Stage 2 Task - Exploratory Data Analysis 📈📊

Task Objective

Perform exploratory data analysis (EDA) on a marketing dataset to uncover key insights that can guide strategic decision-making. Present findings through a well-structured presentation, including relevant visualizations, insights, and code snippets.

Insight Generation Analyze the dataset to extract meaningful insights, such as:

1. Insight into the REVENUE of Company
2. Comparing campaign performance across different channels.
3. Calculating CTR, CPC, and conversion rates to assess campaign effectiveness.
4. Identifying high-performing and under-performing campaigns based on ROI.
5. Exploring location-based trends to uncover demographic or cultural influences on campaign success.

Other Market Insight📑

- Preferred Campaign Type for Each Company
- Preferred Marketing Channel for Each Company
- Most Profitable location for Each Company
- Most Profitable Customer Segment for each Company
- Most Profitable Target Audience for each Company
- Market Trend
- Overall Most Profitable Campaign type
- Overall Campaign type & Marketing Channel with the most Click-Through Rate
- Target Audience with the most Click-Through Rate and Return On Investment

In [443]:
```python
# Import the necessary library
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action="ignore", category=UserWarning)

# Set plot style
sns.set(style="whitegrid")
```

In [444]:
```python
#Load the dataset
market_cmp = pd.read_excel("C:/Users/Mishael/Documents/HNG INTERNSHIP PROGRAM/marketing_campaign_dataset.xlsx")
```

In [445]:
```python
market_cmp.head()
```

Out[445]:

	Campaign_ID	Company	Campaign_Type	Target_Audience	Duration	Channel_Used	Conversion_Rate	Acquisition_Cost	ROI	Location	Date	Clicks	Impressions
0	1	Innovate Industries	Email	Men 18-24	30 days	Google Ads	0.04	16174	6.29	Chicago	2021-01-01 00:00:00	506	1922
1	2	NexGen Systems	Email	Women 35-44	60 days	Google Ads	0.12	11566	5.61	New York	2021-02-01 00:00:00	116	7523
2	3	Alpha Innovations	Influencer	Men 25-34	30 days	YouTube	0.07	10200	7.18	Los Angeles	2021-03-01 00:00:00	584	7698
3	4	DataTech Solutions	Display	All Ages	60 days	YouTube	0.11	12724	5.55	Miami	2021-04-01 00:00:00	217	1820
4	5	NexGen Systems	Email	Men 25-34	15 days	YouTube	0.05	16452	6.50	Los Angeles	2021-05-01 00:00:00	379	4201

In [446]:
```python
market_cmp.shape
```

Out[446]: (200005, 15)

In [447]:
```
market_cmp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200005 entries, 0 to 200004
Data columns (total 15 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   Campaign_ID       200005 non-null  int64  
 1   Company           200005 non-null  object 
 2   Campaign_Type     200005 non-null  object 
 3   Target_Audience   200005 non-null  object 
 4   Duration          200005 non-null  object 
 5   Channel_Used      200005 non-null  object 
 6   Conversion_Rate   200005 non-null  float64
 7   Acquisition_Cost  200005 non-null  int64  
 8   ROI               200005 non-null  float64
 9   Location          200005 non-null  object 
 10  Date              200005 non-null  object 
 11  Clicks            200005 non-null  int64  
 12  Impressions       200005 non-null  int64  
 13  Engagement_Score  200005 non-null  int64  
 14  Customer_Segment  200005 non-null  object 
dtypes: float64(2), int64(5), object(8)
memory usage: 22.9+ MB
```

In [448]:
```
market_cmp.isnull().sum()
```

Out[448]:
```
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
Date                0
Clicks              0
Impressions         0
Engagement_Score    0
Customer_Segment    0
dtype: int64
```

The date column is not formatted to the correct datatype `datetime` . Due to some inconsistent formatting, some date values could not be converted and these unconvertible values are replaced with NaT (Not a Time), which is counted as missing (NaN).
TO RECTIFY THIS INCONSISTENCY, WE NEED TO APPROACH IT THIS WAY:

In [449]:
```
# Convert the datatype to string
market_cmp["Date"] = market_cmp["Date"].astype(str)
print(market_cmp["Date"].str.len().unique())  # Check the unique lengths again
```

```
[19 10]
```

In [450]:
```
# After which you convert to datetime
market_cmp["Date"] = pd.to_datetime(market_cmp["Date"], errors="coerce")
```

In [451]:
```
print("Missing Dates After Conversion:", market_cmp["Date"].isna().sum())
print(market_cmp[market_cmp["Date"].isna()].head(10))  # View rows with missing dates
```

```
Missing Dates After Conversion: 0
Empty DataFrame
Columns: [Campaign_ID, Company, Campaign_Type, Target_Audience, Duration, Channel_Used, Conversion_Rate, Acquisition_Cost, ROI, Location, Date, Clicks, Impressions, Engagement_Score, Customer_Segment]
Index: []
```

1. Insight into the REVENUE of the Companies

In [452]:
```python
# Calculate Revenue using the available ROI and Acquisition Cost (Spend)
market_cmp["Revenue"] = (market_cmp["ROI"] * market_cmp["Acquisition_Cost"]) + market_cmp["Acquisition_Cost"]

# Display basic stats to verify calculations
print("Revenue Statistics:\n", market_cmp["Revenue"].describe())
```

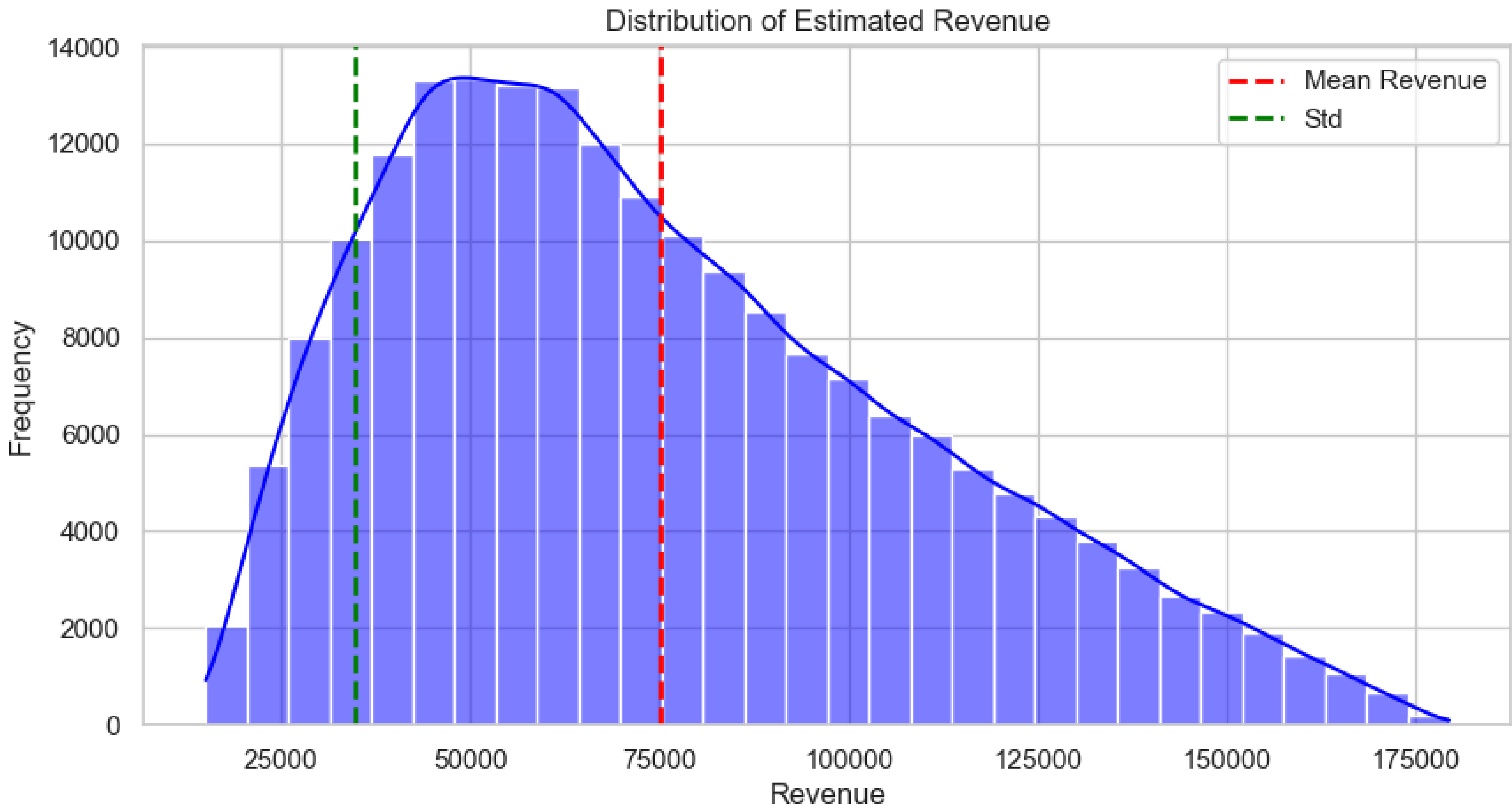
```
Revenue Statistics:
 count    200005.000000
mean      75091.284582
std       34798.987344
min       15071.070000
25%       47728.220000
50%       68815.620000
75%       98146.300000
max      179438.360000
Name: Revenue, dtype: float64
```

In [453]:
```python
# Check sample revenue values
market_cmp[["Company", "ROI", "Acquisition_Cost", "Revenue"]].head(10)
```

Out[453]:

	Company	ROI	Acquisition_Cost	Revenue
0	Innovate Industries	6.29	16174	117908.46
1	NexGen Systems	5.61	11566	76451.26
2	Alpha Innovations	7.18	10200	83436.00
3	DataTech Solutions	5.55	12724	83342.20
4	NexGen Systems	6.50	16452	123390.00
5	DataTech Solutions	4.36	9716	52077.76
6	NexGen Systems	2.86	11067	42718.62
7	DataTech Solutions	5.55	13280	86984.00
8	Alpha Innovations	6.73	18066	139650.18
9	TechCorp	3.78	13766	65801.48

In [454]:
```
plt.figure(figsize=(10, 5))
sns.histplot(market_cmp["Revenue"], bins=30, kde=True, color="blue")
plt.axvline(market_cmp["Revenue"].mean(), color='red', linestyle='dashed', linewidth=2, label="Mean Revenue")
plt.axvline(market_cmp["Revenue"].std(), color='green', linestyle='dashed', linewidth=2, label="Std")
plt.title("Distribution of Estimated Revenue")
plt.xlabel("Revenue")
plt.ylabel("Frequency")
plt.legend()
plt.grid(True)
plt.show()
```



