Online Advertising Performance Data

The dataset provides insights into the online advertising performance of a company, referred to as "Company X", from April 1, 2020, to June 30, 2020. The currency used for transactions is the US dollar.

Metrics:

Day: Date of the advertising campaign.

Campaign: A segmentation variable set by Company X to target specific groups of users with advertisements.

User Engagement: Indicates the level of engagement of users targeted by the advertising campaign.

Banner: Represents the size of the ad served by an advertising platform, referred to as "Advert Firm A".

Placement: Denotes the publisher space where the ad is served by "Advert Firm A", such as websites or apps.

Displays: The number of ads served by "Advert Firm A" during the campaign period.

Cost: The price paid by "Advert Firm A" to serve the ads to the publisher. It reflects the placement cost of the advertisements.

Clicks: The number of times users clicked on the advertisements during the campaign.

Revenue: The price paid by Company X to "Advert Firm A" for the clicks generated through the advertising campaign.

Post Click Conversions: Represents on-site transactions that occurred within the next 30 days after a user clicked on the advertisement.

Post Click Sales Amount: The monetary value of on-site transactions that occurred within the next 30 days after a user clicked on the advertisement.

Additional Information:

- **Engagement**: This variable signifies the type of users targeted by the campaign based on their behavior or characteristics.

- **Banner**: Defines the size of the advertisement or impression served to users.

- **Placement**: Specifies the website or app where the advertisement is being served, without disclosing the specific names of publishers.

Questions:

1. What is the overall trend in user engagement throughout the campaign period?
2. How does the size of the ad (banner) impact the number of clicks generated?
3. Which publisher spaces (placements) yielded the highest number of displays and clicks?
4. Is there a correlation between the cost of serving ads and the revenue generated from clicks?
5. What is the average revenue generated per click for Company X during the campaign period?
6. Which campaigns had the highest post-click conversion rates?
7. Are there any specific trends or patterns in post-click sales amounts over time?
8. How does the level of user engagement vary across different banner sizes?
9. Which placement types result in the highest post-click conversion rates?
10. Can we identify any seasonal patterns or fluctuations in displays and clicks throughout the campaign period?
11. Is there a correlation between user engagement levels and the revenue generated?
12. Are there any outliers in terms of cost, clicks, or revenue that warrant further investigation?
13. How does the effectiveness of campaigns vary based on the size of the ad and placement type?
14. Are there any specific campaigns or banner sizes that consistently outperform others in terms of ROI?
15. What is the distribution of post-click conversions across different placement types?
16. Are there any noticeable differences in user engagement levels between weekdays and weekends?
17. How does the cost per click (CPC) vary across different campaigns and banner sizes?
18. Are there any campaigns or placements that are particularly cost-effective in terms of generating post-click conversions?
19. Can we identify any trends or patterns in post-click conversion rates based on the day of the week?
20. How does the effectiveness of campaigns vary throughout different user engagement types in terms of post-click conversions?

<u>SOLUTION- Ankit Sankar</u>

Step 1: Import Libraries

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import scipy.stats as stats
```

Step 2: Cleaning of data(Including feature engineering)

Code:

```
file_path = '/content/online_advertising_performance_data.csv'

data = pd.read_csv(file_path)

# Check for missing values

print(data.isnull().sum())


data_cleaned = data.dropna()

data_cleaned = data.fillna(0)
```

```
month                          0
day                            0
campaign_number                0
user_engagement                0
banner                         0
placement                    413
displays                       0
cost                           0
clicks                         0
revenue                        0
post_click_conversions         0
post_click_sales_amount        0
Unnamed: 12                15408
Unnamed: 13                15408
dtype: int64
```

Next, Convert relevant columns to numeric types

<u>Code:</u>

```
data_cleaned = data_cleaned.drop_duplicates()

data_cleaned.reset_index(drop=True, inplace=True)

data_cleaned.to_csv('cleaned_data.csv', index=False)

data = pd.read_csv('/content/cleaned_data.csv')

print(data.head())

print(data.info())
```

```
   month  day campaign_number user_engagement     banner placement  displays  \
0  April    1          camp 1            High  160 x 600       abc         4   
1  April    1          camp 1            High  160 x 600       def     20170   
2  April    1          camp 1            High  160 x 600       ghi     14701   
3  April    1          camp 1            High  160 x 600       mno    171259   
4  April    1          camp 1             Low  160 x 600       def       552   

       cost  clicks   revenue  post_click_conversions  \
0    0.0060       0    0.0000                       0   
1   26.7824     158   28.9717                      23   
2   27.6304     158   28.9771                      78   
3  216.8750    1796  329.4518                     617   
4    0.0670       1    0.1834                       0   

   post_click_sales_amount  Unnamed: 12  Unnamed: 13  
0                   0.0000          0.0          0.0  
1                1972.4602          0.0          0.0  
2                2497.2636          0.0          0.0  
3               24625.3234          0.0          0.0  
4                   0.0000          0.0          0.0  
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15403 entries, 0 to 15402
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   month                    15403 non-null  object 
 1   day                      15403 non-null  int64  
 2   campaign_number          15403 non-null  object 
 3   user_engagement          15403 non-null  object 
 4   banner                   15403 non-null  object 
 5   placement                15403 non-null  object 
 6   displays                 15403 non-null  int64  
 7   cost                     15403 non-null  float64
 8   clicks                   15403 non-null  int64  
 9   revenue                  15403 non-null  float64
 10  post_click_conversions   15403 non-null  int64  
 11  post_click_sales_amount  15403 non-null  float64
 12  Unnamed: 12              15403 non-null  float64
 13  Unnamed: 13              15403 non-null  float64
dtypes: float64(5), int64(4), object(5)
memory usage: 1.6+ MB
None
```

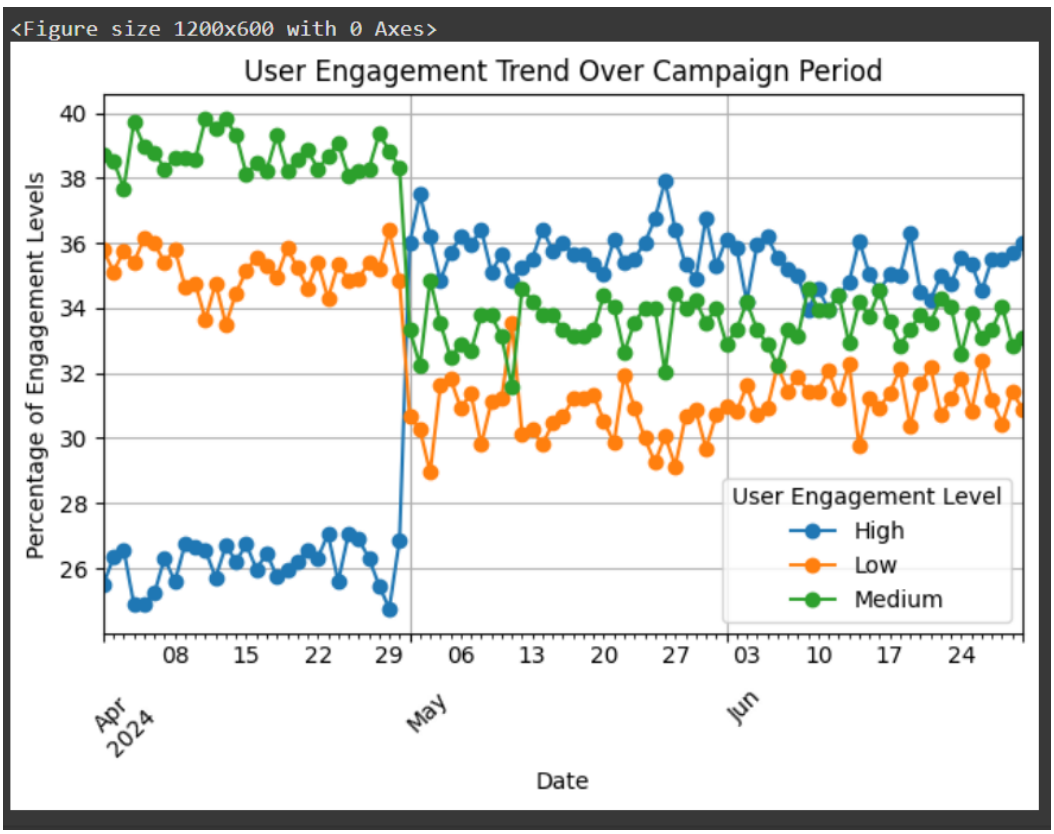
Information is saved in a file named “**cleaned_data.csv**”

Q1) What is the overall trend in user engagement throughout the campaign period?

Code:

```
data = pd.read_csv('cleaned_data.csv')


month_mapping = {
    'January': 1,
    'February': 2,
    'March': 3,
    'April': 4,
    'May': 5,
    'June': 6,
    'July': 7,
    'August': 8,
    'September': 9,
    'October': 10,
    'November': 11,
    'December': 12
}


data['month'] = data['month'].map(month_mapping)


data['date'] = pd.to_datetime(data[['month', 'day']].assign(year=2024))



engagement_trend = data.groupby(['date', 'user_engagement']).size().unstack(fill_value=0)
```

