Importing libraries

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

Loading and Inspecting the Dataset

In [77]:
```
# Load the dataset
df = pd.read_csv('../data/profiles_dataset.csv')
df.head()
```

Out[77]:

	timestamp	account_id	nickname	biography	awg_engagement_rate	commen
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 8_)تيكتككك_ytp_	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 [78]:
```
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[78]: (1000, 18)

Data Cleaning

In [79]:

```
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 [80]:

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

In [81]:
```python
# Create a subset with selected features
df_features = df_clean[feature_cols].copy()
```

In [82]:
```python
# Handle outliers in engagement metrics
engagement_cols = ['awg_engagement_rate', 'comment_engagement_rate', 'like_e
df_no_outliers = remove_outliers_iqr(df_features, engagement_cols)
print(f"Dataset shape after removing outliers: {df_no_outliers.shape}")
```

```
Dataset shape after removing outliers: (683, 8)
```

IQR removal is better for this dataset since it has a lot of outliers and is difficult to visualize the clusters, even though it removed more than the half of the dataset, it's easier to illustrate

Feature Scaling

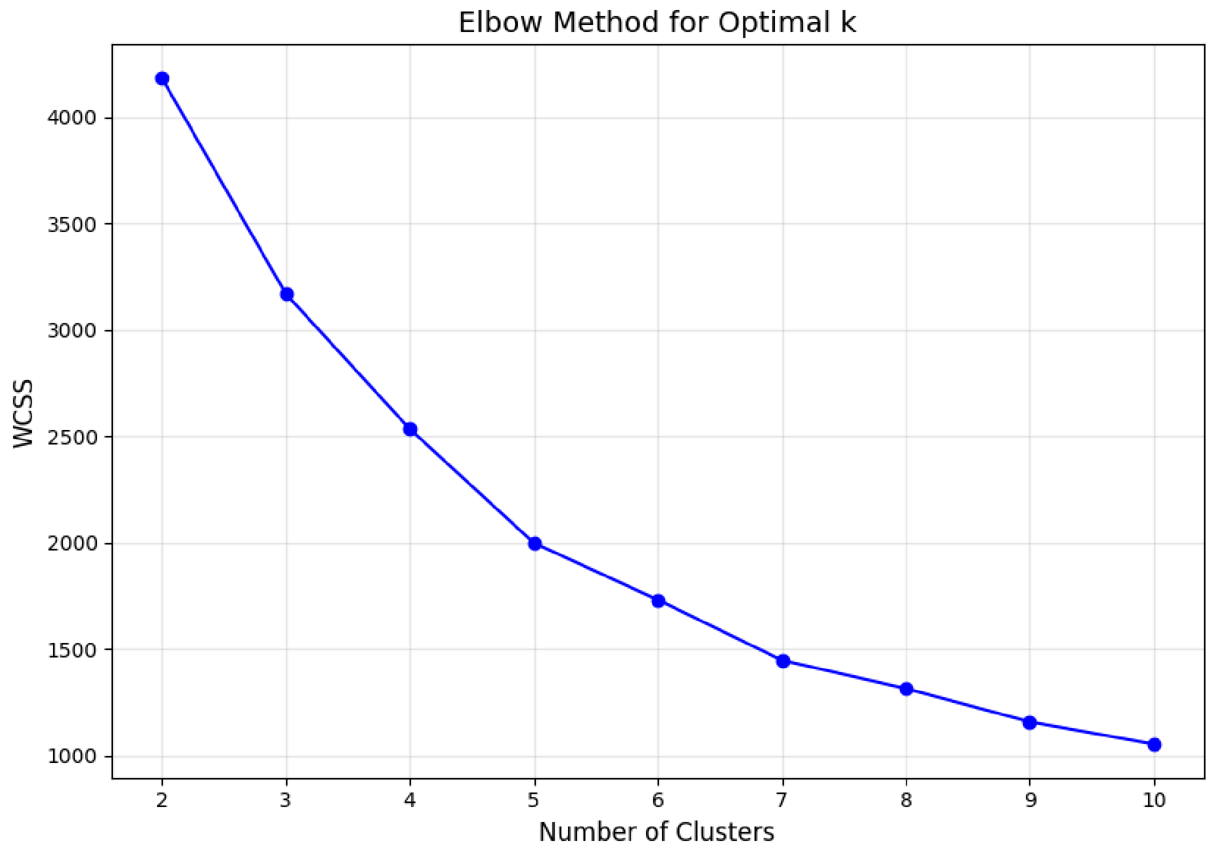
K-means clustering is sensitive to the scale of the data, in this case we apply Standard Scaler because the data is spread out and there are many outliers

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

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 [84]:
```python
# 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.

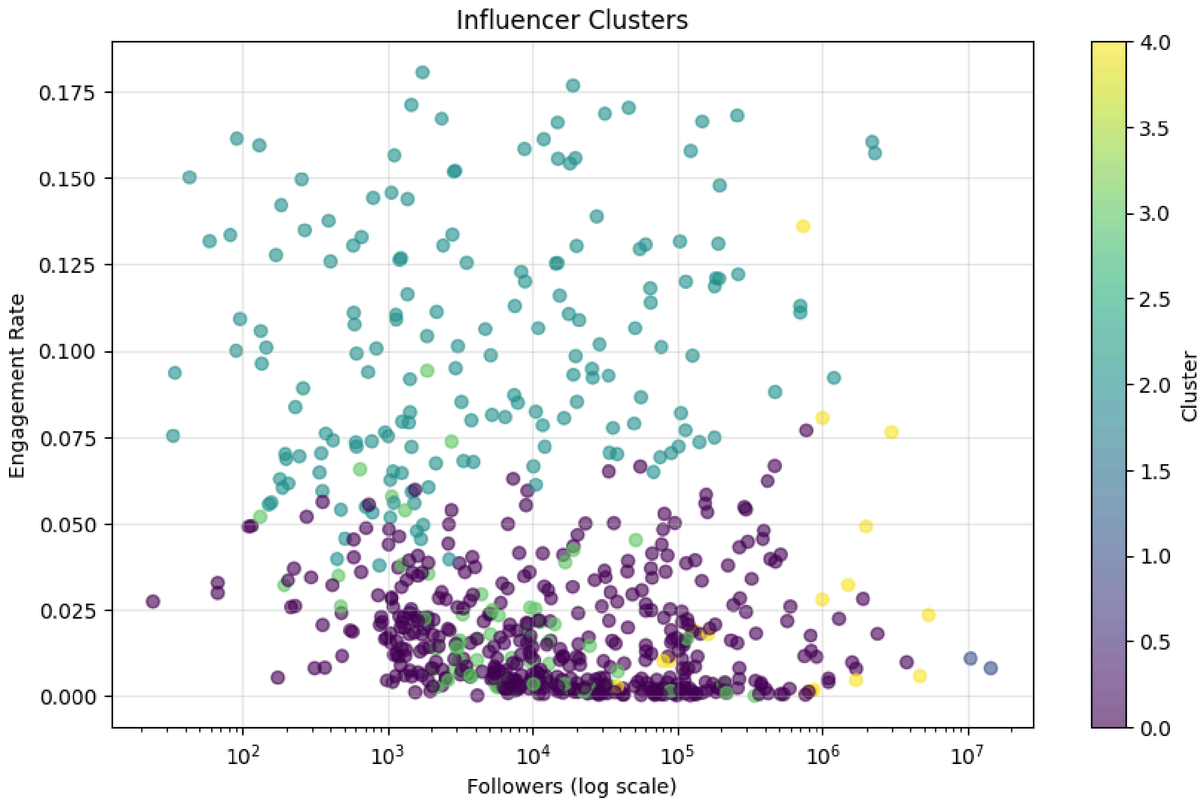
In [94]:
```
# Choose optimal k and perform clustering
optimal_k = 5 # Based on plots
kmeans = KMeans(n_clusters=optimal_k, init='k-means++', random_state=42)
df_no_outliers['cluster'] = kmeans.fit_predict(scaled_features)
```

Visualizing Clusters

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

In [95]:
```
# Visualize the clusters
plt.figure(figsize=(10, 6))
plt.scatter(
    df_no_outliers['followers'],
    df_no_outliers['awg_engagement_rate'],
    c=df_no_outliers['cluster'],
    cmap='viridis',
    alpha=0.6
)
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.show()
```



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 [96]:
```
# Analyze the clusters
cluster_profiles = df_no_outliers.groupby('cluster').mean()
print(cluster_profiles)
```

```
         awg_engagement_rate  comment_engagement_rate  like_engagement_rate
\
cluster
0                   0.017622                 0.000575              0.017047
1                   0.009517                 0.000056              0.009462
2                   0.101997                 0.002679              0.099318
3                   0.018624                 0.001165              0.017460
4                   0.031252                 0.000300              0.030952

            followers    following         likes  videos_count  is_verified
cluster
0        1.066223e+05   792.002336  2.874820e+06    422.656542          0.0
1        1.250000e+07    29.500000  6.052500e+08   1590.000000          0.5
2        6.971139e+04   776.858824  1.858375e+06    155.317647          0.0
3        2.270360e+04  7482.746269  2.128369e+05    580.253731          0.0
4        1.452662e+06   253.250000  3.220774e+07    590.250000          1.0
```

Interpreting the Clusters

- Cluster 2 has the highest engagement rate (10%) but none of the accounts are verified, this cluster shows nano influencers with high engagement rate.
- Cluster 1 has the highest follower count (12.5M) but lowest engagement, this clusters shows big influencers and according to this dataset they have almost no engagement.
- Cluster 4 has all verified accounts (is_verified = 1.0), high followers but also low engagement, similar to cluster 2 but with verified accounts, most probably macro influencers.