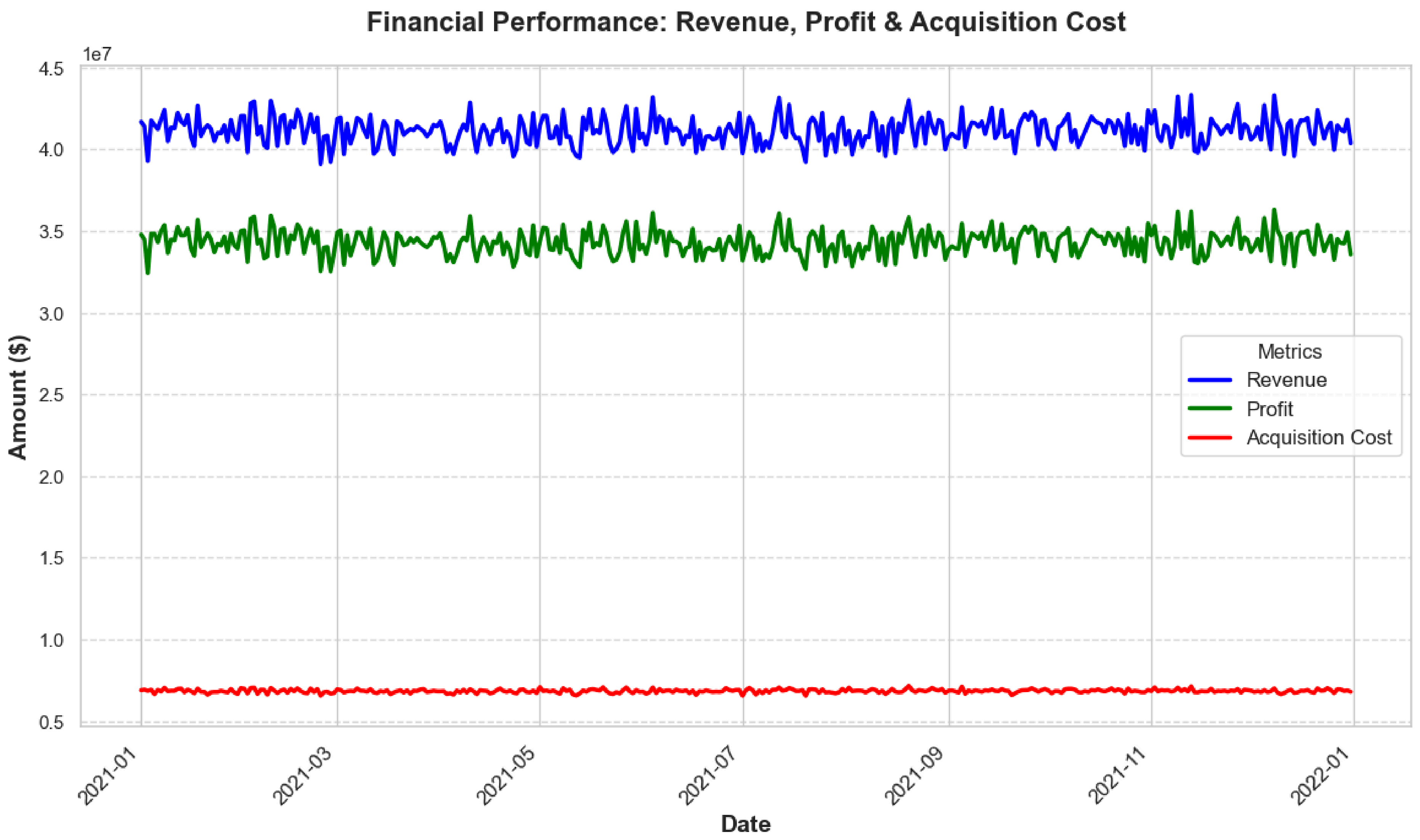
1.1. Revenue and Profit Over Time

In [455]:
```
# Calculate Profit using ROI and Acquisition_Cost
market_cmp["Profit"] = market_cmp["ROI"] * market_cmp["Acquisition_Cost"]

# Display first few rows
market_cmp[["Company", "Campaign_Type", "ROI", "Acquisition_Cost", "Profit", "Revenue"]].head()
```

Out[455]:

	Company	Campaign_Type	ROI	Acquisition_Cost	Profit	Revenue
0	Innovate Industries	Email	6.29	16174	101734.46	117908.46
1	NexGen Systems	Email	5.61	11566	64885.26	76451.26
2	Alpha Innovations	Influencer	7.18	10200	73236.00	83436.00
3	DataTech Solutions	Display	5.55	12724	70618.20	83342.20
4	NexGen Systems	Email	6.50	16452	106938.00	123390.00

In [456]:
```python
# Group data by Date and sum relevant columns
time_series_data = market_cmp.groupby("Date")[["Revenue", "Profit", "Acquisition_Cost"]].sum().reset_index()

# Plot
plt.figure(figsize=(14, 7))

sns.lineplot(data=time_series_data, x="Date", y="Revenue", label="Revenue", color="blue", linewidth=2.5)
sns.lineplot(data=time_series_data, x="Date", y="Profit", label="Profit", color="green", linewidth=2.5)
sns.lineplot(data=time_series_data, x="Date", y="Acquisition_Cost", label="Acquisition Cost", color="red", linewidth=2.5)

# Formatting
plt.xlabel("Date", fontsize=14, fontweight="bold")
plt.ylabel("Amount ($)", fontsize=14, fontweight="bold")
plt.title("Financial Performance: Revenue, Profit & Acquisition Cost", fontsize=16, fontweight="bold", pad=20)
plt.xticks(rotation=45, ha="right", fontsize=12)
plt.legend(title="Metrics", fontsize=12)
plt.grid(axis="y", linestyle="--", alpha=0.7)

# Show plot
plt.show()
```


Financial Performance: Revenue, Profit & Acquisition Cost
1e7
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
Amount ($)
Metrics
Revenue
Profit
Acquisition Cost
2021-01
2021-03
2021-05
2021-07
2021-09
2021-11
2022-01
Date

1.2. Company Revenue and Profit

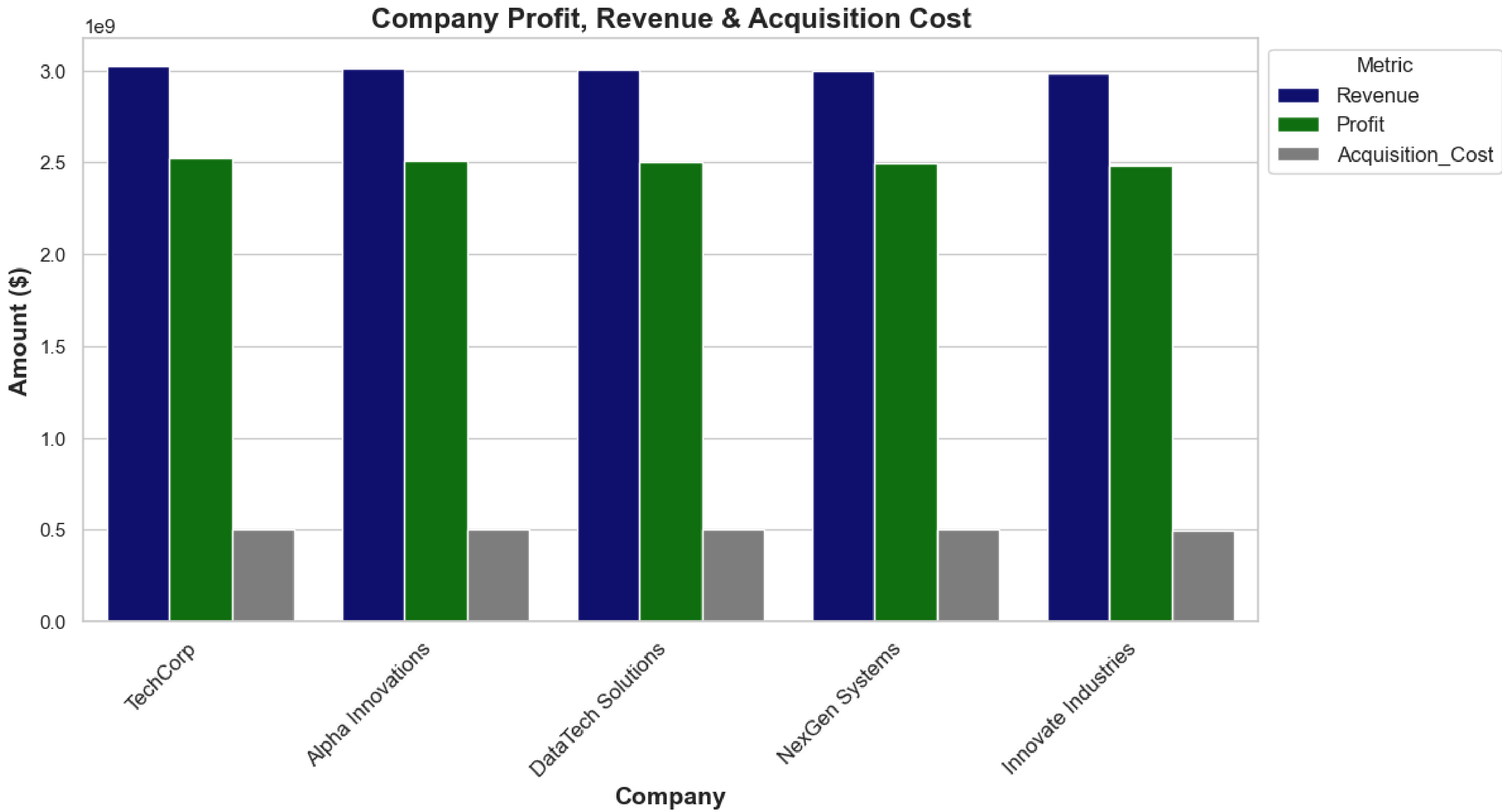
In [457]:

```
# Companies Revenue and Profit
top_market = market_cmp.groupby("Company")[["Revenue", "Profit", "Acquisition_Cost"]].sum().sort_values(ascending = False, by= "Profit").r
top_market
```

Out[457]:

	Company	Revenue	Profit	Acquisition_Cost
0	TechCorp	3.024611e+09	2.521257e+09	503353613
1	Alpha Innovations	3.011679e+09	2.510497e+09	501182021
2	DataTech Solutions	3.004858e+09	2.504555e+09	500302629
3	NexGen Systems	2.995155e+09	2.495458e+09	499696506
4	Innovate Industries	2.982330e+09	2.485914e+09	496416112

In [458]:
```python
# Melt the dataframe to have 'Company', 'Metric' (Revenue/Profit), and 'Value'
top_market_melted = top_market.melt(id_vars="Company", value_vars=["Revenue", "Profit", "Acquisition_Cost"], var_name="Metric", value_name



# Plot grouped bar chart
plt.figure(figsize=(12, 6))
ax = sns.barplot(data=top_market_melted, x="Company", y="Amount", hue="Metric", palette=["Navy", "green", "grey"])

# Formatting
plt.xlabel("Company", fontsize=14, fontweight="bold")
plt.ylabel("Amount ($)", fontsize=14, fontweight="bold")
plt.title("Company Profit, Revenue & Acquisition Cost", fontsize=16, fontweight="bold")
plt.xticks(rotation=45, ha="right", fontsize=12)
plt.legend(title="Metric", fontsize=12, bbox_to_anchor=(1, 1))

# Show plot
plt.show()
```



2. Comparing campaign performance across different channels.

In [459]:

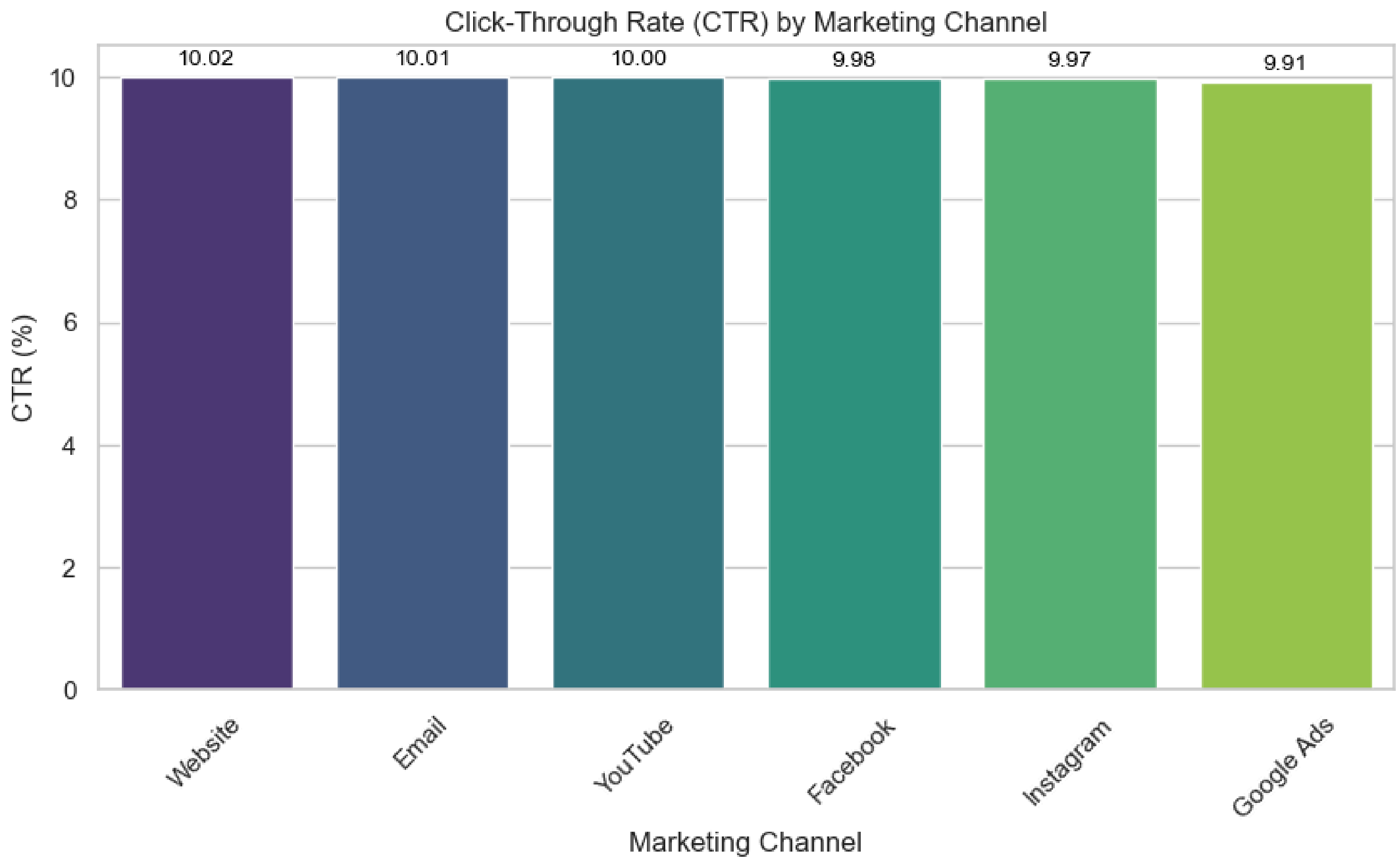
```python
# Group by marketing channel and compute key metrics
channel_performance = market_cmp.groupby("Channel_Used").agg({
    "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",
    "ROI": "mean"
}).reset_index()

# Calculate CTR, CPC, and ROI
channel_performance["CTR"] = (channel_performance["Clicks"] / channel_performance["Impressions"]) * 100
channel_performance["CPC"] = channel_performance["Acquisition_Cost"] / channel_performance["Clicks"]

# Display results
channel_performance.head()
```

Out[459]:

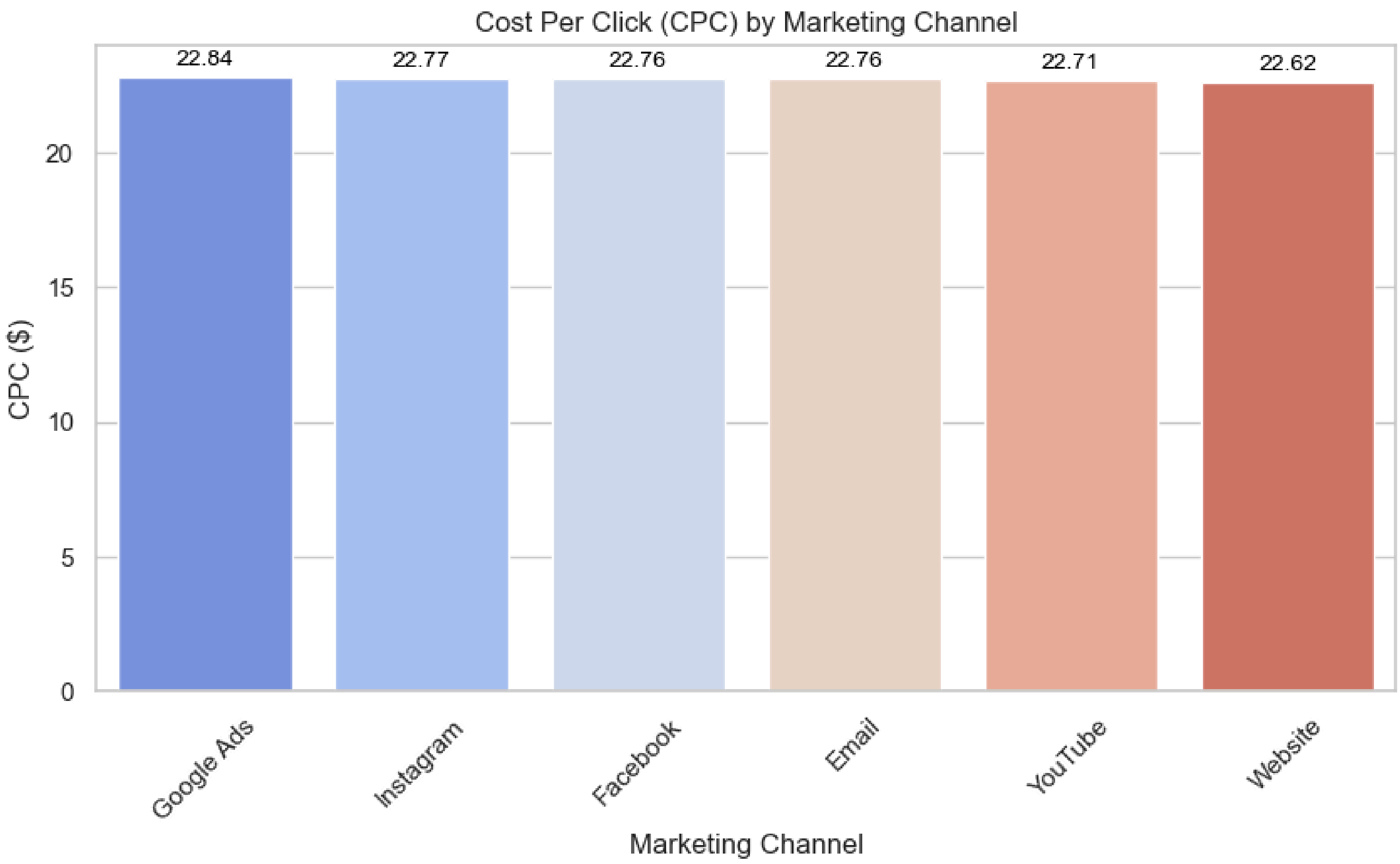
	Channel_Used	Clicks	Impressions	Acquisition_Cost	Conversion_Rate	ROI	CTR	CPC
0	Email	18493963	184801107	420874104	0.080282	4.996487	10.007496	22.757378
1	Facebook	18038175	180662496	410603426	0.079990	5.018672	9.984460	22.763025
2	Google Ads	18342589	185020154	418944514	0.080181	5.003126	9.913833	22.839988
3	Instagram	18316654	183738455	417124850	0.079886	4.988706	9.968873	22.772983
4	Website	18415351	183815901	416606897	0.080182	5.014114	10.018367	22.622805

In [460]:

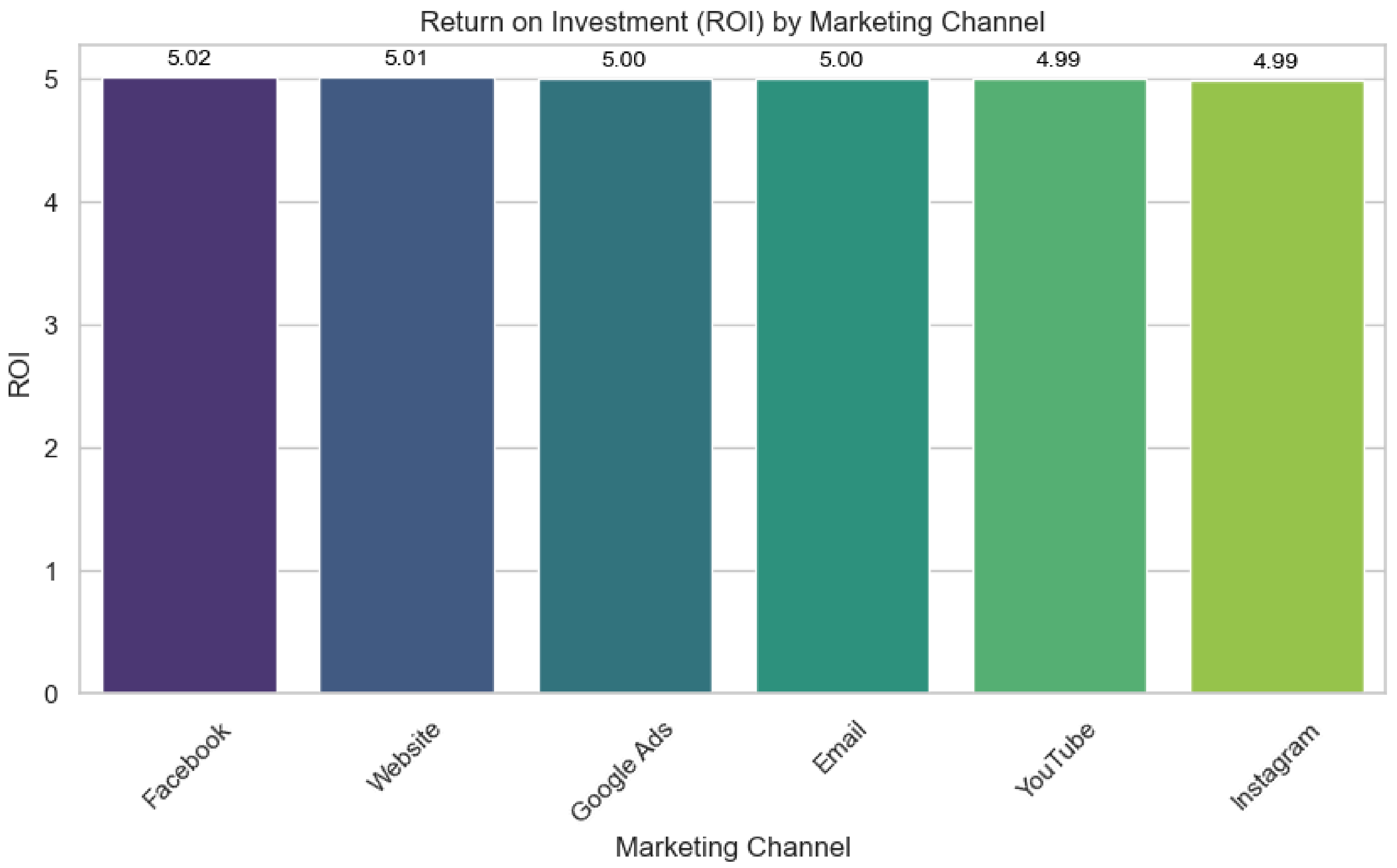
```python
# Plot CTR across channels
plt.figure(figsize=(10, 5))
ax = sns.barplot(x="Channel_Used", y="CTR", data=channel_performance.sort_values(ascending=False, by="CTR"), palette="viridis")

# Add data labels
for container in ax.containers:
    ax.bar_label(container, fmt="%.2f", padding=3, fontsize=10, color="black")

plt.title("Click-Through Rate (CTR) by Marketing Channel")
plt.ylabel("CTR (%)")
plt.xlabel("Marketing Channel")
plt.xticks(rotation=45)
plt.show()
```



In [461]:
```python
# Plot CPC across channels
plt.figure(figsize=(10, 5))
ax = sns.barplot(x="Channel_Used", y="CPC", data=channel_performance.sort_values(ascending=False, by="CPC"), palette="coolwarm")

# Add data labels
for container in ax.containers:
    ax.bar_label(container, fmt="%.2f", padding=3, fontsize=10, color="black")

plt.title("Cost Per Click (CPC) by Marketing Channel")
plt.ylabel("CPC ($)")
plt.xlabel("Marketing Channel")
plt.xticks(rotation=45)
plt.show()
```



In [462]:
```
# Plot ROI across channels
plt.figure(figsize=(10, 5))
ax = sns.barplot(x="Channel_Used", y="ROI", data=channel_performance.sort_values(ascending=False, by="ROI"), palette="viridis")

# Add data labels
for container in ax.containers:
    ax.bar_label(container, fmt="%.2f", padding=3, fontsize=10, color="black")

plt.title("Return on Investment (ROI) by Marketing Channel")
plt.ylabel("ROI")
plt.xlabel("Marketing Channel")
plt.xticks(rotation=45)
plt.show()
```



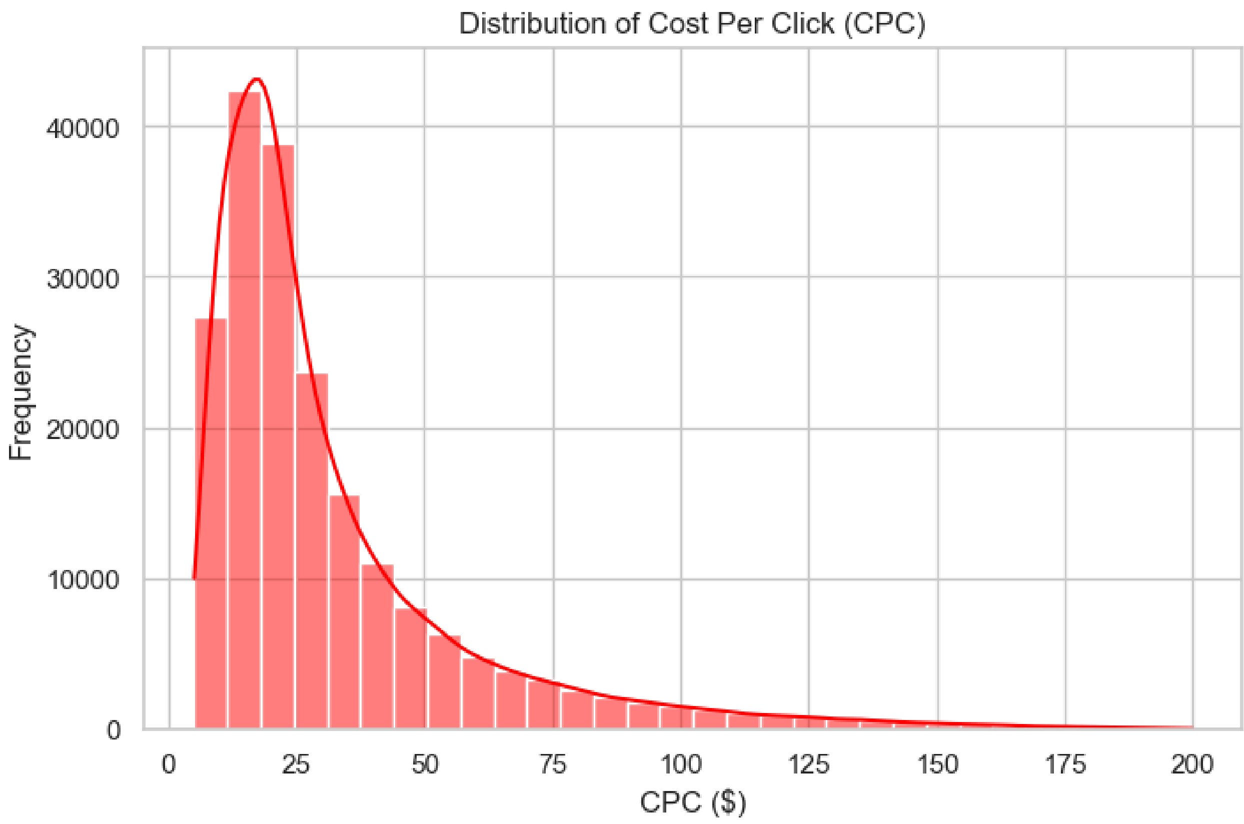
3. Calculating CTR, CPC, and conversion rates to assess campaign effectiveness.

In [463]:
```python
# Calculate CTR and CPC for each campaign
market_cmp["CTR"] = (market_cmp["Clicks"] / market_cmp["Impressions"]) * 100
market_cmp["CPC"] = market_cmp["Acquisition_Cost"] / market_cmp["Clicks"]

# Summary statistics
market_cmp[["CTR", "CPC"]].describe()
```

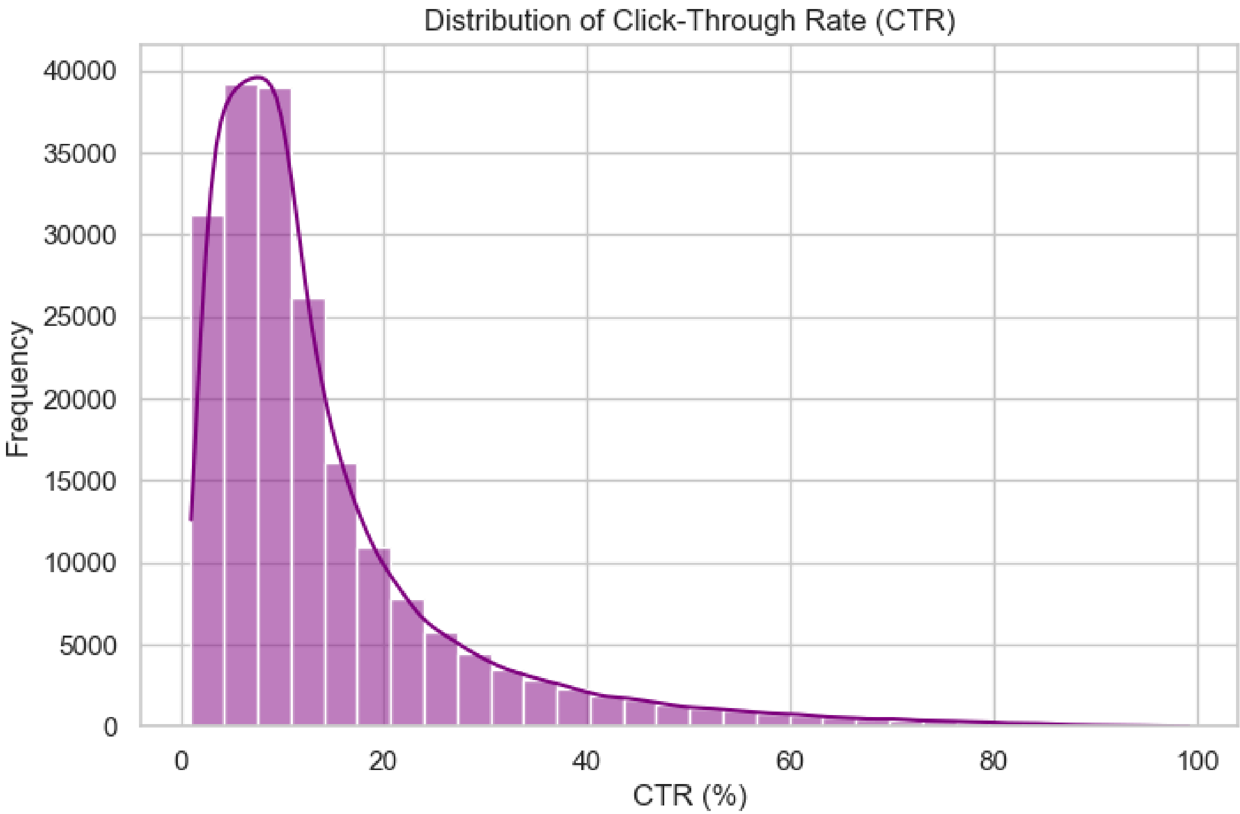
Out[463]:

	CTR	CPC
count	200005.000000	200005.000000
mean	14.040504	32.008319
std	13.087980	26.925841
min	1.005429	5.021084
25%	5.860637	15.092037
50%	9.978960	22.773973
75%	16.969848	38.598253
max	99.202393	199.960000

In [464]:
```
# CPC Distribution Plot
plt.figure(figsize=(8, 5))
sns.histplot(market_cmp["CPC"], bins=30, kde=True, color="red")
plt.title("Distribution of Cost Per Click (CPC)")
plt.xlabel("CPC ($)")
plt.ylabel("Frequency")
plt.show()
```



In [465]:
```
# CTR Distribution Plot
plt.figure(figsize=(8, 5))
sns.histplot(market_cmp["CTR"], bins=30, kde=True, color="purple")
plt.title("Distribution of Click-Through Rate (CTR)")
plt.xlabel("CTR (%)")
plt.ylabel("Frequency")
plt.show()
```



In [466]:
```
# Group by marketing Campaign_Type and compute key metric
Campaign_Type_performance = market_cmp.groupby("Campaign_Type").agg({
    "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean",
    "CTR": "mean",
    "CPC": "sum"# Using mean ROI per campaign
}).reset_index()

# Display results
Campaign_Type_performance.head()
```

Out[466]:

	Campaign_Type	Clicks	Impressions	Acquisition_Cost	Conversion_Rate	ROI	CTR	CPC
0	Display	22031837	220080744	500177139	0.080088	5.006497	14.126483	1.276553e+06
1	Email	21898130	220147995	498197617	0.079787	4.994274	13.948757	1.277456e+06
2	Influencer	22038185	220771844	502419033	0.080315	5.011040	14.030083	1.289563e+06
3	Search	22032144	221415139	501911760	0.080021	5.008357	13.993587	1.283452e+06
4	Social Media	21957371	219073236	498245332	0.080132	4.991781	14.103856	1.274799e+06

4. Identifying high-performing and underperforming campaigns based on ROI.

In [467]:
```python
# Sort campaigns by ROI
top_campaigns = market_cmp.sort_values("ROI", ascending=False).head(20)
low_campaigns = market_cmp.sort_values("ROI", ascending=True).head(10)

print("Top 10 High-Performing Campaigns by ROI:")
top_campaigns[["Campaign_ID", "Company", "Campaign_Type", "Channel_Used", "ROI", "Revenue"]].sort_values("Revenue", ascending=False).head(
```

```
Top 10 High-Performing Campaigns by ROI:
```

Out[467]:

	Campaign_ID	Company	Campaign_Type	Channel_Used	ROI	Revenue
182656	182657	Alpha Innovations	Search	Facebook	8.0	173250.0
83445	83446	Alpha Innovations	Search	Email	8.0	170604.0
47112	47113	DataTech Solutions	Influencer	Google Ads	8.0	161721.0
98646	98647	TechCorp	Search	YouTube	8.0	143586.0
73036	73037	NexGen Systems	Email	YouTube	8.0	138186.0
64516	64517	Innovate Industries	Search	Website	8.0	133596.0
104050	104051	Alpha Innovations	Display	Google Ads	8.0	130527.0
132599	132600	TechCorp	Influencer	Facebook	8.0	127539.0
53538	53539	DataTech Solutions	Search	Email	8.0	123147.0
101573	101574	NexGen Systems	Social Media	YouTube	8.0	121320.0

There are quite a number of high-performing campaign with the peak ROI of 8.0, but the `Campaign ID-182657 (Alpha Innovations)` outpace the others with a `Revenue of 173250`

In [468]:
```
print("\nTop 10 Low-Performing Campaigns by ROI:")
low_campaigns[["Campaign_ID", "Company", "Campaign_Type", "Channel_Used", "ROI", "Revenue"]].sort_values("Revenue", ascending=False).head(
```

```
Top 10 Low-Performing Campaigns by ROI:
```

Out[468]:

	Campaign_ID	Company	Campaign_Type	Channel_Used	ROI	Revenue
175913	175914	DataTech Solutions	Social Media	YouTube	2.0	59136.0
40004	40005	TechCorp	Influencer	Facebook	2.0	58068.0
153591	153592	DataTech Solutions	Email	Instagram	2.0	57309.0
143928	143929	DataTech Solutions	Social Media	Facebook	2.0	56376.0
117384	117385	NexGen Systems	Email	Email	2.0	51252.0

5. Exploring location-based trends to uncover demographic or cultural influences on campaign success.

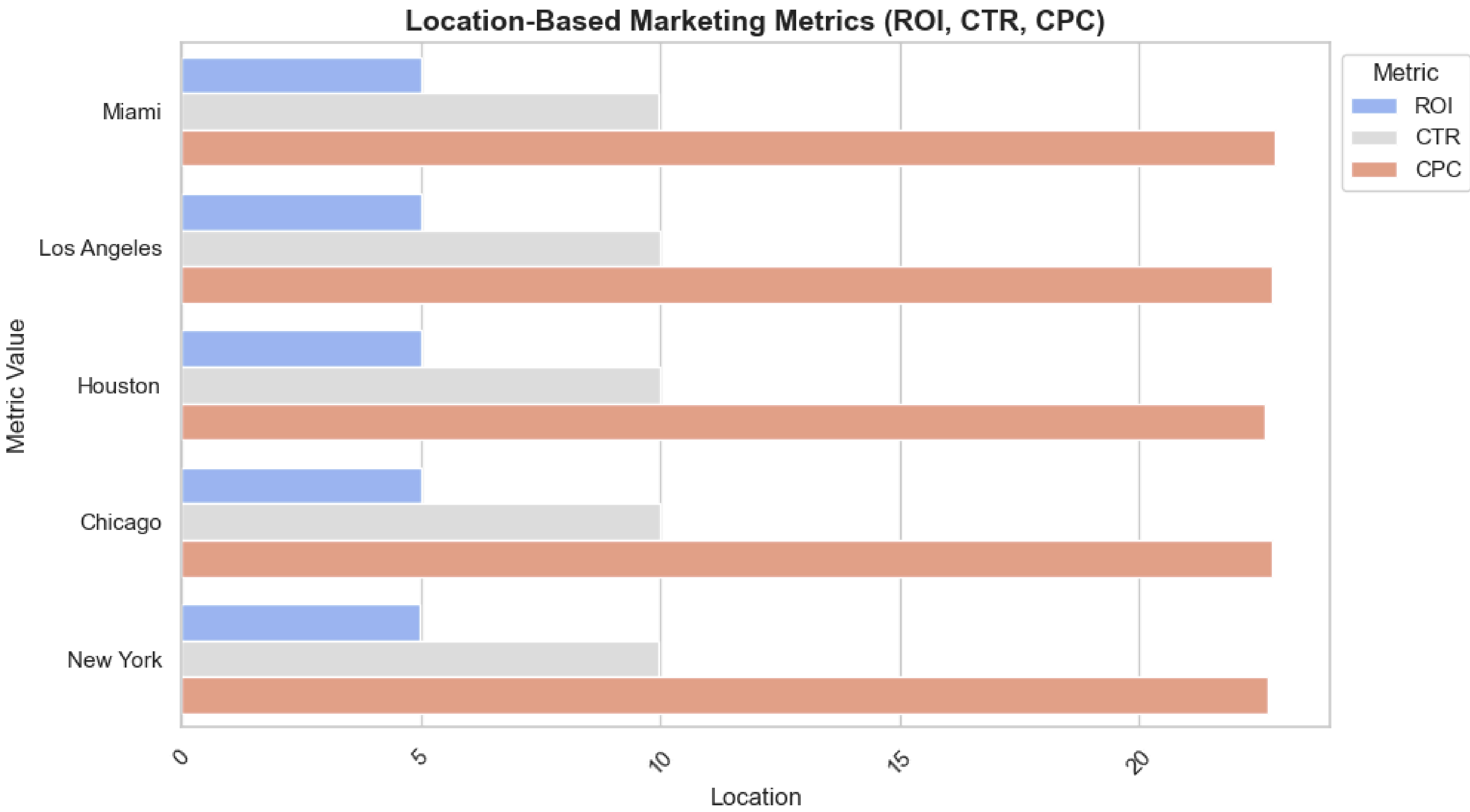
In [469]:
```
# Group by location and calculate key metrics
location_performance = market_cmp.groupby("Location").agg({
      "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean"
}).sort_values(ascending=False, by="ROI").reset_index()

# Calculate CTR and ROI
location_performance["CTR"] = (location_performance["Clicks"] / location_performance["Impressions"]) * 100
location_performance["CPC"] = location_performance["Acquisition_Cost"] / location_performance["Clicks"]

# Display results
location_performance.head()
```

Out[469]:

	Location	Clicks	Impressions	Acquisition_Cost	Conversion_Rate	ROI	CTR	CPC
0	Miami	22056765	221347726	503974911	0.080047	5.012282	9.964758	22.848995
1	Los Angeles	21966553	219652325	500637366	0.080013	5.010876	10.000601	22.790893
2	Houston	21893075	219129799	495080401	0.079949	5.007174	9.990916	22.613562
3	Chicago	21980408	219999352	500771983	0.080131	5.001555	9.991124	22.782652
4	New York	22060866	221359756	500486220	0.080203	4.980185	9.966069	22.686608

In [470]:

```
# Set figure size
plt.figure(figsize=(10, 6))

# Melt data for seaborn compatibility
location_performance_melted = location_performance[["Location", "ROI", "CTR", "CPC"]].melt(id_vars=["Location"], var_name="Metric", value_

# Plot grouped bar chart
sns.barplot(x="Value", y="Location", hue="Metric", data=location_performance_melted, palette="coolwarm")

# Formatting
plt.title("Location-Based Marketing Metrics (ROI, CTR, CPC)", fontsize=14, fontweight="bold")
plt.xlabel("Location", fontsize=12)
plt.ylabel("Metric Value", fontsize=12)
plt.legend(title="Metric", bbox_to_anchor=(1, 1))
plt.xticks(rotation=45)
plt.show()
```



Other Market Insight:

Preferred Campaign Type for Each Company

which Campaign type generate the most ROI?