```
engagement_percentage = engagement_trend.div(engagement_trend.sum(axis=1), axis=0) * 100

plt.figure(figsize=(12, 6))
engagement_percentage.plot(kind='line', marker='o')
plt.title('User Engagement Trend Over Campaign Period')
plt.xlabel('Date')
plt.ylabel('Percentage of Engagement Levels')
plt.xticks(rotation=45)
plt.legend(title='User Engagement Level')
plt.tight_layout()
plt.grid()
plt.show()
```



Ans) The campaign slowly becomes successful as more people are finding the campaign to be relevant,

A significant change occurs around late April to early May, where:

- High engagement increases.
- Low engagement decreases.
- Medium engagement remains relatively stable.

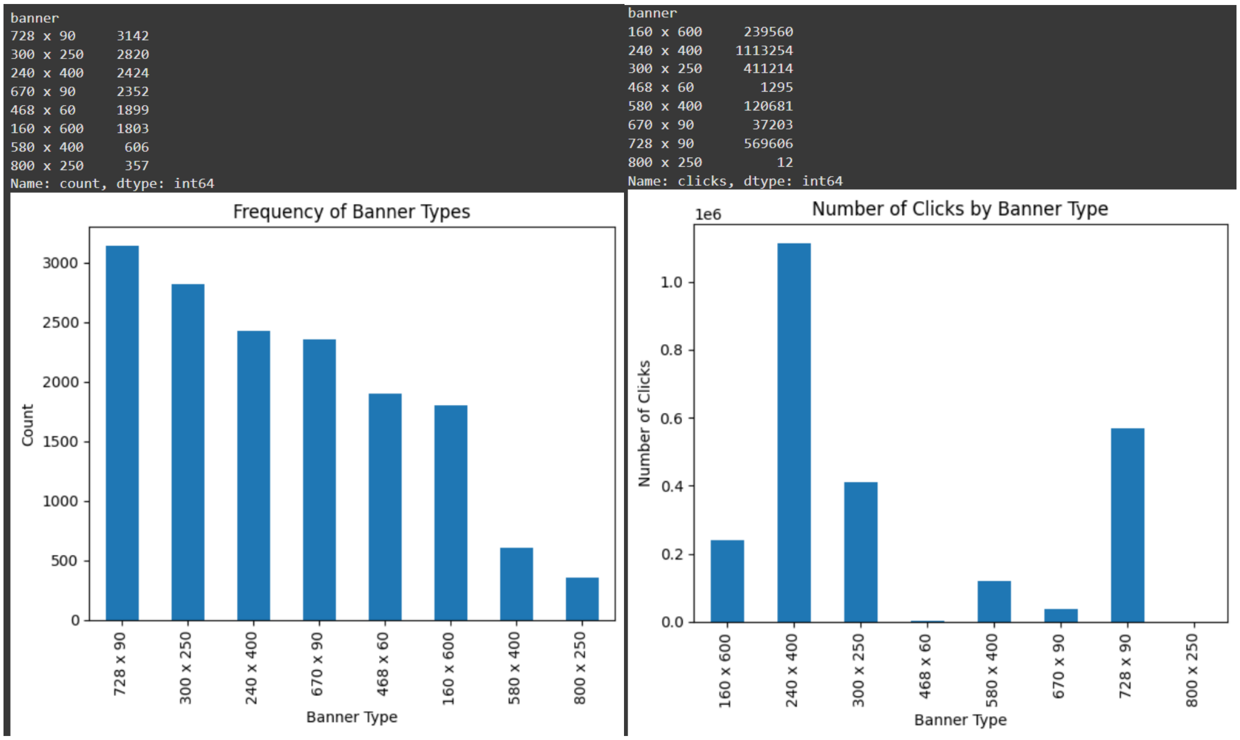
An improvement in high engagement and a reduction in low engagement post-May, suggesting the campaign's positive impact on user interaction.

Q2) How does the size of the ad (banner) impact the number of clicks generated?

Code:

```
banner_counts = data['banner'].value_counts()


print(banner_counts)

banner_counts.plot(kind='bar')

plt.title('Frequency of Banner Types')

plt.xlabel('Banner Type')

plt.ylabel('Count')

plt.show()


clicked_by_banner = data.groupby('banner')['clicks'].sum()

print(clicked_by_banner)

clicked_by_banner.plot(kind='bar')

plt.title('Number of Clicks by Banner Type')

plt.xlabel('Banner Type')

plt.ylabel('Number of Clicks')
```

plt.show()



Ans) **<u>Top Performers:</u>**

- 240 x 400: Attracts the most clicks, indicating it is highly engaging or well-placed.
- 728 x 90 and 300 x 250: Also effective in generating significant user clicks.

<u>Low Performers:</u>

- 800 x 250 and 468 x 60: Extremely low click counts suggest poor design, placement, or audience fit.
- 670 x 90 also shows limited engagement.

Medium-sized banners like 240 x 400 and 728 x 90 appear to be more effective.

Larger banners like 800 x 250 and unconventional dimensions like 468 x 60 perform poorly and may need reconsideration in campaigns.

Q3)Which publisher spaces (placements) yielded the highest number of displays and clicks?

<u>Code:</u>

```
placement_performance = data.groupby('placement')[['displays', 'clicks']].sum()


top_displays = placement_performance['displays'].sort_values(ascending=False)

top_clicks = placement_performance['clicks'].sort_values(ascending=False)


top_displays.head(), top_clicks.head()
```

```
(placement
 mno    143159537
 ghi     59740398
 def     28176283
 jkl      7692732
 abc       242142
 Name: displays, dtype: int64,
 placement
 ghi    1247049
 mno     993029
 def     176095
 jkl      75063
 abc       1584
 Name: clicks, dtype: int64)
```

Ans)Highest Displays:

- mno: 143,164,944 displays,
- ghi: 59,740,415 displays,
- def: 28,177,492 displays

Highest Clicks:

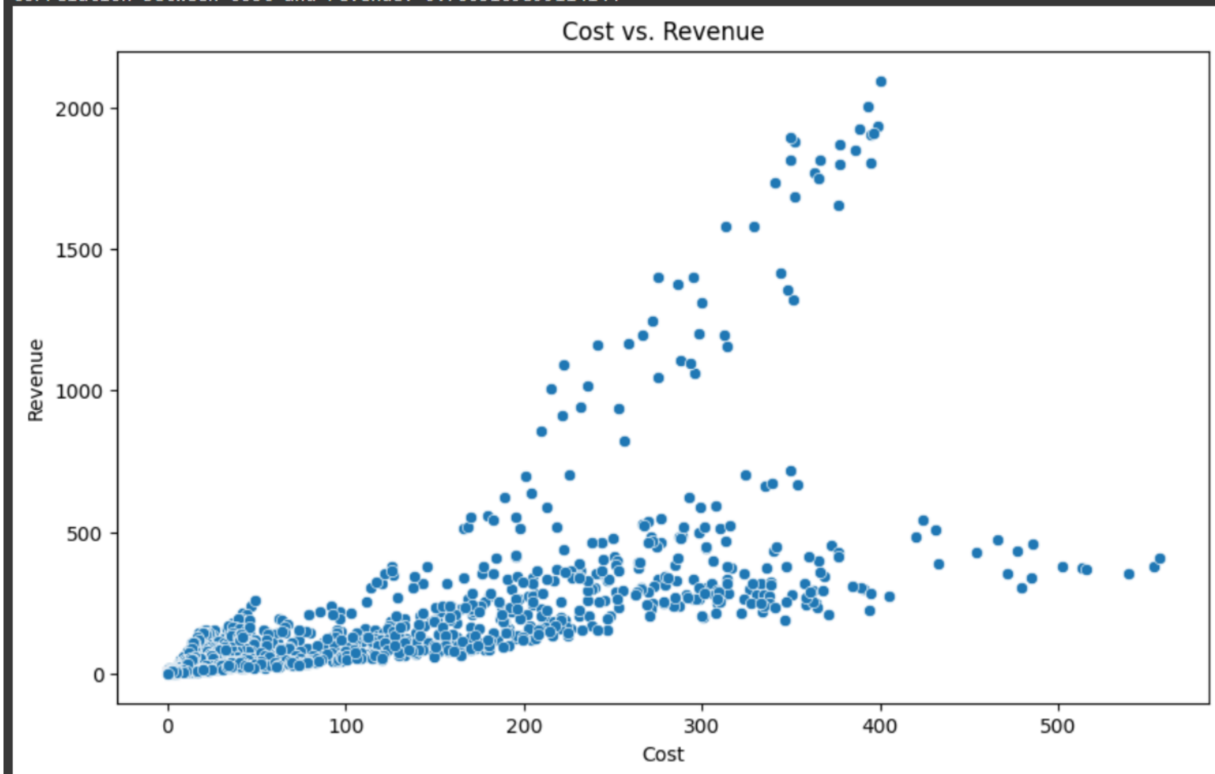
- ghi: 1,247,049 clicks,
- mno: 993,044 clicks,
- def: 176,097 clicks

Q4) Is there a correlation between the cost of serving ads and the revenue generated from clicks?

Code:

```
correlation = data['cost'].corr(data['revenue'])

print("Correlation between cost and revenue:", correlation)



plt.figure(figsize=(10, 6))

sns.scatterplot(x='cost', y='revenue', data=data)

plt.title('Cost vs. Revenue')

plt.xlabel('Cost')

plt.ylabel('Revenue')

plt.show()


pearson_corr, p_value = stats.pearsonr(data['cost'], data['revenue'])

print("Pearson Correlation Coefficient:", pearson_corr)

print("p-value:", p_value)


if p_value < 0.05:

   print("There is a significant correlation between cost and revenue.")

else:

   print("There is no significant correlation between cost and revenue.")
```

```
Correlation between cost and revenue: 0.7605169899114144
```




```
Pearson Correlation Coefficient: 0.7605169899114147
p-value: 0.0
There is a significant correlation between cost and revenue.
```

Ans)The correlation between the cost of serving ads and the revenue generated from clicks is approximately 0.76, indicating a strong positive relationship. Higher advertising costs are generally associated with higher revenues.

Q5)What is the average revenue generated per click for Company X during the campaign period?

Code:

total_revenue = data['revenue'].sum()

total_clicks = data['clicks'].sum()

average_revenue_per_click = total_revenue / total_clicks if total_clicks > 0 else 0

total_revenue, total_clicks, average_revenue_per_click

```
The total revenue is:  276262.6159 The total Clicks:  2492825 Avg Clicks: 0.1108231086819171
```

ANS) The avg revenue per click for Company X is: 0.1108231

Q6)Which campaigns had the highest post-click conversion rates?

<u>Code:</u>

