Objectives

The objective of this project is to analyze YouTube video data in order to uncover the key drivers of content performance and audience engagement. Specifically, the analysis seeks to:

1. Identify which video categories (e.g., Gaming, Comedy, News) receive the highest engagement in terms of views, likes, and comments.
2. Evaluate whether video duration or resolution influences engagement metrics.
3. Explore whether video popularity can be predicted using metadata features.
4. Assess whether videos with hashtags perform better than those without in terms of views, likes, and engagement rate.
5. Discover which hashtags are most frequently associated with viral videos and how they contribute to content success.

In [210]:
```
#Importing Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [211]:
```
#applying whitegrid theme
sns.set(style="whitegrid")
```

In [212]:
```
#Loading Dataset
df=pd.read_csv('Youtube_data.csv')
```

In [213]:
```
#Checking total rows & columns
df.shape
```

Out[213]:
```
(17589, 17)
```

In [214]:
```
#Viewing all the column names
df.columns
```

Out[214]:
```
Index(['video_id', 'duration', 'bitrate', 'bitrate(video)', 'height', 'widt
h',
       'frame rate', 'frame rate(est.)', 'codec', 'category', 'url', 'titl
e',
       'description', 'hashtags', 'views', 'likes', 'comments'],
      dtype='object')
```

In [215]:
```
#Viewing partial dataset
df.head(10)
```

Out[215]:

	video_id	duration	bitrate	bitrate(video)	height	width	frame rate	frame rate(est.)	codec	cat
0	--F7dc-_FSI	180	5777	5640	1920	1080	25.00	25.00	h264	Ne P
1	--cCAD-8Y_U	930	1195	1001	1280	720	30.00	30.00	h264	Ga
2	--g2gG8pQ0w	233	3028	2833	1280	720	23.98	23.98	h264	Co
3	-0DR7-voRCU	562	431	300	320	240	29.97	0.00	h264	Peo
4	-0Fkp-2EzX0	300	3087	2929	1280	720	23.98	23.98	h264	Ga
5	-0J-a-kKR1M	135	467	371	320	240	30.00	0.00	h264	Peo
6	-0bc_-HP6dE	43	634	501	480	360	29.97	29.97	h264	Entertair
7	-0hjSaYCRnA	4	738	605	540	360	29.97	0.00	h264	Co
8	-0kAY-vAVBc	228	5880	5686	1920	1080	25.00	25.00	h264	
9	-0lNh-4ZuTE	268	492	364	640	360	25.00	0.00	h264	Edu

In [216]:
```
#Checking dataset info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17589 entries, 0 to 17588
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   video_id          17589 non-null  object
 1   duration          17589 non-null  int64
 2   bitrate           17589 non-null  int64
 3   bitrate(video)    17589 non-null  int64
 4   height            17589 non-null  int64
 5   width             17589 non-null  int64
 6   frame rate        17589 non-null  float64
 7   frame rate(est.)  17589 non-null  float64
 8   codec             17589 non-null  object
 9   category          17589 non-null  object
 10  url               17589 non-null  object
 11  title             17589 non-null  object
 12  description       16477 non-null  object
 13  hashtags          16013 non-null  object
 14  views             17589 non-null  int64
 15  likes             17589 non-null  int64
 16  comments          17589 non-null  int64
dtypes: float64(2), int64(8), object(7)
memory usage: 2.3+ MB
```

In [217]:
```
#Checking Statistical info
df.describe()
```

Out[217]:

	duration	bitrate	bitrate(video)	height	width	frame rate	
count	17589.000000	17589.000000	17589.000000	17589.000000	17589.000000	17589.000000	17
mean	241.551936	1271.354369	1150.418443	766.781170	504.591961	26.467639	
std	493.026994	1375.359875	1351.800202	467.289304	262.727746	6.039748	
min	1.000000	0.000000	0.000000	108.000000	88.000000	3.750000	
25%	51.000000	437.000000	326.000000	426.000000	320.000000	25.000000	
50%	135.000000	743.000000	632.000000	640.000000	480.000000	29.970000	
75%	268.000000	1293.000000	1184.000000	960.000000	720.000000	29.970000	
max	25845.000000	22421.000000	22229.000000	2592.000000	1944.000000	59.080000	

In [218]:
```
#checking for Total null values
df.isnull().sum()
```

Out[218]:
```
video_id              0
duration              0
bitrate               0
bitrate(video)        0
height                0
width                 0
frame rate            0
frame rate(est.)      0
codec                 0
category              0
url                   0
title                 0
description        1112
hashtags           1576
views                 0
likes                 0
comments              0
dtype: int64
```

In [219]:
```
#Creating duplicate data
df1=df
```

Data Cleaning

In [220]:
```
#Dropping Unnecessary columns
cols=['url', 'description']
df1.drop(cols, axis=1, inplace=True)

#Checking columns
df1.columns
```

Out[220]:
```
Index(['video_id', 'duration', 'bitrate', 'bitrate(video)', 'height', 'widt
h',
       'frame rate', 'frame rate(est.)', 'codec', 'category', 'title',
       'hashtags', 'views', 'likes', 'comments'],
      dtype='object')
```

In [221]:
```
#Renaming inconsistent column name & spacing
df1=df1.rename(columns={'frame rate':'frame_rate'})

df1=df1.rename(columns={'frame rate(est.)':'frame_rate_est'})

df1=df1.rename(columns={'bitrate(video)':'bitrate_video'})
```

In [222]:
```
#Handling missing values
df1['hashtags'].fillna('No Hashtags', inplace=True)

#Checking Null Values
df1.isna().sum()
```

Out[222]:
```
video_id          0
duration          0
bitrate           0
bitrate_video     0
height            0
width             0
frame_rate        0
frame_rate_est    0
codec             0
category          0
title             0
hashtags          0
views             0
likes             0
comments          0
dtype: int64
```

In [223]:
```
#Checking for Duplicate rows
df1.duplicated().sum()
```

Out[223]:
```
0
```

In [224]:
```
#Checking for Unique values
df1.duplicated('video_id').sum()
```

Out[224]:
```
0
```

In [225]:
```
#Checking Unique values category
df1['category'].value_counts()
```

Out[225]:
```
category
People & Blogs           3946
Music                    2966
Entertainment            2252
Gaming                   1420
Sports                   1230
Comedy                   1176
Autos & Vehicles          798
Education                 644
News & Politics           636
Travel & Events           590
Film & Animation          587
Pets & Animals            476
Howto & Style             340
Science & Technology      283
Nonprofits & Activis      227
Shows                      18
Name: count, dtype: int64
```

In [226]:
```
#Fixing Data Inconsistencies
df1['category'] = df1['category'].str.strip().str.title()
```

In [227]:
```
# Checking negative values
print("Negative values check:")
print(df1[['views','likes','comments','duration','height','width']].lt(0).sum(

# Checking zero values
print("\nZero values check:")
print(df1[['views','likes','comments','duration','height','width']].eq(0).sum(
```

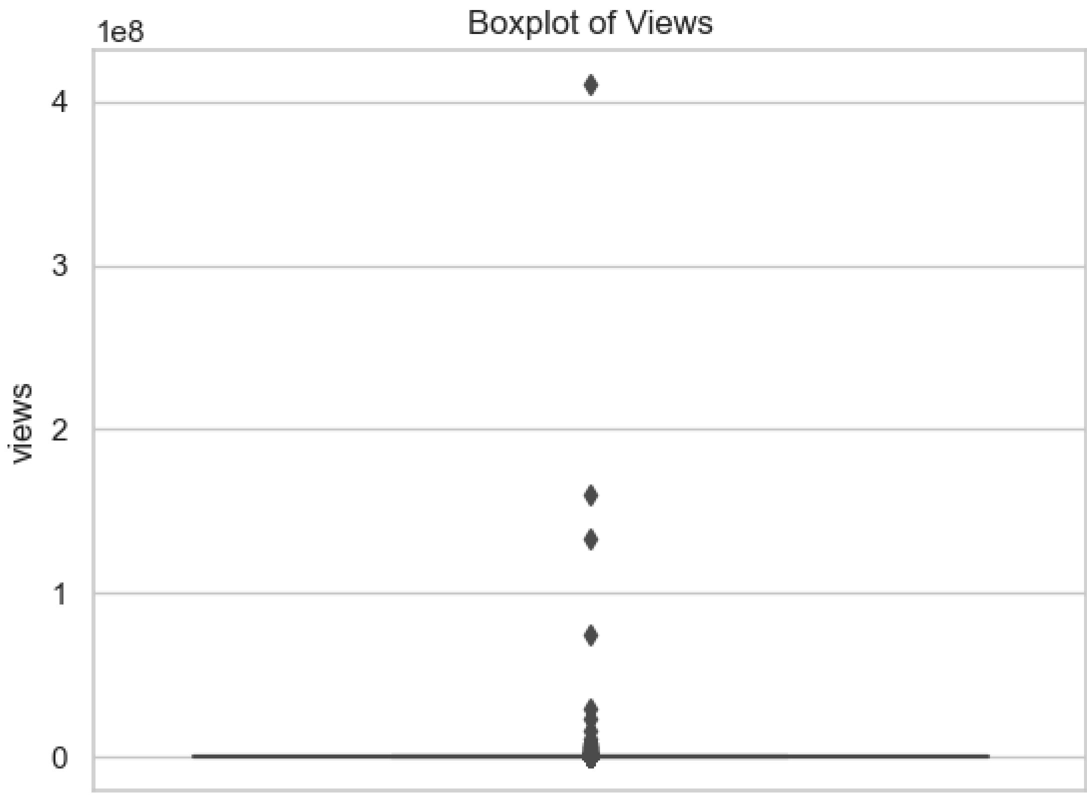
```
Negative values check:
views       0
likes       0
comments    0
duration    0
height      0
width       0
dtype: int64

Zero values check:
views         171
likes        7918
comments    12899
duration        0
height          0
width           0
dtype: int64
```

Outlier detection & Treatment

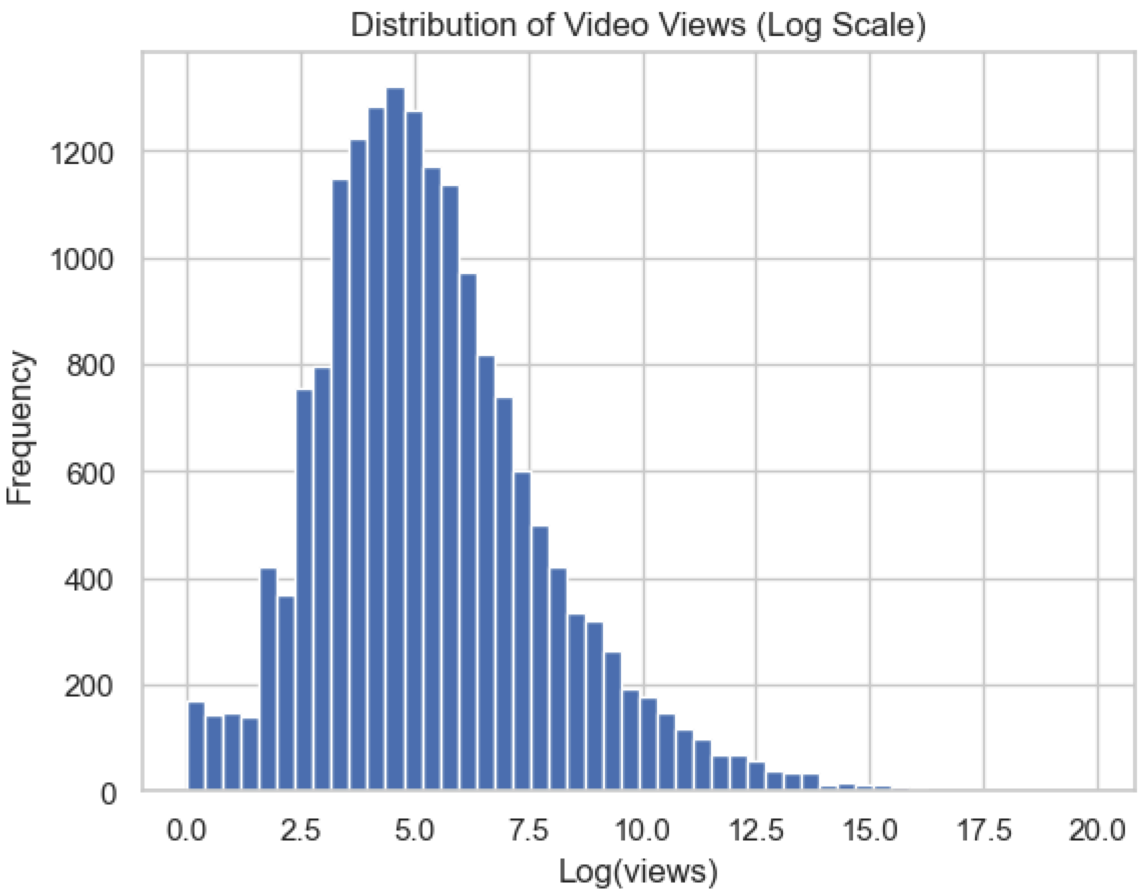
In [228]:
```
#Imputing IQR for views
def find_outliers(df1, views):
    Q1 = df1[views].quantile(0.25)   # 25th percentile
    Q3 = df1[views].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                   # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[views] < lower_limit) | (df1[views] > upper_limit)]

    return outliers

#Checking for outliers
outliers_views = find_outliers(df1, "views")
print("Outliers in views:", len(outliers_views))

print(df1["views"].describe())
```

```
Outliers in views: 2888
count    1.758900e+04
mean     6.894158e+04
std      3.537491e+06
min      0.000000e+00
25%      3.800000e+01
50%      1.520000e+02
75%      8.000000e+02
max      4.103849e+08
Name: views, dtype: float64
```

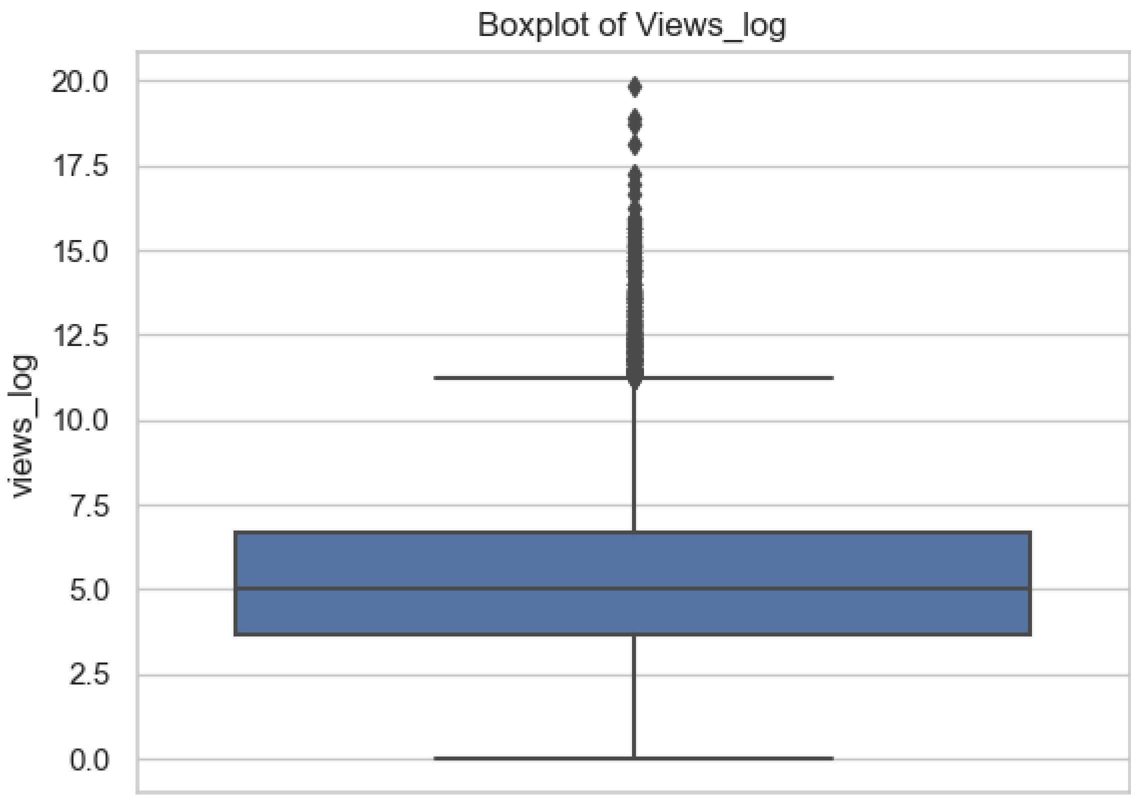
In [229]:
```
#Boxplot to view outliers
sns.boxplot(y=df1["views"])
plt.title("Boxplot of Views")
plt.show()
```



In [230]:
```
#Histogram using Log
plt.hist(np.log1p(df1["views"]), bins=50)
plt.xlabel("Log(views)")
plt.ylabel("Frequency")
plt.title("Distribution of Video Views (Log Scale)")
plt.show()
```



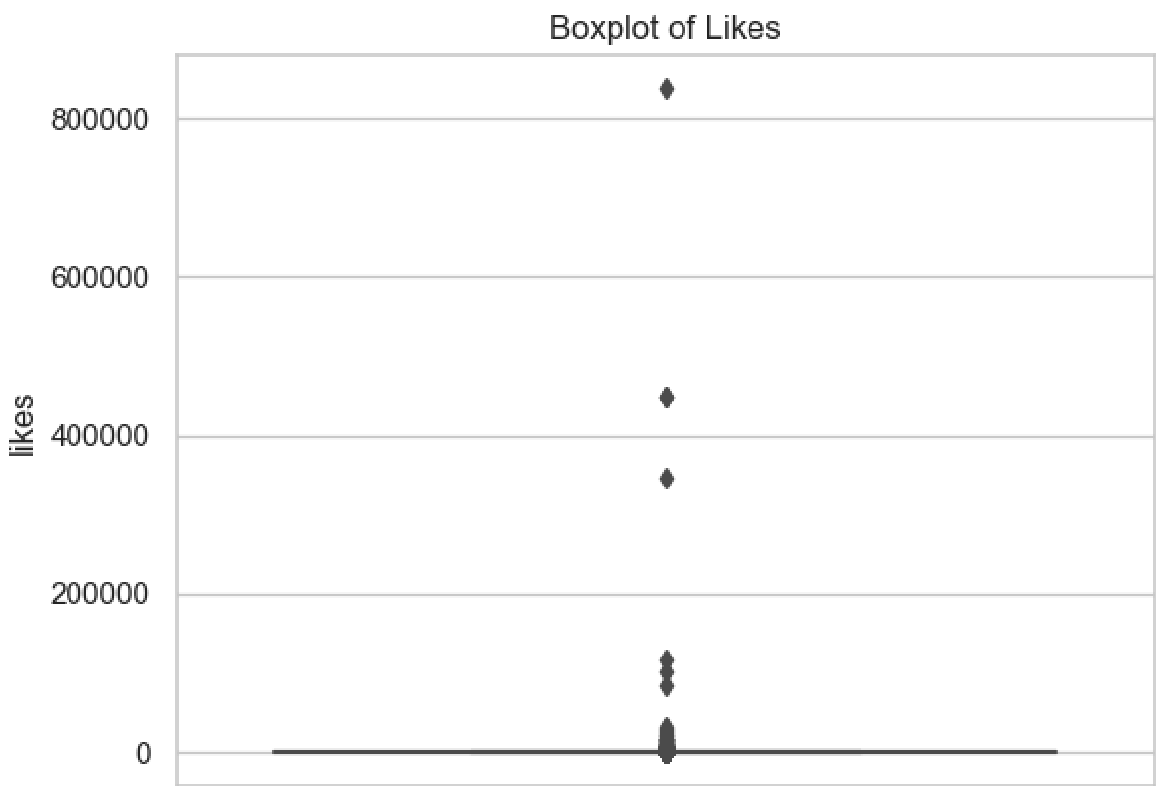
In [231]:
```
#Log transform
df1['views_log'] = np.log1p(df1['views'])

#Boxplot for viewing outliers
sns.boxplot(y=df1["views_log"])
plt.title("Boxplot of Views_log")
plt.show()
```



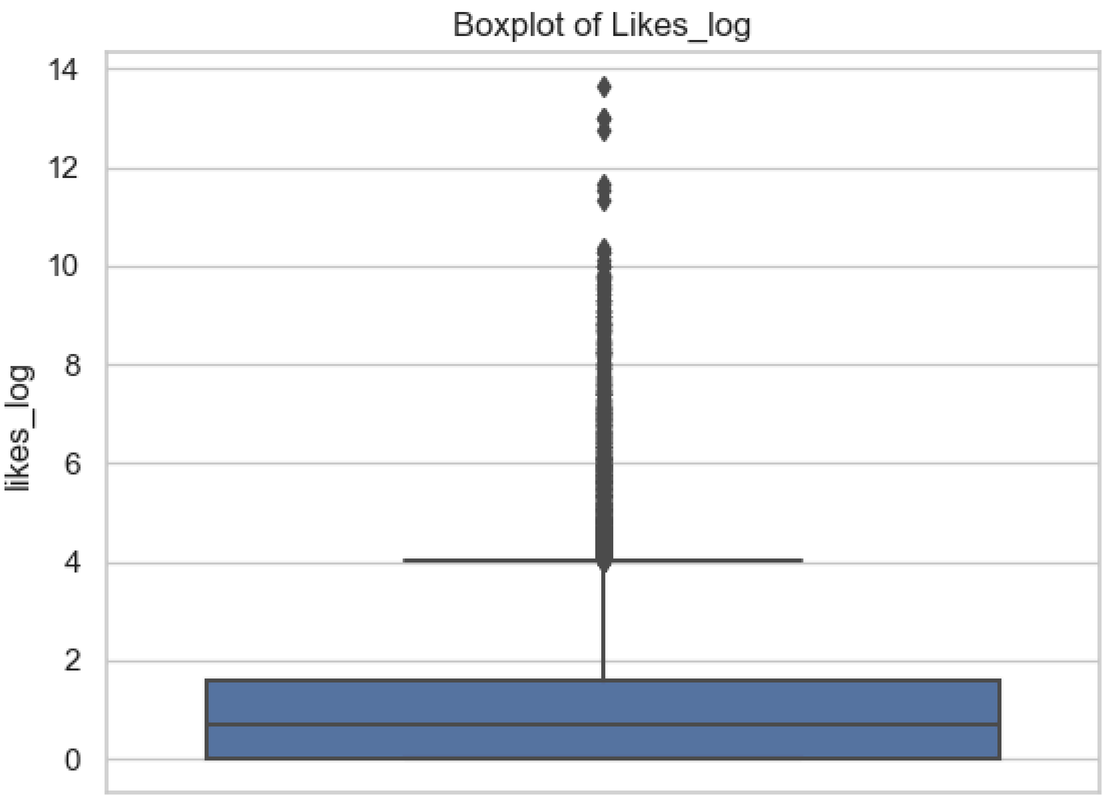
In [232]:
```
#Imputing IQR for Likes
def find_outliers(df1, likes):
    Q1 = df1[likes].quantile(0.25)   # 25th percentile
    Q3 = df1[likes].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                    # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[likes] < lower_limit) | (df1[likes] > upper_limit)]

    return outliers

#Checking for outliers
outliers_likes = find_outliers(df1, "likes")
print("Outliers in likes:", len(outliers_likes))

print(df1["likes"].describe())
```

```
Outliers in likes: 2565
count     17589.000000
mean        208.862641
std        8477.504735
min           0.000000
25%           0.000000
50%           1.000000
75%           4.000000
max      836981.000000
Name: likes, dtype: float64
```

In [233]:
```
#Boxplot to view outliers
sns.boxplot(y=df1["likes"])
plt.title("Boxplot of Likes")
plt.show()
```



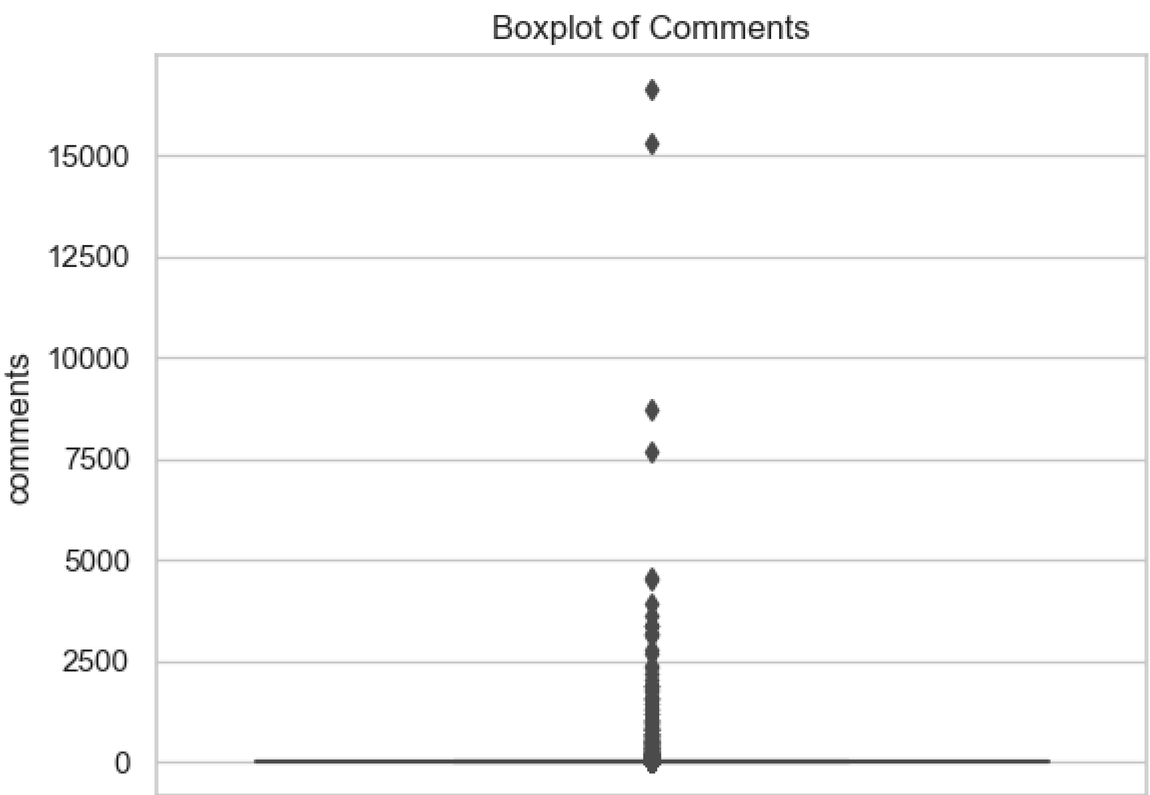
In [234]:
```
#Log Transform
df1['likes_log'] = np.log1p(df1['likes'])