In [471]:

```python
# Group by Company and Campaign Type, and calculate key metrics
company_campaign_performance = market_cmp.groupby(["Company", "Campaign_Type"]).agg({
    "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean"  # Using mean ROI per campaign
}).reset_index()

# Drop NaN values that may have appeared
company_campaign_performance.fillna(0, inplace=True)

# Identify the preferred campaign type per company based on highest ROI
preferred_campaigns = company_campaign_performance.loc[
    company_campaign_performance.groupby("Company")["ROI"].idxmax(),
    ["Company", "Campaign_Type", "ROI", "Conversion_Rate"]
]

# Display results
print("preferred campaign type:")
preferred_campaigns.head()
```

```
preferred campaign type:
```

Out[471]:

	Company	Campaign_Type	ROI	Conversion_Rate
2	Alpha Innovations	Influencer	5.033126	0.080181
5	DataTech Solutions	Display	5.049224	0.080651
10	Innovate Industries	Display	5.018512	0.079666
18	NexGen Systems	Search	5.005118	0.080066
22	TechCorp	Influencer	5.023186	0.079881

The table above shows the best Campaign type appropriate for each comapany given the most ROI

Preferred Marketing Channel for Each Company

In [472]:

```
# Group by Company and Channel_Used, and calculate key metrics
company_Channel_Used_performance = market_cmp.groupby(["Company", "Channel_Used"]).agg({
      "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean"
}).reset_index()

# Identify the preferred Channel_Used per company based on highest ROI
preferred_Channel_Used = company_Channel_Used_performance.loc[
    company_Channel_Used_performance.groupby("Company")["ROI"].idxmax(),
    ["Company", "Channel_Used", "ROI", "Conversion_Rate"]
]

# Display results
print("preferred Marketing Channel:")
preferred_Channel_Used.head()
```

```
preferred Marketing Channel:
```

Out[472]:

	Company	Channel_Used	ROI	Conversion_Rate
5	Alpha Innovations	YouTube	5.036764	0.079800
10	DataTech Solutions	Website	5.040937	0.080472
12	Innovate Industries	Email	5.022140	0.080352
20	NexGen Systems	Google Ads	5.008727	0.079610
25	TechCorp	Facebook	5.031797	0.080012

similarly, above are the most profitable channel by which each company can obtain the most ROI

Most Profitable location for Each Company

In [473]:
```
# Group by Company and Location, and calculate key metrics
company_location_performance = market_cmp.groupby(["Company", "Location"]).agg({
      "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean"
}).reset_index()


# Identify the preferred location per company based on highest ROI
preferred_locations = company_location_performance.loc[
    company_location_performance.groupby("Company")["ROI"].idxmax(),
    ["Company", "Location", "ROI", "Conversion_Rate"]
]

# Identify the preferred location per company based on highest Conversion rate
engage_locations = company_location_performance.loc[
    company_location_performance.groupby("Company")["Conversion_Rate"].idxmax(),
    ["Company", "Location", "ROI",  "Conversion_Rate"]
]

# Display results
print("Most Profitable location for company:")
print(preferred_locations.head())

print("Most engaging location for company:")
print(engage_locations.head())
```

```
Most Profitable location for company:
                Company     Location       ROI  Conversion_Rate
3     Alpha Innovations        Miami  5.033023         0.080376
6    DataTech Solutions      Houston  5.032047         0.079768
10  Innovate Industries      Chicago  5.025324         0.080578
17       NexGen Systems  Los Angeles  5.005830         0.080206
22             TechCorp  Los Angeles  5.022251         0.080344
Most engaging location for company:
                Company  Location       ROI  Conversion_Rate
3     Alpha Innovations     Miami  5.033023         0.080376
8    DataTech Solutions     Miami  5.018247         0.080586
11  Innovate Industries   Houston  5.002987         0.080652
19       NexGen Systems  New York  4.974520         0.080410
24             TechCorp  New York  4.994526         0.080400
```

Most Profitable Customer Segment for each Company

In [474]:
```
# Group by Company and Customer Segment, and calculate key metrics
company_segment_performance = market_cmp.groupby(["Company", "Customer_Segment"]).agg({
      "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean"
}).reset_index()

# Identify the preferred customer segment per company based on highest ROI
preferred_segments = company_segment_performance.loc[
    company_segment_performance.groupby("Company")["ROI"].idxmax(),
    ["Company", "Customer_Segment", "ROI"]
]

# Display results
print("most Profitable Customer Segment for each company:")
preferred_segments.head()
```

```
most Profitable Customer Segment for each company:
```

Out[474]:

	Company	Customer_Segment	ROI
1	Alpha Innovations	Foodies	5.015405
7	DataTech Solutions	Health & Wellness	5.036760
10	Innovate Industries	Fashionistas	5.015358
18	NexGen Systems	Outdoor Adventurers	5.018974
24	TechCorp	Tech Enthusiasts	5.021868

Most Profitable Target Audience for each Company

In [475]:
```
# Group by Company and Target_Audience, and calculate key metrics
company_Target_Audience_performance = market_cmp.groupby(["Company", "Target_Audience"]).agg({
      "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean",
    "CTR": "mean"
}).reset_index()

# Identify the preferred Target_Audience per company based on CTR
preferred_Target_Audience = company_Target_Audience_performance.loc[
    company_Target_Audience_performance.groupby("Company")["CTR"].idxmax(),
    ["Company", "Target_Audience", "CTR"]
].sort_values(ascending=False, by="CTR")

# Display results
print("Most Engaging Target Audience:")
preferred_Target_Audience.head()
```

```
Most Engaging Target Audience:
```

Out[475]:

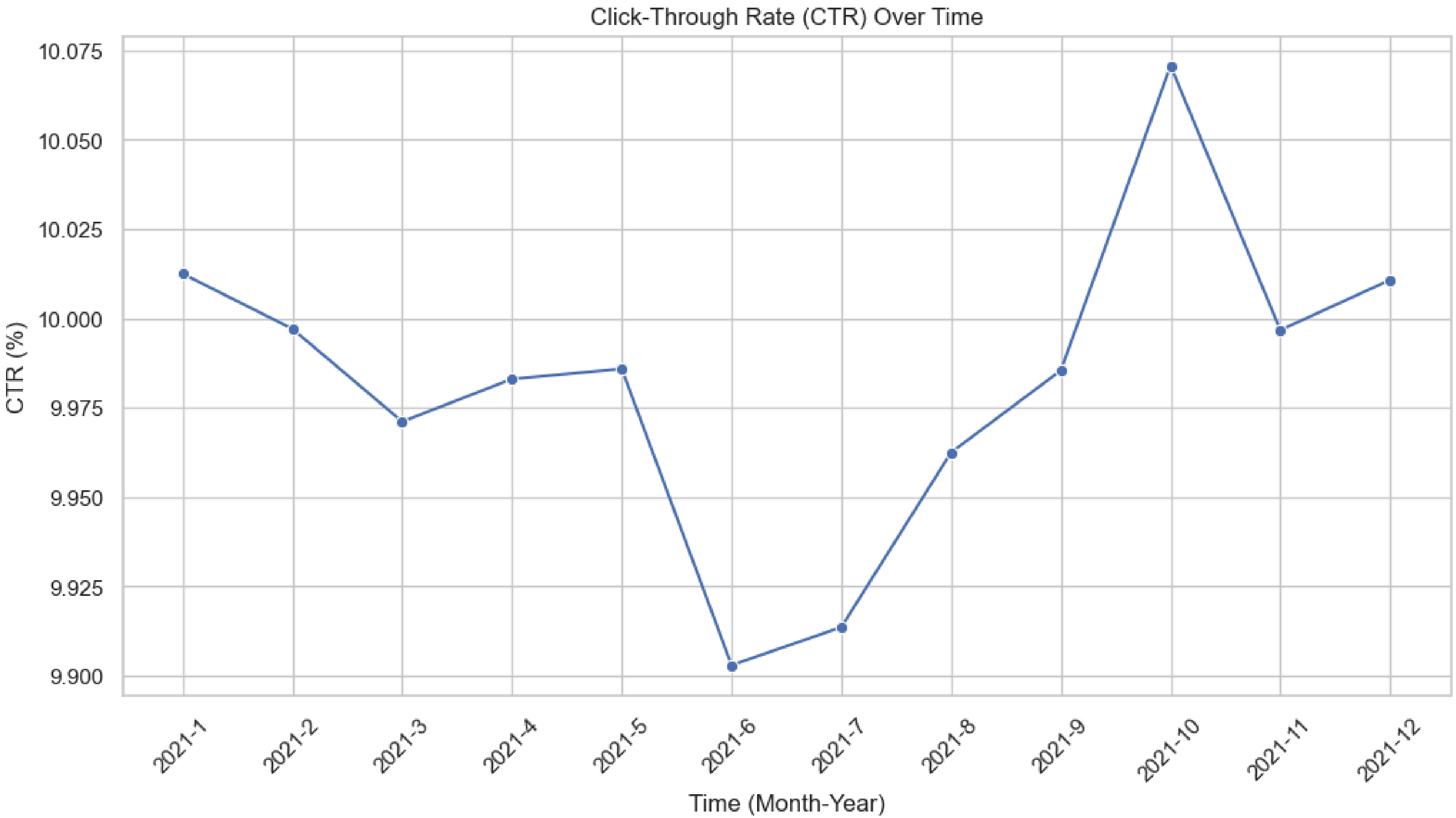
	Company	Target_Audience	CTR
13	Innovate Industries	Women 25-34	14.304282
9	DataTech Solutions	Women 35-44	14.206589
1	Alpha Innovations	Men 18-24	14.193488
22	TechCorp	Men 25-34	14.181205
18	NexGen Systems	Women 25-34	14.132181

📈📉 Market Trend

In [476]:
```
# Extract useful time features
market_cmp["Year"] = market_cmp["Date"].dt.year
market_cmp["Month"] = market_cmp["Date"].dt.month
market_cmp["Quarter"] = market_cmp["Date"].dt.to_period("Q")

# Group data by Month to observe trends
time_analysis = market_cmp.groupby(["Year", "Month"]).agg({
      "Clicks": "sum",
    "Impressions": "sum",
    "Acquisition_Cost": "sum",
    "Conversion_Rate": "mean",  # Mean is better for rates
    "ROI": "mean"
}).reset_index()

# Calculate performance metrics
time_analysis["CTR"] = (time_analysis["Clicks"] / time_analysis["Impressions"]) * 100
time_analysis["CPC"] = time_analysis["Acquisition_Cost"] / time_analysis["Clicks"]
time_analysis["Revenue"] = (time_analysis["ROI"] * time_analysis["Acquisition_Cost"]) + time_analysis["Acquisition_Cost"]


# Create a 'Month-Year' column for easy visualization
time_analysis["Month-Year"] = time_analysis["Year"].astype(str) + "-" + time_analysis["Month"].astype(str)
```

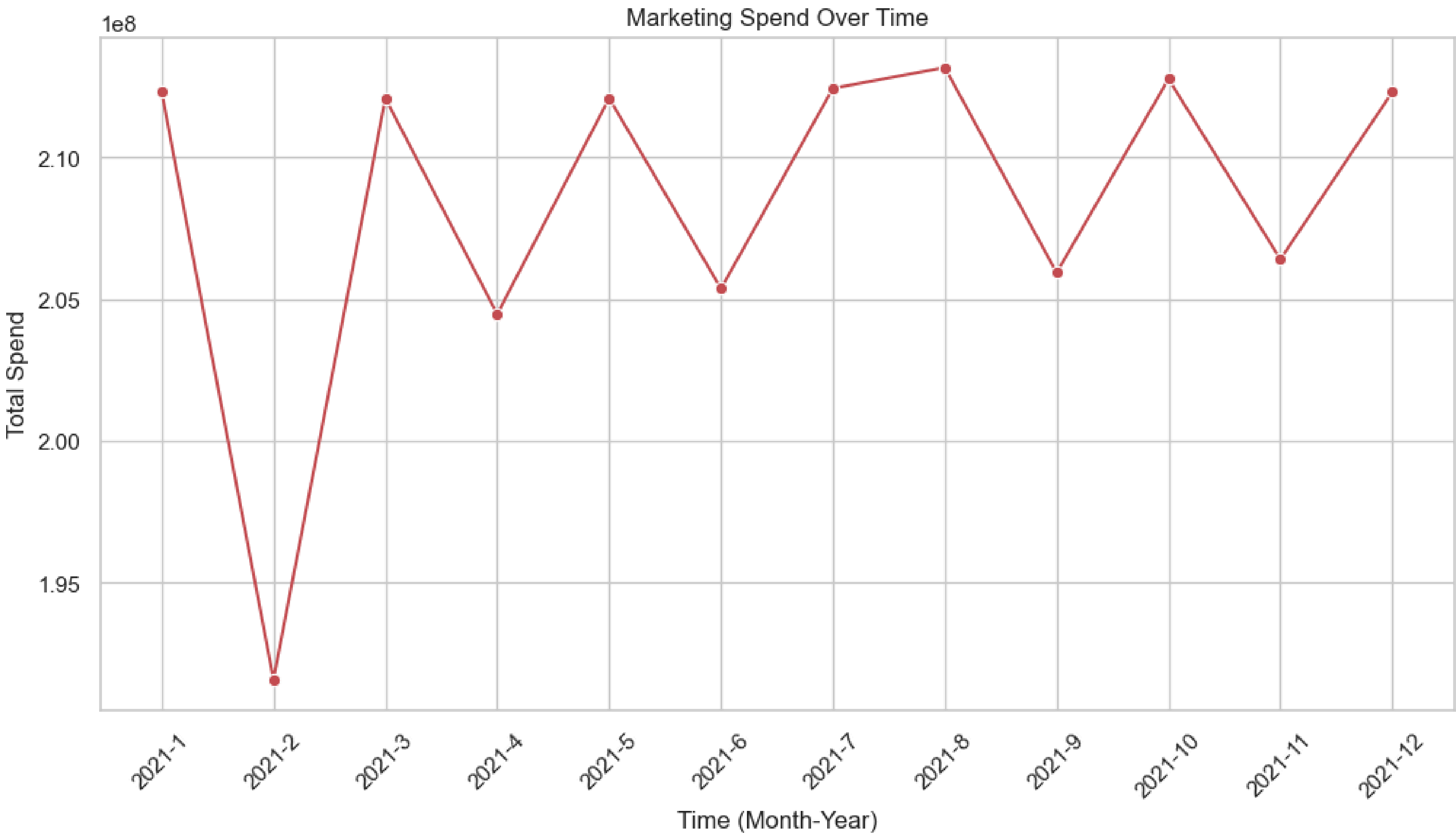
In [477]:

```
#  Visualization - CTR Over Time
plt.figure(figsize=(12, 6))
sns.lineplot(x="Month-Year", y="CTR", data=time_analysis, marker="o", color="b")
plt.title("Click-Through Rate (CTR) Over Time")
plt.xlabel("Time (Month-Year)")
plt.ylabel("CTR (%)")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



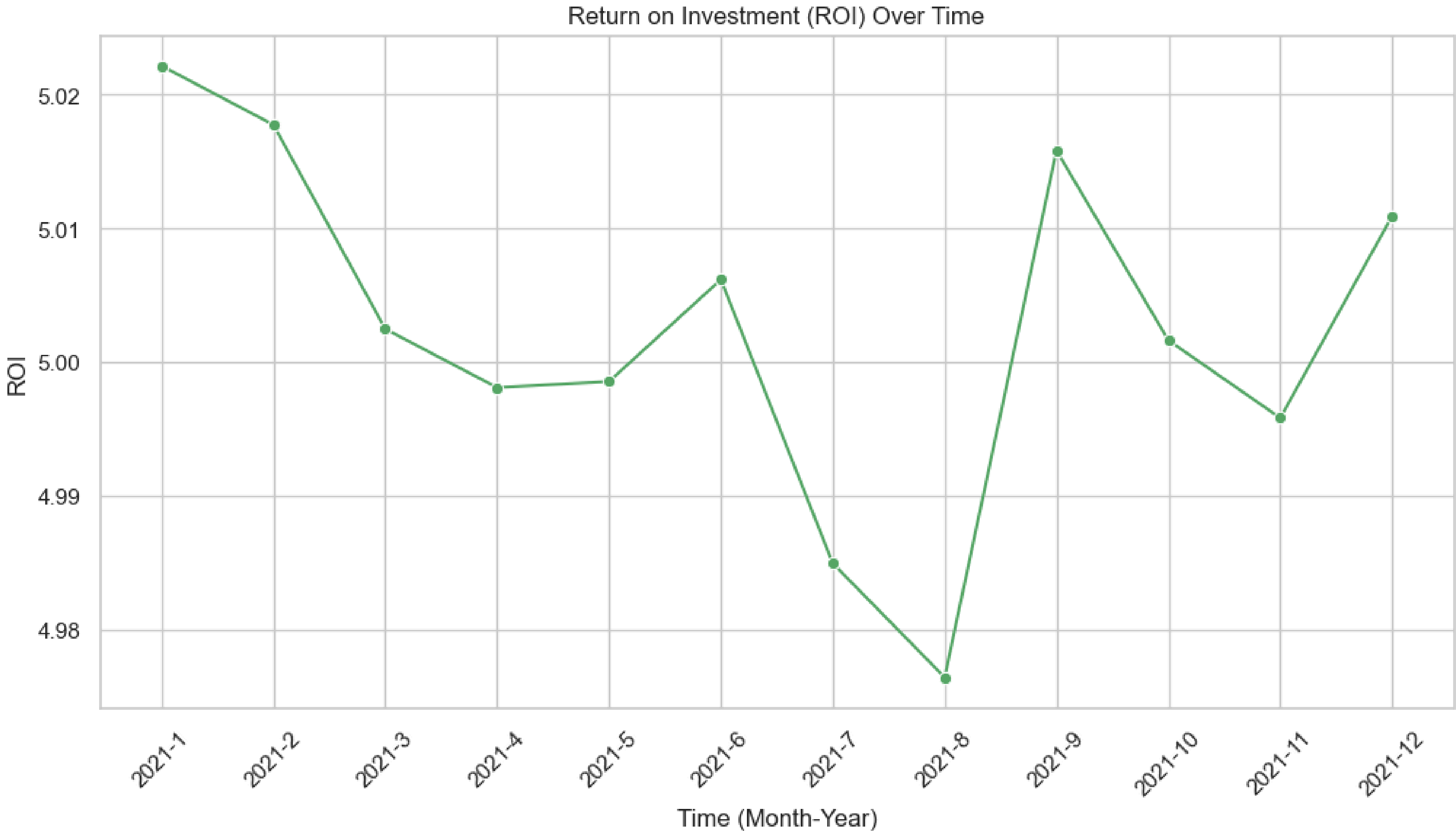
There is a noticeable CTR drop in the month of June and July,this may indicate seasonal disengagement, while CTR in the Month of October is the highest indicating massive engagement overall.

In [478]:
```
# Visualization - Spend Over Time
plt.figure(figsize=(12, 6))
sns.lineplot(x="Month-Year", y="Acquisition_Cost", data=time_analysis, marker="o", color="r")
plt.title("Marketing Spend Over Time")
plt.xlabel("Time (Month-Year)")
plt.ylabel("Total Spend")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