```
data = pd.read_csv('cleaned_data.csv')

data = data[data['clicks'] != 0].copy()

data['conversion_rate'] = data['post_click_conversions'] / data['clicks']


top_campaigns = data.sort_values(by='conversion_rate', ascending=False)


print("Top campaigns by conversion rate:")

print(top_campaigns[['campaign_number', 'conversion_rate']].head())
```

```
Top campaigns by conversion rate:
      campaign_number  conversion_rate
11491          camp 1             16.0
13354          camp 1              9.0
14621          camp 1              9.0
14742          camp 1              9.0
7674           camp 1              8.0
```

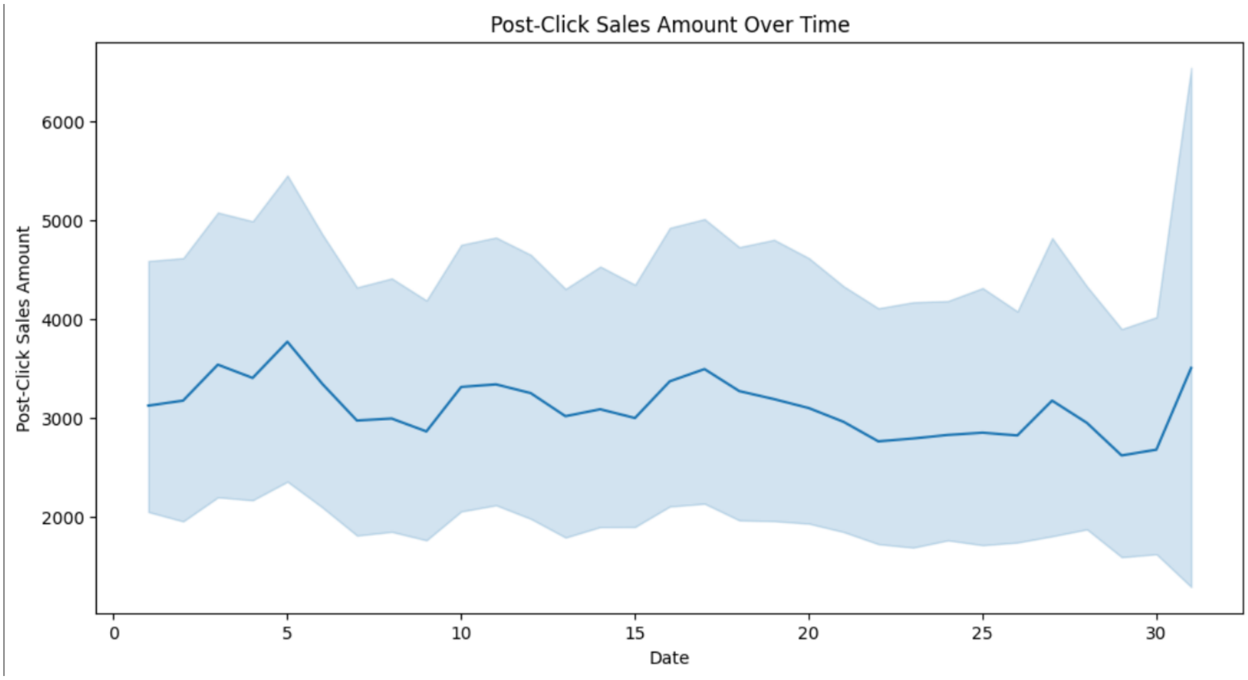
Ans) Campaign 11491 from "camp 1" has the highest post-click conversion rate at 16%, followed by others in the same campaign with rates of 9% and 8%.

Q7)Are there any specific trends or patterns in post-click sales amounts over time?

<u>Code:</u>

```
data.set_index('day', inplace=True)
```

```
plt.figure(figsize=(12, 6))

sns.lineplot(data=data['post_click_sales_amount'])

plt.title('Post-Click Sales Amount Over Time')

plt.xlabel('Date')

plt.ylabel('Post-Click Sales Amount')

plt.show()
```



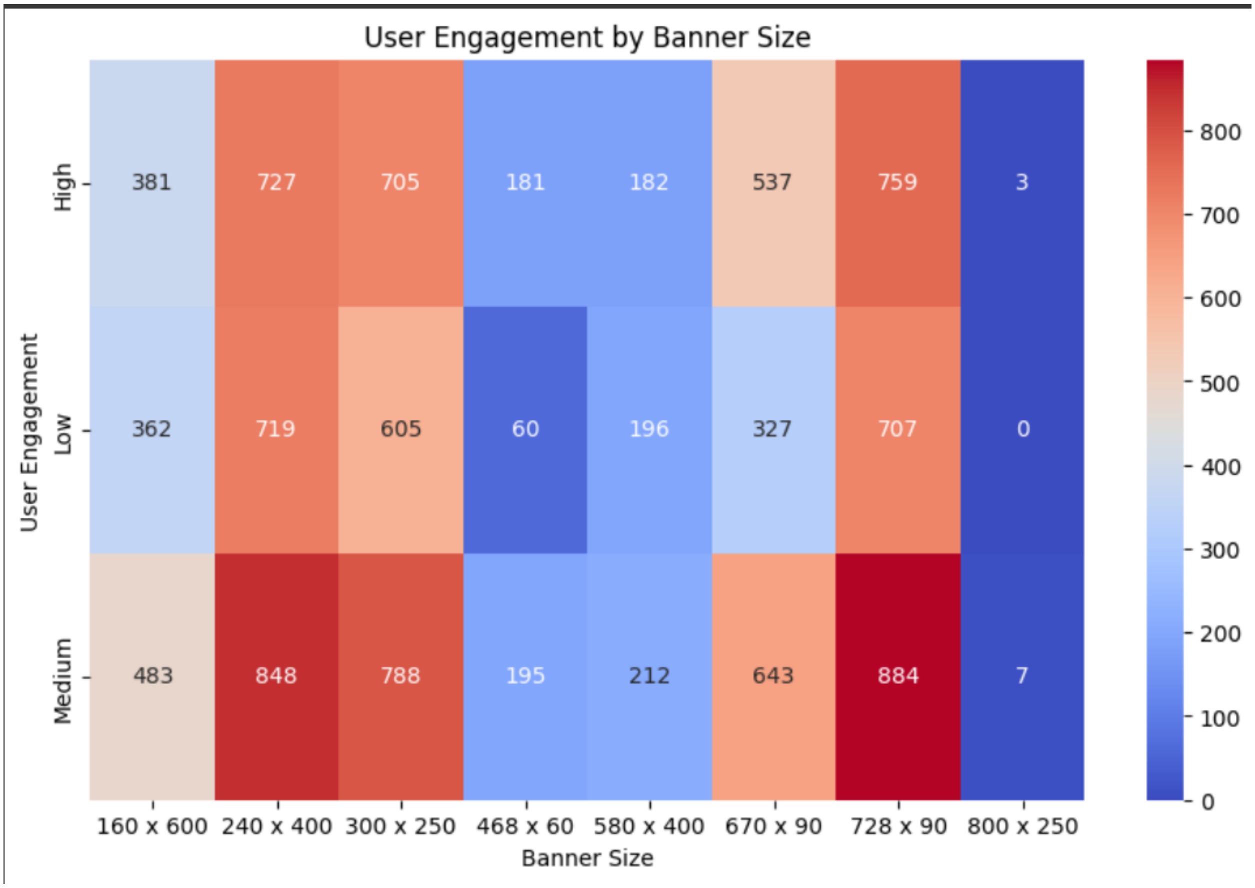
Ans) The post-click sales amounts show some fluctuation over time, with a general consistency in the middle period and a noticeable spike toward the end. The shaded area suggests variability, with larger deviations occurring at specific points.

Q8)How does the level of user engagement vary across different banner sizes?

Code:

```
cross_tab = pd.crosstab(data['user_engagement'], data['banner'])


plt.figure(figsize=(10, 6))

sns.heatmap(cross_tab, annot=True, fmt='d', cmap='coolwarm')
```

```
plt.title('User Engagement by Banner Size')

plt.xlabel('Banner Size')

plt.ylabel('User Engagement')

plt.show()
```



Ans) User engagement varies significantly across banner sizes, with the 240 x 400 and 728 x 90 banners showing the highest engagement, particularly for medium engagement levels. Smaller banners like 468 x 60 tend to have lower engagement overall.

Q9) Which placement types result in the highest post-click conversion rates?

<u>Code:</u>

```
data = data[data['clicks'] != 0].copy()


data['conversion_rate'] = data['post_click_conversions'] / data['clicks']
```

placement_conversion_rates = data.groupby('placement'] /
['conversion_rate'].mean().reset_index()

top_placements = placement_conversion_rates.sort_values(by='conversion_rate',
ascending=False)

print("Top placements by conversion rate:")

print(top_placements)

```
Top placements by conversion rate:
  placement  conversion_rate
1       abc         0.301971
4       jkl         0.224332
3       ghi         0.187649
5       mno         0.182309
2       def         0.152488
0         0         0.000000
```

Ans) The "abc" placement type has the highest conversion rate

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Q10) Can we identify any seasonal patterns or fluctuations in displays and clicks throughout the campaign period?

<u>Code:</u>

plt.figure(figsize=(12, 6))

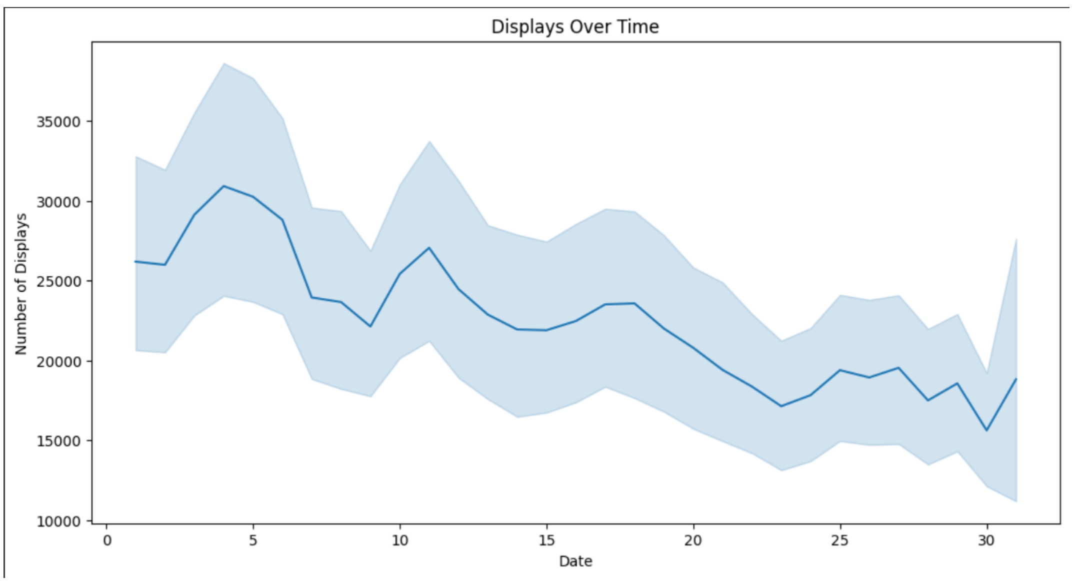
sns.lineplot(data=data['displays'])

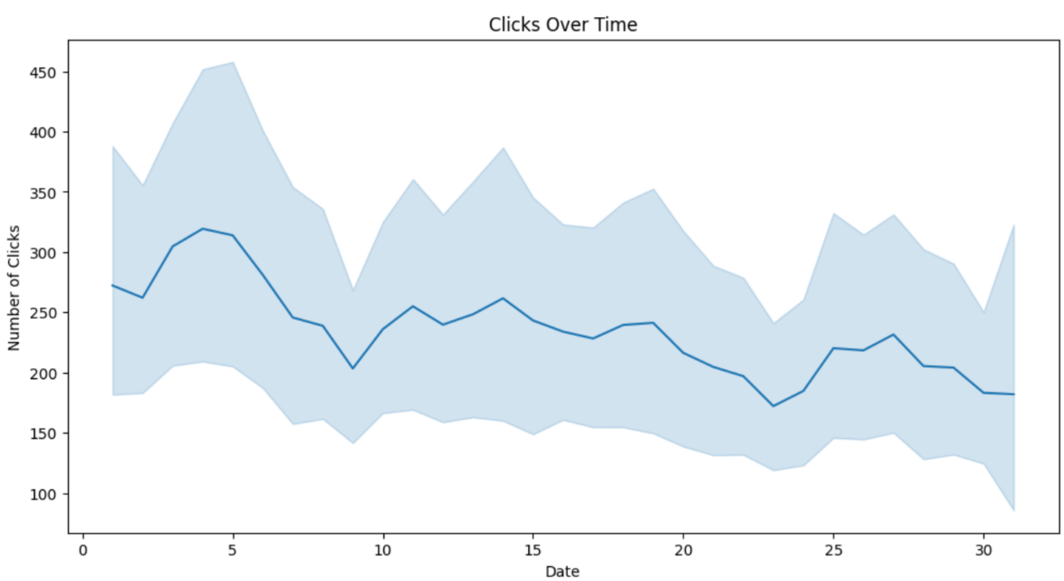
plt.title('Displays Over Time')

plt.xlabel('Date')

plt.ylabel('Number of Displays')