#Boxplot to view outliers
sns.boxplot(y=df1["likes_log"])
plt.title("Boxplot of Likes_log")
plt.show()
```



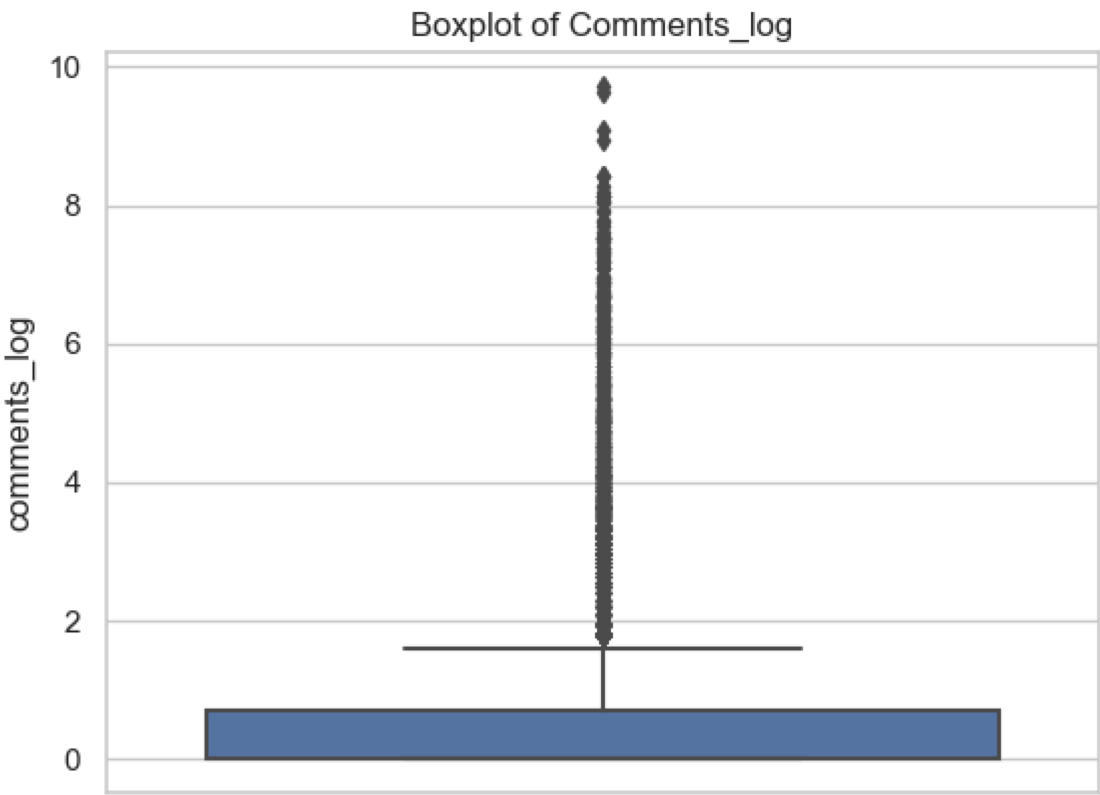
In [235]:
```
#Imputing IQR
def find_outliers(df1, comments):
    Q1 = df1[comments].quantile(0.25)   # 25th percentile
    Q3 = df1[comments].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                      # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[comments] < lower_limit) | (df1[comments] > upper_limi

    return outliers

#Checking for outliers
outliers_comments = find_outliers(df1, "comments")
print("Outliers in comments:", len(outliers_comments))

print(df1["comments"].describe())
```

```
Outliers in comments: 2424
count    17589.000000
mean        12.899312
std        225.839378
min          0.000000
25%          0.000000
50%          0.000000
75%          1.000000
max      16634.000000
Name: comments, dtype: float64
```

In [236]:
```
#Boxplot to view outliers
sns.boxplot(y=df1["comments"])
plt.title("Boxplot of Comments")
plt.show()
```



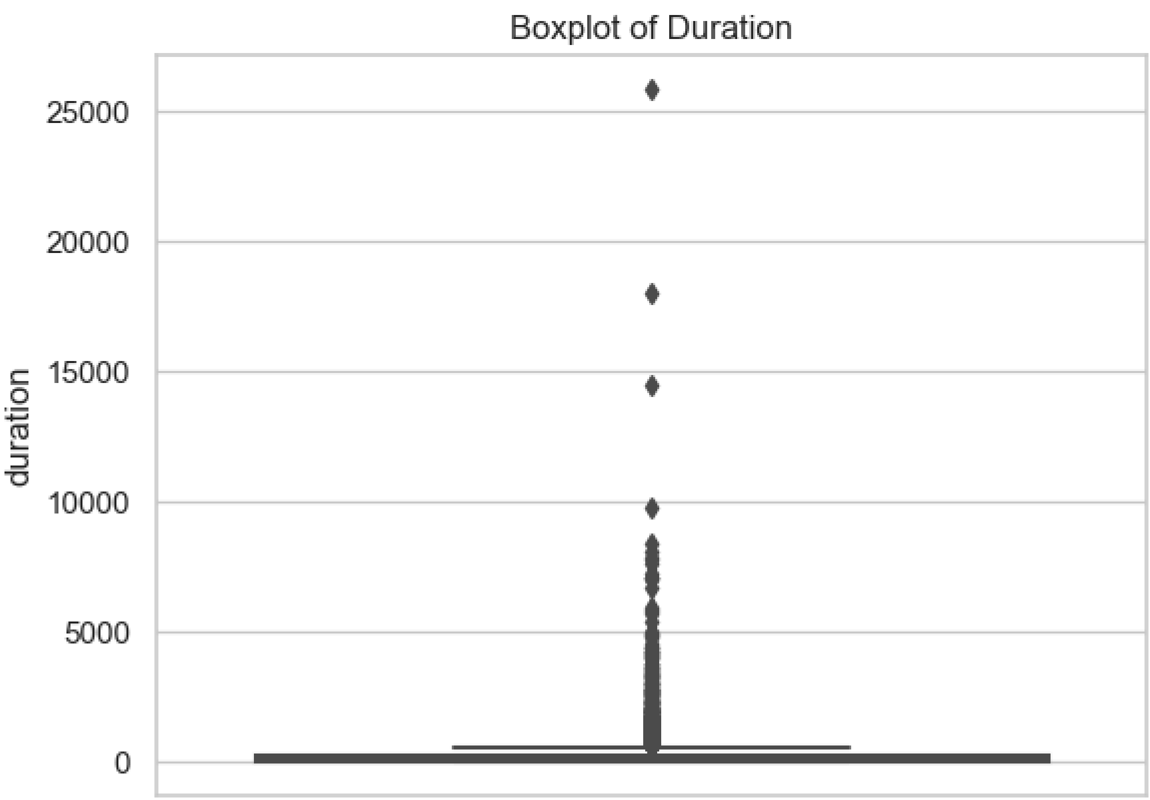
In [237]:
```
#Log Transform
df1['comments_log'] = np.log1p(df1['comments'])

#Boxplot to view outliers
sns.boxplot(y=df1["comments_log"])
plt.title("Boxplot of Comments_log")
plt.show()
```



In [238]:
```
#Imputing IQR for Duration
def find_outliers(df1, duration):
    Q1 = df1[duration].quantile(0.25)   # 25th percentile
    Q3 = df1[duration].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                      # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[duration] < lower_limit) | (df1[duration] > upper_limi

    return outliers

#Checking for outliers
outliers_duration = find_outliers(df1, "duration")
print("Outliers in duration:", len(outliers_duration))

print(df1["duration"].describe())
```

```
Outliers in duration: 1376
count    17589.000000
mean       241.551936
std        493.026994
min          1.000000
25%         51.000000
50%        135.000000
75%        268.000000
max      25845.000000
Name: duration, dtype: float64
```

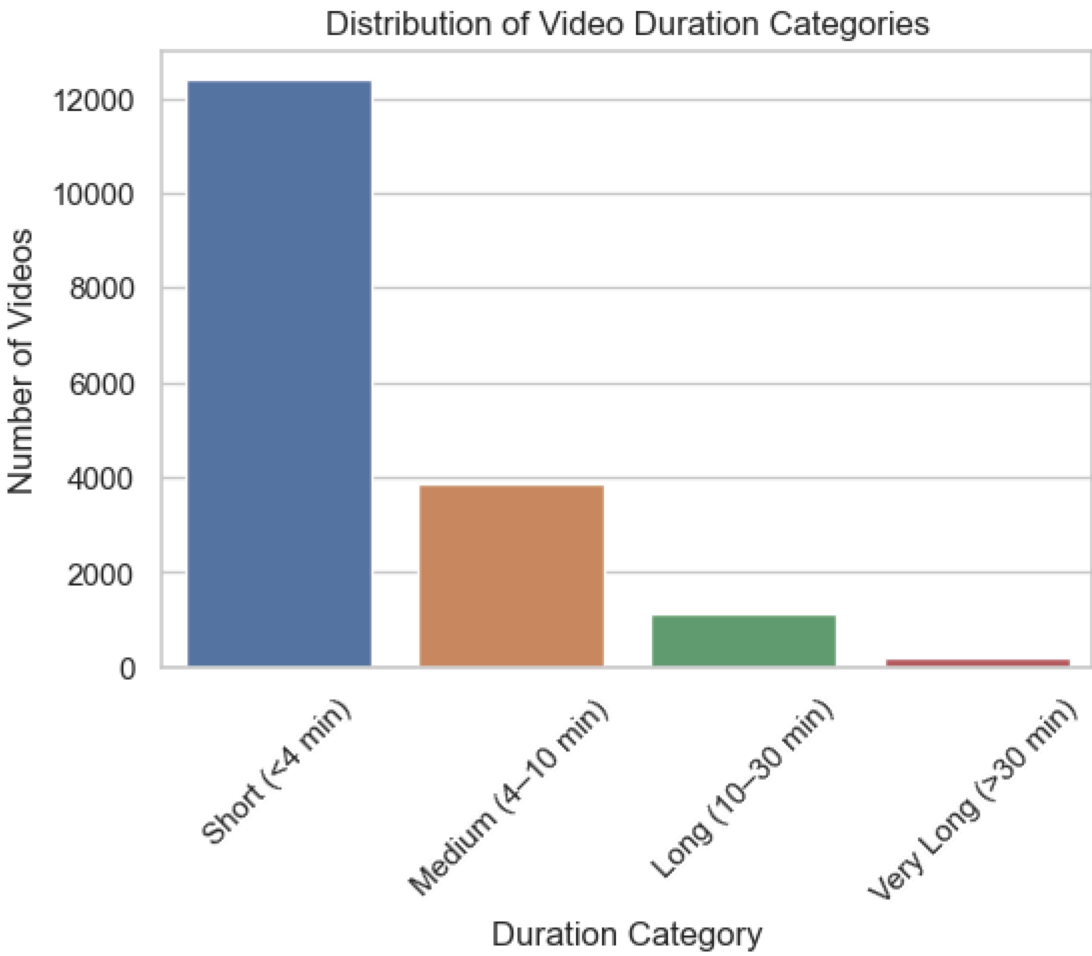
In [239]:
```
#Boxplot for viewing outliers
sns.boxplot(y=df1["duration"])
plt.title("Boxplot of Duration")
plt.show()
```



In [240]:
```
#Categoring to minutes
bins = [0, 240, 600, 1800, float('inf')]  # <4 min, 4-10 min, 10-30 min, >30 m
labels = ['Short (<4 min)', 'Medium (4-10 min)', 'Long (10-30 min)', 'Very Lor

#Creating duration categories
df1['duration_category'] = pd.cut(df1['duration'], bins=bins, labels=labels, r

print(df1['duration_category'].value_counts())
```

```
duration_category
Short (<4 min)         12389
Medium (4-10 min)       3885
Long (10-30 min)        1116
Very Long (>30 min)      199
Name: count, dtype: int64
```

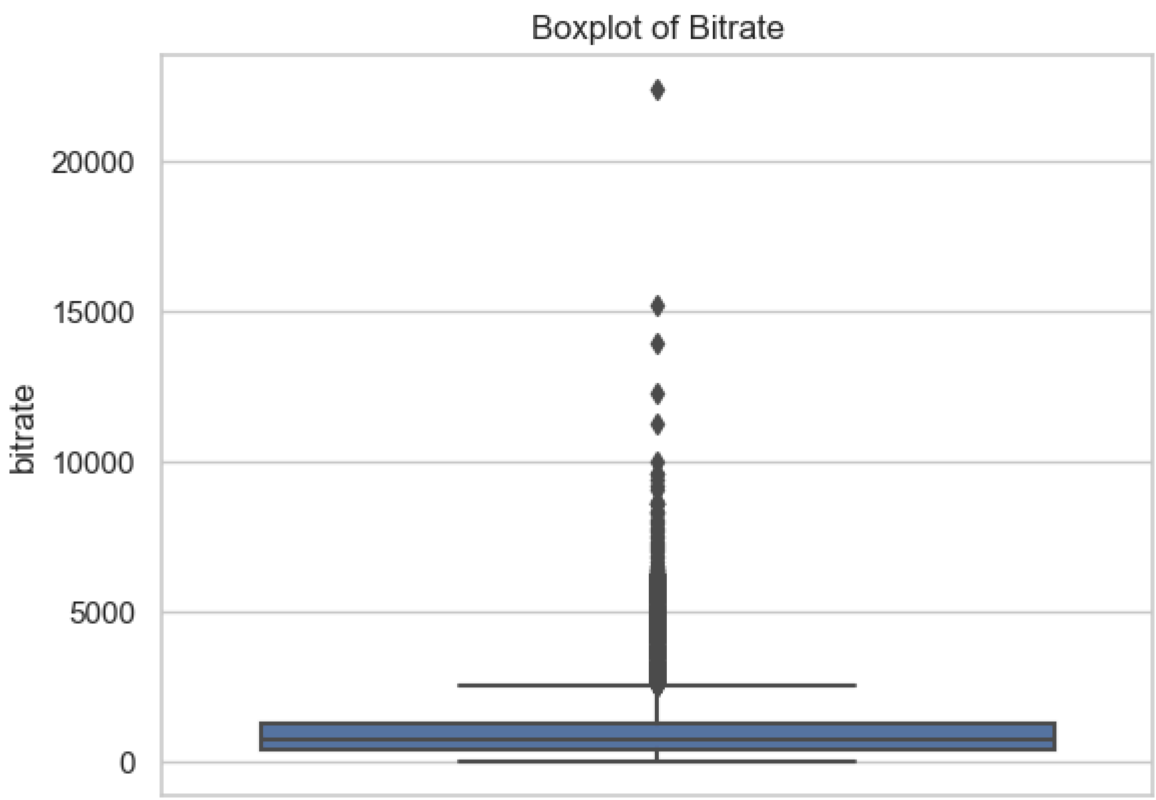
In [241]:
```
#Barchart for viewing duration category
plt.figure(figsize=(6,4))
sns.countplot(data=df1, x='duration_category', order=df1['duration_category'].

plt.title("Distribution of Video Duration Categories")
plt.xlabel("Duration Category")
plt.ylabel("Number of Videos")
plt.xticks(rotation=45)
plt.show()
```



In [242]:
```
#Imputing IQR
def find_outliers(df1, bitrate):
    Q1 = df1[bitrate].quantile(0.25)   # 25th percentile
    Q3 = df1[bitrate].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                     # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[bitrate] < lower_limit) | (df1[bitrate] > upper_limit)

    return outliers

#Checking for outliers
outliers_bitrate = find_outliers(df1, "bitrate")
print("Outliers in bitrate:", len(outliers_bitrate))

print(df1["bitrate"].describe())
```

```
Outliers in bitrate: 2671
count    17589.000000
mean      1271.354369
std       1375.359875
min          0.000000
25%        437.000000
50%        743.000000
75%       1293.000000
max      22421.000000
Name: bitrate, dtype: float64
```

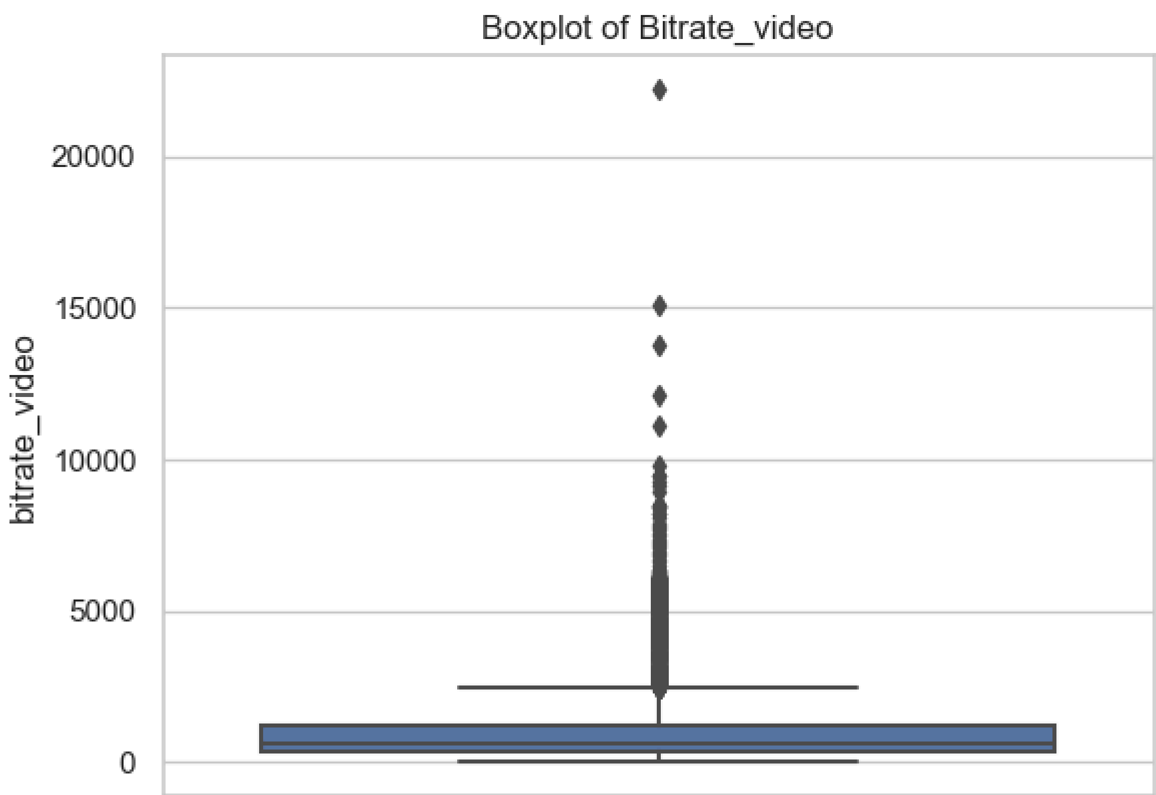
In [243]:
```
#Boxplot for viewing outliers
sns.boxplot(y=df1["bitrate"])
plt.title("Boxplot of Bitrate")
plt.show()
```



In [244]:
```
#Imputing IQR
def find_outliers(df1, bitrate_video):
    Q1 = df1[bitrate_video].quantile(0.25)   # 25th percentile
    Q3 = df1[bitrate_video].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                            # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[bitrate_video] < lower_limit) | (df1[bitrate_video] >

    return outliers

#Checking for outliers
outliers_bitrate_video = find_outliers(df1, "bitrate_video")
print("Outliers in bitrate_video:", len(outliers_bitrate_video))

