audiance-analysis

November 27, 2024

[9]:
```
# Import necessary libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

[10]:
```
# Load the dataset
file_path = (r'C:\Users\divaa\OneDrive\Desktop\pri\Bliend\Bliend␣
 ↪dataset\marketing_campaign_dataset.csv')
data = pd.read_csv(file_path)

# Display the first few rows
print(data.head())
```

```
   Campaign_ID              Company Campaign_Type Target_Audience Duration  \
0            1  Innovate Industries         Email       Men 18-24  30 days
1            2       NexGen Systems         Email     Women 35-44  60 days
2            3    Alpha Innovations    Influencer       Men 25-34  30 days
3            4   DataTech Solutions       Display        All Ages  60 days
4            5       NexGen Systems         Email       Men 25-34  15 days

  Channel_Used  Conversion_Rate Acquisition_Cost   ROI     Location  Language  \
0   Google Ads             0.04       $16,174.00  6.29      Chicago   Spanish
1   Google Ads             0.12       $11,566.00  5.61     New York    German
2      YouTube             0.07       $10,200.00  7.18  Los Angeles    French
3      YouTube             0.11       $12,724.00  5.55        Miami  Mandarin
4      YouTube             0.05       $16,452.00  6.50  Los Angeles  Mandarin

   Clicks  Impressions  Engagement_Score     Customer_Segment        Date
0     506         1922                 6    Health & Wellness  2021-01-01
1     116         7523                 7         Fashionistas  2021-01-02
2     584         7698                 1  Outdoor Adventurers  2021-01-03
3     217         1820                 7    Health & Wellness  2021-01-04
4     379         4201                 3    Health & Wellness  2021-01-05
```

[11]:
```
# Convert Date to datetime format
data['Date'] = pd.to_datetime(data['Date'])

# Check for missing values
print("Missing values per column:\n", data.isnull().sum())
```

```
Missing values per column:
 Campaign_ID         0
Company              0
Campaign_Type        0
Target_Audience      0
Duration             0
Channel_Used         0
Conversion_Rate      0
Acquisition_Cost     0
ROI                  0
Location             0
Language             0
Clicks               0
Impressions          0
Engagement_Score     0
Customer_Segment     0
Date                 0
dtype: int64
```

[12]:
```
# General information and statistics
data.info()
data.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 16 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Campaign_ID       200000 non-null  int64
 1   Company           200000 non-null  object
 2   Campaign_Type     200000 non-null  object
 3   Target_Audience   200000 non-null  object
 4   Duration          200000 non-null  object
 5   Channel_Used      200000 non-null  object
 6   Conversion_Rate   200000 non-null  float64
 7   Acquisition_Cost  200000 non-null  object
 8   ROI               200000 non-null  float64
 9   Location          200000 non-null  object
 10  Language          200000 non-null  object
 11  Clicks            200000 non-null  int64
 12  Impressions       200000 non-null  int64
 13  Engagement_Score  200000 non-null  int64
```