```
plt.show()

plt.figure(figsize=(12, 6))
sns.lineplot(data=data['clicks'])
plt.title('Clicks Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Clicks')
plt.show()
```





Ans)It shows that both clicks and displays exhibit a declining trend throughout the campaign period. Initially, there is a noticeable peak in both metrics, followed by a steady decrease. Displays experience a sharper decline, which might indicate factors such as reduced ad exposure, budget limitations, or audience fatigue.

Clicks, while following a similar pattern, stabilize after the initial drop, implying that user engagement remains relatively consistent despite fewer impressions. Peaks and troughs in both graphs align, highlighting a strong correlation between displays and clicks, where higher impressions generally lead to more user interactions.

This suggests engagement is directly tied to visibility.

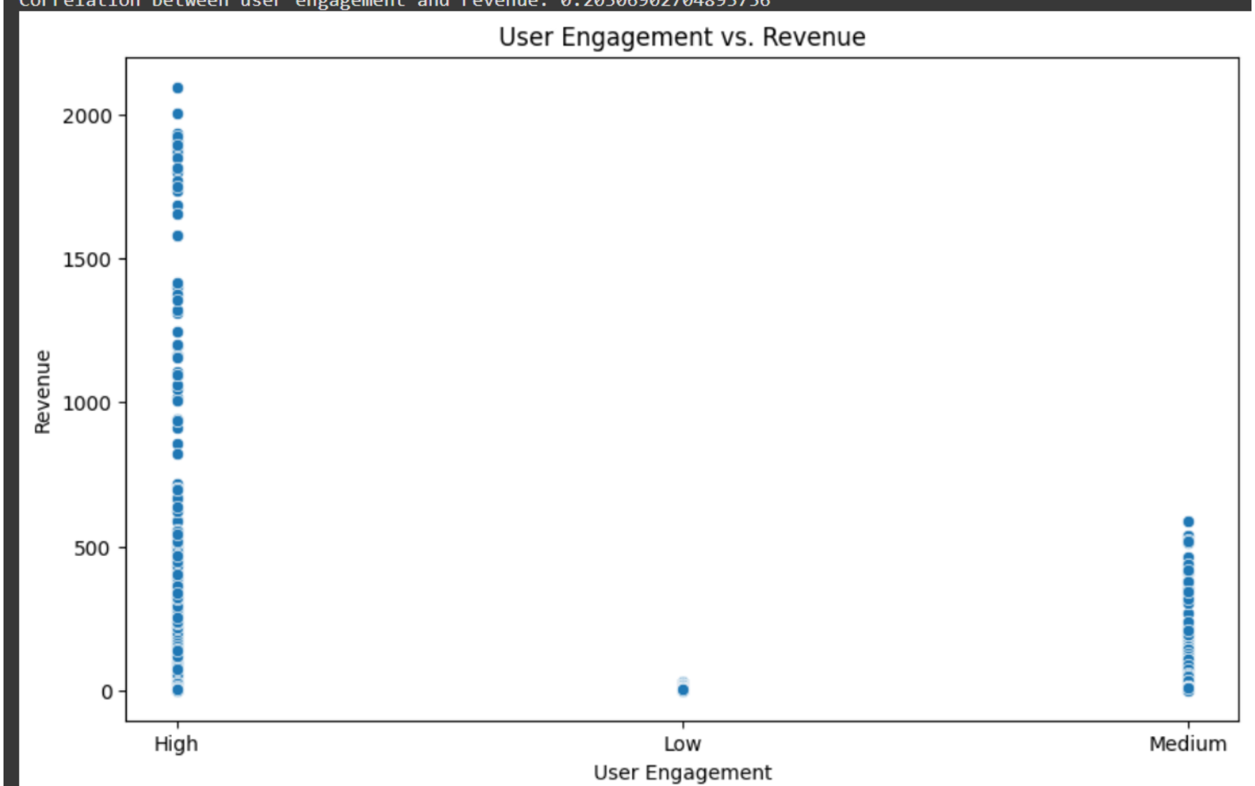
Q11) Is there a correlation between user engagement levels and the revenue generated?

<u>Code:</u>

```
data['engagement_level'] = data['user_engagement'].map({'Low': 1, 'Medium': 2, 'High': 3})

correlation = data['engagement_level'].corr(data['revenue'])
print("Correlation between user engagement and revenue:", correlation)



plt.figure(figsize=(10, 6))
sns.scatterplot(x='user_engagement', y='revenue', data=data)
plt.title('User Engagement vs. Revenue')
plt.xlabel('User Engagement')
plt.ylabel('Revenue')
plt.show()
```

```
pearson_corr, p_value = stats.pearsonr(data['engagement_level'], data['revenue'])

print("Pearson Correlation Coefficient:", pearson_corr)

print("p-value:", p_value)


if p_value < 0.05:

   print("There is a significant correlation between user engagement and revenue.")

else:

   print("There is no significant correlation between user engagement and revenue.")
```

```
Correlation between user engagement and revenue: 0.20306902704893756
```




```
Pearson Correlation Coefficient: 0.2030690270489378
p-value: 3.0501734719630487e-98
There is a significant correlation between user engagement and revenue.
```

Ans)The data suggests that while there is a positive relationship between user engagement and revenue, it's not a very strong one.

Q12) Are there any outliers in terms of cost, clicks, or revenue that warrant further investigation?

Code:

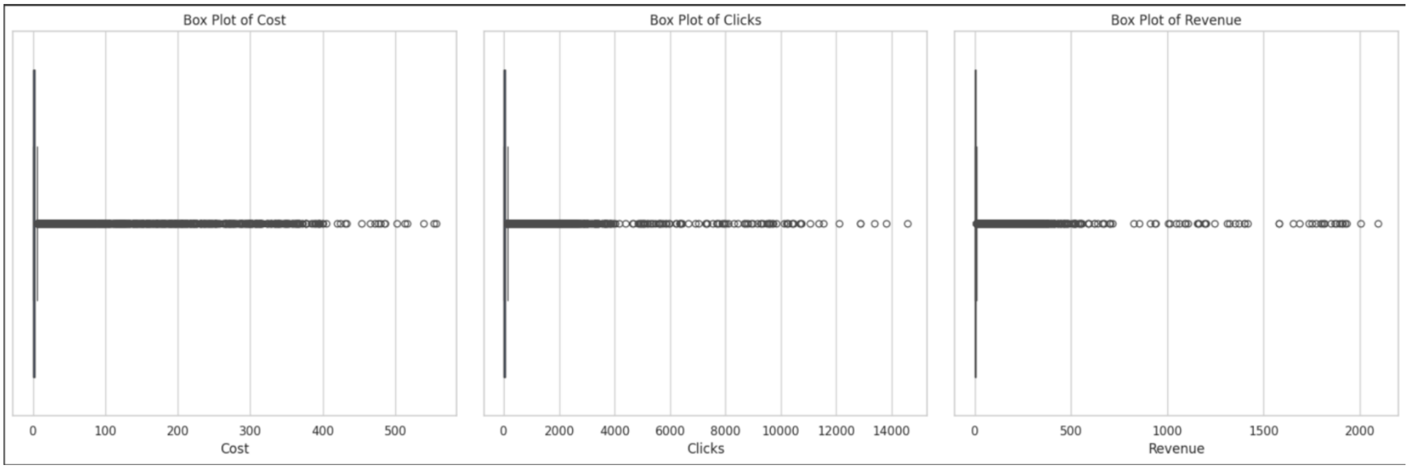
```
data = pd.read_csv('/content/cleaned_data.csv')

# Function to detect outliers using IQR method

def detect_outliers(df, column):

    Q1 = df[column].quantile(0.25)

    Q3 = df[column].quantile(0.75)

    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR

    upper_bound = Q3 + 1.5 * IQR

    return df[(df[column] < lower_bound) | (df[column] > upper_bound)]


cost_outliers = detect_outliers(data, 'cost')

clicks_outliers = detect_outliers(data, 'clicks')

revenue_outliers = detect_outliers(data, 'revenue')


print("Cost Outliers:")

print(cost_outliers)


print("\nClicks Outliers:")

print(clicks_outliers)


print("\nRevenue Outliers:")
```

print(revenue_outliers)

