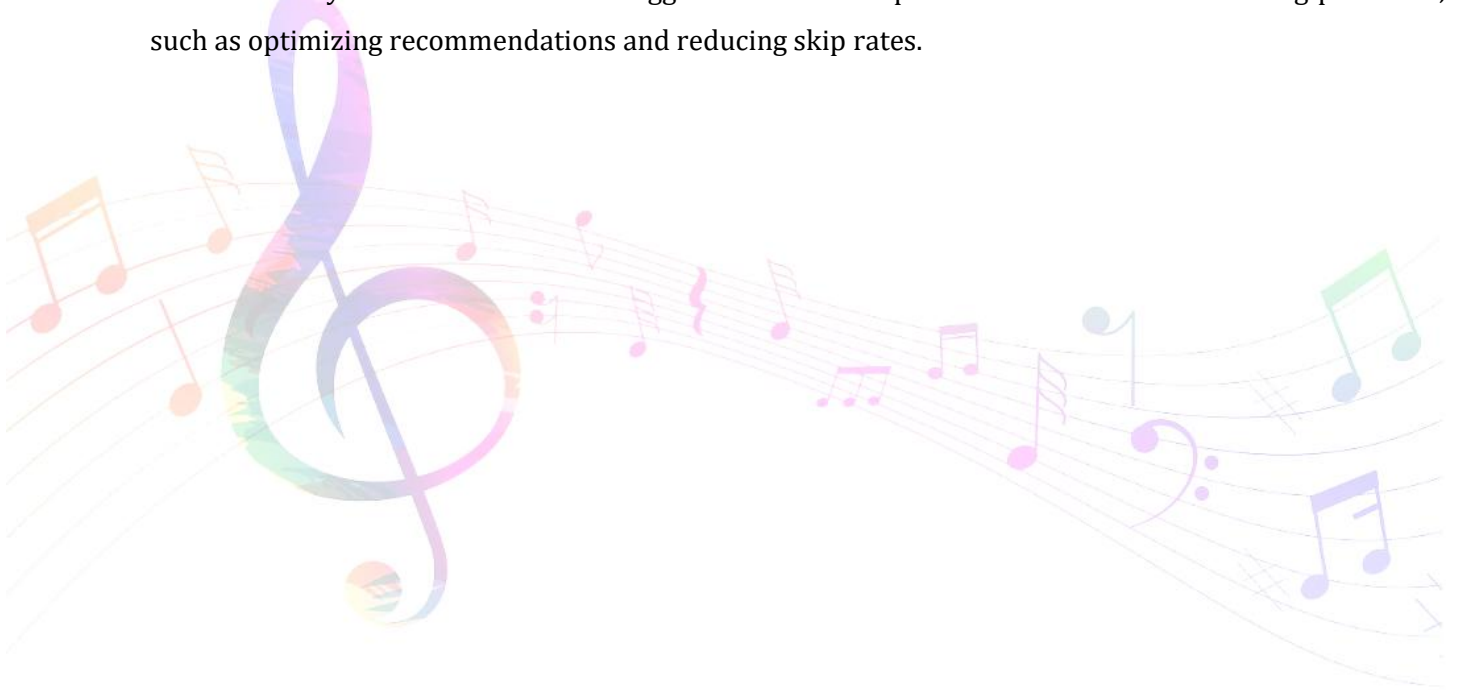


## 6.4 Dashboard Design and Visualization

- Interactive dashboards were built to present insights in a user-friendly format.
- Filters and slicers were added to allow dynamic exploration (e.g., by platform, artist, decade).
- Visualizations were aligned with specific business questions to ensure clarity and relevance.
- Consistent colour schemes, labels, and formatting were applied to enhance readability.

## 6.5 Insight Derivation

- Insights were drawn based on data patterns and visual representations.
- Observations were documented for each dashboard section to support conclusions.
- Final takeaways were formulated to suggest actionable improvements for music streaming platforms, such as optimizing recommendations and reducing skip rates.



## 7. From Data to Discovery: Visualizing the Hidden Layers of Listener Behavior

To extract actionable insights from streaming behaviour, it is essential to understand the various dimensions—or entities—within the dataset. These entities represent different aspects of the user interaction with music content and serve as the building blocks for visualization and analysis in Power BI.

Below are the key entities used in the project:

### 7.1 Track Information

This entity captures metadata related to each song, including:

- **Track Name**
- **Artist Name**
- **Album Name**
- **Release Date**
- **Track Duration**

These fields were used to identify the most popular songs and artists, analyze music trends across decades, and evaluate track playtime.

### 7.2 Playback Details

Playback details record the conditions under which each track was played. Attributes include:

- **Milliseconds Played**
- **Reason Start** (e.g., autoplay, manual click)
- **Reason End** (e.g., back button, end of track, unexpected exit)
- **Shuffle Status**
- **Skip Status**

These variables are crucial for analyzing **user retention**, **skip rates**, and **engagement patterns**.

### 7.3 Platform & Device Data

Understanding where users listen is just as important as what they listen to. This section includes:

- **Platform** (e.g., Android, iOS, Windows, Mac)
- **Device Type**

These fields enabled the creation of visuals that show **platform-specific behaviour**, identifying which devices have higher skip rates or longer listening durations.

## 7.4 Temporal Dimension

Time-based analysis reveals trends and usage cycles. This dimension includes:

- **Play Date**
- **Play Time (Hour of Day, Day of Week, Month, Year)**

Using this data, dashboards were built to uncover **peak listening hours, weekend vs. weekday behaviour,** and **seasonal trends** in music consumption.

## 7.5 Engagement Metrics

Derived fields and DAX measures were used to build advanced KPIs such as:

- **Average Play Duration per Track**
- **Retention Rate (%)**
- **Top 10 Rankings (Tracks, Albums, Artists)**
- **Track Classification by Length (Short, Medium, Long)**
- **Music Categorization by Decade**

These metrics were vital in drawing deeper insights and enhancing the analytical power of the visualizations.

By visualizing these entities, the project transforms raw streaming data into a compelling narrative about how, when, and why users engage with music. Each visual component plays a role in decoding the digital behaviour of listeners and revealing the hidden patterns behind their streaming choices.

# 8. User Engagement case study for “Spotify” platform

## 8.1 User Engagement Insights: Top Artists & Peak Listening Time

- ✓ Which artists have the highest average play duration (indicating deeper engagement).
- ✓ What times and days users are most active on Spotify (helping identify peak engagement hours).

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### 8.1.1 Which Artists Keep Listeners Engaged the Longest?

The line chart visualizes the average track play duration per artist, revealing the top artists that hold listener attention.

#### Observations:

- ✓ Cory Weeds (662 ms avg. play duration) ranks highest, showing that jazz listeners tend to play songs longer.
- ✓ Dan Lacksmann and Dave Matthews Band (645 ms, 642 ms) also rank high, suggesting that their music style encourages longer plays.

Artists with lower play durations (e.g., Les Ya Toupas Du Zaire - 537 ms) might indicate tracks that get skipped more frequently.

**Key Insight:** The genre and artist influence how long a track is played. Jazz and instrumental artists tend to have higher retention, while mainstream or high-energy tracks may see quicker skips.

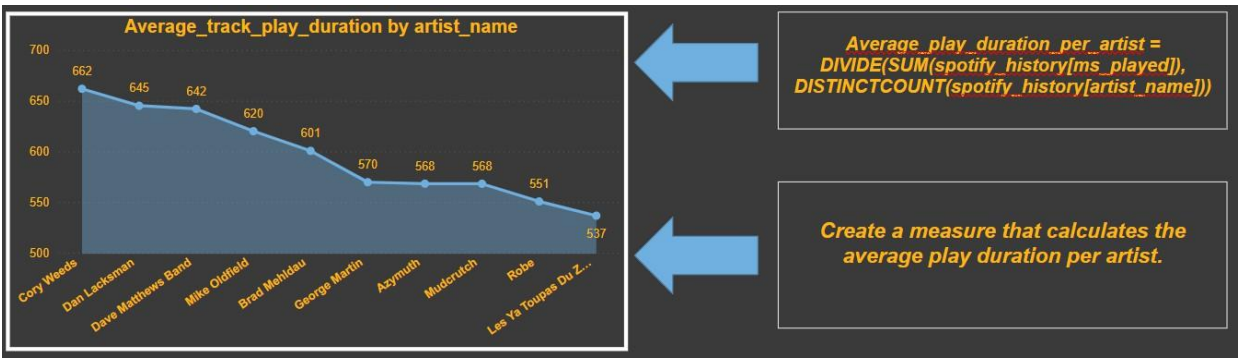


Figure 1: Average track play duration per artist with DAX measure for calculation

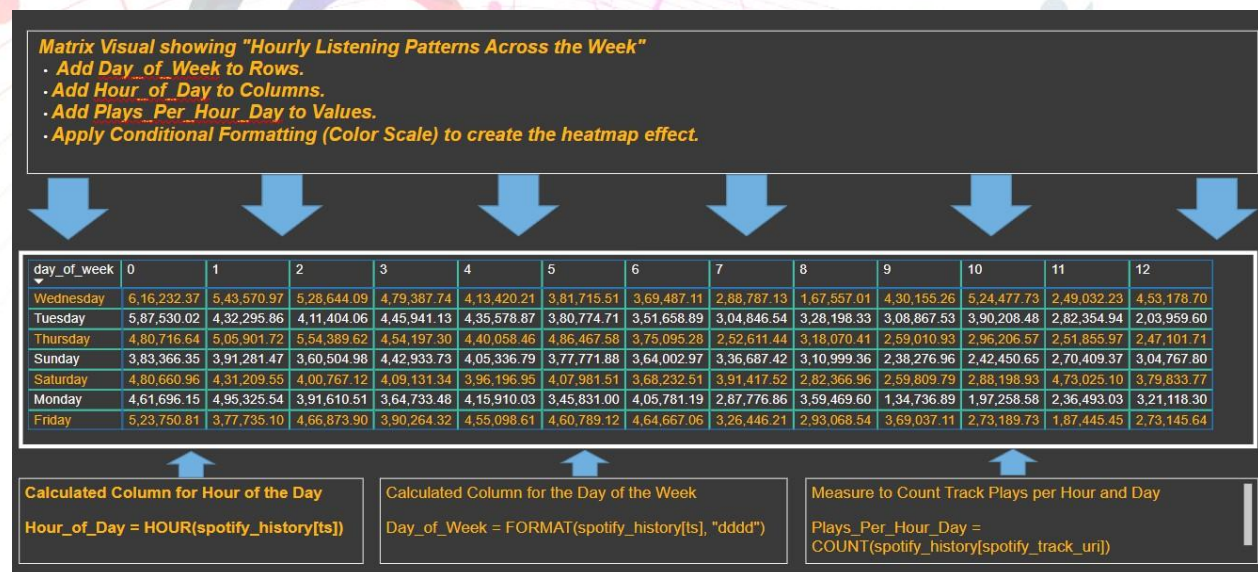
## 8.1.2 When Do People Listen to Music the Most?

The matrix provides a breakdown of track plays per hour and day of the week, showing when users are most engaged.

### Observations:

- ✓ Peak listening hours:
  - Mornings (6 AM - 9 AM) show increasing engagement as users start their day.
  - Evening hours (6 PM - 11 PM) are the busiest, likely when people relax or commute.
- ✓ Most active days:
  - Wednesday and Tuesday have the highest listening activity, suggesting midweek is a prime time for music streaming.
  - Sunday has the lowest activity, likely due to different weekend routines.

**Key Insight:** Listeners tend to play music during their daily routines, particularly in the evenings. Streaming peaks midweek, possibly due to work-related stress relief or background music usage.



**Figure 2: Hourly Listening Patterns Across the Week**



# 8.2 Decoding Spotify Listening Patterns: Track Popularity, Skip Rates & Music Eras

- ✓ Which songs are the most played and ranked highest?
- ✓ How does the reason a song starts influence whether it gets skipped?
- ✓ What era of music dominates user listening habits?

This data-driven journey will help us understand listener engagement, song preferences, and what factors contribute to track skips.

