Importing libraries

In [76]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
from utils import clean_data, find_optimal_clusters, plot_cluster_metr
```

Data transformation and descriptive analysis

In [67]:
```
# Load the dataset
df = pd.read_csv('../data/profiles_dataset.csv')
df.head()
```

Out[67]:

	timestamp	account_id	nickname	biography	awg_engagement_rate
0	2023-08-01	a.r.m.y664	❤️❤️❤️	nazywam się Basia 🇵🇱+🇺🇸 moja mama jest z USA 🖤...	0.049630
1	2023-08-01	a2_9r	ايمن الفستقي 🍺🥃🥂	حسابي الاصلي _ytp_تيكتككك(_8	0.059322
2	2023-07-30	ti.po.check	All	Активный пользователь ТикТока 🌝 \nМеня зовут BD...	0.001399
3	2023-08-06	nutrifersanort	L.N Fernanda Sánchez	Nutrióloga, educadora en diabetes.	0.469767
4	2023-07-25	bhgdee	D💲	Ig-bhg.dee📸 \nSc-dannieo2099 👻\nFb- frank matth...	0.122283

In [68]:
```
df.info()
df.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 18 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   timestamp                1000 non-null   object 
 1   account_id               1000 non-null   object 
 2   nickname                 1000 non-null   object 
 3   biography                997 non-null    object 
 4   awg_engagement_rate      1000 non-null   float64
 5   comment_engagement_rate  1000 non-null   float64
 6   like_engagement_rate     1000 non-null   float64
 7   bio_link                 191 non-null    object 
 8   is_verified              1000 non-null   bool   
 9   followers                1000 non-null   int64  
 10  following                1000 non-null   int64  
 11  likes                    1000 non-null   int64  
 12  videos_count             1000 non-null   int64  
 13  create_time              0 non-null      float64
 14  id                       1000 non-null   int64  
 15  top_videos               1000 non-null   object 
 16  url                      1000 non-null   object 
 17  profile_pic_url          1000 non-null   object 
dtypes: bool(1), float64(4), int64(5), object(8)
memory usage: 133.9+ KB
```

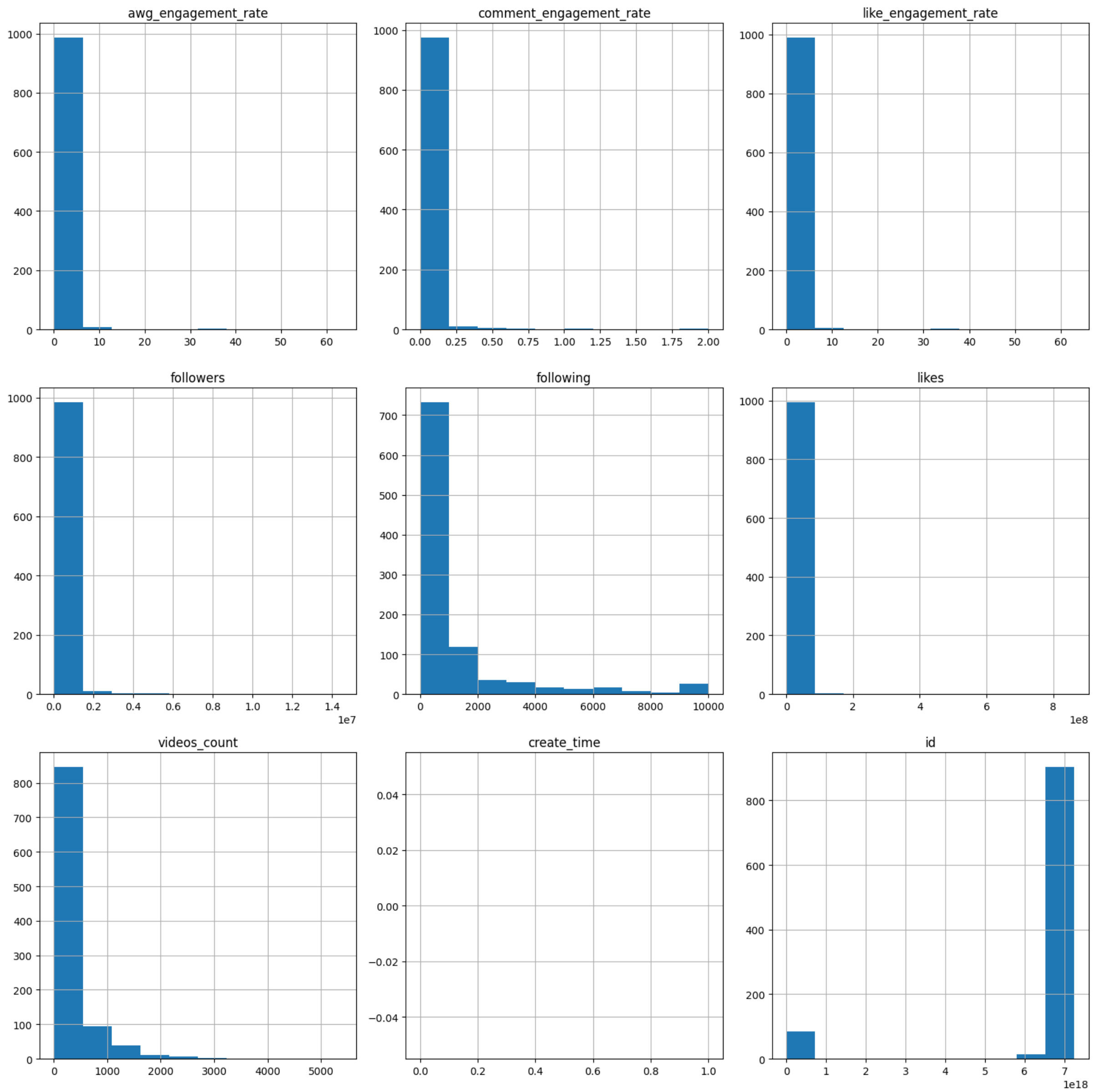
Out[68]: (1000, 18)

In [69]:

```
numeric_cols = df.select_dtypes(include='number').columns
n_cols = 3
n_rows = (len(numeric_cols) + n_cols - 1) // n_cols  # Ceiling divisio
```

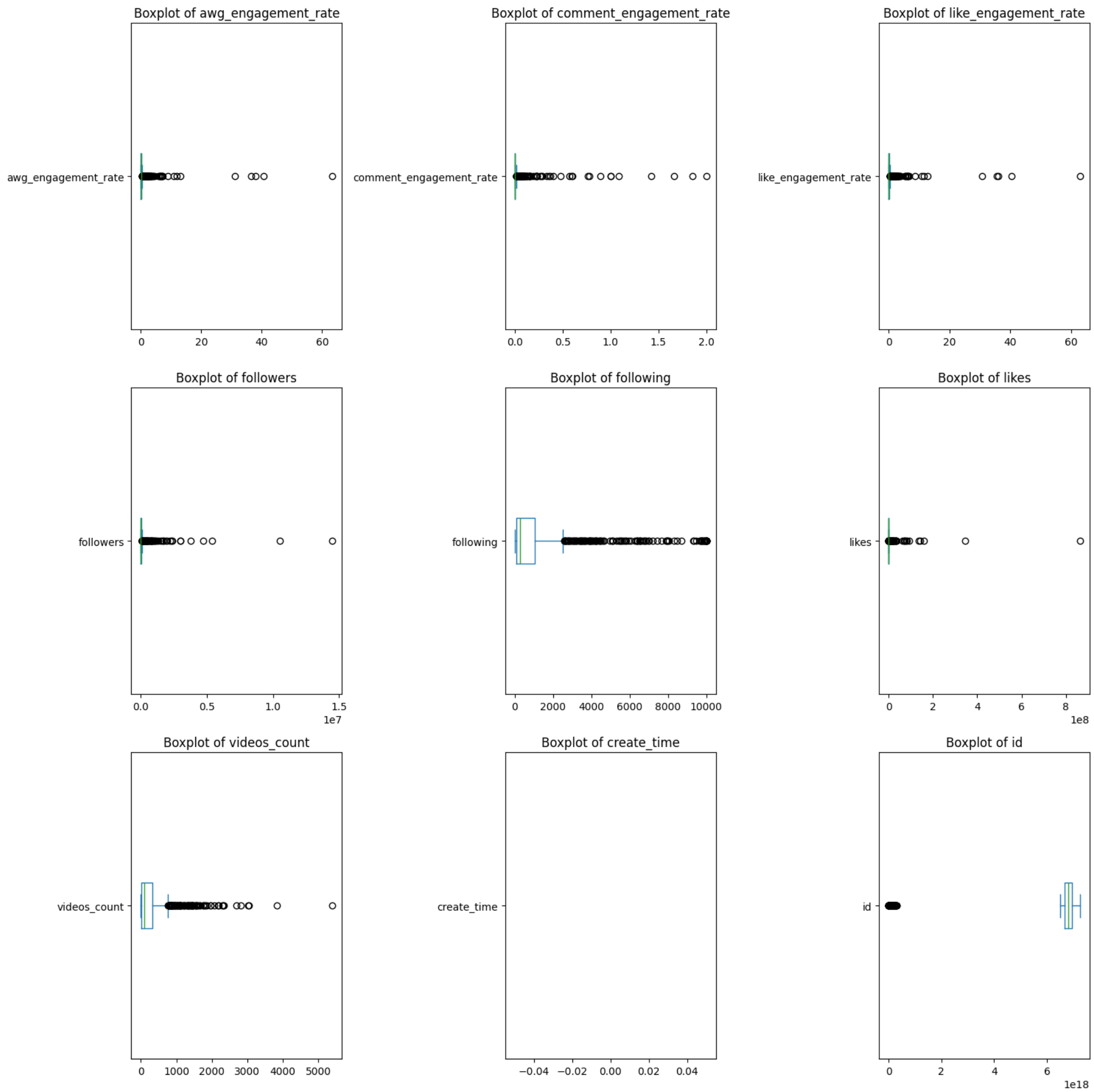
In [70]:

```
### Histograms

plt.figure(figsize=(15, 5 * n_rows))
for idx, col in enumerate(numeric_cols):
    plt.subplot(n_rows, n_cols, idx + 1)
    df[col].hist(bins=10)
    plt.title(col)
plt.tight_layout()
plt.show()
```



In [71]:

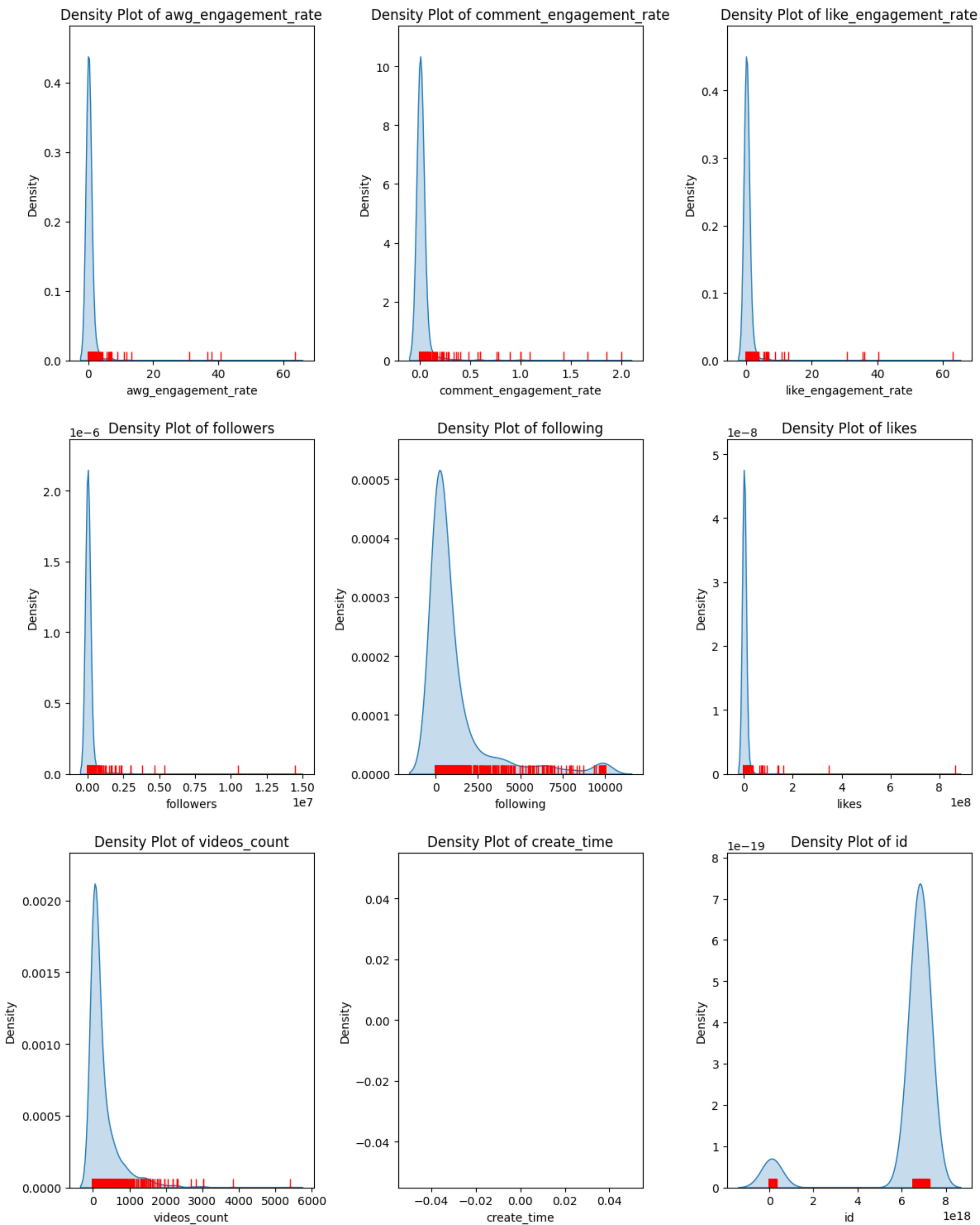
```
### Box Plots
plt.figure(figsize=(15, 5 * n_rows))
for idx, col in enumerate(numeric_cols):
    plt.subplot(n_rows, n_cols, idx + 1)
    df[col].plot(kind='box', vert=False)
    plt.title(f"Boxplot of {col}")
plt.tight_layout()
plt.show()
```



In [72]:

```python
### Density Plots
plt.figure(figsize=(12, 5 * n_rows))
for idx, col in enumerate(numeric_cols):
    plt.subplot(n_rows, n_cols, idx + 1)
    sns.kdeplot(df[col], fill=True)
    sns.rugplot(df[col], color='red')
    plt.title(f"Density Plot of {col}")
plt.tight_layout()
plt.show()
```

```
/var/folders/1x/jp3vqcs53vv9kxc9f40hgztc0000gn/T/ipykernel_64852/406032
6769.py:5: UserWarning: Dataset has 0 variance; skipping density estima
te. Pass `warn_singular=False` to disable this warning.
  sns.kdeplot(df[col], fill=True)
```



In [73]:

```
### Scatter Plot
if "Income_BDSA" in df.columns and "Unemployment_BDSA" in df.columns:
    plt.scatter(df["Income_BDSA"], df["Unemployment_BDSA"], color='blu
    plt.title("Income vs. Unemployment")
    plt.xlabel("Income")
    plt.ylabel("Unemployment Rate")
    plt.axhline(y=6, color='red', linestyle='--')
    plt.tight_layout()
    plt.show()
```

Data Cleaning

In [74]:
```
df_clean = clean_data(df)

# Select features for clustering
feature_cols = [
    'awg_engagement_rate',
    'comment_engagement_rate',
    'like_engagement_rate',
    'followers',
    'following',
    'likes',
    'videos_count',
    'is_verified'
]
```