```
Cost Outliers:
       month  day campaign_number user_engagement     banner placement  \
1      April    1          camp 1            High  160 x 600       def
2      April    1          camp 1            High  160 x 600       ghi
3      April    1          camp 1            High  160 x 600       mno
9      April    1          camp 1          Medium  160 x 600       mno
10     April    1          camp 1            High  240 x 400       def
...      ...  ...             ...             ...        ...       ...
15320   June   30          camp 1            High   728 x 90       ghi
15322   June   30          camp 1            High   728 x 90       mno
15331   June   30          camp 1          Medium   728 x 90       ghi
15337   June   30          camp 3            High  240 x 400       ghi
15352   June   30          camp 3            High  300 x 250       mno

       displays      cost  clicks   revenue  post_click_conversions  \
1         20170   26.7824     158   28.9717                      23
2         14701   27.6304     158   28.9771                      78
3        171259  216.8750    1796  329.4518                     617
9         20152   11.1678     185   33.9397                      13
10        56499   50.5157     309   56.6775                     105
...         ...       ...     ...       ...                     ...
15320    117364  208.0751    1235  139.0000                     789
15322    147455  105.7007     649   73.0000                     424
15331      4792    8.3755     113   12.7235                      11
15337      6556    6.6968      65    3.6596                      15
15352     27927    9.0831      80    4.5038                       7

       post_click_sales_amount  Unnamed: 12  Unnamed: 13
1                    1972.4602          0.0          0.0
2                    2497.2636          0.0          0.0
3                   24625.3234          0.0          0.0
9                     653.1896          0.0          0.0
10                   4288.6699          0.0          0.0
...                        ...          ...          ...
15320               37919.1960          0.0          0.0
15322               17025.8546          0.0          0.0
15331                 653.6581          0.0          0.0
15337                 607.8665          0.0          0.0
15352                 690.0245          0.0          0.0

[2515 rows x 14 columns]
```

```
Clicks Outliers:
       month  day campaign_number user_engagement     banner placement  \
1      April    1          camp 1            High  160 x 600       def
2      April    1          camp 1            High  160 x 600       ghi
3      April    1          camp 1            High  160 x 600       mno
9      April    1          camp 1          Medium  160 x 600       mno
10     April    1          camp 1            High  240 x 400       def
...      ...  ...             ...             ...        ...       ...
15304   June   30          camp 1            High  580 x 400       mno
15320   June   30          camp 1            High   728 x 90       ghi
15322   June   30          camp 1            High   728 x 90       mno
15362   June   30          camp 3          Medium  300 x 250       mno
15401   June   30          camp 3          Medium   728 x 90       mno

       displays      cost  clicks   revenue  post_click_conversions  \
1         20170   26.7824     158   28.9717                      23
2         14701   27.6304     158   28.9771                      78
3        171259  216.8750    1796  329.4518                     617
9         20152   11.1678     185   33.9397                      13
10        56499   50.5157     309   56.6775                     105
...         ...       ...     ...       ...                     ...
15304     27059   45.4395     229   25.0000                     316
15320    117364  208.0751    1235  139.0000                     789
15322    147455  105.7007     649   73.0000                     424
15362     49675    4.8145     182   10.2462                       0
15401     37790    2.6023     195   10.9785                       0

       post_click_sales_amount  Unnamed: 12  Unnamed: 13
1                    1972.4602          0.0          0.0
2                    2497.2636          0.0          0.0
3                   24625.3234          0.0          0.0
9                     653.1896          0.0          0.0
10                   4288.6699          0.0          0.0
...                        ...          ...          ...
15304               15489.0316          0.0          0.0
15320               37919.1960          0.0          0.0
15322               17025.8546          0.0          0.0
15362                   0.0000          0.0          0.0
15401                   0.0000          0.0          0.0

[2325 rows x 14 columns]
```

```
sns.set(style="whitegrid")

fig, axes = plt.subplots(1, 3, figsize=(18, 6))

sns.boxplot(ax=axes[0], x=data['cost'])
axes[0].set_title('Box Plot of Cost')
axes[0].set_xlabel('Cost')

sns.boxplot(ax=axes[1], x=data['clicks'])
axes[1].set_title('Box Plot of Clicks')
axes[1].set_xlabel('Clicks')

sns.boxplot(ax=axes[2], x=data['revenue'])
axes[2].set_title('Box Plot of Revenue')
axes[2].set_xlabel('Revenue')


plt.tight_layout()
plt.show()
```



Ans)

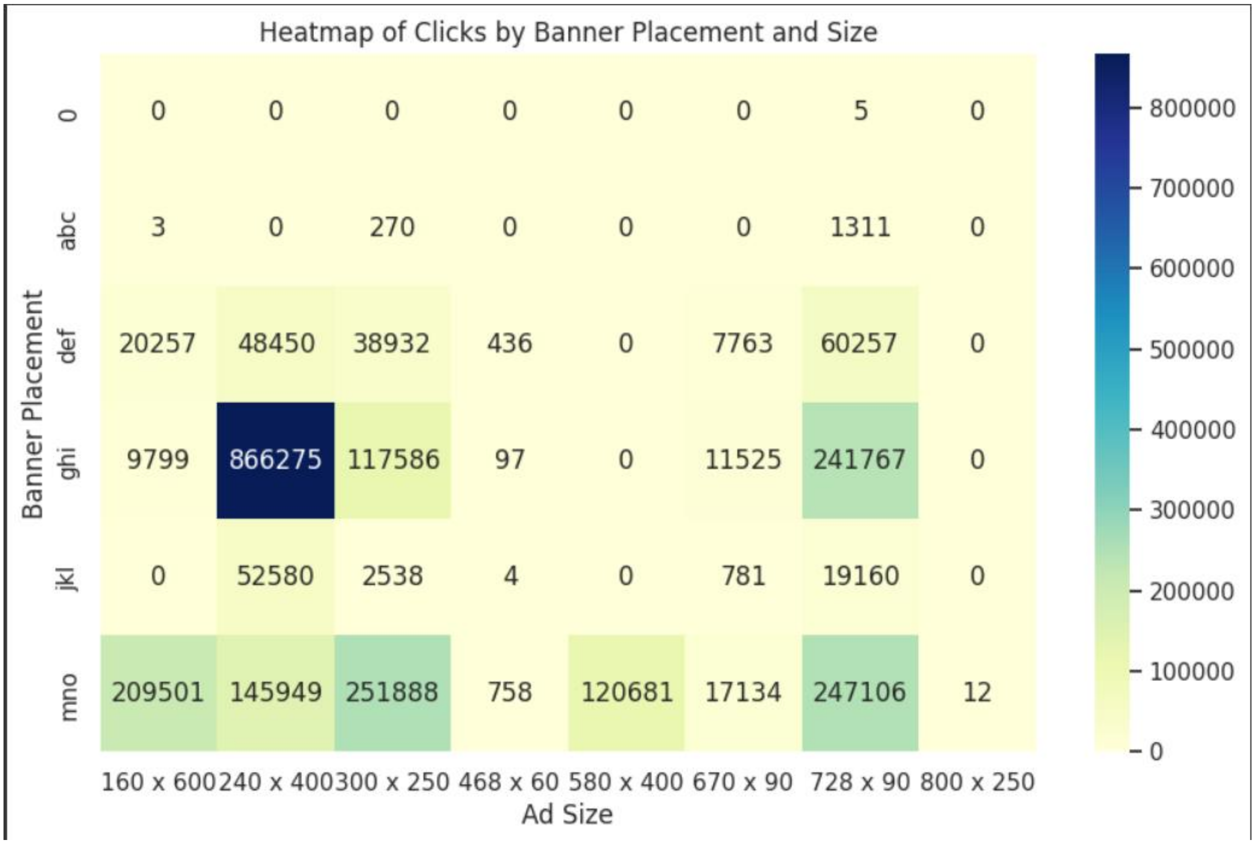
- **Cost:** The box plot for cost indicates a significant number of outliers above the upper whisker.
- **Clicks:** Similarly, the clicks box plot shows many outliers far above the upper whisker, representing campaigns or instances with unusually high click counts. These might indicate very successful campaigns
- **Revenue:** The revenue box plot also has a notable number of outliers above the upper whisker, reflecting instances of high revenue.

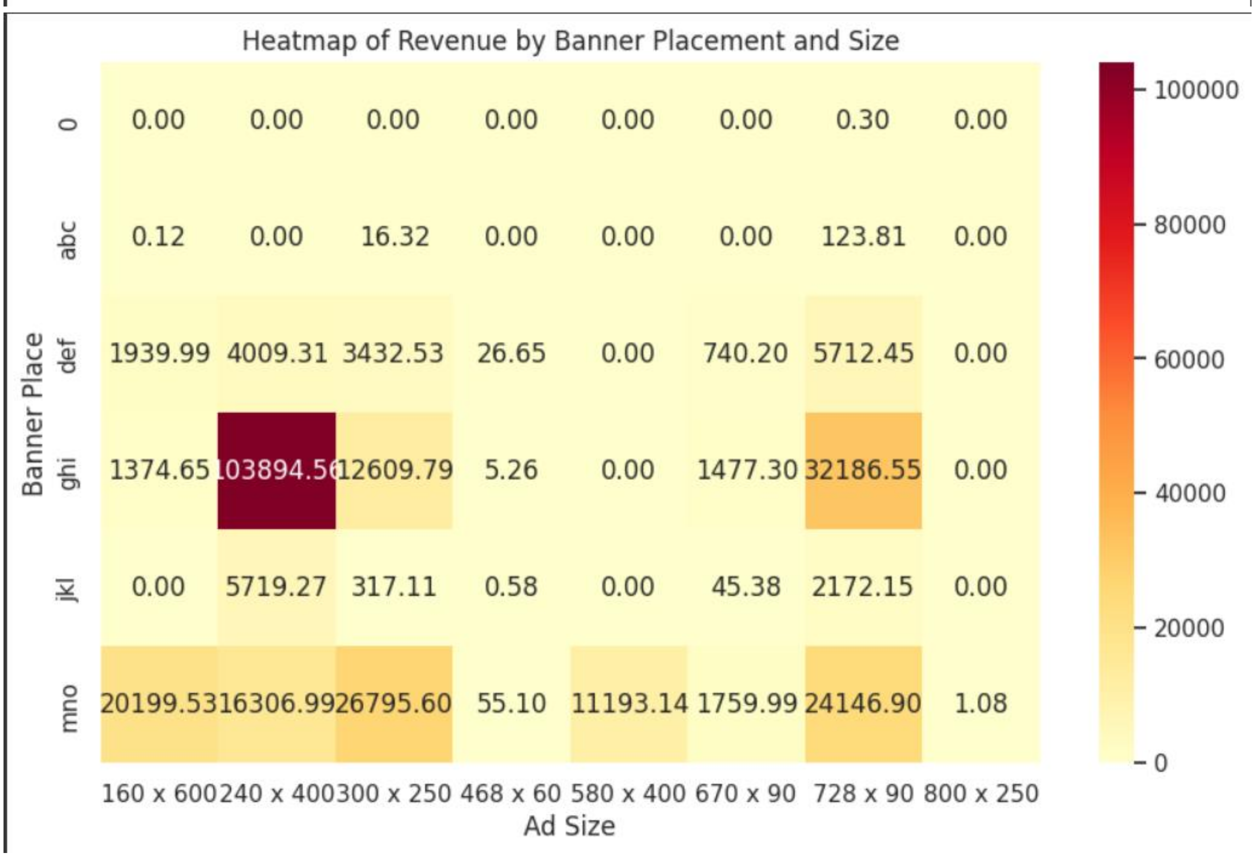
Q13) How does the effectiveness of campaigns vary based on the size of the ad and placement type?

Code:

```
data['banner'] = data['banner'].astype('category')

data['placement'] = data['placement'].astype('category')


data = data[data['clicks'] != 0].copy()

data['conversion_rate'] = data['post_click_conversions'] / data['clicks']


heatmap_data = data.pivot_table(values='clicks',
```

```
                      index='placement',
                      columns='banner',
                      aggfunc='sum').fillna(0)

plt.figure(figsize=(10,6))
sns.heatmap(heatmap_data, annot=True, fmt=".0f", cmap="YlGnBu")
plt.title('Heatmap of Clicks by Banner Placement and Size')
plt.xlabel('Ad Size')
plt.ylabel('Banner Placement')
plt.show()

heatmap_revenue_data = data.pivot_table(values='revenue',
                            index='placement',
                            columns='banner',
                         aggfunc='sum').fillna(0)

plt.figure(figsize=(10,6))
sns.heatmap(heatmap_revenue_data, annot=True, fmt=".2f", cmap="YlOrRd")
plt.title('Heatmap of Revenue by Banner Placement and Size')
plt.xlabel('Ad Size')
plt.ylabel('Banner Place')
plt.show()
```





Ans) Placement ghi:

- Ad size 240 × 400 has the highest clicks (~866,275) and revenue (~103,894.56), making it the most effective combination.

Placement mno:

- Ad sizes 300 × 250 and 728 × 90 perform well in clicks (~251,888 and ~247,106) and generate significant revenue (~26,795.60 and ~24,146.90).

Overall:

- Larger ad sizes (240 × 400, 300 × 250, 728 × 90) perform better, especially in placements ghi and mno.

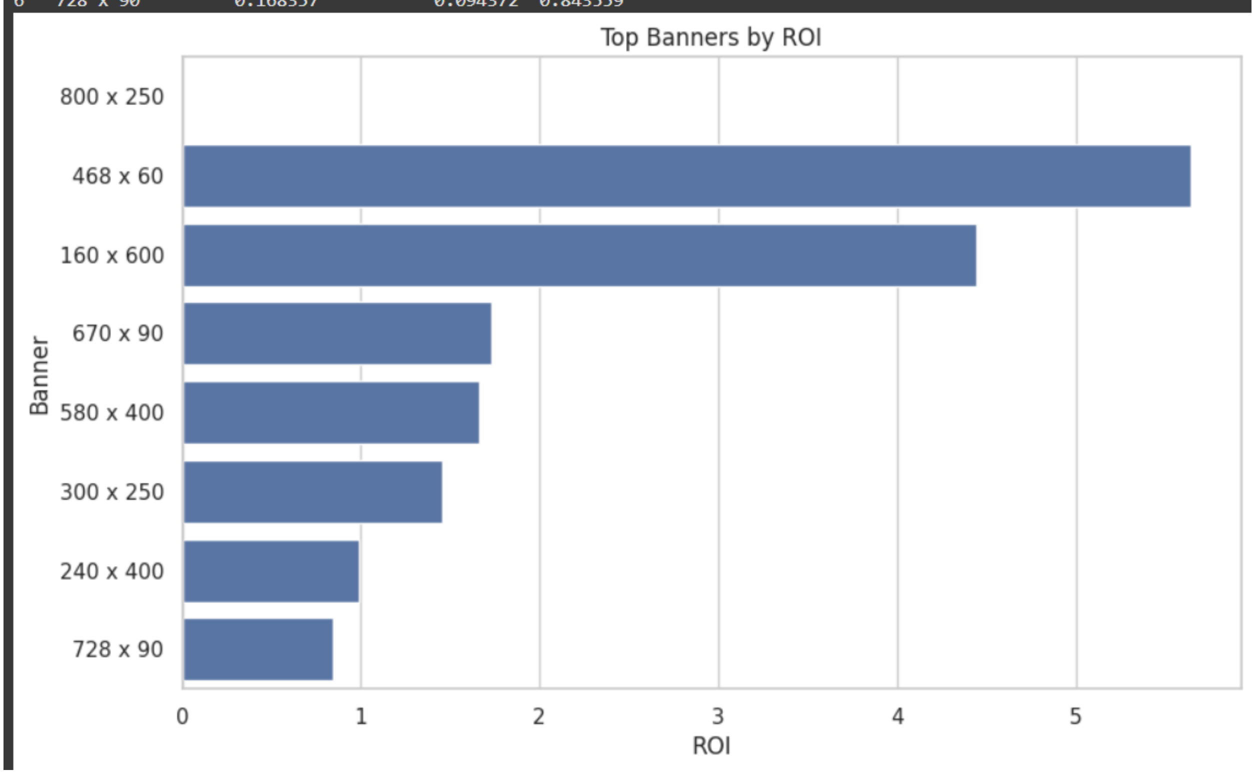
Q14) Are there any specific campaigns or banner sizes that consistently outperform others in terms of ROI?

Code:

```
data = data[data['clicks'] != 0].copy()

data['conversion_rate'] = data['post_click_conversions'] / data['clicks']


data['roi'] = (data['revenue'] - data['cost']) / data['cost']


data['revenue_per_click'] = data['revenue'] / data['clicks']


banner_performance = data.groupby('banner').agg({'conversion_rate': 'mean',
'revenue_per_click': 'mean', 'roi': 'mean'}).reset_index()


top_banners = banner_performance.sort_values(by='roi', ascending=False)
```

```
print("Top banners by ROI:")

print(top_banners)


plt.figure(figsize=(10, 6))

sns.barplot(x='roi', y='banner', data=top_banners)

plt.title('Top Banners by ROI')

plt.xlabel('ROI')

plt.ylabel('Banner')

plt.show()
```

```
Top banners by ROI:
      banner  conversion_rate  revenue_per_click       roi
7  800 x 250         0.100000           0.086280       inf
3   468 x 60         0.480172           0.065576  5.641572
0  160 x 600         0.145204           0.099354  4.443593
5   670 x 90         0.212334           0.088910  1.730681
4  580 x 400         0.175724           0.094262  1.664718
2  300 x 250         0.184054           0.093784  1.459363
1  240 x 400         0.143730           0.094729  0.987108
6   728 x 90         0.168357           0.094372  0.843559
```



Top Performers by ROI:

- 468 × 60: Best ROI (~5.45).

- 160 × 600: Second-best ROI (~4.44).

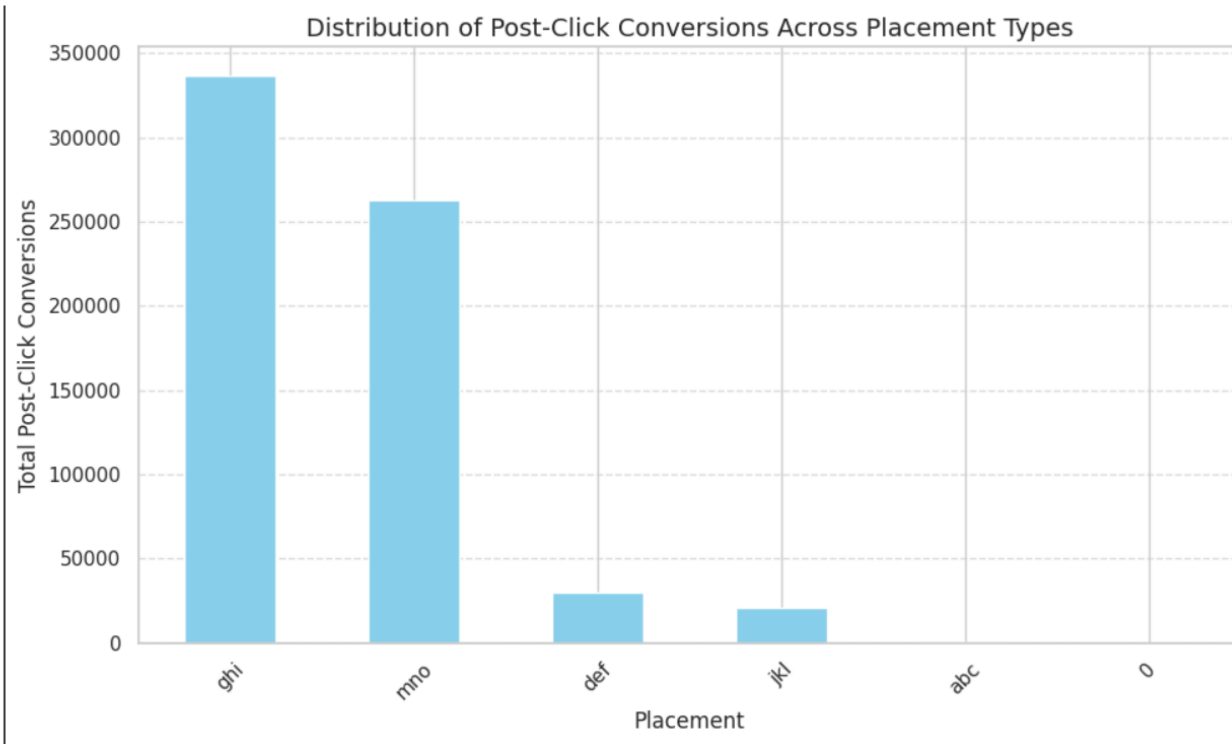
Consistent Outperformers:

- Large banners like 468 × 60 and 160 × 600 consistently deliver high ROI.

Q15) What is the distribution of post-click conversions across different placement types?

Code:

```
placement_conversion_distribution =
data.groupby('placement')['post_click_conversions'].sum()


plt.figure(figsize=(10, 6))
placement_conversion_distribution.sort_values(ascending=False).plot(kind='bar',
color='skyblue')
plt.title('Distribution of Post-Click Conversions Across Placement Types', fontsize=14)
plt.xlabel('Placement', fontsize=12)
plt.ylabel('Total Post-Click Conversions', fontsize=12)
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()


placement_conversion_distribution
```



placement	post_click_conversions
0	0
abc	822
def	29841
ghi	337033
jkl	20848
mno	263156

dtype: int64

Ans)

1. Placement ghi: This placement type has the highest post-click conversions,surpassing 300,000.

2. Placement mno: The second-highest, with post-click

3. Placement def: This placement has significantly fewer post-click conversions compared to ghi and mno, with a small count relative to the top two placements.

4. Placement jkl: Similar to def, this has very few post-click conversions, only slightly less.

5. Placement abc: This placements show negligible or no post-click conversions.

Q16) Are there any noticeable differences in user engagement levels between weekdays and weekends?

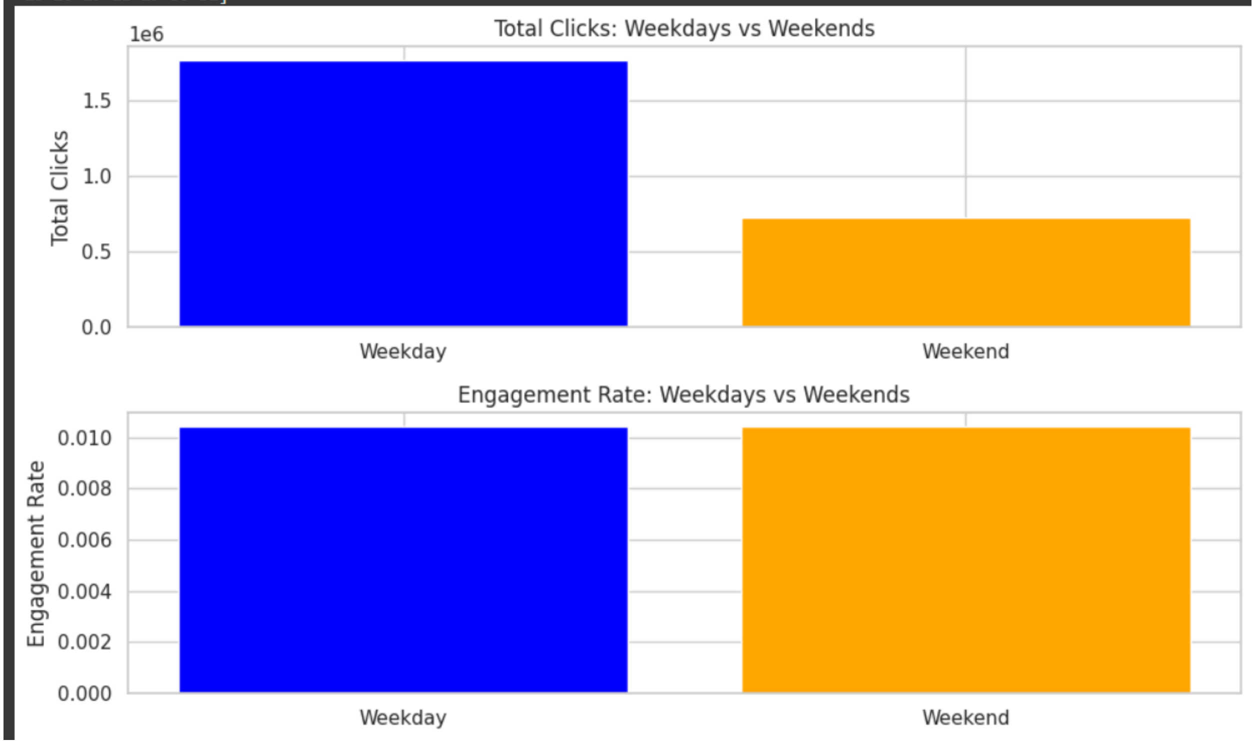
Code:

```
data = pd.read_csv('cleaned_data.csv')


print("Unique months:", data['month'].unique())

print("Unique days:", data['day'].unique())


month_mapping = {

    'January': 1,

    'February': 2,

    'March': 3,

    'April': 4,

    'May': 5,

    'June': 6,

    'July': 7,

    'August': 8,

    'September': 9,

    'October': 10,

    'November': 11,
```

```
    'December': 12
}

data['month'] = data['month'].map(month_mapping)

data['day'] = pd.to_numeric(data['day'], errors='coerce').fillna(1).astype(int)
data['date'] = pd.to_datetime(data[['month', 'day']].assign(year=2024), errors='coerce')

invalid_dates = data[data['date'].isnull()]
if not invalid_dates.empty:
    print(f"Invalid dates:\n{invalid_dates[['month', 'day']]}")

def categorize_day(date):
    if date.weekday() < 5:  # Weekdays (0-4)
        return 'Weekday'
    else:
        return 'Weekend'

if 'date' in data.columns:
    data['day_type'] = data['date'].apply(categorize_day)



    engagement_summary = data.groupby('day_type').agg(
        total_clicks=('clicks', 'sum'),
        total_displays=('displays', 'sum')
    ).reset_index()
```

```
    engagement_summary['engagement_rate'] = engagement_summary['total_clicks'] /
engagement_summary['total_displays']

    plt.figure(figsize=(10, 6))

    plt.subplot(2, 1, 1)
    plt.bar(engagement_summary['day_type'], engagement_summary['total_clicks'],
color=['blue', 'orange'])
    plt.title('Total Clicks: Weekdays vs Weekends')
    plt.ylabel('Total Clicks')

    plt.subplot(2, 1, 2)
    plt.bar(engagement_summary['day_type'], engagement_summary['engagement_rate'],
color=['blue', 'orange'])
    plt.title('Engagement Rate: Weekdays vs Weekends')
    plt.ylabel('Engagement Rate')

    plt.tight_layout()
    plt.show()
else:
    print("Date column was not created successfully.")
```

```
Unique months: ['April' 'May' 'June']
Unique days: [ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
 25 26 27 28 29 30 31]
```



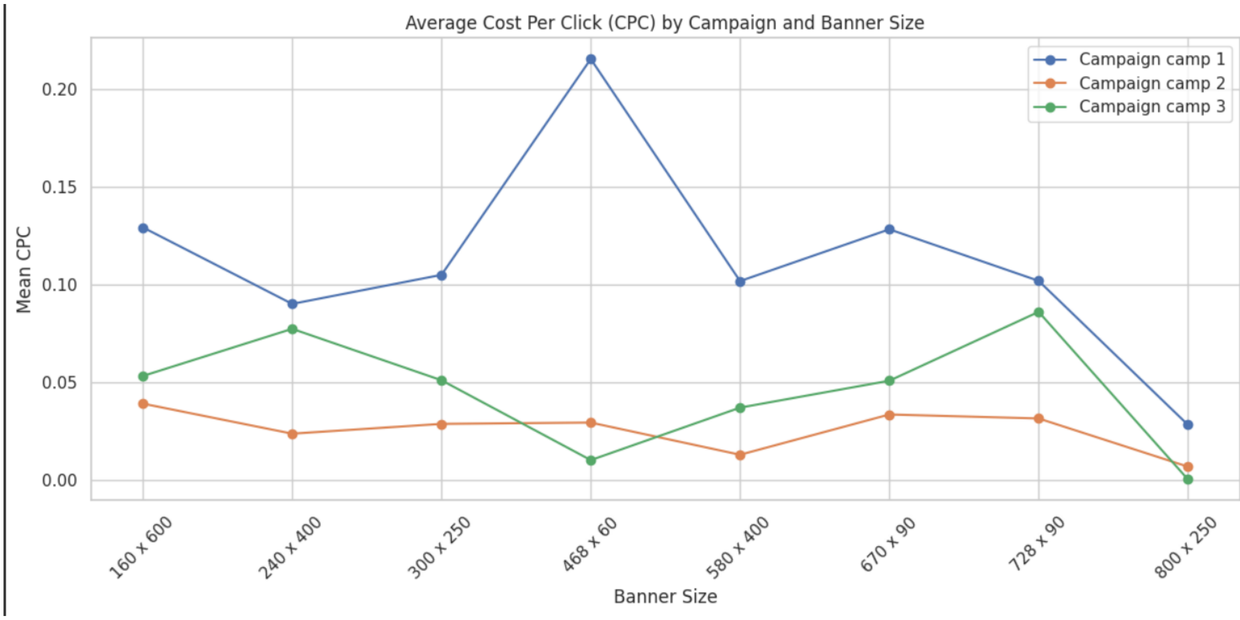
Ans) The graphs show that while total clicks are significantly higher on weekdays (upper graph, blue bar), the engagement rate—measured as interactions relative to total clicks—is greater on weekends (lower graph, orange bar). This suggests that while there is more overall activity during the workweek, users tend to engage more deeply with the content during weekends. This pattern could reflect differences in user behavior and availability, with weekends potentially offering users more time to interact thoughtfully with content.

Q17) How does the cost per click (CPC) vary across different campaigns and banner sizes?

<u>Code:</u>

```
data['CPC'] = data['cost'] / data['clicks'].replace(0, pd.NA)


# Group by campaign number and banner size, calculating mean CPC

cpc_summary = data.groupby(['campaign_number', 'banner']).agg(

    mean_CPC=('CPC', 'mean'),
```

```
    total_clicks=('clicks', 'sum')
).reset_index()

cpc_summary = cpc_summary.dropna(subset=['mean_CPC'])

plt.figure(figsize=(12, 6))
for campaign in cpc_summary['campaign_number'].unique():
    subset = cpc_summary[cpc_summary['campaign_number'] == campaign]
    plt.plot(subset['banner'], subset['mean_CPC'], marker='o', label=f'Campaign {campaign}')

plt.title('Average Cost Per Click (CPC) by Campaign and Banner Size')
plt.xlabel('Banner Size')
plt.ylabel('Mean CPC')
plt.xticks(rotation=45)
plt.legend()
plt.tight_layout()
plt.show()
```



Ans) Campaign Camp 1 is the most cost-intensive, especially for the 670x90 banner, while Campaign Camp 2 is consistently the most cost-effective. The impact of banner size on CPC appears campaign-specific, with different patterns of peaks and dips.

Q18) Are there any campaigns or placements that are particularly cost-effective in terms of generating post-click conversions?

Code:

```
data['Cost per Conversion'] = data['cost'] / data['post_click_conversions'].replace(0, pd.NA)

cost_effectiveness_summary = data.groupby(['campaign_number', 'placement']).agg(
    mean_cost_per_conversion=('Cost per Conversion', 'mean'),
    total_conversions=('post_click_conversions', 'sum')
).reset_index()

cost_effectiveness_summary =
cost_effectiveness_summary.dropna(subset=['mean_cost_per_conversion'])
```

cost_effectiveness_summary =
cost_effectiveness_summary[cost_effectiveness_summary['total_conversions'] > 0]

cost_effectiveness_summary =
cost_effectiveness_summary.sort_values(by='mean_cost_per_conversion')

print(cost_effectiveness_summary)

	campaign_number	placement	mean_cost_per_conversion	total_conversions
0	camp 1	0	0.00825	2
1	camp 1	abc	0.163195	808
4	camp 1	jkl	0.263877	20109
13	camp 3	abc	0.317597	16
3	camp 1	ghi	0.325304	329024
5	camp 1	mno	0.474946	254775
2	camp 1	def	0.576989	28364
14	camp 3	def	0.876116	465
16	camp 3	jkl	0.976729	180
10	camp 2	jkl	1.140003	564
11	camp 2	mno	1.552726	5330
15	camp 3	ghi	1.591719	1190
8	camp 2	def	1.598899	1024
9	camp 2	ghi	1.647937	6849
17	camp 3	mno	1.759456	3062

Ans)Tuesday has the highest average post-click conversion rate (0.206237), while Monday and Saturday have slightly lower rates. Conversion rates are generally consistent across the week, with small variations.

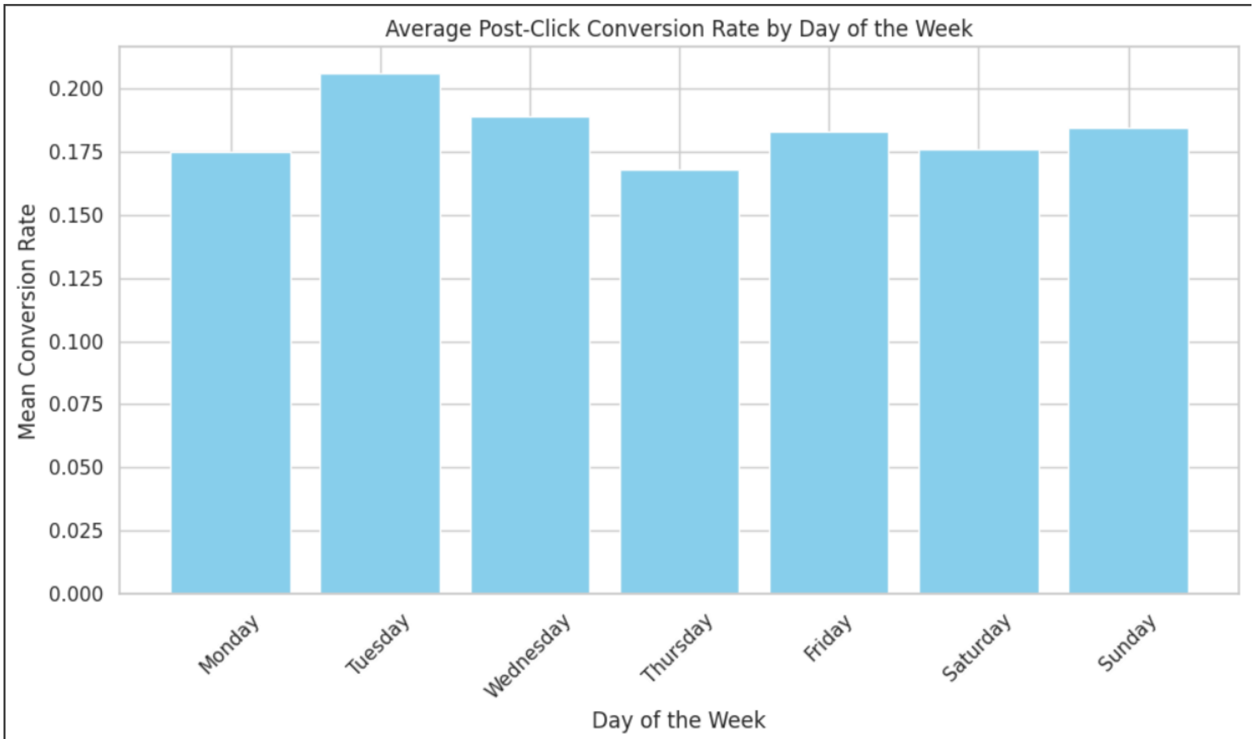
Q19) Can we identify any trends or patterns in post-click conversion rates based on the day of the week?

Code:

data['day_of_week'] = data['date'].dt.day_name()

data['conversion_rate'] = data['post_click_conversions'] / data['clicks'].replace(0, pd.NA)

```
conversion_rate_summary = data.groupby('day_of_week').agg(
    mean_conversion_rate=('conversion_rate', 'mean'),
    total_conversions=('post_click_conversions', 'sum')
).reset_index()


days_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
conversion_rate_summary['day_of_week'] =
pd.Categorical(conversion_rate_summary['day_of_week'], categories=days_order,
ordered=True)
conversion_rate_summary = conversion_rate_summary.sort_values('day_of_week')


plt.figure(figsize=(10, 6))
plt.bar(conversion_rate_summary['day_of_week'],
conversion_rate_summary['mean_conversion_rate'], color='skyblue')
plt.title('Average Post-Click Conversion Rate by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Mean Conversion Rate')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
print(conversion_rate_summary)
```



	day_of_week	mean_conversion_rate	total_conversions
1	Monday	0.174837	97232
5	Tuesday	0.206237	76606
6	Wednesday	0.189205	83300
4	Thursday	0.168277	97613
0	Friday	0.18295	99721
2	Saturday	0.176074	98272
3	Sunday	0.184565	99018

Ans) Tuesday has the highest average post-click conversion rate (0.206237), while Monday and Saturday have slightly lower rates. Conversion rates are generally consistent across the week, with small variations.

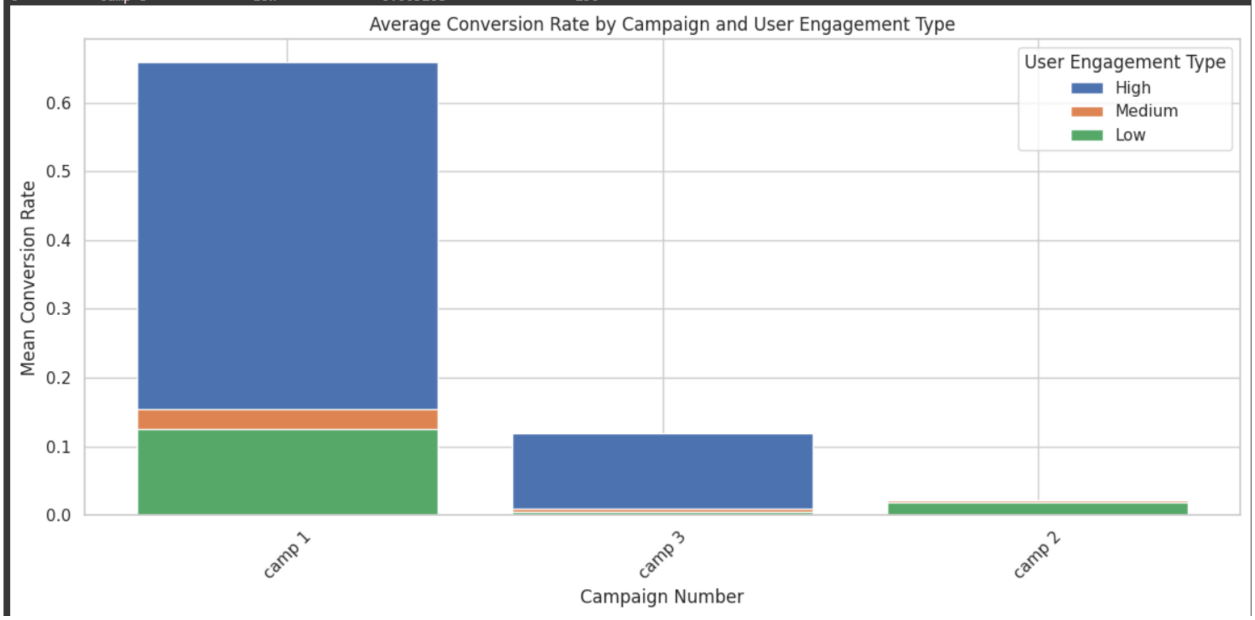
Q20) How does the effectiveness of campaigns vary throughout different user engagement types in terms of post-click conversions?

Code:

```
data['conversion_rate'] = data['post_click_conversions'] / data['clicks'].replace(0, pd.NA)


conversion_rate_summary = data.groupby(['campaign_number', 'user_engagement']).agg(

    mean_conversion_rate=('conversion_rate', 'mean'),
```

```
    total_conversions=('post_click_conversions', 'sum')
).reset_index()


conversion_rate_summary =
conversion_rate_summary.dropna(subset=['mean_conversion_rate'])
conversion_rate_summary =
conversion_rate_summary[conversion_rate_summary['total_conversions'] > 0]


conversion_rate_summary =
conversion_rate_summary.sort_values(by='mean_conversion_rate', ascending=False)


print(conversion_rate_summary)


plt.figure(figsize=(12, 6))
for engagement_type in conversion_rate_summary['user_engagement'].unique():
    subset = conversion_rate_summary[conversion_rate_summary['user_engagement'] ==
engagement_type]
    plt.bar(subset['campaign_number'], subset['mean_conversion_rate'],
label=engagement_type)


plt.title('Average Conversion Rate by Campaign and User Engagement Type')
plt.xlabel('Campaign Number')
plt.ylabel('Mean Conversion Rate')
plt.xticks(rotation=45)
plt.legend(title='User Engagement Type')
plt.tight_layout()
plt.show()
```

	campaign_number	user_engagement	mean_conversion_rate	total_conversions
0	camp 1	High	0.658951	617241
2	camp 1	Medium	0.153676	15249
1	camp 1	Low	0.125076	592
5	camp 3	High	0.119105	3678
4	camp 2	Medium	0.021589	12923
3	camp 2	Low	0.018342	844
7	camp 3	Medium	0.009969	1085
6	camp 3	Low	0.005268	150



Ans) Campaign 1 shows the highest effectiveness, especially for users with high engagement (conversion rate: 0.658951). Medium and low engagement types in Campaign 1 also perform better compared to similar types in other campaigns. Campaigns 2 and 3 have much lower overall conversion rates across all engagement levels, with high-engagement users performing marginally better than medium or low-engagement users.