In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind,f_oneway,kruskal
import warnings
warnings.filterwarnings("ignore")
```

Importing files

In [2]:
```python
customer=pd.read_csv("Customers.csv")
dc=pd.read_csv("Discount_Coupon.csv")
ms=pd.read_csv("Marketing_Spend.csv")
os=pd.read_csv("Online_Sales.csv")
ta=pd.read_csv("Tax_amount.csv")
```

In [3]:
```python
os.head()
```

Out[3]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coup
0	17850	16679	1/1/2019	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16680	1/1/2019	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16681	1/1/2019	GGOEGFKQ020399	Google Laptop and Cell Phone Stickers	Office	1	2.05	6.5	
3	17850	16682	1/1/2019	GGOEGAAB010516	Google Men's 100% Cotton Short Sleeve Hero Tee...	Apparel	5	17.53	6.5	
4	17850	16682	1/1/2019	GGOEGBJL013999	Google Canvas Tote Natural/Navy	Bags	1	16.50	6.5	

In [4]:
```
customer.head()
```

Out[4]:

	CustomerID	Gender	Location	Tenure_Months
0	17850	M	Chicago	12
1	13047	M	California	43
2	12583	M	Chicago	33
3	13748	F	California	30
4	15100	M	California	49

In [5]:
```
dc.head()
```

Out[5]:

	Month	Product_Category	Coupon_Code	Discount_pct
0	Jan	Apparel	SALE10	10
1	Feb	Apparel	SALE20	20
2	Mar	Apparel	SALE30	30
3	Jan	Nest-USA	ELEC10	10
4	Feb	Nest-USA	ELEC20	20

In [6]:
```
ms.head()
```

Out[6]:

	Date	Offline_Spend	Online_Spend
0	1/1/2019	4500	2424.50
1	1/2/2019	4500	3480.36
2	1/3/2019	4500	1576.38
3	1/4/2019	4500	2928.55
4	1/5/2019	4500	4055.30

In [7]:
```
ta.head()
```

Out[7]:

	Product_Category	GST
0	Nest-USA	10%
1	Office	10%
2	Apparel	18%
3	Bags	18%
4	Drinkware	18%

Basic operation on data set

In [8]:

```
os['Transaction_Date'] = pd.to_datetime(os['Transaction_Date'])
os['Month']=os['Transaction_Date'].dt.strftime('%b')
os.head()
```

Out[8]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coup
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Google Laptop and Cell Phone Stickers	Office	1	2.05	6.5	
3	17850	16682	2019-01-01	GGOEGAAB010516	Google Men's 100% Cotton Short Sleeve Hero Tee...	Apparel	5	17.53	6.5	
4	17850	16682	2019-01-01	GGOEGBJL013999	Google Canvas Tote Natural/Navy	Bags	1	16.50	6.5	

In [9]:

```
new=pd.merge(os,dc,on=['Month','Product_Category'],how='left')
new.head()
```

Out[9]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coup
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Google Laptop and Cell Phone Stickers	Office	1	2.05	6.5	
3	17850	16682	2019-01-01	GGOEGAAB010516	Google Men's 100% Cotton Short Sleeve Hero Tee...	Apparel	5	17.53	6.5	
4	17850	16682	2019-01-01	GGOEGBJL013999	Google Canvas Tote Natural/Navy	Bags	1	16.50	6.5	

In [10]:

```
merge_df=pd.merge(new,ta, on = 'Product_Category', how = 'left')
merge_df.head()
```

Out[10]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coup
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Google Laptop and Cell Phone Stickers	Office	1	2.05	6.5	
3	17850	16682	2019-01-01	GGOEGAAB010516	Google Men's 100% Cotton Short Sleeve Hero Tee...	Apparel	5	17.53	6.5	
4	17850	16682	2019-01-01	GGOEGBJL013999	Google Canvas Tote Natural/Navy	Bags	1	16.50	6.5	

In [11]:

```
merge_df['GST'] = merge_df['GST'].str.rstrip('%').astype(float)
merge_df.head()
```

Out[11]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coup
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Google Laptop and Cell Phone Stickers	Office	1	2.05	6.5	
3	17850	16682	2019-01-01	GGOEGAAB010516	Google Men's 100% Cotton Short Sleeve Hero Tee...	Apparel	5	17.53	6.5	
4	17850	16682	2019-01-01	GGOEGBJL013999	Google Canvas Tote Natural/Navy	Bags	1	16.50	6.5	

In [14]:

```
final=pd.merge(merge_df,customer,on=['CustomerID'],how='left')
final.head()
```

Out[14]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coup
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Google Laptop and Cell Phone Stickers	Office	1	2.05	6.5	
3	17850	16682	2019-01-01	GGOEGAAB010516	Google Men's 100% Cotton Short Sleeve Hero Tee...	Apparel	5	17.53	6.5	
4	17850	16682	2019-01-01	GGOEGBJL013999	Google Canvas Tote Natural/Navy	Bags	1	16.50	6.5	

In [15]:
```
final.drop(columns='Product_Description',inplace=True)
```

In [16]:
```
final.head()
exp=final.copy() # fro calculation
```

Numerical Analysis

In [17]:
```
final.shape
```

Out[17]:
```
(52924, 16)
```

In [18]:
```
final.ndim
```

Out[18]:
```
2
```

In [19]:
```
final.size
```

Out[19]:
```
846784
```

In [20]:
```
final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 52924 entries, 0 to 52923
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype         
---  ------            --------------  -----         
 0   CustomerID        52924 non-null  int64         
 1   Transaction_ID    52924 non-null  int64         
 2   Transaction_Date  52924 non-null  datetime64[ns]
 3   Product_SKU       52924 non-null  object        
 4   Product_Category  52924 non-null  object        
 5   Quantity          52924 non-null  int64         
 6   Avg_Price         52924 non-null  float64       
 7   Delivery_Charges  52924 non-null  float64       
 8   Coupon_Status     52924 non-null  object        
 9   Month             52924 non-null  object        
 10  Coupon_Code       52524 non-null  object        
 11  Discount_pct      52524 non-null  float64       
 12  GST               52924 non-null  float64       
 13  Gender            52924 non-null  object        
 14  Location          52924 non-null  object        
 15  Tenure_Months     52924 non-null  int64         
dtypes: datetime64[ns](1), float64(4), int64(4), object(7)
memory usage: 6.5+ MB
```

Handling NULL

In [21]:
```
final.isnull().sum()
```

Out[21]:
```
CustomerID             0
Transaction_ID         0
Transaction_Date       0
Product_SKU            0
Product_Category       0
Quantity               0
Avg_Price              0
Delivery_Charges       0
Coupon_Status          0
Month                  0
Coupon_Code          400
Discount_pct         400
GST                    0
Gender                 0
Location               0
Tenure_Months          0
dtype: int64
```

In [22]:
```
final['Coupon_Code'].fillna('NA',inplace=True)
final['Discount_pct'].fillna(0,inplace=True)
```

In [23]:
```
final['Invoice Value'] = ((final['Quantity'] * final['Avg_Price']) * (1 - final['Discount_pct']/100) * (1 + final['GST']/100)) +
final['Invoice Value']=np.round(final['Invoice Value'],2)
final.head()
```

Out[23]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

In [24]:
```
final.isnull().sum()
```

Out[24]:
```
CustomerID          0
Transaction_ID      0
Transaction_Date    0
Product_SKU         0
Product_Category    0
Quantity            0
Avg_Price           0
Delivery_Charges    0
Coupon_Status       0
Month               0
Coupon_Code         0
Discount_pct        0
GST                 0
Gender              0
Location            0
Tenure_Months       0
Invoice Value       0
dtype: int64
```

In [25]:
```
final.duplicated().value_counts()
```

Out[25]:
```
False    52924
Name: count, dtype: int64
```

In [26]:
```
final.describe()
```

Out[26]:

	CustomerID	Transaction_ID	Transaction_Date	Quantity	Avg_Price	Delivery_Charges	Discount_pct	GST	Tenure_Months	
count	52924.00000	52924.000000	52924	52924.000000	52924.000000	52924.000000	52924.000000	52924.000000	52924.000000	52924.
mean	15346.70981	32409.825675	2019-07-05 19:16:09.450532864	4.497638	52.237646	10.517630	19.802358	13.746183	26.127995	89.
min	12346.00000	16679.000000	2019-01-01 00:00:00	1.000000	0.390000	0.000000	0.000000	5.000000	2.000000	4.
25%	13869.00000	25384.000000	2019-04-12 00:00:00	1.000000	5.700000	6.000000	10.000000	10.000000	15.000000	18.
50%	15311.00000	32625.500000	2019-07-13 00:00:00	1.000000	16.990000	6.000000	20.000000	18.000000	27.000000	40.
75%	16996.25000	39126.250000	2019-09-27 00:00:00	2.000000	102.130000	6.500000	30.000000	18.000000	37.000000	123.
max	18283.00000	48497.000000	2019-12-31 00:00:00	900.000000	355.740000	521.360000	30.000000	18.000000	50.000000	8979.
std	1766.55602	8648.668977	NaN	20.104711	64.006882	19.475613	8.278878	4.582478	13.478285	152.

- There is no Duplicate

Non Graphical Analysis

In [27]:

```
final.head()
```

Out[27]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

In [28]:

```
value_count=["Product_Category","Quantity","Coupon_Status","Month","Coupon_Code",
             "Discount_pct","Gender","Location"]
for col in value_count:
    print("Value counts for column", col)
    print(round(final[col].value_counts(normalize=True)*100,2))
    print()
    print()
```

```
Value counts for column Product_Category
Product_Category
Apparel                 34.25
Nest-USA                26.48
Office                  12.31
Drinkware                6.58
Lifestyle                5.84
Nest                     4.15
Bags                     3.56
Headgear                 1.46
Notebooks & Journals     1.42
Waze                     1.05
Nest-Canada              0.60
Bottles                  0.51
Accessories              0.44
Fun                      0.30
Gift Cards               0.30
Housewares               0.23
Google                   0.20
Backpacks                0.17
More Bags                0.09
Android                  0.08
Name: proportion, dtype: float64


Value counts for column Quantity
Quantity
1      66.77
2      13.26
3       4.32
5       3.28
4       2.34
       ...
176     0.00
78      0.00
220     0.00
146     0.00
209     0.00
Name: proportion, Length: 151, dtype: float64


Value counts for column Coupon_Status
Coupon_Status
Clicked     50.88
```

```
Used        33.83
Not Used    15.29
Name: proportion, dtype: float64


Value counts for column Month
Month
Aug    11.62
Jul     9.92
May     8.64
Dec     8.51
Mar     8.21
Sep     8.10
Jun     7.92
Oct     7.87
Apr     7.84
Jan     7.68
Nov     7.48
Feb     6.21
Name: proportion, dtype: float64


Value counts for column Coupon_Code
Coupon_Code
SALE20     12.04
SALE30     11.18
SALE10     11.03
ELEC10      9.12
ELEC30      8.78
ELEC20      8.58
EXTRA10     4.38
OFF10       4.25
EXTRA20     4.18
OFF20       4.16
OFF30       3.89
EXTRA30     3.87
NE30        1.90
NE20        1.40
AIO10       1.24
AIO20       1.17
AIO30       1.15
NE10        0.86
NA          0.76
NJ20        0.56
```

```
NJ10        0.53
HGEAR20     0.50
HGEAR10     0.50
HGEAR30     0.45
WEMP20      0.39
WEMP30      0.35
NJ30        0.32
WEMP10      0.31
NCA10       0.22
NCA30       0.21
BT10        0.19
ACC20       0.18
NCA20       0.17
GC10        0.17
BT30        0.16
BT20        0.16
ACC30       0.15
ACC10       0.11
HOU20       0.09
HOU10       0.08
GC20        0.08
HOU30       0.06
GC30        0.05
AND30       0.03
AND10       0.03
AND20       0.02
Name: proportion, dtype: float64


Value counts for column Discount_pct
Discount_pct
20.0    33.69
10.0    33.01
30.0    32.54
0.0      0.76
Name: proportion, dtype: float64


Value counts for column Gender
Gender
F    62.37
M    37.63
Name: proportion, dtype: float64
```