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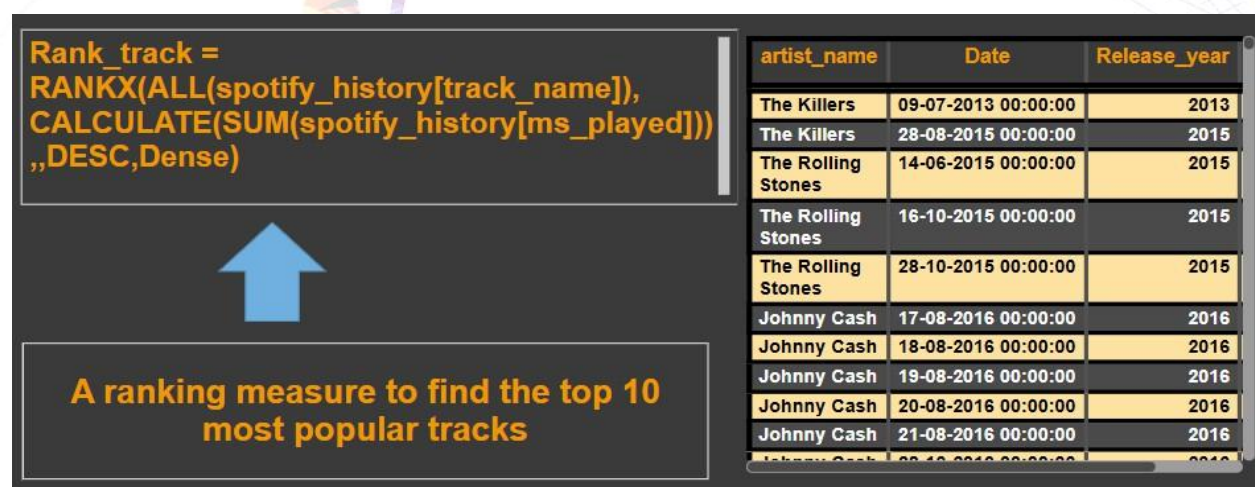
## 8.2.1 Ranking the Most Popular Tracks

The ranking measure (Rank\_track) is used to find the top 10 most popular tracks based on the total play duration (ms\_played). The table visual reveals that The Killers, The Rolling Stones, and Johnny Cash dominate the top spots.

### Observations:

- ✓ The Killers and The Rolling Stones have multiple entries in the top 10, showing strong listener engagement.
- ✓ Johnny Cash appears frequently, indicating a high play rate for classic country music.

**Key Insight:** Popularity isn't just about modern hits—classic rock and country legends continue to capture listener interest.



**Figure 3:** Ranking measure to identify the top 10 most popular artist



## 8.2.2 The Science Behind Skips

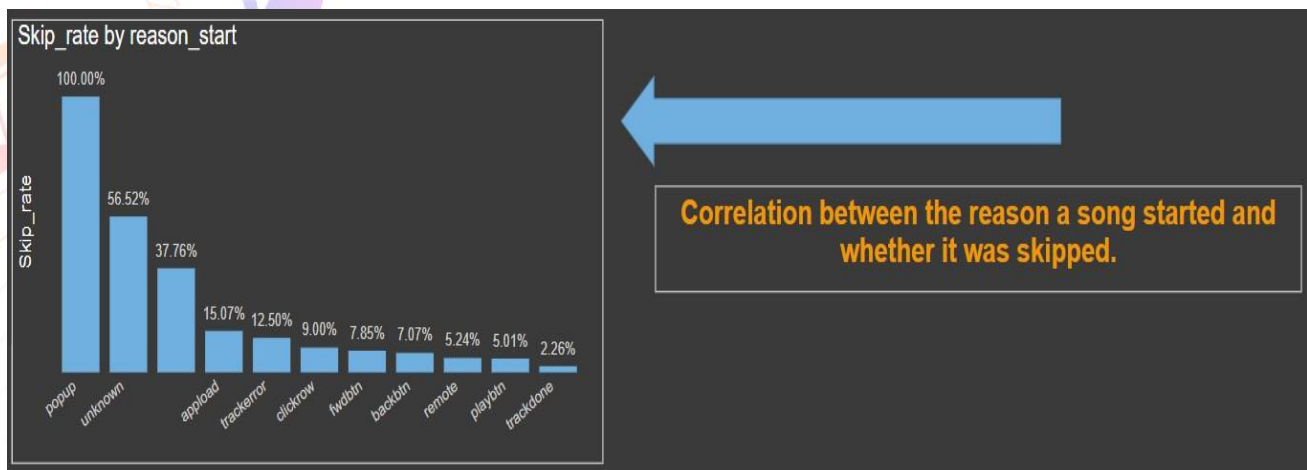
The bar chart visualizes the skip rate by reason\_start, showing why users abandon songs.

### **Observations:**

Popup autoplay has a 100% skip rate, meaning listeners frequently reject automatically played songs.

- ✓ Unknown starts (56.52%) and uploaded tracks (37.76%) also have high skip rates, suggesting a lower engagement with randomly triggered music.
- ✓ Manual selections (clickrow, trackerror, etc.) have much lower skip rates (~5-12%), indicating that users are more likely to finish songs they actively choose.

**Key Insight:** User-initiated plays lead to lower skip rates, while auto-played and unexpected tracks are skipped the most.



**Figure 4:** Correlation between the reason a song started and whether it was skipped

### 8.2.3 What Decades Dominate Listening Habits?

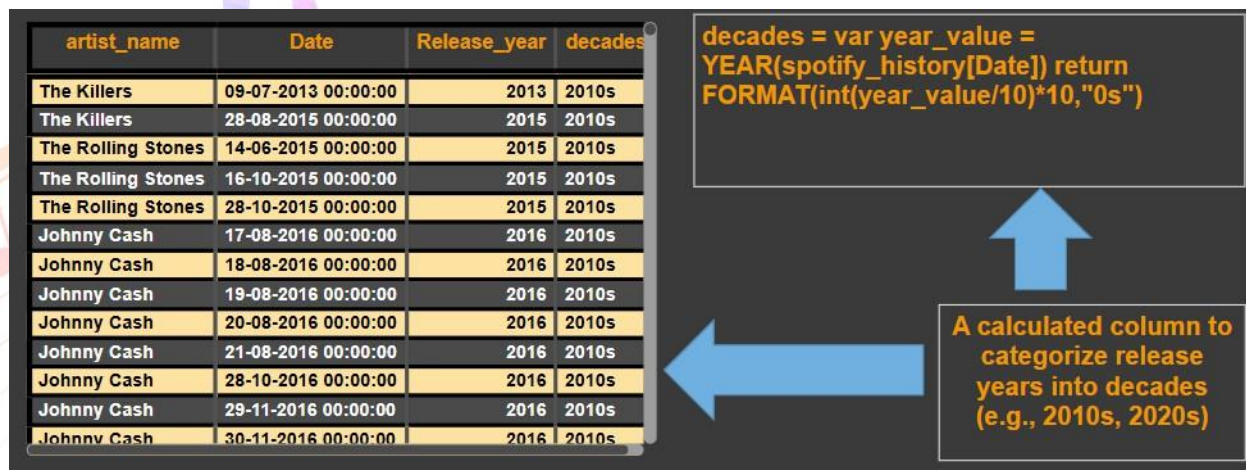
The calculated column categorizing tracks by decade helps identify which music eras are most played.

#### **Observations:**

The dataset focuses on 2010s tracks, as seen in the table.

- ✓ Classic rock (Rolling Stones) and country (Johnny Cash) are still highly ranked, proving that older music remains relevant.

**Key Insight:** Listeners don't just consume modern music; classic hits continue to be a major part of their playlists.



artist_name	Date	Release_year	decades
The Killers	09-07-2013 00:00:00	2013	2010s
The Killers	28-08-2015 00:00:00	2015	2010s
The Rolling Stones	14-06-2015 00:00:00	2015	2010s
The Rolling Stones	16-10-2015 00:00:00	2015	2010s
The Rolling Stones	28-10-2015 00:00:00	2015	2010s
Johnny Cash	17-08-2016 00:00:00	2016	2010s
Johnny Cash	18-08-2016 00:00:00	2016	2010s
Johnny Cash	19-08-2016 00:00:00	2016	2010s
Johnny Cash	20-08-2016 00:00:00	2016	2010s
Johnny Cash	21-08-2016 00:00:00	2016	2010s
Johnny Cash	28-10-2016 00:00:00	2016	2010s
Johnny Cash	29-11-2016 00:00:00	2016	2010s
Johnny Cash	30-11-2016 00:00:00	2016	2010s

```
decades = var year_value =  
YEAR(spotify_history[Date]) return  
FORMAT(int(year_value/10)*10,"0s")
```

A calculated column to categorize release years into decades (e.g., 2010s, 2020s)

**Figure 5:** Categorization of music tracks by release decade to identify popular music eras

#### **Key Takeaways:**

- ✓ The Killers, The Rolling Stones, and Johnny Cash dominate popular track rankings, showing that both modern and classic artists retain listener engagement.
- ✓ High skip rates for autoplayed and unknown tracks suggest that listener control plays a crucial role in engagement.
- ✓ Music from the 2010s is prevalent, but older classics continue to have a strong presence in user preferences.

**Final Thought:**

Understanding these trends can help music platforms optimize recommendations, reduce skip rates, and enhance user experience.



## 8.3 Understanding Track Skipping & Retention Across Platforms

- ✓ Which platforms have the highest track skip rates?
- ✓ How do autoplay and manual selection influence track engagement?
- ✓ What percentage of songs are fully played (retention rate)?

By decoding these insights, we can understand user preferences and platform-specific behaviors.

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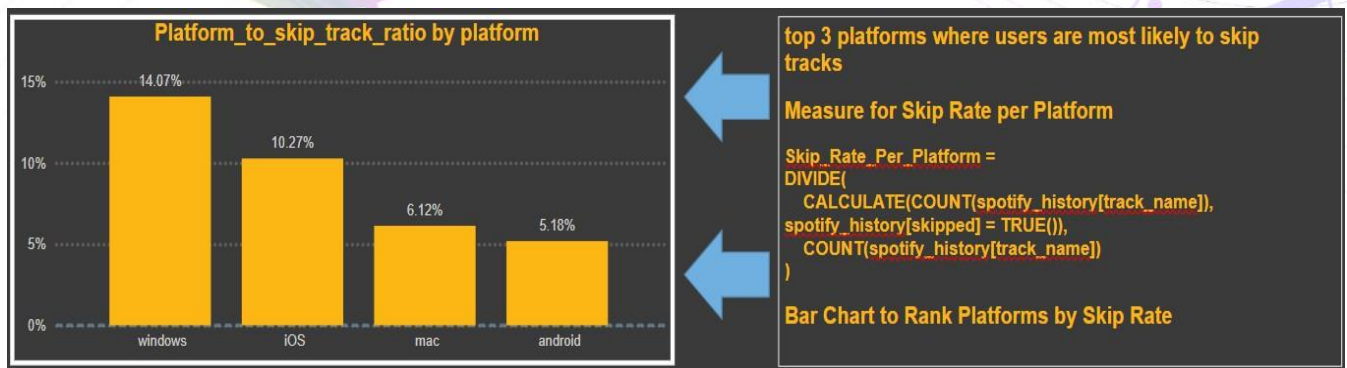
### 8.3.1 Do Some Platforms Encourage More Skipping?

The bar chart visualizes the platform-to-skip-track ratio, ranking platforms by how often users skip tracks.

#### Observations:

- ✓ Windows users skip the most (14.07%), followed by iOS (10.27%).
- ✓ Mac (6.12%) and Android (5.18%) users show lower skip rates, suggesting a more engaged audience.

**Key Insight:** Desktop users (Windows & Mac) might skip more due to multitasking, while mobile users tend to let tracks play longer.



**Figure 6:** Bar Chart to Rank Platforms by Skip Rate

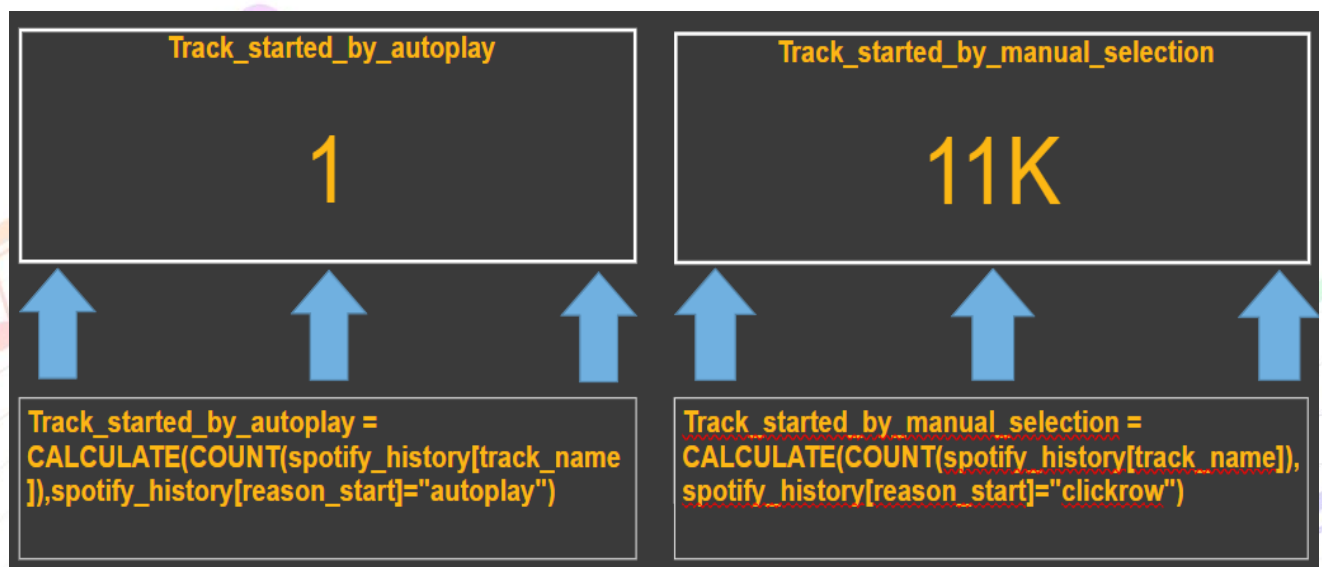
### 8.3.2 The Impact of Autoplay vs. Manual Selection

The number of tracks started by autoplay and manual selection reveals how users initiate playback.

