optimization_marketing_campaigns

June 6, 2025

Marketing Campaign Optimization

Project Goal

The project aims to optimize marketing campaigns by analyzing key factors affecting conversion, identifying the best promotion strategies, and building an effective model to predict the success of marketing activities.

Project Stages

1. Data Preparation
   Removing duplicates Handling outliers and missing values Examining variable distributions
   2. Exploratory Analysis
      Identifying the most successful strategies that lead to high conversion rates. Determining key influencing factors: advertising channels, demographics, engagement. Analyzing correlations between variables to understand dependencies.
      3. Budget Optimization
         Budget allocation across different campaign types and channels using weights and factor importance for conversion

Features

Demographic Information

CustomerID: Unique identifier for each customer. Age: Age of the customer. Gender: Gender of the customer (Male/Female). Income: Annual income of the customer in USD.

Marketing-specific Variables

CampaignChannel: The channel through which the marketing campaign is delivered (Email, Social Media, SEO, PPC, Referral). CampaignType: Type of the marketing campaign (Awareness, Consideration, Conversion, Retention). AdSpend: Amount spent on the marketing campaign in USD. ClickThroughRate: Rate at which customers click on the marketing content. ConversionRate: Rate at which clicks convert to desired actions (e.g., purchases). AdvertisingPlatform: Confidential. AdvertisingTool: Confidential.

Customer Engagement Variables

WebsiteVisits: Number of visits to the website. PagesPerVisit: Average number of pages visited per session. TimeOnSite: Average time spent on the website per visit (in minutes). SocialShares: Number of times the marketing content was shared on social media. EmailOpens: Number of times marketing emails were opened. EmailClicks: Number of times links in marketing emails were clicked.

Historical Data

PreviousPurchases: Number of previous purchases made by the customer. LoyaltyPoints: Number of loyalty points accumulated by the customer.

Target Variable

Conversion: Binary variable indicating whether the customer converted (1) or not (0).

[538]:
```
import numpy as np
import pandas as pd
import scipy as sp
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix, precision_recall_curve,\
roc_auc_score, roc_curve, fbeta_score, cohen_kappa_score, matthews_corrcoef, auc
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
```

[540]:
```
df = pd.read_csv('digital_marketing_campaign_dataset.csv')
```

[542]:
```
df
```

[542]:
```
      CustomerID  Age  Gender  Income CampaignChannel   CampaignType  \
0           8000   56  Female  136912    Social Media      Awareness
1           8001   69    Male   41760           Email      Retention
2           8002   46  Female   88456             PPC      Awareness
3           8003   32  Female   44085             PPC     Conversion
4           8004   60  Female   83964             PPC     Conversion
…            …   …    …      …                 …           …
7995       15995   21    Male   24849           Email      Awareness
7996       15996   43  Female   44718             SEO      Retention
7997       15997   28  Female  125471        Referral  Consideration
7998       15998   19  Female  107862             PPC  Consideration
7999       15999   31  Female   93002           Email      Awareness

          AdSpend  ClickThroughRate  ConversionRate  WebsiteVisits  \
0     6497.870068          0.043919        0.088031              0
1     3898.668606          0.155725        0.182725             42
2     1546.429596          0.277490        0.076423              2
3      539.525936          0.137611        0.088004             47
4     1678.043573          0.252851        0.109940              0
…            …               …               …             …
```

```
7995  8518.308575         0.243792        0.116773                23
7996  1424.613446         0.236740        0.190061                49
7997  4609.534635         0.056526        0.133826                35
7998  9476.106354         0.023961        0.138386                49
7999  7743.627070         0.185670        0.057228                15

      PagesPerVisit  TimeOnSite  SocialShares  EmailOpens  EmailClicks  \
0          2.399017    7.396803            19           6            9
1          2.917138    5.352549             5           2            7
2          8.223619   13.794901             0          11            2
3          4.540939   14.688363            89           2            2
4          2.046847   13.993370             6           6            6
…               …           …             …         …           …
7995       9.693602   14.227794            70          13            6
7996       9.499010    3.501106            52          13            1
7997       2.853241   14.618323            38          16            0
7998       1.002964    3.876623            86           1            5
7999       6.964739   12.763660             2          18            9

      PreviousPurchases  LoyaltyPoints AdvertisingPlatform AdvertisingTool  \
0                     4            688            IsConfid      ToolConfid
1                     2           3459            IsConfid      ToolConfid
2                     8           2337            IsConfid      ToolConfid
3                     0           2463            IsConfid      ToolConfid
4                     8           4345            IsConfid      ToolConfid
…                   …             …                 …             …
7995                  7            286            IsConfid      ToolConfid
7996                  5           1502            IsConfid      ToolConfid
7997                  3            738            IsConfid      ToolConfid
7998                  7           2709            IsConfid      ToolConfid
7999                  9            341            IsConfid      ToolConfid

      Conversion
0              1
1              1
2              1
3              1
4              1
…            …
7995           0
7996           0
7997           1
7998           1
7999           0

[8000 rows x 20 columns]
```

Data preparation

[545]:
```python
df = df.drop(columns=["AdvertisingPlatform", "AdvertisingTool"])
```

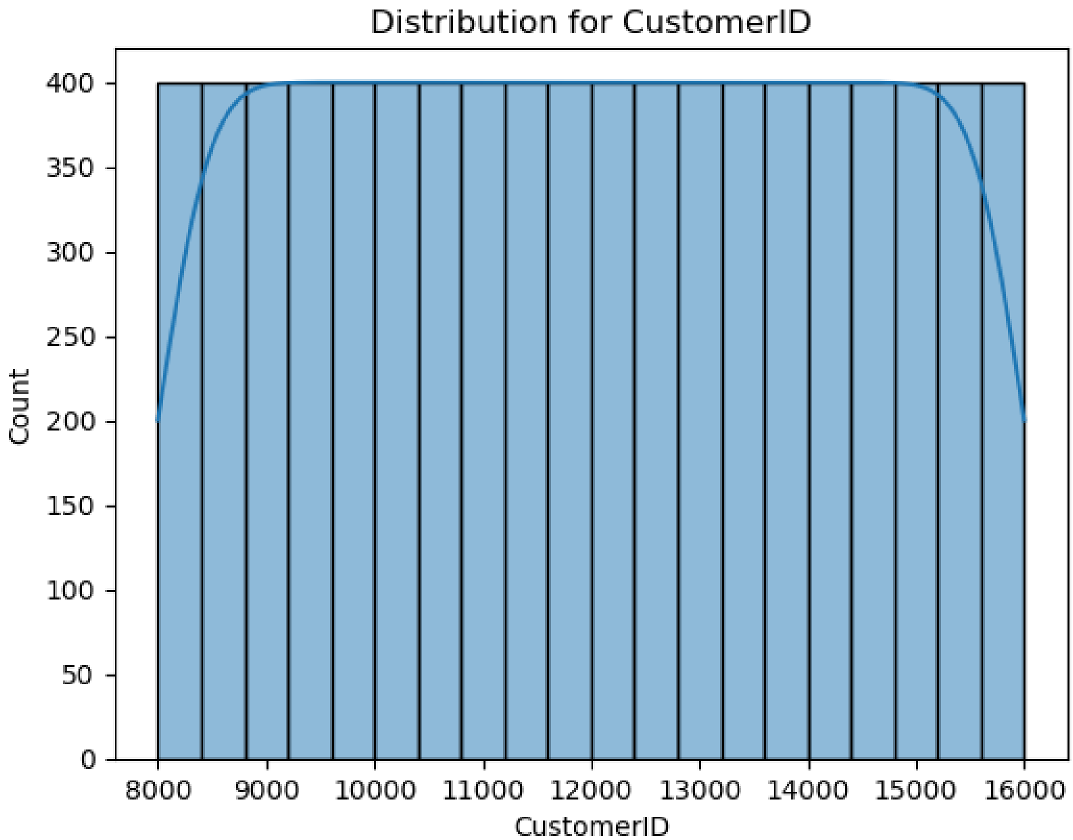
[547]:
```python
df.isnull().sum()
```

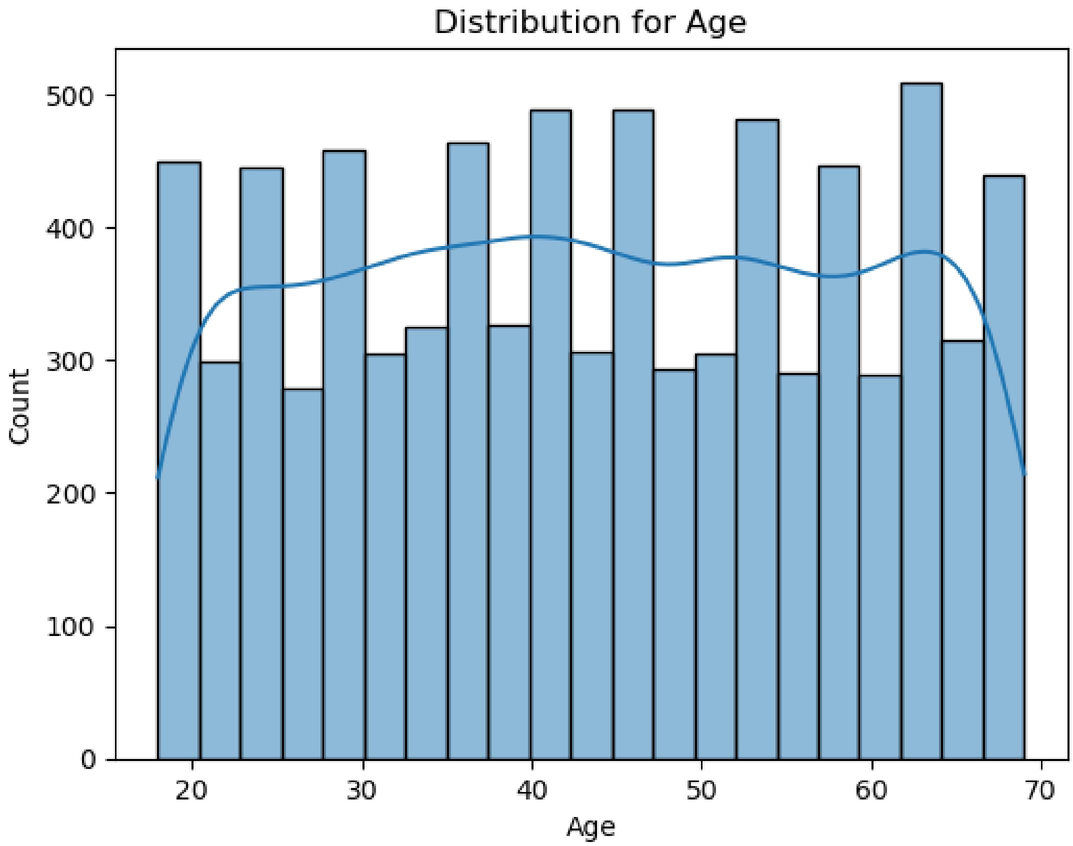
[547]:
```
CustomerID           0
Age                  0
Gender               0
Income               0
CampaignChannel      0
CampaignType         0
AdSpend              0
ClickThroughRate     0
ConversionRate       0
WebsiteVisits        0
PagesPerVisit        0
TimeOnSite           0
SocialShares         0
EmailOpens           0
EmailClicks          0
PreviousPurchases    0
LoyaltyPoints        0
Conversion           0
dtype: int64
```

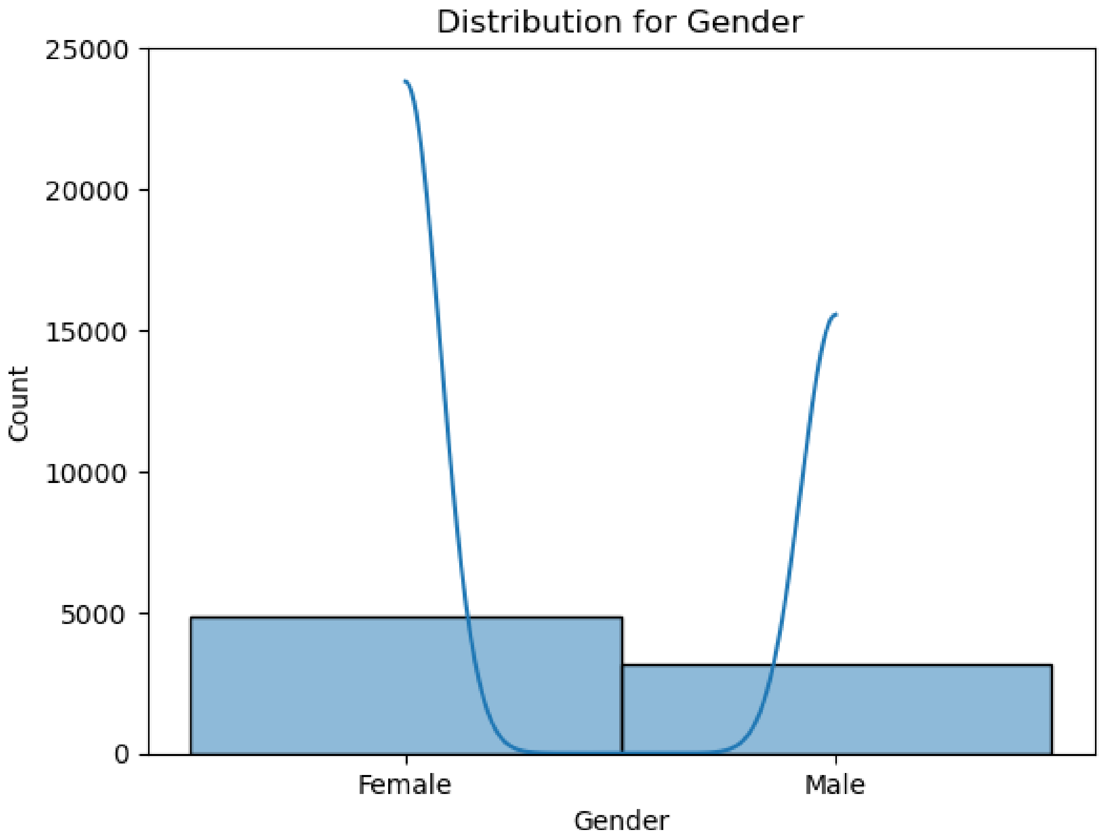
[549]:
```python
df.duplicated().sum()
```

[549]:
```
0
```

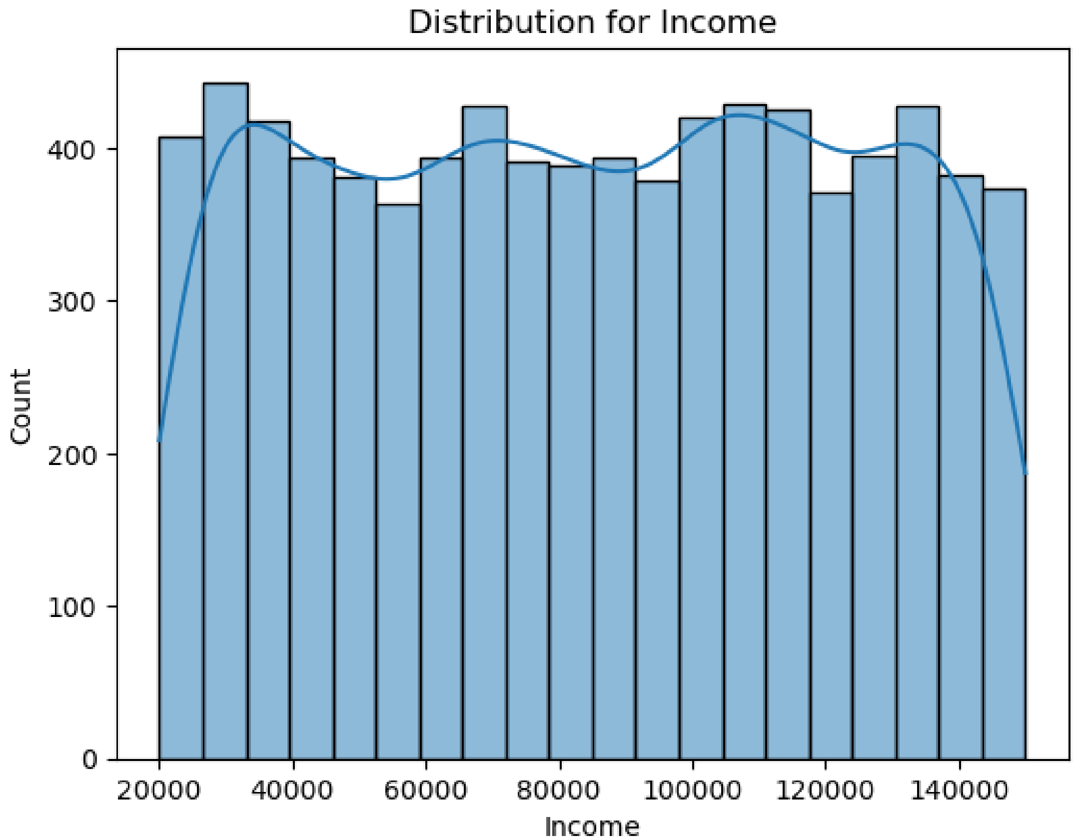
[551]:
```python
for column in df.columns:
    sns.histplot(df[column].dropna(), kde=True)
    plt.title(f'Distribution for {column}')
    plt.show()
```

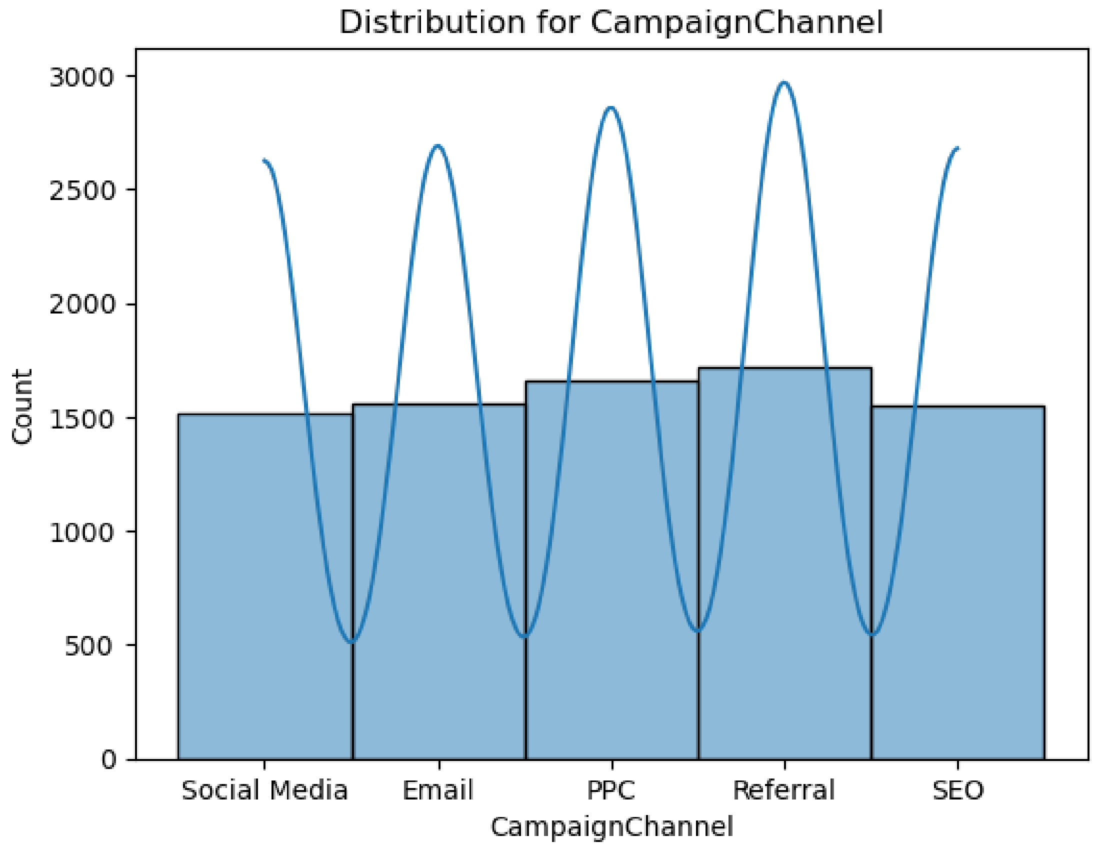

Distribution for CustomerID
Count
CustomerID
400
350
300
250
200
150
100
50
0
8000
9000
10000
11000
12000
13000
14000
15000
16000

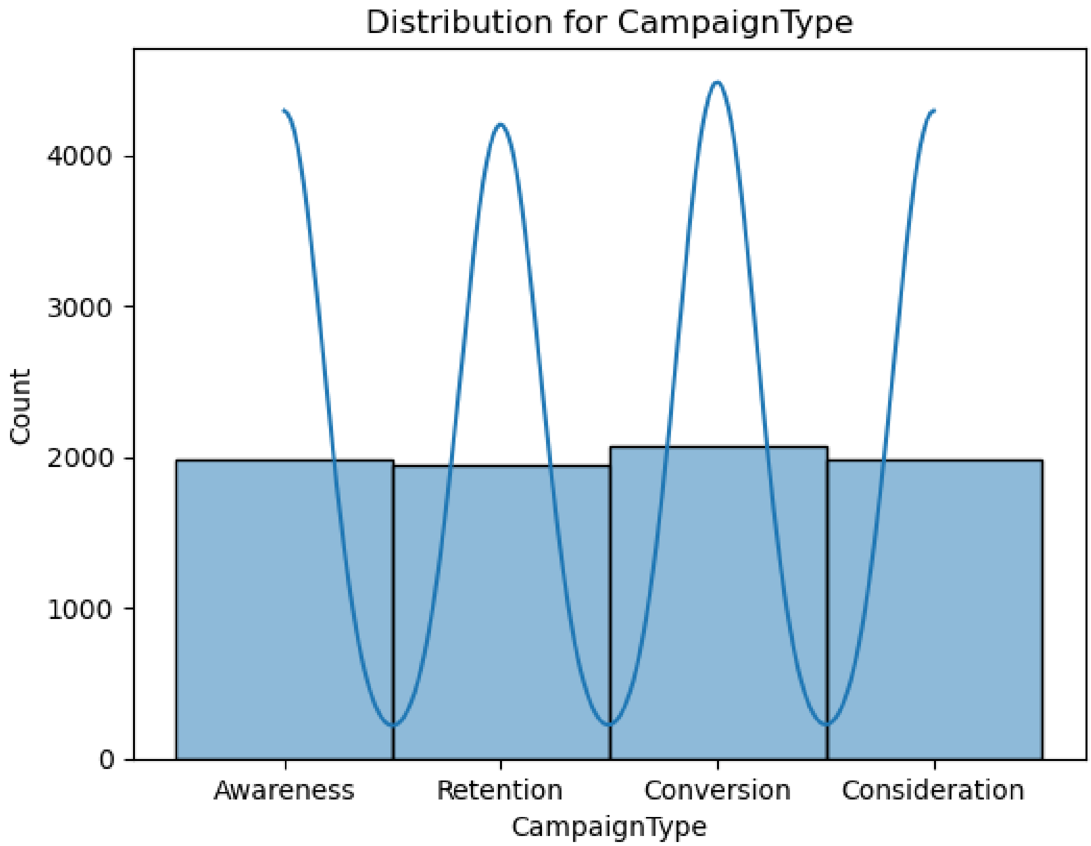

Distribution for Age
Count
0
100
200
300
400
500
20
30
40
50
60
70
Age

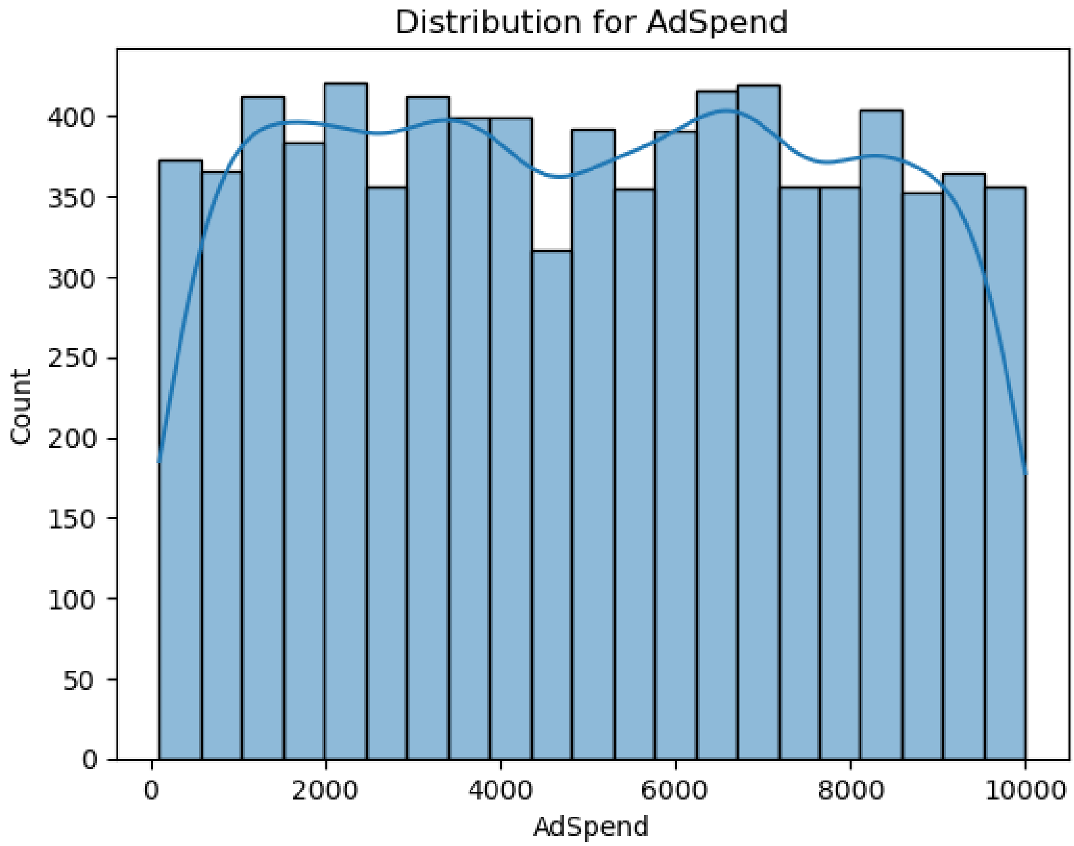


Distribution for Gender
25000
20000
15000
10000
5000
0
Count
Female
Male
Gender

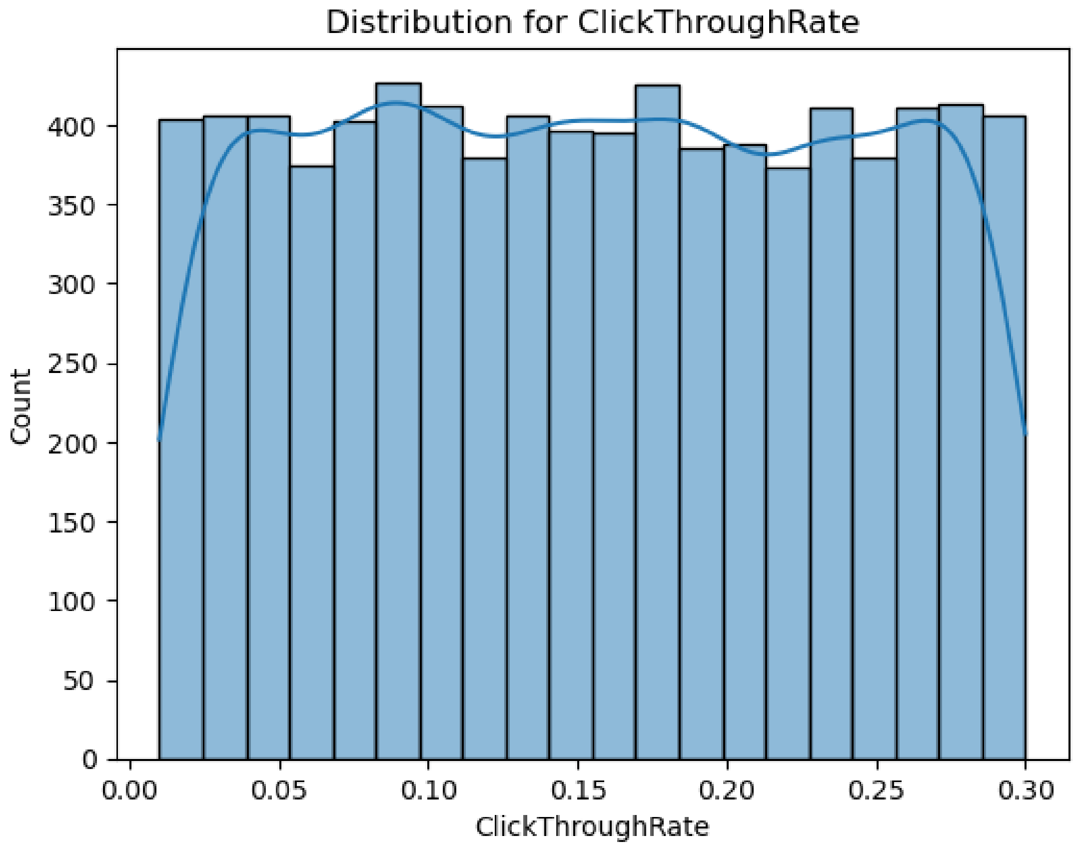

Distribution for Income
Count
Income
0
100
200
300
400
20000
40000
60000
80000
100000
120000
140000