```
Value counts for column Location
Location
Chicago          34.73
California       30.49
New York         21.11
New Jersey        8.51
Washington DC     5.16
Name: proportion, dtype: float64
```

- Among the categories, Apparel (34%) and Nest-USA (24%) contributed to the most sales.
- A majority (66%) of customers preferred one particular quantity.
- Coupon usage was recorded at 34%.
- August saw the highest sales compared to other months.
- The most popular coupon was 'sale20' used at 33.69%.
- Females made up a larger portion of the customers than males.
- Chicago and California had the most sales compared to other locations.

For marketing spend

In [29]:
```
ms.head()
```

Out[29]:

	Date	Offline_Spend	Online_Spend
0	1/1/2019	4500	2424.50
1	1/2/2019	4500	3480.36
2	1/3/2019	4500	1576.38
3	1/4/2019	4500	2928.55
4	1/5/2019	4500	4055.30

In [30]:
```
ms.shape
```

Out[30]: (365, 3)

In [31]:
```
ms.ndim
```

Out[31]: 2

In [32]:
```
ms.size
```

Out[32]: 1095

In [33]:
```
ms.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365 entries, 0 to 364
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Date           365 non-null    object 
 1   Offline_Spend  365 non-null    int64  
 2   Online_Spend   365 non-null    float64
dtypes: float64(1), int64(1), object(1)
memory usage: 8.7+ KB
```

In [34]:
```
ms.describe()
```

Out[34]:

	Offline_Spend	Online_Spend
count	365.000000	365.000000
mean	2843.561644	1905.880740
std	952.292448	808.856853
min	500.000000	320.250000
25%	2500.000000	1258.600000
50%	3000.000000	1881.940000
75%	3500.000000	2435.120000
max	5000.000000	4556.930000

- Average offilne spend is 2843 and Average oline spend is 1905

In [35]:
```
ms.isnull().sum()
```

Out[35]:
```
Date              0
Offline_Spend     0
Online_Spend      0
dtype: int64
```

- There is no null

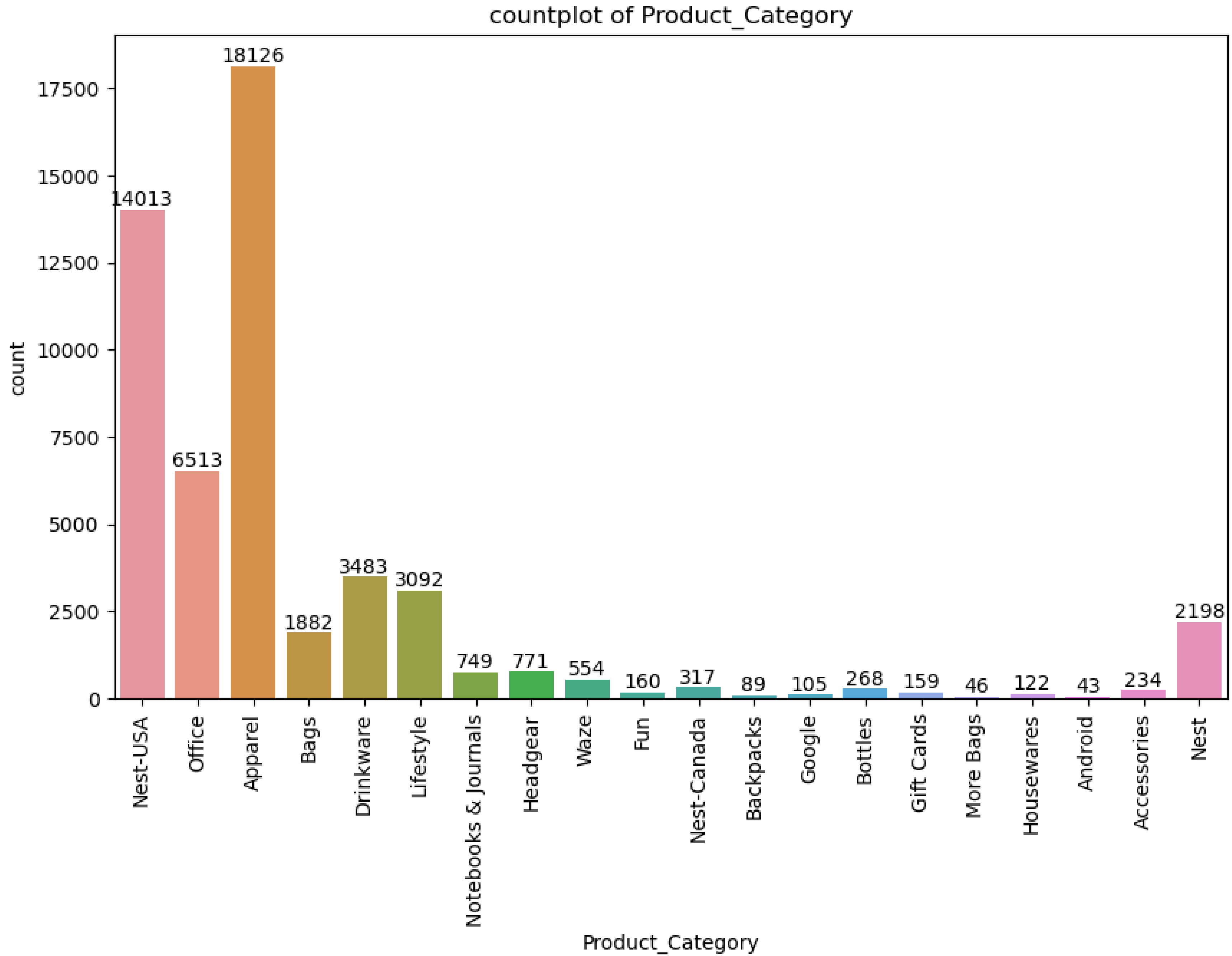
In [36]:
```
ms.duplicated().sum()
```

Out[36]:
```
0
```

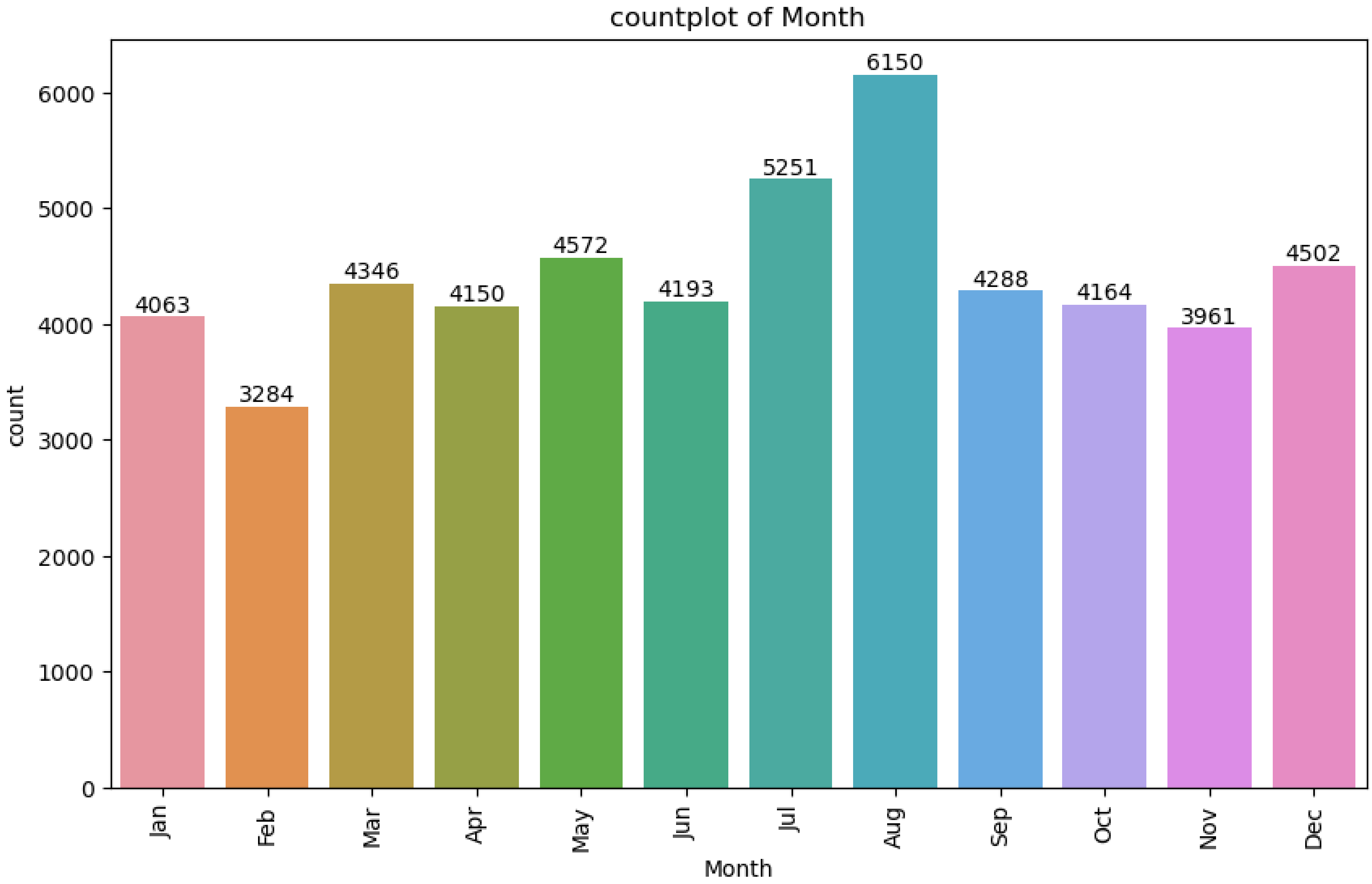
Ther is no duplicate

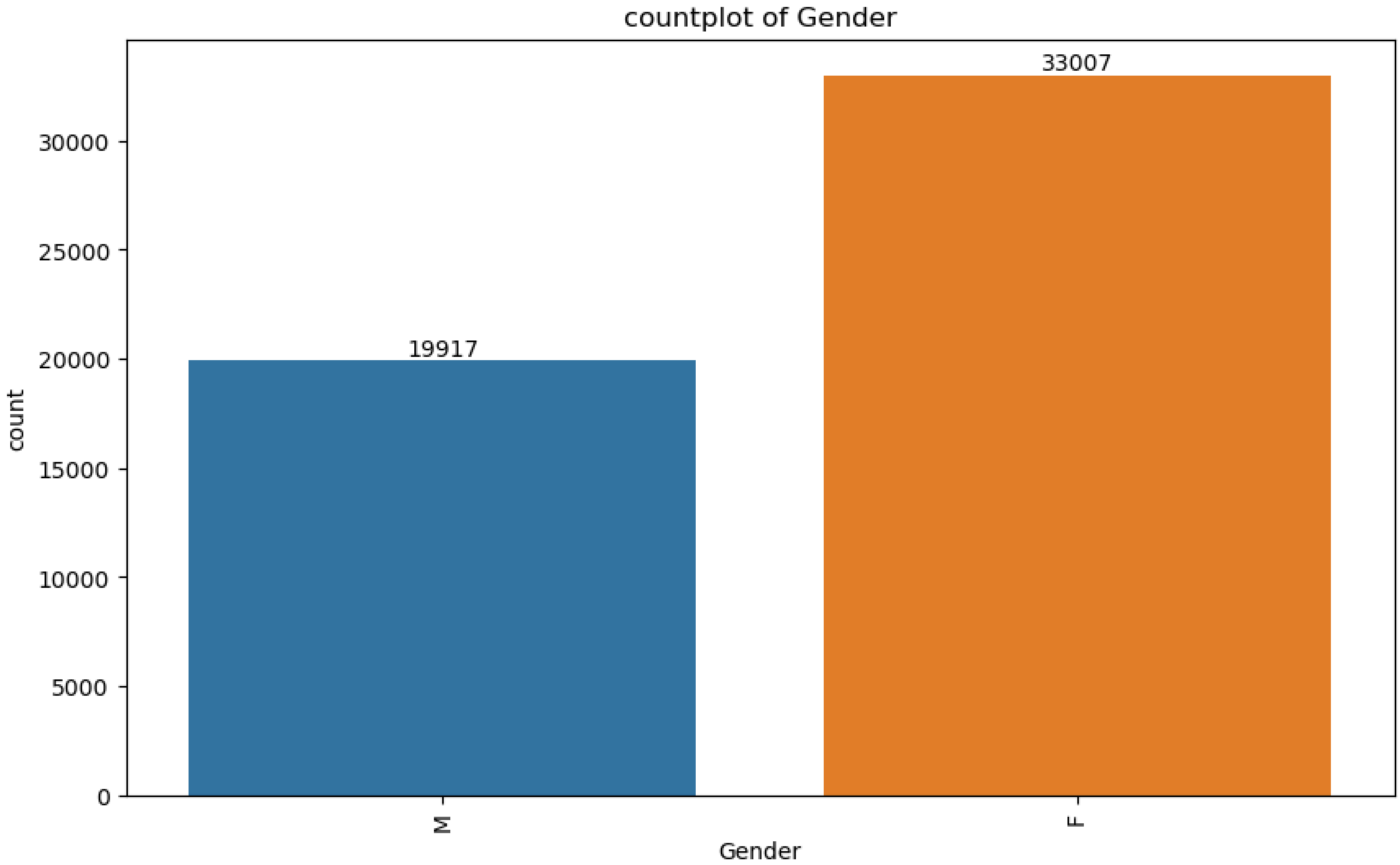
Univarate analyis

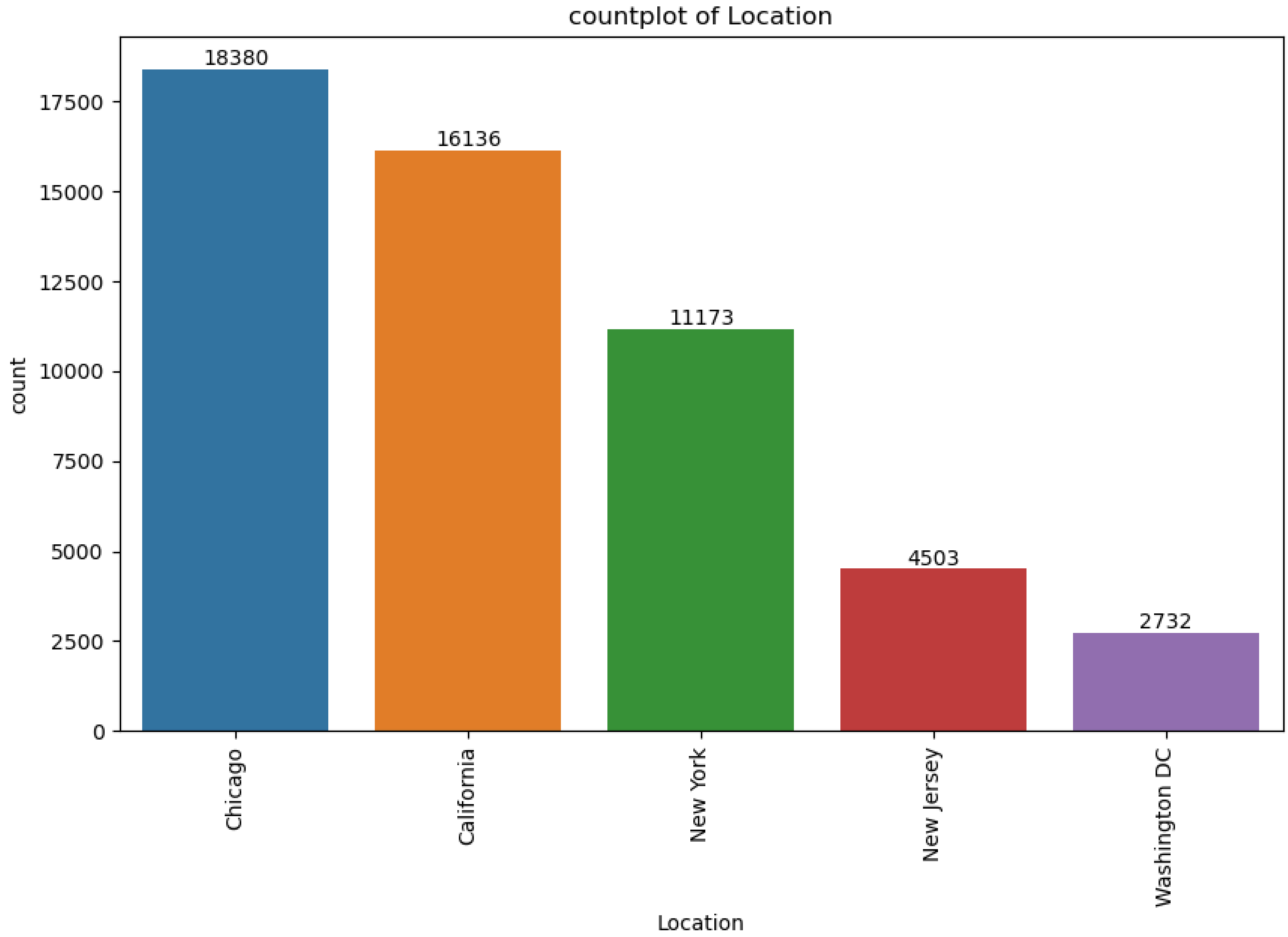
In [37]:
```
univirate=["Product_Category","Month","Gender","Location","Discount_pct","Coupon_Code"]
for i in univirate:
    plt.figure(figsize=(10,6))
    sns.countplot(data=final,x=i)
    plt.xticks(rotation=90)
    plt.title(f"countplot of {i}")
    ax=plt.gca()
    for bars in ax.containers:
        ax.bar_label(bars)
    plt.show()
```

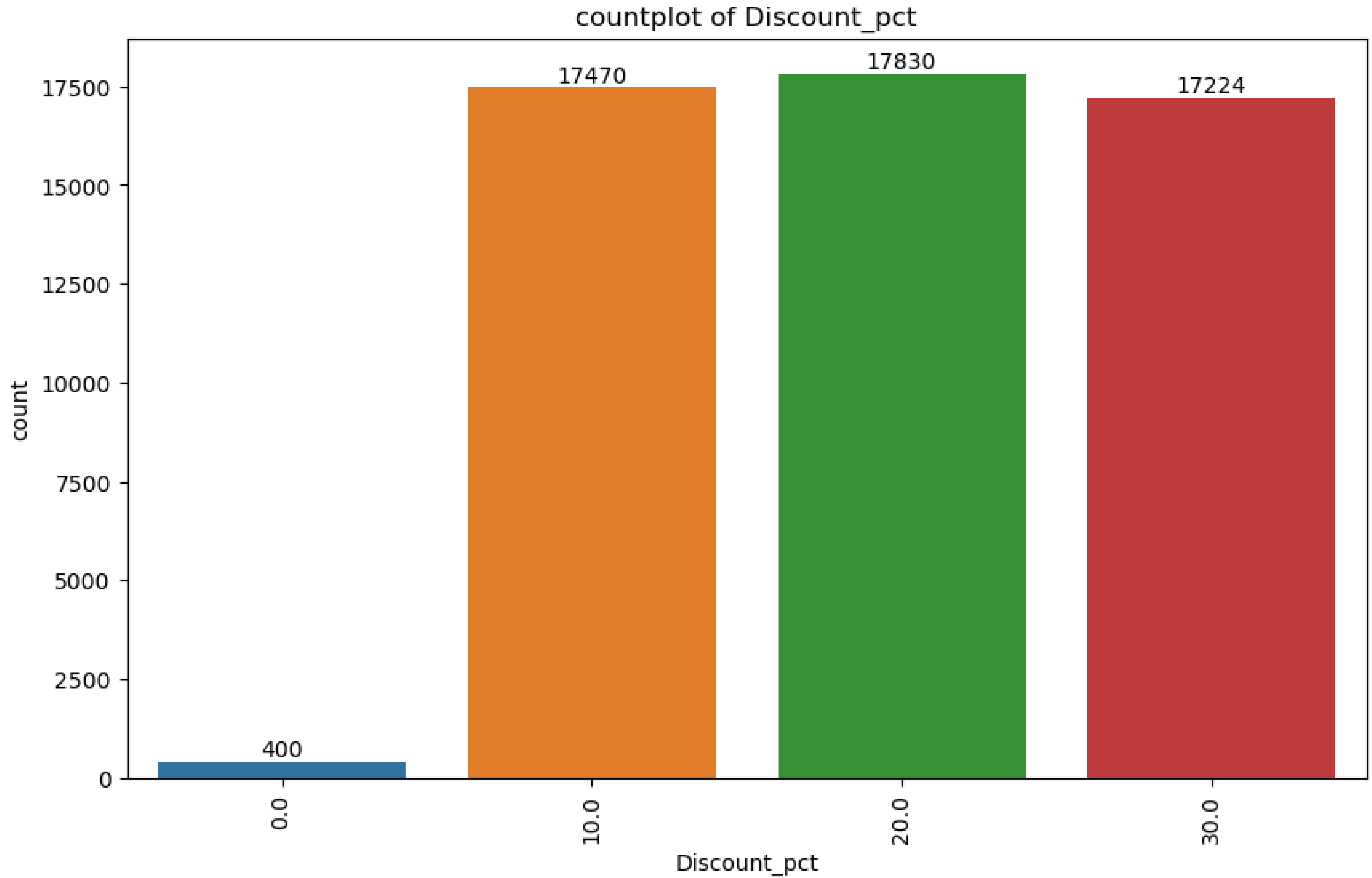


countplot of Product_Category
count
Product_Category
17500
15000
12500
10000
7500
5000
2500
0
14013
6513
18126
1882
3483
3092
749
771
554
160
317
89
105
268
159
46
122
43
234
2198
Nest-USA
Office
Apparel
Bags
Drinkware
Lifestyle
Notebooks & Journals
Headgear
Waze
Fun
Nest-Canada
Backpacks
Google
Bottles
Gift Cards
More Bags
Housewares
Android
Accessories
Nest

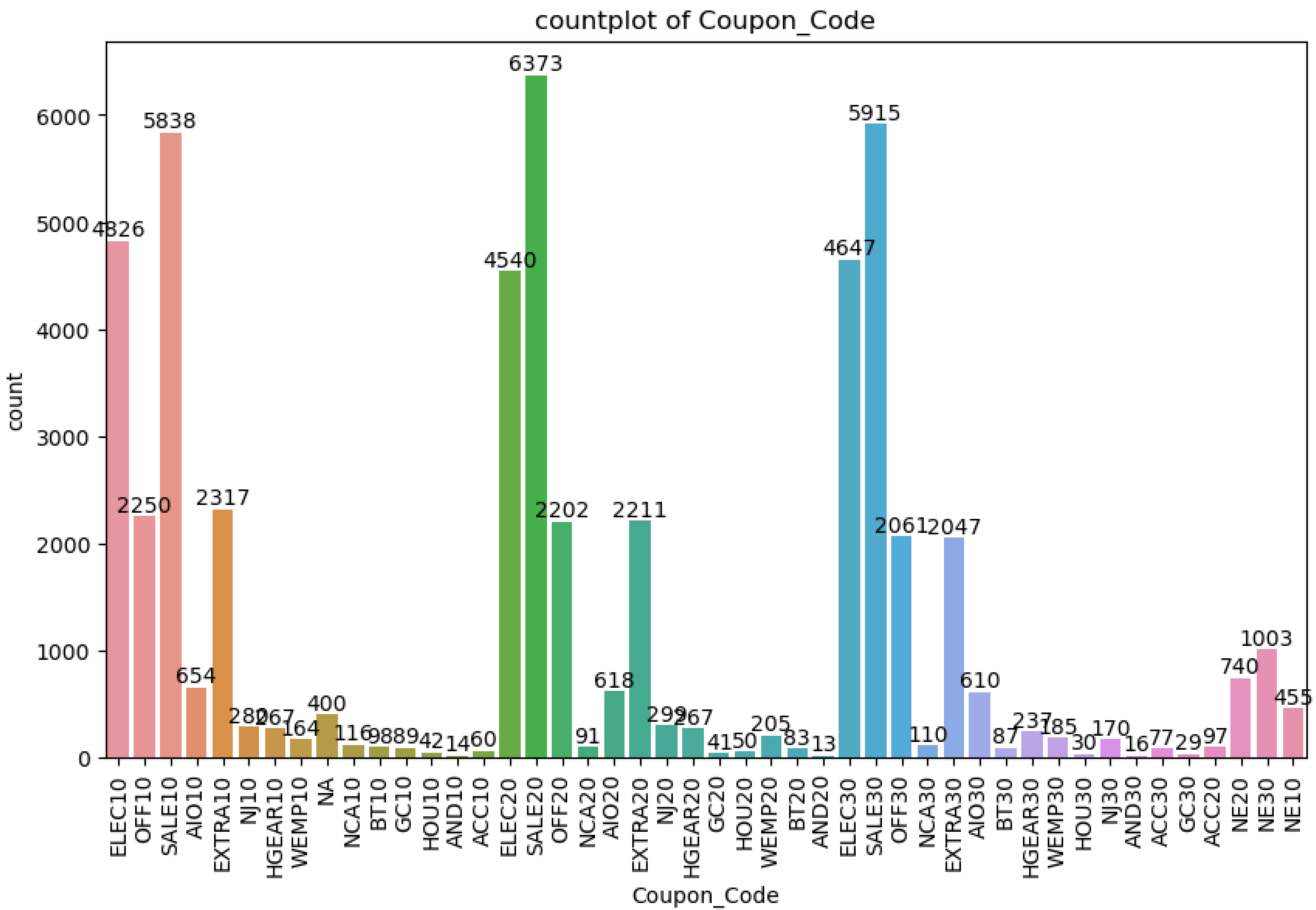

countplot of Month
count
6000
5000
4000
3000
2000
1000
0
4063
3284
4346
4150
4572
4193
5251
6150
4288
4164
3961
4502
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month


countplot of Gender
33007
19917
30000
25000
20000
15000
10000
5000
0
count
M
F
Gender


countplot of Location
18380
16136
11173
4503
2732
count
0
2500
5000
7500
10000
12500
15000
17500
Chicago
California
New York
New Jersey
Washington DC
Location



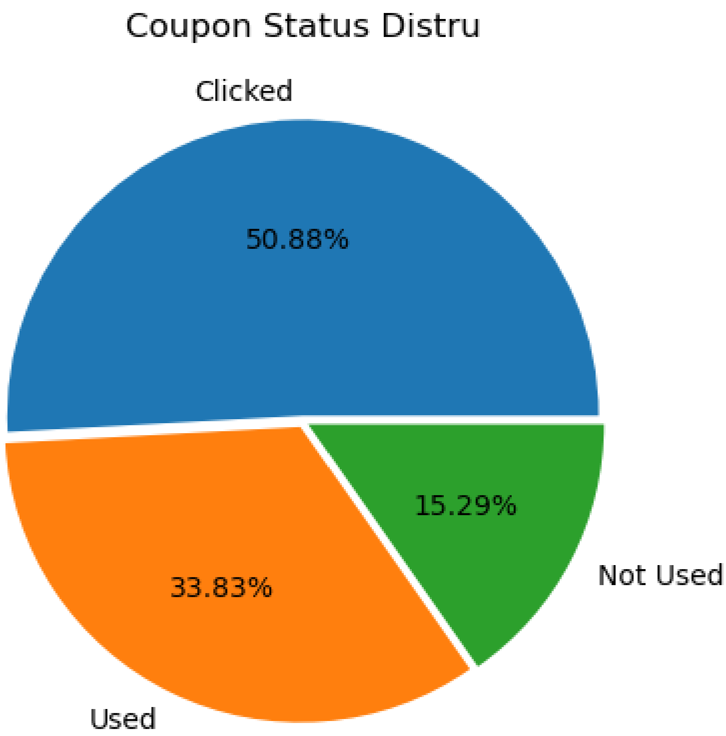
countplot of Discount_pct
17470
17830
17224
400
17500
15000
12500
10000
7500
5000
2500
0
count
0.0
10.0
20.0
30.0
Discount_pct



In [38]:

```
Coupon_Status_count=final['Coupon_Status'].value_counts()
colors = ['#1f77b4', '#ff7f0e', '#2ca02c']
plt.pie(Coupon_Status_count,autopct="%.2f%%",labels=Coupon_Status_count.index,colors=colors,explode=[0.02,.02,.02])
plt.title("Coupon Status Distru")
```

Out[38]: Text(0.5, 1.0, 'Coupon Status Distru')



- Among the categories, Apparel (34%) and Nest-USA (24%) contributed to the most sales.
- The majority (66%) of customers preferred purchasing a single item.
- August saw the highest sales compared to other months.
- Coupon usage was recorded at 34%.
- The most popular coupon was 'sale20' used at 33.69%.
- Females made up a larger portion of the customers than males.
- Chicago and California had the most sales compared to other locations.

In [39]:
```
exp=final.copy()
exp.head()
```

Out[39]:

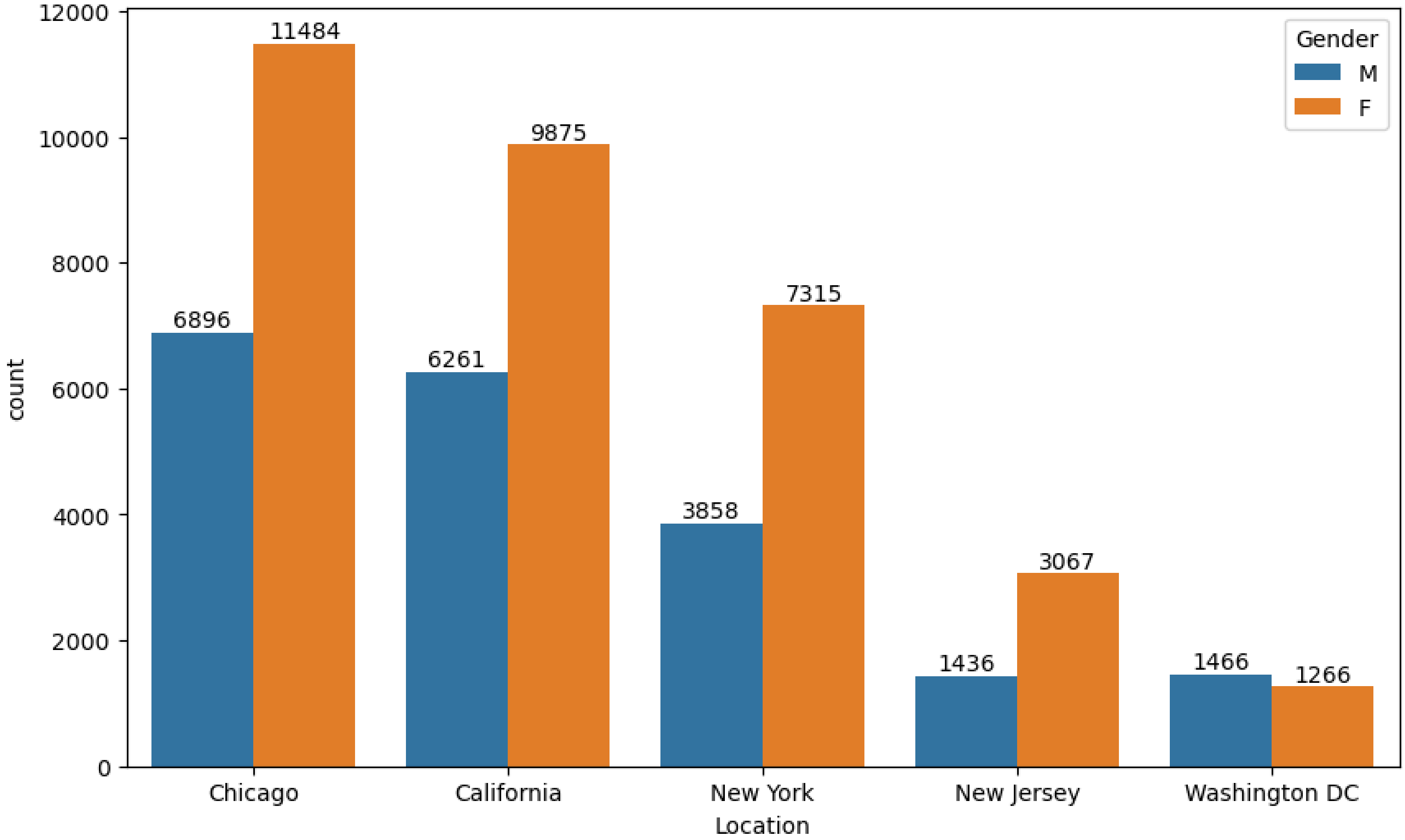
	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

Bivariate Analysis

Gender vs Location

In [40]:

```
plt.figure(figsize=(10,6))
sns.countplot(data=final,x='Location',hue='Gender')
ax = plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



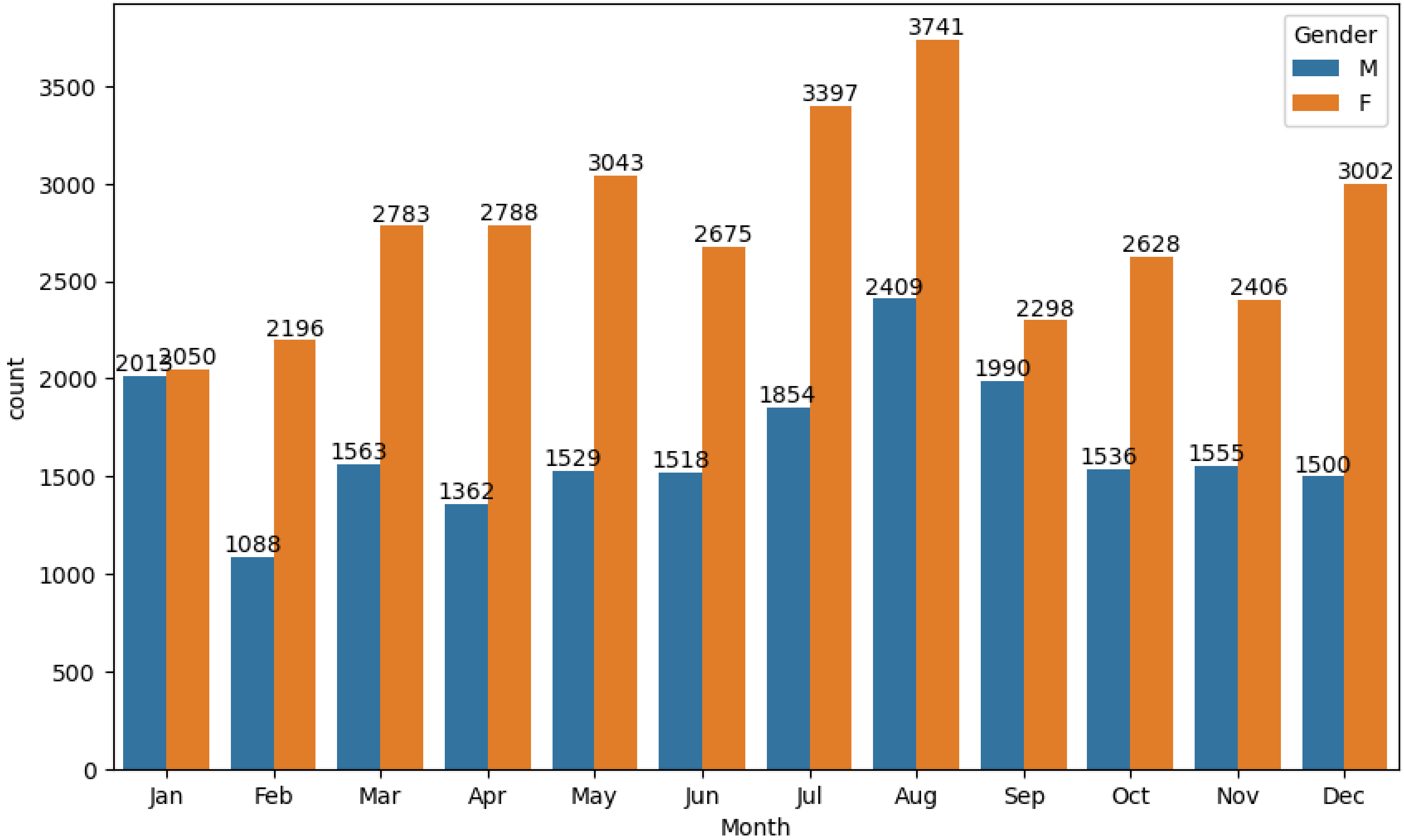
- Except for Washington D.C., all other locations have less male customers.

Month vs Gender

In [41]:

```
plt.figure(figsize=(10,6))
sns.countplot(data=final,x='Month',hue='Gender')
ax=plt.gca()
for bars in ax.containers:
```

```
    ax.bar_label(bars)
plt.show()
```

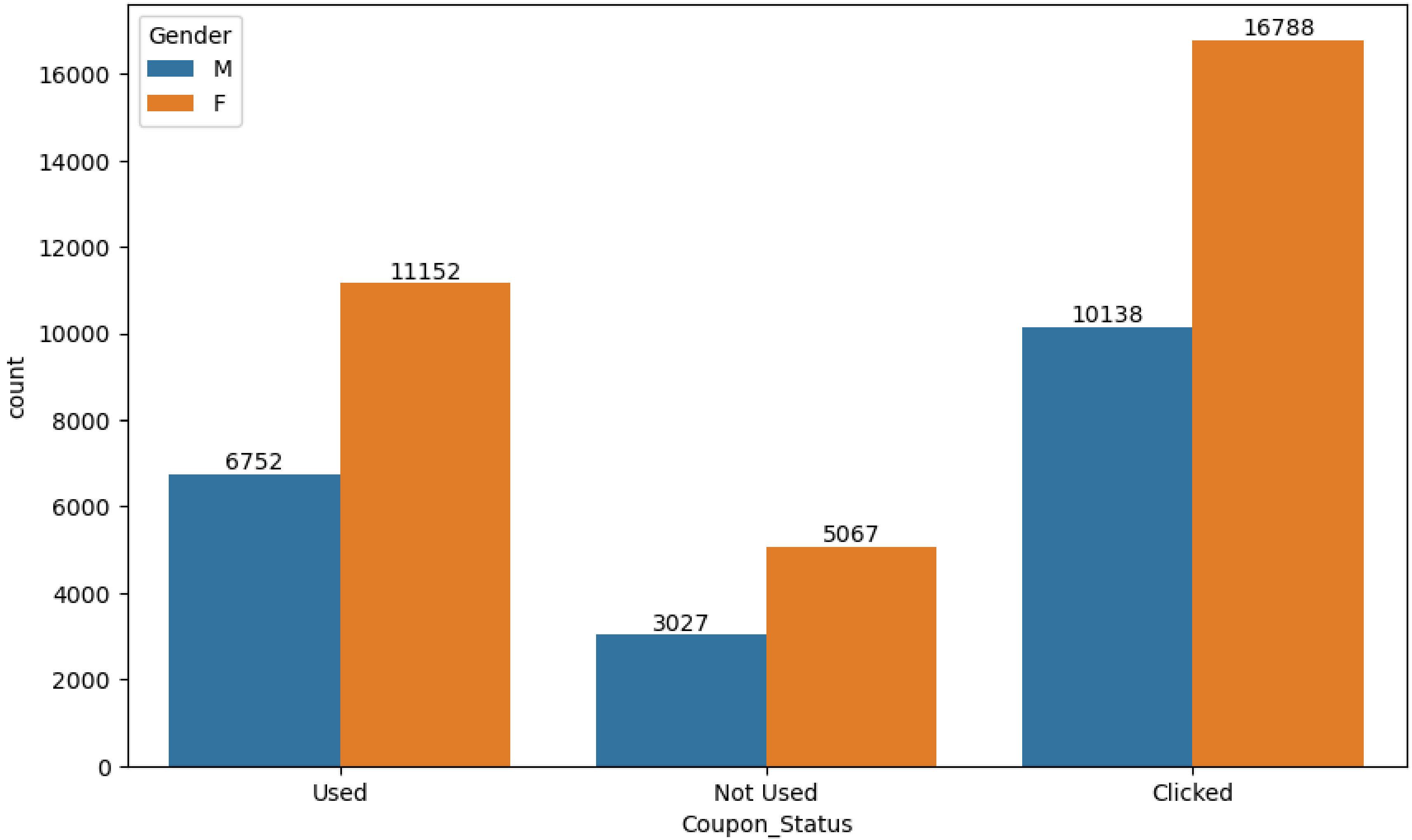


- Except for January, all other months have fewer males.

Coupon_Status vs Gender

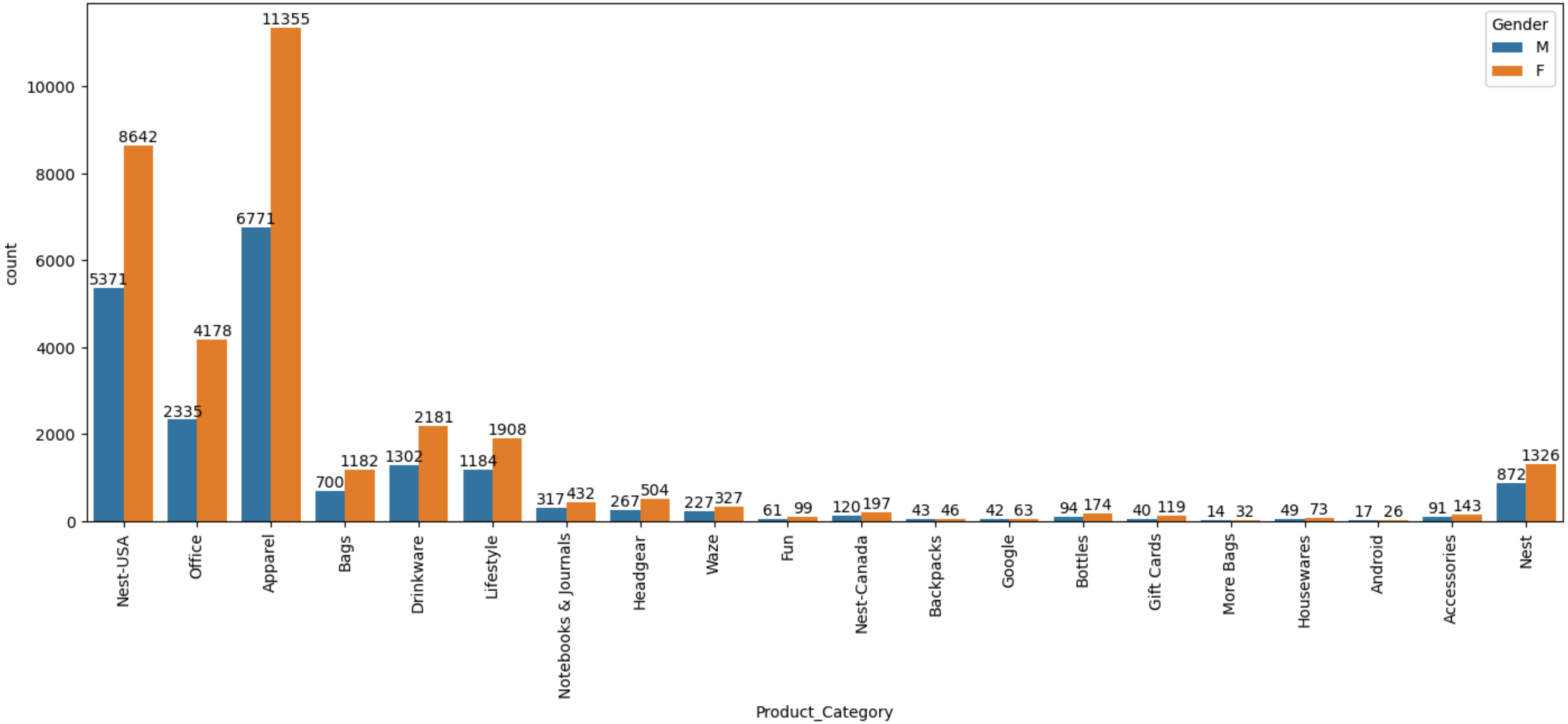
In [42]:

```
plt.figure(figsize=(10,6))
sns.countplot(data=final,x='Coupon_Status',hue='Gender')
ax=plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



- In coupon usage, females are ahead of males.

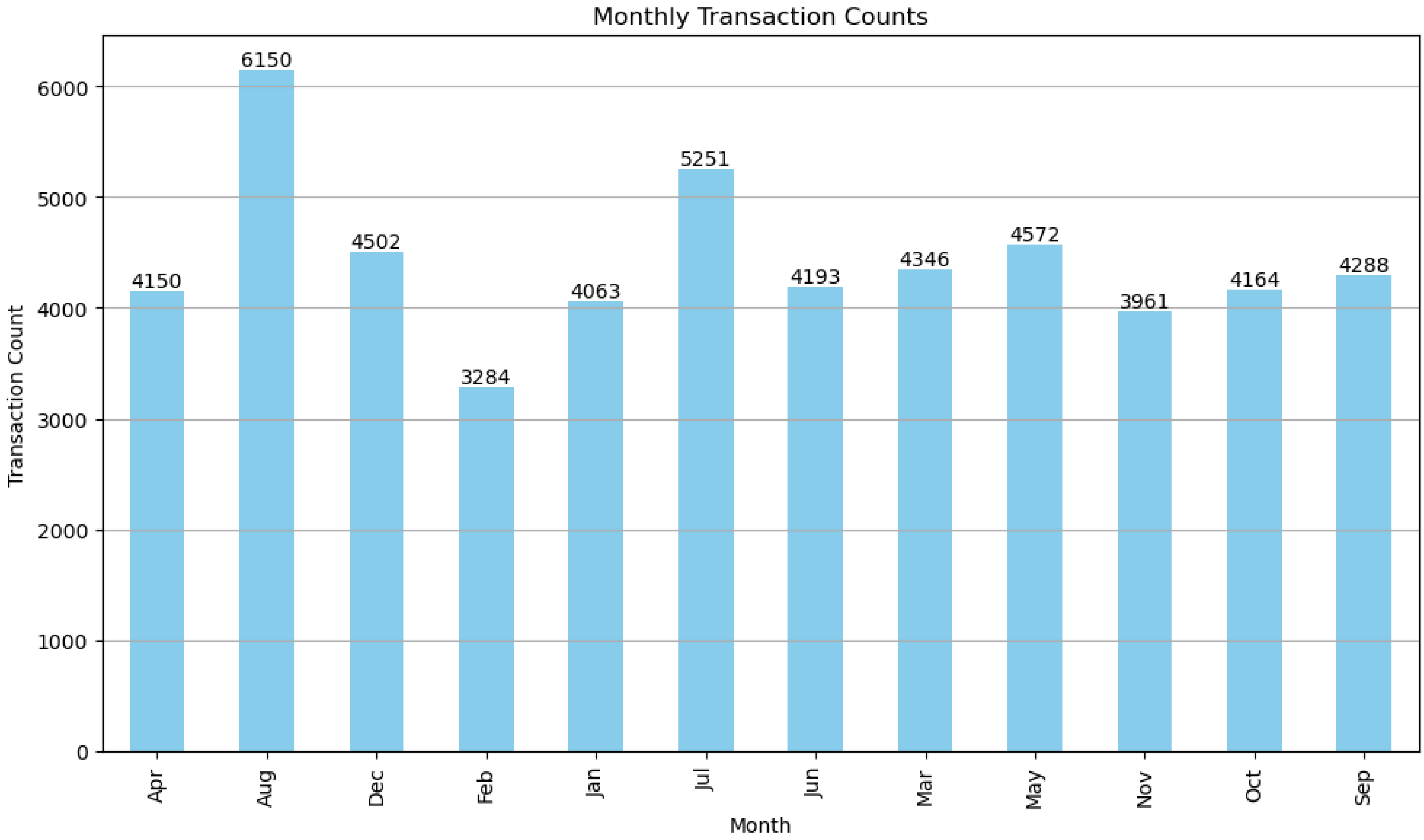
In [43]:
```
plt.figure(figsize=(17,6))
sns.countplot(data=final,x=final['Product_Category'],hue='Gender',)
plt.xticks(rotation=90)
ax=plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



- In the product category, females are predominant.

In [44]:
```
monthly_transaction_counts = final.groupby('Month')['Transaction_ID'].count()
plt.figure(figsize=(10, 6))
monthly_transaction_counts.plot(kind='bar', color='skyblue')
plt.title('Monthly Transaction Counts')
```

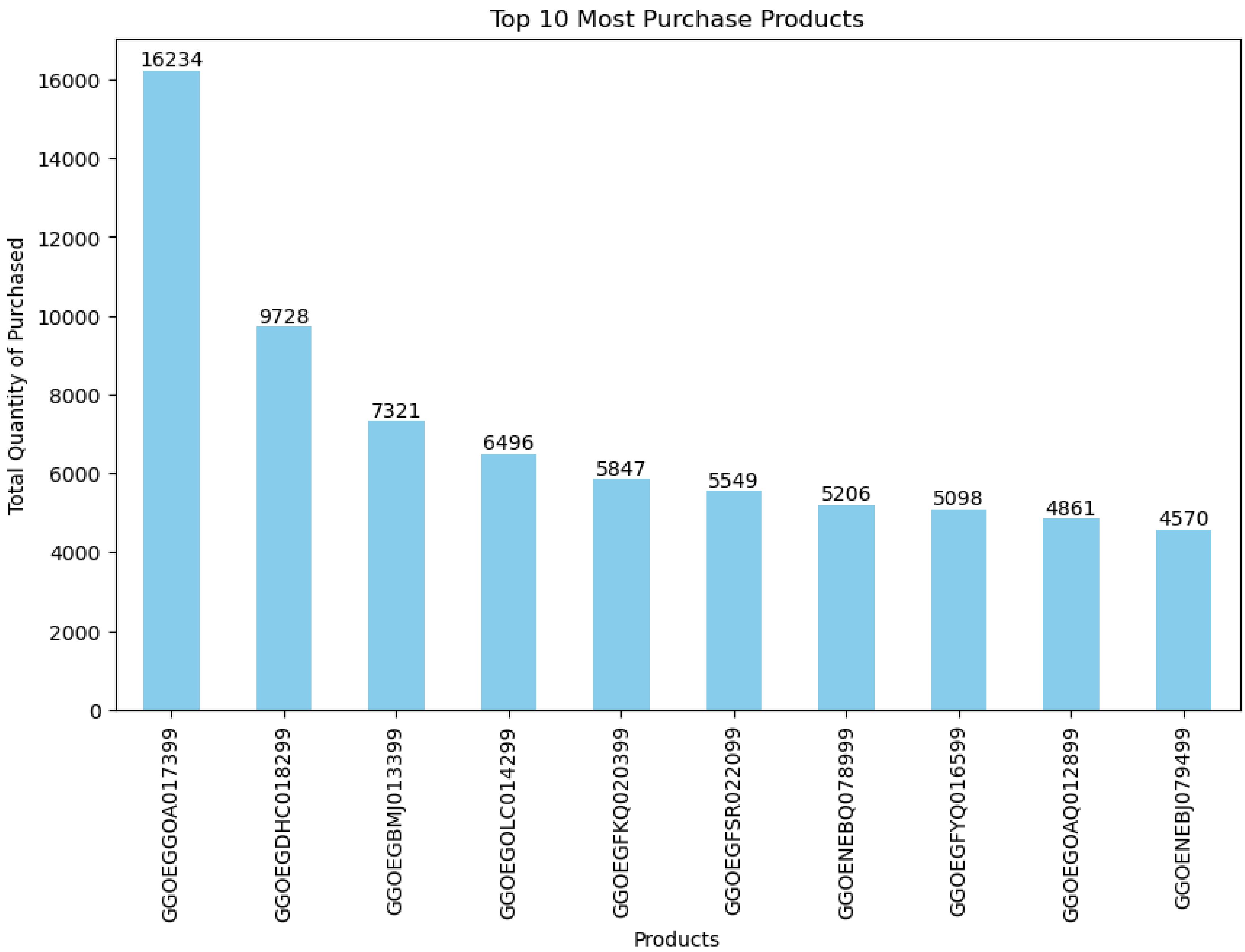
```
plt.xlabel('Month')
plt.ylabel('Transaction Count')
plt.xticks(rotation=90)
plt.grid(axis='y')
plt.tight_layout()
ax=plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



- Most transactions occur in December.

Top 10 Most Purchase Products

In [45]:
```
cat_quatity=final.groupby('Product_SKU')['Quantity'].sum()
top_10_cat=cat_quatity.sort_values(ascending=False).head(10)

plt.figure(figsize=(10,6))
top_10_cat.plot(kind="bar", color='skyblue')
plt.title("Top 10 Most Purchase Products")
plt.xlabel("Products")
plt.ylabel("Total Quantity of Purchased")
ax=plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```



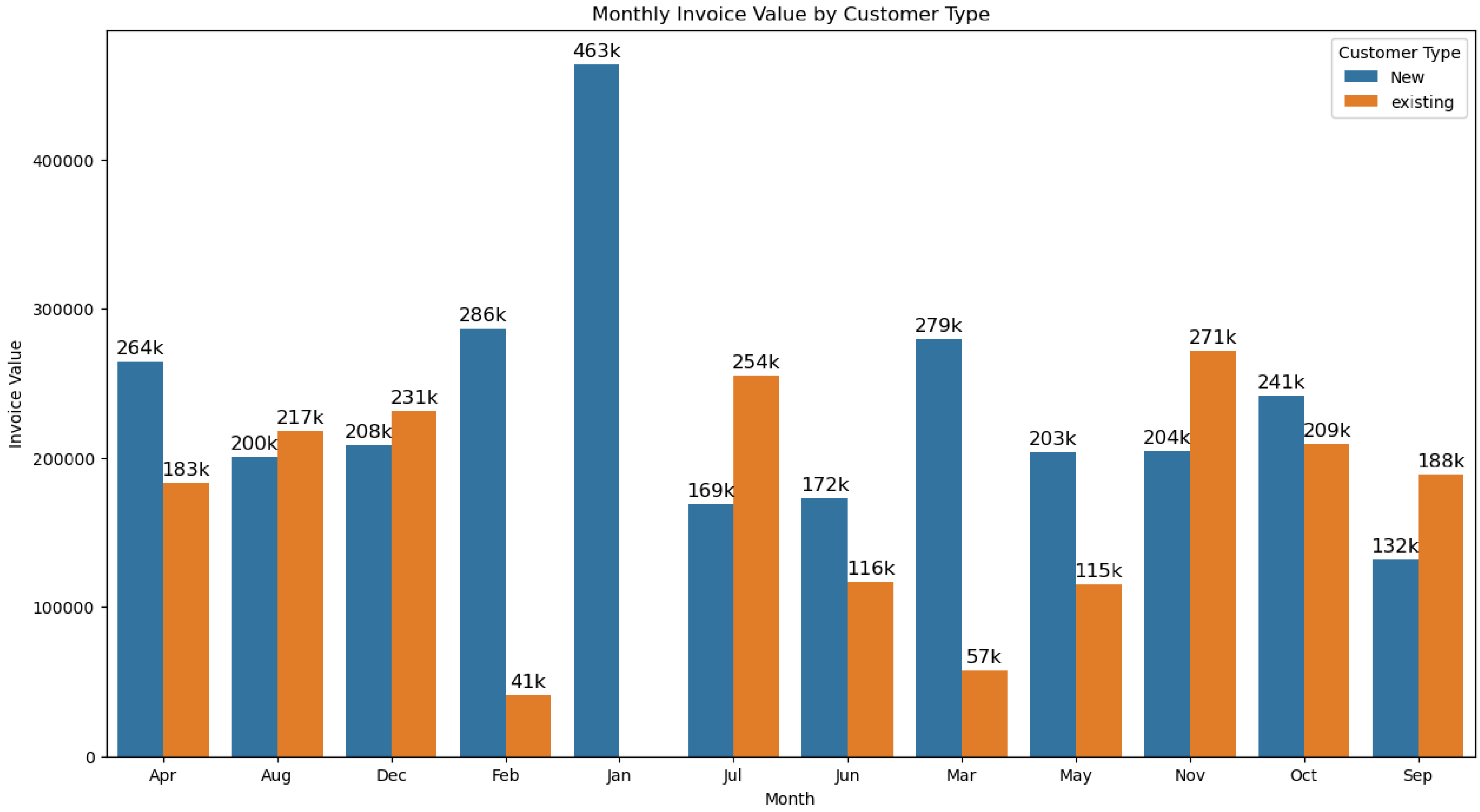
- The product GGOEGGOA017399 has the highest number of purchases

Customer Acquisition & Retention

Old customer vs New customer

In [46]:

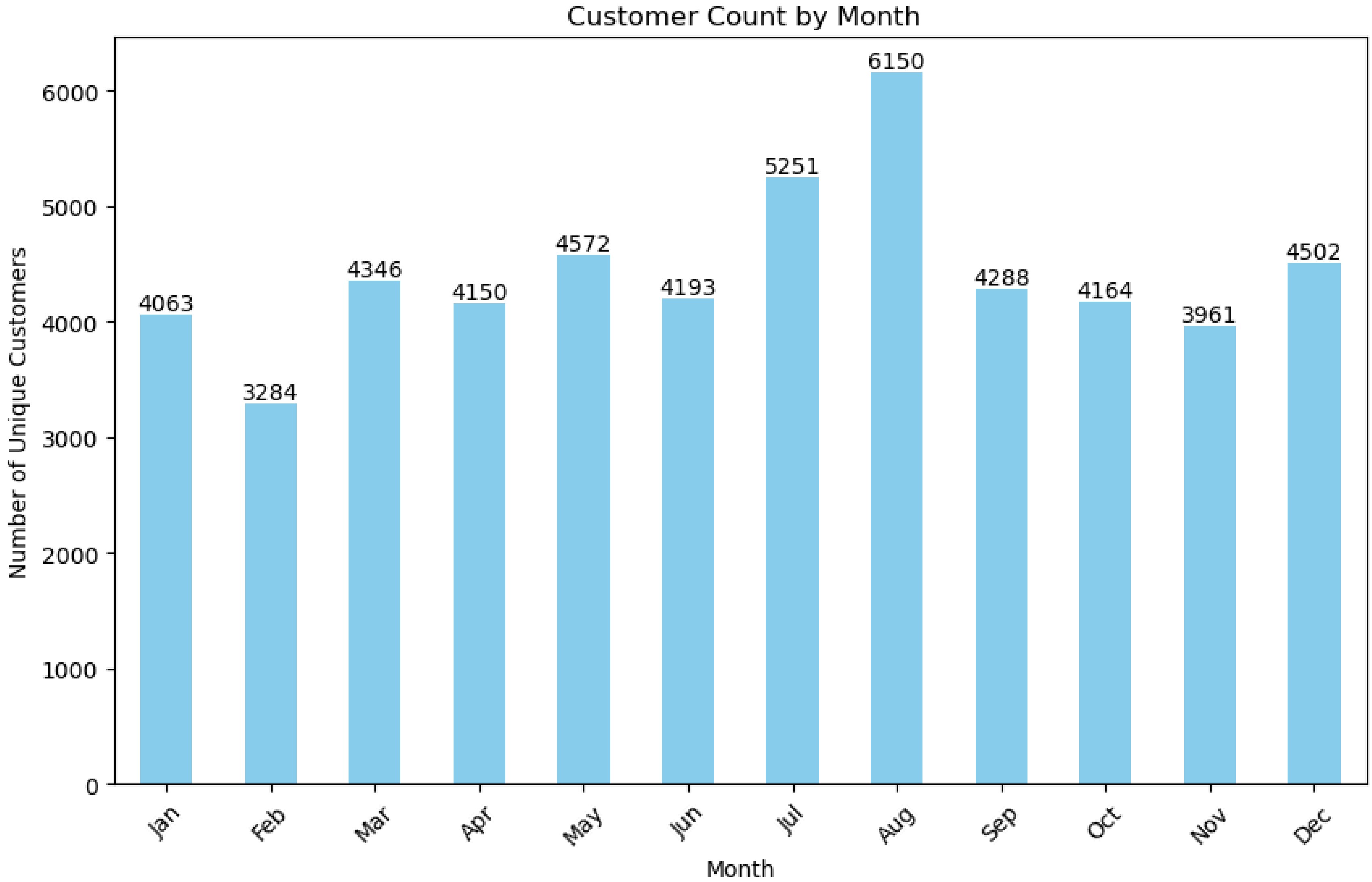
```
exp['first_transaction_date'] = exp.groupby('CustomerID')['Transaction_Date'].transform('min')
exp['transaction_month'] = exp['Transaction_Date'].dt.to_period('M')
exp['first_transaction_month'] = exp['first_transaction_date'].dt.to_period('M')
exp['Customer_type'] = exp.apply(lambda x: 'New' if x['transaction_month'] == x['first_transaction_month'] else 'existing', axis=

monthly_revenue = exp.groupby(['Month', 'Customer_type'])['Invoice Value'].sum()
monthly_revenue1 = monthly_revenue.reset_index()

# Plotting
plt.figure(figsize=(15, 8))
sns.barplot(data=monthly_revenue1, x='Month', y='Invoice Value', hue='Customer_type')
ax=plt.gca()
for bar in ax.patches:
    height = bar.get_height()
    label = f'{int(height / 1000)}k' if not pd.isna(height) else '0k'
    ax.annotate(label,
                (bar.get_x() + bar.get_width() / 2, height),
                ha='center', va='center', size=12, xytext=(0, 8),
                textcoords='offset points')

plt.xlabel('Month')
plt.ylabel('Invoice Value')
plt.title('Monthly Invoice Value by Customer Type')
plt.legend(title='Customer Type')
plt.show()
```



count by month

In [47]:
```
final['Month2'] = pd.to_datetime(final['Month'], format='%b')
customer_count_by_month = final.groupby('Month2')['CustomerID'].count()
plt.figure(figsize=(10,6))
customer_count_by_month.plot(kind='bar', color='skyblue')
plt.xticks(ticks=range(0, 12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], rotat
ax = plt.gca()
for bars in ax.containers:
```

