churn_analysis

March 14, 2025

E-commerce Data Analysis</h1

Project Description

In this project, we will analyze customer behavior and satisfaction based on the provided dataset. The goal of our research is to identify key factors influencing customer retention and satisfaction, as well as to offer recommendations for improving the service.

Research Questions

Churn Analysis

What are the key factors influencing customer churn? How does customer tenure affect the probability of churn? How do churn levels vary depending on the PreferredLoginDevice?

Customer Segmentation

What customer segments can be identified based on CityTier, Gender, and MaritalStatus? How do preferred order categories (PreferedOrderCat) differ across customer segments?

Conversion Analysis

Which PreferredPaymentModes are more successful in driving conversions? How does HourSpendOnApp influence the conversion rate? Is there a relationship between NumberOfDeviceRegistered and the conversion level?

Customer Satisfaction Analysis

Which factors drive high SatisfactionScore among customers? How are complaints (Complain) linked to customer satisfaction levels? Is there a difference in SatisfactionScore across Gender?

Complaint Analysis

What factors most often lead to customer complaints? How does DaySinceLastOrder impact the likelihood of a complaint? How does OrderAmountHikeFromLastYear correlate with the number of complaints?

User Behavior Analysis

How does the NumberOfDeviceRegistered influence user behavior? How does user behavior change with varying distances between WarehouseToHome? How does customer churn vary with the NumberOfAddress added by the user?

Order Growth Analysis

What factors contribute to order growth? How does the use of CouponUsed impact the number of orders? Is there a relationship between CashbackAmount and order growth?

Returns and Cashback Analysis

What factors influence the number of returns and cashback requests? How does CashbackAmount distribution vary across customer segments? Is there a link between CouponUsed and the number of returns?

Description of Variables in the Dataset

[8]:
```python
from IPython.display import Image
Image("churn_analysis_variables.jpg")
```

[8]:

Data	Variable	Discerption
E Comm	CustomerID	Unique customer ID
E Comm	Churn	Churn Flag
E Comm	Tenure	Tenure of customer in organization
E Comm	PreferredLoginDevice	Preferred login device of customer
E Comm	CityTier	City tier
E Comm	WarehouseToHome	Distance in between warehouse to home of customer
E Comm	PreferredPaymentMode	Preferred payment method of customer
E Comm	Gender	Gender of customer
E Comm	HourSpendOnApp	Number of hours spend on mobile application or website
E Comm	NumberOfDeviceRegistered	Total number of deceives is registered on particular customer
E Comm	PreferedOrderCat	Preferred order category of customer in last month
E Comm	SatisfactionScore	Satisfactory score of customer on service
E Comm	MaritalStatus	Marital status of customer
E Comm	NumberOfAddress	Total number of added added on particular customer
E Comm	Complain	Any complaint has been raised in last month
E Comm	OrderAmountHikeFromlastYear	Percentage increases in order from last year
E Comm	CouponUsed	Total number of coupon has been used in last month
E Comm	OrderCount	Total number of orders has been places in last month
E Comm	DaySinceLastOrder	Day Since last order by customer
E Comm	CashbackAmount	Average cashback in last month

[10]:
```python
import numpy as np
import pandas as pd
import scipy as sp
import matplotlib.pyplot as plt
from matplotlib.patches import Patch
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import classification_report, roc_auc_score, r2_score,␣
↪mean_squared_error
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
```

Data Preparation

[12]:
```python
df = pd.read_csv("E Commerce Dataset - E Comm.csv")
```

[13]:
```python
df
```

[13]:
```
      CustomerID  Churn  Tenure PreferredLoginDevice  CityTier  \
0          50001      1     4.0         Mobile Phone         3
```

```
1       50002    1    NaN           Phone      1
2       50003    1    NaN           Phone      1
3       50004    1    0.0           Phone      3
4       50005    1    0.0           Phone      1
…       …    …   …             …     …
5625    55626    0   10.0        Computer      1
5626    55627    0   13.0    Mobile Phone      1
5627    55628    0    1.0    Mobile Phone      1
5628    55629    0   23.0        Computer      3
5629    55630    0    8.0    Mobile Phone      1

      WarehouseToHome PreferredPaymentMode  Gender  HourSpendOnApp  \
0                 6.0           Debit Card  Female             3.0
1                 8.0                  UPI    Male             3.0
2                30.0           Debit Card    Male             2.0
3                15.0           Debit Card    Male             2.0
4                12.0                   CC    Male             NaN
…                 …                  …     …             …
5625             30.0          Credit Card    Male             3.0
5626             13.0          Credit Card    Male             3.0
5627             11.0           Debit Card    Male             3.0
5628              9.0          Credit Card    Male             4.0
5629             15.0          Credit Card    Male             3.0

      NumberOfDeviceRegistered    PreferedOrderCat  SatisfactionScore  \
0                            3  Laptop & Accessory                  2
1                            4              Mobile                  3
2                            4              Mobile                  3
3                            4  Laptop & Accessory                  5
4                            3              Mobile                  5
…                          …                  …                 …
5625                         2  Laptop & Accessory                  1
5626                         5             Fashion                  5
5627                         2  Laptop & Accessory                  4
5628                         5  Laptop & Accessory                  4
5629                         2  Laptop & Accessory                  3

     MaritalStatus  NumberOfAddress  Complain  OrderAmountHikeFromlastYear  \
0           Single                9         1                         11.0
1           Single                7         1                         15.0
2           Single                6         1                         14.0
3           Single                8         0                         23.0
4           Single                3         0                         11.0
…              …              …       …                          …
5625       Married                6         0                         18.0
5626       Married                6         0                         16.0
5627       Married                3         1                         21.0
```

```
5628       Married             4        0                          15.0
5629       Married             4        0                          13.0

      CouponUsed  OrderCount  DaySinceLastOrder  CashbackAmount
0            1.0         1.0                5.0             160
1            0.0         1.0                0.0             121
2            0.0         1.0                3.0             120
3            0.0         1.0                3.0             134
4            1.0         1.0                3.0             130
…          …         …                …              …
5625         1.0         2.0                4.0             151
5626         1.0         2.0                NaN             225
5627         1.0         2.0                4.0             186
5628         2.0         2.0                9.0             179
5629         2.0         2.0                3.0             169

[5630 rows x 20 columns]
```

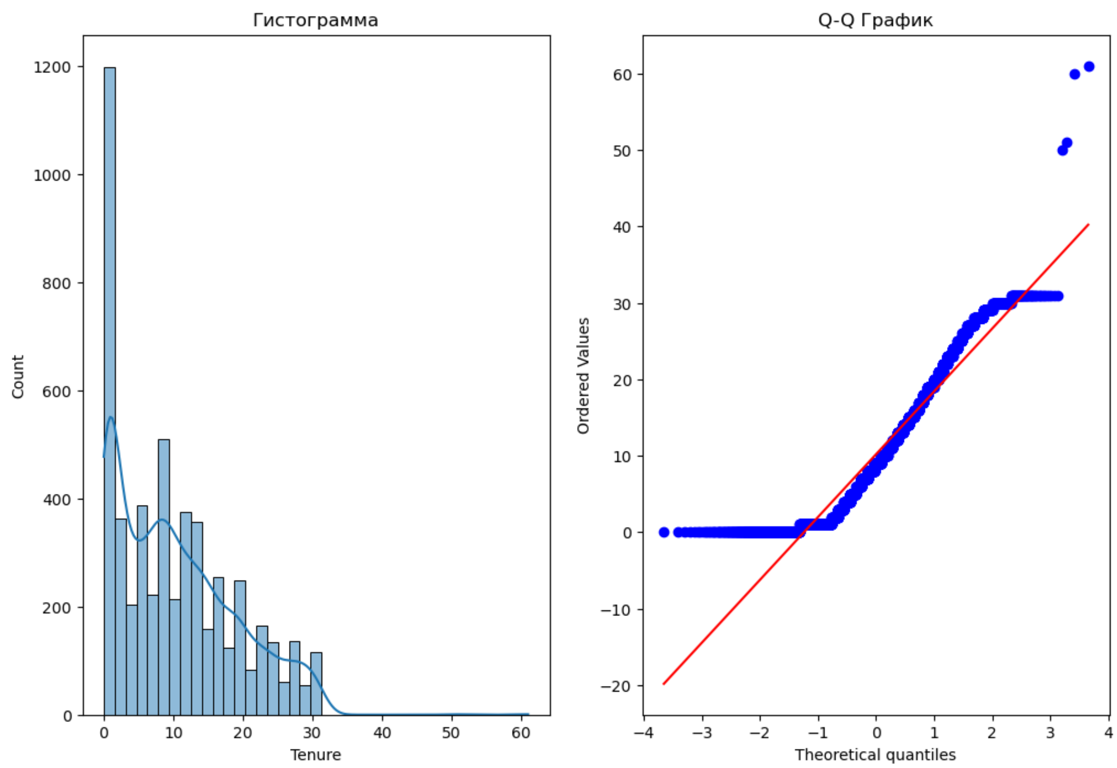
[14]:
```
missing_values = df.isna().sum()
```

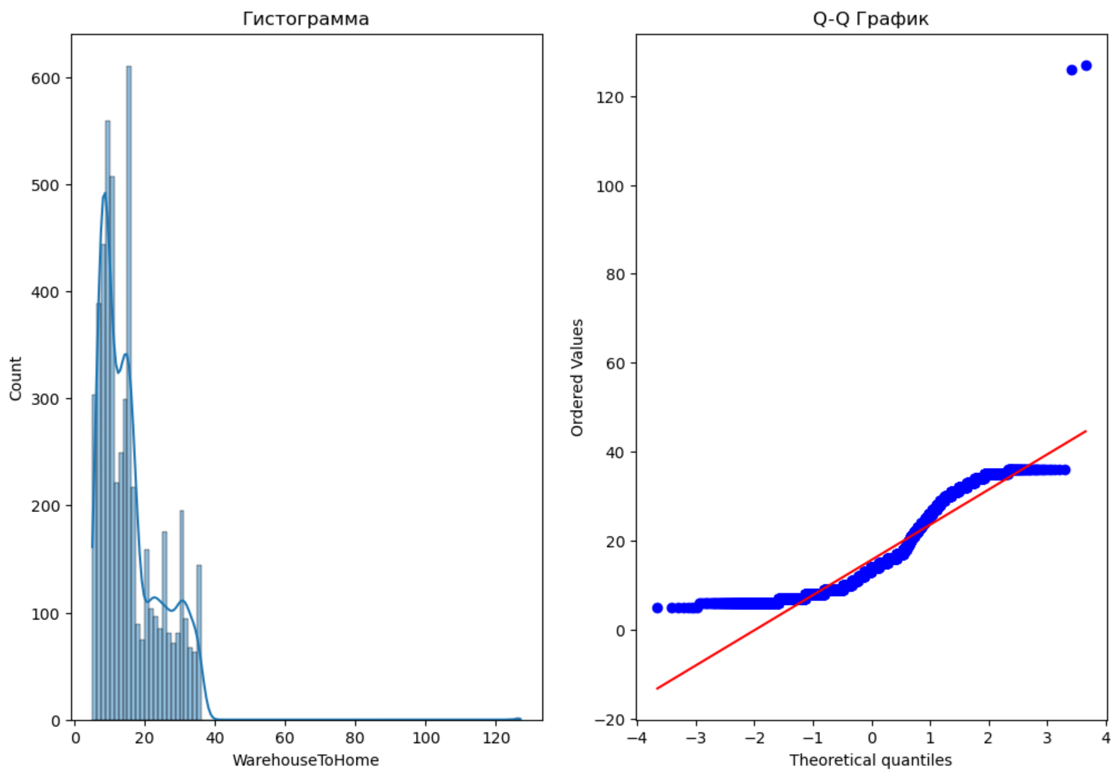
[19]:
```
missing_values
```

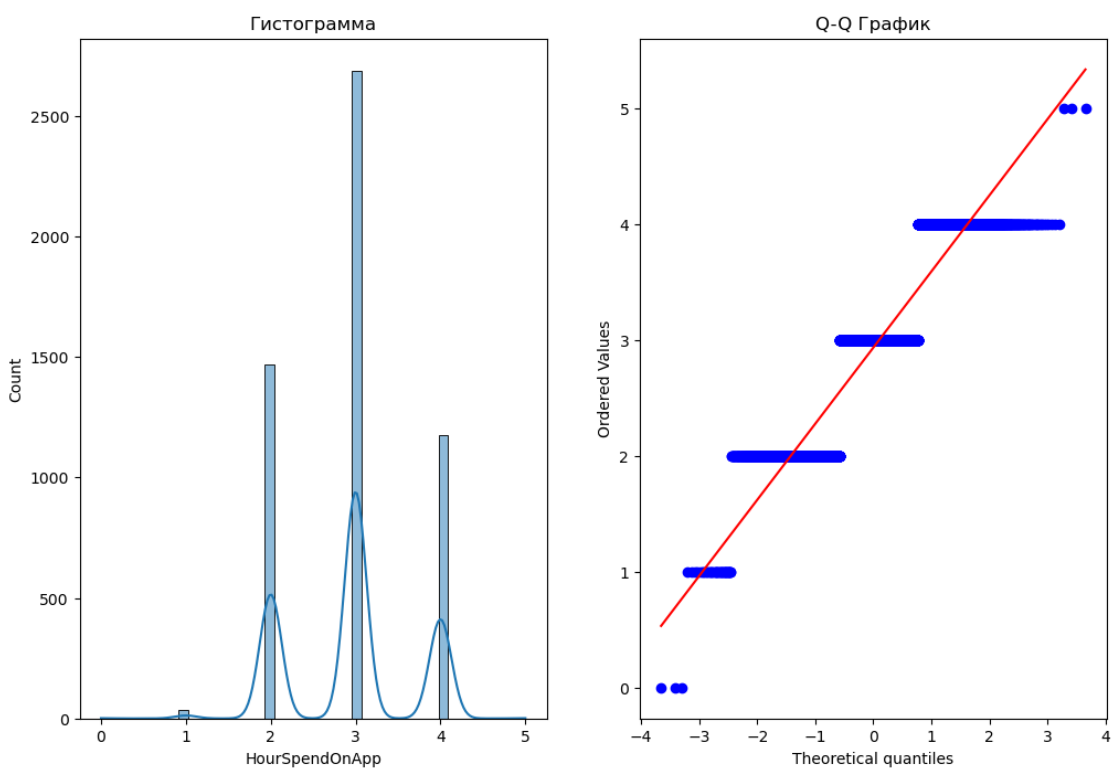
[19]:
```
CustomerID                       0
Churn                            0
Tenure                         264
PreferredLoginDevice             0
CityTier                         0
WarehouseToHome                251
PreferredPaymentMode             0
Gender                           0
HourSpendOnApp                 255
NumberOfDeviceRegistered         0
PreferedOrderCat                 0
SatisfactionScore                0
MaritalStatus                    0
NumberOfAddress                  0
Complain                         0
OrderAmountHikeFromlastYear    265
CouponUsed                     256
OrderCount                     258
DaySinceLastOrder              307
CashbackAmount                   0
dtype: int64
```

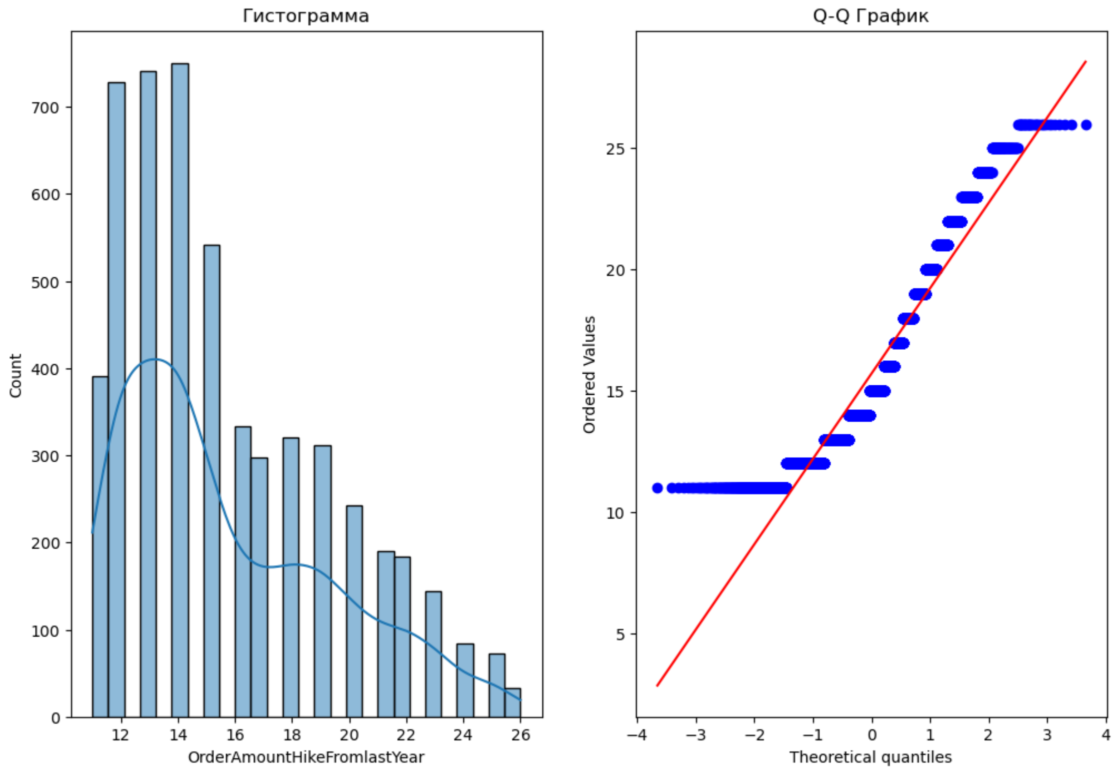
Several variables contain null values. We'll fix this. First, let's check the data for normal distribution.

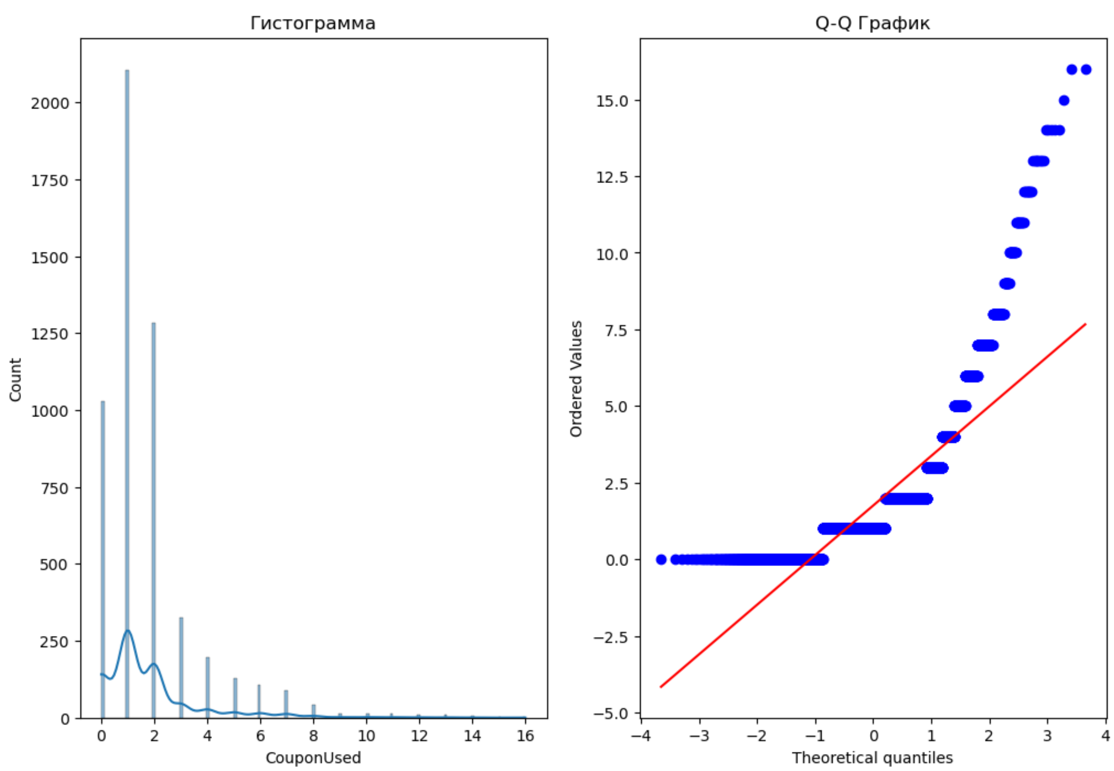
[22]:
```
columns = ['Tenure', 'WarehouseToHome', 'HourSpendOnApp',␣
↪'OrderAmountHikeFromlastYear', 'CouponUsed', 'OrderCount',␣
↪'DaySinceLastOrder']

for column in columns:
    plt.figure(figsize=(12, 8))
    plt.subplot(1, 2, 1)
    sns.histplot(df[column].dropna(), kde=True)
    plt.title('         ')

    plt.subplot(1, 2, 2)
    sp.stats.probplot(df[column].dropna(), dist="norm", plot=plt)
    plt.title('Q-Q     ')

    plt.show()
```

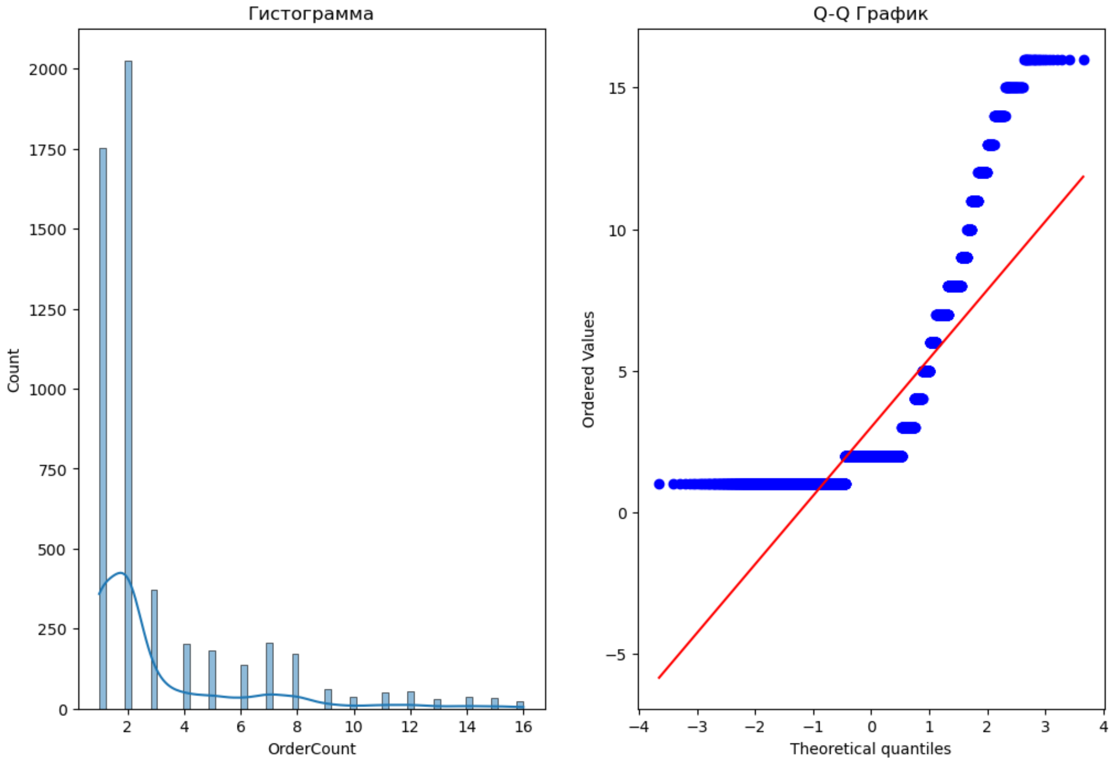



Гистограмма
Count
WarehouseToHome
Q-Q График
Ordered Values
Theoretical quantiles

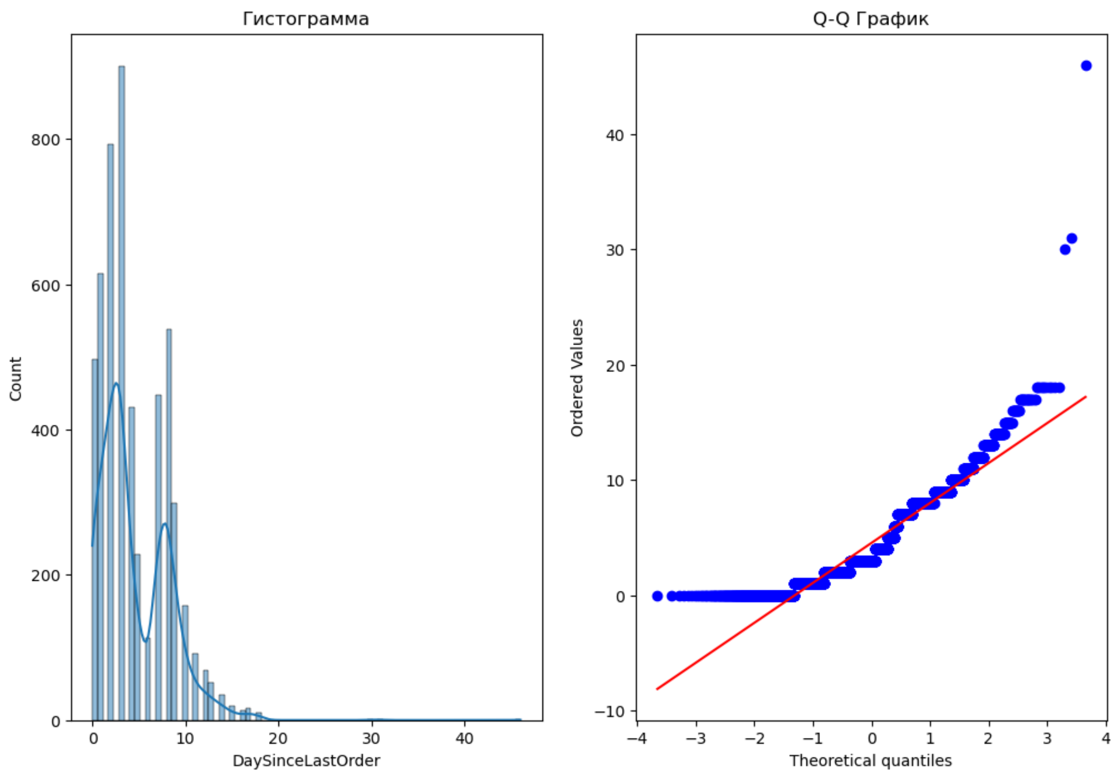

Гистограмма
Count
HourSpendOnApp
Q-Q График
Ordered Values
Theoretical quantiles


Гистограмма
Count
OrderAmountHikeFromlastYear
Q-Q График
Ordered Values
Theoretical quantiles


Гистограмма
Count
CouponUsed
Q-Q График
Ordered Values
Theoretical quantiles



Гистограмма
Count
OrderCount
2000
1750
1500
1250
1000
750
500
250
0
2
4
6
8
10
12
14
16
Q-Q График
Ordered Values
Theoretical quantiles
15
10
5
0
−5
−4
−3
−2
−1
0
1
2
3
4



The distribution is not normal and the data contains outliers, so we decide to replace the missing values with the median.

[24]:
```
for column in columns:
    df[column].fillna(df[column].median(), inplace=True)
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2621601603.py:2:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df[column].fillna(df[column].median(), inplace=True)
```

[25]:
```
df.isna().sum()
```

[25]:
```
CustomerID                     0
Churn                          0
Tenure                         0
PreferredLoginDevice           0
CityTier                       0
WarehouseToHome                0
PreferredPaymentMode           0
Gender                         0
HourSpendOnApp                 0
NumberOfDeviceRegistered       0
PreferedOrderCat               0
SatisfactionScore              0
MaritalStatus                  0
NumberOfAddress                0
Complain                       0
OrderAmountHikeFromlastYear    0
CouponUsed                     0
OrderCount                     0
DaySinceLastOrder              0
CashbackAmount                 0
dtype: int64
```

[26]:
```
df.duplicated().sum()
```

[26]:
```
0
```

The issue with missing values has been resolved. There are no duplicates or errors. Outliers are not anomalies. The data is now cleaned and prepared.

Preliminary Analysis

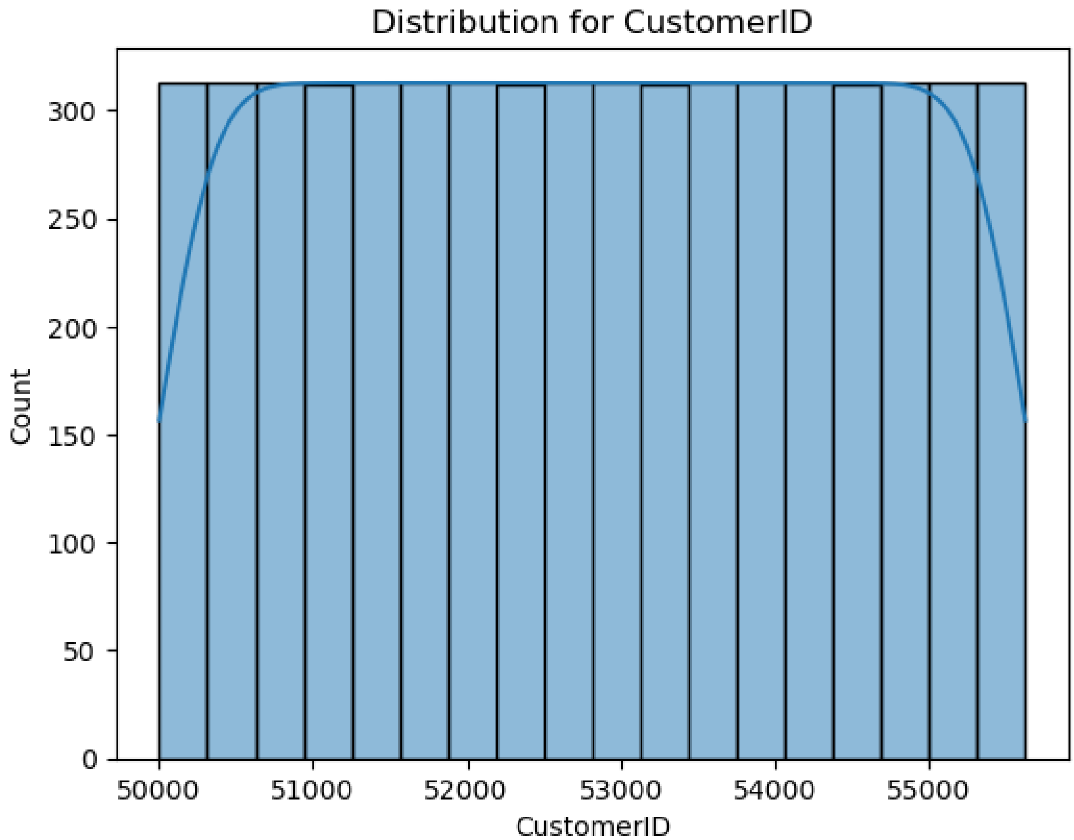
[29]:
```
df.describe()
```

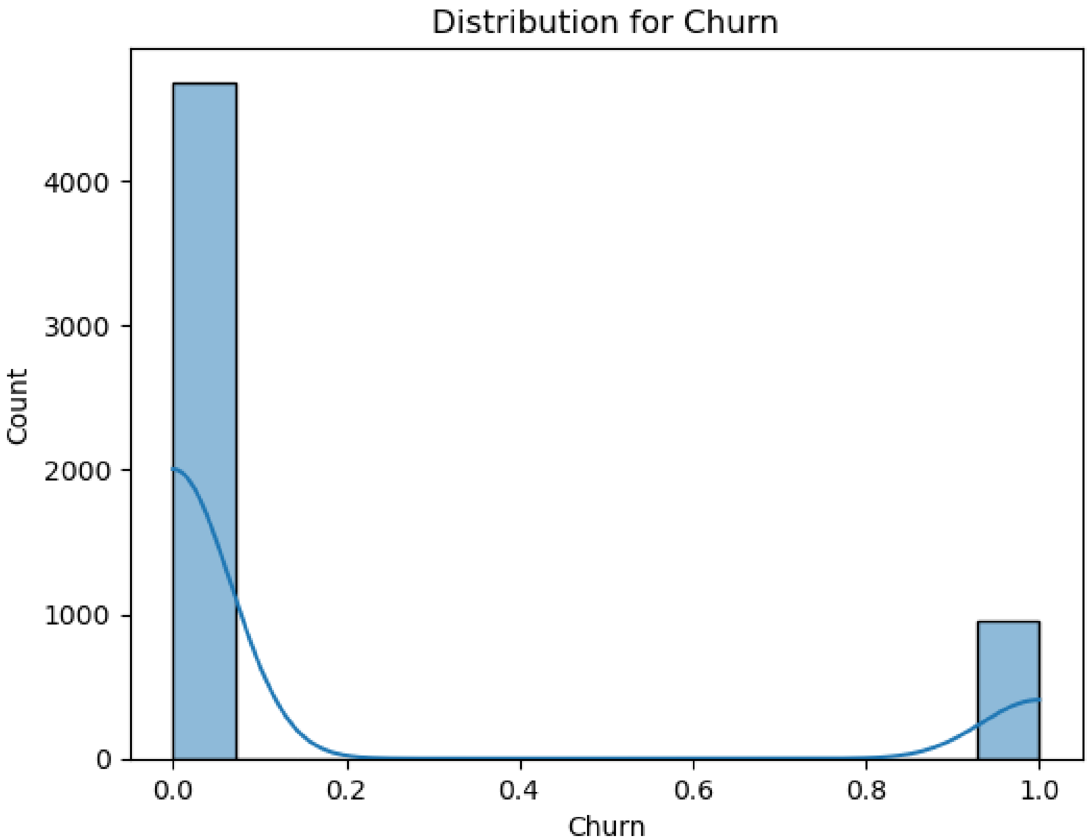
[29]:
```
         CustomerID        Churn       Tenure     CityTier  WarehouseToHome  \
count   5630.000000  5630.000000  5630.000000  5630.000000      5630.000000
mean   52815.500000     0.168384    10.134103     1.654707        15.566785
std     1625.385339     0.374240     8.357951     0.915389         8.345961
min    50001.000000     0.000000     0.000000     1.000000         5.000000
25%    51408.250000     0.000000     3.000000     1.000000         9.000000
50%    52815.500000     0.000000     9.000000     1.000000        14.000000
75%    54222.750000     0.000000    15.000000     3.000000        20.000000
max    55630.000000     1.000000    61.000000     3.000000       127.000000

       HourSpendOnApp  NumberOfDeviceRegistered  SatisfactionScore  \
count     5630.000000               5630.000000        5630.000000
mean         2.934636                  3.688988           3.066785
std          0.705528                  1.023999           1.380194
min          0.000000                  1.000000           1.000000
```