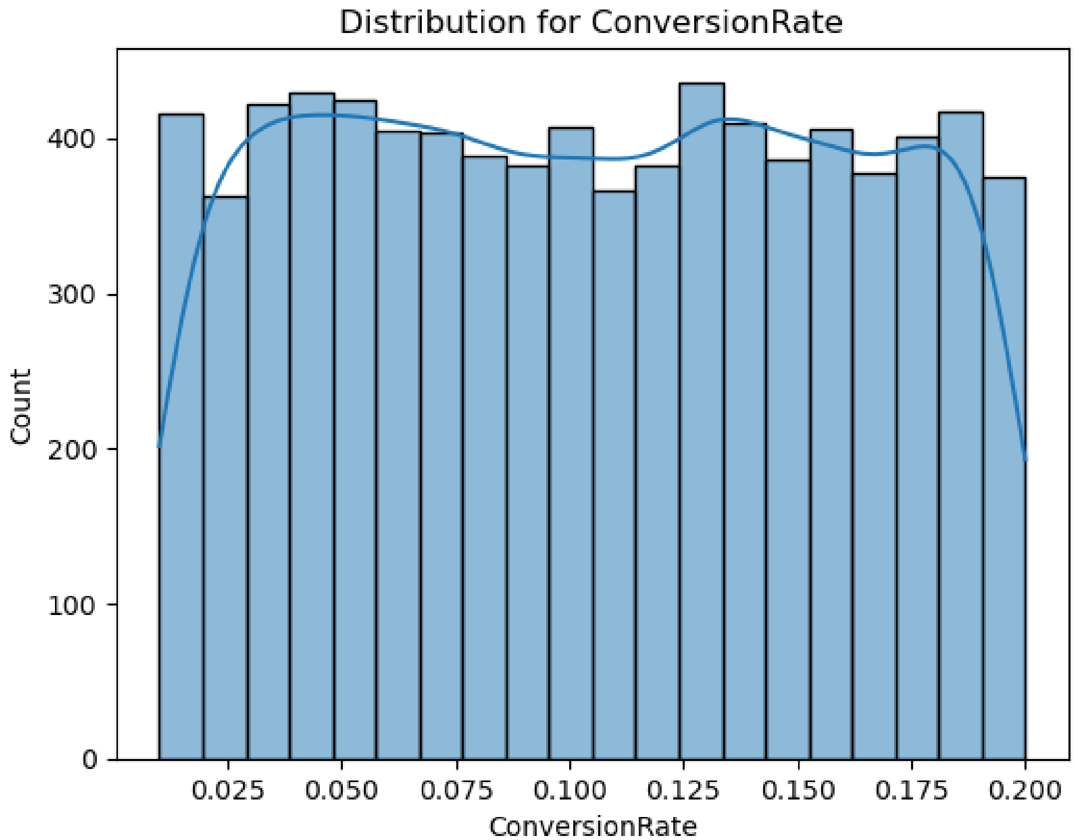

Distribution for CampaignChannel
3000
2500
2000
1500
1000
500
0
Count
Social Media
Email
PPC
Referral
SEO
CampaignChannel


Distribution for CampaignType
Count
CampaignType
0
1000
2000
3000
4000
Awareness
Retention
Conversion
Consideration

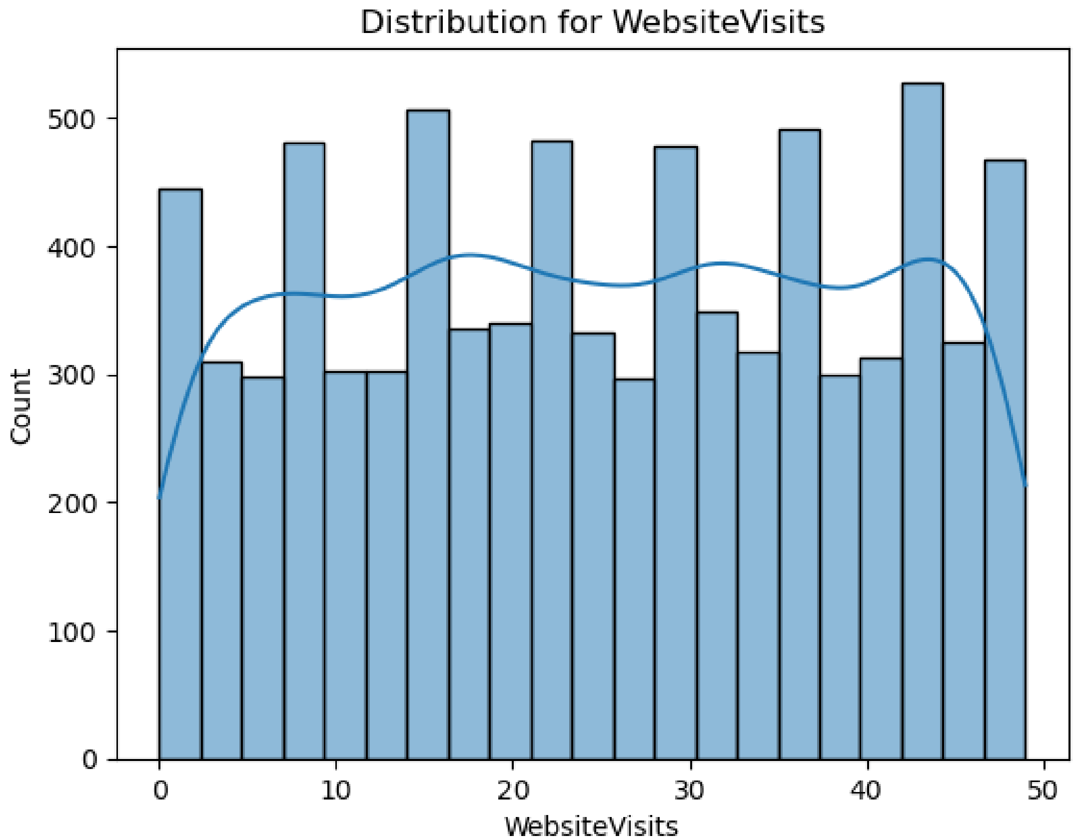


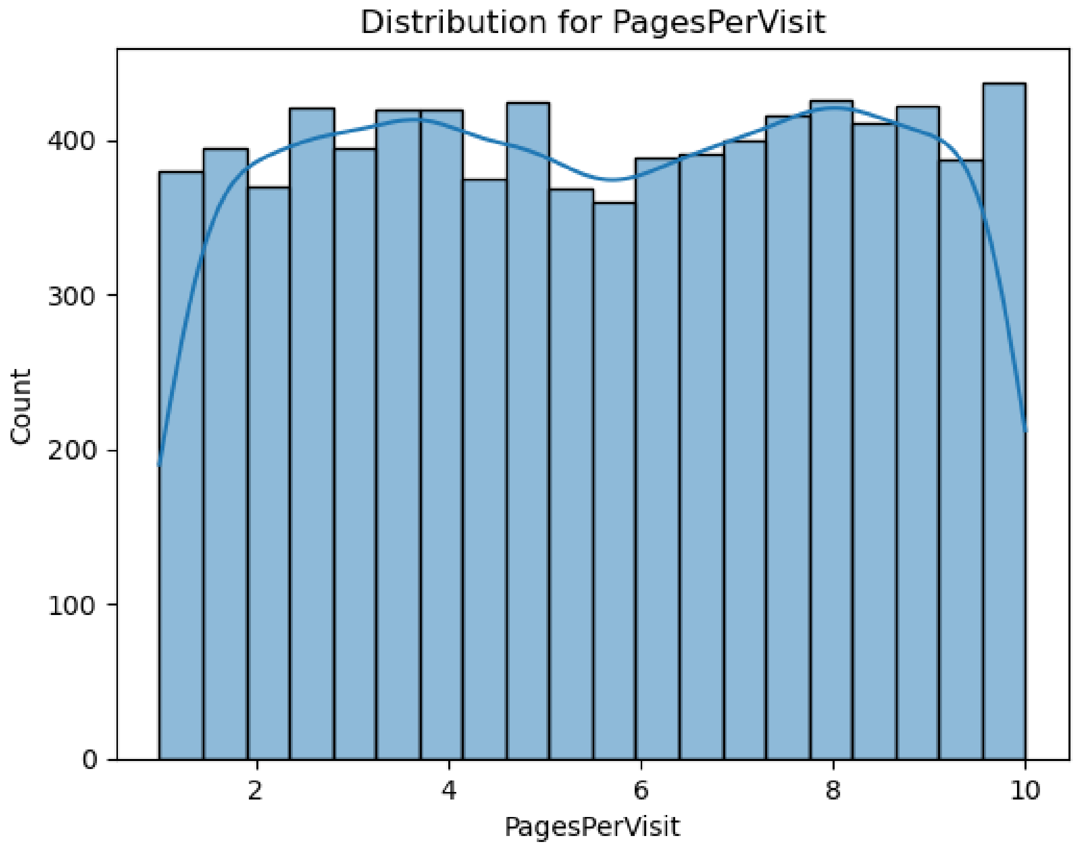
Distribution for AdSpend
Count
0
50
100
150
200
250
300
350
400
0
2000
4000
6000
8000
10000
AdSpend

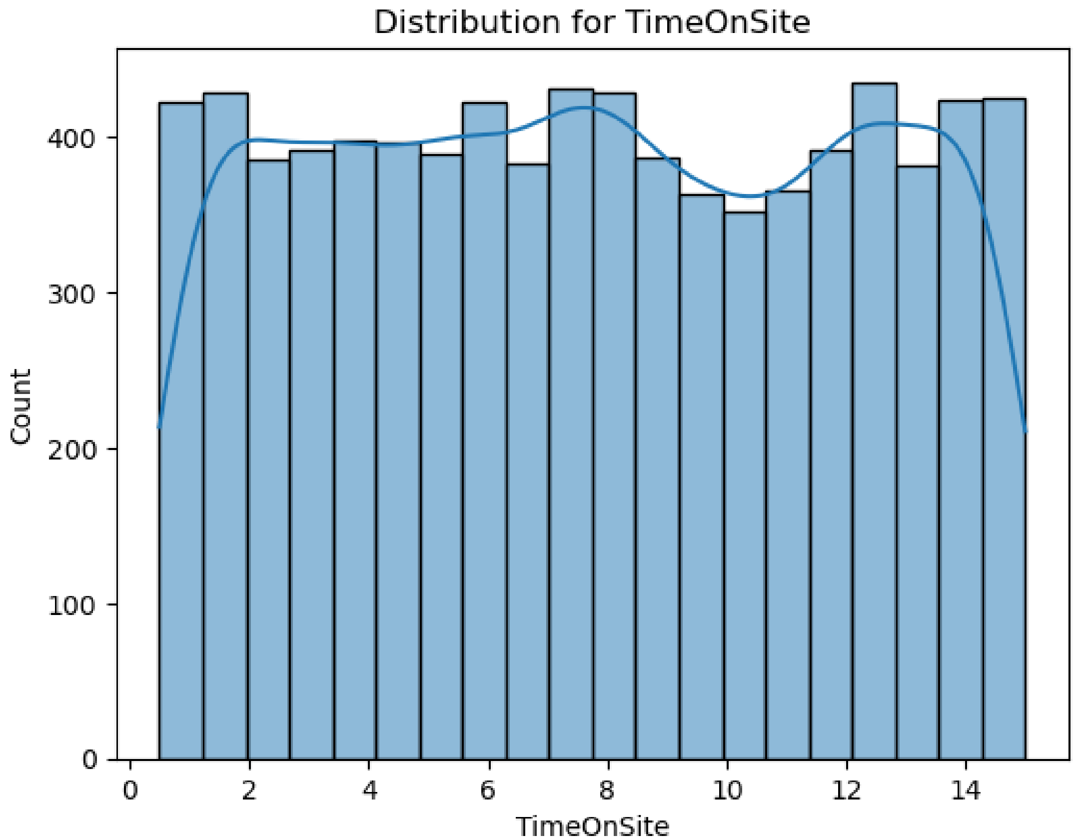

Distribution for ClickThroughRate
Count
ClickThroughRate
0
50
100
150
200
250
300
350
400
0.00
0.05
0.10
0.15
0.20
0.25
0.30

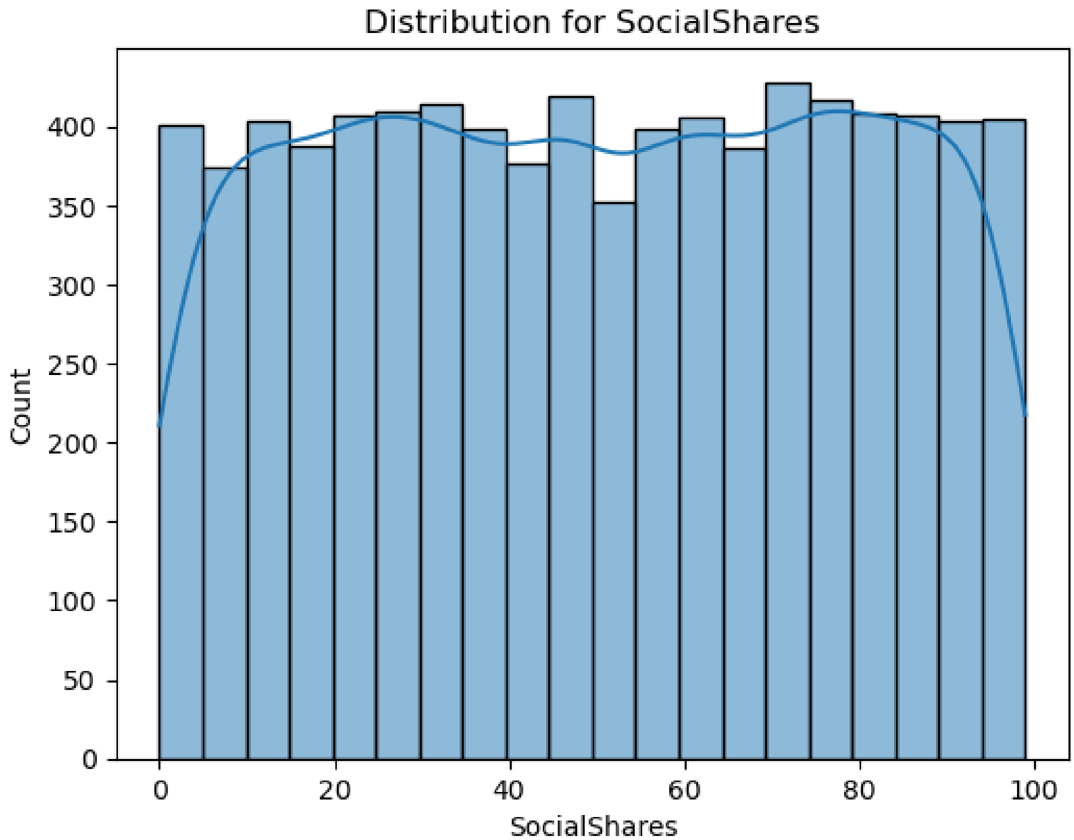


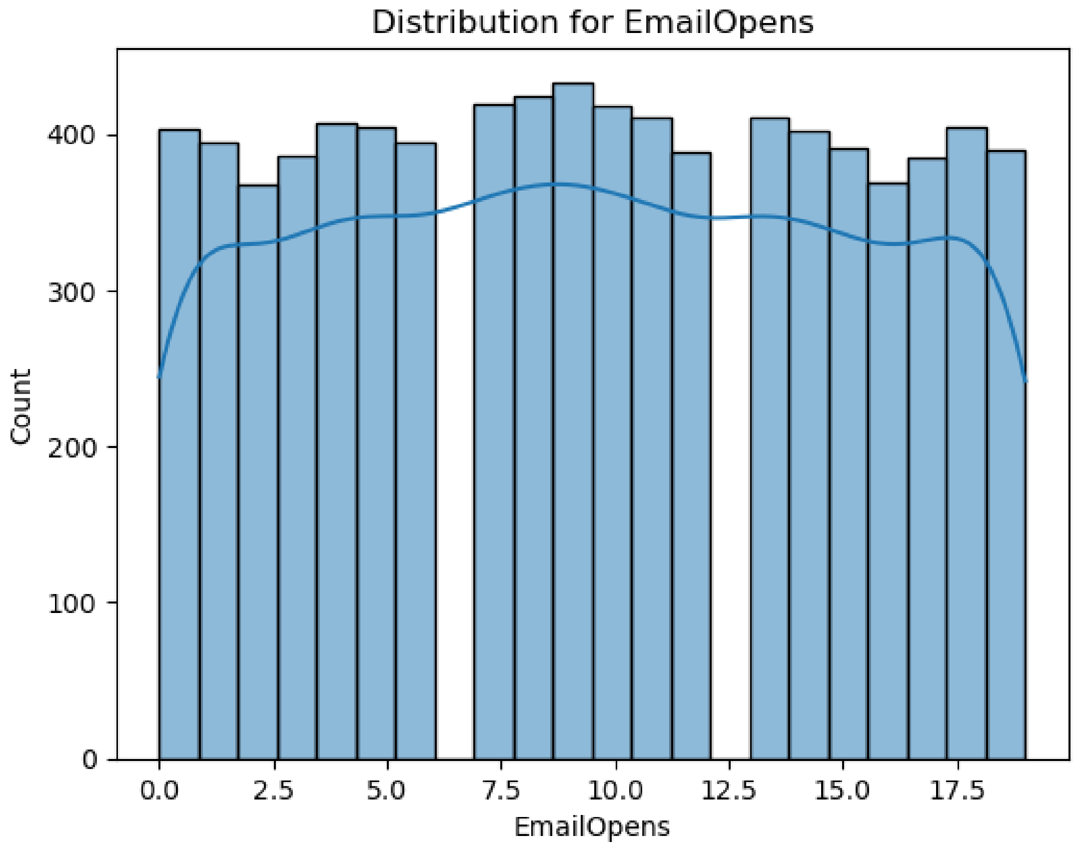
Distribution for ConversionRate
Count
0
100
200
300
400
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
ConversionRate

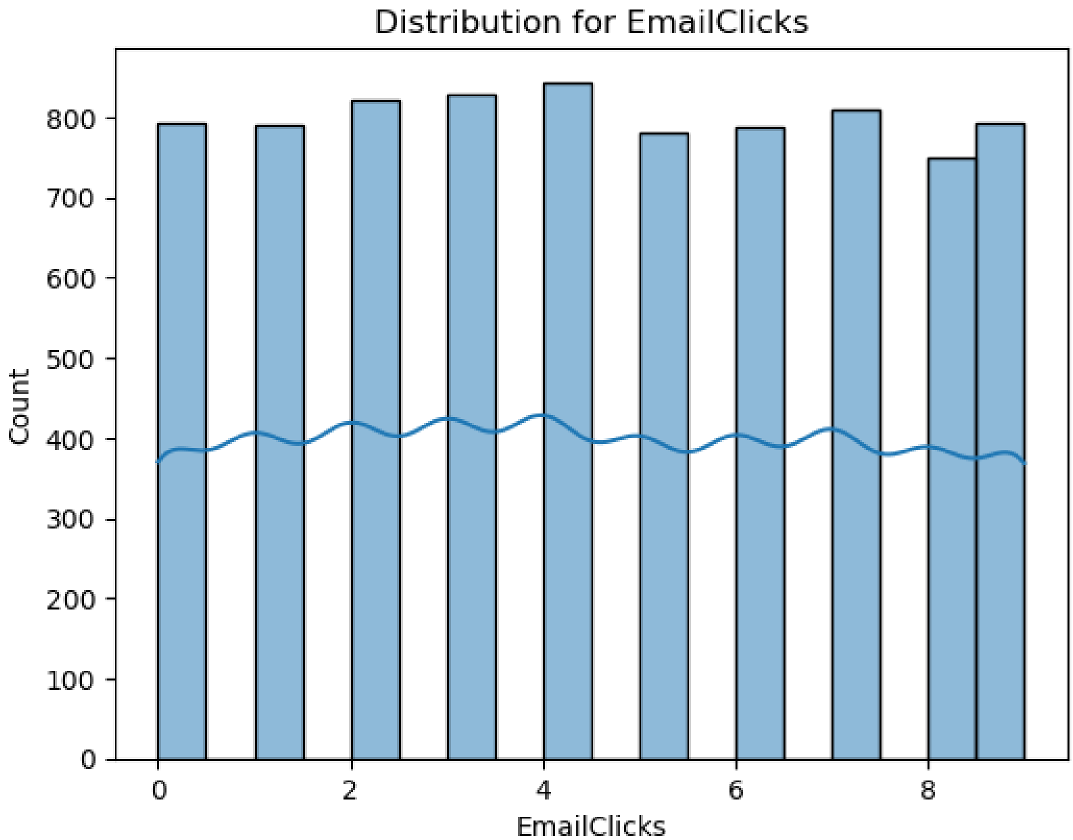

Distribution for WebsiteVisits
Count
0
100
200
300
400
500
0
10
20
30
40
50
WebsiteVisits

