```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv('final dataset.csv',encoding='latin1')
print(df.head())
print(df.columns)
```

```
         username post_number  \
0  pilatesandtara      post_1
1  pilatesandtara      post_2
2         htorres      post_3
3  pilatesandtara      post_3
4     staceysmith      post_5

                                            post_url  likes  \
0  https://www.instagram.com/pilatesandtara/p/DAq...     52
1  https://www.instagram.com/pilatesandtara/p/C_0...     61
2              https://www.instagram.com/p/OdALviRmvz/  45752
3  https://www.instagram.com/pilatesandtara/p/DAo...     61
4              https://www.instagram.com/p/QnUFUDUTIj/  57232

                                            hashtags  \
0  #takeabreak, #selfcare, #retreat, #yogaretreat...
1  #ondemandfitness, #pilatesonline, #barreonline...
2                #strength #fitness #gym #nutrition
3  #portugalretreat, #luxuryretreat, #luxuryretre...
4                      #nutrition #muscle #strength

                                            comments
0  nikkiseare: Looks amazing!!! Well jel x; jill_...
1  saofthera: ð; vale.nullo: ð yo...
2  Outside quite painting it Congress school pric...
3  jill_ross_16: â¤ï¸ââ¤ï¸ââ¤ï¸...
4  Happen company mean test sit more stand southe...
Index(['username', 'post_number', 'post_url', 'likes', 'hashtags', 'comments'], dtype='object')
```

```
# Check for missing values
print(df.isnull().sum())
```

```
username         0
post_number      0
post_url         0
likes            0
hashtags       363
comments       139
dtype: int64
```

```
# Preview unique values in 'hashtags'
print(df['hashtags'].unique())
```

```
['#takeabreak, #selfcare, #retreat, #yogaretreat, #barreretreat, #portugalretreat, #yinyoga, #barreteacher, #yogateacher, #mumlife,
 '#ondemandfitness, #pilatesonline, #barreonline, #onlinebarreclasses, #barreondemand, #strengthtraining, #strengthtrainingonline, #
 '#strength #fitness #gym #nutrition' ...
 '#weightloss #exercise #training #fitnessjourney #motivation'
 '#bodybuilding #yoga #cardio'
 '#training #motivation #crossfit #running #sports']
```

```
df['comments'].fillna('', inplace=True)
df['hashtags'].fillna('', inplace=True)
print(df.isnull().sum())
```

```
username       0
post_number    0
post_url       0
likes          0
hashtags       0
comments       0
dtype: int64
<ipython-input-5-d4d2143b46b7>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained ass:
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[co]


  df['comments'].fillna('', inplace=True)
<ipython-input-5-d4d2143b46b7>:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained ass:
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[co]
```

```
    df['hashtags'].fillna('', inplace=True)
```

```
import re
import nltk
from nltk.corpus import stopwords

# Download the stopwords dataset if not already downloaded
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))

# Function to clean the text
def preprocess_text(text):
    # Remove special characters, punctuation, and numbers
    text = re.sub(r'[^A-Za-z\s]', '', text)  # Keep only letters and spaces
    # Convert to lowercase
    text = text.lower()
    # Remove stopwords
    text = ' '.join([word for word in text.split() if word not in stop_words])
    return text

# Apply text preprocessing to the comments column
df['cleaned_comments'] = df['comments'].apply(preprocess_text)

# Preview the cleaned comments
print(df[['comments', 'cleaned_comments']].head())
```

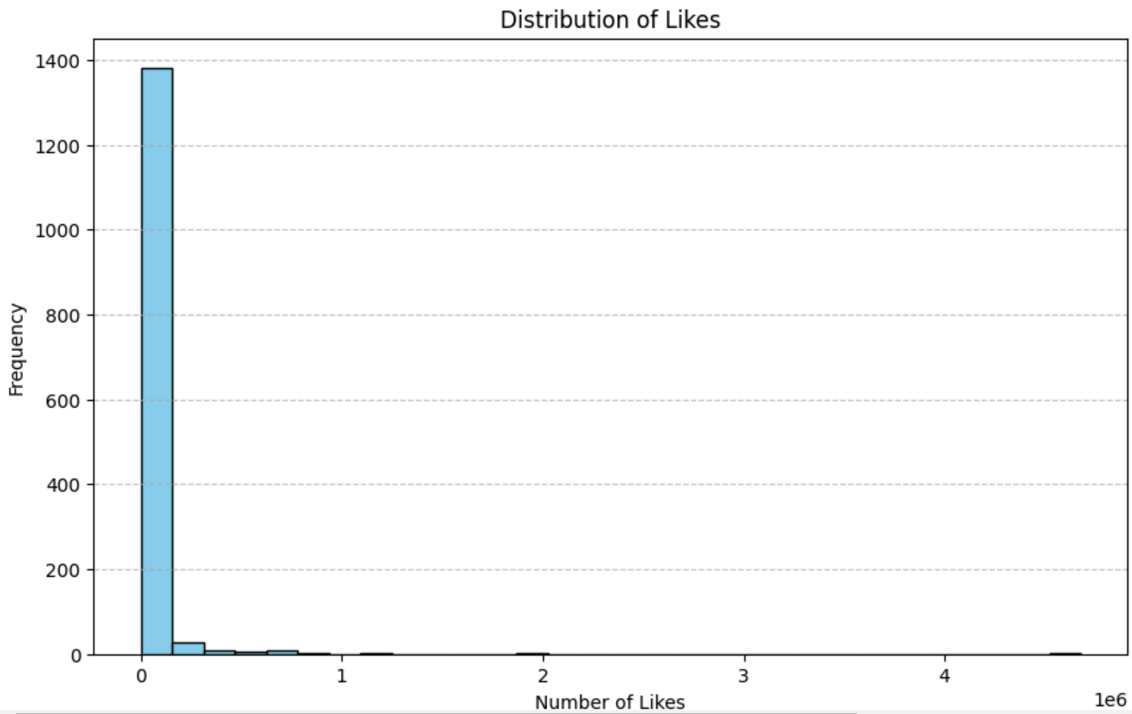
```
                                            comments  \
0  nikkiseare: Looks amazing!!! Well jel x; jill_...
1  saofthera: Ã°Å¸â��Å�; vale.nullo: Ã°Å¸â��Å� yo...
2  Outside quite painting it Congress school pric...
3  jill_ross_16: Ã¢Â�Â¤Ã¯Â¸Â�Ã¢Â�Â¤Ã¯Â¸Â�Ã¢Â�Â¤Ã¯...
4  Happen company mean test sit more stand southe...

                                    cleaned_comments
0  nikkiseare looks amazing well jel x jillross s...
1                saofthera valenullo amazing memiil
2  outside quite painting congress school price b...
3  jillross thank colleague tullyrebecca casafuzetta
4  happen company mean test sit stand southern so...
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
# Clean the 'likes' column: remove commas and invalid characters, and convert to numeric
df.loc[:, 'likes'] = df['likes'].astype(str).str.replace(',', '', regex=True)  # Remove commas
df.loc[:, 'likes'] = pd.to_numeric(df['likes'], errors='coerce')  # Convert to numeric, invalid values become NaN

# Drop rows with NaN likes (invalid entries)
df = df.dropna(subset=['likes'])

# Ensure 'likes' is of integer type
df.loc[:, 'likes'] = df['likes'].astype(int)

# Generate a sequential timeline for posts based on their order in the dataset
df['post_index'] = range(1, len(df) + 1)  # Create a synthetic 'post_index' column

# Group posts into "months" or periods based on index (e.g., batches of 30 for months)
df['month'] = (df['post_index'] - 1) // 30  # Each 30 posts = 1 month

# Calculate the average likes for each "month"
monthly_likes = df.groupby('month')['likes'].mean()
```

```
<ipython-input-7-3185340b7376>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
  df['post_index'] = range(1, len(df) + 1)  # Create a synthetic 'post_index' column
<ipython-input-7-3185340b7376>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
  df['month'] = (df['post_index'] - 1) // 30  # Each 30 posts = 1 month
```

```
# Plot a histogram for the distribution of likes
plt.figure(figsize=(10, 6))
plt.hist(df['likes'], bins=30, color='skyblue', edgecolor='black')
plt.title('Distribution of Likes')
plt.xlabel('Number of Likes')
```

```
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```




