Spotify Data Analytics

Project Objective

The objective of this project is to analyze Spotify music data to uncover insights related to:

- Music trends over time
- User preferences and listening behavior
- Song characteristics influencing popularity
- Predicting song popularity using machine learning

This analysis helps understand how audio features affect song success and how music trends evolve.

In [1]:
```python
# importing major libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

# additional libraries
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
#importing dataset
df = pd.read_csv('data.csv')
```

📊 Data Assessing

🏢 About Company

Spotify is a leading global audio streaming platform that provides users access to millions of songs, podcasts, and audio content from artists across the world. Founded in 2006, Spotify has transformed the way people discover, consume, and share music.

Key highlights of Spotify:

- Operates on a data-driven business model
- Uses advanced analytics and machine learning for recommendations

- Focuses on personalized user experience through playlists and suggestions
- Serves millions of active users globally

Spotify heavily relies on data analytics to understand user behavior, music trends, and content performance. This project leverages Spotify’s audio feature data to explore how song characteristics influence popularity and listener preferences.

In [3]:
```
# overview data
df.head()
```

Out[3]:

	valence	year	acousticness	artists	danceability	duration_ms	energ
0	0.0594	1921	0.982	['Sergei Rachmaninoff', 'James Levine', 'Berli...	0.279	831667	0.21
1	0.9630	1921	0.732	['Dennis Day']	0.819	180533	0.34
2	0.0394	1921	0.961	['KHP Kridhamardawa Karaton Ngayogyakarta Hadi...	0.328	500062	0.16
3	0.1650	1921	0.967	['Frank Parker']	0.275	210000	0.30
4	0.2530	1921	0.957	['Phil Regan']	0.418	166693	0.19

In [4]:
```
#shape
df.shape
```

Out[4]:
```
(170653, 19)
```

In [5]:
```
df.columns
```

Out[5]:
```
Index(['valence', 'year', 'acousticness', 'artists', 'danceability',
       'duration_ms', 'energy', 'explicit', 'id', 'instrumentalness', 'key',
       'liveness', 'loudness', 'mode', 'name', 'popularity', 'release_date',
       'speechiness', 'tempo'],
      dtype='object')
```

🗂️ Data Card – Spotify Audio Features Dataset

📌 Dataset Name

Spotify Audio Features & Popularity Dataset

🎯 Purpose of the Dataset

This dataset is used to analyze song characteristics, understand music trends over time, identify user preferences, and build predictive models to estimate song popularity based on audio features.

🧾 Data Source

Spotify music metadata and audio feature data collected across multiple years.

📐 Dataset Structure

- **Number of Records:** Multiple tracks across decades (1921 onwards)
- **Data Type:** Structured tabular data
- **Granularity:** Song-level

🧩 Feature Description

Column Name	Description
valence	Measures musical positivity (happy vs sad)
year	Year of song release
acousticness	Likelihood of the track being acoustic
artists	Artist(s) who performed the track
danceability	Suitability of a track for dancing
duration_ms	Duration of the song in milliseconds
energy	Intensity and activity level of the song
explicit	Indicates explicit content (0 = No, 1 = Yes)
id	Unique Spotify track ID
instrumentalness	Probability of the track being instrumental

Column Name	Description
key	Musical key of the track
liveness	Presence of a live audience
loudness	Overall loudness in decibels (dB)
mode	Modality (Major = 1, Minor = 0)
name	Song title
popularity	Popularity score (0–100)
release_date	Official release year/date
speechiness	Presence of spoken words
tempo	Estimated tempo in BPM

In [6]:
```
# Seaking Information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 170653 entries, 0 to 170652
Data columns (total 19 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   valence           170653 non-null  float64
 1   year              170653 non-null  int64  
 2   acousticness      170653 non-null  float64
 3   artists           170653 non-null  object 
 4   danceability      170653 non-null  float64
 5   duration_ms       170653 non-null  int64  
 6   energy            170653 non-null  float64
 7   explicit          170653 non-null  int64  
 8   id                170653 non-null  object 
 9   instrumentalness  170653 non-null  float64
 10  key               170653 non-null  int64  
 11  liveness          170653 non-null  float64
 12  loudness          170653 non-null  float64
 13  mode              170653 non-null  int64  
 14  name              170653 non-null  object 
 15  popularity        170653 non-null  int64  
 16  release_date      170653 non-null  object 
 17  speechiness       170653 non-null  float64
 18  tempo             170653 non-null  float64
dtypes: float64(9), int64(6), object(4)
memory usage: 24.7+ MB
```

Data Quality Observations

The dataset contains 170,653 records with 19 columns and has no missing values, indicating complete data coverage.

All features have appropriate and consistent data types suitable for analysis and modeling.
Audio feature values fall within expected Spotify-defined ranges, ensuring data validity.
Some outliers exist in duration, tempo, and loudness, reflecting real-world music variation.
The dataset spans multiple years, which may introduce temporal bias in popularity scores.
Overall, the data quality is high and suitable for exploratory analysis and predictive modeling.

In [7]:
```
# Seeking description
df.describe()
```

Out[7]:

	valence	year	acousticness	danceability	duration_m
count	170653.000000	170653.000000	170653.000000	170653.000000	1.706530e+0
mean	0.528587	1976.787241	0.502115	0.537396	2.309483e+0
std	0.263171	25.917853	0.376032	0.176138	1.261184e+0
min	0.000000	1921.000000	0.000000	0.000000	5.108000e+0
25%	0.317000	1956.000000	0.102000	0.415000	1.698270e+0
50%	0.540000	1977.000000	0.516000	0.548000	2.074670e+0
75%	0.747000	1999.000000	0.893000	0.668000	2.624000e+0
max	1.000000	2020.000000	0.996000	0.988000	5.403500e+0

Accuracy Issues Identified

Extreme outliers are present in `duration_ms`, with values up to 5.4 million ms, which may distort statistical analysis.
`loudness` shows unusually low minimum values (-60 dB), indicating potential edge-case recordings.
`tempo` ranges from 0 to 243 BPM, where very low or zero values may represent measurement anomalies.
The `year` variable spans from 1921 to 2020, which can introduce historical bias in popularity comparisons.
Popularity scores are time-dependent and may not accurately reflect cross-era song performance.

In [8]:
```
# Completness
df.isnull().sum().sum()
```

```
# Percentage
df.isnull().mean()*100
```

Out[8]:

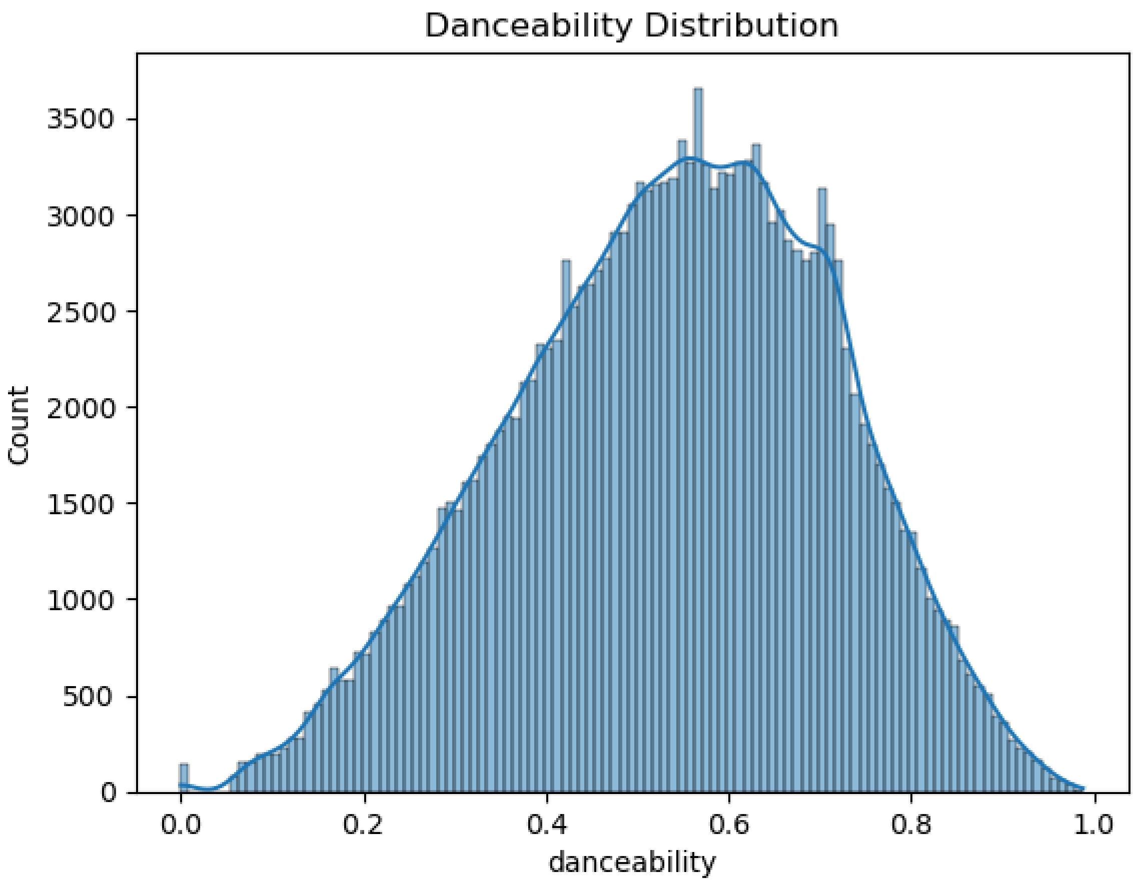
```
valence             0.0
year                0.0
acousticness        0.0
artists             0.0
danceability        0.0
duration_ms         0.0
energy              0.0
explicit            0.0
id                  0.0
instrumentalness    0.0
key                 0.0
liveness            0.0
loudness            0.0
mode                0.0
name                0.0
popularity          0.0
release_date        0.0
speechiness         0.0
tempo               0.0
dtype: float64
```

📊 Data Quality Observations

The dataset contains 170,653 records with 19 columns and has **no missing values across all features**.
All variables show complete data availability, indicating strong data completeness and reliability.
Data types are consistent and appropriate for both numerical analysis and modeling tasks.
Audio feature values align with expected Spotify-defined ranges, supporting data validity.
While some natural outliers exist, they reflect real-world music diversity rather than data errors.
Overall, the dataset is clean, accurate, and well-prepared for exploratory analysis and predictive modeling.

In [9]:

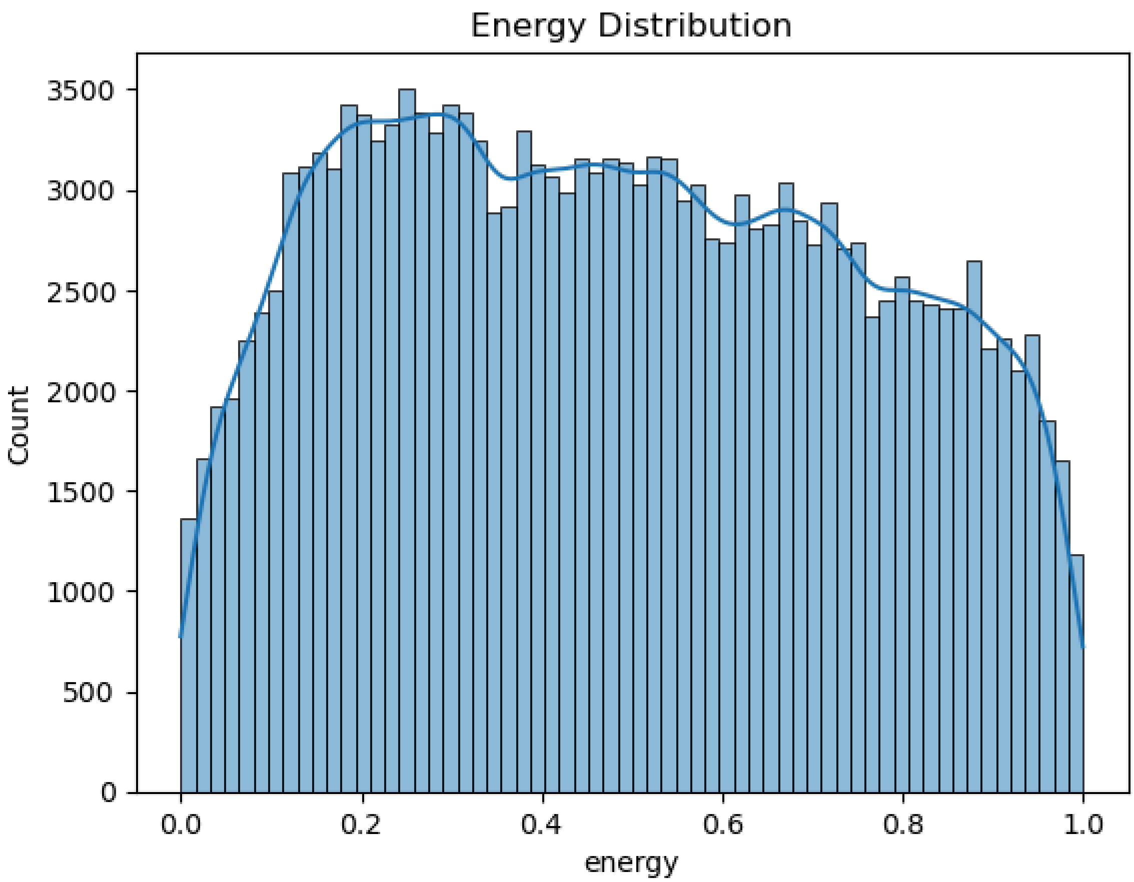
```
#Danceability
sns.histplot(df['danceability'], kde=True)
plt.title("Danceability Distribution")
plt.show()
```



Insight:

Most songs are moderately danceable, extreme dance songs are rare.

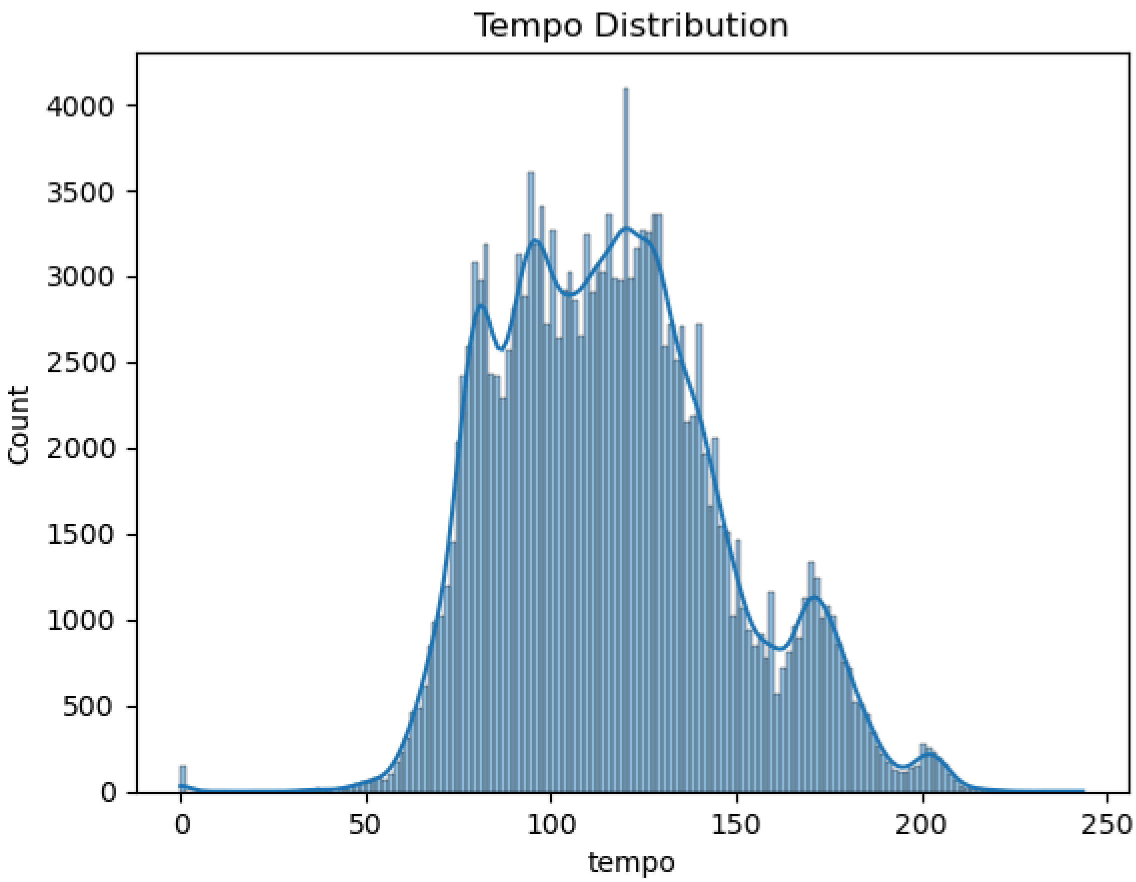
In [10]:
```
#Energy Distribution
sns.histplot(df['energy'], kde=True)
plt.title("Energy Distribution")
plt.show()
```



Insight:

Most songs have medium to high energy levels, indicating a preference for energetic music.