```
Duplicates found: 0
```

Preprocessing the Data

Select relevant features for the analysis, and encode categorical variables if necessary, and getting the data ready for clustering.

In [75]:
```
# Encode the 'is_verified' boolean column as an integer
df_clean['is_verified'] = df_clean['is_verified'].astype(int)
```

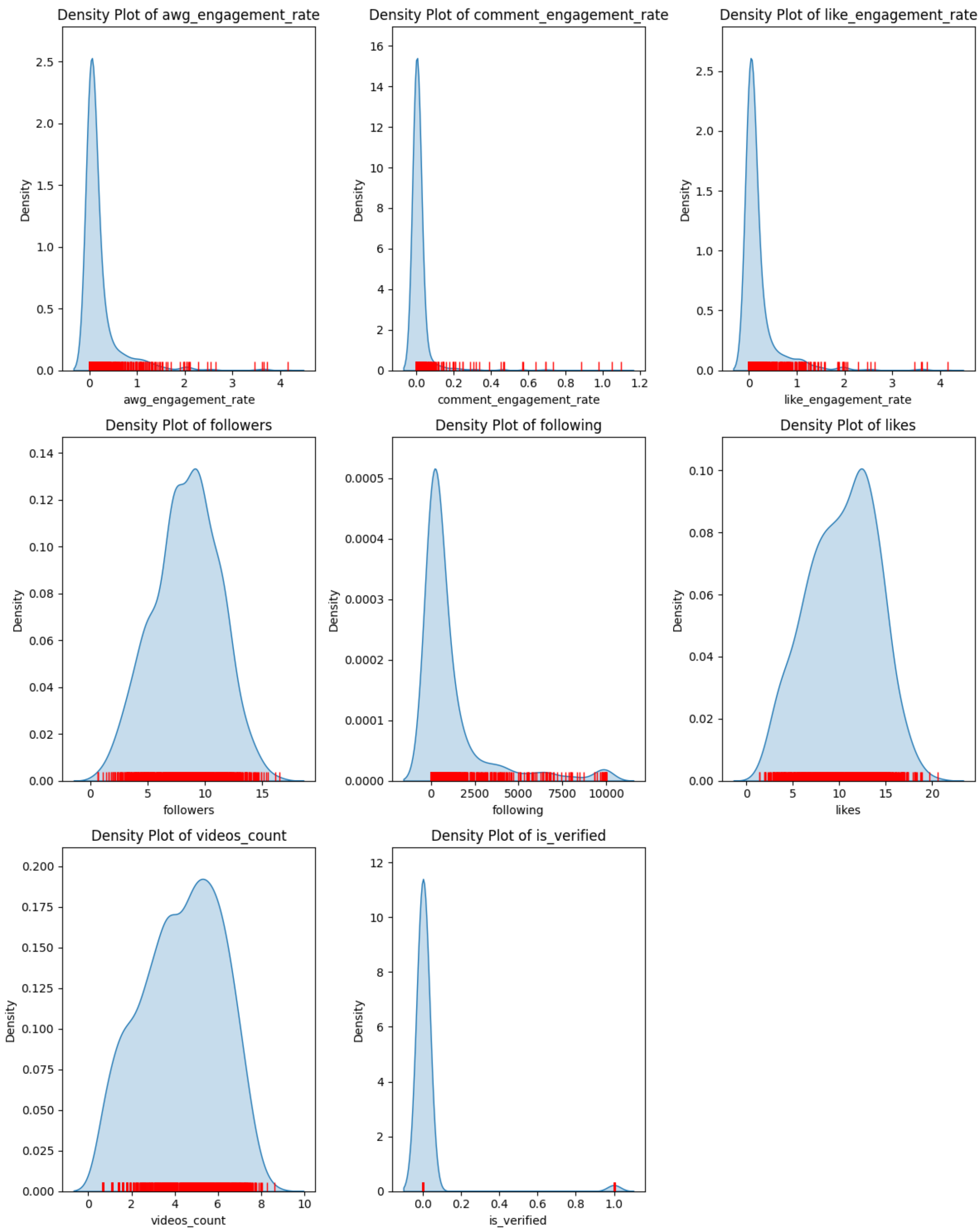
In [78]:
```
# Create a subset with selected features
df_features = df_clean[feature_cols].copy()
```

In [ ]:
```
# Handle outliers in engagement metrics
engagement_cols = ['awg_engagement_rate', 'comment_engagement_rate', '
for col in engagement_cols:
    df_features[col] = np.log1p(df_features[col])
```