```
 14  Customer_Segment  200000 non-null  object
 15  Date              200000 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(2), int64(4), object(9)
memory usage: 24.4+ MB
```

[12]:

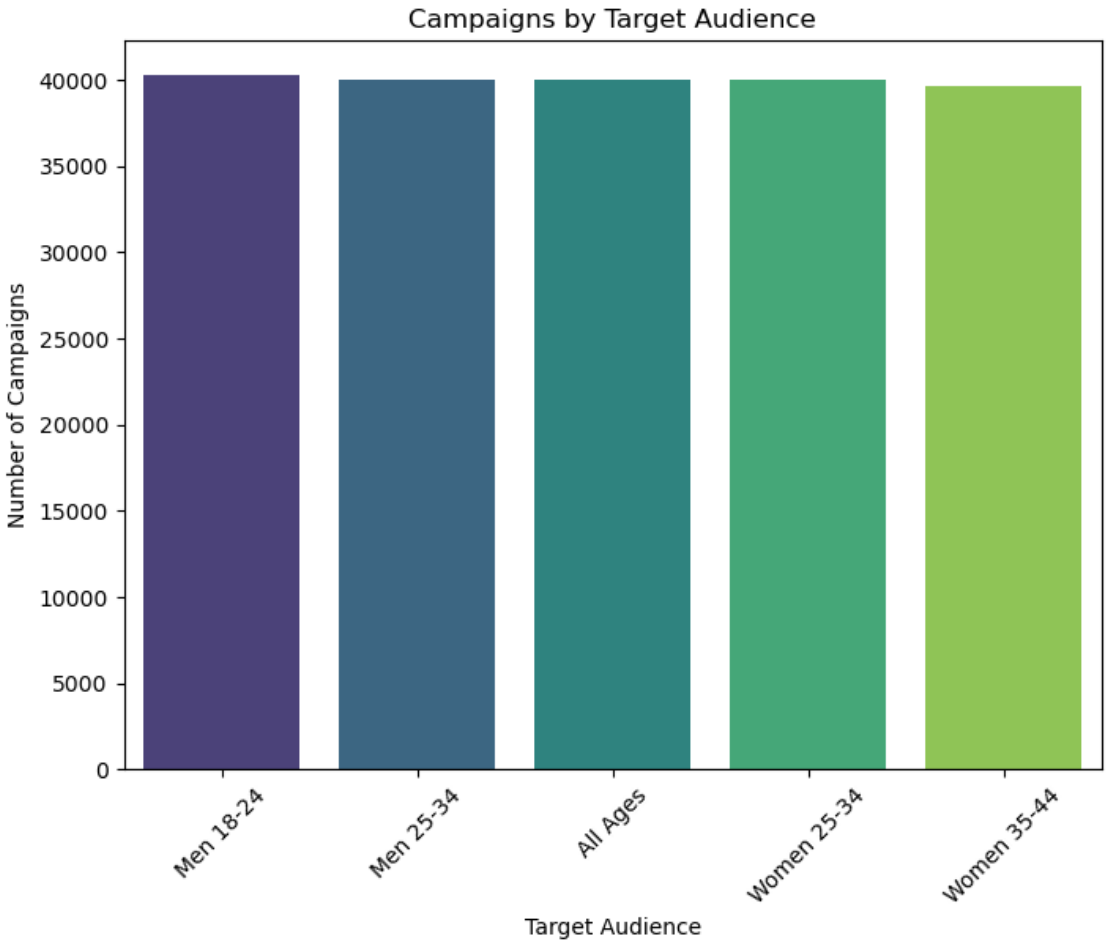
	Campaign_ID	Conversion_Rate	ROI	Clicks
count	200000.000000	200000.000000	200000.000000	200000.000000
mean	100000.500000	0.080070	5.002438	549.772030
min	1.000000	0.010000	2.000000	100.000000
25%	50000.750000	0.050000	3.500000	325.000000
50%	100000.500000	0.080000	5.010000	550.000000
75%	150000.250000	0.120000	6.510000	775.000000
max	200000.000000	0.150000	8.000000	1000.000000
std	57735.171256	0.040602	1.734488	260.019056

	Impressions	Engagement_Score	Date
count	200000.000000	200000.000000	200000
mean	5507.301520	5.494710	2021-07-01 23:35:09.600000
min	1000.000000	1.000000	2021-01-01 00:00:00
25%	3266.000000	3.000000	2021-04-02 00:00:00
50%	5517.500000	5.000000	2021-07-02 00:00:00
75%	7753.000000	8.000000	2021-10-01 00:00:00
max	10000.000000	10.000000	2021-12-31 00:00:00
std	2596.864286	2.872581	NaN

[17]:
```
# Check unique campaign types and target audiences
print("Unique Campaign Types:", data['Campaign_Type'].unique())
print("Unique Target Audiences:", data['Target_Audience'].unique())
```

```
Unique Campaign Types: ['Email' 'Influencer' 'Display' 'Search' 'Social Media']
Unique Target Audiences: ['Men 18-24' 'Women 35-44' 'Men 25-34' 'All Ages'
'Women 25-34']
```

[25]:
```
# Count campaigns for each target audience
audience_distribution = data['Target_Audience'].value_counts()