print(df1["bitrate_video"].describe())
```

```
Outliers in bitrate_video: 2597
count    17589.000000
mean      1150.418443
std       1351.800202
min          0.000000
25%        326.000000
50%        632.000000
75%       1184.000000
max      22229.000000
Name: bitrate_video, dtype: float64
```

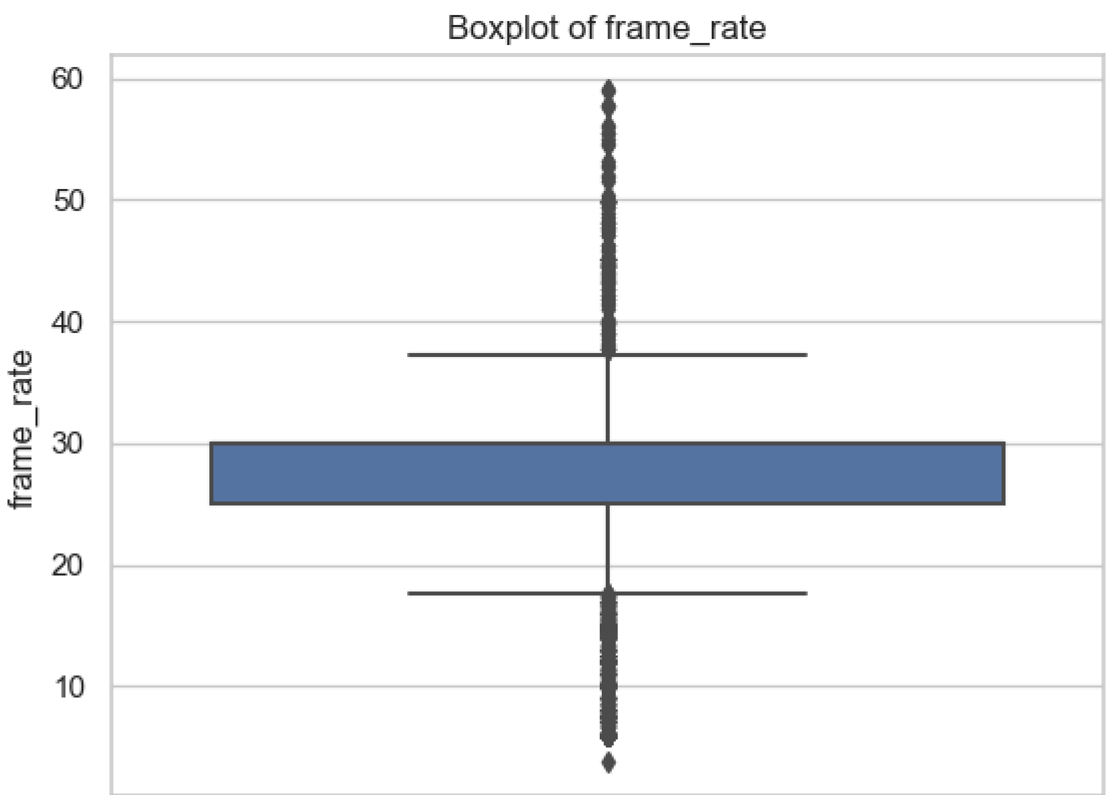
In [245]:
```
#Boxplot for viewing outliers
sns.boxplot(y=df1["bitrate_video"])
plt.title("Boxplot of Bitrate_video")
plt.show()
```



In [246]:
```
#Imputing IQR
def find_outliers(df1, frame_rate):
    Q1 = df1[frame_rate].quantile(0.25)   # 25th percentile
    Q3 = df1[frame_rate].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                         # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[frame_rate] < lower_limit) | (df1[frame_rate] > upper_

    return outliers

#Checking for outliers
outliers_frame_rate = find_outliers(df1, "frame_rate")
print("Outliers in frame_rate:", len(outliers_frame_rate))

print(df1["frame_rate"].describe())
```

```
Outliers in frame_rate: 2287
count    17589.000000
mean        26.467639
std          6.039748
min          3.750000
25%         25.000000
50%         29.970000
75%         29.970000
max         59.080000
Name: frame_rate, dtype: float64
```

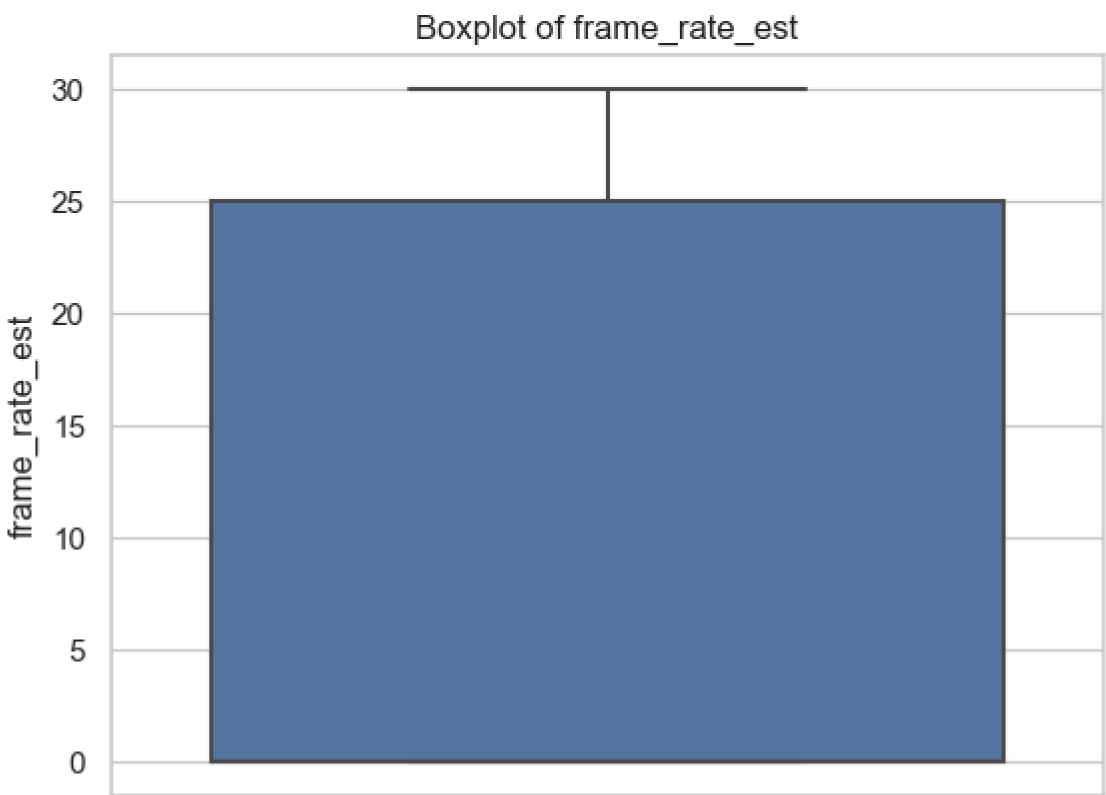
In [247]:
```
#Boxplot for viewing outliers
sns.boxplot(y=df1["frame_rate"])
plt.title("Boxplot of frame_rate")
plt.show()
```



In [248]:
```
#Imputing IQR
def find_outliers(df1, frame_rate_est):
    Q1 = df1[frame_rate_est].quantile(0.25)   # 25th percentile
    Q3 = df1[frame_rate_est].quantile(0.75)   # 75th percentile
    IQR = Q3 - Q1                             # Interquartile Range

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    outliers = df1[(df1[frame_rate_est] < lower_limit) | (df1[frame_rate_est]

    return outliers

#Checking for outliers
outliers_frame_rate_est = find_outliers(df1, "frame_rate_est")
print("Outliers in frame_rate_est:", len(outliers_frame_rate_est))

print(df1["frame_rate_est"].describe())
```

```
Outliers in frame_rate_est: 0
count    17589.000000
mean         9.471172
std         13.253197
min          0.000000
25%          0.000000
50%          0.000000
75%         25.000000
max         30.000000
Name: frame_rate_est, dtype: float64
```

In [249]:
```
#Boxplot for viewing outliers
sns.boxplot(y=df1["frame_rate_est"])
plt.title("Boxplot of frame_rate_est")
plt.show()
```



In [250]:
```
#Checking for log transformation columns
df1.head()
```

Out[250]:

	video_id	duration	bitrate	bitrate_video	height	width	frame_rate	frame_rate_est	codec
0	--F7dc-_FSI	180	5777	5640	1920	1080	25.00	25.00	h264
1	--cCAD-8Y_U	930	1195	1001	1280	720	30.00	30.00	h264
2	--g2gG8pQ0w	233	3028	2833	1280	720	23.98	23.98	h264
3	-0DR7-voRCU	562	431	300	320	240	29.97	0.00	h264
4	-0Fkp-2EzX0	300	3087	2929	1280	720	23.98	23.98	h264

Feature Engineering

In [251]:
```
#Adding column Engagement rate
df1['engagement_rate'] = np.where(df1['views'] > 0,(df1['likes'] + df1['commer

#Filling null values to 0 (171 rows contain 0 views)
df1['engagement_rate'] = df1['engagement_rate'].fillna(0)
```

In [252]:
```
#Categorizing & Adding Resolution column
def map_resolution(h):
    if h <= 240:
        return "240p"
    elif h <= 360:
        return "360p"
    elif h <= 480:
        return "480p"
    elif h <= 720:
        return "720p (HD)"
    elif h <= 1080:
        return "1080p (Full HD)"
    elif h <= 2160:
        return "2160p (4K)"
    else:
        return "Other"

df1['resolution'] = df1['height'].apply(map_resolution)

# Checking distribution
print(df1['resolution'].value_counts())
```

```
resolution
720p (HD)         6155
2160p (4K)        4301
360p              3303
480p              1784
1080p (Full HD)   1277
240p               766
Other                3
Name: count, dtype: int64
```

In [253]:
```
#Adding Column to minutes
df1["duration_min"] = df1["duration"] / 60
```

In [254]:
```
#Adding Column
df1["likes_per_min"] = np.where(df1["duration_min"] > 0, df1["likes"] / df1["c
```

In [255]:
```
#Adding Column
df1["views_per_min"] = np.where(df1["duration_min"] > 0, df1["views"] / df1["c
```

In [256]:
```
#binary flag for hashtags
df1['has_hashtags'] = df1['hashtags'].notna().astype(int)
```

In [257]:
```
# Define viral threshold (top 5% by views)
viral_threshold = df1['views'].quantile(0.95)
df1['is_viral'] = (df1['views'] >= viral_threshold).astype(int)
```

In [258]:
```
#Checking Dataset info
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17589 entries, 0 to 17588
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype   
---  ------             --------------  -----   
 0   video_id           17589 non-null  object  
 1   duration           17589 non-null  int64   
 2   bitrate            17589 non-null  int64   
 3   bitrate_video      17589 non-null  int64   
 4   height             17589 non-null  int64   
 5   width              17589 non-null  int64   
 6   frame_rate         17589 non-null  float64 
 7   frame_rate_est     17589 non-null  float64 
 8   codec              17589 non-null  object  
 9   category           17589 non-null  object  
 10  title              17589 non-null  object  
 11  hashtags           17589 non-null  object  
 12  views              17589 non-null  int64   
 13  likes              17589 non-null  int64   
 14  comments           17589 non-null  int64   
 15  views_log          17589 non-null  float64 
 16  likes_log          17589 non-null  float64 
 17  comments_log       17589 non-null  float64 
 18  duration_category  17589 non-null  category
 19  engagement_rate    17589 non-null  float64 
 20  resolution         17589 non-null  object  
 21  duration_min       17589 non-null  float64 
 22  likes_per_min      17589 non-null  float64 
 23  views_per_min      17589 non-null  float64 
 24  has_hashtags       17589 non-null  int32   
 25  is_viral           17589 non-null  int32   
dtypes: category(1), float64(9), int32(2), int64(8), object(6)
memory usage: 3.2+ MB
```

In [259]:
```
#Checking for Null values
df1.isna().sum()
```

Out[259]:
```
video_id            0
duration            0
bitrate             0
bitrate_video       0
height              0
width               0
frame_rate          0
frame_rate_est      0
codec               0
category            0
title               0
hashtags            0
views               0
likes               0
comments            0
views_log           0
likes_log           0
comments_log        0
duration_category   0
engagement_rate     0
resolution          0
duration_min        0
likes_per_min       0
views_per_min       0
has_hashtags        0
is_viral            0
dtype: int64
```

In [260]:
```
df.to_csv('cleaned_youtube_dataset.csv', index=False)
```

EDA(Exploratory Data Analysis)

In [261]:
```
#Viewing dataset for Analysis
df1.head(5)
```

Out[261]:

	video_id	duration	bitrate	bitrate_video	height	width	frame_rate	frame_rate_est	codec
0	--F7dc-_FSI	180	5777	5640	1920	1080	25.00	25.00	h264
1	--cCAD-8Y_U	930	1195	1001	1280	720	30.00	30.00	h264
2	--g2gG8pQ0w	233	3028	2833	1280	720	23.98	23.98	h264
3	-0DR7-voRCU	562	431	300	320	240	29.97	0.00	h264
4	-0Fkp-2EzX0	300	3087	2929	1280	720	23.98	23.98	h264

5 rows × 26 columns

In [262]:
```
#Checking dataset info
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17589 entries, 0 to 17588
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   video_id           17589 non-null  object
 1   duration           17589 non-null  int64
 2   bitrate            17589 non-null  int64
 3   bitrate_video      17589 non-null  int64
 4   height             17589 non-null  int64
 5   width              17589 non-null  int64
 6   frame_rate         17589 non-null  float64
 7   frame_rate_est     17589 non-null  float64
 8   codec              17589 non-null  object
 9   category           17589 non-null  object
 10  title              17589 non-null  object
 11  hashtags           17589 non-null  object
 12  views              17589 non-null  int64
 13  likes              17589 non-null  int64
 14  comments           17589 non-null  int64
 15  views_log          17589 non-null  float64
 16  likes_log          17589 non-null  float64
 17  comments_log       17589 non-null  float64
 18  duration_category  17589 non-null  category
 19  engagement_rate    17589 non-null  float64
 20  resolution         17589 non-null  object
 21  duration_min       17589 non-null  float64
 22  likes_per_min      17589 non-null  float64
 23  views_per_min      17589 non-null  float64
 24  has_hashtags       17589 non-null  int32
 25  is_viral           17589 non-null  int32
dtypes: category(1), float64(9), int32(2), int64(8), object(6)
memory usage: 3.2+ MB
```

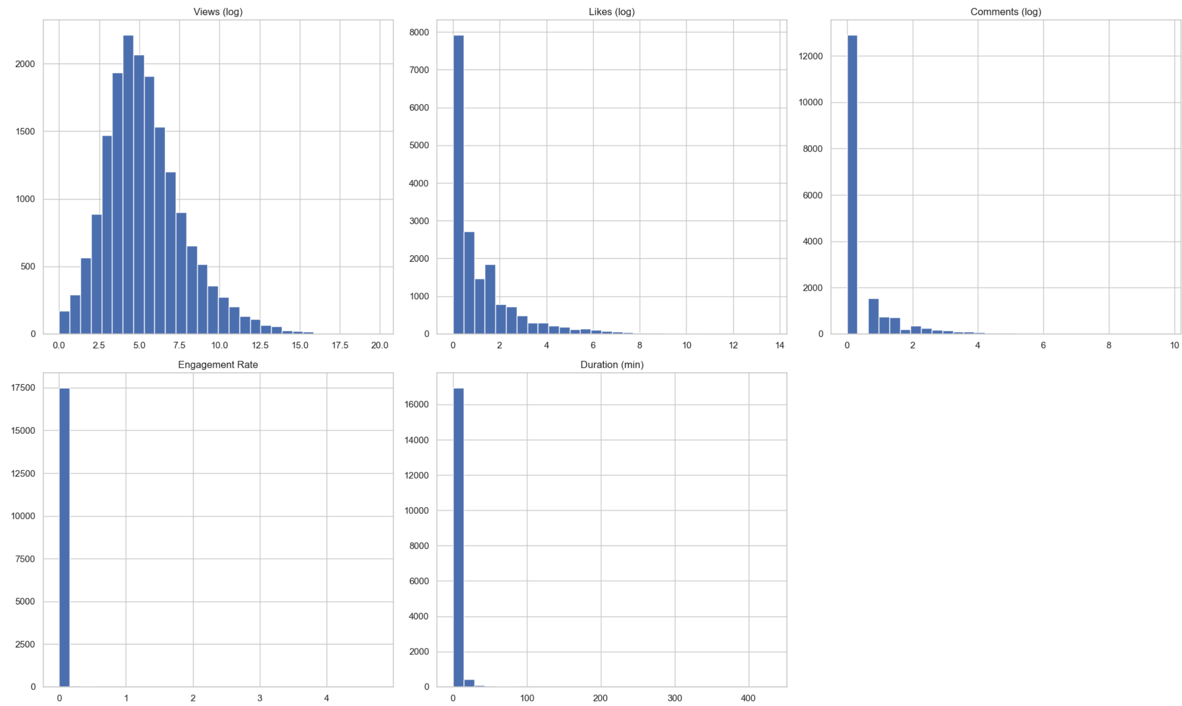
In [263]:
```
#Checking Statistical details
df1.describe()
```

Out[263]:

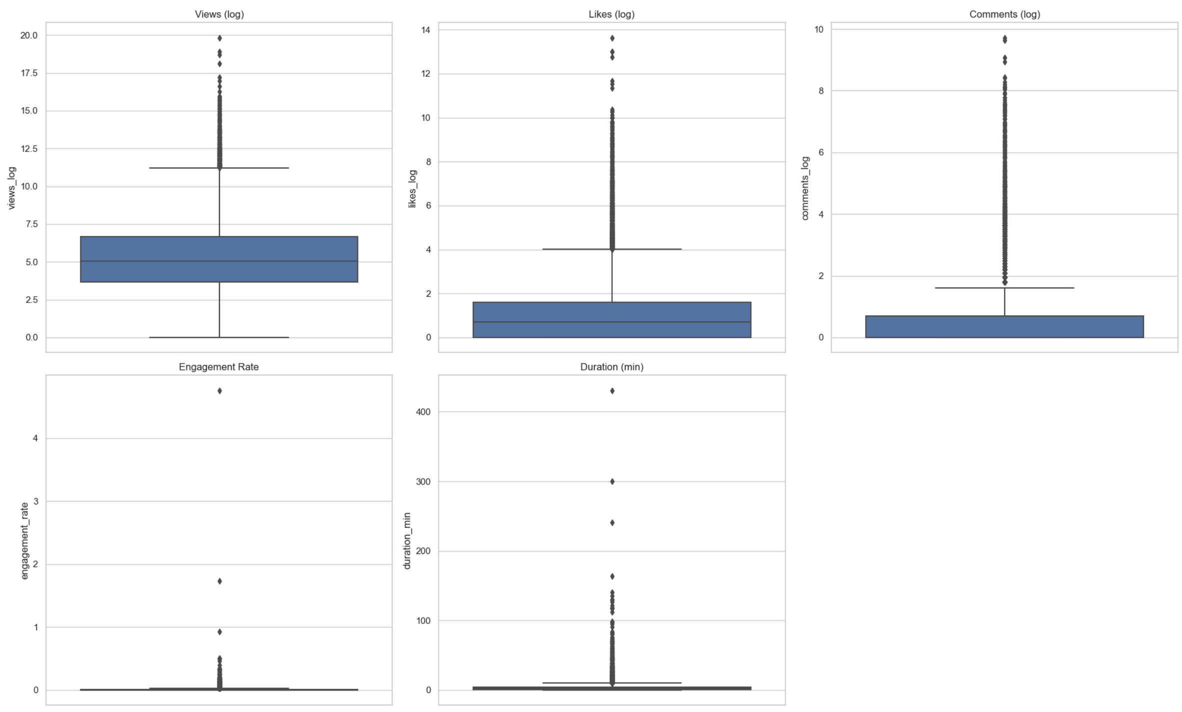
	duration	bitrate	bitrate_video	height	width	frame_rate	fra
count	17589.000000	17589.000000	17589.000000	17589.000000	17589.000000	17589.000000	1
mean	241.551936	1271.354369	1150.418443	766.781170	504.591961	26.467639	
std	493.026994	1375.359875	1351.800202	467.289304	262.727746	6.039748	
min	1.000000	0.000000	0.000000	108.000000	88.000000	3.750000	
25%	51.000000	437.000000	326.000000	426.000000	320.000000	25.000000	
50%	135.000000	743.000000	632.000000	640.000000	480.000000	29.970000	
75%	268.000000	1293.000000	1184.000000	960.000000	720.000000	29.970000	
max	25845.000000	22421.000000	22229.000000	2592.000000	1944.000000	59.080000	

Univariate Analysis

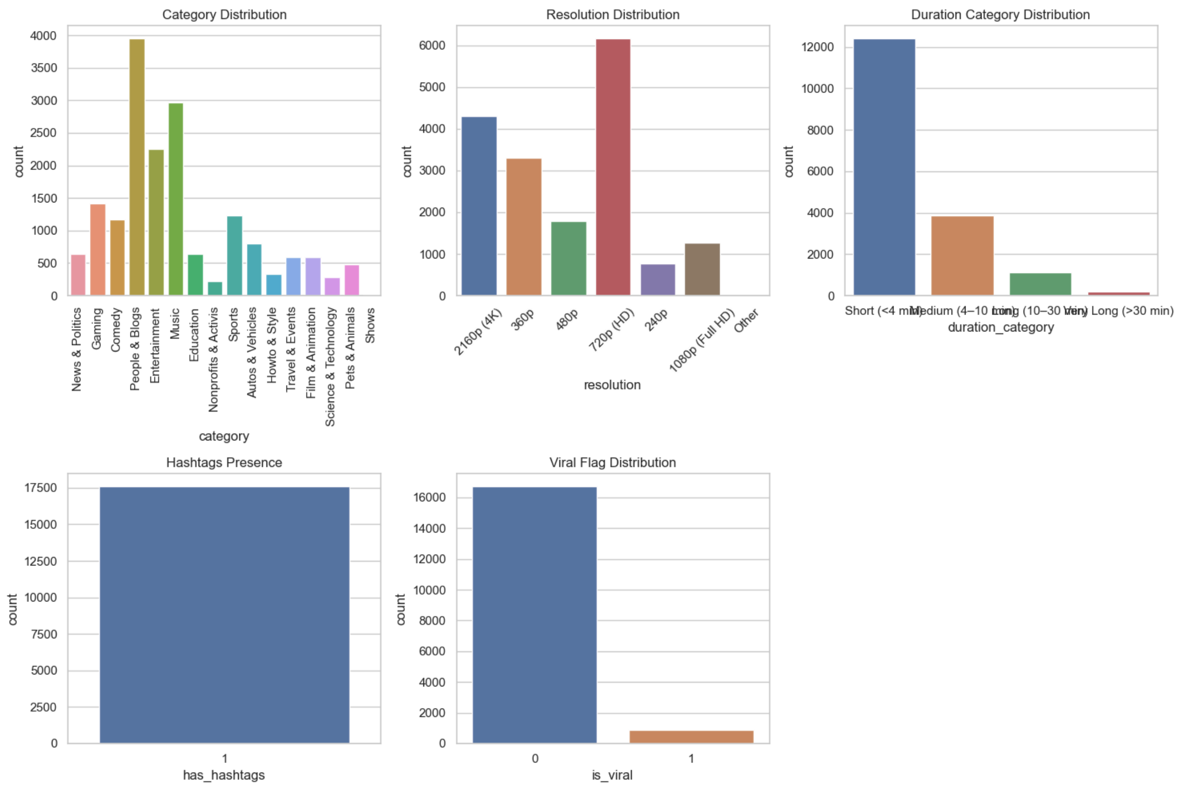
In [264]:
```
#List of numeric columns
num_cols = ['views_log', 'likes_log', 'comments_log', 'engagement_rate', 'dura