```
Dataset shape after removing outliers: (1000, 8)
```

In [81]:
```
numeric_cols = df_features.select_dtypes(include='number').columns
n_cols = 3
n_rows = (len(numeric_cols) + n_cols - 1) // n_cols  # Ceiling divisio
```

In [82]:
```
### Density Plots
plt.figure(figsize=(12, 5 * n_rows))
for idx, col in enumerate(numeric_cols):
    plt.subplot(n_rows, n_cols, idx + 1)
    sns.kdeplot(df_features[col], fill=True)
    sns.rugplot(df_features[col], color='red')
    plt.title(f"Density Plot of {col}")
plt.tight_layout()
plt.show()
```



In the context of social media influencer data, what we're seeing is actually a natural phenomenon rather than problematic outliers.

The distribution typically follows a power law, where:

There are many small accounts (micro-influencers) A moderate number of medium-sized accounts A few very large accounts (mega-influencers/celebrities) In this case, removing outliers might actually eliminate important segments of our analysis, particularly the valuable mega-influencers.

Feature Scaling

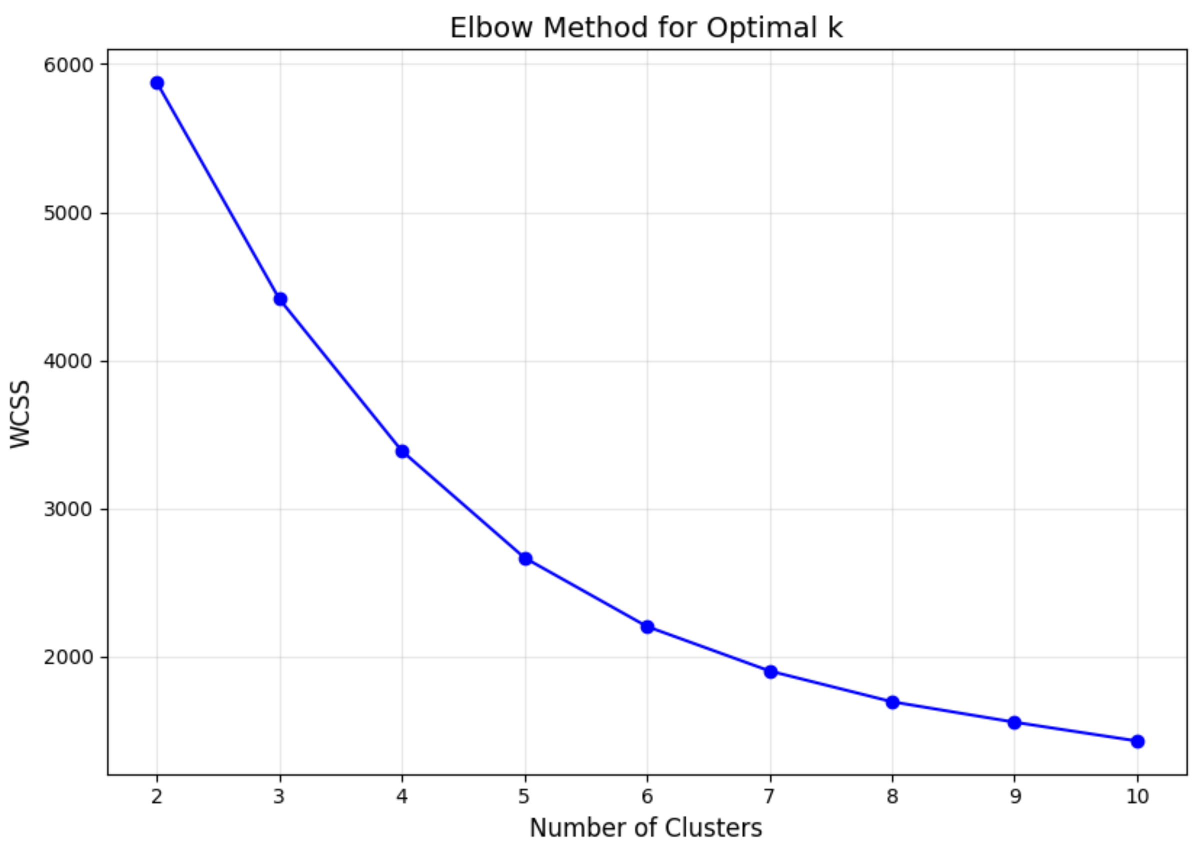
K-means clustering is sensitive to the scale of the data, in this case we apply Standard Scaler because the data is spread out and there are many outliers

In [83]:
```
# Scale the features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(df_features)
```

Optimal Number of Clusters

Use the Elbow Method to determine the most appropriate number of clusters for k-means clustering. Generally the range of cluster values oftenly chosen are from 1 to 7.

In [90]:
```
# Find optimal number of clusters
wcss = find_optimal_clusters(scaled_features)
plot_cluster_metrics(wcss)
```



K-Means Clustering

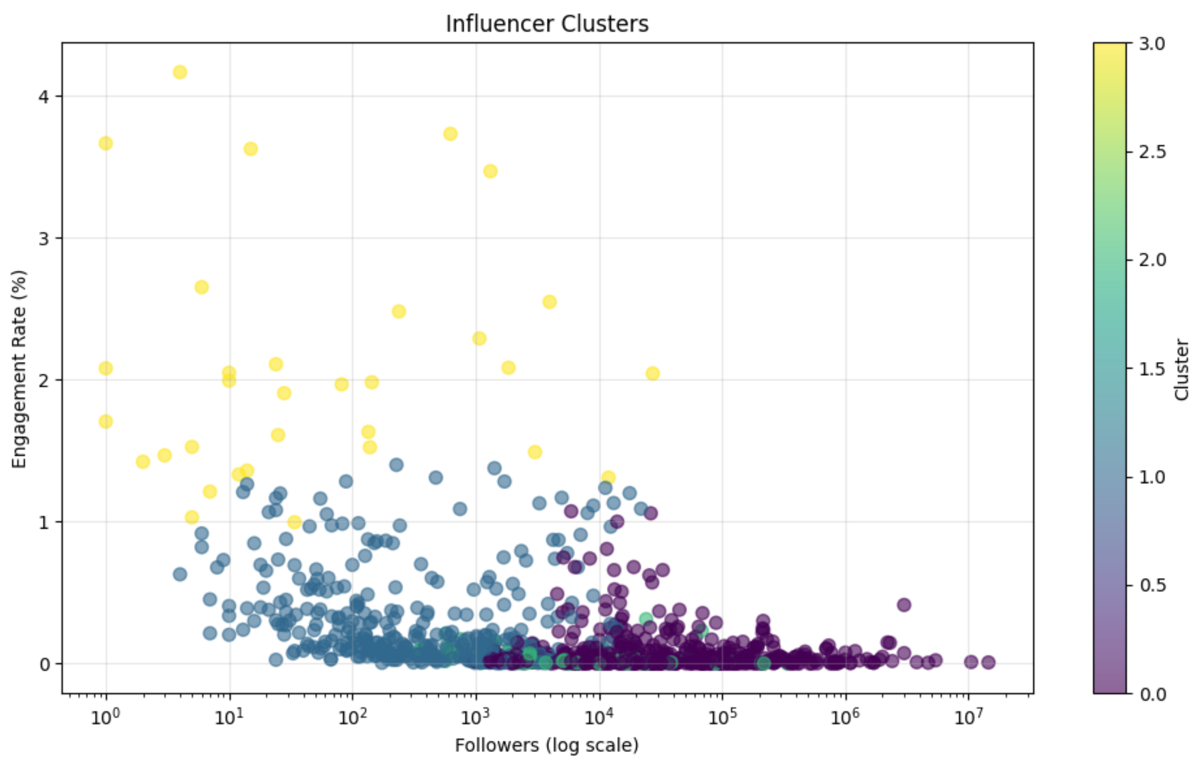
Perform k-means clustering using the optimal number of clusters determined in the previous step.

In [108…
```
# Choose optimal k and perform clustering
optimal_k = 4 # Based on plots
kmeans = KMeans(n_clusters=optimal_k, init='k-means++', random_state=4
df_features['cluster'] = kmeans.fit_predict(scaled_features)
```

Visualizing Clusters

Plot the clusters to visually assess how distinct they are from each other.

In [110…
```
# Visualize the clusters
plt.figure(figsize=(10, 6))
plt.scatter(
    np.exp(df_features['followers']) - 1,  # Reverse log1p transformat
    df_features['awg_engagement_rate'],
    c=df_features['cluster'],
    cmap='viridis',
    alpha=0.6,
    s=50  # Slightly larger point size for better visibility
)
plt.xscale('log')
plt.xlabel('Followers (log scale)')
plt.ylabel('Engagement Rate (%)')
plt.title('Influencer Clusters')
plt.colorbar(label='Cluster')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```



1. Purple Cluster (0): Mega-influencers/Celebrities

- Followers: 10^4 to 10^7 (10,000 to 10M+)
- Very low engagement rates (<0.5%)
- This is typical for very large accounts where the sheer size of the audience leads to lower engagement percentages

2. Blue Cluster (1): Mid-tier Influencers

- Followers: 10^2 to 10^4 (100 to 10,000)
- Moderate engagement rates (0.5-1.5%)
- Represents the "sweet spot" of influencer marketing with decent reach and engagement

3. Yellow Cluster (2): Micro-influencers

- Followers: 10^0 to 10^2 (1 to 1,000)
- High engagement rates (2-4%)
- These are niche accounts with highly engaged communities

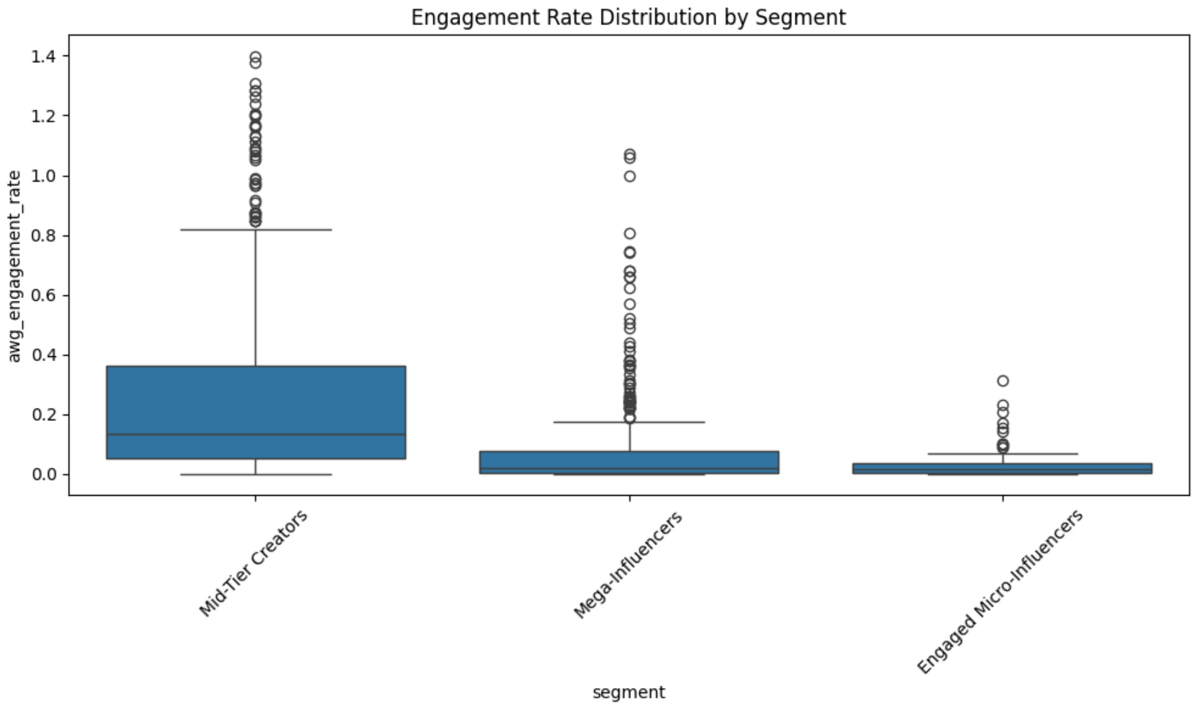
Analyzing Cluster Centroids

Examine the centroids of the clusters to understand the defining characteristics of each cluster. This helps in interpreting the types of influencers within each cluster.

In [111…

```
# Create segment labels
segment_names = {
    0: "Mega-Influencers",
    1: "Mid-Tier Creators",
    2: "Engaged Micro-Influencers"
}

# Map cluster numbers to segment names
df_features['segment'] = df_features['cluster'].map(segment_names)

# Calculate key metrics per segment
segment_analysis = df_features.groupby('segment').agg({
    'followers': ['median', 'count'],
    'awg_engagement_rate': 'mean',
    'videos_count': 'mean',
    'is_verified': 'mean'
}).round(3)

print("\nSegment Analysis:")
print(segment_analysis)

# Visualize engagement distribution by segment
plt.figure(figsize=(10, 6))
sns.boxplot(x='segment', y='awg_engagement_rate', data=df_features)
plt.xticks(rotation=45)
plt.title('Engagement Rate Distribution by Segment')
plt.tight_layout()
plt.show()
```

```
Segment Analysis:
                          followers       awg_engagement_rate videos_co
unt  \
                             median count                mean          m
ean
segment
Engaged Micro-Influencers     8.622    81               0.035         5.
223
Mega-Influencers             10.339   493               0.075         5.
511
Mid-Tier Creators             6.117   394               0.274         2.
899

                          is_verified
                                 mean
segment
Engaged Micro-Influencers       0.000
Mega-Influencers                0.039
Mid-Tier Creators               0.000
```



Engagement Rate Distribution by Segment
awg_engagement_rate
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Mid-Tier Creators
Mega-Influencers
Engaged Micro-Influencers
segment