# Plot audience distribution
plt.figure(figsize=(8, 6))
sns.barplot(x=audience_distribution.index, y=audience_distribution.values,␣
 ↪hue=audience_distribution.index, palette='viridis')
plt.title('Campaigns by Target Audience')
plt.xticks(rotation=45)
plt.xlabel('Target Audience')
plt.ylabel('Number of Campaigns')
plt.show()
```



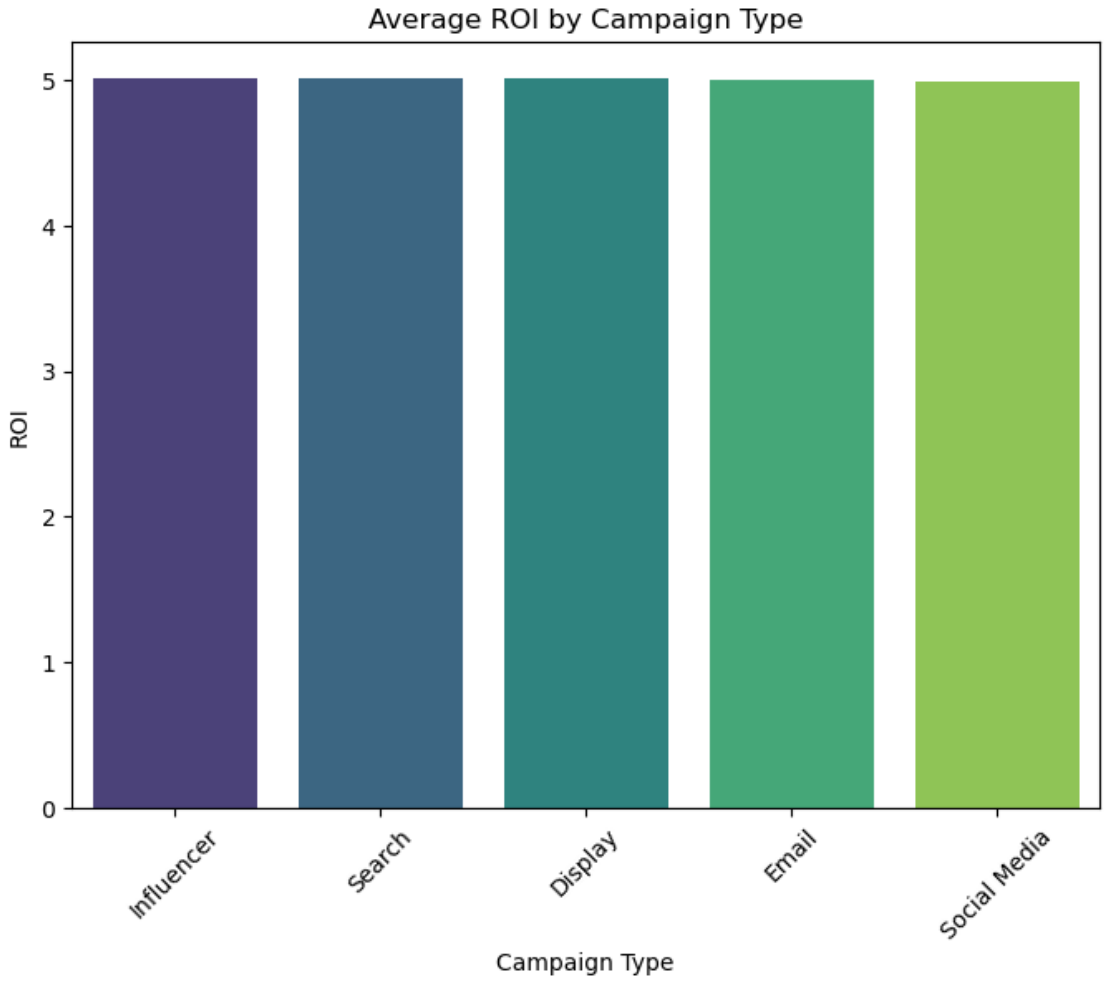
[31]:
```
# Count campaigns for each target audience
audience_distribution = data['Target_Audience'].value_counts()
audience_distribution
```

[31]:
```
Target_Audience
Men 18-24      40258
Men 25-34      40023
All Ages       40019
Women 25-34    40013
Women 35-44    39687
Name: count, dtype: int64
```

EDA

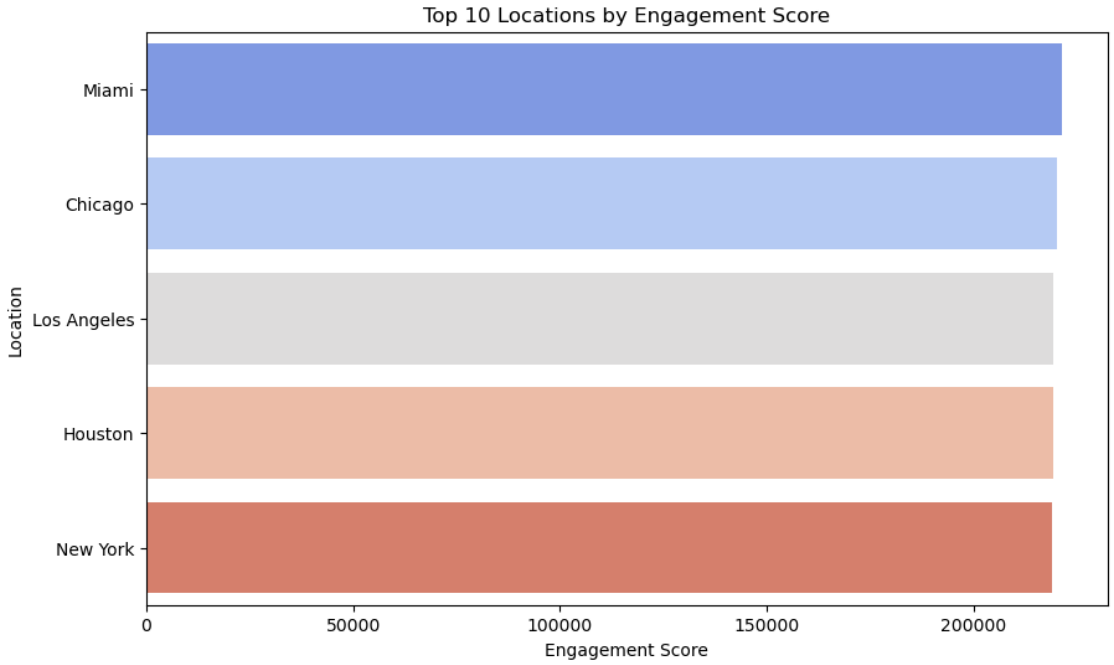
[27]:
```
# Average ROI by Campaign Type
roi_by_campaign_type = data.groupby('Campaign_Type')['ROI'].mean().
↪sort_values(ascending=False)
```

```
# Plot ROI by Campaign Type
plt.figure(figsize=(8, 6))
sns.barplot(x=roi_by_campaign_type.index, y=roi_by_campaign_type.values,␣
 ↪hue=roi_by_campaign_type.index, palette='viridis')
plt.title('Average ROI by Campaign Type')
plt.xlabel('Campaign Type')
plt.ylabel('ROI')
plt.xticks(rotation=45)
plt.show()
```

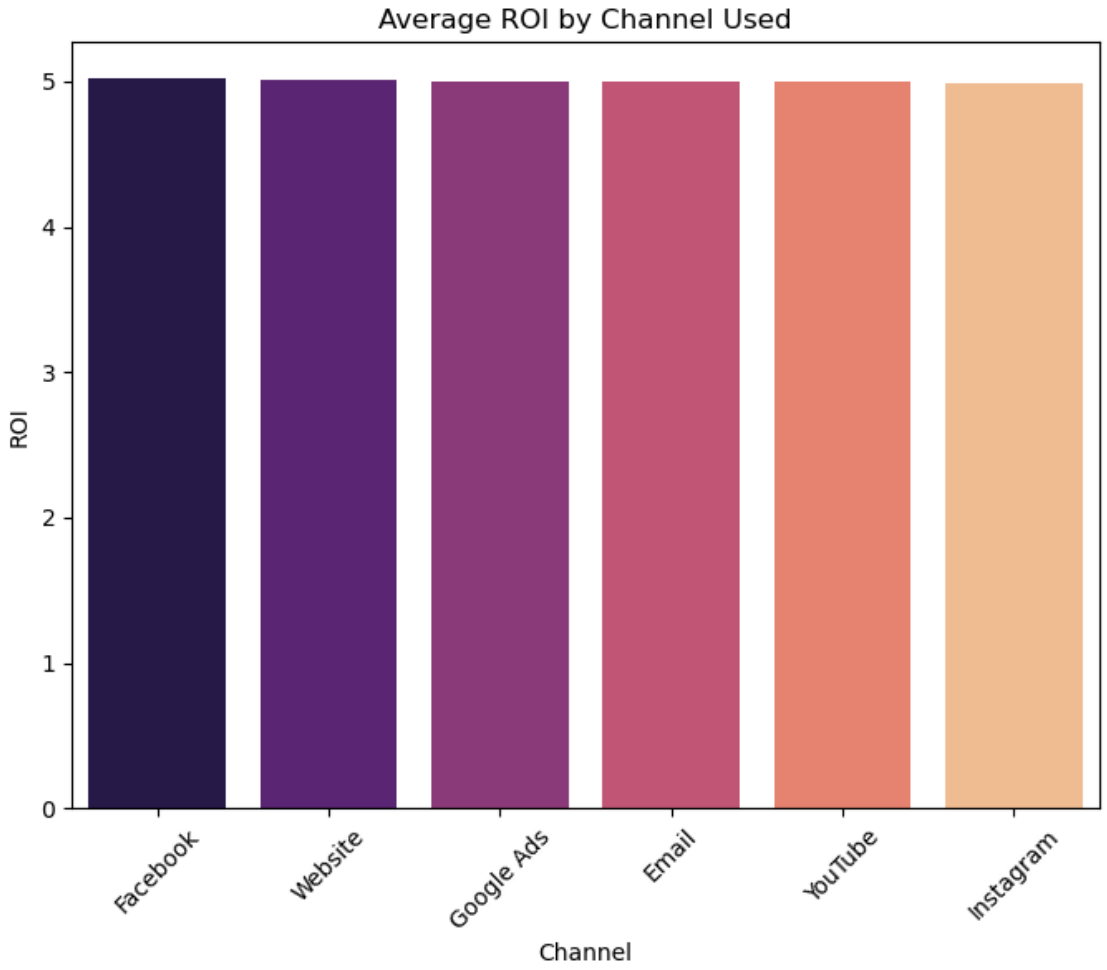


[29]:
```
# Sum Engagement Score by Location
engagement_by_location = data.groupby('Location')['Engagement_Score'].sum().
 ↪sort_values(ascending=False).head(10)

# Plot top 10 locations with hue set to 'y'
plt.figure(figsize=(10, 6))
```

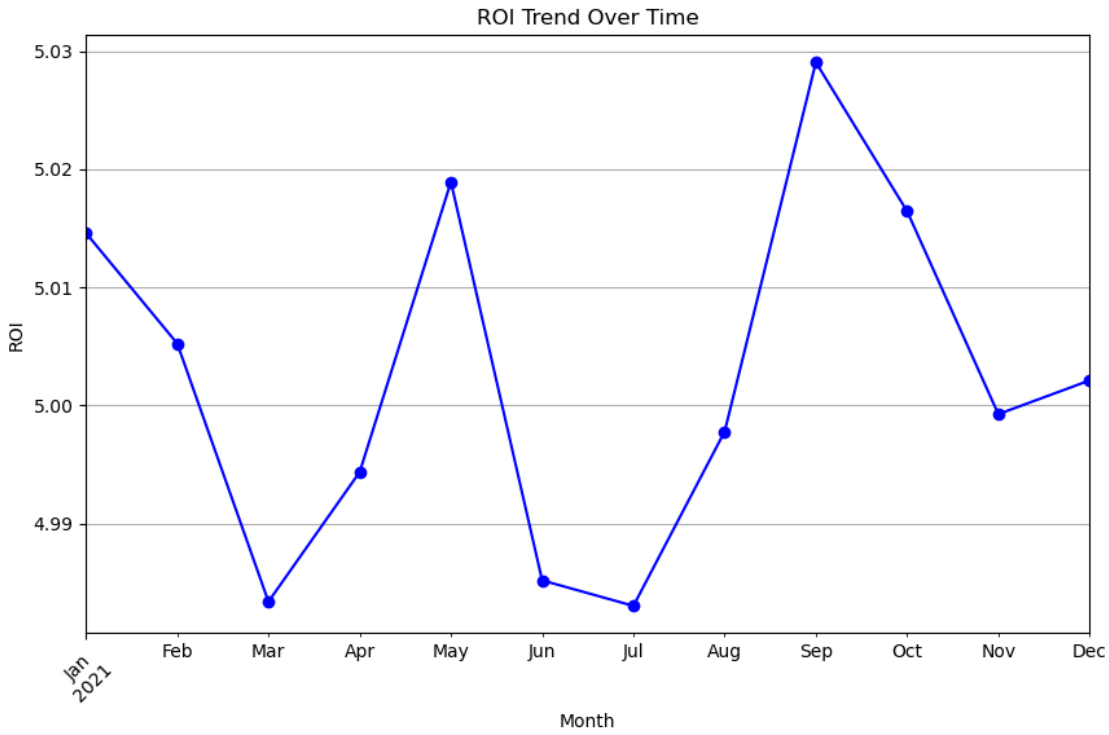
```
sns.barplot(x=engagement_by_location.values, y=engagement_by_location.index,␣
 ↪hue=engagement_by_location.index, palette='coolwarm')
plt.title('Top 10 Locations by Engagement Score')  # Updated title to reflect␣
 ↪top 10
plt.xlabel('Engagement Score')
plt.ylabel('Location')
plt.show()
```



[31]:
```
# Average ROI by Channel Used
roi_by_channel = data.groupby('Channel_Used')['ROI'].mean().
 ↪sort_values(ascending=False)