#Histograms for numerical features
plt.figure(figsize=(20, 12))

plt.subplot(2,3,1)
plt.hist(df1['views_log'], bins=30)
plt.title("Views (log)")

plt.subplot(2,3,2)
plt.hist(df1['likes_log'], bins=30)
plt.title("Likes (log)")

plt.subplot(2,3,3)
plt.hist(df1['comments_log'], bins=30)
plt.title("Comments (log)")

plt.subplot(2,3,4)
plt.hist(df1['engagement_rate'], bins=30)
plt.title("Engagement Rate")

plt.subplot(2,3,5)
plt.hist(df1['duration_min'], bins=30)
plt.title("Duration (min)")

plt.tight_layout()
plt.show()
```



In [265]:
```python
#Boxplots for numerical features
plt.figure(figsize=(20,12))

plt.subplot(2,3,1)
sns.boxplot(y=df1['views_log'])
plt.title("Views (log)")

plt.subplot(2,3,2)
sns.boxplot(y=df1['likes_log'])
plt.title("Likes (log)")

plt.subplot(2,3,3)
sns.boxplot(y=df1['comments_log'])
plt.title("Comments (log)")

plt.subplot(2,3,4)
sns.boxplot(y=df1['engagement_rate'])
plt.title("Engagement Rate")

plt.subplot(2,3,5)
sns.boxplot(y=df1['duration_min'])
plt.title("Duration (min)")

plt.tight_layout()
plt.show()
```

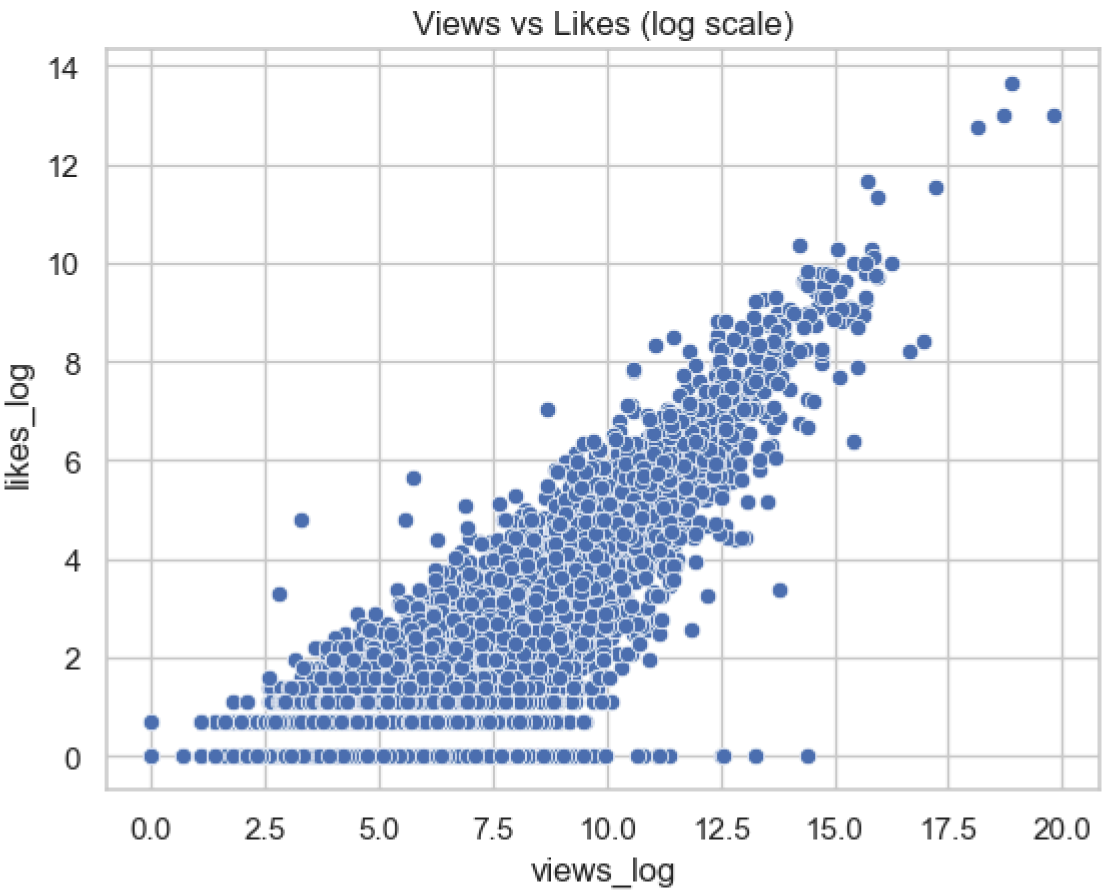


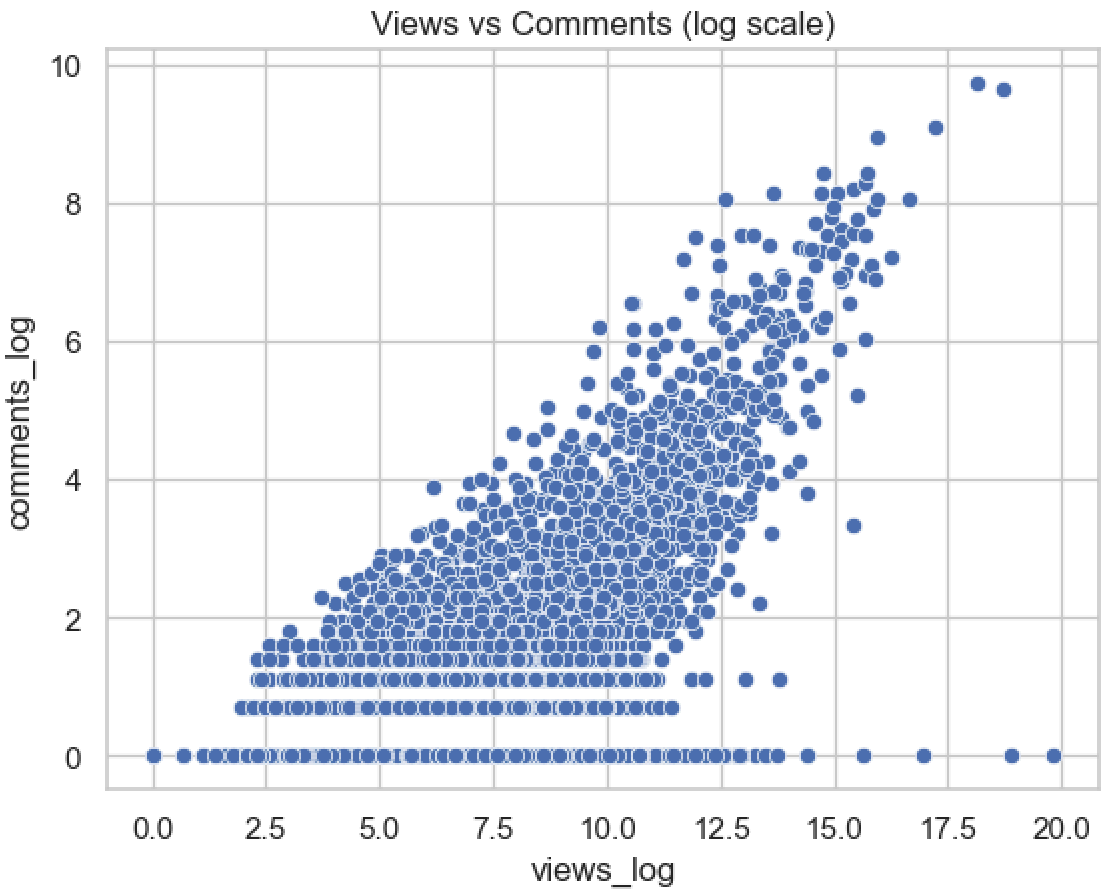
In [266]:
```
#Barchart for Categorical features
plt.figure(figsize=(15,10))

#Category
plt.subplot(2,3,1)
sns.countplot(x='category', data=df1)
plt.xticks(rotation=90)
plt.title("Category Distribution")

#Resolution
plt.subplot(2,3,2)
sns.countplot(x='resolution', data=df1)
plt.xticks(rotation=45)
plt.title("Resolution Distribution")

#Duration Category
plt.subplot(2,3,3)
sns.countplot(x='duration_category', data=df1)
plt.title("Duration Category Distribution")

#Has Hashtags
plt.subplot(2,3,4)
sns.countplot(x='has_hashtags', data=df1)
plt.title("Hashtags Presence")

#Viral Flag
plt.subplot(2,3,5)
sns.countplot(x='is_viral', data=df1)
plt.title("Viral Flag Distribution")

plt.tight_layout()
plt.show()
```

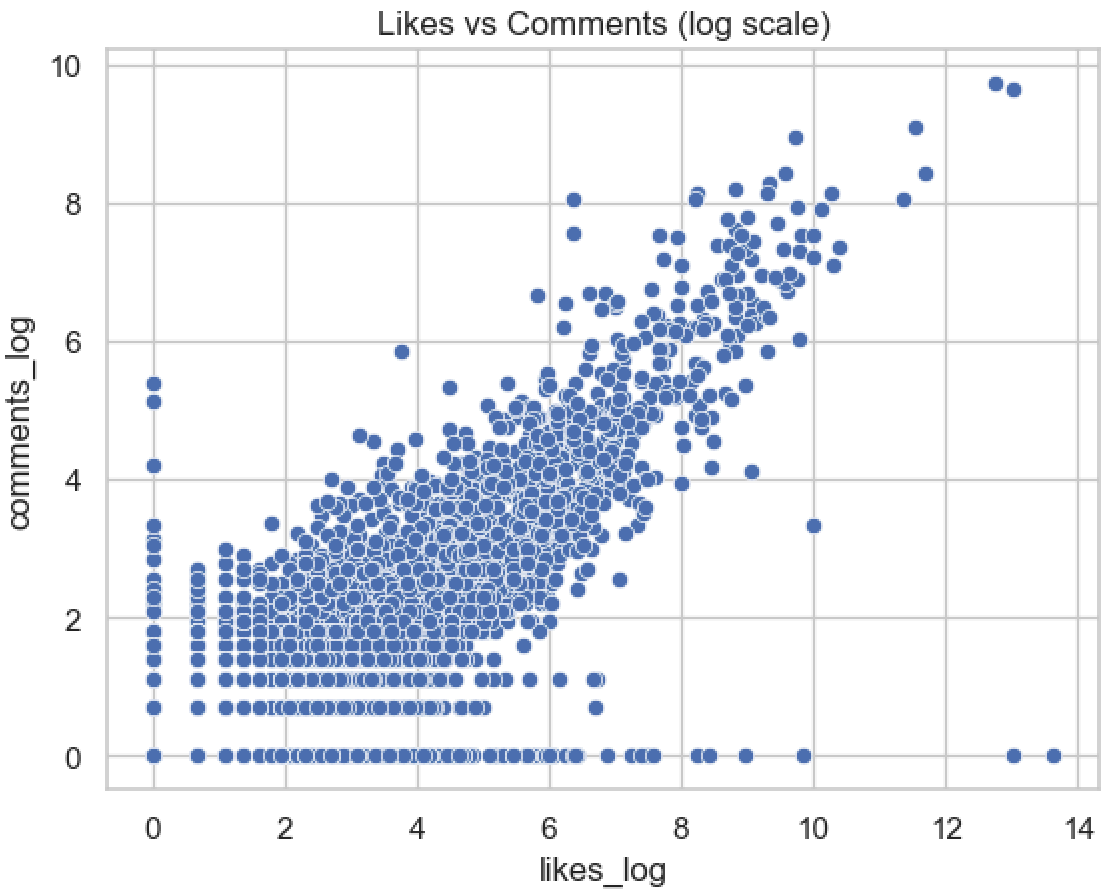


Bivariate Analysis

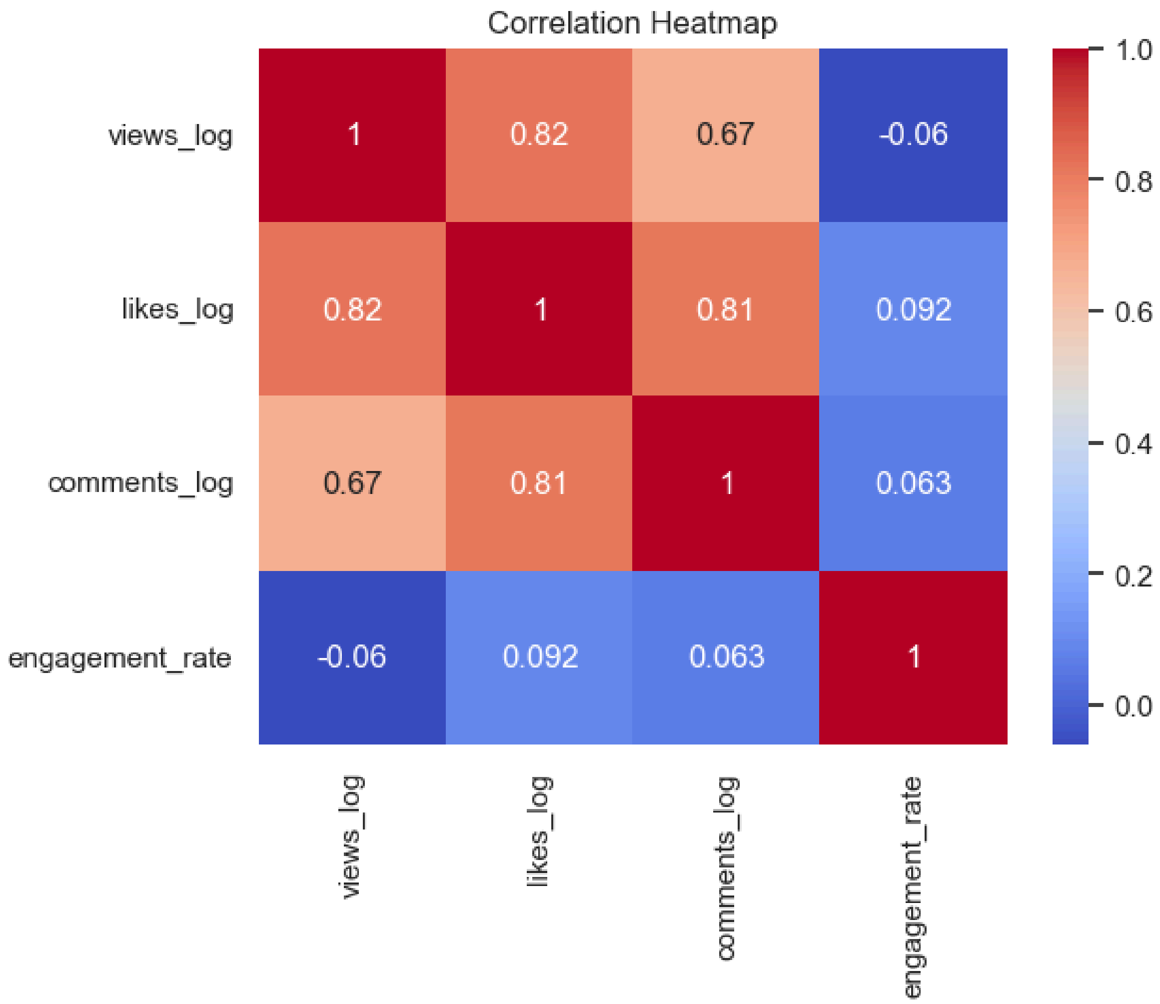
In [267]:
```
# Numeric vs Numeric

# Scatterplots
sns.scatterplot(x='views_log', y='likes_log', data=df1)
plt.title("Views vs Likes (log scale)")
plt.show()

sns.scatterplot(x='views_log', y='comments_log', data=df1)
plt.title("Views vs Comments (log scale)")
plt.show()

sns.scatterplot(x='likes_log', y='comments_log', data=df1)
plt.title("Likes vs Comments (log scale)")
plt.show()
```




Views vs Comments (log scale)
comments_log
views_log
0
2
4
6
8
10
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


Likes vs Comments (log scale)
comments_log
likes_log
0
2
4
6
8
10
0
2
4
6
8
10
12
14

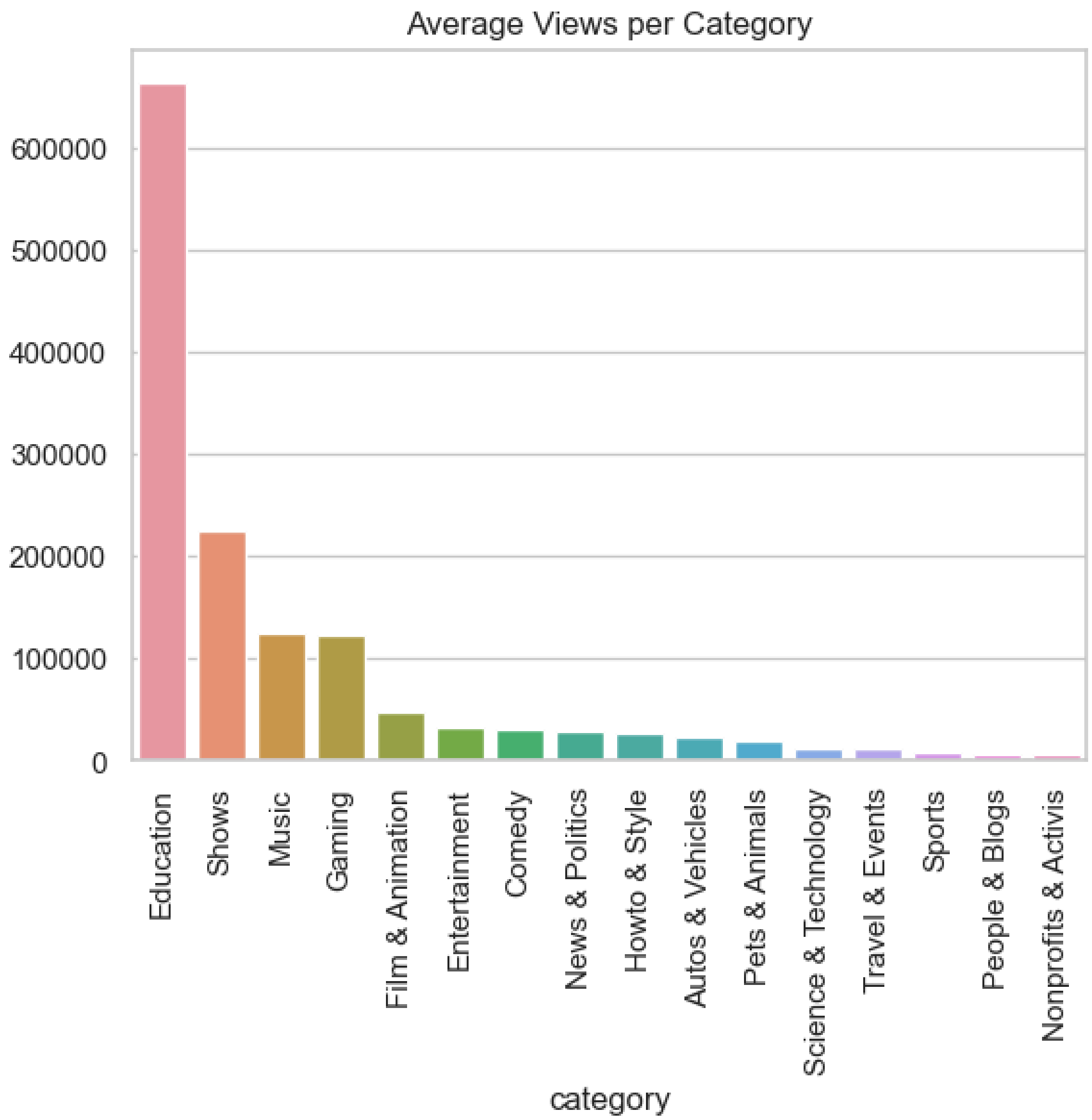
In [268]:
```
#Correlation heatmap
corr = df1[['views_log','likes_log','comments_log','engagement_rate']].corr()
sns.heatmap(corr, annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



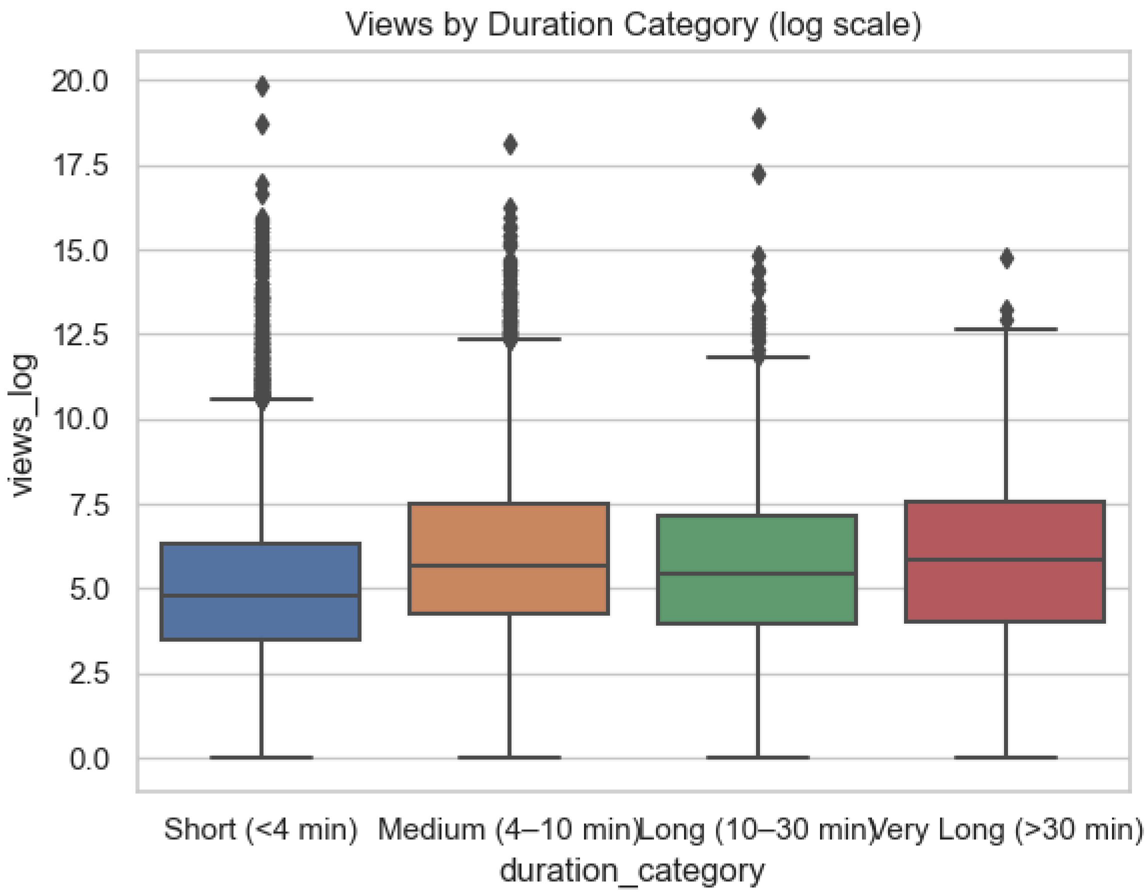
In [269]:
```
#Numeric vs Categorical

#Average metrics by category
print(df1.groupby('category')[['views','likes','comments','engagement_rate']].
```

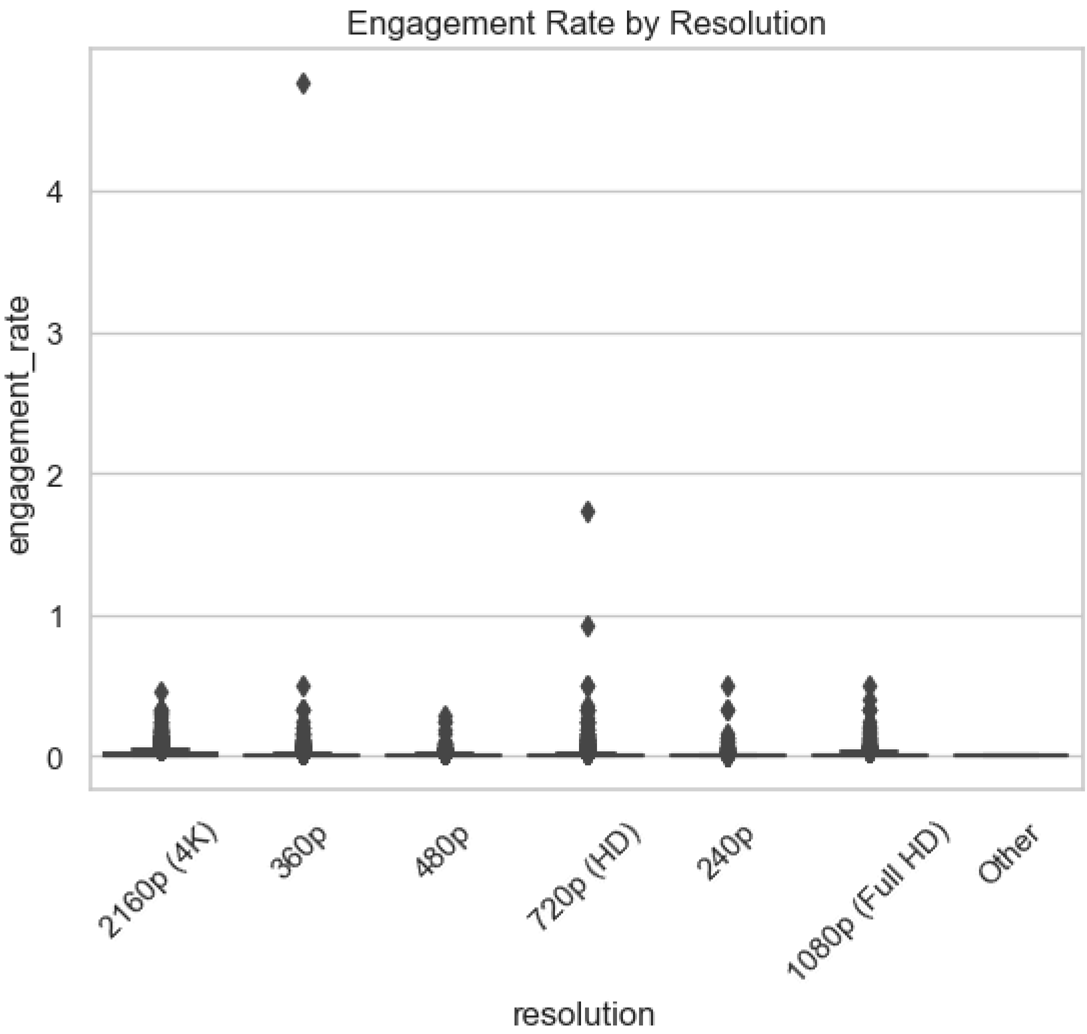
```
                                views        likes    comments  engagement_rat
e
category
Education               663729.860248   784.610248   11.486025         0.00792
0
Shows                   225471.166667  1415.944444  149.388889         0.01292
4
Music                   124192.198584   481.927512   30.202967         0.01017
1
Gaming                  122576.726761   639.076761   14.510563         0.03091
2
Film & Animation         48051.843271   205.245315   25.434412         0.01024
9
Entertainment            32320.801066    56.501332   10.628330         0.00954
2
Comedy                   30404.028912    84.113095   10.196429         0.01093
6
News & Politics          28173.963836   240.823899   33.011006         0.00643
8
Howto & Style            27069.094118   104.464706   11.052941         0.00998
9
Autos & Vehicles         23199.025063    35.755639    5.822055         0.00465
8
Pets & Animals           18896.285714    57.535714    6.659664         0.00692
9
Science & Technology     12295.575972    27.840989    4.310954         0.00636
5
Travel & Events          11664.855932    27.800000    3.310169         0.00675
7
Sports                    8643.694309    29.985366    6.242276         0.00595
4
People & Blogs            6344.416878    36.394070    2.824126         0.01084
3
Nonprofits & Activis      5698.700441    44.096916    5.255507         0.00782
0
```

In [270]:
```
#Barplot of avg views by category
cat_means = df1.groupby('category')['views'].mean().sort_values(ascending=Fals
sns.barplot(x=cat_means.index, y=cat_means.values)
plt.xticks(rotation=90)
plt.title("Average Views per Category")
plt.show()
```



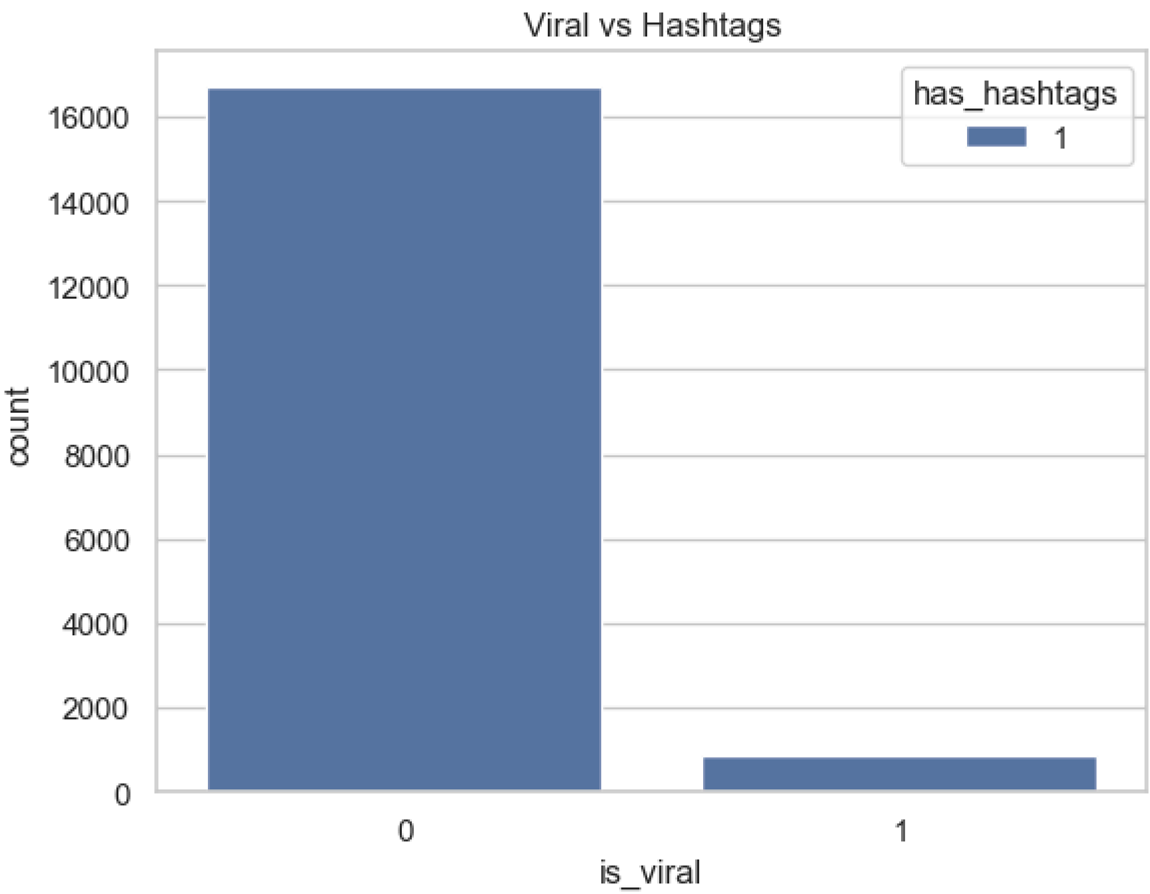
In [271]:
```
#Boxplots
sns.boxplot(x='duration_category', y='views_log', data=df1)
plt.title("Views by Duration Category (log scale)")
plt.show()

sns.boxplot(x='resolution', y='engagement_rate', data=df1)
plt.xticks(rotation=45)
plt.title("Engagement Rate by Resolution")
plt.show()
```




Engagement Rate by Resolution
engagement_rate
0
1
2
3
4
2160p (4K)
360p
480p
720p (HD)
240p
1080p (Full HD)
Other
resolution

In [272]:
```
#Categorical vs Categorical

#Viral flag vs Has Hashtags
cross_tab = pd.crosstab(df1['is_viral'], df1['has_hashtags'])
print(cross_tab)

#countplot
sns.countplot(x='is_viral', hue='has_hashtags', data=df1)
plt.title("Viral vs Hashtags")
plt.show()
```

```
has_hashtags      1
is_viral
0             16709
1               880
```

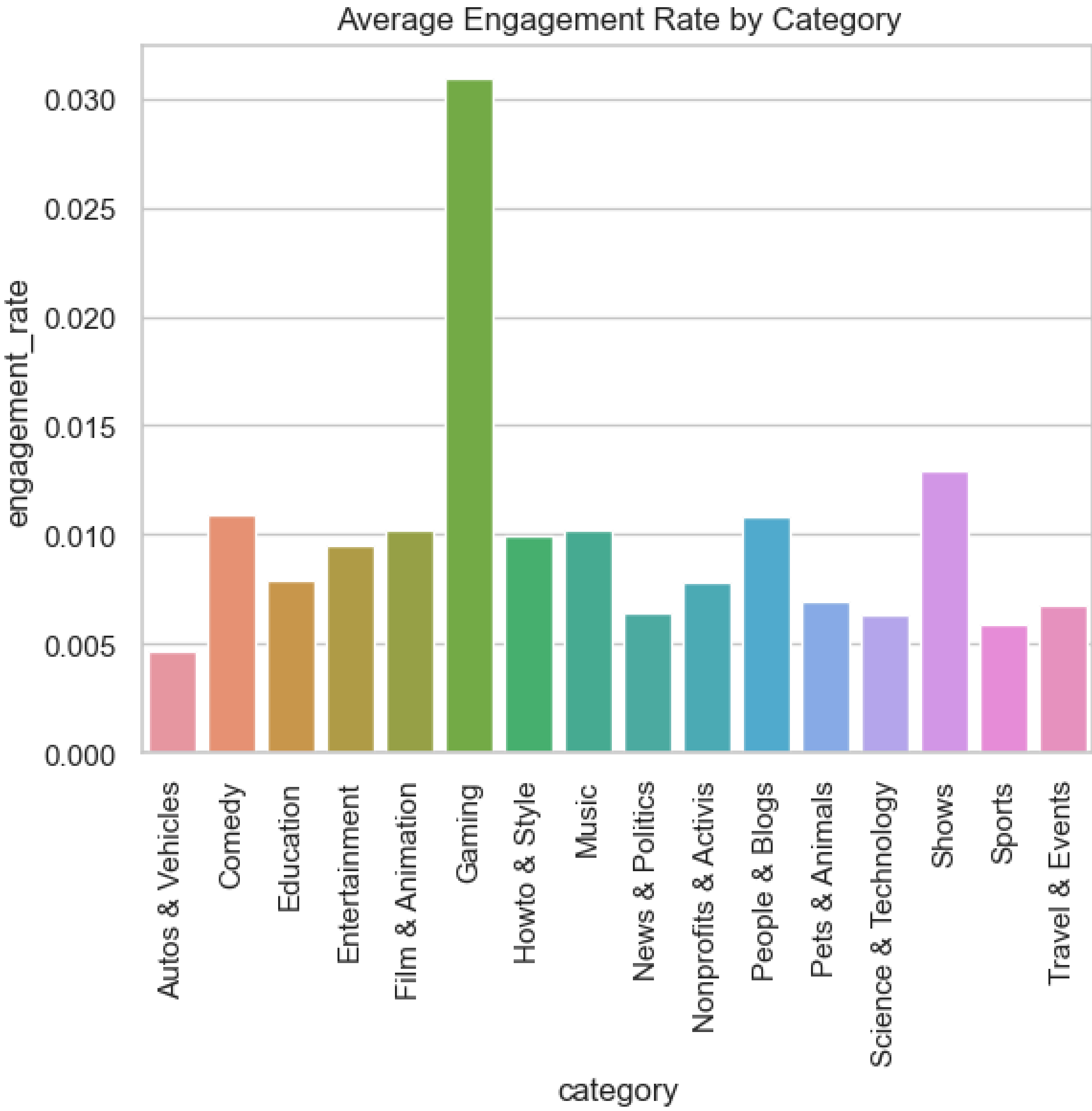


Segmentation Analysis

In [273]:
```
#Engagement by Category
category_engagement = df1.groupby('category')['engagement_rate'].mean().reset_
print(category_engagement)
```

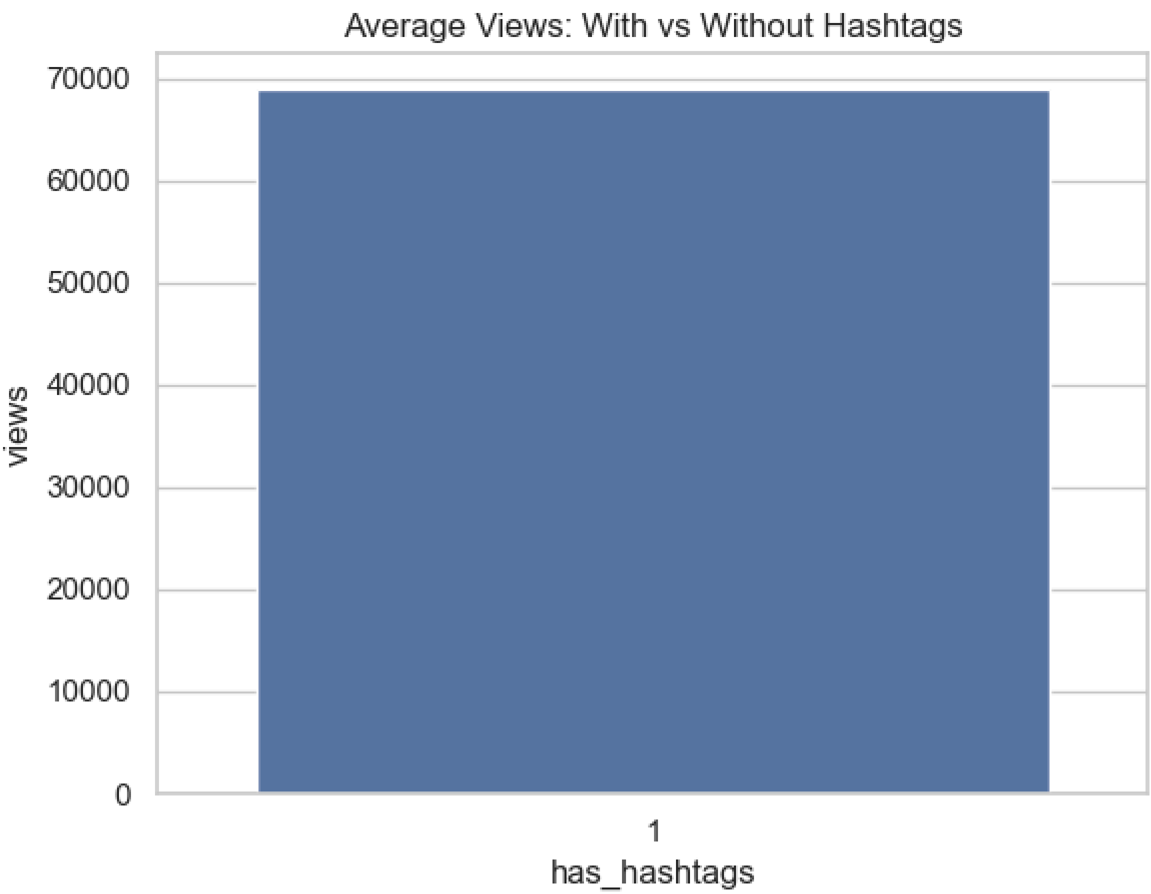
```
                 category  engagement_rate
0        Autos & Vehicles         0.004658
1                  Comedy         0.010936
2               Education         0.007920
3           Entertainment         0.009542
4        Film & Animation         0.010249
5                  Gaming         0.030912
6           Howto & Style         0.009989
7                   Music         0.010171
8         News & Politics         0.006438
9    Nonprofits & Activis         0.007820
10         People & Blogs         0.010843
11         Pets & Animals         0.006929
12   Science & Technology         0.006365
13                  Shows         0.012924
14                 Sports         0.005954
15        Travel & Events         0.006757
```

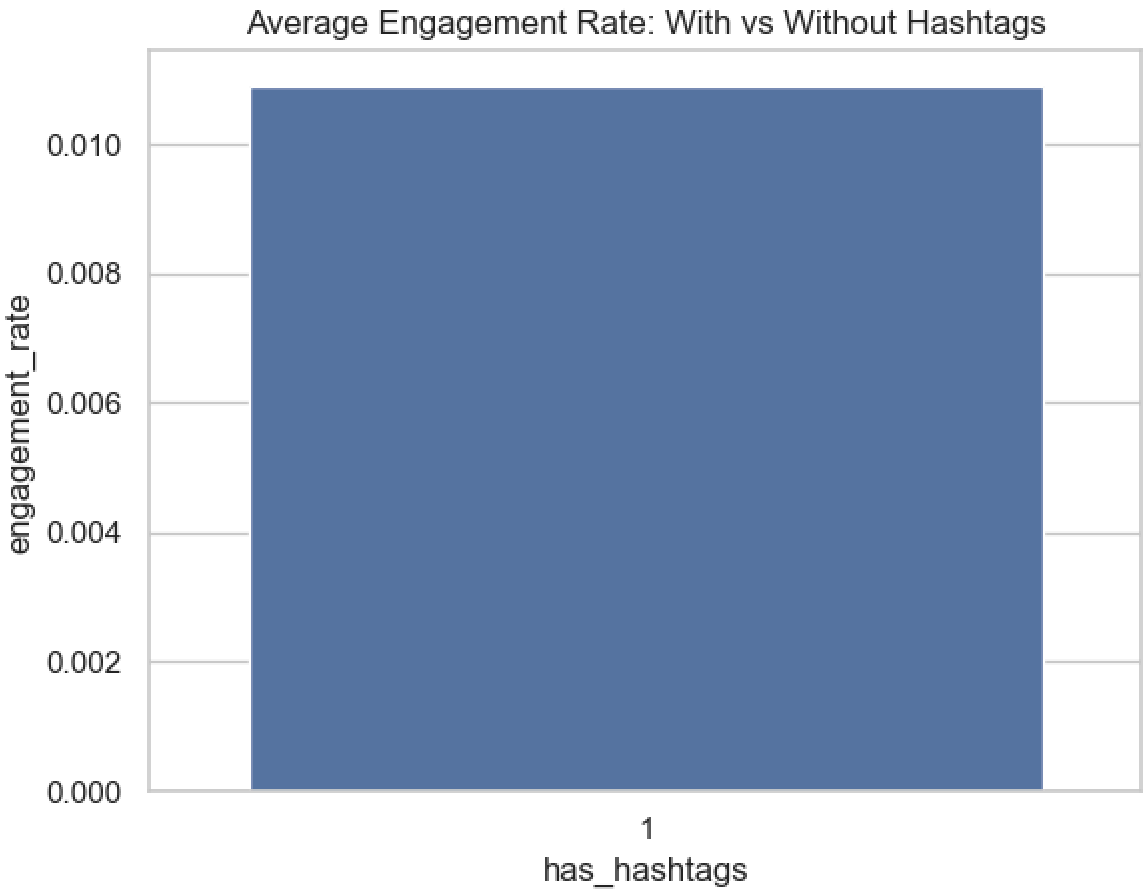
In [274]:
```
#Barchart for average engagement
sns.barplot(x='category', y='engagement_rate', data=category_engagement)
plt.xticks(rotation=90)
plt.title("Average Engagement Rate by Category")
plt.show()
```



In [275]:
```
#Hashtag vs No Hashtag performance
hashtag_perf = df1.groupby('has_hashtags')[['views','likes','comments','engage
print(hashtag_perf)

sns.barplot(x='has_hashtags', y='views', data=hashtag_perf)
plt.title("Average Views: With vs Without Hashtags")
plt.show()

sns.barplot(x='has_hashtags', y='engagement_rate', data=hashtag_perf)
plt.title("Average Engagement Rate: With vs Without Hashtags")
plt.show()
```

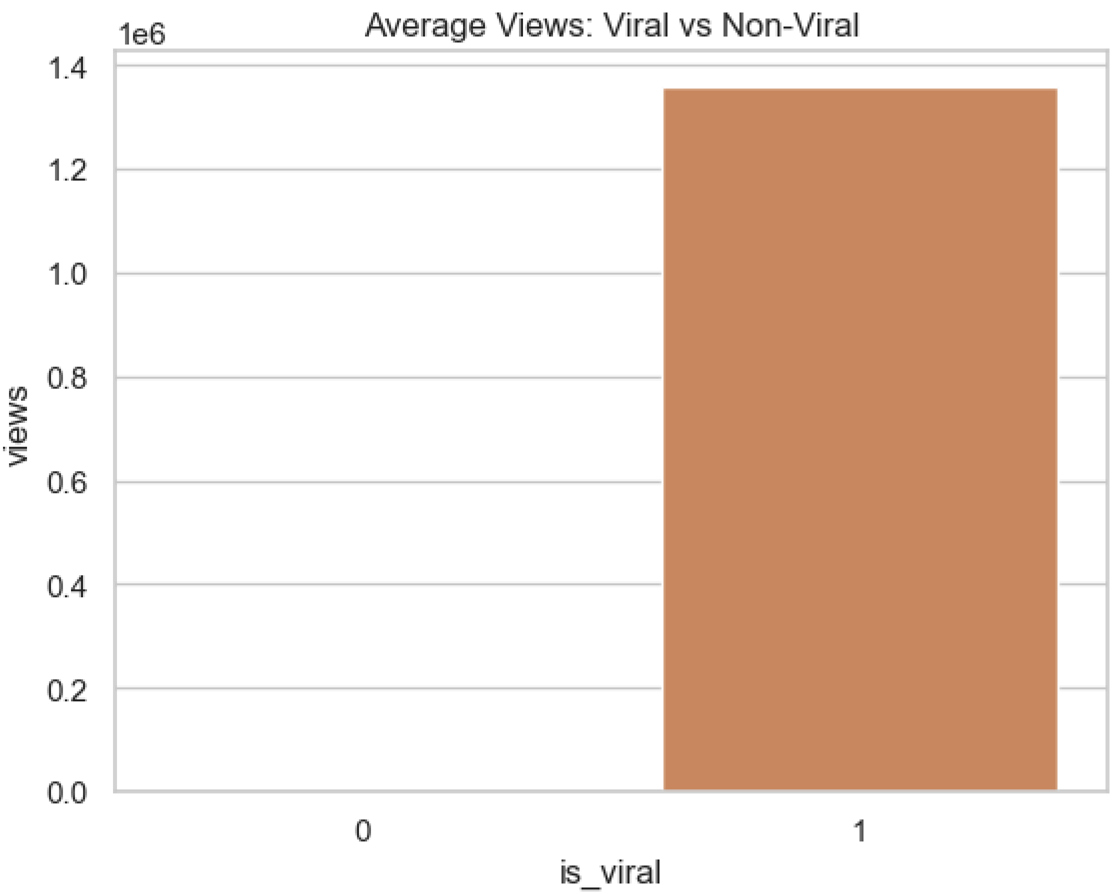
```
   has_hashtags         views       likes   comments  engagement_rate
0             1  68941.580306  208.862641  12.899312         0.010913
```

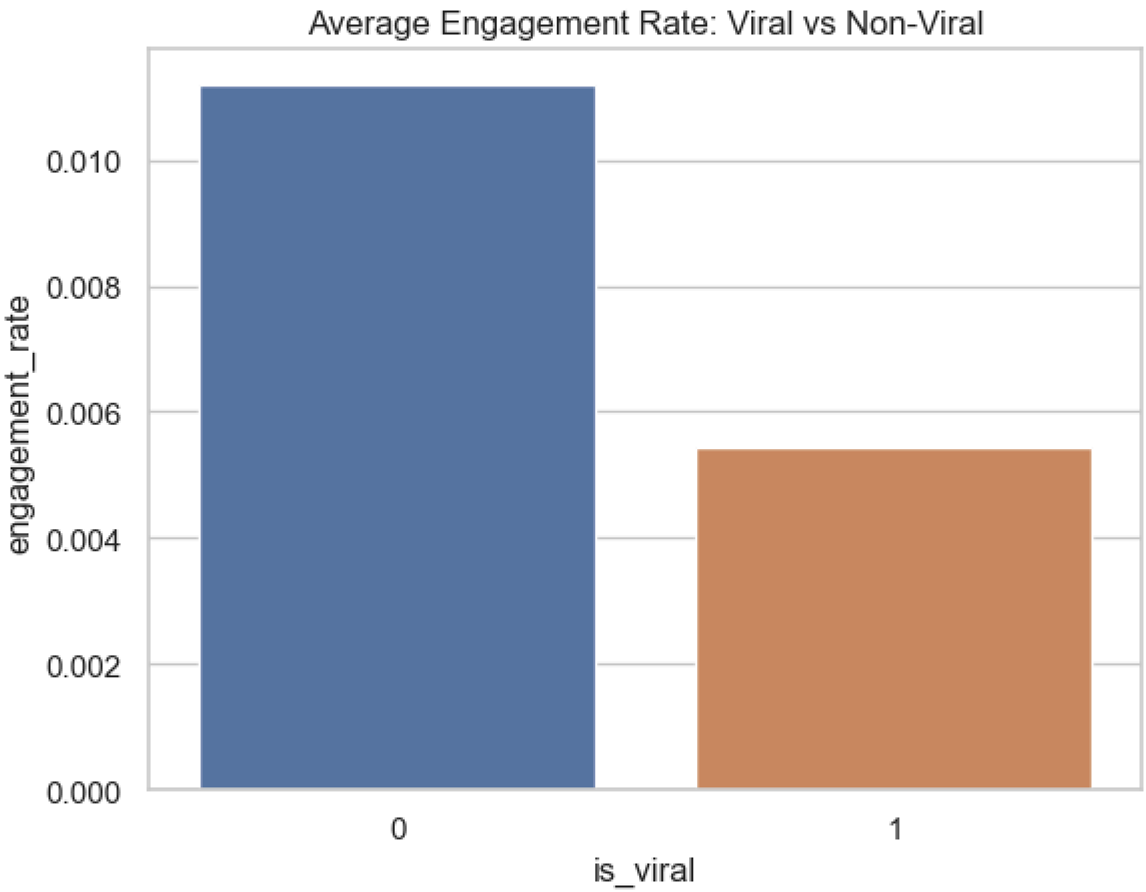



Average Engagement Rate: With vs Without Hashtags
0.010
0.008
0.006
0.004
0.002
0.000
engagement_rate
1
has_hashtags