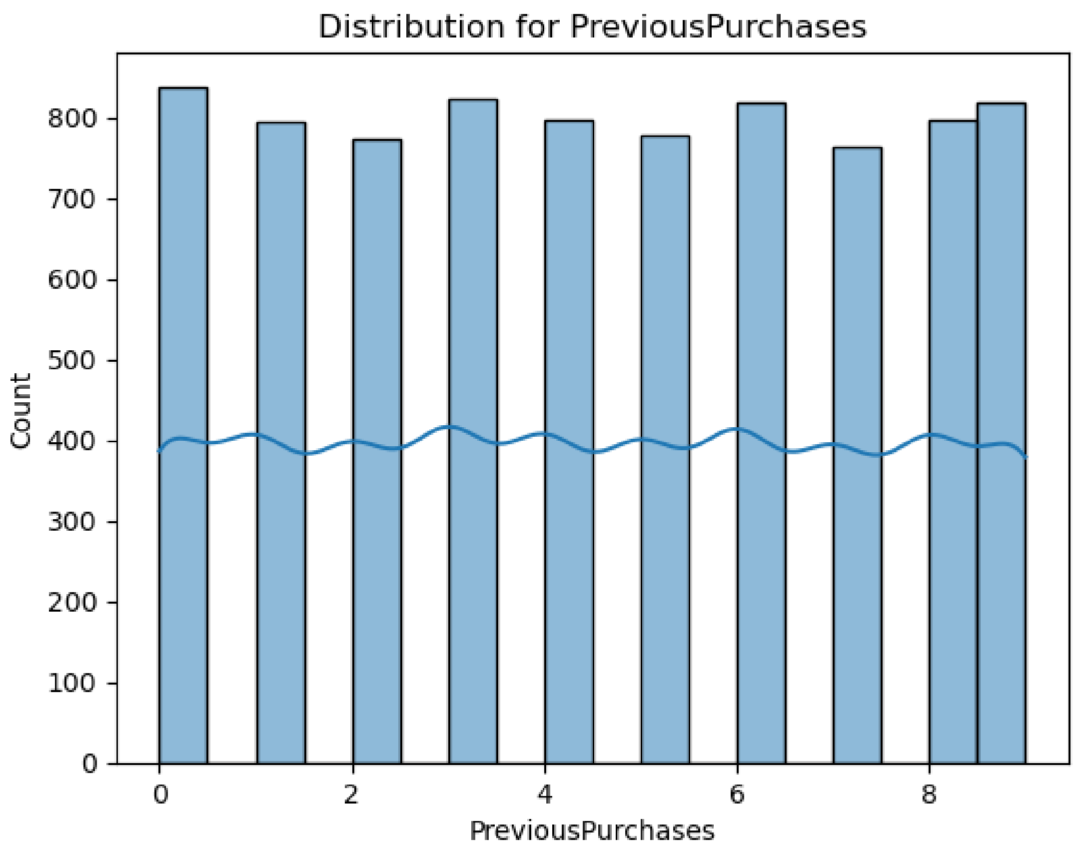

Distribution for PagesPerVisit
Count
PagesPerVisit
0
100
200
300
400
2
4
6
8
10

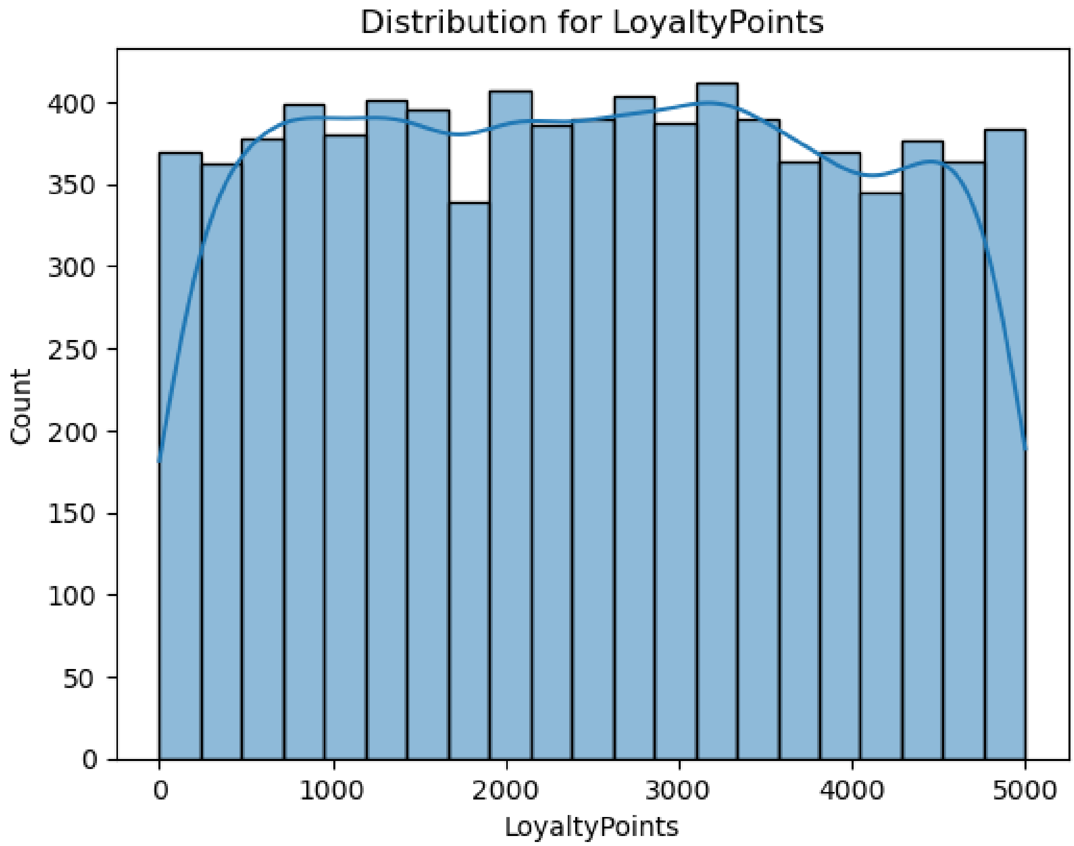

Distribution for TimeOnSite
400
300
200
100
0
Count
0
2
4
6
8
10
12
14
TimeOnSite

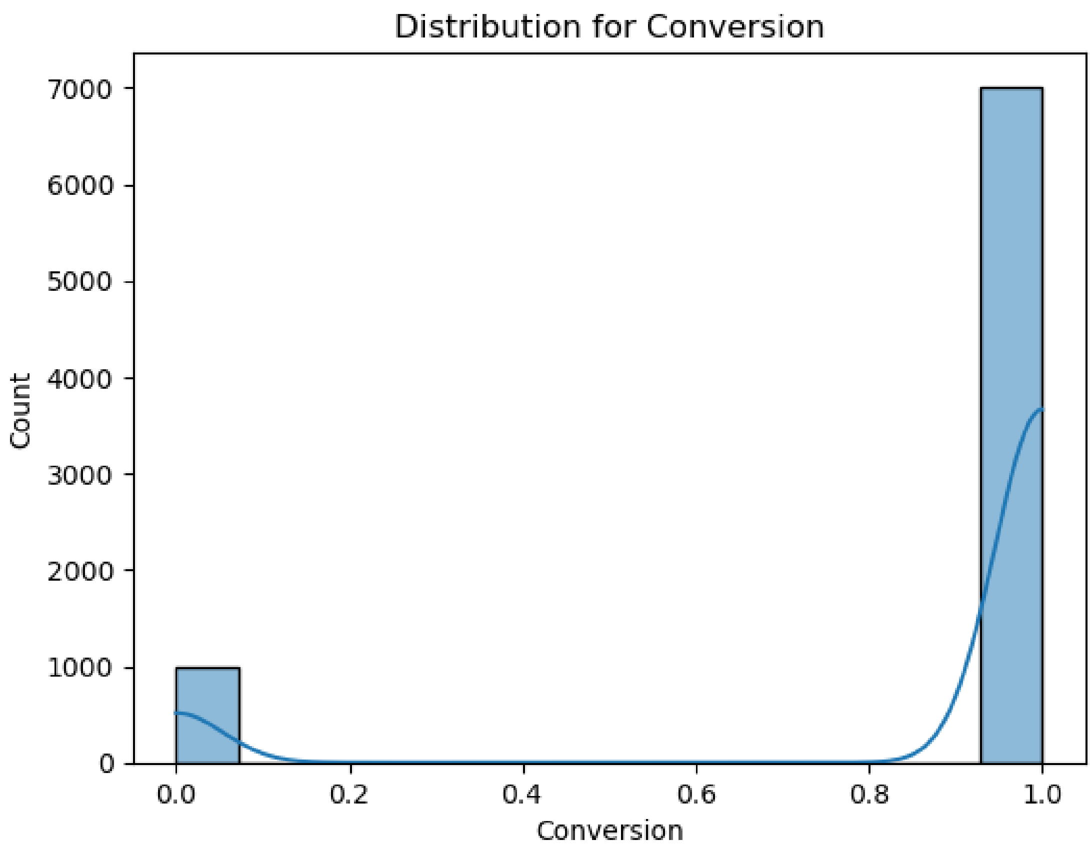

Distribution for SocialShares
Count
SocialShares
0
50
100
150
200
250
300
350
400
0
20
40
60
80
100


Distribution for EmailOpens
Count
400
300
200
100
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
EmailOpens

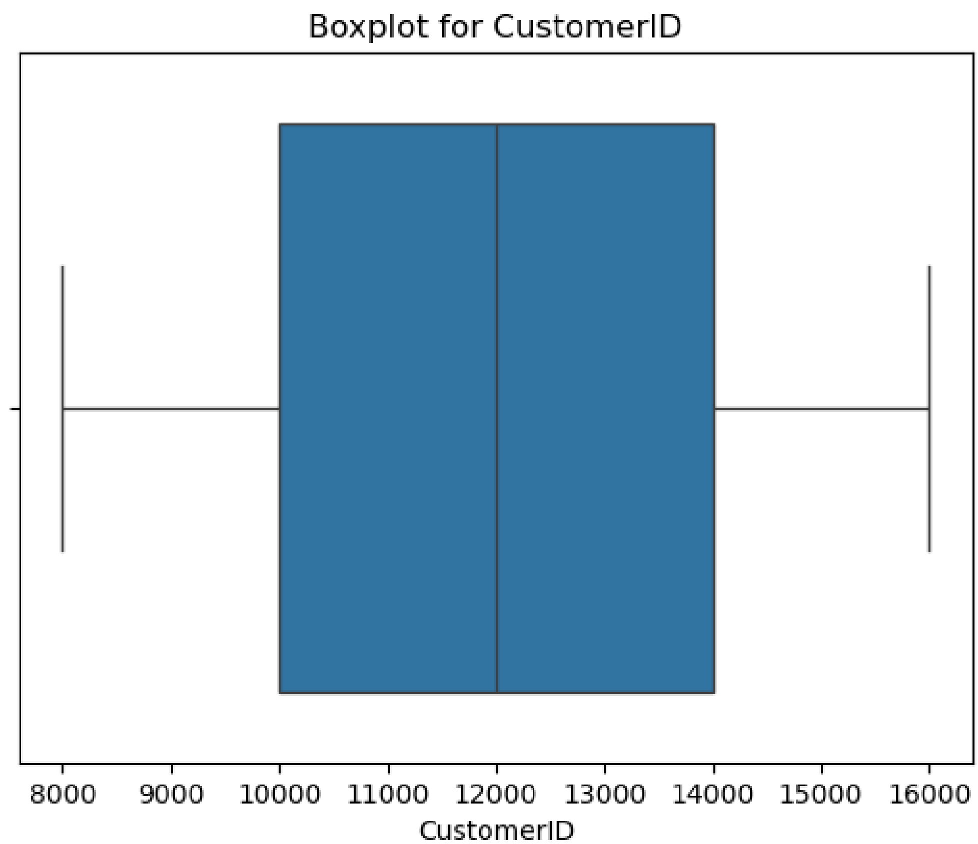

Distribution for EmailClicks
Count
EmailClicks
0
100
200
300
400
500
600
700
800
0
2
4
6
8

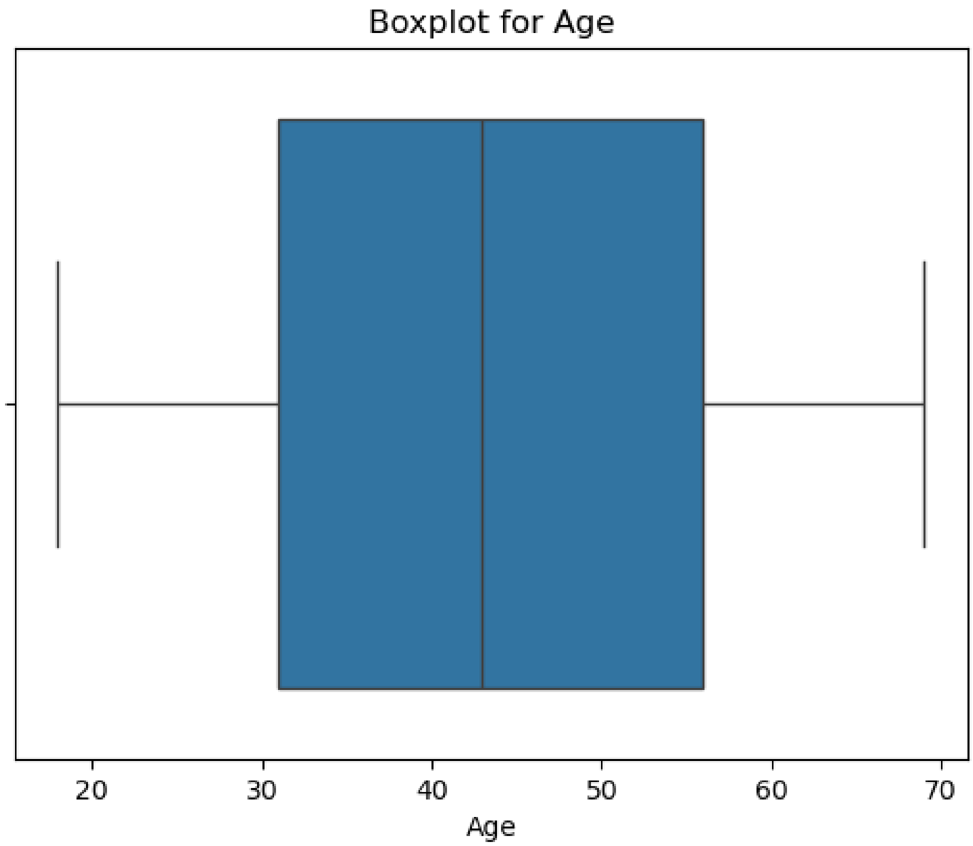

Distribution for PreviousPurchases
Count
800
700
600
500
400
300
200
100
0
0
2
4
6
8
PreviousPurchases

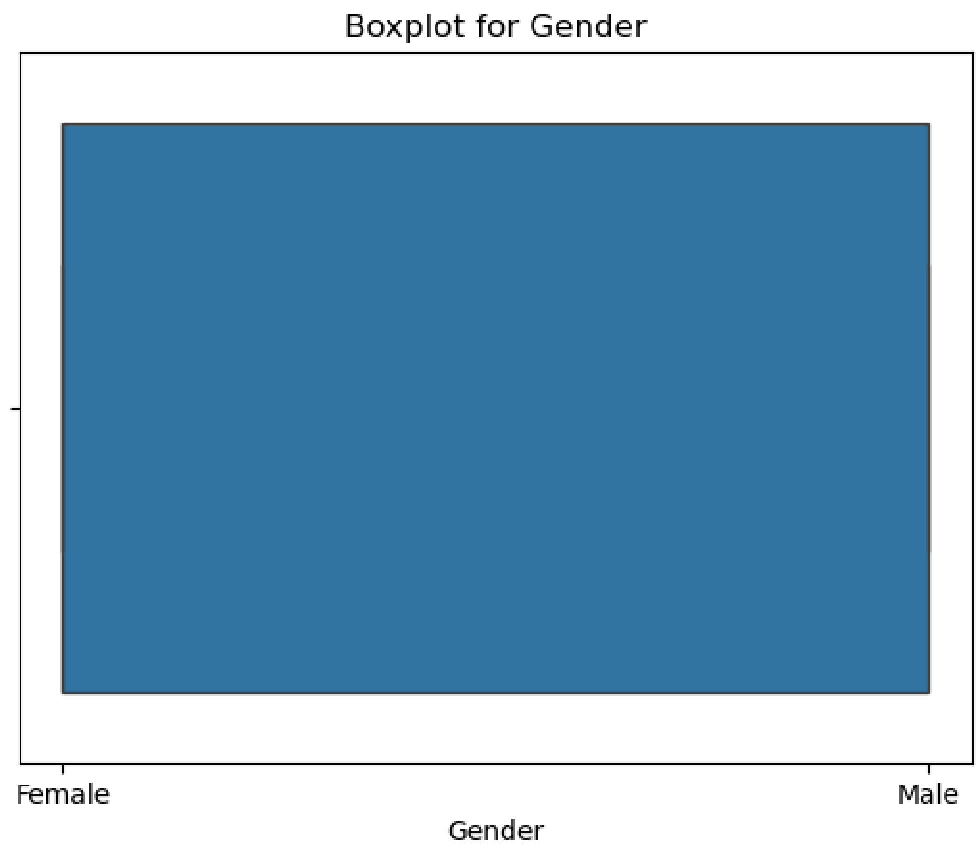

Distribution for LoyaltyPoints
Count
400
350
300
250
200
150
100
50
0
0
1000
2000
3000
4000
5000
LoyaltyPoints

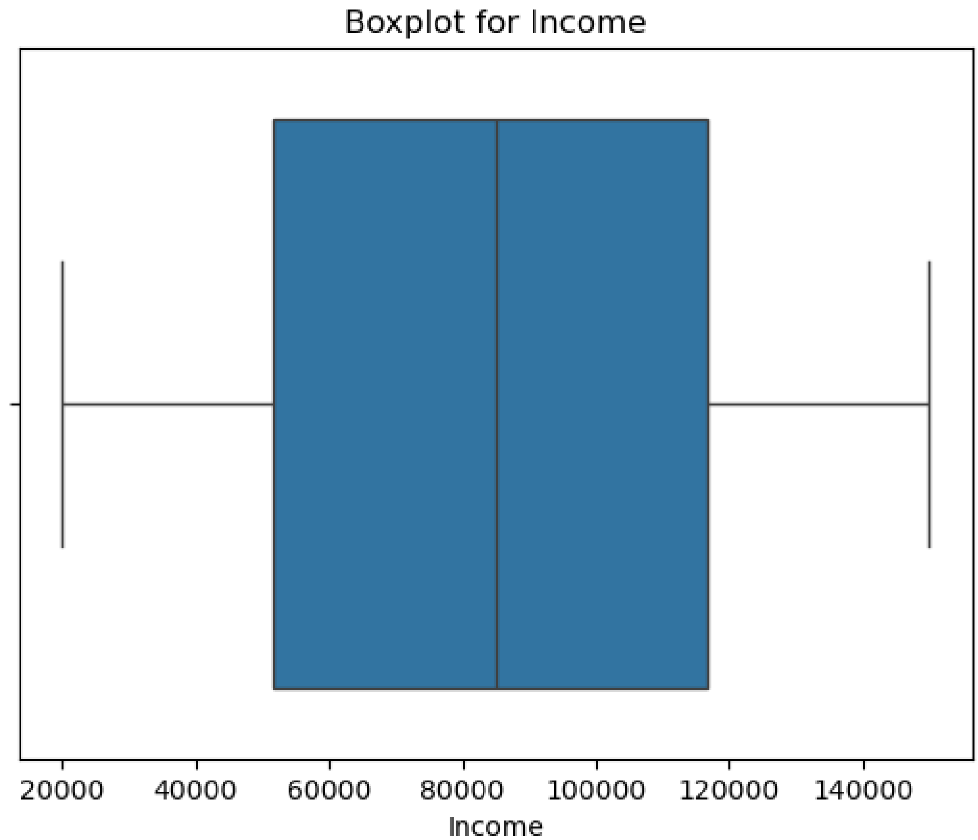


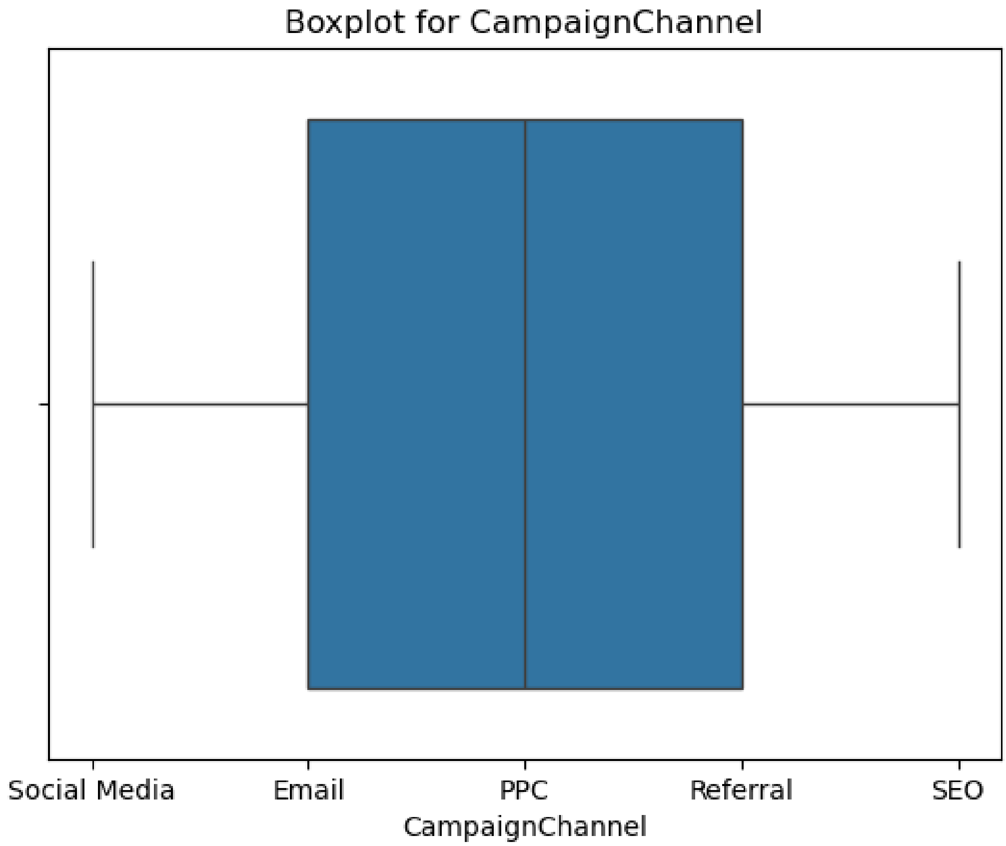
[552]:
```
for column in df.columns:
    sns.boxplot(data=df, x=column)
    plt.title(f'Boxplot for {column}')
    plt.show()
```

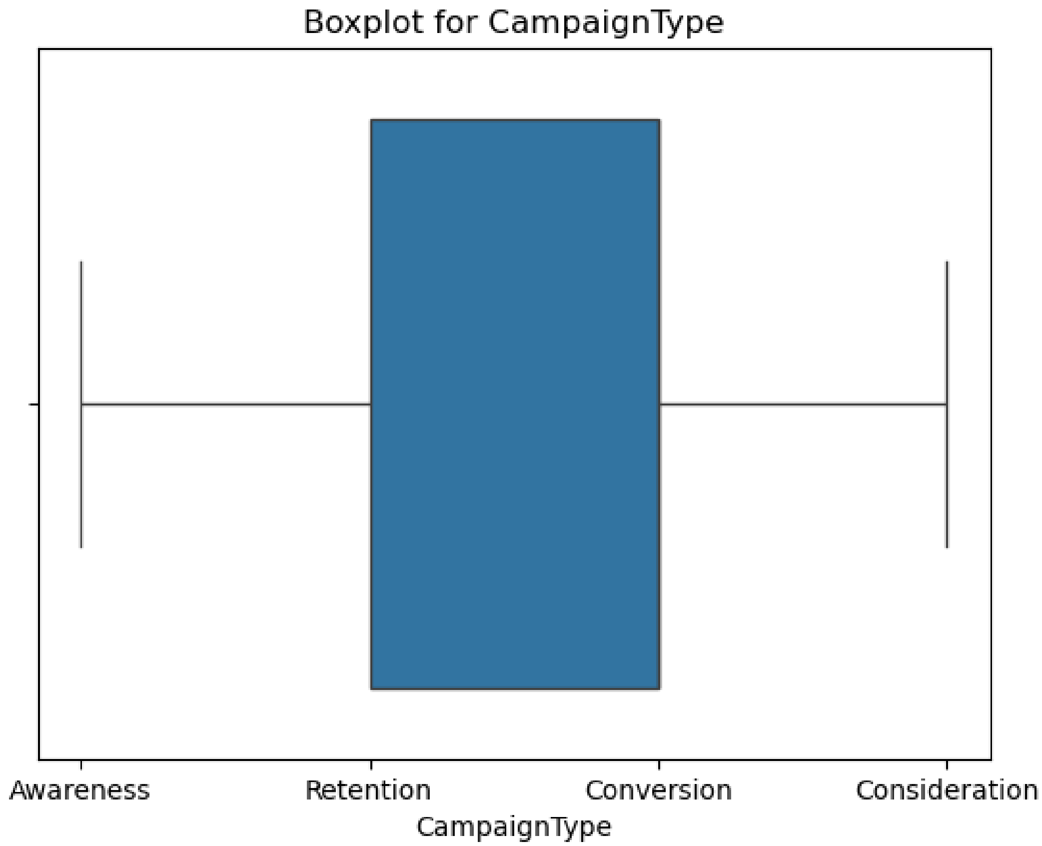

Boxplot for CustomerID
8000
9000
10000
11000
12000
13000
14000
15000
16000
CustomerID