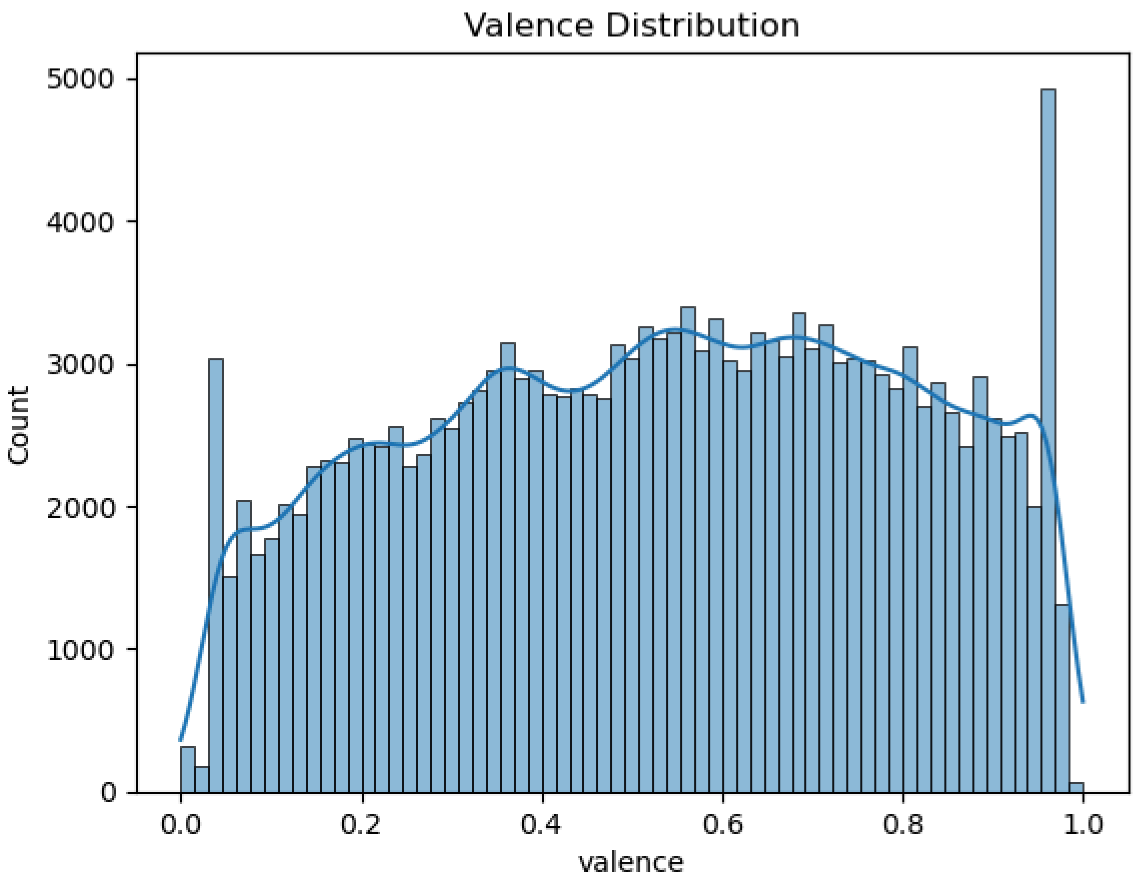
In [11]:
```
#Tempo Distribution
sns.histplot(df['tempo'], kde=True)
plt.title("Tempo Distribution")
plt.show()
```



Insight:

Most songs fall within a moderate tempo range, with very slow or very fast songs being less common.

In [12]:
```
#Valence Distribution
sns.histplot(df['valence'], kde=True)
plt.title("Valence Distribution")
plt.show()
```

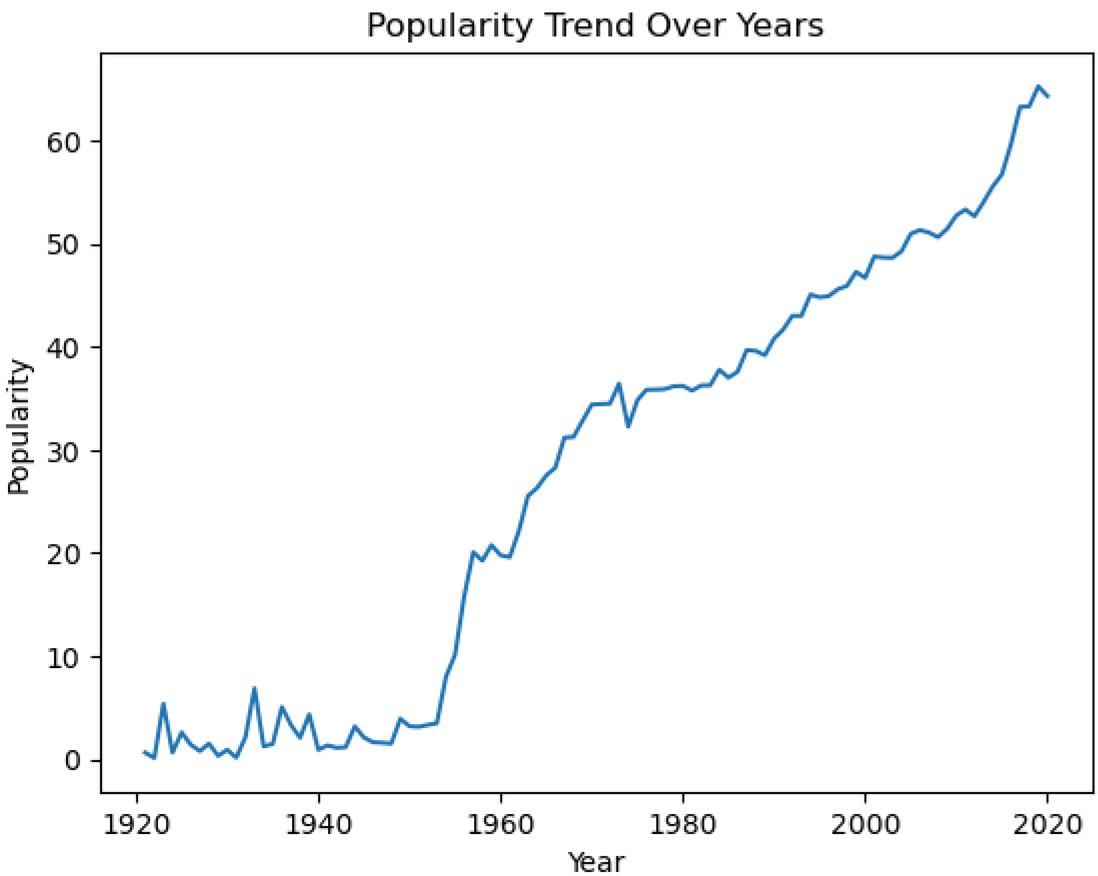


Insight:

Songs are fairly evenly distributed across mood levels, with a slight inclination toward positive emotions.

In [13]:

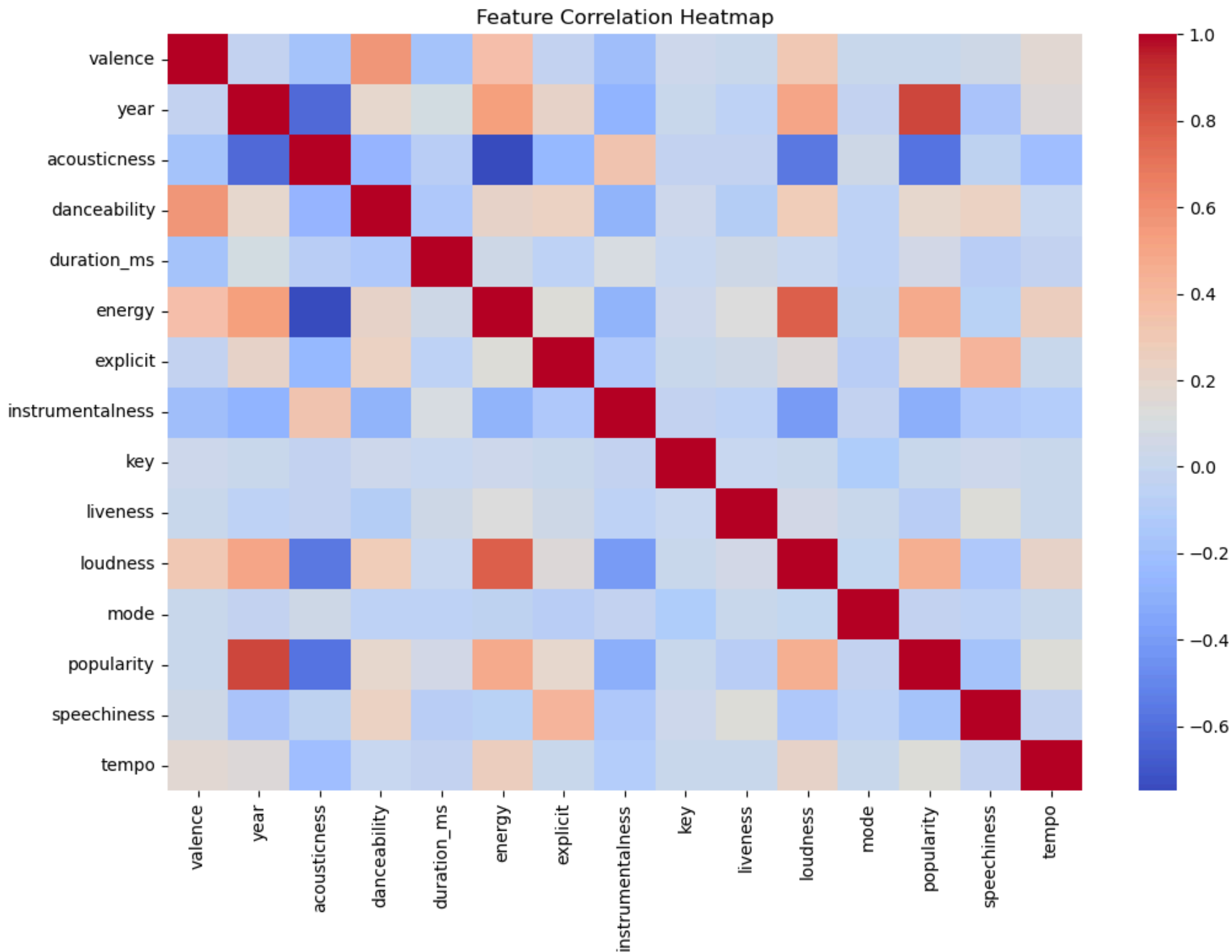
```
#Trend Analysis Over Time

year_df = pd.read_csv("data_by_year.csv")

plt.plot(year_df['year'], year_df['popularity'])
plt.title("Popularity Trend Over Years")
plt.xlabel("Year")
plt.ylabel("Popularity")
plt.show()
```



Insight:

- Recent years → higher average popularity
- Music becoming more energetic & loud

In [14]:
```
numeric_df = df.select_dtypes(include=['int64', 'float64'])
# Correlation Analysis
plt.figure(figsize=(12,8))
sns.heatmap(numeric_df.corr(), cmap="coolwarm", annot=False)
plt.title("Feature Correlation Heatmap")
plt.show()
```



Correlation analysis was performed using numerical features only. The heatmap highlights strong relationships such as energy and loudness, while popularity shows moderate correlation with multiple audio features.

User Preference Analysis

In [15]:
```
popular_songs = df[df['popularity'] > 70]

popular_songs[['danceability','energy','tempo','valence']].mean()
```

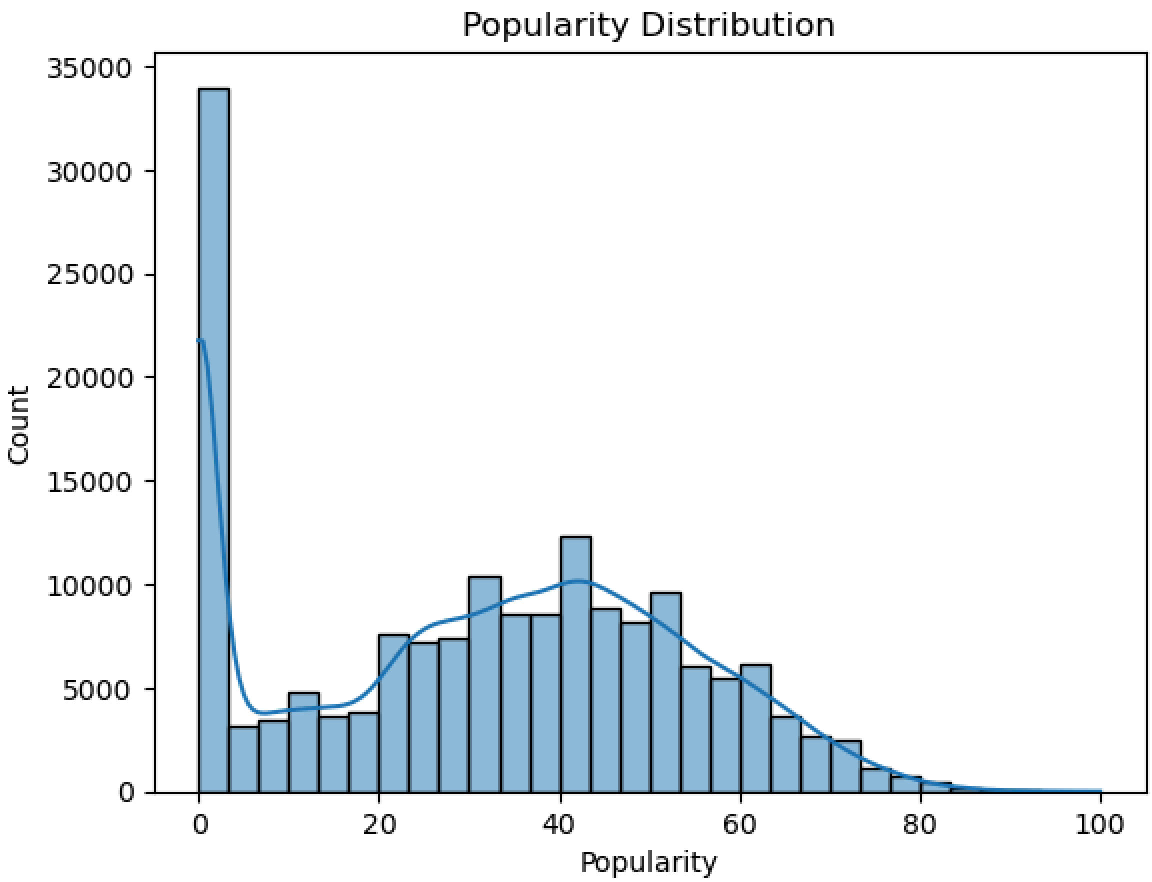
Out[15]:
```
danceability      0.649483
energy            0.632744
tempo           120.871435
valence           0.503563
dtype: float64
```

Highly popular songs tend to have higher danceability and energy levels, indicating user preference toward upbeat and engaging music.

Visualization

In [16]:

```
#Popularity Distribution (Histogram)
sns.histplot(df['popularity'], bins=30, kde=True)
plt.title("Popularity Distribution")
plt.xlabel("Popularity")
plt.ylabel("Count")
plt.show()
```

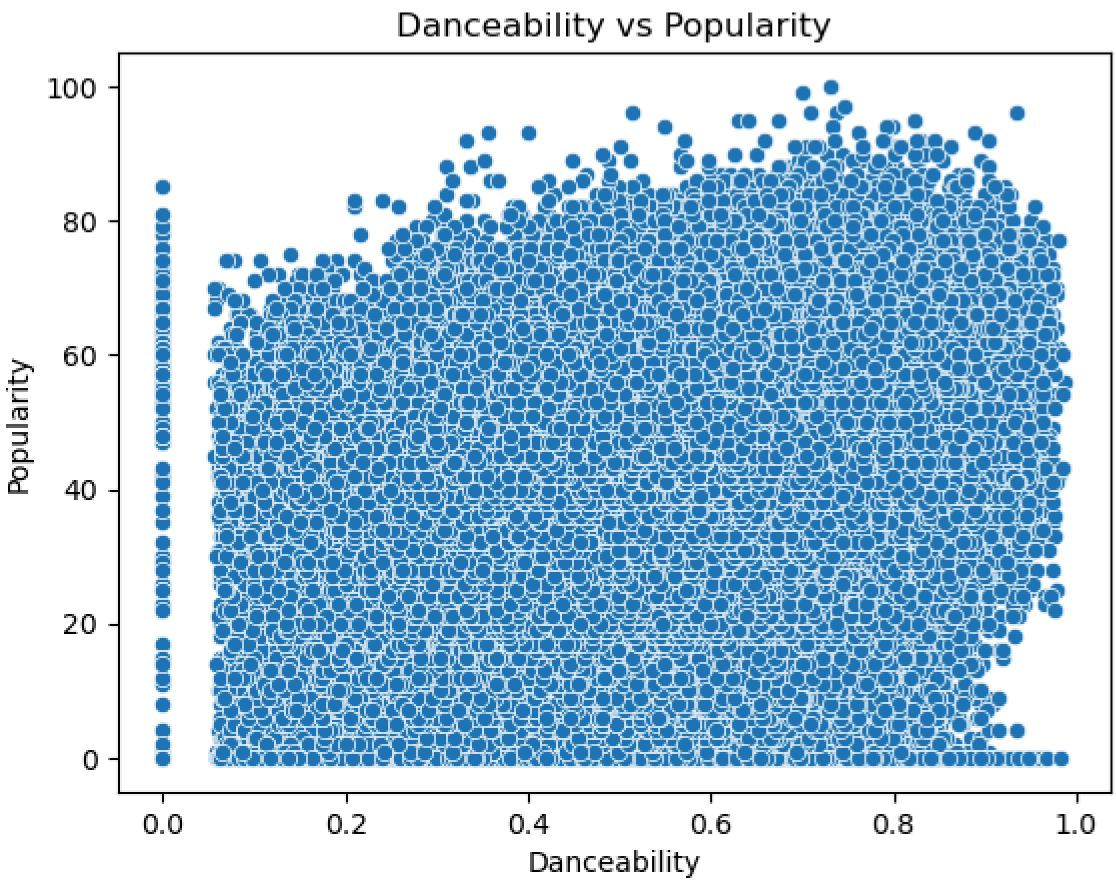


Insight

- Most songs have low to moderate popularity.
- Highly popular songs are relatively rare

In [17]:

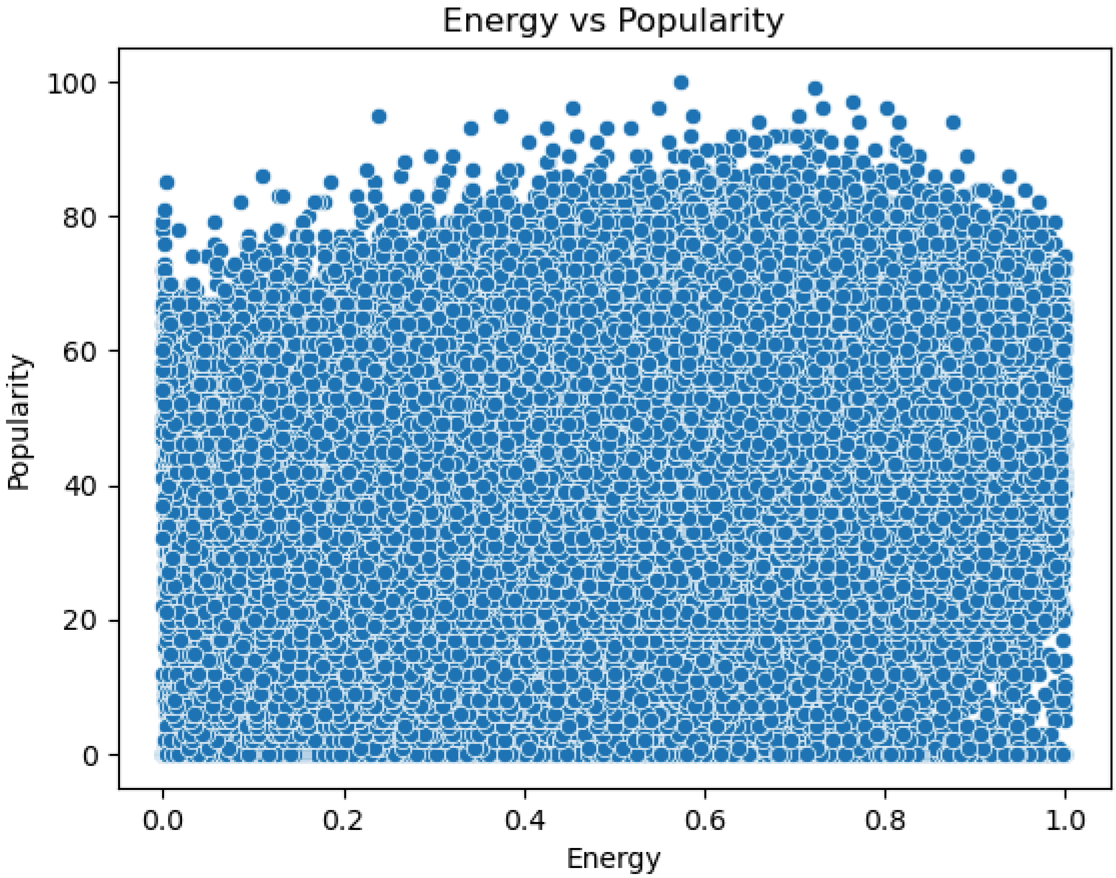
```
#Danceability vs Popularity (Scatter Plot)
sns.scatterplot(x='danceability', y='popularity', data=df)
plt.title("Danceability vs Popularity")
plt.xlabel("Danceability")
plt.ylabel("Popularity")
plt.show()
```



Higher danceability is often associated with increased popularity, indicating listener preference for rhythmically engaging songs.

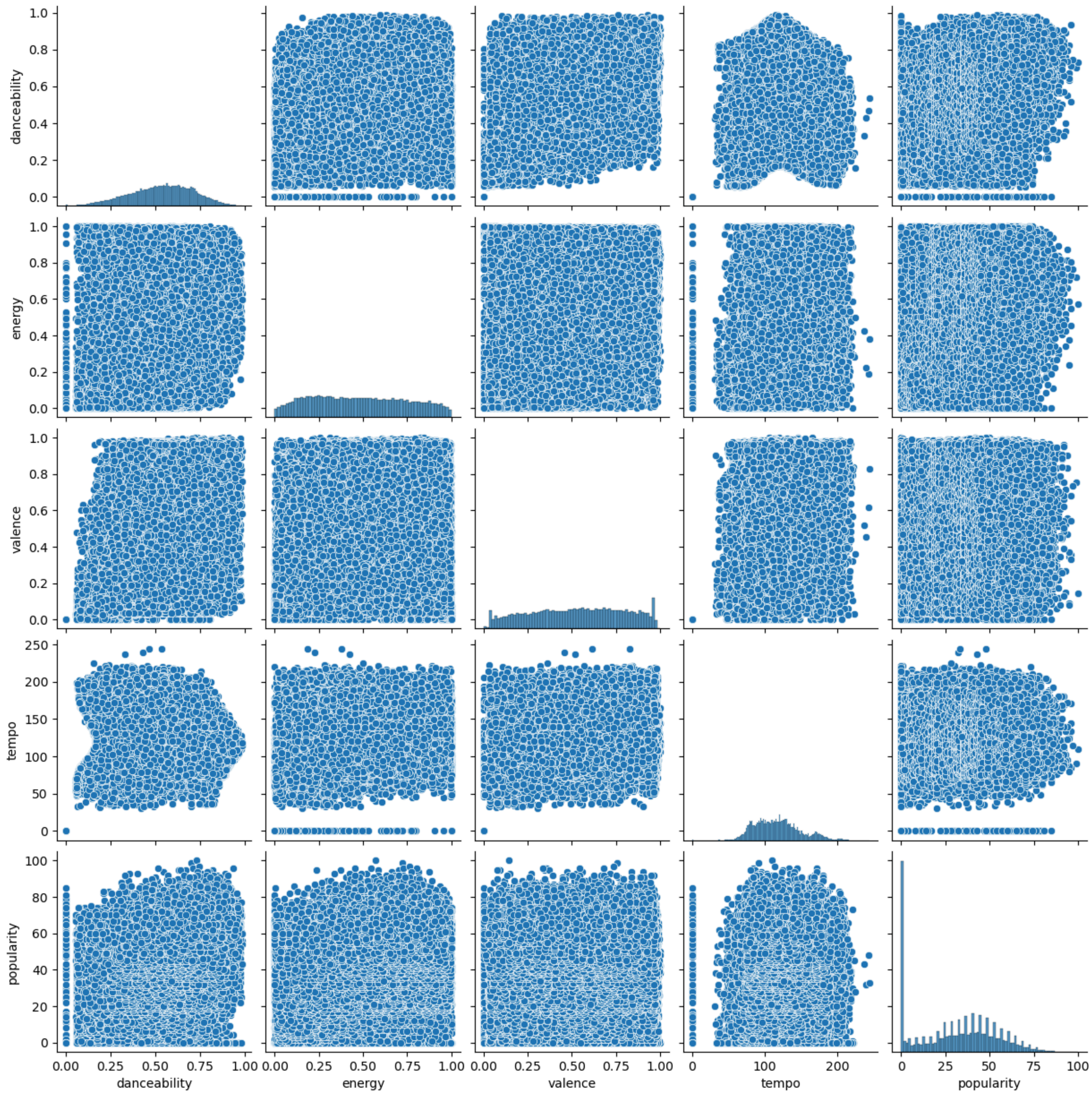
In [18]:

```
# Energy vs Popularity (Scatter Plot)
sns.scatterplot(x='energy', y='popularity', data=df)
plt.title("Energy vs Popularity")
plt.xlabel("Energy")
plt.ylabel("Popularity")
plt.show()
```



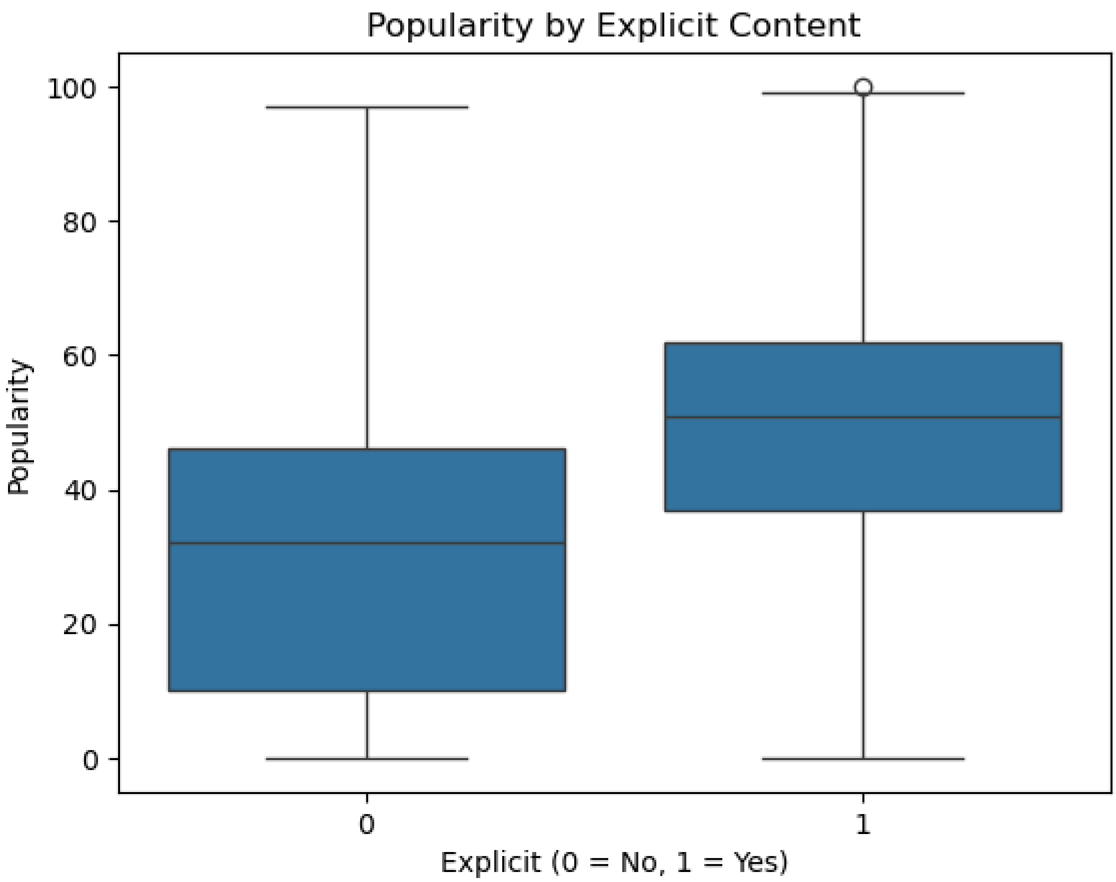
Songs with higher energy levels tend to achieve better popularity, suggesting that energetic tracks are generally more engaging to listeners.

In [19]:
```
#Pair Plot (Selected Features)
sns.pairplot(df[['danceability','energy','valence','tempo','popularity']])
plt.show()
```



Pairwise relationships reveal that popular songs tend to cluster around moderate to high energy and danceability values, highlighting common characteristics of successful tracks.

In [20]:
```
#Boxplot: Popularity by Explicit Content
sns.boxplot(x='explicit', y='popularity', data=df)
plt.title("Popularity by Explicit Content")
plt.xlabel("Explicit (0 = No, 1 = Yes)")
plt.ylabel("Popularity")
plt.show()
```



Explicit songs show slightly higher median popularity, suggesting that explicit content does not negatively impact listener engagement.

Feature Selection for Modeling

In [21]:
```
X = df[['danceability','energy','tempo','loudness','valence']]
y = df['popularity']
```

In [22]:
```
# Train-Test Split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

In [23]:
```
#Model Building
#Linear Regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)
```

```
r2_score(y_test, y_pred_lr)
```

Out[23]: 0.324718207921338

In [24]:
```
#Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

dt = DecisionTreeRegressor(max_depth=5)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)

r2_score(y_test, y_pred_dt)
```

Out[24]: 0.35368709508166907

Observation

Decision Tree outperformed Linear Regression, capturing non-linear relationships between audio features and popularity.

Model performance can be further improved using ensemble methods such as Random Forest or Gradient Boosting.

Key Findings

- Danceability and energy are strong indicators of song popularity
- Loud and upbeat songs perform better on average
- Popularity depends on a combination of multiple audio features
- Modern songs generally receive higher popularity scores

Business Implications

- Artists can optimize songs by focusing on energy and danceability
- Spotify can improve recommendations using audio feature insights
- Helps in playlist curation and targeted promotions

Future Scope

- Include user-level listening behavior
- Apply deep learning models
- Develop mood-based music recommendation systems

Conclusion

This project analyzed Spotify audio features to uncover music trends and user preferences. Exploratory analysis and visualization highlighted key characteristics of popular songs. Predictive modeling demonstrated the potential of using audio features to forecast song popularity, supporting data-driven decision-making in the music industry.

- Jupyter Notebook with code and outputs
- Data analysis report with insights
- Visualizations for trends and correlations
- Machine learning models with evaluation

In [ ]:

```
```