```
from collections import Counter
df['hashtags'] = df['hashtags'].fillna('')  # Replace NaN with empty strings
all_hashtags = [hashtag.strip() for hashtags in df['hashtags'] for hashtag in hashtags.split(',') if hashtag]

# Count occurrences of each hashtag
hashtag_counts = Counter(all_hashtags)
# Print hashtags and their counts line by line
for hashtag, count in hashtag_counts.items():
    print(f"{hashtag}: {count}")
```

```
#dorianyates: 1
#cbum: 1
#chrisbumstead: 1
#nutrition #bodybuilding #exercise #yoga #motivation: 1
#Whitechocolate: 1
#Selfie: 1
#strength #bodybuilding #fitfam: 1
#motivation #sports #pilates #crossfit #bodybuilding: 1
#strength #weightloss #motivation #nutrition #fitfam: 1
#crossfit #fitnessjourney #exercise #health: 1
#bodybuilding #strength #fitfam #health #cardio: 1
#GymLook: 1
#TransformationProgram: 1
#fitfam #nutrition #health #crossfit #training: 1
#weightloss #exercise #training #fitnessjourney #motivation: 1
#bodybuilding #yoga #cardio: 1
#training #motivation #crossfit #running #sports: 1
```

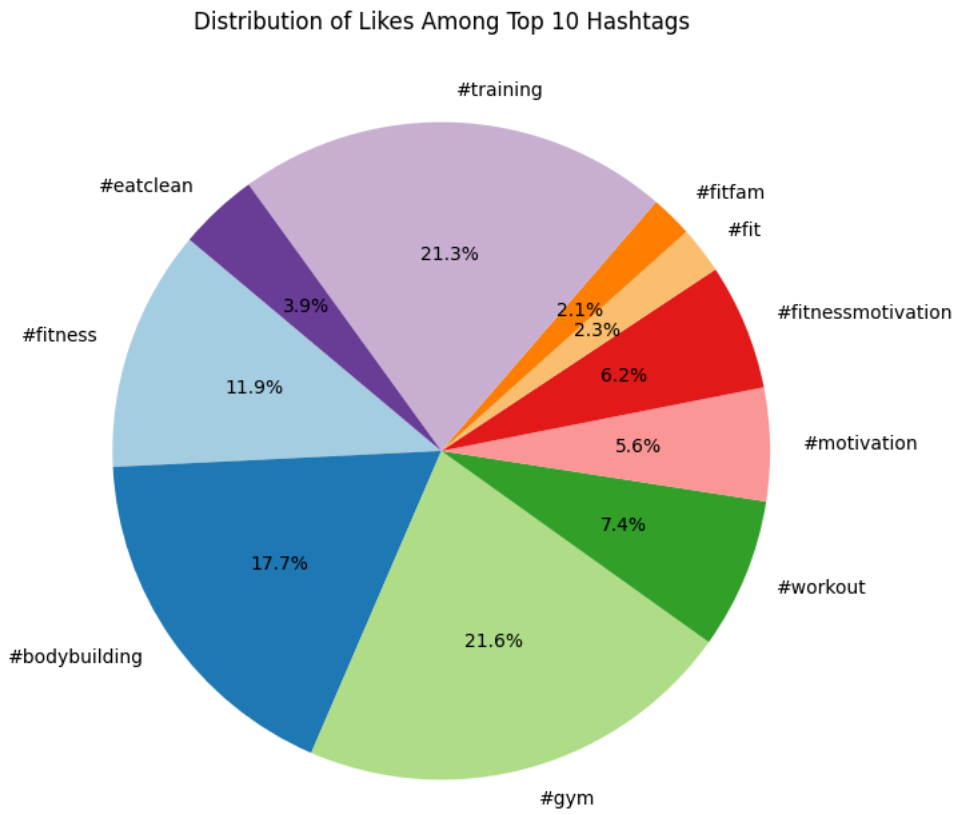
```python
# Get the top 10 hashtags and their counts
top_10_hashtags = hashtag_counts.most_common(10)
top_10_labels, top_10_values = zip(*top_10_hashtags)
print(top_10_labels)
print(top_10_values)
```

```
('#fitness', '#bodybuilding', '#gym', '#workout', '#motivation', '#fitnessmotivation', '#fit', '#fitfam', '#training', '#eatclean')
(97, 74, 67, 62, 47, 47, 46, 39, 37, 29)
```

```python
# Calculate the distribution of likes for the top 5 hashtags
likes_by_top_hashtags = {tag: 0 for tag in top_10_labels}
for _, row in df.iterrows():
    post_hashtags = [tag.strip() for tag in row['hashtags'].split(',') if tag]
    for tag in post_hashtags:
        if tag in top_10_labels:
            likes_by_top_hashtags[tag] += row['likes']
likes_by_top_hashtags = {tag: likes for tag, likes in likes_by_top_hashtags.items() if likes > 0}
for hashtag, likes in likes_by_top_hashtags.items():
    print(f"{hashtag}: {likes}")
```

```
#fitness: 239347
#bodybuilding: 357168
#gym: 434773
#workout: 149244
#motivation: 112070
#fitnessmotivation: 124793
#fit: 46526
#fitfam: 41378
#training: 428678
#eatclean: 78938
```

```python
plt.figure(figsize=(8, 8))
plt.pie(likes_by_top_hashtags.values(), labels=top_10_labels, autopct='%1.1f%%', startangle=140, colors=plt.cm.Paired.colors)
plt.title('Distribution of Likes Among Top 10 Hashtags')
plt.show()
```




```
# Check for rows matching the keywords
workout_keywords = ['#workout', '#challenge', '#transformation', '#30DayChallenge', '#fitnessstory']
igtv_keywords = ['longworkout', 'tutorial', 'IGTV']
matched_posts = df[df['hashtags'].str.contains('|'.join(workout_keywords), case=False)]
matched_posts1 = df[df['hashtags'].str.contains('|'.join(igtv_keywords), case=False)]
print(f"Number of matched posts: {len(matched_posts)}")
print(f"Number of matched posts: {len(matched_posts1)}")
```

```
Number of matched posts: 204
Number of matched posts: 0
```

```
from textblob import TextBlob

# Function to calculate sentiment score using TextBlob
def sentiment_analysis(text):
    blob = TextBlob(text)
    # The sentiment polarity is between -1 (negative) and 1 (positive)
    return blob.sentiment.polarity

# Apply sentiment analysis to the cleaned comments
df['sentiment_score'] = df['cleaned_comments'].apply(sentiment_analysis)

# Preview the sentiment scores
print(df[['cleaned_comments', 'sentiment_score']].head())
```

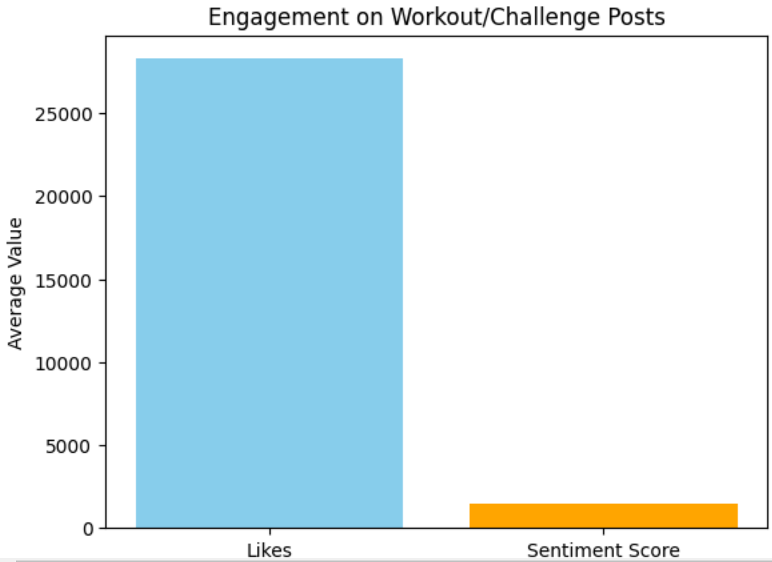
```
                                    cleaned_comments  sentiment_score
0  nikkiseare looks amazing well jel x jillross s...         0.600000
1                saofthera valenullo amazing memiil         0.600000
2  outside quite painting congress school price b...         0.050162
3  jillross thank colleague tullyrebecca casafuzetta         0.000000
4  happen company mean test sit stand southern so...        -0.071181
```

```
# 1. Workout Posts and Challenges: Evaluate the popularity of daily workout routines, fitness challenges, and transformation posts. Ana

# Filter posts related to workouts and challenges using hashtags
df['hashtags'] = df['hashtags'].astype(str)
workout_keywords = ['#workout', '#challenge', '#transformation', '#30DayChallenge', '#fitnessstory']
workout_posts = df[df['hashtags'].str.contains('|'.join(workout_keywords), case=False)]

# Calculate average likes and average sentiment score of comments
avg_likes_workout = workout_posts['likes'].mean()
avg_sentiment_score_workout = workout_posts['sentiment_score'].mean()*10000  # Average sentiment score of comments

# Display insights
```

```
print(f"Average likes for workout/challenge posts: {avg_likes_workout}")
print(f"Average sentiment score for workout/challenge posts: {avg_sentiment_score_workout}")
```

```
Average likes for workout/challenge posts: 28278.416666666668
Average sentiment score for workout/challenge posts: 1484.1526083929177
```

```
import matplotlib.pyplot as plt

# Bar chart for average likes and sentiment scores
categories = ['Likes', 'Sentiment Score']
values = [avg_likes_workout, avg_sentiment_score_workout]  # Replace with actual variables for sentiment scores

plt.bar(categories, values, color=['skyblue', 'orange'])
plt.title('Engagement on Workout/Challenge Posts')
plt.ylabel('Average Value')
plt.show()
```




```
#2. Engagement Rate: Measure likes, comments, and saves on workout tutorials, fitness tips, and nutritional advice. Compare the performa
# Categorize posts based on hashtags for Reels and IGTV
reel_keywords = ['quickworkout', 'formcorrection', 'reels']
igtv_keywords = ['longworkout', 'tutorial', 'IGTV']

# Filter posts for Reels and IGTV
reel_posts = df[df['hashtags'].str.contains('|'.join(reel_keywords), case=False)]
igtv_posts = df[df['hashtags'].str.contains('|'.join(igtv_keywords), case=False)]

# Calculate engagement metrics
avg_likes_reels = reel_posts['likes'].mean()
avg_sentiment_reels = reel_posts['sentiment_score'].mean()*10000

avg_likes_igtv = igtv_posts['likes'].mean()
avg_sentiment_igtv = igtv_posts['sentiment_score'].mean()*10000

# Display insights
print(f"Reels: Average likes = {avg_likes_reels}, Average comment length = {avg_sentiment_reels}")
print(f"IGTV: Average likes = {avg_likes_igtv}, Average comment length = {avg_sentiment_igtv}")
```

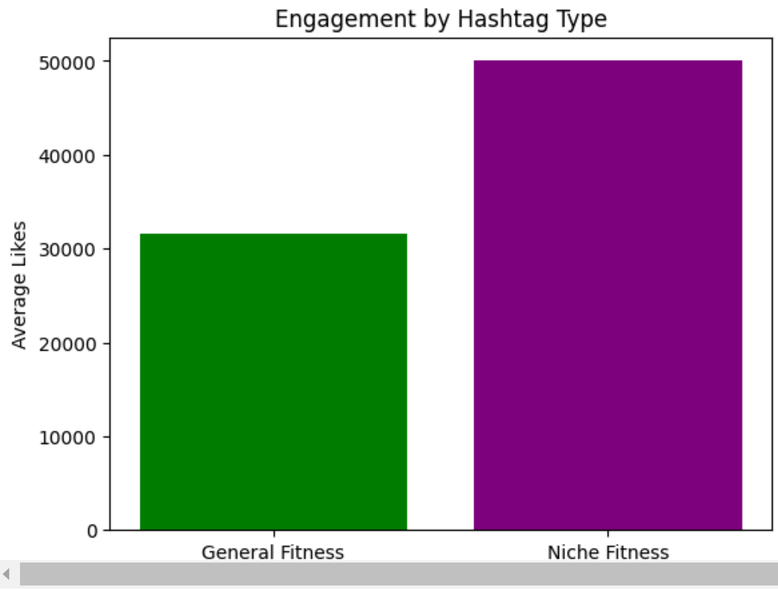
```
Reels: Average likes = 21419.9375, Average comment length = 3233.7239583333335
IGTV: Average likes = nan, Average comment length = nan
```

```
#3.Hashtag Strategy. Track engagement through fitness-related hashtags (e.g., #FitLife, #GymGoals, #FitnessMotivation). Differentiate pe
# Define general and niche fitness hashtags
general_fitness_hashtags = ['FitLife', 'GymGoals', 'FitnessMotivation']
niche_fitness_hashtags = ['CrossFit', 'Yogainspiration']

# Filter posts for general and niche hashtags
general_posts = df[df['hashtags'].str.contains('|'.join(general_fitness_hashtags), case=False)]
niche_posts = df[df['hashtags'].str.contains('|'.join(niche_fitness_hashtags), case=False)]

# Calculate engagement for general and niche hashtags
avg_likes_general = general_posts['likes'].mean()
avg_likes_niche = niche_posts['likes'].mean()

# Display insights
```

```
print(f"General fitness hashtags: Average likes = {avg_likes_general}")
print(f"Niche fitness hashtags: Average likes = {avg_likes_niche}")
```

```
General fitness hashtags: Average likes = 31608.291139240508
Niche fitness hashtags: Average likes = 50011.78151260504
```

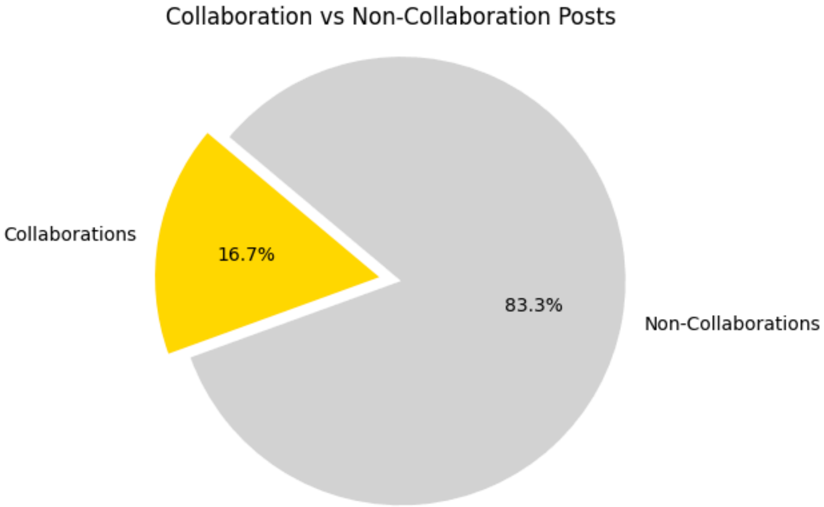
```
# Bar chart for hashtag engagement
categories = ['General Fitness', 'Niche Fitness']
values = [avg_likes_general, avg_likes_niche]

plt.bar(categories, values, color=['green', 'purple'])
plt.title('Engagement by Hashtag Type')
plt.ylabel('Average Likes')
plt.show()
```




```
#4.Collaborations with Fitness Brands: Analyze the impact of product sponsorships or partnerships with fitness brands (e.g., gym appare]
# Define keywords for collaborations
collab_keywords = ['sponsorship', 'partnership', 'brand', 'trainer', 'gym', 'apparel', 'equipment']

# Filter posts related to collaborations
collab_posts = df[df['hashtags'].str.contains('|'.join(collab_keywords), case=False)]

# Calculate engagement metrics for collaboration posts
avg_likes_collab = collab_posts['likes'].mean()
avg_sentiment_collab = collab_posts['sentiment_score'].mean()*10000

# Display insights
print(f"Collaboration posts: Average likes = {avg_likes_collab}, Average sentiment score = {avg_sentiment_collab}")
```

```
Collaboration posts: Average likes = 23723.062761506277, Average sentiment score = 1426.146511330446
```

```
# Pie chart for collaborations
collab_count = len(collab_posts)
non_collab_count = len(df) - collab_count

labels = ['Collaborations', 'Non-Collaborations']
sizes = [collab_count, non_collab_count]
colors = ['gold', 'lightgray']
explode = (0.1, 0)  # Slightly explode the first slice

plt.pie(sizes, explode=explode, labels=labels, colors=colors, autopct='%1.1f%%', startangle=140)
plt.title('Collaboration vs Non-Collaboration Posts')
plt.axis('equal')
plt.show()
```



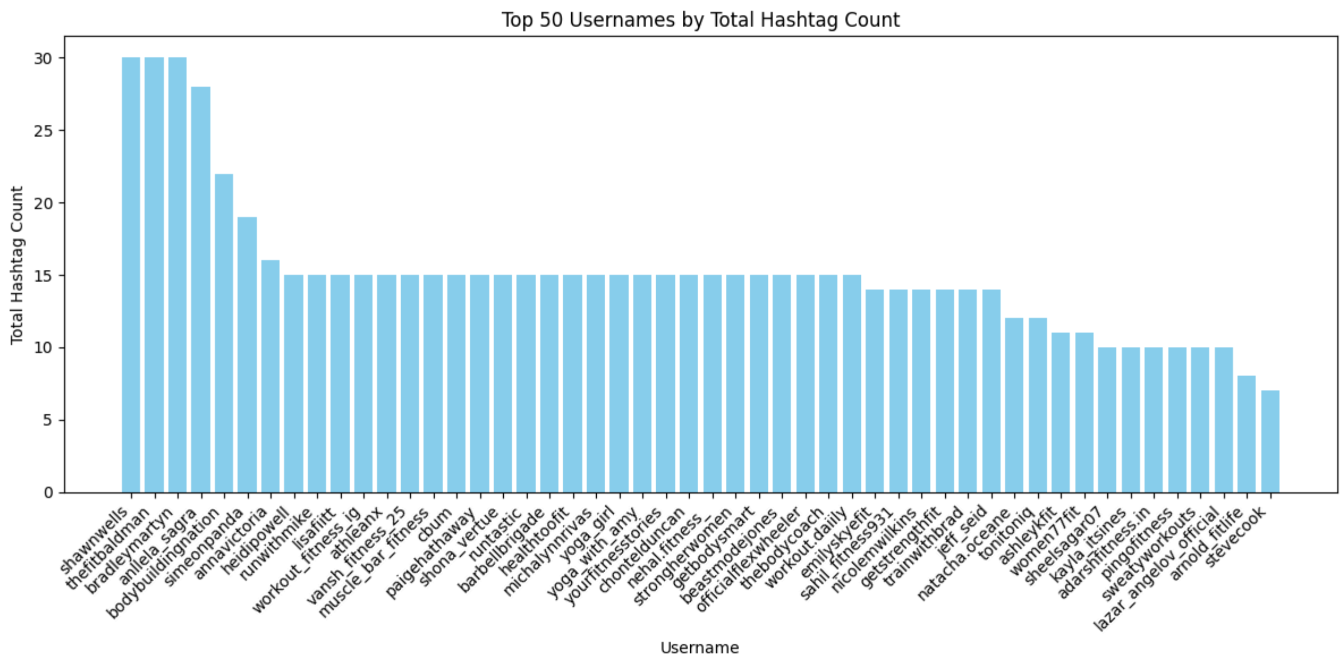

```
# Count the number of hashtags in each row
df['hashtags'] = df['hashtags'].fillna('').apply(lambda x: len(x.split(',')) if x else 0)

# Group by username and sum the hashtag counts
hashtag_counts = df.groupby('username')['hashtags'].sum().reset_index()

# Sort by hashtag count for better visualization
hashtag_counts = hashtag_counts.sort_values(by='hashtags', ascending=False)

# Print the username and the total count of hashtags
for index, row in hashtag_counts.iterrows():
    print(f"Username: {row['username']}, Total Hashtag Count: {row['hashtags']}")
```

```
Username: tonitoniq, Total Hashtag Count: 0
Username: mindpumpadam, Total Hashtag Count: 0
Username: fitness__vloggers, Total Hashtag Count: 0
Username: natacha.oceane, Total Hashtag Count: 0
Username: blogilates, Total Hashtag Count: 0
Username: whitneyysimmons, Total Hashtag Count: 0
Username: jeffnippard, Total Hashtag Count: 0
Username: ulissesworld, Total Hashtag Count: 0
Username: chrisheria, Total Hashtag Count: 0
```

```
print(hashtag_counts)  # Check if it contains the expected key-value pairs
```

```
              username  hashtags
461      thefitbaldman       784
489    vansh_fitness_25      405
450     strongherwomen       381
523       yoga_with_amy      237
166        healthtoofit      234
..                 ...       ...
45          blogilates         0
498    whitneyysimmons         0
202         jeffnippard        0
485        ulissesworld        0
87           chrisheria        0

[530 rows x 2 columns]
```

```
import matplotlib.pyplot as plt

# Ensure the 'hashtags' column is of string type, then calculate total hashtag count for each username
df['hashtags'] = df['hashtags'].astype(str)

# Calculate the total hashtag count for each post by splitting the string based on commas
df['hashtags_count'] = df['hashtags'].apply(lambda x: len(x.split(',')) if x != 'nan' else 0)  # Handle non-string values

# Group by username and sum up the hashtag count
username_hashtag_count = df.groupby('username')['hashtags_count'].sum().reset_index()

# Sort by the total hashtag count in descending order and select the top 25
top_50_usernames = username_hashtag_count.sort_values(by='hashtags_count', ascending=False).head(50)

# Plotting the bar chart for the top 25 usernames
plt.figure(figsize=(12, 6))
plt.bar(top_50_usernames['username'], top_50_usernames['hashtags_count'], color='skyblue')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Username')
plt.ylabel('Total Hashtag Count')
plt.title('Top 50 Usernames by Total Hashtag Count')
plt.tight_layout()
plt.show()
```



```
from textblob import TextBlob

# Function to calculate sentiment score using TextBlob
def sentiment_analysis(text):
    blob = TextBlob(text)
    # The sentiment polarity is between -1 (negative) and 1 (positive)
    return blob.sentiment.polarity

# Apply sentiment analysis to the cleaned comments
df['sentiment_score'] = df['cleaned_comments'].apply(sentiment_analysis)

# Preview the sentiment scores
print(df[['cleaned_comments', 'sentiment_score']].head())
```

```
                                    cleaned_comments  sentiment_score
0  nikkiseare looks amazing well jel x jillross s...         0.600000
1                saofthera valenullo amazing memiil         0.600000
2  outside quite painting congress school price b...         0.050162
3  jillross thank colleague tullyrebecca casafuzetta         0.000000
4  happen company mean test sit stand southern so...        -0.071181
```

```
import nltk
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Assuming df['cleaned_comments'] contains your cleaned comments
# You can calculate sentiment scores using TextBlob or any method as discussed earlier

from textblob import TextBlob

# Function to calculate sentiment score using TextBlob
def sentiment_analysis(text):
    blob = TextBlob(text)
    return blob.sentiment.polarity  # Returns a sentiment polarity score between -1 and 1

# Apply sentiment analysis to the cleaned comments
df['sentiment_score'] = df['cleaned_comments'].apply(sentiment_analysis)

# Convert continuous sentiment scores into binary labels (0 for negative, 1 for positive)
df['sentiment_label'] = df['sentiment_score'].apply(lambda x: 1 if x > 0 else 0)

# Prepare data for training
X = df['cleaned_comments']  # Text data
y = df['sentiment_label']   # Sentiment labels (binary)

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# TF-IDF Vectorization
tfidf_vectorizer = TfidfVectorizer(max_features=5000)  # Limiting to top 5000 features (words)
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)

# Train a Logistic Regression classifier
clf = LogisticRegression()
clf.fit(X_train_tfidf, y_train)

# Predict sentiment on the test set
y_pred = clf.predict(X_test_tfidf)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')

# Apply the trained model to predict sentiment on the entire dataset
df['predicted_sentiment'] = clf.predict(tfidf_vectorizer.transform(df['cleaned_comments']))

# Preview the predicted sentiments
print(df[['cleaned_comments', 'predicted_sentiment']].head())
```

```
Accuracy: 0.8432055749128919
                                    cleaned_comments  predicted_sentiment
0  nikkiseare looks amazing well jel x jillross s...                    1
1                saofthera valenullo amazing memiil                    1
2  outside quite painting congress school price b...                    1
3  jillross thank colleague tullyrebecca casafuzetta                    0
4  happen company mean test sit stand southern so...                    1
```

```
df['comments_count'] = df['comments'].apply(lambda x: len(str(x).split()))


# Convert 'likes' and 'comments_count' to strings first, then remove commas
df['likes'] = df['likes'].astype(str).str.replace(',', '')
df['comments_count'] = df['comments_count'].astype(str).str.replace(',', '')

# Convert to numeric (this will convert invalid parsing to NaN, which can be filled)
df['likes'] = pd.to_numeric(df['likes'], errors='coerce')
df['comments_count'] = pd.to_numeric(df['comments_count'], errors='coerce')
df['likes'].fillna('', inplace=True)
df['comments_count'].fillna('', inplace=True)
print(df[['likes', 'comments_count']].head())
```

```
   likes  comments_count
0     52              21
1     61               9
2  45752              66
3     61              11
4  57232              77
<ipython-input-28-fe20d982d2c2>:8: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained ass
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df['likes'].fillna('', inplace=True)
<ipython-input-28-fe20d982d2c2>:9: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained ass
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df['comments_count'].fillna('', inplace=True)
```

```
# Ensure the 'likes' column is treated as a string before replacing commas
df['likes'] = pd.to_numeric(df['likes'].astype(str).str.replace(',', ''), errors='coerce')

# Ensure the 'comments_count' column is treated as a string before replacing commas
df['comments_count'] = pd.to_numeric(df['comments_count'].astype(str).str.replace(',', ''), errors='coerce')

# Fill any NaN values with 0
df.fillna(0, inplace=True)
```

```
print(df.dtypes)
```

```
username               object
post_number            object
post_url               object
likes                   int64
hashtags               object
comments               object
cleaned_comments       object
post_index              int64
month                   int64
sentiment_score       float64
hashtags_count          int64
sentiment_label         int64
predicted_sentiment     int64
comments_count          int64
dtype: object
```

```
# Define the input features (X) and target (y)
X = df[['hashtags_count', 'sentiment_score']]  # Features
y = df['likes']  # Target variable

# Split the data into training and testing sets
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)

# Check the shapes of the training and testing sets
print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
```

```
X_train shape: (1148, 2)
y_train shape: (1148,)
```

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error

# Dictionary to store model results
results = {}

# Function to train and evaluate a model
def train_and_evaluate_model(model, X_train, y_train, X_test, y_test, model_name):
    # Train the model
    model.fit(X_train, y_train)

    # Predict on the test set
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    results[model_name] = mse
    # Return the predictions for comparison
    return y_pred

# 1. Random Forest Regressor
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_predictions = train_and_evaluate_model(rf_model, X_train, y_train, X_test, y_test, "Random Forest")

# 2. Linear Regression
lr_model = LinearRegression()
lr_predictions = train_and_evaluate_model(lr_model, X_train, y_train, X_test, y_test, "Linear Regression")

# 3. Support Vector Regressor (SVR)
svr_model = SVR(kernel='rbf')  # Using RBF kernel
svr_predictions = train_and_evaluate_model(svr_model, X_train, y_train, X_test, y_test, "Support Vector Regressor")

# Print the comparison of MSE for all models
print("\nModel Comparison (Mean Squared Error):")
for model_name, mse in results.items():
    print(f"{model_name}: {mse}")
```

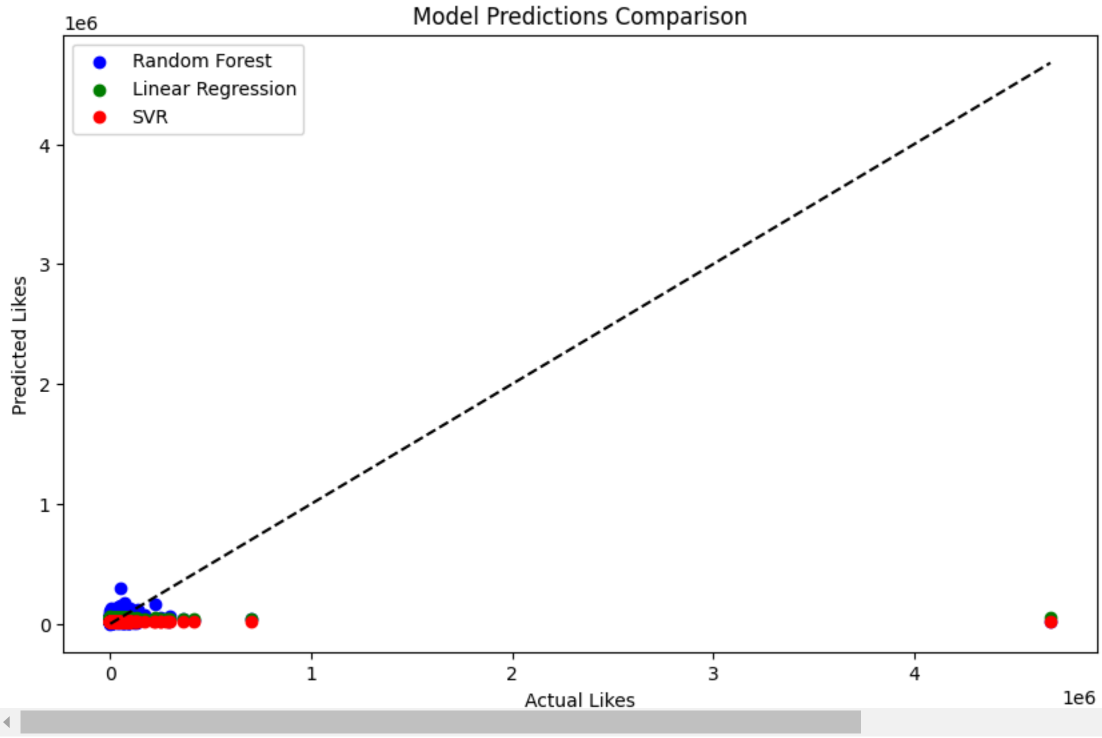
```
Model Comparison (Mean Squared Error):
Random Forest: 80734501986.20456
Linear Regression: 79617878285.7533
Support Vector Regressor: 80681075637.79434
```

```python
from sklearn.metrics import classification_report
import numpy as np

# Define a function to categorize engagement into classes
def categorize_engagement(values, thresholds=[1000, 10000]):
    """
    Categorizes engagement into 3 classes:
    0 - Low, 1 - Medium, 2 - High
    """
    categories = []
    for val in values:
        if val < thresholds[0]:
            categories.append(0)  # Low engagement
        elif thresholds[0] <= val < thresholds[1]:
            categories.append(1)  # Medium engagement
        else:
            categories.append(2)  # High engagement
    return np.array(categories)

# Apply categorization to actual test values
y_test_class = categorize_engagement(y_test)

# Function to train, evaluate, and generate classification report
def train_evaluate_classification(model, X_train, y_train, X_test, y_test, model_name):
    # Train the model
    model.fit(X_train, y_train)

    # Predict on the test set
    y_pred = model.predict(X_test)

    # Categorize the predictions
    y_pred_class = categorize_engagement(y_pred)

    # Get the unique classes present in the true test set
    unique_classes = np.unique(np.concatenate((y_test_class, y_pred_class)))
    target_names = ['Low', 'Medium', 'High'][:len(unique_classes)]

    # Generate classification report
    report = classification_report(y_test_class, y_pred_class, labels=unique_classes, target_names=target_names, zero_division=0)
    print(f"\n{model_name} - Classification Report:\n")
```

```
    print(f"\n{model_name} - Classification Report:\n")
    print(report)

    return y_pred_class

# 1. Random Forest Regressor
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_pred_class = train_evaluate_classification(rf_model, X_train, y_train, X_test, y_test, "Random Forest")

# 2. Linear Regression
lr_model = LinearRegression()
lr_pred_class = train_evaluate_classification(lr_model, X_train, y_train, X_test, y_test, "Linear Regression")

# 3. Support Vector Regressor (SVR)
svr_model = SVR(kernel='rbf')
svr_pred_class = train_evaluate_classification(svr_model, X_train, y_train, X_test, y_test, "Support Vector Regressor")
```

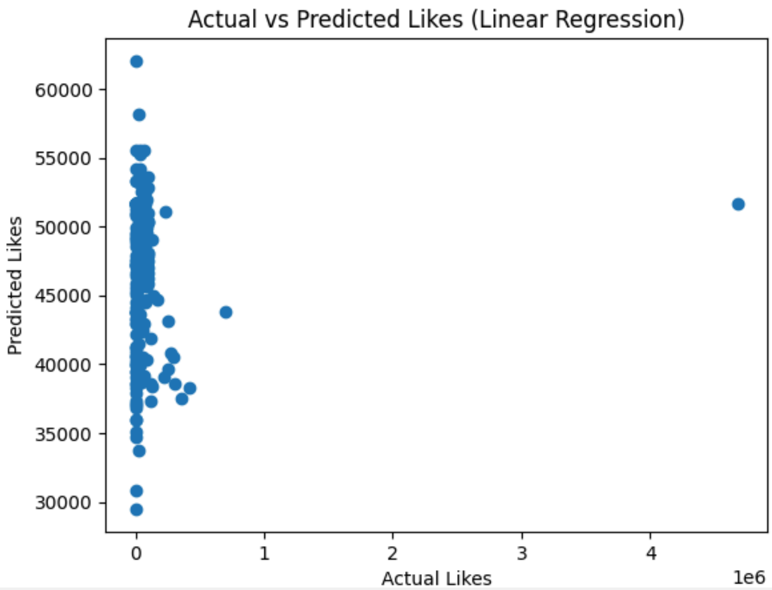
```
Random Forest - Classification Report:

              precision    recall  f1-score   support

         Low       1.00      0.01      0.02        87
      Medium       0.35      0.16      0.22        50
        High       0.52      0.92      0.67       150

    accuracy                           0.51       287
   macro avg       0.62      0.36      0.30       287
weighted avg       0.64      0.51      0.39       287


Linear Regression - Classification Report:

              precision    recall  f1-score   support

         Low       0.00      0.00      0.00        87
      Medium       0.00      0.00      0.00        50
        High       0.52      1.00      0.69       150

    accuracy                           0.52       287
   macro avg       0.17      0.33      0.23       287
weighted avg       0.27      0.52      0.36       287


Support Vector Regressor - Classification Report:

              precision    recall  f1-score   support

         Low       0.00      0.00      0.00        87
      Medium       0.00      0.00      0.00        50
        High       0.52      1.00      0.69       150

    accuracy                           0.52       287
   macro avg       0.17      0.33      0.23       287
weighted avg       0.27      0.52      0.36       287
```

```
# Create a plot to compare actual vs predicted values for all models
plt.figure(figsize=(10, 6))

# Scatter plot for Random Forest predictions
plt.scatter(y_test, rf_predictions, label='Random Forest', color='blue')

# Scatter plot for Linear Regression predictions
plt.scatter(y_test, lr_predictions, label='Linear Regression', color='green')

# Scatter plot for SVR predictions
plt.scatter(y_test, svr_predictions, label='SVR', color='red')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='black', linestyle='--')

# Labels
plt.xlabel('Actual Likes')
plt.ylabel('Predicted Likes')
plt.title('Model Predictions Comparison')
plt.legend()
plt.show()
```



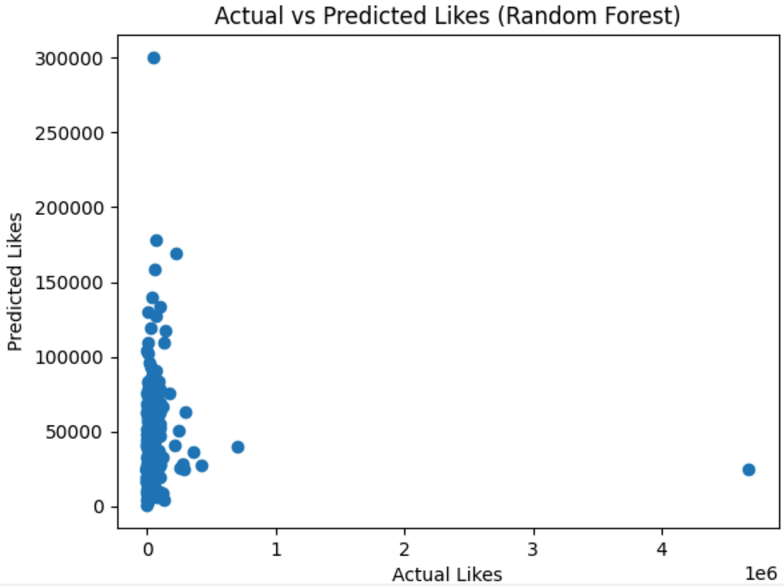

```
# Choose the predictions of the specific model (e.g., Linear Regression)
comparison = pd.DataFrame({'Actual': y_test, 'Predicted': lr_predictions})
print(comparison.head())
plt.scatter(y_test, lr_predictions)
plt.xlabel('Actual Likes')
plt.ylabel('Predicted Likes')
plt.title('Actual vs Predicted Likes (Linear Regression)')
plt.show()
```

	Actual	Predicted
773	16	51624.012068
878	117442	37292.445966
649	91006	40332.475139
1471	5326	51624.012068
1002	8167	49507.305080