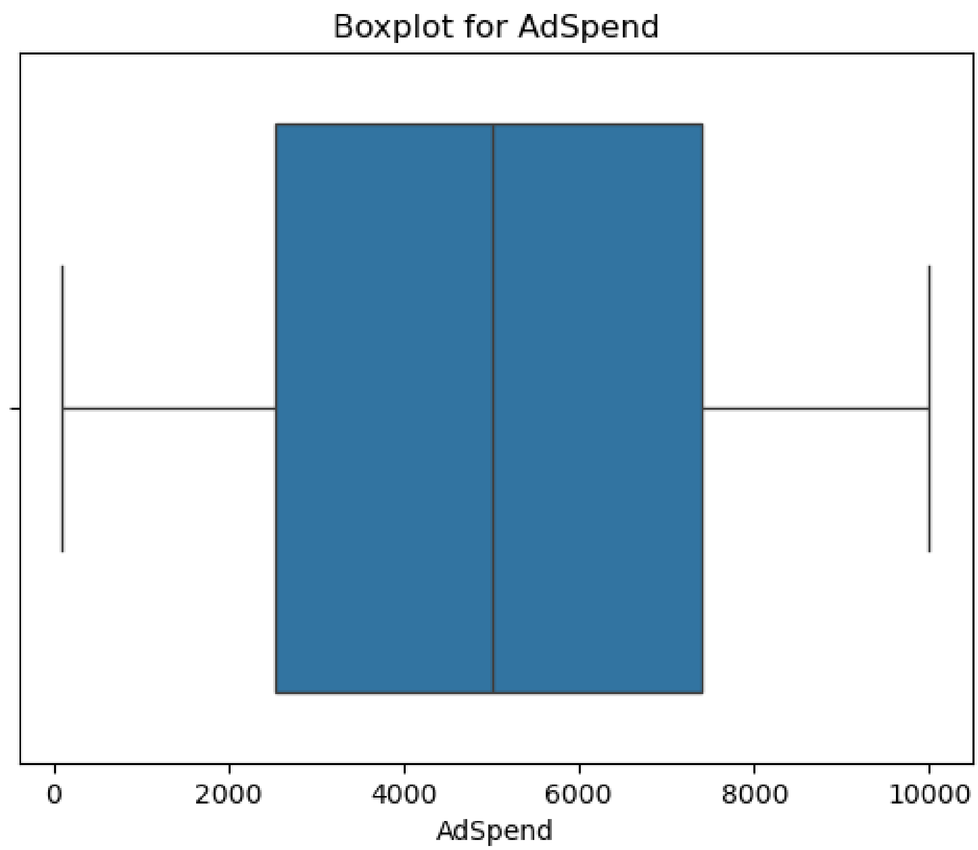

Boxplot for Age
20
30
40
50
60
70
Age

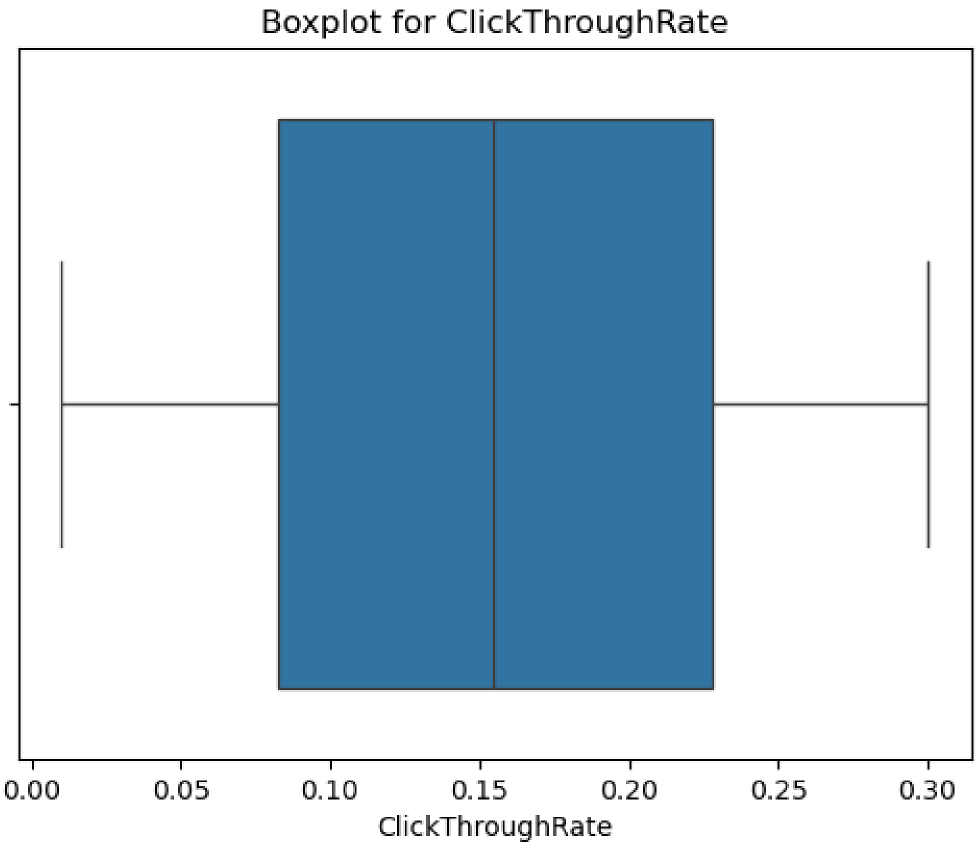

Boxplot for Gender
Female
Male
Gender

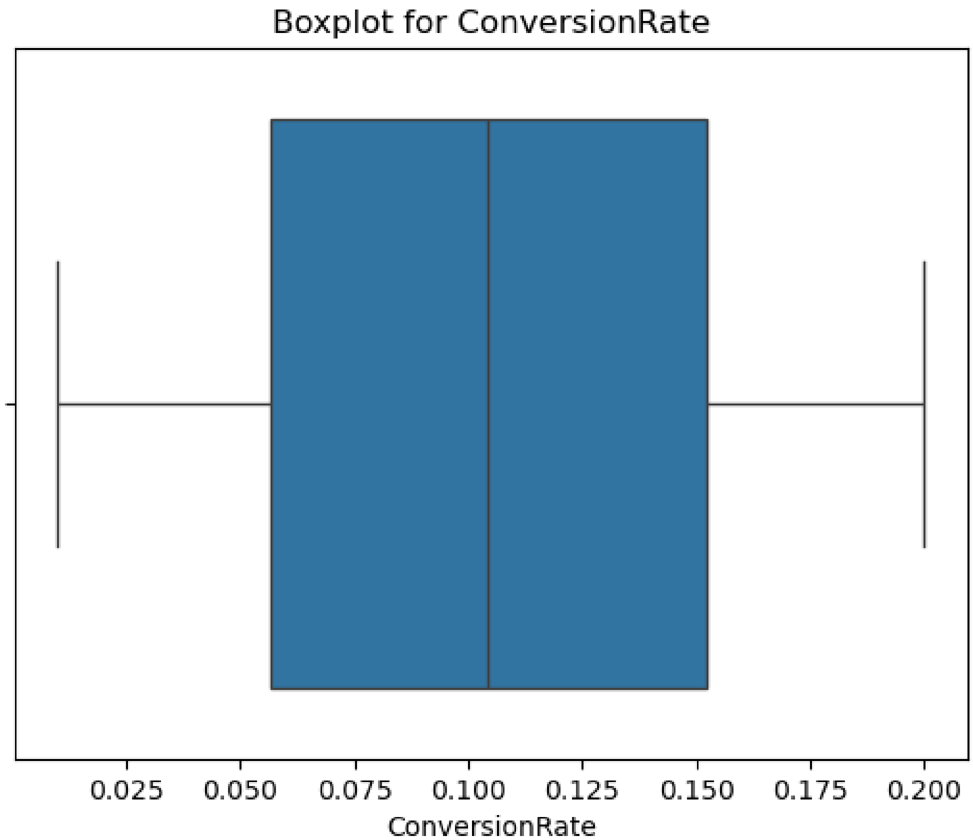

Boxplot for Income
20000
40000
60000
80000
100000
120000
140000
Income


Boxplot for CampaignChannel
Social Media
Email
PPC
Referral
SEO
CampaignChannel

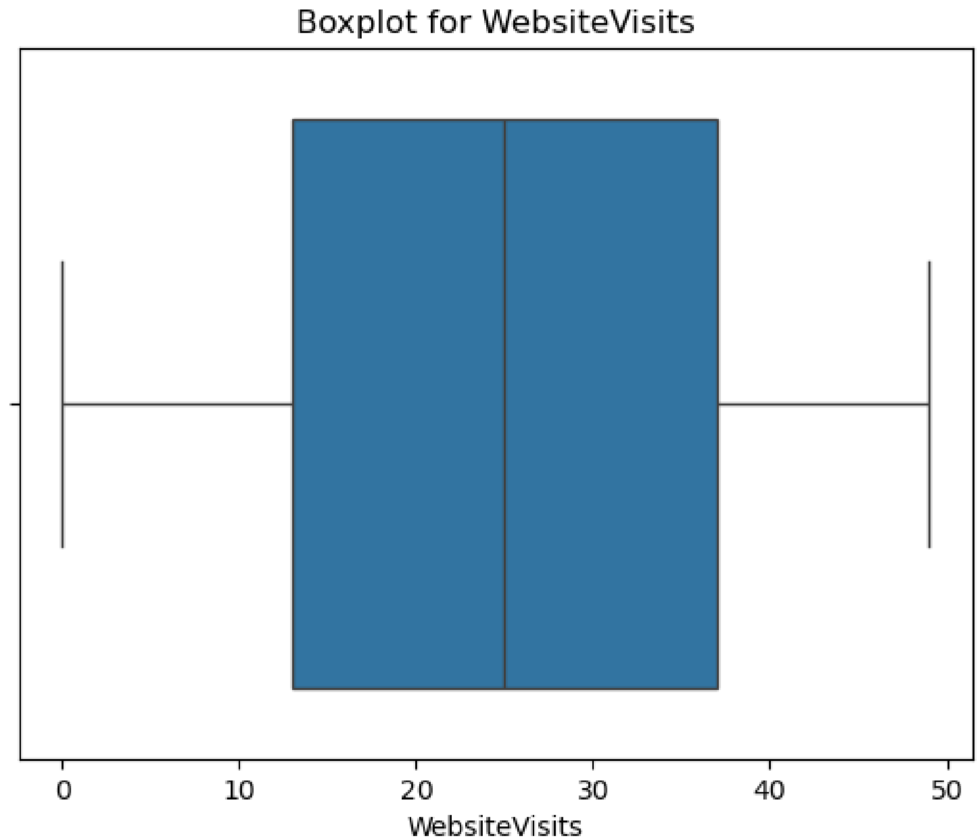

Boxplot for CampaignType
Awareness
Retention
Conversion
Consideration
CampaignType

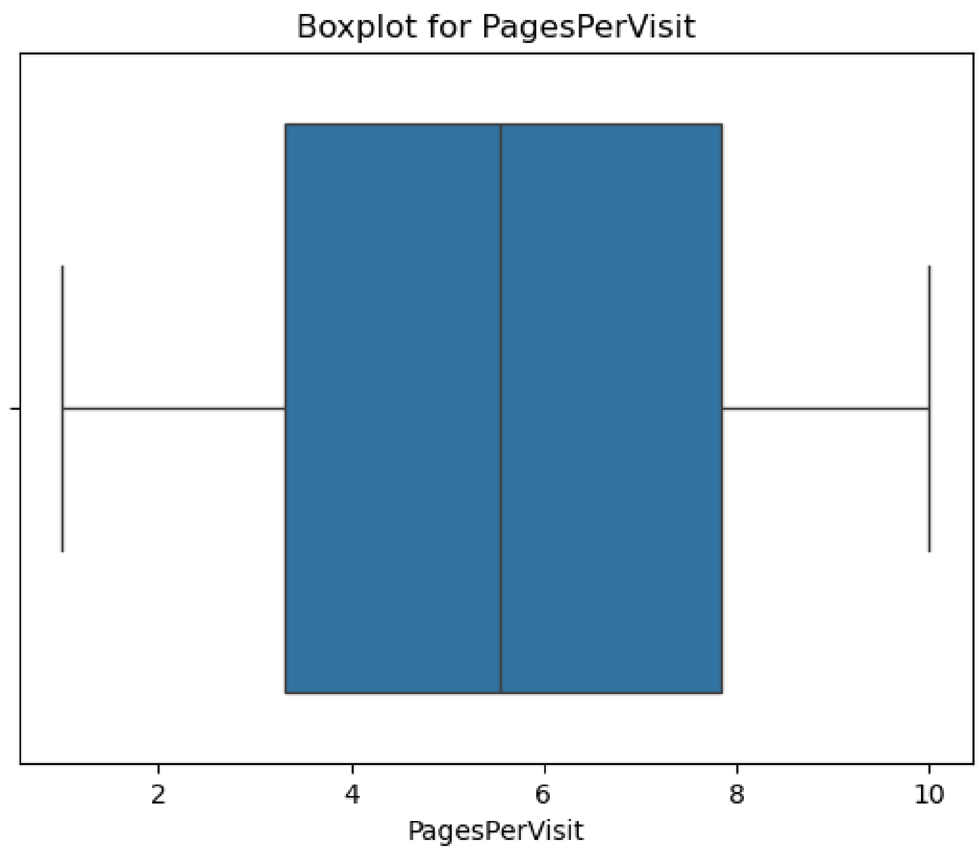

Boxplot for AdSpend
0
2000
4000
6000
8000
10000
AdSpend

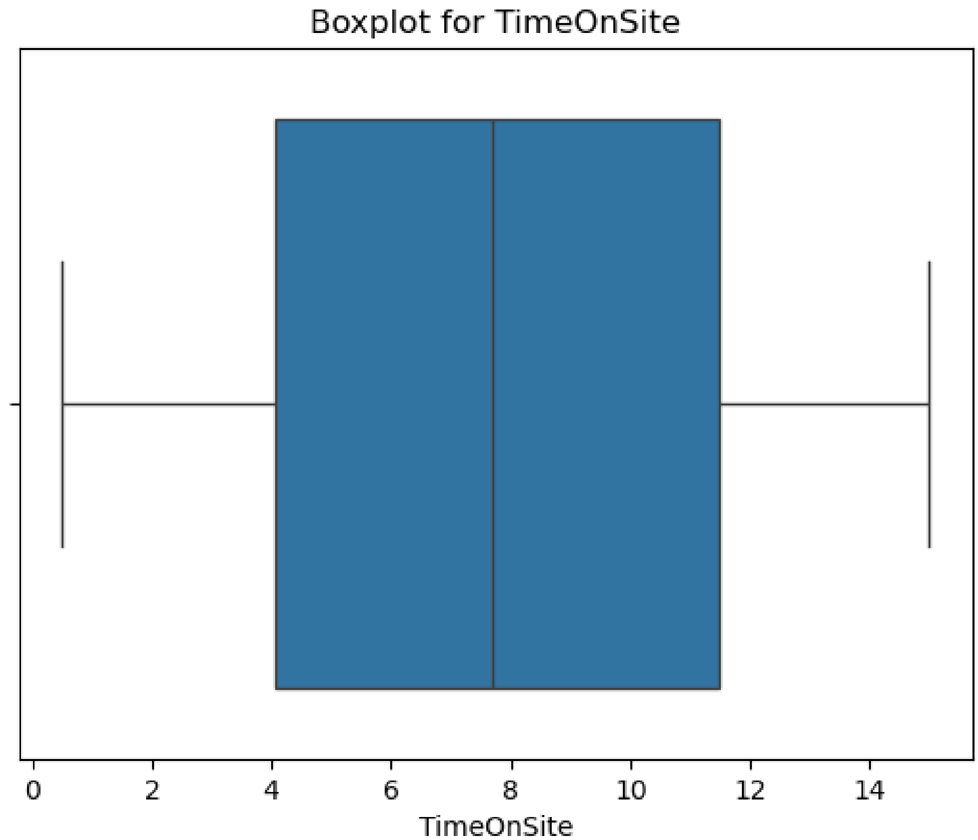

Boxplot for ClickThroughRate
0.00
0.05
0.10
0.15
0.20
0.25
0.30
ClickThroughRate

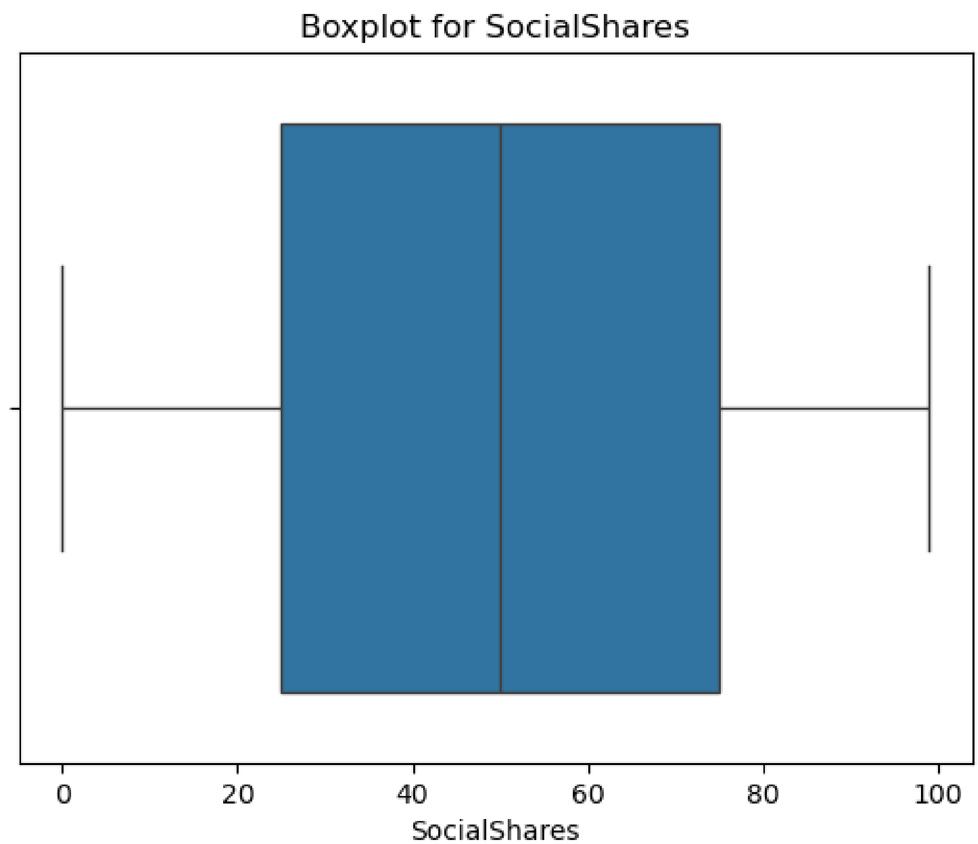


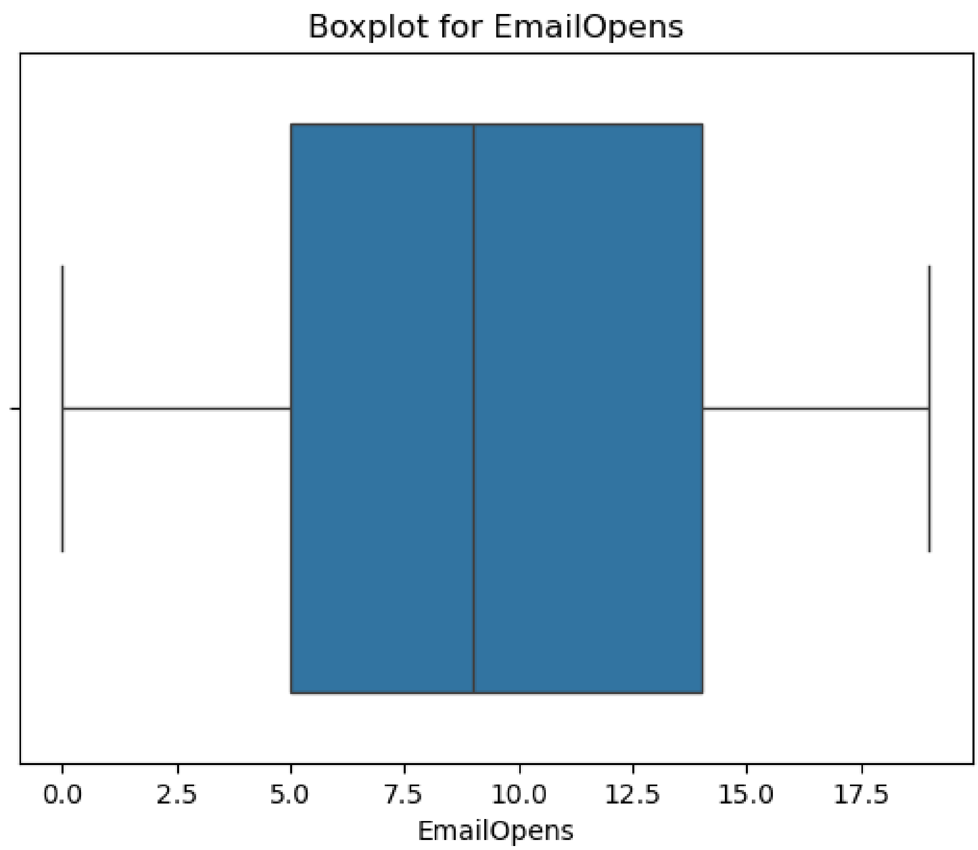
Boxplot for ConversionRate
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
ConversionRate

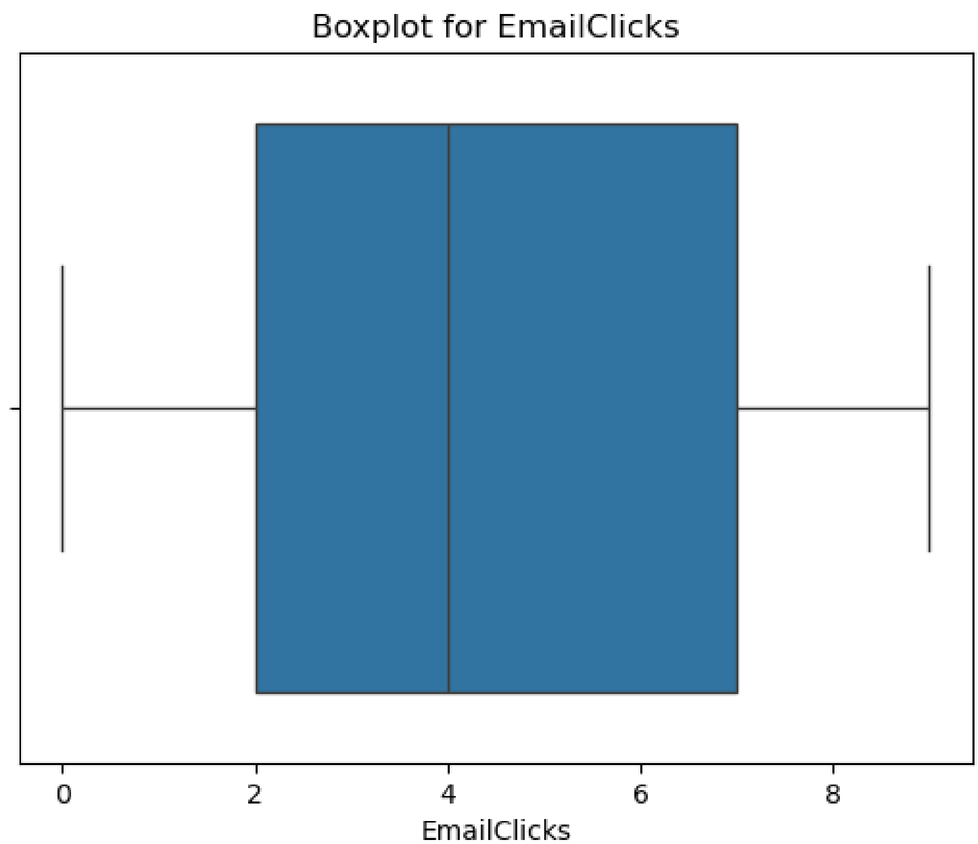

Boxplot for WebsiteVisits
0
10
20
30
40
50
WebsiteVisits

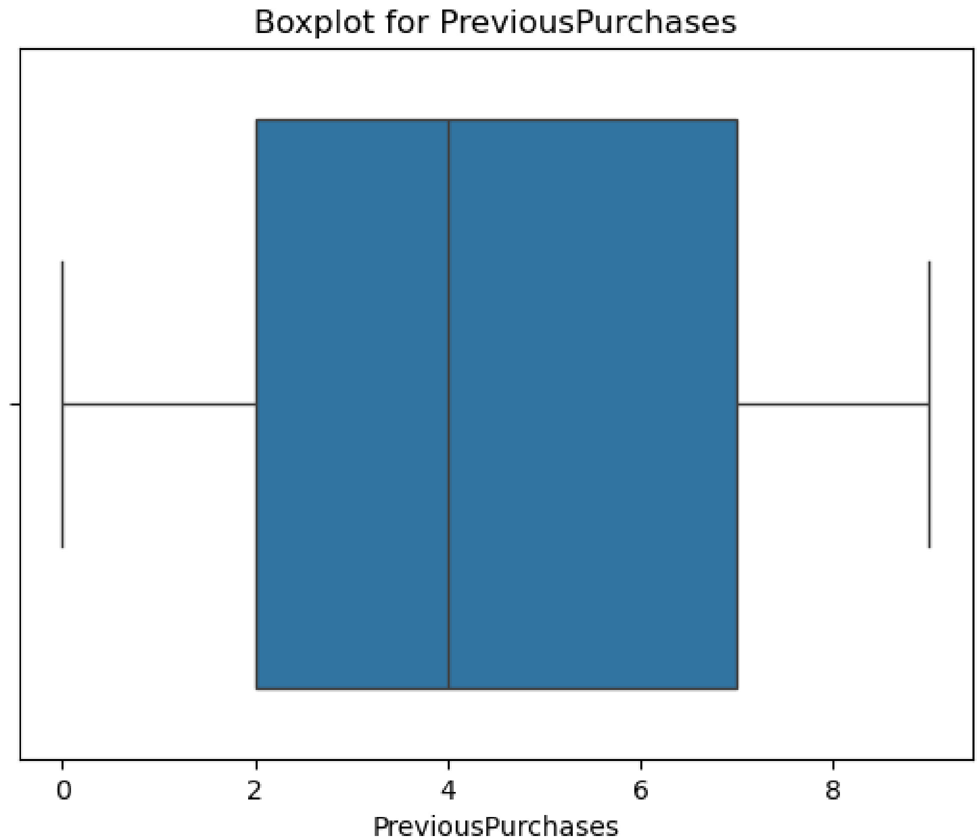

Boxplot for PagesPerVisit
2
4
6
8
10
PagesPerVisit

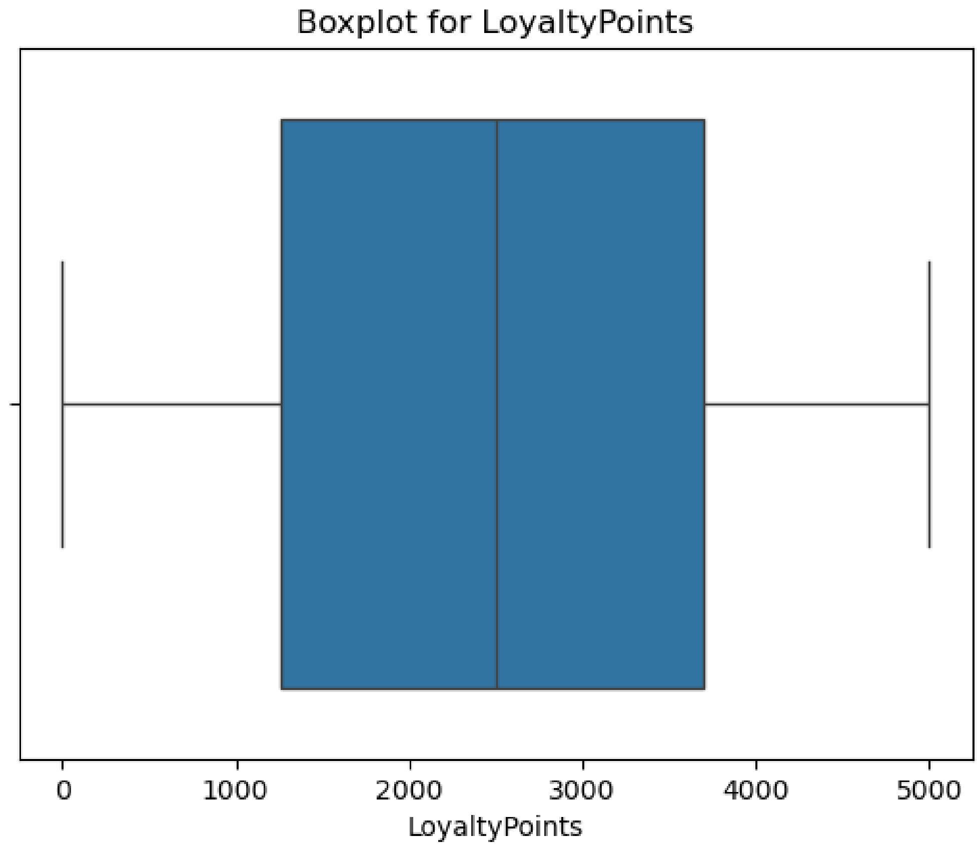

Boxplot for TimeOnSite
0
2
4
6
8
10
12
14
TimeOnSite

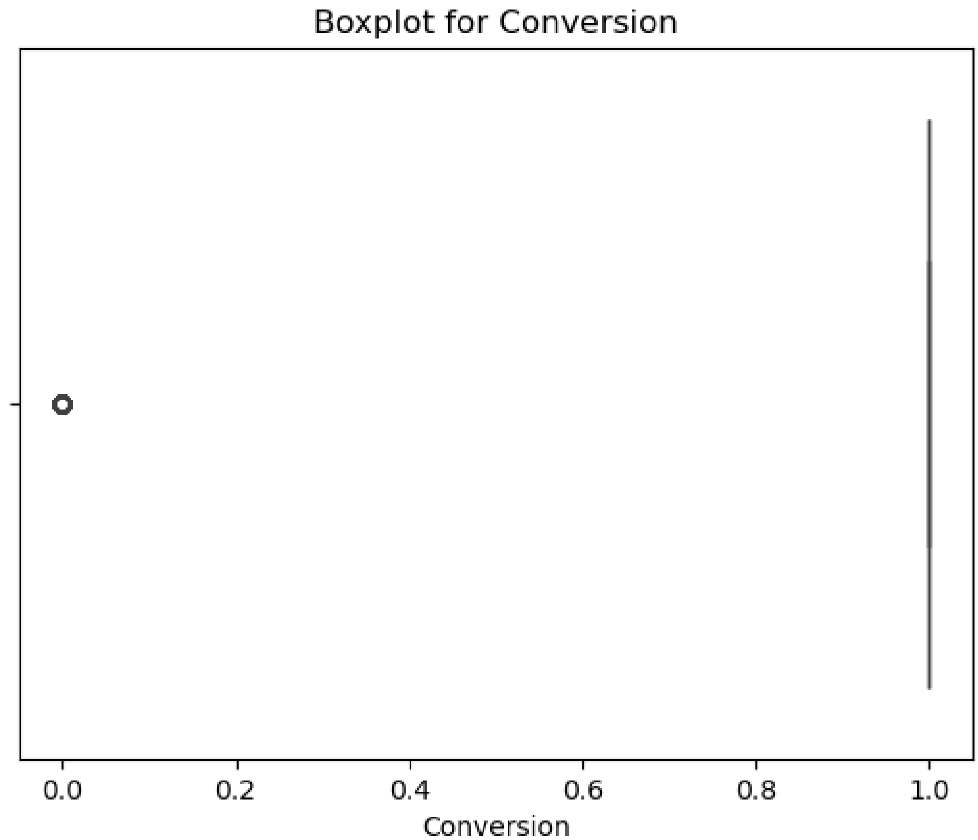

Boxplot for SocialShares
0
20
40
60
80
100
SocialShares


Boxplot for EmailOpens
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
EmailOpens


Boxplot for EmailClicks
0
2
4
6
8
EmailClicks


Boxplot for PreviousPurchases
0
2
4
6
8
PreviousPurchases


Boxplot for LoyaltyPoints
0
1000
2000
3000
4000
5000
LoyaltyPoints



Exploratory analysis

Questions to answer:

Correlations and relationships between variables

How are advertising expenses (AdSpend) related to conversion (Conversion)? How does customer engagement (WebsiteVisits, TimeOnSite) change with increased advertising expenses?