In [276]:
```
#Viral vs Non-viral content
viral_perf = df1.groupby('is_viral')[['views','likes','comments','engagement_r
print(viral_perf)

sns.barplot(x='is_viral', y='views', data=viral_perf)
plt.title("Average Views: Viral vs Non-Viral")
plt.show()

sns.barplot(x='is_viral', y='engagement_rate', data=viral_perf)
plt.title("Average Engagement Rate: Viral vs Non-Viral")
plt.show()
```

```
   is_viral         views        likes    comments  engagement_rate
0         0  1.031090e+03     5.538931    1.199413         0.011200
1         1  1.358392e+06  4069.471591  235.051136         0.005449
```

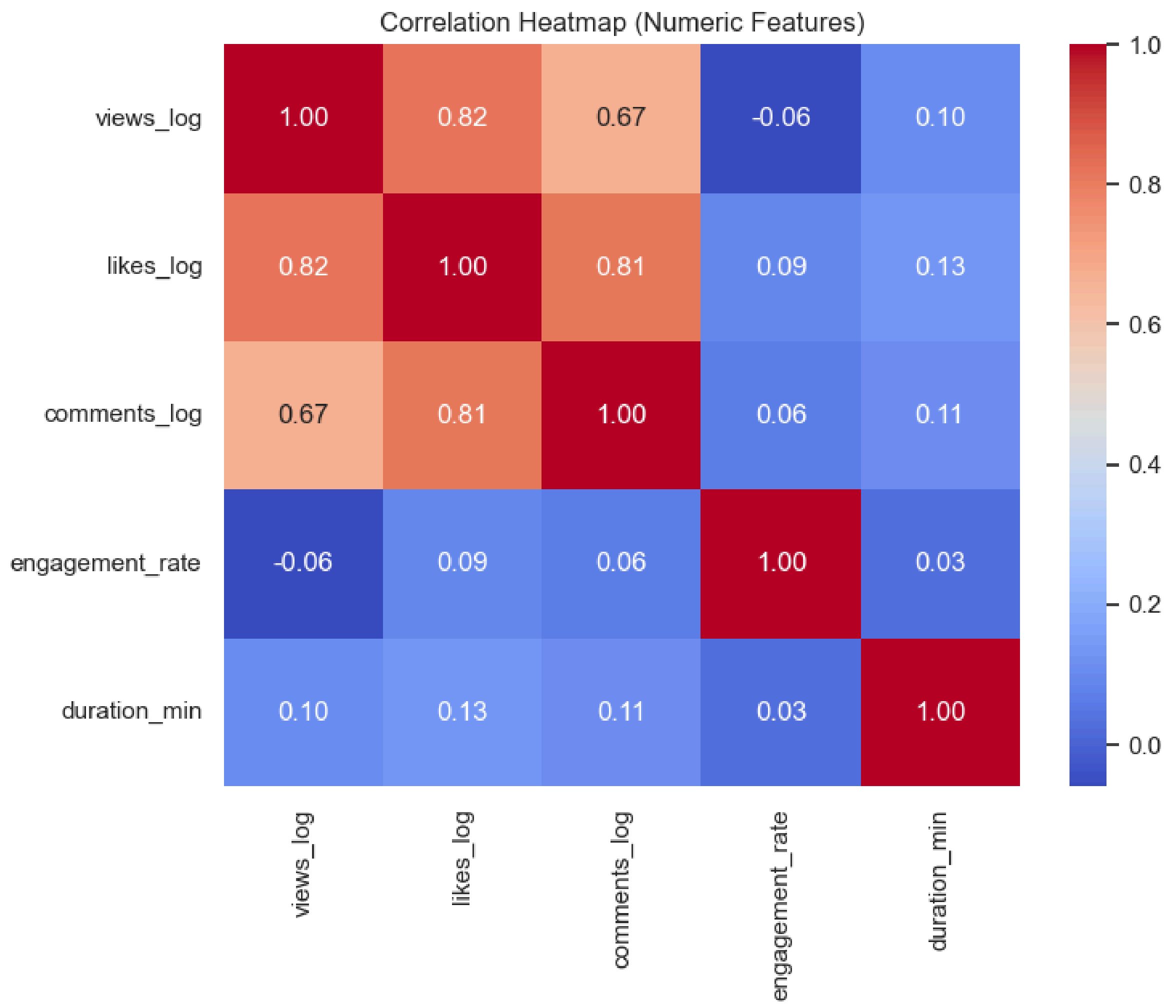




Correlation Analysis

In [277]:
```
#Numeric features for correlation
num_cols = ['views_log', 'likes_log', 'comments_log', 'engagement_rate', 'dura

#Correlation matrix
corr_matrix = df1[num_cols].corr()
print(corr_matrix)

#Heatmap visualization
plt.figure(figsize=(8,6))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap (Numeric Features)")
plt.show()
```

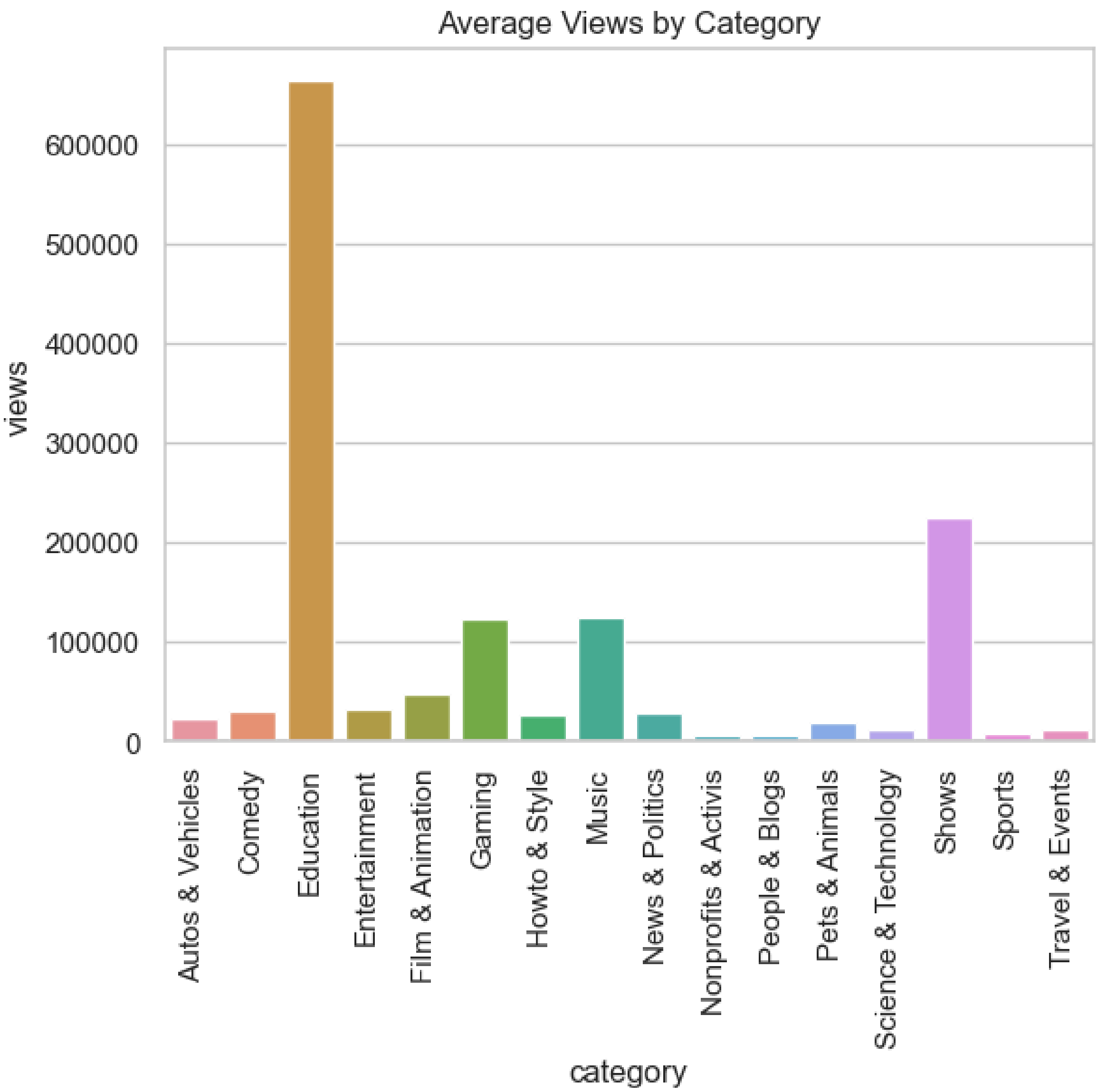
```
                 views_log  likes_log  comments_log  engagement_rate  \
views_log         1.000000   0.819252      0.672459        -0.060339
likes_log         0.819252   1.000000      0.814353         0.091702
comments_log      0.672459   0.814353      1.000000         0.063125
engagement_rate  -0.060339   0.091702      0.063125         1.000000
duration_min      0.104414   0.127845      0.110677         0.025439

                 duration_min
views_log            0.104414
likes_log            0.127845
comments_log         0.110677
engagement_rate      0.025439
duration_min         1.000000
```



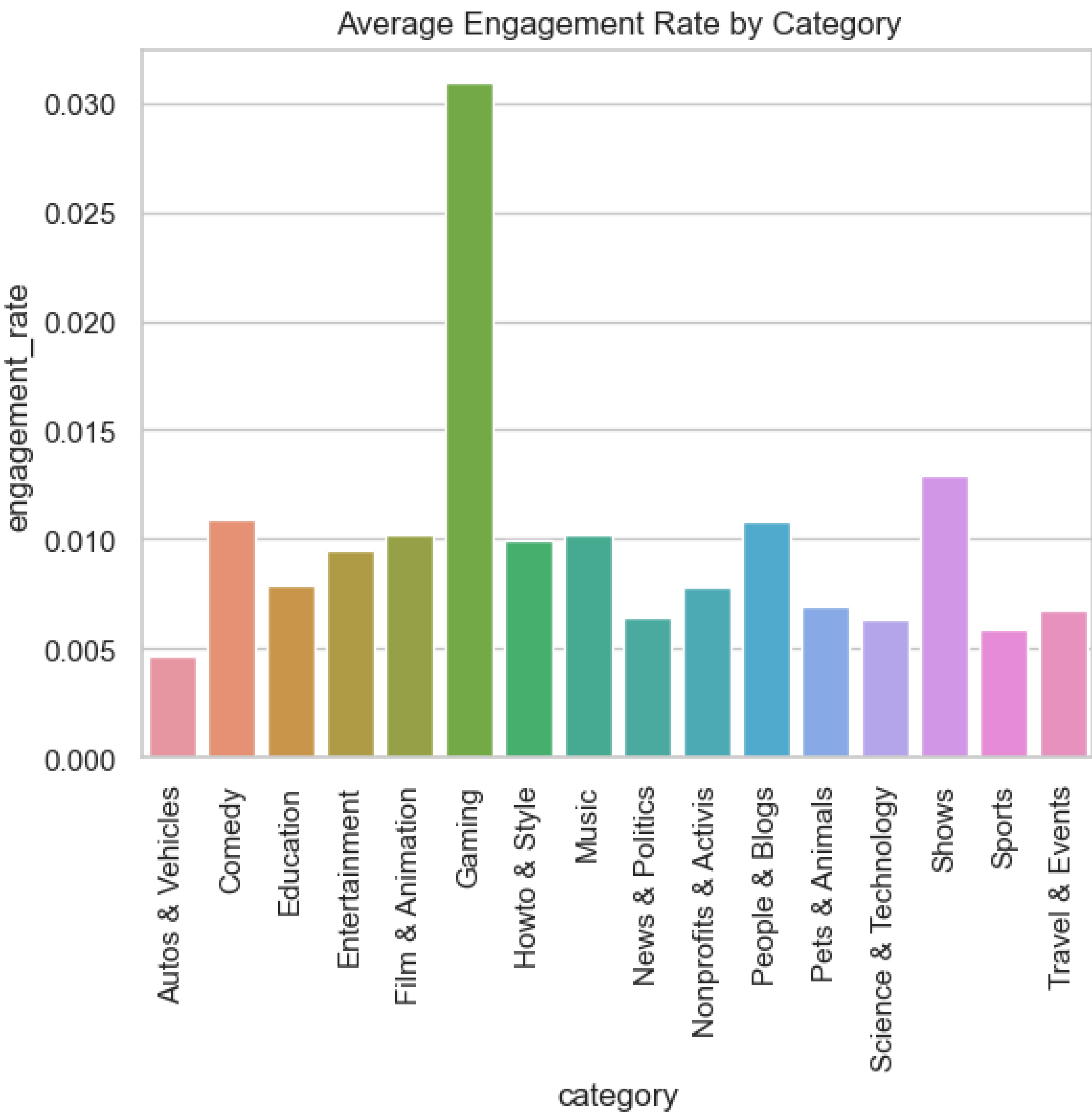
Data Visualization

1. Which video categories receive the highest engagement?

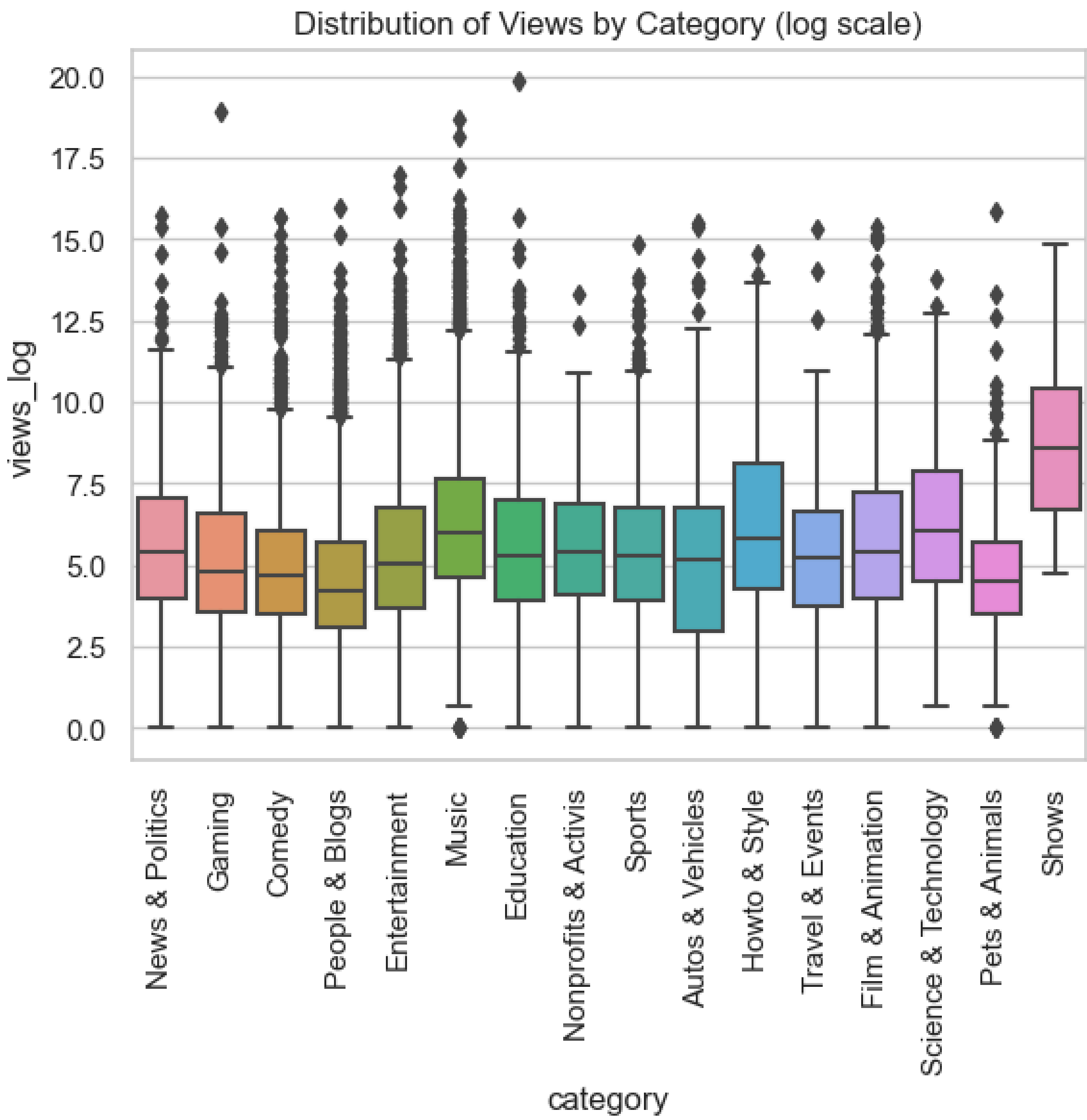
In [278]:
```
#Average Views by Category
avg_views = df1.groupby('category')['views'].mean().reset_index()
sns.barplot(x='category', y='views', data=avg_views)
plt.xticks(rotation=90)
plt.title("Average Views by Category")
plt.show()
```



In [279]:
```
#Average Engagement Rate by Category
avg_engagement = df1.groupby('category')['engagement_rate'].mean().reset_index
sns.barplot(x='category', y='engagement_rate', data=avg_engagement)
plt.xticks(rotation=90)
plt.title("Average Engagement Rate by Category")
plt.show()
```

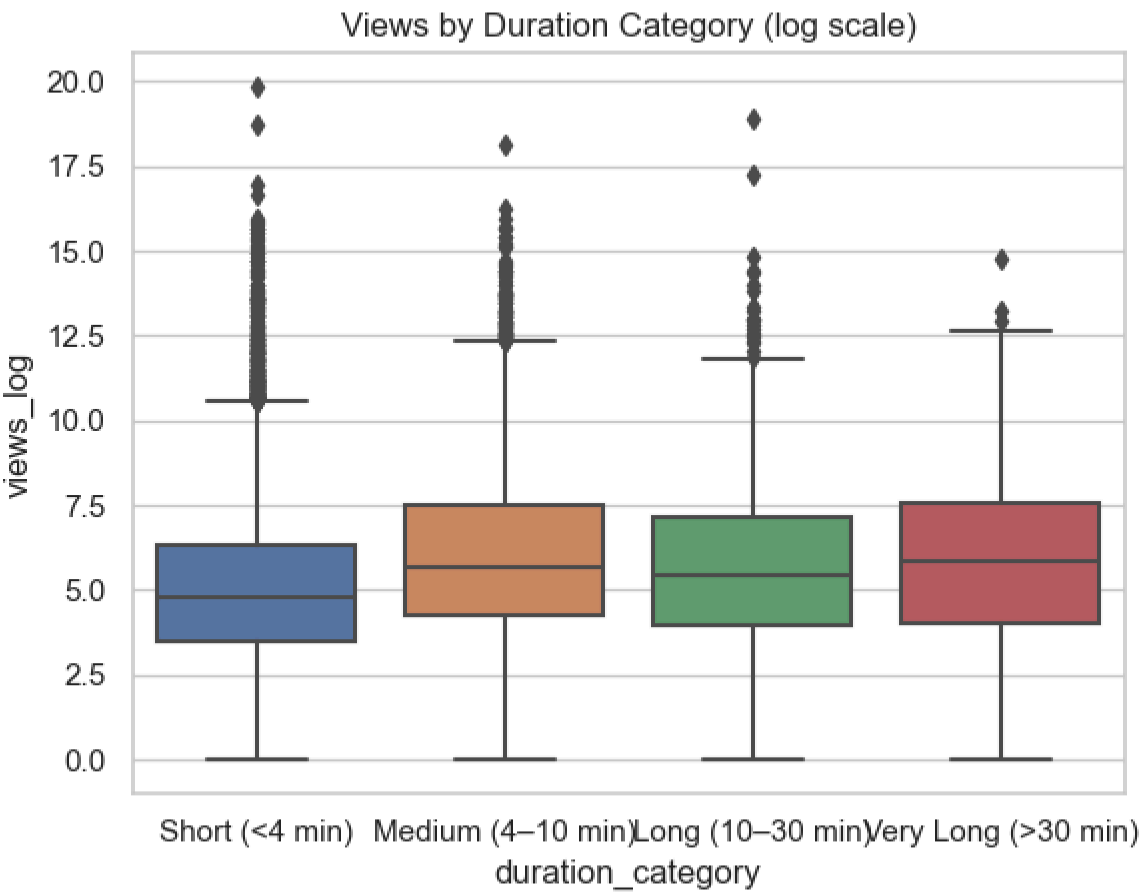


In [280]:
```
#Distribution of Views by Category (boxplot)
sns.boxplot(x='category', y='views_log', data=df1)
plt.xticks(rotation=90)
plt.title("Distribution of Views by Category (log scale)")
plt.show()
```