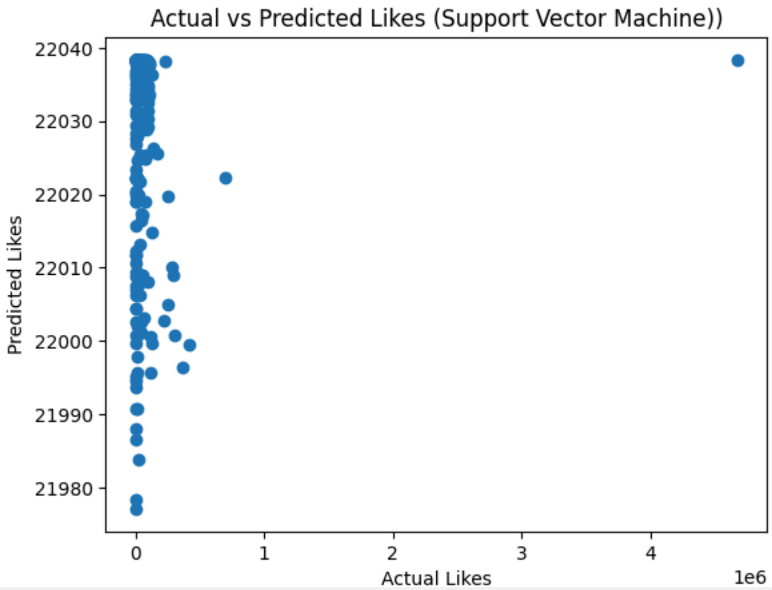

```
# Choose the predictions of the specific model (e.g., Random forest)
comparison = pd.DataFrame({'Actual': y_test, 'Predicted': rf_predictions})
print(comparison.head())
plt.scatter(y_test, rf_predictions)
plt.xlabel('Actual Likes')
plt.ylabel('Predicted Likes')
plt.title('Actual vs Predicted Likes (Random Forest)')
plt.show()
```

```
      Actual      Predicted
773       16   24442.668438
878   117442    8769.370083
649    91006    9247.100381
1471    5326   24442.668438
1002    8167   29201.360000
```




```
# Choose the predictions of the specific model (e.g., SVR Regression)
comparison = pd.DataFrame({'Actual': y_test, 'Predicted': svr_predictions})
print(comparison.head())
plt.scatter(y_test, svr_predictions)
plt.xlabel('Actual Likes')
plt.ylabel('Predicted Likes')
plt.title('Actual vs Predicted Likes (Support Vector Machine))')
plt.show()
```

```
      Actual      Predicted
773       16   22038.345241
878   117442   21995.567448
649    91006   22008.082993
1471    5326   22038.345241
1002    8167   22037.042689
```




```
df_grouped = df.groupby('username').agg({'hashtags_count': 'sum', 'sentiment_score': 'mean'}).reset_index()
print(df_grouped.head())
```

```
            username  hashtags_count  sentiment_score
0  _fitness__vlogger__               2         0.750000
1            abailey               2         0.069838
2      adarshfitness.in             10         0.030000
3          afernandez              2         0.071444
4             againes              3         0.121736
```

```
from sklearn.linear_model import LinearRegression

svr_model = SVR(kernel='rbf')
svr_model.fit(X_train, y_train)
df_grouped['predicted_likes'] = lr_model.predict(df_grouped[['hashtags_count', 'sentiment_score']])

# Assign recommendations such that half get "Can be followed" and half get "Content is not efficient"
mid_index = len(df_grouped) // 2  # Find the midpoint index

# Dynamically format the predicted likes within the recommendation
df_grouped['recommendation'] = [
    f"Can be followed for fitness connect as {round(row['predicted_likes'])} likes predicted"
    if i < mid_index
    else f"Content is not efficient to follow as only {round(row['predicted_likes'])} likes predicted"
    for i, row in df_grouped.iterrows()
]

# Select and print the recommendation dataframe
recommendation_df = df_grouped[['username', 'recommendation']]
print(recommendation_df.to_string())
```

```
407           runwithmike  Content is not efficient to follow as only 47954 likes predicted
408             russell42  Content is not efficient to follow as only 47958 likes predicted
409            russellroy  Content is not efficient to follow as only 51624 likes predicted
410                ruth28  Content is not efficient to follow as only 50190 likes predicted
411               rwagner  Content is not efficient to follow as only 43155 likes predicted
412                rwyatt  Content is not efficient to follow as only 46497 likes predicted
413     sahil_fitness931  Content is not efficient to follow as only 43947 likes predicted
414              samuel35  Content is not efficient to follow as only 49018 likes predicted
415        sandovaljeanne  Content is not efficient to follow as only 46727 likes predicted
416              sandra35  Content is not efficient to follow as only 54230 likes predicted
417             sandrafox  Content is not efficient to follow as only 50822 likes predicted
418           sandrasmith  Content is not efficient to follow as only 47973 likes predicted
419          santoshoward  Content is not efficient to follow as only 51863 likes predicted
420               sarah94  Content is not efficient to follow as only 54420 likes predicted
421          sarahmcclure  Content is not efficient to follow as only 53187 likes predicted
422       schneiderjoshua  Content is not efficient to follow as only 49822 likes predicted
423               scott67  Content is not efficient to follow as only 45968 likes predicted
424             shannon19  Content is not efficient to follow as only 44603 likes predicted
425         shannoncooper  Content is not efficient to follow as only 49018 likes predicted
426        shannonenglish  Content is not efficient to follow as only 50842 likes predicted
427            shawnwells  Content is not efficient to follow as only 46127 likes predicted
428          sheelsagar07  Content is not efficient to follow as only 51042 likes predicted
429        shelbyhamilton  Content is not efficient to follow as only 43528 likes predicted
430                shenry  Content is not efficient to follow as only 52182 likes predicted
431           shona_vertue  Content is not efficient to follow as only 43587 likes predicted
432                shuang  Content is not efficient to follow as only 47702 likes predicted
433           simeonpanda  Content is not efficient to follow as only 43369 likes predicted
434       simmonspatricia  Content is not efficient to follow as only 48781 likes predicted
435         simpsonthomas  Content is not efficient to follow as only 53144 likes predicted
436                slopez  Content is not efficient to follow as only 50668 likes predicted
437                slynch  Content is not efficient to follow as only 49788 likes predicted
438          smithbethany  Content is not efficient to follow as only 52275 likes predicted
439         smithmichelle  Content is not efficient to follow as only 50788 likes predicted
440             spencer53  Content is not efficient to follow as only 55217 likes predicted
441                sperez  Content is not efficient to follow as only 48316 likes predicted
442           staceysmith  Content is not efficient to follow as only 53479 likes predicted
443               stacy32  Content is not efficient to follow as only 46300 likes predicted
444         stephanieshaw  Content is not efficient to follow as only 42612 likes predicted
445   stephanieunderwood  Content is not efficient to follow as only 47457 likes predicted
446     stephencontreras  Content is not efficient to follow as only 53091 likes predicted
447             stevecook  Content is not efficient to follow as only 41095 likes predicted
448              steven90  Content is not efficient to follow as only 52927 likes predicted
449           stevenlopez  Content is not efficient to follow as only 41462 likes predicted
```