Segmentation and user grouping

Which customer groups are more likely to make purchases? Does campaign type (CampaignType) affect conversion across different age groups? What is the average spending (AdSpend) for each customer segment?

Email marketing effectiveness

Which age groups open email campaigns (EmailOpens) more frequently? Does the type of marketing campaign (CampaignType) influence email click rates (EmailClicks)? How many email openings (EmailOpens) lead to conversion?

Evaluation of marketing strategy effectiveness

Which marketing channels (CampaignChannel) demonstrate the highest efficiency? Which campaigns attract new customers, and which are more effective for retention?

Conversion funnel

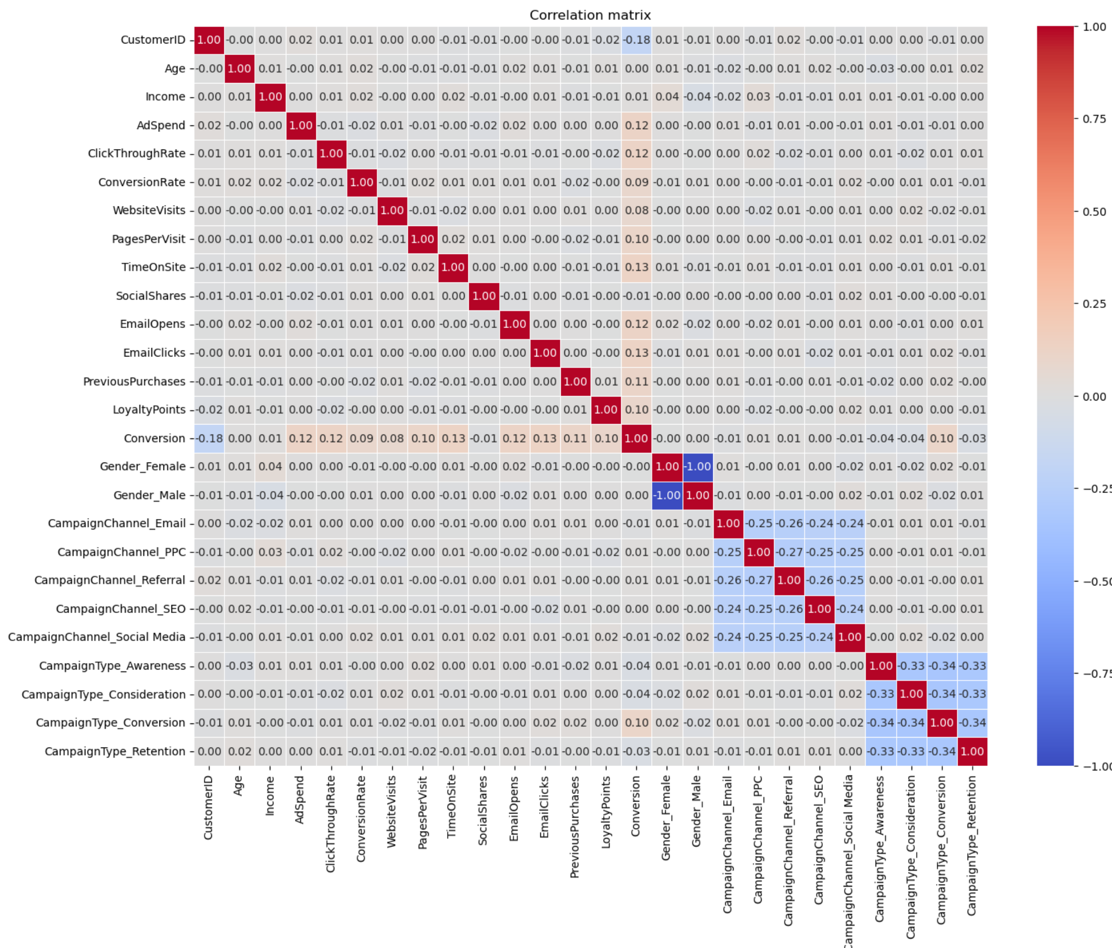
Which advertising campaigns (CampaignType) drive the most traffic to the website? Which marketing channels (CampaignChannel) generate the highest website traffic? What percentage of visitors (WebsiteVisits) view more than one page (PagesPerVisit)? How does time spent on the site (TimeOnSite) affect the likelihood of conversion? Which advertising campaigns (CampaignType) contribute to longer site visits? Which marketing channels (CampaignChannel) encourage users to spend more time on the website? Which advertising campaigns (CampaignType) lead to more page views? Which marketing channels (CampaignChannel) result in higher page views? How does the number of website visits affect conversion? Visualization of the conversion funnel Which factors are most important for conversion?

[555]:
```
df.describe()
```

[555]:
```
        CustomerID          Age         Income      AdSpend  ClickThroughRate  \
count   8000.00000  8000.000000    8000.000000  8000.000000       8000.000000
mean   11999.50000    43.625500   84664.196750  5000.944830          0.154829
std     2309.54541    14.902785   37580.387945  2838.038153          0.084007
min     8000.00000    18.000000   20014.000000   100.054813          0.010005
25%     9999.75000    31.000000   51744.500000  2523.221165          0.082635
50%    11999.50000    43.000000   84926.500000  5013.440044          0.154505
75%    13999.25000    56.000000  116815.750000  7407.989369          0.228207
max    15999.00000    69.000000  149986.000000  9997.914781          0.299968

       ConversionRate  WebsiteVisits  PagesPerVisit   TimeOnSite  \
count     8000.000000    8000.000000    8000.000000  8000.000000
mean         0.104389      24.751625       5.549299     7.727718
std          0.054878      14.312269       2.607358     4.228218
min          0.010018       0.000000       1.000428     0.501669
25%          0.056410      13.000000       3.302479     4.068340
50%          0.104046      25.000000       5.534257     7.682956
75%          0.152077      37.000000       7.835756    11.481468
max          0.199995      49.000000       9.999055    14.995311

       SocialShares   EmailOpens  EmailClicks  PreviousPurchases  \
count   8000.000000  8000.000000  8000.000000        8000.000000
mean      49.799750     9.476875     4.467375           4.485500
std       28.901165     5.711111     2.856564           2.888093
min        0.000000     0.000000     0.000000           0.000000
25%       25.000000     5.000000     2.000000           2.000000
50%       50.000000     9.000000     4.000000           4.000000
75%       75.000000    14.000000     7.000000           7.000000
max       99.000000    19.000000     9.000000           9.000000

       LoyaltyPoints   Conversion
count    8000.000000  8000.000000
mean     2490.268500     0.876500
std      1429.527162     0.329031
```

```
min         0.000000     0.000000
25%      1254.750000     1.000000
50%      2497.000000     1.000000
75%      3702.250000     1.000000
max      4999.000000     1.000000
```

[556]:
```python
df_numeric = pd.get_dummies(df, drop_first=False)
corr_matrix = df_numeric.corr()

plt.figure(figsize=(16, 12))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Correlation matrix")
plt.show()
```

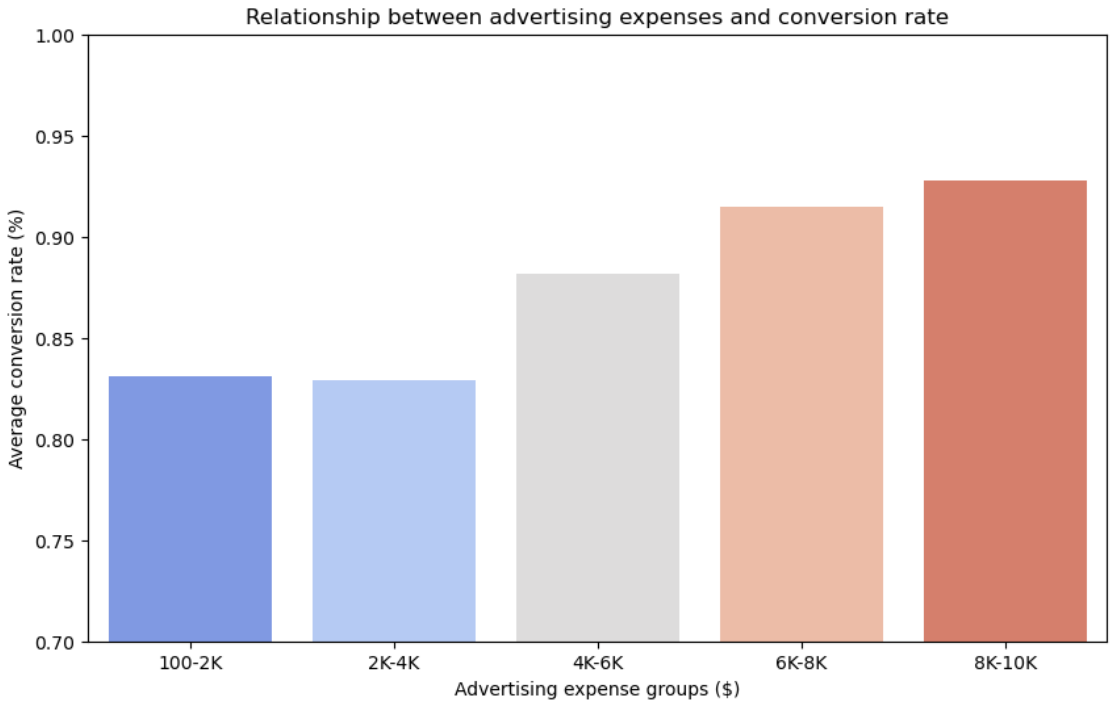


How are advertising expenses (AdSpend) related to conversion (Conversion)?

[558]:

```
bins = [100, 2000, 4000, 6000, 8000, 10000]
labels = ['100-2K', '2K-4K', '4K-6K', '6K-8K', '8K-10K']
df['AdSpendGroup'] = pd.cut(df['AdSpend'], bins=bins, labels=labels)

grouped_data = df.groupby('AdSpendGroup')['Conversion'].mean().reset_index()

plt.figure(figsize=(10, 6))
sns.barplot(x='AdSpendGroup', y='Conversion', data=grouped_data,␣
↪palette='coolwarm')
plt.xlabel("Advertising expense groups ($)")
plt.ylabel("Average conversion rate (%)")
plt.title("Relationship between advertising expenses and conversion rate")
plt.ylim(0.7, 1)
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/4283026523.py:5
: FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_data = df.groupby('AdSpendGroup')['Conversion'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/4283026523.py:8
: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='AdSpendGroup', y='Conversion', data=grouped_data,
palette='coolwarm')
```

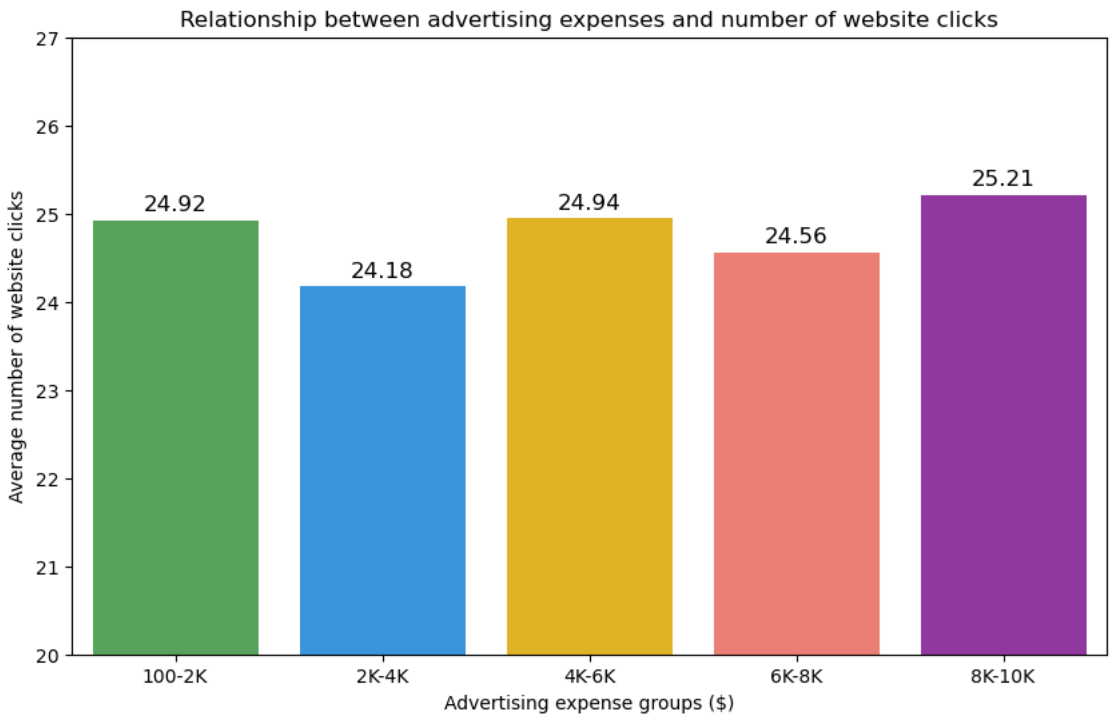


How does customer engagement (WebsiteVisits, TimeOnSite) change with increased advertising expenses?

[560]:
```
grouped_data = df.groupby('AdSpendGroup')['WebsiteVisits'].mean().reset_index()
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='AdSpendGroup', y='WebsiteVisits', data=grouped_data,␣
↪palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61', '#9C27B0'])
plt.xlabel("Advertising expense groups ($)")
plt.ylabel("Average number of website clicks")
plt.title("Relationship between advertising expenses and number of website␣
↪clicks")
plt.ylim(20, 27)
for bar in ax.containers:
    ax.bar_label(bar, fmt='%.2f', label_type='edge', padding=3, color='black',␣
↪fontsize=12)

plt.show()
```

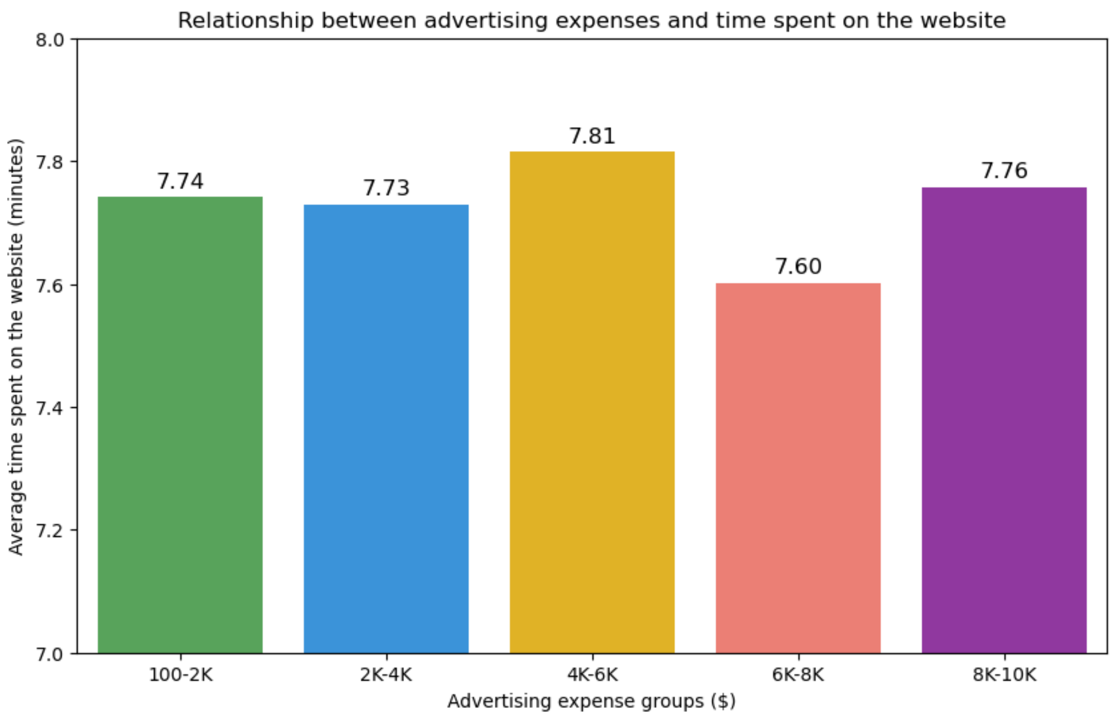
```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/356601795.py:1:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_data =
df.groupby('AdSpendGroup')['WebsiteVisits'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/356601795.py:3:
```

```
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.barplot(x='AdSpendGroup', y='WebsiteVisits', data=grouped_data,
palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61', '#9C27B0'])
```



[561]:
```
grouped_data = df.groupby('AdSpendGroup')['TimeOnSite'].mean().reset_index()
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='AdSpendGroup', y='TimeOnSite', data=grouped_data,␣
 ↪palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61', '#9C27B0'])
plt.xlabel("Advertising expense groups ($)")
plt.ylabel("Average time spent on the website (minutes)")
plt.title("Relationship between advertising expenses and time spent on the␣
 ↪website")

plt.ylim(7, 8)
for bar in ax.containers:
    ax.bar_label(bar, fmt='%.2f', label_type='edge', padding=3, color='black',␣
 ↪fontsize=12)

plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/1096504721.py:1
: FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_data = df.groupby('AdSpendGroup')['TimeOnSite'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/1096504721.py:3
: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.barplot(x='AdSpendGroup', y='TimeOnSite', data=grouped_data,
palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61', '#9C27B0'])
```



Which customer groups are more likely to make purchases?

[563]:
```python
df['AgeGroup'] = pd.cut(df['Age'], bins=[18, 25, 35, 45, 55, 70],
 ↪labels=['18-25', '26-35', '36-45', '46-55', '56+'])
df['IncomeGroup'] = pd.cut(df['Income'], bins=[20000, 50000, 80000, 110000,
 ↪150000], labels = ['Low', 'Medium', 'High', 'Very High'])
grouped_df = df.groupby(['Gender', 'AgeGroup',
 ↪'IncomeGroup'])['PreviousPurchases'].mean().reset_index()
```

```
top_10_groups = grouped_df.sort_values(by='PreviousPurchases', ascending=False).
  ↪head(10)
bottom_10_groups = grouped_df.sort_values(by='PreviousPurchases',␣
  ↪ascending=True).head(10)
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/270844897.py:3:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_df = df.groupby(['Gender', 'AgeGroup',
'IncomeGroup'])['PreviousPurchases'].mean().reset_index()
```

[564]:
```
top_10_groups
```

[564]:

	Gender	AgeGroup	IncomeGroup	PreviousPurchases
14	Female	46-55	High	4.869767
16	Female	56+	Low	4.857143
10	Female	36-45	High	4.845494
28	Male	36-45	Low	4.785714
37	Male	56+	Medium	4.756906
29	Male	36-45	Medium	4.739130
4	Female	26-35	Low	4.725962
1	Female	18-25	Medium	4.709091
24	Male	26-35	Low	4.702532
23	Male	18-25	Very High	4.691057

[566]:
```
bottom_10_groups
```

[566]:

	Gender	AgeGroup	IncomeGroup	PreviousPurchases
0	Female	18-25	Low	3.972028
38	Male	56+	High	4.023697
15	Female	46-55	Very High	4.077739
33	Male	46-55	Medium	4.240260
13	Female	46-55	Medium	4.271845
18	Female	56+	High	4.298361
39	Male	56+	Very High	4.300429
7	Female	26-35	Very High	4.305556
22	Male	18-25	High	4.316832
9	Female	36-45	Medium	4.317391

[567]:
```
grouped_df = df.groupby(['Gender', 'AgeGroup', 'IncomeGroup'])['Conversion'].
  ↪mean().reset_index()

top_10_groups = grouped_df.sort_values(by='Conversion', ascending=False).
  ↪head(10)
bottom_10_groups = grouped_df.sort_values(by='Conversion', ascending=True).
  ↪head(10)
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/3436979725.py:1
: FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_df = df.groupby(['Gender', 'AgeGroup',
'IncomeGroup'])['Conversion'].mean().reset_index()
```

[568]:
```
top_10_groups
```

[568]:

	Gender	AgeGroup	IncomeGroup	Conversion
28	Male	36-45	Low	0.935714
29	Male	36-45	Medium	0.934783
9	Female	36-45	Medium	0.913043
11	Female	36-45	Very High	0.906250
26	Male	26-35	High	0.905109
31	Male	36-45	Very High	0.902174
30	Male	36-45	High	0.895105
18	Female	56+	High	0.895082
37	Male	56+	Medium	0.895028
27	Male	26-35	Very High	0.890710

[569]:
```
bottom_10_groups
```

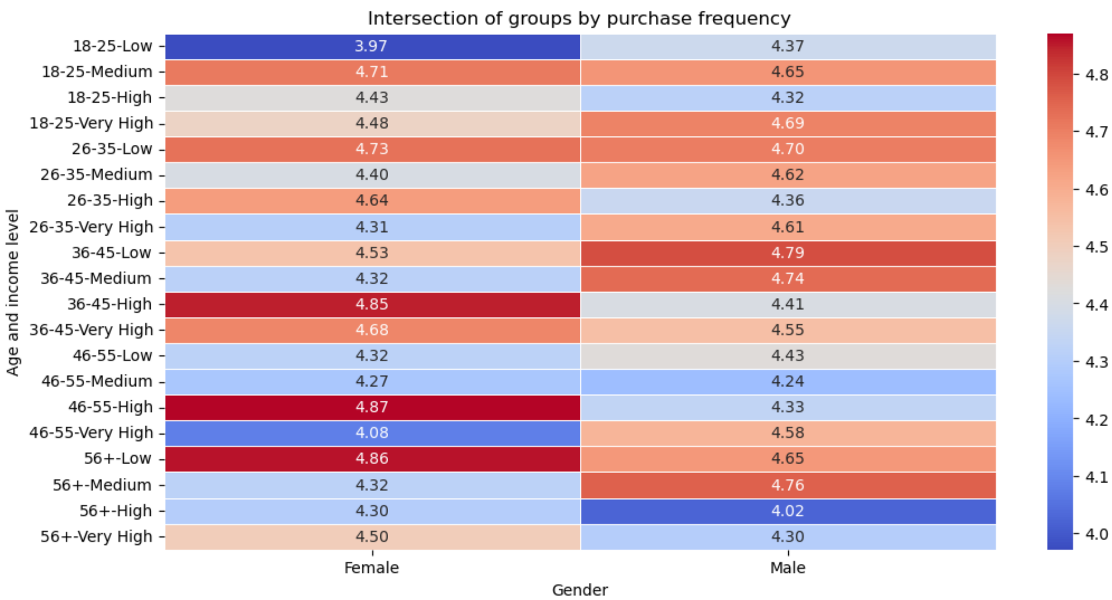
[569]:

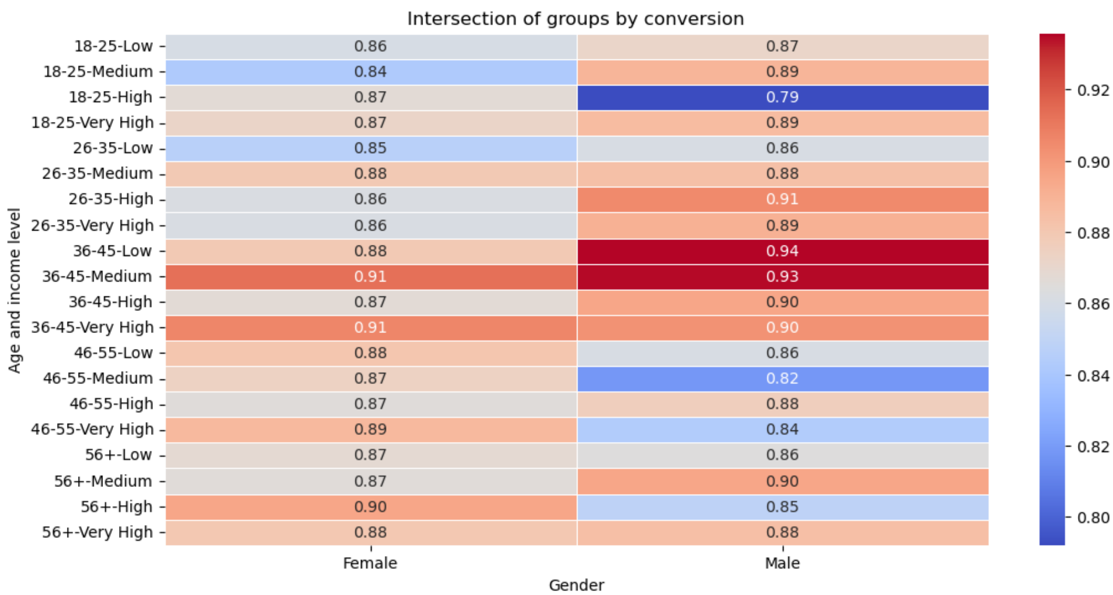
	Gender	AgeGroup	IncomeGroup	Conversion
22	Male	18-25	High	0.792079
33	Male	46-55	Medium	0.818182
1	Female	18-25	Medium	0.842424
35	Male	46-55	Very High	0.843373
4	Female	26-35	Low	0.846154
38	Male	56+	High	0.848341
0	Female	18-25	Low	0.860140
32	Male	46-55	Low	0.860606
24	Male	26-35	Low	0.860759
7	Female	26-35	Very High	0.861111

[570]:
```
pivot_table = df.pivot_table(values=['PreviousPurchases', 'Conversion'],
 ↪index=['AgeGroup', 'IncomeGroup'], columns=['Gender'])

plt.figure(figsize=(12, 6))
sns.heatmap(pivot_table['PreviousPurchases'], annot=True, fmt='.2f',
 ↪cmap='coolwarm', linewidths=0.5)
plt.title("Intersection of groups by purchase frequency")
plt.xlabel("Gender")
plt.ylabel("Age and income level")
plt.show()

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

```
sns.heatmap(pivot_table['Conversion'], annot=True, fmt='.2f', cmap='coolwarm',
  linewidths=0.5)
plt.title("Intersection of groups by conversion")
plt.xlabel("Gender")
plt.ylabel("Age and income level")
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/2636020496.py:1
: FutureWarning: The default value of observed=False is deprecated and will
change to observed=True in a future version of pandas. Specify observed=False to
silence this warning and retain the current behavior
  pivot_table = df.pivot_table(values=['PreviousPurchases', 'Conversion'],
index=['AgeGroup', 'IncomeGroup'], columns=['Gender'])
```





1. Conversion by age and income
   The highest conversion rate is observed in the 36-45 age group, especially among men with low and medium income levels (0.935 and 0.934). Women aged 36-45 with high income also show a high conversion rate (0.906). The lowest conversion rate is seen among men aged 18-25 with high income (0.792), which may indicate low engagement or longer decision-making times in this group.
   2. Average number of previous purchases
      Men aged 36-45 with low income make purchases most frequently (4.79). Women aged 56+ with low income (4.85) also exhibit high purchasing activity, possibly due to stable product needs. The lowest average number of purchases is seen among men aged 56+ with high income (4.02), which may suggest fewer but larger transactions.
      3. Gender differences in purchasing behavior
         Men aged 36-45 with low income are the most active buyers. Women aged 56+ make purchases consistently, regardless of income level. Women aged 18-25 with medium income make more purchases (4.7) than men (4.65), which may indicate a preference for frequent purchases.
         4. Income impact
            Medium income often demonstrates a higher conversion rate than high income (e.g., among 36-45-year-olds). High income does not always lead to more frequent purchases—groups with high income tend to shop less often.
            Business conclusions:
            The primary buyers are men aged 36-45 with low income and women aged 56+ with low income. Marketing campaigns for high conversion rates should target men aged 36-45 and women aged 56+. Personalization strategies can help improve engagement and purchasing behavior among men aged 56+. Women aged 18-25 with medium income tend to shop frequently, making them a strong target for subscription-based services.
            Most efficient groups (high purchases + high conversion)

men aged 36-45 with low income (0.935 conversion, 4.79 purchases) — highest conversion rate, frequent buyers. women aged 36-45 with medium income (0.913 conversion, 4.31 purchases) — high conversion, stable purchasing behavior. men aged 26-35 with high income (0.905 conversion, 4.35 purchases) — strong conversion rate, relatively active buyers. women aged 56+ with low income (0.867 conversion, 4.85 purchases) — frequent shoppers, despite lower income, strong conversion. women aged 36-45 with high income (0.906 conversion, 4.84 purchases) — stable and active buyers.

Least efficient groups (low purchases + low conversion)

men aged 18-25 with high income (0.792 conversion, 4.31 purchases) — low conversion, infrequent purchases. women aged 46-55 with high income (0.865 conversion, 4.87 purchases) — frequent purchases, but lower conversion rate. men aged 56+ with high income (0.848 conversion, 4.02 purchases) — lowest purchase frequency. women aged 18-25 with low income (0.860 conversion, 3.97 purchases) — low purchasing volume. men aged 46-55 with medium income (0.818 conversion, 4.24 purchases) — low engagement levels.

Business conclusions:

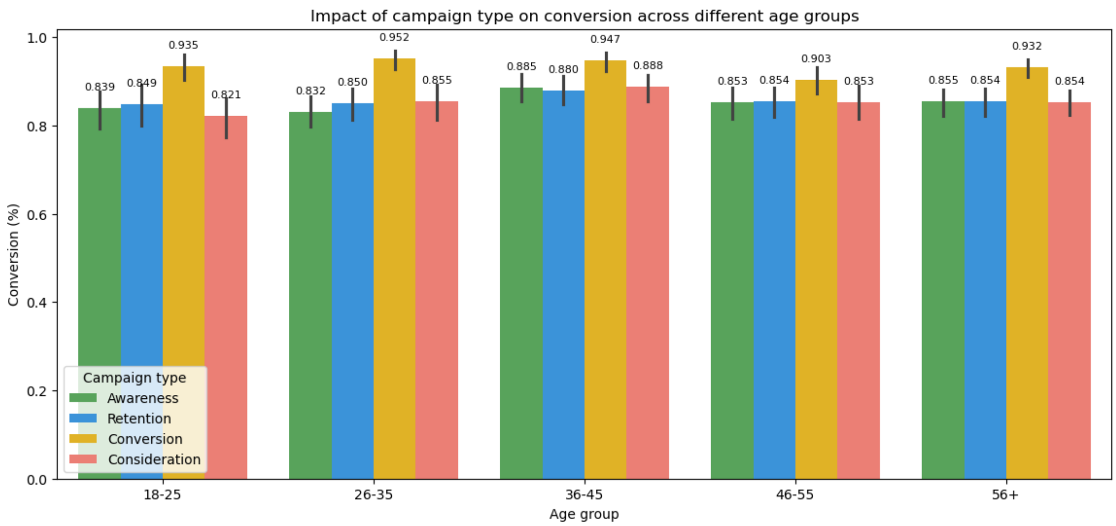
focus on men aged 36-45 with low income, as they lead in purchases and conversions. women aged 56+ with low income are stable buyers, making them a valuable audience for mass-market products. men aged 18-25 with high income may require adjusted marketing strategies to better engage them. men aged 56+ with high income could be targeted for larger one-time purchases.

Does the campaign type (CampaignType) affect conversion across different age groups?

[576]:
```
grouped_df = df.groupby(['AgeGroup', 'CampaignType'])['Conversion'].mean().
 ↪reset_index()
grouped_df.sort_values(by='Conversion', ascending=False)

plt.figure(figsize=(14, 6))
ax = sns.barplot(x='AgeGroup', y='Conversion', hue='CampaignType', data=df,␣
 ↪palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61', '#9C27B0'])

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=12, color='black',␣
 ↪fontsize=8)

plt.xlabel("Age group")
plt.ylabel("Conversion (%)")
plt.title("Impact of campaign type on conversion across different age groups")
plt.legend(title="Campaign type")
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/1876055778.py:1
: FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  grouped_df = df.groupby(['AgeGroup',
```

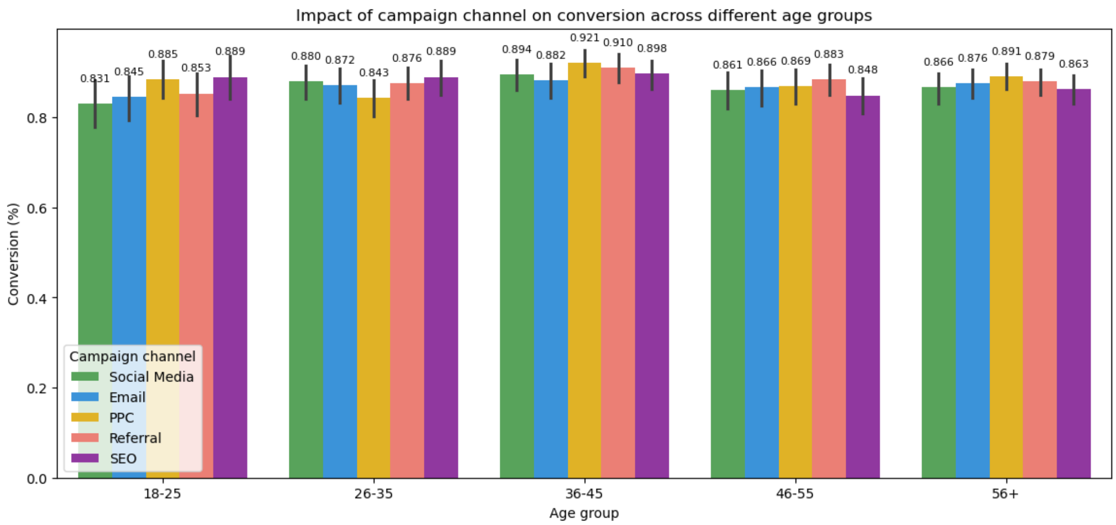
```
'CampaignType'])['Conversion'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/1876055778.py:5
: UserWarning: The palette list has more values (5) than needed (4), which may
not be intended.
  ax = sns.barplot(x='AgeGroup', y='Conversion', hue='CampaignType', data=df,
palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61', '#9C27B0'])
```



[577]:
```
grouped_df = df.groupby(['AgeGroup', 'CampaignChannel'])['Conversion'].mean().
 ↪reset_index()
grouped_df.sort_values(by='Conversion', ascending=False)

plt.figure(figsize=(14, 6))
ax = sns.barplot(x='AgeGroup', y='Conversion', hue='CampaignChannel', data=df,␣
 ↪palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61', '#9C27B0'])

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=15, color='black',␣
 ↪fontsize=8)

plt.xlabel("Age group")
plt.ylabel("Conversion (%)")
plt.title("Impact of campaign channel on conversion across different age␣
 ↪groups")
plt.legend(title="Campaign channel")

plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/3952508184.py:1
: FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
```

```
behavior or observed=True to adopt the future default and silence this warning.
  grouped_df = df.groupby(['AgeGroup',
'CampaignChannel'])['Conversion'].mean().reset_index()
```



Most effective combinations (high conversion):

PPC (Pay-Per-Click Advertising) in the 36-45 age group (0.921) This group shows the highest conversion rate among all channels. PPC performs well for this age category, likely due to their tendency for targeted purchases. Referral marketing in the 36-45 age group (0.910) A high conversion rate suggests strong trust in recommendations, especially among people in this age bracket. SEO (Search Engine Optimization) in the 36-45 age group (0.898) This indicates that organic search plays a key role in their purchasing decisions. PPC in the 56+ age group (0.890) Paid ads are also effective for older audiences, likely because they prefer direct messaging and are ready to take action. SEO in the 18-25 age group (0.889) Young consumers frequently rely on search engines when choosing products or services.

Least effective combinations (low conversion):

Social Media for the 18-25 age group (0.831) Despite high social media usage, conversion rates are lower than other channels. Young users may engage with content but take longer to make purchasing decisions. PPC for the 26-35 age group (0.843) The conversion rate is lower than in other age categories, possibly indicating a more rational approach to purchases. Email marketing in the 18-25 age group (0.844) Younger consumers are less responsive to email campaigns, as their attention is often focused on other channels. SEO for the 46-55 age group (0.848) Search is less effective at converting buyers in this age bracket, possibly because they rely more on recommendations. Referral marketing for the 18-25 age group (0.853) Recommendations are less influential among young consumers, likely because they prefer independent research and comparisons.

General conclusions:

Best channels: PPC and referral marketing for the 36-45 age group. SEO delivers good results for younger consumers (18-25 years old). Social media works well for engagement but does not lead to high conversions. Email is effective for older demographics but weaker for younger segments.

Strategy optimization:

Strengthen PPC for 36-45 and 56+ years. Increase trust-based marketing (Referral) for middle-age segments. Reassess Social Media and Email marketing for younger consumers.

Most effective campaign types (high conversion):

Conversion campaigns yield the best results across all age groups. The highest conversion rate is observed in the 26-35 age group (0.951), indicating their readiness to make purchases. 36-45 years (0.946) also exhibit strong conversion rates, confirming their decisiveness. 18-25 years (0.935) show high conversion, likely due to their impulse-driven purchasing behavior. 56+ years (0.931) respond well to conversion-focused campaigns, demonstrating a willingness to act.

Less effective campaigns (low conversion):

Awareness campaigns show the lowest conversion rates, particularly in the 18-25 age group (0.838). This suggests that brand-awareness-focused efforts do not immediately lead to purchases. 26-35 years (0.831) also show low conversion, possibly due to insufficient motivation to take action. Consideration campaigns similarly yield lower conversion rates, especially for the 18-25 group (0.821). This may indicate that young consumers tend to explore options but delay decision-making.

Other insights:

Retention campaigns are most effective for 36-45 and 56+ years, confirming that loyal older customers respond well to retention-focused strategies. Consideration and awareness campaigns play an important role for 46-55 and 56+ years, possibly because they make more thoughtful decisions and require additional information.

Business conclusions:

Prioritize conversion campaigns, especially for the 26-35 and 36-45 age groups. Awareness campaigns are less effective for younger consumers—direct offers or promotions may work better. Retention strategies are crucial for consumers aged 36+, as loyalty campaigns drive engagement. Optimizing consideration campaigns for the 18-25 age group through interactive and personalized offers could improve performance.

What is the average advertising spend (AdSpend) for each customer segment?

[590]:
```python
avg_ad_spend = df.groupby(['Gender', 'AgeGroup', 'IncomeGroup'])['AdSpend'].
  ↪mean().reset_index()
avg_ad_spend = avg_ad_spend.sort_values(by='AdSpend', ascending=False)

avg_ad_spend.head(5)
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/2841502055.py:1
: FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  avg_ad_spend = df.groupby(['Gender', 'AgeGroup',
'IncomeGroup'])['AdSpend'].mean().reset_index()
```

[590]:
```
    Gender AgeGroup IncomeGroup      AdSpend
22    Male    18-25        High  5436.881631
4   Female    26-35         Low  5424.542116
20    Male    18-25         Low  5388.525293
24    Male    26-35         Low  5337.734579
9   Female    36-45      Medium  5299.330935
```

[593]:
```python
avg_ad_spend.tail(5)
```

[593]:
```
    Gender AgeGroup IncomeGroup      AdSpend
18  Female      56+        High  4779.197470
12  Female    46-55         Low  4745.416904
37    Male      56+      Medium  4741.535916
3   Female    18-25   Very High  4593.637646
1   Female    18-25      Medium  4438.523145
```

Most efficient groups (high conversion with reasonable expenses):

Men aged 36-45 (low and medium income) — 0.935 and 0.934 High conversion with moderate advertising expenses (not among the top spenders). These groups respond well to marketing campaigns, making them worth retaining. Women aged 36-45 (very high income) — 0.906 Excellent conversion rate, despite advertising expenses not being among the highest, making this group attractive from an investment perspective. Men aged 26-35 (high and very high income) — 0.905 and 0.890 A good balance between conversion and advertising expenses. Women aged 56+ (high income) — 0.895 High conversion but moderate expenses. This segment can yield stable profits with relatively low ad spending.

Least efficient groups (low conversion with high expenses):

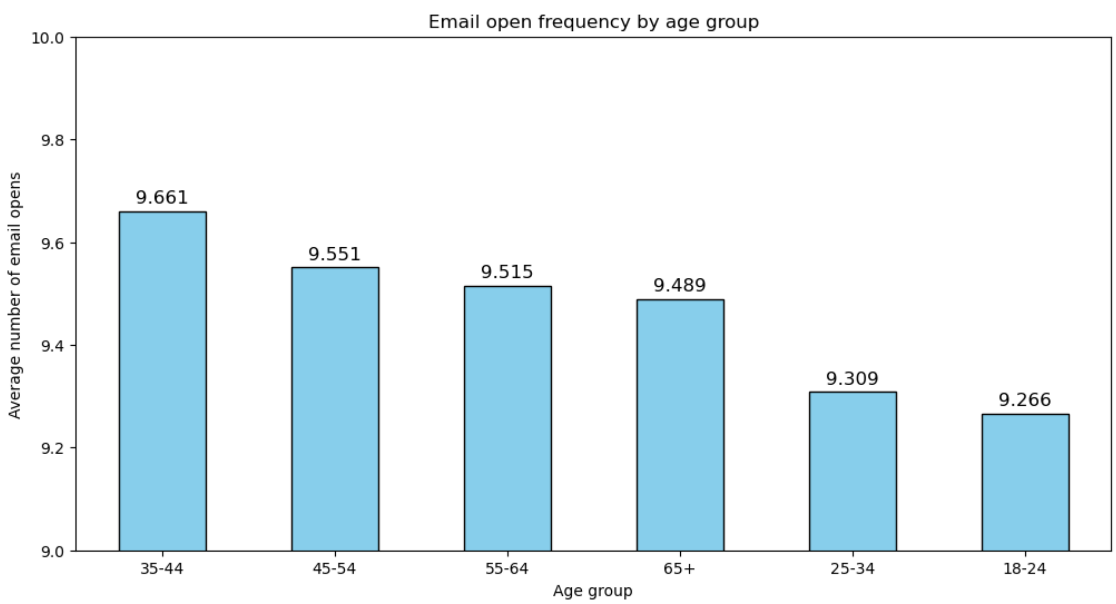
Men aged 18-25 (high income) — 0.792, but AdSpend = 5436 High advertising expenses but lowest conversion rate among all groups. This strategy needs reconsideration, as it may be inefficient. Women aged 26-35 (low income) — 0.846, but AdSpend = 5424 Moderate conversion but very high advertising costs, making this segment less profitable. Men aged 18-25 (low income) — 0.860, but AdSpend = 5388 Similar to the previous case, above-average spending but unimpressive conversion. Women aged 36-45 (medium income) — 0.913, but AdSpend = 5299 Despite high conversion, advertising costs are also high. The strategy should be optimized to reduce expenses without losing effectiveness.

Which age groups open email campaigns (EmailOpens) more frequently?

[597]:
```python
bins = [18, 25, 35, 45, 55, 65, 100]
labels = ["18-24", "25-34", "35-44", "45-54", "55-64", "65+"]
df["AgeGroup"] = pd.cut(df["Age"], bins=bins, labels=labels, right=False)

email_opens_by_age = df.groupby("AgeGroup")["EmailOpens"].mean().
    ↪sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = email_opens_by_age.plot(kind="bar", color="skyblue", edgecolor="black")
```

```
for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
↪fontsize=12)

plt.xlabel("Age group")
plt.ylabel("Average number of email opens")
plt.title("Email open frequency by age group")
plt.xticks(rotation=0)
plt.ylim(9, 10)
plt.show()
```

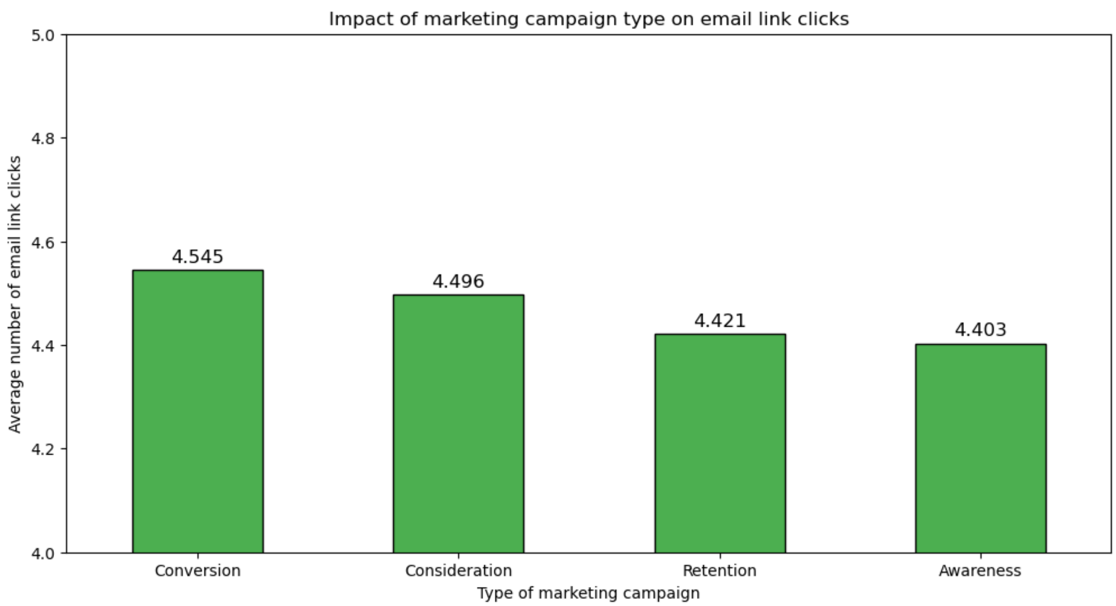
```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/3378274548.py:5
: FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  email_opens_by_age =
df.groupby("AgeGroup")["EmailOpens"].mean().sort_values(ascending=False)
```



Does the type of marketing campaign (CampaignType) affect the email click-through rate (EmailClicks)?

[600]:
```
email_clicks_by_campaign_type = df.groupby("CampaignType")["EmailClicks"].
↪mean().sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = email_clicks_by_campaign_type.plot(kind="bar", color="#4CAF50",␣
↪edgecolor="black")
```

```
for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
 ↪fontsize=12)

plt.xlabel("Type of marketing campaign")
plt.ylabel("Average number of email link clicks")
plt.title("Impact of marketing campaign type on email link clicks")
plt.xticks(rotation=0)
plt.ylim(4, 5)
plt.show()
```



How many email opens (EmailOpens) lead to conversions?

[605]:
```
converted_df = df[df["Conversion"] == 1]
average_email_opens = converted_df["EmailOpens"].mean()
average_email_opens
```

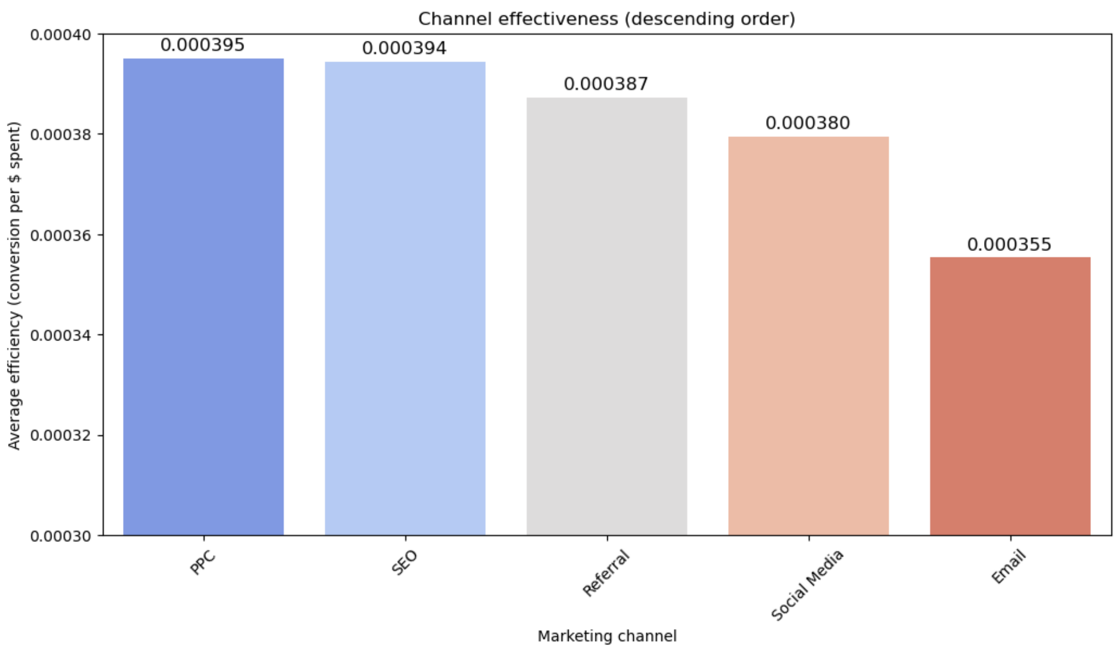
[605]: 9.744580718767827

Which marketing channels (CampaignChannel) demonstrate the best effectiveness?

[609]:
```
df['Efficiency'] = df['Conversion'] / df['AdSpend']
grouped_df = df.groupby(['CampaignChannel'])['Efficiency'].mean().reset_index()
grouped_df_sorted = grouped_df.sort_values(by='Efficiency', ascending=False)

plt.figure(figsize=(12, 6))
ax = sns.barplot(x='CampaignChannel', y='Efficiency', data=grouped_df_sorted,␣
 ↪palette='coolwarm', order=grouped_df_sorted['CampaignChannel'])
```

