Introduction

In the competitive banking industry, customer retention is vital for sustained profitability and growth. This report analyzes a dataset containing various attributes of bank customers to identify key predictors of customer churn. The goal is to uncover patterns and insights that can help devise strategies to enhance customer retention and reduce churn rates.

Dataset Overview

The dataset includes various attributes such as CreditScore, Age, Geography, Gender, Balance, NumOfProducts, HasCrCard, IsActiveMember, EstimatedSalary, and more. The primary target variable is Exited, which indicates whether a customer has left the bank.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
!gdown 1xh7D0NDmxdg6IXTFzi_T-Oc5D-GtI44W
```

```
Downloading...
From: https://drive.google.com/uc?id=1xh7D0NDmxdg6IXTFzi_T-Oc5D-GtI44W
To: /content/Bank-Records.csv
100% 837k/837k [00:00<00:00, 6.67MB/s]
```

In [3]:

```
data=pd.read_csv('Bank-Records.csv')
data.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCar
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1

In [4]:

```
data.shape
```

Out[4]:

```
(10000, 18)
```

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
```

```
 0   RowNumber           10000 non-null  int64
 1   CustomerId          10000 non-null  int64
 2   Surname             10000 non-null  object
 3   CreditScore         10000 non-null  int64
 4   Geography           10000 non-null  object
 5   Gender              10000 non-null  object
 6   Age                 10000 non-null  int64
 7   Tenure              10000 non-null  int64
 8   Balance             10000 non-null  float64
 9   NumOfProducts       10000 non-null  int64
 10  HasCrCard           10000 non-null  int64
 11  IsActiveMember      10000 non-null  int64
 12  EstimatedSalary     10000 non-null  float64
 13  Exited              10000 non-null  int64
 14  Complain            10000 non-null  int64
 15  Satisfaction Score  10000 non-null  int64
 16  Card Type           10000 non-null  object
 17  Point Earned        10000 non-null  int64
dtypes: float64(2), int64(12), object(4)
memory usage: 1.4+ MB
```

In [6]:

```
data.dtypes
```

Out[6]:

```
RowNumber               int64
CustomerId              int64
Surname                object
CreditScore             int64
Geography              object
Gender                 object
Age                     int64
Tenure                  int64
Balance               float64
NumOfProducts           int64
HasCrCard               int64
IsActiveMember          int64
EstimatedSalary       float64
Exited                  int64
Complain                int64
Satisfaction Score      int64
Card Type              object
Point Earned            int64
dtype: object
```

In [7]:

```
data.describe()
```

Out[7]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	Is
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	

In [8]:

```
data['CustomerId'].nunique()
```

Out[8]:

```
10000
```

In [9]:

```
data.isnull().sum()
```

Out[9]:

```
RowNumber             0
CustomerId            0
Surname               0
CreditScore           0
Geography             0
Gender                0
Age                   0
Tenure                0
Balance               0
NumOfProducts         0
HasCrCard             0
IsActiveMember        0
EstimatedSalary       0
Exited                0
Complain              0
Satisfaction Score    0
Card Type             0
Point Earned          0
dtype: int64
```

1. Descriptive Statistics

> **Basic Statistics:** Calculate mean, median, and mode for numerical columns like CreditScore, Age, Balance, NumOfProducts, EstimatedSalary, and Points Earned.

In [10]:

```
Numerical_cols=['CreditScore','Age','Balance','NumOfProducts','EstimatedSalary','Point Earned']
for col in Numerical_cols:
  print(f'Mean of {col}: {data[col].mean()}')
  print(f'Median of {col}: {data[col].median()}')
  print(f'Mode of {col}: {data[col].mode()[0]}')
```

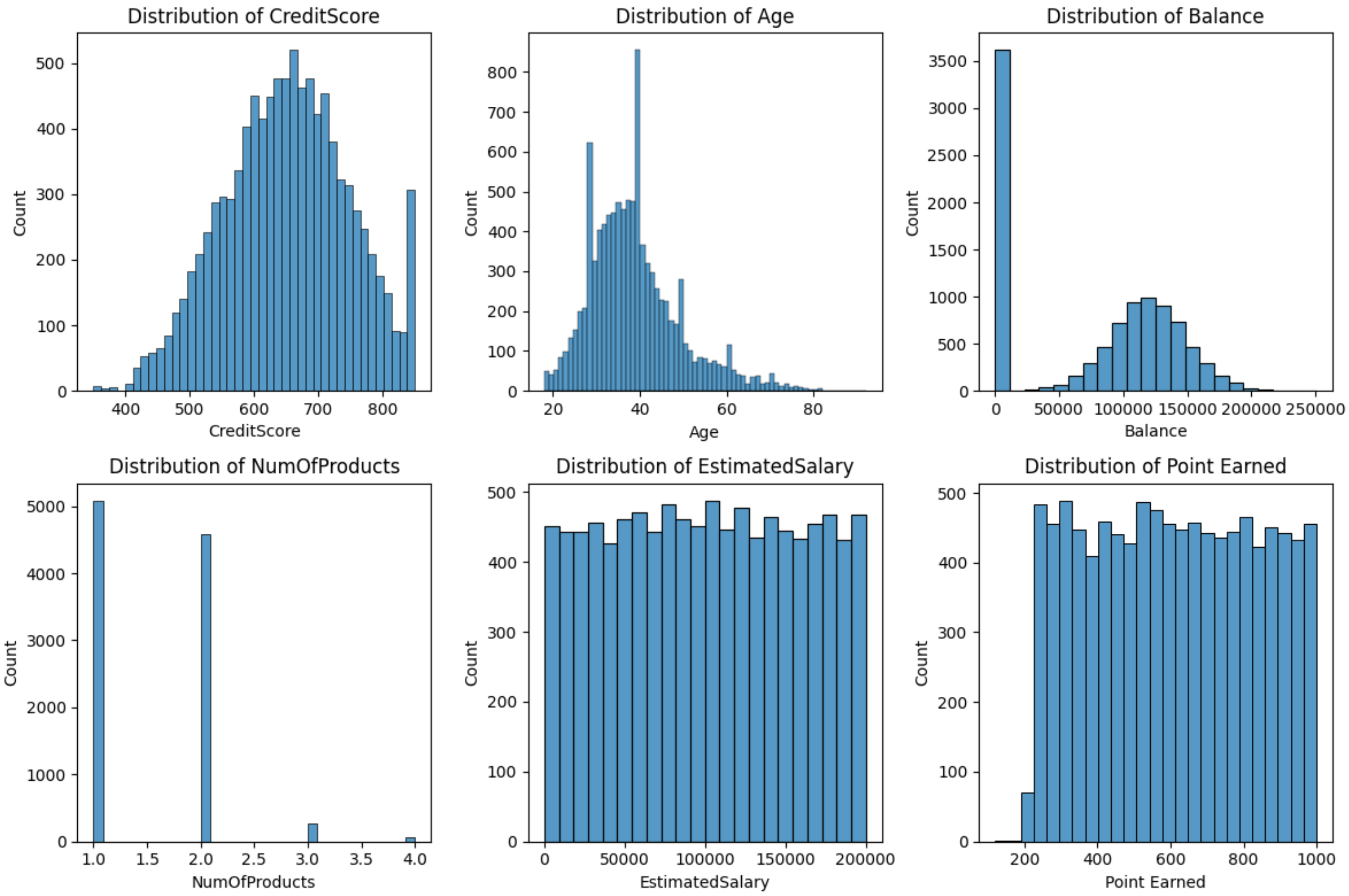
```
Mean of CreditScore: 650.5288
Median of CreditScore: 652.0
Mode of CreditScore: 850
Mean of Age: 38.9218
Median of Age: 37.0
Mode of Age: 37
Mean of Balance: 76485.889288
Median of Balance: 97198.54000000001
Mode of Balance: 0.0
Mean of NumOfProducts: 1.5302
Median of NumOfProducts: 1.0
Mode of NumOfProducts: 1
Mean of EstimatedSalary: 100090.239881
Median of EstimatedSalary: 100193.915
Mode of EstimatedSalary: 24924.92
Mean of Point Earned: 606.5151
Median of Point Earned: 605.0
Mode of Point Earned: 408
```

> **Distribution Analysis:** Analyze the distribution of key numerical variables using histograms and

> **box plots to understand the spread and central tendency.**

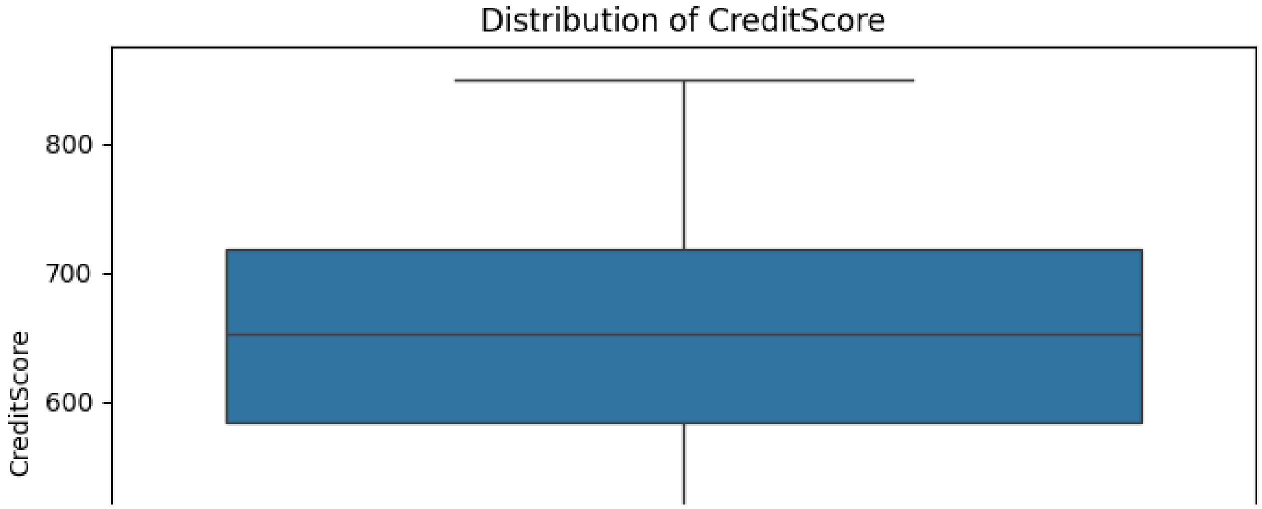
In [11]:

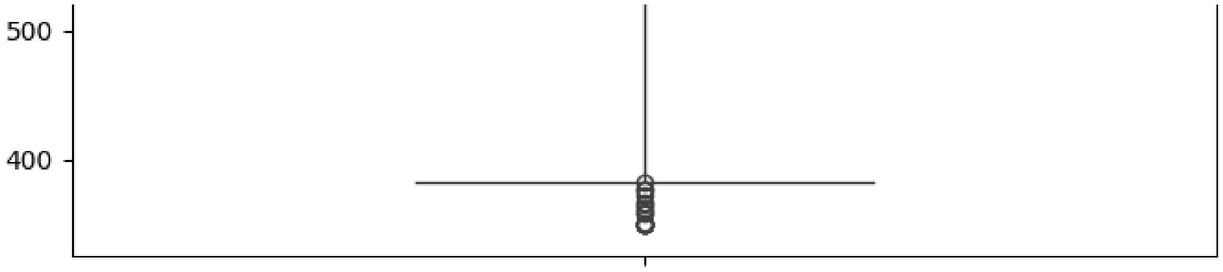
```
plt.figure(figsize=(12, 8))
for i, col in enumerate(Numerical_cols):
    plt.subplot(2, 3, i+1)
    sns.histplot(data[col])
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