# Plot ROI by Channel with hue set to 'x'
plt.figure(figsize=(8, 6))
sns.barplot(x=roi_by_channel.index, y=roi_by_channel.values, hue=roi_by_channel.
 ↪index, palette='magma')
plt.title('Average ROI by Channel Used')
plt.xlabel('Channel')
plt.ylabel('ROI')
plt.xticks(rotation=45)
plt.show()
```



[37]:
```
# Group by Month to calculate average ROI
data['Month'] = data['Date'].dt.to_period('M')
roi_trend = data.groupby('Month')['ROI'].mean()

# Plot ROI trend
plt.figure(figsize=(10, 6))
roi_trend.plot(marker='o', color='blue')
plt.title('ROI Trend Over Time')
plt.xlabel('Month')
plt.ylabel('ROI')
plt.xticks(rotation=45)
plt.grid()
plt.show()
```



CTR for every month

[47]:
```
# Aggregate clicks and impressions by month
clicks_impressions = data.groupby('Month')[['Clicks', 'Impressions']].sum()
# Step 2: Calculate CTR for each month
clicks_impressions['CTR (%)'] = (clicks_impressions['Clicks'] /␣
 ↪clicks_impressions['Impressions']) * 100

# Display the result
print(clicks_impressions)
```

```
          Clicks  Impressions    CTR (%)
Month
2021-01  9349618     92956072  10.058104
2021-02  8433037     84493850   9.980652
2021-03  9367374     93804488   9.986062
2021-04  8992709     90677348   9.917261
2021-05  9335696     93384968   9.997001
2021-06  9046697     91119478   9.928390
2021-07  9347146     93060793  10.044129
2021-08  9308212     93801223   9.923338
2021-09  9069330     90658302  10.003860
2021-10  9384834     93264009  10.062653
2021-11  9029761     90734678   9.951830
```

```
2021-12  9289992     93505095   9.935279
```

[54]:
```python
import pandas as pd

# Example: Calculate correlation between numeric columns
numeric_cols = ['Conversion_Rate', 'Acquisition_Cost', 'ROI', 'Clicks',␣
 ↪'Impressions', 'Engagement_Score']

# Correlation matrix
correlation_matrix = data[numeric_cols].corr()

# Display the correlation matrix
print("Correlation Matrix:")
print(correlation_matrix)

# Save the correlation matrix to a CSV if needed
correlation_matrix.to_csv("correlation_matrix.csv")
```

```
Correlation Matrix:
                 Conversion_Rate  Acquisition_Cost       ROI    Clicks  \
Conversion_Rate         1.000000          0.000718 -0.001143  0.000269
Acquisition_Cost        0.000718          1.000000  0.004585  0.000141
ROI                    -0.001143          0.004585  1.000000 -0.002040
Clicks                  0.000269          0.000141 -0.002040  1.000000
Impressions            -0.002834          0.000329  0.002257  0.000033
Engagement_Score       -0.000638         -0.003218  0.000588 -0.001908

                 Impressions  Engagement_Score
Conversion_Rate    -0.002834         -0.000638
Acquisition_Cost    0.000329         -0.003218
ROI                 0.002257          0.000588
Clicks              0.000033         -0.001908
Impressions         1.000000          0.003030
Engagement_Score    0.003030          1.000000
```

[63]:
```python
# Top campaigns based on engagement score
top_campaigns = data.sort_values('Engagement_Score', ascending=False).head(10)

# Display top campaigns
print("Top 10 Campaigns by Engagement Score:")
print(top_campaigns[['Campaign_ID', 'Company', 'Engagement_Score', 'ROI']])
```

```
Top 10 Campaigns by Engagement Score:
        Campaign_ID              Company  Engagement_Score   ROI
185745       185746  Innovate Industries                10  5.25
122856       122857             TechCorp                10  3.01
122873       122874   DataTech Solutions                10  7.59
122869       122870  Innovate Industries                10  3.34
```