```
for bar in ax.containers:
    ax.bar_label(bar, fmt='%.6f', label_type='edge', padding=3, color='black',␣
 ↪fontsize=12)

plt.xlabel("Marketing channel")
plt.ylabel("Average efficiency (conversion per $ spent)")
plt.title("Channel effectiveness (descending order)")
plt.xticks(rotation=45)
plt.ylim(0.0003, 0.0004)
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_13099/1609171232.py:6
: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.barplot(x='CampaignChannel', y='Efficiency', data=grouped_df_sorted,
palette='coolwarm', order=grouped_df_sorted['CampaignChannel'])
```



Which campaigns attract new customers, and which are better for retention?

[612]:
```
df["new_customer_ratio"] = df["ClickThroughRate"] * df["ConversionRate"]
df["retention_ratio"] = df["PreviousPurchases"] + df["LoyaltyPoints"]
```

```
new_customer_threshold = df["new_customer_ratio"].median()
retention_threshold = df["retention_ratio"].median()

result_df = df.groupby("CampaignType")[["new_customer_ratio",␣
↪"retention_ratio"]].mean().reset_index()
result_df
```

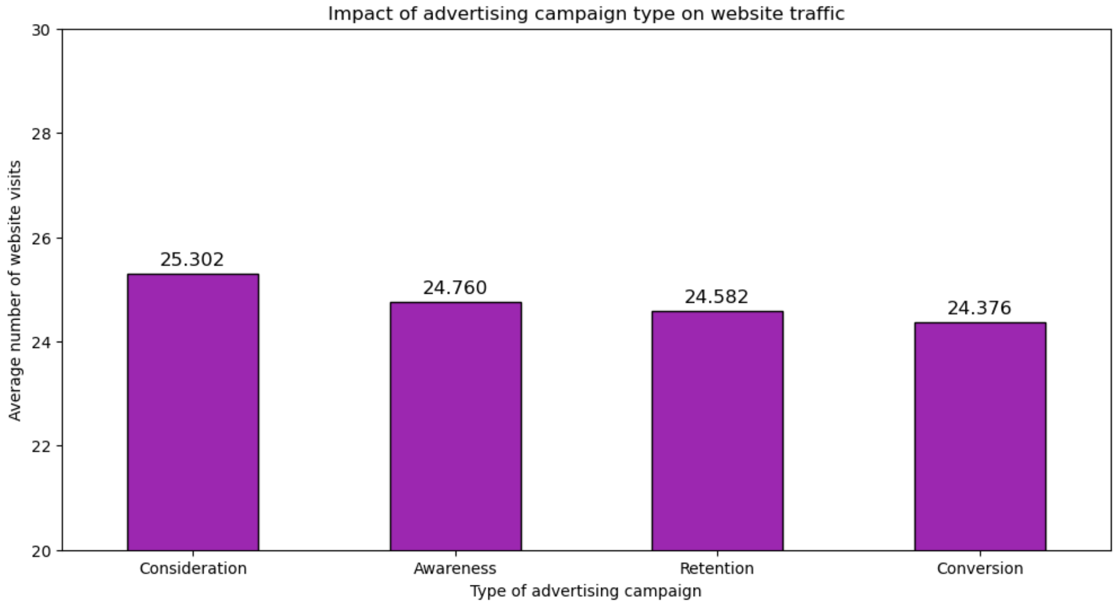
[612]:

	CampaignType	new_customer_ratio	retention_ratio
0	Awareness	0.016103	2507.114185
1	Consideration	0.015974	2502.758048
2	Conversion	0.016298	2495.562831
3	Retention	0.016117	2473.098100

Thus, Conversion campaigns are ideal for actively attracting new customers. Awareness and Consideration campaigns help gradually engage customers and maintain their long-term interest in the brand.

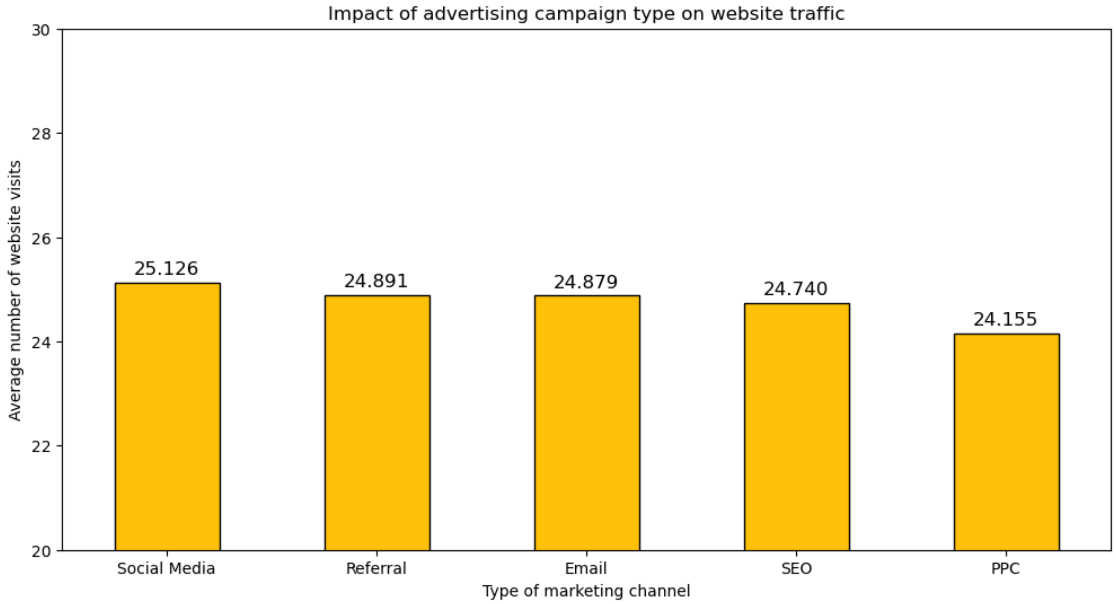
Which advertising campaigns (CampaignType) generate the most website traffic?

[616]:
```
traffic_by_campaign_type = df.groupby("CampaignType")["WebsiteVisits"].mean().
↪sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = traffic_by_campaign_type.plot(kind="bar", color='#9C27B0',␣
↪edgecolor="black")

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
↪fontsize=12)

plt.xlabel("Type of advertising campaign")
plt.ylabel("Average number of website visits")
plt.title("Impact of advertising campaign type on website traffic")
plt.xticks(rotation=0)
plt.ylim(20, 30)
plt.show()
```



Which advertising channels (CampaignChannel) drive the most website traffic?

[619]:
```
traffic_by_campaign_channel = df.groupby("CampaignChannel")["WebsiteVisits"].
    ↪mean().sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = traffic_by_campaign_channel.plot(kind="bar", color='#FFC107',␣
    ↪edgecolor="black")

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
    ↪fontsize=12)

plt.xlabel("Type of marketing channel")
plt.ylabel("Average number of website visits")
plt.title("Impact of advertising campaign type on website traffic")
plt.xticks(rotation=0)
plt.ylim(20, 30)
plt.show()
```



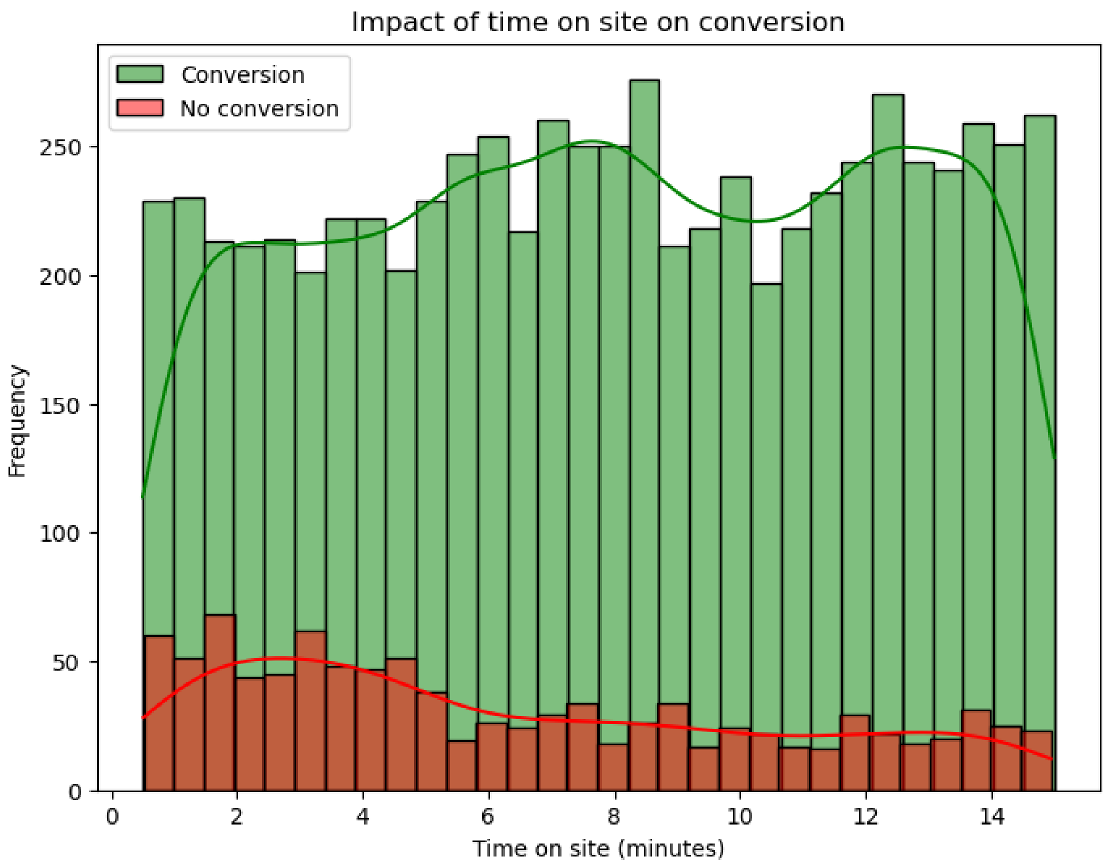
What percentage of visitors (WebsiteVisits) view more than one page (PagesPerVisit)?

[622]:
```
percentage_more_than_one_page = (df[df["PagesPerVisit"] > 1]["WebsiteVisits"].
    ↪sum() / df["WebsiteVisits"].sum()) * 100
percentage_more_than_one_page
```

[622]: 100.0

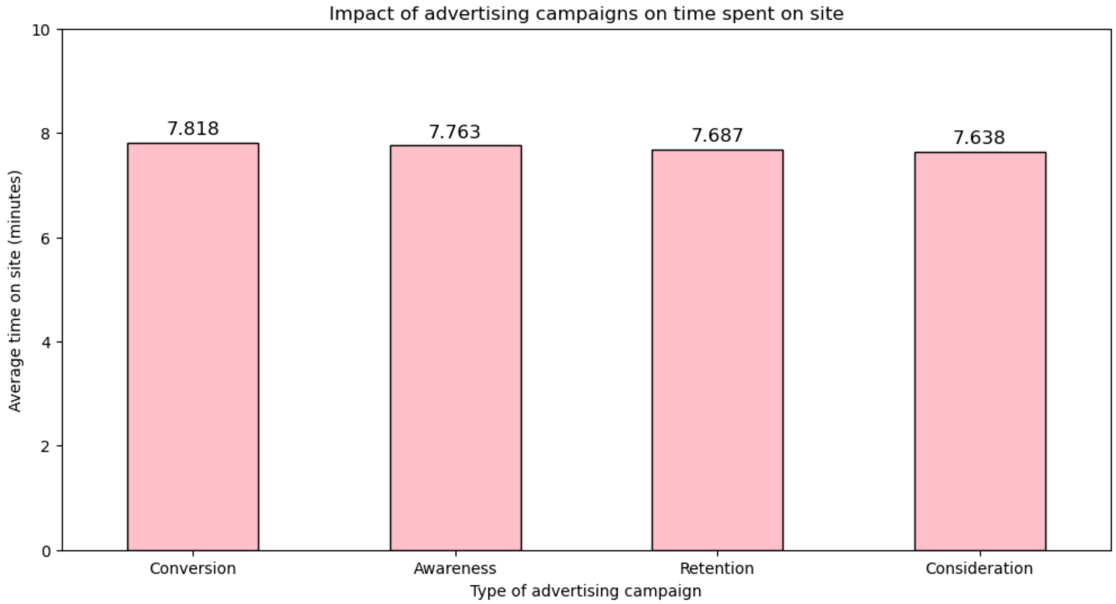
How does the duration of time spent on a website (TimeOnSite) affect conversion probability?

[625]:
```
converted = df[df["Conversion"] == 1]["TimeOnSite"]
not_converted = df[df["Conversion"] == 0]["TimeOnSite"]

plt.figure(figsize=(8, 6))
sns.histplot(converted, color="green", label="Conversion", kde=True, bins=30)
sns.histplot(not_converted, color="red", label="No conversion", kde=True,␣
    ↪bins=30)
plt.xlabel("Time on site (minutes)")
plt.ylabel("Frequency")
plt.title("Impact of time on site on conversion")
plt.legend()
plt.show()
```



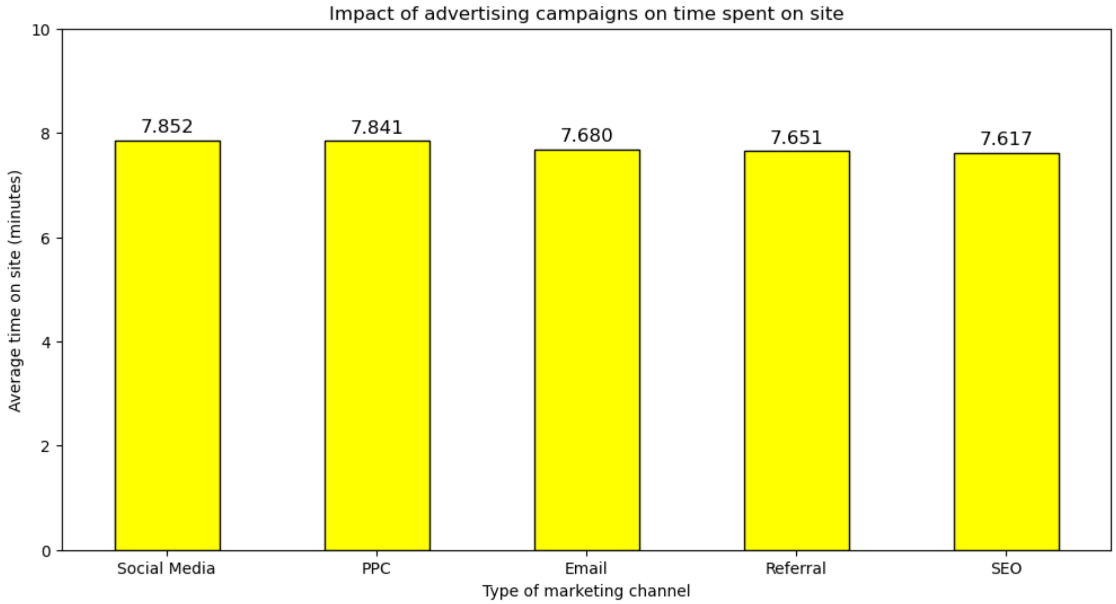
Which advertising campaigns (CampaignType) contribute to longer time spent on the website?

[628]:
```
time_by_campaign_type = df.groupby("CampaignType")["TimeOnSite"].mean().
    ↪sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = time_by_campaign_type.plot(kind="bar", color='pink', edgecolor="black")

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
    ↪fontsize=12)

plt.xlabel("Type of advertising campaign")
plt.ylabel("Average time on site (minutes)")
plt.title("Impact of advertising campaigns on time spent on site")

plt.xticks(rotation=0)
plt.ylim(0, 10)
plt.show()
```



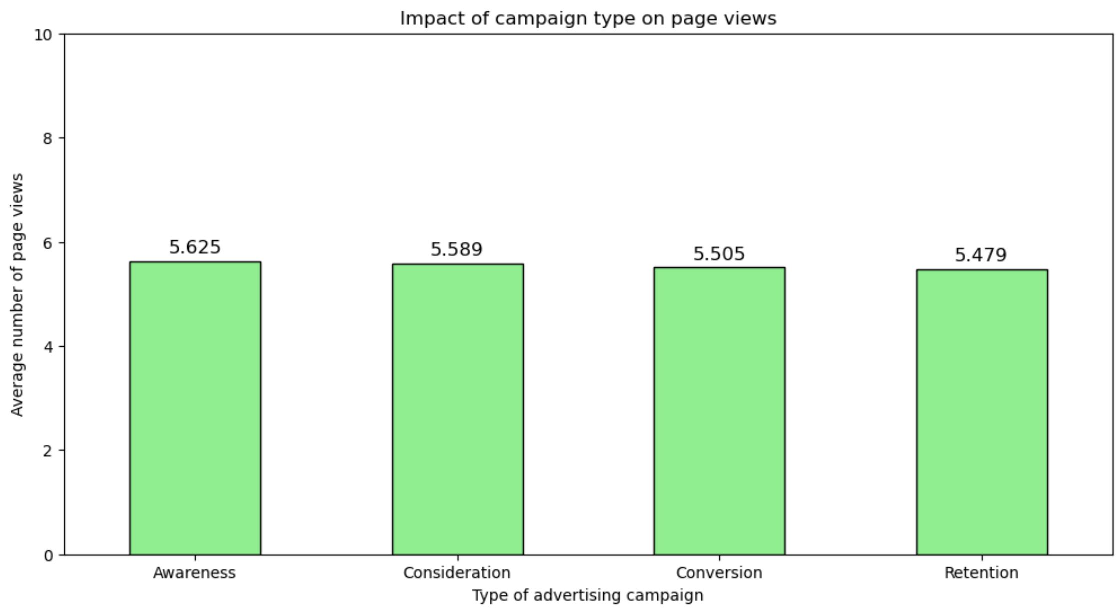
Which advertising channels (CampaignChannel) contribute to longer time spent on the website?

[631]:
```
time_by_campaign_channel = df.groupby("CampaignChannel")["TimeOnSite"].mean().
 ↪sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = time_by_campaign_channel.plot(kind="bar", color='yellow',␣
 ↪edgecolor="black")

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
 ↪fontsize=12)

plt.xlabel("Type of marketing channel")
plt.ylabel("Average time on site (minutes)")
plt.title("Impact of advertising campaigns on time spent on site")
plt.xticks(rotation=0)
plt.ylim(0, 10)
plt.show()
```



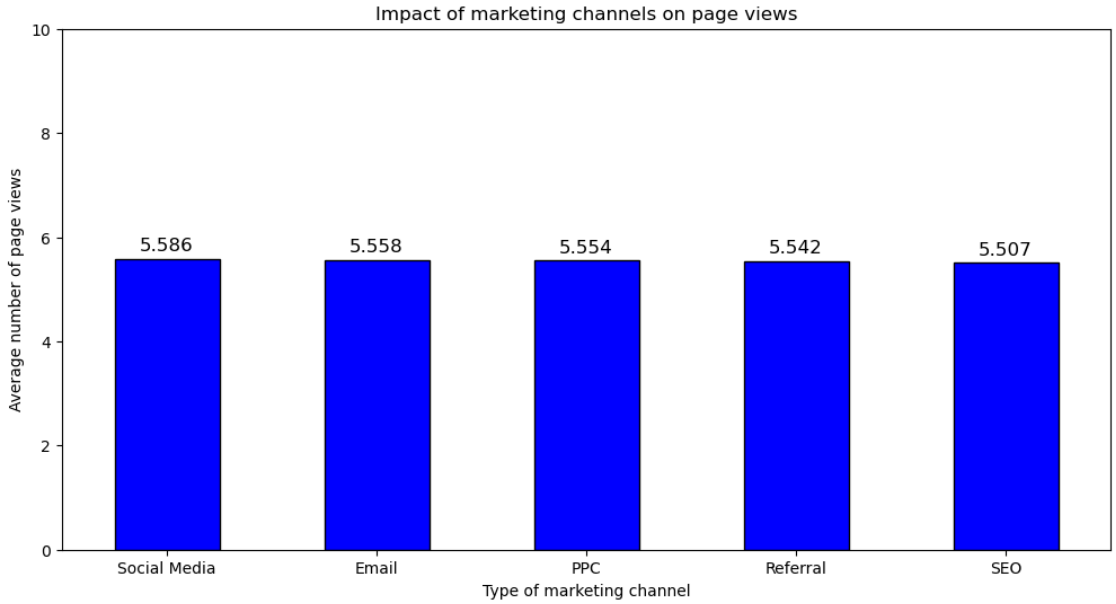
Which advertising campaigns (CampaignType) contribute to a higher number of page views?

[634]:
```
pages_by_campaign_type = df.groupby("CampaignType")["PagesPerVisit"].mean().
↪sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = pages_by_campaign_type.plot(kind="bar", color='lightgreen',␣
↪edgecolor="black")

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
↪fontsize=12)

plt.xlabel("Type of advertising campaign")
plt.ylabel("Average number of page views")
plt.title("Impact of campaign type on page views")
plt.xticks(rotation=0)
plt.ylim(0, 10)
plt.show()
```



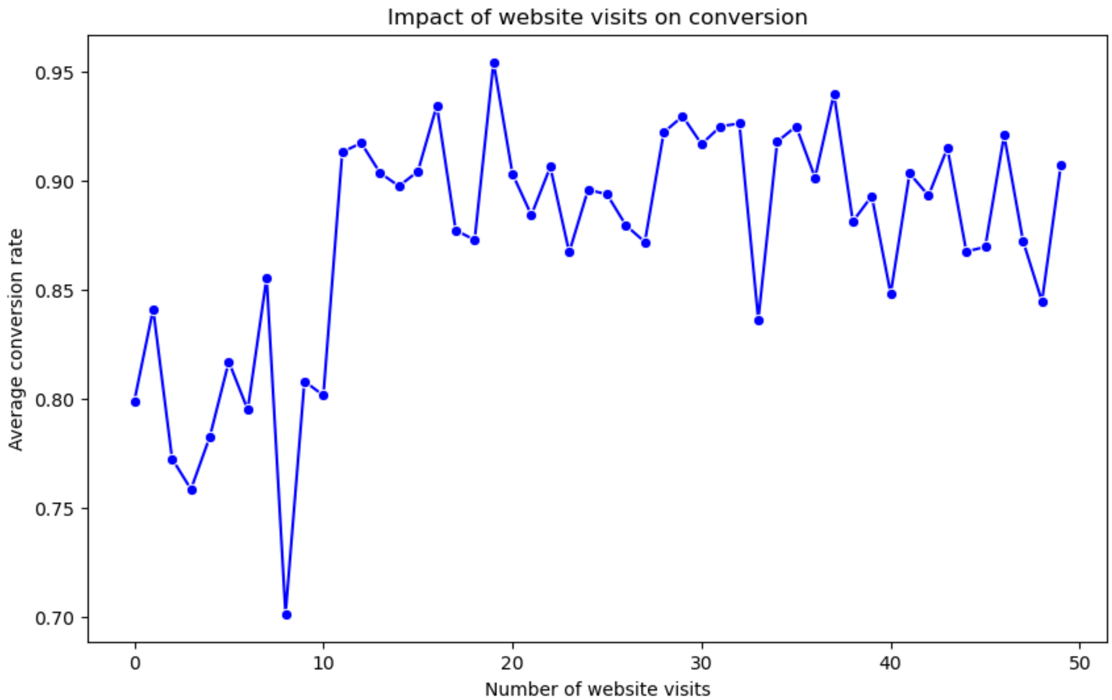
Which advertising channels (CampaignChannel) contribute to a higher number of page views?

[637]:
```
pages_by_campaign_channel = df.groupby("CampaignChannel")["PagesPerVisit"].
 ↪mean().sort_values(ascending=False)

plt.figure(figsize=(12, 6))
ax = pages_by_campaign_channel.plot(kind="bar", color='blue', edgecolor="black")

for bar in ax.containers:
    ax.bar_label(bar, fmt='%.3f', label_type='edge', padding=3, color='black',␣
 ↪fontsize=12)

plt.xlabel("Type of marketing channel")
plt.ylabel("Average number of page views")
plt.title("Impact of marketing channels on page views")
plt.xticks(rotation=0)
plt.ylim(0, 10)
plt.show()
```



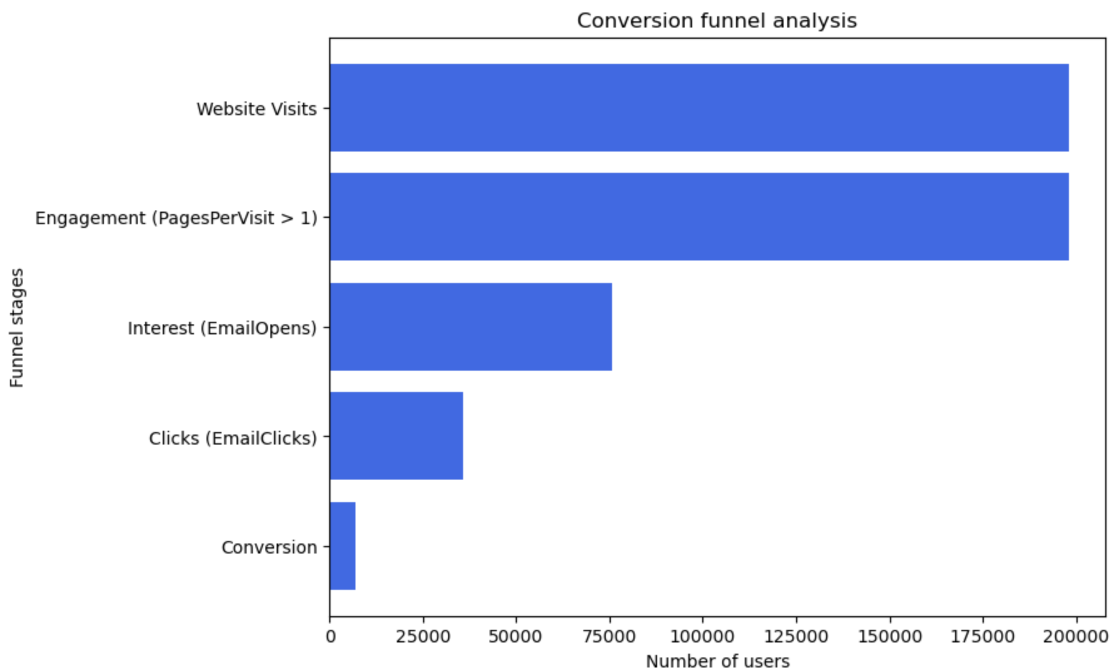
How does the number of website visits affect conversion?

[640]:
```
conversion_by_visits = df.groupby("WebsiteVisits")["Conversion"].mean().
↪reset_index()

plt.figure(figsize=(10, 6))
sns.lineplot(x="WebsiteVisits", y="Conversion", data=conversion_by_visits,␣
↪marker="o", color="blue")
plt.xlabel("Number of website visits")
plt.ylabel("Average conversion rate")
plt.title("Impact of website visits on conversion")
plt.show()
```



Conversion funnel analysis

[643]:
```
stages = {
    "Website Visits": df["WebsiteVisits"].sum(),
    "Engagement (PagesPerVisit > 1)": df[df["PagesPerVisit"] >␣
↪1]["WebsiteVisits"].sum(),
    "Interest (EmailOpens)": df["EmailOpens"].sum(),
    "Clicks (EmailClicks)": df["EmailClicks"].sum(),
    "Conversion": df["Conversion"].sum()
}

funnel_df = pd.DataFrame(list(stages.items()), columns=["Stage", "Users"])

plt.figure(figsize=(8, 6))
plt.barh(funnel_df["Stage"], funnel_df["Users"], color="royalblue")
plt.xlabel("Number of users")
plt.ylabel("Funnel stages")
plt.title("Conversion funnel analysis")
plt.gca().invert_yaxis()
plt.show()
```



The main issue is the low email open rate. If users don't open emails, they never reach the click stage, which impacts overall conversions. Possible reasons for low open rates: Unattractive subject line – If it doesn't grab attention, the email remains unopened. Sending time – If the email arrives at an inconvenient time, users may overlook it. Trust in the sender – The sender's address might not inspire confidence, or the email may look like spam. Email fatigue – If users receive too many emails, yours might get lost in the clutter. What can be improved: Test subject lines – Conduct A/B testing to determine which topics attract attention best. Optimize sending time – Analyze audience activity and send emails at the most convenient hours. Increase personalization – Emails that feel personal are opened more often. Use recipients' names, interaction history, and personalized recommendations. Improve email reputation – Ensure emails come from a recognizable, trustworthy address. Use intriguing content – Create a sense of value and curiosity in the first sentence. The issue isn't just about open rates—it also affects click-through rates. Enhancing the email text, call-to-action (CTA), and design can further improve engagement.

Which factors are most important for conversion?

We encode categorical variables using the One-Hot Encoding method since these variables do not have a natural order.

[648]:
```
df = df.drop(columns=['AdSpendGroup', 'AgeGroup', 'IncomeGroup', 'Efficiency',␣
↪'new_customer_ratio', 'retention_ratio'])
df = pd.get_dummies(df, columns=['Gender', 'CampaignChannel', 'CampaignType'])
bool_columns = df.select_dtypes(include=['bool']).columns
df[bool_columns] = df[bool_columns].astype(int)
```

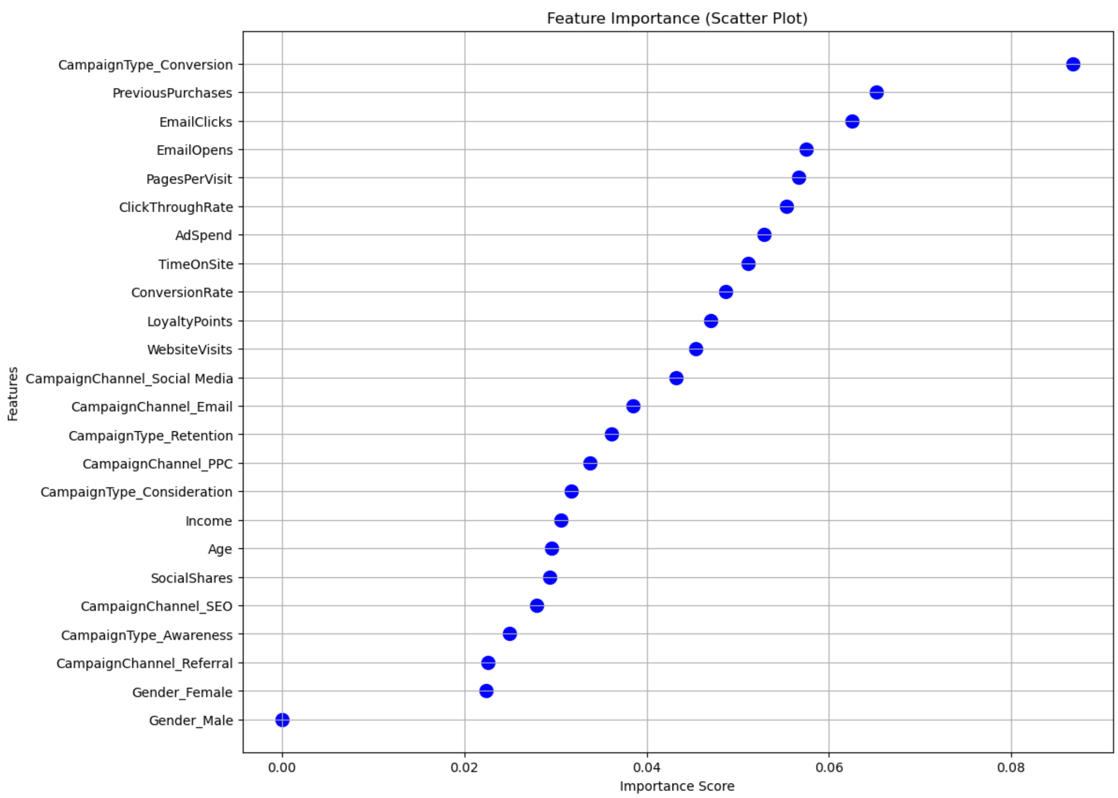
We normalize numerical variables to ensure consistency in scale. For variables with a small range, we use Min-Max Scaler. For other data, since they do not follow a normal distribution and contain outliers, we first apply Robust Scaler and then Min-Max Scaler to bring them to a common scale.

[651]:
```
scaler = RobustScaler()
df['Age'] = scaler.fit_transform(df[['Age']])
df['Income'] = scaler.fit_transform(df[['Income']])
df['AdSpend'] = scaler.fit_transform(df[['AdSpend']])
df['WebsiteVisits'] = scaler.fit_transform(df[['WebsiteVisits']])
df['SocialShares'] = scaler.fit_transform(df[['SocialShares']])
df['LoyaltyPoints'] = scaler.fit_transform(df[['LoyaltyPoints']])

scaler = MinMaxScaler()
df['PagesPerVisit'] = scaler.fit_transform(df[['PagesPerVisit']])
df['TimeOnSite'] = scaler.fit_transform(df[['TimeOnSite']])
df['EmailOpens'] = scaler.fit_transform(df[['EmailOpens']])
df['EmailClicks'] = scaler.fit_transform(df[['EmailClicks']])

df['Age'] = scaler.fit_transform(df[['Age']])
df['Income'] = scaler.fit_transform(df[['Income']])
df['AdSpend'] = scaler.fit_transform(df[['AdSpend']])
df['WebsiteVisits'] = scaler.fit_transform(df[['WebsiteVisits']])
df['SocialShares'] = scaler.fit_transform(df[['SocialShares']])
df['LoyaltyPoints'] = scaler.fit_transform(df[['LoyaltyPoints']])
```

[653]:
```
X = df.drop(columns=['Conversion', 'CustomerID'])
y = df['Conversion']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

model = XGBClassifier(random_state=42)

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

feature_importance = model.feature_importances_
features = X.columns

features_sorted = [x for _, x in sorted(zip(feature_importance, features))]
importance_sorted = sorted(feature_importance)

plt.figure(figsize=(12, 10))
```

```
plt.scatter(importance_sorted, features_sorted, color='blue', s=100)
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.title("Feature Importance (Scatter Plot)")
plt.grid()
plt.show()
```

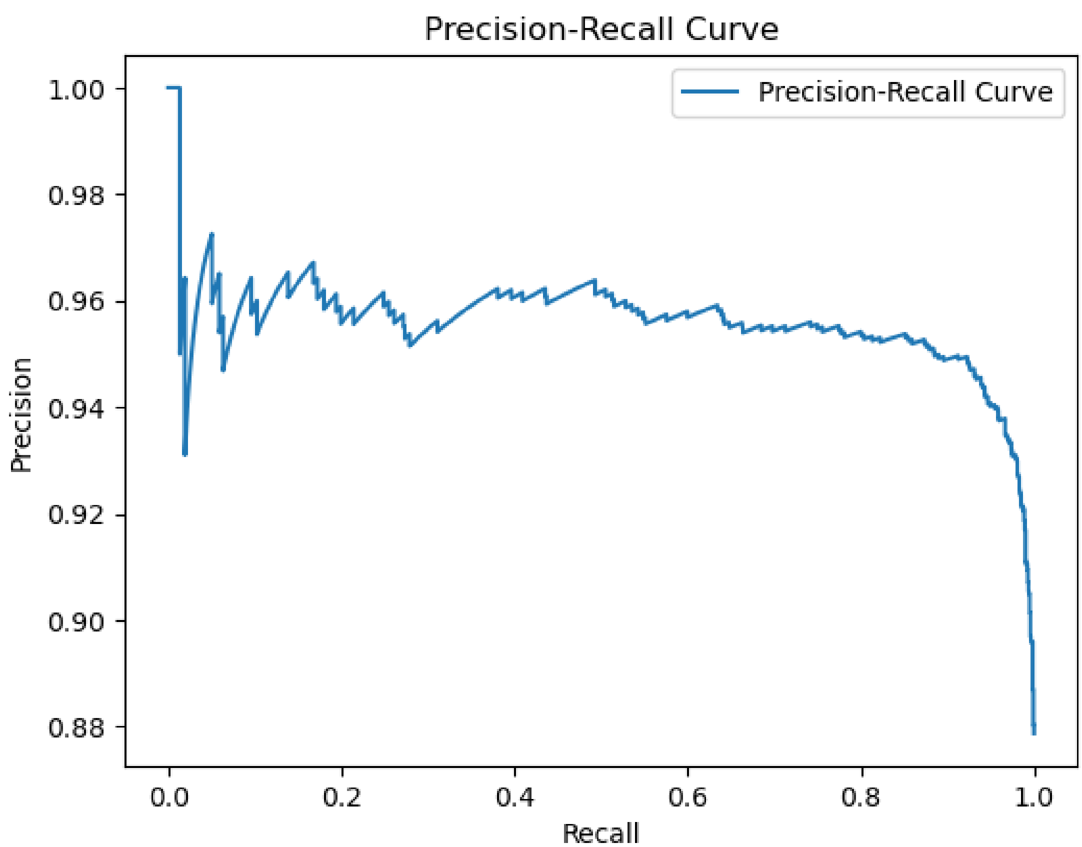
```
Accuracy: 0.92

Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.45      0.57       194
           1       0.93      0.98      0.95      1406

    accuracy                           0.92      1600
   macro avg       0.85      0.72      0.76      1600
weighted avg       0.91      0.92      0.91      1600
```



[654]:
```
y_prob = model.predict_proba(X_test)[:, 1]
```

```
precision, recall, thresholds = precision_recall_curve(y_test, y_prob)

f1_scores = 2 * (precision * recall) / (precision + recall)
optimal_threshold = thresholds[f1_scores.argmax()]

print("Optimal threshold:", optimal_threshold)

plt.plot(recall, precision, label="Precision-Recall Curve")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.legend()
plt.show()
```

```
Optimal threshold: 0.528863
```



[656]:
```
param_grid = {
    "max_depth": [3, 5, 7, 10],
    "learning_rate": [0.01, 0.1, 0.2, 0.3],
    "n_estimators": [50, 100, 200],
```

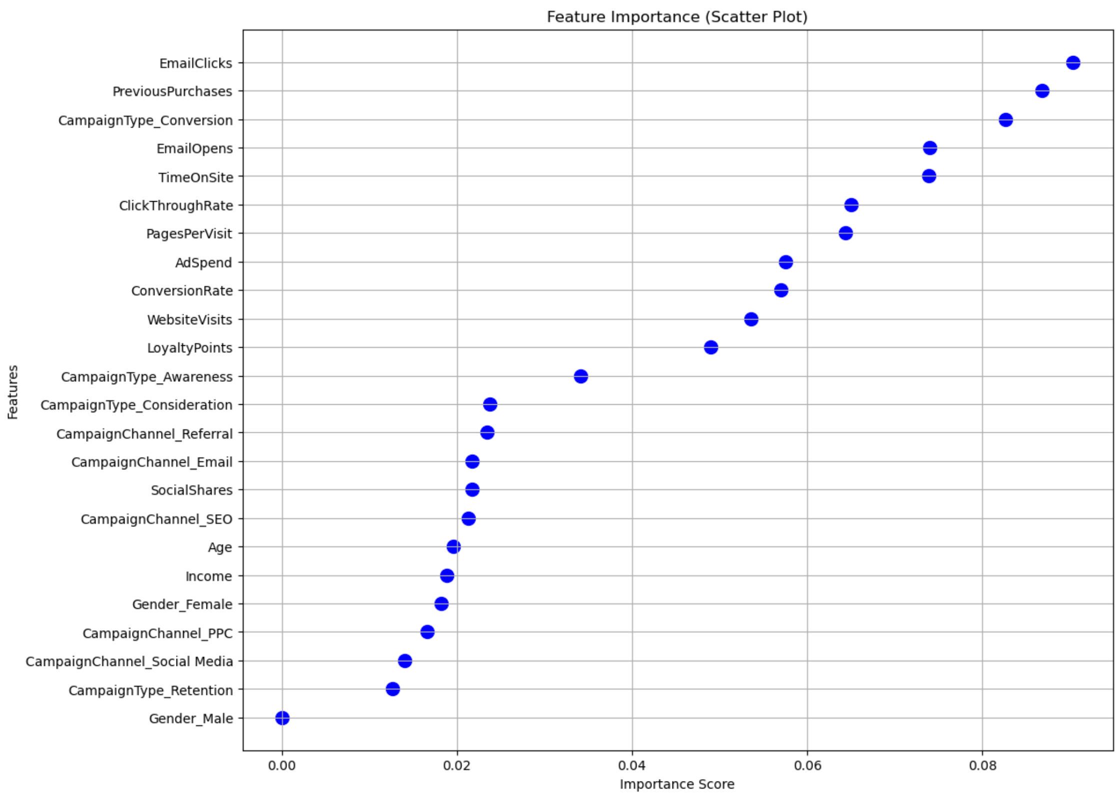
```
    "subsample": [0.8, 1],
    "colsample_bytree": [0.8, 1]
}

grid_search = GridSearchCV(XGBClassifier(random_state=42), param_grid, cv=3,␣
↪scoring="accuracy", n_jobs=1)
grid_search.fit(X_train, y_train)

print("Best parameters:", grid_search.best_params_)
```

```
Best parameters: {'colsample_bytree': 1, 'learning_rate': 0.1, 'max_depth': 3,
'n_estimators': 200, 'subsample': 1}
```

[658]:
```
X = df.drop(columns=["Conversion", 'CustomerID'])
y = df["Conversion"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

model = XGBClassifier(random_state=42, colsample_bytree=1, learning_rate=0.1,␣
↪max_depth=3, n_estimators=200,
                      subsample=1, reg_alpha=0.1, reg_lambda=1.0)
model.fit(X_train, y_train)

y_proba = model.predict_proba(X_test)[:, 1]

optimal_threshold = 0.5558796
y_pred = (y_proba >= optimal_threshold).astype(int)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

feature_importance = model.feature_importances_
features = X.columns

features_sorted = [x for _, x in sorted(zip(feature_importance, features))]
importance_sorted = sorted(feature_importance)

plt.figure(figsize=(12, 10))
plt.scatter(importance_sorted, features_sorted, color="blue", s=100)
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.title("Feature Importance (Scatter Plot)")
plt.grid()
```

```
plt.show()
```

```
Accuracy: 0.94

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.59      0.69       194
           1       0.95      0.98      0.96      1406

    accuracy                           0.94      1600
   macro avg       0.89      0.79      0.83      1600
weighted avg       0.93      0.94      0.93      1600
```



Thus, the most important factors for conversion are CampaignType_Conversion, EmailClicks, PreviousPurchases, TimeOnSite, and EmailOpens. To maximize results, focus on the following aspects: CampaignType_Conversion – If a specific campaign type leads to better conversions, increasing investment in scaling it can be beneficial. EmailClicks & EmailOpens – Optimizing email content (headlines, CTA, personalization) is crucial to increasing open and click rates. PreviousPurchases – Analyzing customer purchase behavior helps personalize offers and encourage repeat sales. TimeOnSite – A high metric may indicate interest, but if conversions are low, UX/UI improvements and stronger CTAs should be considered.

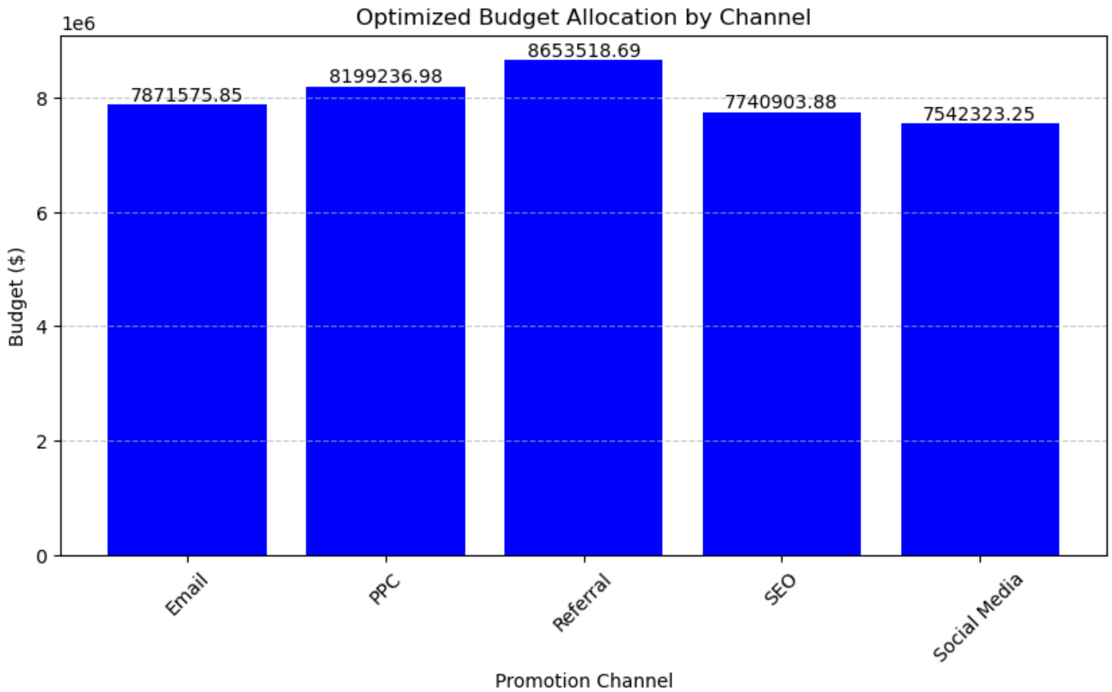
Budget optimization

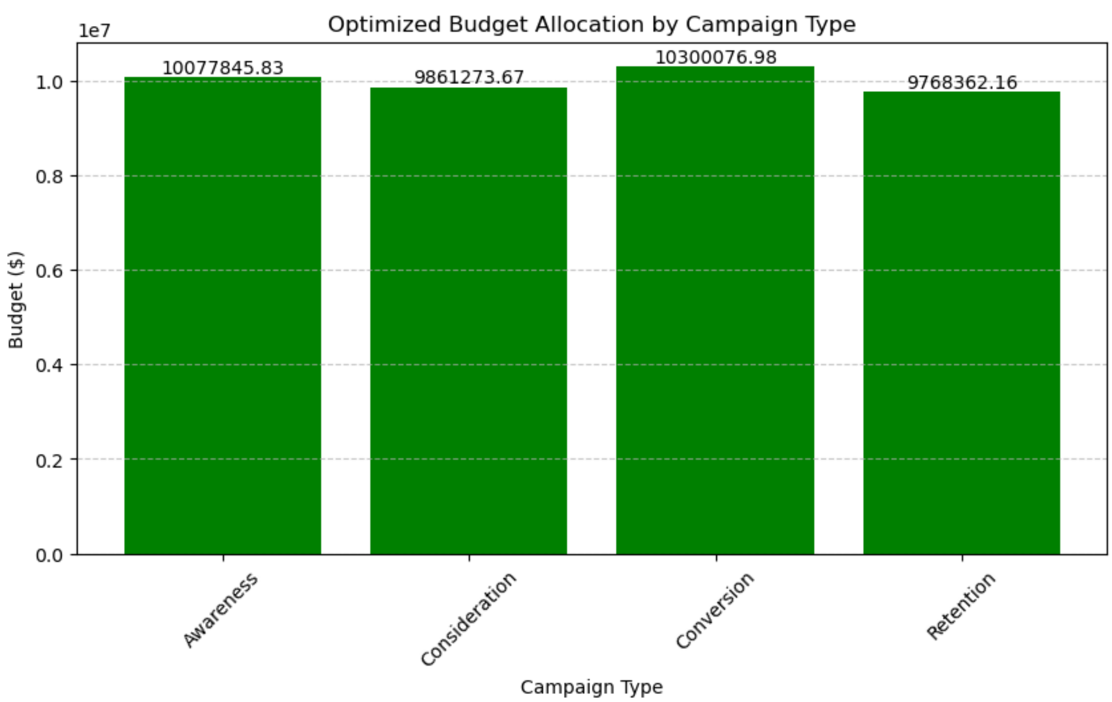
[661]:
```
df = pd.read_csv('digital_marketing_campaign_dataset.csv')
```

[662]:
```
factor_importance = pd.Series(model.feature_importances_, index=X_train.columns)
factor_importance /= factor_importance.sum()

channel_performance = df.groupby("CampaignChannel").agg(
    Conversion=("Conversion", "sum"),
    ConversionRate=("ConversionRate", "mean"),
    ClickThroughRate=("ClickThroughRate", "mean"),
    AdSpend=("AdSpend", "sum")
)

campaign_performance = df.groupby("CampaignType").agg(
    Conversion=("Conversion", "sum"),
    ConversionRate=("ConversionRate", "mean"),
    ClickThroughRate=("ClickThroughRate", "mean"),
    AdSpend=("AdSpend", "sum")
)

valid_factors = ["Conversion", "ConversionRate", "ClickThroughRate"]
available_factors = [f for f in valid_factors if f in factor_importance.index]

channel_weights = sum(
    factor_importance[factor] * (channel_performance[factor] /␣
 ↪channel_performance[factor].sum())
    for factor in available_factors
)

campaign_weights = sum(
    factor_importance[factor] * (campaign_performance[factor] /␣
 ↪campaign_performance[factor].sum())
    for factor in available_factors
)

channel_weights = np.array(channel_weights)
campaign_weights = np.array(campaign_weights)

total_budget = df["AdSpend"].sum()

def optimize_budget(weights, current_spend):
    constraints = {'type': 'eq', 'fun': lambda budget_allocation: np.
 ↪sum(budget_allocation) - total_budget}
    bounds = [(0.01 * total_budget, 0.8 * total_budget)] * len(weights)
    initial_budget = current_spend.to_numpy() if isinstance(current_spend, pd.
 ↪Series) else np.array(current_spend)
```

```
    result = minimize(lambda b: -np.dot(weights, b), initial_budget,␣
↪bounds=bounds, constraints=constraints, method='SLSQP')
    return result.x

optimized_channel_budget = optimize_budget(channel_weights,␣
↪channel_performance["AdSpend"])
optimized_campaign_budget = optimize_budget(campaign_weights,␣
↪campaign_performance["AdSpend"])

channel_budget_distribution = {channel: round(optimized_channel_budget[i], 2)␣
↪for i, channel in enumerate(channel_performance.index)}
campaign_budget_distribution = {campaign: round(optimized_campaign_budget[i],␣
↪2) for i, campaign in enumerate(campaign_performance.index)}
```

[663]:
```
plt.figure(figsize=(10, 5))
bars = plt.bar(channel_budget_distribution.keys(), channel_budget_distribution.
↪values(), color='blue')

for bar in bars:
    plt.text(
        bar.get_x() + bar.get_width()/2, bar.get_height(),
        f"{bar.get_height():.2f}", ha='center', va='bottom', fontsize=10
    )

plt.xlabel("Promotion Channel")
plt.ylabel("Budget ($)")
plt.title("Optimized Budget Allocation by Channel")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()

plt.figure(figsize=(10, 5))
bars = plt.bar(campaign_budget_distribution.keys(),␣
↪campaign_budget_distribution.values(), color='green')

for bar in bars:
    plt.text(
        bar.get_x() + bar.get_width()/2, bar.get_height(),
        f"{bar.get_height():.2f}", ha='center', va='bottom', fontsize=10
    )

plt.xlabel("Campaign Type")
plt.ylabel("Budget ($)")
plt.title("Optimized Budget Allocation by Campaign Type")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```


Optimized Budget Allocation by Channel
1e6
7871575.85
8199236.98
8653518.69
7740903.88
7542323.25
Budget ($)
0
2
4
6
8
Email
PPC
Referral
SEO
Social Media
Promotion Channel


Optimized Budget Allocation by Campaign Type
1e7
10077845.83
9861273.67
10300076.98
9768362.16
Budget ($)
0.0
0.2
0.4
0.6
0.8
1.0
Awareness
Consideration
Conversion
Retention
Campaign Type