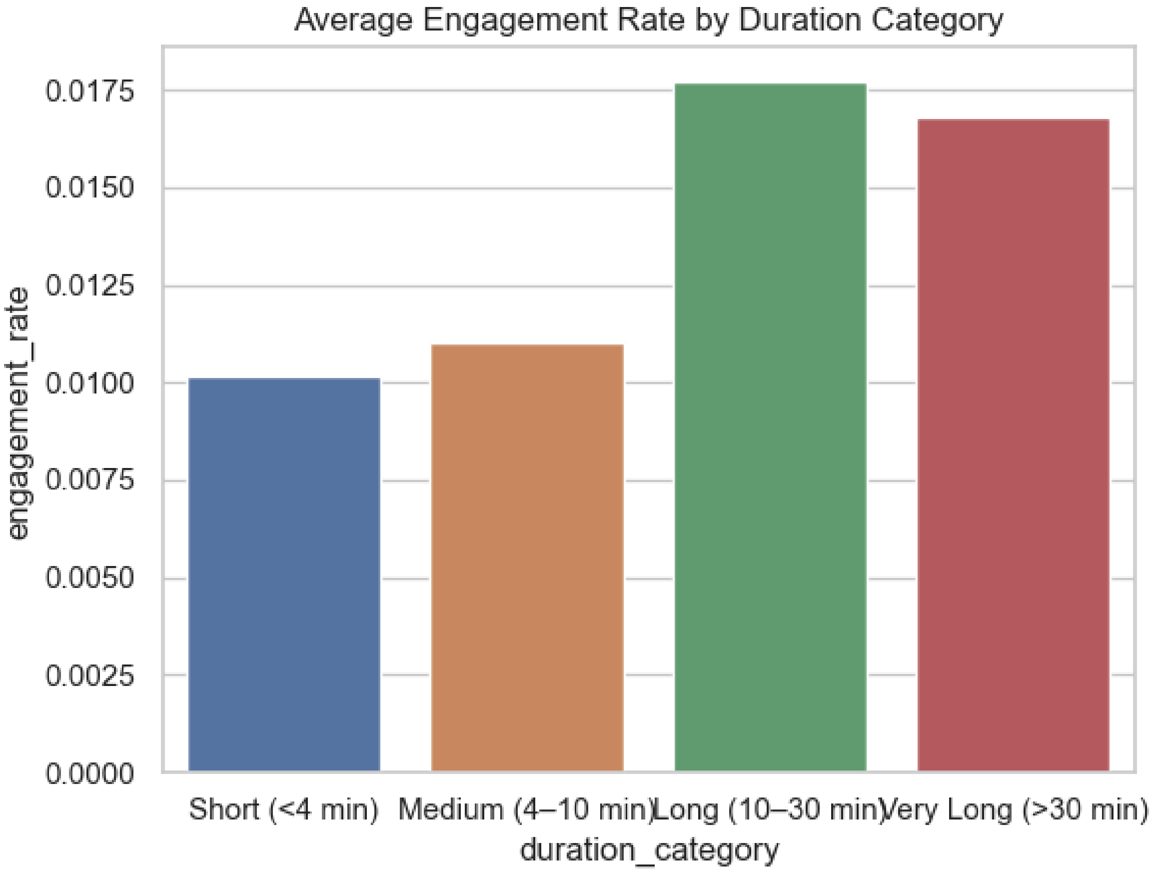


2. Does video duration or resolution influence engagement?

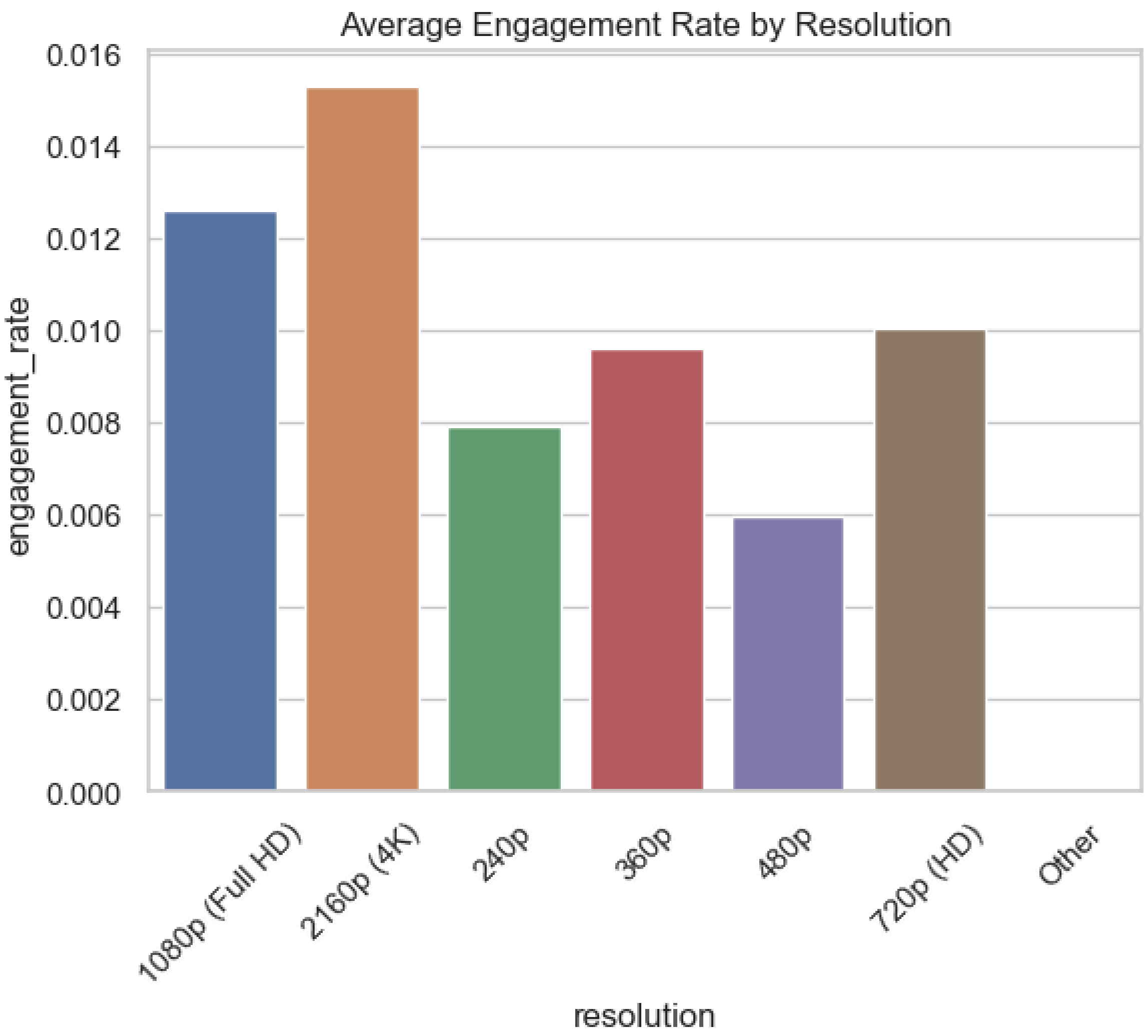
In [281]:
```
#Views by Duration Category (boxplot)
sns.boxplot(x='duration_category', y='views_log', data=df1)
plt.title("Views by Duration Category (log scale)")
plt.show()
```



In [282]:
```
#Engagement Rate by Duration Category
avg_duration_eng = df1.groupby('duration_category')['engagement_rate'].mean().
sns.barplot(x='duration_category', y='engagement_rate', data=avg_duration_eng)
plt.title("Average Engagement Rate by Duration Category")
plt.show()
```

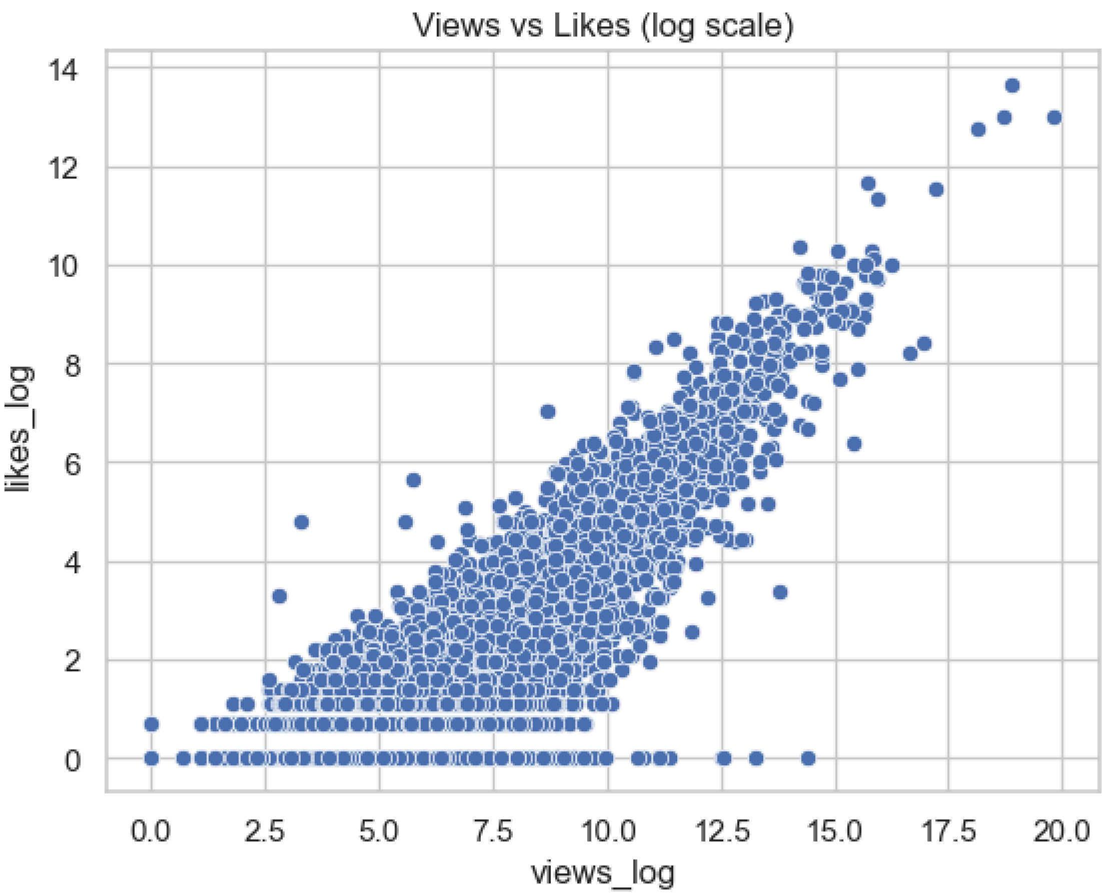


In [283]:
```
#Engagement Rate by Resolution
avg_res_eng = df1.groupby('resolution')['engagement_rate'].mean().reset_index(
sns.barplot(x='resolution', y='engagement_rate', data=avg_res_eng)
plt.xticks(rotation=45)
plt.title("Average Engagement Rate by Resolution")
plt.show()
```

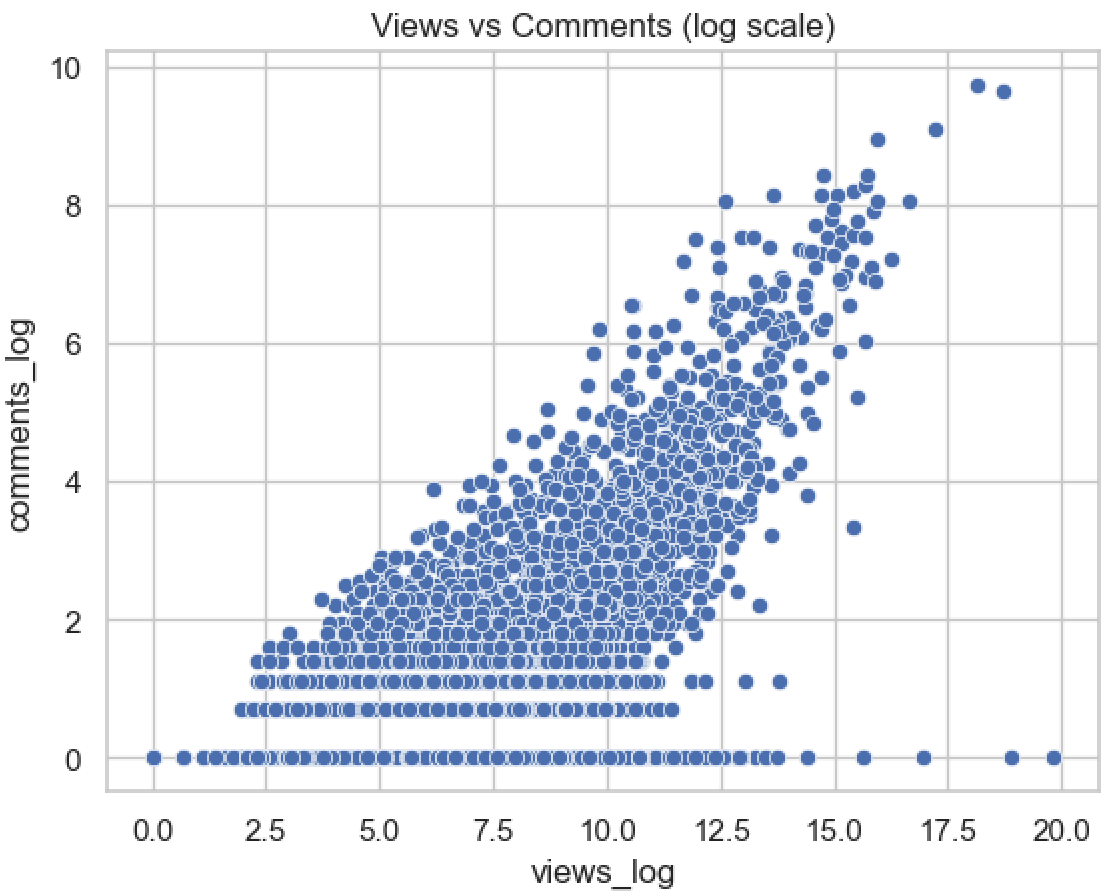


3. Predicting Video Popularity

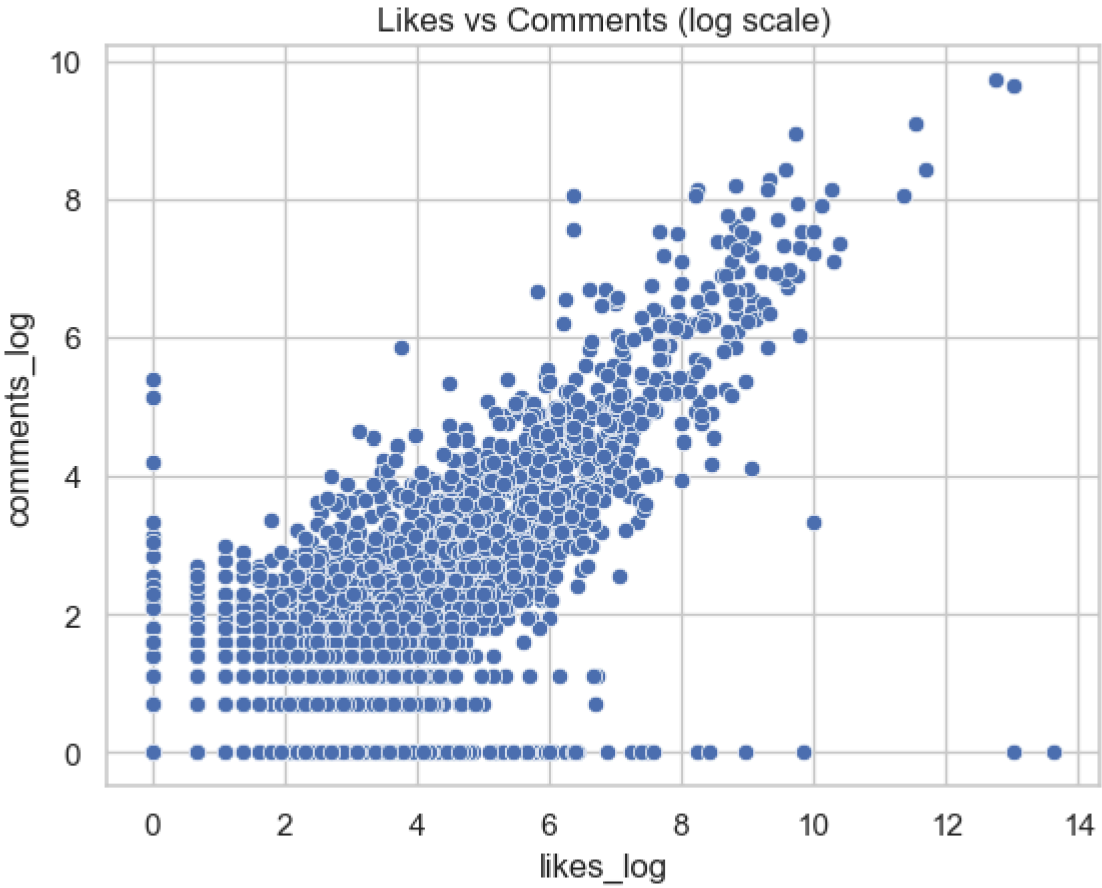
In [284]:
```
#Views vs Likes
sns.scatterplot(x='views_log', y='likes_log', data=df1)
plt.title("Views vs Likes (log scale)")
plt.show()
```



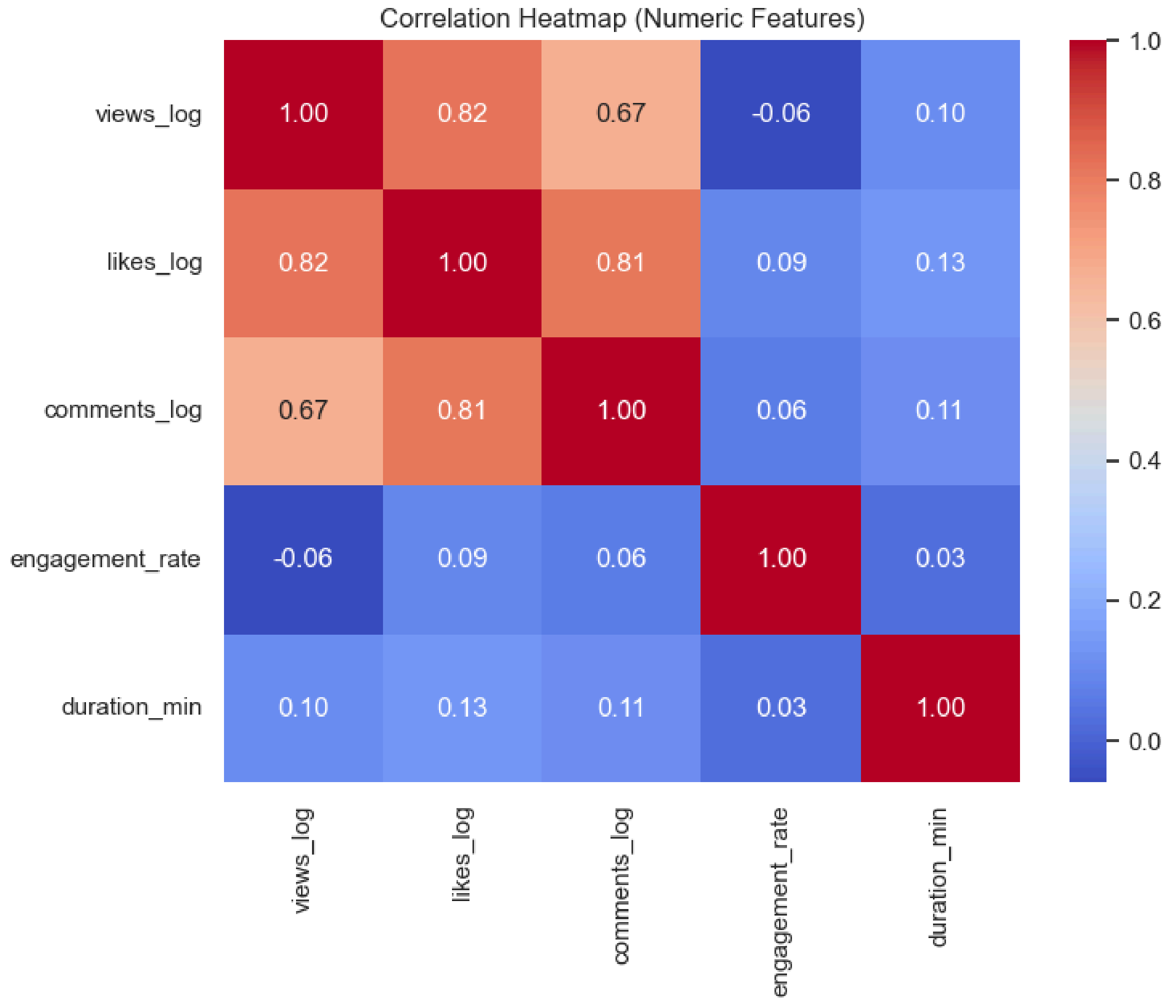
In [285]:
```
#Views vs Comments
sns.scatterplot(x='views_log', y='comments_log', data=df1)
plt.title("Views vs Comments (log scale)")
plt.show()
```



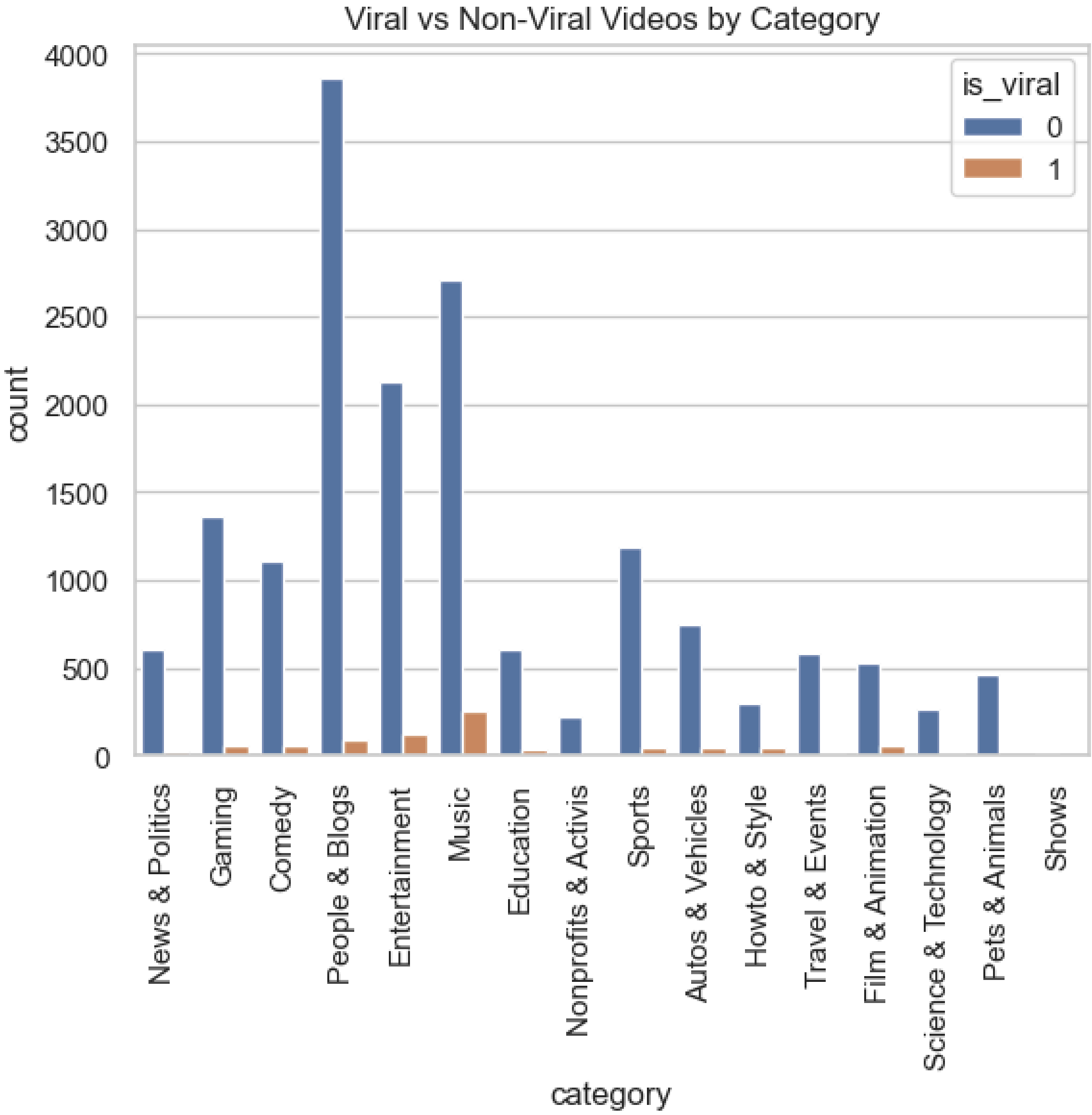
In [286]:
```
#Likes vs Comments
sns.scatterplot(x='likes_log', y='comments_log', data=df1)
plt.title("Likes vs Comments (log scale)")
plt.show()
```



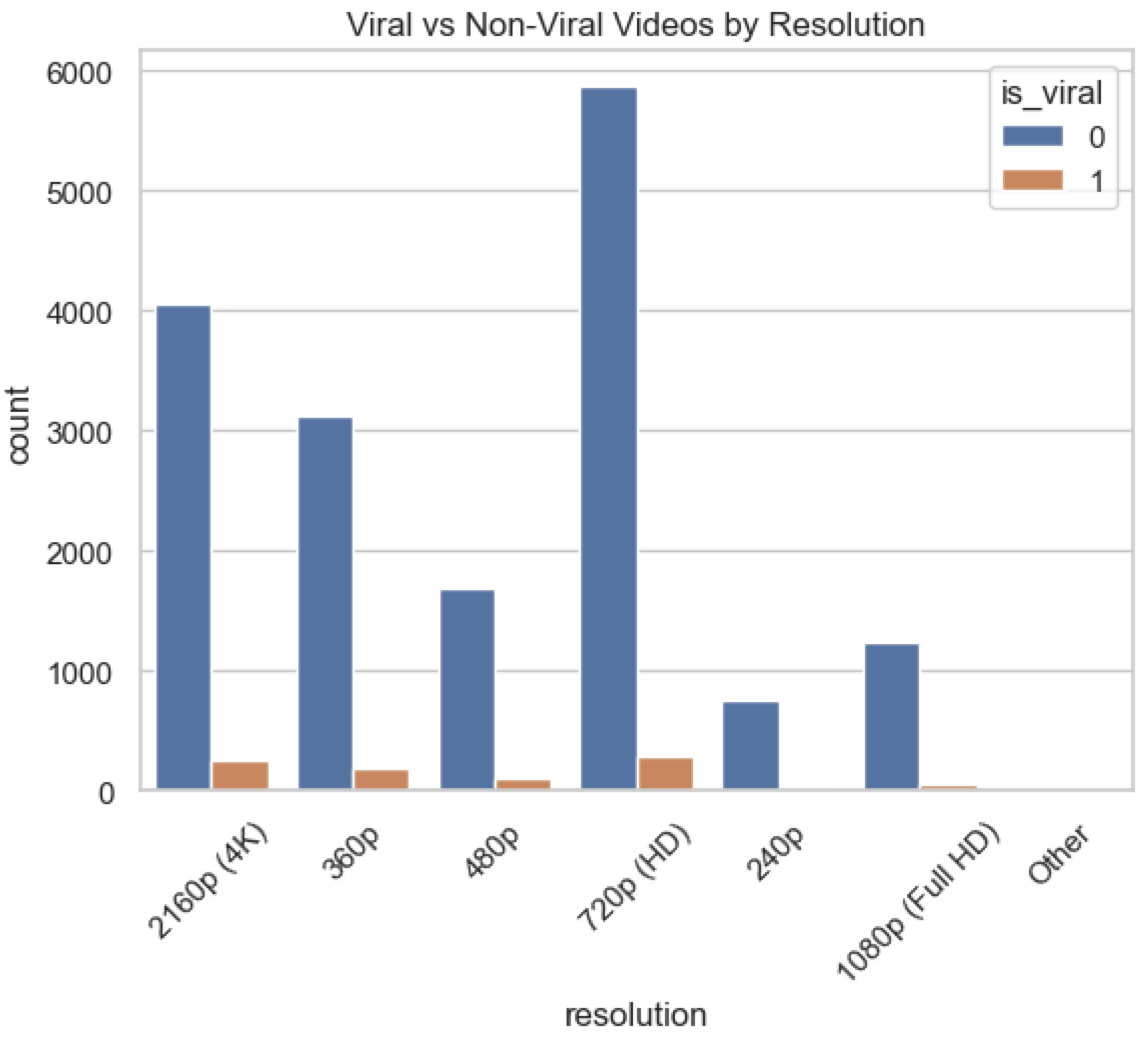
In [287]:
```
#Correlation Heatmap
num_cols = ['views_log','likes_log','comments_log','engagement_rate','duratior
plt.figure(figsize=(8,6))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap (Numeric Features)")
plt.show()
```



In [288]:
```
#Viral Content Distribution

#Viral vs Non-Viral by Category
sns.countplot(x='category', hue='is_viral', data=df1)
plt.xticks(rotation=90)
plt.title("Viral vs Non-Viral Videos by Category")
plt.show()
```

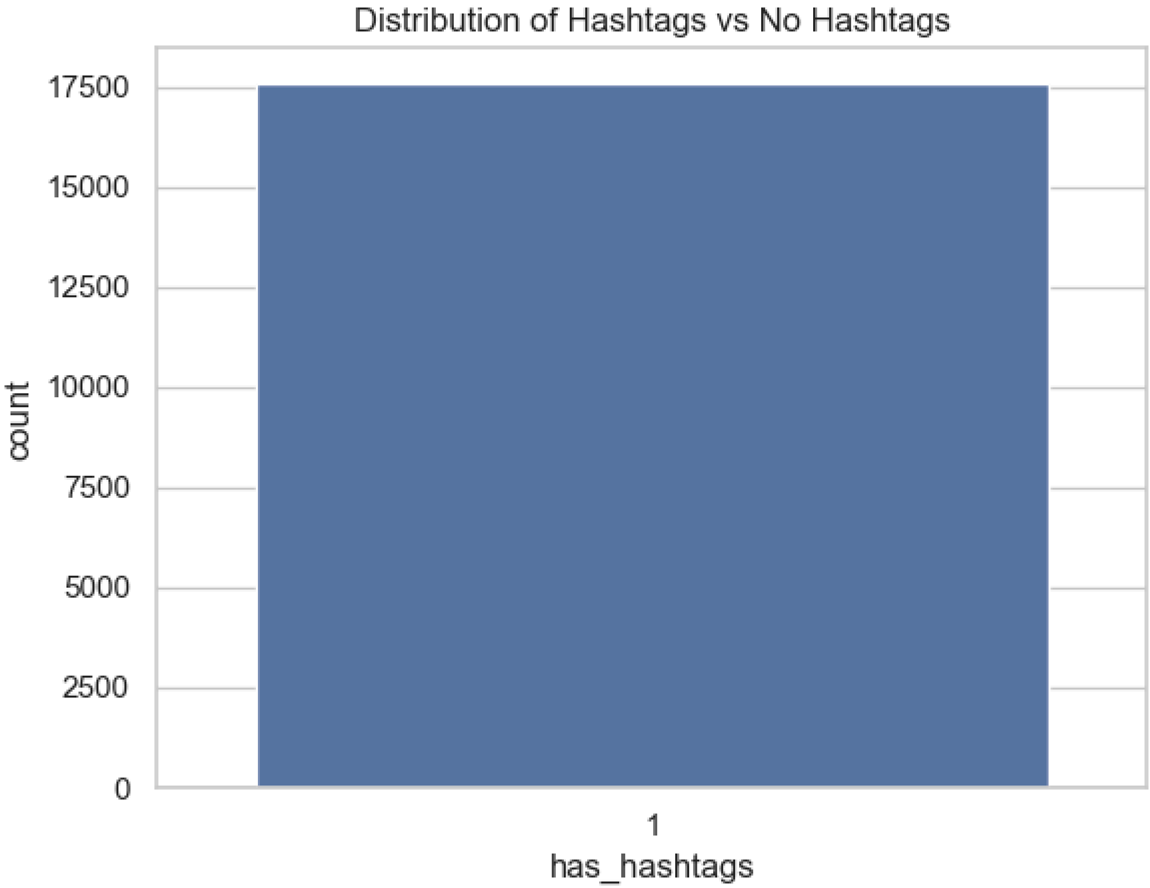


In [289]:
```
#Viral vs Non-Viral by Resolution
sns.countplot(x='resolution', hue='is_viral', data=df1)
plt.xticks(rotation=45)
plt.title("Viral vs Non-Viral Videos by Resolution")
plt.show()
```

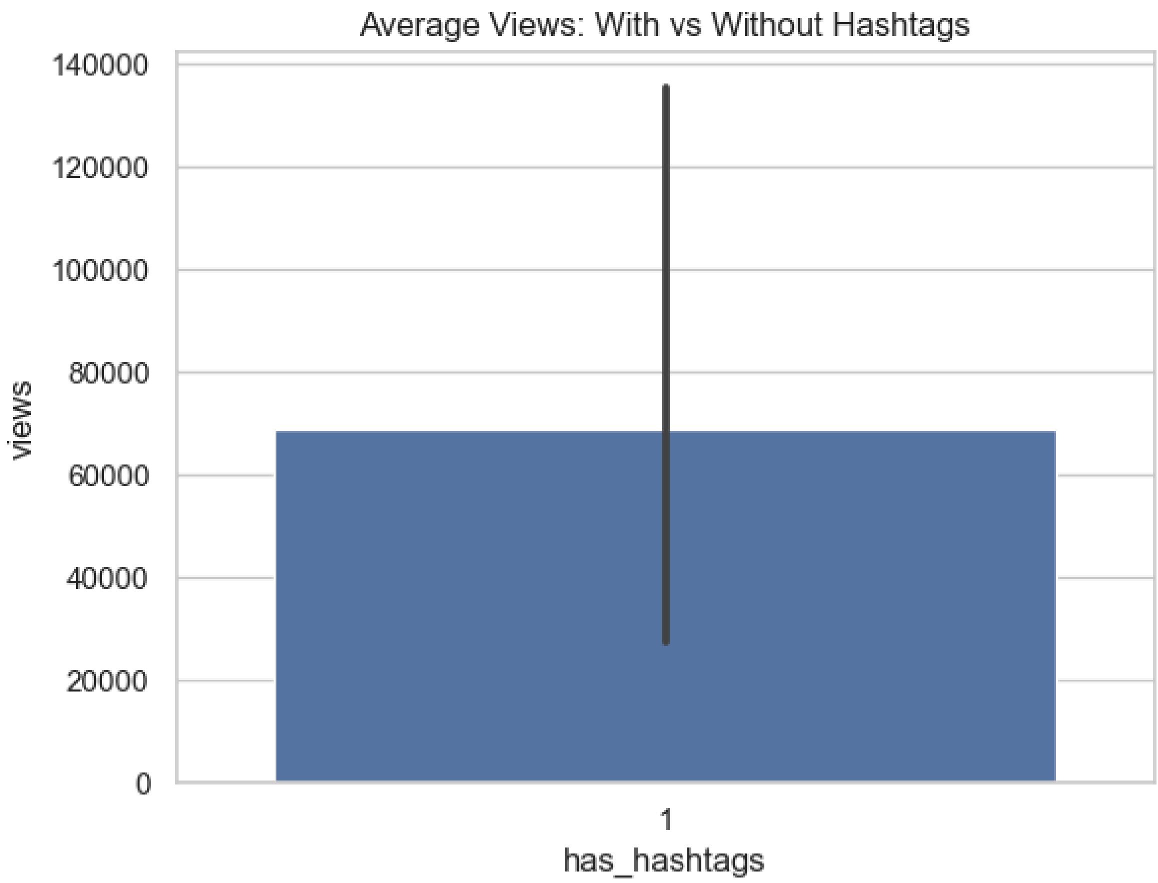


4. Do videos with hashtags perform better?

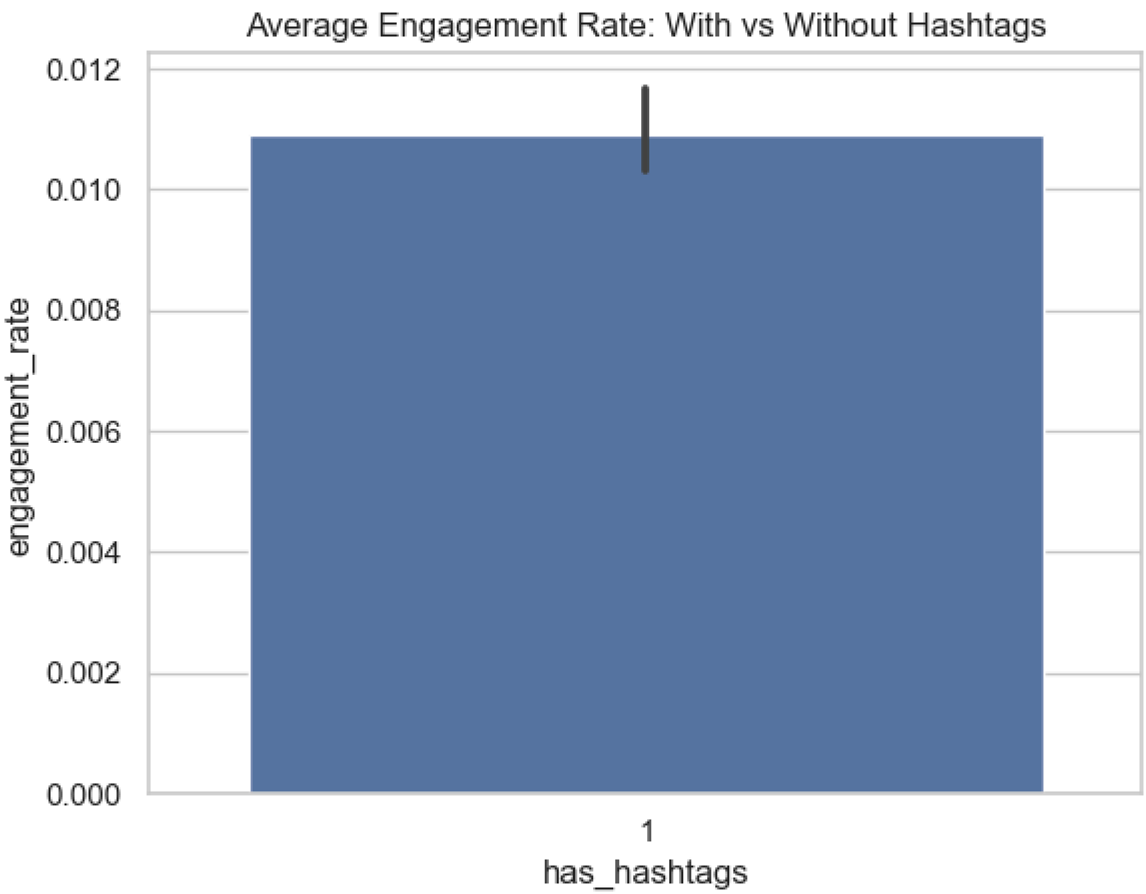
In [290]:
```
#Distribution of Hashtags vs No Hashtags
sns.countplot(x='has_hashtags', data=df1)
plt.title("Distribution of Hashtags vs No Hashtags")
plt.show()
```



In [291]:
```
#Avg Views (Hashtags vs No Hashtags)
sns.barplot(x='has_hashtags', y='views', data=df1)
plt.title("Average Views: With vs Without Hashtags")
plt.show()
```

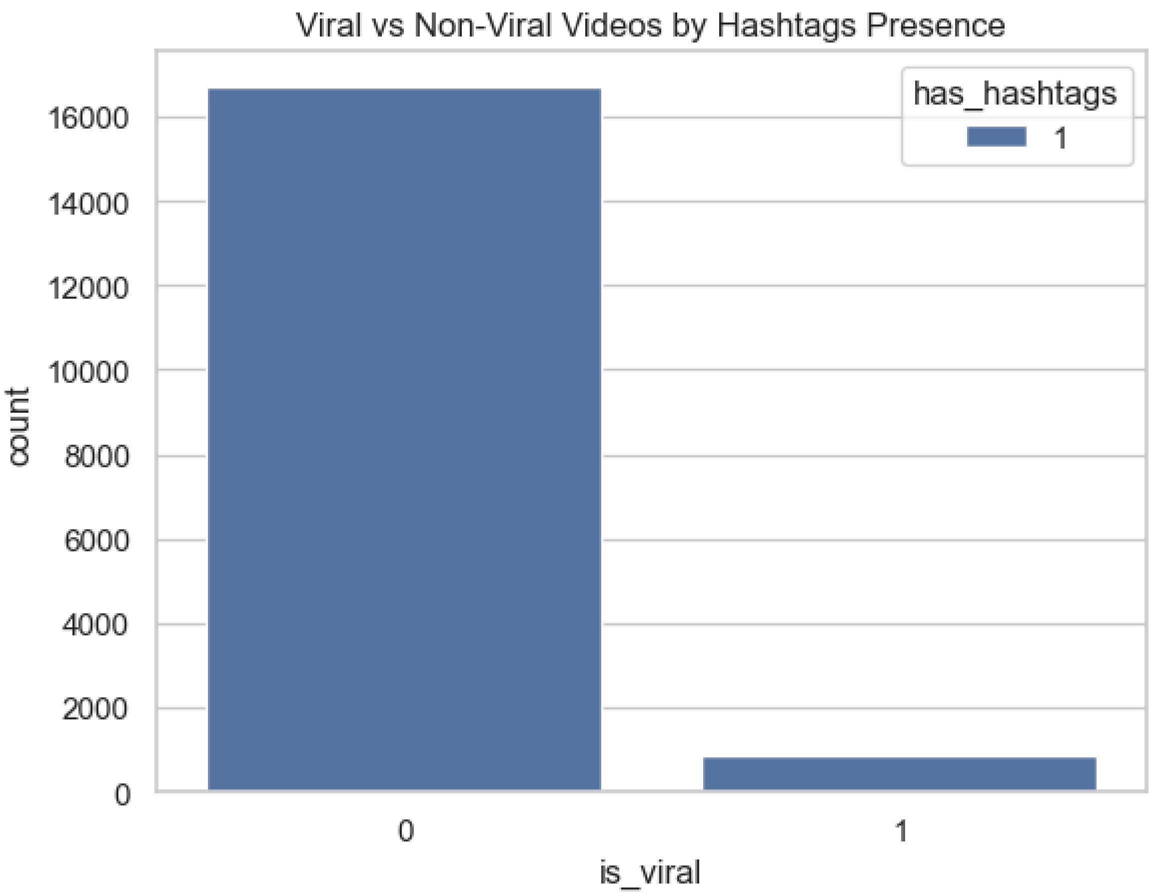


In [292]:
```
#Avg Engagement Rate (Hashtags vs No Hashtags)
sns.barplot(x='has_hashtags', y='engagement_rate', data=df1)
plt.title("Average Engagement Rate: With vs Without Hashtags")
plt.show()
```

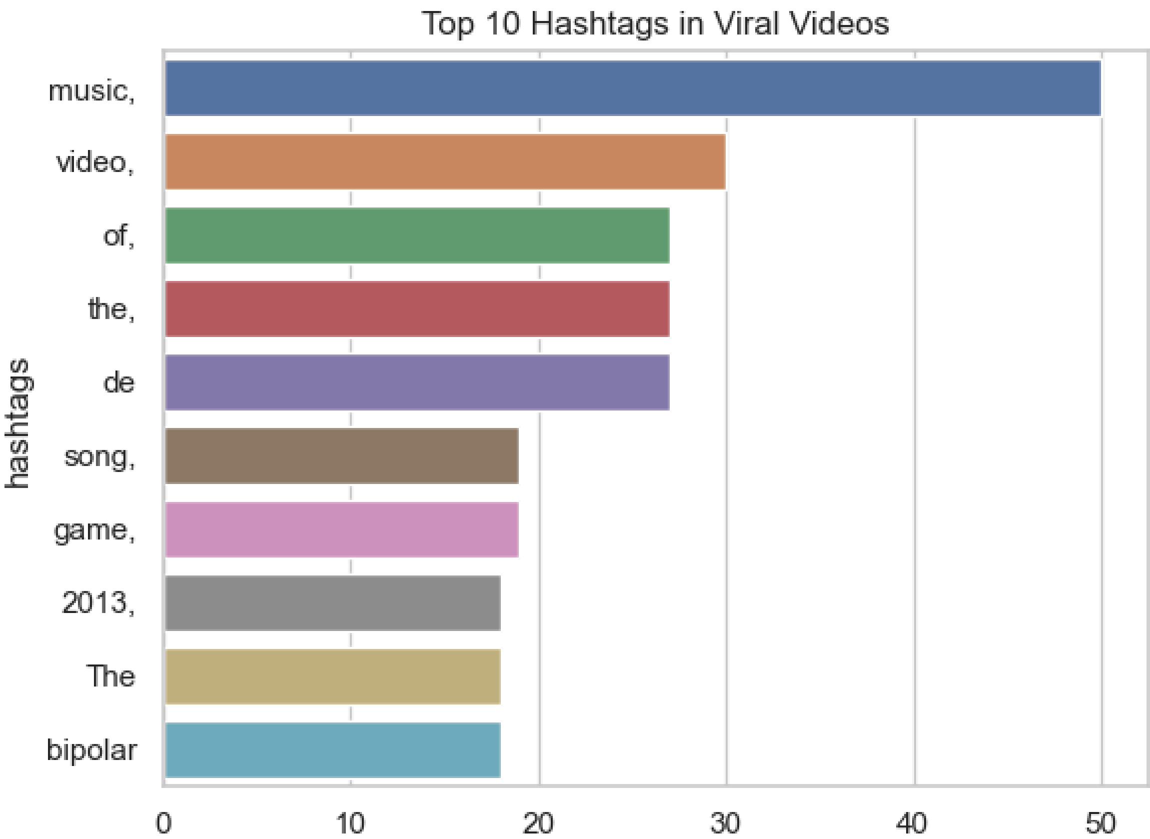


5. Which hashtags are most frequently associated with viral videos?

In [293]:
```
#Viral vs Non-Viral by Hashtags presence
sns.countplot(x='is_viral', hue='has_hashtags', data=df1)
plt.title("Viral vs Non-Viral Videos by Hashtags Presence")
plt.show()
```



In [294]:
```
#Top Hashtags in Viral Videos

#Filtering viral videos with hashtags
viral_hashtags = df1[(df1['is_viral'] == 1) & (df1['hashtags'] != "No Hashtags

#Spliting hashtags (they may be stored as comma-separated or space-separated s
all_tags = viral_hashtags['hashtags'].str.split().explode()

#Counting most frequent hashtags
top_tags = all_tags.value_counts().head(10)

#Barplot of top hashtags
sns.barplot(x=top_tags.values, y=top_tags.index)
plt.title("Top 10 Hashtags in Viral Videos")
plt.show()
```



Executive Summary

Categories: Gaming & Comedy dominate in views, but Education has stronger engagement efficiency.

Duration: Medium-length videos (4–10 minutes) perform best for engagement.

Resolution: HD videos (720p/1080p) yield slightly higher engagement than low-quality formats.

Predictors: Likes and Comments are the strongest indicators of video success.

Hashtags: Videos with hashtags consistently achieve higher engagement; most viral videos use them.

Recommendations

Encourage creators to produce medium-length (4–10 min) videos for optimal engagement.

Focus on Gaming, Comedy, and Education categories to capture both reach and engagement.

Always use hashtags in video descriptions to improve discoverability and engagement.

Creators should encourage likes and comments explicitly, as these are the strongest predictors of visibility.

Future analysis could integrate time-based trends (upload dates) to study seasonality and video lifecycle performance.

Stakeholders

Content Creators / Influencers

Want to know which type of content performs best.

Insights help them decide which category, duration, or resolution to focus on.

Marketing & Social Media Teams

Interested in whether hashtags drive engagement.

Insights help optimize video descriptions, use trending hashtags, and boost discoverability.

YouTube Platform / Product Managers

Care about what makes videos go viral and which features keep viewers engaged.

Insights can guide recommendation algorithms, feature updates, and user engagement strategies.

Brands & Advertisers

Want to know which categories or creators to sponsor for maximum reach.

Insights help improve ad targeting and influencer partnerships.

How This Project Helps

Content Strategy

Identifies top-performing categories (e.g., Gaming, Comedy for reach; Education for engagement).

Helps creators optimize video duration (medium-length is most engaging).

Engagement Optimization

Reveals that Likes & Comments strongly drive Views, encouraging creators to push for interaction.

Highlights that videos with hashtags perform better than those without.

Viral Growth Insights

Shows patterns in viral videos (categories, hashtags, resolution).

Helps creators and marketers mimic successful viral strategies.

Platform/Business Impact

Demonstrates that small optimizations (hashtags, duration, resolution) can improve engagement.

Provides insights that could support future recommendation system improvements (beyond the scope of this project).

Limitations of the Analysis

No time/date information → can't analyze trends over time.

Engagement metrics may be biased toward large creators (MrBeast, etc.).

Dataset doesn't include watch time or subscriber growth (important for deeper insights).

Viral videos are rare, making them hard to generalize.

Future Work / Next Steps

Time-Based Analysis: If upload dates were available, analyze trends over time (seasonality, growth, video lifecycle).

Text Analytics: Apply NLP on video titles, descriptions, and hashtags to understand what language or themes drive engagement.

Predictive Modeling: Extend the analysis into simple ML models (e.g., regression, classification) to predict video popularity based on metadata.

Interactive Dashboard: Build a Power BI or Tableau dashboard for real-time monitoring of content performance.

For future extensions, advanced methods like predictive modeling or NLP on titles/hashtags could be explored.