```
167674       167675  Innovate Industries                10  6.66
122860       122861   DataTech Solutions                10  6.79
15005         15006       NexGen Systems                10  4.57
181872       181873  Innovate Industries                10  4.69
181874       181875  Innovate Industries                10  5.82
26839         26840  Innovate Industries                10  4.23
```

[92]:
```
highest_conversion = data.groupby(['Company',␣
 ↪'Campaign_ID'])['Conversion_Rate'].max().reset_index()
highest_conversion_sorted = highest_conversion.
 ↪sort_values(by='Conversion_Rate', ascending=False)
print(highest_conversion_sorted.head())  # Display the top companies with their␣
 ↪campaigns
```

```
                  Company  Campaign_ID  Conversion_Rate
22107     Alpha Innovations       109657             0.15
66775    DataTech Solutions       133703             0.15
111542  Innovate Industries       158774             0.15
129544       NexGen Systems        49547             0.15
183184             TechCorp       116096             0.15
```

[96]:
```
data['CTR'] = data['Clicks'] / data['Impressions']
ctr_by_segment = data.groupby('Customer_Segment')['CTR'].mean().reset_index()
ctr_by_segment_sorted = ctr_by_segment.sort_values(by='CTR', ascending=False)
print(ctr_by_segment_sorted.head())
```

```
     Customer_Segment       CTR
1             Foodies  0.141413
4    Tech Enthusiasts  0.141127
0        Fashionistas  0.139953
2   Health & Wellness  0.139857
3  Outdoor Adventurers  0.139665
```

[98]:
```
roi_by_location = data.groupby('Location')['ROI'].mean().reset_index()
roi_by_location_sorted = roi_by_location.sort_values(by='ROI', ascending=False)
print(roi_by_location_sorted.head())
```

```
     Location       ROI
3       Miami  5.012282
2  Los Angeles  5.010876
1      Houston  5.007203
0      Chicago  5.001590
4     New York  4.980228
```

[68]:
```
engagement_by_channel = data.groupby('Channel_Used')['Engagement_Score'].mean().
 ↪reset_index()
engagement_by_channel_sorted = engagement_by_channel.
 ↪sort_values(by='Engagement_Score', ascending=False)
```

```
print(engagement_by_channel_sorted.head())
```

```
  Channel_Used  Engagement_Score
4      Website          5.508903
1     Facebook          5.503702
2   Google Ads          5.494049
3    Instagram          5.489039
0        Email          5.487842
```

[72]:
```
impressions_by_campaign = data.groupby('Campaign_Type')['Impressions'].sum().
 ↪reset_index()
impressions_clicks_correlation = data[['Impressions', 'Clicks']].corr().iloc[0,␣
 ↪1]
print(impressions_by_campaign.sort_values(by='Impressions', ascending=False))
print(f"Correlation between Impressions and Clicks:␣
 ↪{impressions_clicks_correlation}")
```

```
  Campaign_Type  Impressions
3        Search    221415139
2    Influencer    220769081
1         Email    220144927
0       Display    220074756
4  Social Media    219056401
Correlation between Impressions and Clicks: 3.306901393742096e-05
```

[74]:
```
acquisition_and_roi = data.groupby('Company')[['Acquisition_Cost', 'ROI']].
 ↪mean().reset_index()
efficient_companies = acquisition_and_roi.sort_values(by='ROI', ascending=False)
print(efficient_companies.head())
```

```
               Company  Acquisition_Cost       ROI
4              TechCorp      12509.263812  5.007143
0    Alpha Innovations      12513.595690  5.005944
1   DataTech Solutions      12503.275617  5.005537
2  Innovate Industries      12500.535622  5.002175
3       NexGen Systems      12495.224075  4.991353
```

[76]:
```
engagement_by_campaign_type = data.groupby('Campaign_Type')['Engagement_Score'].
 ↪mean().reset_index()
engagement_by_campaign_type_sorted = engagement_by_campaign_type.
 ↪sort_values(by='Engagement_Score', ascending=False)
print(engagement_by_campaign_type_sorted.head())
```

```
  Campaign_Type  Engagement_Score
0       Display          5.505889
1         Email          5.499624
4  Social Media          5.497878
```

```
3        Search          5.487138
2    Influencer          5.483134
```