#### **Observations:**

- ✓ Autoplay triggered only 1 track, showing minimal reliance on auto-started music.
- ✓ Manual selection (clickrow) accounts for 11K tracks, indicating that most users prefer choosing their own music.

**Key Insight:** Users prefer actively selecting songs, rather than passively consuming autoplayed content.



**Figure 7:** Track started (Autoplay Vs. Manual Selection)

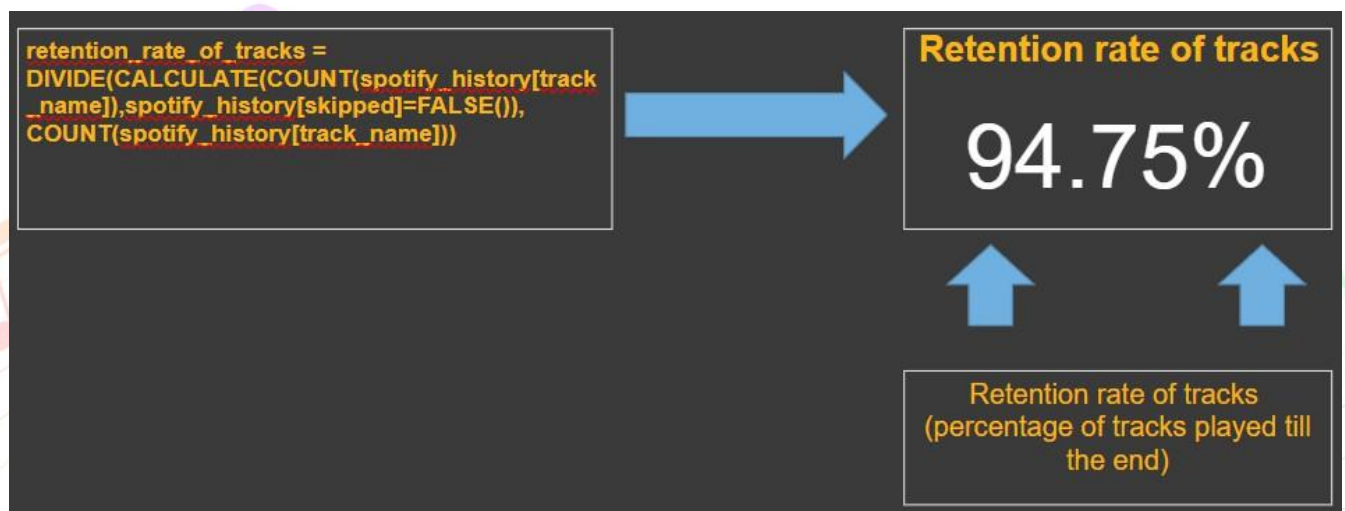
### 8.3.3 How Many Tracks Are Fully Played?

The retention rate of tracks is displayed as 94.75%, showing the percentage of songs played till the end.

#### **Observations:**

- ✓ With a high retention rate, most tracks are listened to in full rather than skipped.
- ✓ This contrasts with the earlier skip rate insights, suggesting that when users do pick a song, they tend to commit to it.

**Key Insight:** While skipping is common, once a track starts, users are highly likely to finish it.



**Figure 8:** Retention rate of tracks

#### **Key Takeaways:**

- ✓ Windows and iOS users skip tracks the most, while Android and Mac users tend to be more engaged.
- ✓ Manual selection dominates (11K plays) over autoplay (only 1 track started), proving that users want control over what they listen to.
- ✓ Despite skipping behavior, the overall retention rate is high (94.75%), meaning most played tracks are completed.



**Final Thought:**

These insights can help music platforms optimize recommendations and autoplay features to better match user behavior.



## 8.4 The Influence of Autoplay vs. Manual Selection on Track Retention

The way a track is started—whether through autoplay or manual selection—can significantly impact whether listeners stick with it or skip it. This analysis explores how different start methods affect track retention rates and what this means for user behavior.

### 8.4.1: Does Autoplay Keep Listeners Engaged?

The retention rate for autoplay is 0%, meaning that every track that started via autoplay was skipped before completion.

#### **Observations:**

- ✓ No autoplay tracks were fully played, suggesting that users are highly likely to skip tracks that they didn't choose themselves.
- ✓ This aligns with previous findings, where users tend to prefer manual track selection over autoplay.

**Key Insight:** Autoplay may not be an effective way to engage listeners, as they prefer having control over their music choices.

### 8.4.2: How Does Manual Selection Affect Retention?

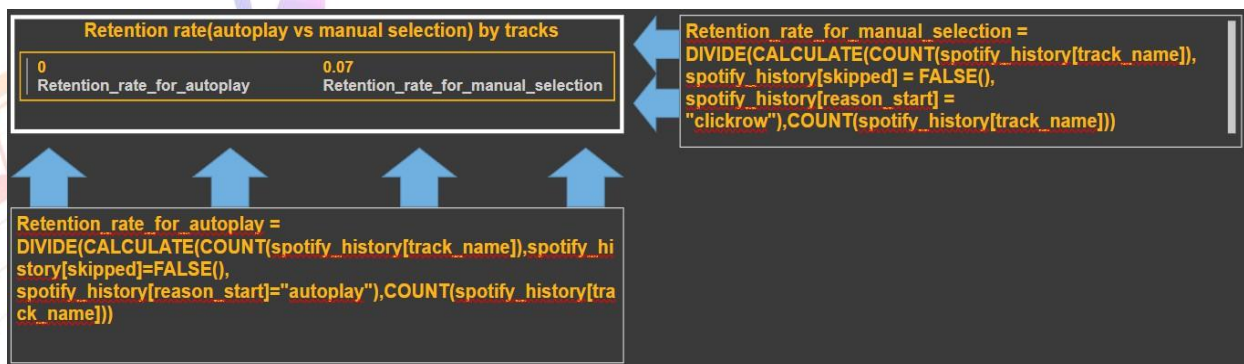
The retention rate for manually selected tracks is 7%, indicating that users who pick songs themselves are more likely to listen to them fully.

#### Observations:

- ✓ While 7% may seem low, it's infinitely better than autoplay's 0%.
- ✓ This supports the earlier insight that listeners are more invested in songs they actively choose.

The trend suggests that recommendation algorithms should focus on making better suggestions before playback starts, rather than relying on autoplay.

**Key Insight:** Users are far more engaged when they select their own music. Personalized playlists and better song recommendations could improve retention.



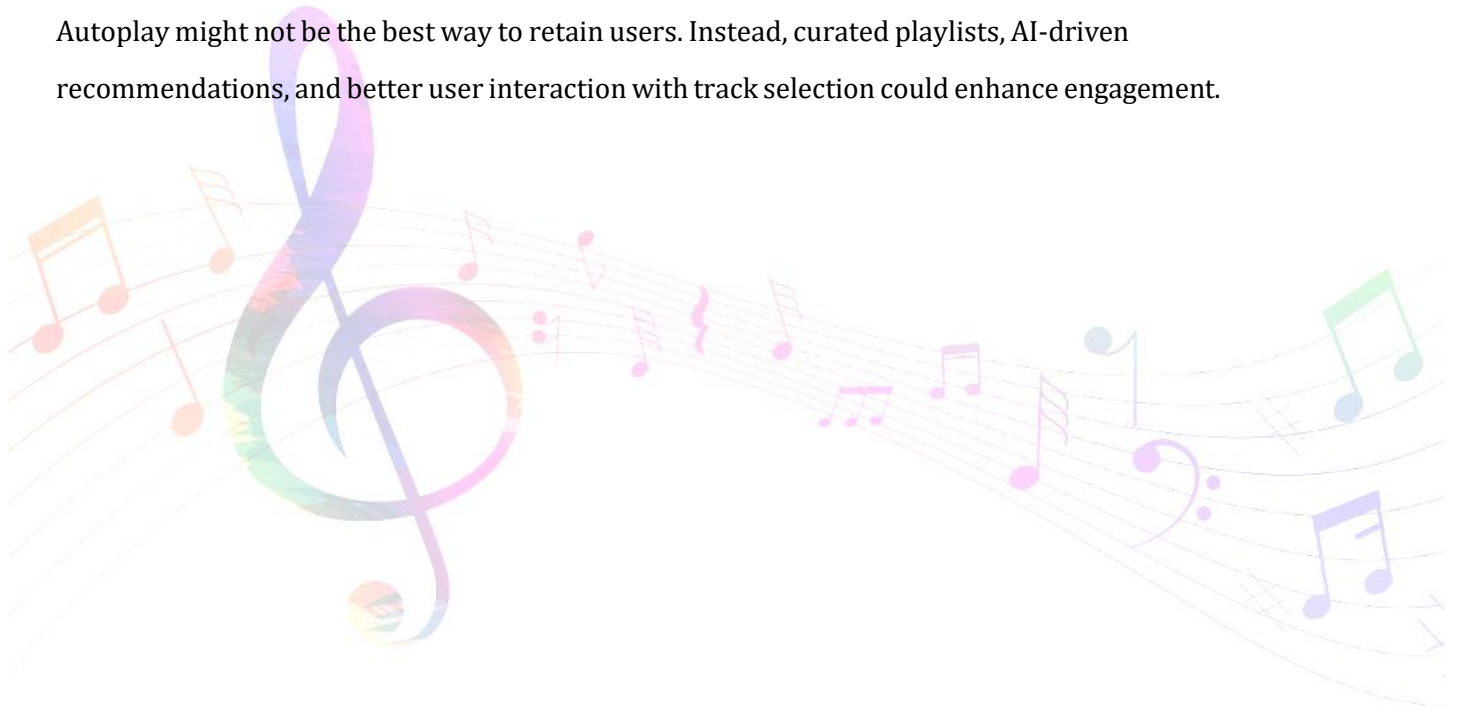
**Figure 9: Retention Rate (Autoplay Vs. Manual Selection) by track**

### **Key Takeaways:**

- ✓ Autoplay tracks have a 0% retention rate, showing that listeners don't engage with music that plays automatically.
- ✓ Manually selected tracks have a 7% retention rate, proving that users are more likely to finish songs they actively choose.
- ✓ Streaming platforms should focus on improving song recommendations before playback begins, rather than relying on autoplay to engage listeners.

### **Final Thought:**

Autoplay might not be the best way to retain users. Instead, curated playlists, AI-driven recommendations, and better user interaction with track selection could enhance engagement.



# 8.5 The Evolution of Music Consumption: A Deep Dive into Track Playback Trends

- ✓ In today’s digital streaming era, users engage with music across multiple devices. But which platform dominates the listening experience?
- ✓ Which artists and tracks are capturing the audience’s attention?

This analysis unveils key insights into music consumption habits based on platform usage and track preferences.

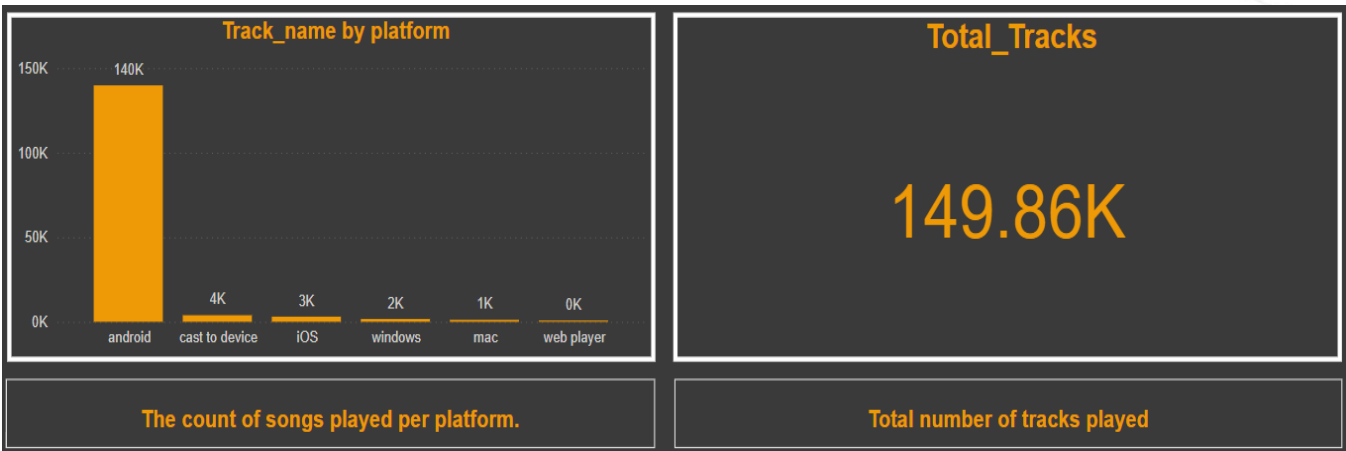
## 8.5.1 The Reign of Mobile Streaming

The bar chart highlights a staggering dominance of Android devices in music playback. Out of 149.86K total tracks played, a massive 140K were streamed on Android.

### Observations:

- ✓ Android dominates music playback with over 93% of total plays.
- ✓ Other platforms such as iOS (3K), Windows (2K), and Mac (1K) see significantly lower engagement.
- ✓ Web Player has 0 track plays, suggesting users prefer dedicated apps over browser-based streaming.

**Key Insight:** The overwhelming preference for Android devices indicates that mobile accessibility is crucial for music engagement. Streaming services should focus on optimizing their Android experience.



**Figure 10:** Distribution of songs plays across different platforms, highlighting Android as the most used device

## 8.5.2 The Power of Tracks and Artists

The data table showcases a diverse range of tracks, artists, and albums, shedding light on what users are listening to.

### Observations:

- ✓ Artists like Coldplay, Billie Eilish, David Bowie, and The Gaslight Anthem appear in the dataset, highlighting a mix of modern pop, alternative rock, and classic hits.
- ✓ Classical and jazz music also feature, with tracks from Louis Armstrong and María Grever showing variety in listener preferences.
- ✓ Some tracks, such as "Hit the Quan" by iLoveMemphis, hint at viral or trend-driven listening habits.

**Key Insight:** User engagement spans across multiple genres, from contemporary pop to classical and jazz, indicating a broad musical taste.



track_name	artist_name	album_name
"C" Jam Blues - Live At Symphony Hall, Boston, MA/1947	Coldplay	Music Of The Spheres
"Heroes" / "Helden" - 2001 Remaster	Billie Eilish	WHEN WE ALL FALL ASLEEP, WHERE DO WE GO?
"Hit the Quan" #HTQ	The Gaslight Anthem	Handwritten
"I Know"	Louis Armstrong	Satchmo At Symphony Hall 65th Anniversary: The Complete Performa
"Mucho, mucho" (Muñequita Linda)	David Bowie	'Heroes' / 'Helden' / 'Héros'
"Mucho, mucho" (Muñequita Linda)	iLoveMemphis	"Hit the Quan" #HTQ
"Siboney"	Trent Reznor and Atticus Ross	Challengers (Original Score)
"Volver" - Arr. Roberto Pansera	María Grever	50 Greatest Tracks
"Was He Slow?" - Music From The Motion Picture Baby Driver	María Grever	Plácido Domingo - Be My Love
	Ernesto Lecuona	50 Greatest Tracks
	Carlos Gardel	50 Greatest Tracks
	Kid Koala	Baby Driver (Music from the Motion Picture)

**Figure 11:** List of tracks with their respective artists and album names, showcasing a diverse range of musical genres.

### Key Takeaways:

- ✓ Android is the go-to platform for music streaming, accounting for 93% of total track plays.
- ✓ iOS, Windows, and Mac have significantly lower engagement, and web players see no activity.
- ✓ Users have a diverse taste in music, ranging from pop and rock to classical and jazz.
- ✓ Trending tracks and timeless classics coexist, showing how modern streaming caters to both new hits and evergreen favorites.



**Final Thought:**

With mobile streaming leading the way, platforms must prioritize mobile-first strategies to keep users engaged. Additionally, AI-driven recommendations should consider both current trends and evergreen music to enhance user satisfaction.



# 8.6 Decoding Music Popularity: Artists, Albums, and Tracks

- ✓ Music streaming trends reveal fascinating insights into listener preferences.
- ✓ Which artists dominate?
- ✓ Which albums resonate the most & which tracks are on repeat?

This analysis unveils the Top 10 most popular artists, albums, and tracks, highlighting what captivates listeners.

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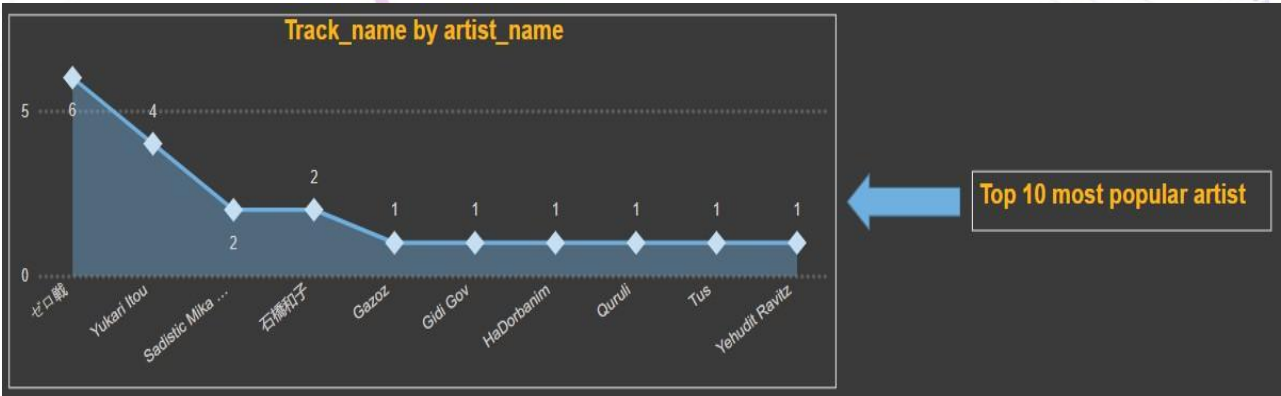
## 8.6.1 The Most Popular Artists

The top-left chart showcases the most-played artists, ranked by the number of tracks listened to.

### Observations:

- ✓ Yukari Itou tops the chart with 4 tracks played, followed by Sadistic Mika Band with 4 tracks.
- ✓ Other notable artists include Gazoz, Gidi Gov, and Yehudit Ravitz, each with one track in the top 10.

**Key Insight:** Yukari Itou and Sadistic Mika Band dominate listener preferences, suggesting a strong interest in their discography.



**Figure 12:** Top 10 most popular artist

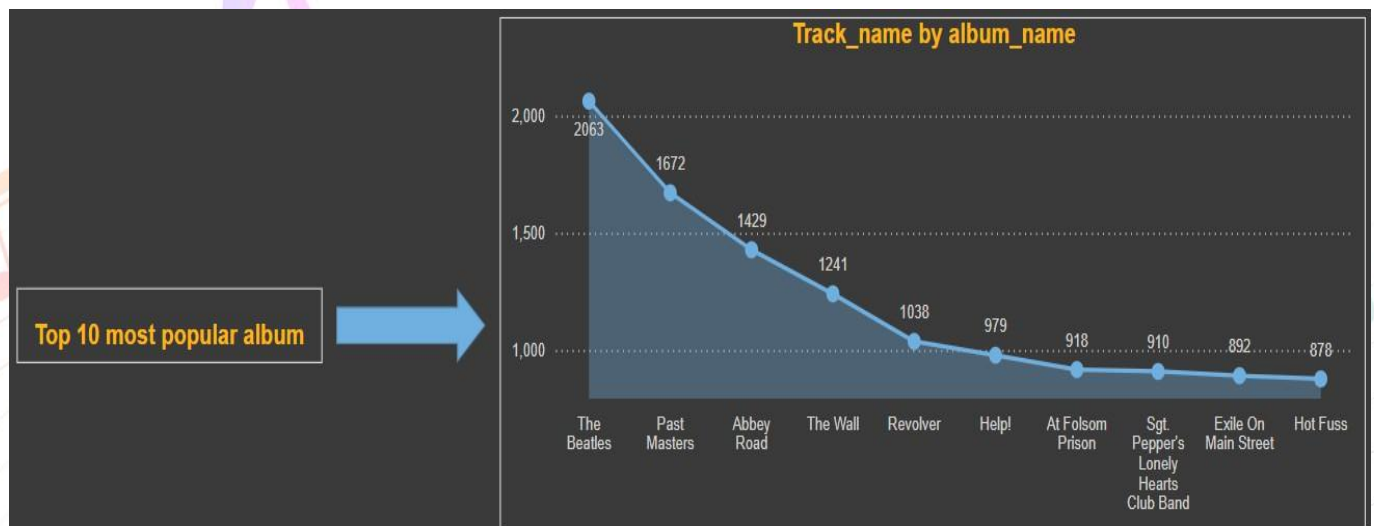
## 8.6.2 The Albums That Define Listening Habits

The middle-right chart reveals the Top 10 most popular albums, measured by track play count.

### Observations:

- ✓ The Beatles lead with 2,063 plays, followed by Past Masters (1,672 plays) and Abbey Road (1,429 plays).
- ✓ Classic albums dominate the list, including The Wall, Revolver, and At Folsom Prison.

**Key Insight:** Classic rock albums remain highly popular, showcasing their timeless appeal across generations.



**Figure 13:** Top 10 most popular album

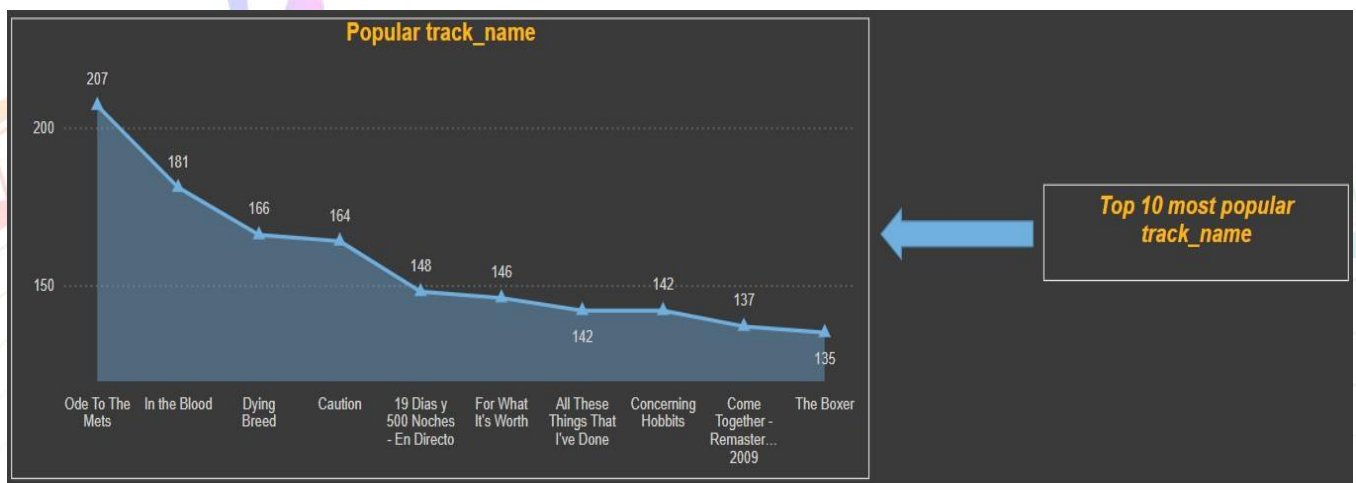
### 8.6.3 The Songs That Keep Playing

The bottom chart highlights the Top 10 most popular tracks, ranked by the number of times they've been played.

#### **Observations:**

- ✓ "Ode to the" is the most popular track, played 207 times.
- ✓ Other frequently played tracks include "In the Blood" (181 plays), "Dying Breed" (166 plays), and "Caution" (164 plays).
- ✓ The Beatles' "Come Together" also appears, reinforcing the band's dominance.

**Key Insight:** A mix of modern hits and classic rock tracks shapes listening habits, balancing nostalgia with contemporary favorites.



**Figure 14:** Top 10 most popular song tracks

#### **Final Takeaways:**

- ✓ Yukari Itou and Sadistic Mika Band are the most-played artists, suggesting niche but dedicated listener engagement.
- ✓ Classic albums from The Beatles and Pink Floyd dominate listening trends, proving their enduring appeal.
- ✓ Both modern and classic songs rank among the most-played tracks, indicating diverse musical tastes.

# 8.7 Music Streaming Analysis: Skips, Platforms & Listening Behavior

Review music streaming trends & investigate how often tracks are skipped, which platforms users prefer, and the diversity of artists in the dataset.

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## 8.7.1 The Skip Phenomenon

The top-left metric reveals that a staggering 149.86K tracks were skipped.

**Observations:**

- ✓ This is a significant number, implying users frequently move between tracks.
- ✓ Understanding why users skip songs (e.g., autoplay vs. manual selection, genre preference) could be valuable.

**Key Insight:** High skip rates might indicate dissatisfaction, discovery behavior, or a preference for certain types of songs.



**Figure 15:** Number of tracks skipped

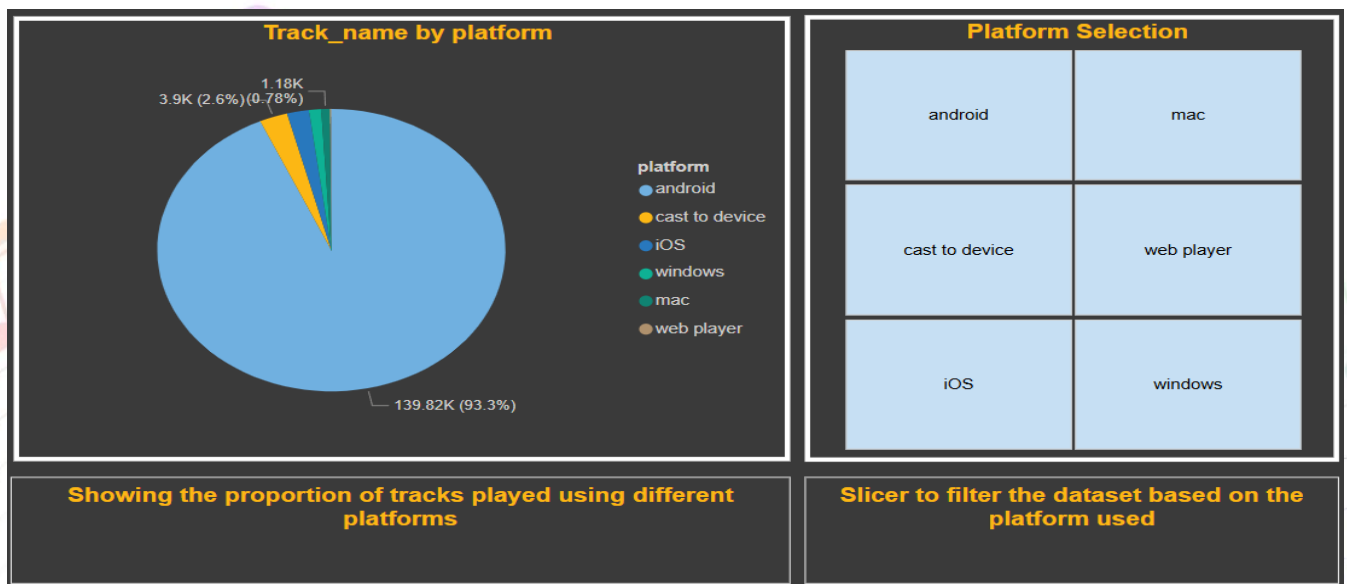
## 8.7.2 Where Are People Listening?

The pie chart in the top-center visualizes the proportion of tracks played per platform.

### **Observations:**

- ✓ Android dominates with 93.3% of all plays (139.82K tracks).
- ✓ Other platforms like iOS, mac, web player, and Windows contribute marginally.

**Key Insight:** Android users are the primary audience, so optimizing the music experience for this platform is crucial.



**Figure 16:** The proportion of tracks played using different platforms



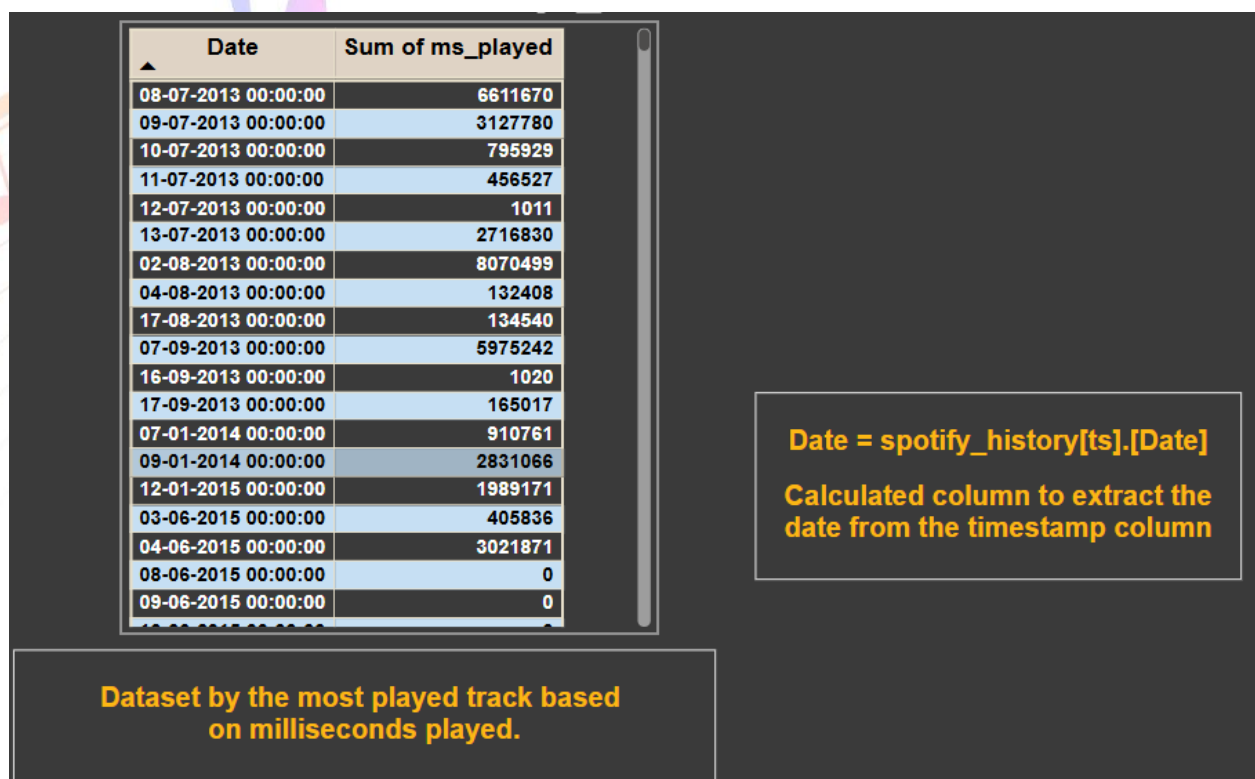
### 8.7.3 Tracking Listening Behavior Over Time

The bottom-left section presents dates and corresponding milliseconds played, showing track engagement over time.

#### Observations:

- ✓ Some days have significantly higher engagement (e.g., 08-07-2013 has the highest at 1.56 million milliseconds played).
- ✓ This might correlate with user activity patterns, such as weekends or holidays.

**Key Insight:** Analyzing spikes in engagement can help identify when users are most active and inform promotional strategies.



**Figure 17:** Most played track based on milliseconds

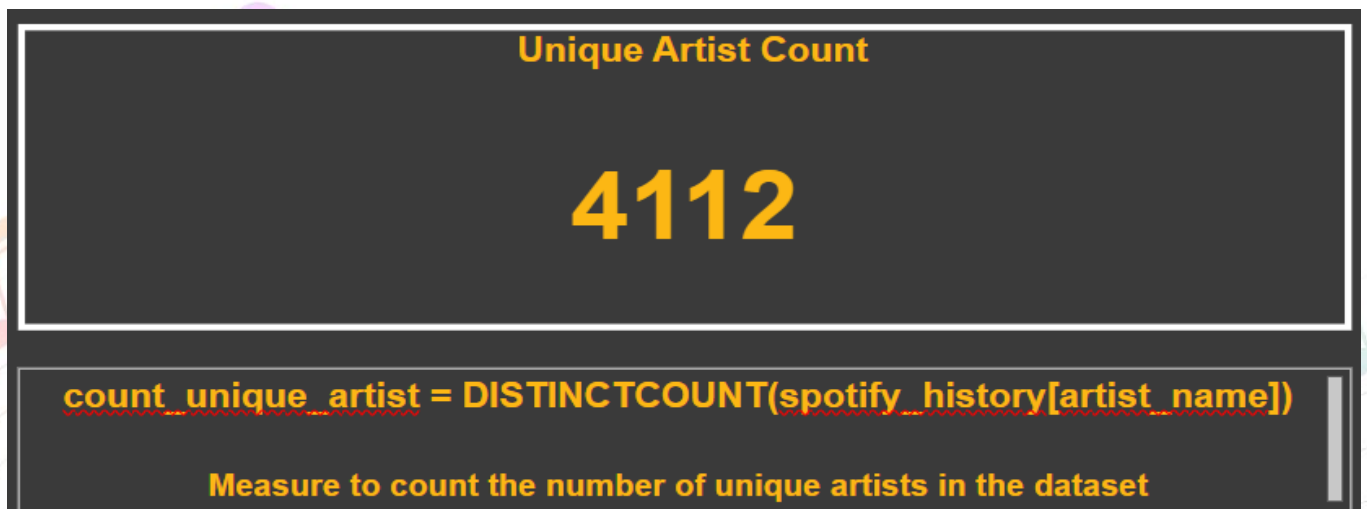
### 8.7.4 How Many Artists Are in the Mix?

The bottom-right metric reveals 4,112 unique artists in the dataset.

#### **Observations:**

- ✓ A wide variety of artists indicates a diverse music library.
- ✓ Identifying the most frequently played artists can help curate better recommendations.

**Key Insight:** Users are exploring a broad range of music, suggesting a need for personalized playlists and better song recommendations.



**Figure 18:** Count of unique artist in the dataset, highlighting the diversity of the user's music library.

#### **Final Takeaways:**

- ✓ Skip rates are high, indicating potential dissatisfaction or discovery-driven listening habits.
- ✓ Android is the dominant platform, so optimization efforts should prioritize this user base.
- ✓ Listening time varies by date, suggesting trends in user engagement.
- ✓ With over 4,000 unique artists, diversity in music selection is a key factor in user experience.

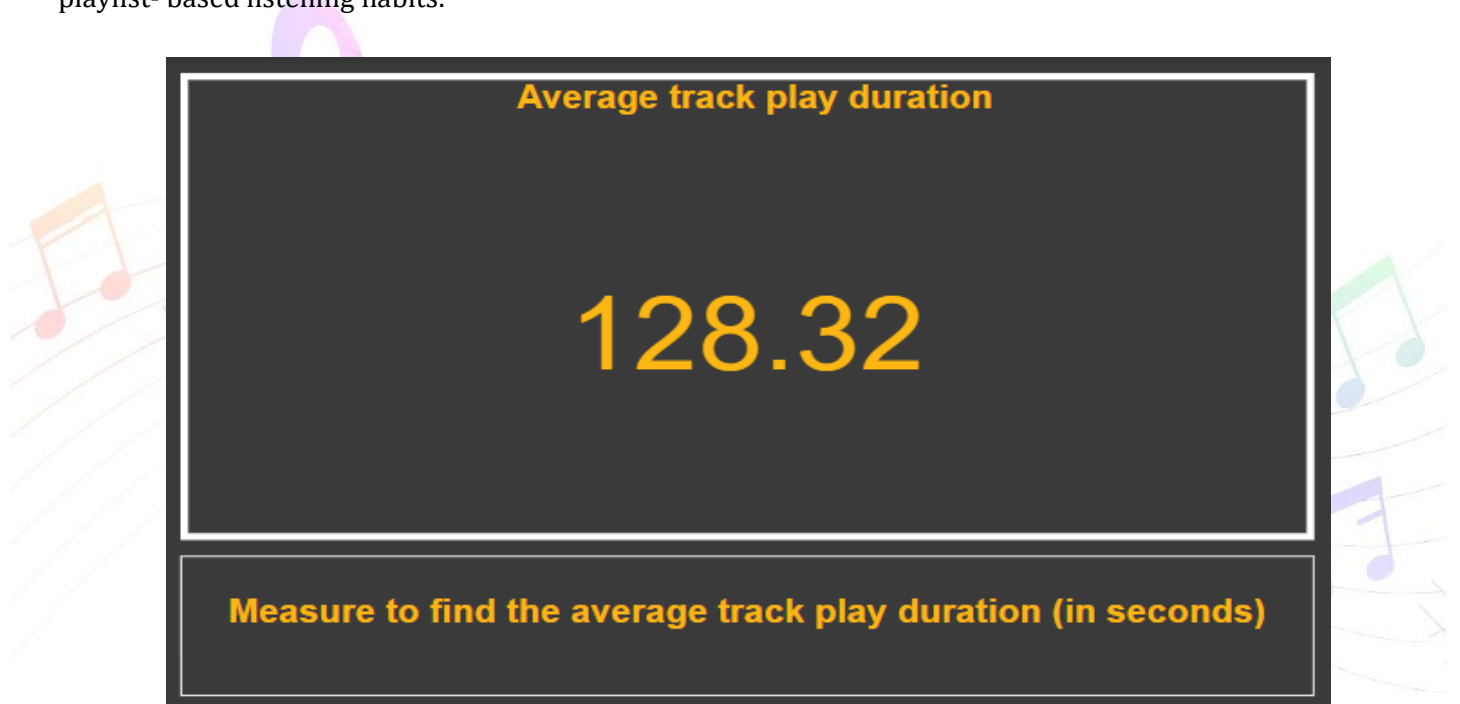
## 8.8 Music Streaming Analysis: Play Duration, Artist Popularity & Listening Trends

This dashboard provides deeper insights into listening habits, focusing on average play duration, most played artists, seasonal trends, and track-ending reasons.

### 8.8.1 How Long Do Users Listen?

- ✓ Average track play duration is 128.32 seconds (~2 minutes).
- ✓ This suggests many users might not complete full tracks or prefer shorter content.

Key Insight: Users engage for ~2 minutes per track, possibly indicating short attention spans or playlist-based listening habits.

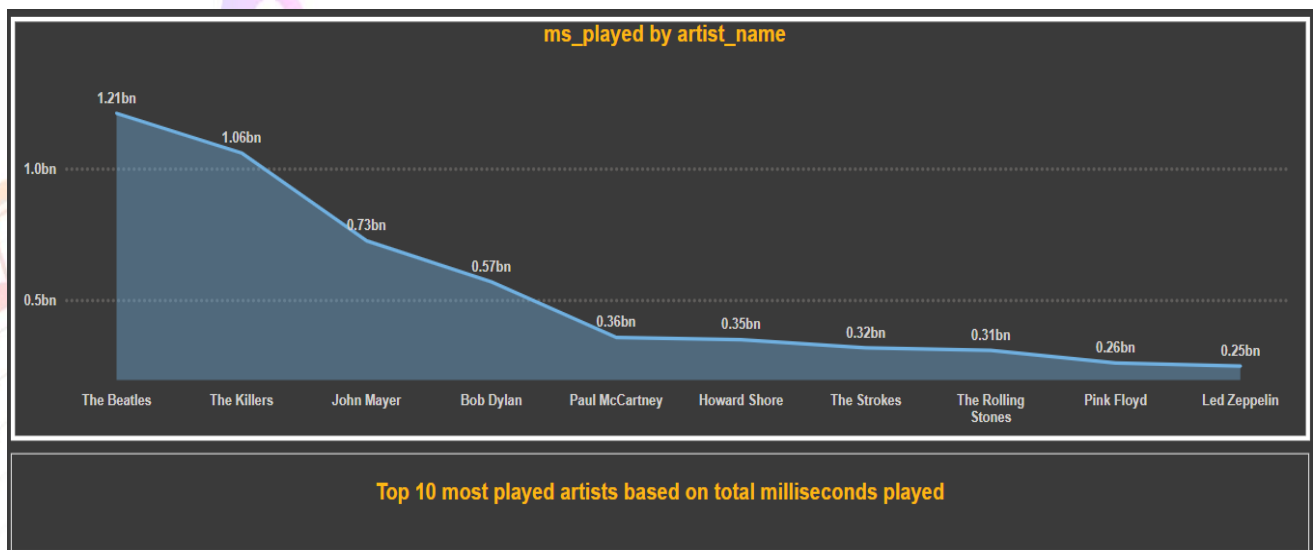


**Figure 19:** Average track play duration, providing insight into user listening habits.

## 8.8.2 Which Artists Get the Most Playtime?

- ✓ The most played artist (by total milliseconds played) is The Beatles (1.21 billion ms played).
- ✓ Other top artists:
  - The Killers – 1.06B ms
  - John Mayer – 0.73B ms
  - Bob Dylan – 0.57B ms
  - Paul McCartney – 0.36B ms

**Key Insight:** Classic rock and alternative artists dominate playtime, suggesting user preference for legacy and mainstream artists.

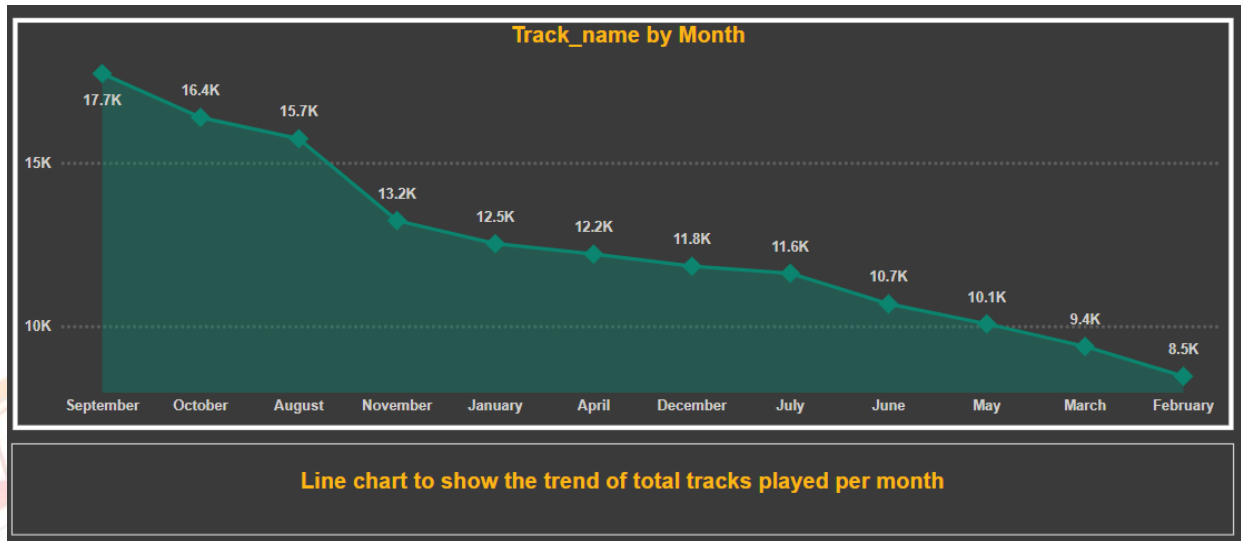


**Figure 20:** The most played artists based on total milliseconds played, highlighting the dominance of classic rock and alternative artists such as **The Beatles, The Killers and Bob Dylan.**

### 8.8.3 Listening Trends Over Time

- ✓ Peak months: September (18K plays) and October (16K plays).
- ✓ Declining trend in play counts from September to February (8K plays in February).

**Key Insight:** Music engagement drops post-holiday season—potentially due to lifestyle changes or seasonal music preferences.



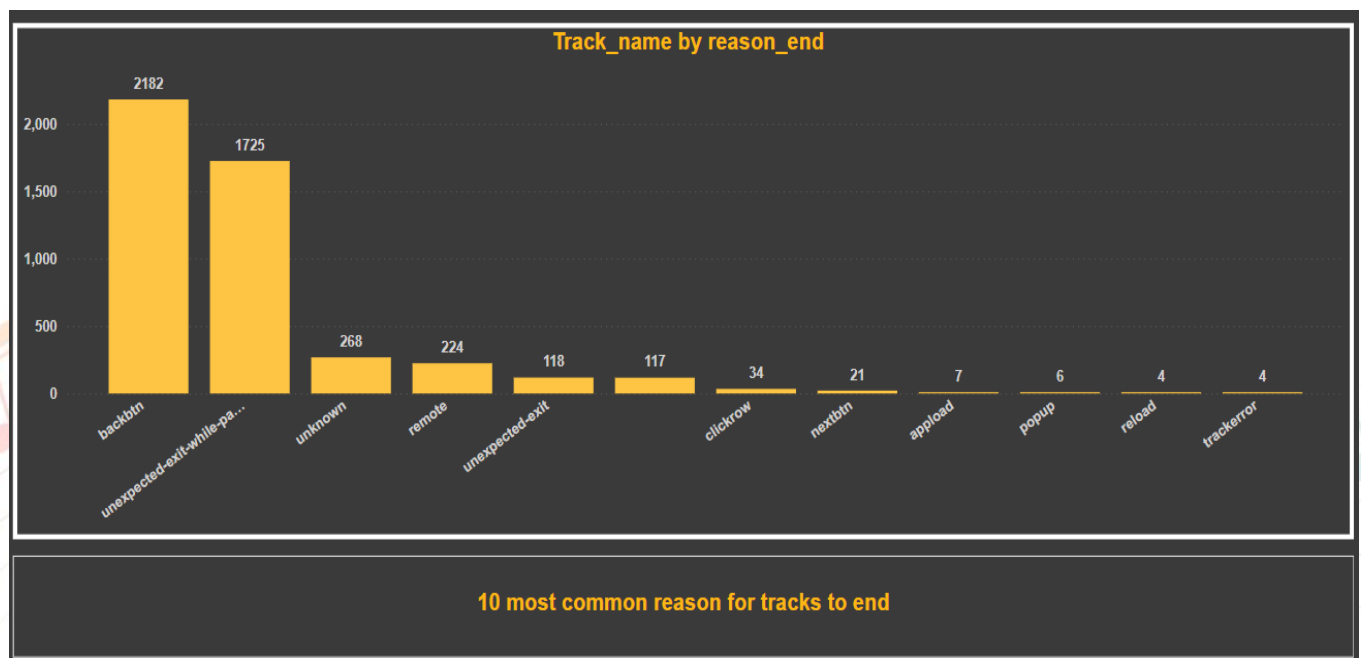
**Figure 21:** A line chart displaying the trend of total tracks played per month, showing gradual decline in listening activity over time.

## 8.8.4 Why Do Tracks End?

### ✓ Top 2 reasons:

- Backbutton (2.2K times) → Users manually skip songs.
- Unexpeted-exit-while-paused (1.7K times) → Possible autoplay stops or technical issues.

**Key Insight:** Manual skips (backbutton) are the dominant track-ending reason, reinforcing the high skip behaviour seen earlier.



**Figure 22:** A bar chart displaying the most common reasons for tracks ending, highlighting that manual skips (back buttons) are the dominant cause, reinforcing earlier insights on high skip behavior

### Final Takeaways:

- ✓ Users only engage for ~2 minutes per track, suggesting preference for short listening sessions.
- ✓ Classic rock and alternative artists receive the most total playtime.
- ✓ Music engagement declines after October, indicating seasonal trends in listening habits.
- ✓ Manual skips (backbutton) are the primary reason tracks end, emphasizing selective listening behavior.



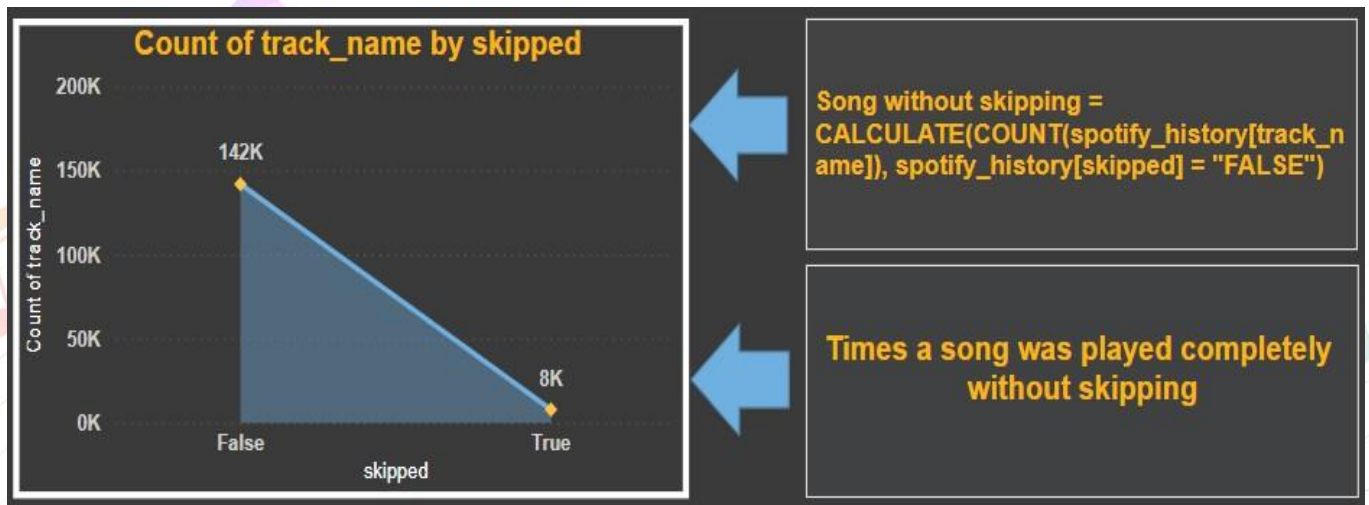
## 8.9 Music Listening Behavior: Skipping, Shuffle, Usage & Track Lengths

This dashboard explores track skipping behavior, shuffle mode usage, and song length classification to understand user listening habits.

### 8.9.1: Do Users Skip Tracks?

- ✓ 142K tracks were played without skipping, while 8K tracks were not fully played.
- ✓ This suggests that the vast majority of tracks are skipped at some point.

**Key Insight:** Users frequently skip tracks, reinforcing short attention spans or selective listening.

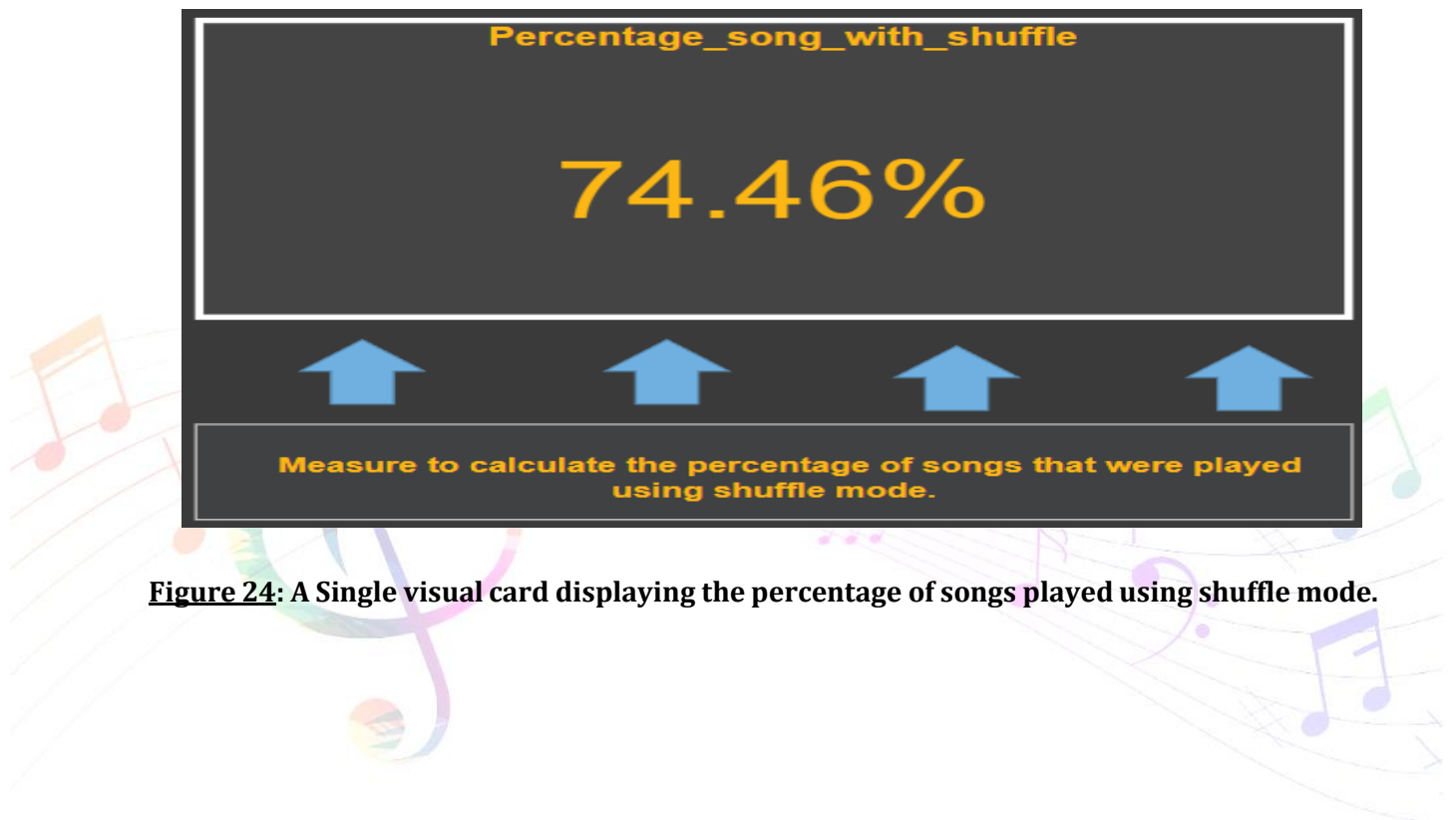


**Figure 23:** A line chart showing the count of tracks that were skipped versus those play completely.

### 8.9.2 How Many Songs Were Played on Shuffle?

- ✓ 74.46% of tracks were played using shuffle mode.
- ✓ This suggests most users prefer randomized listening experiences over structured playlists or album-based listening.

**Key Insight:** Shuffle mode dominates playback, indicating a strong preference for spontaneous music selection.

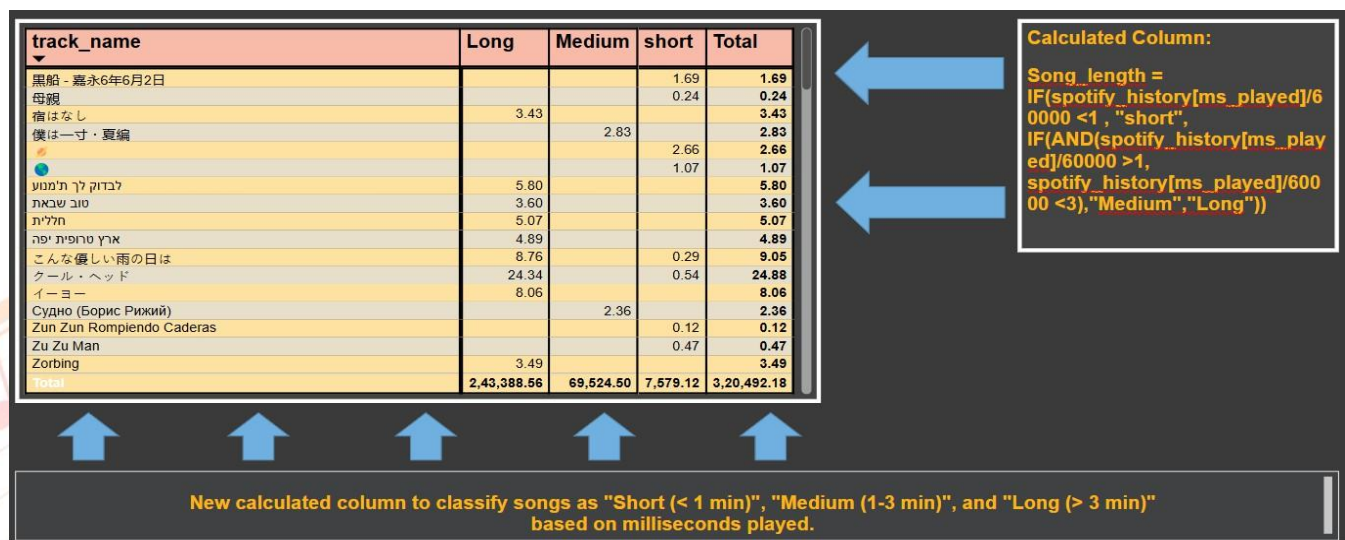


**Figure 24:** A Single visual card displaying the percentage of songs played using shuffle mode.

### 8.9.3 How Long Are the Played Tracks?

- ✓ Tracks were classified into Short (<1 min), Medium (1-3 min), and Long (>3 min) based on milliseconds played.
- ✓ Long songs (>3 min) account for the majority of playtime (~243K minutes), while short tracks (<1 min) were played the least (~7.5K minutes).

**Key Insight:** Despite high skipping behavior, users spend most of their time on long tracks, suggesting they do complete full songs selectively.



**Figure 25:** A table displaying track names categorized into "short", "Medium" and "Long" based on playtime in milliseconds.

#### **Final Takeaways:**

- ✓ Skipping behavior is high, reinforcing short attention spans or selective listening habits.
- ✓ Shuffle mode dominates playback, suggesting users enjoy unpredictable music experiences.
- ✓ Users spend most of their listening time on long tracks, indicating a preference for completing tracks when they fit their taste.

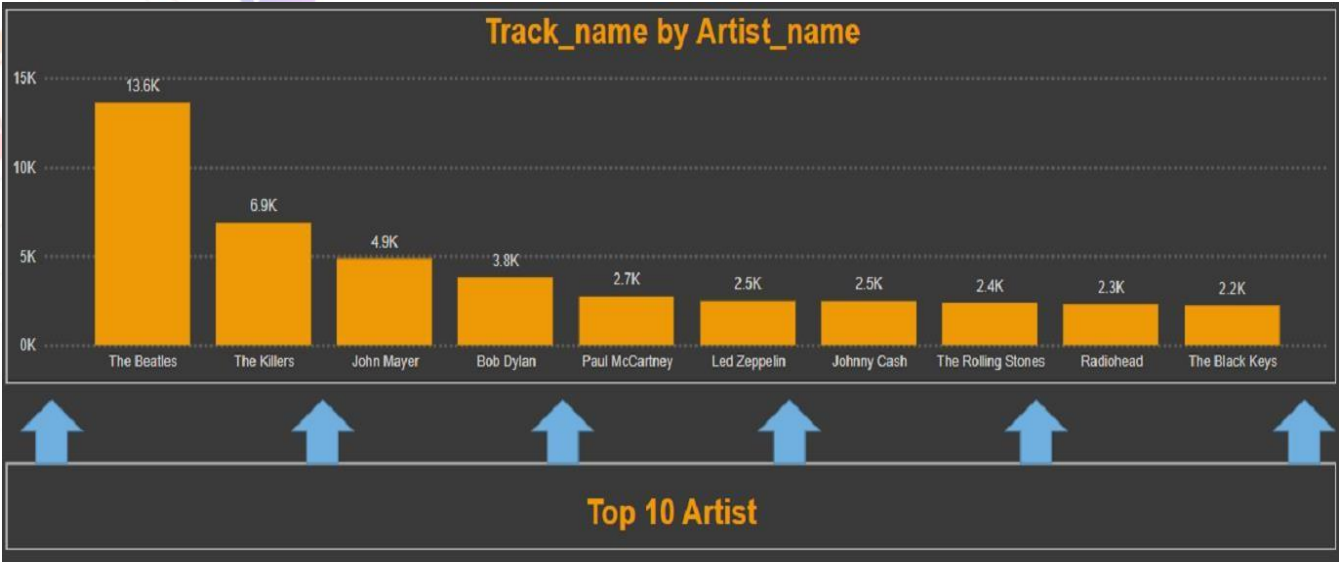
# 8.10 Music Listening Behavior: Artists & Skipping Trends

This dashboard explores top played artists, track skipping behavior, and monthly skipping trends to uncover user listening habits.

## 8.10.1 Who Are the Most Played Artists?

- ✓ Top 3 artists:
  - The Beatles (13.6K plays)
  - The Killers (6.9K plays)
  - John Mayer (4.9K plays)
- ✓ Other notable artists include Bob Dylan, Led Zeppelin, and Radiohead.

**Key Insight:** Classic rock and alternative rock artists dominate user preferences.

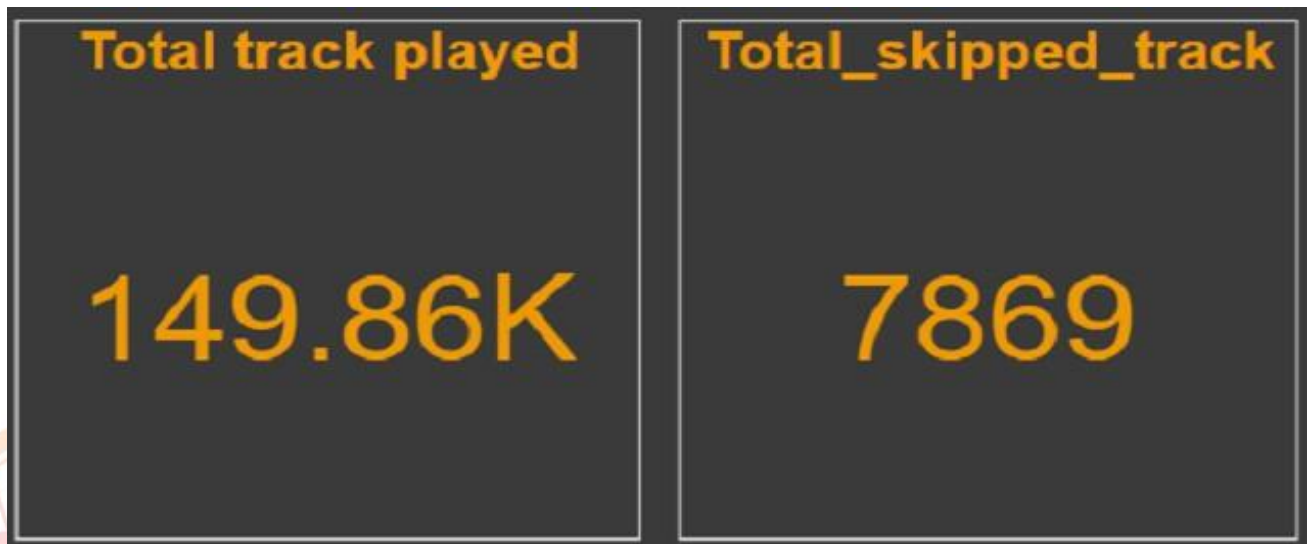


**Figure 26:** A bar chart displaying the top 10 most played artists

### 8.10.2 How Many Tracks Were Skipped?

- ✓ Total Tracks Played: 149.86K
- ✓ Total Skipped Tracks: 7,869 (5.2% of total plays)

**Key Insight:** A small portion of tracks were skipped, indicating users generally listen to full songs.

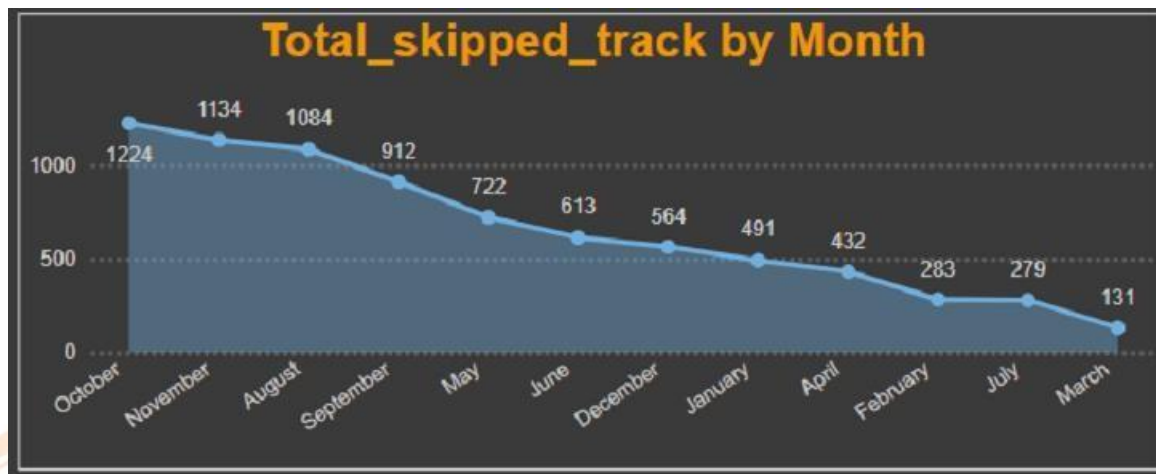


**Figure 27: Total track Played Vs Total Skipped Tracks**

### 8.10.3 How Has Skipping Behavior Changed Over Time?

- ✓ Skipping peaked in October (1,224 skips) and November (1,134 skips).
- ✓ Skipped tracks have decreased over time, dropping to 131 in March.

**Key Insight:** Users may have refined their playlists over time, leading to fewer skips.



**Figure 28: Total Skipped Tracks by Month**

#### **Final Takeaways:**

- ✓ Users prefer classic and alternative rock, with The Beatles leading the way.
- ✓ Track skipping is relatively low, suggesting users enjoy most of their selected music.
- ✓ Skipping behavior has declined over time, possibly due to better playlist curation.



## 9. Discussion

### 9.1 Interpretation of Findings

The visual exploration of the Spotify dataset has revealed compelling insights into how users interact with music on streaming platforms. Each dashboard was designed to answer specific analytical questions, and the resulting patterns offer a deeper understanding of listener behaviour, preferences, and engagement.

#### 9.1.1 Listener Preferences Are Artist-Driven but Genre-Inclusive

Artists like *The Beatles*, *The Killers*, and *Johnny Cash* emerged as top performers across multiple metrics—total playtime, ranking, and play count. Interestingly, users exhibited a balanced interest in both classic and contemporary music. Genres such as **rock, jazz, and country** performed well, suggesting that music taste is not restricted to modern releases but spans decades and styles.

#### 9.1.2 Manual Selection Increases Engagement

Findings clearly show that tracks manually selected by users (via clicks) have significantly lower skip rates and higher retention compared to auto played songs. Auto played tracks had a 0% retention rate, while manually selected songs-maintained listener attention, reinforcing the idea that **control over content** drives deeper engagement.

#### 9.1.3 Peak Listening Times Reflect Daily Routines

Engagement peaks in the morning (6–9 AM) and evening (6–11 PM), aligning with user routines such as commuting, working, or relaxing after the day. Tuesday and Wednesday emerged as the most active days, while Sunday saw the least engagement, possibly due to irregular weekend schedules.

#### 9.1.4 Platform Usage Influences Behaviour

The data shows Android as the dominant streaming platform, accounting for over 93% of plays. However, skip rates were highest on Windows and iOS, suggesting that desktop users may be more likely to multitask or skip songs frequently. In contrast, Android users tended to be more consistent in their listening habits.

#### 9.1.5 Skip Behaviour Indicates Selective Listening

Although skipping is a common behaviour, the majority of songs were still played in full. Skips were most frequent when tracks started unexpectedly (e.g., autoplay, unknown reasons), highlighting the



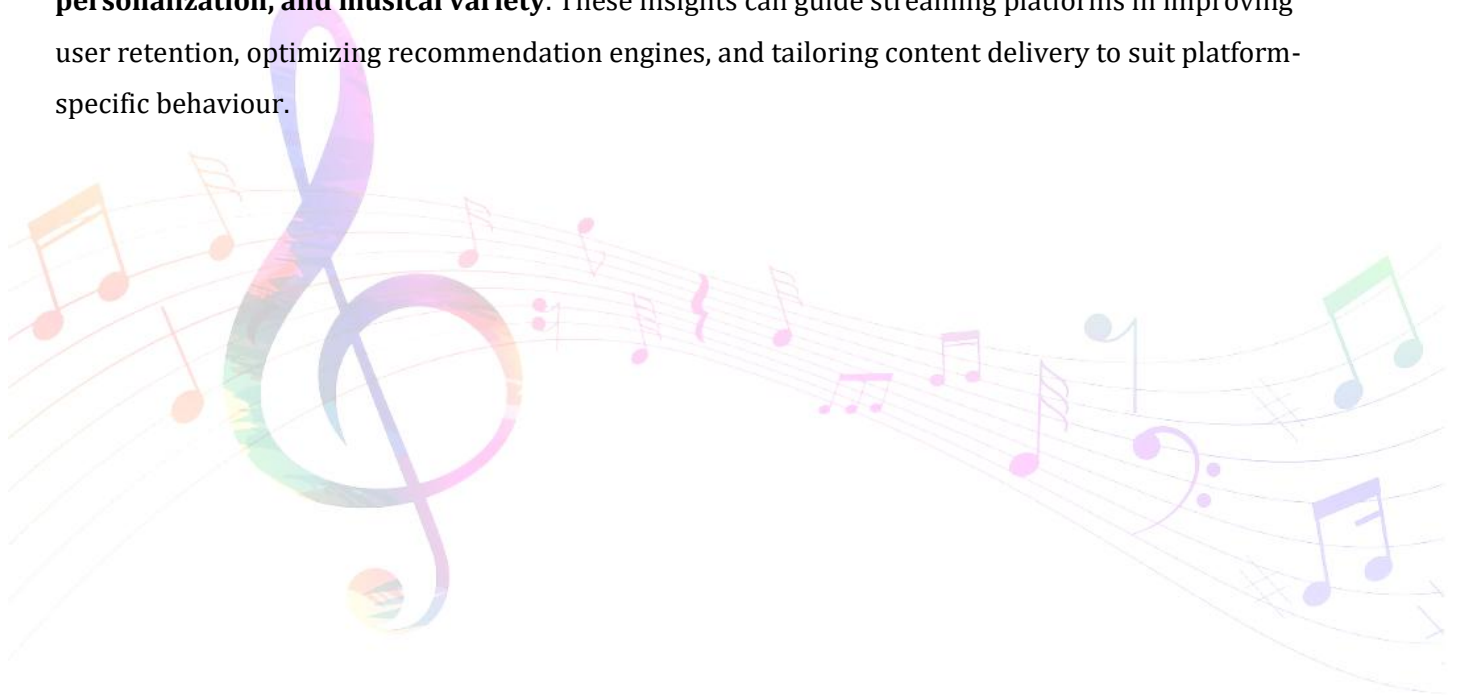
importance of **personalized recommendations** before playback. Manual skips (via back button) were the top reason for ending tracks, reinforcing the notion of selective consumption.

### 9.1.6 Shuffle Mode and Long Tracks Still Engage Users

Despite the randomness of shuffle mode (used in ~74% of plays), listeners showed a willingness to engage with longer tracks. Most total listening time was attributed to songs over 3 minutes long, suggesting that users are selective but **willing to commit** to tracks that match their taste.

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Overall, the findings point toward a modern streaming audience that values **choice, personalization, and musical variety**. These insights can guide streaming platforms in improving user retention, optimizing recommendation engines, and tailoring content delivery to suit platform-specific behaviour.



## 10. Future Work / Potential

While this project has successfully uncovered key insights into user behaviour on a music streaming platform, there is considerable scope for future enhancement and deeper exploration. Building upon the current findings, the following areas present strong potential for continued analysis and improvement:

### 10.1 Incorporating User Demographics

Adding demographic data such as age, gender, or geographic location would allow for **audience segmentation**. This could help identify how listening habits differ across user groups and enable more targeted recommendations and marketing strategies.

### 10.2 Sentiment Analysis on Lyrics or User Feedback

Integrating song lyrics and applying sentiment analysis could provide deeper insights into **emotional engagement**. Similarly, analysing user ratings or reviews (if available) can enhance understanding of track preferences beyond just playtime and skip rate.

### 10.3 Predictive Modelling

Using machine learning models, one could predict:

- **Likelihood of a track being skipped**
- **User churn or retention risk**
- **Future listening behaviour** based on past patterns

This would turn the current analysis from descriptive to predictive, offering actionable insights in real-time scenarios.

### 10.4 Real-Time Data Integration

Connecting Power BI to a real-time data source or API (e.g., Spotify's developer API) could allow for **live dashboards**, making insights more dynamic and relevant for ongoing platform optimization.

## 10.5 Enhanced Genre & Mood Analysis

Categorizing tracks by **genre, mood, or tempo** could add a new layer to the analysis. Understanding how these elements influence skip rates, retention, and listening patterns could support **more personalized curation** of playlists.

## 10.6 Cross-Platform Behaviour Analysis

While platform-specific behaviour was touched upon, a deeper exploration into how users **switch between devices**, and how that affects engagement, could yield useful insights for platform design and experience continuity.

## 10.7 Integration with Subscription and Ad Interaction Data

Combining streaming behaviour with subscription type (free vs. premium) or advertisement interaction data could reveal patterns in **monetization** and user lifetime value, enhancing business decision-making.

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By pursuing these directions, the analytical scope of this project can evolve significantly—from descriptive visual storytelling to **action-oriented insights** that support smarter, user-centric strategies for streaming platforms.

## 11. Conclusion

This project leveraged the power of Power BI to analyse and visualize streaming behaviour, user engagement, and content interaction on a music platform. Through a structured approach—starting from data cleaning and modelling to the creation of interactive dashboards—key insights were derived about how users listen to, skip, and interact with music content.

The analysis revealed that user engagement is strongly influenced by factors such as platform type, time of day, manual vs. autoplay selection, and artist popularity. Classic rock and alternative music continue to maintain a strong presence, while user-controlled playback (manual selection) leads to significantly higher retention and lower skip rates. Mobile platforms, especially Android, dominate usage, reflecting a shift toward mobile-first streaming habits.

These findings not only provide a window into listener preferences but also highlight opportunities for improving user experience through better recommendations, smarter autoplay strategies, and enhanced personalization.

In summary, this project demonstrates how data visualization can transform raw streaming data into meaningful insights. It lays the groundwork for further exploration using advanced analytics, real-time tracking, and predictive modelling to drive even more impactful user engagement strategies in the digital music industry.

## 12. Analyst Profile

- **Name:** Anurag Yadav
- **Role:** Data Analyst | Business Intelligence Developer
- **Technical Skills:** Power BI, DAX, SQL, MySQL, Python (pandas, numpy, seaborn, streamlit), Excel, Data Cleaning, Data Modelling, Data Visualization
- **Industry Experience:** 7+ years in the IT industry with hands-on experience in data analysis, reporting, and visualization solutions.
- **Project Focus:** Skilled in transforming raw data into actionable insights through interactive dashboards and reports. Passionate about uncovering patterns in user behaviour and improving decision-making through data.
- **Tools Used in This Project:** Power BI Desktop, DAX, Power Query
- **Professional Interests:** Data storytelling, user engagement analytics, dashboard design, predictive analytics, and music data analysis.

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