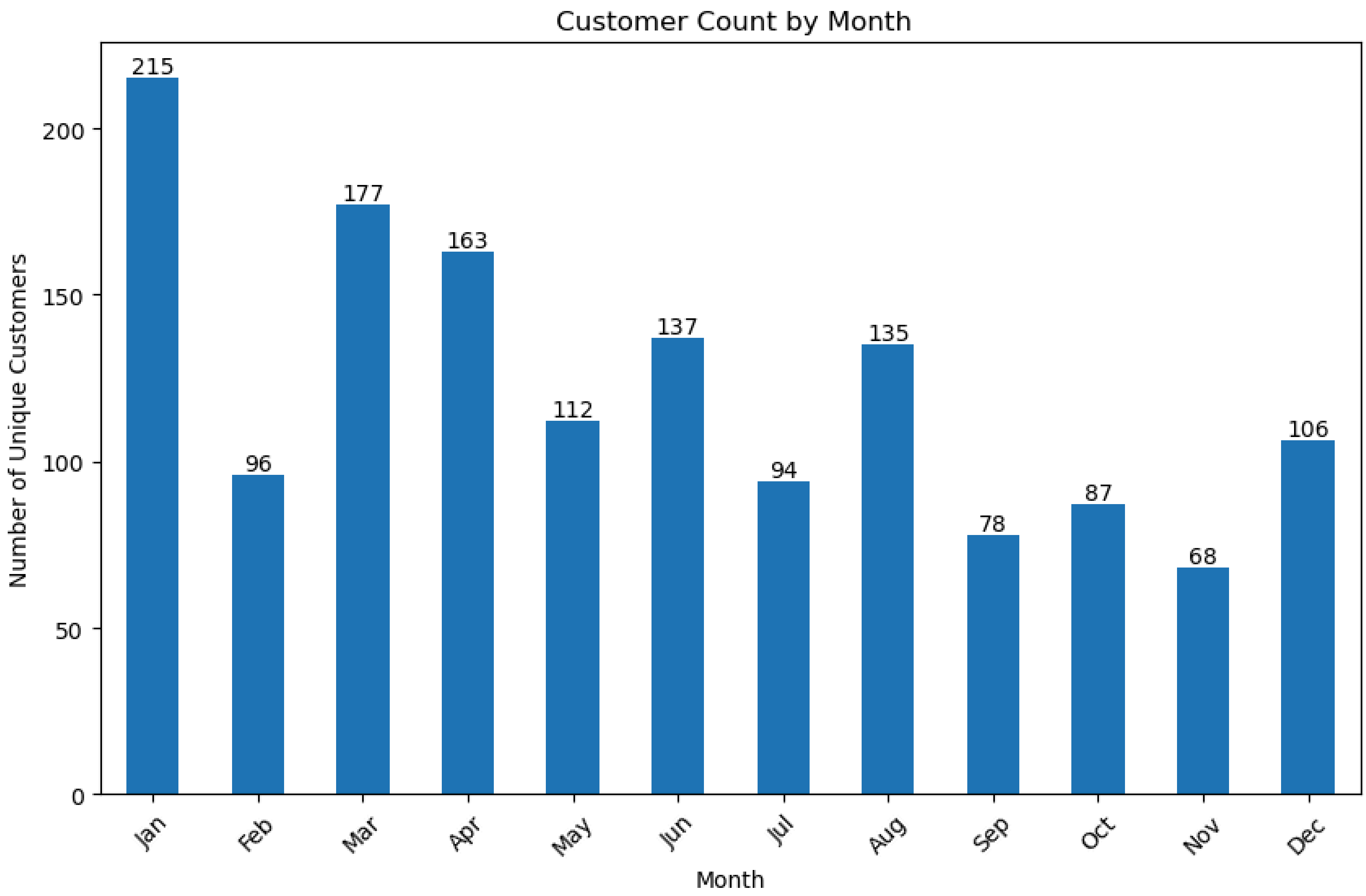
```
    ax.bar_label(bars)
plt.title(' Customer Count by Month')
plt.xlabel('Month')
plt.ylabel('Number of Unique Customers')
plt.show()
```



Customer Acquisition by Month

In [48]:

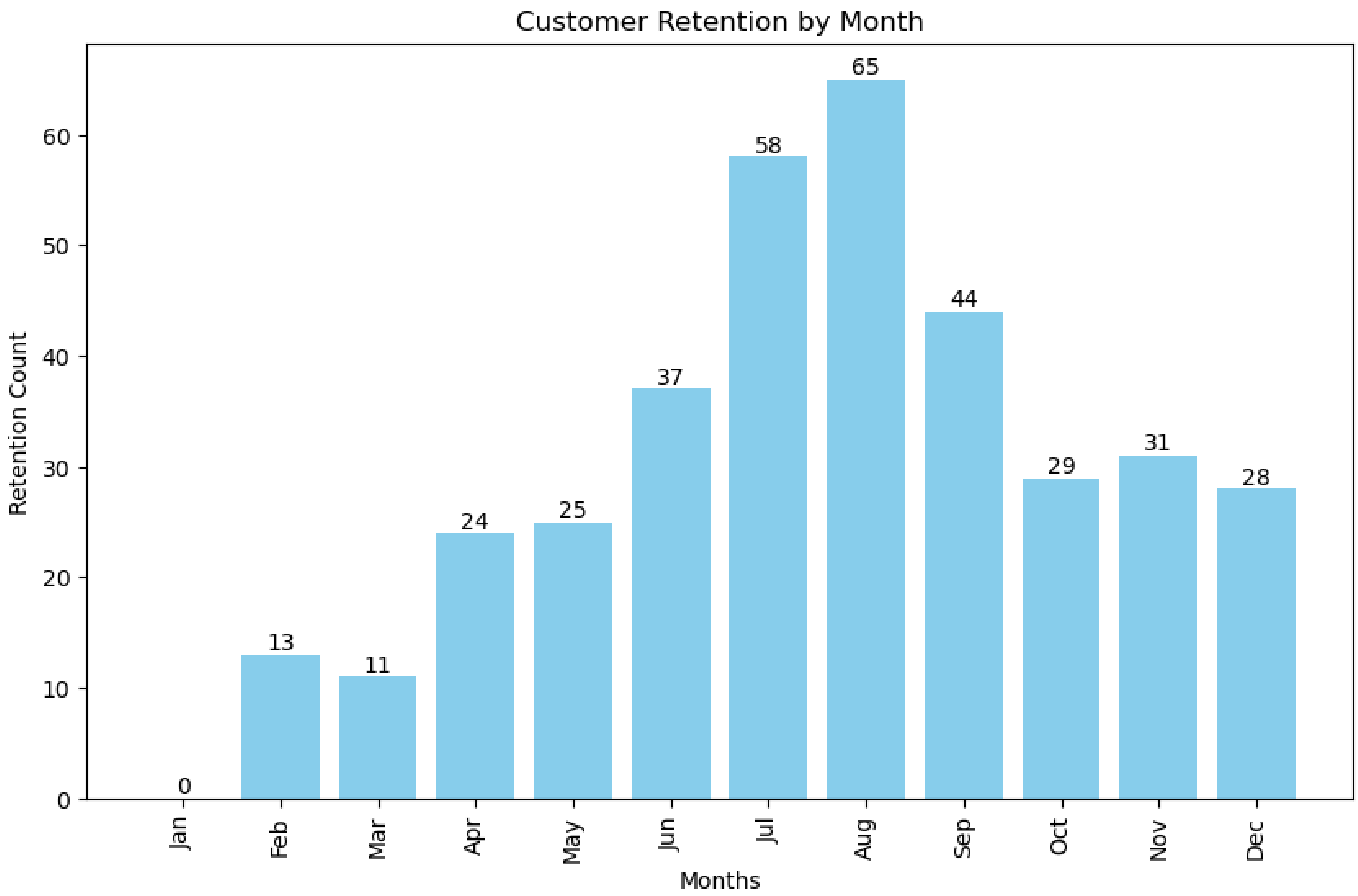
```
s=exp.groupby("first_transaction_month")['CustomerID'].nunique()
plt.figure(figsize=(10,6))
s.plot(kind="bar")
plt.xticks(ticks=range(0, 12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], rotat
ax = plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)
plt.title(' Customer Count by Month')
plt.xlabel('Month')
plt.ylabel('Number of Unique Customers')
plt.show()
```



Customer Retention by month

In [49]:
```
month_dict = {}
for i in final['Month'].unique():
   month_dict[i] = final[final['Month']==i]['CustomerID'].unique().tolist()

months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
```

```python
retention = [0]
for i in range(11):
  set1 = set(month_dict[months[i]])
  set2 = set(month_dict[months[i+1]])
  common_items = len(set1.intersection(set2))
  retention.append(common_items)

plt.figure(figsize=(10,6))
plt.bar(months, retention, color='skyblue')
plt.xlabel('Months')
plt.ylabel('Retention Count')
plt.title('Customer Retention by Month')
plt.xticks(rotation=90)
ax = plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```

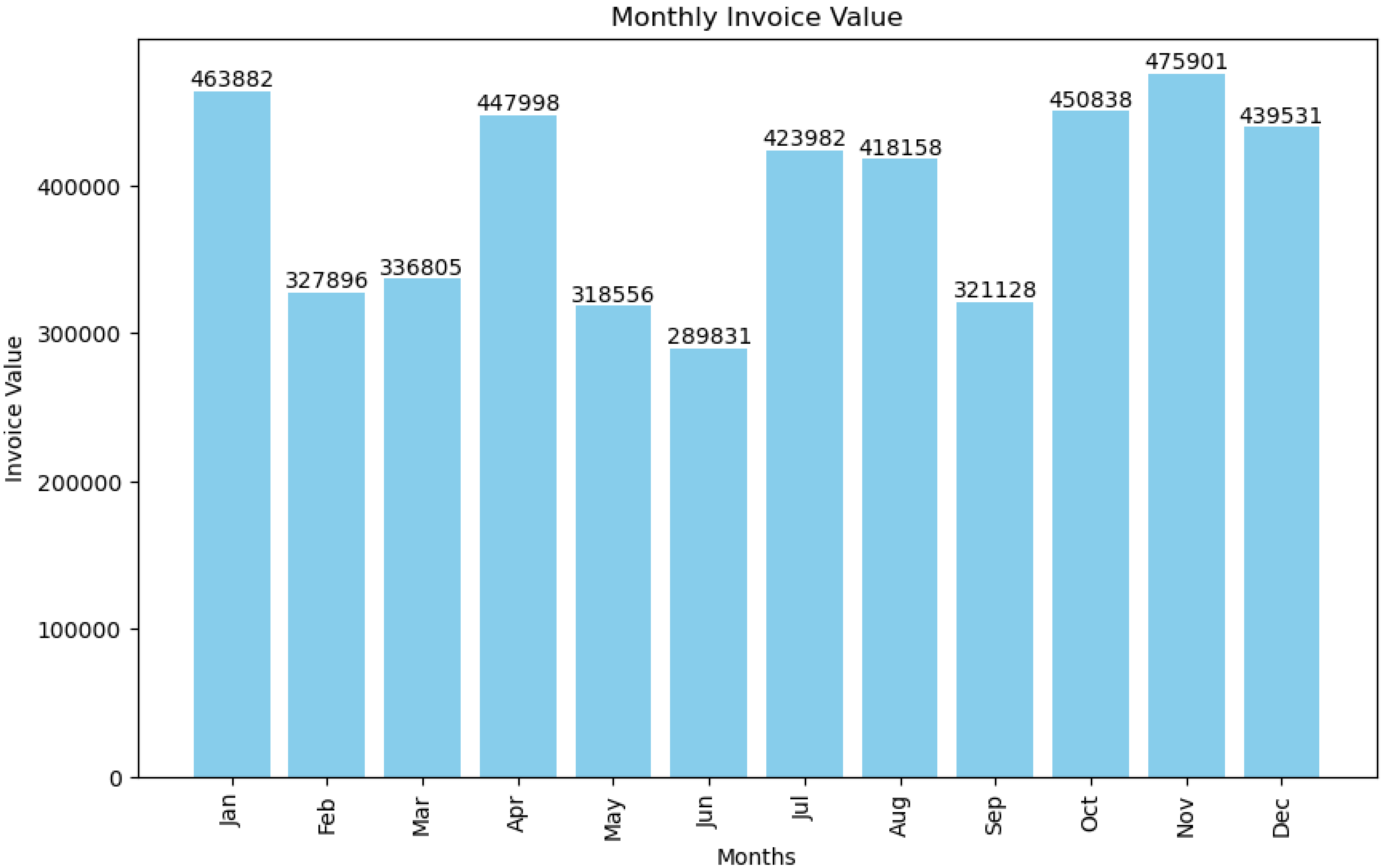


- The retention rate is high in July, August, and September

Revenu by month

In [50]:

```
month_wise_revenue=final.groupby("Month")["Invoice Value"].sum().reindex(
    ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
)
plt.figure(figsize=(10, 6))
plt.bar(month_wise_revenue.index, month_wise_revenue.values, color='skyblue')
plt.xlabel('Months')
plt.ylabel('Invoice Value')
plt.title('Monthly Invoice Value')
plt.xticks(rotation=90)
ax = plt.gca()
for bars in ax.containers:
    ax.bar_label(bars)

plt.show()
```



Marketing Campaign Impact

In [51]:
```
ms.head()
```

Out[51]:

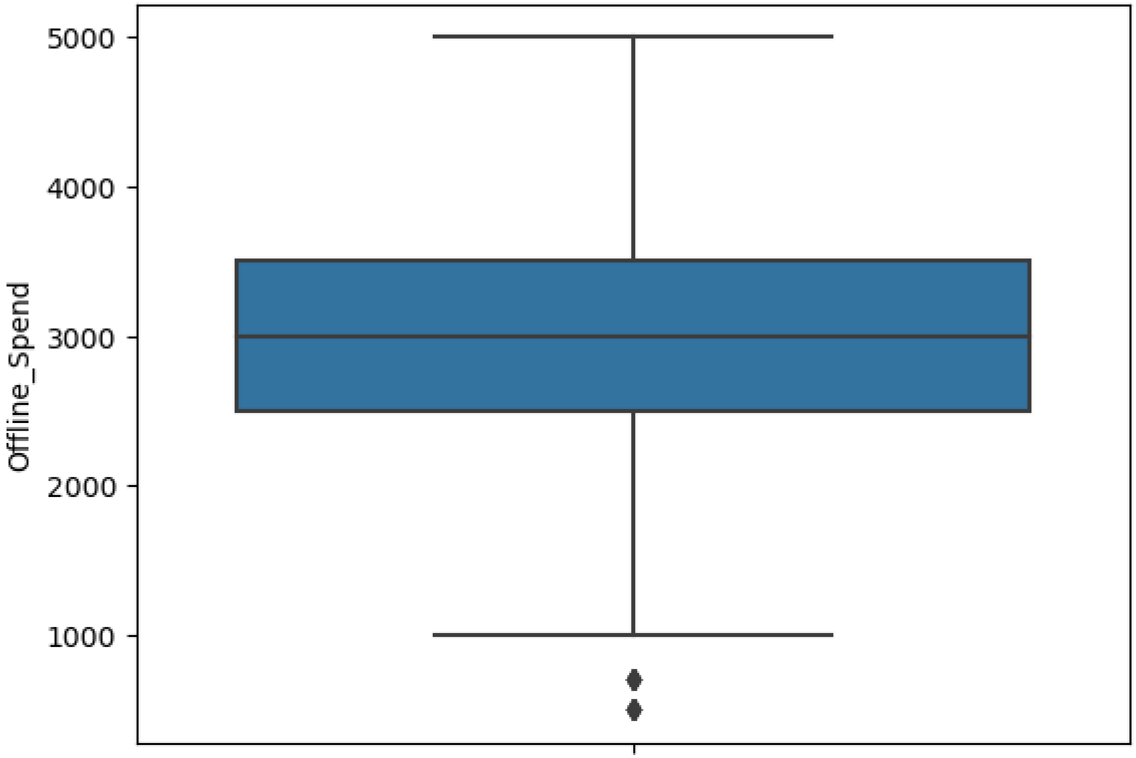
	Date	Offline_Spend	Online_Spend
0	1/1/2019	4500	2424.50
1	1/2/2019	4500	3480.36
2	1/3/2019	4500	1576.38
3	1/4/2019	4500	2928.55
4	1/5/2019	4500	4055.30

In [52]:

```
sns.boxplot(data=ms,y='Offline_Spend')
```

Out[52]:

```
<Axes: ylabel='Offline_Spend'>
```



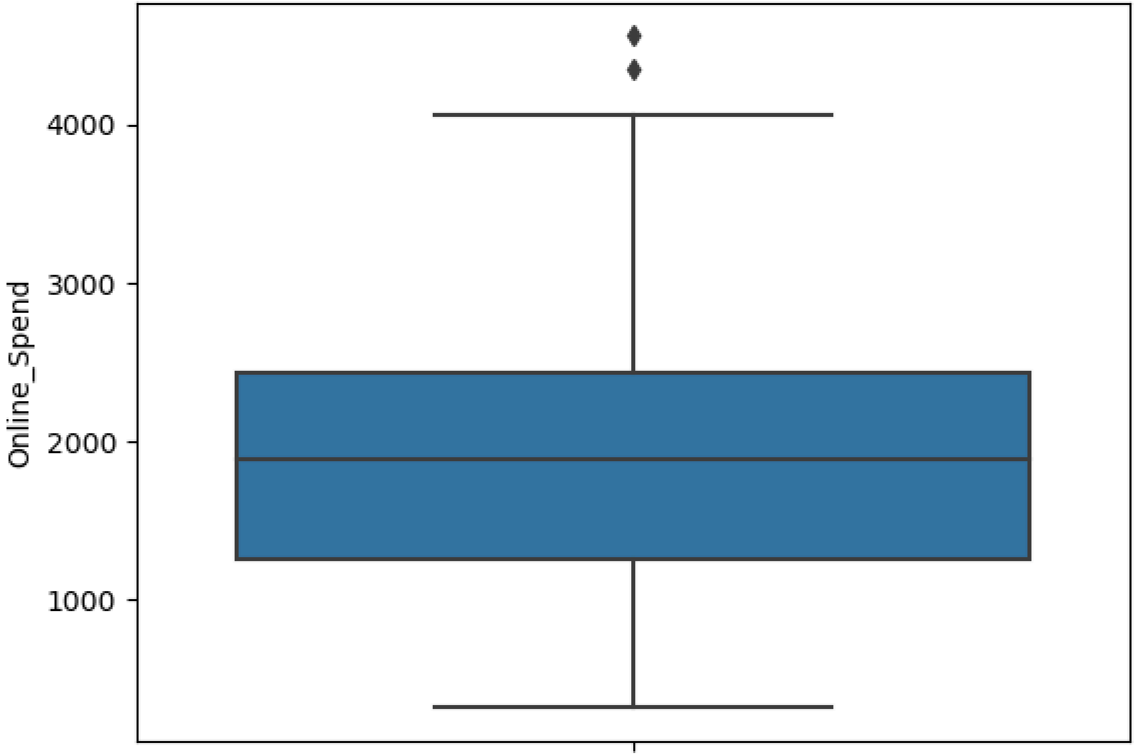
In [53]:

```
(ms['Offline_Spend'].quantile(.25),
ms['Offline_Spend'].quantile(.75))
```

Out[53]: (2500.0, 3500.0)

- The majority of offline spending is between 2500 and 3500.

In [54]:
```
sns.boxplot(data=ms,y='Online_Spend')
ax=plt.gca()
for i in ax.containers:
    ax.bar_label(i)
```



In [55]:
```
(ms['Online_Spend'].quantile(.25),
ms['Online_Spend'].quantile(.75))
```

Out[55]: (1258.6, 2435.12)

- Most of the online spending is between 1258 and 435.

Hypothesis testing

Test 1

- Null(H0):There is no significance difference between the mean of offline spend and online spend
- Alternative (H1):There is significance difference between the mean of offline spend and online spend

In [56]:
```
alpha=0.05
s,p=ttest_ind(ms['Online_Spend'],ms['Offline_Spend'])
print(f"statistic value: {s} and p-value: {p}")
if p<alpha:
    print("Reject Null,There is significance difference between the mean of offline spend and online spend")
else:
    print("Fail to reject null,There is no significance difference between the mean of offline spend and online spend")
```

```
statistic value: -14.337872271632449 and p-value: 3.0117050723039 23e-41
Reject Null,There is significance difference between the mean of offline spend and online spend
```

- Here wew conclude that there is significance difference between the mean of offline spend and online spend

Test 2

- Null(H0):There is no sginificance difference between the mean of Male revenue and female revenue
- Alternative (H1):There is sginificance difference between the mean of Male revenue and female revenue

In [57]:
```
male =final[final["Gender"]=="M"]['Invoice Value']
female=final[final["Gender"]=="F"]['Invoice Value']

alpha=0.05
s,p=ttest_ind(male,female)
print(f"statistic value: {s} and p-value: {p}")
if p<alpha:
```

```
    print("Reject Null,There is sginificance difference between the mean of Male revenue  and female revenue")
else:
    print("Fail to reject null,There is no sginificance difference between the mean of Male revenue  and female revenue")
```

```
statistic value: 0.17201582058911902 and p-value: 0.8634257490902747
Fail to reject null,There is no sginificance difference between the mean of Male revenue  and female revenue
```

- Here we conclude that,There is no sginificance difference between the mean of Male revenue and female revenue

Test 3

- Null(H0):There is no significance difference across the mean of all the location
- Alternative(H1):There is significance difference across the mean of all the location

In [58]:

```
Chicago =final[final["Location"]=="Chicago"]['Invoice Value']
California =final[final["Location"]=="California"]['Invoice Value']
New_York =final[final["Location"]=="New York"]['Invoice Value']
New_Jersey =final[final["Location"]=="New Jersey"]['Invoice Value']
Washington_DC =final[final["Location"]=="Washington DC"]['Invoice Value']


alpha=0.05
s,p=f_oneway(Chicago,California,New_York,New_Jersey,Washington_DC)
print(f"statistic value: {s} and p-value: {p}")
if p<alpha:
    print("Reject Null,There is significance difference  across the mean of all the location  ")
else:
    print("Fail to reject null,There is no significance difference  across the mean of all the location ")
```

```
statistic value: 2.701953854090806 and p-value: 0.02882189631217692
Reject Null,There is significance difference  across the mean of all the location
```

- Therefore we conclue that There is significance difference across the mean of all the location

In [59]:

```
final.head()
```

Out[59]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

Test 4

In [60]:
```
final['Coupon_Status'].value_counts()
```

Out[60]:
```
Coupon_Status
Clicked     26926
Used        17904
Not Used     8094
Name: count, dtype: int64
```

- Null(H0):There is no significance difference across the mean of various coupon status
- Alternative(H1):There is significance difference across the mean of various coupon status

In [61]:
```
Clicked =final[final["Coupon_Status"]=="Clicked"]['Invoice Value']
Used =final[final["Coupon_Status"]=="Used"]['Invoice Value']
Not_Used =final[final["Coupon_Status"]=="Not Used"]['Invoice Value']

alpha=0.05
s,p=kruskal(Clicked,Used,Not_Used)
print(f"statistic value: {s} and p-value: {p}")
if p<alpha:
    print("Reject Null,There is significance difference across the mean of various coupon status")
```

```python
else:
    print("Fail to reject null,there is no significance difference across the mean of various coupon status")
```

```
statistic value: 1.709922299041085 and p-value: 0.4252997138591098
Fail to reject null,there is no significance difference across the mean of various coupon status
```

- Here we conclude that, there is no significance difference across the mean of various coupon status

RFM Analysis

In [62]:

```python
final.head()
```

Out[62]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

In [63]:

```python
current_date=pd.to_datetime('2019-12-31')
segmentation=final.groupby("CustomerID").agg({'Transaction_Date':lambda x:(current_date-x.max()).days,
                                              'Transaction_ID':'count',
                                              'Invoice Value':'sum'})
segmentation.rename(columns = {'Transaction_Date':'Recency', 'Transaction_ID':'Frequency', 'Invoice Value':'Monetory'}, inplace =
segmentation.reset_index(inplace=True)

# fro Recency_bin
bins = [0,40,120,220,300,500]
labels = [1,2,3,4,5]
```

```python
segmentation['recency_bin'] = pd.cut(segmentation['Recency'], bins = bins, labels = labels,right=False)

# for Frequency_bin
bins = [0,15,35,60,85,900]
labels = [5,4,3,2,1]
segmentation['frequency_bin'] = pd.cut(segmentation['Frequency'], bins = bins, labels = labels,right=False)

# for Monetry Bin
bins = [0,2000,3500,5000,7000,90000]
labels = [5,4,3,2,1]
segmentation['monetory_bin'] = pd.cut(segmentation['Monetory'], bins = bins, labels = labels,right=False)

#Converitng into int
segmentation['recency_bin'] = segmentation['recency_bin'].astype('int')
segmentation['frequency_bin'] = segmentation['frequency_bin'].astype('int')
segmentation['monetory_bin'] = segmentation['monetory_bin'].astype('int')

segmentation['RFM'] = segmentation['recency_bin'] + segmentation['frequency_bin'] + segmentation['monetory_bin']

def rfm_analysis(rfm):
    if rfm >= 11:
        return 'Premium'
    elif rfm > 5 and rfm < 11:
        return 'Gold'
    else:
        return 'Silver'
```

In [64]:

```python
segmentation['Customer_segmentation'] = segmentation['RFM'].apply(rfm_analysis)
segmentation
```

Out[64]:

	CustomerID	Recency	Frequency	Monetory	recency_bin	frequency_bin	monetory_bin	RFM	Customer_segmentation
0	12346	107	2	174.98	2	5	5	12	Premium
1	12347	59	60	12090.30	2	2	1	5	Silver
2	12348	73	23	1501.90	2	4	5	11	Premium
3	12350	17	17	1183.72	1	4	5	10	Gold
4	12356	107	36	1753.42	2	3	5	10	Gold
...	...	...	...	...	...	...	...	...	...
1463	18259	270	7	816.43	4	5	5	14	Premium
1464	18260	87	40	2647.24	2	3	4	9	Gold
1465	18269	194	8	155.66	3	5	5	13	Premium
1466	18277	69	1	301.02	2	5	5	12	Premium
1467	18283	82	102	6970.80	2	1	2	5	Silver

1468 rows × 9 columns

In [65]:

```
df=segmentation[['CustomerID','Customer_segmentation']]
final2=pd.merge(final,df,on='CustomerID',how='left')
final2.head()
```

Out[65]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

Discount Analysis

Impact of Discount on Average Order Value

In [66]:

```
aov_with_discount_30 = final[final['Discount_pct'] == 30.0]['Invoice Value'].mean()
aov_with_discount_20 = final[final['Discount_pct'] == 20.0]['Invoice Value'].mean()
aov_with_discount_10 = final[final['Discount_pct'] == 10.0]['Invoice Value'].mean()
aov_with_discount_0 = final[final['Discount_pct'] == 0.0]['Invoice Value'].mean()

# Printing the results
print(f"AOV using 30% discount is {round(aov_with_discount_30,2)}")
print(f"AOV using 20% discount is {round(aov_with_discount_20,2)}")
print(f"AOV using 10% discount is {round(aov_with_discount_10,2)}")
print(f"AOV without discount is {round(aov_with_discount_0,2)}")
```

```
AOV using 30% discount is 79.98
AOV using 20% discount is 85.76
AOV using 10% discount is 101.36
AOV without discount is 92.37
```

Discount impacting on revenue

In [67]:
```
gold_with_discount_30 = final2[(final2['Discount_pct'] == 30.0) & (final2['Customer_segmentation'] == 'Gold')]['CustomerID'].cour
gold_with_discount_20 = final2[(final2['Discount_pct'] == 20.0) & (final2['Customer_segmentation'] == 'Gold')]['CustomerID'].cour
gold_with_discount_10 = final2[(final2['Discount_pct'] == 10.0) & (final2['Customer_segmentation'] == 'Gold')]['CustomerID'].cour
gold_with_discount_0 = final2[(final2['Discount_pct'] == 0.0) & (final2['Customer_segmentation'] == 'Gold')]['CustomerID'].count(

print(f"Gold segment customer with 30% discount: {round(gold_with_discount_30, 2)}")
print(f"Gold segment customer with 20% discount: {round(gold_with_discount_20, 2)}")
print(f"Gold segment customer with 10% discount: {round(gold_with_discount_10, 2)}")
print(f"Gold segment customer with 0% discount: {round(gold_with_discount_0, 2)}")
```

```
Gold segment customer with 30% discount: 32.95
Gold segment customer with 20% discount: 33.29
Gold segment customer with 10% discount: 32.98
Gold segment customer with 0% discount: 0.78
```

In [68]:
```
silver_with_discount_30 = final2[(final2['Discount_pct'] == 30.0) & (final2['Customer_segmentation'] == 'Silver')]['CustomerID'].
silver_with_discount_20 = final2[(final2['Discount_pct'] == 20.0) & (final2['Customer_segmentation'] == 'Silver')]['CustomerID'].
silver_with_discount_10 = final2[(final2['Discount_pct'] == 10.0) & (final2['Customer_segmentation'] == 'Silver')]['CustomerID'].
silver_with_discount_0 = final2[(final2['Discount_pct'] == 0.0) & (final2['Customer_segmentation'] == 'Silver')]['CustomerID'].cc

print(f"Silver segment with 30% discount: {round(silver_with_discount_30, 2)}")
print(f"Silver segment with 20% discount: {round(silver_with_discount_20, 2)}")
print(f"Silver segment with 10% discount: {round(silver_with_discount_10, 2)}")
print(f"Silver segment with 0% discount: {round(silver_with_discount_0, 2)}")
```

```
Silver segment with 30% discount: 31.68
Silver segment with 20% discount: 35.12
Silver segment with 10% discount: 32.47
Silver segment with 0% discount: 0.73
```

In [69]:
```
premium_with_discount_30 = final2[(final2['Discount_pct'] == 30.0) & (final2['Customer_segmentation'] == 'Premium')]['CustomerID'
premium_with_discount_20 = final2[(final2['Discount_pct'] == 20.0) & (final2['Customer_segmentation'] == 'Premium')]['CustomerID'
premium_with_discount_10 = final2[(final2['Discount_pct'] == 10.0) & (final2['Customer_segmentation'] == 'Premium')]['CustomerID'
premium_with_discount_0 = final2[(final2['Discount_pct'] == 0.0) & (final2['Customer_segmentation'] == 'Premium')]['CustomerID'].

print(f"Premium segment with 30% discount: {round(premium_with_discount_30, 2)}%")
print(f"Premium segment with 20% discount: {round(premium_with_discount_20, 2)}%")
print(f"Premium segment with 10% discount: {round(premium_with_discount_10, 2)}%")
print(f"Premium segment with 0% discount: {round(premium_with_discount_0, 2)}%")
```

```
Premium segment with 30% discount: 33.22%
Premium segment with 20% discount: 32.05%
Premium segment with 10% discount: 33.97%
Premium segment with 0% discount: 0.75%
```

In [70]:
```python
final.head()
```

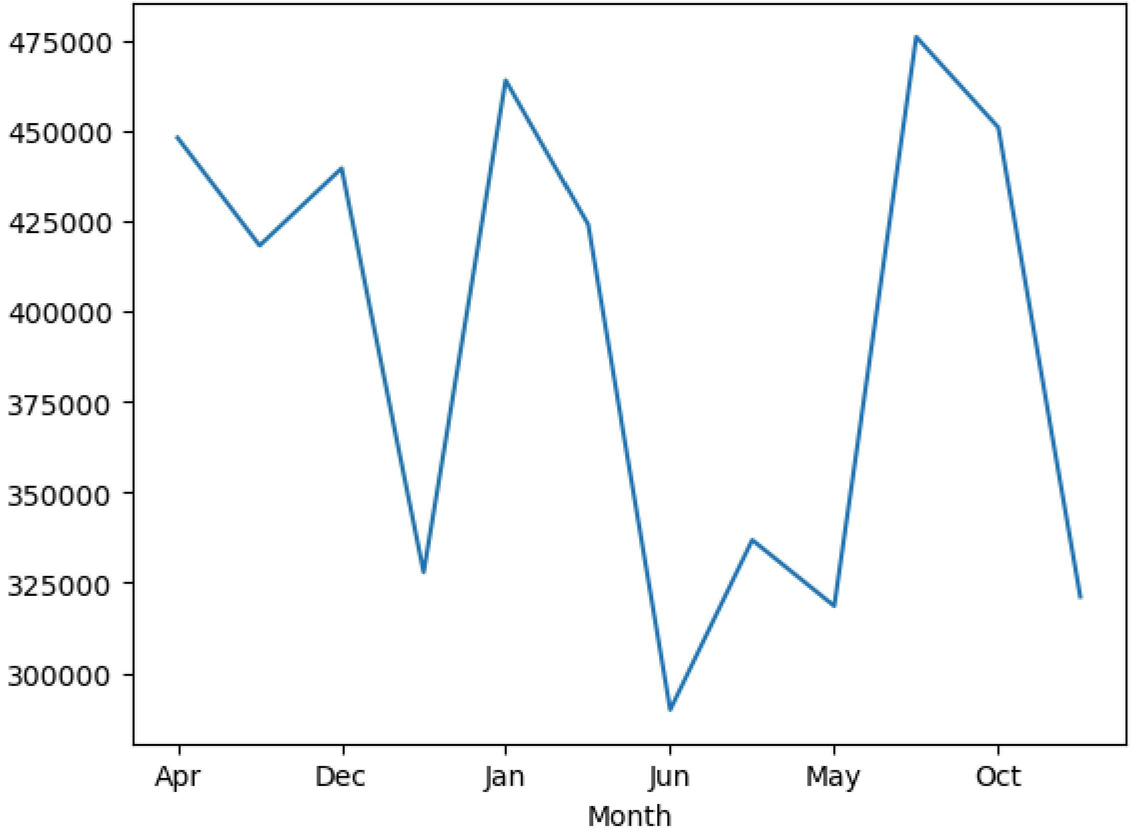
Out[70]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

Seasonality & Trends

In [71]:
```python
# month wise highest Revenue
month=final2.groupby('Month')['Invoice Value'].sum()
print(month)
month.plot()
plt.show()
```

```
Month
Apr    447998.27
Aug    418158.14
Dec    439531.46
Feb    327896.25
Jan    463881.87
Jul    423981.63
Jun    289831.04
Mar    336805.27
May    318556.12
Nov    475901.17
Oct    450838.47
Sep    321128.14
Name: Invoice Value, dtype: float64
```



In [72]:
```
# Week wise highest Revenue
final2['week']=pd.to_datetime(final2['Transaction_Date']).dt.strftime("%Y-%U")
```

```python
top_weeks=final2.groupby("week")['Invoice Value'].sum()
top_weeks.nlargest(5)
```

Out[72]:

```
week
2019-47    148842.57
2019-15    129306.23
2019-50    126055.23
2019-28    123184.03
2019-30    120746.53
Name: Invoice Value, dtype: float64
```

In [73]:

```python
# Day wise Revenue
final2['Day']=pd.to_datetime(final2['Transaction_Date']).dt.date
top_weeks=final2.groupby("Day")['Invoice Value'].sum()
top_weeks.nlargest(5)
```

Out[73]:

```
Day
2019-04-05    56753.03
2019-04-18    50158.96
2019-11-27    49267.73
2019-07-18    39867.30
2019-08-02    37138.37
Name: Invoice Value, dtype: float64
```

In [74]:

```python
final2.head()
```

Out[74]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	...
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	...
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	...
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	...
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	...
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	...

5 rows × 21 columns

key performance indicators (KPIs)

Revenue by Product Category, month,week,day

In [75]:

```
print('Top 5 Product_Category by revenue')
revenue_cat=final2.groupby('Product_Category')['Invoice Value'].sum()
print(revenue_cat.nlargest(5))
print()
print("_______________________________________________________________")

print('Top 5 Month by revenue')
revenue_month=final2.groupby('Month')['Invoice Value'].sum()
print(revenue_month.nlargest(5))
print()
print("_______________________________________________________________")
print()

print('Top 5 Week by revenue')
revenue_week=final2.groupby('week')['Invoice Value'].sum()
```

```
print(revenue_week.nlargest(5))
print()
print("_______________________________________________________________")
print()

print('Top 5 Day by revenue')
revenue_Day=final2.groupby('Day')['Invoice Value'].sum()
print(revenue_Day.nlargest(5))
print()
print("_______________________________________________________________")
print()
```

```
Top 5 Product_Category by revenue
Product_Category
Nest-USA     2351314.07
Apparel       735448.41
Nest          439979.13
Office        343998.29
Drinkware     240267.79
Name: Invoice Value, dtype: float64
```

```
Top 5 Month by revenue
Month
Nov    475901.17
Jan    463881.87
Oct    450838.47
Apr    447998.27
Dec    439531.46
Name: Invoice Value, dtype: float64
```

```
Top 5 Week by revenue
week
2019-47    148842.57
2019-15    129306.23
2019-50    126055.23
2019-28    123184.03
2019-30    120746.53
Name: Invoice Value, dtype: float64
```

```
Top 5 Day by revenue
Day
2019-04-05    56753.03
2019-04-18    50158.96
2019-11-27    49267.73
2019-07-18    39867.30
2019-08-02    37138.37
Name: Invoice Value, dtype: float64
```

Number of orders by Product Category, month,week,day

In [76]:
```
print('Top 5 Product_Category by No of Orders')
no_of_Orders_cat=final2.groupby('Product_Category')['Transaction_ID'].count()
print(no_of_Orders_cat.nlargest(5))
print()
print("_______________________________________________________________")

print('Top 5 Month by No of Orders')
no_of_Orders_month=final2.groupby('Month')['Transaction_ID'].count()
print(no_of_Orders_month.nlargest(5))
print()
print("_______________________________________________________________")
print()

print('Top 5 Week by No of Orders')
no_of_Orders_week=final2.groupby('week')['Transaction_ID'].count()
print(no_of_Orders_week.nlargest(5))
print()
print("_______________________________________________________________")
print()

print('Top 5 Day by No of Orders')
No_of_Orders_Day=final2.groupby('Day')['Transaction_ID'].count()
print(No_of_Orders_Day.nlargest(5))
print()
print("_______________________________________________________________")
print()
```

```
Top 5 Product_Category by No of Orders
Product_Category
Apparel      18126
Nest-USA     14013
Office        6513
Drinkware     3483
Lifestyle     3092
Name: Transaction_ID, dtype: int64
```

```
Top 5 Month by No of Orders
Month
Aug    6150
Jul    5251
May    4572
Dec    4502
Mar    4346
Name: Transaction_ID, dtype: int64
```

```
Top 5 Week by No of Orders
week
2019-30    1515
2019-28    1413
2019-32    1392
2019-31    1358
2019-34    1343
Name: Transaction_ID, dtype: int64
```

```
Top 5 Day by No of Orders
Day
2019-11-27    335
2019-07-13    311
2019-08-16    298
2019-08-02    292
2019-07-31    291
Name: Transaction_ID, dtype: int64
```

Aaverage order value by Product Category, month,week,day

In [77]:
```
print('Top 5 Product_Category by AOV')
avg_order_value_by_category=revenue_cat/no_of_Orders_cat
print(round(avg_order_value_by_category,2).nlargest(5))
print()
print("_______________________________________________________________")

print('Top 5 Month by AOV')
avg_order_value_by_month=revenue_month/no_of_Orders_month
print(round(avg_order_value_by_month,2).nlargest(5))
print()
print("_______________________________________________________________")
print()

print('Top 5 Week by AOV')
avg_order_value_by_week=revenue_week/no_of_Orders_week
print(round(avg_order_value_by_week,2).nlargest(5))
print()
print("_______________________________________________________________")
print()

print('Top 5 Day by AOV')
avg_order_value_by_day=revenue_Day/No_of_Orders_Day
print(round(avg_order_value_by_day,2).nlargest(5))
print()
print("_______________________________________________________________")
print()
```

```
Top 5 Product_Category by AOV
Product_Category
Nest-Canada              206.77
Nest                     200.17
Nest-USA                 167.80
Notebooks & Journals     146.02
Google                   125.42
dtype: float64
```

```
Top 5 Month by AOV
Month
Nov    120.15
Jan    114.17
Oct    108.27
Apr    107.95
Feb     99.85
dtype: float64
```

```
Top 5 Week by AOV
week
2019-47    130.45
2019-13    124.45
2019-46    123.50
2019-15    121.30
2019-41    119.90
dtype: float64
```

```
Top 5 Day by AOV
Day
2019-04-05    298.70
2019-04-18    192.18
2019-10-16    175.28
2019-07-01    174.51
2019-01-28    166.39
dtype: float64
```

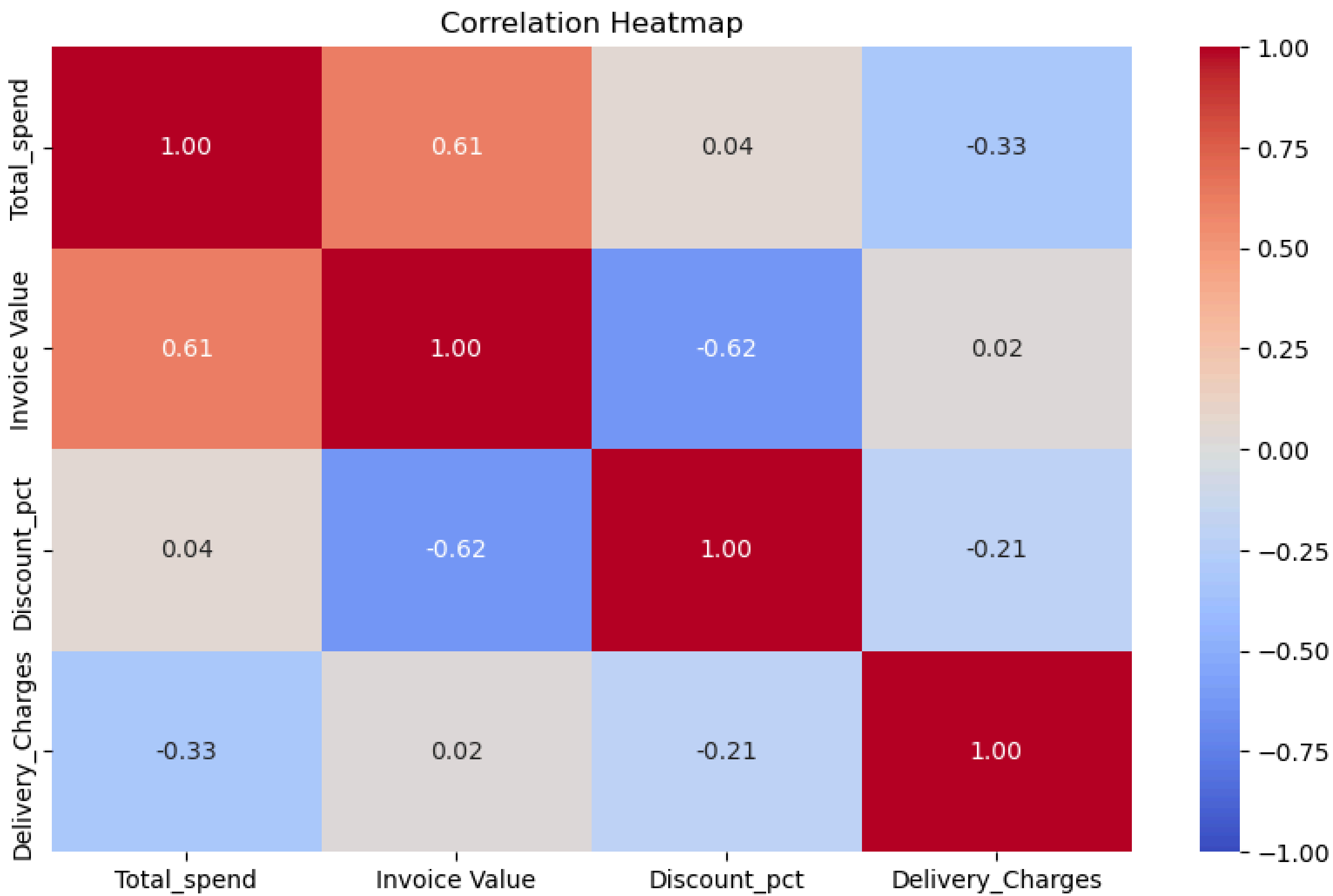
Marketing Spend & Revenue

In [78]:
```
ms['Date'] = pd.to_datetime(ms['Date'], format='%m/%d/%Y')
ms['Month']= pd.to_datetime(ms['Date']).dt.strftime("%b")
ms['Total_spend']=ms['Offline_Spend']+ms['Online_Spend']

x = ms.groupby('Month')['Total_spend'].sum().reset_index()
y = final2.groupby('Month')['Invoice Value'].sum().reset_index()
z = final2.groupby('Month')['Discount_pct'].mean().reset_index()
deli_charg = final2.groupby('Month')['Delivery_Charges'].sum().reset_index()

result = x.merge(y, on='Month', how='inner')
result = result.merge(z, on='Month', how='inner')
# result = result.merge(tax, on='Month', how='inner')
result = result.merge(deli_charg, on='Month', how='inner')

market_spend_corr=result.corr(numeric_only=True)
market_spend_corr
```

Out[78]:

	Total_spend	Invoice Value	Discount_pct	Delivery_Charges
Total_spend	1.000000	0.614748	0.044452	-0.325481
Invoice Value	0.614748	1.000000	-0.619476	0.024394
Discount_pct	0.044452	-0.619476	1.000000	-0.206736
Delivery_Charges	-0.325481	0.024394	-0.206736	1.000000

In [79]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(market_spend_corr, annot=True, cmap='coolwarm', fmt=".2f", vmin=-1, vmax=1)
plt.title('Correlation Heatmap')
plt.show()
```



In [ ]:

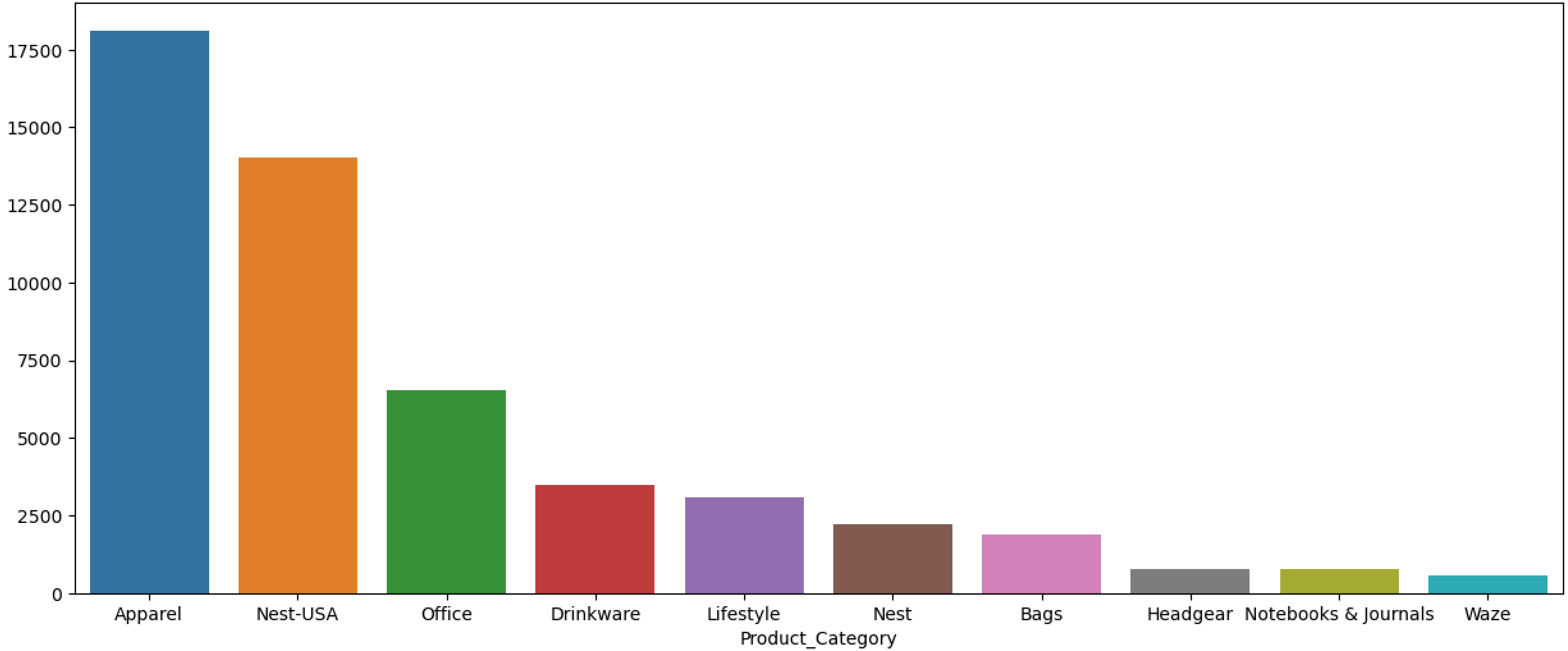
```

```

Product & Customer Relationships (Market basket analysis)

In [80]:

```
x=final2['Product_Category'].value_counts().sort_values(ascending=False)[:10]
```

In [81]:
```
plt.figure(figsize=(15,6))
sns.barplot(x=x.index,y=x.values)
plt.show()
```



By Apriori Algorithum

In [82]:
```
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
```

In [83]:
```
Basket = final2.groupby(['Transaction_ID', 'Product_Category'])['Quantity'].sum().unstack().fillna(0)
```

In [84]:
```
Basket
```

Out[84]:

Product_Category	Accessories	Android	Apparel	Backpacks	Bags	Bottles	Drinkware	Fun	Gift Cards	Google	Headgear	Housewares	Lifestyle	More Bags	N
Transaction_ID															
16679	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16680	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16681	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16682	0.0	0.0	10.0	0.0	16.0	0.0	35.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16684	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
48493	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48494	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48495	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48496	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48497	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

25061 rows × 20 columns

In [85]:

```
# Encoding
Basket[Basket > 0] = 1
Basket
```

Out[85]:

Product_Category	Accessories	Android	Apparel	Backpacks	Bags	Bottles	Drinkware	Fun	Gift Cards	Google	Headgear	Housewares	Lifestyle	More Bags	N
Transaction_ID															
16679	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16680	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16681	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16682	0.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16684	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
48493	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48494	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48495	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48496	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
48497	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

25061 rows × 20 columns

In [86]:

```
frequent_item=apriori(Basket,min_support=0.03,use_colnames=True)
rules=association_rules(frequent_item,metric='lift',min_threshold=.05)
```

```
C:\Users\CHETAN\AppData\Roaming\Python\Python311\site-packages\mlxtend\frequent_patterns\fpcommon.py:109: DeprecationWarning: DataFrames with non-bool types result in worse computationalperformance and their support might be discontinued in the future.Please use a DataFrame with bool type
  warnings.warn(
```

In [87]:

```
rules.head()
```

Out[87]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(Apparel)	(Drinkware)	0.324369	0.100714	0.045010	0.138762	1.377784	0.012342	1.044179	0.405838
1	(Drinkware)	(Apparel)	0.100714	0.324369	0.045010	0.446910	1.377784	0.012342	1.221557	0.304905
2	(Apparel)	(Lifestyle)	0.324369	0.068313	0.033079	0.101981	1.492836	0.010921	1.037491	0.488630
3	(Lifestyle)	(Apparel)	0.068313	0.324369	0.033079	0.484229	1.492836	0.010921	1.309945	0.354340
4	(Apparel)	(Office)	0.324369	0.140697	0.062128	0.191536	1.361343	0.016491	1.062884	0.392864

In [88]:

```
frequent_item['itemsets']
```

Out[88]:

```
0                (Apparel)
1                   (Bags)
2              (Drinkware)
3              (Lifestyle)
4                   (Nest)
5               (Nest-USA)
6                 (Office)
7     (Apparel, Drinkware)
8     (Apparel, Lifestyle)
9        (Apparel, Office)
10     (Office, Drinkware)
11     (Office, Lifestyle)
Name: itemsets, dtype: object
```

Customers are buying the following product categories together:

- Apparel and Drinkware
- Lifestyle and Apparel
- Apparel and Office
- Office and Drinkware
- Lifestyle and Office

Customer Lifetime Value (CLTV):

In [90]:

```
max_date=final2['Transaction_Date'].max()
df=final2.groupby('CustomerID').agg(
```

```
    {'Transaction_Date':lambda x:(max_date-x.min()).days,
     'Transaction_ID':lambda x: len(x),
     'Quantity': lambda x: x.sum(),
     'Invoice Value': lambda x: x.sum()})
df.head()
```

Out[90]:

CustomerID	Transaction_Date	Transaction_ID	Quantity	Invoice Value
12346	107	2	3	174.98
12347	282	60	342	12090.30
12348	192	23	209	1501.90
12350	17	17	21	1183.72
12356	107	36	56	1753.42

In [91]:

```
df.columns=['age','No_of_tran','Quantity','total_revenue']
df=df[df['Quantity']>0]
df.head()
```

Out[91]:

CustomerID	age	No_of_tran	Quantity	total_revenue
12346	107	2	3	174.98
12347	282	60	342	12090.30
12348	192	23	209	1501.90
12350	17	17	21	1183.72
12356	107	36	56	1753.42

In [92]:

```
df['AVO']=df['total_revenue']/df['No_of_tran']
df.head()
```

Out[92]:

	age	No_of_tran	Quantity	total_revenue	AVO
CustomerID					
12346	107	2	3	174.98	87.490000
12347	282	60	342	12090.30	201.505000
12348	192	23	209	1501.90	65.300000
12350	17	17	21	1183.72	69.630588
12356	107	36	56	1753.42	48.706111

In [93]:
```
pruchase_fre=sum(df['No_of_tran'])/len(df)
pruchase_fre
```

Out[93]: 36.05177111716621

In [94]:
```
#repeat rate
repeat_rate = round(df[df['No_of_tran'] > 1].shape[0]/df.shape[0],2)
repeat_rate
```

Out[94]: 0.96

In [95]:
```
# chrun rate
churn_rate = 1-repeat_rate
churn_rate
```

Out[95]: 0.040000000000000036

In [96]:
```
df['Profit_Margin'] = df['total_revenue']*0.1
df.head()
```

Out[96]:

	age	No_of_tran	Quantity	total_revenue	AVO	Profit_Margin
CustomerID						
12346	107	2	3	174.98	87.490000	17.498
12347	282	60	342	12090.30	201.505000	1209.030
12348	192	23	209	1501.90	65.300000	150.190
12350	17	17	21	1183.72	69.630588	118.372
12356	107	36	56	1753.42	48.706111	175.342

In [97]:

```
df['CLTV'] = round((((df['AVO']*pruchase_fre)/churn_rate)*0.10,2)
df.head()
```

Out[97]:

	age	No_of_tran	Quantity	total_revenue	AVO	Profit_Margin	CLTV
CustomerID							
12346	107	2	3	174.98	87.490000	17.498	7885.42
12347	282	60	342	12090.30	201.505000	1209.030	18161.53
12348	192	23	209	1501.90	65.300000	150.190	5885.45
12350	17	17	21	1183.72	69.630588	118.372	6275.77
12356	107	36	56	1753.42	48.706111	175.342	4389.85

In [98]:

```
cltv=df.sort_values('CLTV', ascending = False).head(10)
```

In [99]:

```
cltv
```

Out[99]:

CustomerID	age	No_of_tran	Quantity	total_revenue	AVO	Profit_Margin	CLTV
13929	109	3	157	2213.20	737.733333	221.320	66491.48
15070	346	1	103	541.15	541.150000	54.115	48773.54
13531	268	15	199	6995.54	466.369333	699.554	42033.60
15845	152	13	373	5155.75	396.596154	515.575	35744.98
15351	323	53	2160	19496.50	367.858491	1949.650	33154.88
16553	270	18	265	6307.05	350.391667	630.705	31580.60
15380	256	1	7	349.44	349.440000	34.944	31494.83
14457	20	4	106	1347.49	336.872500	134.749	30362.13
13113	271	62	2494	20767.65	334.962097	2076.765	30189.94
12935	76	27	49	9013.22	333.822963	901.322	30087.27

Cohort Analysis

In [116…

```
data=final2.copy()
```

In [117…

```
data.drop(columns=["Month2","week","Day"],inplace=True)
```

In [118…

```
import datetime as dt
def get_month(x):
    return dt.datetime(x.year, x.month,1)

data['InvoiceMonth'] = data['Transaction_Date'].apply(get_month)
data.tail()
```

Out[118]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Montl
52919	14410	48493	2019-12-31	GGOENEBB078899	Nest-USA	1	121.30	6.50	Clicked	De
52920	14410	48494	2019-12-31	GGOEGAEB091117	Apparel	1	48.92	6.50	Used	De
52921	14410	48495	2019-12-31	GGOENEBQ084699	Nest-USA	1	151.88	6.50	Used	De
52922	14600	48496	2019-12-31	GGOENEBQ079199	Nest-USA	5	80.52	6.50	Clicked	De
52923	14600	48497	2019-12-31	GGOENEBQ079099	Nest-USA	4	80.52	19.99	Clicked	De

In [119…

```
#create a column index with the minimum invoice date aka first time customer was acquired
data['Cohort Month'] =  data.groupby('CustomerID')['InvoiceMonth'].transform('min')
data.head(30)
```

Out[119]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.50	Used	Jan
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.50	Used	Jan
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.50	Used	Jan
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.50	Not Used	Jan
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.50	Used	Jan
5	17850	16682	2019-01-01	GGOEGBMJ013399	Bags	15	5.15	6.50	Used	Jan
6	17850	16682	2019-01-01	GGOEGDHC018299	Drinkware	15	3.08	6.50	Not Used	Jan
7	17850	16682	2019-01-01	GGOEGDHG014499	Drinkware	15	10.31	6.50	Clicked	Jan
8	17850	16682	2019-01-01	GGOEGDWC020199	Drinkware	5	9.27	6.50	Used	Jan
9	13047	16682	2019-01-01	GGOEGGOA017399	Office	52	0.98	6.50	Used	Jan
10	13047	16682	2019-01-01	GGOEGOFH020299	Office	31	1.99	6.50	Clicked	Jan
11	13047	16682	2019-01-01	GGOEGOXQ016399	Office	31	1.99	6.50	Clicked	Jan
12	13047	16682	2019-01-01	GGOEYAAB031816	Apparel	5	17.53	6.50	Used	Jan
13	13047	16684	2019-01-01	GGOENEBQ078999	Nest-USA	2	122.77	6.50	Clicked	Jan
14	13047	16684	2019-01-01	GGOENEBQ079199	Nest-USA	1	81.50	6.50	Used	Jan

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month
15	13047	16685	2019-01-01	GGOEGAAR010714	Apparel	1	14.02	6.50	Used	Jan
16	13047	16685	2019-01-01	GGOEGAEQ027913	Apparel	1	14.02	6.50	Clicked	Jan
17	13047	16685	2019-01-01	GGOEGDWR015799	Drinkware	1	10.72	6.50	Not Used	Jan
18	13047	16687	2019-01-01	GGOEGFQB013799	Lifestyle	1	9.27	6.50	Clicked	Jan
19	13047	16687	2019-01-01	GGOEGGOA017399	Office	3	1.02	6.50	Used	Jan
20	13047	16687	2019-01-01	GGOEGOAQ012899	Office	1	2.58	6.50	Not Used	Jan
21	13047	16687	2019-01-01	GGOEGOAR021999	Office	3	1.55	6.50	Clicked	Jan
22	13047	16687	2019-01-01	GGOEGOBG023599	Office	1	3.08	6.50	Used	Jan
23	13047	16687	2019-01-01	GGOEGOLC013299	Office	1	6.18	6.50	Clicked	Jan
24	13047	16688	2019-01-01	GGOENEBB078899	Nest-USA	1	122.77	6.50	Used	Jan
25	13047	16689	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.50	Used	Jan
26	12583	16692	2019-01-01	GGOEAFKQ020599	Office	1	2.47	102.79	Used	Jan
27	12583	16692	2019-01-01	GGOEGDHC015299	Drinkware	26	8.72	102.79	Clicked	Jan
28	12583	16692	2019-01-01	GGOEGFKQ020399	Office	1	1.64	102.79	Clicked	Jan
29	12583	16692	2019-01-01	GGOEYFKQ020699	Office	1	1.64	102.79	Clicked	Jan

In [121…

```
def get_date_elements(df, column):
    day = df[column].dt.day
    month = df[column].dt.month
    year = df[column].dt.year
    return day, month, year
```

In [122…

```
# get date elements for our cohort and invoice columns
_,Invoice_month,Invoice_year =  get_date_elements(data,'InvoiceMonth')
_,Cohort_month,Cohort_year =  get_date_elements(data,'Cohort Month')
```

In [123…

```
Cohort_year[:10]
```

Out[123]:

```
0    2019
1    2019
2    2019
3    2019
4    2019
5    2019
6    2019
7    2019
8    2019
9    2019
Name: Cohort Month, dtype: int32
```

In [124…

```
data.head()
```

Out[124]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Month	Co
0	17850	16679	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
1	17850	16680	2019-01-01	GGOENEBJ079499	Nest-USA	1	153.71	6.5	Used	Jan	
2	17850	16681	2019-01-01	GGOEGFKQ020399	Office	1	2.05	6.5	Used	Jan	
3	17850	16682	2019-01-01	GGOEGAAB010516	Apparel	5	17.53	6.5	Not Used	Jan	
4	17850	16682	2019-01-01	GGOEGBJL013999	Bags	1	16.50	6.5	Used	Jan	

In [125…

```
#create index
year_diff = Invoice_year -Cohort_year
month_diff = Invoice_month - Cohort_month
data['CohortIndex'] = year_diff*12+month_diff+1
data.tail()
```

Out[125]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Category	Quantity	Avg_Price	Delivery_Charges	Coupon_Status	Montl
52919	14410	48493	2019-12-31	GGOENEBB078899	Nest-USA	1	121.30	6.50	Clicked	De
52920	14410	48494	2019-12-31	GGOEGAEB091117	Apparel	1	48.92	6.50	Used	De
52921	14410	48495	2019-12-31	GGOENEBQ084699	Nest-USA	1	151.88	6.50	Used	De
52922	14600	48496	2019-12-31	GGOENEBQ079199	Nest-USA	5	80.52	6.50	Clicked	De
52923	14600	48497	2019-12-31	GGOENEBQ079099	Nest-USA	4	80.52	19.99	Clicked	De

5 rows × 21 columns

In [126…

```
#count the customer ID by grouping by Cohort Month  and Cohort Index
cohort_data = data.groupby(['Cohort Month','CohortIndex'])['CustomerID'].apply(pd.Series.nunique).reset_index()
cohort_data
```

Out[126]:

	Cohort Month	CohortIndex	CustomerID
0	2019-01-01	1	215
1	2019-01-01	2	13
2	2019-01-01	3	24
3	2019-01-01	4	34
4	2019-01-01	5	23
...	...	...	...
73	2019-10-01	2	6
74	2019-10-01	3	4
75	2019-11-01	1	68
76	2019-11-01	2	7
77	2019-12-01	1	106

78 rows × 3 columns

In [127…

```
# create a pivot table
cohort_table = cohort_data.pivot(index='Cohort Month', columns=['CohortIndex'],values='CustomerID')
cohort_table
```

Out[127]:

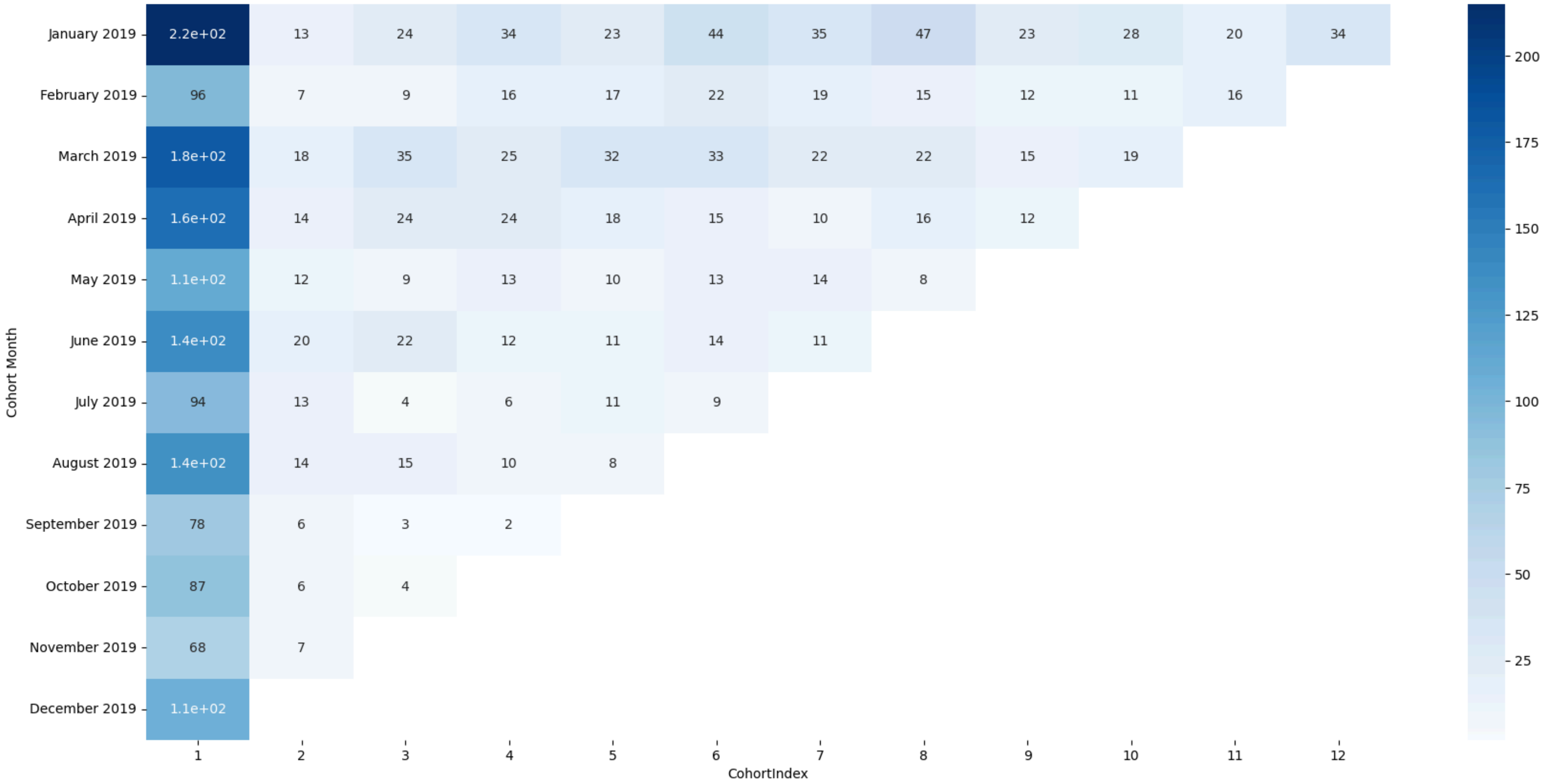
CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12
Cohort Month												
2019-01-01	215.0	13.0	24.0	34.0	23.0	44.0	35.0	47.0	23.0	28.0	20.0	34.0
2019-02-01	96.0	7.0	9.0	16.0	17.0	22.0	19.0	15.0	12.0	11.0	16.0	NaN
2019-03-01	177.0	18.0	35.0	25.0	32.0	33.0	22.0	22.0	15.0	19.0	NaN	NaN
2019-04-01	163.0	14.0	24.0	24.0	18.0	15.0	10.0	16.0	12.0	NaN	NaN	NaN
2019-05-01	112.0	12.0	9.0	13.0	10.0	13.0	14.0	8.0	NaN	NaN	NaN	NaN
2019-06-01	137.0	20.0	22.0	12.0	11.0	14.0	11.0	NaN	NaN	NaN	NaN	NaN
2019-07-01	94.0	13.0	4.0	6.0	11.0	9.0	NaN	NaN	NaN	NaN	NaN	NaN
2019-08-01	135.0	14.0	15.0	10.0	8.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-09-01	78.0	6.0	3.0	2.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-10-01	87.0	6.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-11-01	68.0	7.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-12-01	106.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [129…

```
# change index
cohort_table.index = cohort_table.index.strftime('%B %Y')
#visualize our results in heatmap
plt.figure(figsize=(21,10))
sns.heatmap(cohort_table,annot=True,cmap='Blues')
```

Out[129]:

```
<Axes: xlabel='CohortIndex', ylabel='Cohort Month'>
```



In [130…

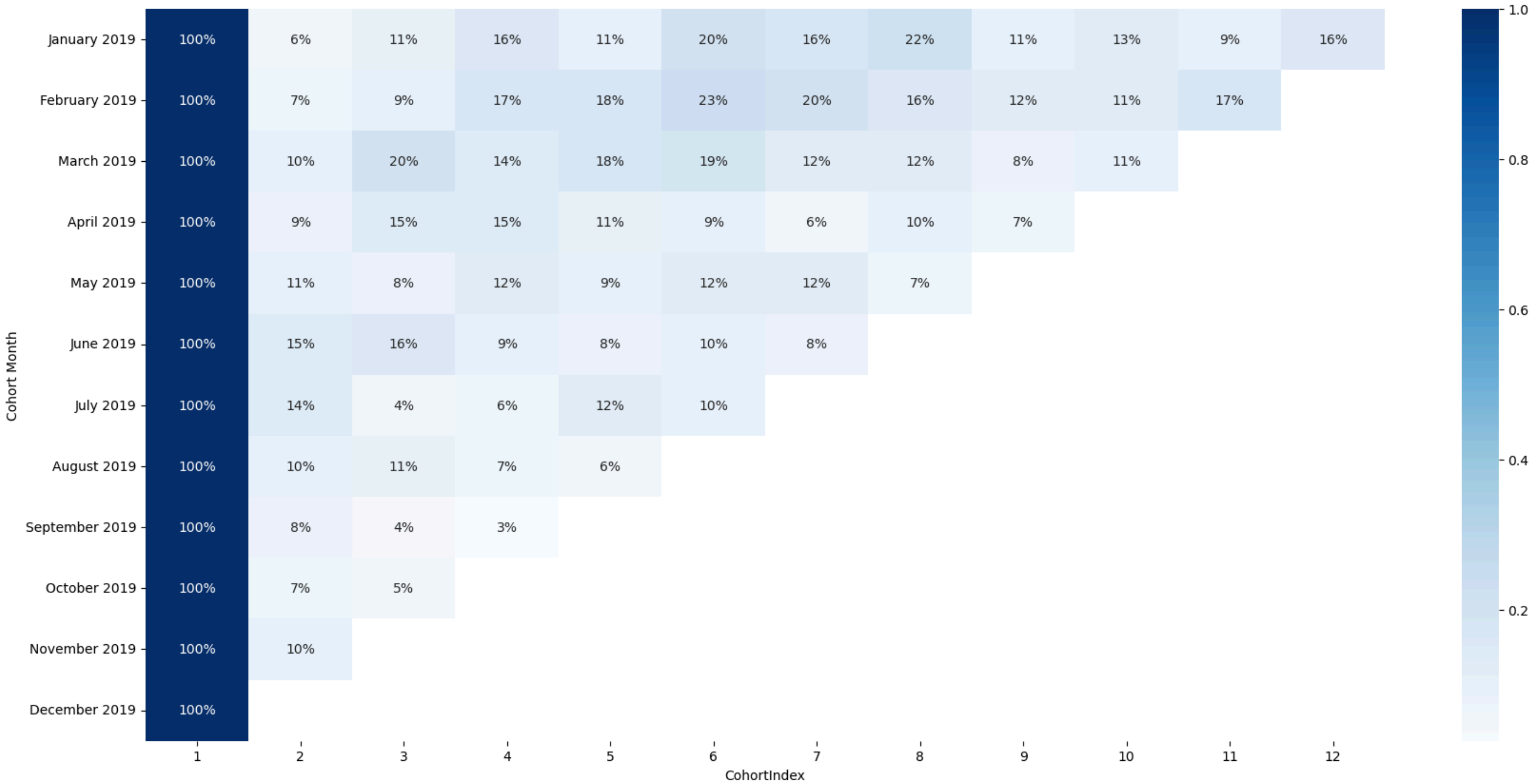
```
#cohort table for %
new_cohort_table = cohort_table.divide(cohort_table.iloc[:,0],axis=0)
new_cohort_table
```

Out[130]:

CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12
Cohort Month												
January 2019	1.0	0.060465	0.111628	0.158140	0.106977	0.204651	0.162791	0.218605	0.106977	0.130233	0.093023	0.15814
February 2019	1.0	0.072917	0.093750	0.166667	0.177083	0.229167	0.197917	0.156250	0.125000	0.114583	0.166667	NaN
March 2019	1.0	0.101695	0.197740	0.141243	0.180791	0.186441	0.124294	0.124294	0.084746	0.107345	NaN	NaN
April 2019	1.0	0.085890	0.147239	0.147239	0.110429	0.092025	0.061350	0.098160	0.073620	NaN	NaN	NaN
May 2019	1.0	0.107143	0.080357	0.116071	0.089286	0.116071	0.125000	0.071429	NaN	NaN	NaN	NaN
June 2019	1.0	0.145985	0.160584	0.087591	0.080292	0.102190	0.080292	NaN	NaN	NaN	NaN	NaN
July 2019	1.0	0.138298	0.042553	0.063830	0.117021	0.095745	NaN	NaN	NaN	NaN	NaN	NaN
August 2019	1.0	0.103704	0.111111	0.074074	0.059259	NaN	NaN	NaN	NaN	NaN	NaN	NaN
September 2019	1.0	0.076923	0.038462	0.025641	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
October 2019	1.0	0.068966	0.045977	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
November 2019	1.0	0.102941	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
December 2019	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [134…

```
#final chart
plt.figure(figsize=(21,10))
sns.heatmap(new_cohort_table,annot=True,fmt='.0%',cmap='Blues')
plt.show()
```



Insights

- Among the categories, Apparel (34%) and Nest-USA (24%) contributed to the most sales.
- A majority (66%) of customers preferred one particular quantity.
- Coupon usage was recorded at 34%.
- August saw the highest sales compared to other months.
- The most popular coupon was 'sale20' used at 33.69%.
- Females made up a larger portion of the customers than males.

- Chicago and California had the most sales compared to other locations.
- The product GGOEGGOA017399 has the highest number of purchases
- The retention rate is high in July, August, and September
- The majority of offline spending is between 2500 and 3500.
- Most of the online spending is between 1258 and 435.

Recommendations:

1. Focus Marketing on Top Categories:

- Since Apparel and Nest-USA contribute significantly to sales, prioritize marketing efforts and promotions for these categories.
- Consider special campaigns or exclusive deals to boost their sales further.

2. Geographic Focus on Chicago and California:

- With Chicago and California leading in sales, allocate more resources to these regions.
- This could include targeted advertising, pop-up stores, or special events to further engage customers in these locations.

3. Retention Strategies for Key Months:

- With high retention rates in July, August, and September, implement loyalty programs, special offers, or exclusive content during these months to maintain and increase retention.
- Encourage repeat purchases by providing incentives for returning customers.

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