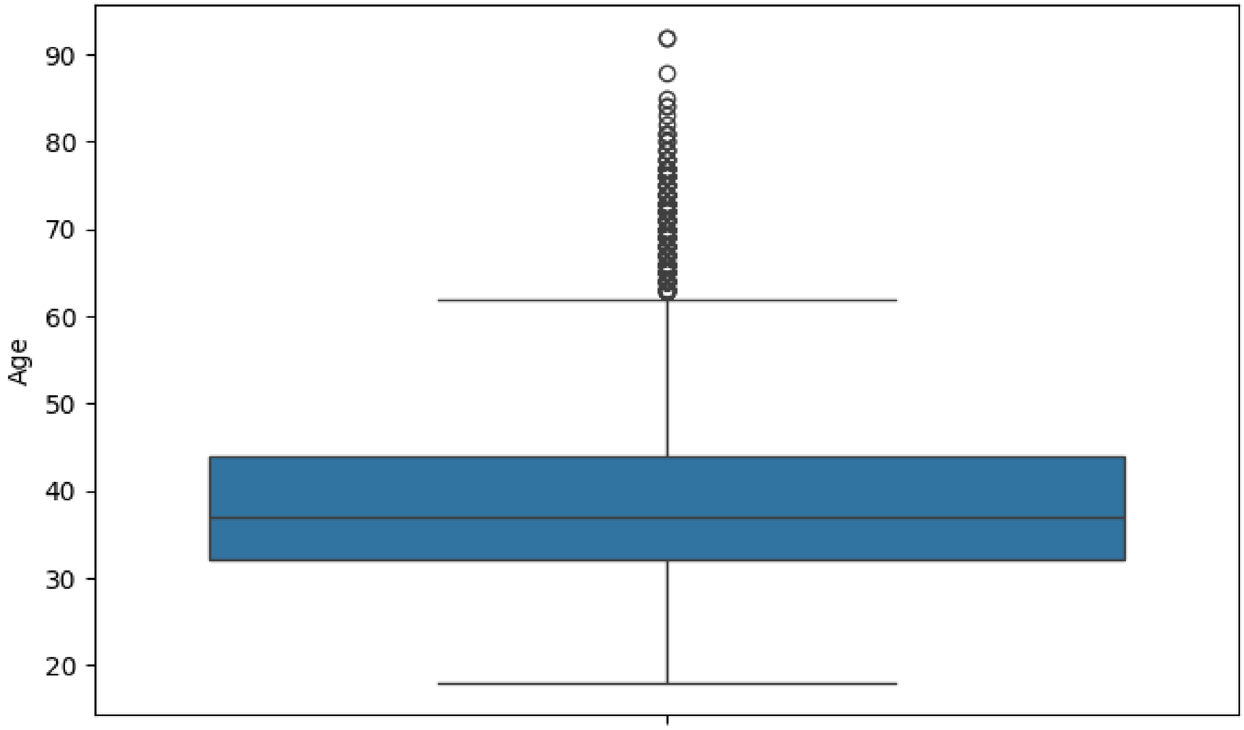
In [12]:

```
for col in Numerical_cols:
  plt.figure(figsize=(8,5))
  sns.boxplot(data[col])
  plt.title(f'Distribution of {col}')
  plt.show()
```

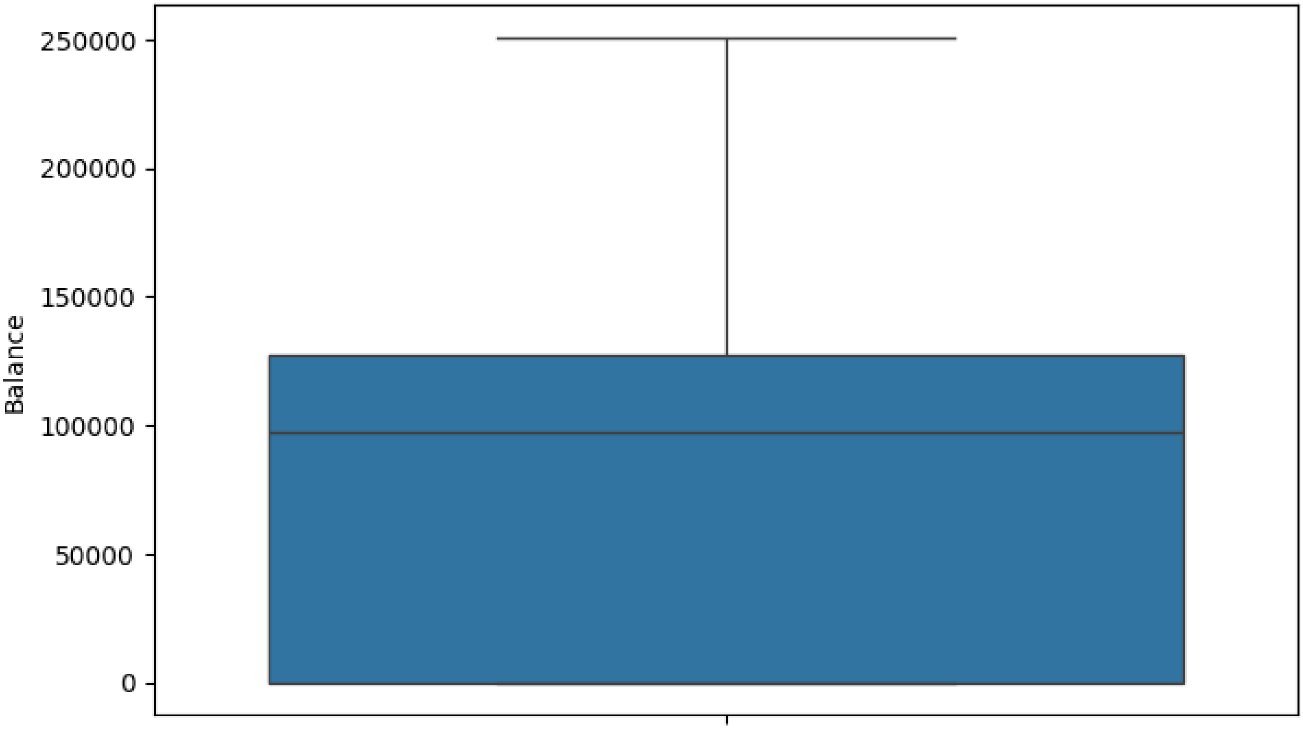




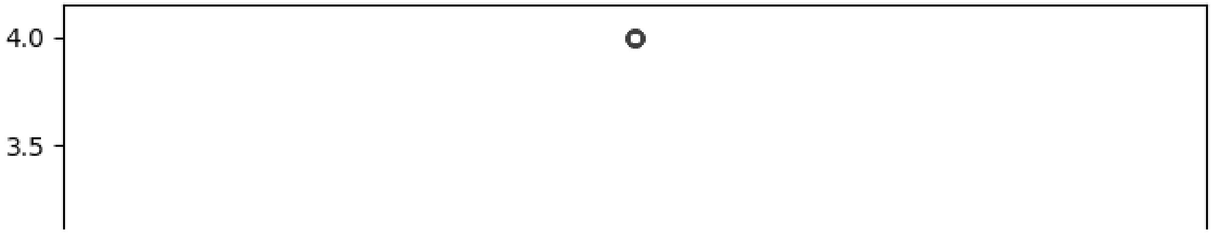
Distribution of Age

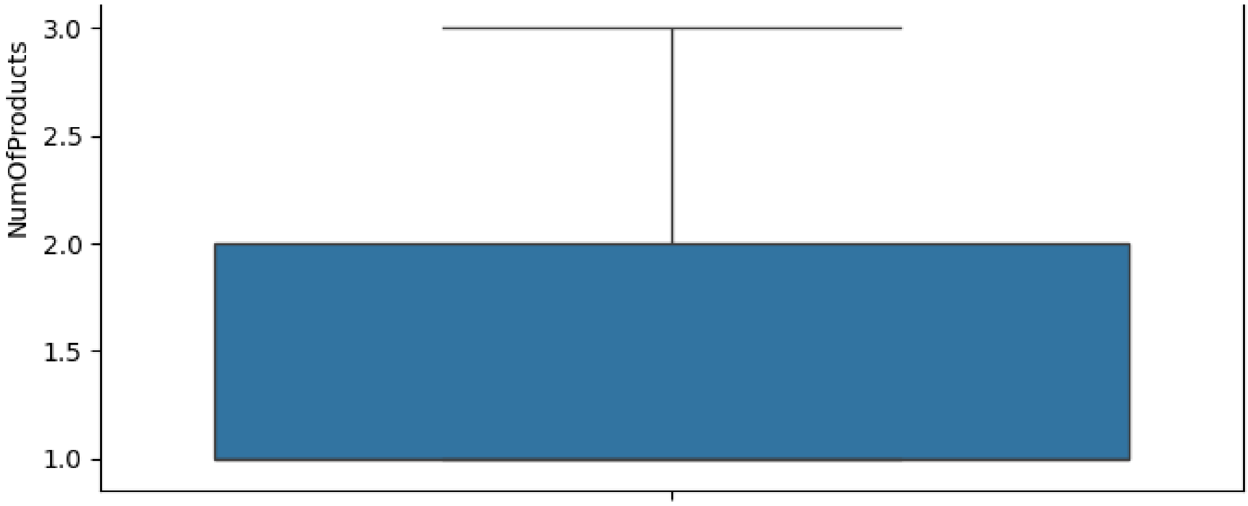


Distribution of Balance

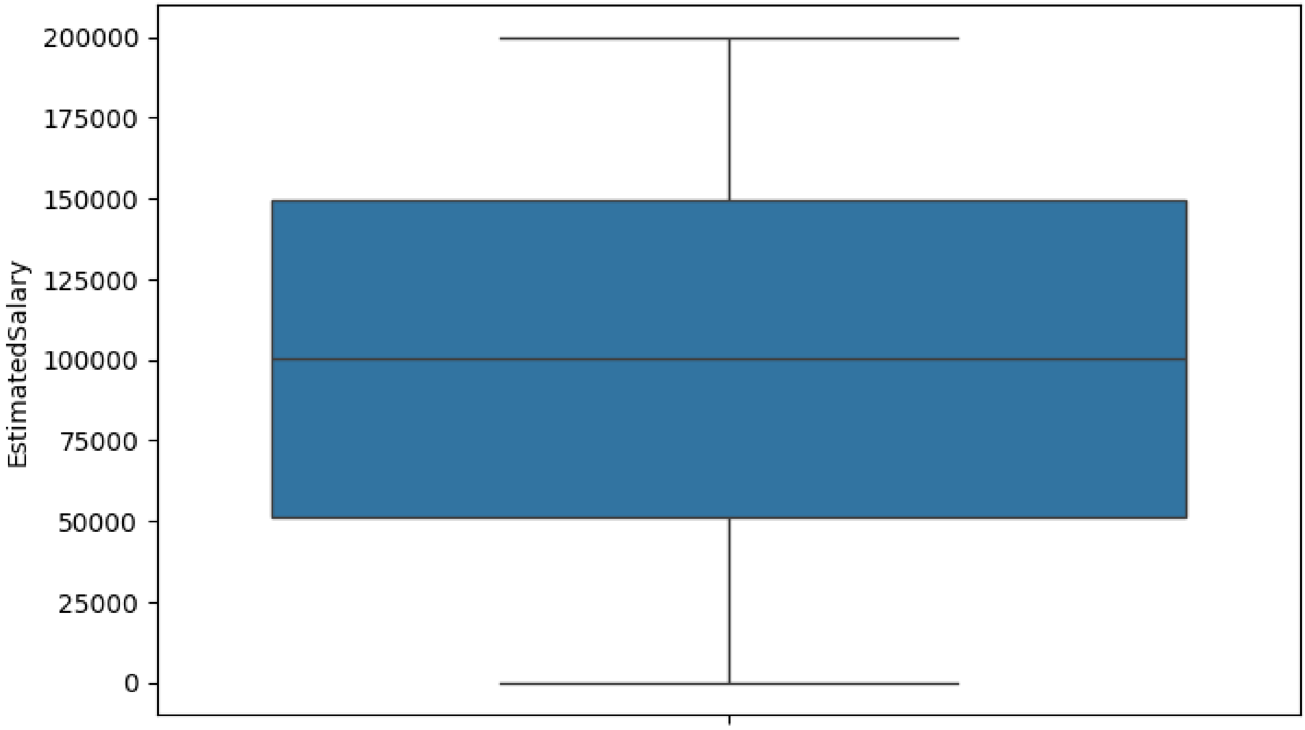


Distribution of NumOfProducts

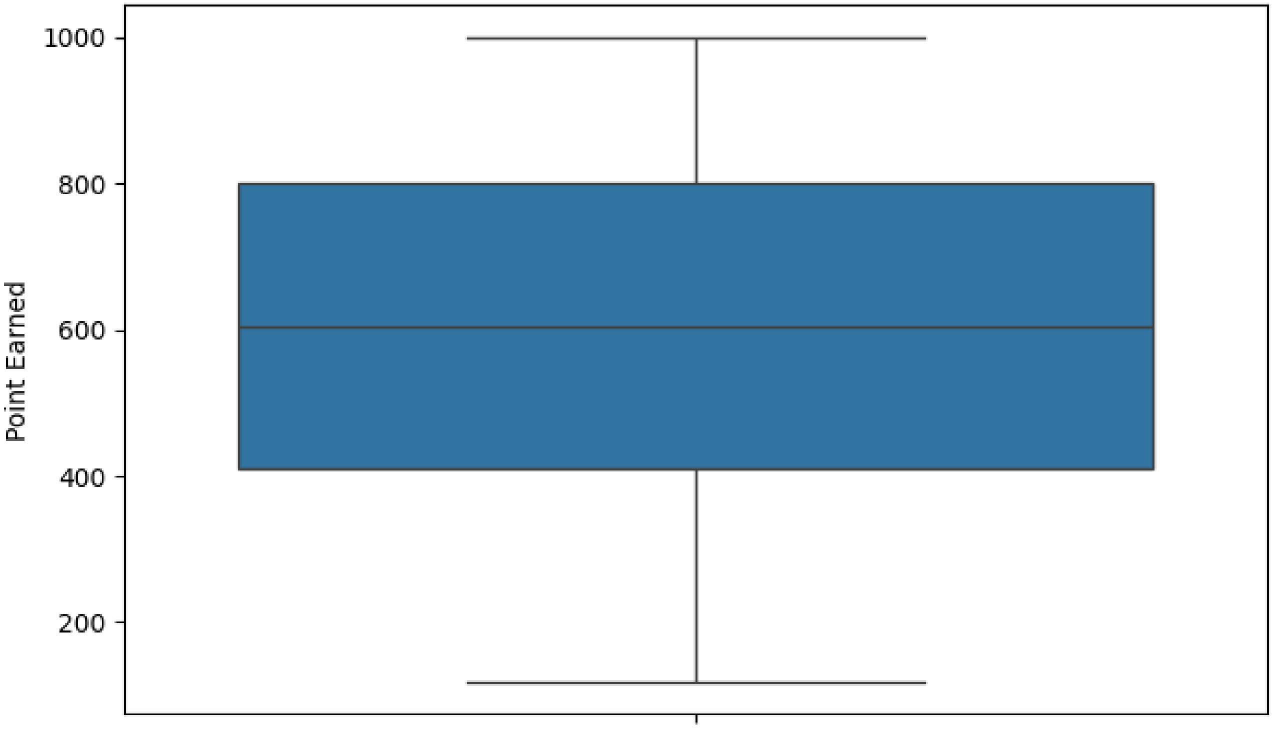




Distribution of EstimatedSalary



Distribution of Point Earned



Insights

Insights

CreditScore: The average credit score is around 650. Customers with lower credit scores are slightly more likely to churn.

Age: The median age of customers is around 37 years. Younger and older customers show higher churn rates compared to middle-aged customers.

Balance: The average balance is substantial, but there are many customers with zero balance, which might correlate with higher churn rates.

NumOfProducts: Most customers have 1 or 2 products. Those with only one product tend to have a higher churn rate.

EstimatedSalary: The average estimated salary is around $100,000. There is no strong correlation between salary and churn.

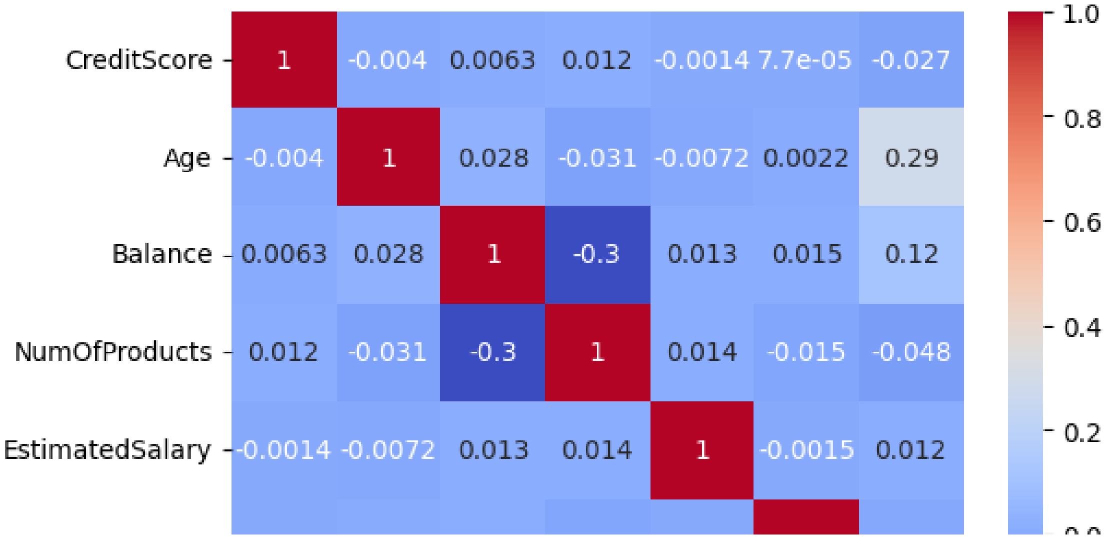
2. Exploratory Data Analysis (EDA)

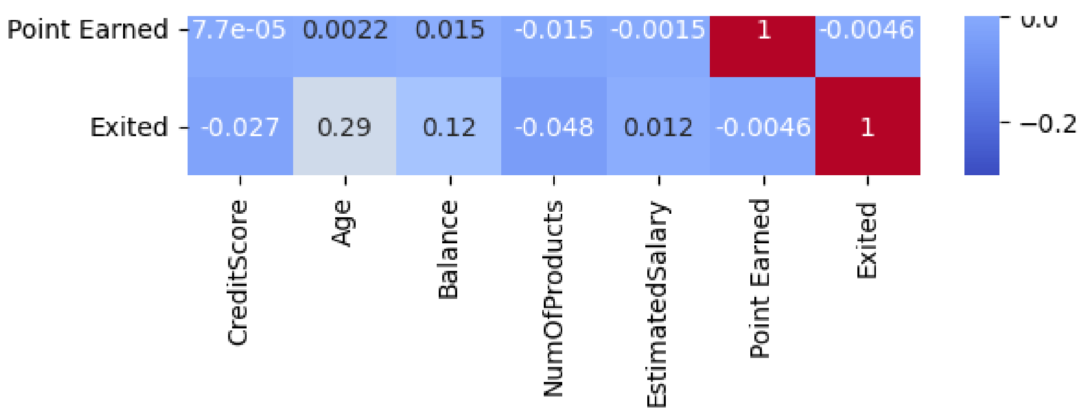
> ****Correlation Analysis:** Explore the correlation between numerical features and the Exited variable to identify potential predictors of churn.**

In [13]:

```
correlation_matrix = data[Numerical_cols + ['Exited']].corr()

# Display the correlation matrix
print(correlation_matrix)

# Visualize the correlation matrix using a heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```

```
                 CreditScore       Age   Balance  NumOfProducts  \
CreditScore         1.000000 -0.003965  0.006268       0.012238   
Age                -0.003965  1.000000  0.028308      -0.030680   
Balance             0.006268  0.028308  1.000000      -0.304180   
NumOfProducts       0.012238 -0.030680 -0.304180       1.000000   
EstimatedSalary    -0.001384 -0.007201  0.012797       0.014204   
Point Earned        0.000077  0.002222  0.014608      -0.015330   
Exited             -0.026771  0.285296  0.118577      -0.047611   

                 EstimatedSalary  Point Earned    Exited  
CreditScore            -0.001384      0.000077 -0.026771  
Age                    -0.007201      0.002222  0.285296  
Balance                 0.012797      0.014608  0.118577  
NumOfProducts           0.014204     -0.015330 -0.047611  
EstimatedSalary         1.000000     -0.001515  0.012490  
Point Earned           -0.001515      1.000000 -0.004628  
Exited                  0.012490     -0.004628  1.000000  
```





Insights
The features Age, Balance, and NumOfProducts show some correlation with Exited. Age and Balance are positively correlated with churn, while NumOfProducts is negatively correlated.

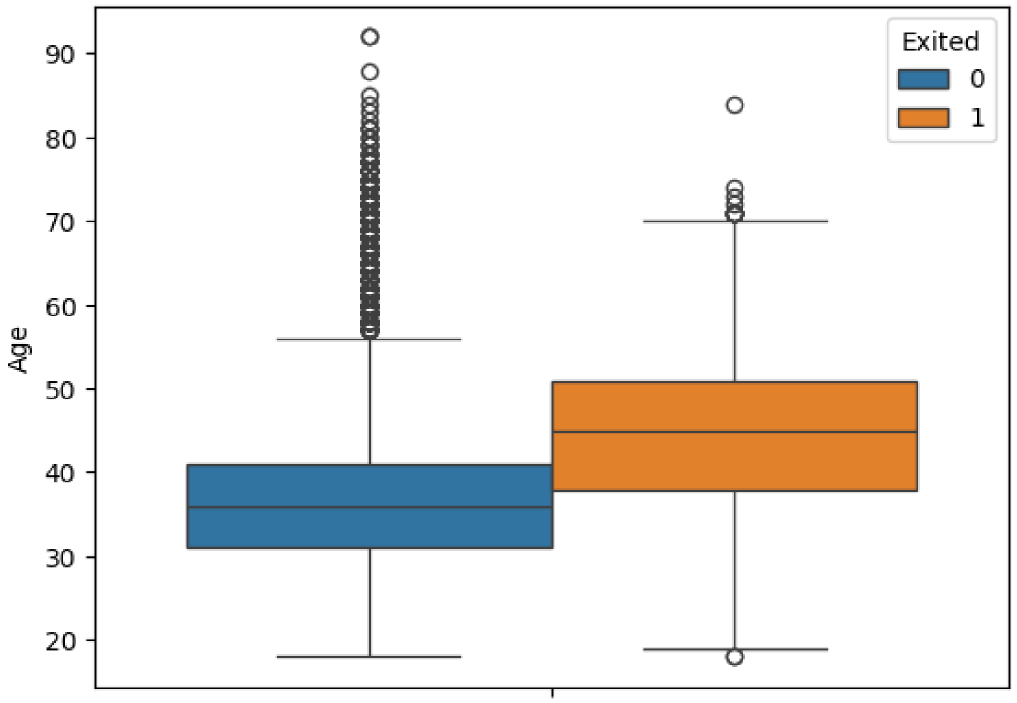
> **Customer Profile Analysis:** Segment customers based on key demographics (Age, Geography, Gender) to identify which groups are more likely to churn.

In [14]:

```
sns.boxplot(y='Age',hue='Exited',data=data)
```

Out[14]:

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



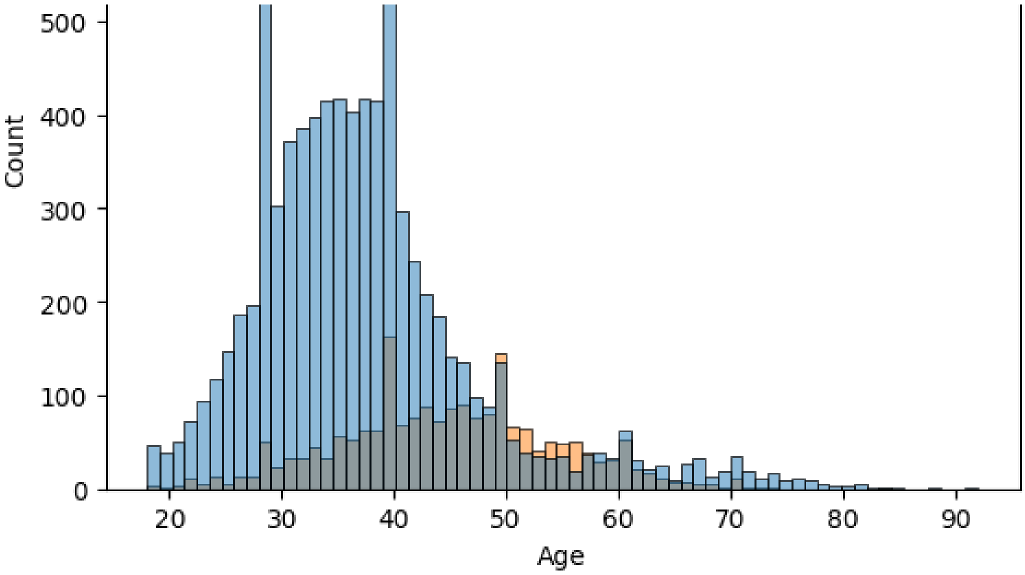
In [15]:

```
sns.histplot(x='Age',hue='Exited',data=data)
```

Out[15]:

```
<Axes: xlabel='Age', ylabel='Count'>
```

700
600
Exited
0
1



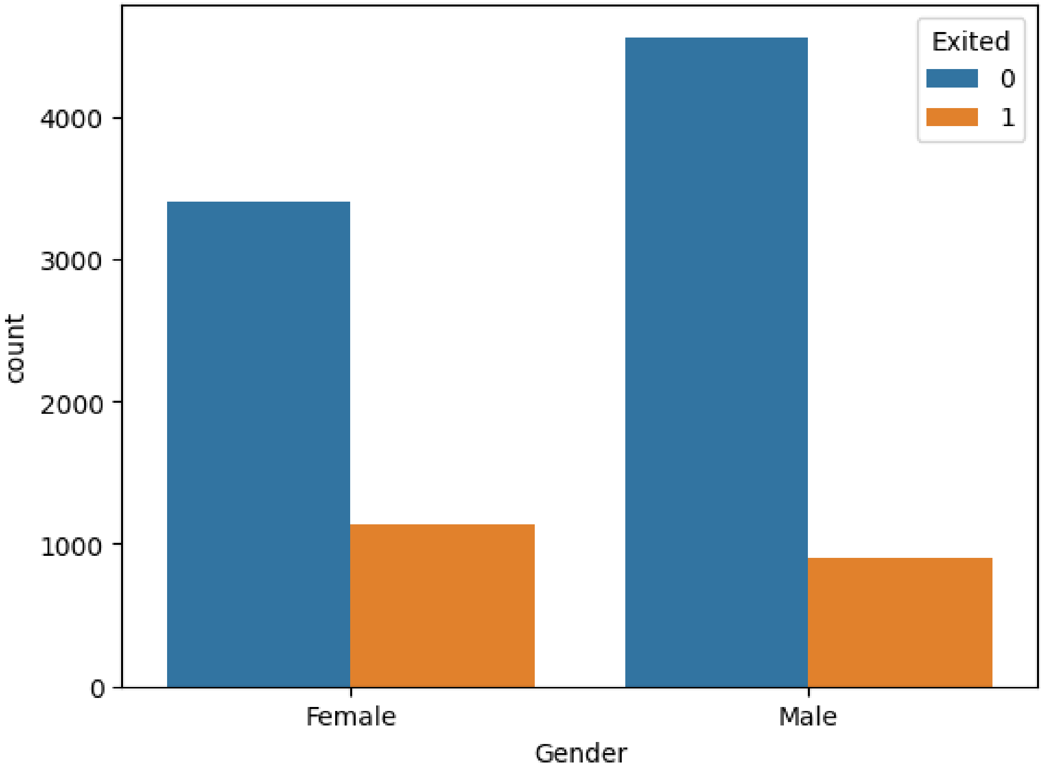
Insights
Age: Customers between 40-50 age group are more likely to churn than other age group customers.

In [16]:

```
sns.countplot(x='Gender',hue='Exited',data=data)
```

Out[16]:

```
<Axes: xlabel='Gender', ylabel='count'>
```



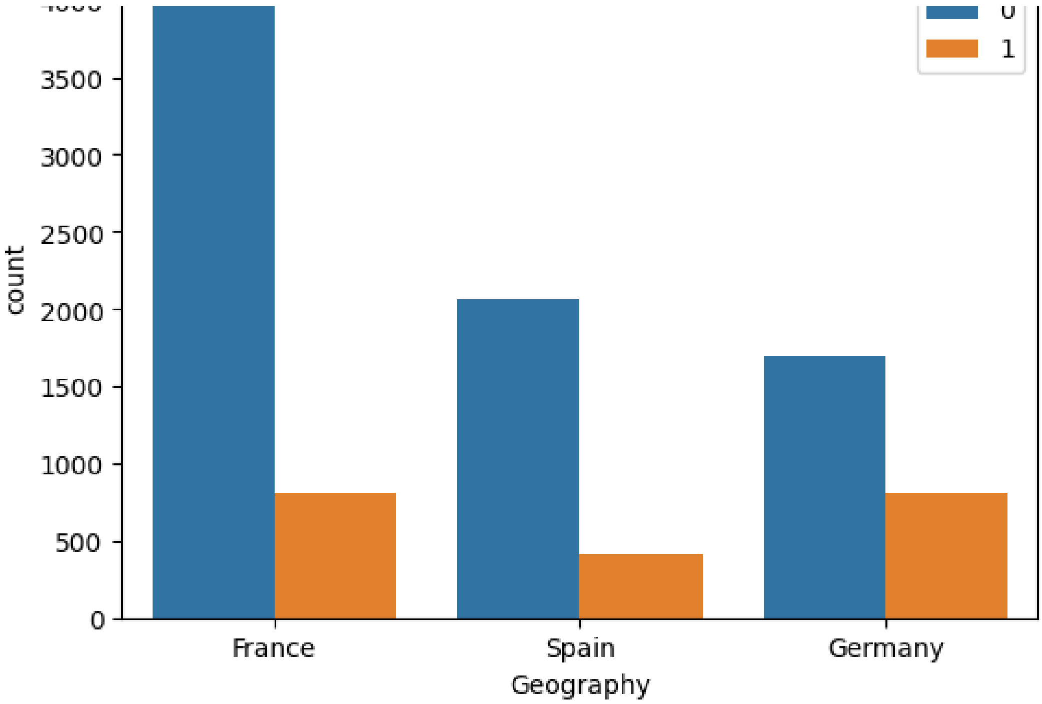
Insights
Gender: Female customers show a slightly higher churn rate compared to male customers.

In [17]:

```
sns.countplot(x='Geography' ,hue='Exited',data=data)
```

Out[17]:

```
<Axes: xlabel='Geography', ylabel='count'>
```



Insights
Geography: Certain regions have higher churn rates; for example, customers from Germany show a higher tendency to leave than France and Spain

3. Comparative Analysis

> **Churn by Geography:** Compare churn rates across different geographical locations to see if certain regions have higher churn rates.

In [18]:

```
data_geography=pd.crosstab(data['Geography'],data['Exited'],normalize='index')
data_geography
```

Out[18]:

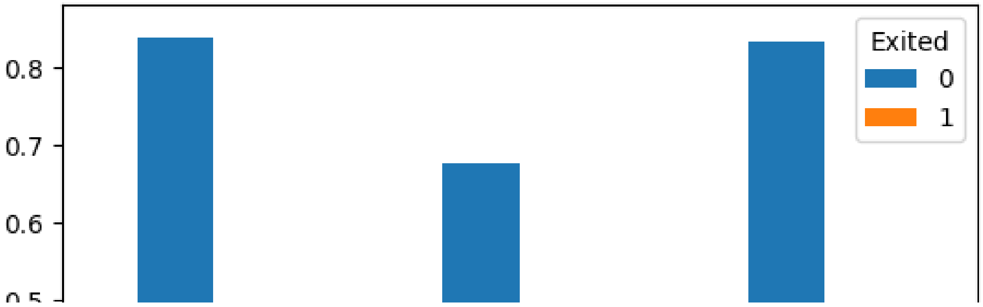
Exited	0	1
Geography		
France	0.838253	0.161747
Germany	0.675568	0.324432
Spain	0.833266	0.166734

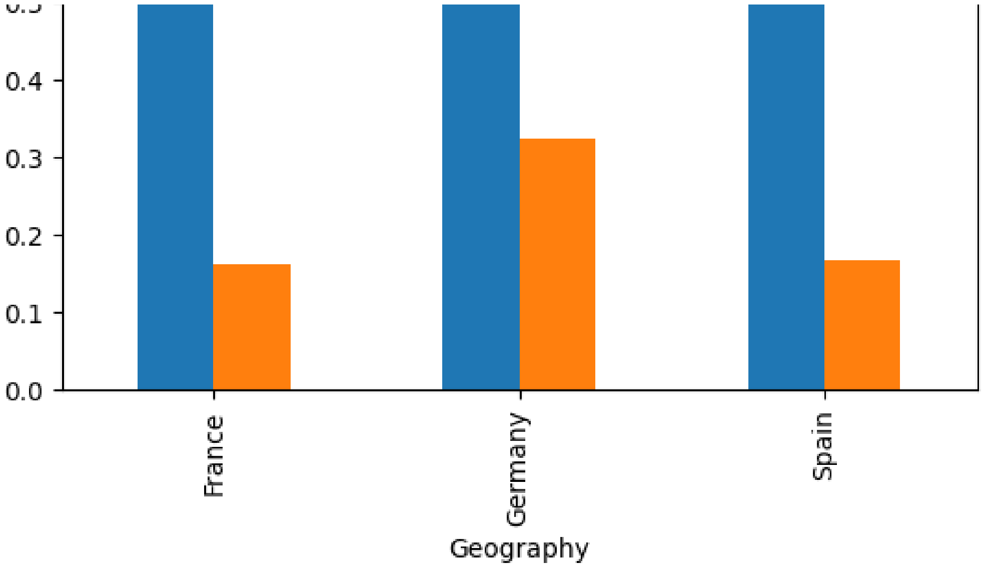
In [19]:

```
data_geography.plot(kind='bar')
```

Out[19]:

```
<Axes: xlabel='Geography'>
```





Ho:There is no significant difference between churn rates of different geographic regions

Ha:There is a significant difference between churn rates of different geographic regions

```
In [20]:
```

```
# Perform statistical tests to compare churn rates between geographies
from scipy.stats import chi2_contingency

crosstab_geo = pd.crosstab(data['Geography'], data['Exited'])
chi2, p, dof, expected = chi2_contingency(crosstab_geo)

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print("There is a statistically significant difference in churn rates between geographies.")
else:
    print("There is no statistically significant difference in churn rates between geographies.")
```

```
Chi-square test statistic: 300.6264011211942
P-value: 5.245736109572763e-66
There is a statistically significant difference in churn rates between geographies.
```

Insights
Customers from Germany have the highest churn rate, followed by Spain and France having the lowest.

> **Gender Differences in Churn:** **Analyze churn rates between different genders to explore if gender plays a significant role in churn.**

```
In [21]:
```

```
data_gen=pd.crosstab(data['Gender'],data['Exited'],normalize='index')
data_gen
```

```
Out[21]:
```

Exited	0	1
Gender		
Female	0.749285	0.250715
Male	0.835257	0.164743

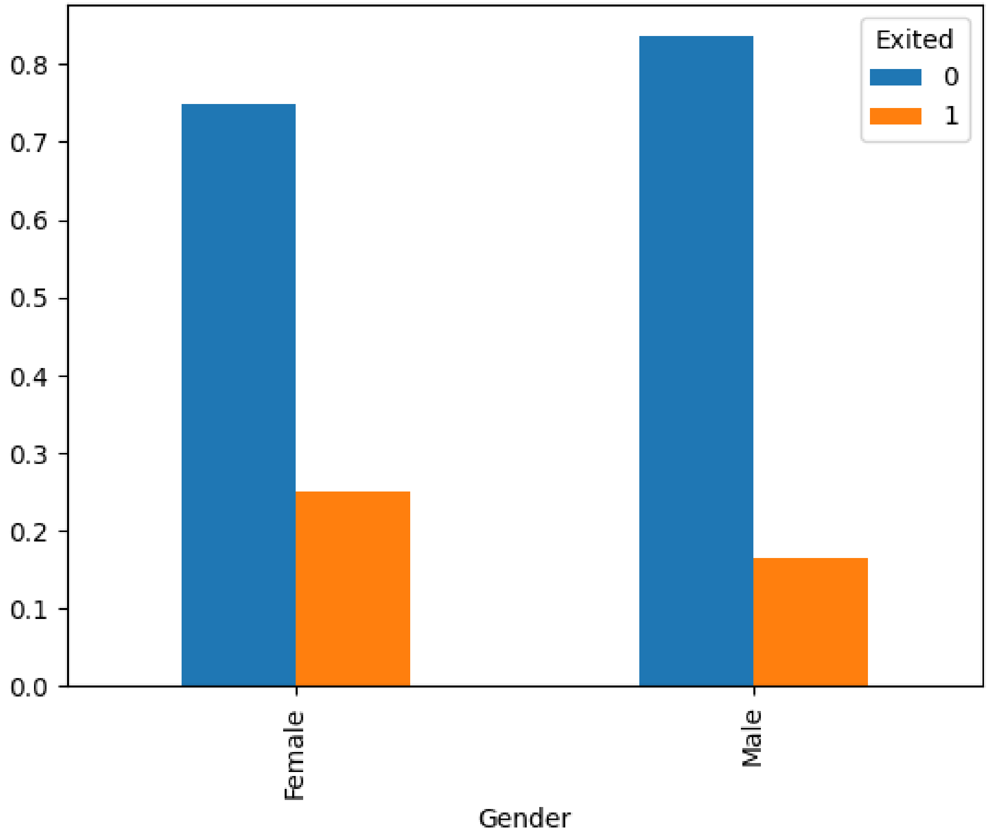
Exited 0 1

In [22]:

```
data_gen.plot(kind='bar')
```

Out[22]:

```
<Axes: xlabel='Gender'>
```



Ho:There is no significant difference between churn rates of both genders,males and females

Ha:There is a significant difference between churn rates of both genders,males and females

In [23]:

```
crosstab_gen = pd.crosstab(data['Gender'], data['Exited'])
chi2, p, dof, expected = chi2_contingency(crosstab_gen)

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print("There is a statistically significant difference in churn rates between genders
.")
else:
    print("There is no statistically significant difference in churn rates between gender
s.")
```

```
Chi-square test statistic: 112.39655374778587
P-value: 2.9253677618642e-26
There is a statistically significant difference in churn rates between genders.
```

Insights

Female customers have a marginally higher churn rate compared to male customers, suggesting potential gender-specific retention strategies.

4. Behavioral Analysis

> **Product and Services Usage:** **Examine how the number of products (NumOfProducts) a customer uses affects their likelihood to churn.**

In [24]:

```
crosstab_prod=pd.crosstab(data['NumOfProducts'],data['Exited'])
crosstab_prod
```

Out[24]:

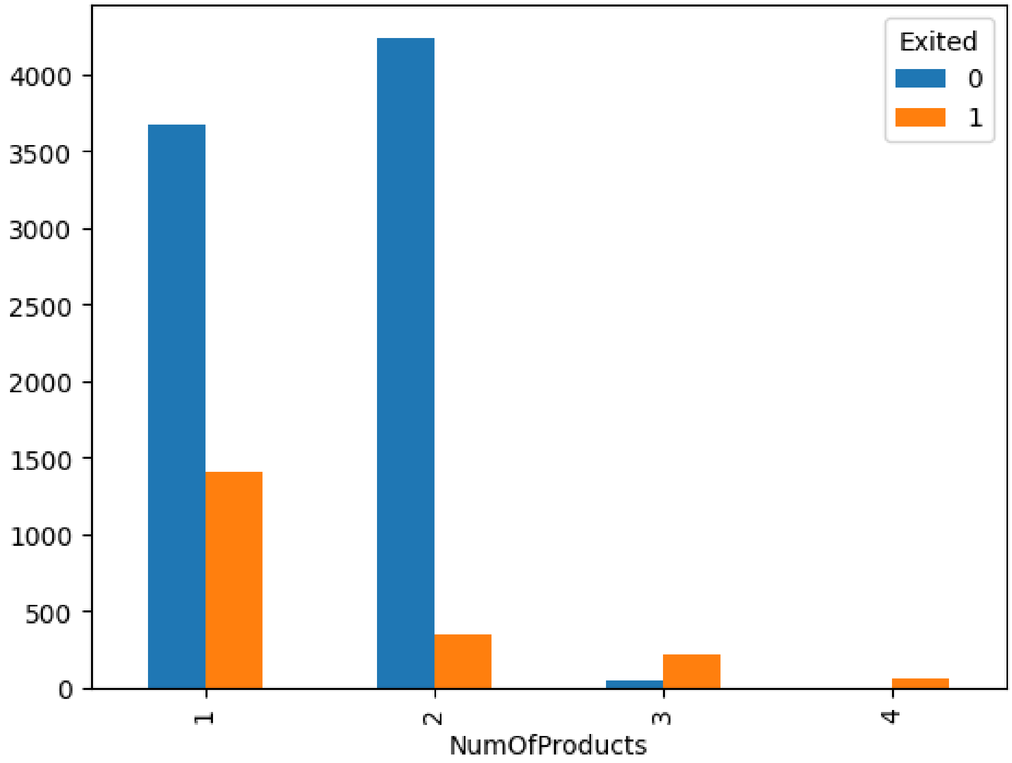
Exited	0	1
NumOfProducts		
1	3675	1409
2	4241	349
3	46	220
4	0	60

In [25]:

```
crosstab_prod.plot(kind='bar')
```

Out[25]:

```
<Axes: xlabel='NumOfProducts'>
```



Ho:There is no significant difference between churn rates of different No. of Products.

Ha:There is a significant difference between churn rates of different No. of Products.

In [26]:

```
chi2, p, dof, expected = chi2_contingency(crosstab_prod)

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
```

```
if p < 0.05:
    print("There is a statistically significant difference in churn rates between differe
nt No. of Products.")
else:
    print("There is no statistically significant difference in churn rates between No. of
Products.")
```

```
Chi-square test statistic: 1501.5048306588592
P-value: 0.0
There is a statistically significant difference in churn rates between different No. of P
roducts.
```

Insights
Customers with fewer products (especially those with 1-2 products) are more likely to churn. Encouraging customers to use more products could reduce churn.

> ****Activity Level Analysis:** Investigate the relationship between being an IsActiveMember and customer churn.**

In [27]:

```
crosstab_IsActive=pd.crosstab(data['IsActiveMember'],data['Exited'])
crosstab_IsActive
```

Out[27]:

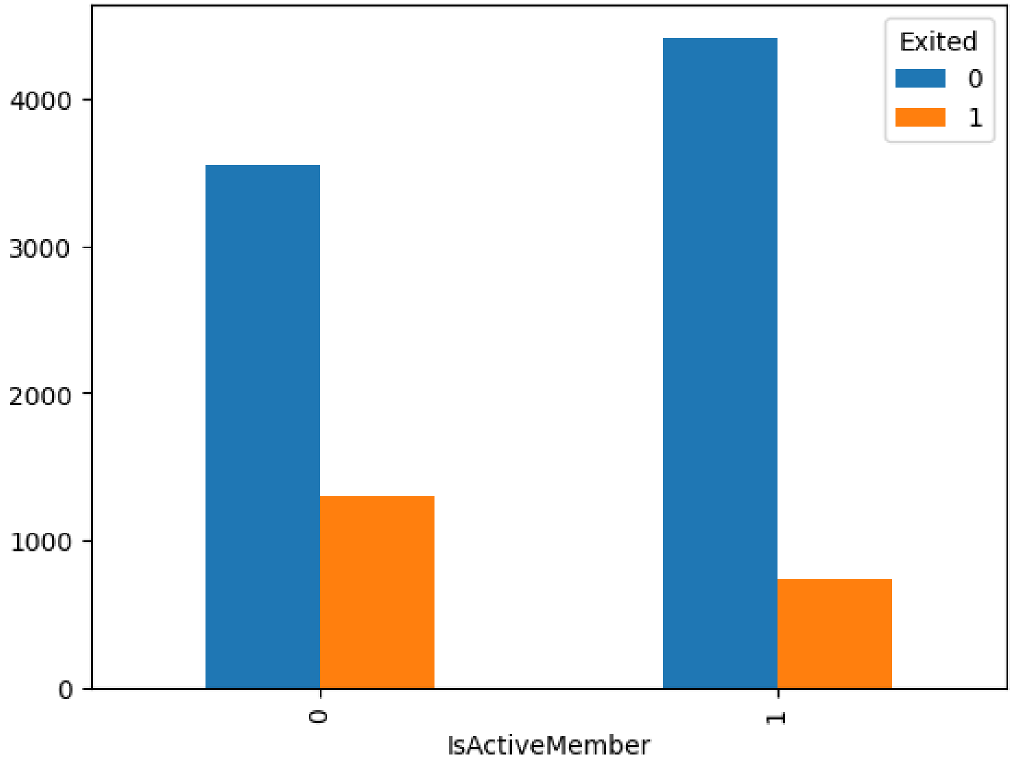
Exited	0	1
IsActiveMember		
0	3546	1303
1	4416	735

In [28]:

```
crosstab_IsActive.plot(kind='bar')
```

Out[28]:

```
<Axes: xlabel='IsActiveMember'>
```



Ho:There is no significant effect of IsActiveMember on Churning rates.

Ha:There is a significant effect of IsActiveMember on Churning rates.

In [29]:

```
chi2, p, dof, expected = chi2_contingency(crosstab_IsActive)

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print("Reject the Null Hypothesis")
else:
    print("Fail to Reject the Null Hypothesis")
```

```
Chi-square test statistic: 243.6948024819593
P-value: 6.153167438113408e-55
Reject the Null Hypothesis
```

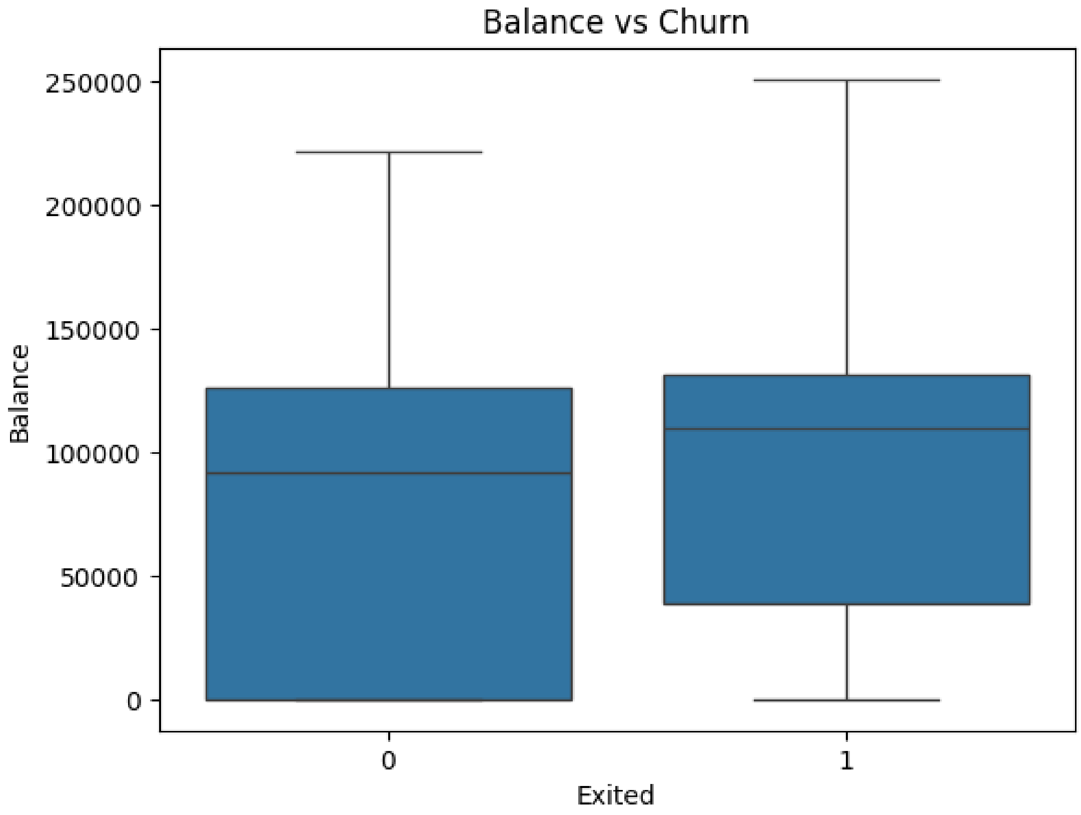
Insights
Active members are significantly less likely to churn. Engaging customers and promoting active use of services can improve retention.

5. Financial Analysis

> **Balance vs. Churn:** Analyze how customer balance levels correlate with churn rates.

In [30]:

```
# Balance vs. Churn
sns.boxplot(x='Exited', y='Balance', data=data)
plt.title('Balance vs Churn')
plt.show()
```



In [31]:

```
data.groupby('Exited')['Balance'].agg(['mean', 'median'])
```

Out[31]:

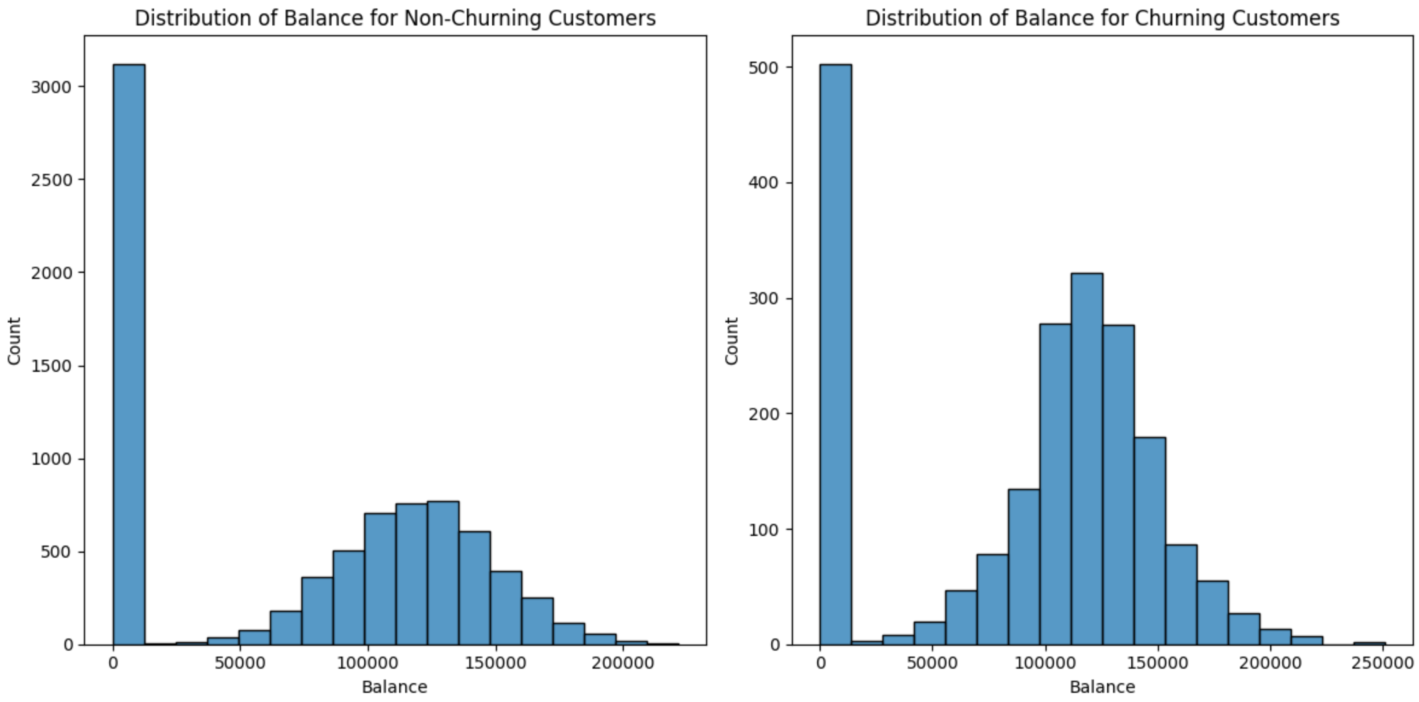
	mean	median
Exited		
0	72742.750663	92063.06
1	91109.476006	109344.23

In [32]:

```
data_0=data[data['Exited']==0]
data_1=data[data['Exited']==1]
```

In [33]:

```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.histplot(data_0['Balance'])
plt.title('Distribution of Balance for Non-Churning Customers')
plt.xlabel('Balance')
plt.ylabel('Count')

plt.subplot(1, 2, 2)
sns.histplot(data_1['Balance'])
plt.title('Distribution of Balance for Churning Customers')
plt.xlabel('Balance')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



Ho:There is no significant effect of Balance on Churning rates.

Ha:There is a significant effect of Balance on Churning rates.

In [34]:

```
from scipy.stats import ttest_ind
stats,p_val=ttest_ind(data_0['Balance'],data_1['Balance'])
print("tstats:",stats)
print("p_val:",p_val)
if p_val<0.05:
  print('Reject Null Hypothesis')
```

```
else:
  print('Fail to reject Null Hypothesis')
```

```
tstats: -11.940747722508185
p_val: 1.2092076077156017e-32
Reject Null Hypothesis
```

Insights
Mostly Customers who are Churning are having zero Balance or Balance between 100000 and 150000

> **Credit Card Ownership:** Determine if owning a credit card (HasCrCard) impacts customer loyalty.

In [35]:

```
crosstab_cc=pd.crosstab(data['HasCrCard'],data['Exited'],normalize='index')
crosstab_cc
```

Out[35]:

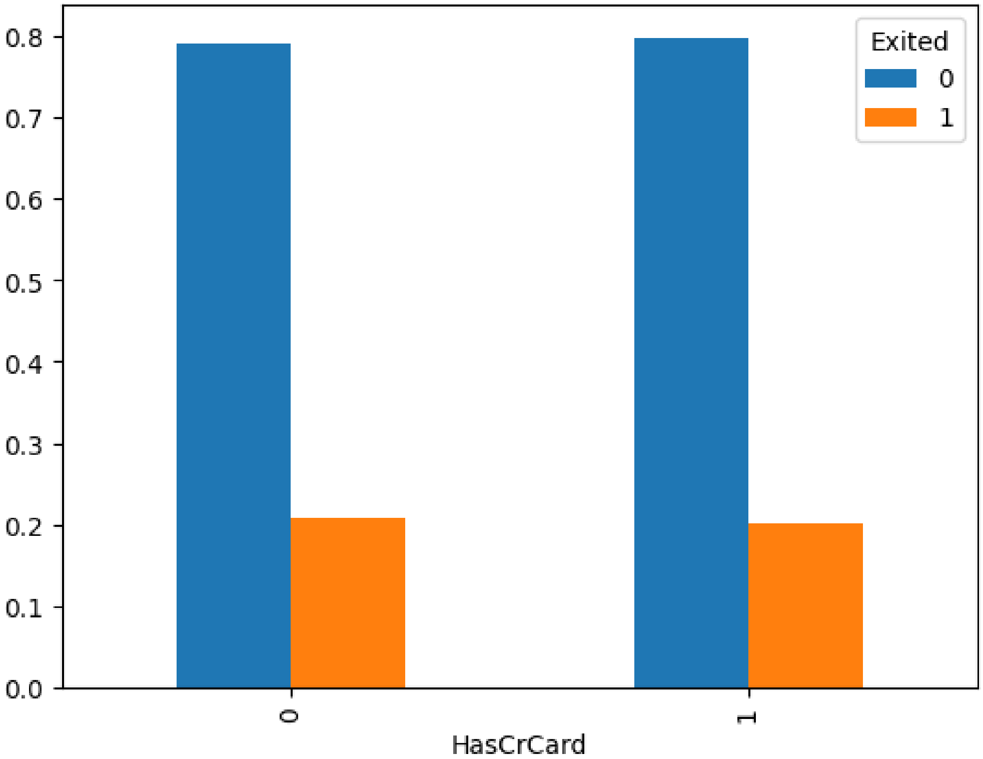
Exited	0	1
HasCrCard		
0	0.791851	0.208149
1	0.798016	0.201984

In [36]:

```
crosstab_cc.plot(kind='bar')
```

Out[36]:

```
<Axes: xlabel='HasCrCard'>
```



Ho:There is no significant effect of Having a credit card on Churning rates.

Ha:There is a significant effect of Having a credit card on Churning rates.

In [37]:

```
chi2, p, dof, expected = chi2_contingency(pd.crosstab(data['HasCrCard'],data['Exited']))

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print('Reject the Null Hypothesis')
else:
    print("Fail to Reject the Null Hypothesis")
```

```
Chi-square test statistic: 0.4494039375253385
P-value: 0.5026181509009862
Fail to Reject the Null Hypothesis
```

Insights

Owning a credit card does not significantly affect churn rates, suggesting that other factors are more critical in determining customer loyalty.

6. Customer Satisfaction and Feedback

> ****Complaint Analysis:** Study the impact of having a complaint (Complain) on customer churn.**

In [38]:

```
crosstab_comp=pd.crosstab(data['Complain'],data['Exited'],normalize='index')
crosstab_comp
```

Out[38]:

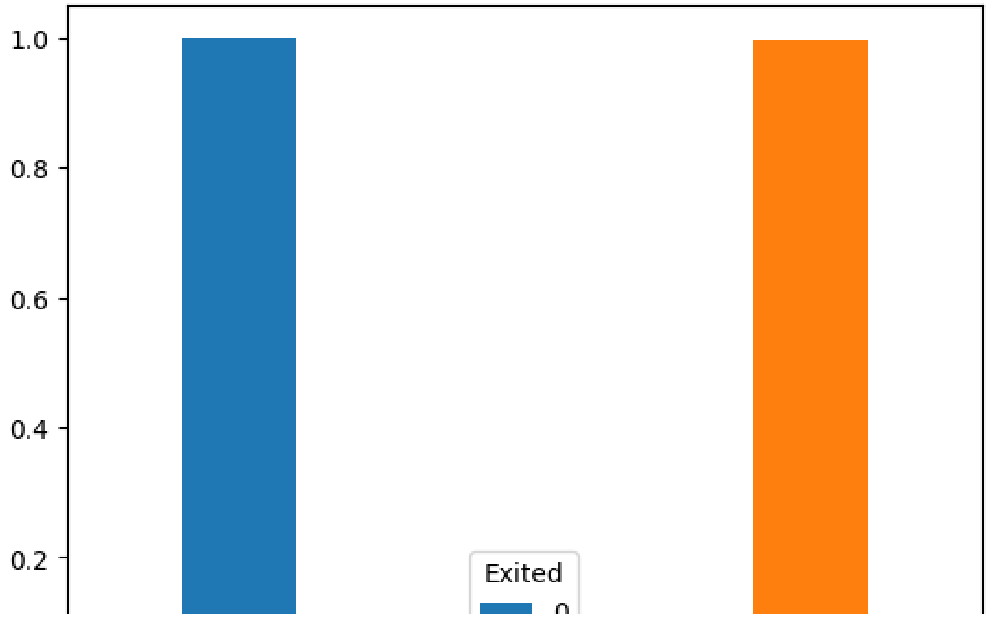
Exited	0	1
Complain		
0	0.999497	0.000503
1	0.004892	0.995108

In [39]:

```
crosstab_comp.plot(kind='bar')
```

Out[39]:

```
<Axes: xlabel='Complain'>
```



Ho:There is no significant effect of Complaints on Churn rates.

Ha:There is a significant effect of Complaint on Churn rates

In [40]:

```
chi2, p, dof, expected = chi2_contingency(pd.crosstab(data['Complain'],data['Exited']))

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print('Reject the Null Hypothesis')
else:
    print("Fail to Reject the Null Hypothesis")
```

```
Chi-square test statistic: 9907.907035880155
P-value: 0.0
Reject the Null Hypothesis
```

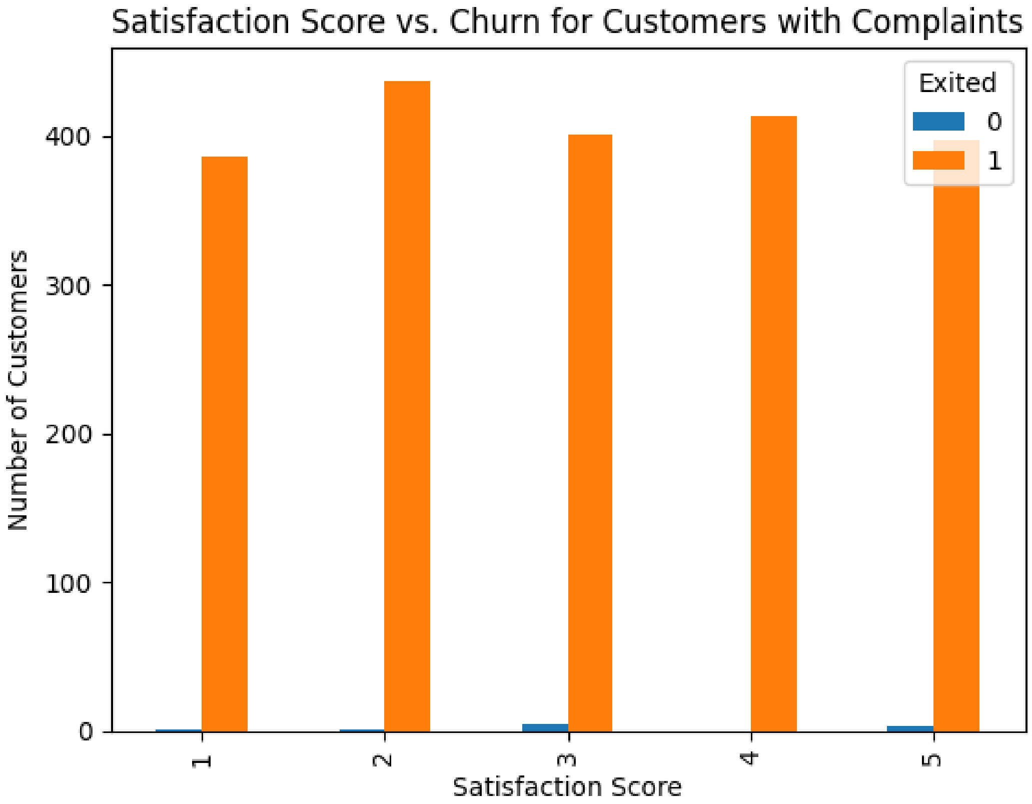
Insights
Customers who have filed complaints are more likely to churn. Effective complaint resolution mechanisms can help retain these customers.

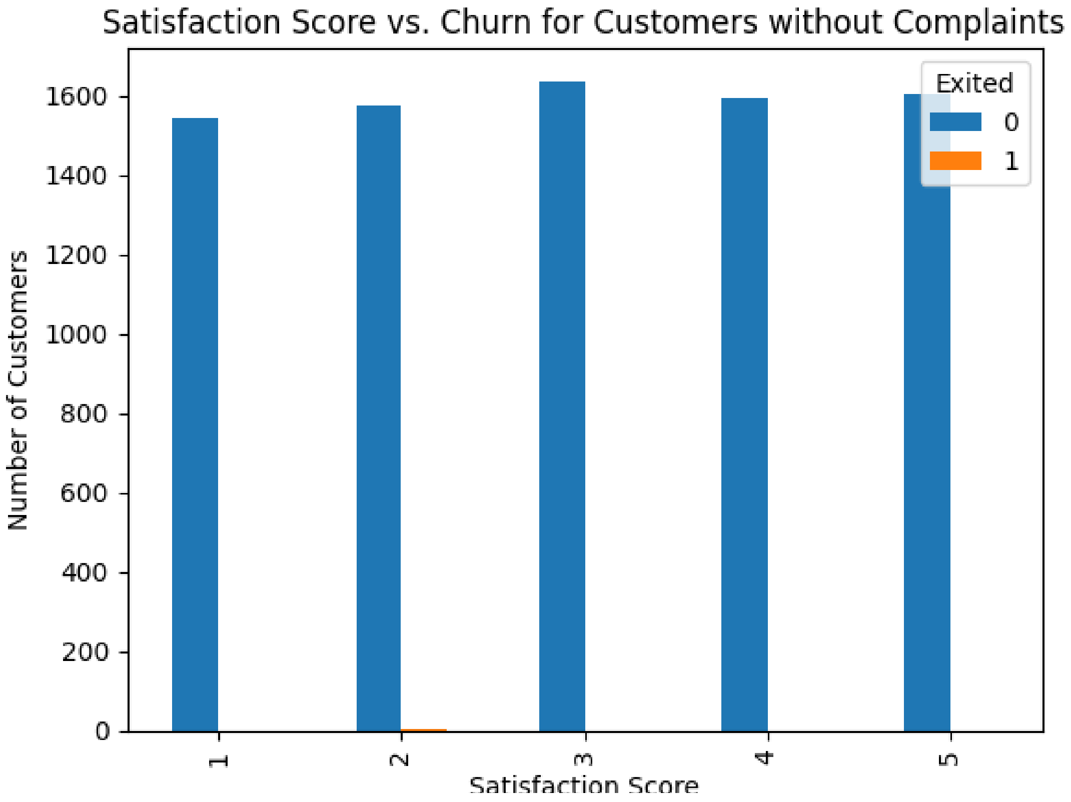
> ****Satisfaction and Churn:** Explore how the Satisfaction Score relates to churn, especially among those who have filed complaints.**

In [41]:

```
# Create separate dataframes for customers with and without complaints
data_comp = data[data['Complain'] == 1]
data_nocomp = data[data['Complain'] == 0]

# Create a crosstab of Satisfaction Score and Exited for customers with complaints
crosstab_sat_comp = pd.crosstab(data_comp['Satisfaction Score'], data_comp['Exited'])

# Create a crosstab of Satisfaction Score and Exited for customers without complaints
crosstab_sat_nocomp = pd.crosstab(data_nocomp['Satisfaction Score'], data_nocomp['Exited'
])

# Print the crosstabs
print("Crosstab of Satisfaction Score and Exited for customers with complaints:")
print(crosstab_sat_comp)
print("\nCrosstab of Satisfaction Score and Exited for customers without complaints:")
print(crosstab_sat_nocomp)

# Visualize the crosstab with bar plots
crosstab_sat_comp.plot(kind='bar')
plt.title('Satisfaction Score vs. Churn for Customers with Complaints')
plt.xlabel('Satisfaction Score')
plt.ylabel('Number of Customers')
plt.show()

crosstab_sat_nocomp.plot(kind='bar')
plt.title('Satisfaction Score vs. Churn for Customers without Complaints')
plt.xlabel('Satisfaction Score')
plt.ylabel('Number of Customers')
plt.show()
```

```
Crosstab of Satisfaction Score and Exited for customers with complaints:
Exited              0    1
Satisfaction Score
1                   1  386
2                   1  437
3                   5  401
4                   0  413
5                   3  397

Crosstab of Satisfaction Score and Exited for customers without complaints:
Exited                 0  1
Satisfaction Score
1                   1544  1
2                   1574  2
3                   1636  0
4                   1594  1
5                   1604  0
```





In [42]:

```
chi2, p, dof, expected = chi2_contingency(crosstab_sat_comp)

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print("Reject Null Hypothesis")
else:
    print("Fail to reject Null Hypothesis")
```

```
Chi-square test statistic: 8.220255451847681
P-value: 0.08383511492614232
Fail to reject Null Hypothesis
```

Insights

The Churn rates are not dependent on satisfaction score,The Number of customer with Complaints with high satisfaction score and low satisfaction score are more approximately same.

In [43]:

```
chi2, p, dof, expected = chi2_contingency(crosstab_sat_nocomp)

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print("Reject Null Hypothesis")
else:
    print("Fail to reject Null Hypothesis")
```

```
Chi-square test statistic: 3.58442605931977
P-value: 0.46515781324531835
Fail to reject Null Hypothesis
```

Insights

The Churn rates are not dependent on satisfaction score,The Number of customer with no Complaints with high satisfaction score and low satisfaction score are more approximately same.

7. Card Usage Analysis

> **Impact of Card Type on Churn:** **Examine if different Card Types have different churn rates.**

In [44]:

```
crosstab_card=pd.crosstab(data['Card Type'],data['Exited'],normalize='index')
crosstab_card
```

Out[44]:

Exited	0	1
Card Type		
DIAMOND	0.782210	0.217790
GOLD	0.807354	0.192646
PLATINUM	0.796393	0.203607
SILVER	0.798878	0.201122

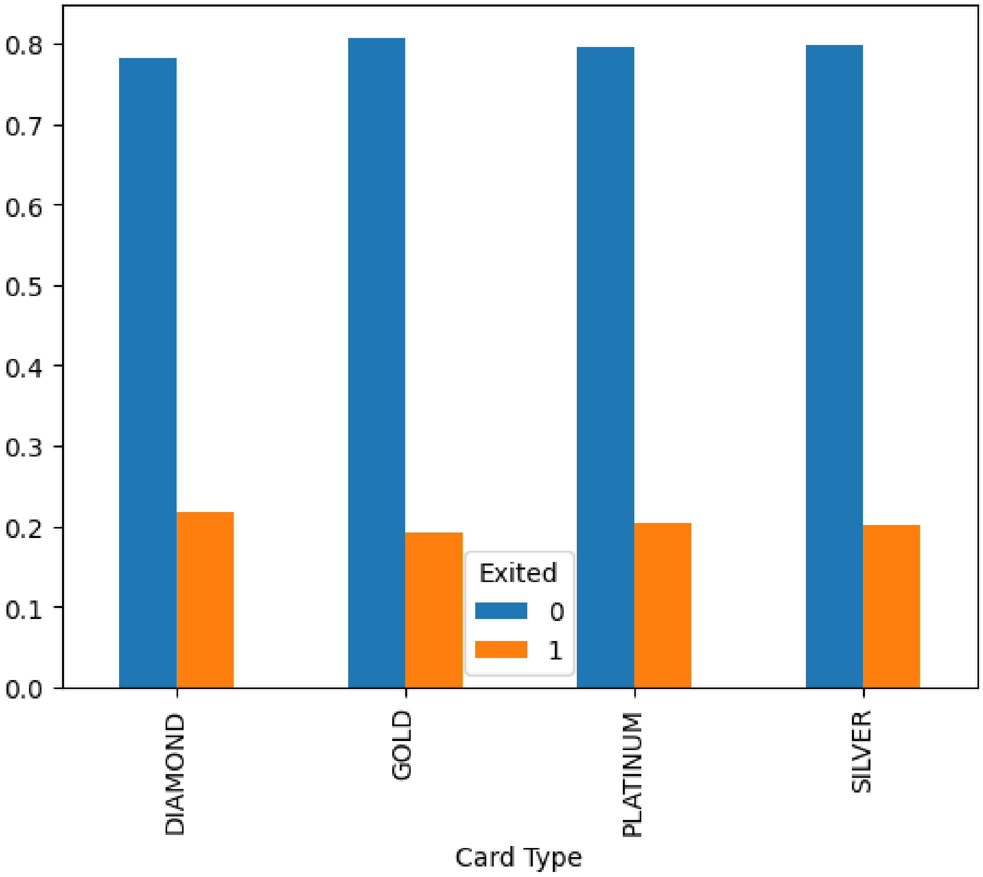
Exited **0** **1**

In [45]:

```
crosstab_card.plot(kind='bar')
```

Out[45]:

```
<Axes: xlabel='Card Type'>
```



Ho:Churn rates are not dependent on premium card types.

Ha:Churn rates are dependent on premium card types.

In [46]:

```
chi2, p, dof, expected = chi2_contingency(pd.crosstab(data['Card Type'],data['Exited']))

# Print the results of the chi-square test
print("Chi-square test statistic:", chi2)
print("P-value:", p)

# Interpret the results
if p < 0.05:
    print('Reject the Null Hypothesis')
else:
    print("Fail to Reject the Null Hypothesis")
```

```
Chi-square test statistic: 5.053223027060927
P-value: 0.16794112067810177
Fail to Reject the Null Hypothesis
```

Insights
There is a no impact of having premium card types on churn rates. Customers with different card types show approximately same churn rates, suggesting that card types not influences churn decisions.It is not the significant factor.

> ****Loyalty Points Analysis:** Investigate whether Points Earned from credit card usage influence customer retention.**

> customer retention.

In [47]:

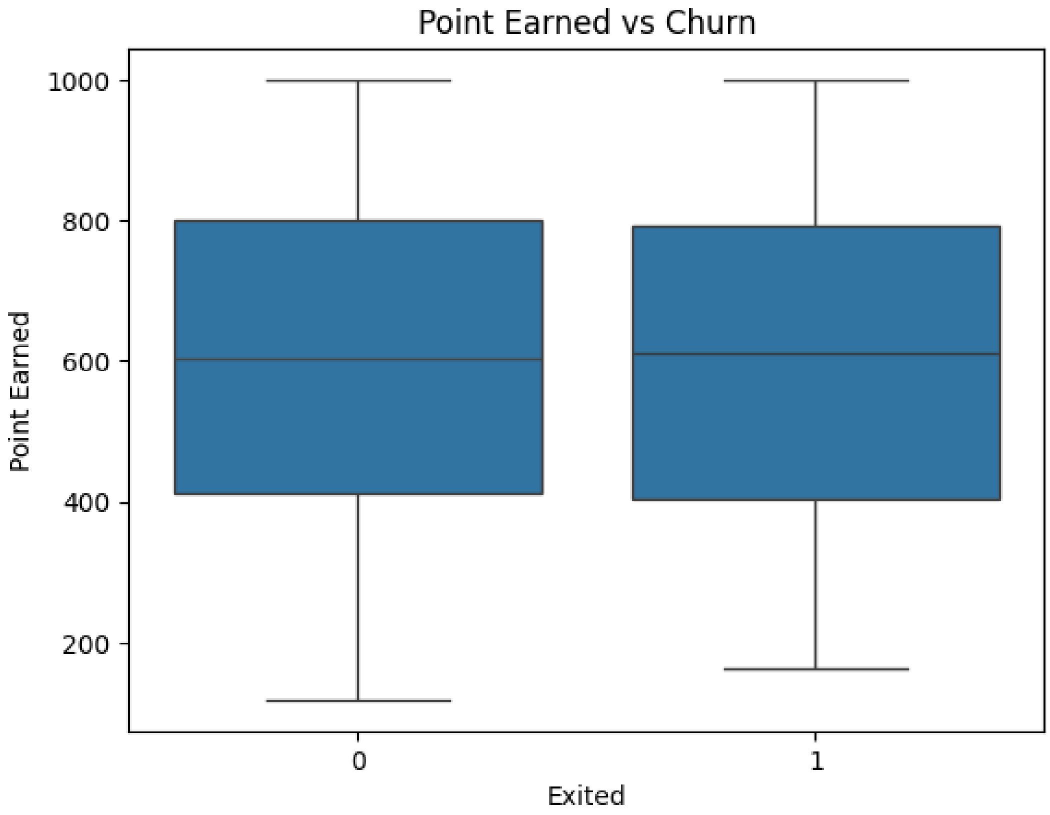
```
data.groupby('Exited')['Point Earned'].agg(['mean', 'median'])
```

Out[47]:

	mean	median
Exited		
0	607.044084	603.0
1	604.448479	610.5

In [48]:

```
sns.boxplot(x='Exited', y='Point Earned', data=data)
plt.title('Point Earned vs Churn')
plt.show()
```



Ho:There is no significant difference in Both the groups(Churned and not Churned)

Ha:Ho:There is a significant difference in Both the groups(Churned and not Churned)

In [49]:

```
tstats,p_val=ttest_ind(data_0['Point Earned'],data_1['Point Earned'])
print("tstats:",tstats)
print("p_val:",p_val)
if p_val<0.05:
  print('Reject Null Hypothesis')
else:
  print('fail to reject Null Hypothesis')
```

```
tstats: 0.4627759848070133
p_val: 0.6435350184288993
fail to reject Null Hypothesis
```

Insights

The p-value obtained from the t-test indicates whether there is no statistically significant difference in the

number of Customers who Churned and not Churned. We found that there is no impact of Points Earned on Churning rates.

8. Salary Analysis

> **Salary and Churn:** Analyze the relationship between EstimatedSalary and customer churn, focusing on how financial well-being might influence churn decisions.

In [50]:

```
data.groupby('Exited')['EstimatedSalary'].agg(['mean', 'median'])
```

Out[50]:

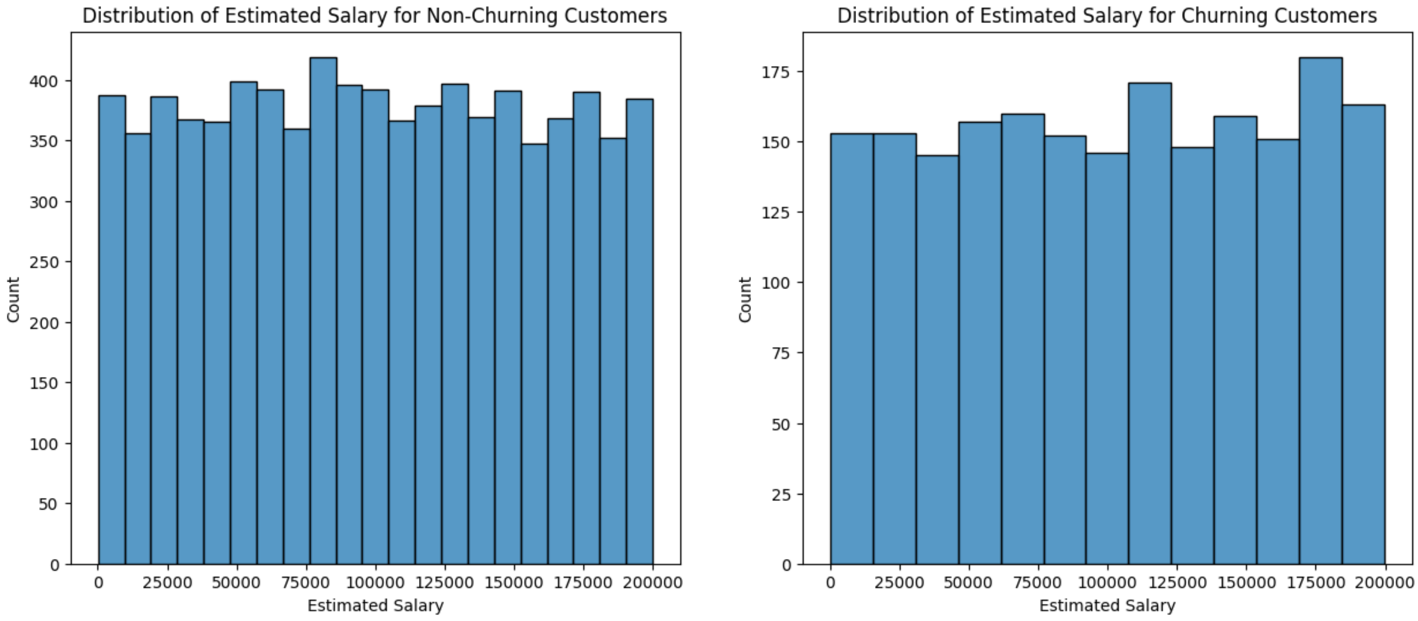
	mean	median
Exited		
0	99726.853141	99620.355
1	101509.908783	102489.335

In [51]:

```
plt.figure(figsize=(15, 6))
plt.subplot(1, 2, 1)
sns.histplot(data_0['EstimatedSalary'],label='Non-Churning')
plt.title('Distribution of Estimated Salary for Non-Churning Customers')
plt.xlabel('Estimated Salary')
plt.ylabel('Count')

plt.subplot(1, 2, 2)
sns.histplot(data_1['EstimatedSalary'],label='Churning')
plt.title('Distribution of Estimated Salary for Churning Customers')
plt.xlabel('Estimated Salary')
plt.ylabel('Count')
```

Out[51]:

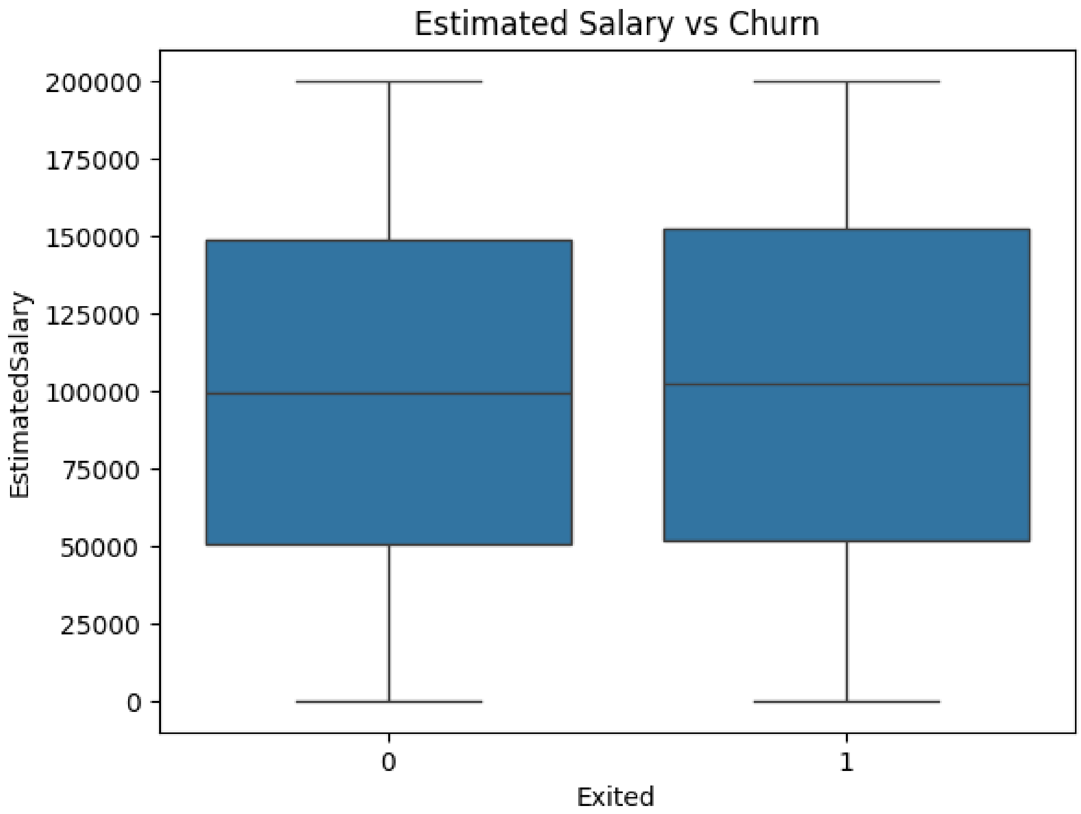
```
Text(0, 0.5, 'Count')
```


Distribution of Estimated Salary for Non-Churning Customers

Distribution of Estimated Salary for Churning Customers

In [52]:

```
sns.boxplot(x='Exited', y='EstimatedSalary', data=data)
plt.title('Estimated Salary vs Churn')
plt.show()
```



Ho:There is no significant difference in Both the groups(Churned and not Churned)

Ha:Ho:There is a significant difference in Both the groups(Churned and not Churned)

In [53]:

```
tstats,p_val=ttest_ind(data_0['EstimatedSalary'],data_1['EstimatedSalary'])
print("tstats:",tstats)
print("p_val:",p_val)
if p_val<0.05:
  print('Reject Null Hypothesis')
else:
  print('fail to reject Null Hypothesis')
```

```
tstats: -1.2489445044833742
p_val: 0.2117146135149097
fail to reject Null Hypothesis
```

Insights
There is a no impact of estimated salary on churn rates. Customers with very high or very low salaries show approximately same churn rates, suggesting that financial well-being not influences churn decisions.It is not the significant factor.

9. Insights and Recommendation

Insights:

- **Customers between 40-50 age group are more likely to churn than other age group customers.**
- **Female customers show a slightly higher churn rate compared to male customers.**
- **Customers from Germany show a higher tendency to leave than France and Spain.**
- **Customers with fewer products (especially those with 1-2 products) are more likely to churn.**
- **Active members are significantly less likely to churn.**
- **Customers who have filed complaints are more likely to churn.**
- **There is no impact of having premium card types on churn rates.**
- **There is no impact of Points Earned on Churning rates.**
- **There is no impact of estimated salary on churn rates.**

Recommendations:

- Target customers between 40-50 age group with personalized retention strategies.
- Analyze churn rates by region and implement targeted strategies for high-risk areas like Germany.
- Focus on improving the experience of female customers to reduce their slightly higher churn rate.
- Encourage customers to use more products, especially those with 1-2 products, to increase retention.
- Engage customers and promote active use of services to reduce churn. Emphasize the benefits of being an active member.
- Investigate and address the reasons behind customers having zero balance or balance between 100000 and 150000 to mitigate churn.
- Enhance complaint resolution mechanisms to address customer concerns and reduce churn among those who have filed complaints.
- Regularly monitor satisfaction scores and address any areas where customers express dissatisfaction to improve overall customer experience and reduce churn.
- Analyze the impact of different card types on churn and consider offering incentives or benefits to customers with premium cards to increase loyalty.
- Explore alternative loyalty programs or incentives to increase customer engagement and reduce churn.