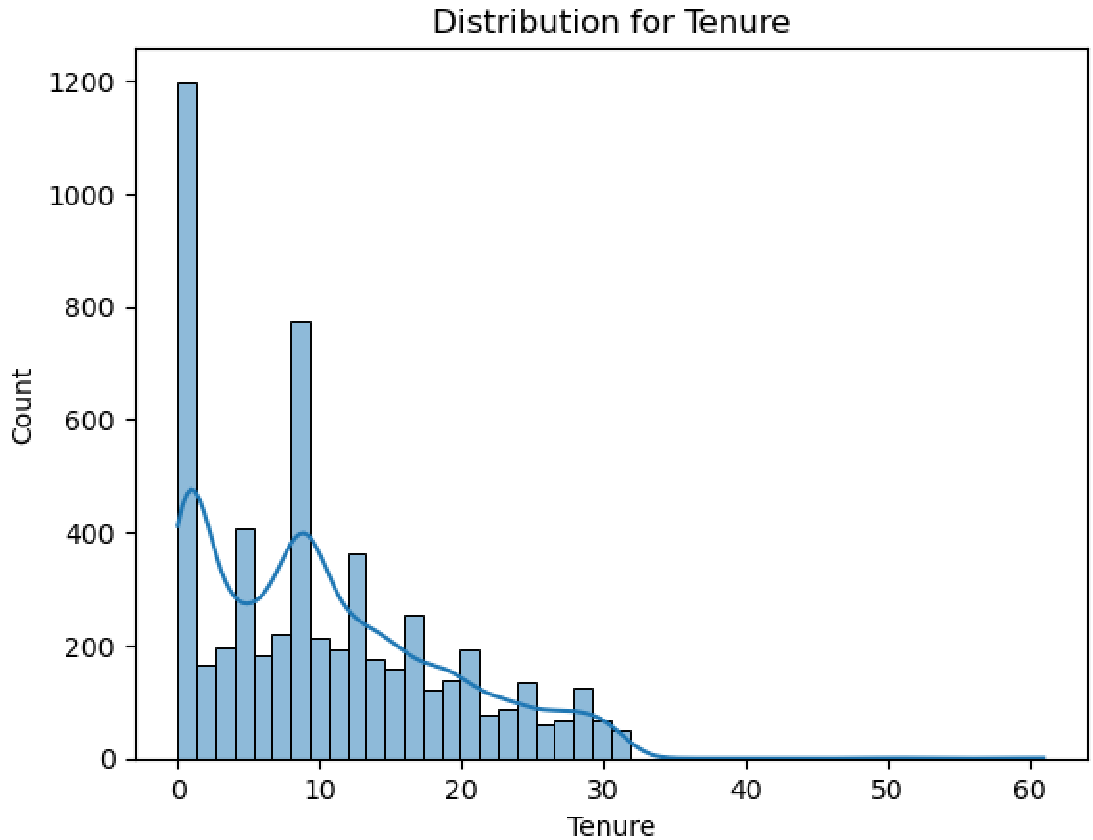
```
25%          2.000000                       3.000000            2.000000
50%          3.000000                       4.000000            3.000000
75%          3.000000                       4.000000            4.000000
max          5.000000                       6.000000            5.000000

       NumberOfAddress     Complain  OrderAmountHikeFromlastYear   CouponUsed  \
count      5630.000000  5630.000000                  5630.000000  5630.000000
mean          4.214032     0.284902                    15.674600     1.716874
std           2.583586     0.451408                     3.591058     1.857640
min           1.000000     0.000000                    11.000000     0.000000
25%           2.000000     0.000000                    13.000000     1.000000
50%           3.000000     0.000000                    15.000000     1.000000
75%           6.000000     1.000000                    18.000000     2.000000
max          22.000000     1.000000                    26.000000    16.000000

        OrderCount  DaySinceLastOrder  CashbackAmount
count  5630.000000        5630.000000     5630.000000
mean      2.961812           4.459325      177.221492
std       2.879248           3.570626       49.193869
min       1.000000           0.000000        0.000000
25%       1.000000           2.000000      146.000000
50%       2.000000           3.000000      163.000000
75%       3.000000           7.000000      196.000000
max      16.000000          46.000000      325.000000
```

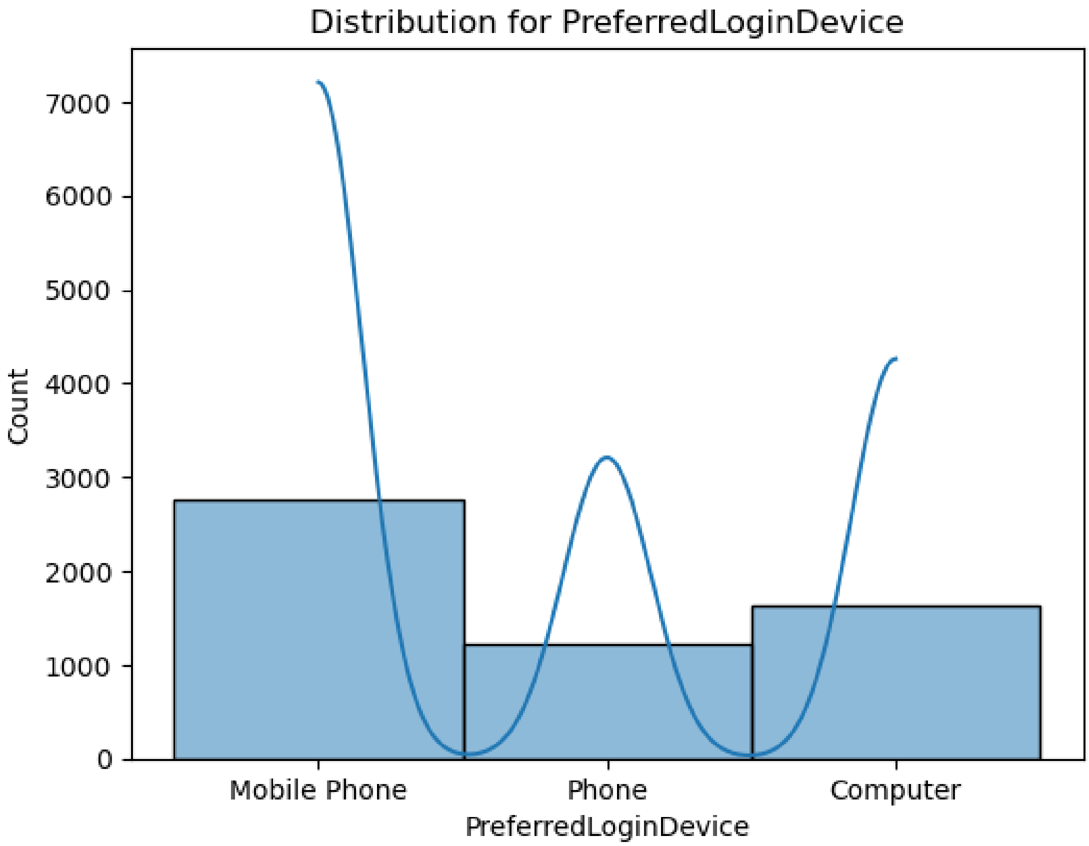
[30]:

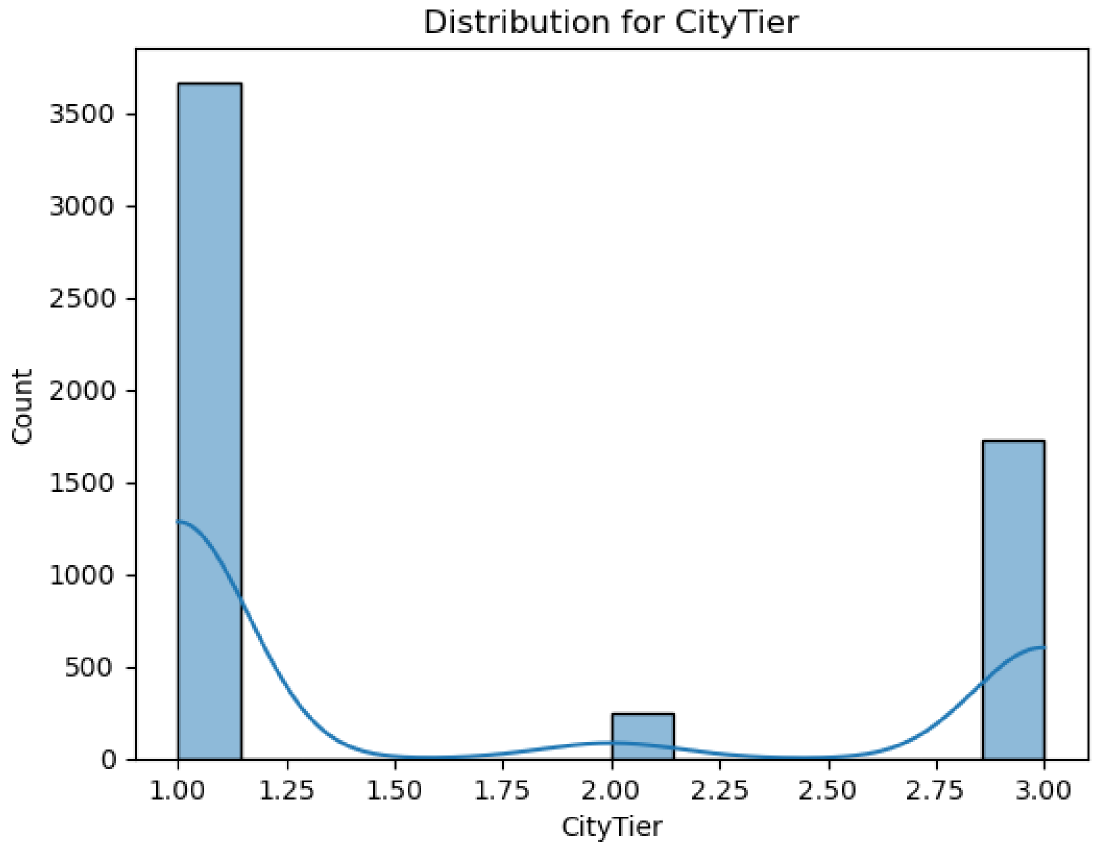
```
for column in df.columns:
    sns.histplot(df[column].dropna(), kde=True)
    plt.title(f'Distribution for {column}')
    plt.show()
```

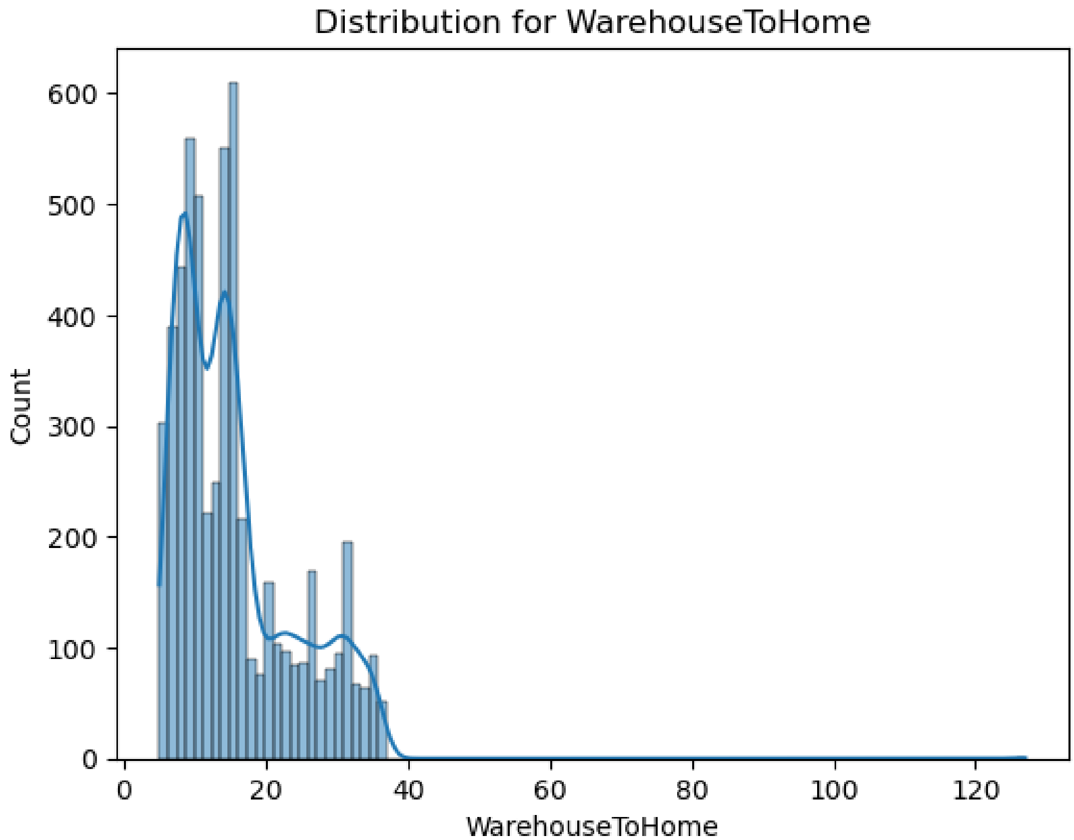

Distribution for CustomerID
300
250
200
150
100
50
0
Count
50000
51000
52000
53000
54000
55000
CustomerID

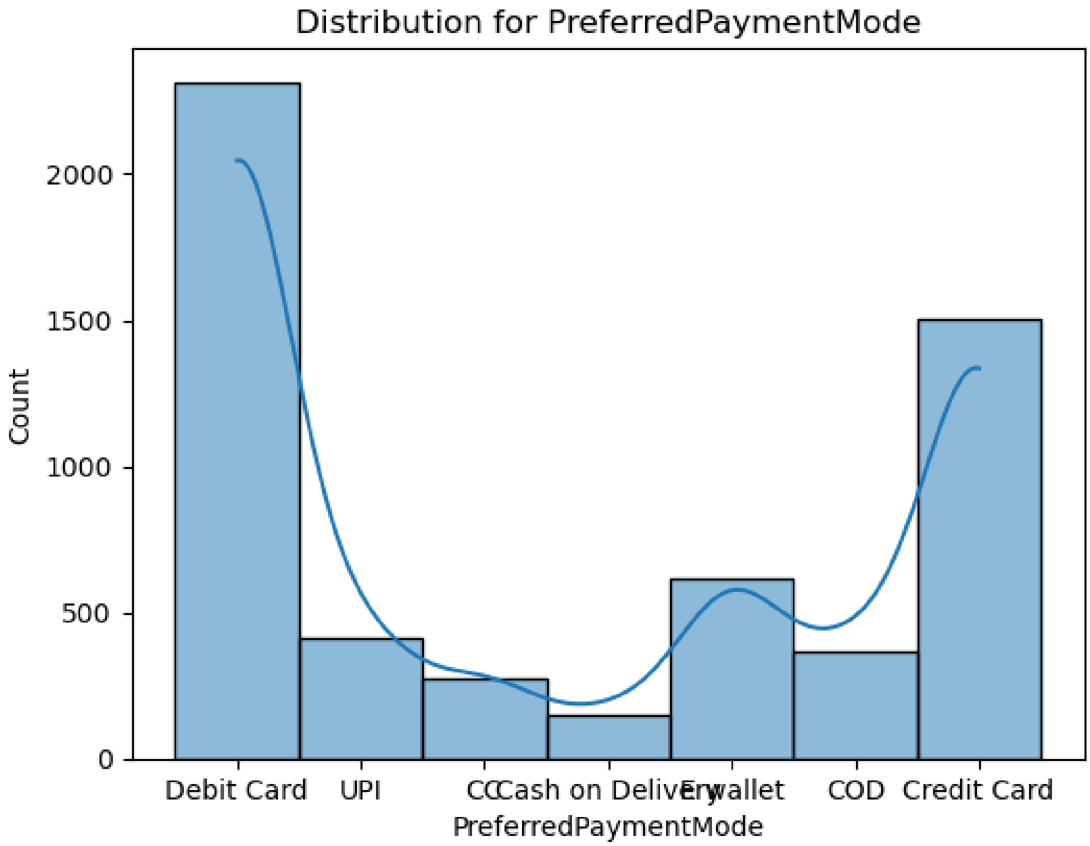

Distribution for Churn
4000
3000
2000
1000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
Churn

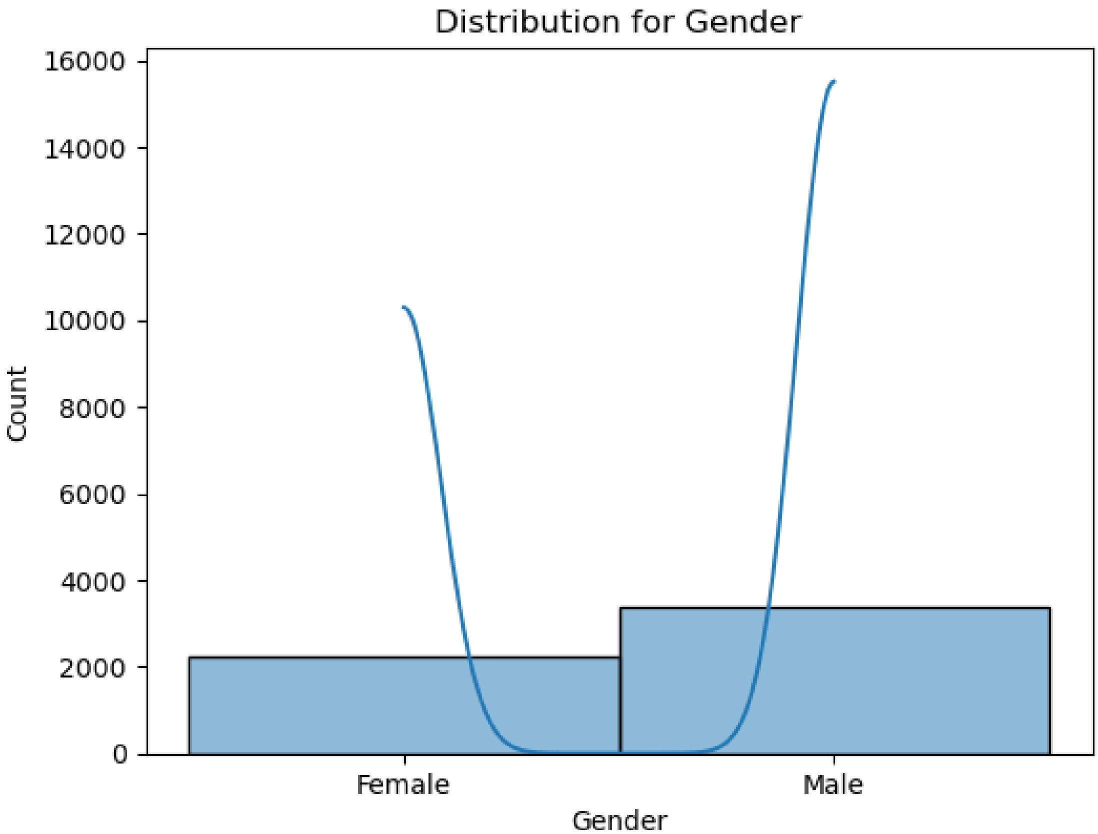

Distribution for Tenure
Count
Tenure
0
200
400
600
800
1000
1200
0
10
20
30
40
50
60

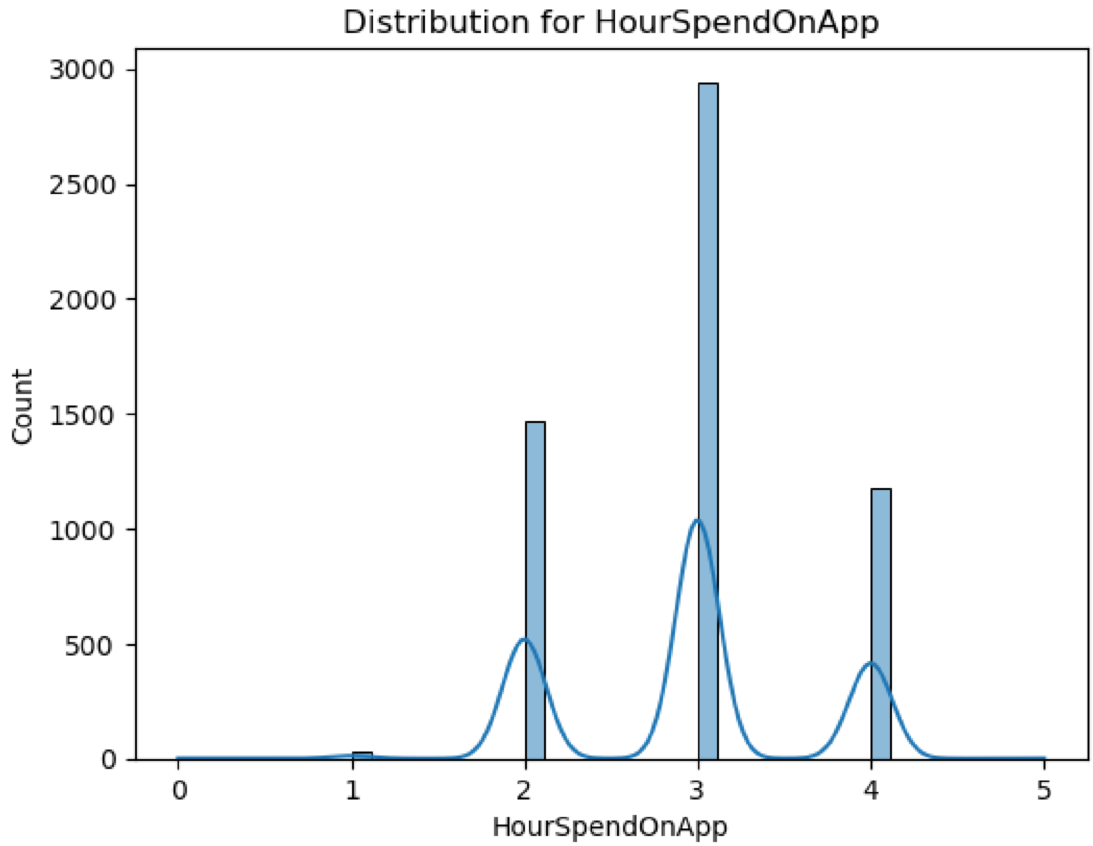

Distribution for PreferredLoginDevice
Count
0
1000
2000
3000
4000
5000
6000
7000
Mobile Phone
Phone
Computer
PreferredLoginDevice

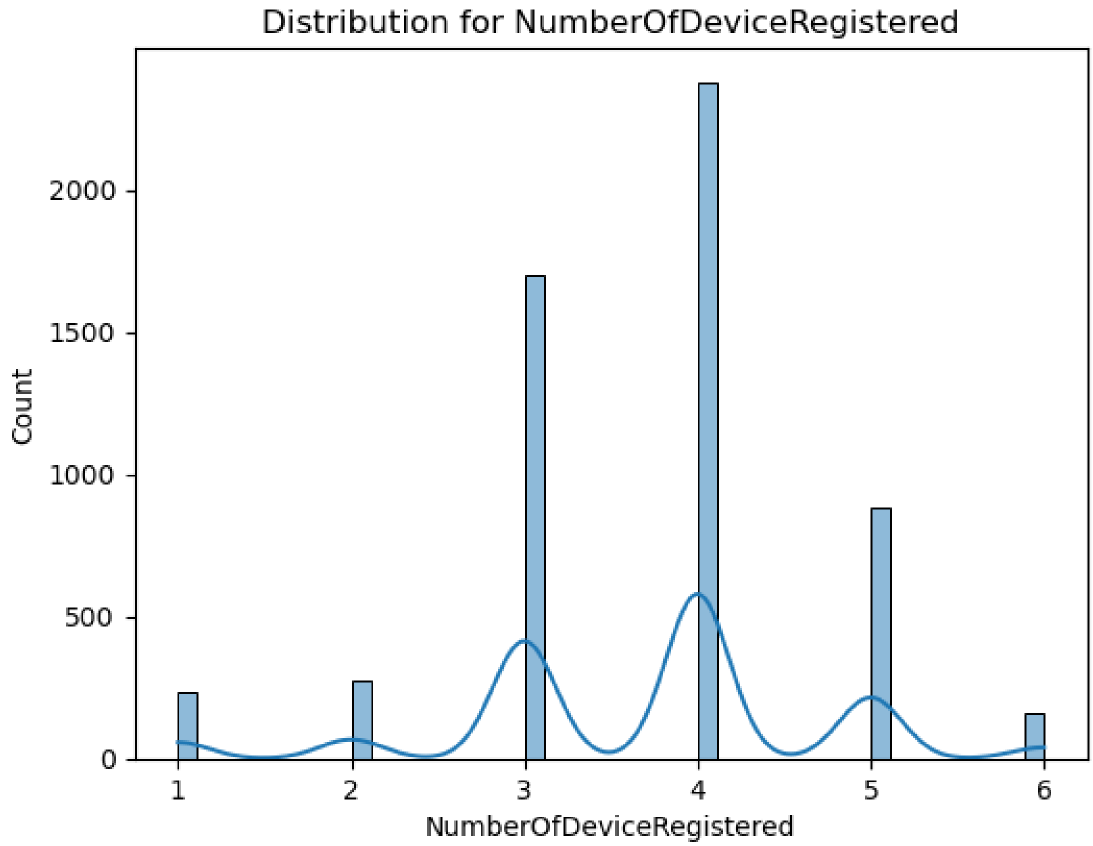

Distribution for CityTier
Count
CityTier
0
500
1000
1500
2000
2500
3000
3500
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00

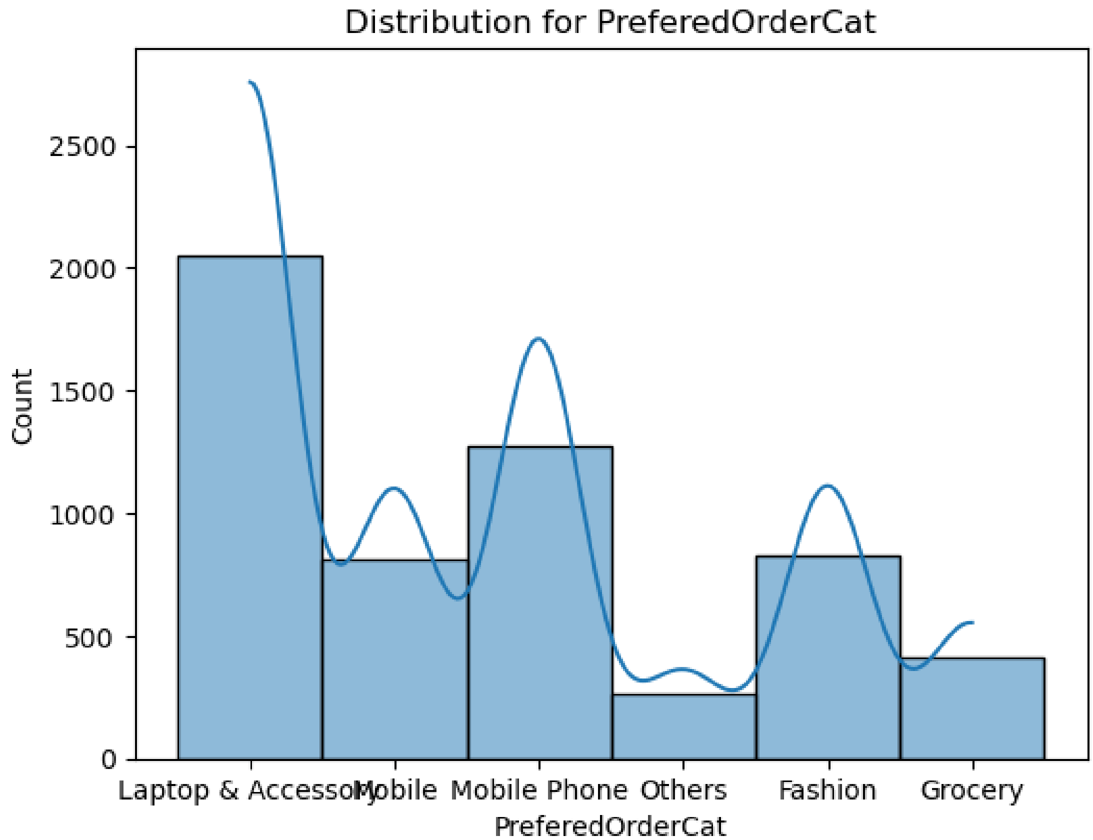

Distribution for WarehouseToHome
Count
WarehouseToHome
0
100
200
300
400
500
600
0
20
40
60
80
100
120

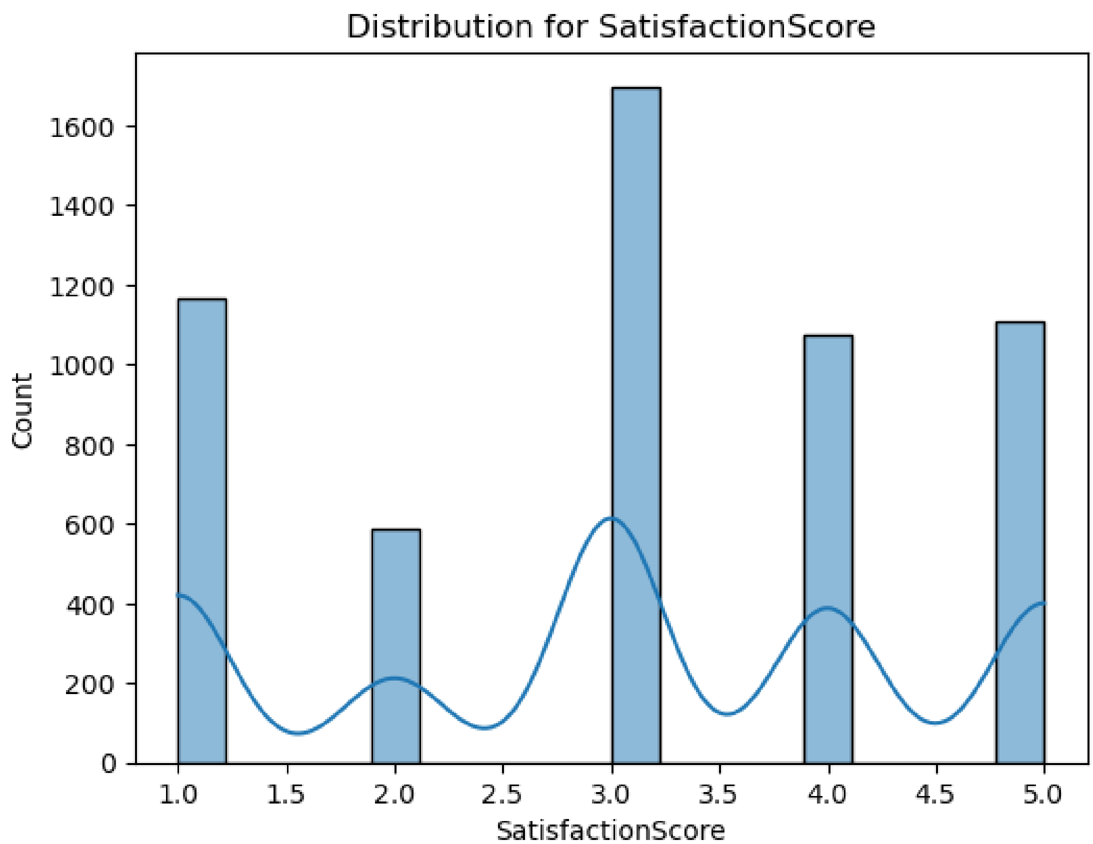

Distribution for PreferredPaymentMode
Count
2000
1500
1000
500
0
Debit Card
UPI
CC
Cash on Delivery
E wallet
COD
Credit Card
PreferredPaymentMode