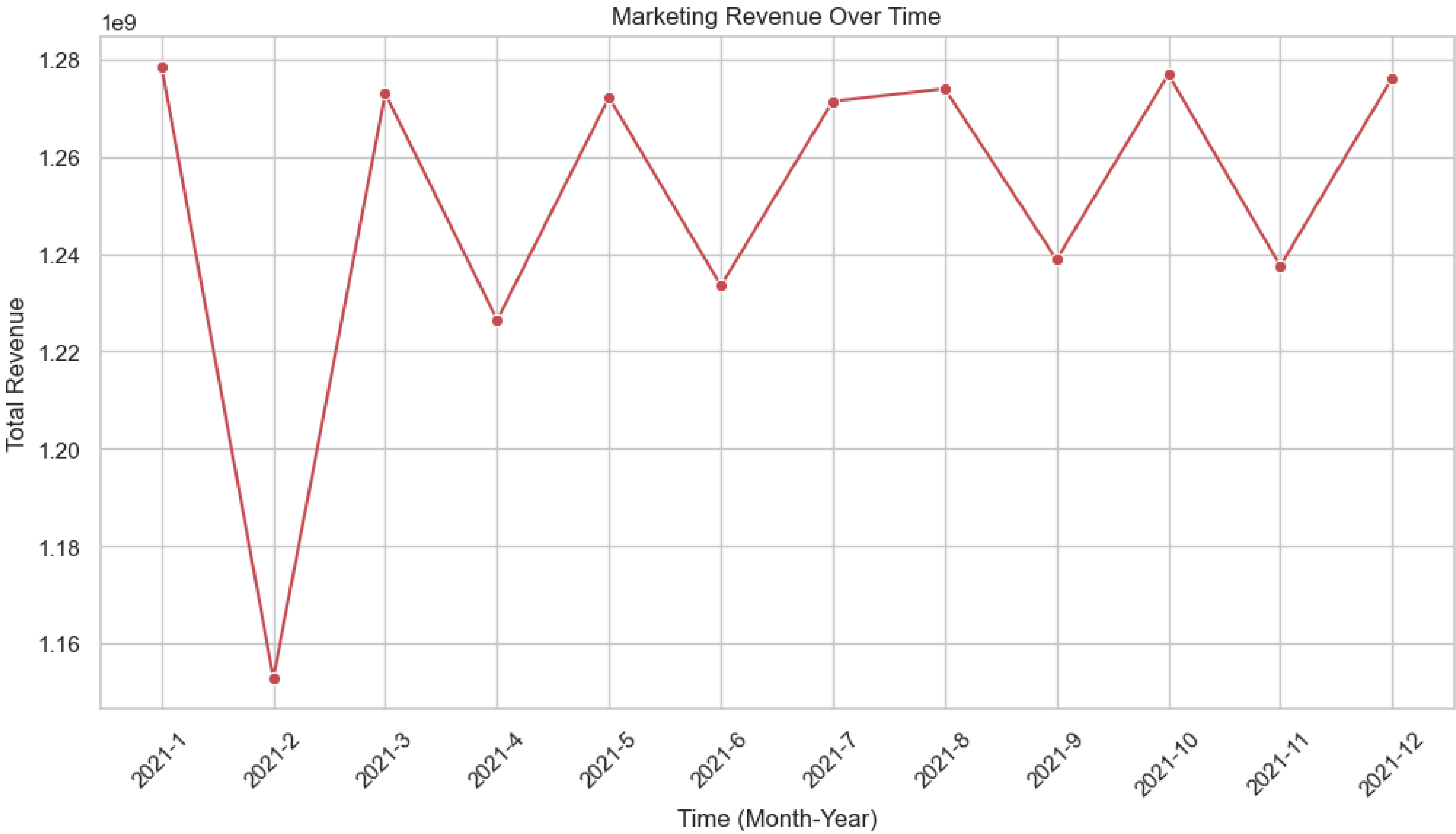
It is evident that the total Acquisition cost for the Month of July is significantly among the highest, yet it has the second lowest CTR, which could indicate inefficiencient Market Cost appropriation. The Same applies to June.
Hence, campaigns may need optimization.

In [479]:
```
# Visualization - ROI Over Time
plt.figure(figsize=(12, 6))
sns.lineplot(x="Month-Year", y="ROI", data=time_analysis, marker="o", color="g")
plt.title("Return on Investment (ROI) Over Time")
plt.xlabel("Time (Month-Year)")
plt.ylabel("ROI")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



The month of August has the lowest Return on Investment but has the highest amount of Acquisition Cost. Hence, it is advised to adjust marketing strategies by increase spending in high-performing periods to maximize campaign success

In [480]:
```
# Visualization - Revenue Over Time
plt.figure(figsize=(12, 6))
sns.lineplot(x="Month-Year", y="Revenue", data=time_analysis, marker="o", color="r")
plt.title("Marketing Revenue Over Time")
plt.xlabel("Time (Month-Year)")
plt.ylabel("Total Revenue")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



Overall Most Profitable Campaign type

In [481]:
```
market_cmp.groupby("Campaign_Type")["ROI"].mean().sort_values(ascending = False).reset_index()
```

Out[481]:

	Campaign_Type	ROI
0	Influencer	5.011040
1	Search	5.008357
2	Display	5.006497
3	Email	4.994274
4	Social Media	4.991781

On Average, Influencer are the best Campaign Type

Overall Campaign type & Marketing Channel with the most Click-Through Rate

In [482]:
```
market_cmp.groupby(["Campaign_Type", "Channel_Used" ])[["CTR", "ROI"]].mean().sort_values("CTR", ascending = False).reset_index().head(10)
```

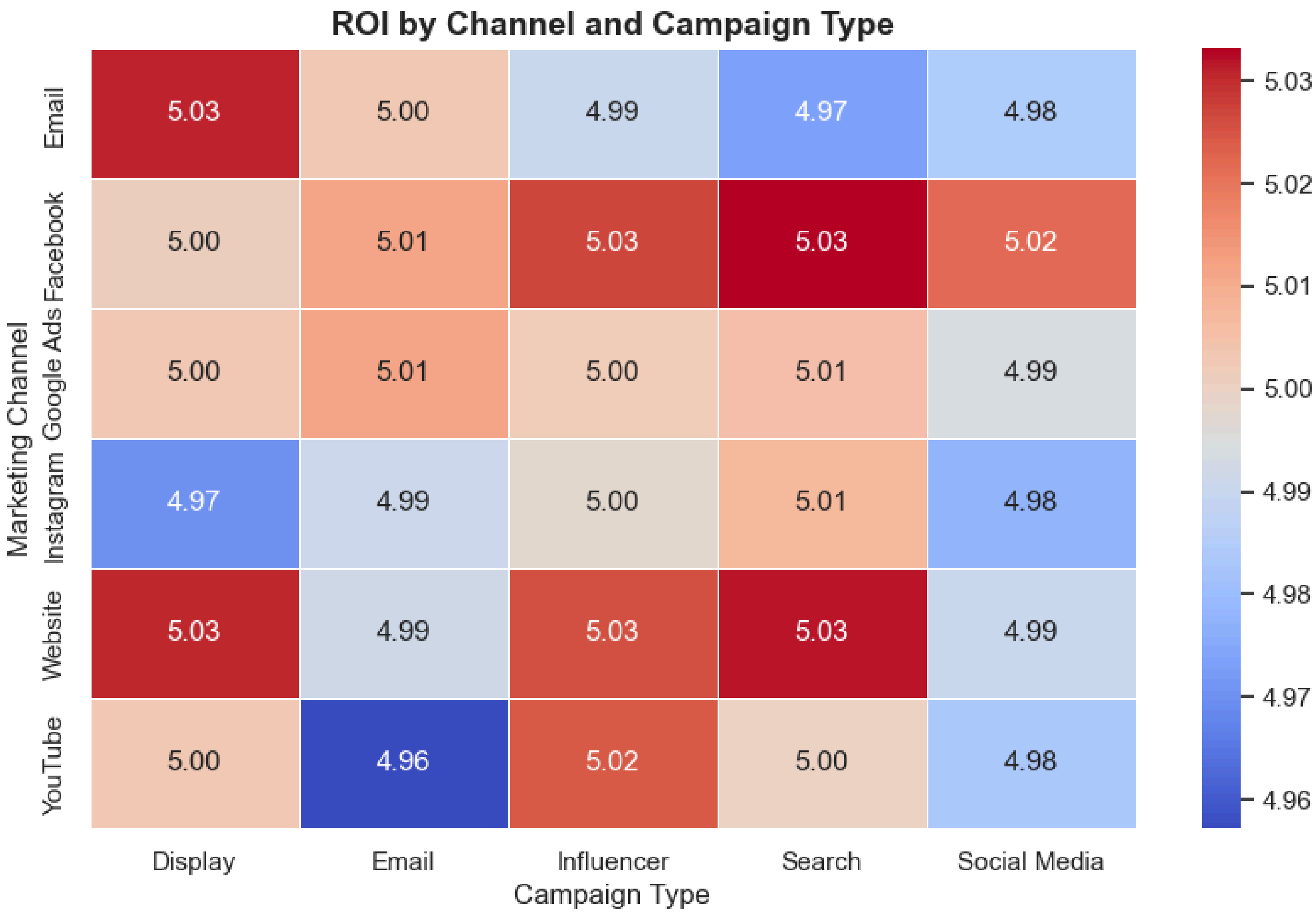
Out[482]:

	Campaign_Type	Channel_Used	CTR	ROI
0	Social Media	YouTube	14.407540	4.983104
1	Display	YouTube	14.375909	5.003317
2	Display	Email	14.210915	5.030919
3	Social Media	Email	14.187147	4.984613
4	Influencer	Facebook	14.162924	5.026686
5	Social Media	Facebook	14.142632	5.021544
6	Influencer	Website	14.124674	5.025426
7	Display	Website	14.121174	5.030686
8	Social Media	Website	14.113091	4.990242
9	Search	Website	14.101192	5.031826

The table shows which pair of the `Campaign_Type` and `Channel_Used` are most likely to increase engagement and ROI

In [483]:

```
# Pivot the data to structure it for the heatmap
heatmap_data = market_cmp.pivot_table(index="Channel_Used",
                                      columns="Campaign_Type",
                                      values="ROI",
                                      aggfunc="mean")

# Set figure size
plt.figure(figsize=(10, 6))

# Create the heatmap
sns.heatmap(heatmap_data, annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)

# Formatting
plt.title("ROI by Channel and Campaign Type", fontsize=14, fontweight="bold")
plt.xlabel("Campaign Type", fontsize=12)
plt.ylabel("Marketing Channel", fontsize=12)
plt.show()
```



High ROI Campaigns:

The Display and Website campaigns show the highest ROI across multiple marketing channels, indicating their effectiveness. Facebook (Influencer & Search campaigns) also perform well in terms of ROI

Low ROI Campaigns:

YouTube Email campaigns have the lowest ROI, suggesting they might not be as effective. Instagram and Social Media channels generally show lower ROI values compared to other platforms. Marketing Channel Effectiveness:

Email and Website channels tend to generate high ROI across various campaign types. Social Media and YouTube campaigns may require better targeting or improved

Target Audience with the most Click-Through Rate and Return On Investment

In [484]:
```
market_cmp.groupby("Target_Audience")[["CTR", "ROI"]].mean().sort_values("ROI", ascending = False).reset_index()
```

Out[484]:

	Target_Audience	CTR	ROI
0	Men 25-34	14.013255	5.020605
1	Women 35-44	14.057855	5.006371
2	All Ages	13.980318	5.005091
3	Women 25-34	14.103079	4.997351
4	Men 18-24	14.048126	4.982810

In [ ]:

Conclusion

In [ ]:

In [ ]:

In [ ]: