# Bank Churners Analysis

## Data Loading

```
import pandas as pd
import matplotlib.pyplot as plt
bdata=pd.read_csv('BankChurners.csv')
bdata.head()
```

```
   CLIENTNUM     Attrition_Flag  Customer_Age Gender  Dependent_count
\
0  768805383  Existing Customer            45      M                3

1  818770008  Existing Customer            49      F                5

2  713982108  Existing Customer            51      M                3

3  769911858  Existing Customer            40      F                4

4  709106358  Existing Customer            40      M                3


  Education_Level Marital_Status Income_Category Card_Category  \
0     High School        Married     $60K - $80K          Blue
1        Graduate         Single  Less than $40K          Blue
2        Graduate        Married    $80K - $120K          Blue
3     High School        Unknown  Less than $40K          Blue
4      Uneducated        Married     $60K - $80K          Blue

   Months_on_book  ...  Months_Inactive_12_mon  Contacts_Count_12_mon
\
0              39  ...                       1                      3

1              44  ...                       1                      2

2              36  ...                       1                      0

3              34  ...                       4                      1

4              21  ...                       1                      0


   Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1  \
0       12691.0                  777          11914.0
1.335
1        8256.0                  864           7392.0
1.541
2        3418.0                    0           3418.0
```

```
2.594
3       3313.0                 2517           796.0
1.405
4       4716.0                    0          4716.0
2.175

   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio
0             1144              42                1.625
0.061
1             1291              33                3.714
0.105
2             1887              20                2.333
0.000
3             1171              20                2.333
0.760
4              816              28                2.500
0.000

[5 rows x 21 columns]
```

```
bdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 10127 non-null  int64
 1   Attrition_Flag            10127 non-null  object
 2   Customer_Age              10127 non-null  int64
 3   Gender                    10127 non-null  object
 4   Dependent_count           10127 non-null  int64
 5   Education_Level           10127 non-null  object
 6   Marital_Status            10127 non-null  object
 7   Income_Category           10127 non-null  object
 8   Card_Category             10127 non-null  object
 9   Months_on_book            10127 non-null  int64
 10  Total_Relationship_Count  10127 non-null  int64
 11  Months_Inactive_12_mon    10127 non-null  int64
 12  Contacts_Count_12_mon     10127 non-null  int64
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64
 18  Total_Trans_Ct            10127 non-null  int64
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
```

```
dtypes: float64(5), int64(10), object(6)
memory usage: 1.6+ MB
```

## Data Cleaning

```
bdata.drop_duplicates(inplace=True)

bdata.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 10127 non-null  int64
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 3   Gender                    10127 non-null  object
 4   Dependent_count           10127 non-null  int64
 5   Education_Level           10127 non-null  object
 6   Marital_Status            10127 non-null  object
 7   Income_Category           10127 non-null  object
 8   Card_Category             10127 non-null  object
 9   Months_on_book            10127 non-null  int64
 10  Total_Relationship_Count  10127 non-null  int64
 11  Months_Inactive_12_mon    10127 non-null  int64
 12  Contacts_Count_12_mon     10127 non-null  int64
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64
 18  Total_Trans_Ct            10127 non-null  int64
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: float64(5), int64(10), object(6)
memory usage: 1.6+ MB
```

## statistical analysis

```
bdata.describe()

          CLIENTNUM  Customer_Age  Dependent_count  Months_on_book  \
count  1.012700e+04  10127.000000     10127.000000    10127.000000
mean   7.391776e+08     46.325960         2.346203       35.928409
std    3.690378e+07      8.016814         1.298908        7.986416
min    7.080821e+08     26.000000         0.000000       13.000000
25%    7.130368e+08     41.000000         1.000000       31.000000
50%    7.179264e+08     46.000000         2.000000       36.000000
75%    7.731435e+08     52.000000         3.000000       40.000000
```

```
max    8.283431e+08     73.000000         5.000000      56.000000

       Total_Relationship_Count  Months_Inactive_12_mon  \
count              10127.000000            10127.000000   
mean                   3.812580                2.341167   
std                    1.554408                1.010622   
min                    1.000000                0.000000   
25%                    3.000000                2.000000   
50%                    4.000000                2.000000   
75%                    5.000000                3.000000   
max                    6.000000                6.000000   

       Contacts_Count_12_mon  Credit_Limit  Total_Revolving_Bal  \
count           10127.000000  10127.000000         10127.000000   
mean                2.455317   8631.953698          1162.814061   
std                 1.106225   9088.776650           814.987335   
min                 0.000000   1438.300000             0.000000   
25%                 2.000000   2555.000000           359.000000   
50%                 2.000000   4549.000000          1276.000000   
75%                 3.000000  11067.500000          1784.000000   
max                 6.000000  34516.000000          2517.000000   

       Avg_Open_To_Buy  Total_Amt_Chng_Q4_Q1  Total_Trans_Amt
Total_Trans_Ct  \
count     10127.000000          10127.000000     10127.000000
10127.000000   
mean       7469.139637              0.759941      4404.086304
64.858695   
std        9090.685324              0.219207      3397.129254
23.472570   
min           3.000000              0.000000       510.000000
10.000000   
25%        1324.500000              0.631000      2155.500000
45.000000   
50%        3474.000000              0.736000      3899.000000
67.000000   
75%        9859.000000              0.859000      4741.000000
81.000000   
max       34516.000000              3.397000     18484.000000
139.000000   

       Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
count         10127.000000           10127.000000
mean              0.712222               0.274894
std               0.238086               0.275691
min               0.000000               0.000000
25%               0.582000               0.023000
50%               0.702000               0.176000
75%               0.818000               0.503000
max               3.714000               0.999000
```

## solving questions

## What are the characteristics of customers who are likely to churn?

```
bdata.head()
```

```
   CLIENTNUM     Attrition_Flag  Customer_Age Gender  Dependent_count
\
0  768805383  Existing Customer            45      M                3

1  818770008  Existing Customer            49      F                5

2  713982108  Existing Customer            51      M                3

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  Education_Level Marital_Status Income_Category Card_Category  \
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   Months_on_book  ...  Months_Inactive_12_mon  Contacts_Count_12_mon
\
0              39  ...                       1                      3

1              44  ...                       1                      2

2              36  ...                       1                      0

3              34  ...                       4                      1

4              21  ...                       1                      0


   Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1  \
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3        3313.0                 2517            796.0
1.405
```

```
4        4716.0                    0           4716.0
2.175

   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio
0             1144              42                1.625
0.061
1             1291              33                3.714
0.105
2             1887              20                2.333
0.000
3             1171              20                2.333
0.760
4              816              28                2.500
0.000

[5 rows x 21 columns]
```

```
bdata['Attrition_Flag'].value_counts()
```

```
Attrition_Flag
Existing Customer    8500
Attrited Customer    1627
Name: count, dtype: int64
```

```
acust=bdata[bdata['Attrition_Flag']== 'Attrited Customer']
```

```
acust
```

```
       CLIENTNUM     Attrition_Flag  Customer_Age Gender
Dependent_count  \
21     708508758  Attrited Customer            62      F
0
39     708300483  Attrited Customer            66      F
0
51     779471883  Attrited Customer            54      F
1
54     714374133  Attrited Customer            56      M
2
61     712030833  Attrited Customer            48      M
2
...          ...                ...           ...    ...
...
10119  716893683  Attrited Customer            55      F
3
10123  710638233  Attrited Customer            41      M
2
10124  716506083  Attrited Customer            44      F
1
10125  717406983  Attrited Customer            30      M
2
```

```
10126  714337233  Attrited Customer            43      F
2

      Education_Level Marital_Status Income_Category Card_Category  \
21           Graduate        Married  Less than $40K          Blue
39          Doctorate        Married         Unknown          Blue
51           Graduate        Married  Less than $40K          Blue
54           Graduate        Married         $120K +          Blue
61           Graduate        Married     $60K - $80K        Silver
...               ...            ...             ...           ...
10119      Uneducated         Single         Unknown          Blue
10123         Unknown       Divorced     $40K - $60K          Blue
10124     High School        Married  Less than $40K          Blue
10125        Graduate        Unknown     $40K - $60K          Blue
10126        Graduate        Married  Less than $40K        Silver

       Months_on_book  ...  Months_Inactive_12_mon
Contacts_Count_12_mon  \
21                 49  ...                       3
3
39                 56  ...                       4
3
51                 40  ...                       3
1
54                 36  ...                       3
3
61                 35  ...                       4
4
...               ...  ...                     ...
...
10119              47  ...                       3
3
10123              25  ...                       2
3
10124              36  ...                       3
4
10125              36  ...                       3
3
10126              25  ...                       2
4

       Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy  \
21           1438.3                    0           1438.3
39           7882.0                  605           7277.0
51           1438.3                  808            630.3
54          15769.0                    0          15769.0
61          34516.0                    0          34516.0
...             ...                  ...              ...
10119       14657.0                 2517          12140.0
10123        4277.0                 2186           2091.0
```

```
10124       5409.0                    0         5409.0
10125       5281.0                    0         5281.0
10126      10388.0                 1961         8427.0

       Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  Total_Trans_Ct  \
21                    1.047              692              16
39                    1.052              704              16
51                    0.997              705              19
54                    1.041              602              15
61                    0.763              691              15
...                     ...              ...             ...
10119                 0.166             6009              53
10123                 0.804             8764              69
10124                 0.819            10291              60
10125                 0.535             8395              62
10126                 0.703            10294              61

       Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
21                   0.600                  0.000
39                   0.143                  0.077
51                   0.900                  0.562
54                   0.364                  0.000
61                   0.500                  0.000
...                    ...                    ...
10119                0.514                  0.172
10123                0.683                  0.511
10124                0.818                  0.000
10125                0.722                  0.000
10126                0.649                  0.189

[1627 rows x 21 columns]
```

```
acust.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1627 entries, 21 to 10126
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 1627 non-null   int64
 1   Attrition_Flag            1627 non-null   object
 2   Customer_Age              1627 non-null   int64
 3   Gender                    1627 non-null   object
 4   Dependent_count           1627 non-null   int64
 5   Education_Level           1627 non-null   object
 6   Marital_Status            1627 non-null   object
 7   Income_Category           1627 non-null   object
 8   Card_Category             1627 non-null   object
 9   Months_on_book            1627 non-null   int64
 10  Total_Relationship_Count  1627 non-null   int64
```

```
 11  Months_Inactive_12_mon    1627 non-null   int64
 12  Contacts_Count_12_mon     1627 non-null   int64
 13  Credit_Limit              1627 non-null   float64
 14  Total_Revolving_Bal       1627 non-null   int64
 15  Avg_Open_To_Buy           1627 non-null   float64
 16  Total_Amt_Chng_Q4_Q1      1627 non-null   float64
 17  Total_Trans_Amt           1627 non-null   int64
 18  Total_Trans_Ct            1627 non-null   int64
 19  Total_Ct_Chng_Q4_Q1       1627 non-null   float64
 20  Avg_Utilization_Ratio     1627 non-null   float64
dtypes: float64(5), int64(10), object(6)
memory usage: 279.6+ KB
```

```
churned=1627/10127*100
print(f'total churn percentage={churned}')
```

```
total churn percentage=16.065962279055988
```

Average Age

```
avg_age=acust['Customer_Age'].mean()

print(f"the average age of a churning customer is:{avg_age}")
```

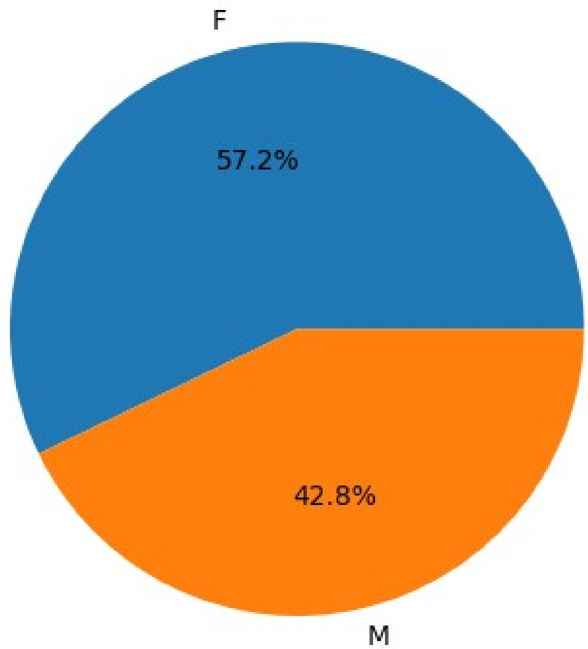
```
the average age of a churning customer is:46.659496004917024
```

Gender Distribution

```
gender_dist=acust.groupby('Gender')
['Attrition_Flag'].count().reset_index()
gender_dist
```

| | Gender | Attrition_Flag |
|---|---|---|
| 0 | F | 930 |
| 1 | M | 697 |

```
plt.pie(
    gender_dist['Attrition_Flag'],
    labels=gender_dist['Gender'],
    autopct='%1.1f%%'  # Display percentages with one decimal place
)
plt.show()
```




Education Distribution

```
edudist=acust.groupby('Education_Level')
['Attrition_Flag'].count().reset_index()
edudist
```

| | Education_Level | Attrition_Flag |
|---|---|---|
| 0 | College | 154 |
| 1 | Doctorate | 95 |
| 2 | Graduate | 487 |
| 3 | High School | 306 |
| 4 | Post-Graduate | 92 |
| 5 | Uneducated | 237 |
| 6 | Unknown | 256 |

```
import plotly.express as px




# Create a bar chart
fig = px.bar(
    edudist,
    x='Education_Level',
    y='Attrition_Flag',
    color='Attrition_Flag',
    barmode='group',
    title='Attrition by Education Level'
```

```
)


fig.show()
```


```
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```

```
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```

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dependent or not

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dcount=bdata.groupby('Attrition_Flag')
['Dependent_count'].mean().reset_index()
dcount
```

| | Attrition_Flag | Dependent_count |
|---|---|---|
| 0 | Attrited Customer | 2.402581 |
| 1 | Existing Customer | 2.335412 |

martial distribution

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fig.show()
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```

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{"anchor":"x","domain":[0,1],"title":{"text":"count"}}}}
```



Income Category

```
ic=acust.groupby('Income_Category')
['Attrition_Flag'].count().reset_index()
ic
```

```
  Income_Category  Attrition_Flag
0         $120K +             126
1     $40K - $60K             271
2     $60K - $80K             189
3    $80K - $120K             242
4  Less than $40K             612
5         Unknown             187
```

card_category

```
cc=acust.groupby('Card_Category')
['Attrition_Flag'].count().reset_index()
cc
```

```
  Card_Category  Attrition_Flag
0          Blue            1519
1          Gold              21
2      Platinum               5
3        Silver              82
```

# Report

# Customer Churn Analysis

## Characteristics of Customers Likely to Churn

Based on the analysis and graphical representation of data, the following characteristics are commonly found in churned customers:

1. **Average Age of Churning Customers**:
   The average age of a churned customer is approximately **46.66** years.

2. **Gender Distribution**:
   Female customers are more likely to churn compared to male customers.

3. **Dependency Status**:
   Churned customers tend to have lower dependency compared to non-churned customers.

4. **Card Category Usage**:
   Customers who have churned often use the **Blue card** category.

5. **Income Level**:
   Churned customers typically have an income of less than **$40K**.

6. **Education Level**:
   The education levels of churned customers are often either **Graduate** or **High School**.

7. **Marital Status**:
   Churned customers are more likely to be either **Married** or **Single**.

These insights provide a deeper understanding of the common characteristics of customers who are likely to churn.

# 2)Are there any patterns based on customer demographics (age, gender, etc.)

```
nacust=bdata[bdata['Attrition_Flag']== 'Existing Customer']

nacust['Customer_Age'].mean()

46.26211764705882
```

# Report

# Customer Churn Analysis

## 1. Age:

- **Average Age**:
  Churned customers tend to be slightly older (46.66 years) compared to existing customers (46.26 years).
- **Pattern**:
  Older customers may have higher expectations for service or may feel less attached to the institution, making them more likely to leave.

## 2. Gender:

- **Churn Distribution**:
  57.16% of churned customers are female, compared to 42.84% male.
- **Pattern**:
  Female customers show a slightly higher likelihood of churn, which could be influenced by service preferences or marketing strategies not resonating as strongly with this demographic.

## 3. Education Level:

- **Top Groups Among Churned Customers**:
  - Graduate: 29.93%

- High School: 28.75%

- **Pattern**:
  Customers with moderate education levels may churn due to unmet financial expectations or insufficient engagement from the bank.

# 4. Marital Status:

- **Marital Status of Churned Customers**:
  - Married: 43.58%

  - Single: 40.38%
- **Pattern**:
  Married individuals may have joint accounts or multiple financial commitments, which could make them more sensitive to fees, benefits, or service quality.

# 5. Income Category:

- **Income of Churned Customers**:
  - Less than $40K: 37.61%

  - $40K–$60K: 19.31%
- **Pattern**:
  Lower-income groups dominate the churned customer base, suggesting financial constraints or dissatisfaction with fees and rewards.

# 6. Dependent Count:

- **Dependents Among Churned Customers**:
  Churned customers have slightly more dependents (2.40) compared to existing customers (2.33).
- **Pattern**:
  Customers with more dependents might leave due to increased financial pressure or lack of suitable products like family plans.

```
nacust.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8500 entries, 0 to 10122
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   CLIENTNUM                 8500 non-null   int64 
 1   Attrition_Flag            8500 non-null   object
 2   Customer_Age              8500 non-null   int64 
 3   Gender                    8500 non-null   object
 4   Dependent_count           8500 non-null   int64 
 5   Education_Level           8500 non-null   object
 6   Marital_Status            8500 non-null   object
 7   Income_Category           8500 non-null   object
 8   Card_Category             8500 non-null   object
```

```
 9   Months_on_book            8500 non-null   int64
 10  Total_Relationship_Count  8500 non-null   int64
 11  Months_Inactive_12_mon    8500 non-null   int64
 12  Contacts_Count_12_mon     8500 non-null   int64
 13  Credit_Limit              8500 non-null   float64
 14  Total_Revolving_Bal       8500 non-null   int64
 15  Avg_Open_To_Buy           8500 non-null   float64
 16  Total_Amt_Chng_Q4_Q1      8500 non-null   float64
 17  Total_Trans_Amt           8500 non-null   int64
 18  Total_Trans_Ct            8500 non-null   int64
 19  Total_Ct_Chng_Q4_Q1       8500 non-null   float64
 20  Avg_Utilization_Ratio     8500 non-null   float64
dtypes: float64(5), int64(10), object(6)
memory usage: 1.4+ MB
```

## 3)Can you identify factors that seem to influence a customer's likelihood to leave the bank?

Months on Book

```
churnedtotalm=acust['Months_on_book'].mean()
churnedtotalm
```

```
36.178242163491085
```

```
nchurnedtotalm=nacust['Months_on_book'].mean()
nchurnedtotalm
```

```
35.88058823529412
```

Inactivity:

```
churnInactivity=acust['Months_Inactive_12_mon'].mean()
churnInactivity
```

```
2.693300553165335
```

```
nchurnInactivity=nacust['Months_Inactive_12_mon'].mean()
nchurnInactivity
```

```
2.273764705882353
```

Contact Frequency

```
churnContact=acust['Contacts_Count_12_mon'].mean()
churnContact
```

```
2.972341733251383
```

```
nchurnContact=nacust['Contacts_Count_12_mon'].mean()
nchurnContact
```

```
2.3563529411764708

nacust

       CLIENTNUM     Attrition_Flag  Customer_Age Gender
Dependent_count  \
0      768805383  Existing Customer            45      M
3
1      818770008  Existing Customer            49      F
5
2      713982108  Existing Customer            51      M
3
3      769911858  Existing Customer            40      F
4
4      709106358  Existing Customer            40      M
3
...          ...                ...           ...    ...
...
10116  714109308  Existing Customer            46      M
5
10117  712503408  Existing Customer            57      M
2
10120  710841183  Existing Customer            54      M
1
10121  713899383  Existing Customer            56      F
1
10122  772366833  Existing Customer            50      M
2

      Education_Level Marital_Status Income_Category Card_Category  \
0         High School        Married     $60K - $80K          Blue
1            Graduate         Single  Less than $40K          Blue
2            Graduate        Married    $80K - $120K          Blue
3         High School        Unknown  Less than $40K          Blue
4          Uneducated        Married     $60K - $80K          Blue
...               ...            ...             ...           ...
10116         College         Single    $80K - $120K          Blue
10117        Graduate        Married    $80K - $120K          Blue
10120     High School         Single     $60K - $80K          Blue
10121        Graduate         Single  Less than $40K          Blue
10122        Graduate         Single     $40K - $60K          Blue

       Months_on_book  ...  Months_Inactive_12_mon
Contacts_Count_12_mon  \
0                  39  ...                       1
3
1                  44  ...                       1
2
2                  36  ...                       1
0
```

```
3                    34  ...                         4
1
4                    21  ...                         1
0
...                 ...  ...                       ...
...
10116                36  ...                         2
3
10117                40  ...                         3
4
10120                34  ...                         2
0
10121                50  ...                         1
4
10122                40  ...                         2
3

       Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy  \
0           12691.0                  777          11914.0
1            8256.0                  864           7392.0
2            3418.0                    0           3418.0
3            3313.0                 2517            796.0
4            4716.0                    0           4716.0
...             ...                  ...              ...
10116       13187.0                 2241          10946.0
10117       17925.0                 1909          16016.0
10120       13940.0                 2109          11831.0
10121        3688.0                  606           3082.0
10122        4003.0                 1851           2152.0

       Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  Total_Trans_Ct  \
0                     1.335             1144              42
1                     1.541             1291              33
2                     2.594             1887              20
3                     1.405             1171              20
4                     2.175              816              28
...                     ...              ...             ...
10116                 0.689            15354             112
10117                 0.712            17498             111
10120                 0.660            15577             114
10121                 0.570            14596             120
10122                 0.703            15476             117

       Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
0                    1.625                  0.061
1                    3.714                  0.105
2                    2.333                  0.000
3                    2.333                  0.760
4                    2.500                  0.000
...                    ...                    ...
```

```
10116                    0.931                      0.170
10117                    0.820                      0.106
10120                    0.754                      0.151
10121                    0.791                      0.164
10122                    0.857                      0.462

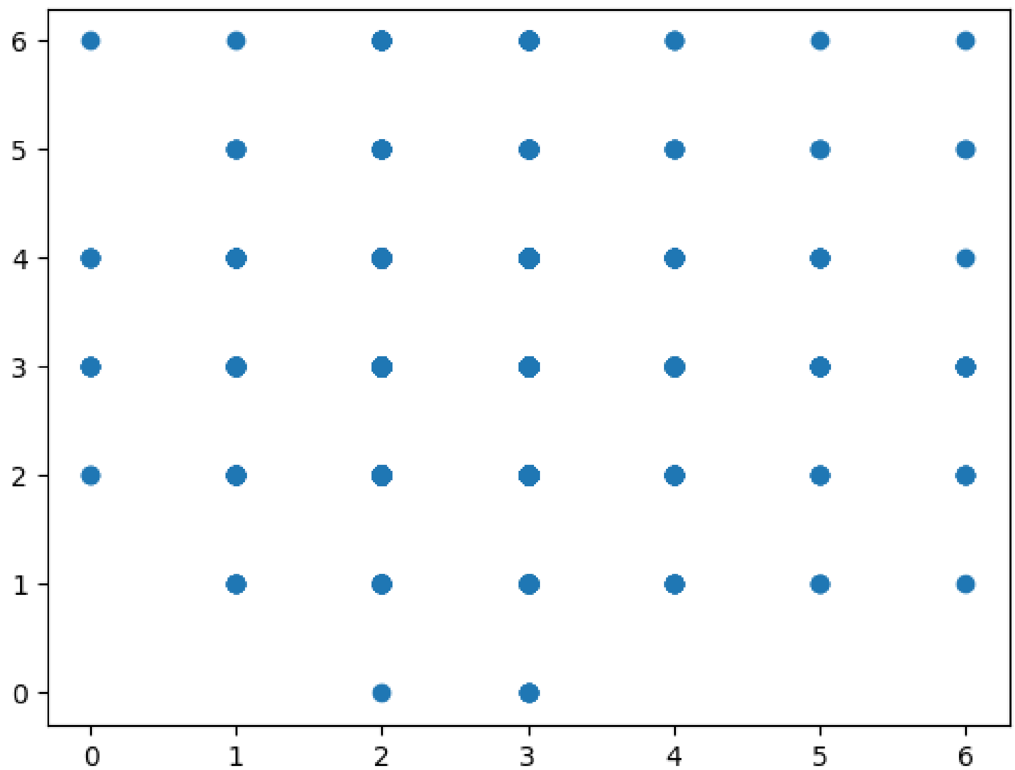
[8500 rows x 21 columns]
```

```
correlation =
acust['Months_Inactive_12_mon'].corr(acust['Contacts_Count_12_mon'])
print("Correlation coefficient:", correlation)
```

```
Correlation coefficient: 0.01203500426791782
```

```
plt.scatter(acust['Months_Inactive_12_mon'],acust['Contacts_Count_12_m
on'])
```

```
<matplotlib.collections.PathCollection at 0x1528c0f6500>
```



Report

# Customer Churn Analysis

## 1. Demographic Factors

### Age:

- **Churned Customers**: Slightly older, with an average age of **46.66 years**, compared to retained customers (average age: **46.26 years**).
- **Pattern**: Older customers might have higher expectations or require more personalized financial services, which can contribute to churn.

### Gender:

- **Churn Distribution**: **57.16%** of churned customers are female.
- **Pattern**: Female customers may be more likely to churn due to unmet service expectations or a lack of targeted offerings.

### Income Level:

- **Income of Churned Customers**: **37.61%** of churned customers earn less than **$40K**.
- **Pattern**: Financial strain or dissatisfaction with account fees and benefits could be contributing factors for churn among lower-income customers.

## 2. Behavioral Factors

### Months on Book:

- **Average Duration with the Bank**: Churned customers have been with the bank for an average of **36.18 months**.
- **Pattern**: Dissatisfaction might build over time, suggesting that banks should focus on early-stage engagement and periodic satisfaction surveys.

### Inactivity:

- **Inactivity Levels**: Churned customers show an average of **2.69 months** of inactivity in the past year.
- **Pattern**: Inactivity is often a precursor to disengagement, which can lead to churn.

### Contact Frequency:

- **Customer Interaction**: Churned customers had an average of **2.97** contacts with the bank in the past year.
- **Pattern**: A higher number of contacts may indicate dissatisfaction or unresolved issues during interactions with the bank.

# 3. Financial Factors

## Credit Utilization Ratio:

- **Average Utilization Ratio for Churned Customers**: **16.25%**.
- **Pattern**: A low utilization ratio might indicate underutilization of the bank's credit services, leading to reduced engagement.

## Dependent Count:

- **Dependents Among Churned Customers:** Churned customers have an average of **2.40** dependents, compared to **2.33** for retained customers.
- **Pattern**: More dependents could increase financial pressure, making fees or account terms more critical, which could drive churn.

## Product Relationships:

- **Product Variety:** Customers with fewer or less diverse products are more likely to churn.
- **Pattern**: A lack of diverse product relationships may lead to weaker attachment to the bank.

# 4)Relationship and Distribution

Churned customers

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

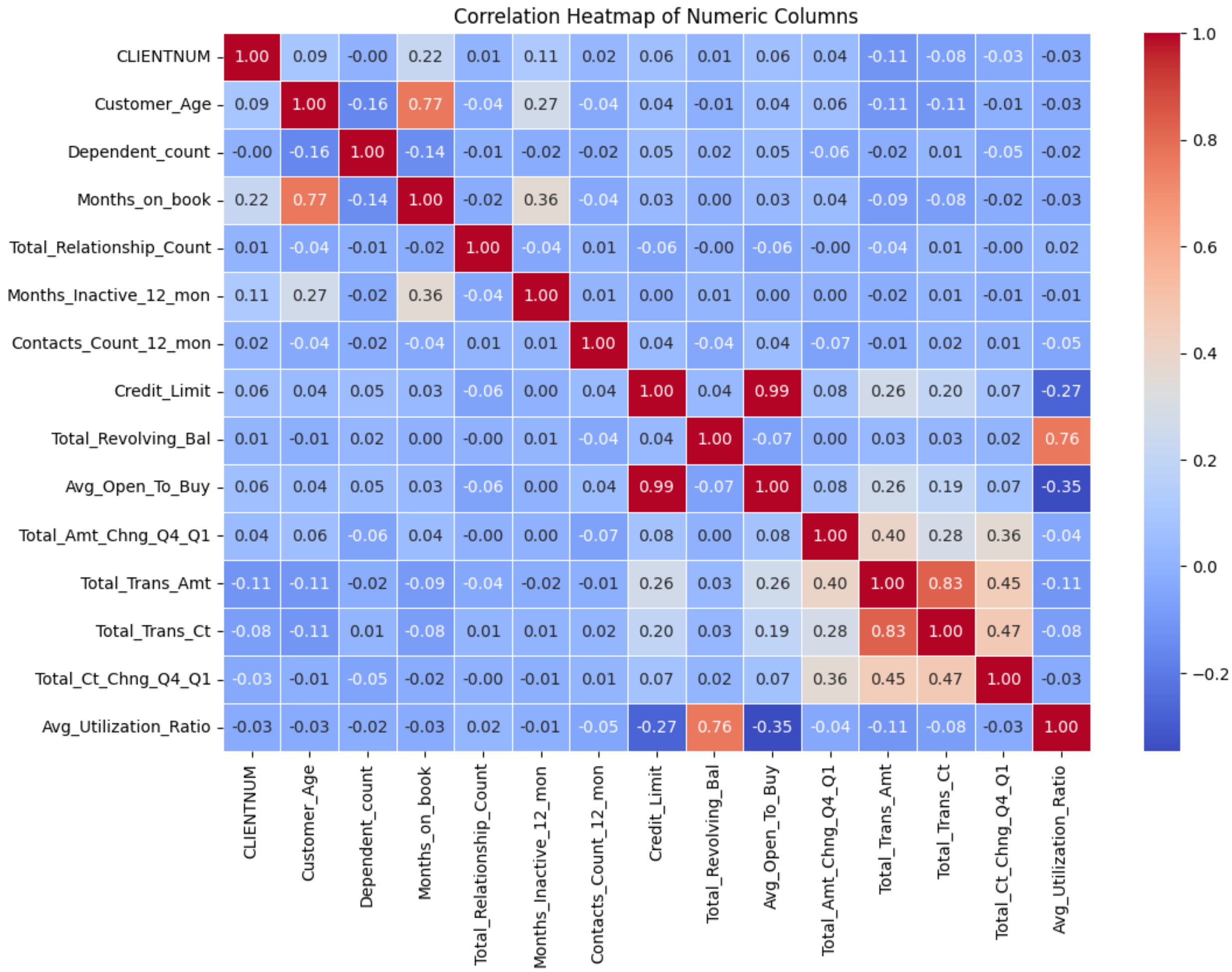
# Select columns with numeric data types (int or float)
numeric_columns = acust.select_dtypes(include=['int64', 'float64'])

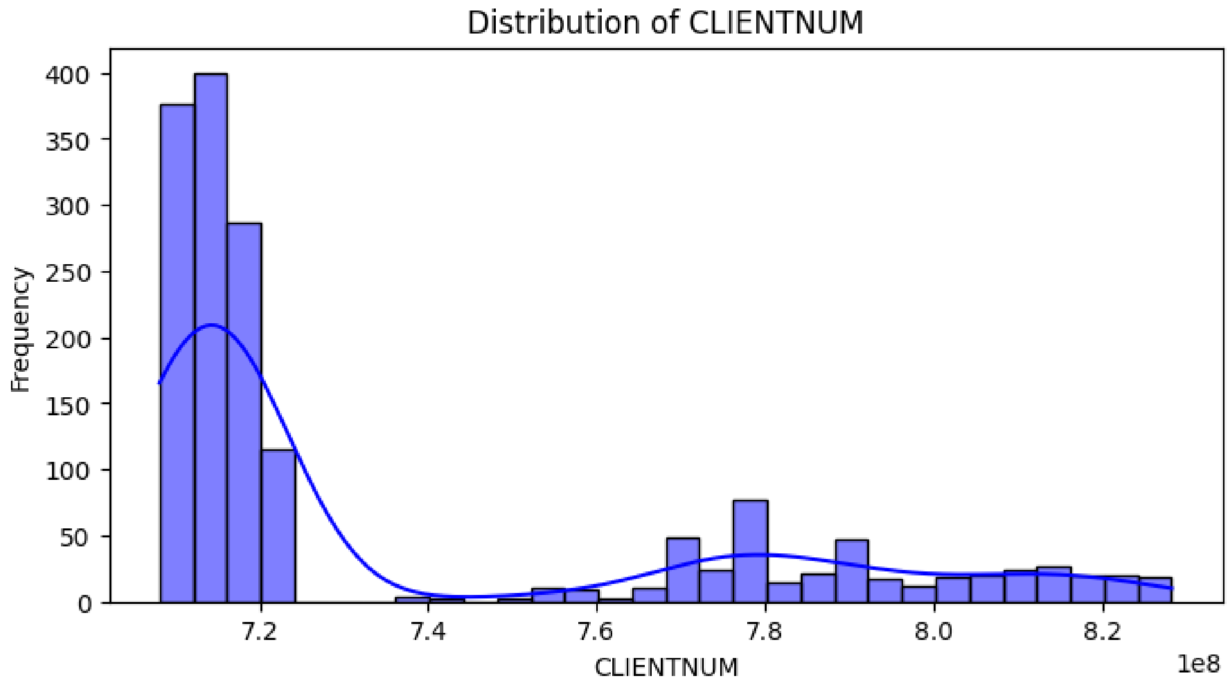
# Calculate the correlation matrix
correlation_matrix = numeric_columns.corr()

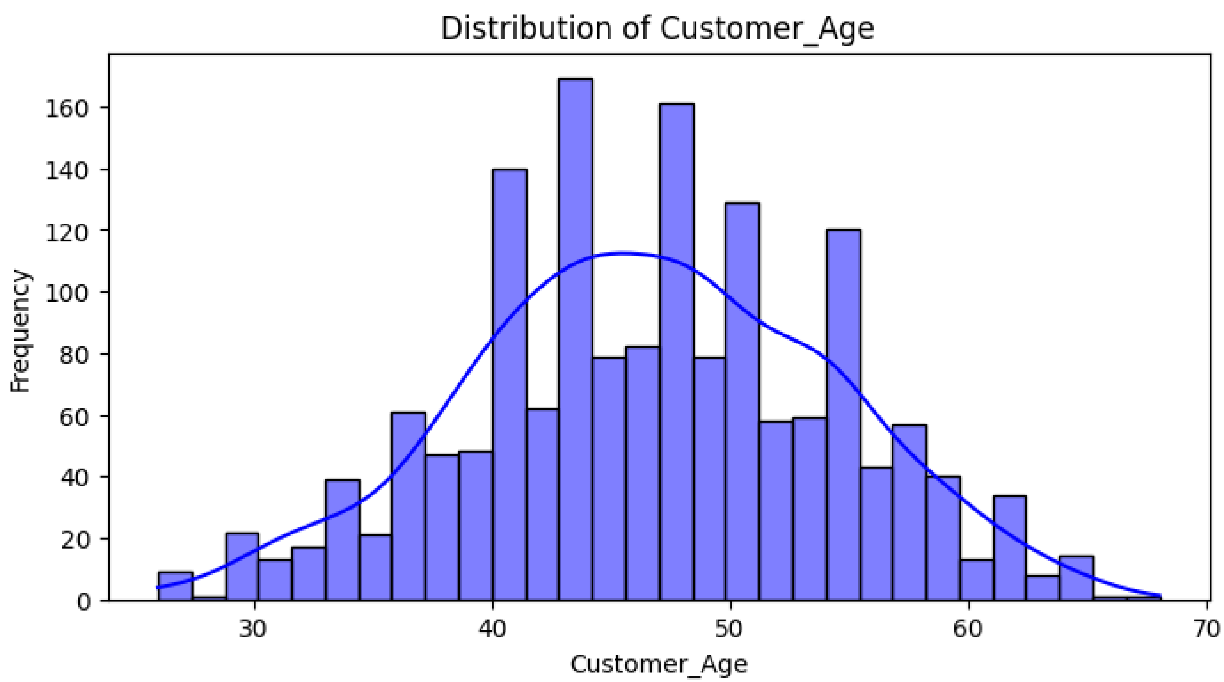
# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm",
fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap of Numeric Columns')
plt.show()

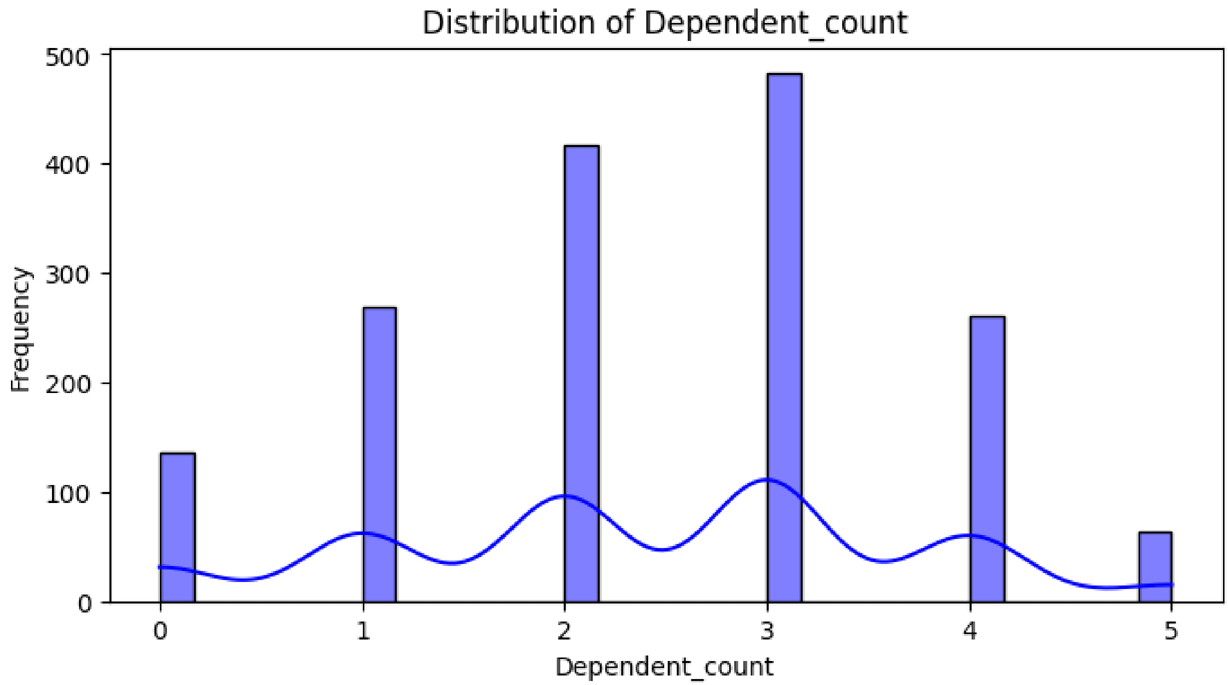
# Plot distributions of numeric columns
for column in numeric_columns.columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(numeric_columns[column], kde=True, color="blue",
bins=30)
    plt.title(f'Distribution of {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency')
```

```
plt.show()
```

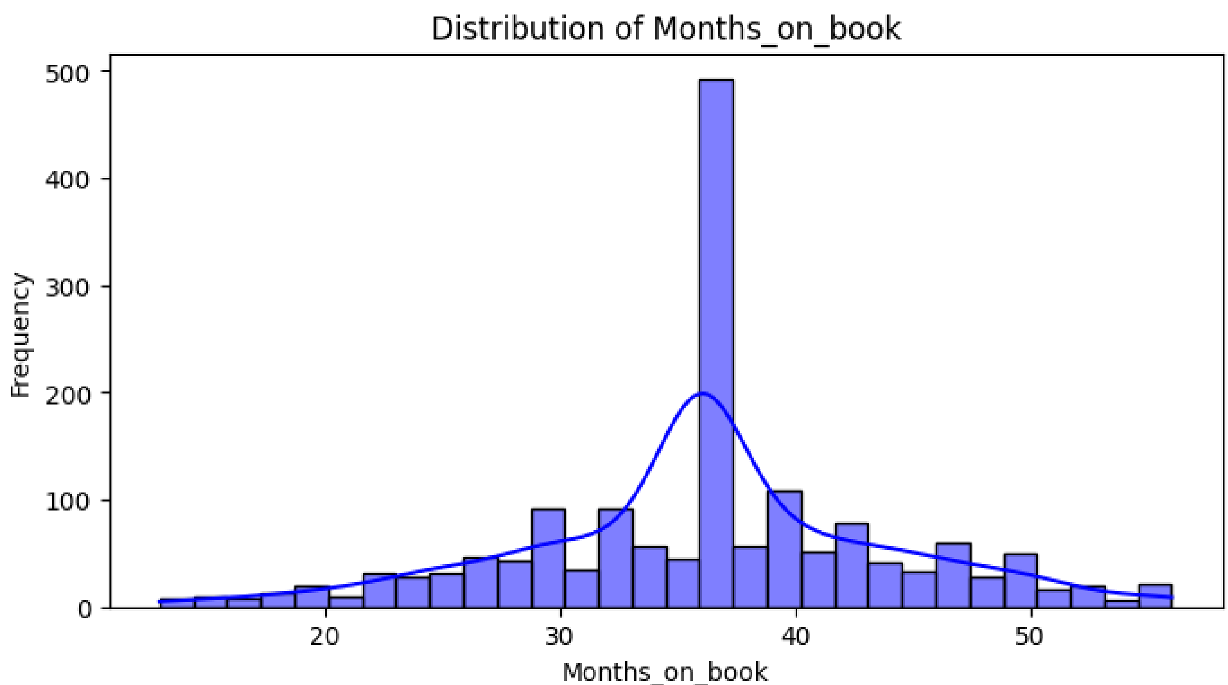

Correlation Heatmap of Numeric Columns
CLIENTNUM
Customer_Age
Dependent_count
Months_on_book
Total_Relationship_Count
Months_Inactive_12_mon
Contacts_Count_12_mon
Credit_Limit
Total_Revolving_Bal
Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1
Total_Trans_Amt
Total_Trans_Ct
Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


Distribution of CLIENTNUM
Frequency
0
50
100
150
200
250
300
350
400
7.2
7.4
7.6
7.8
8.0
8.2
1e8
CLIENTNUM

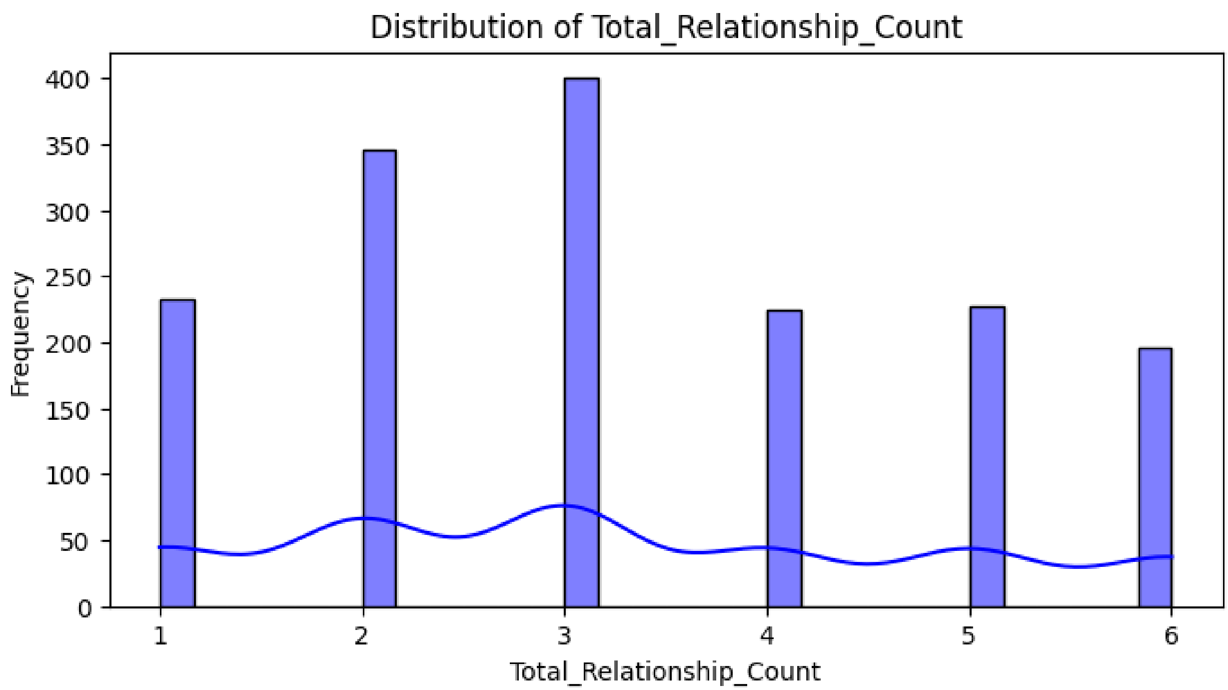

Distribution of Customer_Age
Frequency
0
20
40
60
80
100
120
140
160
30
40
50
60
70
Customer_Age

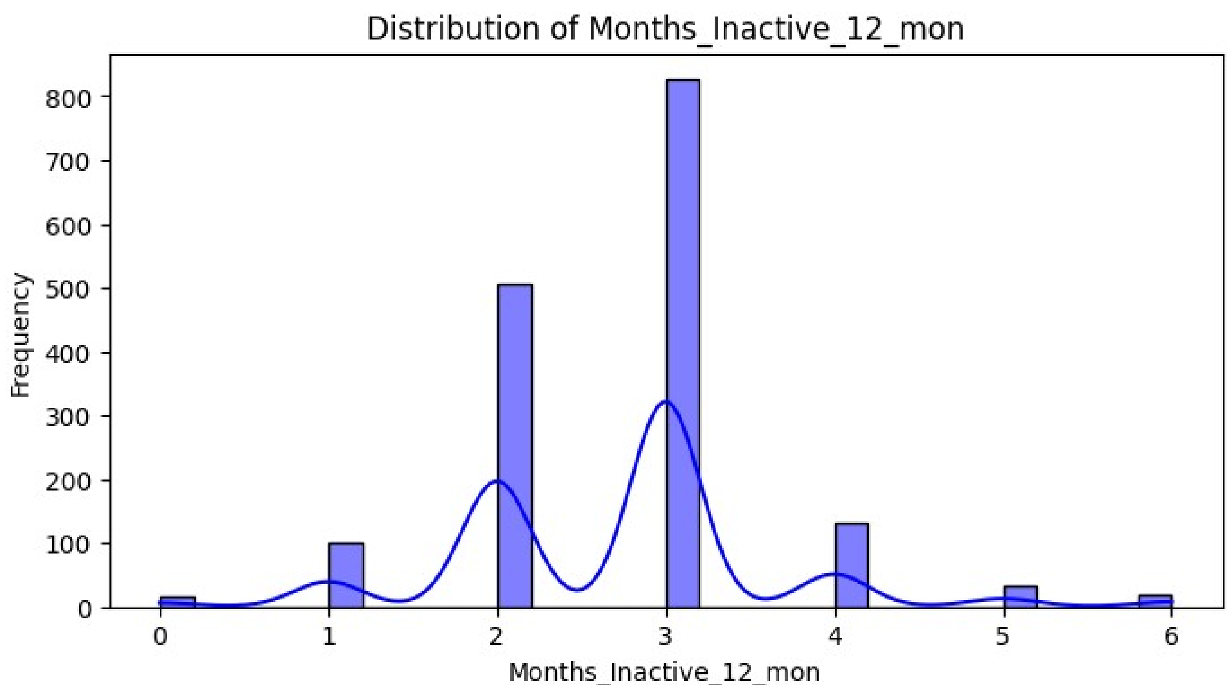


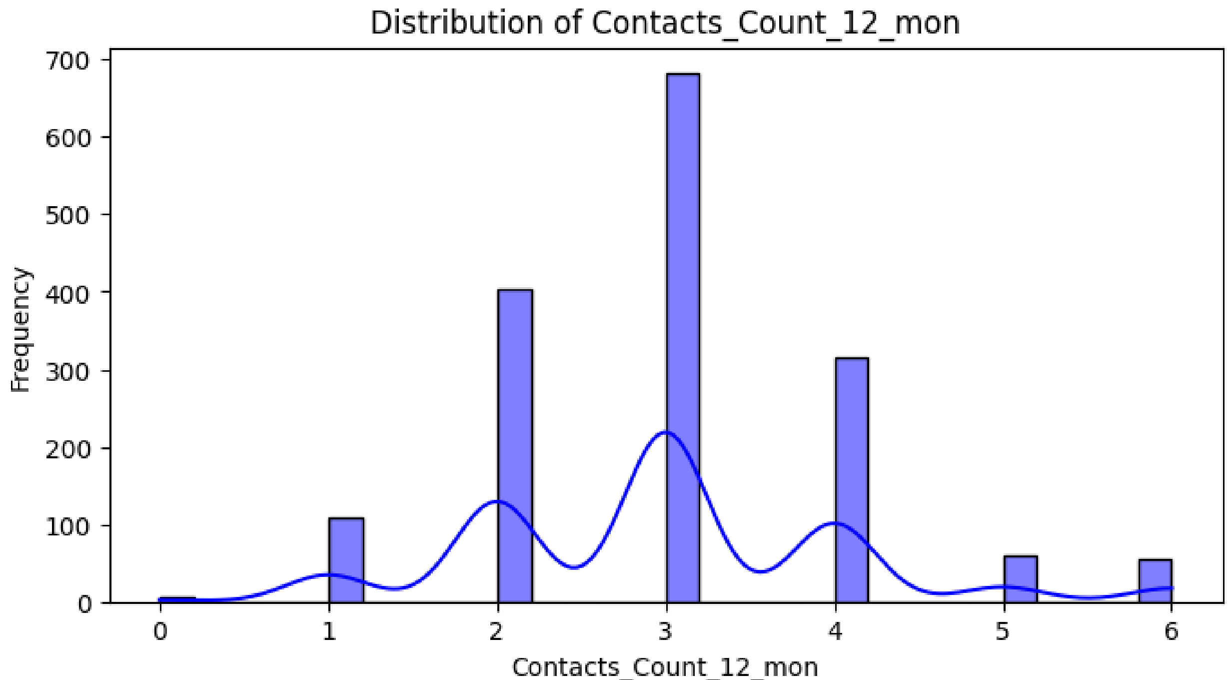
Distribution of Dependent_count
Frequency
Dependent_count
0
100
200
300
400
500
0
1
2
3
4
5

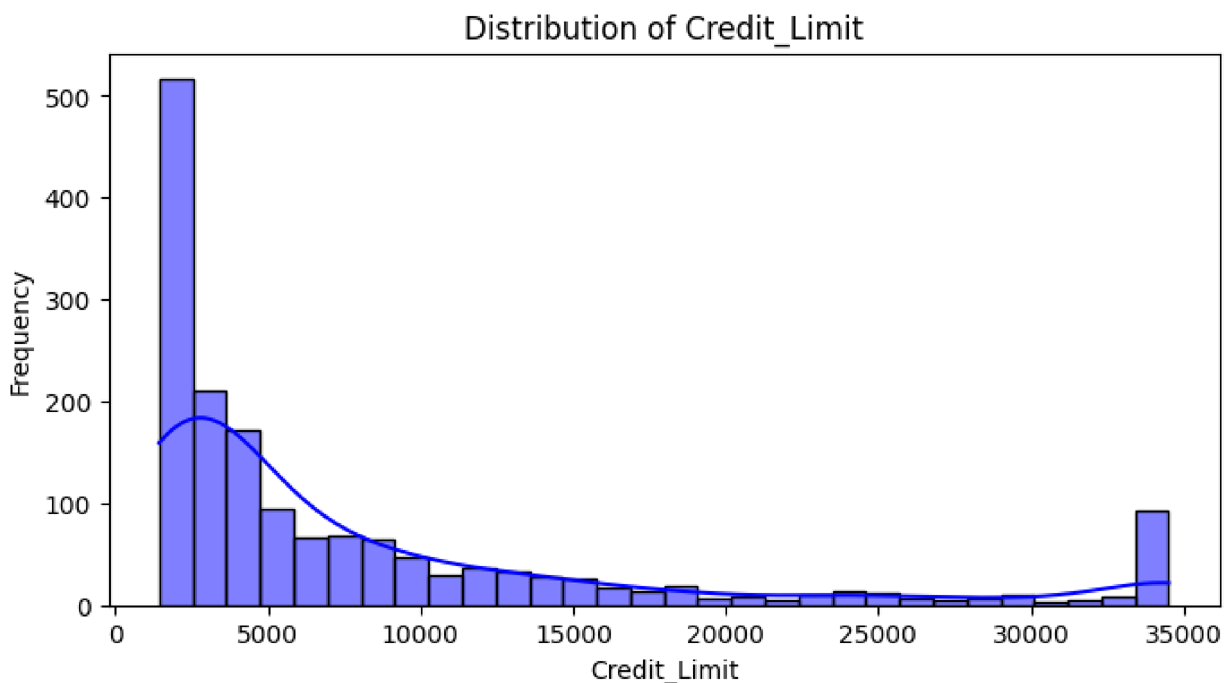



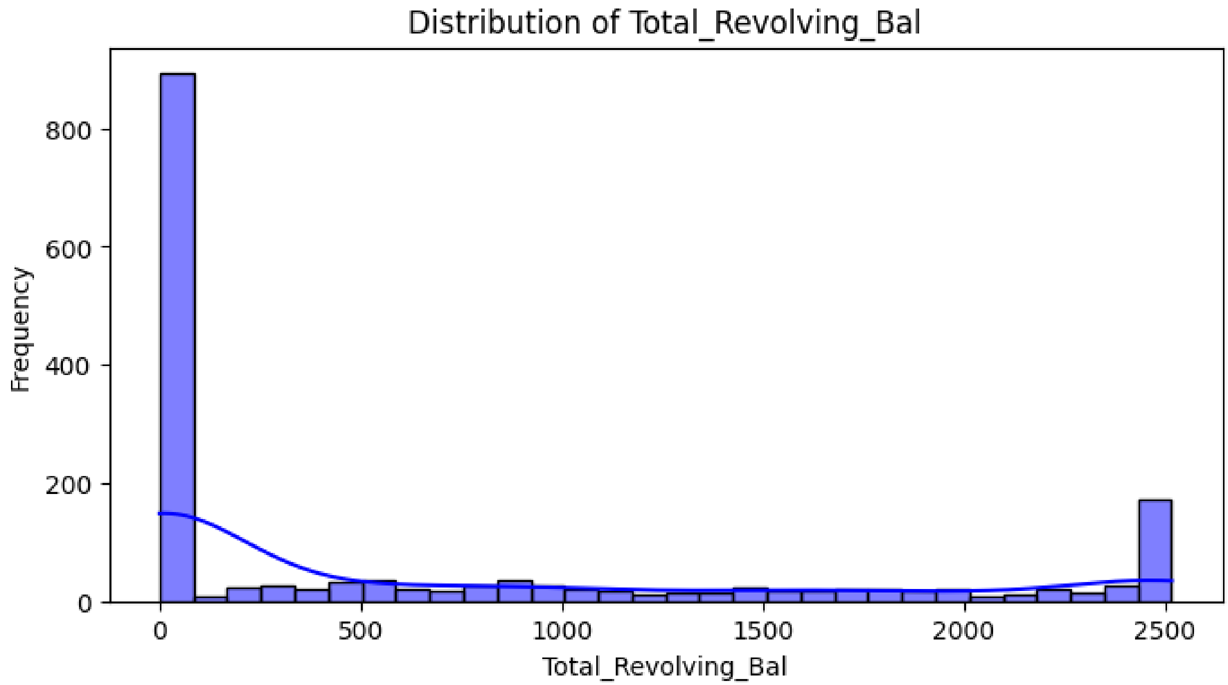
Distribution of Months_on_book
Frequency
Months_on_book
0
100
200
300
400
500
20
30
40
50

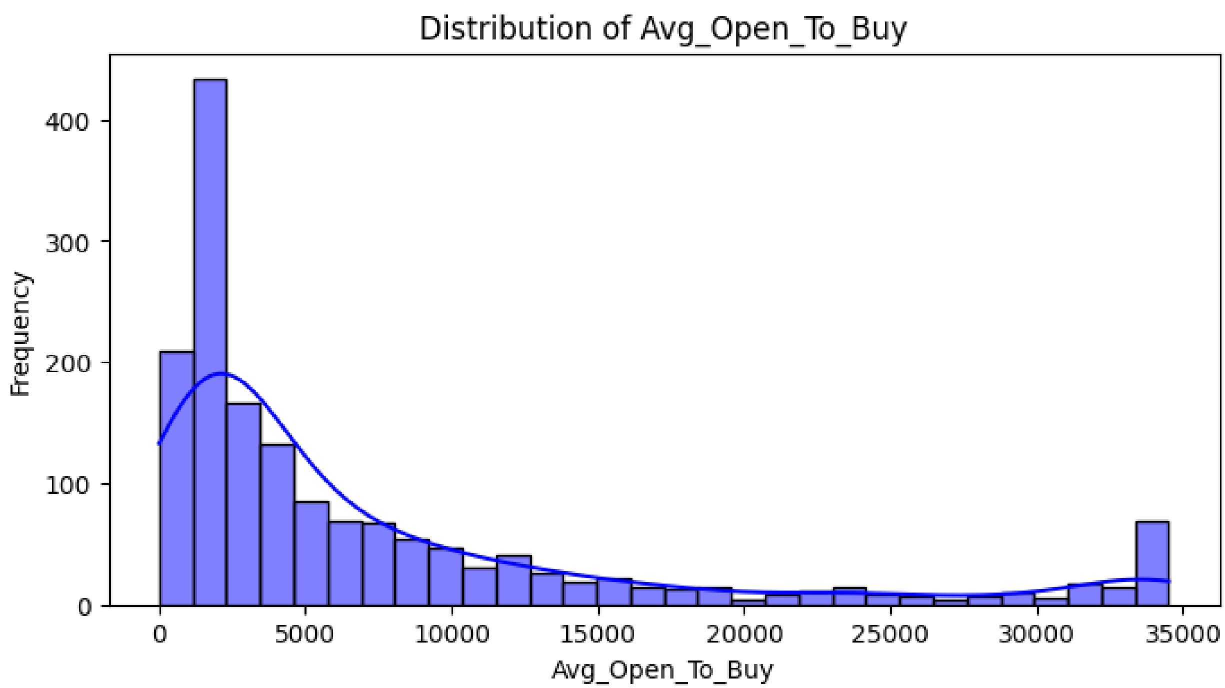

Distribution of Total_Relationship_Count
Frequency
0
50
100
150
200
250
300
350
400
1
2
3
4
5
6
Total_Relationship_Count

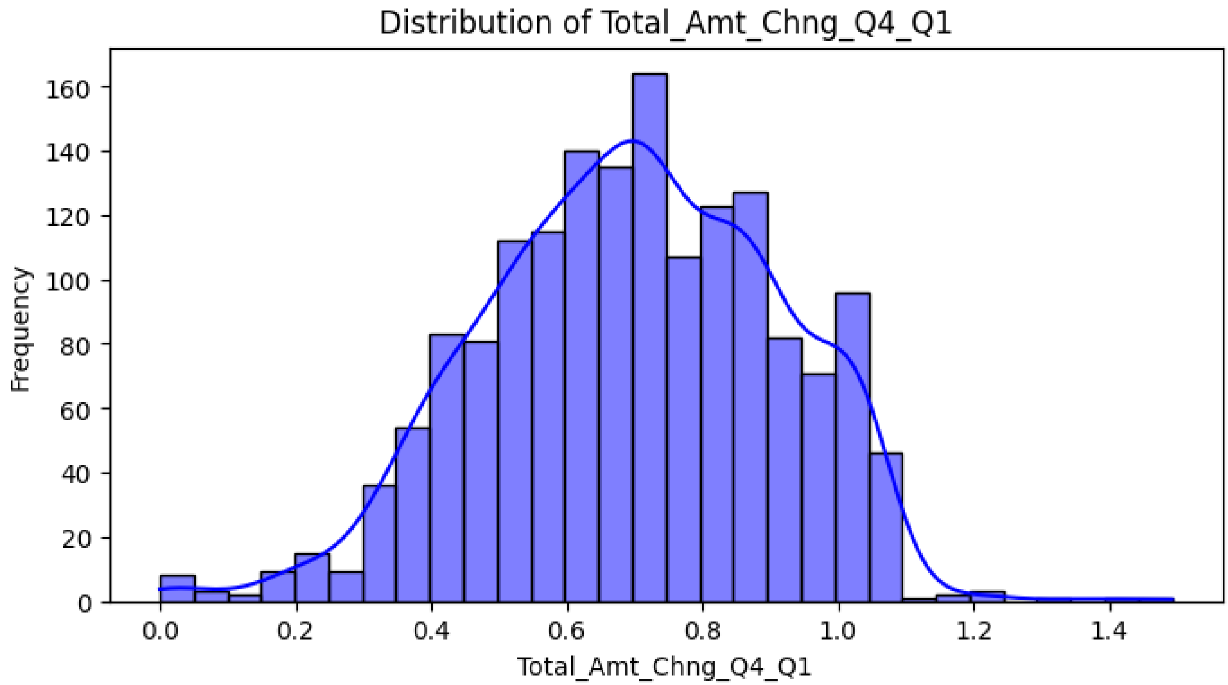

Distribution of Months_Inactive_12_mon
Frequency
0
100
200
300
400
500
600
700
800
0
1
2
3
4
5
6
Months_Inactive_12_mon

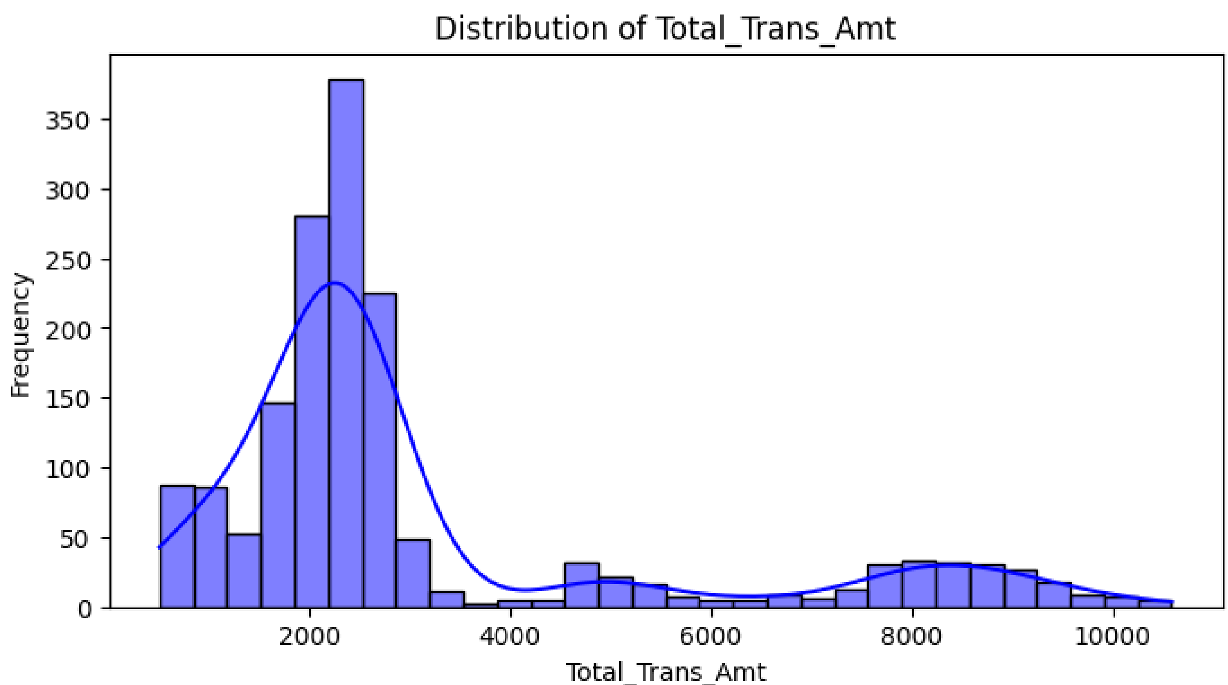

Distribution of Contacts_Count_12_mon
Frequency
700
600
500
400
300
200
100
0
0
1
2
3
4
5
6
Contacts_Count_12_mon

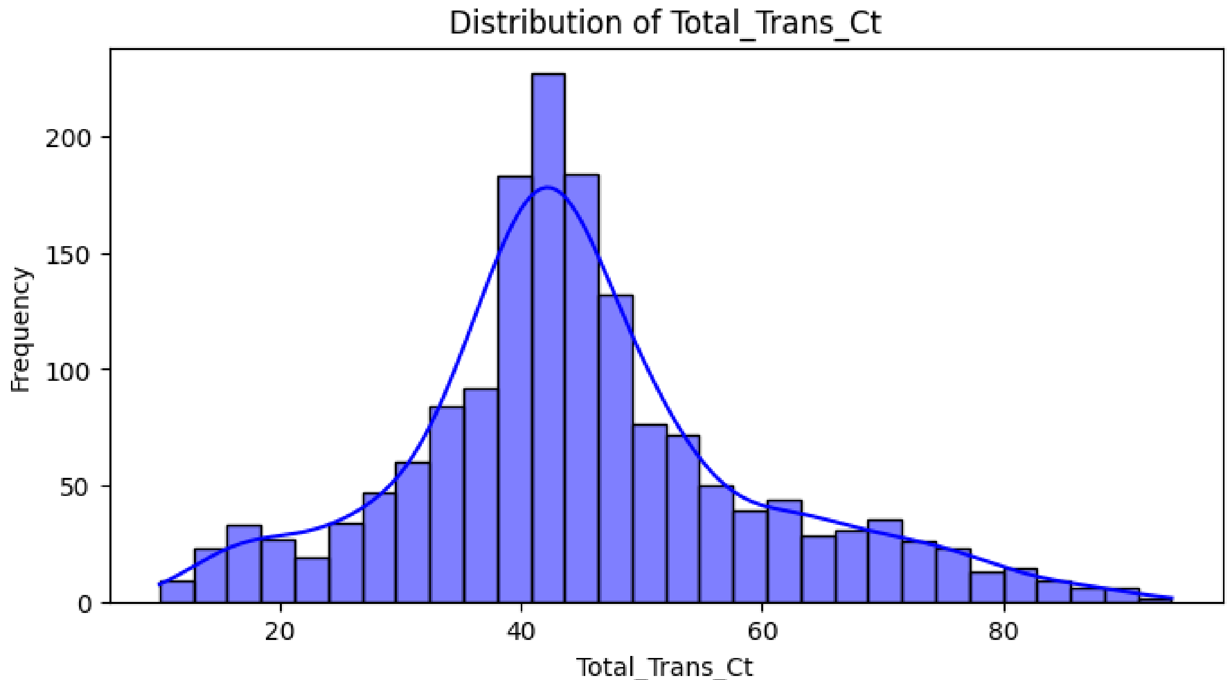

Distribution of Credit_Limit
Frequency
500
400
300
200
100
0
0
5000
10000
15000
20000
25000
30000
35000
Credit_Limit

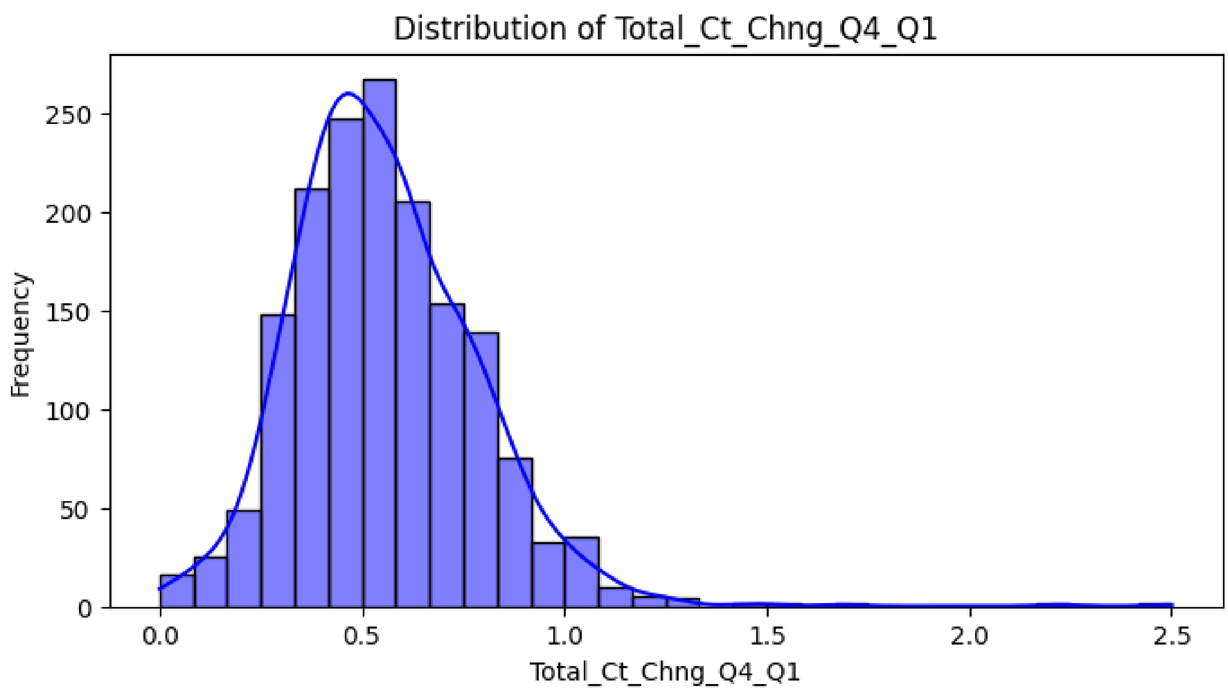

Distribution of Total_Revolving_Bal
Frequency
Total_Revolving_Bal
0
200
400
600
800
0
500
1000
1500
2000
2500

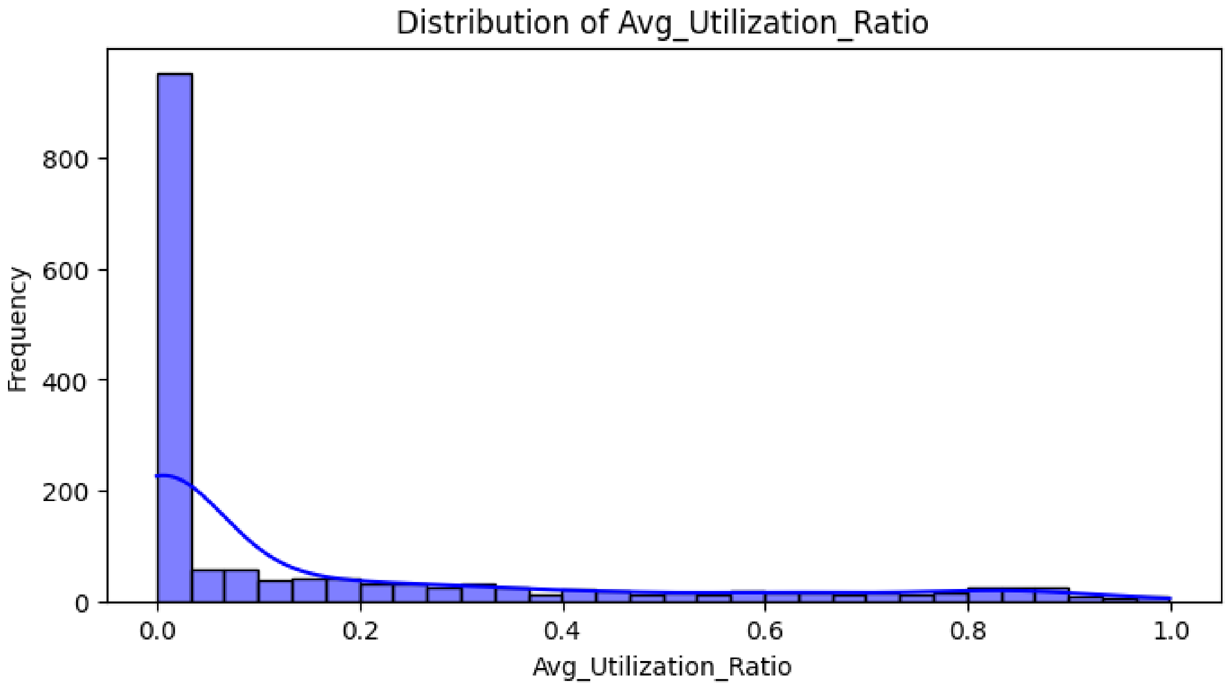

Distribution of Avg_Open_To_Buy
Frequency
Avg_Open_To_Buy
0
100
200
300
400
0
5000
10000
15000
20000
25000
30000
35000


Distribution of Total_Amt_Chng_Q4_Q1
Frequency
0
20
40
60
80
100
120
140
160
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
Total_Amt_Chng_Q4_Q1


Distribution of Total_Trans_Amt
Frequency
0
50
100
150
200
250
300
350
2000
4000
6000
8000
10000
Total_Trans_Amt


Distribution of Total_Trans_Ct
Frequency
0
50
100
150
200
20
40
60
80
Total_Trans_Ct


Distribution of Total_Ct_Chng_Q4_Q1
Frequency
0
50
100
150
200
250
0.0
0.5
1.0
1.5
2.0
2.5
Total_Ct_Chng_Q4_Q1




non churn customers

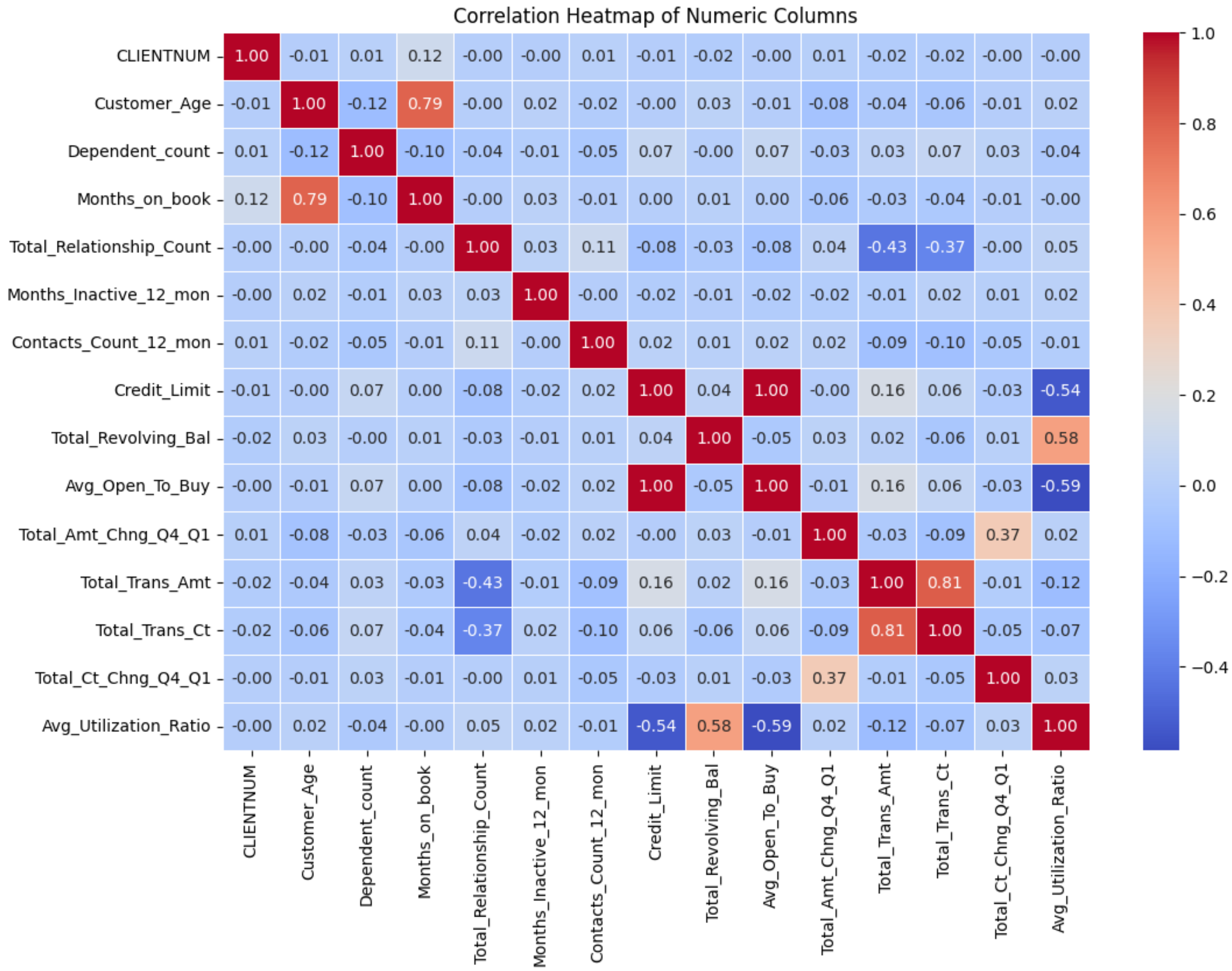
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

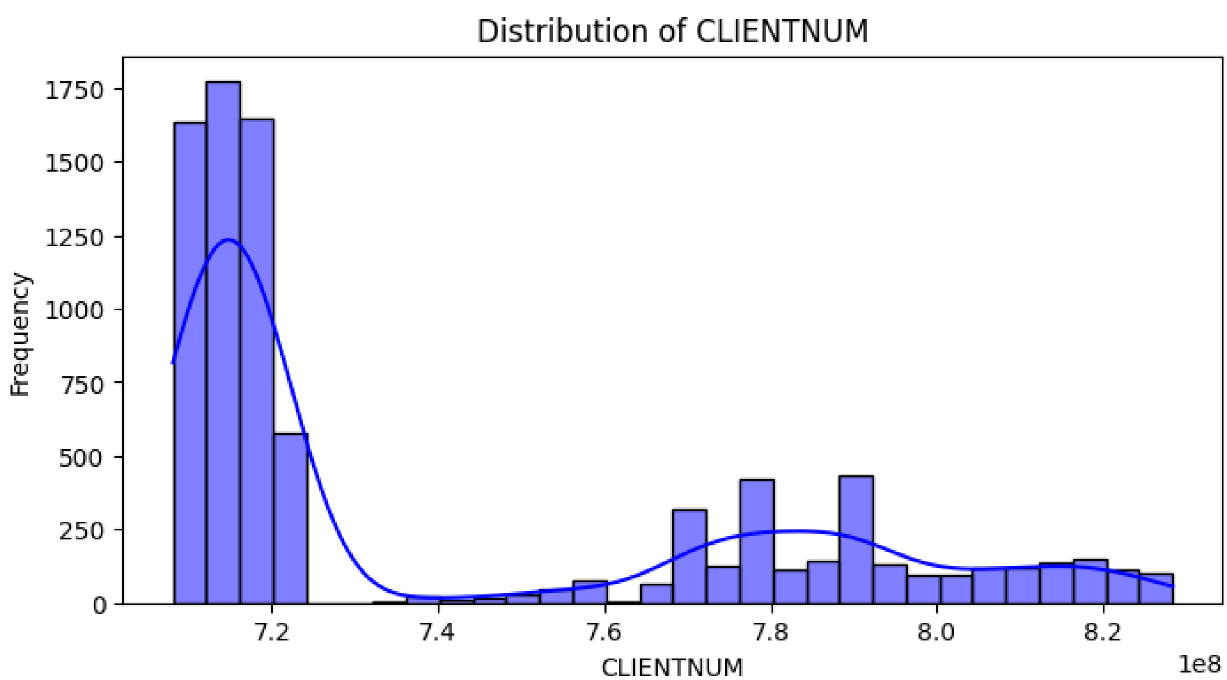
# Select columns with numeric data types (int or float)
numeric_columns = nacust.select_dtypes(include=['int64', 'float64'])

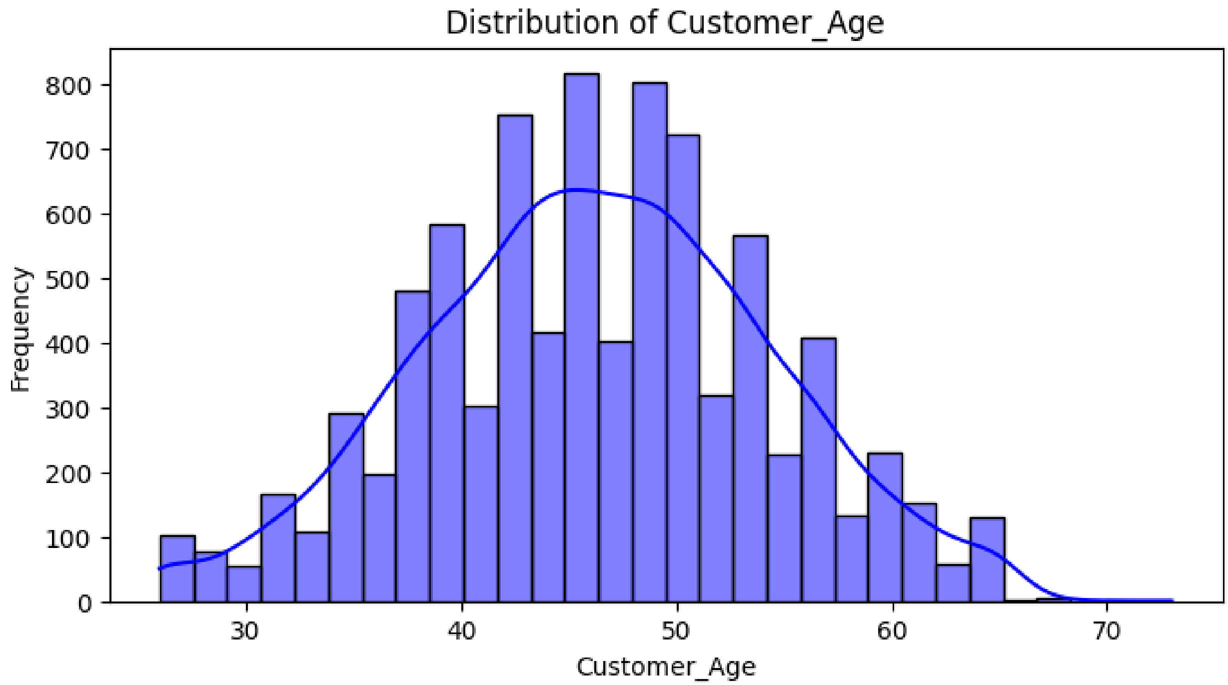
# Calculate the correlation matrix
correlation_matrix = numeric_columns.corr()

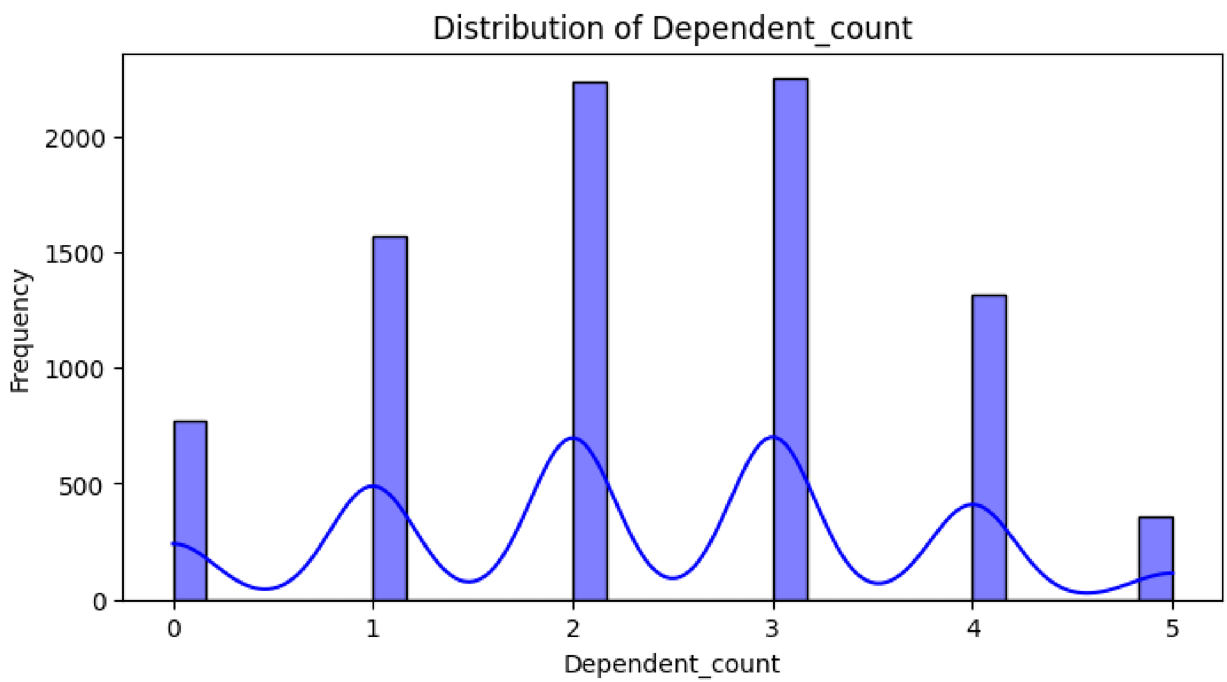
# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm",
fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap of Numeric Columns')
plt.show()

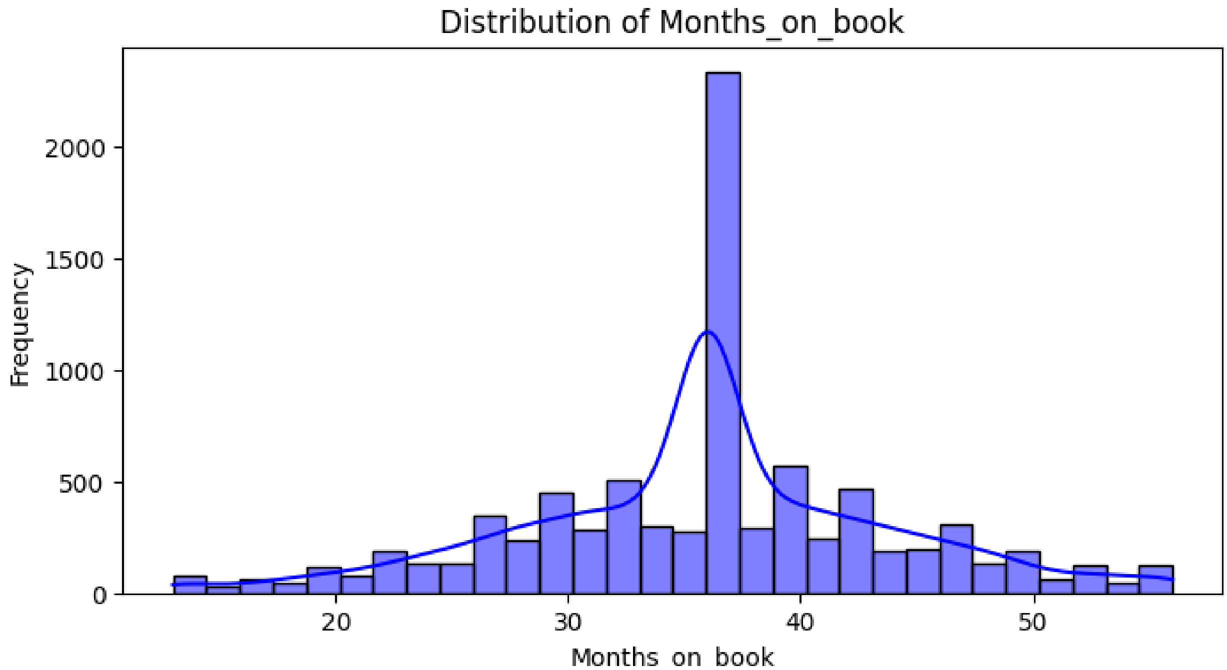
# Plot distributions of numeric columns
for column in numeric_columns.columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(numeric_columns[column], kde=True, color="blue",
bins=30)
    plt.title(f'Distribution of {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency')
    plt.show()
```

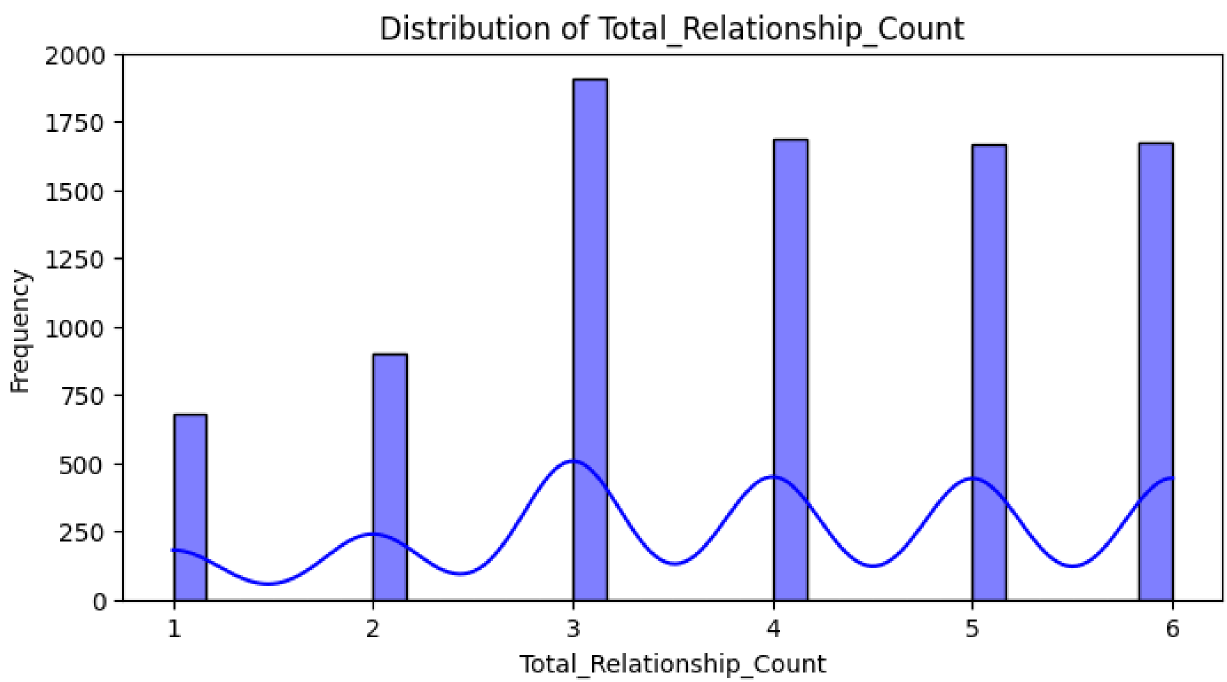

Correlation Heatmap of Numeric Columns
CLIENTNUM
Customer_Age
Dependent_count
Months_on_book
Total_Relationship_Count
Months_Inactive_12_mon
Contacts_Count_12_mon
Credit_Limit
Total_Revolving_Bal
Avg_Open_To_Buy
Total_Amt_Chng_Q4_Q1
Total_Trans_Amt
Total_Trans_Ct
Total_Ct_Chng_Q4_Q1
Avg_Utilization_Ratio
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

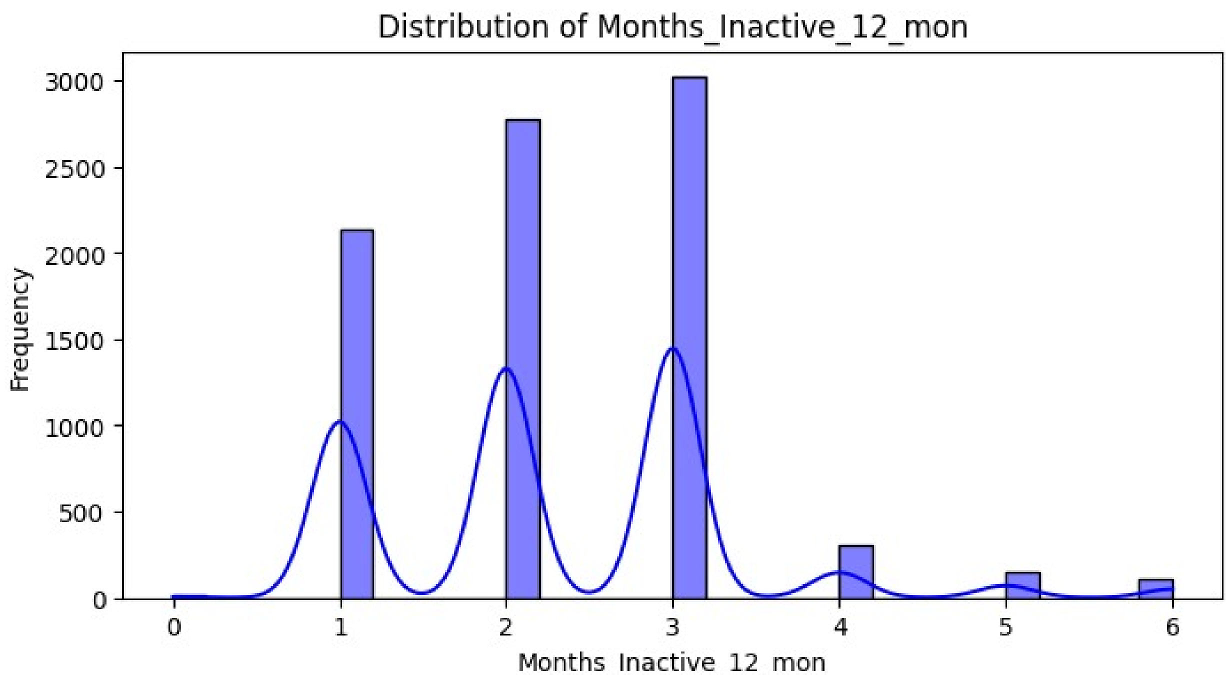

Distribution of CLIENTNUM
Frequency
CLIENTNUM
1e8
0
250
500
750
1000
1250
1500
1750
7.2
7.4
7.6
7.8
8.0
8.2


Distribution of Customer_Age
Frequency
0
100
200
300
400
500
600
700
800
30
40
50
60
70
Customer_Age

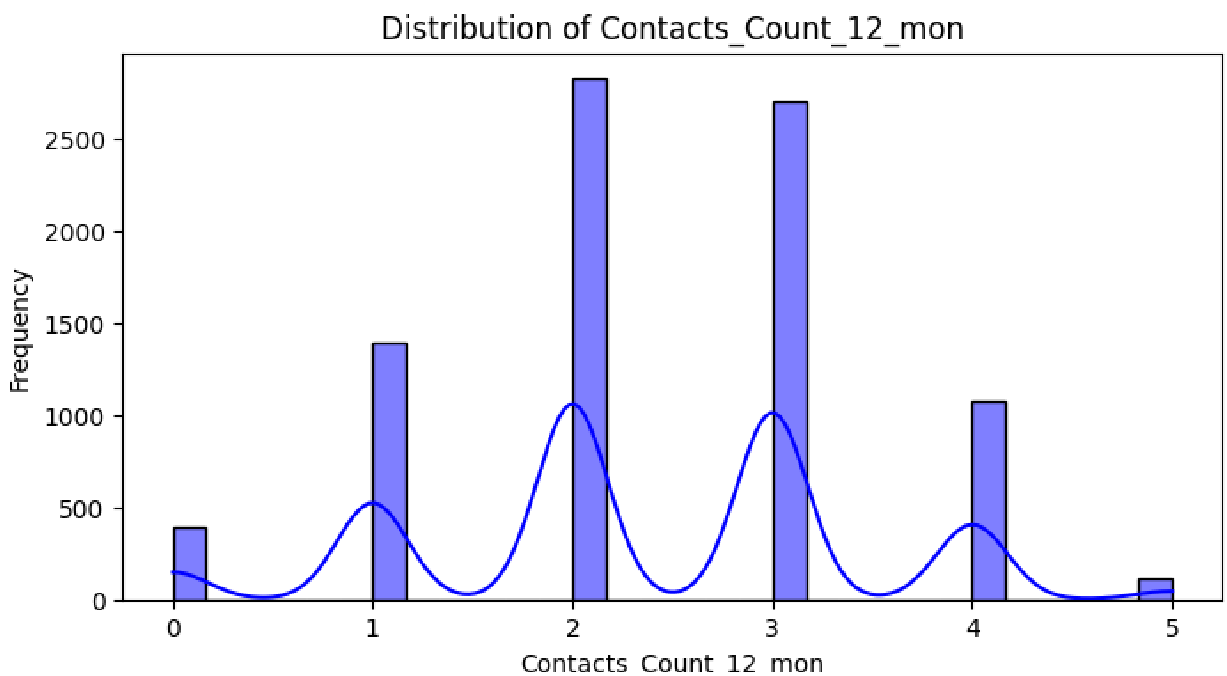

Distribution of Dependent_count
Frequency
0
500
1000
1500
2000
0
1
2
3
4
5
Dependent_count


Distribution of Months_on_book
Frequency
Months_on_book
0
500
1000
1500
2000
20
30
40
50

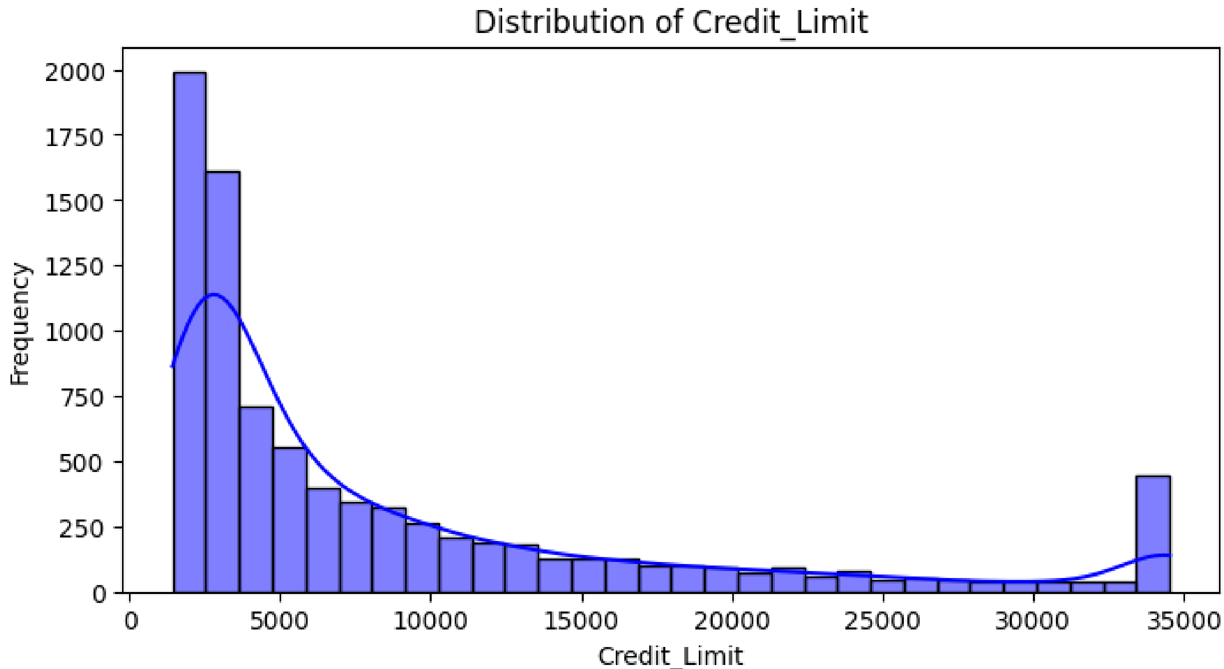

Distribution of Total_Relationship_Count
Frequency
Total_Relationship_Count
0
250
500
750
1000
1250
1500
1750
2000
1
2
3
4
5
6

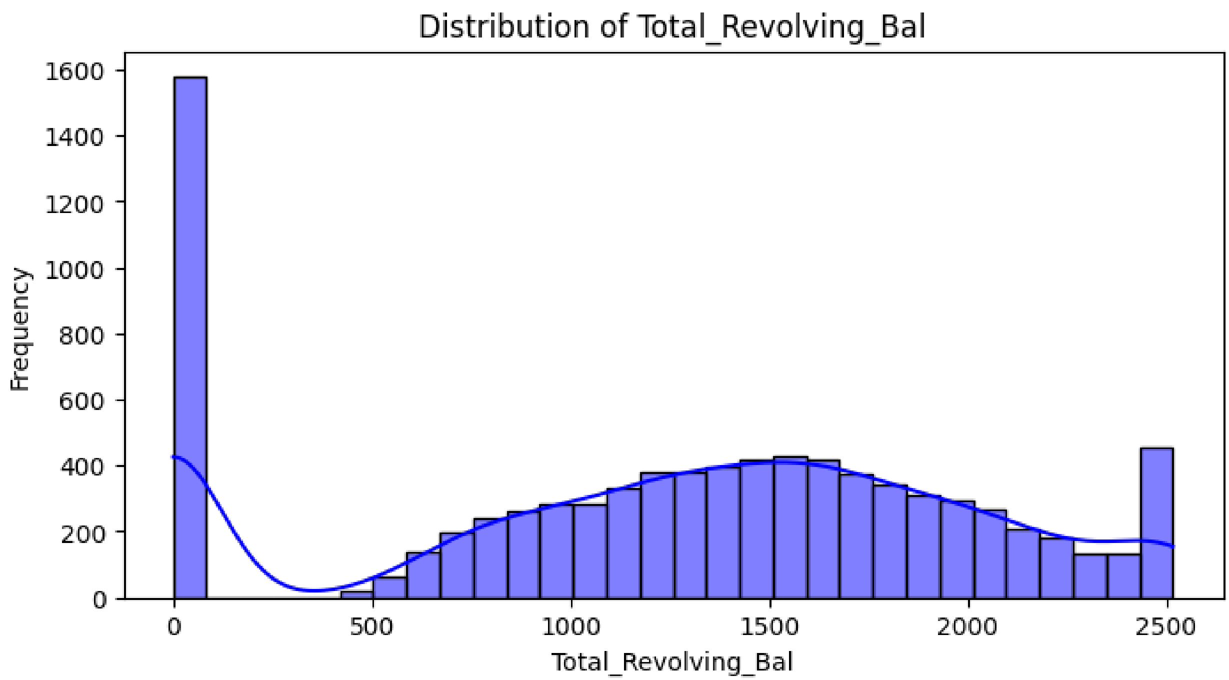


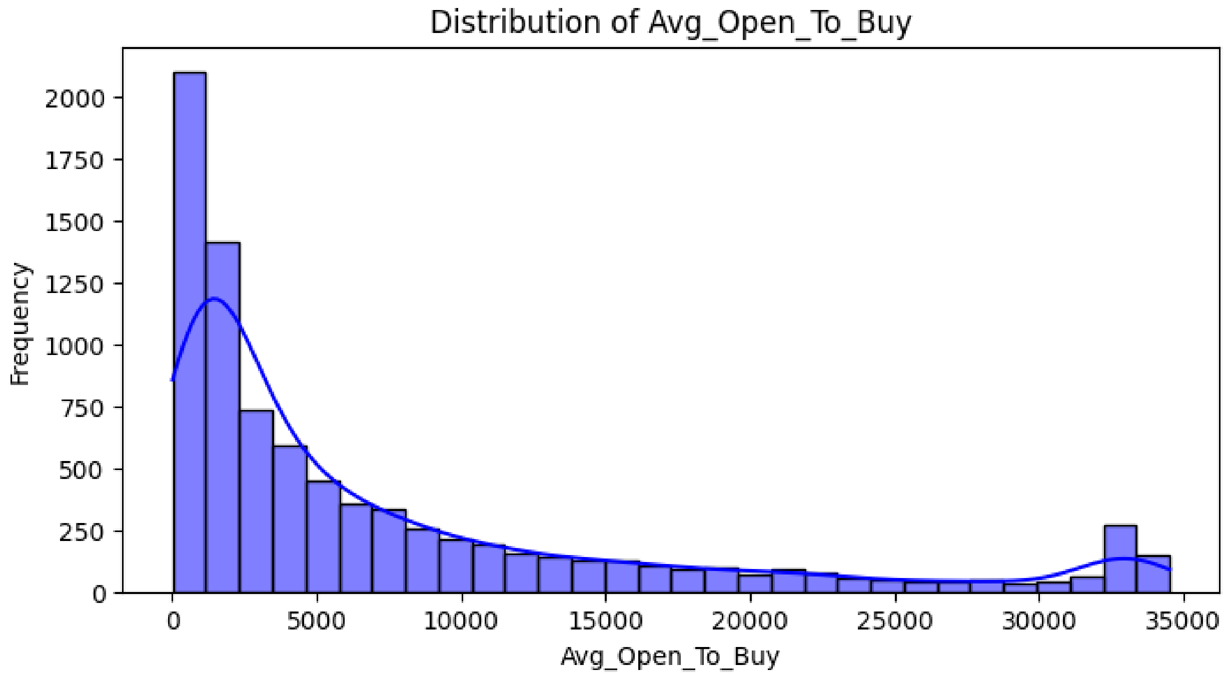
Distribution of Months_Inactive_12_mon
Frequency
3000
2500
2000
1500
1000
500
0
0
1
2
3
4
5
6
Months_Inactive_12_mon

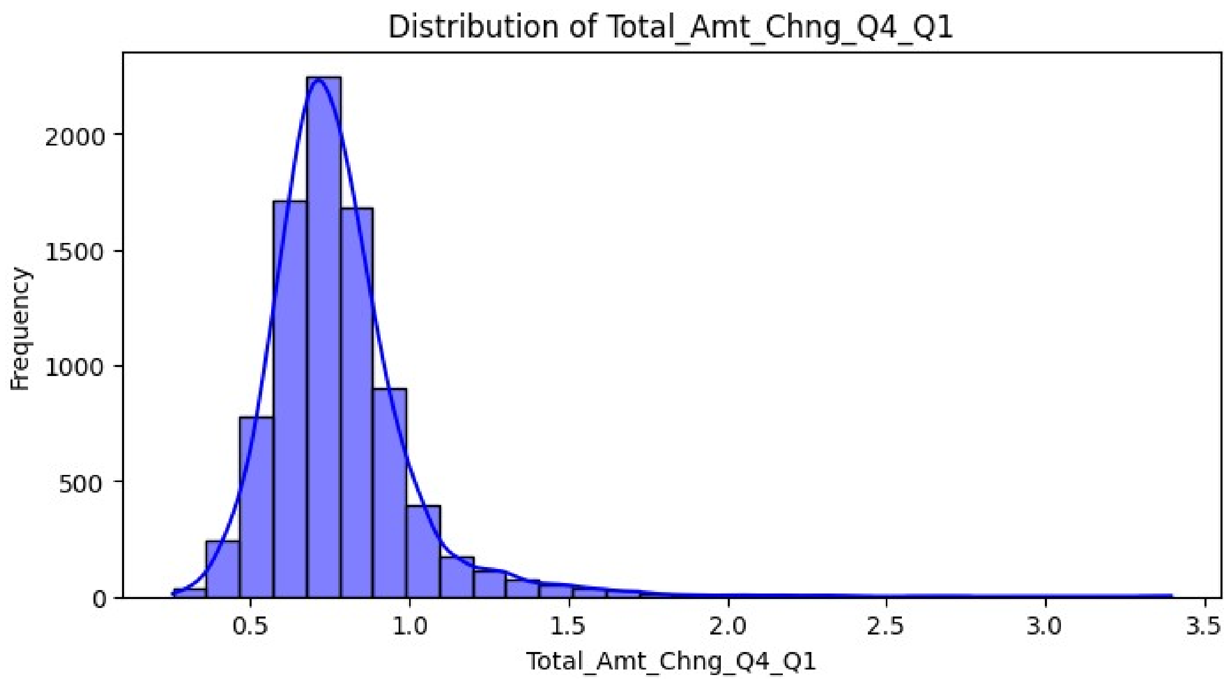



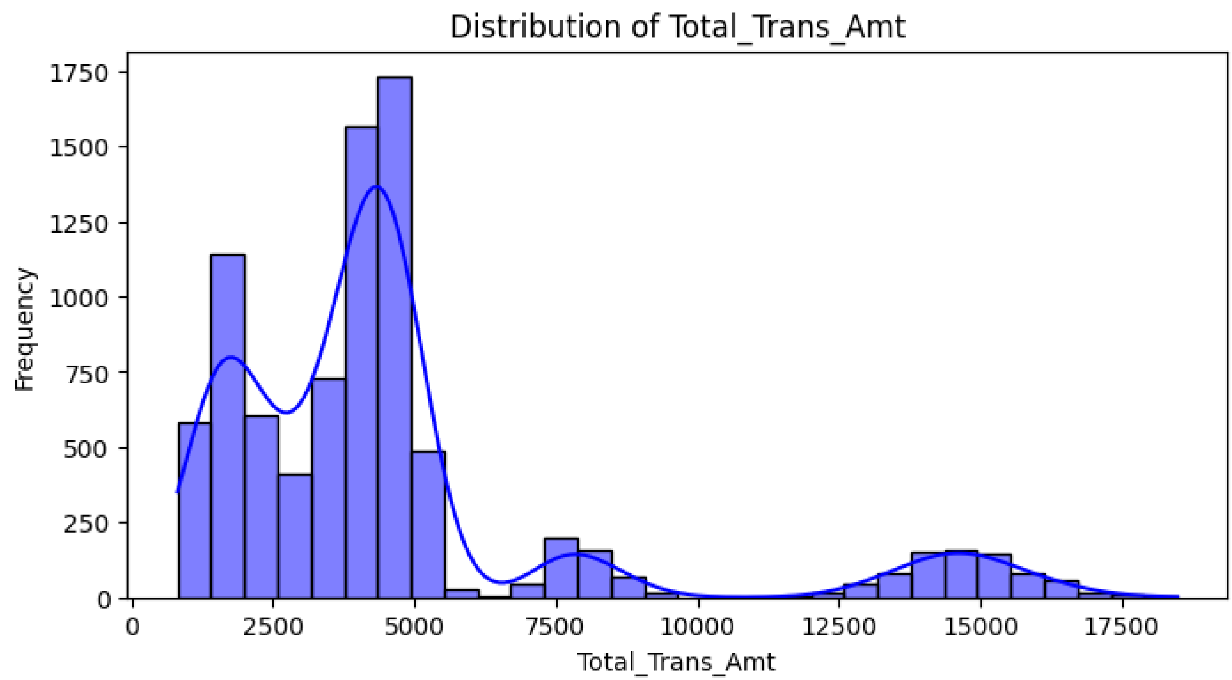
Distribution of Contacts_Count_12_mon
Frequency
2500
2000
1500
1000
500
0
0
1
2
3
4
5
Contacts_Count_12_mon


Distribution of Credit_Limit
Frequency
Credit_Limit
0
250
500
750
1000
1250
1500
1750
2000
5000
10000
15000
20000
25000
30000
35000

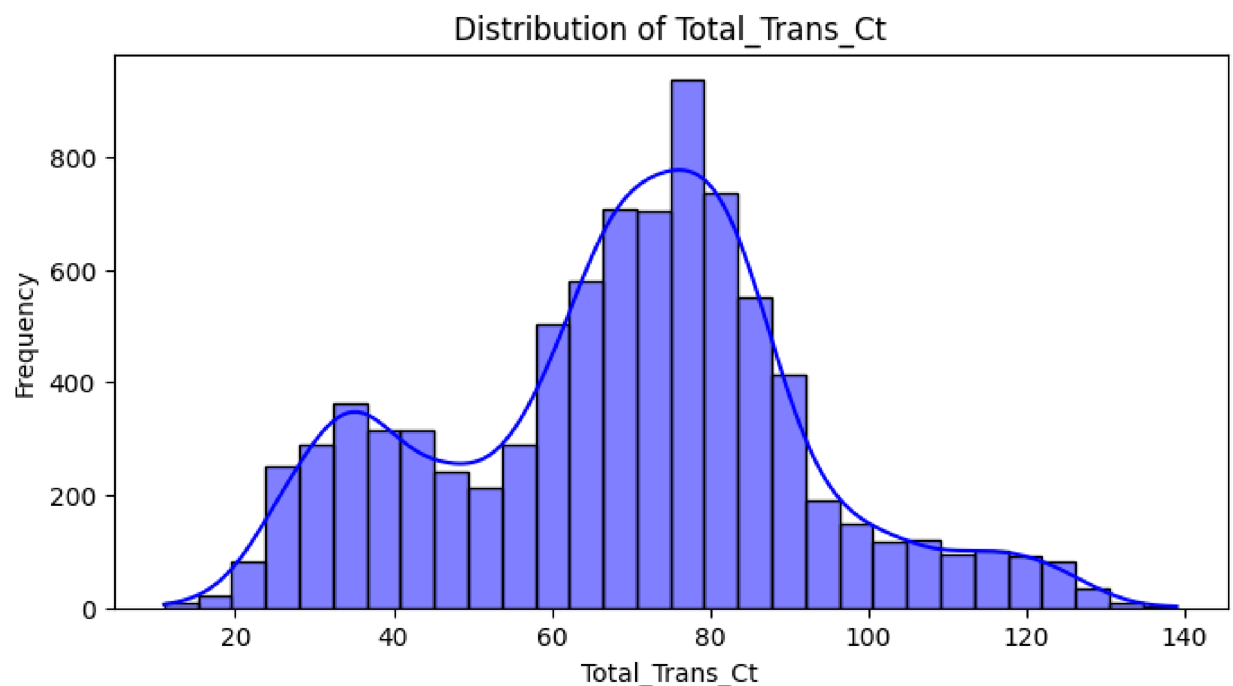

Distribution of Total_Revolving_Bal
Frequency
Total_Revolving_Bal
0
200
400
600
800
1000
1200
1400
1600
500
1000
1500
2000
2500


Distribution of Avg_Open_To_Buy
Frequency
0
250
500
750
1000
1250
1500
1750
2000
0
5000
10000
15000
20000
25000
30000
35000
Avg_Open_To_Buy

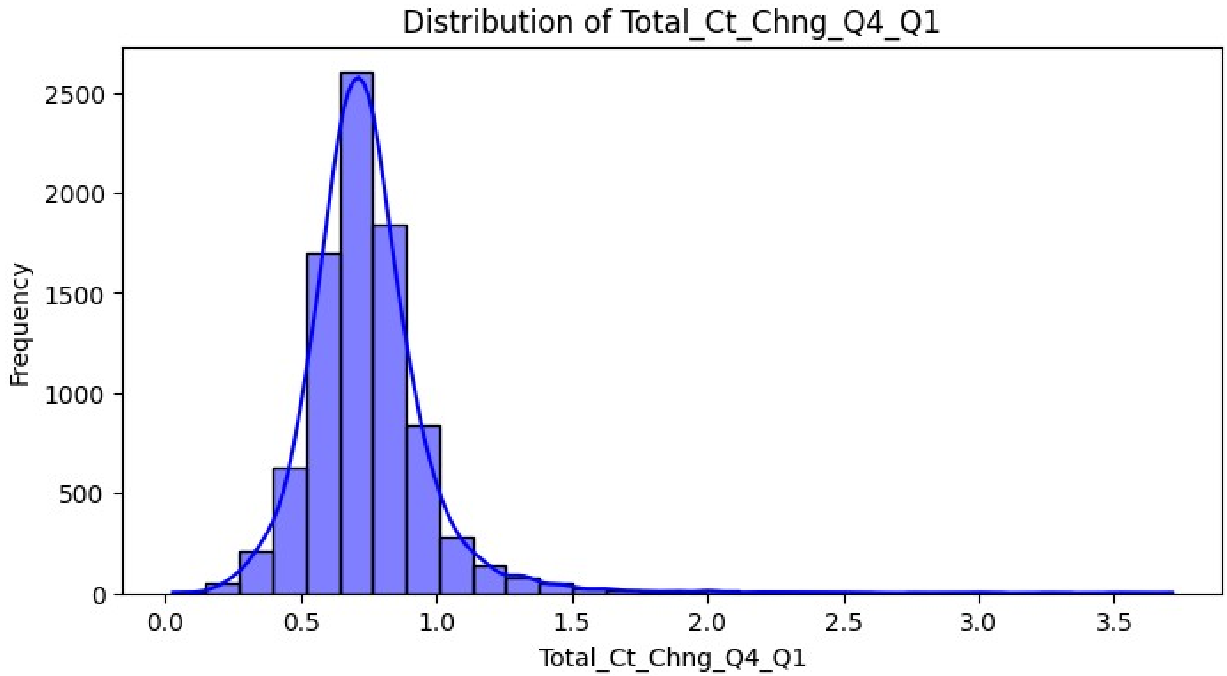

Distribution of Total_Amt_Chng_Q4_Q1
Frequency
0
500
1000
1500
2000
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Total_Amt_Chng_Q4_Q1

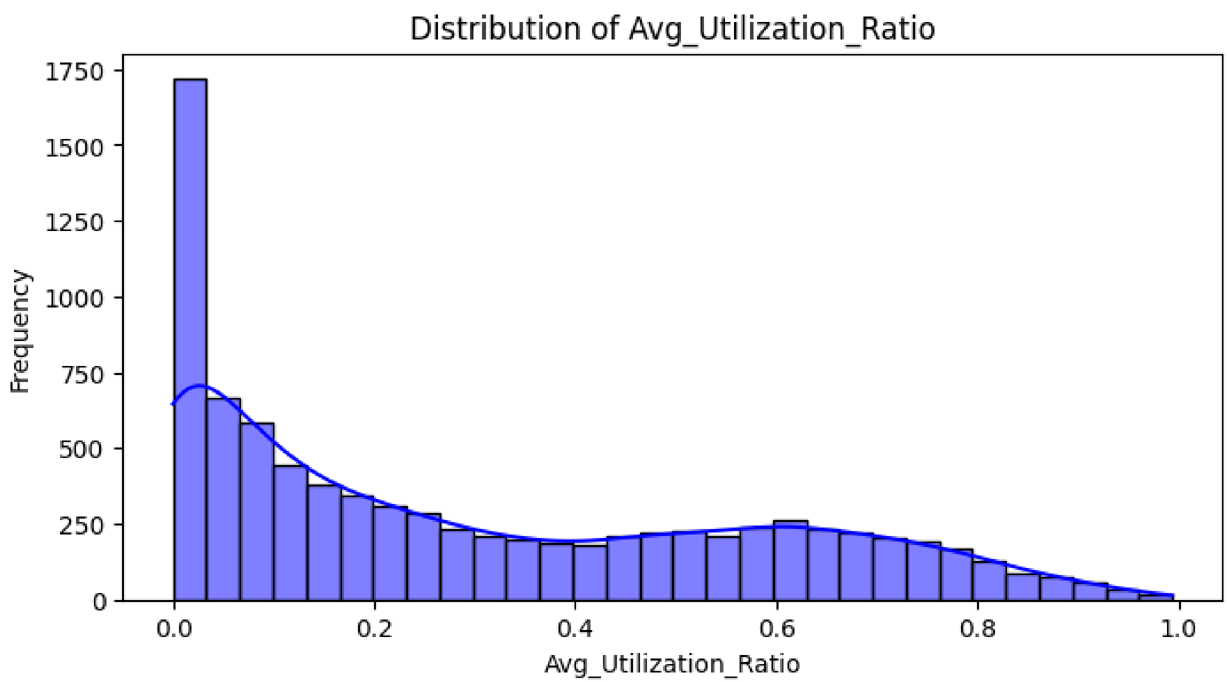


Distribution of Total_Trans_Amt
Frequency
0
250
500
750
1000
1250
1500
1750
0
2500
5000
7500
10000
12500
15000
17500
Total_Trans_Amt

Distribution of Total_Trans_Ct
Frequency
0
200
400
600
800
20
40
60
80
100
120
140
Total_Trans_Ct


Distribution of Total_Ct_Chng_Q4_Q1
Frequency
0
500
1000
1500
2000
2500
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Total_Ct_Chng_Q4_Q1


Distribution of Avg_Utilization_Ratio
Frequency
0
250
500
750
1000
1250
1500
1750
0.0
0.2
0.4
0.6
0.8
1.0
Avg_Utilization_Ratio

# Churned Customers Report

# Retention Analysis: Insights and Correlations For Churned Customer

## 1. Strong Positive Correlations

### Avg_Open_To_Buy and Credit_Limit (0.99)

- **Insight**: Retained customers with higher credit limits also have more available credit.
- **Pattern**: This strong correlation indicates that these features are nearly interchangeable in representing financial capacity.

### Total_Trans_Amt and Total_Trans_Ct (0.83)

- **Insight**: Customers who remain loyal tend to make more transactions with higher transaction amounts.
- **Pattern**: High engagement and frequent transactions are key traits of retained customers.

### Months_on_book and Customer_Age (0.79)

- **Insight**: Older retained customers have been with the bank longer.
- **Pattern**: Long tenure correlates strongly with customer age, reflecting typical retention patterns.

## 2. Moderate Positive Correlations

### Total_Relationship_Count and Contacts_Count_12_mon (0.43)

- **Insight**: Retained customers with more relationships with the bank also show slightly higher contact frequency in the past year.
- **Pattern**: Increased touchpoints may indicate higher engagement or satisfaction.

### Total_Ct_Chng_Q4_Q1 and Total_Amt_Chng_Q4_Q1 (0.37)

- **Insight**: A moderate correlation between changes in transaction counts and amounts shows active engagement among retained customers.
- **Pattern**: Consistent transactional growth signals customer loyalty.

## 3. Strong Negative Correlations

### Avg_Utilization_Ratio and Avg_Open_To_Buy (-0.59)

- **Insight**: Retained customers with higher utilization ratios tend to have lower available credit.
- **Pattern**: Reflects financial discipline or well-matched credit limits.

### Avg_Utilization_Ratio and Credit_Limit (-0.54)

- **Insight**: Retained customers with high credit limits tend to use a smaller proportion of their available credit.
- **Pattern**: Indicates responsible credit use and financial stability.

## 4. Weak or No Correlation

### Dependent_Count and Most Variables

- **Insight**: The number of dependents has minimal impact on other numeric features.
- **Pattern**: Dependents do not significantly influence retention metrics.

### Months_Inactive_12_mon and Most Variables

- **Insight**: Inactivity within the last 12 months shows no strong linear relationships with other factors.
- **Pattern**: Inactivity does not strongly predict other retention characteristics.

## 5. Insights for Retention Strategies

### Credit Management

- **Recommendation**: Focus on tailored credit limit increases for retained customers with high financial capacity.
- **Objective**: Strengthen loyalty by matching credit offerings with customer needs.

### Engagement Metrics

- **Recommendation**: Incentivize higher transaction activity through rewards programs.
- **Objective**: Encourage frequent and higher-value transactions.

### Age & Tenure

- **Recommendation**: Offer loyalty benefits to younger customers to increase retention over time.
- **Objective**: Build long-term customer relationships.

### Feature Reduction

- **Recommendation**: Drop one of the highly correlated features, such as `Avg_Open_To_Buy` or `Credit_Limit`, to simplify predictive models.
- **Objective**: Improve model efficiency without sacrificing accuracy.

# Non Churned Customer Report

# Retention Analysis: Correlation Among Numeric Variables for Non-Churned Customers

## Overview

This analysis explores the correlation among numeric variables for non-churned customers, providing insights into factors contributing to customer retention. Understanding these relationships can guide retention strategies and model optimization.

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## Key Observations

### 1. Strong Positive Correlations

#### Avg_Open_To_Buy and Credit_Limit (0.99)

- **Insight**: Retained customers with higher credit limits also have more available credit.
- **Pattern**: This near-perfect correlation highlights the close relationship between these features in indicating financial capacity.

#### Total_Trans_Amt and Total_Trans_Ct (0.83)

- **Insight**: Customers who stay tend to perform a larger number of transactions with higher amounts.
- **Pattern**: High transactional engagement is a critical factor in retention.

#### Months_on_book and Customer_Age (0.79)

- **Insight**: Older retained customers typically have longer tenures with the bank.
- **Pattern**: Retention is positively influenced by age and relationship longevity.

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### 2. Moderate Positive Correlations

#### Total_Relationship_Count and Contacts_Count_12_mon (0.43)

- **Insight**: Retained customers with more relationships (e.g., multiple accounts) tend to have slightly higher contact frequency with the bank.
- **Pattern**: More touchpoints can strengthen engagement.

#### Total_Ct_Chng_Q4_Q1 and Total_Amt_Chng_Q4_Q1 (0.37)

- **Insight**: Changes in transaction count and amount show a moderate correlation, suggesting that actively engaged customers are more likely to stay.
- **Pattern**: Growth in transactions is a signal of strong customer relationships.

---

### 3. Strong Negative Correlations

**Avg_Utilization_Ratio and Avg_Open_To_Buy (-0.59)**

- **Insight**: Customers with higher credit utilization ratios tend to have lower available credit.
- **Pattern**: Indicates financial discipline or appropriate credit allocation.

**Avg_Utilization_Ratio and Credit_Limit (-0.54)**

- **Insight**: Retained customers with high credit limits tend to use a smaller proportion of their available credit.
- **Pattern**: Reflects responsible credit use and financial stability.

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### 4. Weak or No Correlation

**Dependent_Count and Most Variables**

- **Insight**: The number of dependents has minimal impact on other numeric features.
- **Pattern**: Dependents do not play a significant role in customer retention.

**Months_Inactive_12_mon and Most Variables**

- **Insight**: Inactivity within the last year does not strongly correlate with other factors.
- **Pattern**: Inactivity alone is not a strong predictor of retention.

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## Insights for Retention Strategies

### 1. **Credit Management**

- Retained customers often have high credit limits and low utilization ratios.
- **Strategy**: Offer tailored credit limit increases to customers with good credit behavior to strengthen their loyalty.

### 2. **Engagement Metrics**

- Higher transaction amounts and frequencies are characteristic of retained customers.
- **Strategy**: Incentivize activity through rewards programs, cashback offers, or personalized product recommendations.

### 3. **Age & Tenure**

- Older, long-term customers are more likely to stay.
- **Strategy**: Introduce loyalty benefits targeted at younger customers to foster longer retention periods.

### 4. **Feature Reduction**

- Features like `Avg_Open_To_Buy` and `Credit_Limit` are highly correlated.

- **Strategy**: Drop one of these features to simplify predictive models while maintaining accuracy.

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# Conclusion

This analysis highlights key correlations and actionable insights for improving customer retention. By focusing on credit management, transactional engagement, and targeted loyalty programs, financial institutions can foster stronger relationships with their customers and reduce churn.