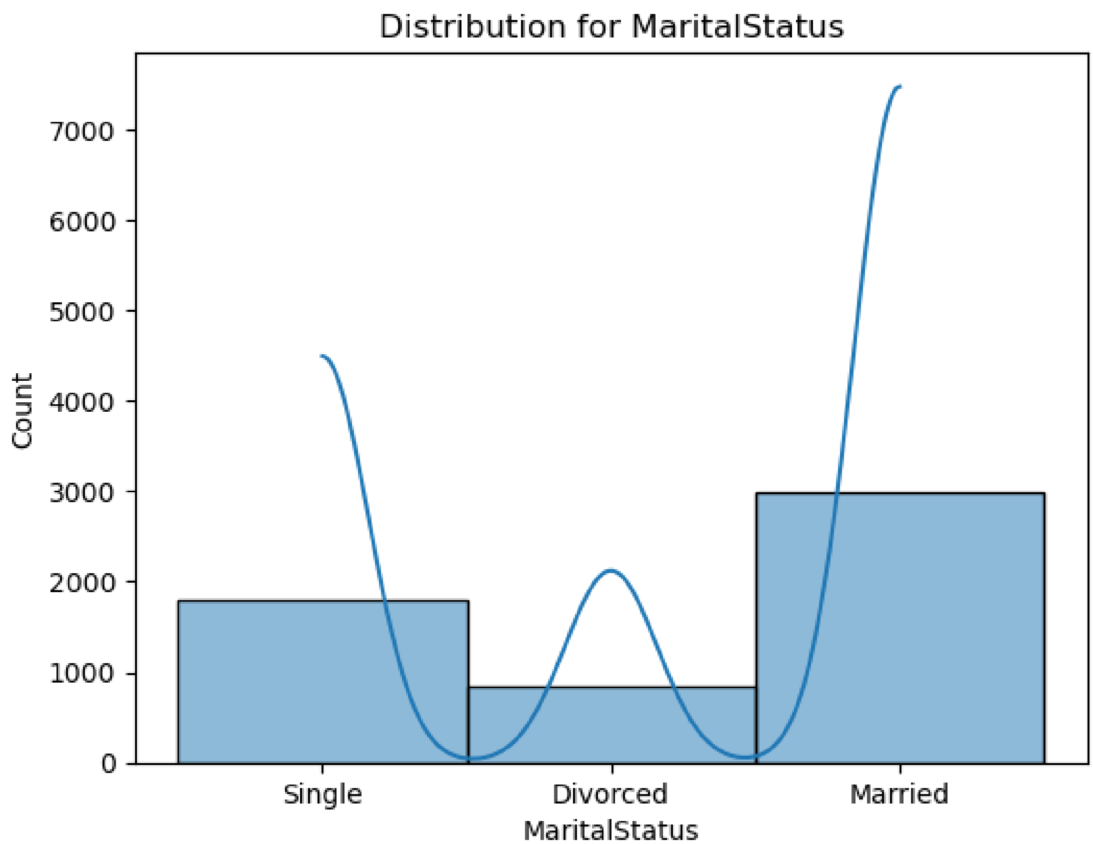

Distribution for Gender
16000
14000
12000
10000
8000
6000
4000
2000
0
Count
Female
Male
Gender

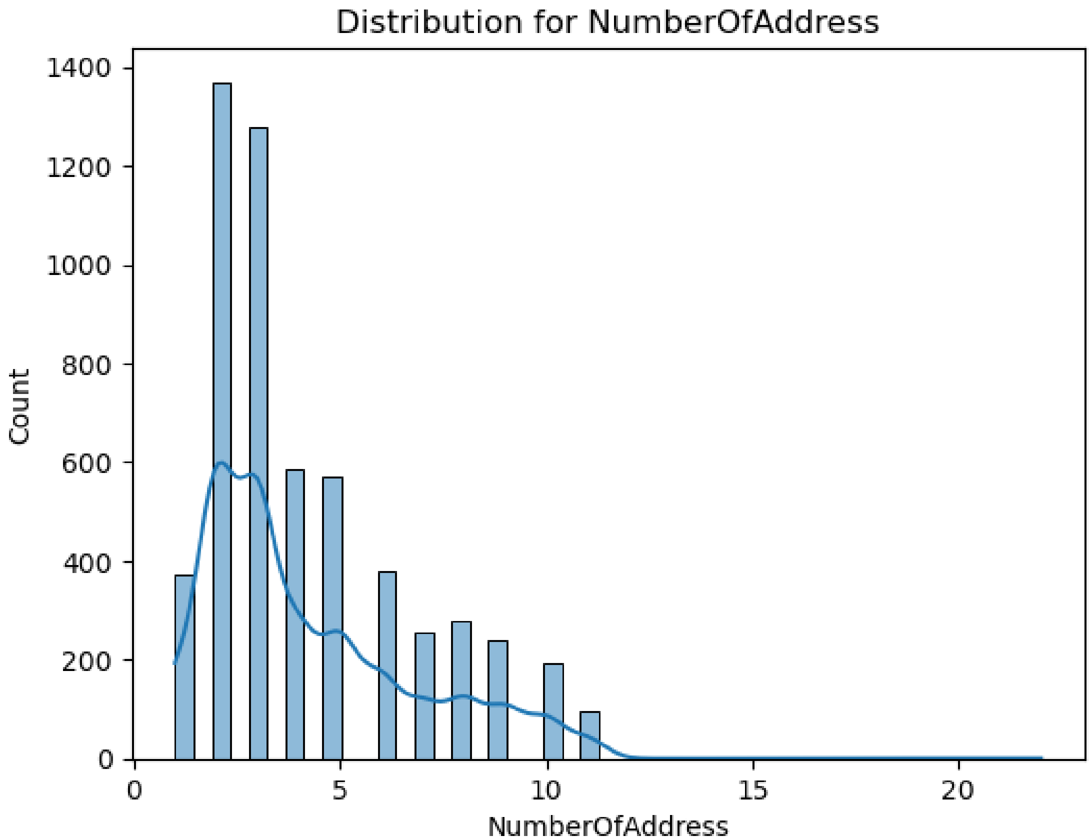

Distribution for HourSpendOnApp
Count
3000
2500
2000
1500
1000
500
0
0
1
2
3
4
5
HourSpendOnApp

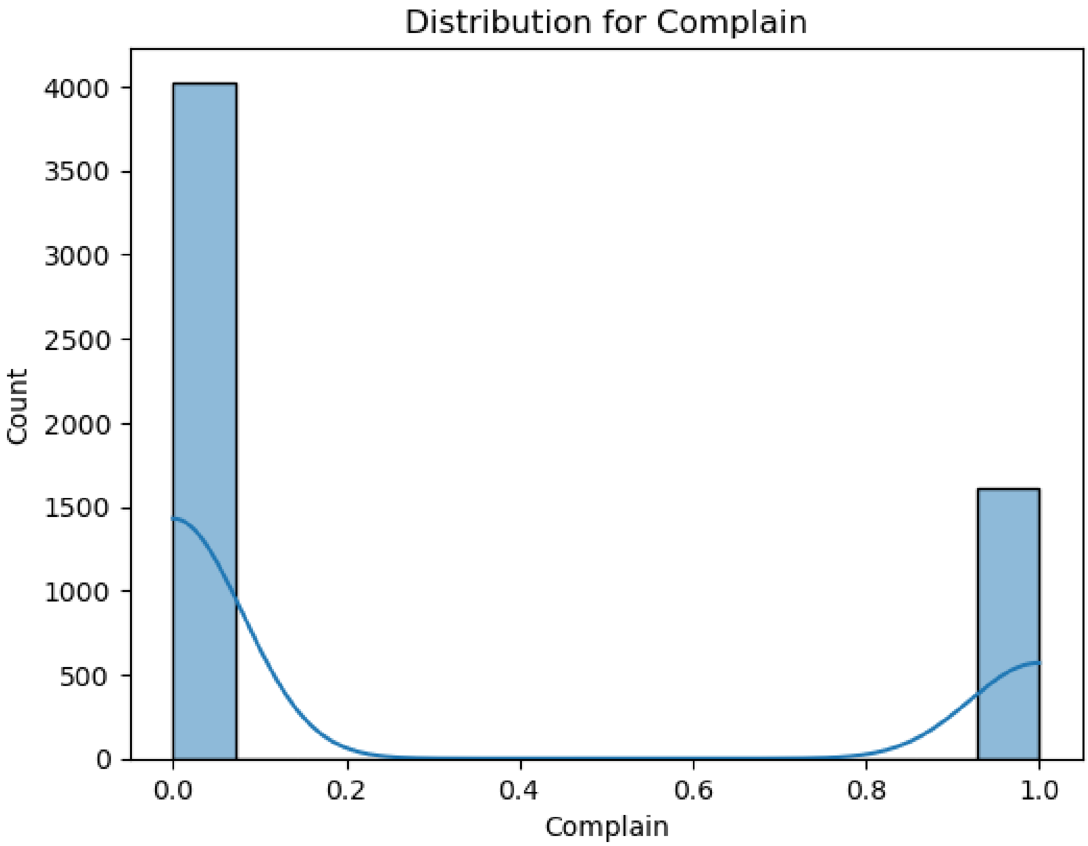

Distribution for NumberOfDeviceRegistered
Count
2000
1500
1000
500
0
1
2
3
4
5
6
NumberOfDeviceRegistered

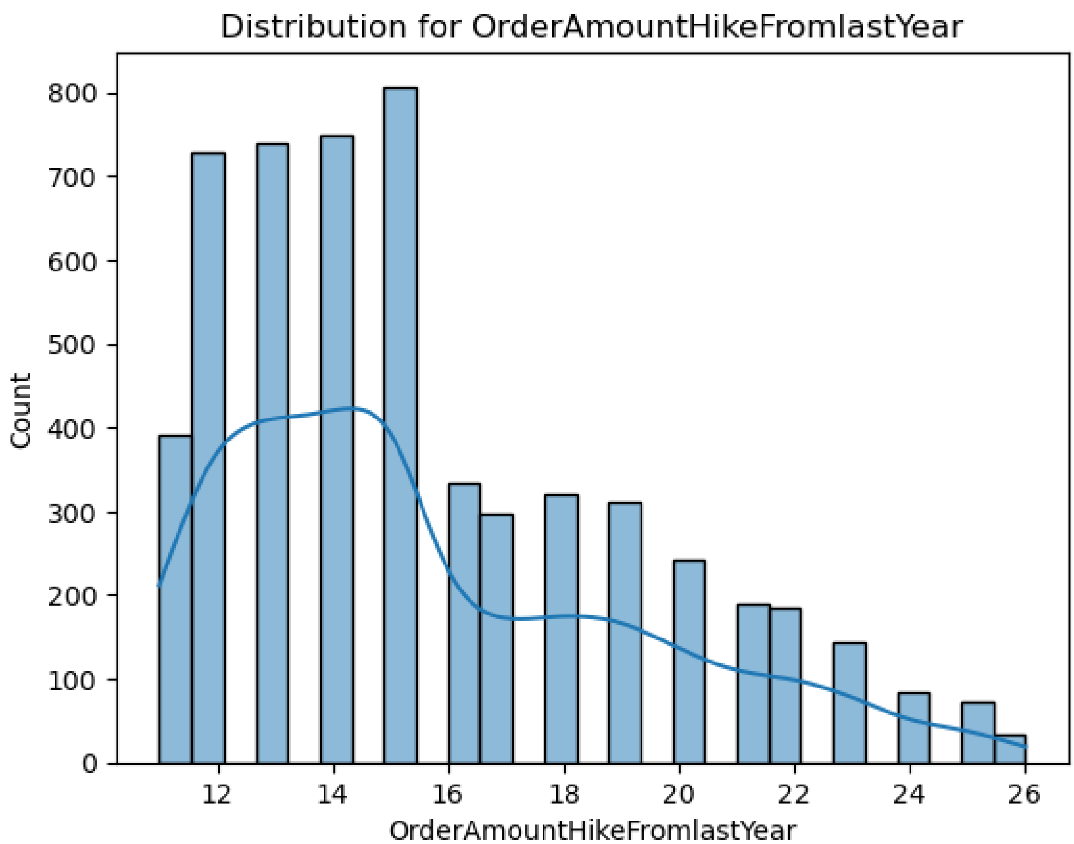

Distribution for PreferedOrderCat
2500
2000
1500
1000
500
0
Count
Laptop & Accessory
Mobile
Mobile Phone
Others
Fashion
Grocery
PreferedOrderCat

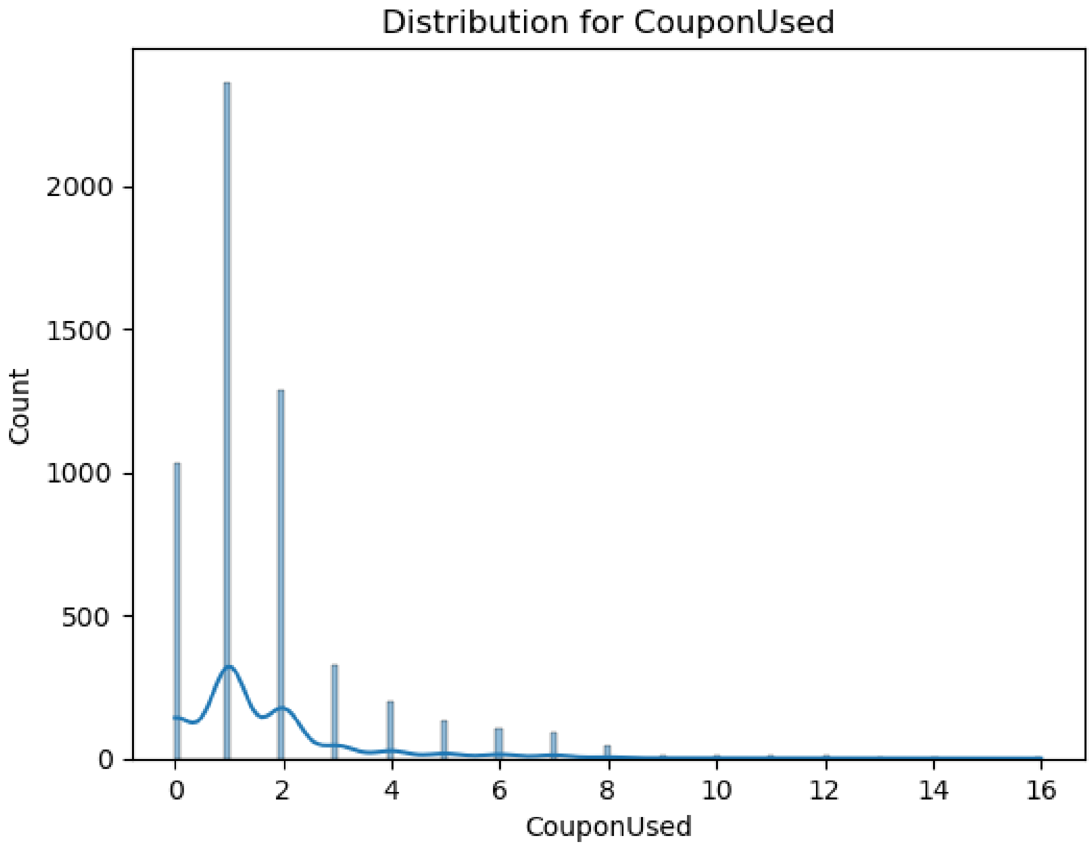

Distribution for SatisfactionScore
Count
SatisfactionScore
0
200
400
600
800
1000
1200
1400
1600
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

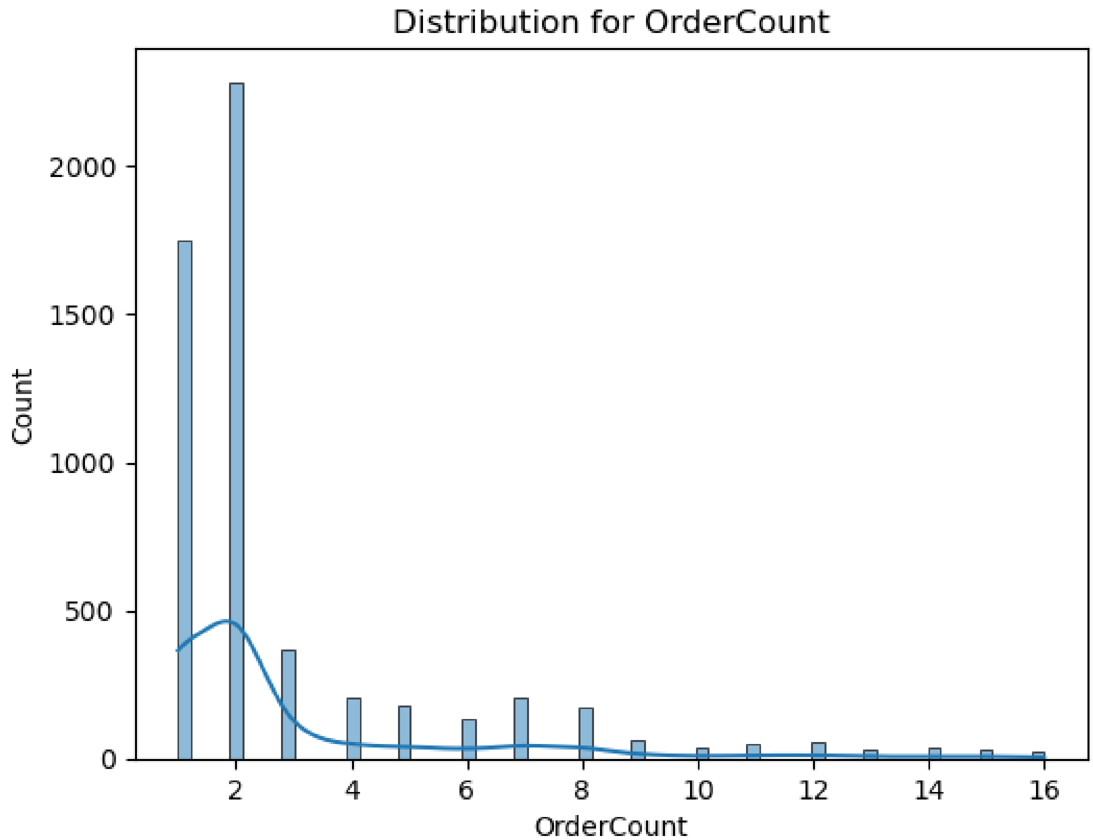

Distribution for MaritalStatus
Count
0
1000
2000
3000
4000
5000
6000
7000
Single
Divorced
Married
MaritalStatus

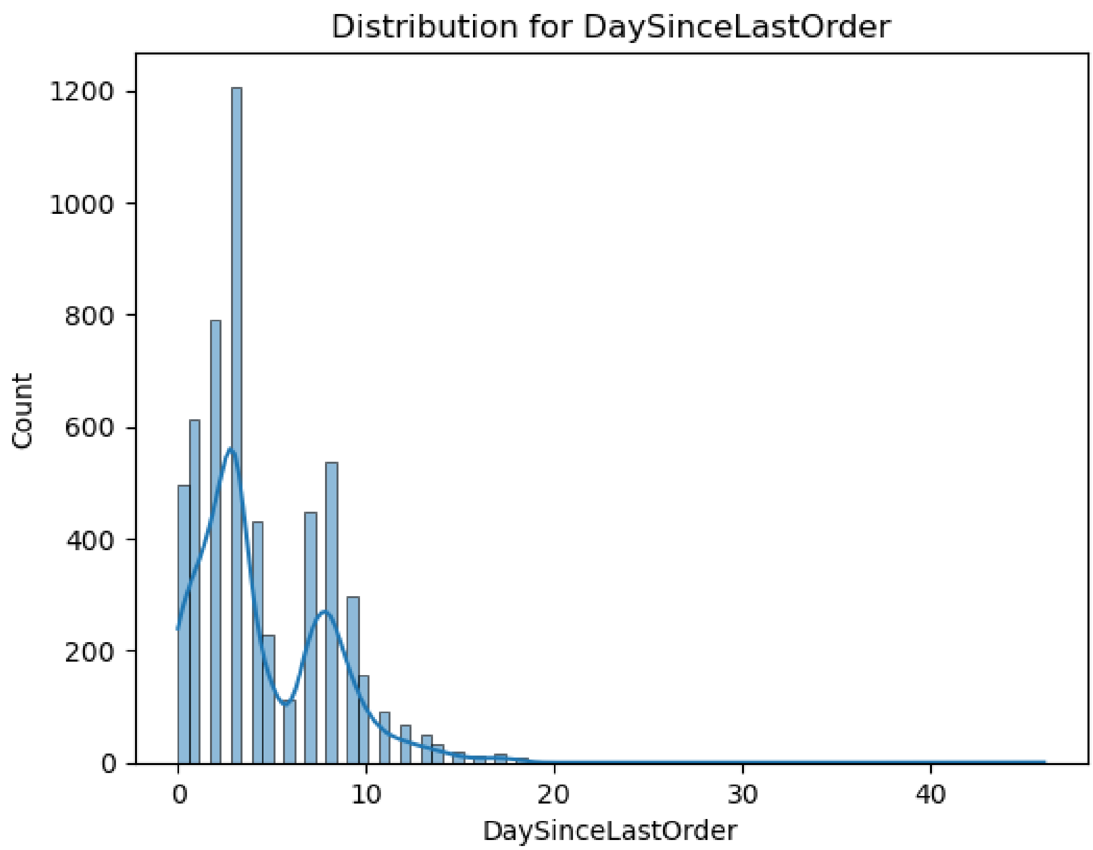

Distribution for NumberOfAddress
Count
NumberOfAddress
0
200
400
600
800
1000
1200
1400
0
5
10
15
20

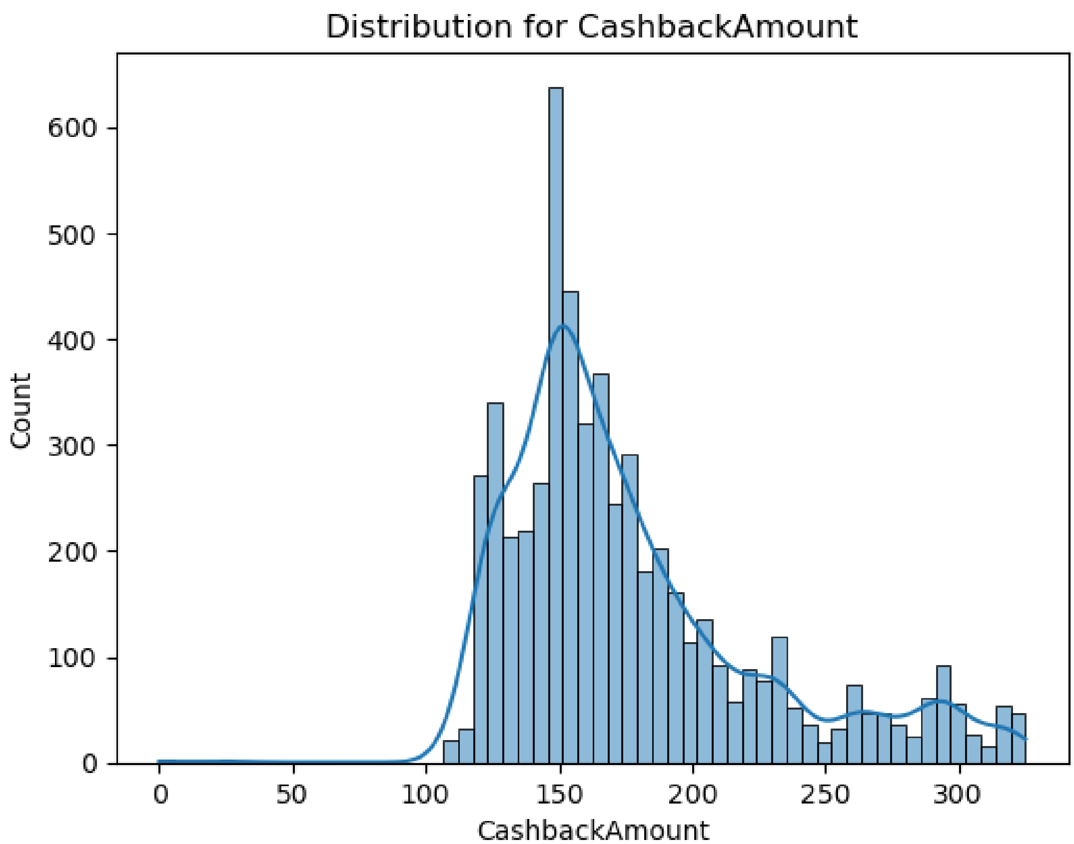

Distribution for Complain
4000
3500
3000
2500
2000
1500
1000
500
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
Complain


Distribution for OrderAmountHikeFromlastYear
Count
OrderAmountHikeFromlastYear
0
100
200
300
400
500
600
700
800
12
14
16
18
20
22
24
26

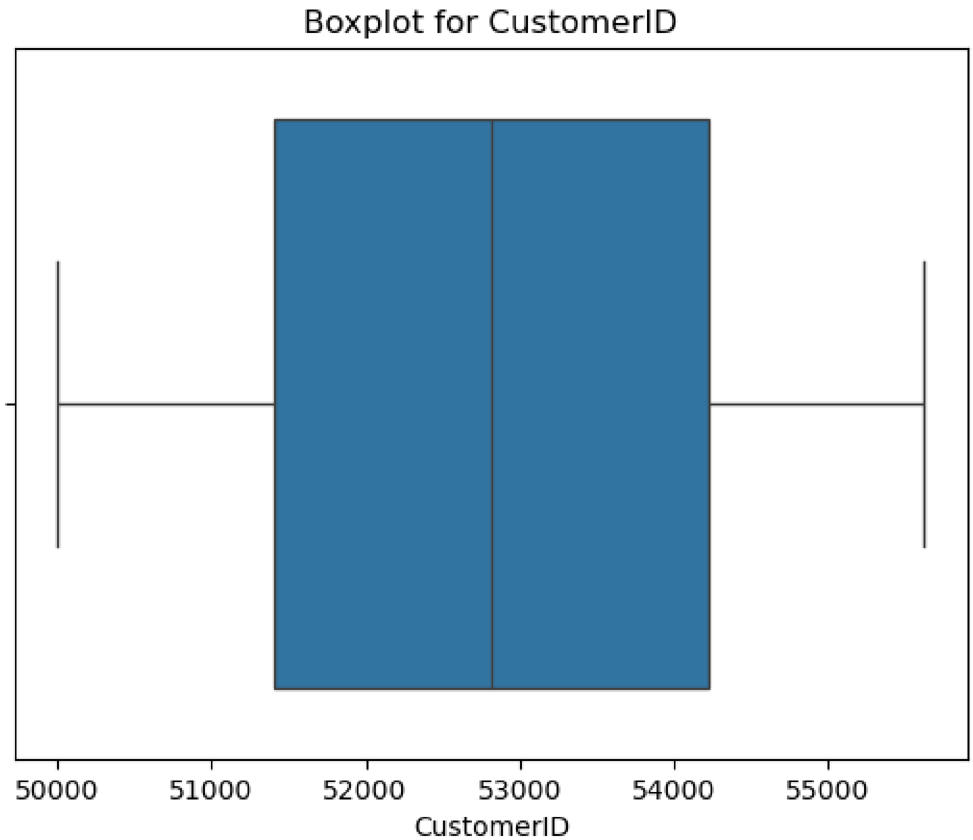

Distribution for CouponUsed
Count
0
500
1000
1500
2000
0
2
4
6
8
10
12
14
16
CouponUsed

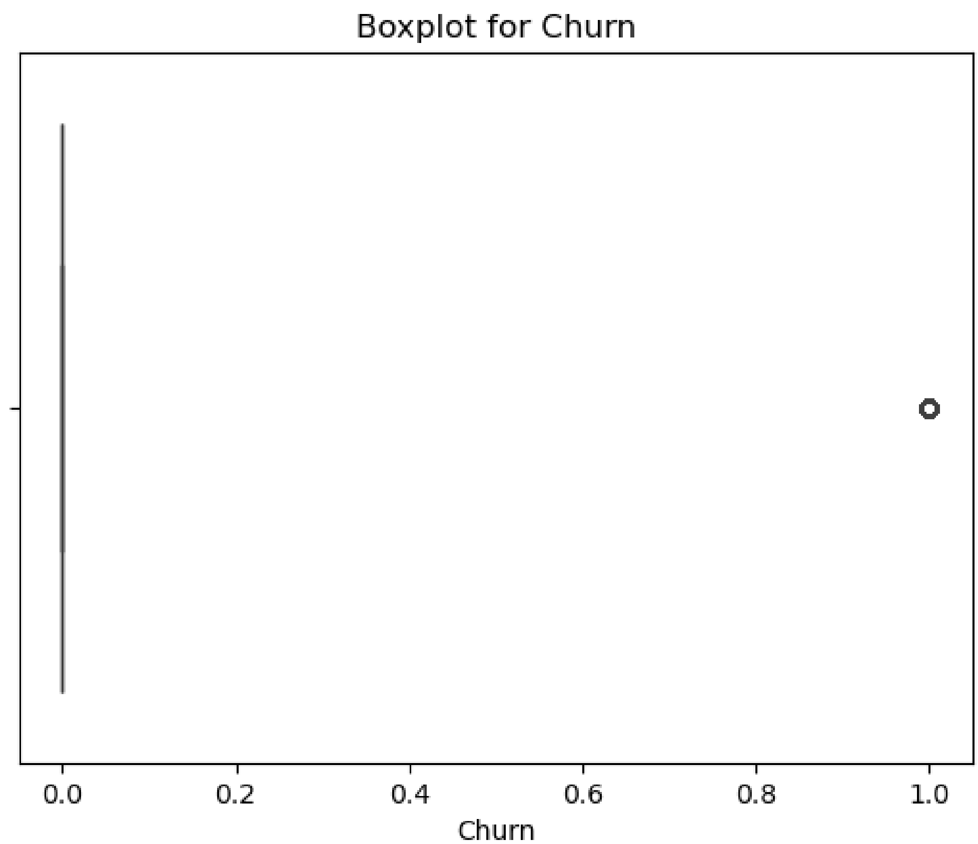

Distribution for OrderCount
Count
OrderCount
0
500
1000
1500
2000
2
4
6
8
10
12
14
16

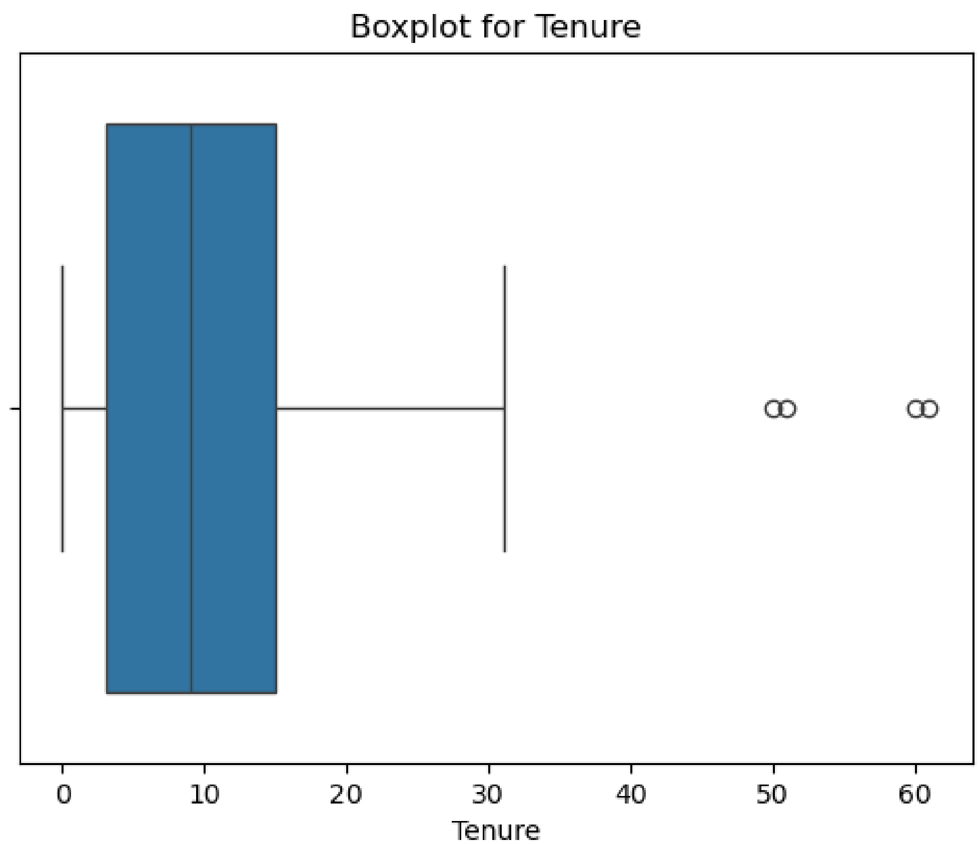

Distribution for DaySinceLastOrder
Count
DaySinceLastOrder
0
200
400
600
800
1000
1200
0
10
20
30
40

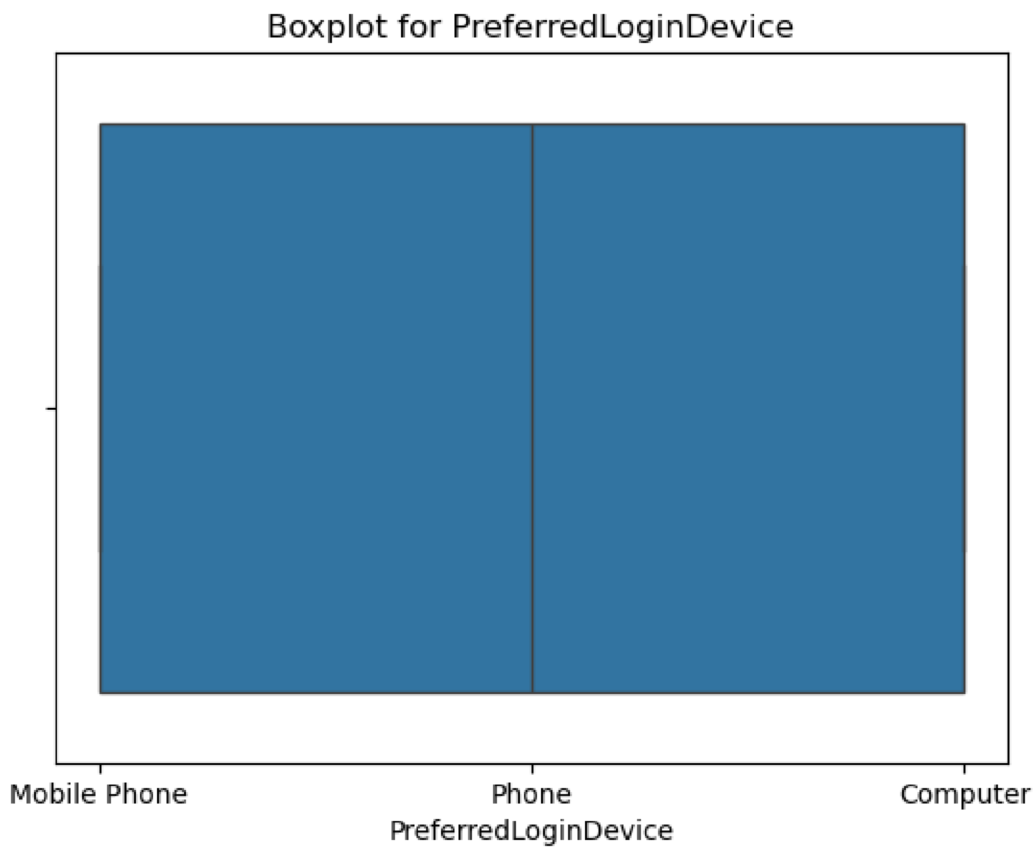


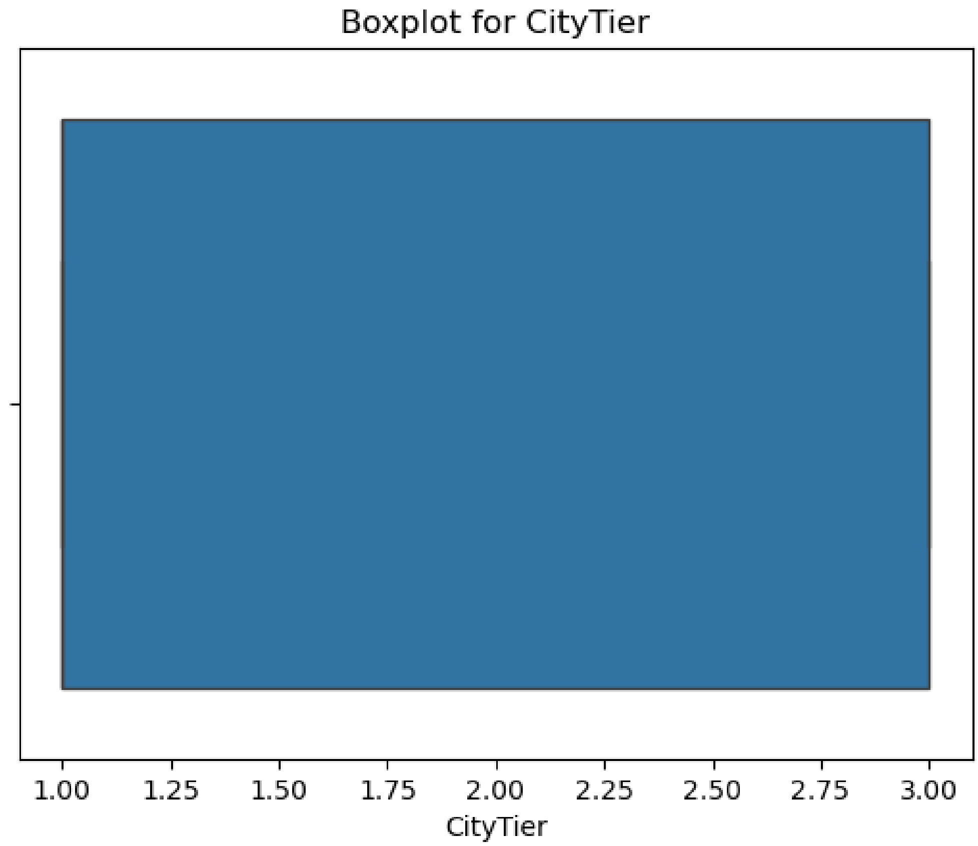
[31]:
```
for column in df.columns:
    sns.boxplot(data=df, x=column)
    plt.title(f'Boxplot for {column}')
    plt.show()
```

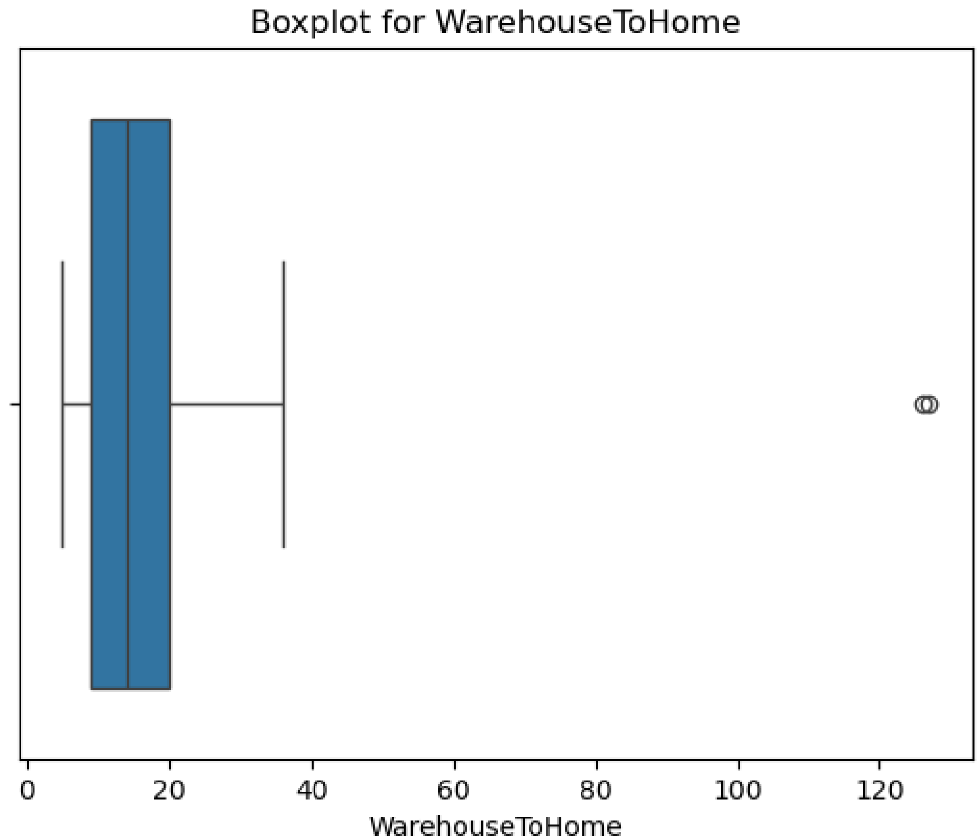

Boxplot for CustomerID
50000
51000
52000
53000
54000
55000
CustomerID

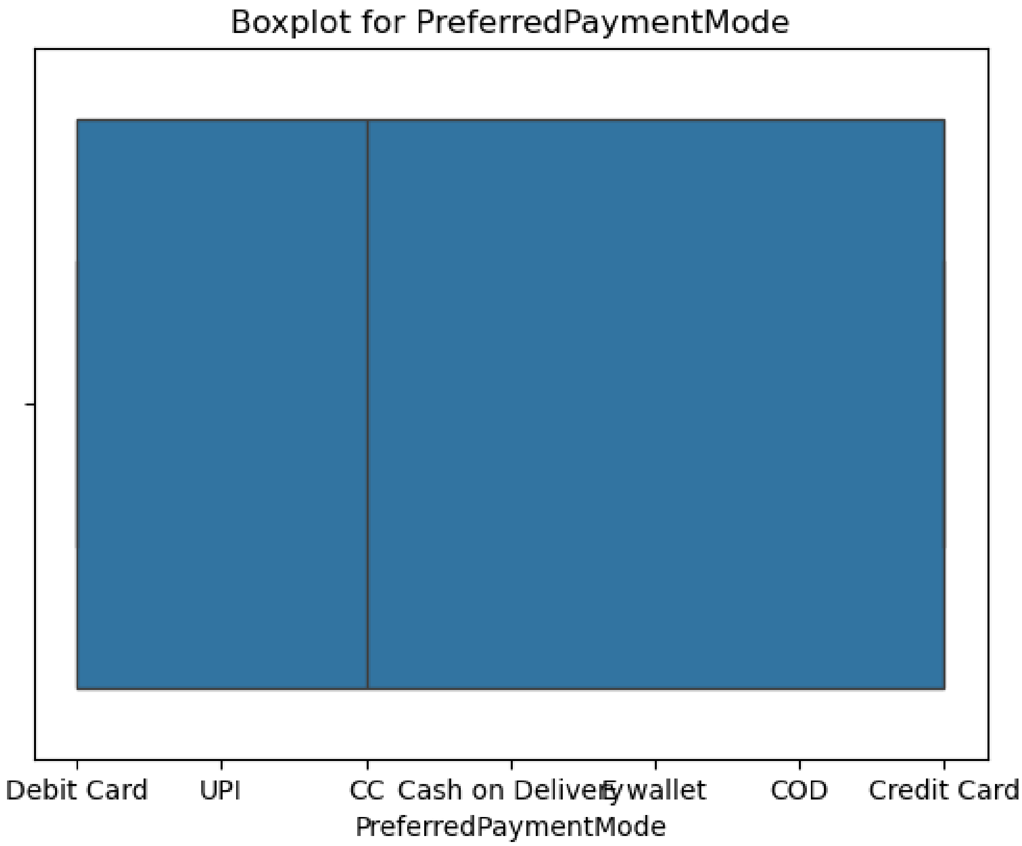

Boxplot for Churn
0.0
0.2
0.4
0.6
0.8
1.0
Churn


Boxplot for Tenure
0
10
20
30
40
50
60
Tenure

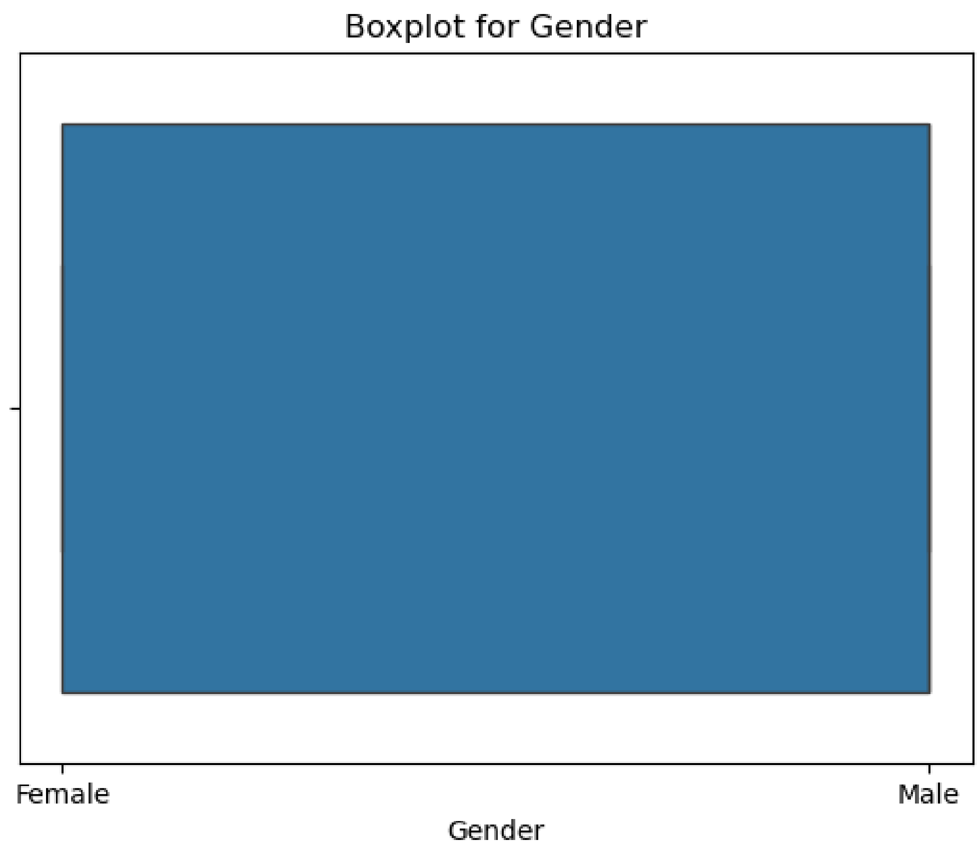

Boxplot for PreferredLoginDevice
Mobile Phone
Phone
Computer
PreferredLoginDevice

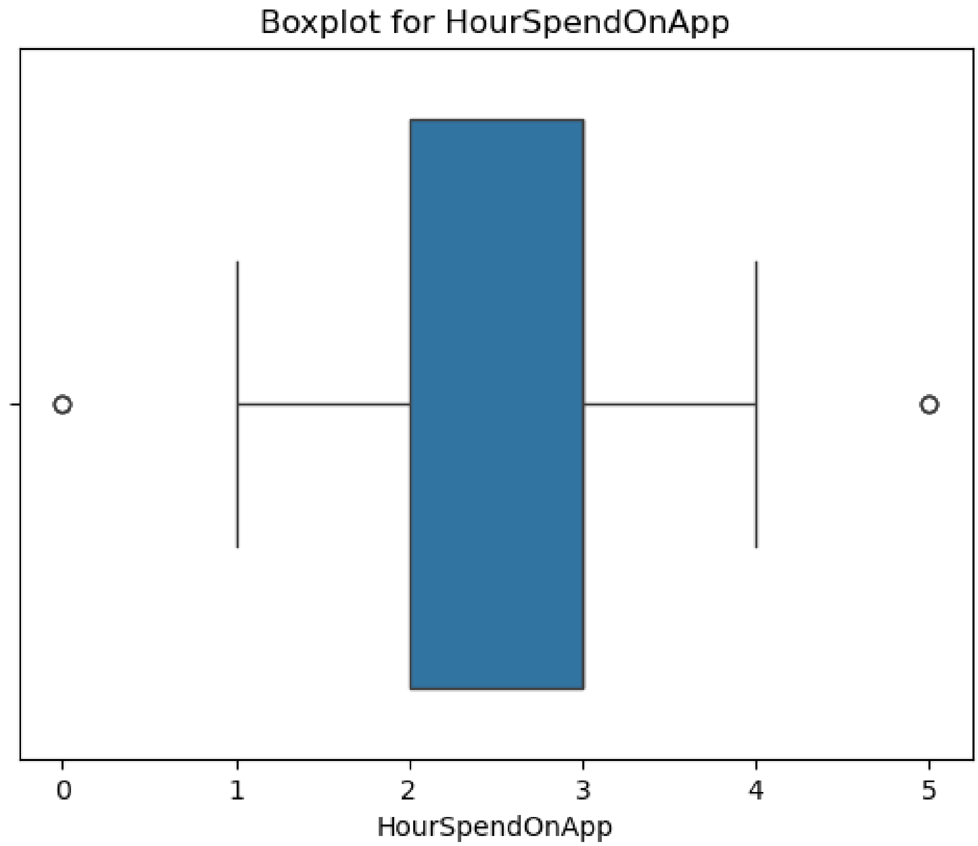

Boxplot for CityTier
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
CityTier

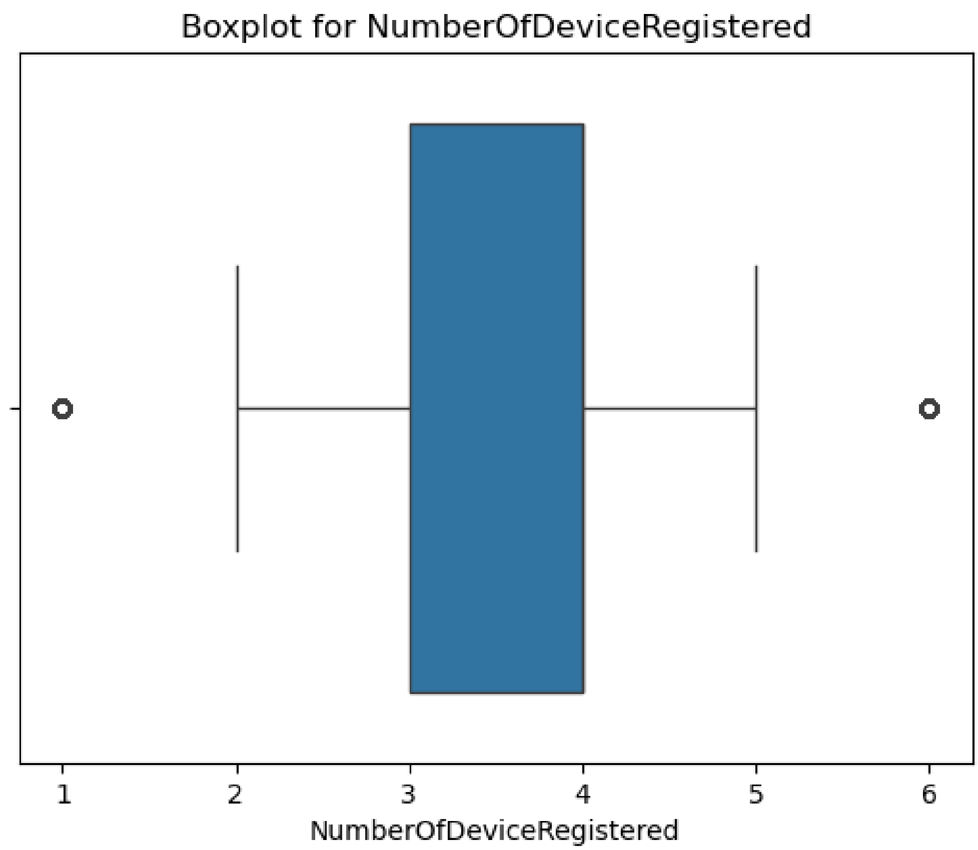

Boxplot for WarehouseToHome
0
20
40
60
80
100
120
WarehouseToHome

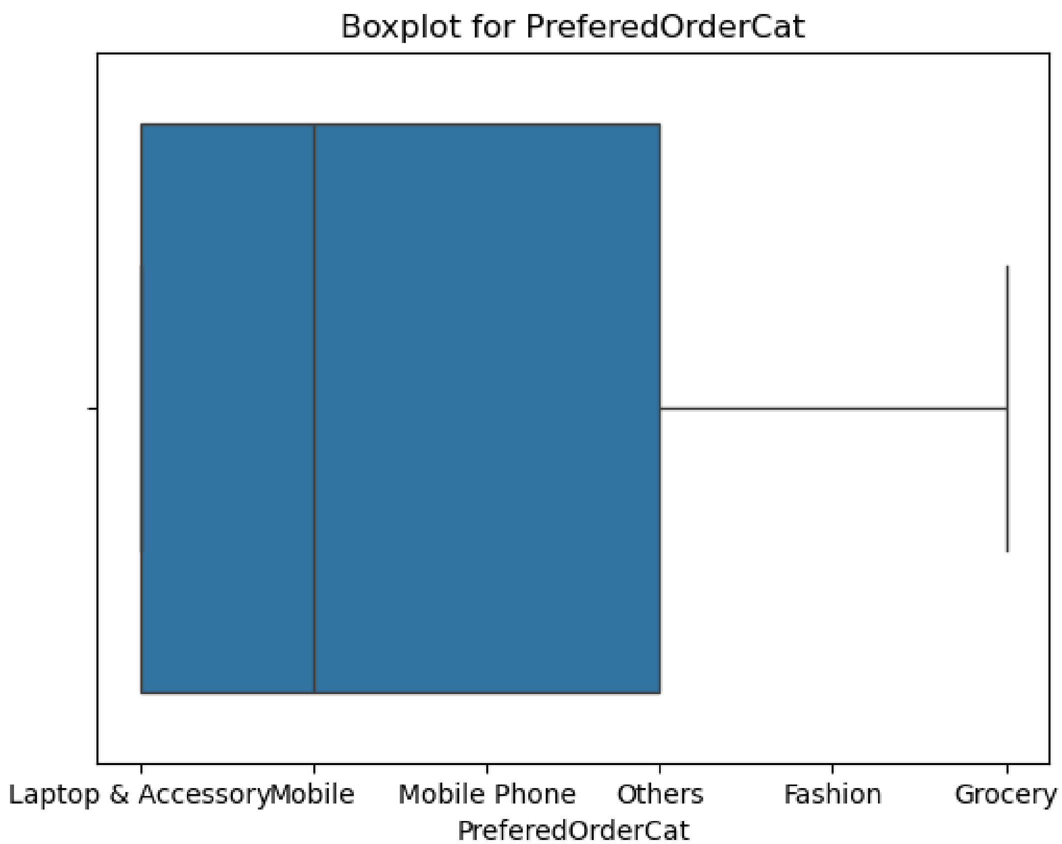


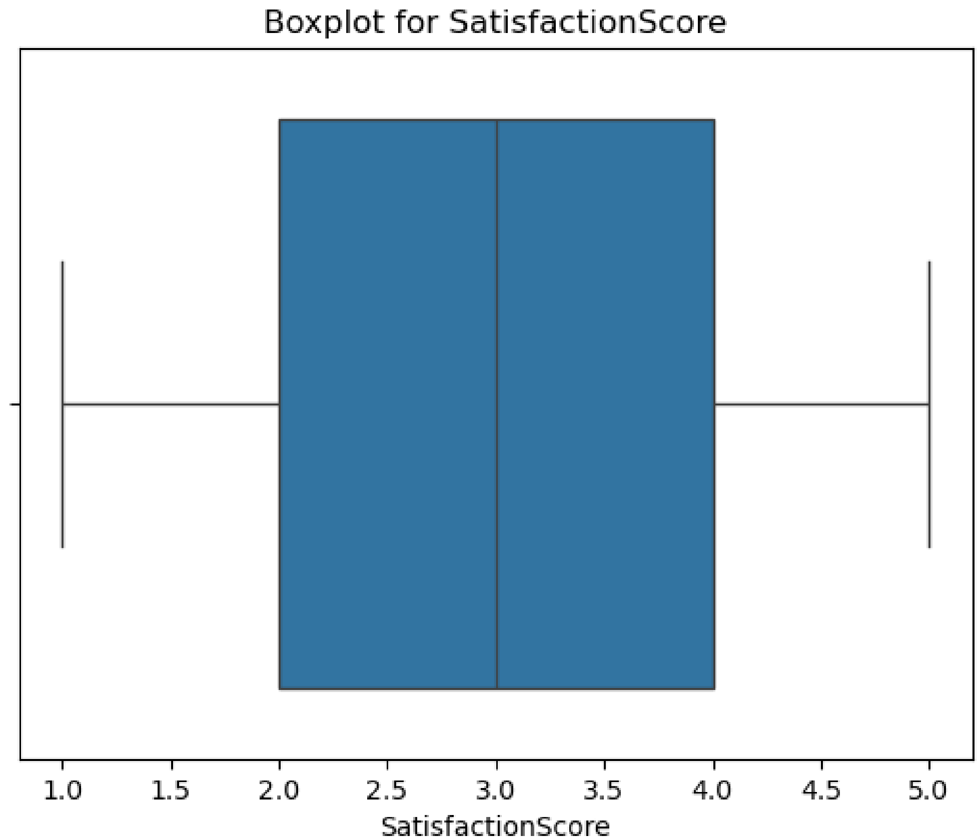
Boxplot for PreferredPaymentMode
Debit Card
UPI
CC
Cash on Delivery
E wallet
COD
Credit Card
PreferredPaymentMode

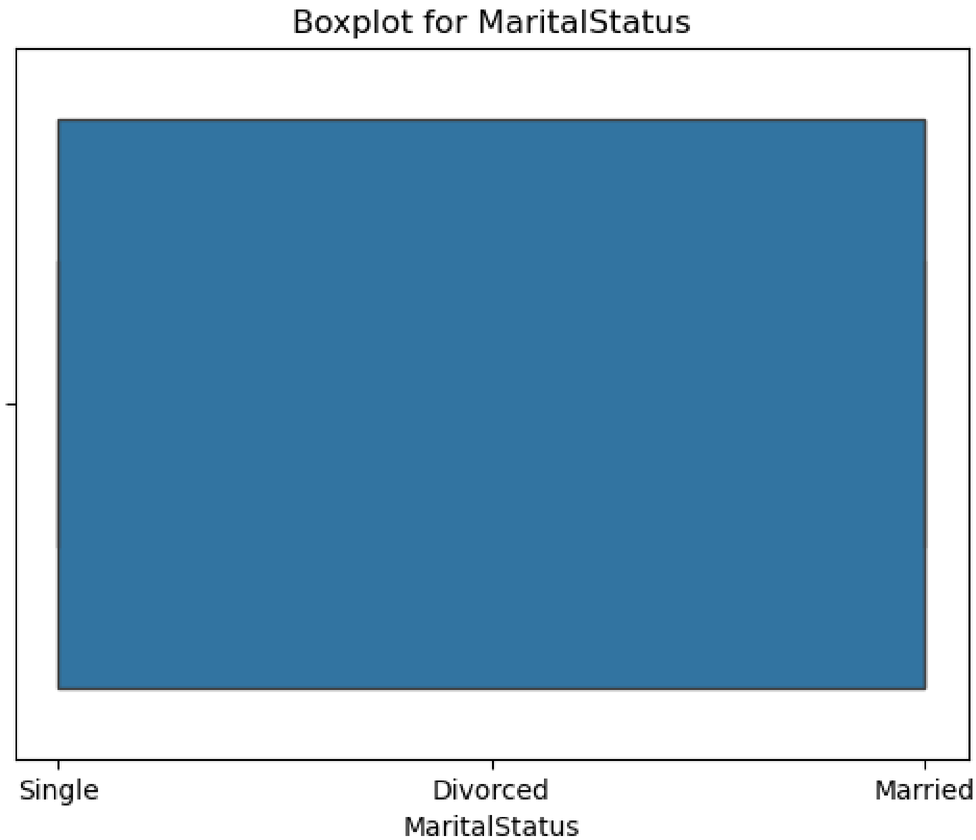

Boxplot for Gender
Female
Male
Gender

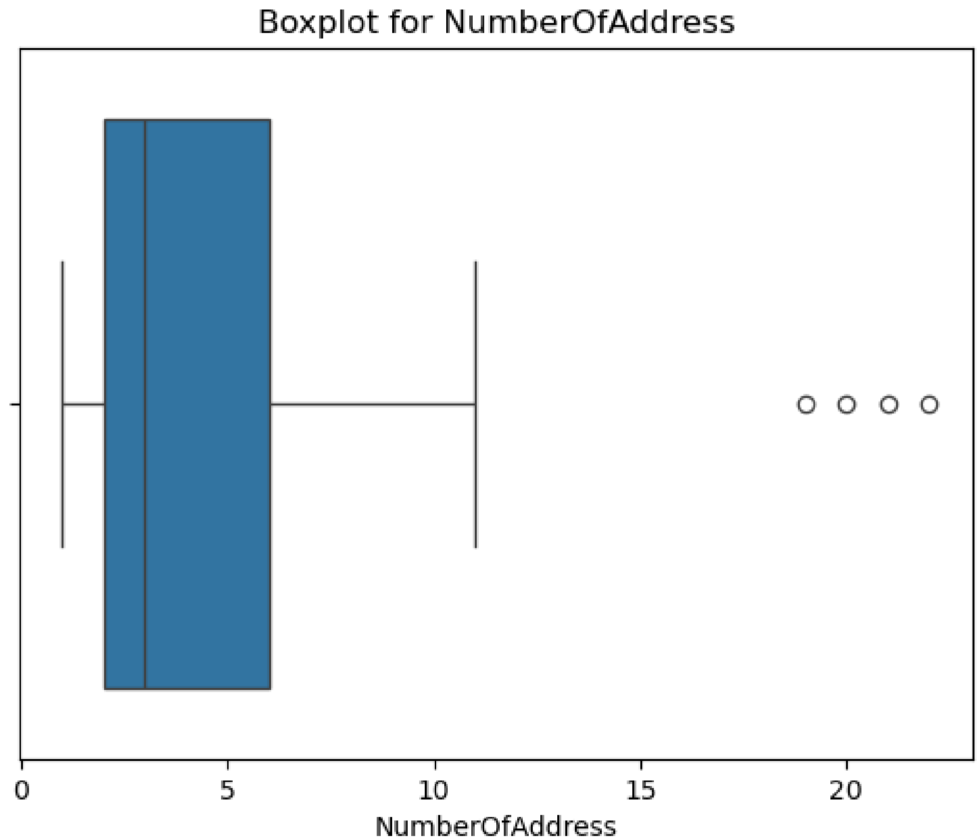

Boxplot for HourSpendOnApp
0
1
2
3
4
5
HourSpendOnApp

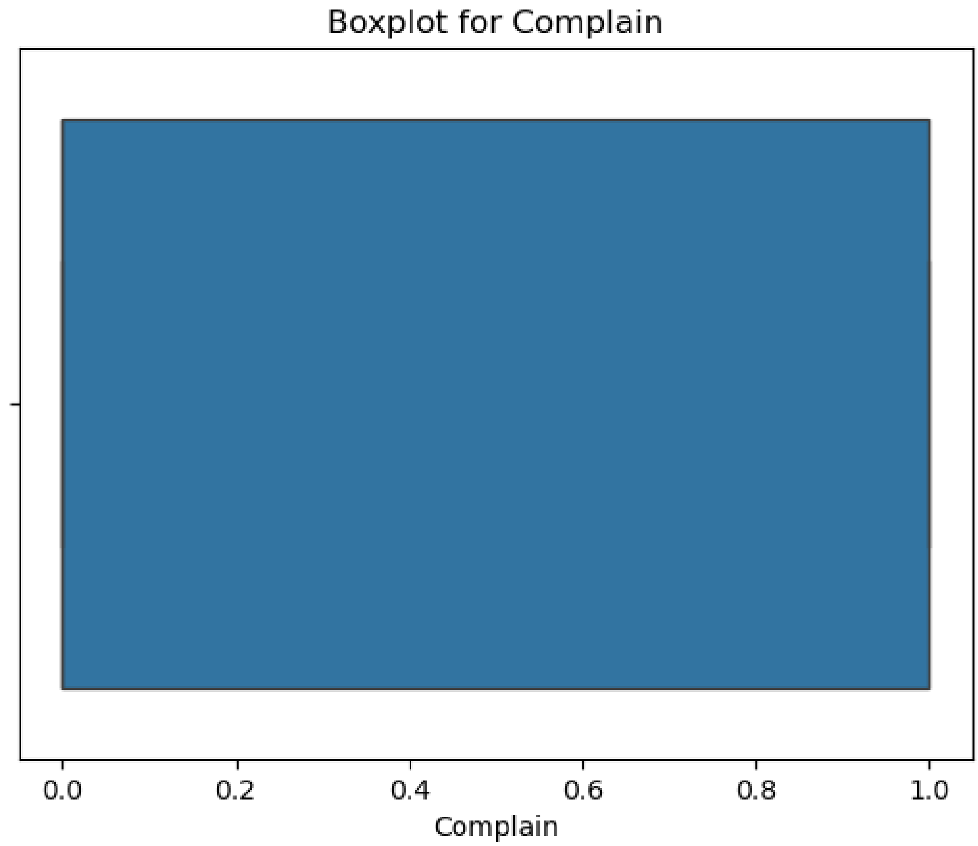

Boxplot for NumberOfDeviceRegistered
1
2
3
4
5
6
NumberOfDeviceRegistered

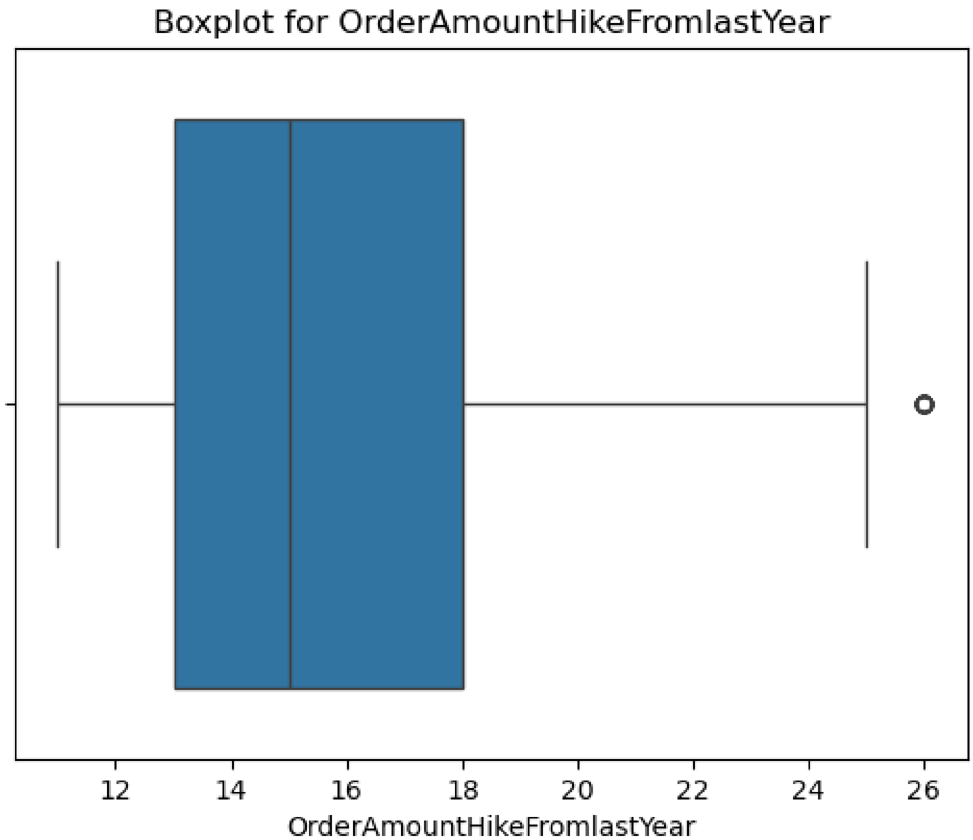

Boxplot for PreferedOrderCat
Laptop & Accessory
Mobile
Mobile Phone
Others
Fashion
Grocery
PreferedOrderCat

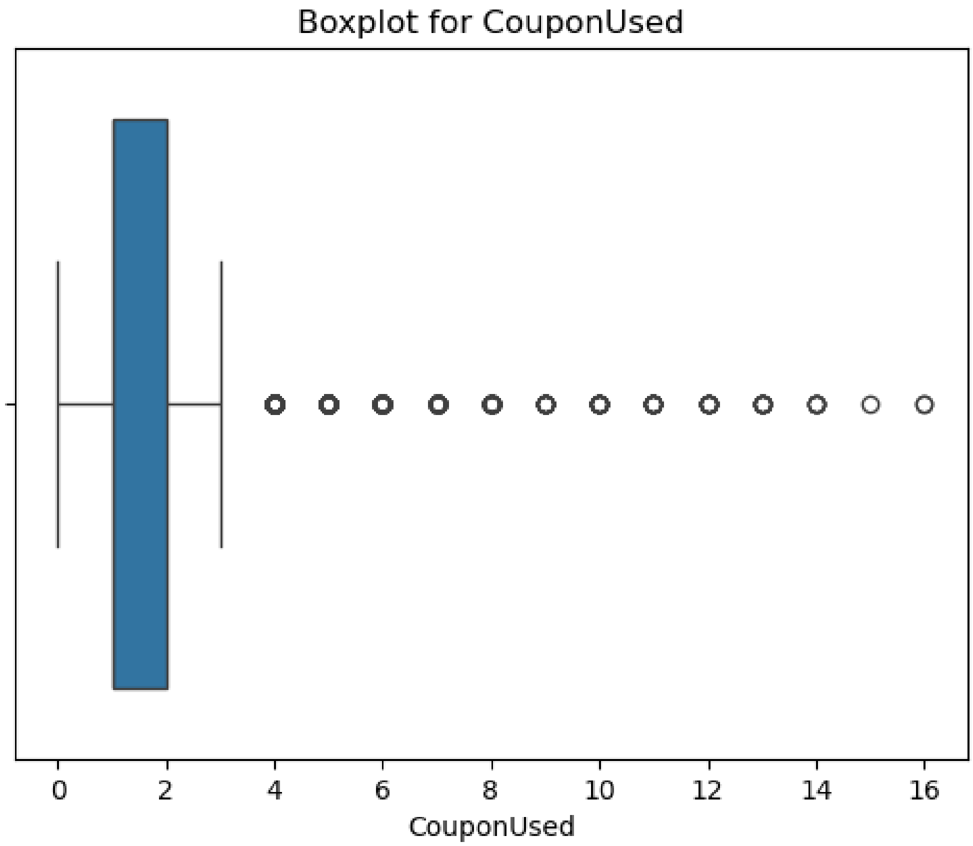

Boxplot for SatisfactionScore
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
SatisfactionScore

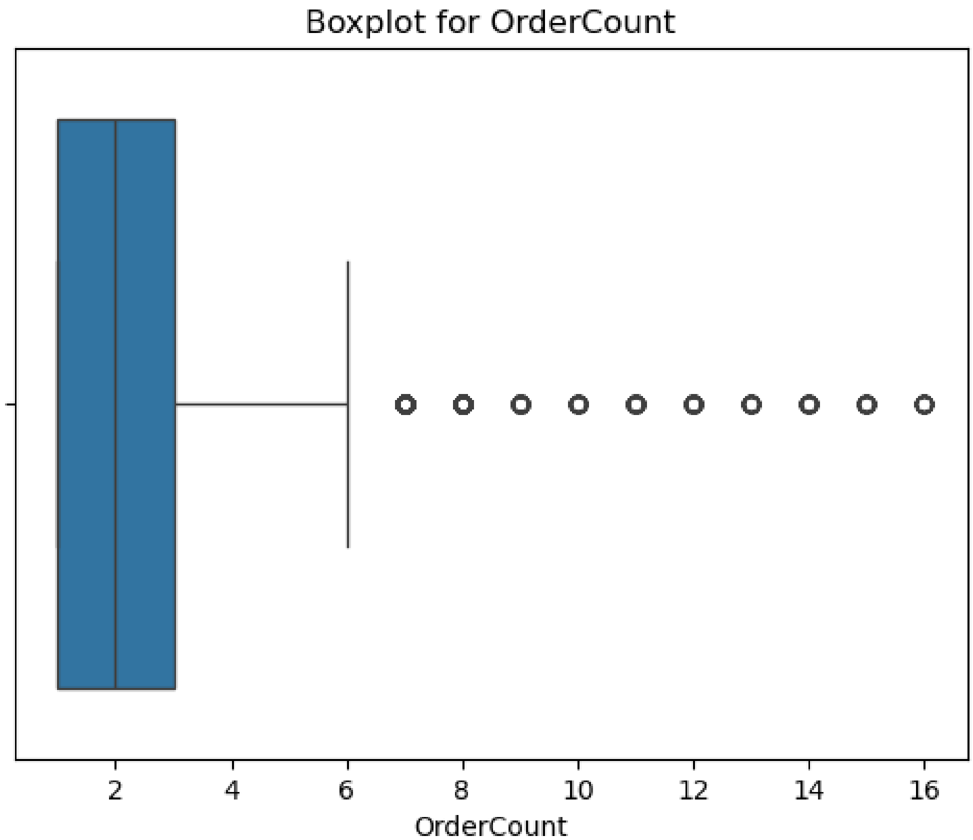

Boxplot for MaritalStatus
Single
Divorced
Married
MaritalStatus

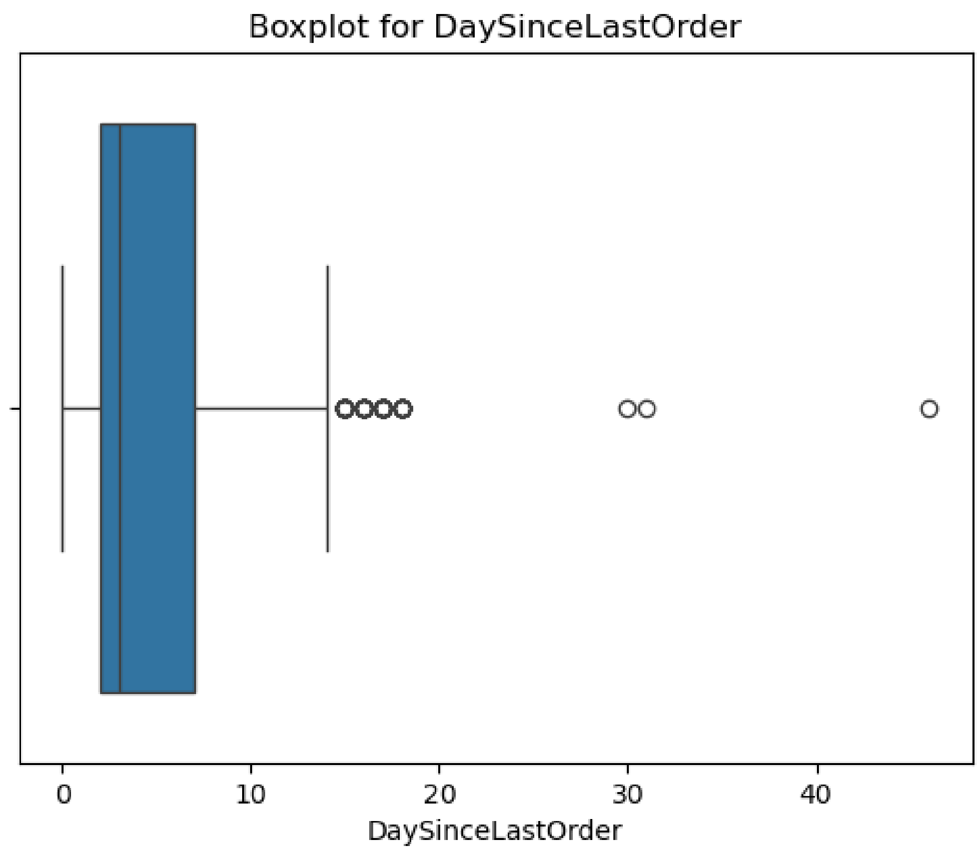

Boxplot for NumberOfAddress
0
5
10
15
20
NumberOfAddress


Boxplot for Complain
0.0
0.2
0.4
0.6
0.8
1.0
Complain

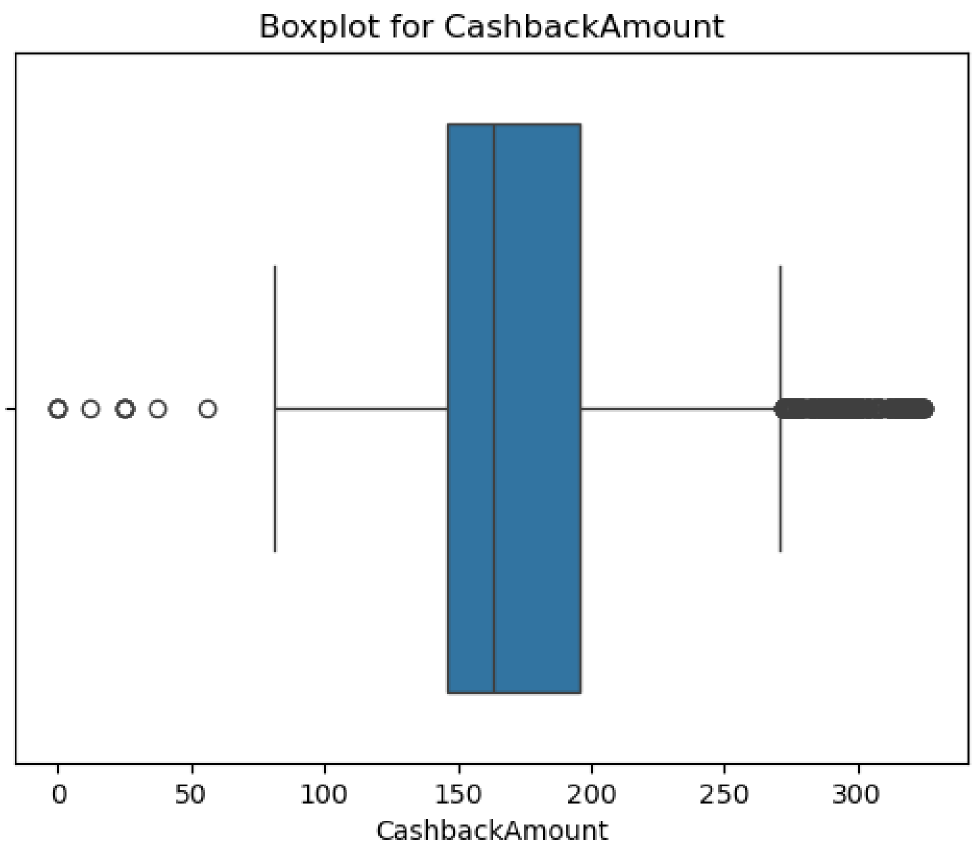

Boxplot for OrderAmountHikeFromlastYear
12
14
16
18
20
22
24
26
OrderAmountHikeFromlastYear


Boxplot for CouponUsed
0
2
4
6
8
10
12
14
16
CouponUsed


Boxplot for OrderCount
2
4
6
8
10
12
14
16
OrderCount



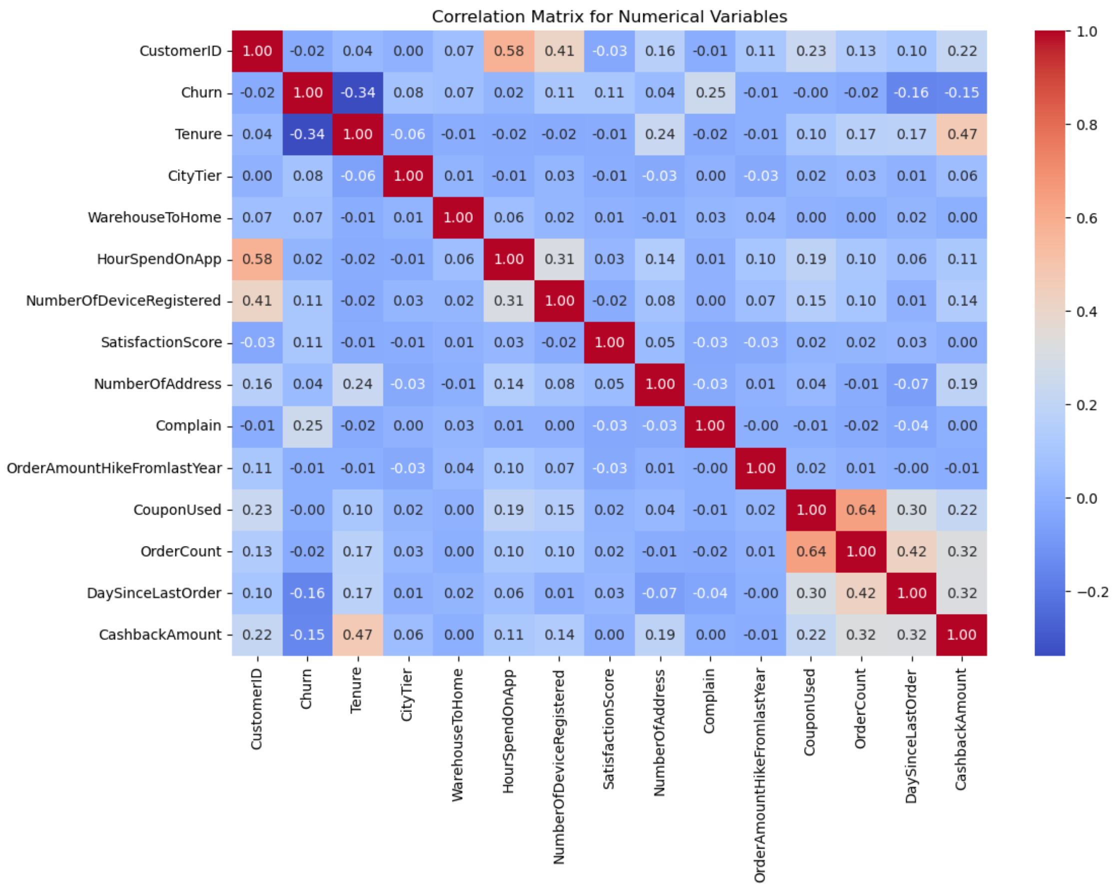
Boxplot for DaySinceLastOrder
0
10
20
30
40
DaySinceLastOrder



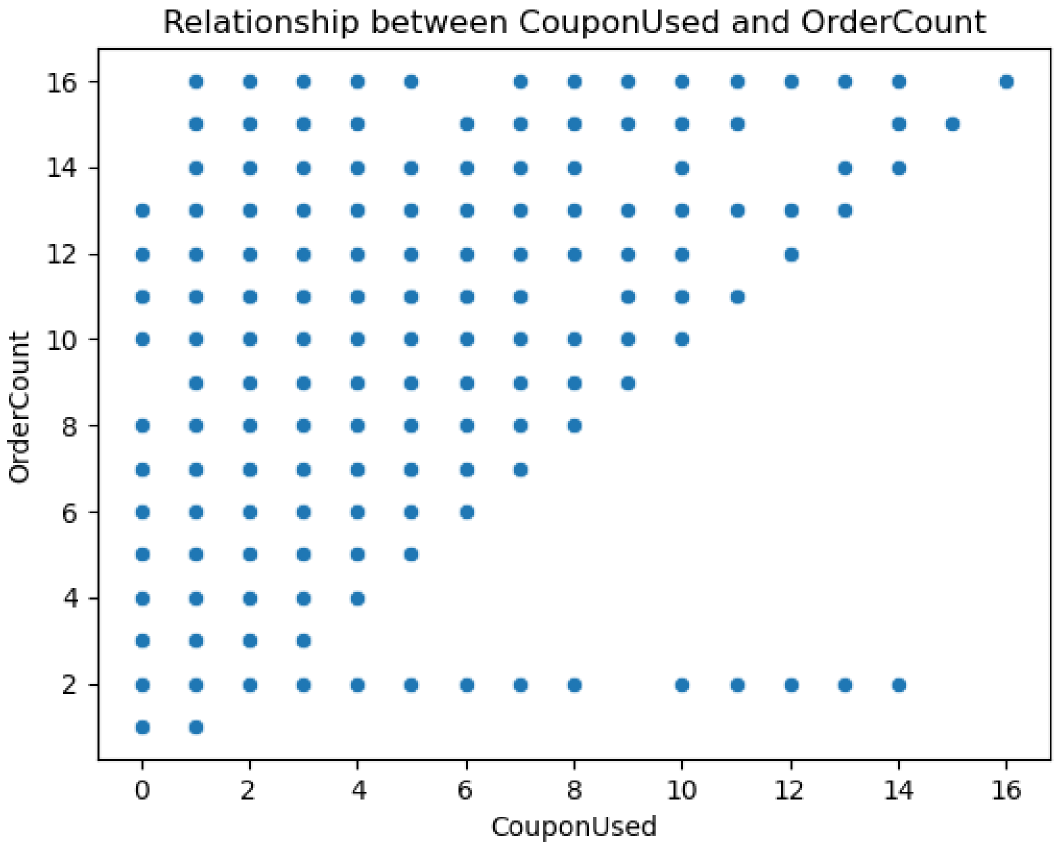
The data is not normally distributed, and some variables have outliers that are not errors. Outliers may hold valuable information, so they should be included in the analysis. The data should be analyzed considering its actual distribution. In the subsequent analysis, we will use methods that are robust to non-normal data distribution and resistant to outliers.

[38]:
```
numeric_df = df.select_dtypes(include=['number'])
correlation_matrix = numeric_df.corr()
```

[39]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Correlation Matrix for Numerical Variables")
plt.show()
```



[40]:
```python
sns.scatterplot(data=df, x='CouponUsed', y='OrderCount')
plt.title("Relationship between CouponUsed and OrderCount")
plt.show()
```



Based on the provided correlations, the following initial conclusions can be drawn:

A correlation of 0.64 between the variables CouponUsed (use of coupons) and OrderCount (number of orders) indicates a strong positive relationship. This means that an increase in the number of coupons used is associated with a rise in the number of orders. DaysSinceLastOrder and OrderCount (0.42): A moderate positive correlation suggests that customers who place orders more frequently (high OrderCount) spend less time between orders (DaysSinceLastOrder). CashbackAmount and Tenure (0.47): A moderate positive correlation indicates that customers who receive higher cashback amounts (CashbackAmount) are often those with longer tenures (Tenure). NumberOfDeviceRegister and HoursSpendOnApp (0.31): A weak positive correlation suggests that customers with more registered devices spend slightly more time using the app. A weak positive correlation (0.25) implies that customers with more complaints (Complain) are somewhat less likely to leave the service (Churn). A weak positive correlation (0.3) may suggest that customers who order less frequently (higher DaysSinceLastOrder) tend to use coupons more often (CouponUsed). DaysSinceLastOrder and CashbackAmount (0.32): A weak positive correlation might indicate that customers who place orders less frequently receive slightly higher cashback amounts. The correlation between OrderCount (number of orders) and CashbackAmount (cashback amount), equal to 0.3, suggests a moderate positive relationship. This means that as the number of orders increases, the cashback amount tends to slightly increase. Other correlations are extremely small, making it difficult to draw meaningful conclusions.

Main Analysis

Churn Analysis

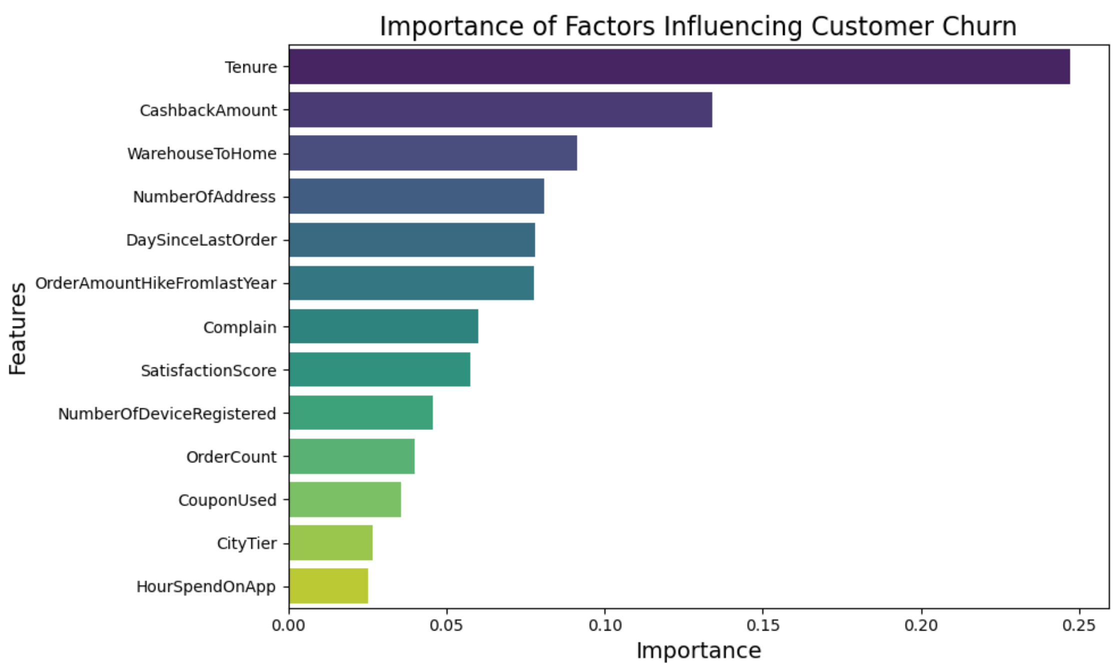
What factors have the greatest impact on customer churn?

[45]:
```
numeric_df = numeric_df.drop(columns=['CustomerID'])
X = numeric_df.drop(columns=['Churn'])
y = numeric_df['Churn']

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

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

y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
print(f"ROC-AUC: {roc_auc_score(y_test, model.predict_proba(X_test)[:, 1])}")

importance = pd.Series(model.feature_importances_, index=X.columns)
print("Importance of Factors:")
print(importance.sort_values(ascending=False))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.99       941
           1       0.99      0.86      0.92       185

    accuracy                           0.98      1126
   macro avg       0.98      0.93      0.95      1126
weighted avg       0.98      0.98      0.97      1126

ROC-AUC: 0.986104489186317
Importance of Factors:
Tenure                         0.246984
CashbackAmount                 0.134192
WarehouseToHome                0.091206
NumberOfAddress                0.080860
DaySinceLastOrder              0.078037
OrderAmountHikeFromlastYear    0.077750
Complain                       0.060118
SatisfactionScore              0.057434
NumberOfDeviceRegistered       0.045757
OrderCount                     0.039966
CouponUsed                     0.035810
CityTier                       0.026554
HourSpendOnApp                 0.025332
dtype: float64
```

[46]:
```
importance_df = importance.sort_values(ascending=False).reset_index()
importance_df.columns = ['Feature', 'Importance']

plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df, palette="viridis")
plt.title("Importance of Factors Influencing Customer Churn", fontsize=16)
plt.xlabel("Importance", fontsize=14)
plt.ylabel("Features", fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/103830534.py:5:
FutureWarning:

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

  sns.barplot(x='Importance', y='Feature', data=importance_df,
palette="viridis")
```

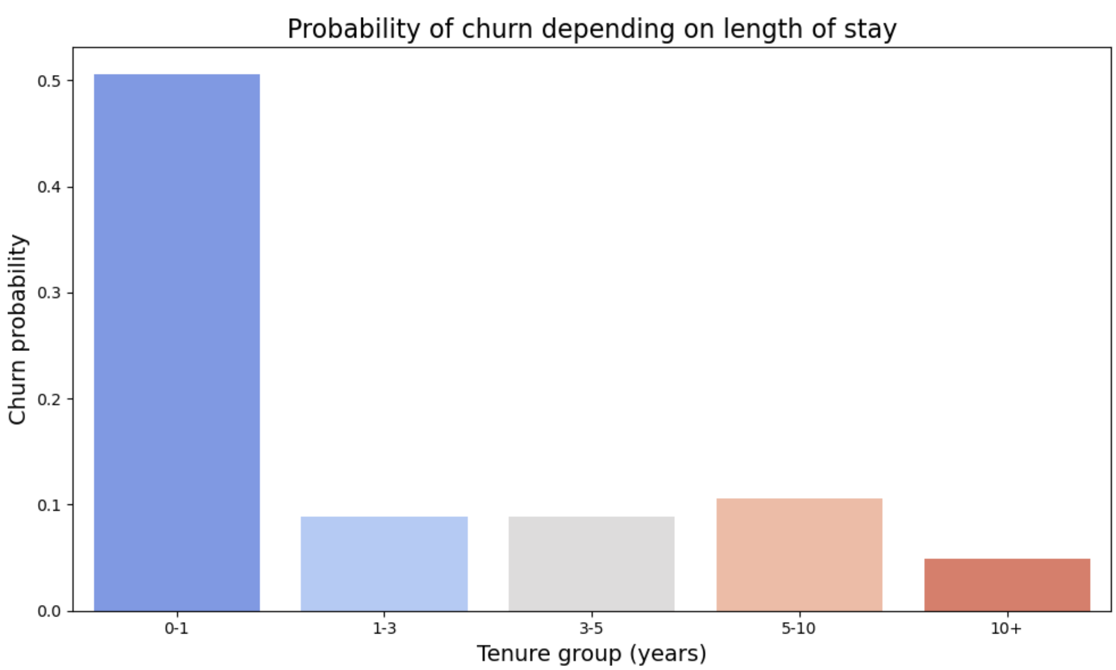


What is the probability of churn depending on the customer's tenure in the organization?

[48]:
```
df['TenureGroup'] = pd.cut(df['Tenure'], bins=[0, 1, 3, 5, 10, 100],␣
↪labels=['0-1', '1-3', '3-5', '5-10', '10+'])
```

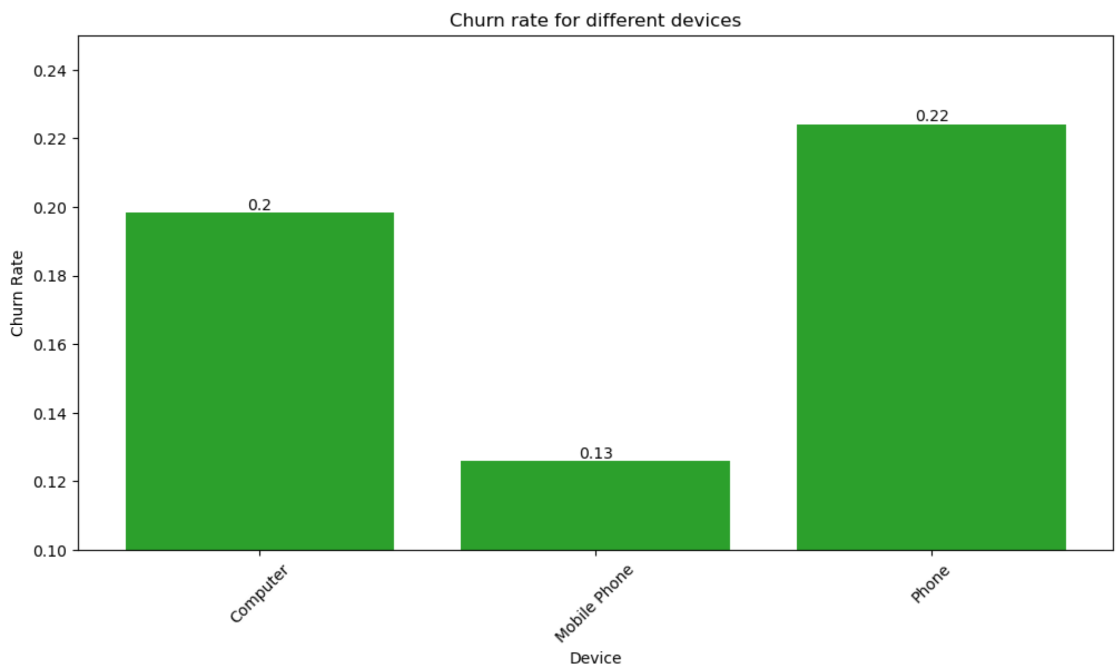
```
churn_rate = df.groupby('TenureGroup')['Churn'].mean().reset_index()

plt.figure(figsize=(10, 6))
sns.barplot(x='TenureGroup', y='Churn', data=churn_rate, palette="coolwarm")
plt.title("Probability of churn depending on length of stay", fontsize=16)
plt.xlabel("Tenure group (years)", fontsize=14)
plt.ylabel("Churn probability", fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/3777859179.py:4:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  churn_rate = df.groupby('TenureGroup')['Churn'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/3777859179.py:7:
FutureWarning:

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

  sns.barplot(x='TenureGroup', y='Churn', data=churn_rate, palette="coolwarm")
```



How Churn Levels Vary by PreferredLoginDevice?

[51]:
```python
churn_by_device = df.groupby('PreferredLoginDevice')['Churn'].mean()
# churn_by_device.rename(columns={'Churn': 'ChurnRate'}, inplace=True)
device = churn_by_device.index.tolist()
value = churn_by_device.values.tolist()

plt.figure(figsize=(12, 6))
bars = plt.bar(device, value, color='#2ca02c')
plt.xlabel('Device')
plt.ylabel('Churn Rate')
plt.title('Churn rate for different devices')
plt.xticks(rotation=45)
plt.ylim(0.1, 0.25)
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2),␣
 ↪ha='center', va='bottom')
plt.show()
```

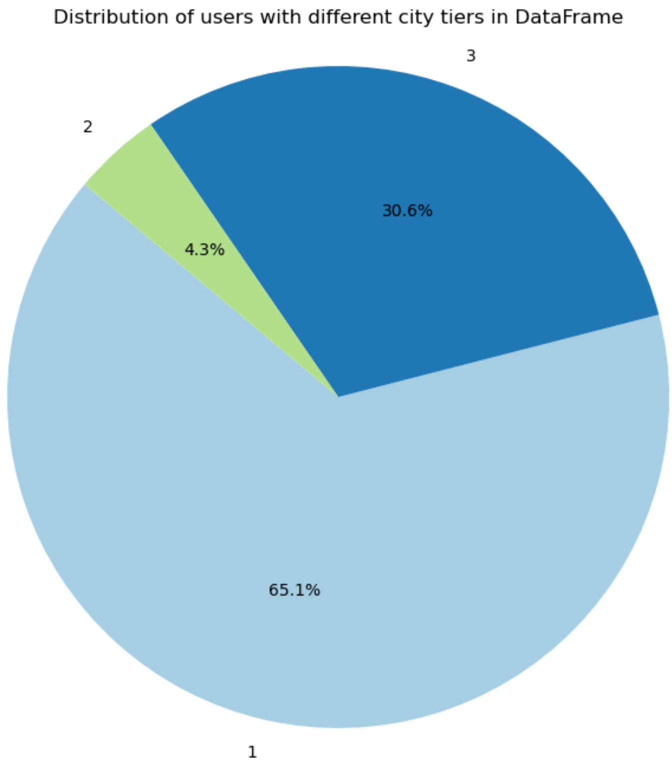


Customer Segmentation

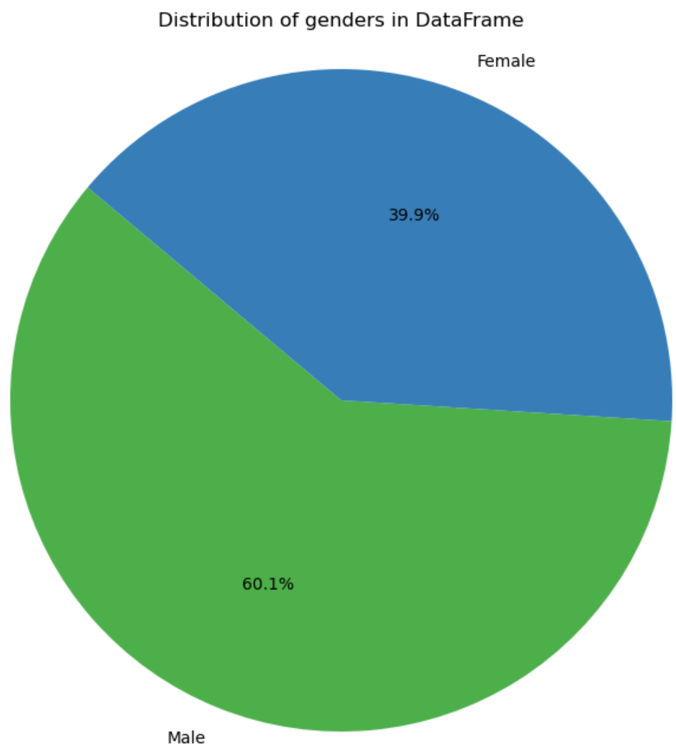
What customer segments can be identified based on CityTier, Gender, and MaritalStatus?

[54]:
```python
city_tier_counts = df['CityTier'].value_counts()
gender_counts = df['Gender'].value_counts()
marital_status_counts = df['MaritalStatus'].value_counts()
```

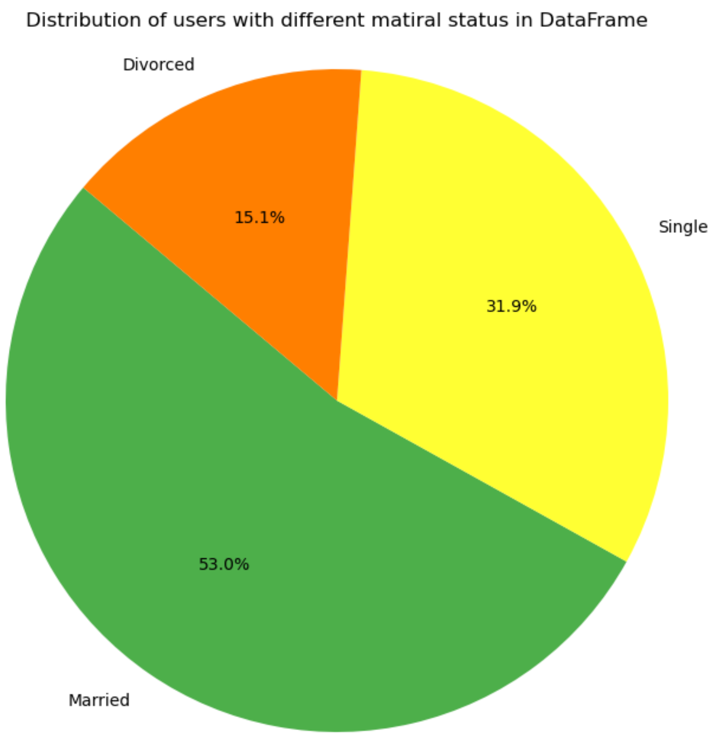
[55]:
```
plt.figure(figsize=(12, 8))
plt.pie(city_tier_counts, labels=city_tier_counts.index, autopct='%1.1f%%',␣
↪startangle=140, colors=plt.cm.Paired.colors)
plt.title('Distribution of users with different city tiers in DataFrame')
plt.axis('equal')
plt.show()
```



[58]:
```
plt.figure(figsize=(12, 8))
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%',␣
↪startangle=140, colors=['#4daf4a', '#377eb8', '#ff7f00'])
plt.title('Distribution of genders in DataFrame')
plt.axis('equal')
plt.show()
```

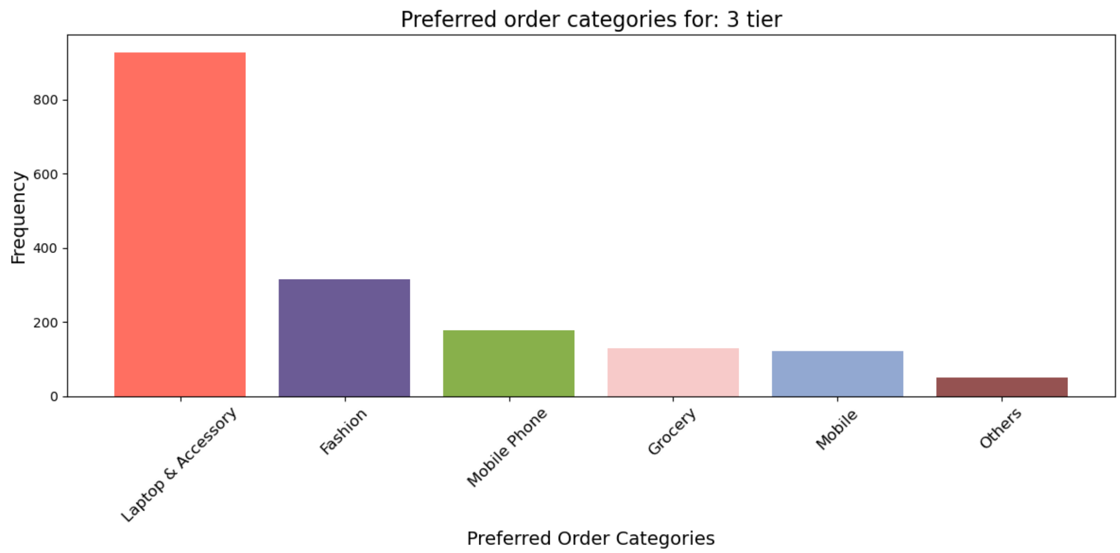


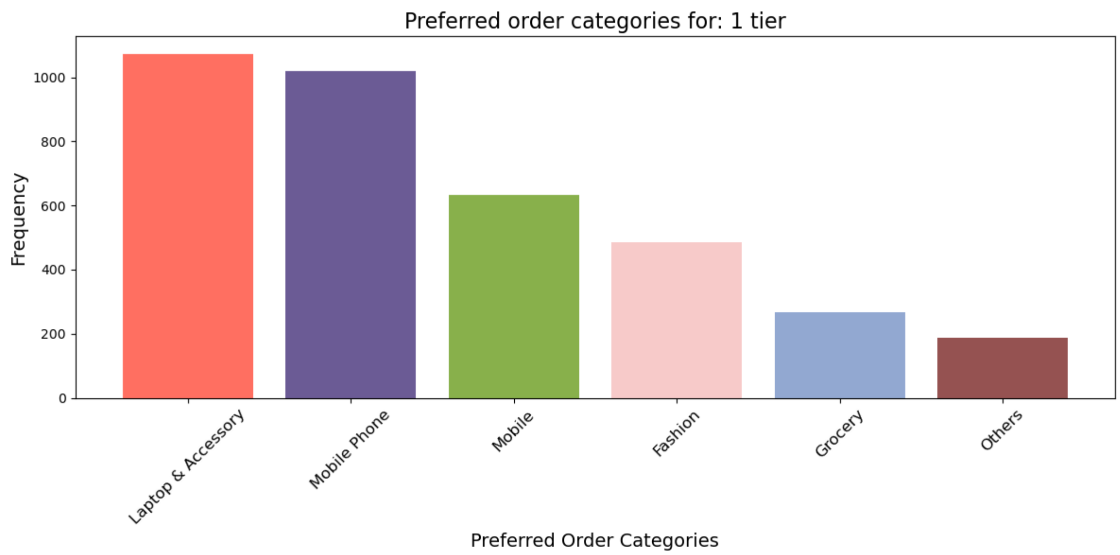
[61]:
```
plt.figure(figsize=(12, 8))
plt.pie(marital_status_counts, labels=marital_status_counts.index, autopct='%1.
↪1f%%', startangle=140, colors=['#4daf4a', '#ffff33', '#ff7f00'])
plt.title('Distribution of users with different matiral status in DataFrame')
plt.axis('equal')
plt.show()
```

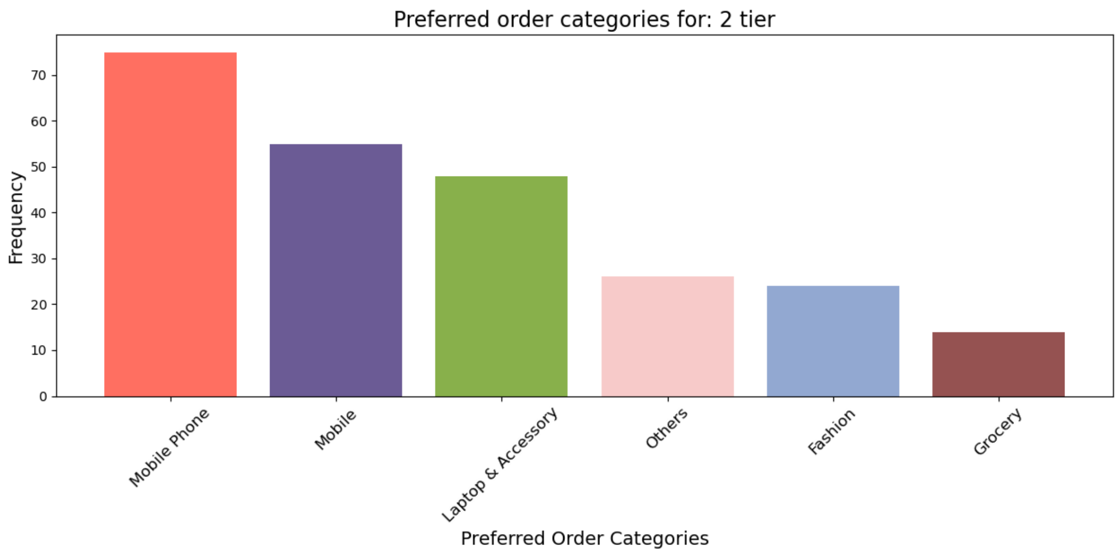


How PreferedOrderCat Differs Across Customer Segments?

[65]:
```
city_tiers = df['CityTier'].unique()

for tier in city_tiers:
    if tier:
        plt.figure(figsize=(12, 6))
        sub_df = df[df['CityTier'] == tier]
        frequency_counts = sub_df['PreferedOrderCat'].value_counts()
        plt.bar(frequency_counts.index, frequency_counts, color=['#ff6f61',␣
↪'#6b5b95', '#88b04b', '#f7cac9', '#92a8d1', '#955251'])
        plt.title(f'Preferred order categories for: {tier} tier', fontsize=16)
        plt.xlabel('Preferred Order Categories', fontsize=14)
        plt.ylabel('Frequency', fontsize=14)
        plt.xticks(rotation=45, fontsize=12)
        plt.tight_layout()
        plt.show()
```

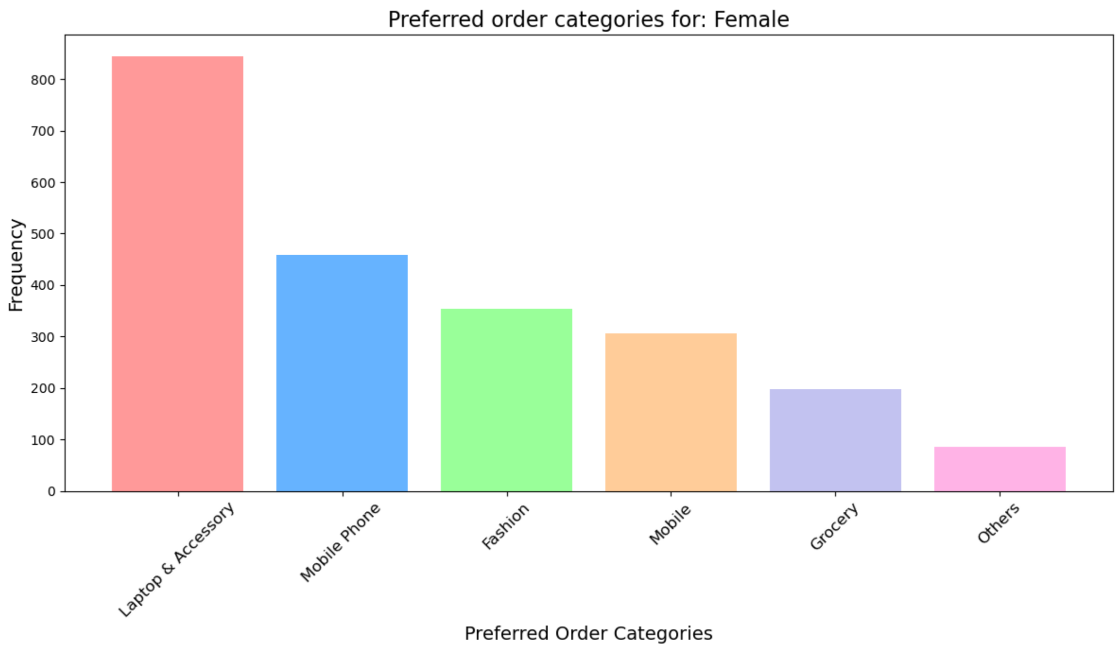

Preferred order categories for: 3 tier
Frequency
0
200
400
600
800
Laptop & Accessory
Fashion
Mobile Phone
Grocery
Mobile
Others
Preferred Order Categories

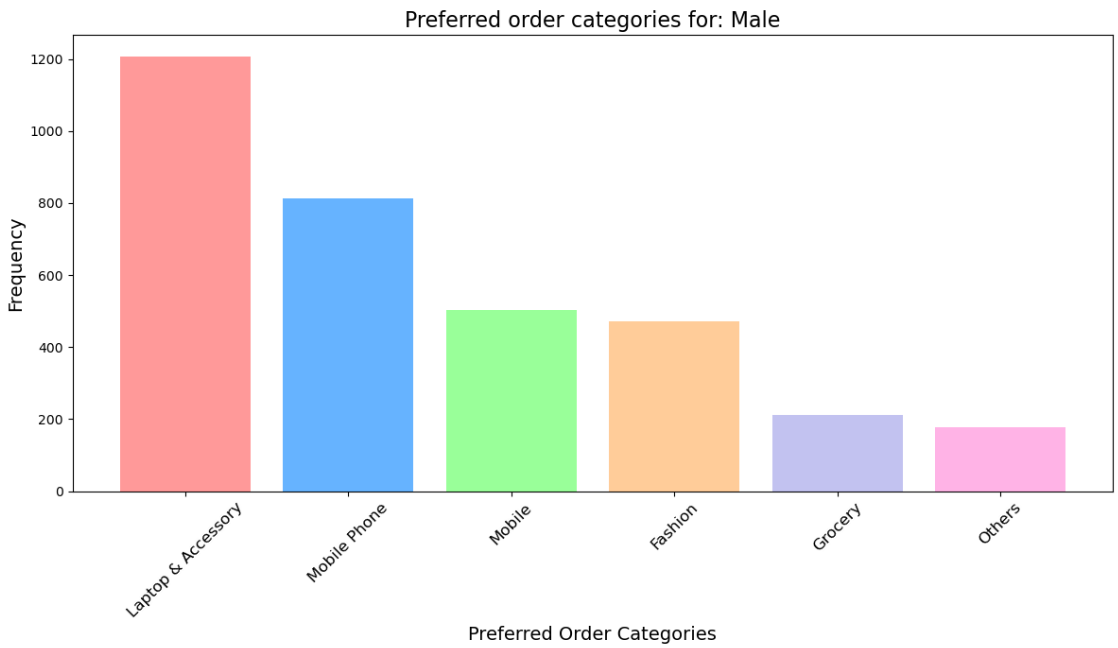

Preferred order categories for: 1 tier
Frequency
0
200
400
600
800
1000
Laptop & Accessory
Mobile Phone
Mobile
Fashion
Grocery
Others
Preferred Order Categories



[68]:

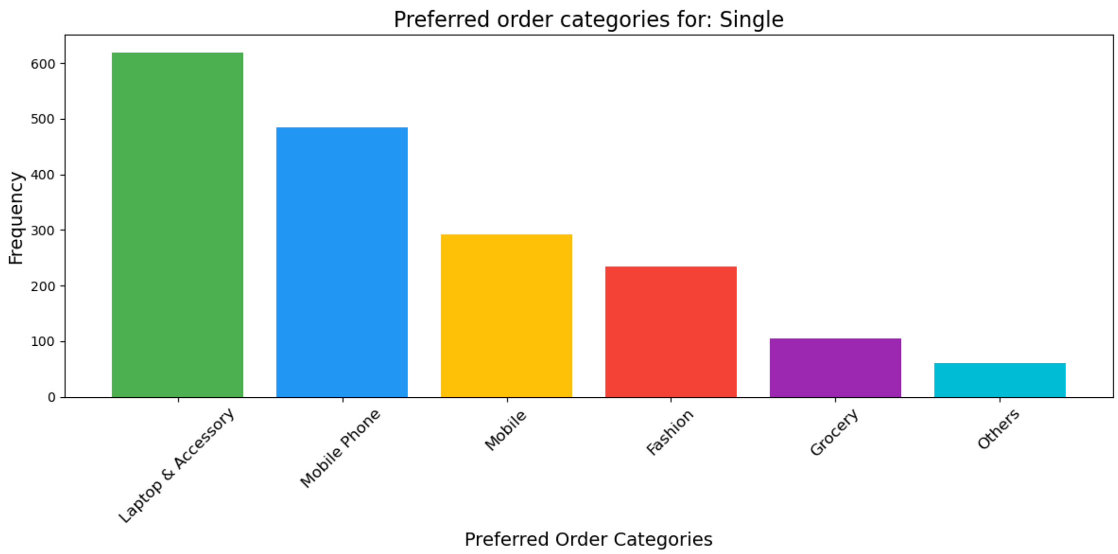
```
genders = df['Gender'].unique()

for gender in genders:
    if gender:
        plt.figure(figsize=(12, 7))
        sub_df = df[df['Gender'] == gender]
        frequency_counts = sub_df['PreferedOrderCat'].value_counts()
        plt.bar(frequency_counts.index, frequency_counts, color=['#ff9999',␣
↪'#66b3ff', '#99ff99', '#ffcc99', '#c2c2f0', '#ffb3e6'])
        plt.title(f'Preferred order categories for: {gender}', fontsize=16)
        plt.xlabel('Preferred Order Categories', fontsize=14)
        plt.ylabel('Frequency', fontsize=14)
        plt.xticks(rotation=45, fontsize=12)
        plt.tight_layout()
        plt.show()
```

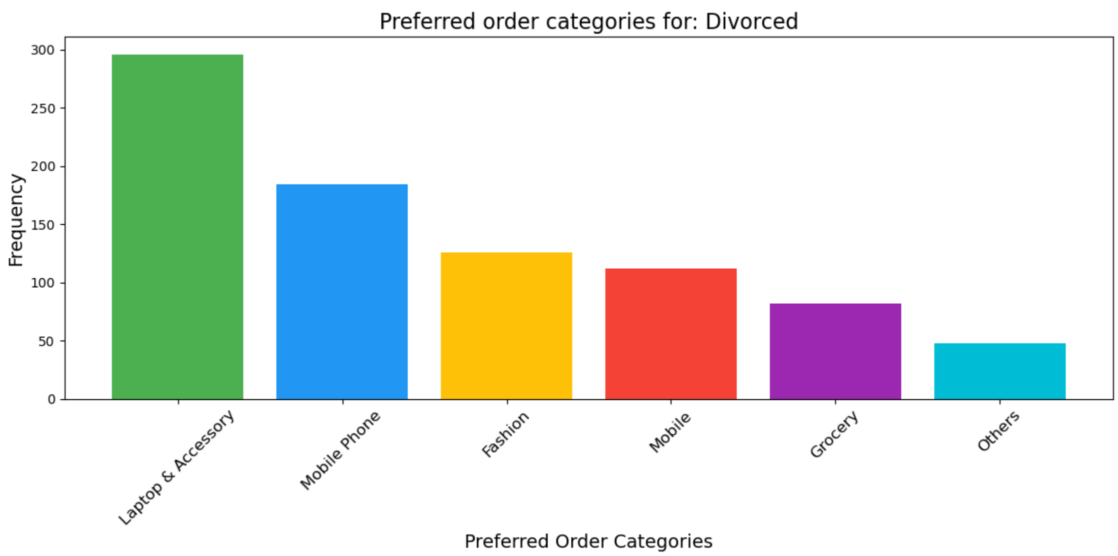


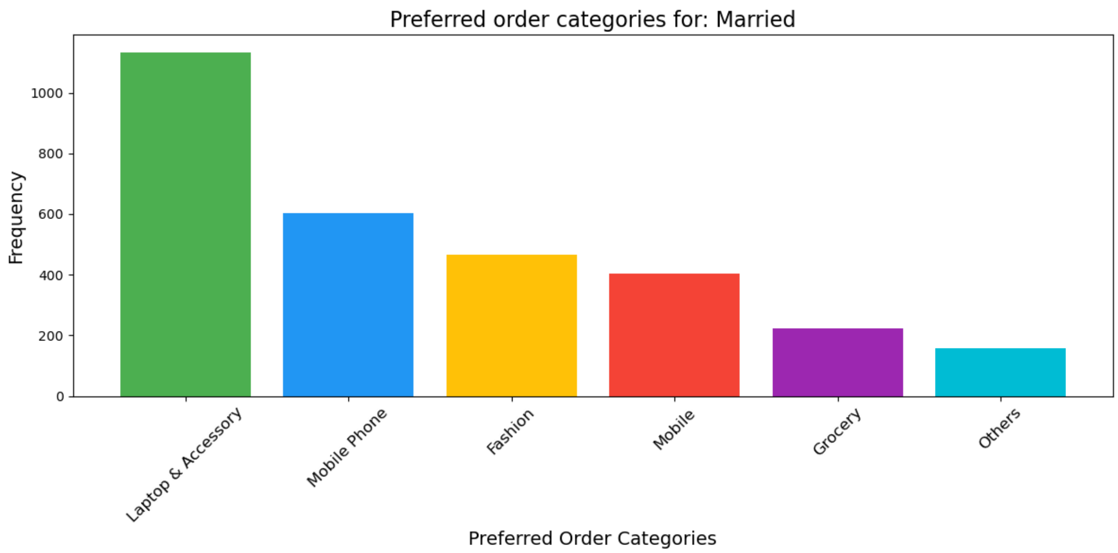


[72]:
```
marital_status = df['MaritalStatus'].unique()

for status in marital_status:
    if status:
        plt.figure(figsize=(12, 6))
```

```
        sub_df = df[df['MaritalStatus'] == status]
        frequency_counts = sub_df['PreferedOrderCat'].value_counts()
        plt.bar(frequency_counts.index, frequency_counts, color=['#4CAF50',␣
↪'#2196F3', '#FFC107', '#F44336', '#9C27B0', '#00BCD4'])
        plt.title(f'Preferred order categories for: {status}', fontsize=16)
        plt.xlabel('Preferred Order Categories', fontsize=14)
        plt.ylabel('Frequency', fontsize=14)
        plt.xticks(rotation=45, fontsize=12)
        plt.tight_layout()
        plt.show()
```





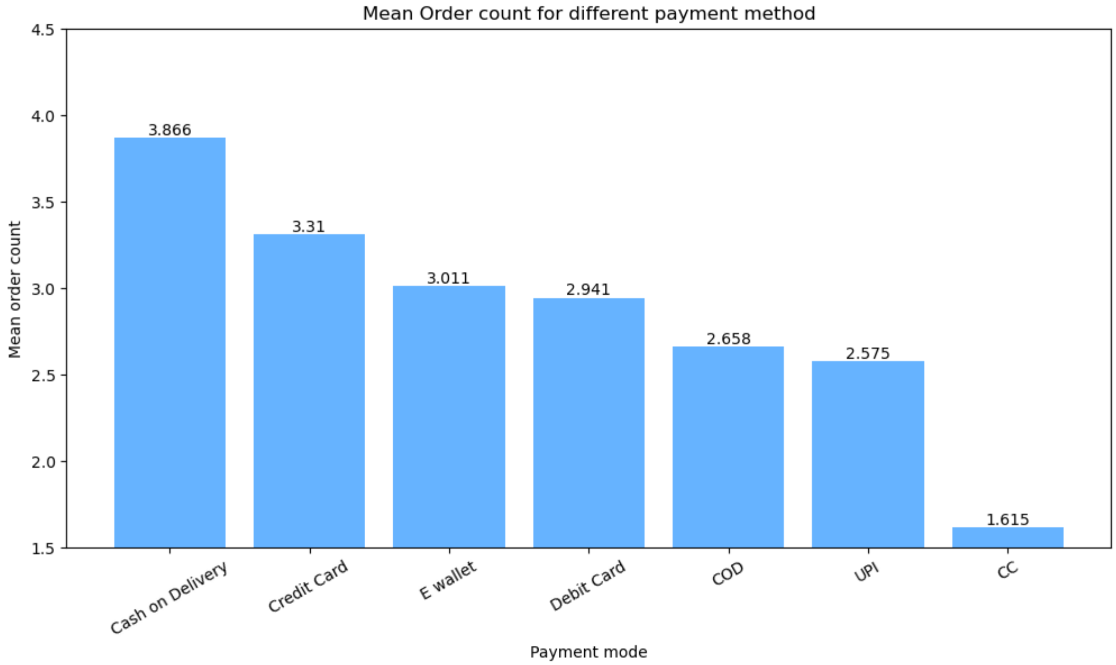


Conversion Analysis

Which Preferred Payment Modes Are More Successful in Conversion

[76]:
```
conversion_by_payment_mode = df.groupby('PreferredPaymentMode')['OrderCount'].
↪mean().sort_values(ascending=False)
payment_mode = conversion_by_payment_mode.index.tolist()
mean_order_count = conversion_by_payment_mode.values.tolist()
```

[78]:
```
plt.figure(figsize=(12, 6))
bars = plt.bar(payment_mode, mean_order_count, color='#66b3ff')
plt.xlabel('Payment mode')
plt.ylabel('Mean order count')
plt.title('Mean Order count for different payment method')
plt.xticks(rotation=30)
plt.ylim(1.5, 4.5)
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 3),␣
↪ha='center', va='bottom')
plt.show()
```



How the Number of Hours Spent on the App (HourSpendOnApp) Influences Conversion?

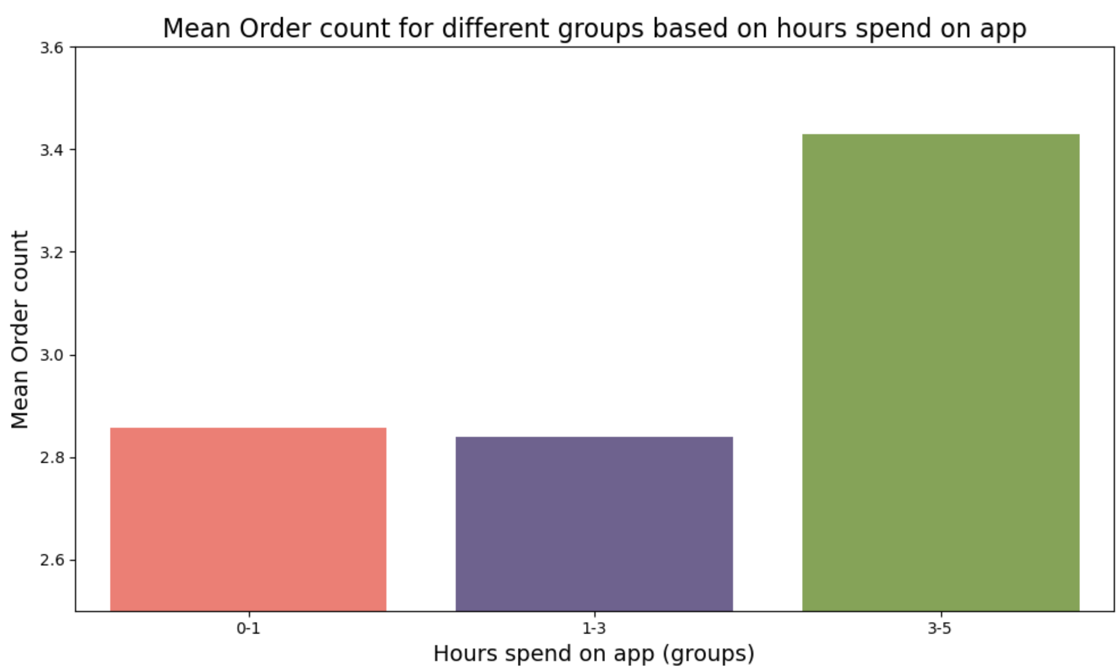
[82]:
```
df['HourSpendOnApp'].describe()
```

[82]:
```
count    5630.000000
mean        2.934636
std         0.705528
min         0.000000
25%         2.000000
50%         3.000000
75%         3.000000
max         5.000000
Name: HourSpendOnApp, dtype: float64
```

[85]:
```
df['HoursSpendOnAppGroup'] = pd.cut(df['HourSpendOnApp'], bins=[0, 1, 3, 5],␣
↪labels=['0-1', '1-3', '3-5'])

hours_order_count_rate = df.groupby('HoursSpendOnAppGroup')['OrderCount'].
↪mean().reset_index()
plt.figure(figsize=(10, 6))
sns.barplot(x='HoursSpendOnAppGroup', y='OrderCount',␣
↪data=hours_order_count_rate, palette=['#ff6f61', '#6b5b95', '#88b04b'])
plt.title("Mean Order count for different groups based on hours spend on app",␣
↪fontsize=16)
plt.xlabel("Hours spend on app (groups)", fontsize=14)
```

```
plt.ylabel("Mean Order count", fontsize=14)
plt.ylim(2.5, 3.6)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/849859181.py:3:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  hours_order_count_rate =
df.groupby('HoursSpendOnAppGroup')['OrderCount'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/849859181.py:5:
FutureWarning:

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

  sns.barplot(x='HoursSpendOnAppGroup', y='OrderCount',
data=hours_order_count_rate, palette=['#ff6f61', '#6b5b95', '#88b04b'])
```



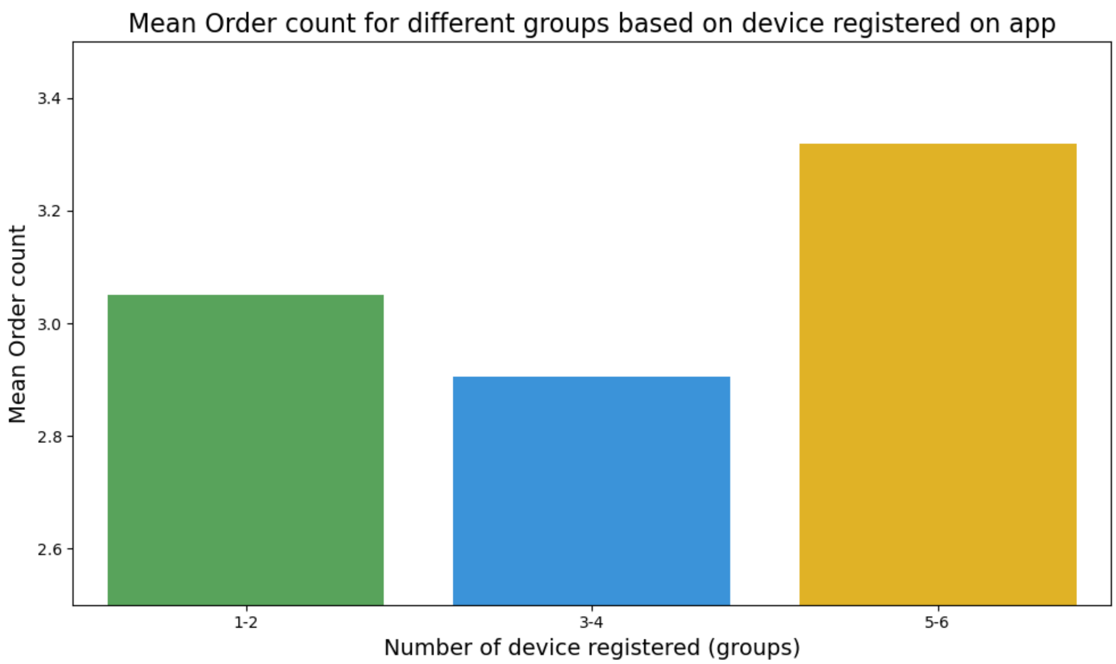
Is there a relationship between the number of registered devices (NumberOfDeviceRegistered) and the conversion rate?

[88]:
```
df['NumberOfDeviceRegistered'].describe()
```

[88]:
```
count    5630.000000
mean        3.688988
std         1.023999
min         1.000000
25%         3.000000
50%         4.000000
75%         4.000000
max         6.000000
Name: NumberOfDeviceRegistered, dtype: float64
```

[90]:
```python
df['NumberOfDeviceRegisteredGroup'] = pd.cut(df['NumberOfDeviceRegistered'],␣
↪bins=[1, 2, 4, 6], labels=['1-2', '3-4', '5-6'])

device_order_count_rate = df.
↪groupby('NumberOfDeviceRegisteredGroup')['OrderCount'].mean().reset_index()
plt.figure(figsize=(10, 6))
sns.barplot(x='NumberOfDeviceRegisteredGroup', y='OrderCount',␣
↪data=device_order_count_rate, palette=['#4CAF50', '#2196F3', '#FFC107'])
plt.title("Mean Order count for different groups based on device registered on␣
↪app", fontsize=16)
plt.xlabel("Number of device registered (groups)", fontsize=14)
plt.ylabel("Mean Order count", fontsize=14)
plt.ylim(2.5, 3.5)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2709105217.py:3:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  device_order_count_rate =
df.groupby('NumberOfDeviceRegisteredGroup')['OrderCount'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2709105217.py:5:
FutureWarning:

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

  sns.barplot(x='NumberOfDeviceRegisteredGroup', y='OrderCount',
data=device_order_count_rate, palette=['#4CAF50', '#2196F3', '#FFC107'])
```



Customer Satisfaction Analysis

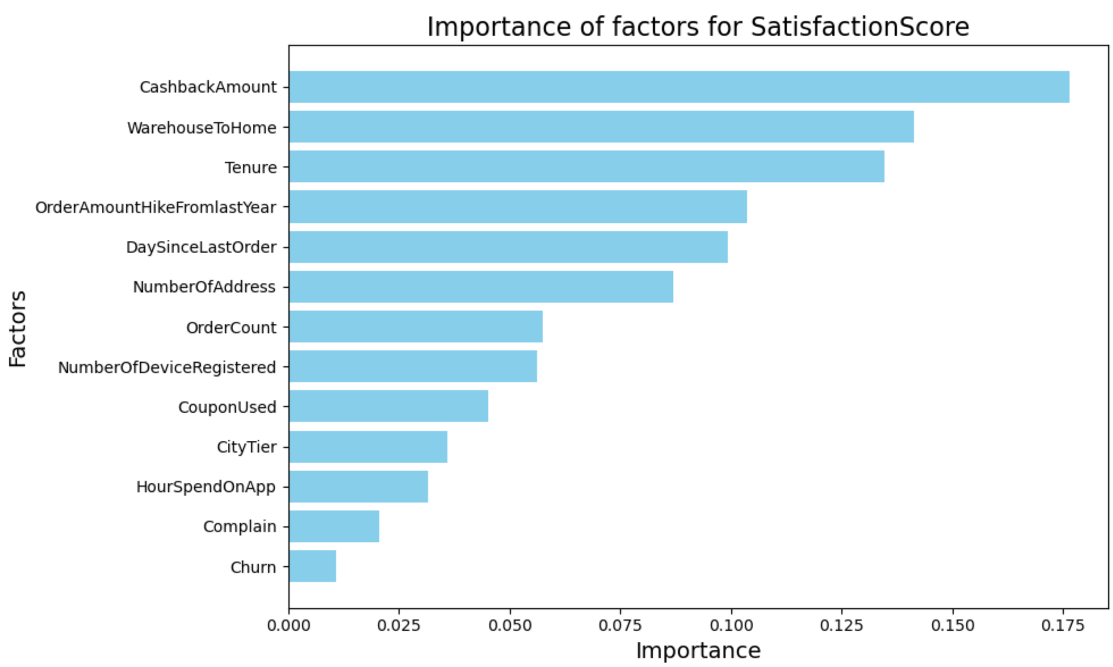
What Factors Influence High Levels of Customer Satisfaction (SatisfactionScore)?

[93]:
```
X = numeric_df.drop(columns=['SatisfactionScore'])
y = numeric_df['SatisfactionScore']

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

rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

y_pred = rf_model.predict(X_test)

feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("Importance of factors:")
print(feature_importances)
```

```
Importance of factors:
                        Feature  Importance
12               CashbackAmount    0.176360
3                WarehouseToHome    0.141366
```

```
1                         Tenure    0.134764
8    OrderAmountHikeFromlastYear    0.103599
11              DaySinceLastOrder    0.099235
6                NumberOfAddress    0.086922
10                    OrderCount    0.057498
5       NumberOfDeviceRegistered    0.056198
9                     CouponUsed    0.045142
2                       CityTier    0.035977
4                 HourSpendOnApp    0.031598
7                       Complain    0.020511
0                          Churn    0.010830
```

[94]:
```python
feature_importances = feature_importances.sort_values(by='Importance',␣
↪ascending=False)

plt.figure(figsize=(10, 6))
plt.barh(feature_importances['Feature'], feature_importances['Importance'],␣
↪color='skyblue')
plt.title('Importance of factors for SatisfactionScore', fontsize=16)
plt.xlabel('Importance', fontsize=14)
plt.ylabel('Factors', fontsize=14)
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



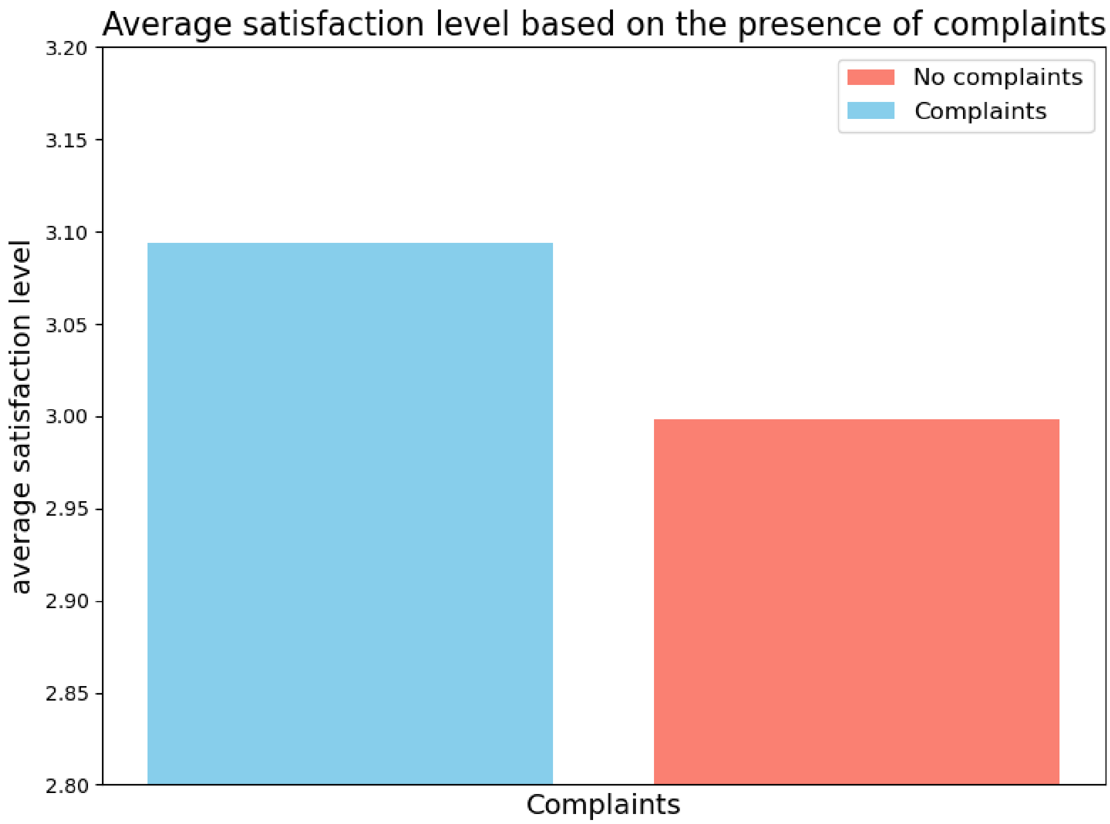
How Complaints (Complain) Relate to Customer Satisfaction Levels?

[96]:
```
satisfaction_by_complaint = df.groupby('Complain')['SatisfactionScore'].mean().
↪reset_index()
satisfaction_by_complaint
```

[96]:

	Complain	SatisfactionScore
0	0	3.093890
1	1	2.998753

[97]:
```
plt.figure(figsize=(8, 6))
plt.bar(satisfaction_by_complaint['Complain'],␣
↪satisfaction_by_complaint['SatisfactionScore'], color=['skyblue', 'salmon']
)

legend_elements = [
    Patch(facecolor='salmon', label='No complaints'),
    Patch(facecolor='skyblue', label='Complaints')
]

plt.legend(handles=legend_elements, loc='upper right', fontsize=12)
plt.title('Average satisfaction level based on the presence of complaints',␣
↪fontsize=16)
plt.xlabel('Complaints', fontsize=14)
plt.ylabel('average satisfaction level', fontsize=14)
plt.ylim(2.8, 3.2)
plt.xticks([])
plt.tight_layout()
```



[98]:
```
correlation = df['Complain'].corr(df['SatisfactionScore'])
correlation
```

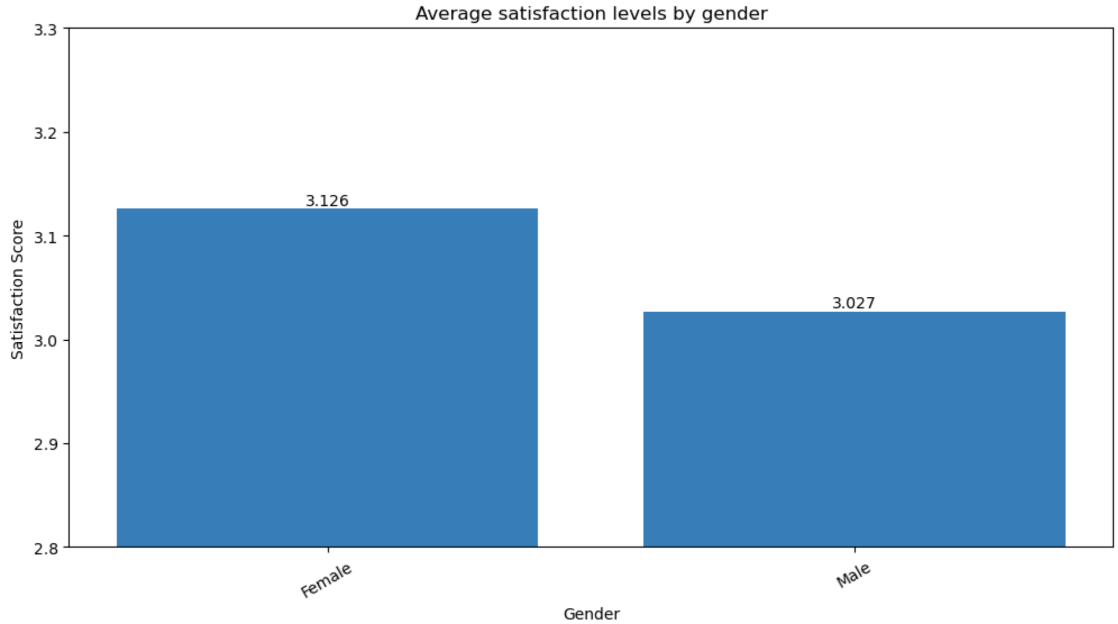
[98]: -0.031115486331220132

Is there a difference in satisfaction levels based on the customer's gender (Gender)?

[105]:
```
satisfaction_by_gender = df.groupby('Gender')['SatisfactionScore'].mean().
 ↪sort_values(ascending=False)
gender = satisfaction_by_gender.index.tolist()
satisfaction = satisfaction_by_gender.values.tolist()
```

[107]:
```
plt.figure(figsize=(12, 6))
bars = plt.bar(gender, satisfaction, color='#377eb8') #377eb8
plt.xlabel('Gender')
plt.ylabel('Satisfaction Score')
plt.title('Average satisfaction levels by gender')
plt.xticks(rotation=30)
plt.ylim(2.8, 3.3)

for bar in bars:
```

```
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 3),␣
↪ha='center', va='bottom')
plt.show()
```



Complaint Analysis

What factors most often lead to customer complaints?

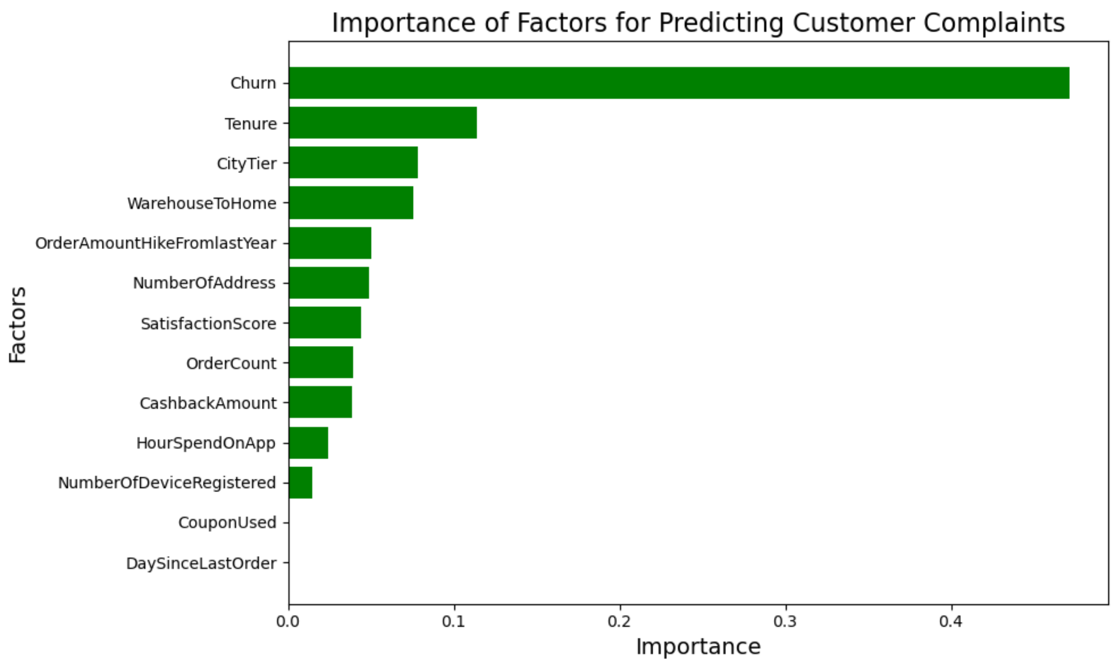
[110]:
```
X = numeric_df.drop(columns=['Complain'])
y = numeric_df['Complain']

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

tree_model = DecisionTreeClassifier(random_state=42, max_depth=5)
tree_model.fit(X_train, y_train)

y_pred = tree_model.predict(X_test)

print("Classification report:")
print(classification_report(y_test, y_pred))

feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': tree_model.feature_importances_
}).sort_values(by='Importance', ascending=False)
```

```python
print("Importance of factors:")
print(feature_importances)
```

```
Classification report:
              precision    recall  f1-score   support

           0       0.76      0.94      0.84       815
           1       0.61      0.23      0.33       311

    accuracy                           0.75      1126
   macro avg       0.68      0.59      0.59      1126
weighted avg       0.72      0.75      0.70      1126

Importance of factors:
                       Feature  Importance
0                        Churn    0.471195
1                       Tenure    0.114118
2                     CityTier    0.078330
3              WarehouseToHome    0.075348
8   OrderAmountHikeFromlastYear    0.050237
7              NumberOfAddress    0.049091
6            SatisfactionScore    0.044305
10                  OrderCount    0.039604
12              CashbackAmount    0.038775
4               HourSpendOnApp    0.024479
5     NumberOfDeviceRegistered    0.014516
9                   CouponUsed    0.000000
11           DaySinceLastOrder    0.000000
```

[112]:

```python
plt.figure(figsize=(10, 6))
plt.barh(feature_importances['Feature'], feature_importances['Importance'],␣
↪color='green')
plt.title('Importance of Factors for Predicting Customer Complaints',␣
↪fontsize=16)
plt.xlabel('Importance', fontsize=14)
plt.ylabel('Factors', fontsize=14)
plt.tight_layout()
plt.gca().invert_yaxis()

plt.show()
```



How does the number of days since the last order (DaySinceLastOrder) affect the likelihood of filing a complaint?

[115]:
```
df['DaySinceLastOrder'].describe()
```

[115]:
```
count    5630.000000
mean        4.459325
std         3.570626
min         0.000000
25%         2.000000
50%         3.000000
75%         7.000000
max        46.000000
Name: DaySinceLastOrder, dtype: float64
```

[117]:
```
df['LastOrderGroup'] = pd.cut(df['DaySinceLastOrder'], bins=[0, 10, 20, 50,],
 ↪labels=['0-10', '10-20', '20+'])
group_analysis = df.groupby('LastOrderGroup')['Complain'].mean().reset_index()
group_analysis
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/3117888745.py:2:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  group_analysis = df.groupby('LastOrderGroup')['Complain'].mean().reset_index()
```

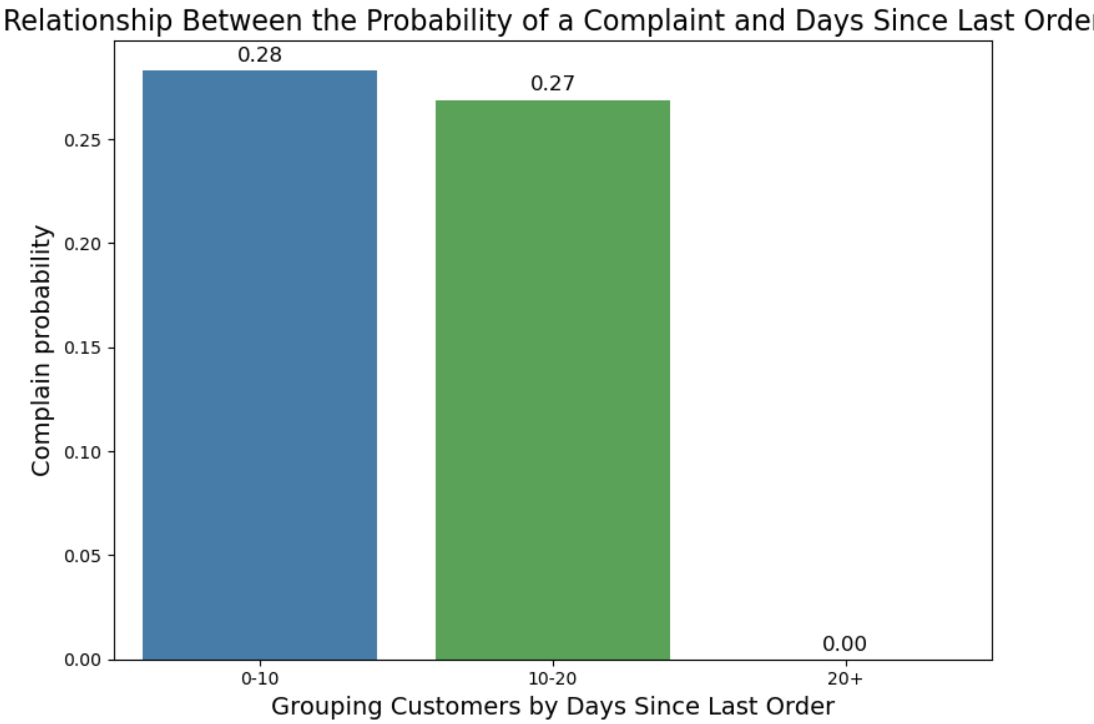
[117]:

	LastOrderGroup	Complain
0	0-10	0.283050
1	10-20	0.268852
2	20+	0.000000

[118]:

```
plt.figure(figsize=(8, 6))
barplot = sns.barplot(x='LastOrderGroup', y='Complain', data=group_analysis,␣
↪palette=['#377eb8', '#4daf4a'])

for i in barplot.containers:
    barplot.bar_label(i, fmt='%.2f', label_type='edge', fontsize=12, padding=3)

plt.title('Relationship Between the Probability of a Complaint and Days Since␣
↪Last Order', fontsize=16)
plt.xlabel('Grouping Customers by Days Since Last Order', fontsize=14)
plt.ylabel('Complain probability', fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2686107604.py:2:
FutureWarning:

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

  barplot = sns.barplot(x='LastOrderGroup', y='Complain', data=group_analysis,
palette=['#377eb8', '#4daf4a'])
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2686107604.py:2:
UserWarning:
The palette list has fewer values (2) than needed (3) and will cycle, which may
produce an uninterpretable plot.
  barplot = sns.barplot(x='LastOrderGroup', y='Complain', data=group_analysis,
palette=['#377eb8', '#4daf4a'])
```



How does the percentage increase in orders from last year (OrderAmountHikeFromlastYear) relate to the number of complaints?

[122]:
```
df['OrderAmountHikeFromlastYear'].describe()
```

[122]:
```
count    5630.000000
mean       15.674600
std         3.591058
min        11.000000
25%        13.000000
50%        15.000000
75%        18.000000
max        26.000000
Name: OrderAmountHikeFromlastYear, dtype: float64
```

[124]:
```
df['YearHikeGroup'] = pd.cut(df['OrderAmountHikeFromlastYear'], bins=[0, 15,␣
↪20, 30], labels=['0-15', '15-20', '20+'])
group_analysis = df.groupby('YearHikeGroup')['Complain'].mean().reset_index()
group_analysis
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/4205175972.py:2:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  group_analysis = df.groupby('YearHikeGroup')['Complain'].mean().reset_index()
```

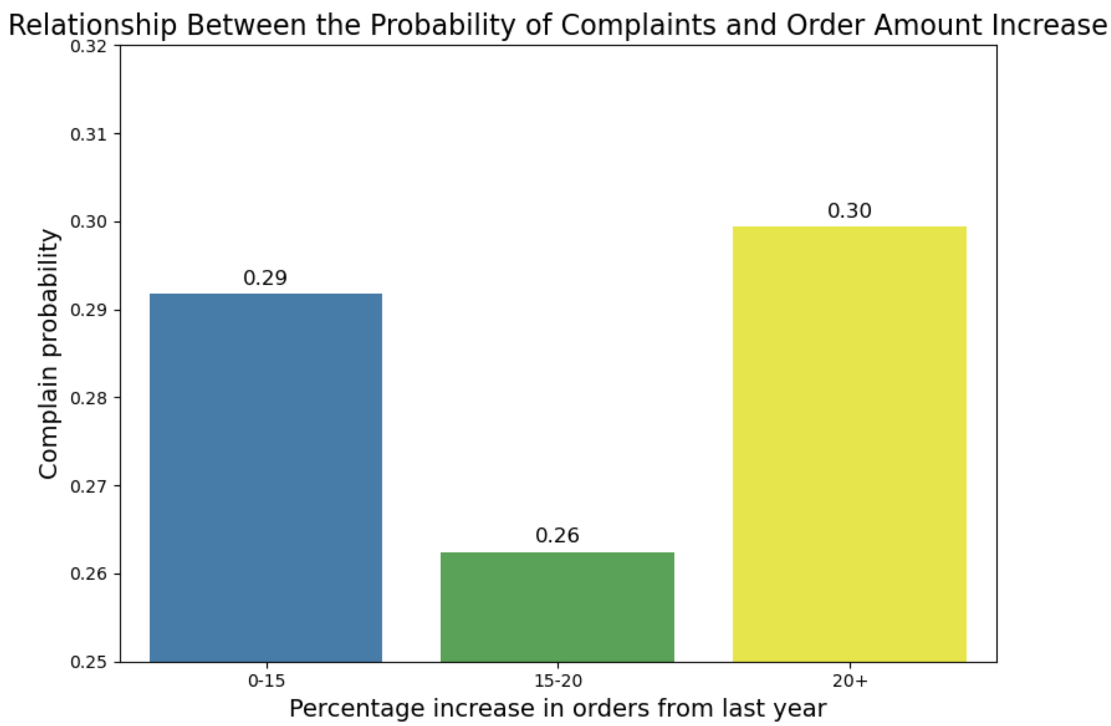
[124]:

	YearHikeGroup	Complain
0	0-15	0.291776
1	15-20	0.262458
2	20+	0.299435

[126]:

```
plt.figure(figsize=(8, 6))
barplot = sns.barplot(x='YearHikeGroup', y='Complain', data=group_analysis,␣
↪palette=['#377eb8', '#4daf4a', '#ffff33'])

for i in barplot.containers:
    barplot.bar_label(i, fmt='%.2f', label_type='edge', fontsize=12, padding=3)

plt.title('Relationship Between the Probability of Complaints and Order Amount␣
↪Increase', fontsize=16)
plt.xlabel('Percentage increase in orders from last year', fontsize=14)
plt.ylabel('Complain probability', fontsize=14)
plt.tight_layout()
plt.ylim(0.25, 0.32)
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2649507799.py:2:
FutureWarning:

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

  barplot = sns.barplot(x='YearHikeGroup', y='Complain', data=group_analysis,
palette=['#377eb8', '#4daf4a', '#ffff33'])
```



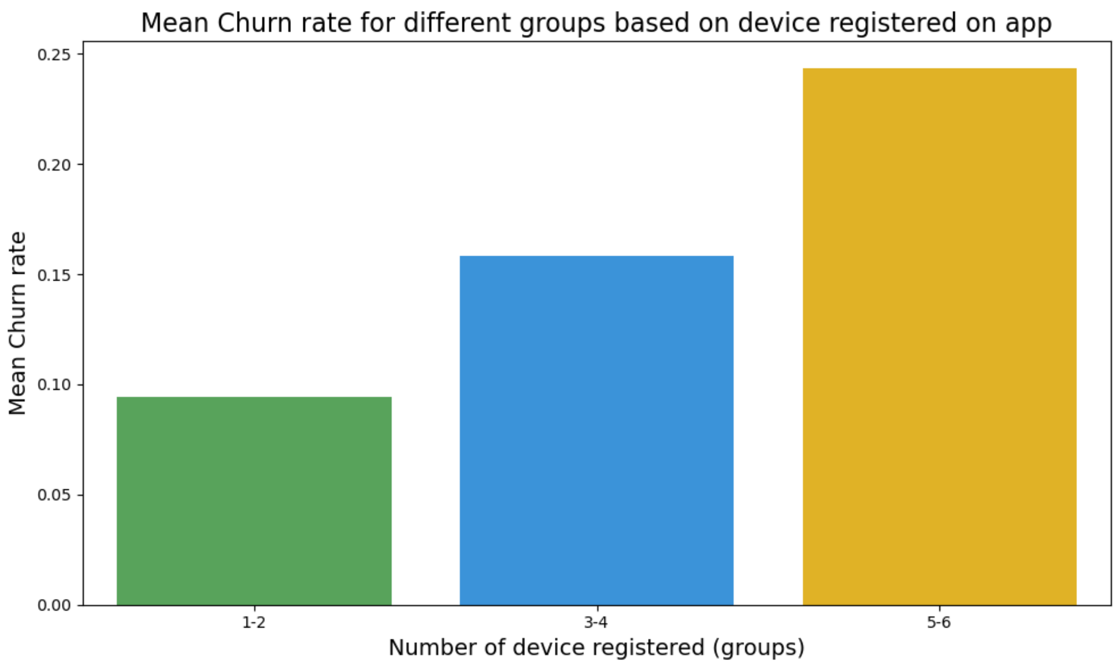
User Behavior Analysis

How the Number of Registered Devices (NumberOfDeviceRegistered) Influences User Behavior?

[129]:
```python
device_churn_rate = df.groupby('NumberOfDeviceRegisteredGroup')['Churn'].mean().
    ↪reset_index()
plt.figure(figsize=(10, 6))
sns.barplot(x='NumberOfDeviceRegisteredGroup', y='Churn',␣
    ↪data=device_churn_rate, palette=['#4CAF50', '#2196F3', '#FFC107'])
plt.title("Mean Churn rate for different groups based on device registered on␣
    ↪app", fontsize=16)
plt.xlabel("Number of device registered (groups)", fontsize=14)
plt.ylabel("Mean Churn rate", fontsize=14)
# plt.ylim(2.5, 3.5)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/749836930.py:1:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  device_churn_rate =
df.groupby('NumberOfDeviceRegisteredGroup')['Churn'].mean().reset_index()
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/749836930.py:3:
FutureWarning:
```

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

  sns.barplot(x='NumberOfDeviceRegisteredGroup', y='Churn',
data=device_churn_rate, palette=['#4CAF50', '#2196F3', '#FFC107'])
```



How Does User Behavior Change Depending on the Distance Between the Warehouse and the Home (WarehouseToHome)?

[132]:
```python
df['WarehouseToHome'].describe()
```

[132]:
```
count    5630.000000
mean       15.566785
std         8.345961
min         5.000000
25%         9.000000
50%        14.000000
75%        20.000000
max       127.000000
Name: WarehouseToHome, dtype: float64
```

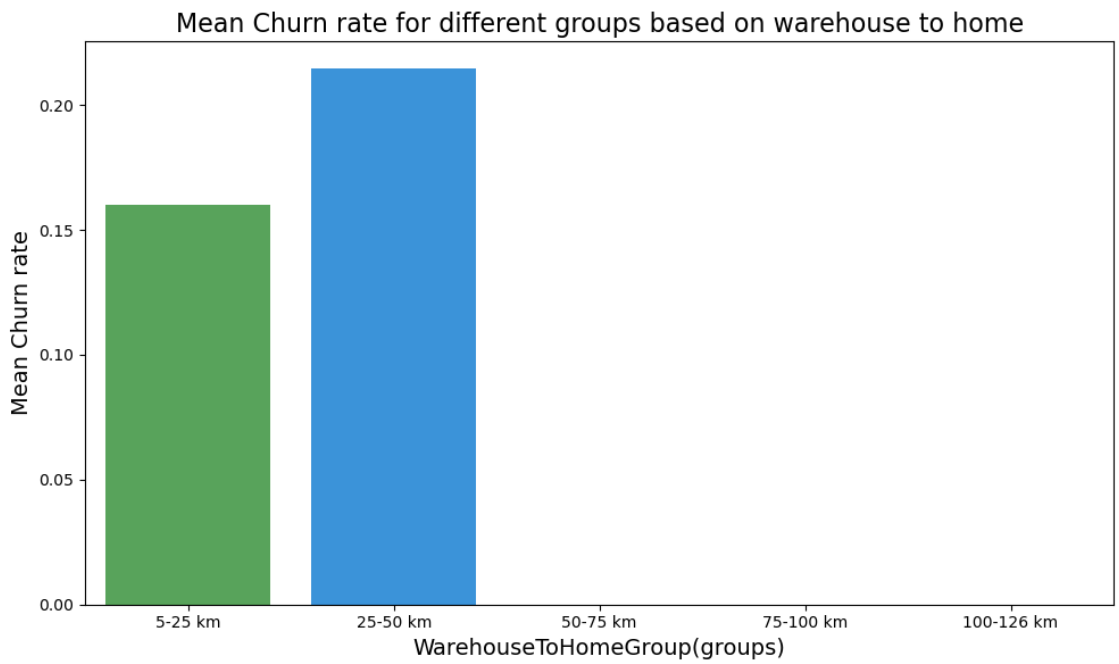
[134]:
```python
df['WarehouseToHomeGroup'] = pd.cut(df['WarehouseToHome'], bins=[5, 25, 50, 75,␣
↪100, 130], labels=['5-25 km', '25-50 km', '50-75 km', '75-100 km', '100-126␣
↪km'])
```

```
group_analysis = df.groupby('WarehouseToHomeGroup')['Churn'].mean().
↪reset_index()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2894683589.py:2:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  group_analysis =
df.groupby('WarehouseToHomeGroup')['Churn'].mean().reset_index()
```

[136]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='WarehouseToHomeGroup', y='Churn', data=group_analysis,␣
↪palette=['#4CAF50', '#2196F3', '#FFC107'])
plt.title("Mean Churn rate for different groups based on warehouse to home",␣
↪fontsize=16)
plt.xlabel("WarehouseToHomeGroup(groups)", fontsize=14)
plt.ylabel("Mean Churn rate", fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/157121045.py:2:
FutureWarning:

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

  sns.barplot(x='WarehouseToHomeGroup', y='Churn', data=group_analysis,
palette=['#4CAF50', '#2196F3', '#FFC107'])
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/157121045.py:2:
UserWarning:
The palette list has fewer values (3) than needed (5) and will cycle, which may
produce an uninterpretable plot.
  sns.barplot(x='WarehouseToHomeGroup', y='Churn', data=group_analysis,
palette=['#4CAF50', '#2196F3', '#FFC107'])
```



How does user churn change based on the number of added customer addresses (NumberOfAddress)?

[139]:
```
df['NumberOfAddress'].describe()
```

[139]:
```
count    5630.000000
mean        4.214032
std         2.583586
min         1.000000
25%         2.000000
50%         3.000000
75%         6.000000
max        22.000000
Name: NumberOfAddress, dtype: float64
```

[141]:
```
df['AddressGroup'] = pd.cut(df['NumberOfAddress'], bins=[1, 5, 10, 15, 20, 22],
                            labels=['1-5 addresses', '6-10 addresses', '11-15␣
 ↪addresses', '16-20 addresses', '21-22 addresses'])
group_analysis = df.groupby('AddressGroup')['Churn'].mean().reset_index()
group_analysis
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/1157714355.py:3:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  group_analysis = df.groupby('AddressGroup')['Churn'].mean().reset_index()
```

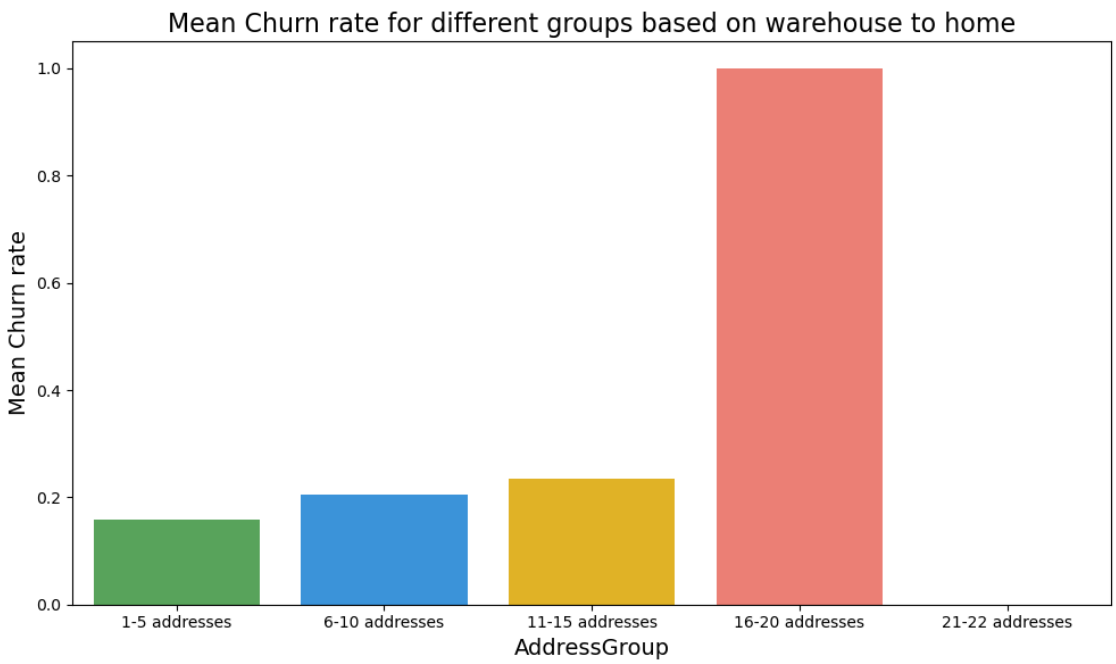
[141]:

	AddressGroup	Churn
0	1-5 addresses	0.157909
1	6-10 addresses	0.205033
2	11-15 addresses	0.234694
3	16-20 addresses	1.000000
4	21-22 addresses	0.000000

[143]:

```
plt.figure(figsize=(10, 6))
sns.barplot(x='AddressGroup', y='Churn', data=group_analysis,␣
  ↪palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61'])
plt.title("Mean Churn rate for different groups based on warehouse to home",␣
  ↪fontsize=16)
plt.xlabel("AddressGroup", fontsize=14)
plt.ylabel("Mean Churn rate", fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/3676435624.py:2:
FutureWarning:

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

  sns.barplot(x='AddressGroup', y='Churn', data=group_analysis,
palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61'])
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/3676435624.py:2:
UserWarning:
The palette list has fewer values (4) than needed (5) and will cycle, which may
produce an uninterpretable plot.
  sns.barplot(x='AddressGroup', y='Churn', data=group_analysis,
palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61'])
```



Order Growth Analysis

What factors contribute to the growth of orders?

[146]:
```
df['OrderCount'].describe()
```

[146]:
```
count    5630.000000
mean        2.961812
std         2.879248
min         1.000000
25%         1.000000
50%         2.000000
75%         3.000000
max        16.000000
Name: OrderCount, dtype: float64
```

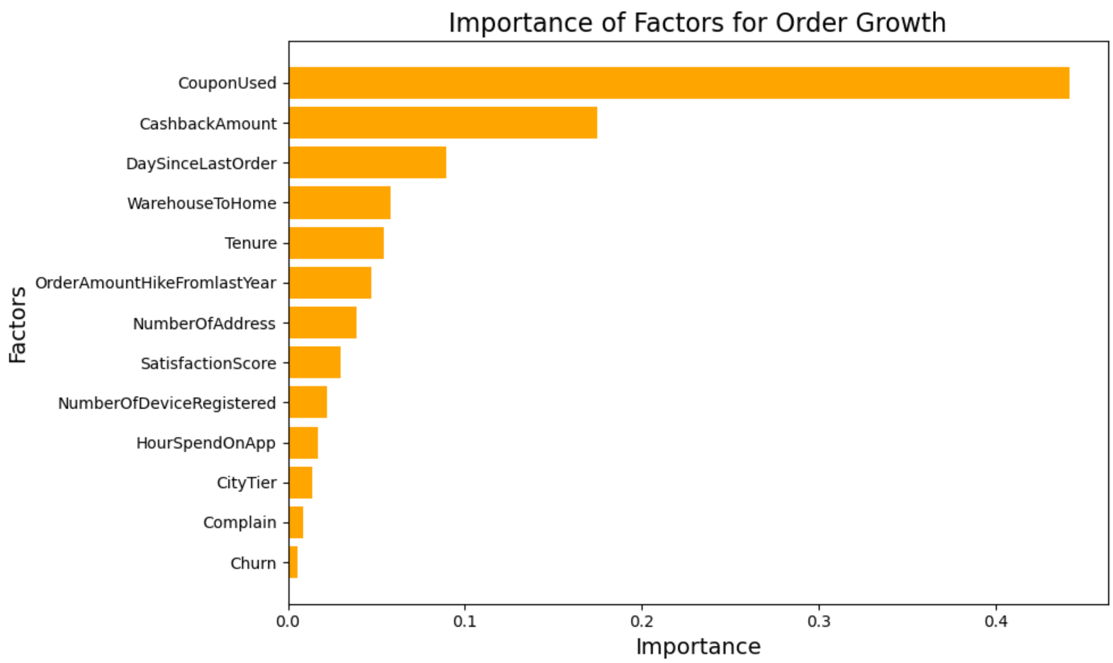
[148]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
```

[150]:
```
X = numeric_df.drop(columns=['OrderCount'])
y = numeric_df['OrderCount']

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

rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

```python
y_pred = rf_model.predict(X_test)

feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("Importance of factors:")
print(feature_importances)
```

```
Importance of factors:
                        Feature  Importance
10                   CouponUsed    0.441523
12               CashbackAmount    0.174987
11            DaySinceLastOrder    0.089406
3               WarehouseToHome    0.057993
1                        Tenure    0.053857
9   OrderAmountHikeFromlastYear    0.046939
7               NumberOfAddress    0.038556
6             SatisfactionScore    0.030015
5      NumberOfDeviceRegistered    0.021760
4                HourSpendOnApp    0.016867
2                      CityTier    0.013698
8                      Complain    0.008885
0                         Churn    0.005514
```

[151]:
```python
plt.figure(figsize=(10, 6))
plt.barh(feature_importances['Feature'], feature_importances['Importance'],␣
 ↪color='orange')
plt.title('Importance of Factors for Order Growth', fontsize=16)
plt.xlabel('Importance', fontsize=14)
plt.ylabel('Factors', fontsize=14)
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



How does the use of coupons (CouponUsed) affect the number of orders?

[153]:
```
df['CouponUsed'].describe()
```

[153]:
```
count    5630.000000
mean        1.716874
std         1.857640
min         0.000000
25%         1.000000
50%         1.000000
75%         2.000000
max        16.000000
Name: CouponUsed, dtype: float64
```

[155]:
```
df['CouponUsedGroup'] = pd.cut(df['CouponUsed'], bins=[0, 4, 8, 12, 16],
                            labels=['0-4 coupon', '5-8 coupon', '9-12 coupon',␣
 ↪'13-16 coupon'], include_lowest=True)
group_analysis = df.groupby('CouponUsedGroup')['OrderCount'].mean().
 ↪reset_index()
group_analysis
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2854901831.py:3:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  group_analysis =
```

```
df.groupby('CouponUsedGroup')['OrderCount'].mean().reset_index()
```

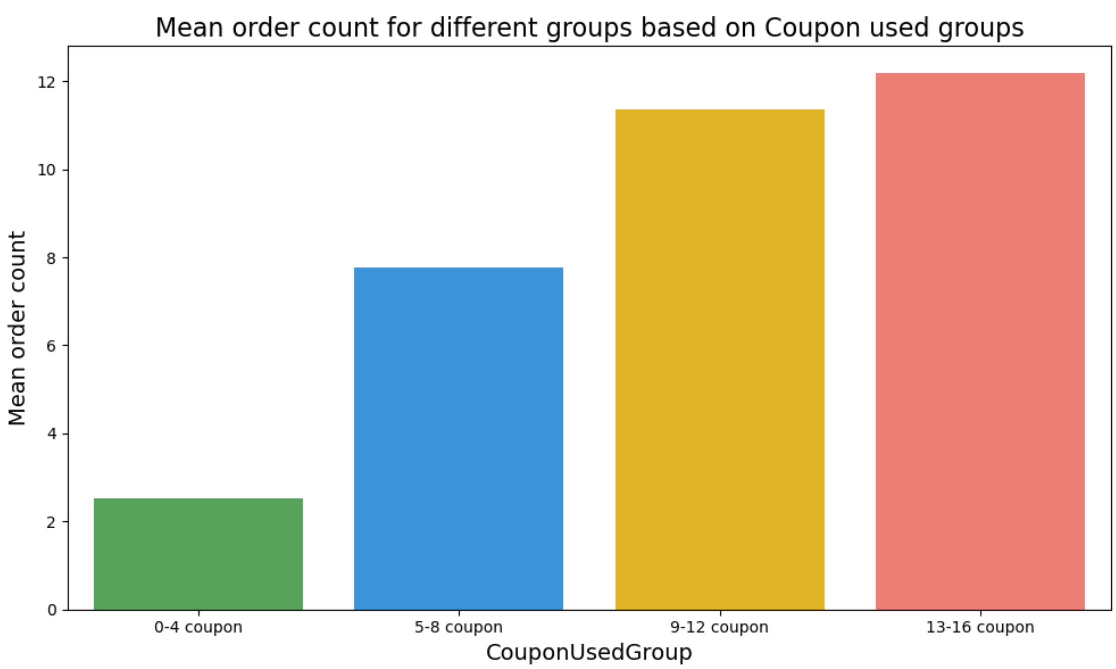
[155]:

	CouponUsedGroup	OrderCount
0	0-4 coupon	2.515006
1	5-8 coupon	7.777174
2	9-12 coupon	11.354167
3	13-16 coupon	12.187500

[159]:

```
plt.figure(figsize=(10, 6))
sns.barplot(x='CouponUsedGroup', y='OrderCount', data=group_analysis,␣
 ↪palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61'])
plt.title("Mean order count for different groups based on Coupon used groups",␣
 ↪fontsize=16)
plt.xlabel("CouponUsedGroup", fontsize=14)
plt.ylabel("Mean order count", fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/225996141.py:2:
FutureWarning:

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

  sns.barplot(x='CouponUsedGroup', y='OrderCount', data=group_analysis,
palette=['#4CAF50', '#2196F3', '#FFC107', '#ff6f61'])
```



Is there a relationship between the average cashback amount (CashbackAmount) and order growth?

[162]:
```
df['CashbackAmount'].describe()
```

[162]:
```
count    5630.000000
mean      177.221492
std        49.193869
min         0.000000
25%       146.000000
50%       163.000000
75%       196.000000
max       325.000000
Name: CashbackAmount, dtype: float64
```

[164]:
```
df['CashbackGroup'] = pd.cut(df['CashbackAmount'], bins=[0, 65, 130, 195, 260,␣
↪325],
                              labels=['0-65', '66-130', '131-195', '196-260',␣
↪'261-325'],
                              include_lowest=True)
group_analysis = df.groupby('CashbackGroup')['OrderCount'].mean().reset_index()
group_analysis
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/740877937.py:4:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  group_analysis =
df.groupby('CashbackGroup')['OrderCount'].mean().reset_index()
```

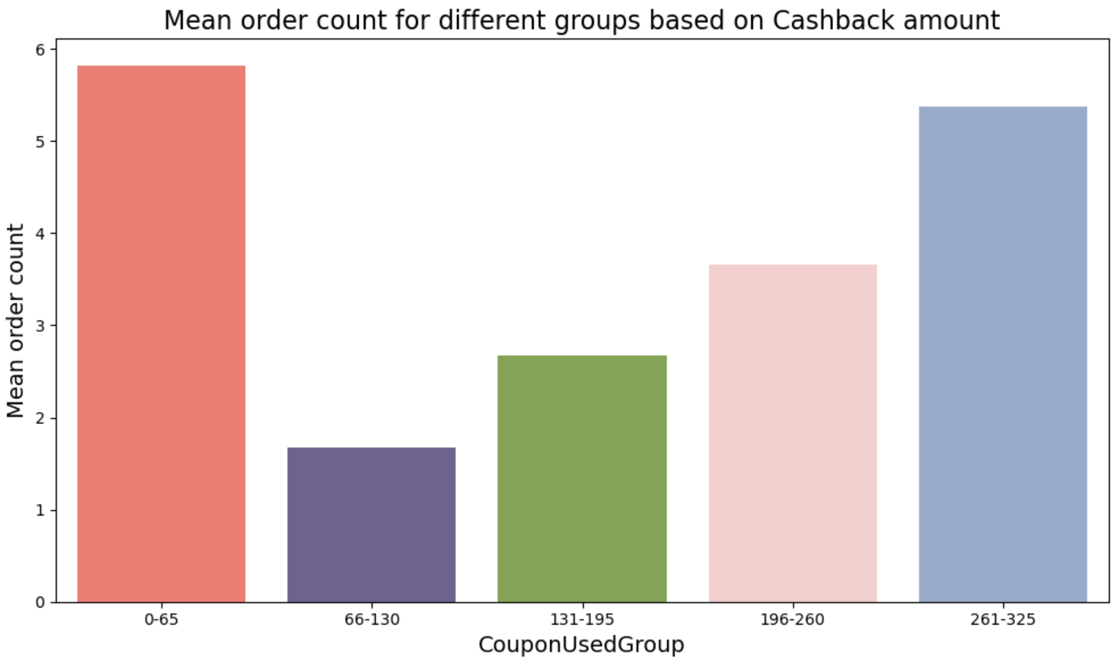
[164]:

	CashbackGroup	OrderCount
0	0-65	5.818182
1	66-130	1.667979
2	131-195	2.676977
3	196-260	3.653061
4	261-325	5.372263

[166]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='CashbackGroup', y='OrderCount', data=group_analysis,␣
↪palette=['#ff6f61', '#6b5b95', '#88b04b', '#f7cac9', '#92a8d1'])
plt.title("Mean order count for different groups based on Cashback amount",␣
↪fontsize=16)
plt.xlabel("CouponUsedGroup", fontsize=14)
plt.ylabel("Mean order count", fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2439140302.py:2:
```

```
FutureWarning:

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

  sns.barplot(x='CashbackGroup', y='OrderCount', data=group_analysis,
palette=['#ff6f61', '#6b5b95', '#88b04b', '#f7cac9', '#92a8d1'])
```



Cashback Analysis

What factors influence the number of cashbacks?

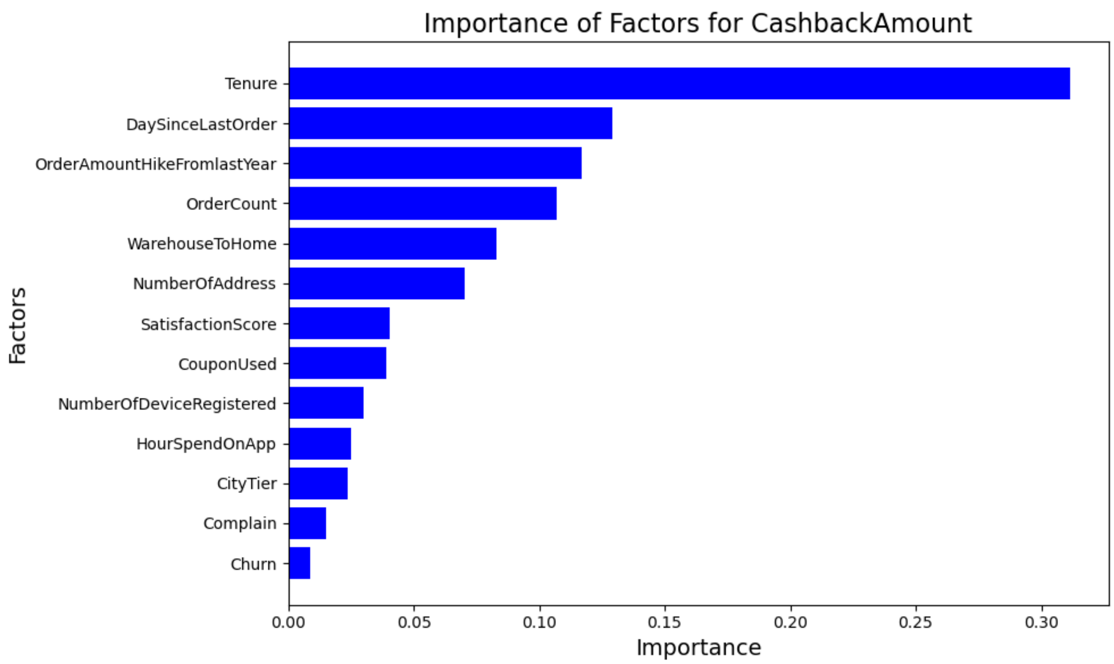
[169]:
```
X = numeric_df.drop(columns=['CashbackAmount'])
y = numeric_df['CashbackAmount']

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

model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

feature_importances = pd.DataFrame({
    'Feature': X.columns,
```

```
    'Importance': model.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("Importance of factors:")
print(feature_importances)
```

```
Importance of factors:
                        Feature  Importance
1                        Tenure    0.311339
12             DaySinceLastOrder    0.129264
9   OrderAmountHikeFromlastYear    0.117142
11                   OrderCount    0.106856
3               WarehouseToHome    0.082920
7               NumberOfAddress    0.070079
6             SatisfactionScore    0.040556
10                   CouponUsed    0.039145
5      NumberOfDeviceRegistered    0.030252
4                HourSpendOnApp    0.025081
2                      CityTier    0.023602
8                      Complain    0.014904
0                         Churn    0.008861
```

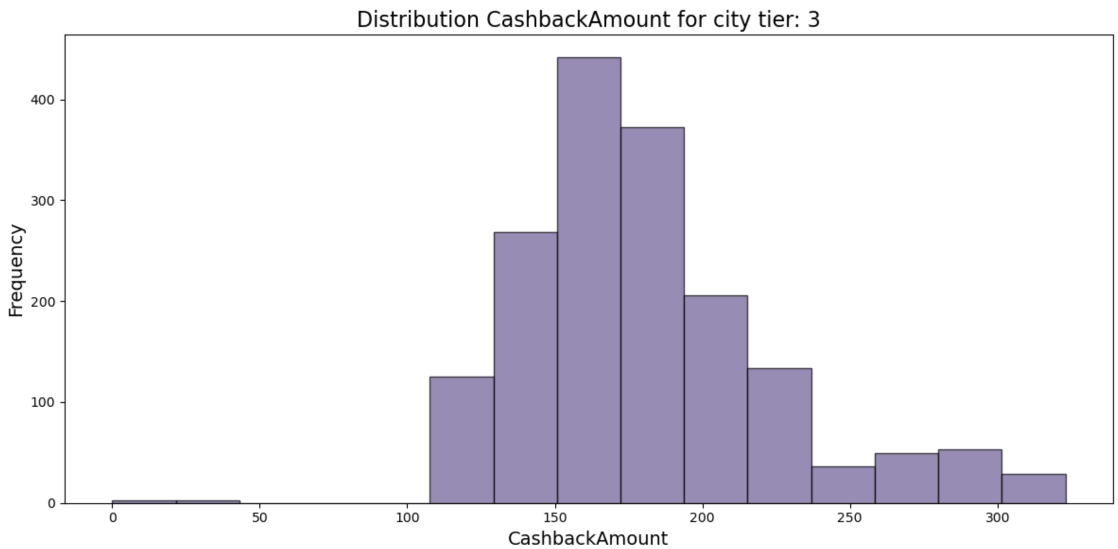
[170]:

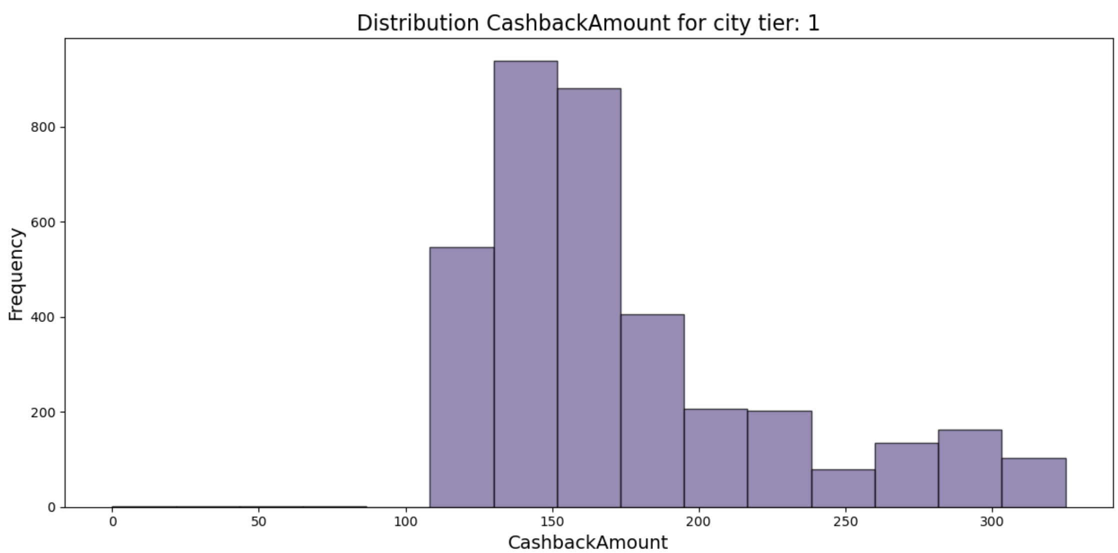
```
plt.figure(figsize=(10, 6))
plt.barh(feature_importances['Feature'], feature_importances['Importance'],␣
 ↪color='blue')
plt.title('Importance of Factors for CashbackAmount', fontsize=16)
plt.xlabel('Importance', fontsize=14)
plt.ylabel('Factors', fontsize=14)
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

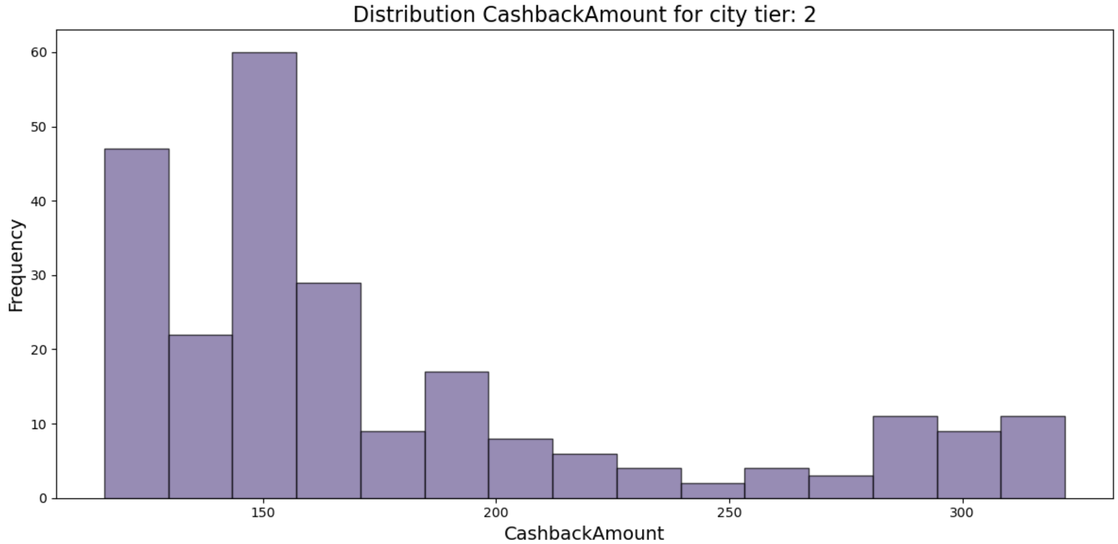


How does the distribution of cashbacks (CashbackAmount) differ across various customer segments?

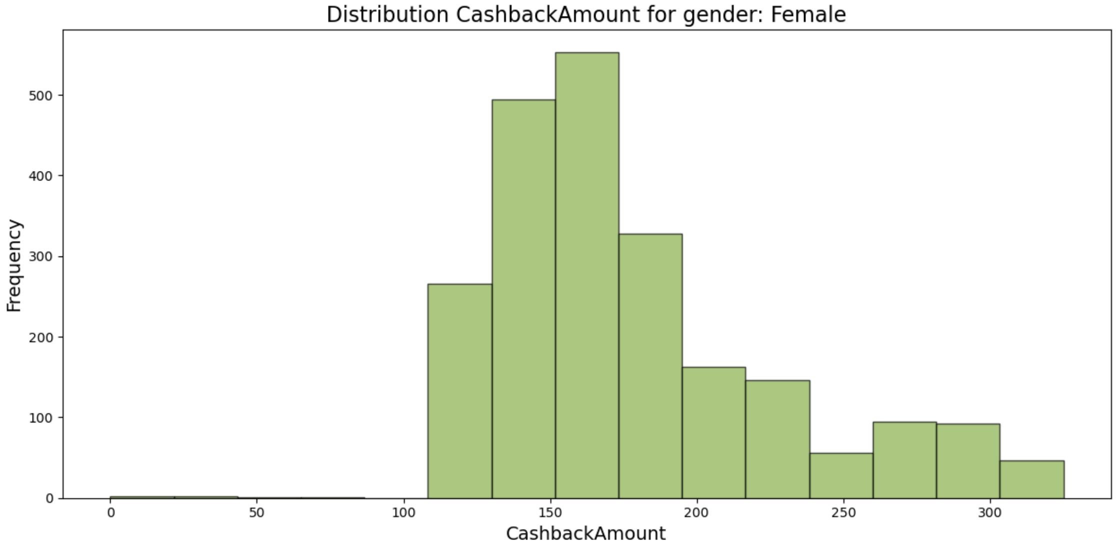
[172]:
```
for tier in city_tiers:
    if tier:
        plt.figure(figsize=(12, 6))

        sub_df = df[df['CityTier'] == tier]

        plt.hist(sub_df['CashbackAmount'], bins=15, color='#6b5b95', alpha=0.7,␣
↪edgecolor='black')

        plt.title(f'Distribution CashbackAmount for city tier: {tier}',␣
↪fontsize=16)
        plt.xlabel('CashbackAmount', fontsize=14)
        plt.ylabel('Frequency', fontsize=14)
        plt.tight_layout()
        plt.show()
```

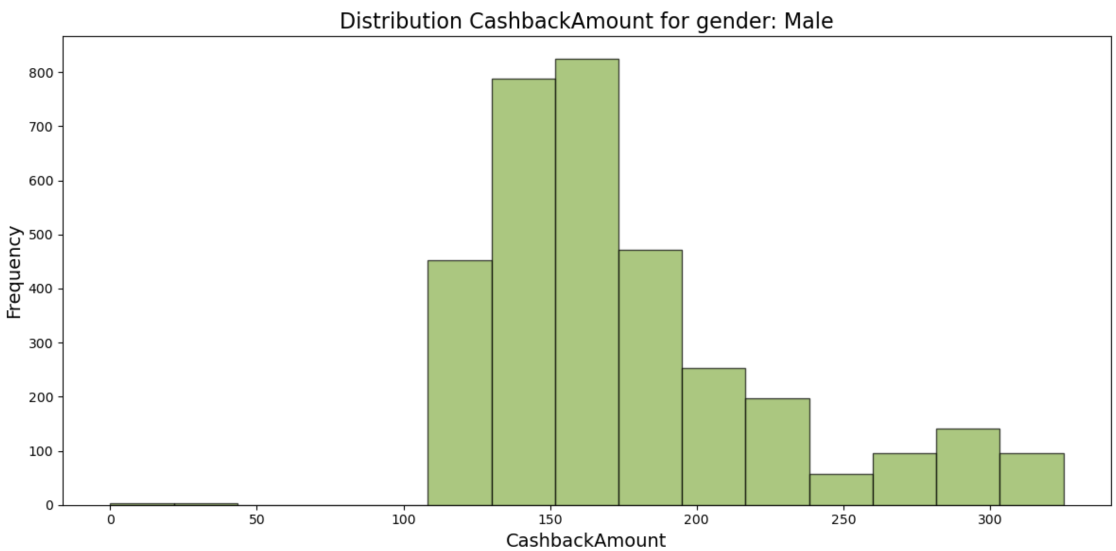

Distribution CashbackAmount for city tier: 3
Frequency
CashbackAmount
0
100
200
300
400
0
50
100
150
200
250
300


Distribution CashbackAmount for city tier: 1
Frequency
CashbackAmount
0
200
400
600
800
0
50
100
150
200
250
300



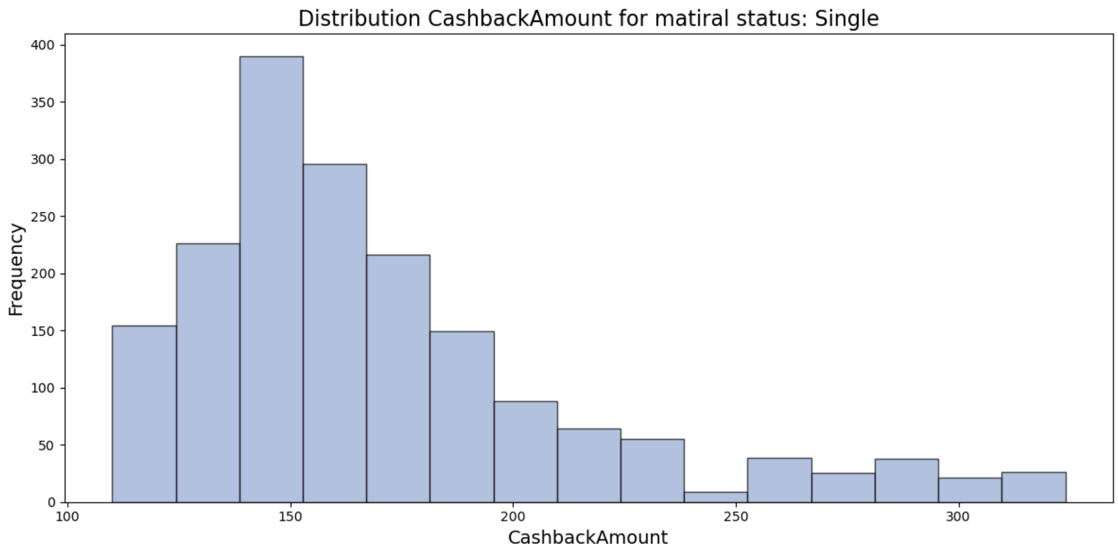
[173]:
```
for gender in genders:
    if gender:
        plt.figure(figsize=(12, 6))

        sub_df = df[df['Gender'] == gender]

        plt.hist(sub_df['CashbackAmount'], bins=15, color='#88b04b', alpha=0.7,␣
 ↪edgecolor='black')

        plt.title(f'Distribution CashbackAmount for gender: {gender}',␣
 ↪fontsize=16)
        plt.xlabel('CashbackAmount', fontsize=14)
        plt.ylabel('Frequency', fontsize=14)
        plt.tight_layout()
        plt.show()
```

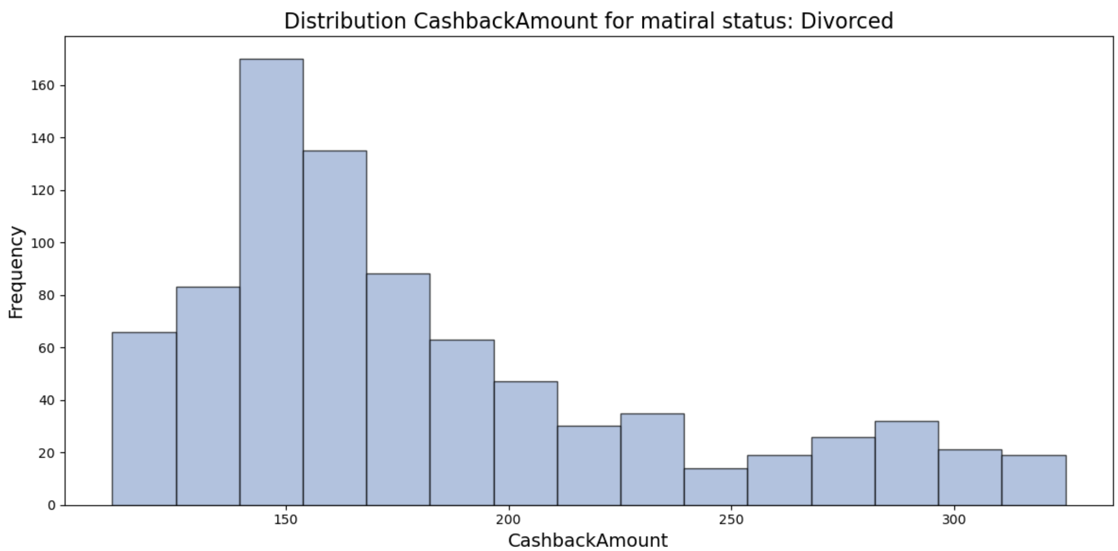


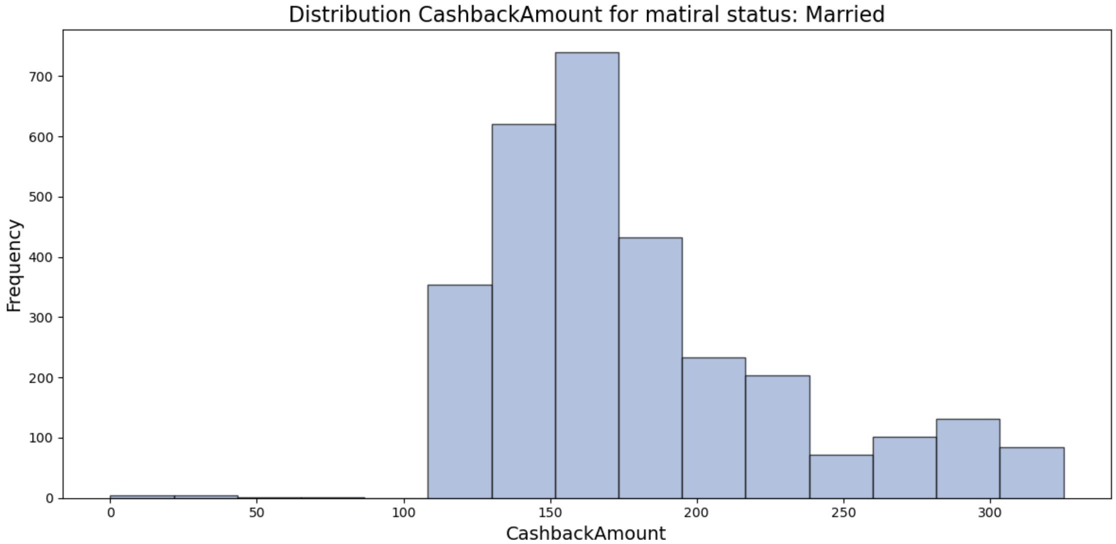


[175]:
```
for status in marital_status:
    if status:
        plt.figure(figsize=(12, 6))

        sub_df = df[df['MaritalStatus'] == status]

        plt.hist(sub_df['CashbackAmount'], bins=15, color='#92a8d1', alpha=0.7,␣
 ↪edgecolor='black')
```

```
        plt.title(f'Distribution CashbackAmount for matiral status: {status}',␣
↪fontsize=16)
        plt.xlabel('CashbackAmount', fontsize=14)
        plt.ylabel('Frequency', fontsize=14)
        plt.tight_layout()
        plt.show()
```







Is there a relationship between the number of coupons used (CouponUsed) and the number of cashbacks?

[179]:
```
group_analysis = df.groupby('CashbackGroup')['CouponUsed'].mean().reset_index()
group_analysis
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/1018720562.py:1:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  group_analysis =
df.groupby('CashbackGroup')['CouponUsed'].mean().reset_index()
```

[179]:

	CashbackGroup	CouponUsed
0	0-65	3.545455
1	66-130	0.856955
2	131-195	1.656551
3	196-260	2.430839
4	261-325	2.104015

[181]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='CashbackGroup', y='CouponUsed', data=group_analysis,␣
↪palette=['#ff6f61', '#6b5b95', '#88b04b', '#f7cac9', '#92a8d1'])
plt.title("Mean coupon used for different groups based on Cashback amount",␣
↪fontsize=16)
plt.xlabel("CashbackGroup", fontsize=14)
plt.ylabel("Mean coupon used", fontsize=14)
plt.tight_layout()
plt.show()
```

```
/var/folders/g_/dlksrxdd3pz88bqsmz91cx540000gn/T/ipykernel_9223/2146772315.py:2:
FutureWarning:

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

  sns.barplot(x='CashbackGroup', y='CouponUsed', data=group_analysis,
palette=['#ff6f61', '#6b5b95', '#88b04b', '#f7cac9', '#92a8d1'])
```