In [2]:
```
# IMPORT LIBRARIES

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.cluster import KMeans, DBSCAN
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
import joblib as jl
```

In [3]:
```
# IMPORT DATAFRAME

df_amc = pd.read_csv(r"D:\WORKOUTS\DATA_CLEANING\Dataset CSV\single_genre_artists.c
df_amc.head(5)
```

Out[3]:

	id_songs	name_song	popularity_songs	duration_ms	explicit	
0	0IA0Hju8CAgYfV1hwhidBH	La Java	0	161427	0	4AxgXfD
1	1b8HZQCqcqwbzlA1jRTp6E	En Douce	0	223440	0	4AxgXfD
2	5d5gQxHwYovxR5pqETOIAa	J'en Ai Marre	0	208267	0	4AxgXfD
3	1EO65UEEPfy7CR0NK2sDxy	Ils n'ont pas ca	0	161933	0	4AxgXfD
4	6a58gXSgqbIsXUhVZ6ZJqe	La belote	0	167973	0	4AxgXfD

5 rows × 23 columns

In [4]:
```
# COLUMNS

df_amc.columns
```

Out[4]:
```
Index(['id_songs', 'name_song', 'popularity_songs', 'duration_ms', 'explicit',
       'id_artists', 'release_date', 'danceability', 'energy', 'key',
       'loudness', 'mode', 'speechiness', 'acousticness', 'instrumentalness',
       'liveness', 'valence', 'tempo', 'time_signature', 'followers', 'genres',
       'name_artists', 'popularity_artists'],
      dtype='object')
```

In [5]:
```
# CHECK NULL VALUES

df_amc.isna().sum()
```

Out[5]:
```
id_songs              0
name_song             0
popularity_songs      0
duration_ms           0
explicit              0
id_artists            0
release_date          0
danceability          0
energy                0
key                   0
loudness              0
mode                  0
speechiness           0
acousticness          0
instrumentalness      0
liveness              0
valence               0
tempo                 0
time_signature        0
followers             0
genres                0
name_artists          0
popularity_artists    0
dtype: int64
```

In [6]:
```
# CHECK DUPLICATES

df_amc.duplicated().sum()
```

Out[6]:
```
np.int64(0)
```

In [7]:
```
# FIX DATATYPE ISSUES

df_amc['duration_ms'] = pd.to_numeric(df_amc['duration_ms'], errors='coerce')
df_amc['duration_ms'] = (df_amc['duration_ms'] / (1000 * 60)).round(2)

df_amc['release_date'] = pd.to_datetime(df_amc['release_date'], format='mixed')
```

In [8]:
```
# INFO

df_amc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 95837 entries, 0 to 95836
Data columns (total 23 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   id_songs            95837 non-null  object
 1   name_song           95837 non-null  object
 2   popularity_songs    95837 non-null  int64
 3   duration_ms         95837 non-null  float64
 4   explicit            95837 non-null  int64
 5   id_artists          95837 non-null  object
 6   release_date        95837 non-null  datetime64[ns]
 7   danceability        95837 non-null  float64
 8   energy              95837 non-null  float64
 9   key                 95837 non-null  int64
 10  loudness            95837 non-null  float64
 11  mode                95837 non-null  int64
 12  speechiness         95837 non-null  float64
 13  acousticness        95837 non-null  float64
 14  instrumentalness    95837 non-null  float64
 15  liveness            95837 non-null  float64
 16  valence             95837 non-null  float64
 17  tempo               95837 non-null  float64
 18  time_signature      95837 non-null  int64
 19  followers           95837 non-null  float64
 20  genres              95837 non-null  object
 21  name_artists        95837 non-null  object
 22  popularity_artists  95837 non-null  int64
dtypes: datetime64[ns](1), float64(11), int64(6), object(5)
memory usage: 16.8+ MB
```

In [9]:

```
# NORMALISATION USING STANDARD SCALER

df_clean = df_amc.drop(columns=['name_artists', 'id_artists', 'id_songs', 'name_son
                                'popularity_songs', 'explicit', 'release_date', 'mo
                                'key', 'time_signature', 'followers', 'genres', 'po

numeric_cols = df_clean.select_dtypes(include=['int64', 'float64']).columns

scaler = StandardScaler()
X_scaled = scaler.fit_transform(df_clean)

print(df_clean.head())
```

```
   duration_ms  danceability  energy  loudness  speechiness  acousticness  \
0         2.69         0.563   0.184   -13.757       0.0512         0.993
1         3.72         0.427   0.180   -15.375       0.0670         0.989
2         3.47         0.511   0.206   -15.514       0.0592         0.995
3         2.70         0.676   0.467   -12.393       0.1650         0.991
4         2.80         0.650   0.298   -13.806       0.1380         0.991

   instrumentalness  liveness  valence    tempo
0          0.000016     0.325    0.654  133.088
1          0.000000     0.128    0.431   78.459
2          0.000000     0.418    0.481   70.443
3          0.000000     0.219    0.726  129.775
4          0.000000     0.373    0.844   75.950
```

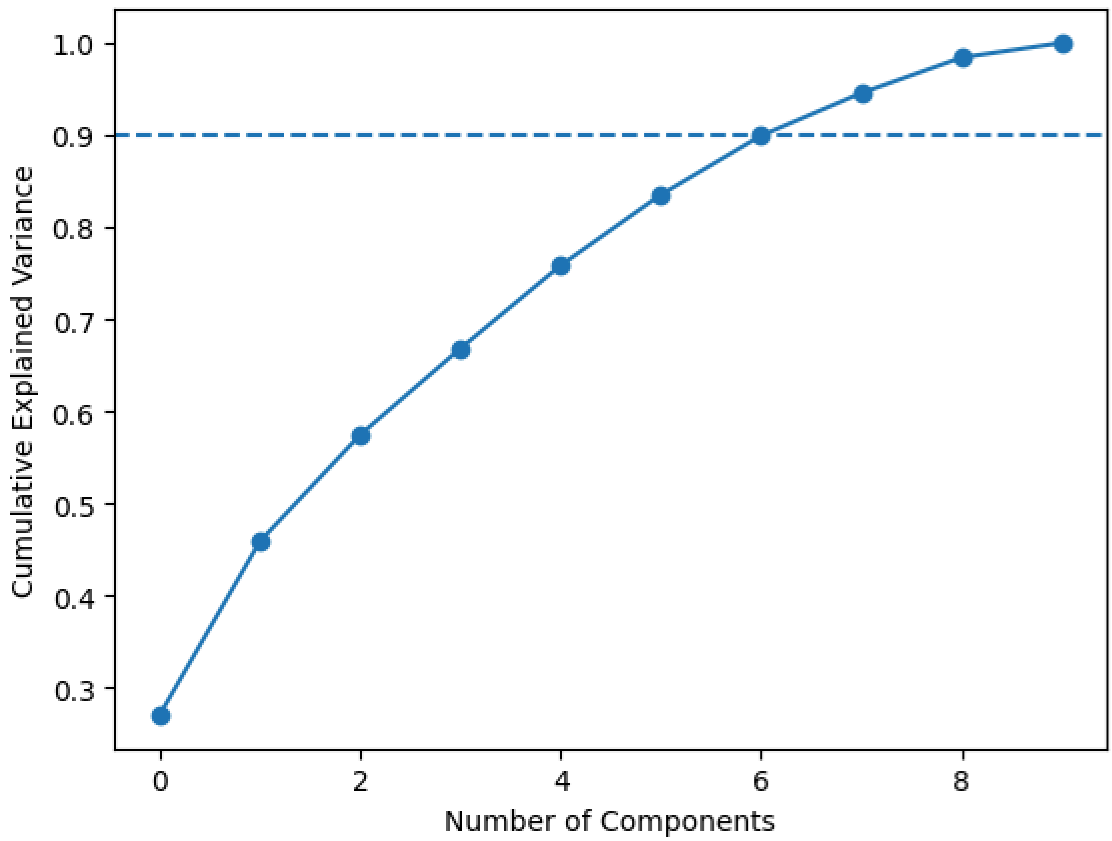
In [10]:

```python
# DIMENSIONALITY REDUCTION USING PCA

from sklearn.decomposition import PCA

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

print("Shape after PCA:", X_pca.shape)
print("Variance Explained:", pca.explained_variance_ratio_)
```

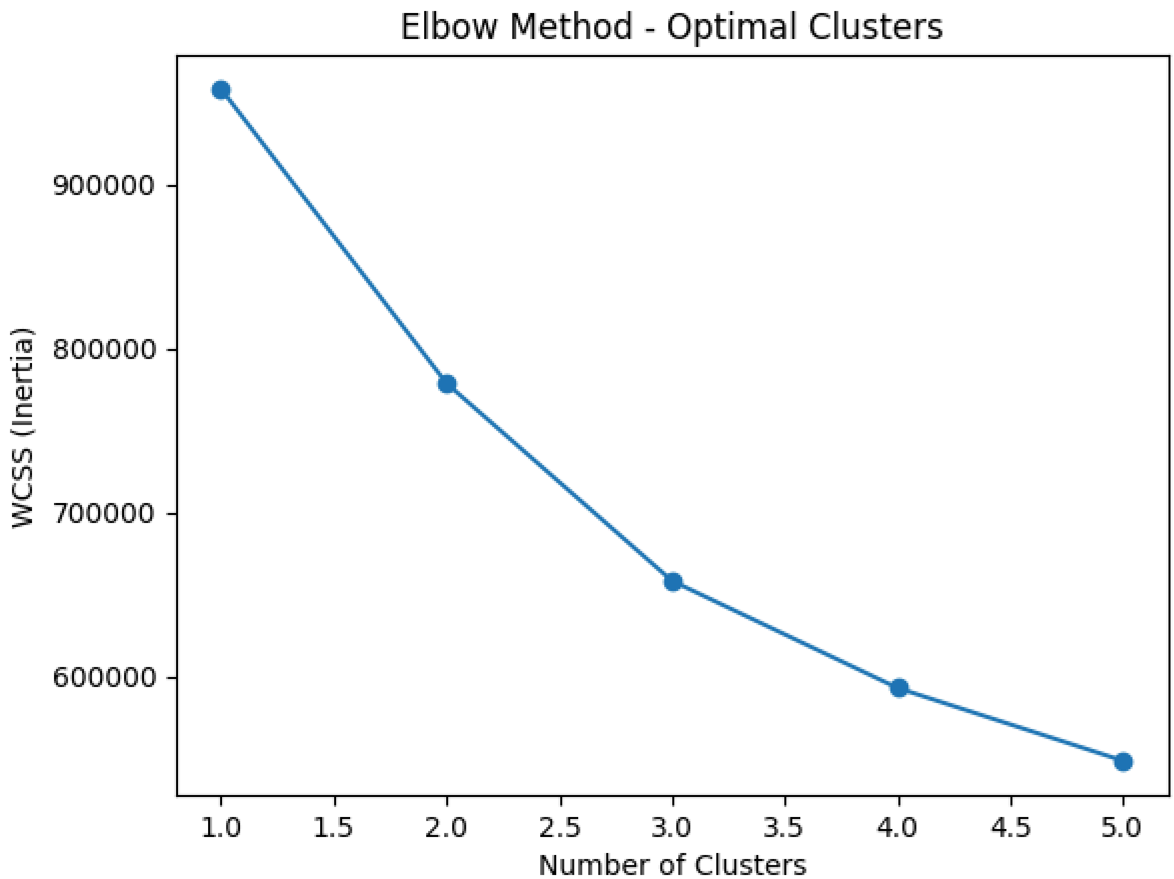
```
Shape after PCA: (95837, 2)
Variance Explained: [0.27079549 0.1882147 ]
```

In [11]:

```python
# VISUAL JUSTIFICATION

pca_full = PCA()
pca_full.fit(X_scaled)

plt.plot(np.cumsum(pca_full.explained_variance_ratio_), marker='o')
plt.axhline(y=0.9, linestyle='--')
plt.xlabel("Number of Components")
plt.ylabel("Cumulative Explained Variance")
plt.show()
```



In [12]:
```
# CLUSTERING - ELBOW METHOD

wcss = []

for k in range(1, 6):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)

clusters = kmeans.fit_predict(X_scaled)

df_amc['cluster'] = clusters

plt.figure()
plt.plot(range(1, 6), wcss, marker='o')
plt.title("Elbow Method - Optimal Clusters")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS (Inertia)")
plt.show()
```



In [13]:

```
# SAVE CLUSTERED DATASET FOR STREAMLIT

df_amc.to_csv(
    "single_genre_artists_clustered.csv",
    index=False
)

df_amc["cluster"] = kmeans.labels_

df_amc.to_csv("amazon_music_clustered.csv", index=False)

print("✅ Clustered dataset saved successfully")
```

✅ Clustered dataset saved successfully

In [14]:

```
# VERIFICATION THE DATA

df_amc[['name_song', 'cluster']].head()
```

Out[14]:

	name_song	cluster
0	La Java	3
1	En Douce	3
2	J'en Ai Marre	3
3	Ils n'ont pas ca	3
4	La belote	3

In [15]:

```
# SILHOUETTE SCORE

scores = {}
for k in range(2, 6):
    kmeans = KMeans(n_clusters=k, random_state=42)
    labels = kmeans.fit_predict(X_scaled)
    scores[k] = silhouette_score(X_scaled, labels)

print("Silhouette Score:", scores)
```

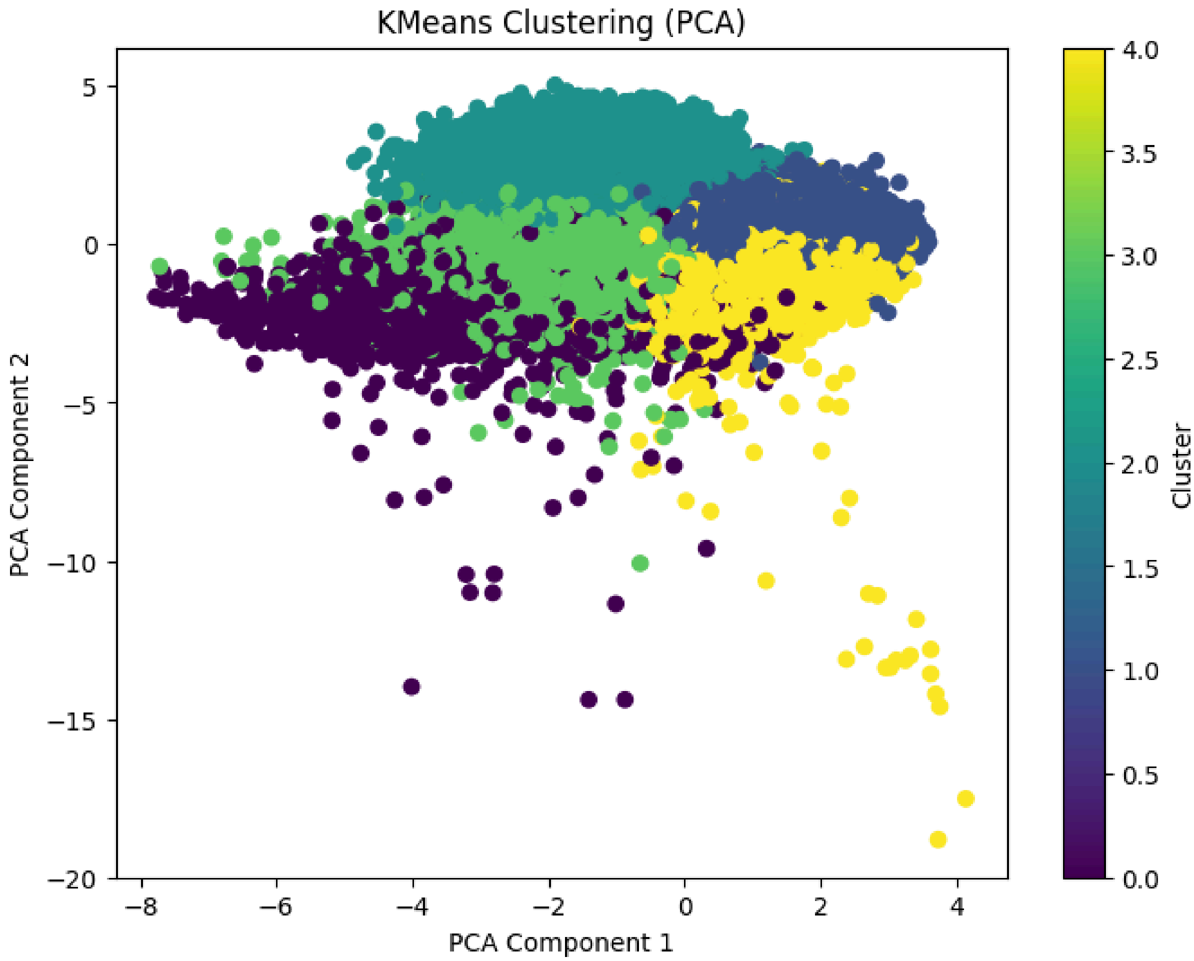
```
Silhouette Score: {2: 0.2031782412803395, 3: 0.24240157523065226, 4: 0.2310664525528
5027, 5: 0.1859826295647418}
```

In [16]:

```
# DBSCAN WITH TUNING

dbscan = DBSCAN(eps=0.5, min_samples=5)
labels = dbscan.fit_predict(X_scaled)

outliers = X_scaled[labels == -1]

num_outliers = sum(labels == -1)
```

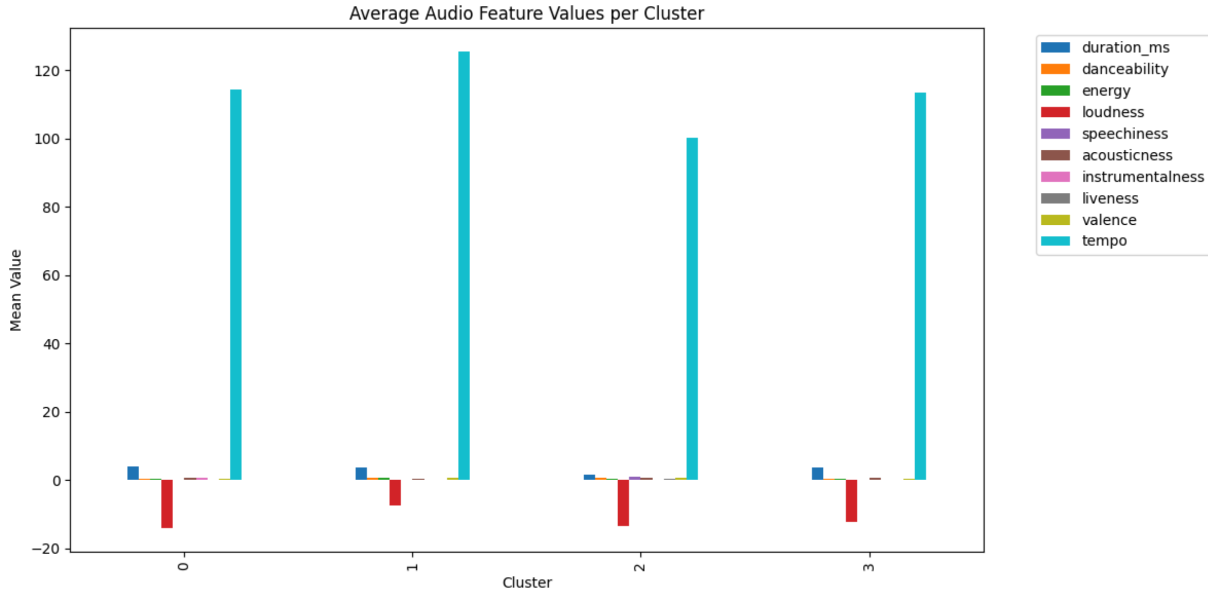
In [17]:

```
# VISUALIZATION

# 2D Scatter Plot (PCA + K-Means)

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Plot
plt.figure(figsize=(8, 6))
plt.scatter(
    X_pca[:, 0],
    X_pca[:, 1],
    c=df_amc['cluster'],
    cmap='viridis'
)

plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.title("KMeans Clustering (PCA)")
plt.colorbar(label="Cluster")
plt.show()
```

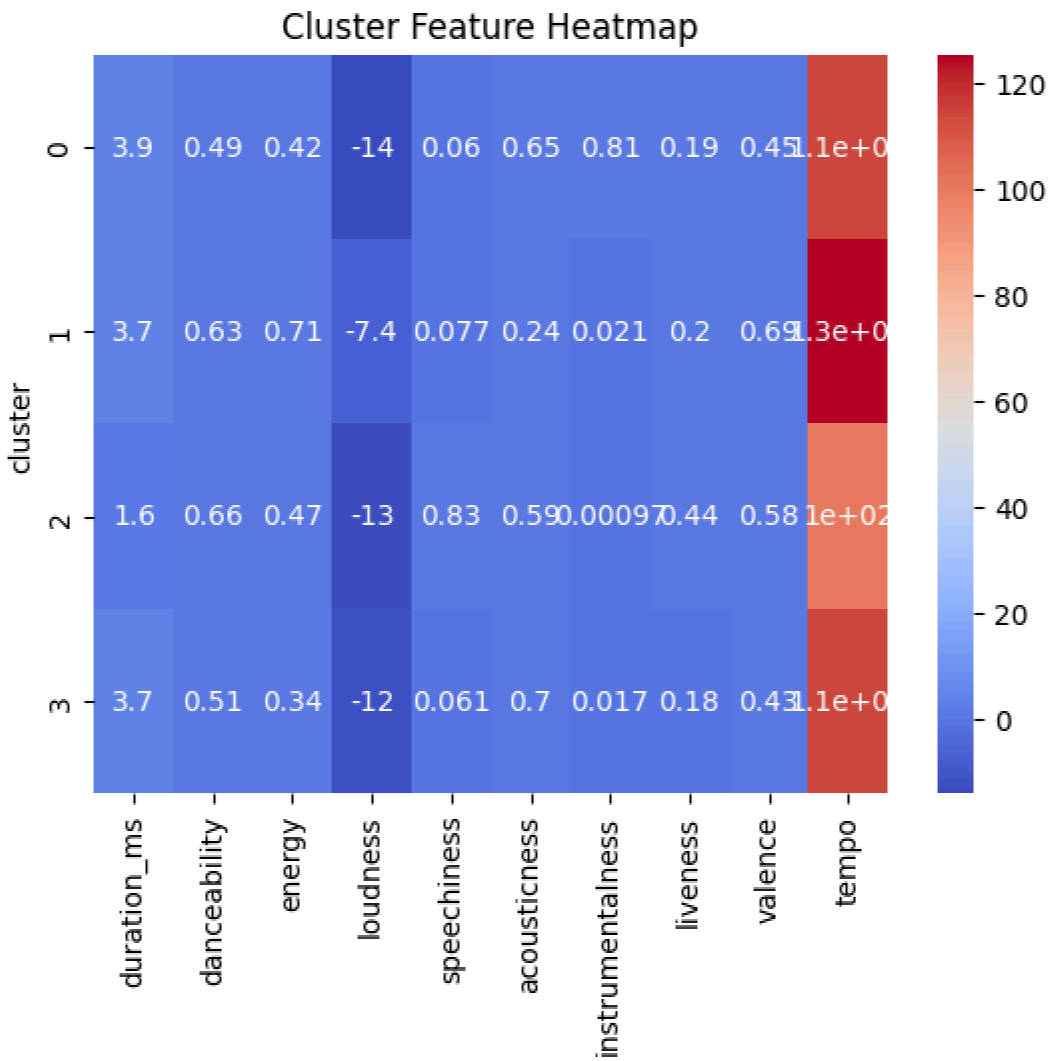


In [18]:

```
# BAR CHART - AVERAGE FEATURE VALUES PER CLUSTER

kmeans = KMeans(n_clusters=4, random_state=42)
df_clean['cluster'] = kmeans.fit_predict(X_scaled)

features = [
    'duration_ms', 'danceability', 'energy', 'loudness', 'speechiness',
    'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo'
]

cluster_means = df_clean.groupby('cluster')[features].mean()

cluster_means.plot(kind='bar', figsize=(12, 6))
plt.title("Average Audio Feature Values per Cluster")
plt.xlabel("Cluster")
plt.ylabel("Mean Value")
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

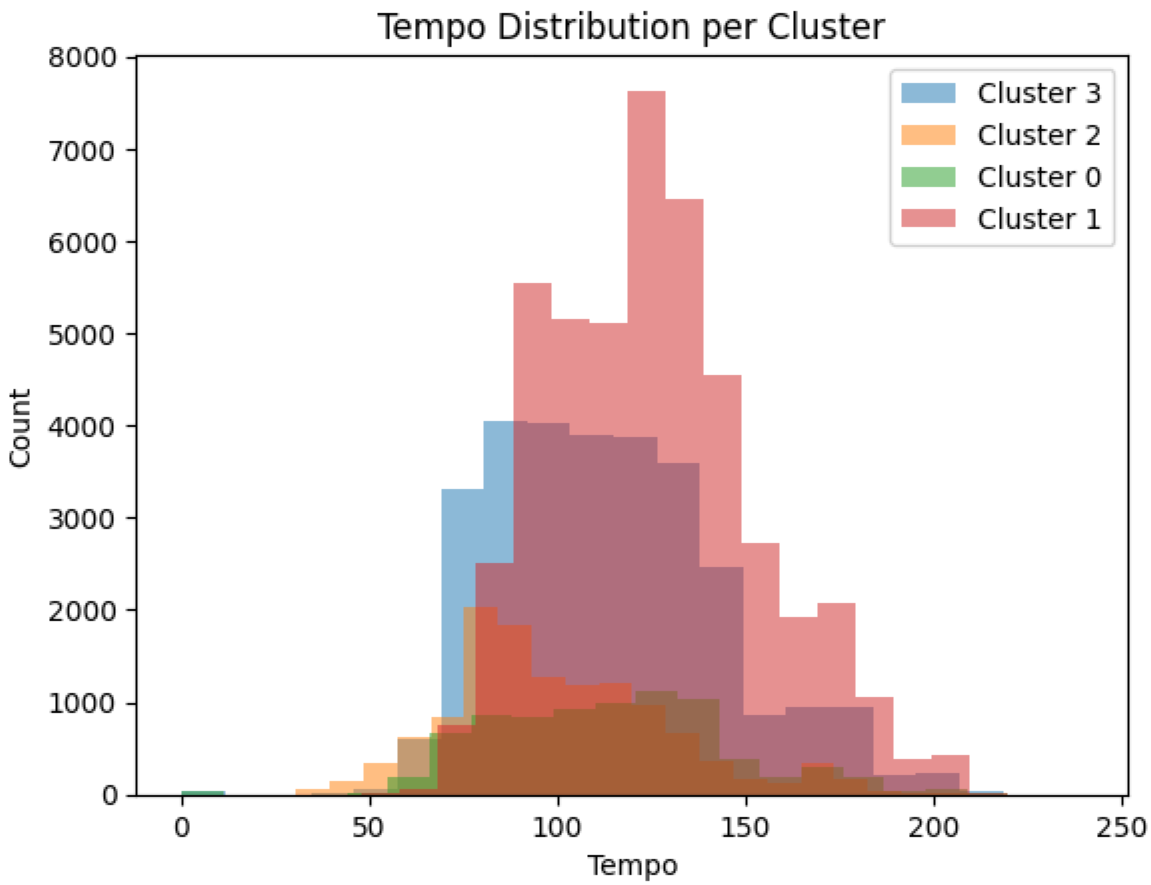


In [19]:
```
# HEATMAP - FEATURE COMPARISON ACROSS CLUSTERS

sns.heatmap(cluster_means, annot=True, cmap='coolwarm')
plt.title("Cluster Feature Heatmap")
plt.show()
```



In [20]:

```
# DISTRIBUTION PLOTS (WITHIN EACH CLUSTER)

for c in df_clean['cluster'].unique():
    subset = df_clean[df_clean['cluster'] == c]
    plt.hist(
        subset['tempo'],
        bins=20,
        alpha=0.5,
        label=f'Cluster {c}'
    )

plt.xlabel("Tempo")
plt.ylabel("Count")
plt.title("Tempo Distribution per Cluster")
plt.legend()
plt.show()
```



In [21]:
```
# FINAL REPORT

# ADD CLUSTER TO THE ORIGINAL DATAFRAME

# Final clustering model
kmeans = KMeans(n_clusters=4, random_state=42)
df_amc['cluster'] = kmeans.fit_predict(X_scaled)

df_amc[['name_song', 'cluster']].head()
```

Out[21]:

	name_song	cluster
0	La Java	3
1	En Douce	3
2	J'en Ai Marre	3
3	Ils n'ont pas ca	3
4	La belote	3

In [22]:
```
# PROFILE CLUSTERS USING MEAN FEATURES

audio_features = [
    'danceability', 'energy', 'acousticness',
    'speechiness', 'instrumentalness',
    'valence', 'tempo'
```

```
]

cluster_summary = (
    df_amc
    .groupby('cluster')[audio_features]
    .mean()
    .round(3)
)

cluster_summary
```

Out[22]:

cluster	danceability	energy	acousticness	speechiness	instrumentalness	valence	tempo
0	0.485	0.416	0.647	0.060	0.811	0.450	114.301
1	0.635	0.708	0.242	0.077	0.021	0.686	125.293
2	0.664	0.466	0.586	0.835	0.001	0.584	100.336
3	0.505	0.342	0.699	0.061	0.017	0.427	113.406

In [23]:

```
# READABLE CLUSTER LABELS

def label_cluster(row):
    if row['danceability'] > 0.65 and row['energy'] > 0.65:
        return "Party / Dance Tracks"
    elif row['energy'] < 0.4 and row['acousticness'] > 0.6:
        return "Chill Acoustic"
    elif row['energy'] > 0.7 and row['valence'] > 0.6:
        return "Workout / Feel-Good"
    else:
        return "Calm / Mixed Mood"

cluster_summary['cluster_profile'] = cluster_summary.apply(
    label_cluster, axis=1
)

cluster_summary
```

Out[23]:

cluster	danceability	energy	acousticness	speechiness	instrumentalness	valence	tempo
0	0.485	0.416	0.647	0.060	0.811	0.450	114.301
1	0.635	0.708	0.242	0.077	0.021	0.686	125.293
2	0.664	0.466	0.586	0.835	0.001	0.584	100.336
3	0.505	0.342	0.699	0.061	0.017	0.427	113.406

In [24]:

```
# MAP CLUSTER DESCRIPTION BASED ON SONGS

profile_map = cluster_summary['cluster_profile'].to_dict()

df_amc['cluster_profile'] = df_amc['cluster'].map(profile_map)

df_amc[['name_song', 'cluster', 'cluster_profile']].head()
```

Out[24]:

	name_song	cluster	cluster_profile
0	La Java	3	Chill Acoustic
1	En Douce	3	Chill Acoustic
2	J'en Ai Marre	3	Chill Acoustic
3	Ils n'ont pas ca	3	Chill Acoustic
4	La belote	3	Chill Acoustic

In [25]:

```
# SHOW TOP TRACKS PER CLUSTER

top_tracks = (
    df_amc
    .sort_values(['cluster', 'popularity_songs'], ascending=[True, False])
    .groupby('cluster')
    .head(10)
)

top_tracks[['cluster', 'cluster_profile', 'name_song', 'popularity_songs']]
```

Out[25]:

	cluster	cluster_profile	name_song	popularity_songs
35463	0	Calm / Mixed Mood	ROLLIN N CONTROLLIN FREESTYLE	83
35303	0	Calm / Mixed Mood	YKWIM?	79
34908	0	Calm / Mixed Mood	Buttercup	78
35333	0	Calm / Mixed Mood	Jealous	78
35332	0	Calm / Mixed Mood	Jealous	77
35079	0	Calm / Mixed Mood	Soft Brown Noise	76
34934	0	Calm / Mixed Mood	Friendships	75
35086	0	Calm / Mixed Mood	Show Me How	75
34935	0	Calm / Mixed Mood	Brahms Lullaby	74
35381	0	Calm / Mixed Mood	Snowman	74
35665	1	Workout / Feel-Good	Astronaut In The Ocean	98
35398	1	Workout / Feel-Good	WITHOUT YOU	94
35422	1	Workout / Feel-Good	Hecha Pa' Mi	92
35532	1	Workout / Feel-Good	911	91
35287	1	Workout / Feel-Good	RAPSTAR	89
35432	1	Workout / Feel-Good	Whoopty	89
35434	1	Workout / Feel-Good	Goosebumps	89
35284	1	Workout / Feel-Good	Martin & Gina	88
35668	1	Workout / Feel-Good	Tapão Na Raba	87

	cluster	cluster_profile	name_song	popularity_songs
32855	1	Workout / Feel-Good	Hayloft	86
35294	2	Calm / Mixed Mood	Beautiful Pain (Losin My Mind)	72
61359	2	Calm / Mixed Mood	Siempre Fine	72
34969	2	Calm / Mixed Mood	Gentleman	70
35292	2	Calm / Mixed Mood	Neva Cared	70
90870	2	Calm / Mixed Mood	The Chicken Wing Beat	70
34514	2	Calm / Mixed Mood	Ain't Nobody Takin My Baby	69
41676	2	Calm / Mixed Mood	VIP in der Psychiatrie	65
42034	2	Calm / Mixed Mood	Rohdiamant ٢٠٢٠	64
34511	2	Calm / Mixed Mood	You Reposted in the Wrong Neighborhood I Glue7...	63
61354	2	Calm / Mixed Mood	Ella Se Arrebata	63
35241	3	Chill Acoustic	What You Know Bout Love	91
35233	3	Chill Acoustic	Arcade	89
35436	3	Chill Acoustic	Put Your Records On	87
34858	3	Chill Acoustic	Hold On	83
35234	3	Chill Acoustic	Arcade	83
35500	3	Chill Acoustic	Party Girl	81
34650	3	Chill Acoustic	Go Fuck Yourself	80
34884	3	Chill Acoustic	Beautiful Crazy	80
35505	3	Chill Acoustic	Control	80
34886	3	Chill Acoustic	Better Together	79

In [26]:

```
# EXPORT FINAL DATASET

df_amc.to_csv(
    "AMC_Music_Clustered_Final.csv",
    index=False
```

```
)

cluster_summary.to_csv(
    "AMC_Cluster_Profiles.csv"
)

print("✅ Final datasets exported successfully")
```

```
✅ Final datasets exported successfully
```

In [ ]: