bhargav-nte-casestudy

June 13, 2025

#Case Study Title: Audience Scoring for Direct Mail Marketing

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

0.1 Data Loading

[2]:
```
Sales_df=pd.read_csv('06052025_Sales_Data.csv')
Dates_df=pd.read_csv('06052025_DM_Dates.csv')
Sales_df
```

[2]:
```
        Gold_Cust_ID    Post_Cd    Tran_Dt  Dept ID             Dept Name  \
0                213  344813463  5/16/2023     5611          Ocala Retail
1                213  344813463  5/16/2023     5611          Ocala Retail
2                213  344813463  5/16/2023     5611          Ocala Retail
3                213  344813463  5/16/2023     5611          Ocala Retail
4                213  344813463  5/16/2023     5611          Ocala Retail
…                  …          …          …        …                     …
271130      37543211  273499366  4/30/2025     5518     Burlington Retail
271131      37544105  321193400   5/1/2025     2191            E-Commerce
271132      37545460  276042489   5/1/2025     5513    East Raleigh Retail
271133      37545460  276042489   5/1/2025     5513    East Raleigh Retail
271134      37545944        NaN   5/1/2025     5505  North Charlotte Retail

       Division   Channel     Online Store   Itm_Id Class Code  \
0        Retail    Retail  /Not Applicable    18359         57
1        Retail    Retail  /Not Applicable    18359         57
2        Retail    Retail  /Not Applicable    18359         57
3        Retail    Retail  /Not Applicable    18359         57
4        Retail    Retail  /Not Applicable    18359         57
…           …         …               …        …          …
271130   Retail    Retail  /Not Applicable   111740         33
271131   Direct  Internet          NTE.com  5864861          7
271132   Retail    Retail  /Not Applicable    41911          7
```

```
271133   Retail    Retail  /Not Applicable    41911          7
271134   Retail    Retail  /Not Applicable    26911         13

                             Class Name        Brand Name  Price Paid  Units  \
0       TRAILERS/TRAILER PARTS          /Not Applicable        6.99    1.0
1       TRAILERS/TRAILER PARTS          /Not Applicable        6.99    1.0
2       TRAILERS/TRAILER PARTS          /Not Applicable        6.99    1.0
3       TRAILERS/TRAILER PARTS          /Not Applicable        6.99    1.0
4       TRAILERS/TRAILER PARTS          /Not Applicable        6.99    1.0
…                            …                 …         …     …
271130  POWER TOOLS                     /Not Applicable       39.97    1.0
271131  AUTOMOTIVE ACCESSORIES          /Not Applicable     1129.00    1.0
271132  AUTOMOTIVE ACCESSORIES            Northern Tool     1694.96    4.0
271133  AUTOMOTIVE ACCESSORIES            Northern Tool     1694.96    4.0
271134  CLEANING SUPPLIES/TOOLS         /Not Applicable       19.99    1.0

        Shipping Cost  DMCouponInd  Return_Ind
0                 NaN            0           0
1                 NaN            0           0
2                 NaN            0           0
3                 NaN            0           0
4                 NaN            0           0
…               …           …          …
271130            NaN            0           0
271131          41.49            0           0
271132            NaN            0           0
271133            NaN            1           0
271134            NaN            0           0

[271135 rows x 17 columns]
```

0.2 Exploratory Data Analysis

[3]:
```
Dates_df
```

[3]:
```
       Gold_Cust_ID DM Mail Date
0               213     5/8/2023
1               213     9/9/2024
2               213    11/6/2023
3               213     4/8/2024
4               213     4/7/2025
…               …          …
29963      36904813     4/7/2025
29964      36905023     4/7/2025
29965      36916725     4/7/2025
29966      36924552     4/7/2025
29967      36981351     4/7/2025
```

```
[29968 rows x 2 columns]
```

[4]:
```
print(Sales_df.info())
print(Dates_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271135 entries, 0 to 271134
Data columns (total 17 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Gold_Cust_ID   271135 non-null  int64
 1   Post_Cd        264758 non-null  object
 2   Tran_Dt        271135 non-null  object
 3   Dept ID        271135 non-null  int64
 4   Dept Name      271135 non-null  object
 5   Division       271135 non-null  object
 6   Channel        271135 non-null  object
 7   Online Store   271135 non-null  object
 8   Itm_Id         271135 non-null  object
 9   Class Code     271135 non-null  object
 10  Class Name     271135 non-null  object
 11  Brand Name     271135 non-null  object
 12  Price Paid     271135 non-null  float64
 13  Units          271135 non-null  float64
 14  Shipping Cost  12732 non-null   float64
 15  DMCouponInd    271135 non-null  int64
 16  Return_Ind     271135 non-null  int64
dtypes: float64(3), int64(4), object(10)
memory usage: 35.2+ MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29968 entries, 0 to 29967
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Gold_Cust_ID  29968 non-null  int64
 1   DM Mail Date  29968 non-null  object
dtypes: int64(1), object(1)
memory usage: 468.4+ KB
None
```

0.3 Data Cleaning

[5]:
```
Sales_df.isnull().sum()
```

[5]:
```
Gold_Cust_ID          0
Post_Cd            6377
Tran_Dt               0
Dept ID               0
Dept Name             0
Division              0
Channel               0
Online Store          0
Itm_Id                0
Class Code            0
Class Name            0
Brand Name            0
Price Paid            0
Units                 0
Shipping Cost    258403
DMCouponInd           0
Return_Ind            0
dtype: int64
```

[6]:
```python
Sales_df.duplicated().sum()
```

[6]:
```
np.int64(216376)
```

[7]:
```python
Sales_df.nunique()
```

[7]:
```
Gold_Cust_ID     10000
Post_Cd           8967
Tran_Dt            728
Dept ID            150
Dept Name          150
Division             2
Channel              4
Online Store         7
Itm_Id           11856
Class Code         110
Class Name          56
Brand Name          18
Price Paid        6426
Units               55
Shipping Cost     1072
DMCouponInd          2
Return_Ind           2
dtype: int64
```

[8]:
```python
Sales_df.drop_duplicates(inplace=True)
```

[9]:
```python
Sales_df.axes
```

```
[9]: [Index([     0,     10,     20,     30,     31,     60,     80,    100,    110,
                120,
        …
        271125, 271126, 271127, 271128, 271129, 271130, 271131, 271132, 271133,
        271134],
       dtype='int64', length=54759),
 Index(['Gold_Cust_ID', 'Post_Cd', 'Tran_Dt', 'Dept ID', 'Dept Name',
        'Division', 'Channel', 'Online Store', 'Itm_Id', 'Class Code',
        'Class Name', 'Brand Name', 'Price Paid', 'Units', 'Shipping Cost',
        'DMCouponInd', 'Return_Ind'],
       dtype='object')]
```

```
[10]: Sales_df.shape
```

```
[10]: (54759, 17)
```

0.3.1 convert the object data to Datatime

```
[11]: Dates_df['DM Mail Date'] = pd.to_datetime(Dates_df['DM Mail Date'],␣
      ↪errors='coerce')
      Dates_df.dtypes
```

```
[11]: Gold_Cust_ID             int64
      DM Mail Date    datetime64[ns]
      dtype: object
```

```
[12]: Sales_df['Tran_Dt'] = pd.to_datetime(Sales_df['Tran_Dt'], errors='coerce')
      Sales_df['Post_Cd'] = Sales_df['Post_Cd'].astype(str)
      Sales_df.dtypes
```

```
[12]: Gold_Cust_ID              int64
      Post_Cd                  object
      Tran_Dt          datetime64[ns]
      Dept ID                   int64
      Dept Name                object
      Division                 object
      Channel                  object
      Online Store             object
      Itm_Id                   object
      Class Code               object
      Class Name               object
      Brand Name               object
      Price Paid              float64
      Units                   float64
      Shipping Cost           float64
      DMCouponInd               int64
      Return_Ind                int64
```

```
dtype: object
```

[13]:
```python
print("Mean of Shipping Cost: ",Sales_df['Shipping Cost'].mean())
print("Median of Shipping Cost: ",Sales_df['Shipping Cost'].median())
```

```
Mean of Shipping Cost:  11.17155603508772
Median of Shipping Cost:  0.0
```

[14]:
```python
Sales_df['Shipping Cost'].fillna(Sales_df['Shipping Cost'].mean(),inplace=True)
Sales_df.isnull().sum()
```

[14]:
```
Gold_Cust_ID     0
Post_Cd          0
Tran_Dt          0
Dept ID          0
Dept Name        0
Division         0
Channel          0
Online Store     0
Itm_Id           0
Class Code       0
Class Name       0
Brand Name       0
Price Paid       0
Units            0
Shipping Cost    0
DMCouponInd      0
Return_Ind       0
dtype: int64
```

[15]:
```python
Sales_df.describe()
```

[15]:
```
        Gold_Cust_ID                        Tran_Dt        Dept ID   Price Paid  \
count   5.475900e+04                          54759   54759.000000  54759.00000
mean    1.913001e+07  2024-04-22 22:18:02.780913152    5258.631768     75.15660
min     2.130000e+02            2023-05-01 00:00:00    2101.000000  -9999.99000
25%     5.921431e+06            2023-10-19 00:00:00    5506.000000      6.99000
50%     1.828684e+07            2024-04-23 00:00:00    5563.000000     19.97000
75%     3.275347e+07            2024-10-28 00:00:00    5650.000000     54.44000
max     3.754594e+07            2025-05-01 00:00:00    5695.000000  16999.99000
std     1.310654e+07                            NaN     994.488319    339.77446

               Units  Shipping Cost   DMCouponInd    Return_Ind
count   54759.000000   54759.000000  54759.000000  54759.000000
mean        1.251694      11.171556      0.133932      0.034040
min       -33.000000       0.000000      0.000000      0.000000
25%         1.000000      11.171556      0.000000      0.000000
```

```
50%        1.000000     11.171556     0.000000     0.000000
75%        1.000000     11.171556     0.000000     0.000000
max      144.000000   1387.410000     1.000000     1.000000
std        1.787558     14.789561     0.340583     0.181334
```

[16]:
```
Dates_df.describe()
```

[16]:
```
       Gold_Cust_ID                   DM Mail Date
count  2.996800e+04                          29968
mean   1.340509e+07  2024-03-17 09:12:18.067271680
min    2.130000e+02            2023-05-08 00:00:00
25%    2.750468e+06            2023-09-05 00:00:00
50%    1.207334e+07            2024-04-08 00:00:00
75%    2.292054e+07            2024-09-09 00:00:00
max    3.698135e+07            2025-04-07 00:00:00
std    1.050861e+07                            NaN
```

[17]:
```
Sales_df.dtypes
```

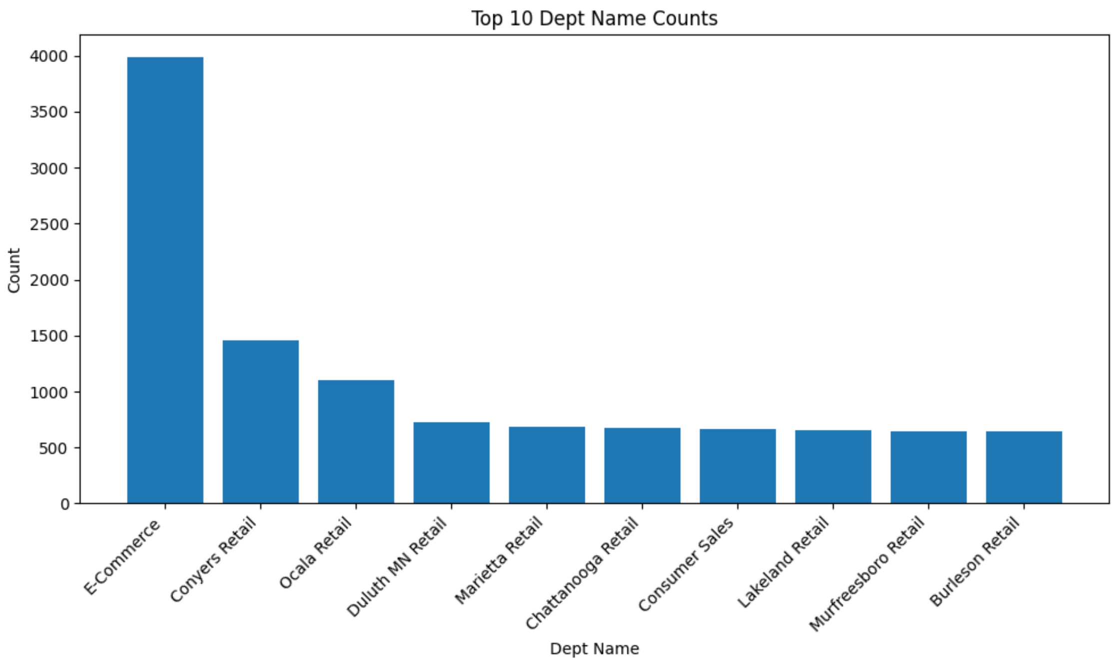
[17]:
```
Gold_Cust_ID              int64
Post_Cd                  object
Tran_Dt          datetime64[ns]
Dept ID                   int64
Dept Name                object
Division                 object
Channel                  object
Online Store             object
Itm_Id                   object
Class Code               object
Class Name               object
Brand Name               object
Price Paid              float64
Units                   float64
Shipping Cost           float64
DMCouponInd               int64
Return_Ind                int64
dtype: object
```

0.4 Data Visualization with single column

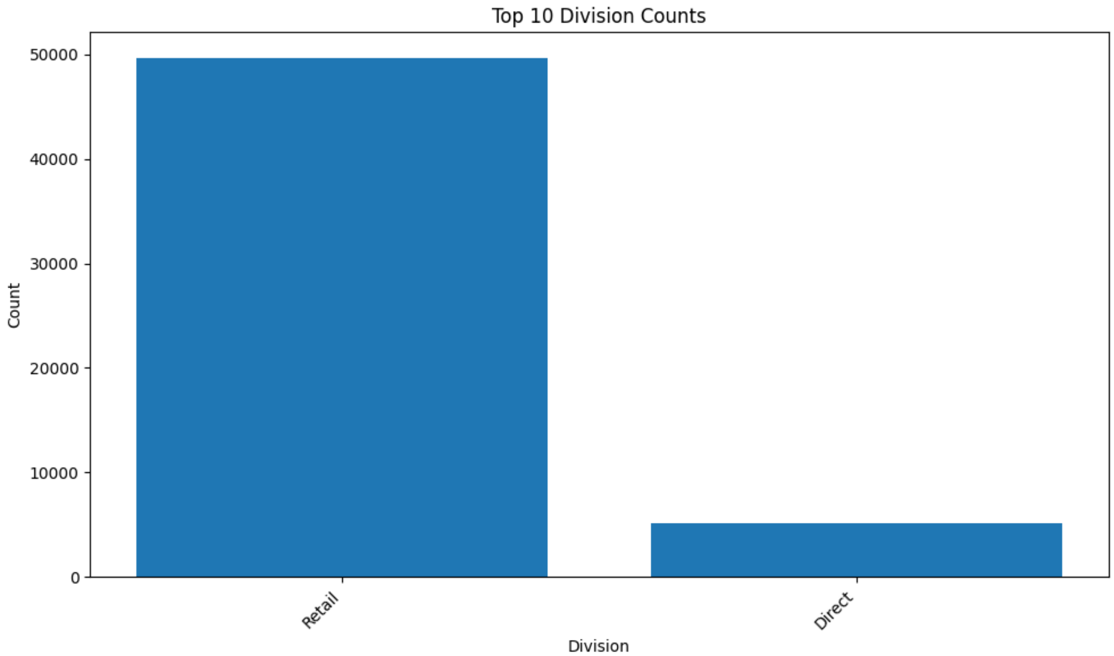
[18]:
```
print("\nSales_Data.csv Value Counts (Top 10):")
for col in ['Dept Name', 'Division', 'Channel', 'Online Store', 'Class Name',␣
 ↪'Brand Name']:
    print(f"\n{col}:")
    top_10_counts = Sales_df[col].value_counts().head(10)
    plt.figure(figsize=(10, 6)) # Create a new figure for each plot
    plt.bar(top_10_counts.index, top_10_counts.values)
```

```
    plt.title(f'Top 10 {col} Counts')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
    plt.show()
```

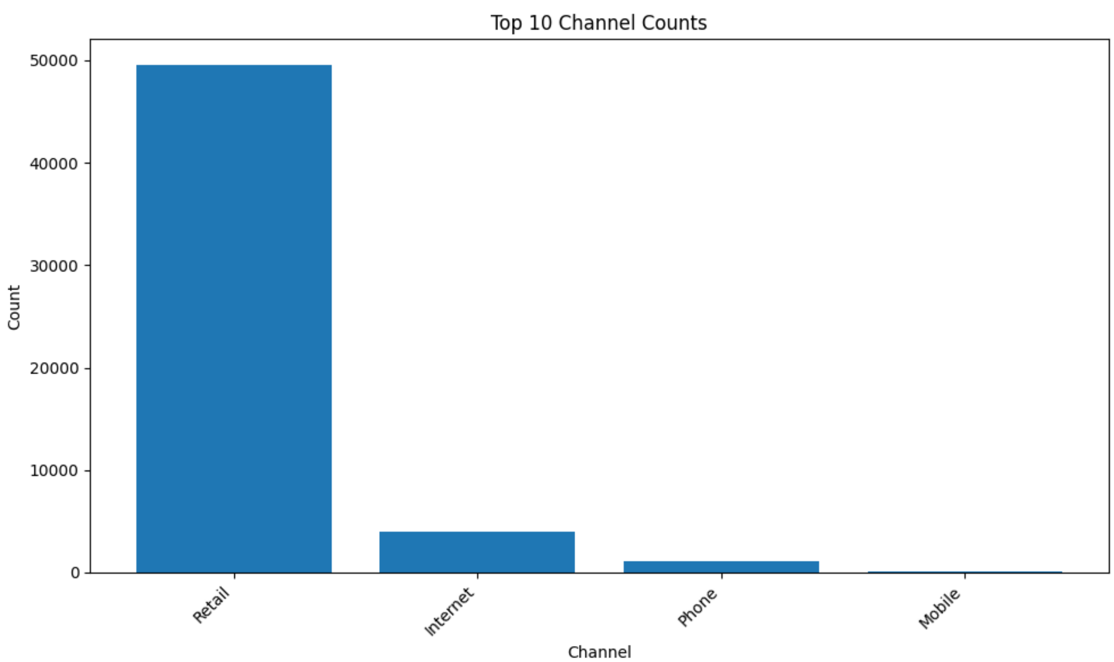
```
Sales_Data.csv Value Counts (Top 10):

Dept Name:
```



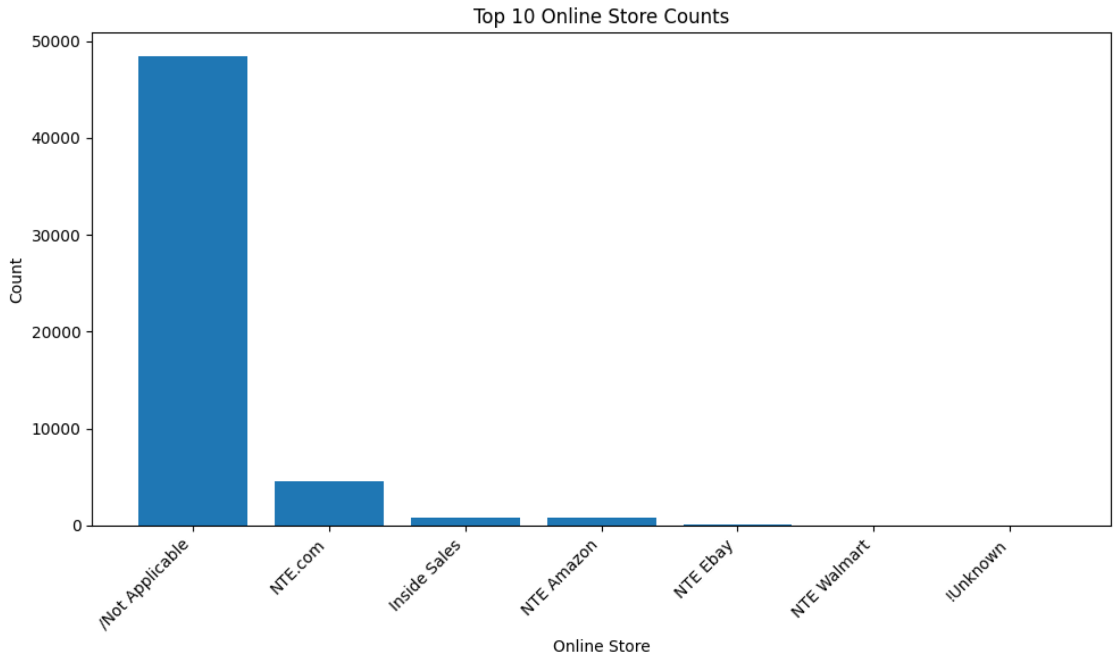

```
Division:
```


Top 10 Division Counts
50000
40000
30000
20000
10000
0
Count
Retail
Direct
Division

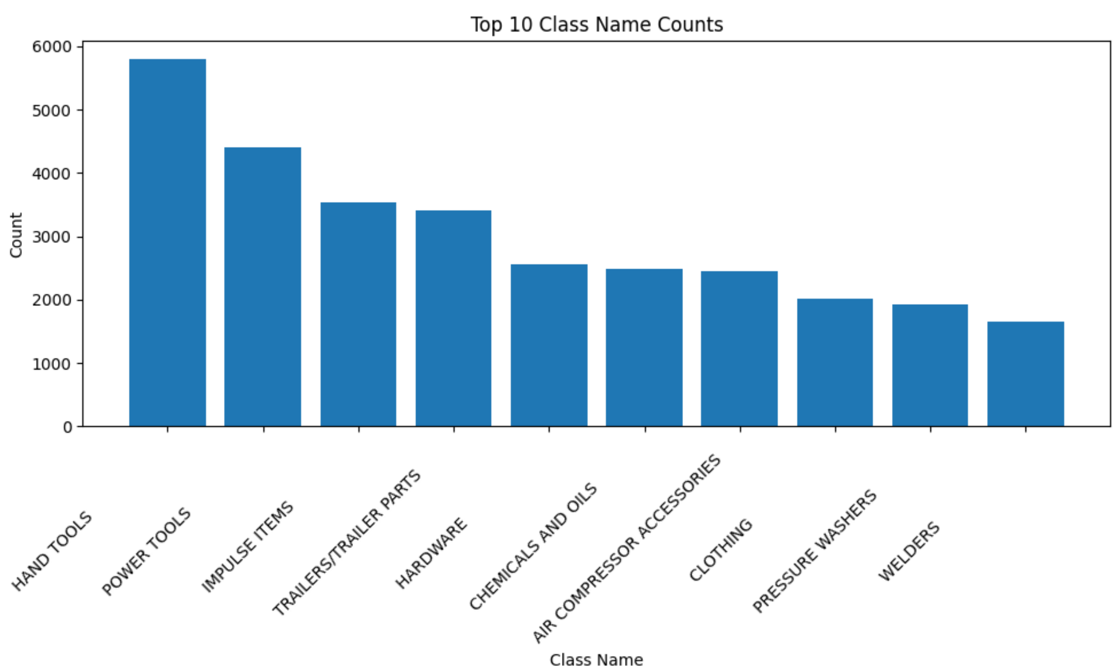
`Channel:`


Top 10 Channel Counts
50000
40000
30000
20000
10000
0
Count
Retail
Internet
Phone
Mobile
Channel

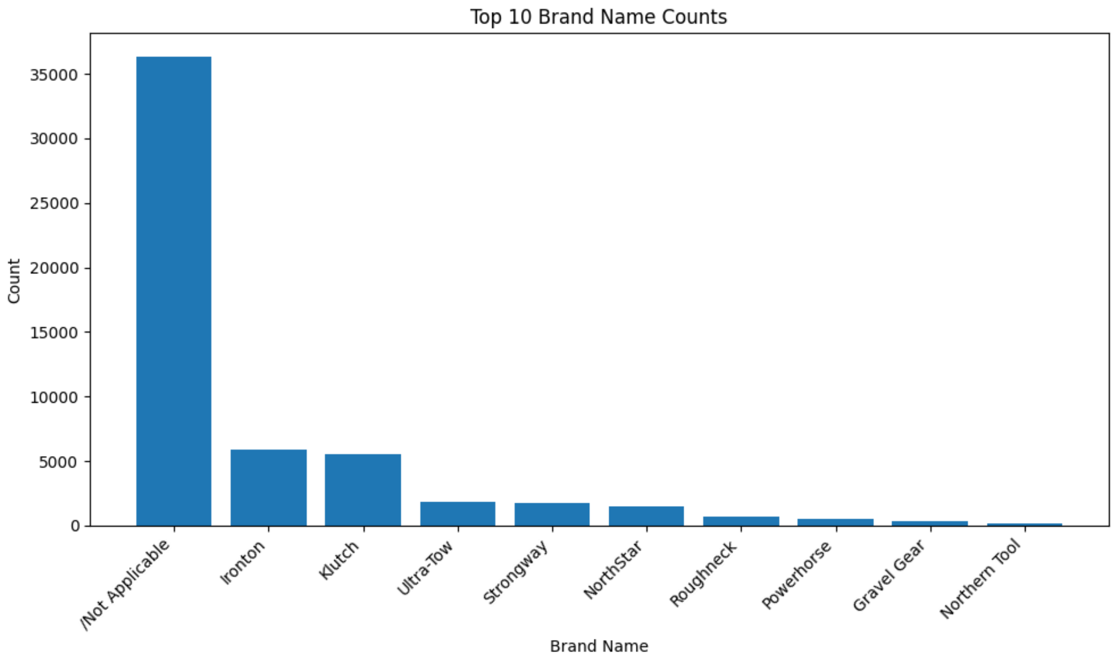
Online Store:



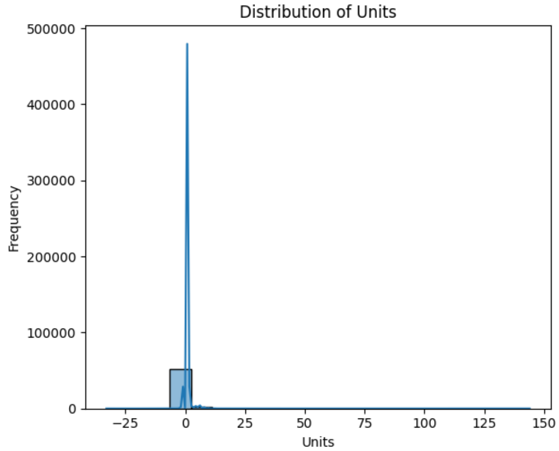
Class Name:



Brand Name:



[19]:
```python
# Histograms for 'Price Paid' and 'Units'
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
sns.histplot(Sales_df['Price Paid'].dropna(), bins=50, kde=True)
plt.title('Distribution of Price Paid')
plt.xlabel('Price Paid')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
sns.histplot(Sales_df['Units'].dropna(), bins=20, kde=True)
plt.title('Distribution of Units')
plt.xlabel('Units')
plt.ylabel('Frequency')

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



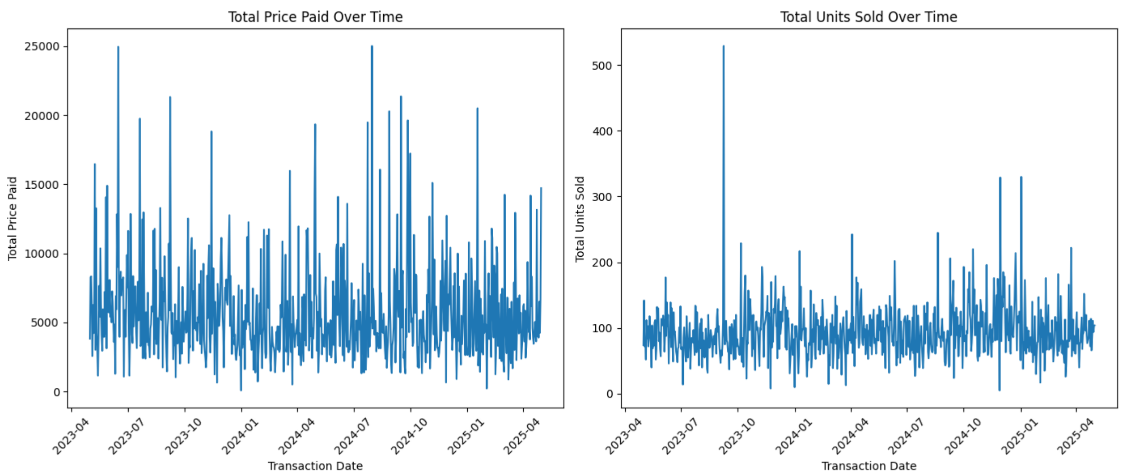
0.5 Data Visualization with two Columns

[20]:
```
# Group by transaction date and calculate total price paid and units
sales_over_time = Sales_df.groupby('Tran_Dt')[['Price Paid', 'Units']].sum().
 ↪reset_index()
sales_over_time
```

[20]:
```
        Tran_Dt    Price Paid  Units
0    2023-05-01   3820.530000   74.0
1    2023-05-02   8251.210000  142.0
2    2023-05-03   8335.870000   72.0
3    2023-05-04   6475.920000   80.0
4    2023-05-05   2562.840000   52.0
..          …             …      …
723  2025-04-27   3899.460000   86.0
724  2025-04-28   6500.490001  111.0
725  2025-04-29   4241.470000   94.0
726  2025-04-30   6680.600000  103.0
727  2025-05-01  14718.010000  104.0

[728 rows x 3 columns]
```

[21]:
```
# Visualize sales trends over time
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
sns.lineplot(data=sales_over_time, x='Tran_Dt', y='Price Paid')
plt.title('Total Price Paid Over Time')
plt.xlabel('Transaction Date')
plt.ylabel('Total Price Paid')
plt.xticks(rotation=45)
```

```
plt.subplot(1, 2, 2)
sns.lineplot(data=sales_over_time, x='Tran_Dt', y='Units')
plt.title('Total Units Sold Over Time')
plt.xlabel('Transaction Date')
plt.ylabel('Total Units Sold')
plt.xticks(rotation=45)

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

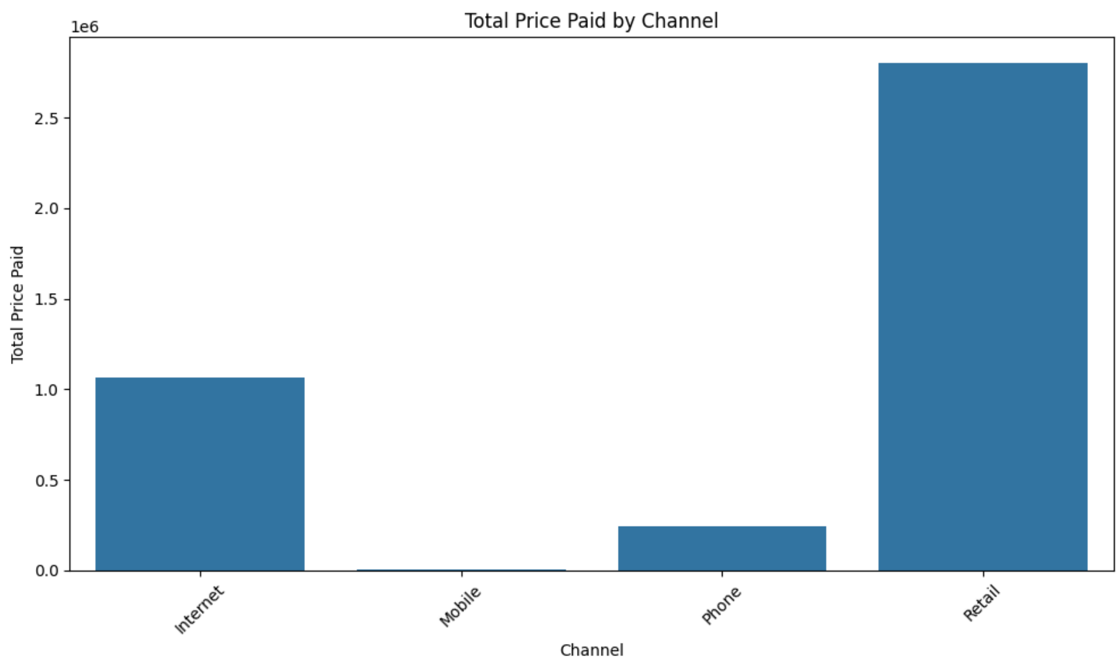


[22]:
```
# Analyze sales by Channel
sales_by_channel = Sales_df.groupby('Channel')['Price Paid'].sum().reset_index()
sales_by_channel
```

[22]:

	Channel	Price Paid
0	Internet	1.066056e+06
1	Mobile	3.544730e+03
2	Phone	2.419144e+05
3	Retail	2.803985e+06

[23]:
```
plt.figure(figsize=(10, 6))
sns.barplot(data=sales_by_channel, x='Channel', y='Price Paid')
plt.title('Total Price Paid by Channel')
plt.xlabel('Channel')
plt.ylabel('Total Price Paid')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

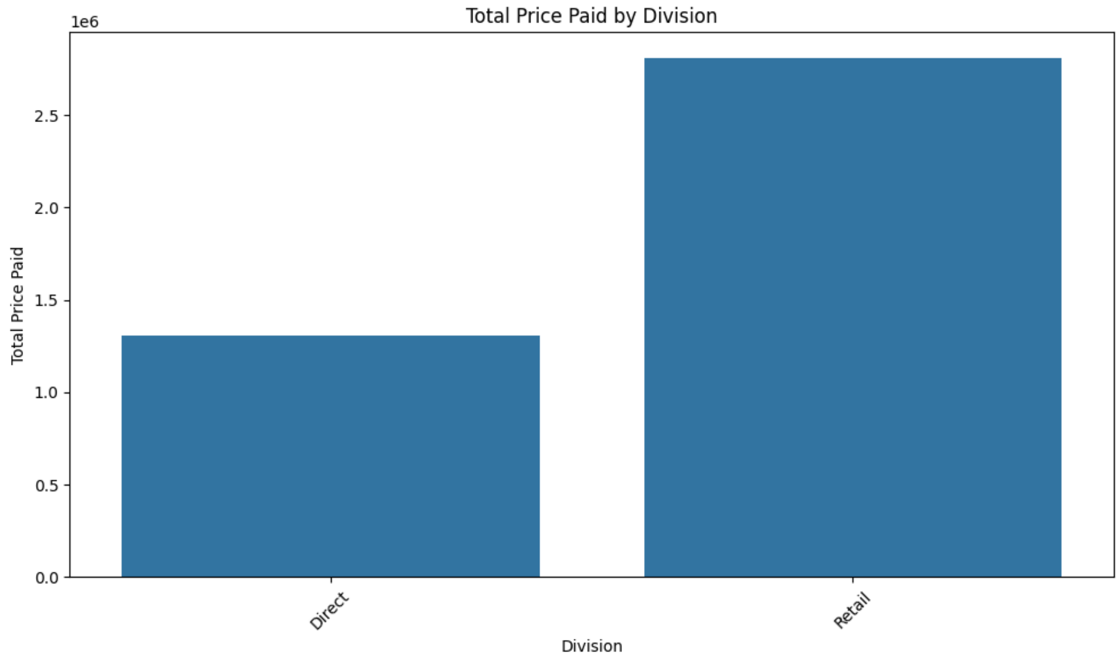



```
[24]: # Analyze sales by Division
sales_by_division = Sales_df.groupby('Division')['Price Paid'].sum().
 ↪reset_index()
sales_by_division
```

[24]:

	Division	Price Paid
0	Direct	1.307970e+06
1	Retail	2.807530e+06

```
[25]: plt.figure(figsize=(10, 6))
sns.barplot(data=sales_by_division, x='Division', y='Price Paid')
plt.title('Total Price Paid by Division')
plt.xlabel('Division')
plt.ylabel('Total Price Paid')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



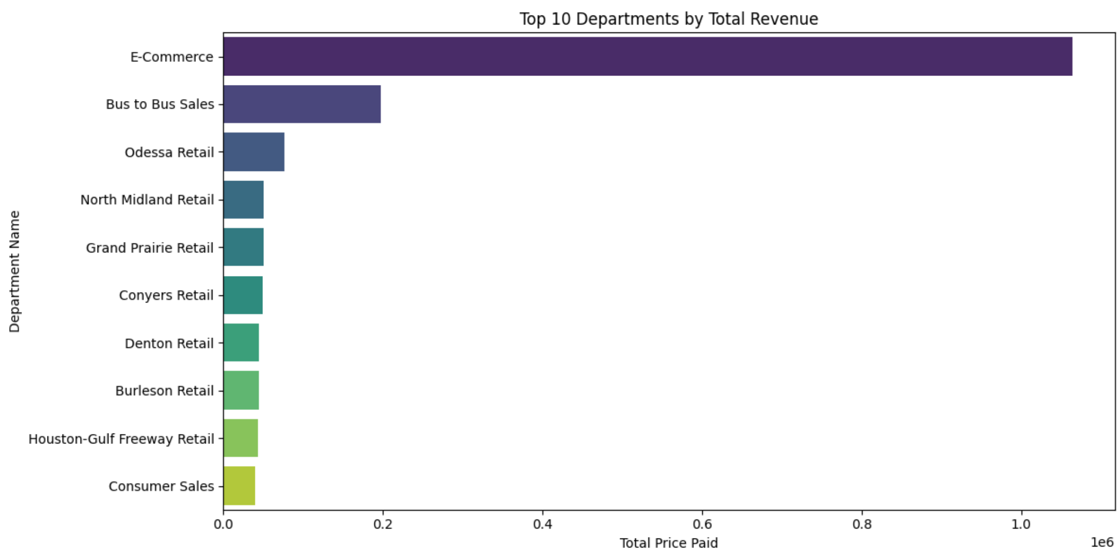
[26]:
```
# Group by 'Dept Name' and calculate total price paid and units
sales_by_department = Sales_df.groupby('Dept Name')[['Price Paid', 'Units']].
    ↪sum().reset_index()
```

[27]:
```
# Sort by total price paid and display top 10 departments
top_10_revenue_departments = sales_by_department.sort_values(by='Price Paid',␣
    ↪ascending=False).head(10)
print("Top 10 Departments by Total Revenue:")
display(top_10_revenue_departments)
```

```
Top 10 Departments by Total Revenue:

                         Dept Name    Price Paid   Units
38                      E-Commerce  1.064622e+06  5915.0
19                Bus to Bus Sales  1.971518e+05  1211.0
111                 Odessa Retail  7.601413e+04   747.0
108           North Midland Retail  5.062689e+04   769.0
53            Grand Prairie Retail  5.021415e+04   697.0
29                 Conyers Retail  4.875858e+04  1755.0
34                  Denton Retail  4.459278e+04   557.0
16                Burleson Retail  4.455192e+04   847.0
60    Houston-Gulf Freeway Retail  4.388297e+04   762.0
28                 Consumer Sales  3.930975e+04   651.0
```

[28]:
```
# Visualize top 10 departments by revenue
plt.figure(figsize=(12, 6))
```

```
sns.barplot(data=top_10_revenue_departments, x='Price Paid', y='Dept Name',␣
↪palette='viridis')
plt.title('Top 10 Departments by Total Revenue')
plt.xlabel('Total Price Paid')
plt.ylabel('Department Name')
plt.tight_layout()
plt.show()
```

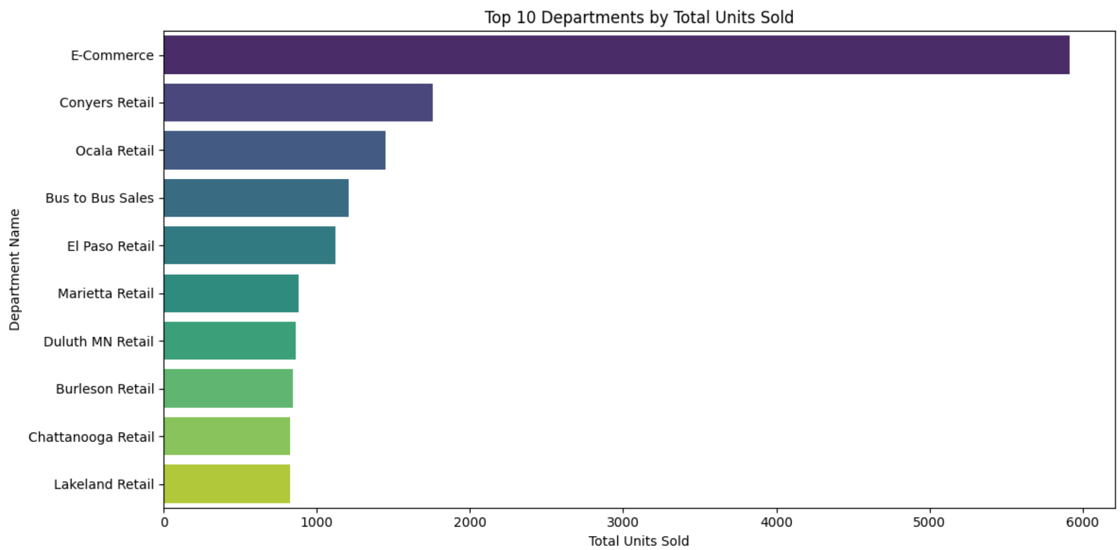


[29]:
```
# Sort by total units sold and display top 10 departments
top_10_units_departments = sales_by_department.sort_values(by='Units',␣
↪ascending=False).head(10)
print("\nTop 10 Departments by Total Units Sold:")
display(top_10_units_departments)
```

```
Top 10 Departments by Total Units Sold:

               Dept Name    Price Paid   Units
38            E-Commerce  1.064622e+06  5915.0
29        Conyers Retail  4.875858e+04  1755.0
110         Ocala Retail  2.717839e+04  1449.0
19      Bus to Bus Sales  1.971518e+05  1211.0
42        El Paso Retail  2.244786e+04  1125.0
86       Marietta Retail  3.511488e+04   882.0
37      Duluth MN Retail  3.333268e+04   861.0
16       Burleson Retail  4.455192e+04   847.0
24    Chattanooga Retail  3.052109e+04   828.0
75        Lakeland Retail  1.802721e+04   824.0
```

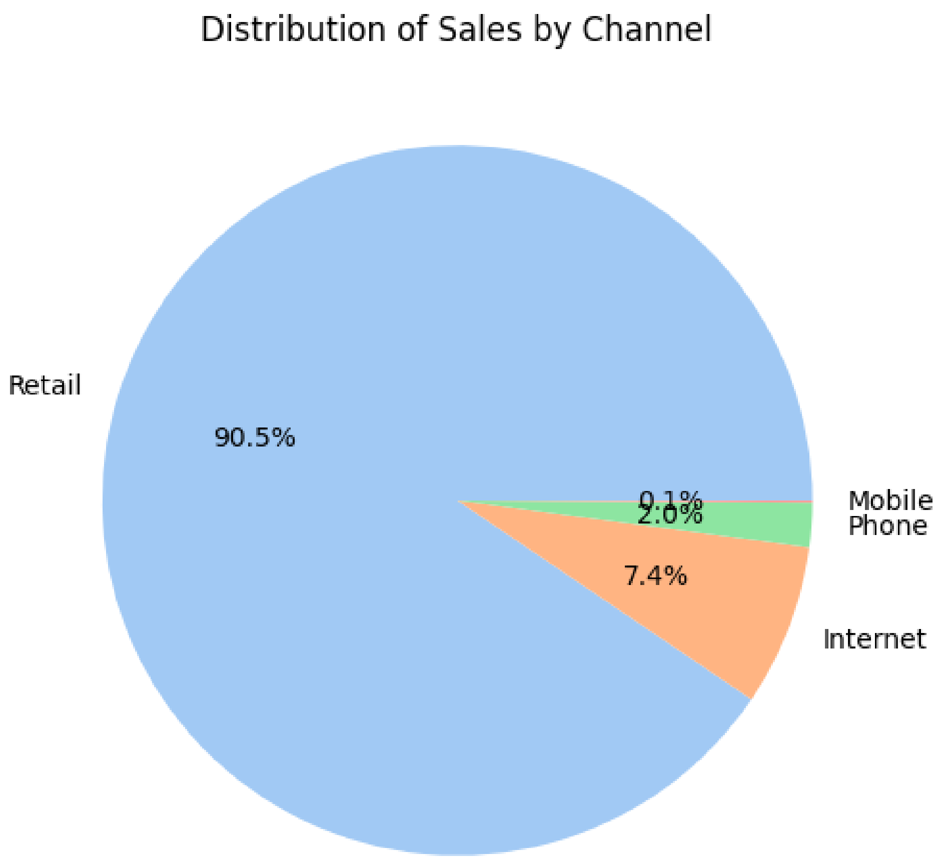
[30]:

```
# Visualize top 10 departments by units sold
plt.figure(figsize=(12, 6))
sns.barplot(data=top_10_units_departments, x='Units', y='Dept Name',
 ↪palette='viridis')
plt.title('Top 10 Departments by Total Units Sold')
plt.xlabel('Total Units Sold')
plt.ylabel('Department Name')
plt.tight_layout()
plt.show()
```

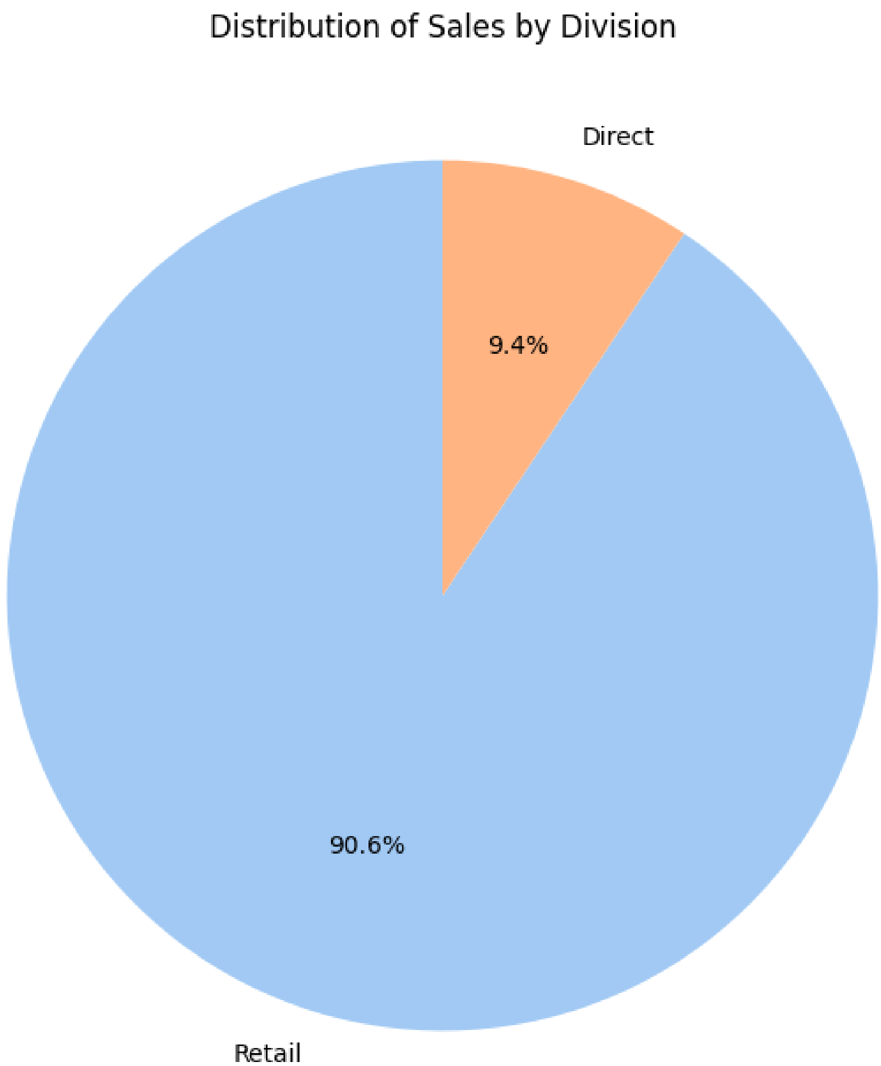


[31]:

```
# Pie chart for 'Channel' distribution
channel_counts = Sales_df['Channel'].value_counts()
plt.figure(figsize=(6,6))
plt.pie(channel_counts, labels=channel_counts.index, autopct='%1.1f%%',
 ↪startangle=0, colors=sns.color_palette('pastel'))
plt.title('Distribution of Sales by Channel')
plt.show()
```

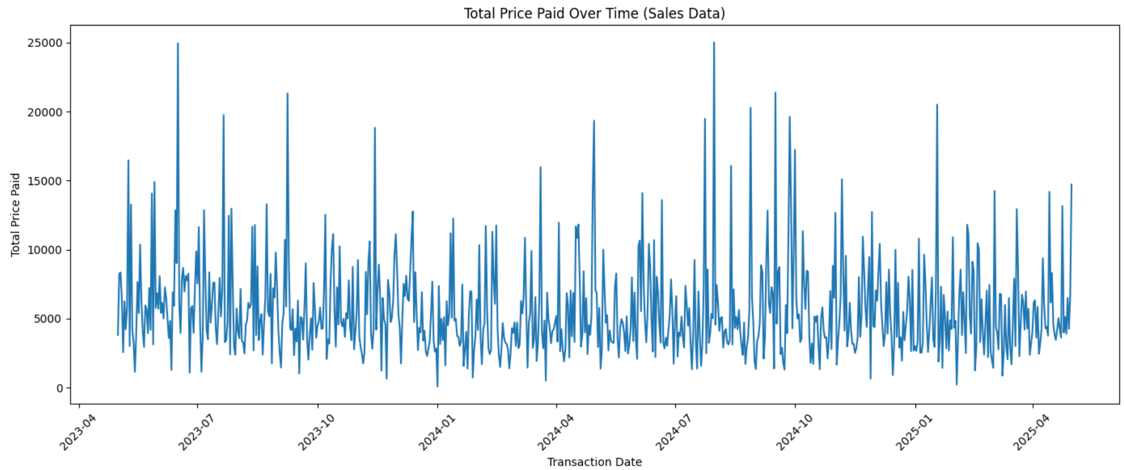


[32]:
```
# Pie chart for 'Division' distribution
division_counts = Sales_df['Division'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(division_counts, labels=division_counts.index, autopct='%1.1f%%',␣
↪startangle=90, colors=sns.color_palette('pastel'))
plt.title('Distribution of Sales by Division')
plt.show()
```

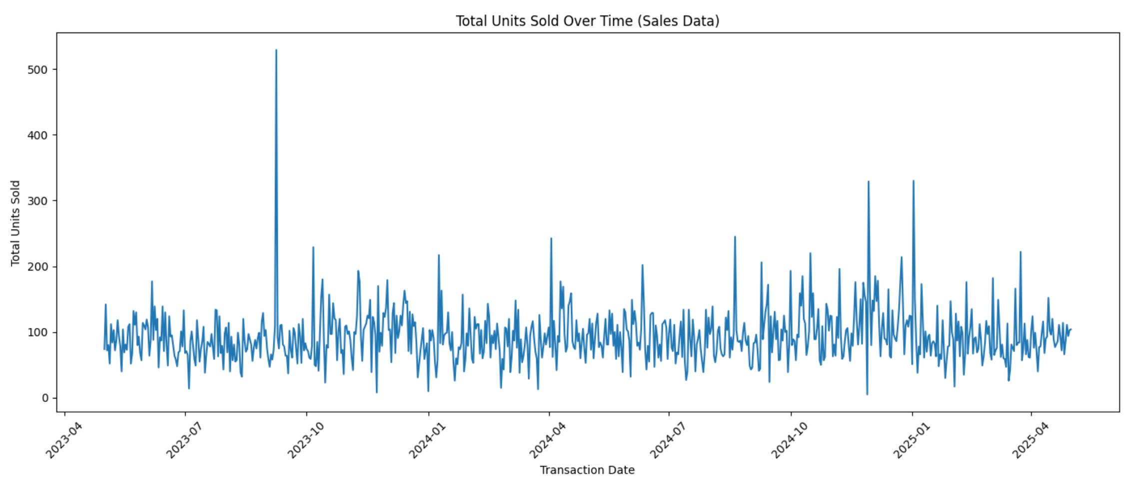


[33]:
```
# Group by transaction date and calculate total price paid and units
# Ensure 'Tran_Dt' is in datetime format
Sales_df['Tran_Dt'] = pd.to_datetime(Sales_df['Tran_Dt'], errors='coerce')
sales_over_time_sales_df = Sales_df.groupby('Tran_Dt')[['Price Paid', 'Units']].
  ↪sum().reset_index()

# Line chart for total 'Price Paid' over time
plt.figure(figsize=(14, 6))
sns.lineplot(data=sales_over_time_sales_df, x='Tran_Dt', y='Price Paid')
plt.title('Total Price Paid Over Time (Sales Data)')
plt.xlabel('Transaction Date')
plt.ylabel('Total Price Paid')
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[34]:
```
# Line chart for total 'Units' sold over time
plt.figure(figsize=(14, 6))
sns.lineplot(data=sales_over_time_sales_df, x='Tran_Dt', y='Units')
plt.title('Total Units Sold Over Time (Sales Data)')
plt.xlabel('Transaction Date')
plt.ylabel('Total Units Sold')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



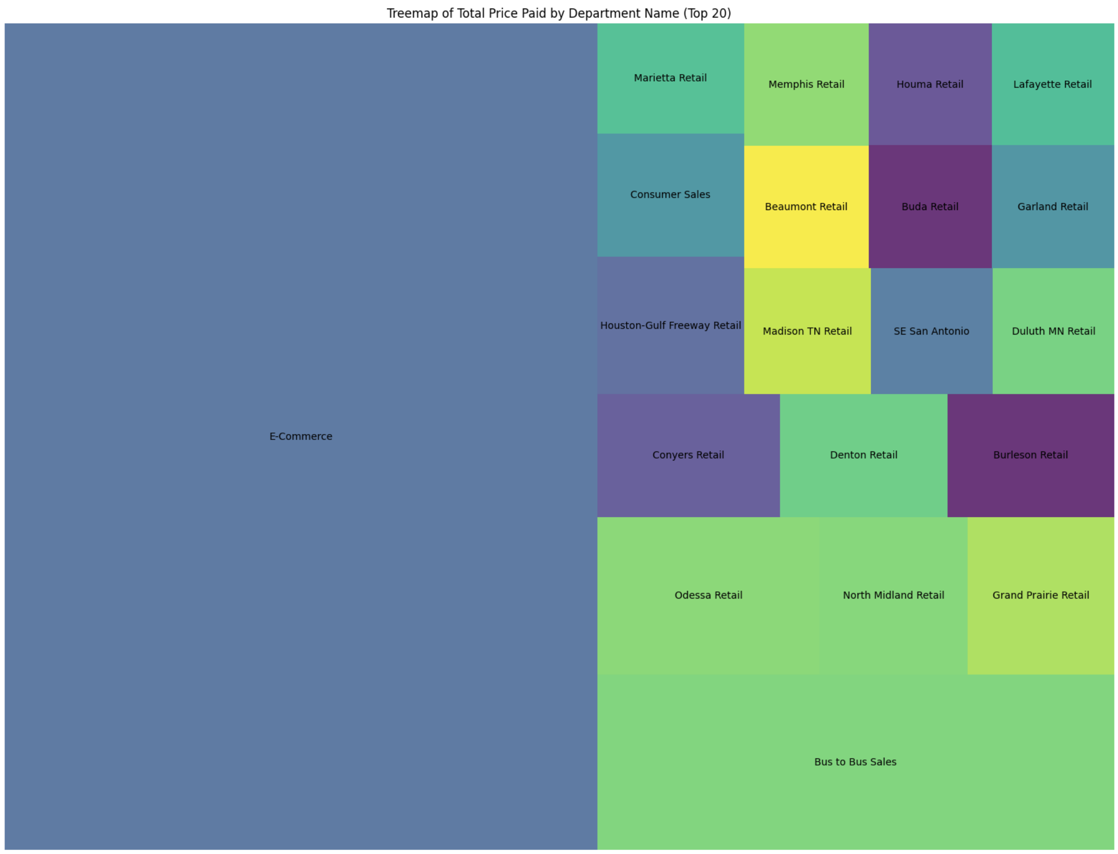
[35]:
```
%pip install squarify
```

```
Requirement already satisfied: squarify in /usr/local/lib/python3.11/dist-
packages (0.4.4)
```

[36]:
```
import squarify
# Treemap
# Aggregate sales data by Department Name
treemap_data = Sales_df.groupby('Dept Name')['Price Paid'].sum().reset_index()
treemap_data
```

[36]:
```
                   Dept Name    Price Paid
0             Abilene Retail  17236.169993
1            Amarillo Retail  16743.810000
2            Appleton Retail  16725.290000
3              Arnold Retail   8429.770000
4           Asheville Retail  22330.299999
..                       …           …
145       West Allis Retail  24387.790000
146  White Bear Lake Retail   7133.469994
147            Wichita Retail   7968.980000
148        Willowbrook Retail  17328.649995
149          Woodbury Retail  12597.399992

[150 rows x 2 columns]
```

[37]:
```
# Sort the data and select top N departments for better visualization if there␣
↪are many departments
treemap_data = treemap_data.sort_values(by='Price Paid', ascending=False).
↪head(20)
plt.figure(figsize=(20,15))
squarify.plot(sizes=treemap_data['Price Paid'], label=treemap_data['Dept␣
↪Name'], alpha=.8)
plt.title('Treemap of Total Price Paid by Department Name (Top 20)')
plt.axis('off')
plt.show()
```



[38]:
```python
num_Sales_df=Sales_df.select_dtypes(include=['int64','float64'])
num_Sales_df
```

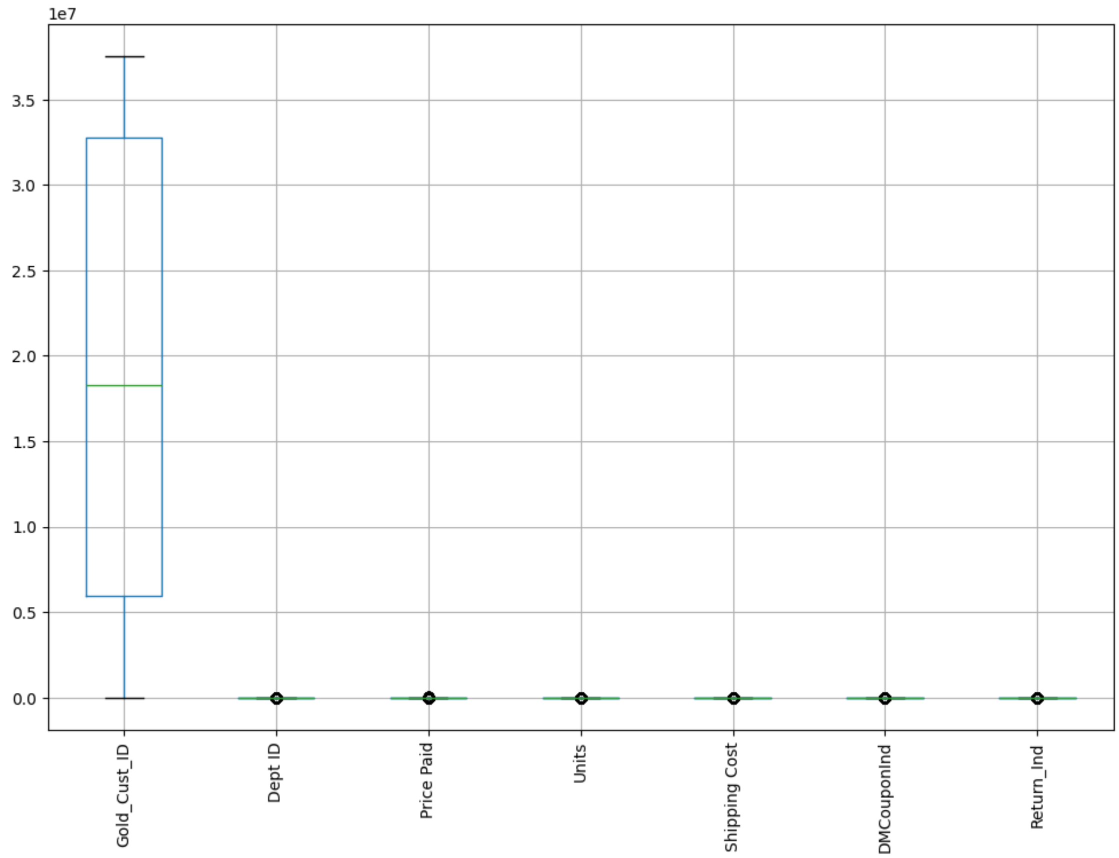
[38]:
```
        Gold_Cust_ID  Dept ID  Price Paid  Units  Shipping Cost  DMCouponInd  \
0                213     5611        6.99    1.0      11.171556            0
10               213     5611      179.99    1.0      11.171556            0
20               213     5611       14.99    1.0      11.171556            0
30               213     5611        3.49    1.0      11.171556            0
31               213     5611       11.99    1.0      11.171556            0
…                  …        …           …      …              …            …
271130      37543211     5518       39.97    1.0      11.171556            0
271131      37544105     2191     1129.00    1.0      41.490000            0
271132      37545460     5513     1694.96    4.0      11.171556            0
271133      37545460     5513     1694.96    4.0      11.171556            1
271134      37545944     5505       19.99    1.0      11.171556            0

        Return_Ind
0                0
10               0
20               0
```

```
30                0
31                0
…              …
271130            0
271131            0
271132            0
271133            0
271134            0

[54759 rows x 7 columns]
```

0.6 Data Visualization on numerical columns

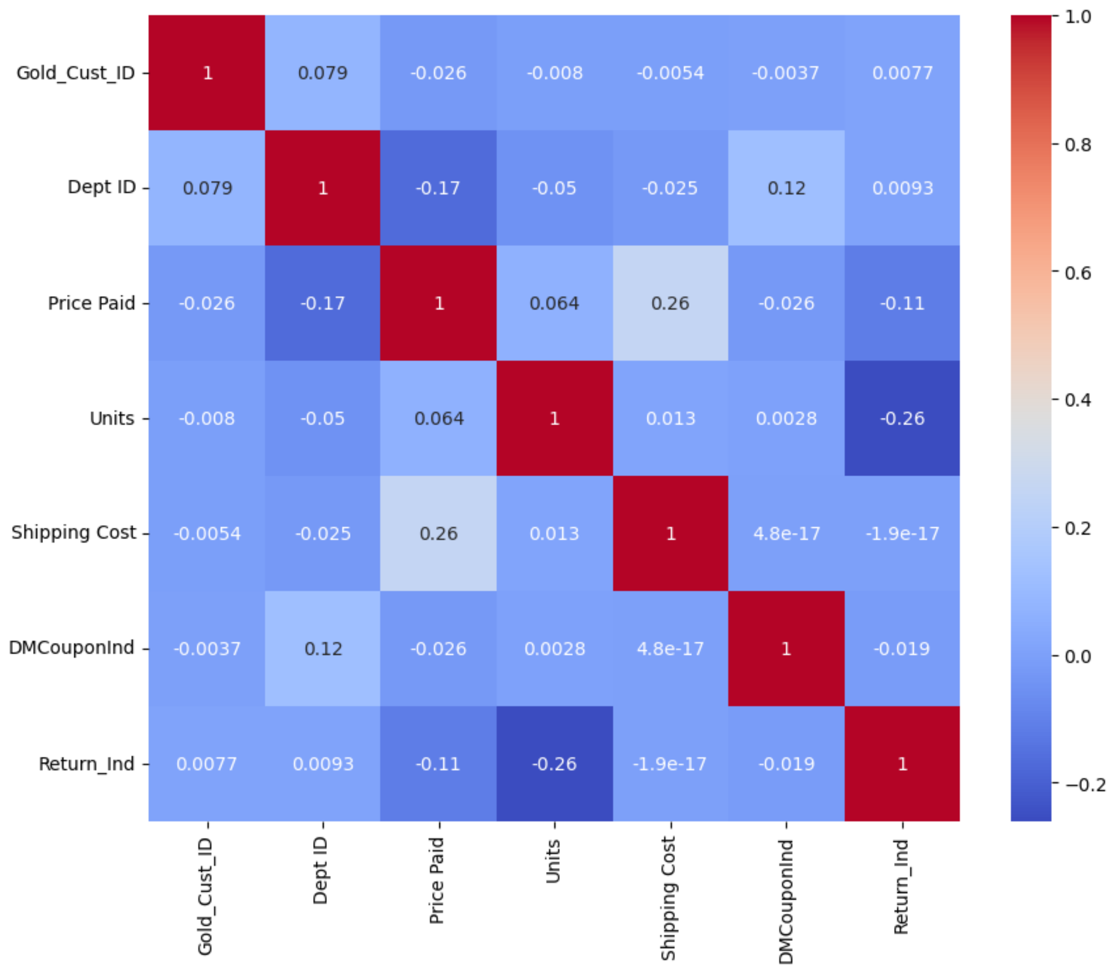
[39]:
```
num_Sales_df.boxplot(figsize=(12,8))
plt.xticks(rotation=90)
```

[39]:
```
(array([1, 2, 3, 4, 5, 6, 7]),
 [Text(1, 0, 'Gold_Cust_ID'),
  Text(2, 0, 'Dept ID'),
  Text(3, 0, 'Price Paid'),
  Text(4, 0, 'Units'),
  Text(5, 0, 'Shipping Cost'),
  Text(6, 0, 'DMCouponInd'),
  Text(7, 0, 'Return_Ind')])
```



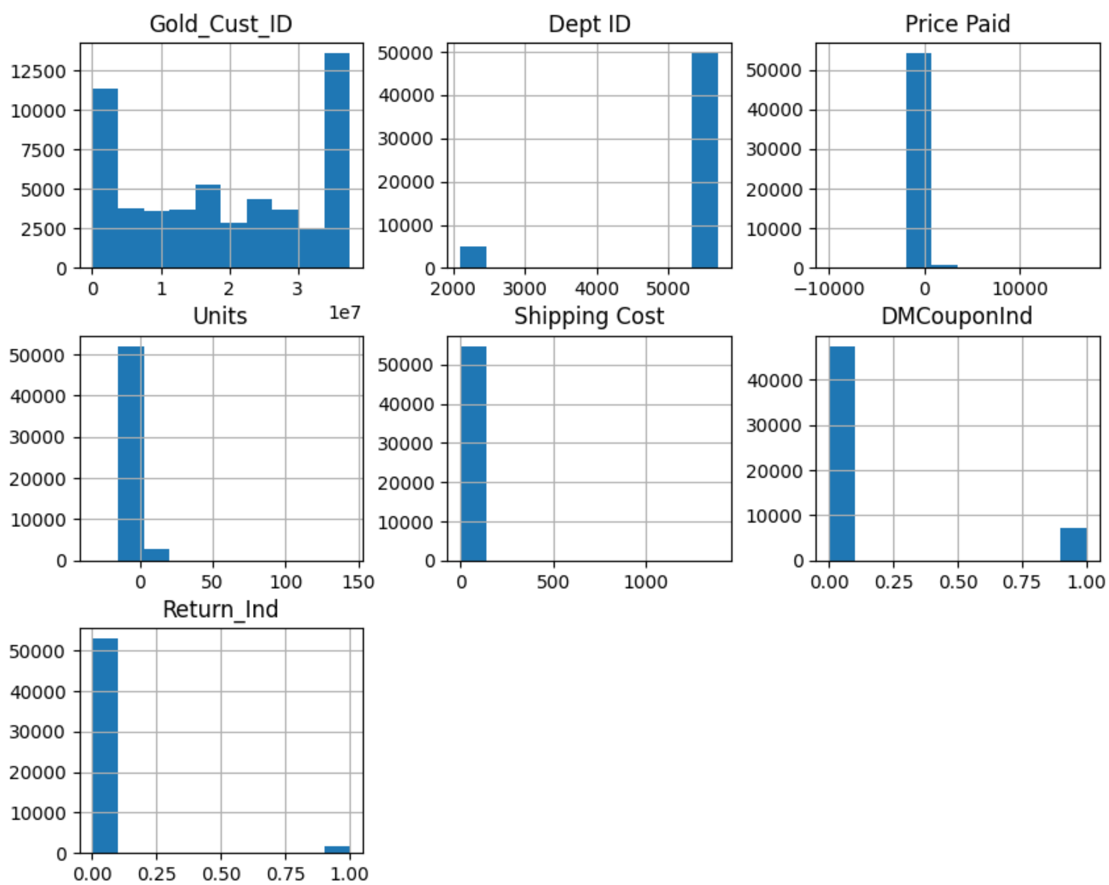
[40]:
```
corr=num_Sales_df.corr()
plt.figure(figsize=(10,8))
sns.heatmap(corr,annot=True,cmap='coolwarm')
```

[40]: <Axes: >



[41]:

```
num_Sales_df.hist(figsize=(10,8))
plt.show()
```



0.7 Merged two Dataset with left join

[42]:
```python
merged_df=Sales_df.merge(Dates_df, on='Gold_Cust_ID', how='left')
merged_df
```

[42]:
```
        Gold_Cust_ID    Post_Cd     Tran_Dt  Dept ID              Dept Name  \
0                213  344813463  2023-05-16     5611           Ocala Retail
1                213  344813463  2023-05-16     5611           Ocala Retail
2                213  344813463  2023-05-16     5611           Ocala Retail
3                213  344813463  2023-05-16     5611           Ocala Retail
4                213  344813463  2023-05-16     5611           Ocala Retail
…                  …          …           …        …                      …
257648      37543211  273499366  2025-04-30     5518      Burlington Retail
257649      37544105  321193400  2025-05-01     2191             E-Commerce
257650      37545460  276042489  2025-05-01     5513     East Raleigh Retail
257651      37545460  276042489  2025-05-01     5513     East Raleigh Retail
257652      37545944        nan  2025-05-01     5505  North Charlotte Retail

       Division    Channel     Online Store    Itm_Id Class Code  \
```

```
0        Retail    Retail  /Not Applicable    18359         57
1        Retail    Retail  /Not Applicable    18359         57
2        Retail    Retail  /Not Applicable    18359         57
3        Retail    Retail  /Not Applicable    18359         57
4        Retail    Retail  /Not Applicable    18359         57
…          …        …               …      …        …
257648   Retail    Retail  /Not Applicable   111740         33
257649   Direct  Internet          NTE.com  5864861          7
257650   Retail    Retail  /Not Applicable    41911          7
257651   Retail    Retail  /Not Applicable    41911          7
257652   Retail    Retail  /Not Applicable    26911         13

                           Class Name       Brand Name  Price Paid  Units  \
0       TRAILERS/TRAILER PARTS         /Not Applicable        6.99    1.0
1       TRAILERS/TRAILER PARTS         /Not Applicable        6.99    1.0
2       TRAILERS/TRAILER PARTS         /Not Applicable        6.99    1.0
3       TRAILERS/TRAILER PARTS         /Not Applicable        6.99    1.0
4       TRAILERS/TRAILER PARTS         /Not Applicable        6.99    1.0
…                                …                …         …     …
257648  POWER TOOLS                    /Not Applicable       39.97    1.0
257649  AUTOMOTIVE ACCESSORIES         /Not Applicable     1129.00    1.0
257650  AUTOMOTIVE ACCESSORIES           Northern Tool     1694.96    4.0
257651  AUTOMOTIVE ACCESSORIES           Northern Tool     1694.96    4.0
257652  CLEANING SUPPLIES/TOOLS        /Not Applicable       19.99    1.0

        Shipping Cost  DMCouponInd  Return_Ind DM Mail Date
0           11.171556            0           0   2023-05-08
1           11.171556            0           0   2024-09-09
2           11.171556            0           0   2023-11-06
3           11.171556            0           0   2024-04-08
4           11.171556            0           0   2025-04-07
…                 …          …          …           …
257648      11.171556            0           0          NaT
257649      41.490000            0           0          NaT
257650      11.171556            0           0          NaT
257651      11.171556            1           0          NaT
257652      11.171556            0           0          NaT

[257653 rows x 18 columns]
```

[43]:
```
merged_df.dtypes
```

[43]:
```
Gold_Cust_ID                int64
Post_Cd                    object
Tran_Dt            datetime64[ns]
Dept ID                     int64
Dept Name                  object
```

```
Division                    object
Channel                     object
Online Store                object
Itm_Id                      object
Class Code                  object
Class Name                  object
Brand Name                  object
Price Paid                 float64
Units                      float64
Shipping Cost              float64
DMCouponInd                  int64
Return_Ind                   int64
DM Mail Date        datetime64[ns]
dtype: object
```

0.8 Data Cleaning on Merged Dataset

[44]:
```
merged_df.isnull().sum()
```

[44]:
```
Gold_Cust_ID         0
Post_Cd              0
Tran_Dt              0
Dept ID              0
Dept Name            0
Division             0
Channel              0
Online Store         0
Itm_Id               0
Class Code           0
Class Name           0
Brand Name           0
Price Paid           0
Units                0
Shipping Cost        0
DMCouponInd          0
Return_Ind           0
DM Mail Date     19784
dtype: int64
```

[45]:
```
merged_df.duplicated().sum()
```

[45]:
```
np.int64(7035)
```

[46]:
```
merged_df.drop_duplicates(inplace=True)
merged_df.dropna(inplace=True)
```

0.8.1 It calculates if a purchase happened 30 days before or after the DM date

[47]:
```
from datetime import timedelta

merged_df['Days_From_DM'] = (merged_df['Tran_Dt'] - merged_df['DM Mail Date']).
  ↪dt.days
merged_df['Pre_DM'] = merged_df['Days_From_DM'].between(-30, -1)
merged_df['Post_DM'] = merged_df['Days_From_DM'].between(0, 30)
```

0.9 It creates customer-level features:

- Spend and units before/after DM
- Average coupon use rate
- Ratio of online purchases

[48]:
```
# Aggregate spend
pre_spend = merged_df[merged_df['Pre_DM']].groupby('Gold_Cust_ID')['Price␣
  ↪Paid'].sum().rename('Spend_Before')
post_spend = merged_df[merged_df['Post_DM']].groupby('Gold_Cust_ID')['Price␣
  ↪Paid'].sum().rename('Spend_After')

# Units
pre_units = merged_df[merged_df['Pre_DM']].groupby('Gold_Cust_ID')['Units'].
  ↪sum().rename('Units_Before')
post_units = merged_df[merged_df['Post_DM']].groupby('Gold_Cust_ID')['Units'].
  ↪sum().rename('Units_After')

# Coupon usage
coupon_rate = merged_df.groupby('Gold_Cust_ID')['DMCouponInd'].mean().
  ↪rename('Coupon_Usage_Rate')

# Online Store to 1 and '/Not Applicable' to 0
merged_df['Is_Online'] = merged_df['Online Store'].apply(lambda x: 0 if x == '/
  ↪Not Applicable' else 1)

# calculate the proportion of online orders per customer
channel_rate = merged_df.groupby('Gold_Cust_ID')['Is_Online'].mean().
  ↪rename('Online_Store_Rate')
```

0.9.1 Create new Table called Feature with Customer level

[49]:
```
features = pre_spend.to_frame().join([
    post_spend, pre_units, post_units, coupon_rate, channel_rate
]).fillna(0).reset_index()
features
```

[49]:
```
      Gold_Cust_ID  Spend_Before  Spend_After  Units_Before  Units_After  \
0              213        214.45       243.40           5.0         10.0
1              801         61.98         0.00           2.0          0.0
2             5038        208.22         0.00           4.0          0.0
3            16010        234.97       679.98           3.0          2.0
4            19413       1884.91         0.00           5.0          0.0
…                …             …            …             …            …
1598      35723689        102.96        55.23           4.0          7.0
1599      35766496        142.18       235.35           2.0          8.0
1600      35947203          8.77         0.00           3.0          0.0
1601      36054508        104.97       124.98           3.0          2.0
1602      36924552        -45.02         0.00           2.0          0.0

      Coupon_Usage_Rate  Online_Store_Rate
0              0.000000           0.000000
1              0.000000           0.000000
2              0.000000           0.000000
3              0.000000           0.200000
4              0.071429           0.000000
…                     …                  …
1598           0.000000           0.000000
1599           0.727273           0.090909
1600           0.000000           0.000000
1601           0.000000           0.894737
1602           0.000000           0.000000

[1603 rows x 7 columns]
```

[50]:
```python
def label_influence(row):
    if row['Spend_Before'] == 0 and row['Spend_After'] > 0:
        return 1
    if row['Spend_After'] > 1.2 * row['Spend_Before']:
        return 1
    return 0

features['Target'] = features.apply(label_influence, axis=1)
features
```

[50]:
```
      Gold_Cust_ID  Spend_Before  Spend_After  Units_Before  Units_After  \
0              213        214.45       243.40           5.0         10.0
1              801         61.98         0.00           2.0          0.0
2             5038        208.22         0.00           4.0          0.0
3            16010        234.97       679.98           3.0          2.0
4            19413       1884.91         0.00           5.0          0.0
…                …             …            …             …            …
1598      35723689        102.96        55.23           4.0          7.0
1599      35766496        142.18       235.35           2.0          8.0
```

```
1600    35947203      8.77      0.00          3.0          0.0
1601    36054508    104.97    124.98          3.0          2.0
1602    36924552    -45.02      0.00          2.0          0.0

      Coupon_Usage_Rate  Online_Store_Rate  Target
0              0.000000           0.000000       0
1              0.000000           0.000000       0
2              0.000000           0.000000       0
3              0.000000           0.200000       1
4              0.071429           0.000000       0
…                     …                  …       …
1598           0.000000           0.000000       0
1599           0.727273           0.090909       1
1600           0.000000           0.000000       0
1601           0.000000           0.894737       0
1602           0.000000           0.000000       1

[1603 rows x 8 columns]
```

0.10 Exploratory Data Analysis on features table

[51]:
```
features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1603 entries, 0 to 1602
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Gold_Cust_ID       1603 non-null   int64
 1   Spend_Before       1603 non-null   float64
 2   Spend_After        1603 non-null   float64
 3   Units_Before       1603 non-null   float64
 4   Units_After        1603 non-null   float64
 5   Coupon_Usage_Rate  1603 non-null   float64
 6   Online_Store_Rate  1603 non-null   float64
 7   Target             1603 non-null   int64
dtypes: float64(6), int64(2)
memory usage: 100.3 KB
```

[52]:
```
features.describe()
```

[52]:
```
       Gold_Cust_ID  Spend_Before   Spend_After  Units_Before  Units_After  \
count  1.603000e+03   1603.000000   1603.000000   1603.000000  1603.000000
mean   1.299954e+07    322.046787    234.440387      6.205552     5.471616
std    1.052069e+07    801.702959    609.684380     14.367773    15.898701
min    2.130000e+02   -399.990000  -1400.000000     -2.000000    -2.000000
25%    2.586444e+06     36.955000      0.000000      1.000000     0.000000
```

```
50%    1.105064e+07    105.930000    37.040000    3.000000    1.000000
75%    2.243449e+07    310.925000   214.725000    6.000000    6.000000
max    3.692455e+07  20482.020000 10569.480000  410.000000  449.000000

       Coupon_Usage_Rate  Online_Store_Rate       Target
count        1603.000000        1603.000000  1603.000000
mean            0.139728           0.101218     0.262009
std             0.269082           0.268180     0.439865
min             0.000000           0.000000     0.000000
25%             0.000000           0.000000     0.000000
50%             0.000000           0.000000     0.000000
75%             0.166667           0.000000     1.000000
max             1.000000           1.000000     1.000000
```

[53]:
```python
features.axes
```

[53]:
```
[RangeIndex(start=0, stop=1603, step=1),
 Index(['Gold_Cust_ID', 'Spend_Before', 'Spend_After', 'Units_Before',
        'Units_After', 'Coupon_Usage_Rate', 'Online_Store_Rate', 'Target'],
       dtype='object')]
```

[54]:
```python
features.nunique()
```

[54]:
```
Gold_Cust_ID         1603
Spend_Before         1234
Spend_After           867
Units_Before           60
Units_After            62
Coupon_Usage_Rate     169
Online_Store_Rate      80
Target                  2
dtype: int64
```

0.11 Data Cleaning on features table

[55]:
```python
features.isnull().sum()
```

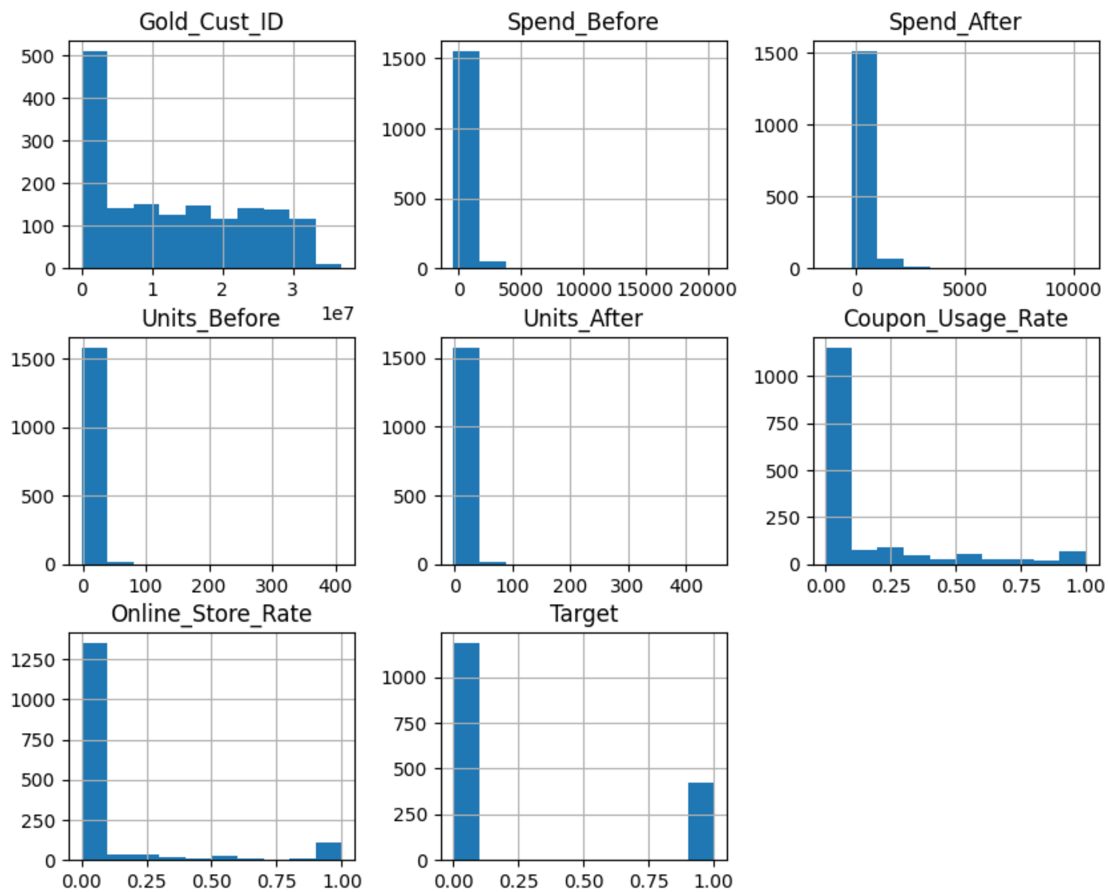
[55]:
```
Gold_Cust_ID         0
Spend_Before         0
Spend_After          0
Units_Before         0
Units_After          0
Coupon_Usage_Rate    0
Online_Store_Rate    0
Target               0
dtype: int64
```

[56]:
```
features.duplicated().sum()
```

[56]:
```
np.int64(0)
```

0.11.1 Data Visualization on feature table

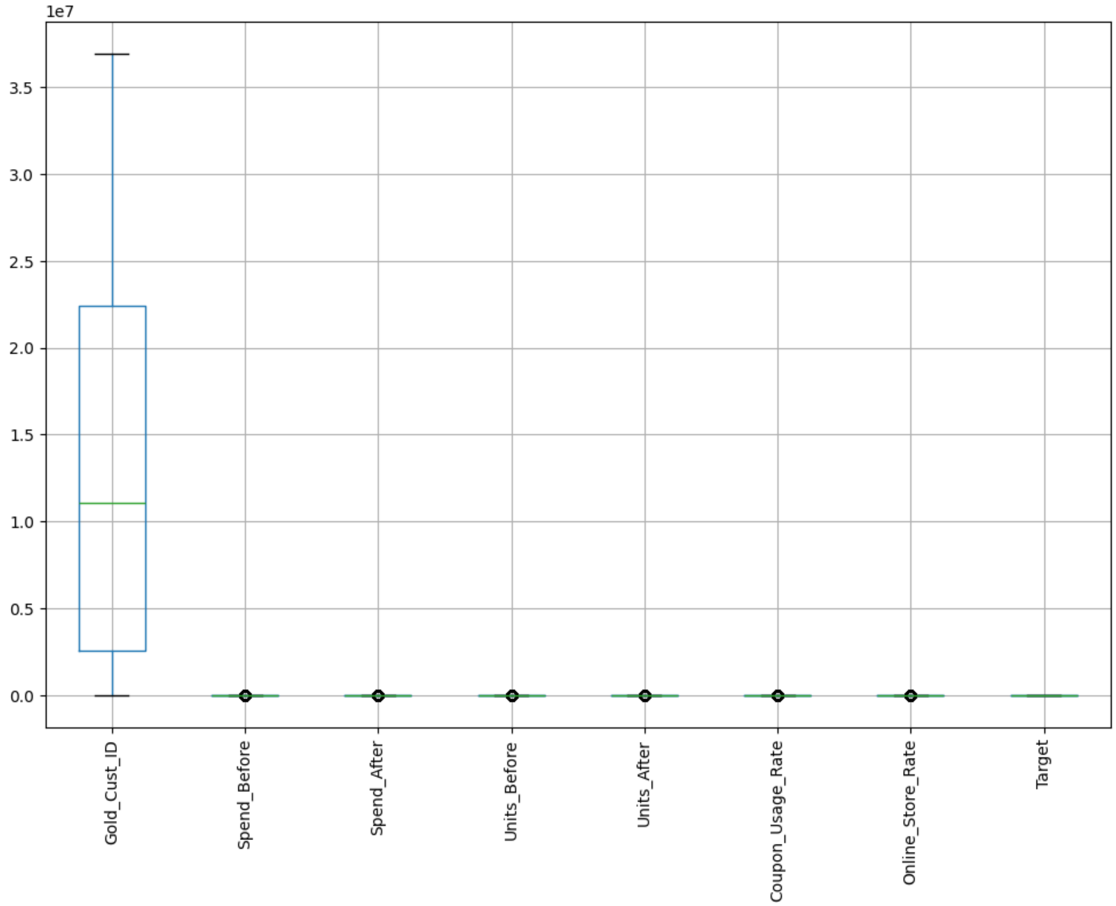
[57]:
```
features.hist(figsize=(10,8))
plt.show()
```



[58]:
```
features.boxplot(figsize=(12,8))
plt.xticks(rotation=90)
```

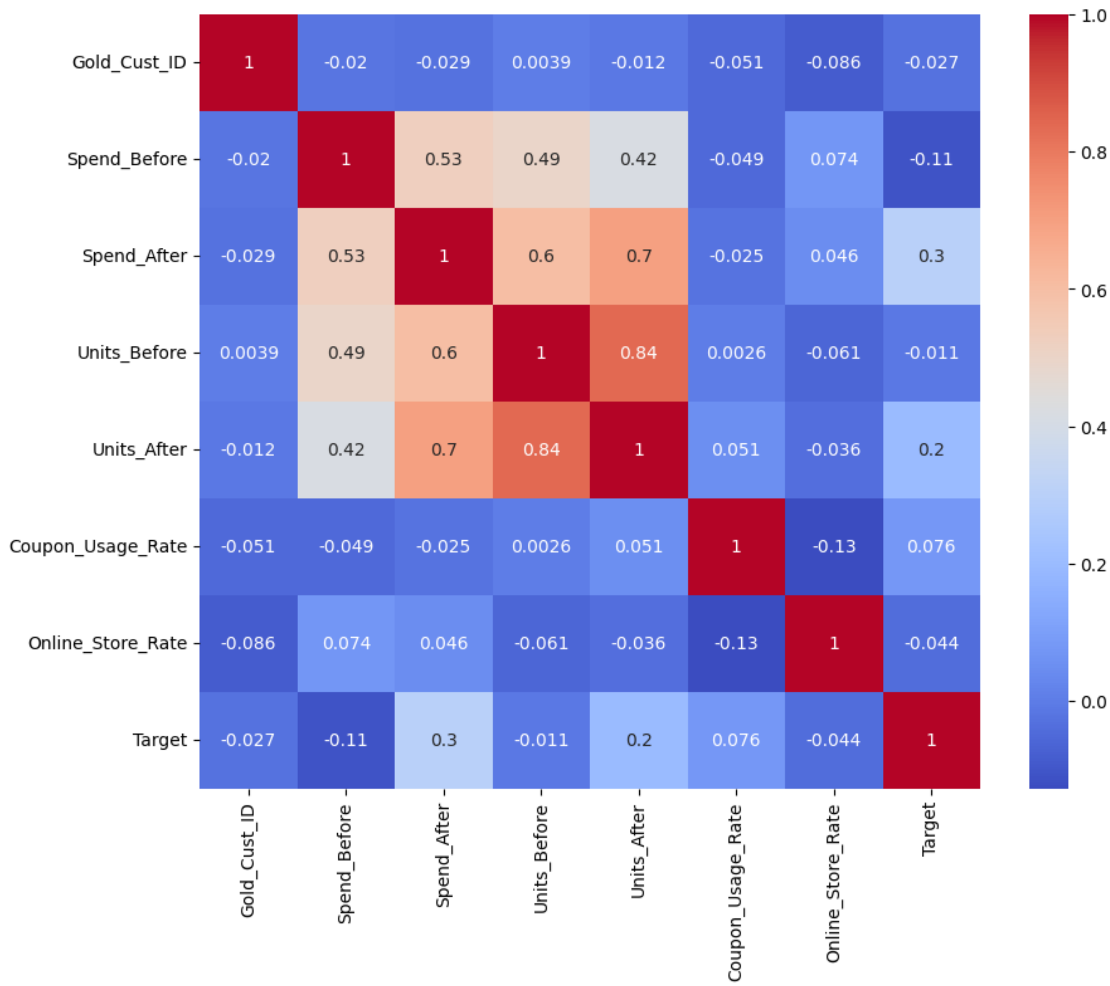
[58]:
```
(array([1, 2, 3, 4, 5, 6, 7, 8]),
 [Text(1, 0, 'Gold_Cust_ID'),
  Text(2, 0, 'Spend_Before'),
  Text(3, 0, 'Spend_After'),
  Text(4, 0, 'Units_Before'),
  Text(5, 0, 'Units_After'),
  Text(6, 0, 'Coupon_Usage_Rate'),
```

```
 Text(7, 0, 'Online_Store_Rate'),
 Text(8, 0, 'Target')])
```

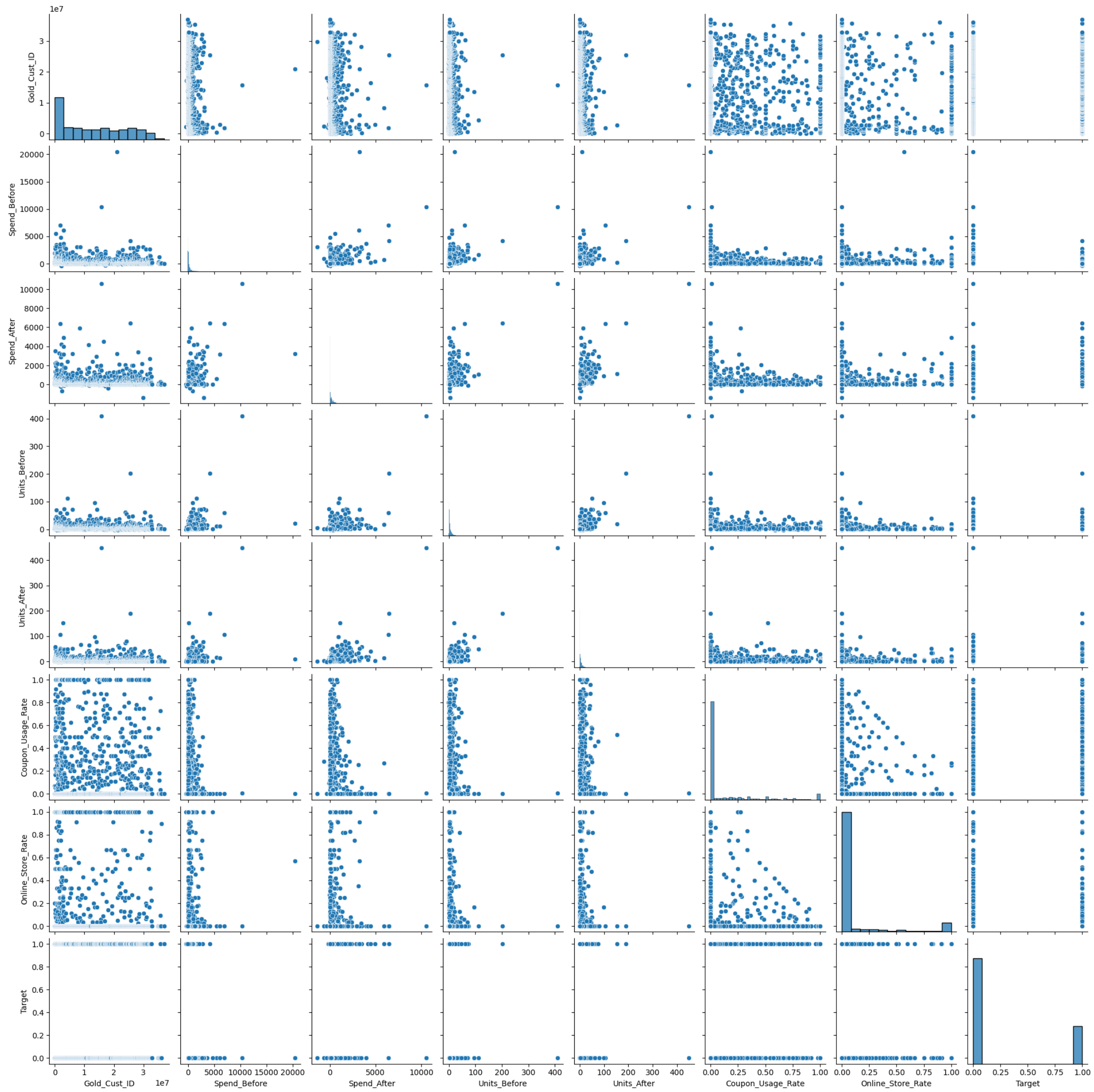


[59]:
```
corr=features.corr()
plt.figure(figsize=(10,8))
sns.heatmap(corr,annot=True,cmap='coolwarm')
```

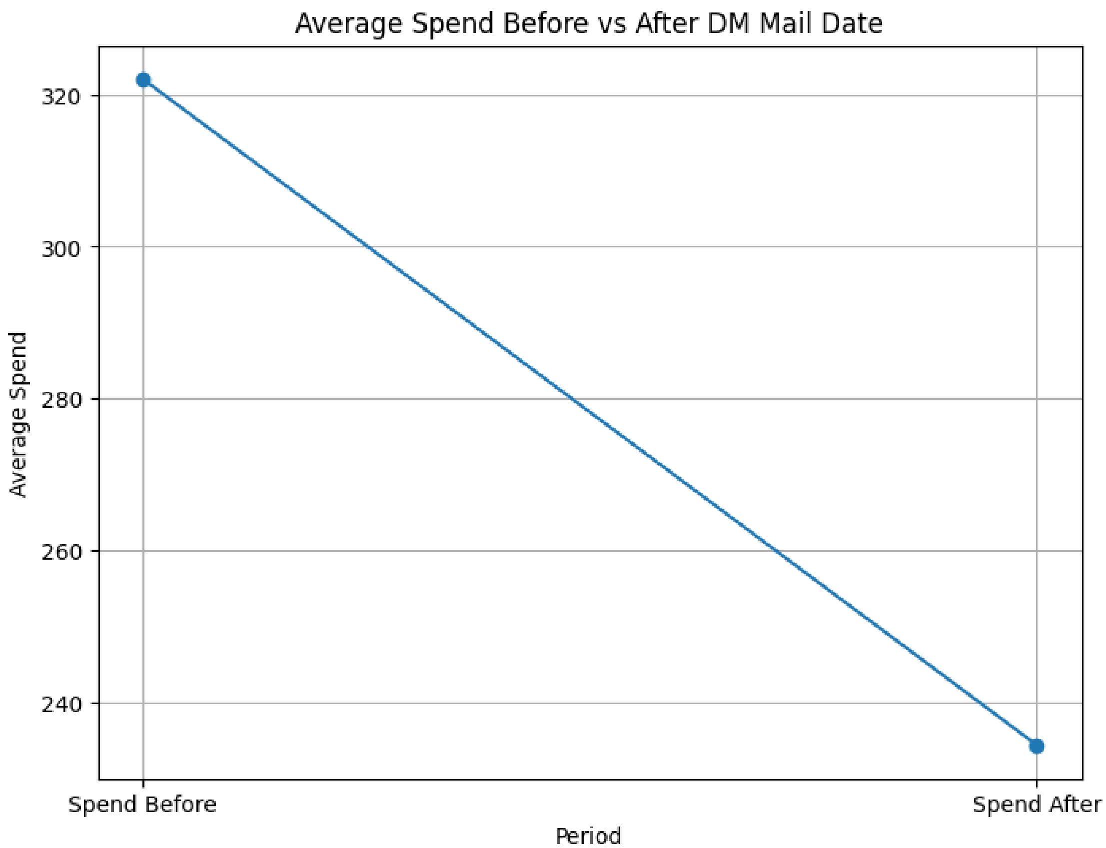
[59]: <Axes: >



[60]:
```
sns.pairplot(features)
plt.show()
```

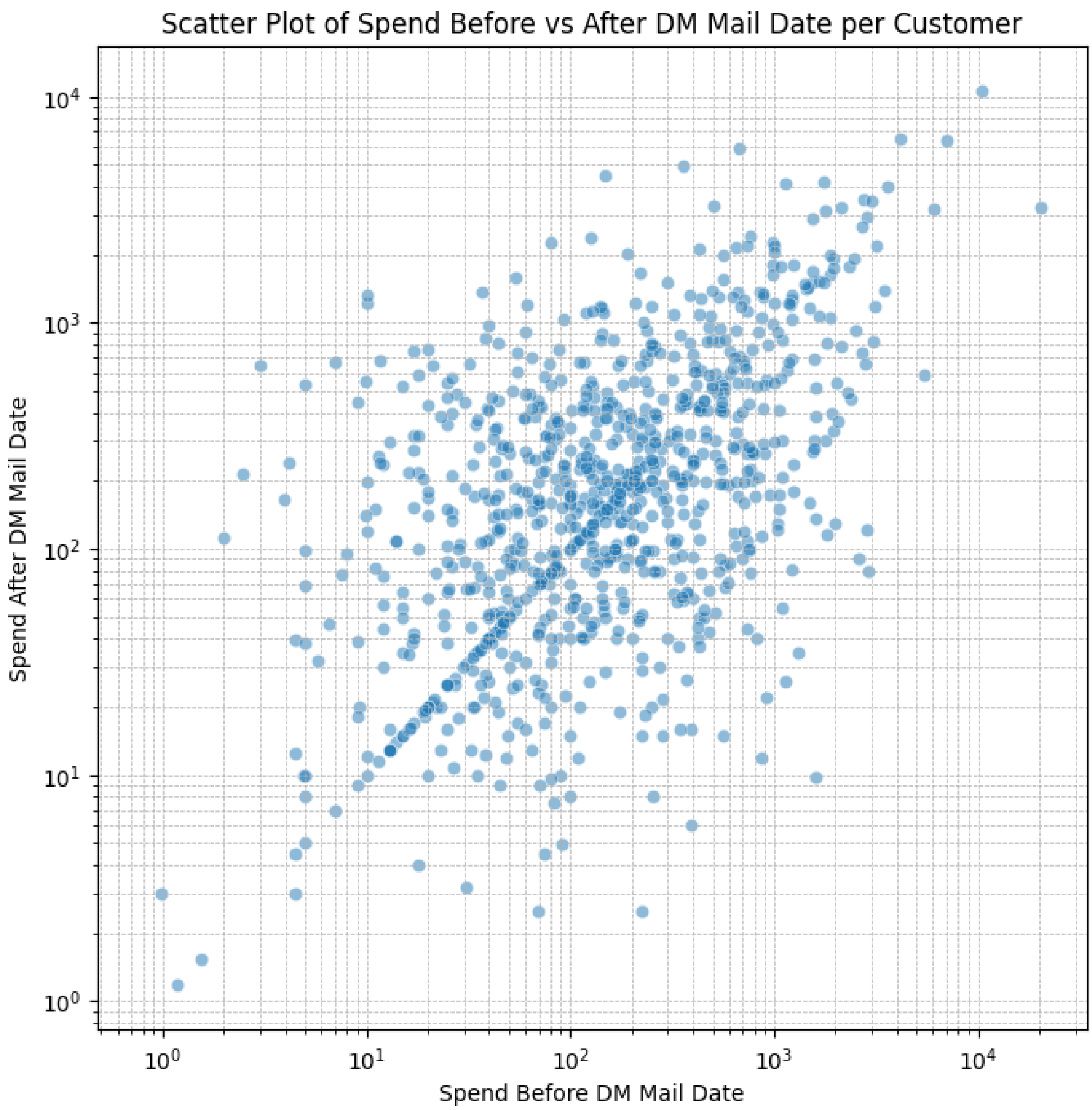


[61]:
```
# A direct line plot between Spend_Before and Spend_After for each customer␣
↪might be messy.
# A better approach might be to compare the average spend in the two periods.
average_spend = features[['Spend_Before', 'Spend_After']].mean()

plt.figure(figsize=(8, 6))
average_spend.plot(kind='line', marker='o')
plt.title('Average Spend Before vs After DM Mail Date')
plt.xlabel('Period')
plt.ylabel('Average Spend')
plt.xticks(ticks=[0, 1], labels=['Spend Before', 'Spend After'])
plt.grid(True)
plt.show()
```



[62]:

```
# Alternatively, we could plot a scatter plot if we want to see the
↪relationship per customer
plt.figure(figsize=(8, 8))
sns.scatterplot(data=features, x='Spend_Before', y='Spend_After', alpha=0.5)
plt.title('Scatter Plot of Spend Before vs After DM Mail Date per Customer')
plt.xlabel('Spend Before DM Mail Date')
plt.ylabel('Spend After DM Mail Date')
plt.xscale('log') # Using log scale can help visualize data with wide range
plt.yscale('log')
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.show()
```



0.12 Model Building on features table

[63]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

X = features.drop(columns=['Gold_Cust_ID', 'Target'])
y = features['Target']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪test_size=0.3, random_state=42)

lr_model = LogisticRegression(random_state=42)
```

```python
lr_model.fit(X_train, y_train)

y_pred_lr = lr_model.predict(X_test)
y_prob_lr = lr_model.predict_proba(X_test)[:, 1]
```

[64]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_auc_score

rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)
y_prob_rf = rf_model.predict_proba(X_test)[:, 1]
```

[65]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, roc_auc_score


dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)

y_pred_dt = dt_model.predict(X_test)
y_prob_dt = dt_model.predict_proba(X_test)[:, 1]
```

[66]:
```python
from sklearn.ensemble import GradientBoostingClassifier

gb_model = GradientBoostingClassifier(random_state=42)
gb_model.fit(X_train, y_train)

y_pred_gb = gb_model.predict(X_test)
y_prob_gb = gb_model.predict_proba(X_test)[:, 1]
```

0.13 Report of Model building wkith classification report

[67]:
```python
from sklearn.metrics import classification_report, roc_auc_score

models = {
    'Logistic Regression': (y_pred_lr, y_prob_lr),
    'Random Forest': (y_pred_rf, y_prob_rf),
    'Decision Tree': (y_pred_dt, y_prob_dt),
    'Gradient Boosting': (y_pred_gb, y_prob_gb)
}

results = {}

for name, (y_pred, y_prob) in models.items():
```

```python
    results[name] = {
        'report': classification_report(y_test, y_pred, output_dict=True),
        'auc': roc_auc_score(y_test, y_prob)
    }

    print(f"===== {name} =====")
    print("Classification Report:")
    print(classification_report(y_test, y_pred))
    print(f"AUC Score: {results[name]['auc']:.4f}\n")
```

```
===== Logistic Regression =====
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       355
           1       0.97      0.99      0.98       126

    accuracy                           0.99       481
   macro avg       0.98      0.99      0.99       481
weighted avg       0.99      0.99      0.99       481

AUC Score: 0.9999

===== Random Forest =====
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.97       355
           1       0.97      0.89      0.93       126

    accuracy                           0.96       481
   macro avg       0.96      0.94      0.95       481
weighted avg       0.96      0.96      0.96       481

AUC Score: 0.9871

===== Decision Tree =====
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.97      0.97       355
           1       0.91      0.92      0.92       126

    accuracy                           0.96       481
   macro avg       0.94      0.94      0.94       481
weighted avg       0.96      0.96      0.96       481
```

```
AUC Score: 0.9448

===== Gradient Boosting =====
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.98      0.97       355
           1       0.94      0.91      0.93       126

    accuracy                           0.96       481
   macro avg       0.96      0.95      0.95       481
weighted avg       0.96      0.96      0.96       481

AUC Score: 0.9916
```

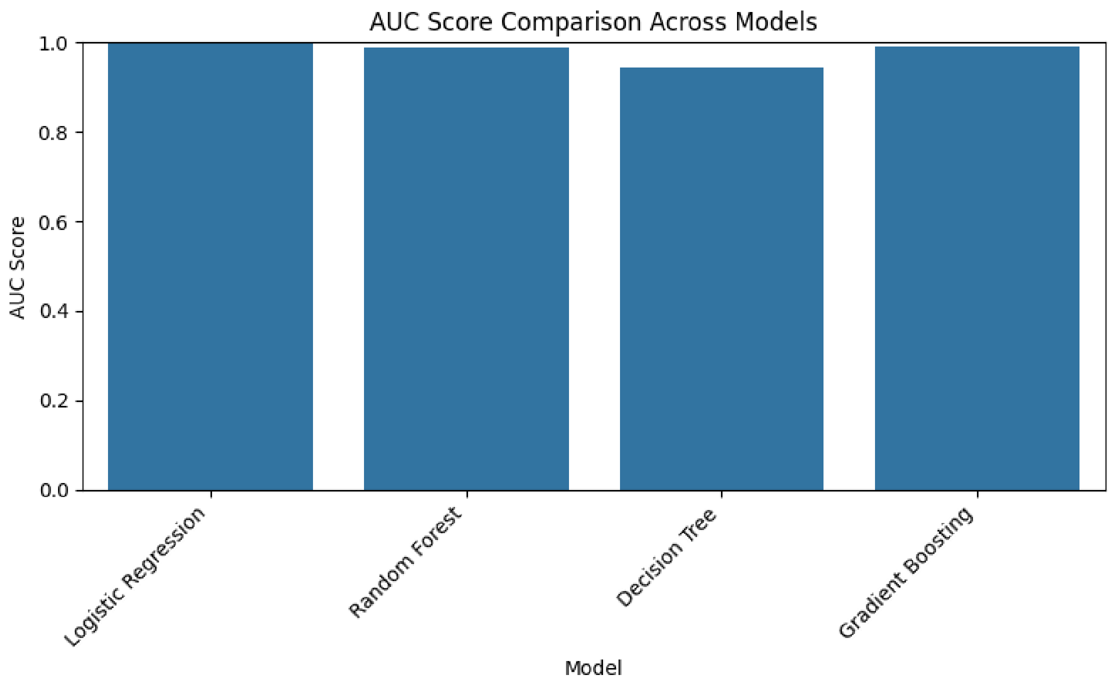
0.14 Model Comparison Summary

[68]:
```python
# Summarize key metrics
summary_data = []
for model_name, model_results in results.items():
    report = model_results['report']
    summary_data.append({
        'Model': model_name,
        'Accuracy': report['accuracy'],
        'Precision (Weighted Avg)': report['weighted avg']['precision'],
        'Recall (Weighted Avg)': report['weighted avg']['recall'],
        'F1-Score (Weighted Avg)': report['weighted avg']['f1-score'],
        'AUC Score': model_results['auc']
    })

summary_df = pd.DataFrame(summary_data)
print("===== Model Comparison Summary =====")
display(summary_df)
```

```
===== Model Comparison Summary =====

                 Model  Accuracy  Precision (Weighted Avg)  \
0  Logistic Regression  0.989605                  0.989781
1        Random Forest  0.962578                  0.962658
2        Decision Tree  0.956341                  0.956462
3    Gradient Boosting  0.962578                  0.962356

   Recall (Weighted Avg)  F1-Score (Weighted Avg)  AUC Score
0               0.989605                 0.989644   0.999866
1               0.962578                 0.962065   0.987112
2               0.956341                 0.956396   0.944825
3               0.962578                 0.962381   0.991639
```

0.15 Visualize AUC scores

[69]:
```
plt.figure(figsize=(8, 5))
sns.barplot(x='Model', y='AUC Score', data=summary_df)
plt.title('AUC Score Comparison Across Models')
plt.ylabel('AUC Score')
plt.ylim(0, 1)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



0.16 Influence_probability with logistics regression

[70]:
```
features['Influence_Probability'] = lr_model.predict_proba(X)[:, 1]
features
```

[70]:

	Gold_Cust_ID	Spend_Before	Spend_After	Units_Before	Units_After	\
0	213	214.45	243.40	5.0	10.0	
1	801	61.98	0.00	2.0	0.0	
2	5038	208.22	0.00	4.0	0.0	
3	16010	234.97	679.98	3.0	2.0	
4	19413	1884.91	0.00	5.0	0.0	
…	…	…	…	…	…	
1598	35723689	102.96	55.23	4.0	7.0	
1599	35766496	142.18	235.35	2.0	8.0	

```
1600      35947203       8.77       0.00          3.0          0.0
1601      36054508     104.97     124.98          3.0          2.0
1602      36924552     -45.02       0.00          2.0          0.0

      Coupon_Usage_Rate  Online_Store_Rate  Target  Influence_Probability
0              0.000000           0.000000       0           6.966567e-07
1              0.000000           0.000000       0           2.166450e-44
2              0.000000           0.000000       0          6.995317e-145
3              0.000000           0.200000       1           1.000000e+00
4              0.071429           0.000000       0           0.000000e+00
…                     …                …     …                      …
1598           0.000000           0.000000       0           5.877527e-39
1599           0.727273           0.090909       1           1.000000e+00
1600           0.000000           0.000000       0           1.146103e-07
1601           0.000000           0.894737       0           1.098346e-01
1602           0.000000           0.000000       1           1.000000e+00

[1603 rows x 9 columns]
```

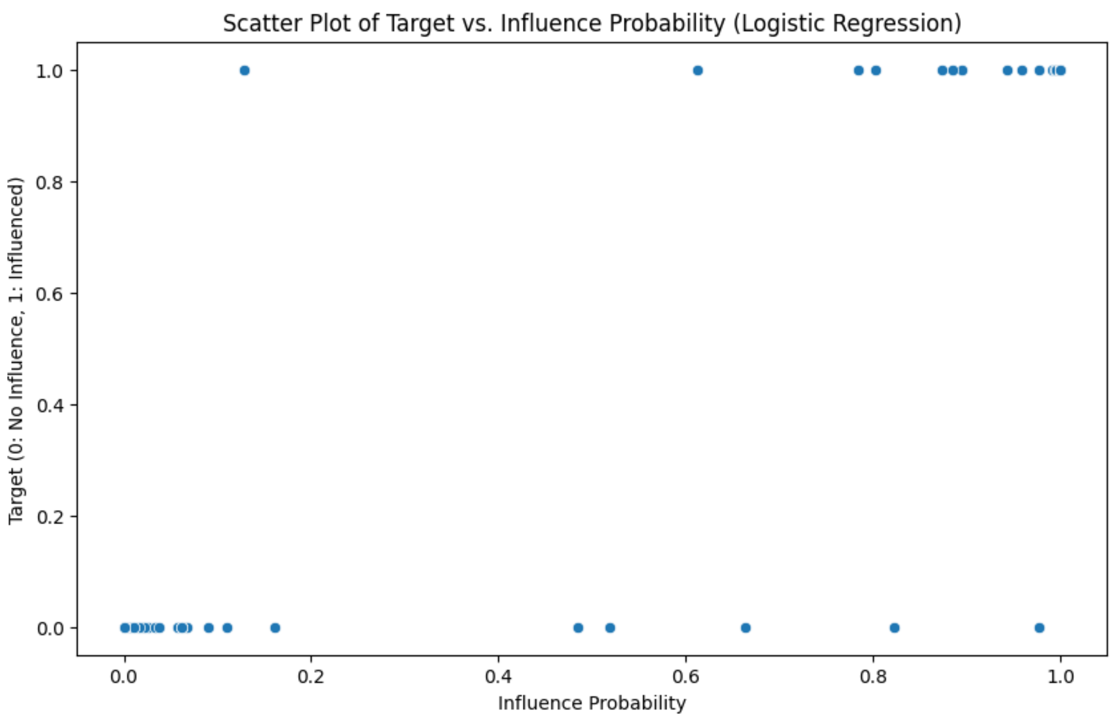
[71]:
```python
pd.options.display.float_format = '{:.6f}'.format
display(features)
```

```
      Gold_Cust_ID  Spend_Before  Spend_After  Units_Before  Units_After  \
0              213    214.450000   243.400000      5.000000    10.000000
1              801     61.980000     0.000000      2.000000     0.000000
2             5038    208.220000     0.000000      4.000000     0.000000
3            16010    234.970000   679.980000      3.000000     2.000000
4            19413   1884.910000     0.000000      5.000000     0.000000
…                …             …           …             …            …
1598      35723689    102.960000    55.230000      4.000000     7.000000
1599      35766496    142.180000   235.350000      2.000000     8.000000
1600      35947203      8.770000     0.000000      3.000000     0.000000
1601      36054508    104.970000   124.980000      3.000000     2.000000
1602      36924552    -45.020000     0.000000      2.000000     0.000000

      Coupon_Usage_Rate  Online_Store_Rate  Target  Influence_Probability
0              0.000000           0.000000       0               0.000001
1              0.000000           0.000000       0               0.000000
2              0.000000           0.000000       0               0.000000
3              0.000000           0.200000       1               1.000000
4              0.071429           0.000000       0               0.000000
…                     …                …     …                      …
1598           0.000000           0.000000       0               0.000000
1599           0.727273           0.090909       1               1.000000
1600           0.000000           0.000000       0               0.000000
1601           0.000000           0.894737       0               0.109835
1602           0.000000           0.000000       1               1.000000
```

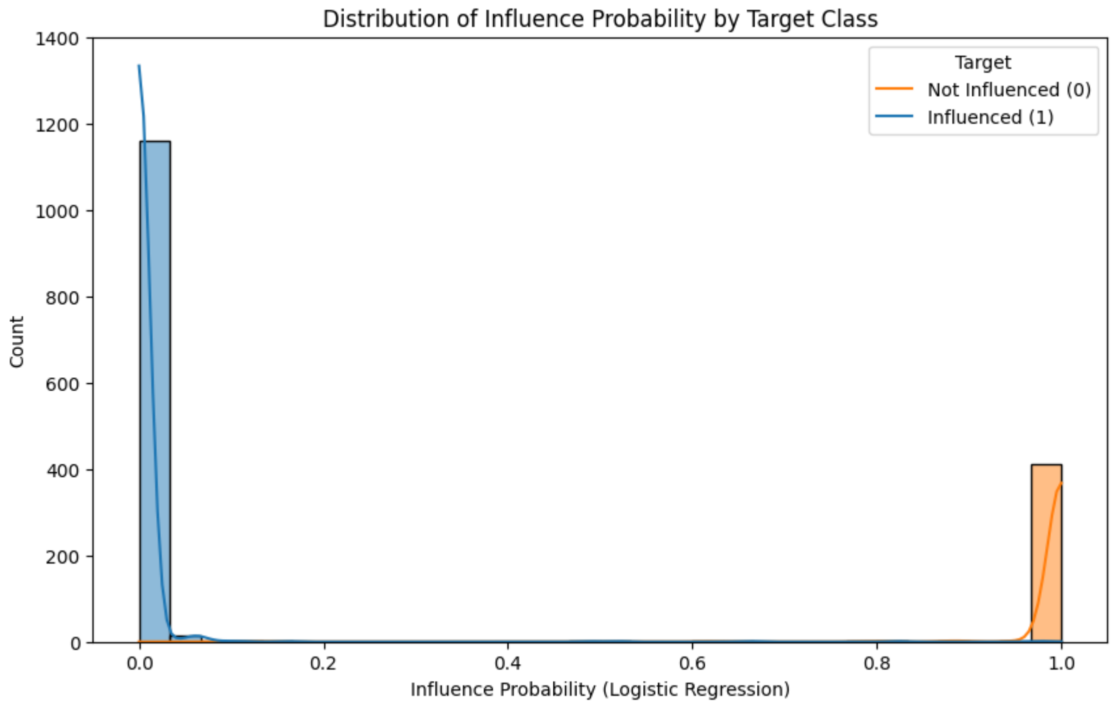
```
[1603 rows x 9 columns]
```

0.16.1 few visualization on results

[72]:
```python
plt.figure(figsize=(10, 6))
sns.scatterplot(data=features, x='Influence_Probability', y='Target')
plt.title('Scatter Plot of Target vs. Influence Probability (Logistic␣
↪Regression)')
plt.xlabel('Influence Probability')
plt.ylabel('Target (0: No Influence, 1: Influenced)')
plt.show()
```



[73]:
```python
# Distribution of Influence Probability by Target Class
plt.figure(figsize=(10, 6))
sns.histplot(data=features, x='Influence_Probability', hue='Target', kde=True,␣
↪bins=30)
plt.title('Distribution of Influence Probability by Target Class')
plt.xlabel('Influence Probability (Logistic Regression)')
plt.ylabel('Count')
plt.legend(title='Target', labels=['Not Influenced (0)', 'Influenced (1)'])
plt.show()
```



0.16.2 Hyperparameter tuning(Random Search cv) with gradient Boosting

[74]:
```python
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform, randint

# Define a parameter distribution for RandomizedSearchCV
param_dist = {
    'n_estimators': randint(100, 300),  # Sample from 100 to 300
    'learning_rate': uniform(0.01, 0.2), # Sample from 0.01 to 0.2
    'max_depth': randint(3, 6), # Sample from 3 to 6
    'min_samples_split': randint(2, 20), # Sample from 2 to 20
    'min_samples_leaf': randint(1, 10) # Sample from 1 to 10
}

random_search = RandomizedSearchCV(estimator=gb_model,␣
 ↪param_distributions=param_dist,
                                   n_iter=50, cv=3, scoring='roc_auc',␣
 ↪n_jobs=-1, verbose=2, random_state=42)


# Fit the randomized search to the training data
random_search.fit(X_train, y_train)

# Get the best parameters and best score
```

```
best_params = random_search.best_params_
best_score = random_search.best_score_

print(f"Best parameters found: {best_params}")
print(f"Best cross-validation AUC score: {best_score:.4f}")

# Evaluate the best model on the test set
best_gb_model = random_search.best_estimator_
y_pred_gb_tuned = best_gb_model.predict(X_test)
y_prob_gb_tuned = best_gb_model.predict_proba(X_test)[:, 1]

print("\n===== Tuned Gradient Boosting (Randomized Search) =====")
print("Classification Report:")
print(classification_report(y_test, y_pred_gb_tuned))
print(f"AUC Score: {roc_auc_score(y_test, y_prob_gb_tuned):.4f}\n")
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits
Best parameters found: {'learning_rate': np.float64(0.029082023298082266),
'max_depth': 5, 'min_samples_leaf': 7, 'min_samples_split': 6, 'n_estimators':
198}
Best cross-validation AUC score: 0.9933

===== Tuned Gradient Boosting (Randomized Search) =====
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.98      0.98       355
           1       0.95      0.92      0.94       126

    accuracy                           0.97       481
   macro avg       0.96      0.95      0.96       481
weighted avg       0.97      0.97      0.97       481

AUC Score: 0.9935
```

0.16.3 Model Comparison Summary (Including Tuned GB)

[75]:
```
import pandas as pd
import matplotlib.pyplot as plt
# Compare the tuned GB model with the original models
summary_data_tuned = summary_data.copy() # Start with the original summary
summary_data_tuned.append({
    'Model': 'Gradient Boosting (Tuned)',
    'Accuracy': classification_report(y_test, y_pred_gb_tuned,␣
 ↪output_dict=True)['accuracy'],
```

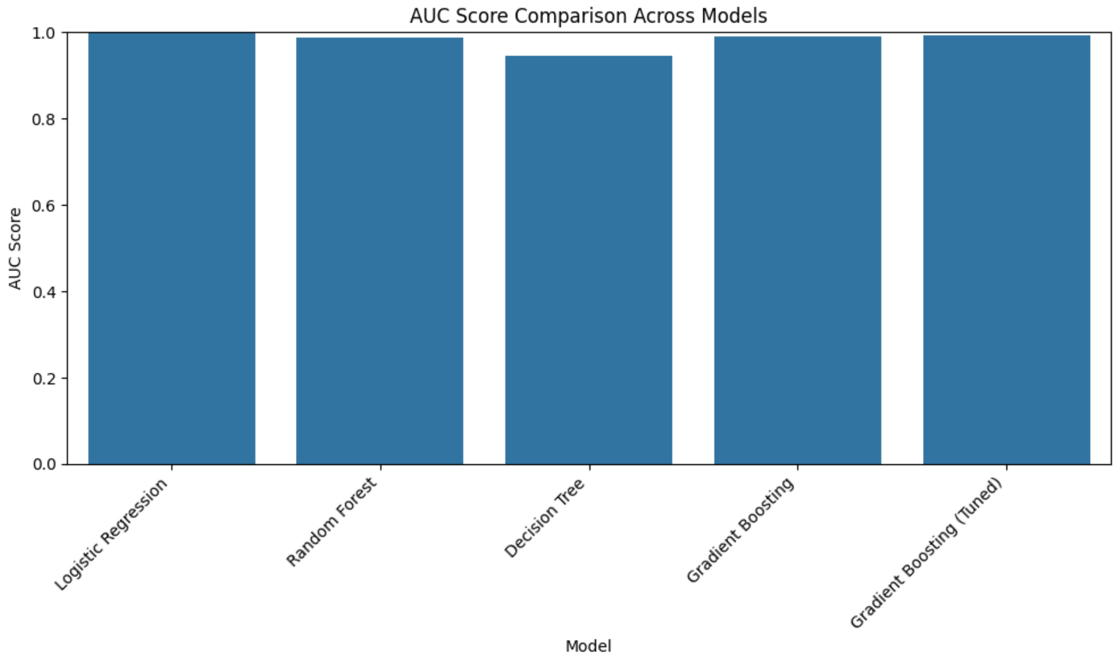
```
    'Precision (Weighted Avg)': classification_report(y_test, y_pred_gb_tuned,␣
↪output_dict=True)['weighted avg']['precision'],
    'Recall (Weighted Avg)': classification_report(y_test, y_pred_gb_tuned,␣
↪output_dict=True)['weighted avg']['recall'],
    'F1-Score (Weighted Avg)': classification_report(y_test, y_pred_gb_tuned,␣
↪output_dict=True)['weighted avg']['f1-score'],
    'AUC Score': roc_auc_score(y_test, y_prob_gb_tuned)
})

summary_df_tuned = pd.DataFrame(summary_data_tuned)
print("===== Model Comparison Summary (Including Tuned GB) =====")
display(summary_df_tuned)
```

```
===== Model Comparison Summary (Including Tuned GB) =====

                      Model  Accuracy  Precision (Weighted Avg)  \
0       Logistic Regression  0.989605                  0.989781
1             Random Forest  0.962578                  0.962658
2             Decision Tree  0.956341                  0.956462
3         Gradient Boosting  0.962578                  0.962356
4  Gradient Boosting (Tuned)  0.966736                  0.966559

   Recall (Weighted Avg)  F1-Score (Weighted Avg)  AUC Score
0               0.989605                 0.989644   0.999866
1               0.962578                 0.962065   0.987112
2               0.956341                 0.956396   0.944825
3               0.962578                 0.962381   0.991639
4               0.966736                 0.966561   0.993472
```

0.16.4 AUC Score Comparison Across Models

[76]:

```
# Visualize AUC scores
plt.figure(figsize=(10, 6))
sns.barplot(x='Model', y='AUC Score', data=summary_df_tuned)
plt.title('AUC Score Comparison Across Models')
plt.ylabel('AUC Score')
plt.ylim(0, 1)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



0.17 Influence_Probability on logistics regression and gradient boost with tuning

[77]:
```
features['Influence_Probability'] = lr_model.predict_proba(X)[:, 1]
features
```

[77]:
```
      Gold_Cust_ID  Spend_Before  Spend_After  Units_Before  Units_After  \
0              213    214.450000   243.400000      5.000000    10.000000
1              801     61.980000     0.000000      2.000000     0.000000
2             5038    208.220000     0.000000      4.000000     0.000000
3            16010    234.970000   679.980000      3.000000     2.000000
4            19413   1884.910000     0.000000      5.000000     0.000000
…              …           …            …            …            …
1598      35723689    102.960000    55.230000      4.000000     7.000000
1599      35766496    142.180000   235.350000      2.000000     8.000000
1600      35947203      8.770000     0.000000      3.000000     0.000000
1601      36054508    104.970000   124.980000      3.000000     2.000000
1602      36924552    -45.020000     0.000000      2.000000     0.000000

      Coupon_Usage_Rate  Online_Store_Rate  Target  Influence_Probability
0              0.000000           0.000000       0               0.000001
1              0.000000           0.000000       0               0.000000
2              0.000000           0.000000       0               0.000000
3              0.000000           0.200000       1               1.000000
4              0.071429           0.000000       0               0.000000
```

```
…                   …                    …       …                    …
1598         0.000000             0.000000       0                 0.000000
1599         0.727273             0.090909       1                 1.000000
1600         0.000000             0.000000       0                 0.000000
1601         0.000000             0.894737       0                 0.109835
1602         0.000000             0.000000       1                 1.000000

[1603 rows x 9 columns]
```

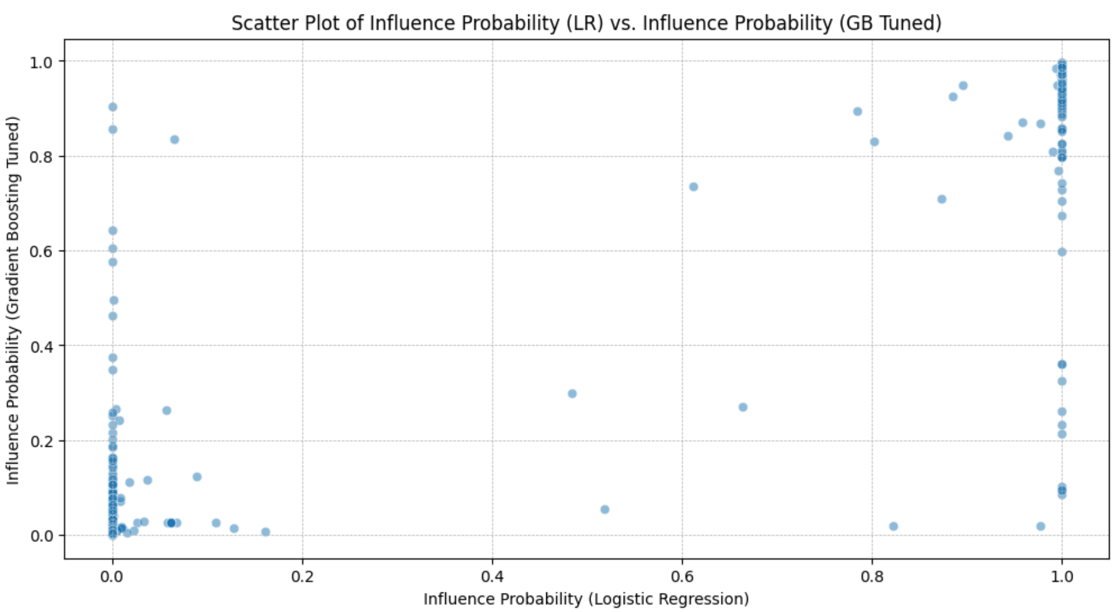
[78]:
```
features['Influence_Probability_GB_Tuned'] = best_gb_model.predict_proba(X)[:,
 ↪1]
display(features)
```

```
      Gold_Cust_ID  Spend_Before  Spend_After  Units_Before  Units_After  \
0              213    214.450000   243.400000      5.000000    10.000000
1              801     61.980000     0.000000      2.000000     0.000000
2             5038    208.220000     0.000000      4.000000     0.000000
3            16010    234.970000   679.980000      3.000000     2.000000
4            19413   1884.910000     0.000000      5.000000     0.000000
…              …             …           …             …           …
1598      35723689    102.960000    55.230000      4.000000     7.000000
1599      35766496    142.180000   235.350000      2.000000     8.000000
1600      35947203      8.770000     0.000000      3.000000     0.000000
1601      36054508    104.970000   124.980000      3.000000     2.000000
1602      36924552    -45.020000     0.000000      2.000000     0.000000

      Coupon_Usage_Rate  Online_Store_Rate  Target  Influence_Probability  \
0              0.000000           0.000000       0               0.000001
1              0.000000           0.000000       0               0.000000
2              0.000000           0.000000       0               0.000000
3              0.000000           0.200000       1               1.000000
4              0.071429           0.000000       0               0.000000
…                   …                …       …                    …
1598           0.000000           0.000000       0               0.000000
1599           0.727273           0.090909       1               1.000000
1600           0.000000           0.000000       0               0.000000
1601           0.000000           0.894737       0               0.109835
1602           0.000000           0.000000       1               1.000000

      Influence_Probability_GB_Tuned
0                           0.093891
1                           0.002597
2                           0.001972
3                           0.983393
4                           0.001048
…                                …
1598                        0.013048
```

```
1599                        0.972016
1600                        0.004198
1601                        0.026533
1602                        0.986110

[1603 rows x 10 columns]
```

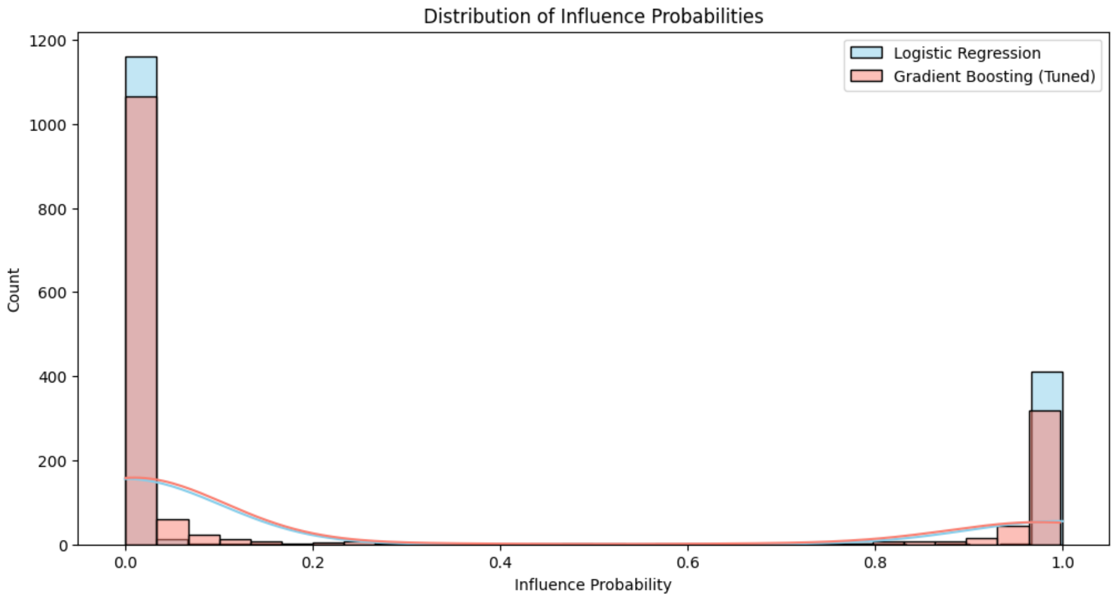
0.18 few more visualization on Influence_Probability

[79]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(12, 6))
sns.scatterplot(data=features, x='Influence_Probability',␣
 ↪y='Influence_Probability_GB_Tuned', alpha=0.5)
plt.title('Scatter Plot of Influence Probability (LR) vs. Influence Probability␣
 ↪(GB Tuned)')
plt.xlabel('Influence Probability (Logistic Regression)')
plt.ylabel('Influence Probability (Gradient Boosting Tuned)')
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.show()
```

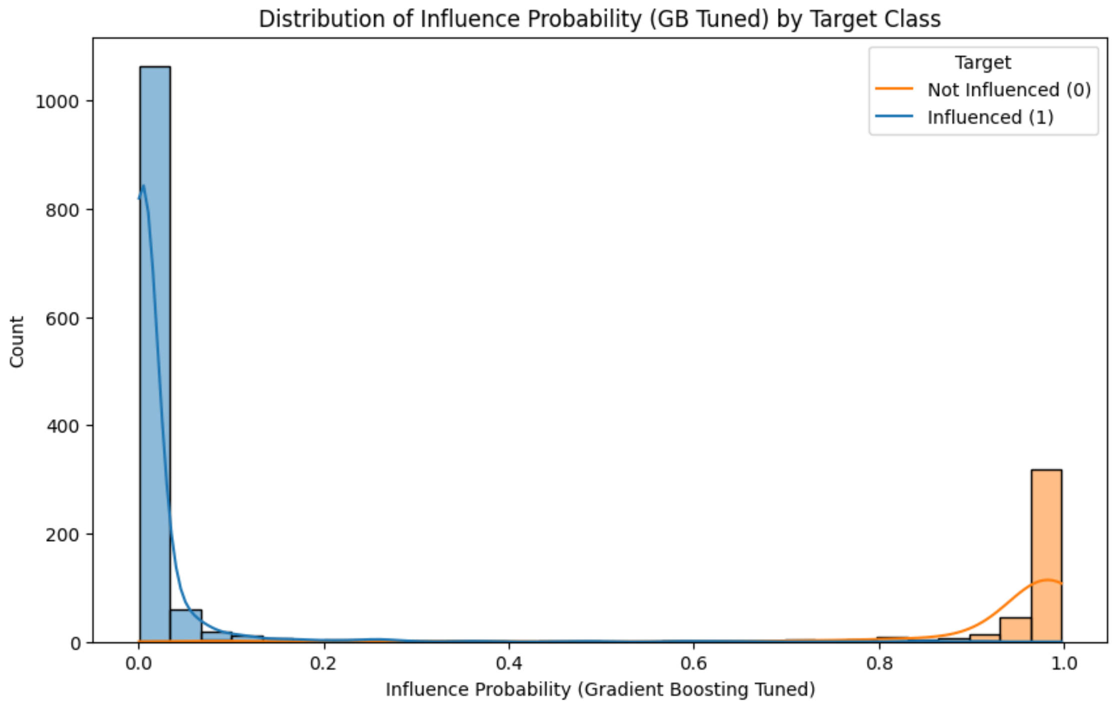


[80]:
```
# Distribution of both influence probabilities
plt.figure(figsize=(12, 6))
sns.histplot(data=features, x='Influence_Probability', label='Logistic␣
 ↪Regression', kde=True, bins=30, color='skyblue')
sns.histplot(data=features, x='Influence_Probability_GB_Tuned', label='Gradient␣
 ↪Boosting (Tuned)', kde=True, bins=30, color='salmon')
plt.title('Distribution of Influence Probabilities')
```

```
plt.xlabel('Influence Probability')
plt.ylabel('Count')
plt.legend()
plt.show()
```




```
[81]: # Distribution of Influence Probability (GB Tuned) by Target Class
plt.figure(figsize=(10, 6))
sns.histplot(data=features, x='Influence_Probability_GB_Tuned', hue='Target',␣
↪kde=True, bins=30)
plt.title('Distribution of Influence Probability (GB Tuned) by Target Class')
plt.xlabel('Influence Probability (Gradient Boosting Tuned)')
plt.ylabel('Count')
plt.legend(title='Target', labels=['Not Influenced (0)', 'Influenced (1)'])
plt.show()
```

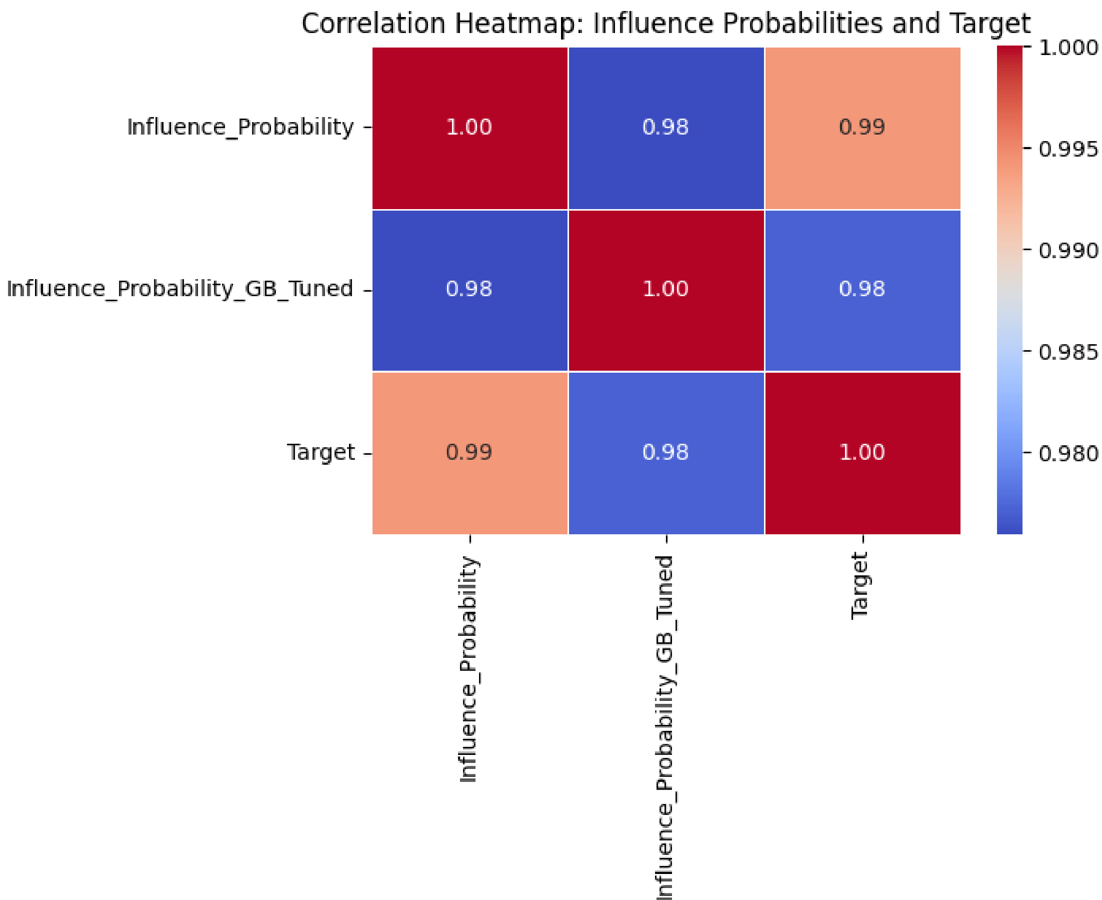


0.18.1 Compare correlations of the two probabilities with the target

[82]:
```
print("Correlation of Influence Probability (LR) with Target:",␣
↪features['Influence_Probability'].corr(features['Target']))
print("Correlation of Influence Probability (GB Tuned) with Target:",␣
↪features['Influence_Probability_GB_Tuned'].corr(features['Target']))
```

```
Correlation of Influence Probability (LR) with Target: 0.993999256156432
Correlation of Influence Probability (GB Tuned) with Target: 0.9770610384972637
```

[83]:
```
# Visualize the correlations using a heatmap for selected columns
correlation_matrix = features[['Influence_Probability',␣
↪'Influence_Probability_GB_Tuned', 'Target']].corr()

plt.figure(figsize=(6, 4))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
↪linewidths=.5)
plt.title('Correlation Heatmap: Influence Probabilities and Target')
plt.show()
```


Correlation Heatmap: Influence Probabilities and Target
Influence_Probability
Influence_Probability_GB_Tuned
Target
1.00
0.98
0.99
0.98
1.00
0.98
0.99
0.98
1.00
1.000
0.995
0.990
0.985
0.980