Market Basket Analysis with Python - eBay

1. Project Objective

📌 1. Overview

This project analyzes customer behavior and perception of personalized recommendations using survey data from an e-commerce platform (eBay). The analysis focuses on purchase behavior, browsing patterns, satisfaction levels, review trust, and the effectiveness of personalized recommendations to derive actionable business insights.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

2. Dataset Overview

In [2]:
```
df = pd.read_csv(r"D:\Internshala Projects\Ebay Project\eBay.csv")
df.head()
```

Out[2]:

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023/06/07 11:44:55 AM GMT+5:30	32	Prefer not to say	Multiple times a week	Groceries and Gourmet Food;Home and Kitchen	
1	2023/06/07 9:28:09 AM GMT+5:30	47	Female	Multiple times a week	Groceries and Gourmet Food;Beauty and Personal...	
2	2023/06/05 10:09:03 PM GMT+5:30	50	Female	Once a month	Groceries and Gourmet Food;Beauty and Personal...	
3	2023/06/07 5:58:12 PM GMT+5:30	6	Others	Once a month	Groceries and Gourmet Food;Beauty and Personal...	
4	2023/06/07 11:46:52 AM GMT+5:30	61	Male	Once a week	Groceries and Gourmet Food;Clothing and Fashion	

5 rows × 24 columns

In [3]:

```
df.columns
```

Out[3]:

```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Personalized_Recommendation_Frequency ', 'Recommendation_Helpfulnes
s',
       'Rating_Accuracy ', 'Shopping_Satisfaction', 'Service_Appreciation',
       'Improvement_Areas', 'transaction'],
      dtype='object')
```

3. Data Cleaning and Preprocessing

In [4]:

```
df.isnull().sum()
```

Out[4]:
```
Timestamp                                  0
age                                        0
Gender                                     0
Purchase_Frequency                         0
Purchase_Categories                        0
Personalized_Recommendation_Frequency      0
Browsing_Frequency                         0
Product_Search_Method                    161
Search_Result_Exploration                  0
Customer_Reviews_Importance                0
Add_to_Cart_Browsing                       0
Cart_Completion_Frequency                  0
Cart_Abandonment_Factors                   0
Saveforlater_Frequency                     0
Review_Left                                0
Review_Reliability                         0
Review_Helpfulness                         0
Personalized_Recommendation_Frequency      0
Recommendation_Helpfulness                 0
Rating_Accuracy                            0
Shopping_Satisfaction                      0
Service_Appreciation                       0
Improvement_Areas                          0
transaction                                0
dtype: int64
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 24 columns):
 #   Column                                  Non-Null Count  Dtype 
---  ------                                  --------------  ----- 
 0   Timestamp                               800 non-null    object
 1   age                                     800 non-null    int64 
 2   Gender                                  800 non-null    object
 3   Purchase_Frequency                      800 non-null    object
 4   Purchase_Categories                     800 non-null    object
 5   Personalized_Recommendation_Frequency   800 non-null    object
 6   Browsing_Frequency                      800 non-null    object
 7   Product_Search_Method                   639 non-null    object
 8   Search_Result_Exploration               800 non-null    object
 9   Customer_Reviews_Importance             800 non-null    int64 
 10  Add_to_Cart_Browsing                    800 non-null    object
 11  Cart_Completion_Frequency               800 non-null    object
 12  Cart_Abandonment_Factors                800 non-null    object
 13  Saveforlater_Frequency                  800 non-null    object
 14  Review_Left                             800 non-null    object
 15  Review_Reliability                      800 non-null    object
 16  Review_Helpfulness                      800 non-null    object
 17  Personalized_Recommendation_Frequency   800 non-null    int64 
 18  Recommendation_Helpfulness              800 non-null    object
 19  Rating_Accuracy                         800 non-null    int64 
 20  Shopping_Satisfaction                   800 non-null    int64 
 21  Service_Appreciation                    800 non-null    object
 22  Improvement_Areas                       800 non-null    object
 23  transaction                             800 non-null    int64 
dtypes: int64(6), object(18)
memory usage: 150.1+ KB
```

Remove duplicate or inconsistent survey responses.

In [6]:
```
df.duplicated().sum()
```

Out[6]:
```
0
```

As We can See We Dont have an duplicated values Not neccesaary to drop any of it

In [7]:
```
df.columns
```

```
Out[7]: Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
               'Purchase_Categories', 'Personalized_Recommendation_Frequency',
               'Browsing_Frequency', 'Product_Search_Method',
               'Search_Result_Exploration', 'Customer_Reviews_Importance',
               'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
               'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
               'Review_Reliability', 'Review_Helpfulness',
               'Personalized_Recommendation_Frequency ', 'Recommendation_Helpfulnes
        s',
               'Rating_Accuracy ', 'Shopping_Satisfaction', 'Service_Appreciation',
               'Improvement_Areas', 'transaction'],
              dtype='object')
```

```
In [8]: df.shape
```

```
Out[8]: (800, 24)
```

```
In [9]: df['Gender'].value_counts()
```

```
Out[9]: Gender
        Others               209
        Prefer not to say    202
        Female               198
        Male                 191
        Name: count, dtype: int64
```

```
In [10]: df['Purchase_Frequency'].value_counts()
```

```
Out[10]: Purchase_Frequency
         Few times a month          172
         Less than once a month     172
         Once a month               160
         Multiple times a week      148
         Once a week                148
         Name: count, dtype: int64
```

```
In [11]: df['Product_Search_Method'].value_counts()
```

```
Out[11]: Product_Search_Method
         Keyword       175
         others        164
         categories    158
         Filter        142
         Name: count, dtype: int64
```

Standardizing text responses

```
In [12]: df["Gender"] = df["Gender"].astype(str).str.strip().str.title()
         df["Purchase_Frequency"] = df["Purchase_Frequency"].astype(str).str.strip().st
         df["Product_Search_Method"] = df["Product_Search_Method"].astype(str).str.stri
```

```
In [13]: df['Purchase_Frequency'].value_counts()
```

Out[13]:
```
Purchase_Frequency
Few Times A Month          172
Less Than Once A Month     172
Once A Month               160
Multiple Times A Week      148
Once A Week                148
Name: count, dtype: int64
```

In [14]:
```
df['Review_Left'].value_counts()
```

Out[14]:
```
Review_Left
Yes    413
No     387
Name: count, dtype: int64
```

In [15]:
```
df['Review_Reliability'].value_counts()
```

Out[15]:
```
Review_Reliability
Rarely          185
Never           164
Moderately      159
Heavily         150
Occasionally    142
Name: count, dtype: int64
```

In [16]:
```
df['Add_to_Cart_Browsing'].value_counts()
```

Out[16]:
```
Add_to_Cart_Browsing
Yes      283
No       266
Maybe    251
Name: count, dtype: int64
```

Handle missing values and inconsistent formats in Product_Search_Method and other fields

In [17]:
```
df['Product_Search_Method'].value_counts()
```

Out[17]:
```
Product_Search_Method
Keyword       175
Others        164
Nan           161
Categories    158
Filter        142
Name: count, dtype: int64
```

In [18]:
```
df['Product_Search_Method'] = df['Product_Search_Method'].replace("Nan", np.na
df['Product_Search_Method'] = df['Product_Search_Method'].fillna("Unknown")
```

In [19]:
```
df['Product_Search_Method'].value_counts()
```

Out[19]:
```
Product_Search_Method
Keyword       175
Others        164
Unknown       161
Categories    158
Filter        142
Name: count, dtype: int64
```

In [20]:
```
yes_no_cols = ['Review_Left', 'Add_to_Cart_Browsing']
for col in yes_no_cols:
    df[col] = df[col].astype(str).str.strip().str.title()
```

In [21]:
```
df['Review_Helpfulness'].value_counts()
```

Out[21]:
```
Review_Helpfulness
Sometimes    286
Yes          263
No           251
Name: count, dtype: int64
```

In [22]:
```
df.head()
```

Out[22]:

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023/06/07 11:44:55 AM GMT+5:30	32	Prefer Not To Say	Multiple Times A Week	Groceries and Gourmet Food;Home and Kitchen	
1	2023/06/07 9:28:09 AM GMT+5:30	47	Female	Multiple Times A Week	Groceries and Gourmet Food;Beauty and Personal...	
2	2023/06/05 10:09:03 PM GMT+5:30	50	Female	Once A Month	Groceries and Gourmet Food;Beauty and Personal...	
3	2023/06/07 5:58:12 PM GMT+5:30	6	Others	Once A Month	Groceries and Gourmet Food;Beauty and Personal...	
4	2023/06/07 11:46:52 AM GMT+5:30	61	Male	Once A Week	Groceries and Gourmet Food;Clothing and Fashion	

5 rows × 24 columns

In [23]:
```
df['Timestamp'] = pd.to_datetime(df['Timestamp'], errors='coerce')
```

```
C:\Users\Asus\AppData\Local\Temp\ipykernel_11504\3212250920.py:1: UserWarning:
Could not infer format, so each element will be parsed individually, falling ba
ck to `dateutil`. To ensure parsing is consistent and as-expected, please speci
fy a format.
  df['Timestamp'] = pd.to_datetime(df['Timestamp'], errors='coerce')
```

In [24]:
```
df.head()
```

Out[24]:

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Perso
0	2023-06-07 11:44:55-05:30	32	Prefer Not To Say	Multiple Times A Week	Groceries and Gourmet Food;Home and Kitchen	
1	2023-06-07 09:28:09-05:30	47	Female	Multiple Times A Week	Groceries and Gourmet Food;Beauty and Personal...	
2	2023-06-05 22:09:03-05:30	50	Female	Once A Month	Groceries and Gourmet Food;Beauty and Personal...	
3	2023-06-07 17:58:12-05:30	6	Others	Once A Month	Groceries and Gourmet Food;Beauty and Personal...	
4	2023-06-07 11:46:52-05:30	61	Male	Once A Week	Groceries and Gourmet Food;Clothing and Fashion	

5 rows × 24 columns

In [25]:
```
df['Date'] = df['Timestamp'].dt.date
```

In [26]:
```
df['Timestamp'] = df['Timestamp'].dt.date
```

In [27]:
```
df['Timestamp'].dtype
```

Out[27]: dtype('O')

In [28]:
```
df['Timestamp'] = pd.to_datetime(df['Timestamp'], errors='coerce', infer_datet
```

```
C:\Users\Asus\AppData\Local\Temp\ipykernel_11504\4208827248.py:1: UserWarning:
The argument 'infer_datetime_format' is deprecated and will be removed in a fut
ure version. A strict version of it is now the default, see https://pandas.pyda
ta.org/pdeps/0004-consistent-to-datetime-parsing.html. You can safely remove th
is argument.
  df['Timestamp'] = pd.to_datetime(df['Timestamp'], errors='coerce', infer_date
time_format=True)
```

In [29]:
```
df['Timestamp'].dtype
```

Out[29]: dtype('<M8[ns]')

In [30]:
```
df['Year'] = df['Timestamp'].dt.year
df['Month'] = df['Timestamp'].dt.month
df['Day'] = df['Timestamp'].dt.day
df['Weekday'] = df['Timestamp'].dt.day_name()
```

In [31]:
```
df.head()
```

Out[31]:

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023-06-07	32	Prefer Not To Say	Multiple Times A Week	Groceries and Gourmet Food;Home and Kitchen	
1	2023-06-07	47	Female	Multiple Times A Week	Groceries and Gourmet Food;Beauty and Personal...	
2	2023-06-05	50	Female	Once A Month	Groceries and Gourmet Food;Beauty and Personal...	
3	2023-06-07	6	Others	Once A Month	Groceries and Gourmet Food;Beauty and Personal...	
4	2023-06-07	61	Male	Once A Week	Groceries and Gourmet Food;Clothing and Fashion	

5 rows × 29 columns

In [32]:
```
df['Timestamp'].isna().sum()
```

Out[32]:
```
0
```

In [33]:
```
df.columns
```

Out[33]:
```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Personalized_Recommendation_Frequency ', 'Recommendation_Helpfulnes
s',
       'Rating_Accuracy ', 'Shopping_Satisfaction', 'Service_Appreciation',
       'Improvement_Areas', 'transaction', 'Date', 'Year', 'Month', 'Day',
       'Weekday'],
      dtype='object')
```

In [34]:
```
df['Improvement_Areas'].value_counts()
```

Out[34]:
```
Improvement_Areas
Scrolling option would be much better than going to next page
60
Shipping speed and reliability
51
.
50
User interface
49
Quality of product is very poor according to the big offers
49
No problems with Amazon
46
Product quality and accuracy
46
I have no problem with Amazon yet. But others tell me about the refund issues
45
Nil
45
User interface of app
44
Irrelevant product suggestions
41
I don't have any problem with Amazon
40
Reducing packaging waste
40
Add more familiar brands to the list
40
Nothing
39
better app interface and lower shipping charges
39
Customer service responsiveness
38
UI
38
Name: count, dtype: int64
```

In [35]:
```
df['Improvement_Areas'] = df['Improvement_Areas'].replace('.', 'Not Available'
df['Improvement_Areas'].value_counts()
```

Out[35]:
```
Improvement_Areas
Scrolling option would be much better than going to next page
60
Shipping speed and reliability
51
Not Available
50
User interface
49
Quality of product is very poor according to the big offers
49
No problems with Amazon
46
Product quality and accuracy
46
I have no problem with Amazon yet. But others tell me about the refund issues
45
Nil
45
User interface of app
44
Irrelevant product suggestions
41
I don't have any problem with Amazon
40
Reducing packaging waste
40
Add more familiar brands to the list
40
Nothing
39
better app interface and lower shipping charges
39
Customer service responsiveness
38
UI
38
Name: count, dtype: int64
```

In [36]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 29 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Timestamp                               800 non-null    datetime64[ns]
 1   age                                     800 non-null    int64
 2   Gender                                  800 non-null    object
 3   Purchase_Frequency                      800 non-null    object
 4   Purchase_Categories                     800 non-null    object
 5   Personalized_Recommendation_Frequency   800 non-null    object
 6   Browsing_Frequency                      800 non-null    object
 7   Product_Search_Method                   800 non-null    object
 8   Search_Result_Exploration               800 non-null    object
 9   Customer_Reviews_Importance             800 non-null    int64
 10  Add_to_Cart_Browsing                    800 non-null    object
 11  Cart_Completion_Frequency               800 non-null    object
 12  Cart_Abandonment_Factors                800 non-null    object
 13  Saveforlater_Frequency                  800 non-null    object
 14  Review_Left                             800 non-null    object
 15  Review_Reliability                      800 non-null    object
 16  Review_Helpfulness                      800 non-null    object
 17  Personalized_Recommendation_Frequency   800 non-null    int64
 18  Recommendation_Helpfulness              800 non-null    object
 19  Rating_Accuracy                         800 non-null    int64
 20  Shopping_Satisfaction                   800 non-null    int64
 21  Service_Appreciation                    800 non-null    object
 22  Improvement_Areas                       800 non-null    object
 23  transaction                             800 non-null    int64
 24  Date                                    800 non-null    object
 25  Year                                    800 non-null    int32
 26  Month                                   800 non-null    int32
 27  Day                                     800 non-null    int32
 28  Weekday                                 800 non-null    object
dtypes: datetime64[ns](1), int32(3), int64(6), object(19)
memory usage: 172.0+ KB
```

📌 2. Data Preparation & Cleaning

Removed duplicates and handled missing values

Converted timestamp into date-based features (Year, Month, Weekday)

Standardized categorical variables (Yes / No / Sometimes, frequency levels)

Encoded ordinal variables for analytical purposes

Transformed multi-label purchase categories using explode for accurate category-level analysis

Convert numerical rating columns (e.g., Customer_Reviews_Importance, Shopping_Satisfaction) to appropriate numeric types for analysis.

4. Exploratory Data Analysis (EDA)

Task 2: Descriptive Behavior Analysis

Splitting the Product_categories

In [37]:
```
df['Purchase_Categories'] = df['Purchase_Categories'].str.split(';')
```

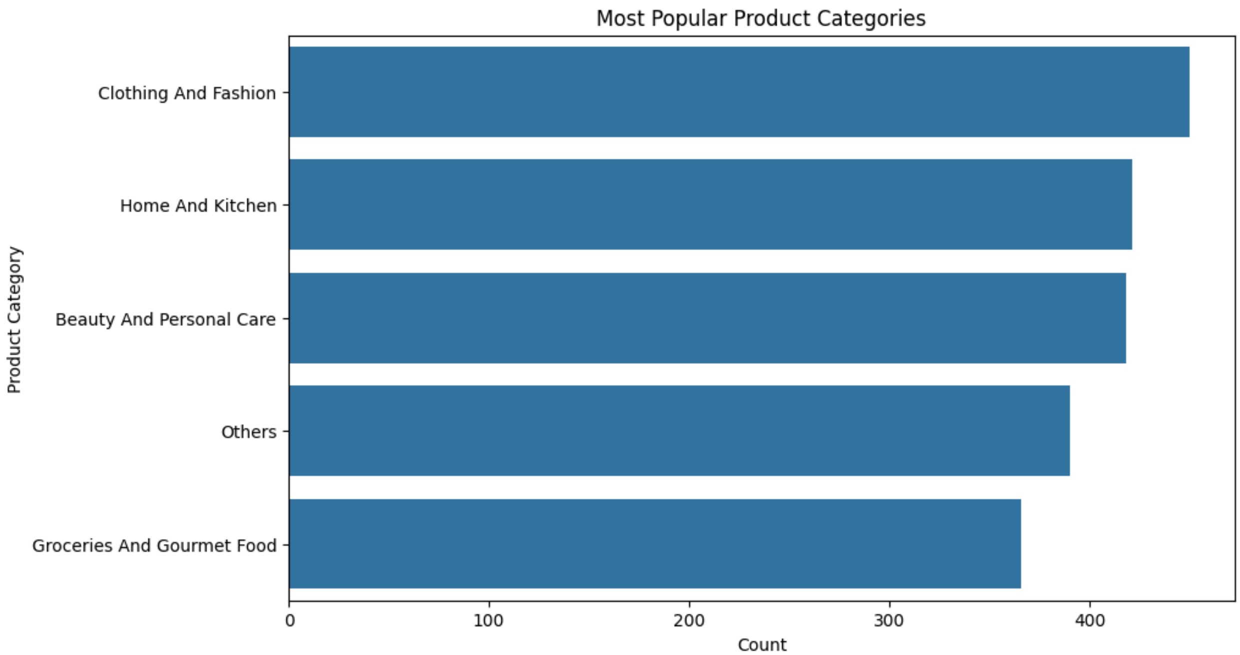
In [38]:
```
df_exploded = df.explode('Purchase_Categories')
```

In [39]:
```
df_exploded['Purchase_Categories'] = (
    df_exploded['Purchase_Categories']
    .str.strip()
    .str.title()
)
```

In [40]:
```
category_counts = df_exploded['Purchase_Categories'].value_counts()
print(category_counts)
```

```
Purchase_Categories
Clothing And Fashion          450
Home And Kitchen              421
Beauty And Personal Care      418
Others                        390
Groceries And Gourmet Food    366
Name: count, dtype: int64
```

In [41]:
```
plt.figure(figsize=(10,6))
sns.barplot(
    y=category_counts.index,
    x=category_counts.values
)
plt.title("Most Popular Product Categories")
plt.xlabel("Count")
plt.ylabel("Product Category")
plt.show()
```



4.1 Customer Demographics Analysis

In [42]:
```
# AGE SUMMARY
```

In [43]:
```
print("Age Summary:")
print(df['age'].describe())
```

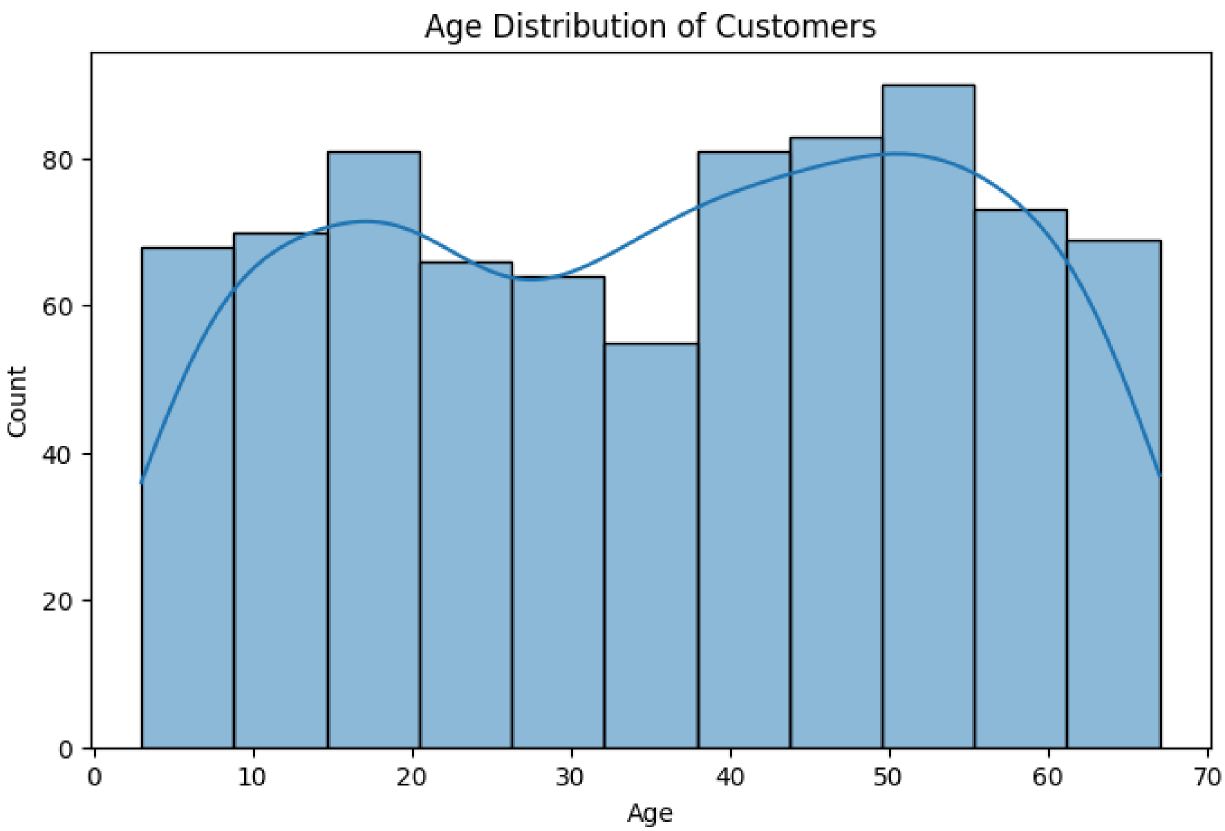
```
Age Summary:
count    800.000000
mean      35.730000
std       18.588141
min        3.000000
25%       19.000000
50%       37.000000
75%       52.000000
max       67.000000
Name: age, dtype: float64
```

In [44]:
```
# GENDER DISTRIBUTION
print("\nGender Distribution:")
print(df['Gender'].value_counts())
print("\nGender Distribution (%):")
print(df['Gender'].value_counts(normalize=True) * 100)
```

```
Gender Distribution:
Gender
Others               209
Prefer Not To Say    202
Female               198
Male                 191
Name: count, dtype: int64

Gender Distribution (%):
Gender
Others               26.125
Prefer Not To Say    25.250
Female               24.750
Male                 23.875
Name: proportion, dtype: float64
```

In [45]:

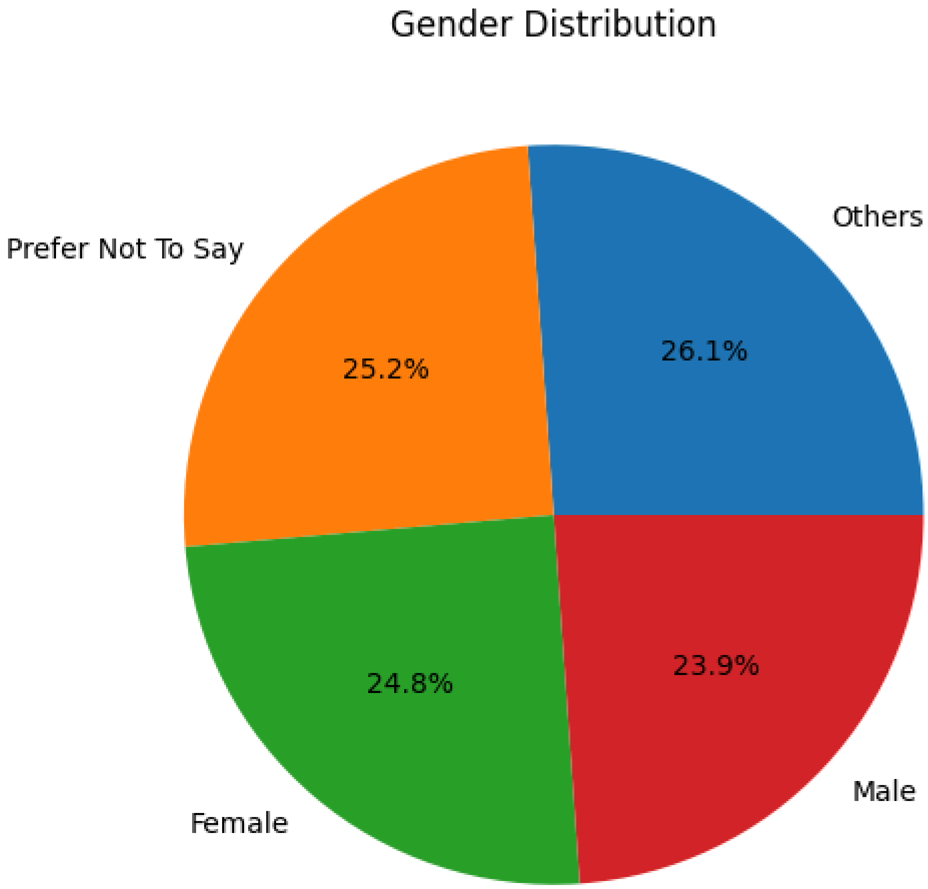
```python
# AGE DISTRIBUTION PLOT
plt.figure(figsize=(8,5))
sns.histplot(df['age'], kde=True)
plt.title("Age Distribution of Customers")
plt.xlabel("Age")
plt.ylabel("Count")
plt.show()
```



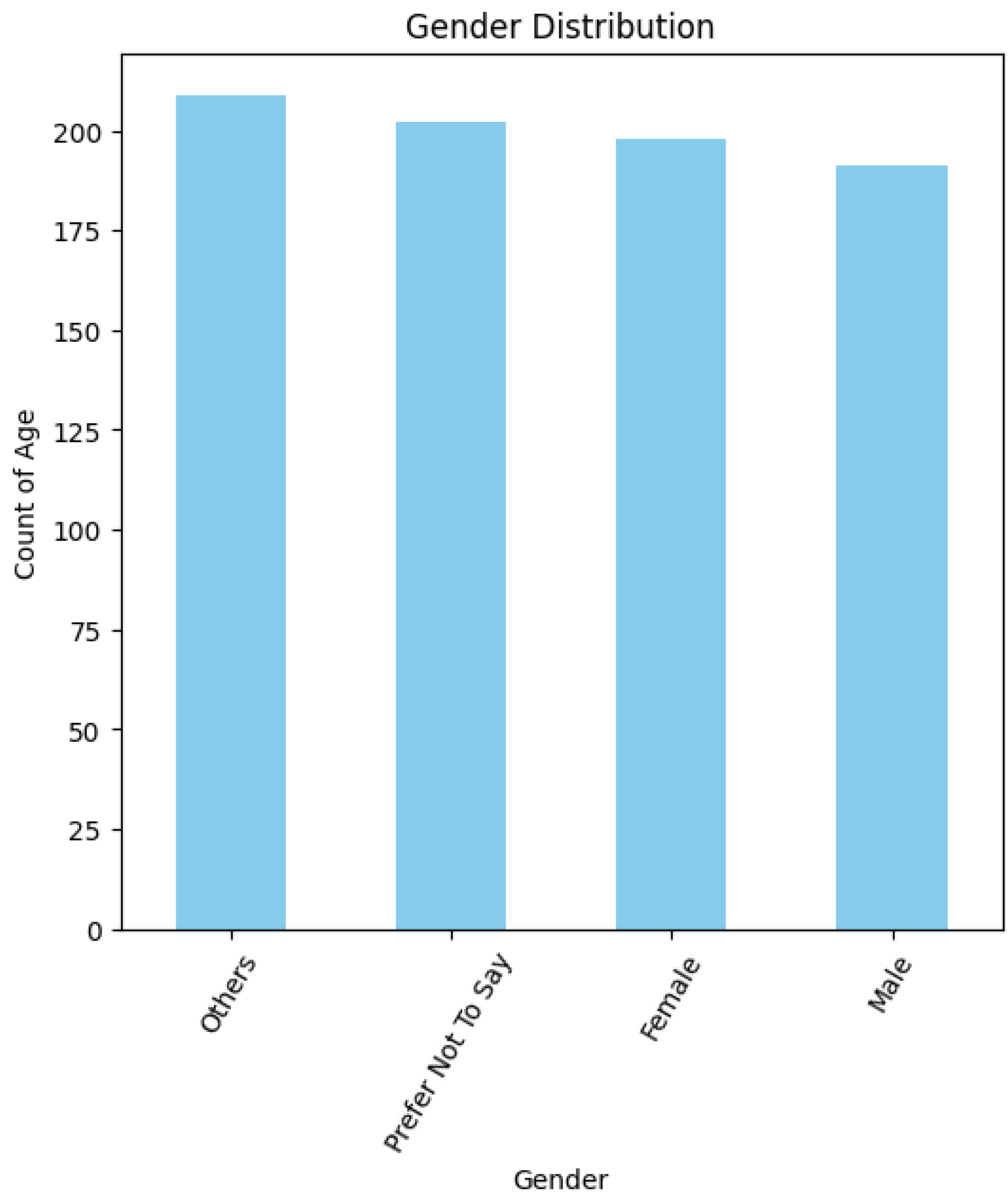
In [46]:

```python
# GENDER PIE CHART
plt.figure(figsize=(6,6))
df['Gender'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.title("Gender Distribution")
```

```
plt.ylabel("")
plt.show()
```



In [47]:
```
# GENDER Bar CHART
plt.figure(figsize=(6,6))
df['Gender'].value_counts().plot(kind='bar',color="Skyblue")
plt.title("Gender Distribution")
plt.ylabel("Count of Age")
plt.xticks(rotation =60)
plt.show()
```



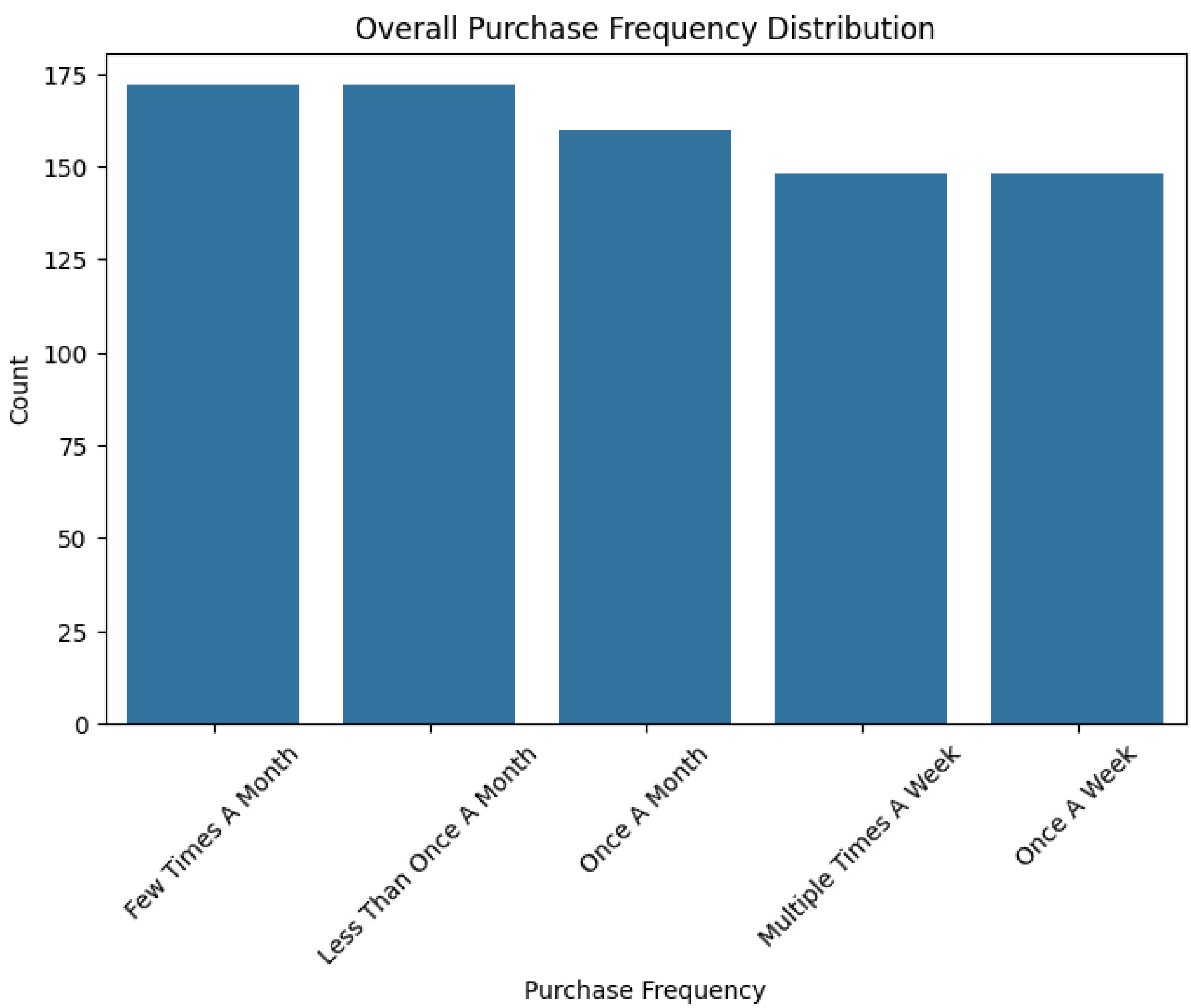
4.2 Purchase Behavior Analysis

In [48]:
```
# Analyze overall purchase frequency and most popular product categories.
```

In [49]:
```
# PURCHASE FREQUENCY COUNTS
print("Purchase Frequency Counts:")
print(df['Purchase_Frequency'].value_counts())

print("\nPurchase Frequency (%):")
print(df['Purchase_Frequency'].value_counts(normalize=True) * 100)

# BAR PLOT — PURCHASE FREQUENCY
plt.figure(figsize=(8,5))
sns.countplot(data=df, x='Purchase_Frequency', order=df['Purchase_Frequency'].
```

```python
plt.title("Overall Purchase Frequency Distribution")
plt.xlabel("Purchase Frequency")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```

```
Purchase Frequency Counts:
Purchase_Frequency
Few Times A Month          172
Less Than Once A Month     172
Once A Month               160
Multiple Times A Week      148
Once A Week                148
Name: count, dtype: int64

Purchase Frequency (%):
Purchase_Frequency
Few Times A Month          21.5
Less Than Once A Month     21.5
Once A Month               20.0
Multiple Times A Week      18.5
Once A Week                18.5
Name: proportion, dtype: float64
```



4.3 Browsing Behavior Analysis

In [50]:
```
# PRODUCT CATEGORY COUNTS
print("\nProduct Category Counts:")
print(df['Purchase_Categories'].value_counts())
```

```
Product Category Counts:
Purchase_Categories
[Clothing and Fashion, others]
40
[Clothing and Fashion, Home and Kitchen, others]
36
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion, Ho
me and Kitchen]            35
[Groceries and Gourmet Food, Home and Kitchen]
34
[Groceries and Gourmet Food, Clothing and Fashion, Home and Kitchen]
33
[Groceries and Gourmet Food, Beauty and Personal Care]
33
[Beauty and Personal Care, Clothing and Fashion, Home and Kitchen]
33
[Beauty and Personal Care, Clothing and Fashion, Home and Kitchen, others]
31
[others]
30
[Groceries and Gourmet Food, Beauty and Personal Care, others]
29
[Beauty and Personal Care, Home and Kitchen, others]
29
[Beauty and Personal Care]
29
[Beauty and Personal Care, others]
29
[Beauty and Personal Care, Clothing and Fashion]
28
[Beauty and Personal Care, Clothing and Fashion, others]
27
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion, Ho
me and Kitchen, others]    27
[Home and Kitchen]
26
[Home and Kitchen, others]
26
[Groceries and Gourmet Food, Clothing and Fashion]
25
[Beauty and Personal Care, Home and Kitchen]
24
[Groceries and Gourmet Food, Clothing and Fashion, others]
23
[Groceries and Gourmet Food, Clothing and Fashion, Home and Kitchen, others]
23
[Clothing and Fashion, Home and Kitchen]
23
[Clothing and Fashion]
23
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion]
23
[Groceries and Gourmet Food, Beauty and Personal Care, Home and Kitchen]
21
```

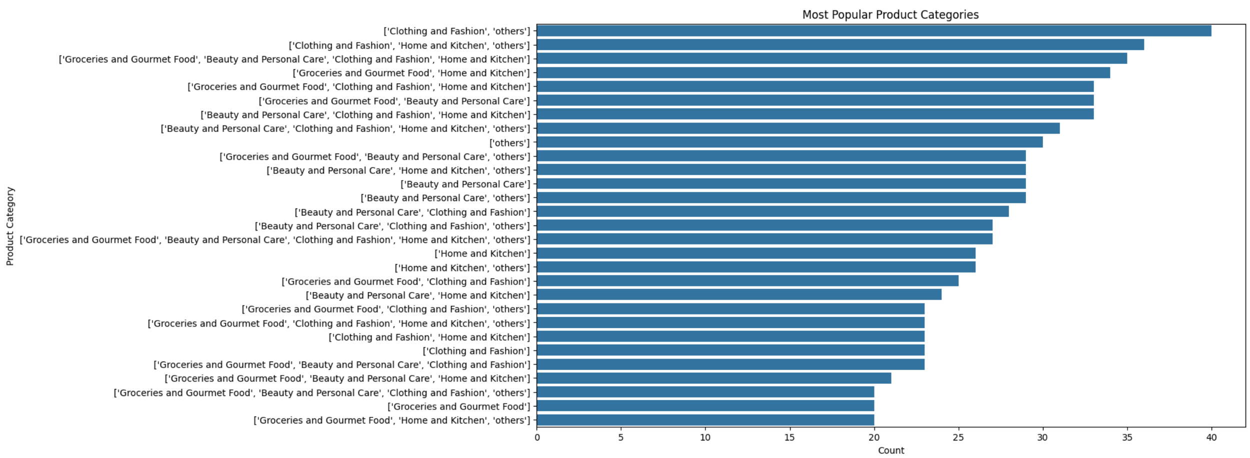
```
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion, ot
hers]                      20
[Groceries and Gourmet Food]
20
[Groceries and Gourmet Food, Home and Kitchen, others]
20
Name: count, dtype: int64
```

In [51]:
```
print("\nProduct Category (%):")
print(df['Purchase_Categories'].value_counts(normalize=True) * 100)
```

```
Product Category (%):
Purchase_Categories
[Clothing and Fashion, others]
5.000
[Clothing and Fashion, Home and Kitchen, others]
4.500
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion, Ho
me and Kitchen]            4.375
[Groceries and Gourmet Food, Home and Kitchen]
4.250
[Groceries and Gourmet Food, Clothing and Fashion, Home and Kitchen]
4.125
[Groceries and Gourmet Food, Beauty and Personal Care]
4.125
[Beauty and Personal Care, Clothing and Fashion, Home and Kitchen]
4.125
[Beauty and Personal Care, Clothing and Fashion, Home and Kitchen, others]
3.875
[others]
3.750
[Groceries and Gourmet Food, Beauty and Personal Care, others]
3.625
[Beauty and Personal Care, Home and Kitchen, others]
3.625
[Beauty and Personal Care]
3.625
[Beauty and Personal Care, others]
3.625
[Beauty and Personal Care, Clothing and Fashion]
3.500
[Beauty and Personal Care, Clothing and Fashion, others]
3.375
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion, Ho
me and Kitchen, others]    3.375
[Home and Kitchen]
3.250
[Home and Kitchen, others]
3.250
[Groceries and Gourmet Food, Clothing and Fashion]
3.125
[Beauty and Personal Care, Home and Kitchen]
3.000
[Groceries and Gourmet Food, Clothing and Fashion, others]
2.875
[Groceries and Gourmet Food, Clothing and Fashion, Home and Kitchen, others]
2.875
[Clothing and Fashion, Home and Kitchen]
2.875
[Clothing and Fashion]
2.875
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion]
2.875
[Groceries and Gourmet Food, Beauty and Personal Care, Home and Kitchen]
2.625
```

```
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion, ot
hers]                         2.500
[Groceries and Gourmet Food]
2.500
[Groceries and Gourmet Food, Home and Kitchen, others]
2.500
Name: proportion, dtype: float64
```

In [52]:
```python
# BAR PLOT – POPULAR PRODUCT CATEGORIES
plt.figure(figsize=(14,8))
sns.countplot(data=df, y='Purchase_Categories', order=df['Purchase_Categories'
plt.title("Most Popular Product Categories")
plt.xlabel("Count")
plt.ylabel("Product Category")
plt.show()
```



4.4 Customer Satisfaction Analysis

Identify top browsing methods and most common cart abandonment factors.

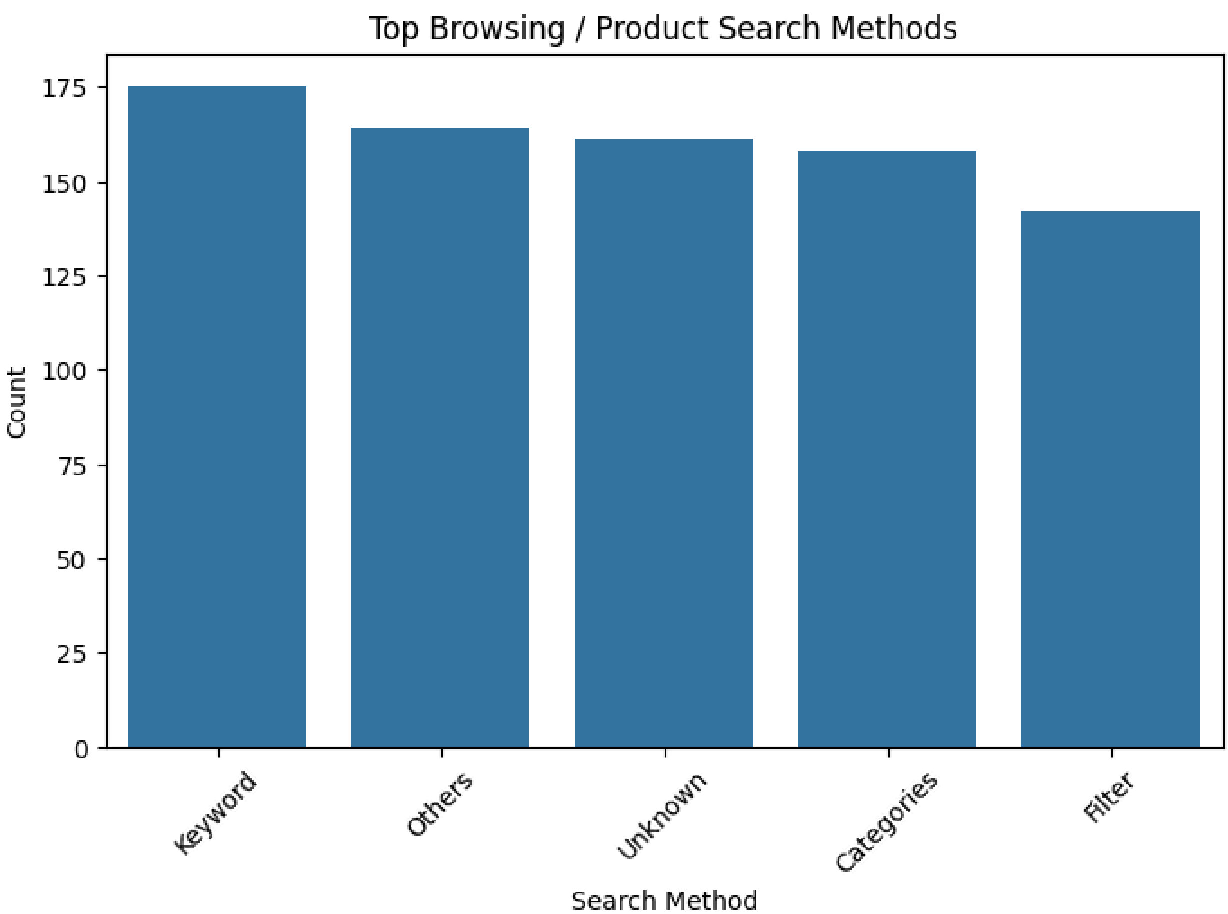
In [53]:
```python
# BROWSING METHODS COUNTS
print("Browsing / Search Method Counts:")
print(df['Product_Search_Method'].value_counts())
```

```
Browsing / Search Method Counts:
Product_Search_Method
Keyword       175
Others        164
Unknown       161
Categories    158
Filter        142
Name: count, dtype: int64
```

In [54]:
```python
print("\nBrowsing / Search Method (%):")
print(df['Product_Search_Method'].value_counts(normalize=True) * 100)
```

```
Browsing / Search Method (%):
Product_Search_Method
Keyword       21.875
Others        20.500
Unknown       20.125
Categories    19.750
Filter        17.750
Name: proportion, dtype: float64
```

In [55]:
```
# BAR PLOT
plt.figure(figsize=(8,5))
sns.countplot(
    data=df,
    x='Product_Search_Method',
    order=df['Product_Search_Method'].value_counts().index
)
plt.title("Top Browsing / Product Search Methods")
plt.xlabel("Search Method")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```



In [56]:
```
df.columns
```

Out[56]:
```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Personalized_Recommendation_Frequency ', 'Recommendation_Helpfulnes
s',
       'Rating_Accuracy ', 'Shopping_Satisfaction', 'Service_Appreciation',
       'Improvement_Areas', 'transaction', 'Date', 'Year', 'Month', 'Day',
       'Weekday'],
      dtype='object')
```

In [57]:
```
df['Cart_Abandonment_Factors'].value_counts()
```

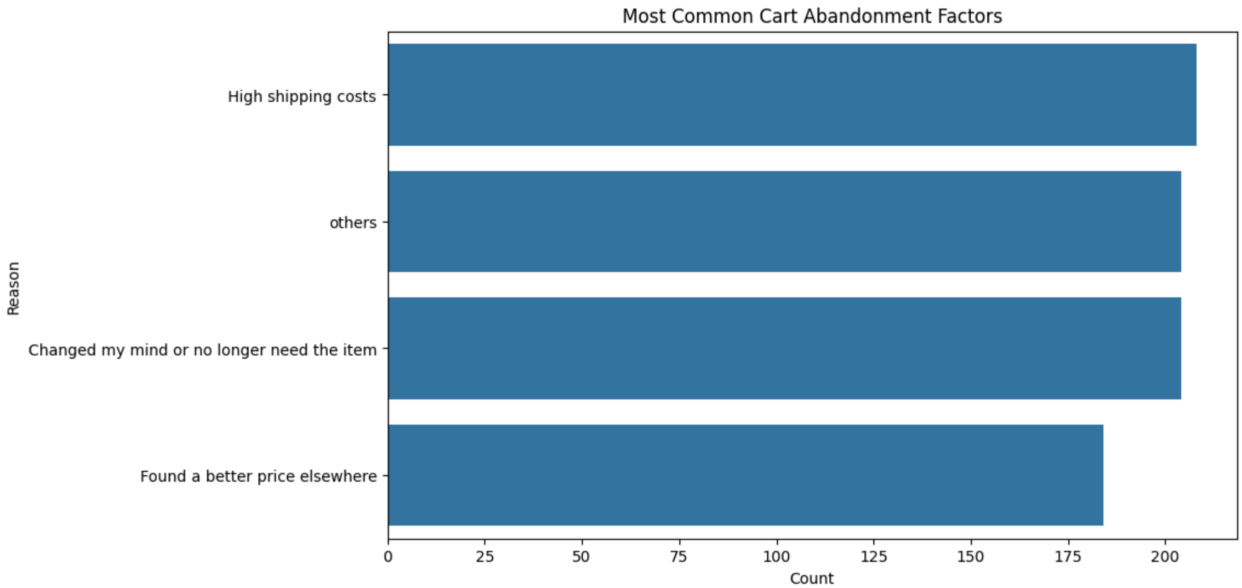
Out[57]:
```
Cart_Abandonment_Factors
High shipping costs                              208
others                                           204
Changed my mind or no longer need the item      204
Found a better price elsewhere                   184
Name: count, dtype: int64
```

In [58]:
```
factor_counts = df['Cart_Abandonment_Factors'].value_counts()
```

In [59]:
```
print("\nPercentage:")
print(factor_counts / factor_counts.sum() * 100)
```

```
Percentage:
Cart_Abandonment_Factors
High shipping costs                              26.0
others                                           25.5
Changed my mind or no longer need the item      25.5
Found a better price elsewhere                   23.0
Name: count, dtype: float64
```

In [60]:
```
# STEP 5: Visualization
plt.figure(figsize=(10,6))
sns.barplot(
    y=factor_counts.index,
    x=factor_counts.values
)
plt.title("Most Common Cart Abandonment Factors")
plt.xlabel("Count")
plt.ylabel("Reason")
plt.show()
```



Calculate mean and median satisfaction, recommendation helpfulness, and rating accuracy

In [61]:
```
df.head(2)
```

Out[61]:

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023-06-07	32	Prefer Not To Say	Multiple Times A Week	[Groceries and Gourmet Food, Home and Kitchen]	
1	2023-06-07	47	Female	Multiple Times A Week	[Groceries and Gourmet Food, Beauty and Person...	

2 rows × 29 columns

In [62]:
```
df.columns = df.columns.str.strip()
```

In [63]:
```
df['Rating_Accuracy'].describe()
```

Out[63]:
```
count    800.000000
mean       3.086250
std        1.420857
min        1.000000
25%        2.000000
50%        3.000000
75%        4.000000
max        5.000000
Name: Rating_Accuracy, dtype: float64
```

In [64]:
```
df.head()
```

Out[64]:

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023-06-07	32	Prefer Not To Say	Multiple Times A Week	[Groceries and Gourmet Food, Home and Kitchen]	
1	2023-06-07	47	Female	Multiple Times A Week	[Groceries and Gourmet Food, Beauty and Person...	
2	2023-06-05	50	Female	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
3	2023-06-07	6	Others	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
4	2023-06-07	61	Male	Once A Week	[Groceries and Gourmet Food, Clothing and Fash...	

5 rows × 29 columns

In [65]:
```
df.columns
```

Out[65]:
```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Personalized_Recommendation_Frequency', 'Recommendation_Helpfulness',
       'Rating_Accuracy', 'Shopping_Satisfaction', 'Service_Appreciation',
       'Improvement_Areas', 'transaction', 'Date', 'Year', 'Month', 'Day',
       'Weekday'],
      dtype='object')
```

In [66]:
```
df.columns = df.columns.str.strip()
```

In [67]:
```
df.columns.tolist()
```

Out[67]:
```
['Timestamp',
 'age',
 'Gender',
 'Purchase_Frequency',
 'Purchase_Categories',
 'Personalized_Recommendation_Frequency',
 'Browsing_Frequency',
 'Product_Search_Method',
 'Search_Result_Exploration',
 'Customer_Reviews_Importance',
 'Add_to_Cart_Browsing',
 'Cart_Completion_Frequency',
 'Cart_Abandonment_Factors',
 'Saveforlater_Frequency',
 'Review_Left',
 'Review_Reliability',
 'Review_Helpfulness',
 'Personalized_Recommendation_Frequency',
 'Recommendation_Helpfulness',
 'Rating_Accuracy',
 'Shopping_Satisfaction',
 'Service_Appreciation',
 'Improvement_Areas',
 'transaction',
 'Date',
 'Year',
 'Month',
 'Day',
 'Weekday']
```

In [68]:
```
df = df.loc[:, ~df.columns.duplicated()]
```

In [69]:
```
df['Personalized_Recommendation_Frequency'].unique()
```

Out[69]:
```
array(['Sometimes', 'No', 'Yes'], dtype=object)
```

In [70]:
```
df[['Customer_Reviews_Importance',
    'Rating_Accuracy',
    'Shopping_Satisfaction']].describe()
```

Out[70]:

	Customer_Reviews_Importance	Rating_Accuracy	Shopping_Satisfaction
count	800.000000	800.000000	800.000000
mean	3.001250	3.086250	2.866250
std	1.391463	1.420857	1.429481
min	1.000000	1.000000	1.000000
25%	2.000000	2.000000	2.000000
50%	3.000000	3.000000	3.000000
75%	4.000000	4.000000	4.000000
max	5.000000	5.000000	5.000000

In [71]:
```
df['Personalized_Recommendation_Frequency'].value_counts()
```

Out[71]:
```
Personalized_Recommendation_Frequency
No           279
Yes          261
Sometimes    260
Name: count, dtype: int64
```

In [72]:
```
col = 'Personalized_Recommendation_Frequency'
print("\nValue counts (frequency):")
print(df[col].value_counts())

print("\nValue counts with percentages:")
print(df[col].value_counts(normalize=True) * 100)

print("\nData type:")
print(df[col].dtype)
```

```
Value counts (frequency):
Personalized_Recommendation_Frequency
No           279
Yes          261
Sometimes    260
Name: count, dtype: int64

Value counts with percentages:
Personalized_Recommendation_Frequency
No           34.875
Yes          32.625
Sometimes    32.500
Name: proportion, dtype: float64

Data type:
object
```

In [73]:
```
col = "Personalized_Recommendation_Frequency"
```

```python
# Step 1: Standardize text values
df[col] = (
    df[col]
    .astype(str)
    .str.strip()
    .str.title()
)

# Step 2: Create your custom mapping
mapping = {
    "No": 0,
    "Yes": 1,
    "Sometimes": 2
}

# Step 3: Apply the mapping and create the new encoded column
df["Personalized_Recommendation_Frequency_Encoded"] = df[col].map(mapping)
```

In [74]:

```python
metrics = ['Shopping_Satisfaction',
           'Personalized_Recommendation_Frequency_Encoded',
           'Rating_Accuracy']

for col in metrics:
    print(f"\n--- {col} ---")
    print("Mean:", df[col].mean())
    print("Median:", df[col].median())
```

```
--- Shopping_Satisfaction ---
Mean: 2.86625
Median: 3.0

--- Personalized_Recommendation_Frequency_Encoded ---
Mean: 0.97625
Median: 1.0

--- Rating_Accuracy ---
Mean: 3.08625
Median: 3.0
```

In [75]:

```python
df.columns
```

Out[75]:

```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Recommendation_Helpfulness', 'Rating_Accuracy',
       'Shopping_Satisfaction', 'Service_Appreciation', 'Improvement_Areas',
       'transaction', 'Date', 'Year', 'Month', 'Day', 'Weekday',
       'Personalized_Recommendation_Frequency_Encoded'],
      dtype='object')
```

In [76]:
```python
df.describe()
```

Out[76]:

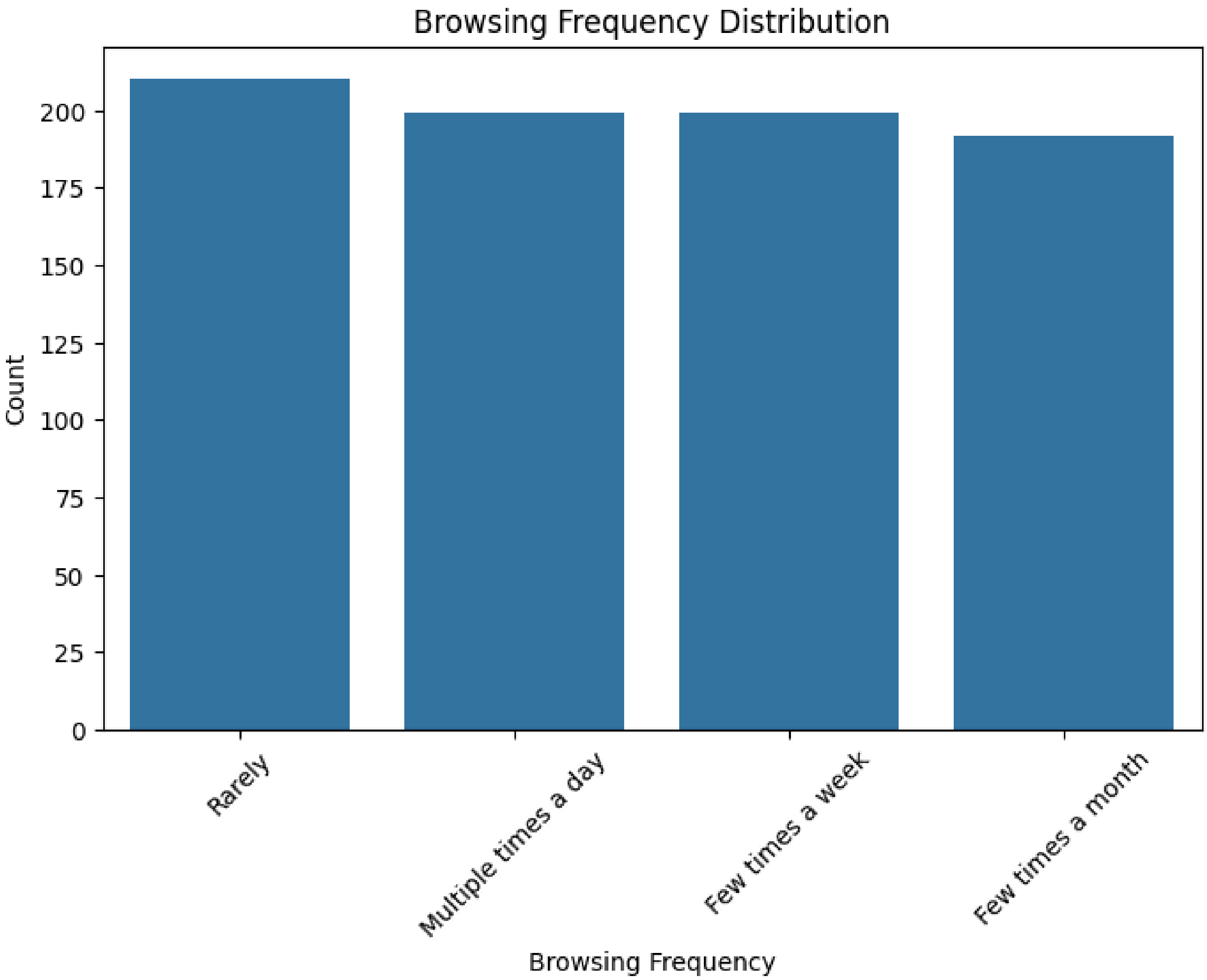
	Timestamp	age	Customer_Reviews_Importance	Rating_Accuracy
count	800	800.000000	800.000000	800.000000
mean	2023-06-07 17:16:48	35.730000	3.001250	3.086250
min	2023-06-04 00:00:00	3.000000	1.000000	1.000000
25%	2023-06-06 00:00:00	19.000000	2.000000	2.000000
50%	2023-06-08 00:00:00	37.000000	3.000000	3.000000
75%	2023-06-09 00:00:00	52.000000	4.000000	4.000000
max	2023-06-16 00:00:00	67.000000	5.000000	5.000000
std	NaN	18.588141	1.391463	1.420857

In [77]:
```python
behavior_cols = [
    'Browsing_Frequency',
    'Product_Search_Method',
    'Purchase_Frequency',
    'Shopping_Satisfaction',
    'Rating_Accuracy',
    'Personalized_Recommendation_Frequency_Encoded',
    'Cart_Completion_Frequency'
]

print(df[behavior_cols].describe(include='all'))
```

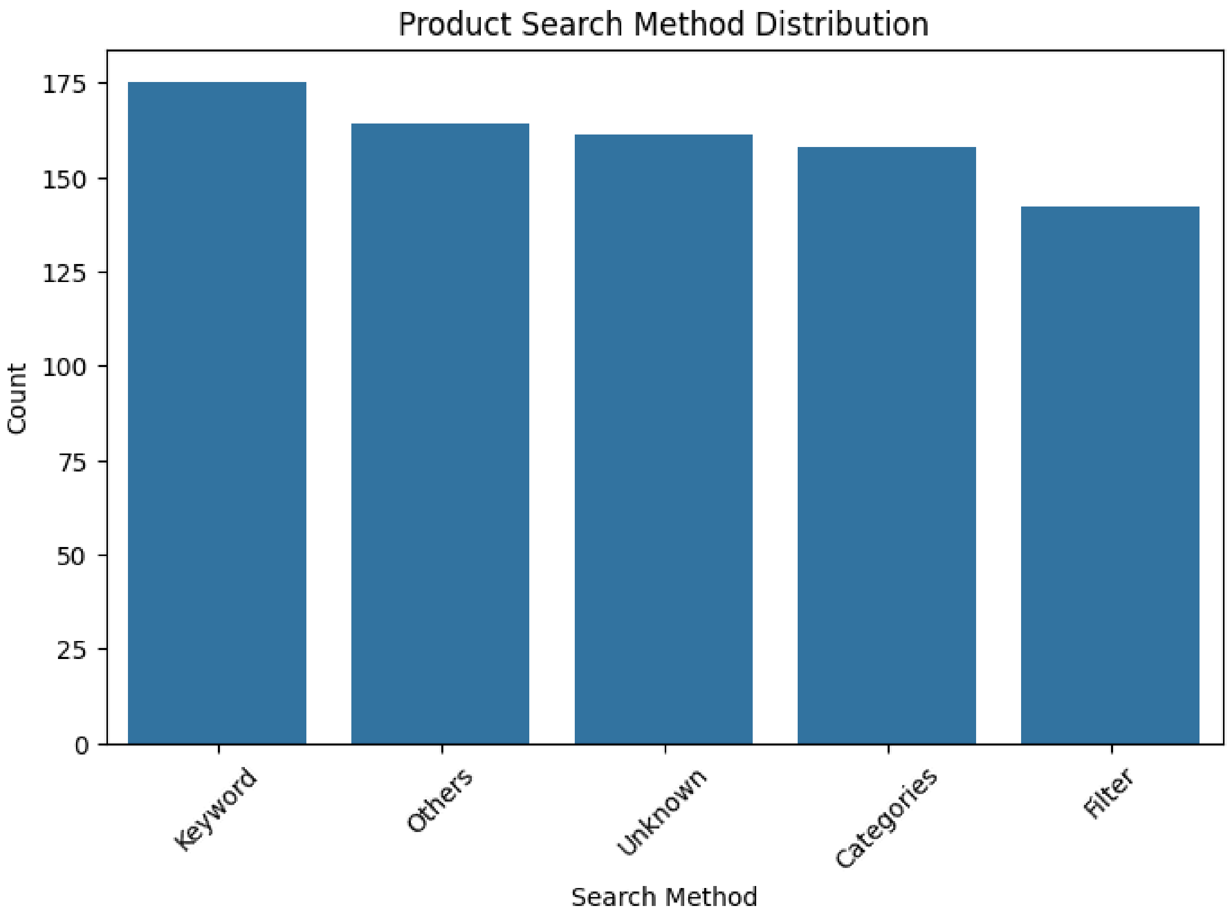
```
       Browsing_Frequency Product_Search_Method Purchase_Frequency  \
count                 800                   800                800   
unique                  4                     5                  5   
top                Rarely               Keyword  Few Times A Month   
freq                  210                   175                172   
mean                  NaN                   NaN                NaN   
std                   NaN                   NaN                NaN   
min                   NaN                   NaN                NaN   
25%                   NaN                   NaN                NaN   
50%                   NaN                   NaN                NaN   
75%                   NaN                   NaN                NaN   
max                   NaN                   NaN                NaN   

        Shopping_Satisfaction  Rating_Accuracy   \
count              800.000000       800.000000   
unique                    NaN              NaN   
top                       NaN              NaN   
freq                      NaN              NaN   
mean                 2.866250         3.086250   
std                  1.429481         1.420857   
min                  1.000000         1.000000   
25%                  2.000000         2.000000   
50%                  3.000000         3.000000   
75%                  4.000000         4.000000   
max                  5.000000         5.000000   

        Personalized_Recommendation_Frequency_Encoded  \
count                                      800.000000   
unique                                            NaN   
top                                               NaN   
freq                                              NaN   
mean                                         0.976250   
std                                          0.820992   
min                                          0.000000   
25%                                          0.000000   
50%                                          1.000000   
75%                                          2.000000   
max                                          2.000000   

       Cart_Completion_Frequency  
count                        800  
unique                         5  
top                    Sometimes  
freq                         181  
mean                         NaN  
std                          NaN  
min                          NaN  
25%                          NaN  
50%                          NaN  
75%                          NaN  
max                          NaN  
```

In [78]:
```python
plt.figure(figsize=(8,5))
sns.countplot(data=df, x='Browsing_Frequency', order=df['Browsing_Frequency'].
```

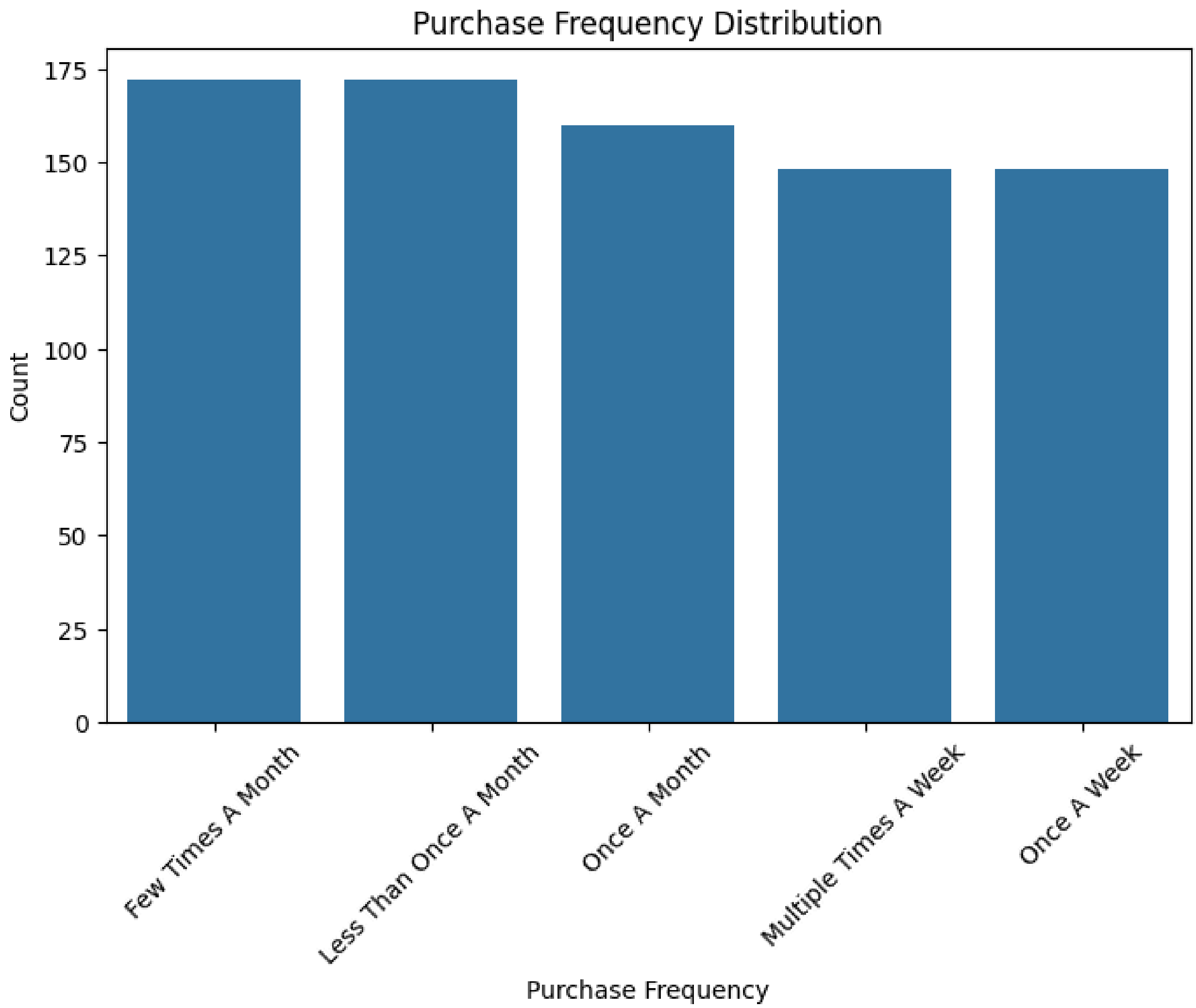
```
plt.title("Browsing Frequency Distribution")
plt.xlabel("Browsing Frequency")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```



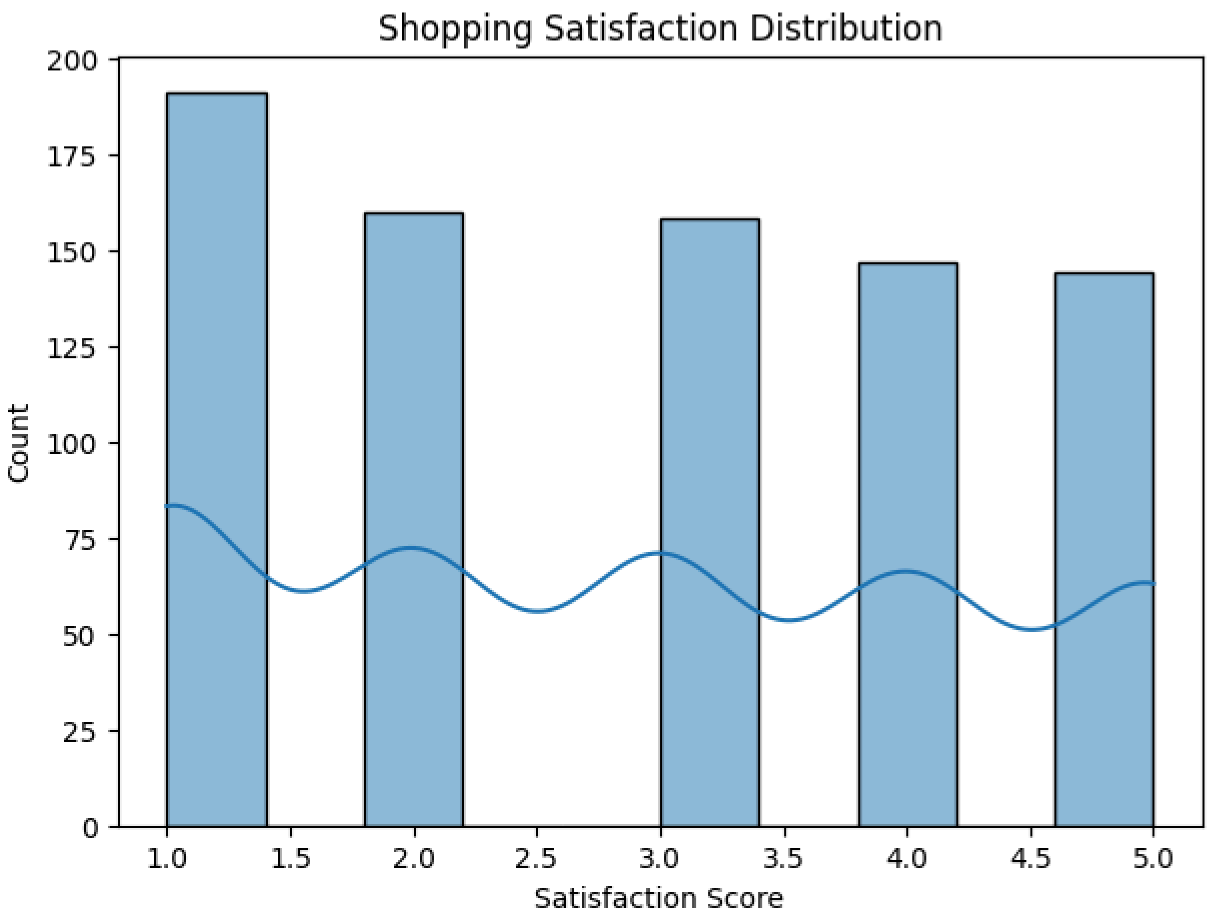
In [79]:
```
plt.figure(figsize=(8,5))
sns.countplot(data=df, x='Product_Search_Method', order=df['Product_Search_Met
plt.title("Product Search Method Distribution")
plt.xlabel("Search Method")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```



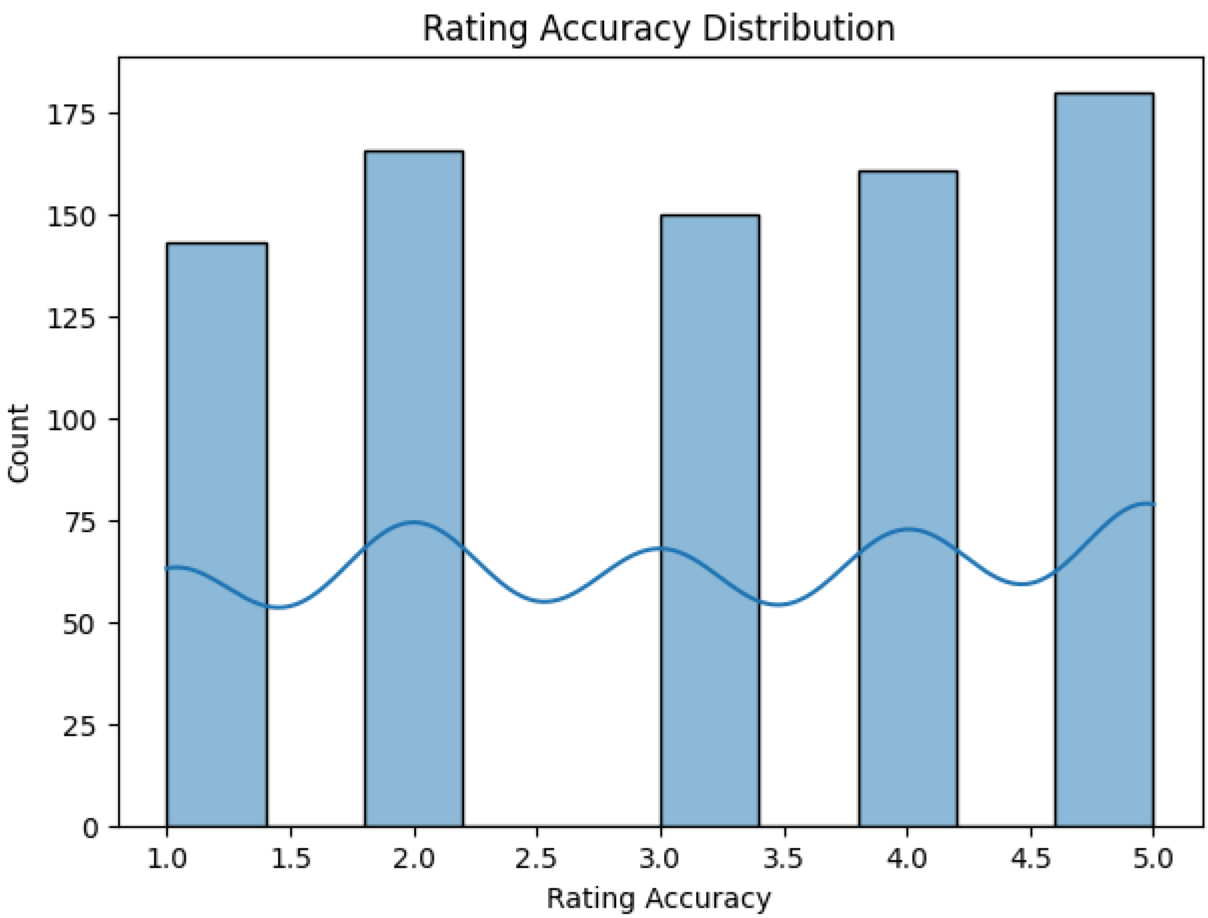
In [80]:
```
plt.figure(figsize=(8,5))
sns.countplot(data=df, x='Purchase_Frequency', order=df['Purchase_Frequency'].
plt.title("Purchase Frequency Distribution")
plt.xlabel("Purchase Frequency")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```



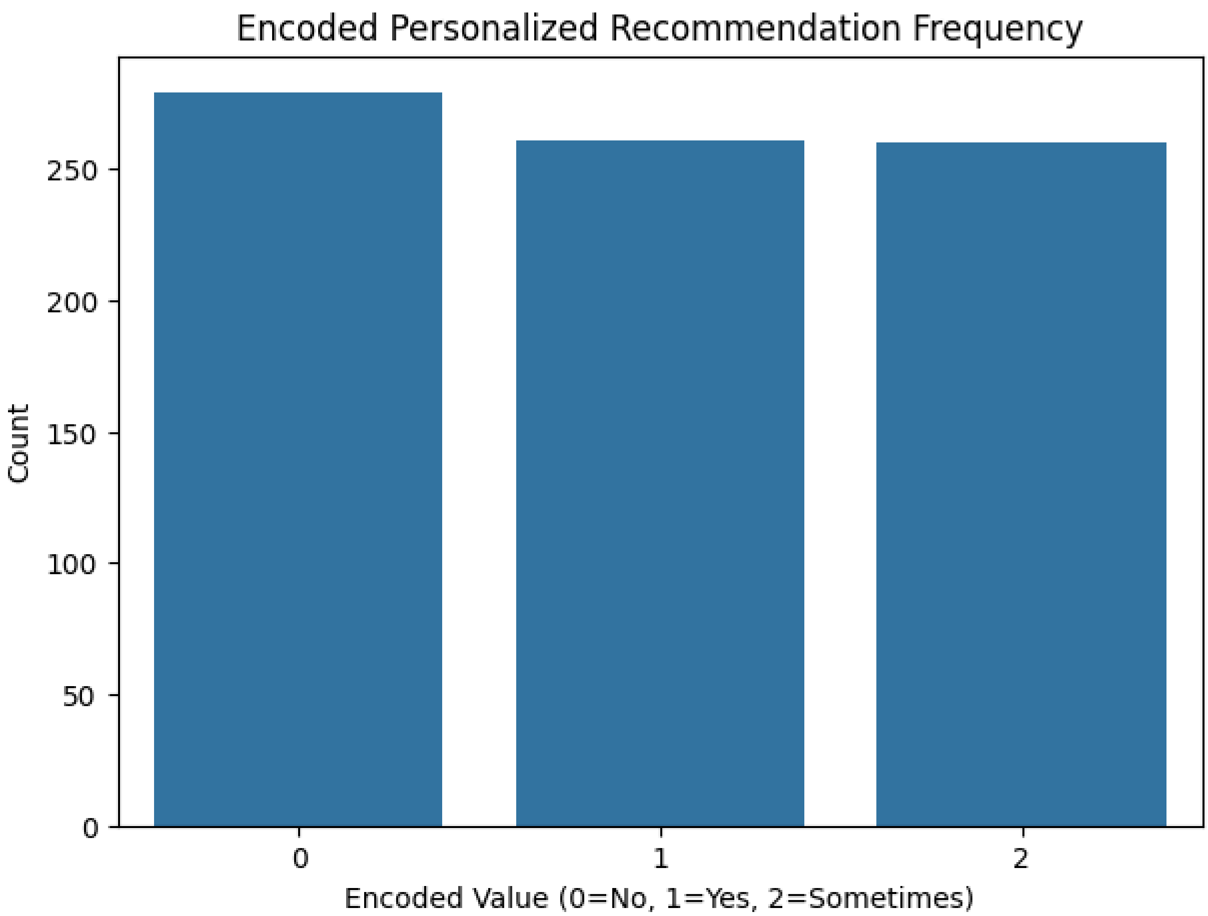
In [81]:
```
plt.figure(figsize=(7,5))
sns.histplot(df['Shopping_Satisfaction'], bins=10, kde=True)
plt.title("Shopping Satisfaction Distribution")
plt.xlabel("Satisfaction Score")
plt.ylabel("Count")
plt.show()
```



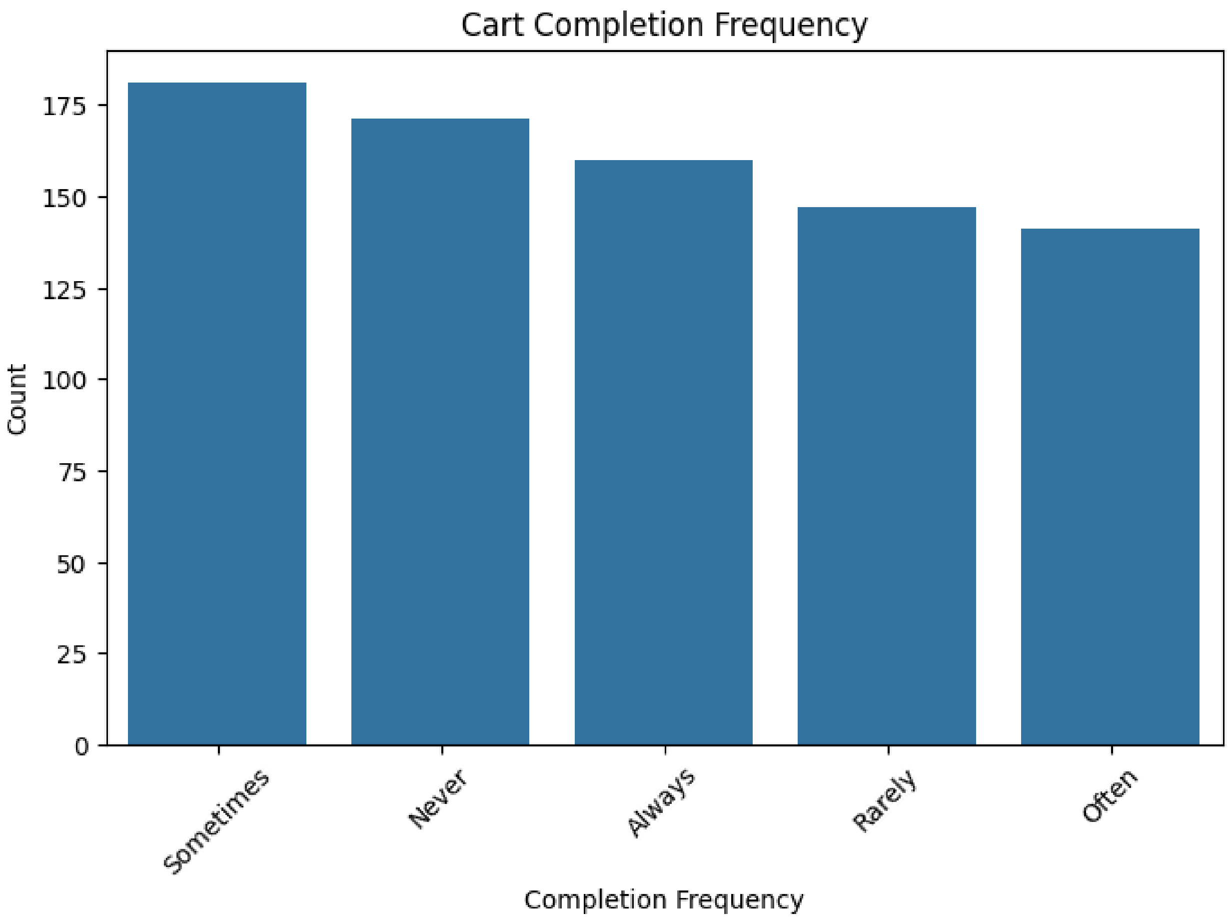
In [82]:
```
plt.figure(figsize=(7,5))
sns.histplot(df['Rating_Accuracy'], bins=10, kde=True)
plt.title("Rating Accuracy Distribution")
plt.xlabel("Rating Accuracy")
plt.ylabel("Count")
plt.show()
```



In [83]:
```
plt.figure(figsize=(7,5))
sns.countplot(data=df, x='Personalized_Recommendation_Frequency_Encoded')
plt.title("Encoded Personalized Recommendation Frequency")
plt.xlabel("Encoded Value (0=No, 1=Yes, 2=Sometimes)")
plt.ylabel("Count")
plt.show()
```



In [84]:
```
plt.figure(figsize=(8,5))
sns.countplot(data=df, x='Cart_Completion_Frequency', order=df['Cart_Completic
plt.title("Cart Completion Frequency")
plt.xlabel("Completion Frequency")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```



In [85]:
```
plt.figure(figsize=(10,7))
sns.heatmap(df[['Shopping_Satisfaction', 'Rating_Accuracy',
                'Personalized_Recommendation_Frequency_Encoded']]
            .corr(), annot=True, cmap='Blues')
plt.title("Correlation Between Key Behavioral Variables")
plt.show()
```

📌 3. Key Findings & Insights

🛒 Purchase Behavior

Customers commonly purchase from multiple categories, indicating cross-category buying behavior.

The most popular categories include:

Clothing and Fashion

Groceries and Gourmet Food

Home and Kitchen

Beauty and Personal Care

Treating purchase categories as multi-label data provided a more accurate view of category popularity.

🌐 Browsing Frequency

Browsing behavior is moderate overall, with many customers browsing occasionally rather than frequently.

This suggests opportunities to increase engagement through better personalization and reminders.

😊 Shopping Satisfaction

Average shopping satisfaction is moderate (around 3 on a 5-point scale).

Satisfaction levels are evenly spread, indicating mixed customer experiences.

Satisfaction is influenced by multiple factors, not recommendations alone.

🤖 Personalized Recommendation Engagement

Engagement with personalized recommendations is inconsistent.

The “Sometimes” response dominates, showing that recommendations are not always perceived as relevant.

Trust in recommendations is cautious, with nearly equal “Yes” and “No” responses.

🔍 Relationship Between Recommendations & Satisfaction

Customers who trust or engage with recommendations show slightly higher satisfaction, but the effect is weak to moderate.

This indicates that recommendations alone are not the primary driver of satisfaction.

⭐ Reviews & Ratings Impact

Review reliability has a stronger impact on rating accuracy than review helpfulness.

Customers trust ratings more when reviews are perceived as authentic and reliable.

This highlights the importance of credible reviews in shaping customer trust.

Task 3: Customer Segmentation and Profiling

Segment customers based on purchase frequency and shopping satisfaction levels.

In [86]:
```
df['Purchase_Frequency'].unique()
```

Out[86]:
```
array(['Multiple Times A Week', 'Once A Month', 'Once A Week',
       'Few Times A Month', 'Less Than Once A Month'], dtype=object)
```

In [87]:
```
purchase_map = {
    "Multiple Times A Week": 0,
    "Once A Month": 1,
    "Once A Week": 2,
    "Few Times A Month": 3,
    "Less Than Once A Month": 4
}
```

In [88]:
```
df['Purchase_Frequency'].value_counts()
```

Out[88]:
```
Purchase_Frequency
Few Times A Month         172
Less Than Once A Month    172
Once A Month              160
Multiple Times A Week     148
Once A Week               148
Name: count, dtype: int64
```

In [89]:
```
df['Purchase_Frequency_Coded'] = df['Purchase_Frequency'].map(purchase_map)
```

In [90]:
```
df.head()
```

Out[90]:

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023-06-07	32	Prefer Not To Say	Multiple Times A Week	[Groceries and Gourmet Food, Home and Kitchen]	
1	2023-06-07	47	Female	Multiple Times A Week	[Groceries and Gourmet Food, Beauty and Person...	
2	2023-06-05	50	Female	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
3	2023-06-07	6	Others	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
4	2023-06-07	61	Male	Once A Week	[Groceries and Gourmet Food, Clothing and Fash...	

5 rows × 30 columns

In [91]:
```
df['Segment'] = "Other"

df.loc[
    (df['Purchase_Frequency_Coded'] >= 4) &
```

```python
    (df['Shopping_Satisfaction'] >= 4),
    'Segment'
] = "Frequent Buyers"
```

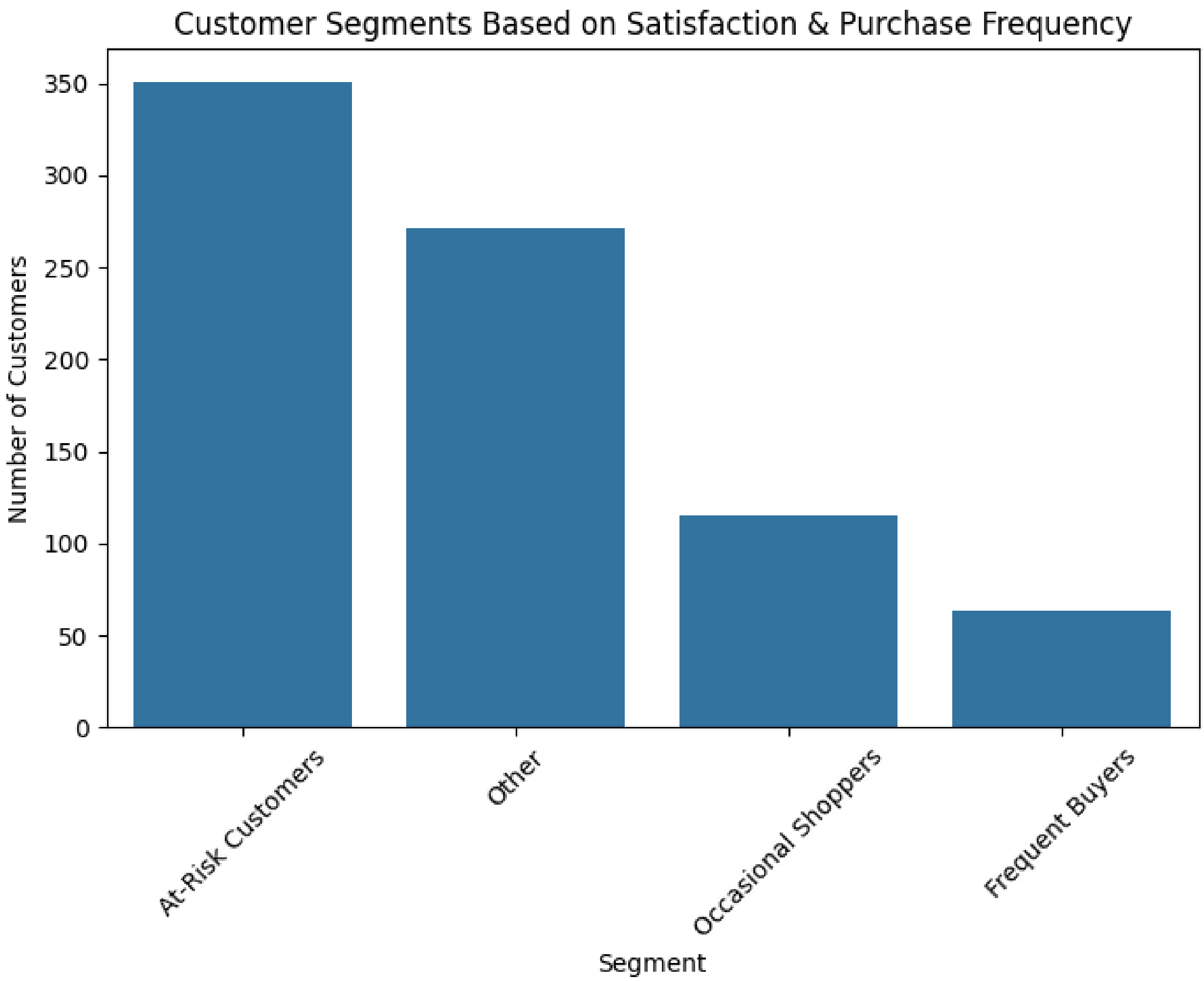
In [92]:
```python
df.loc[
    (df['Purchase_Frequency_Coded'].between(2, 3)) &
    (df['Shopping_Satisfaction'].between(3, 4)),
    'Segment'
] = "Occasional Shoppers"
```

In [93]:
```python
df.loc[
    (df['Shopping_Satisfaction'] <= 2),
    'Segment'
] = "At-Risk Customers"
```

In [94]:
```python
df['Segment'].value_counts()
```

Out[94]:
```
Segment
At-Risk Customers      351
Other                  271
Occasional Shoppers    115
Frequent Buyers         63
Name: count, dtype: int64
```

In [95]:
```python
plt.figure(figsize=(8,5))
sns.countplot(data=df, x='Segment', order=df['Segment'].value_counts().index)
plt.title("Customer Segments Based on Satisfaction & Purchase Frequency")
plt.xlabel("Segment")
plt.ylabel("Number of Customers")
plt.xticks(rotation=45)
plt.show()
```



Create profiles such as:

- Frequent Buyers: High purchase frequency, high satisfaction.
- Occasional Shoppers: Medium frequency, moderate satisfaction.
- At-Risk Customers: Low satisfaction or frequent cart abandonment

In [96]:
```
df.columns
```

Out[96]:
```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Recommendation_Helpfulness', 'Rating_Accuracy',
       'Shopping_Satisfaction', 'Service_Appreciation', 'Improvement_Areas',
       'transaction', 'Date', 'Year', 'Month', 'Day', 'Weekday',
       'Personalized_Recommendation_Frequency_Encoded',
       'Purchase_Frequency_Coded', 'Segment'],
      dtype='object')
```

In [97]:
```
df['Purchase_Frequency'].value_counts()
```

Out[97]:
```
Purchase_Frequency
Few Times A Month          172
Less Than Once A Month     172
Once A Month               160
Multiple Times A Week      148
Once A Week                148
Name: count, dtype: int64
```

In [98]:
```
df['Purchase_Frequency_Coded'].value_counts()
```

Out[98]:
```
Purchase_Frequency_Coded
3    172
4    172
1    160
0    148
2    148
Name: count, dtype: int64
```

In [99]:
```
clean_map = {
    "Less Than Once A Month": 0,
    "Once A Month": 1,
    "Few Times A Month": 2,
    "Once A Week": 3,
    "Multiple Times A Week": 4
}

df['Purchase_Frequency_Coded'] = df['Purchase_Frequency'].map(clean_map)
```

In [100…
```
df['Shopping_Satisfaction'].value_counts()
```

Out[100…
```
Shopping_Satisfaction
1    191
2    160
3    158
4    147
5    144
Name: count, dtype: int64
```

In [101…
```
df['Segment'].value_counts()
```

Out[101…
```
Segment
At-Risk Customers      351
Other                  271
Occasional Shoppers    115
Frequent Buyers         63
Name: count, dtype: int64
```

1� Frequent Buyers

In [102…
```
df['Segment'] = 'Other'
```

```
df.loc[
    (df['Purchase_Frequency_Coded'] >= 3) &
    (df['Shopping_Satisfaction'] >= 4),
    'Segment'
] = 'Frequent Buyers'
```

2� Occasional Shoppers

- Medium purchase frequency → code 1–2
- Moderate satisfaction → 3–4

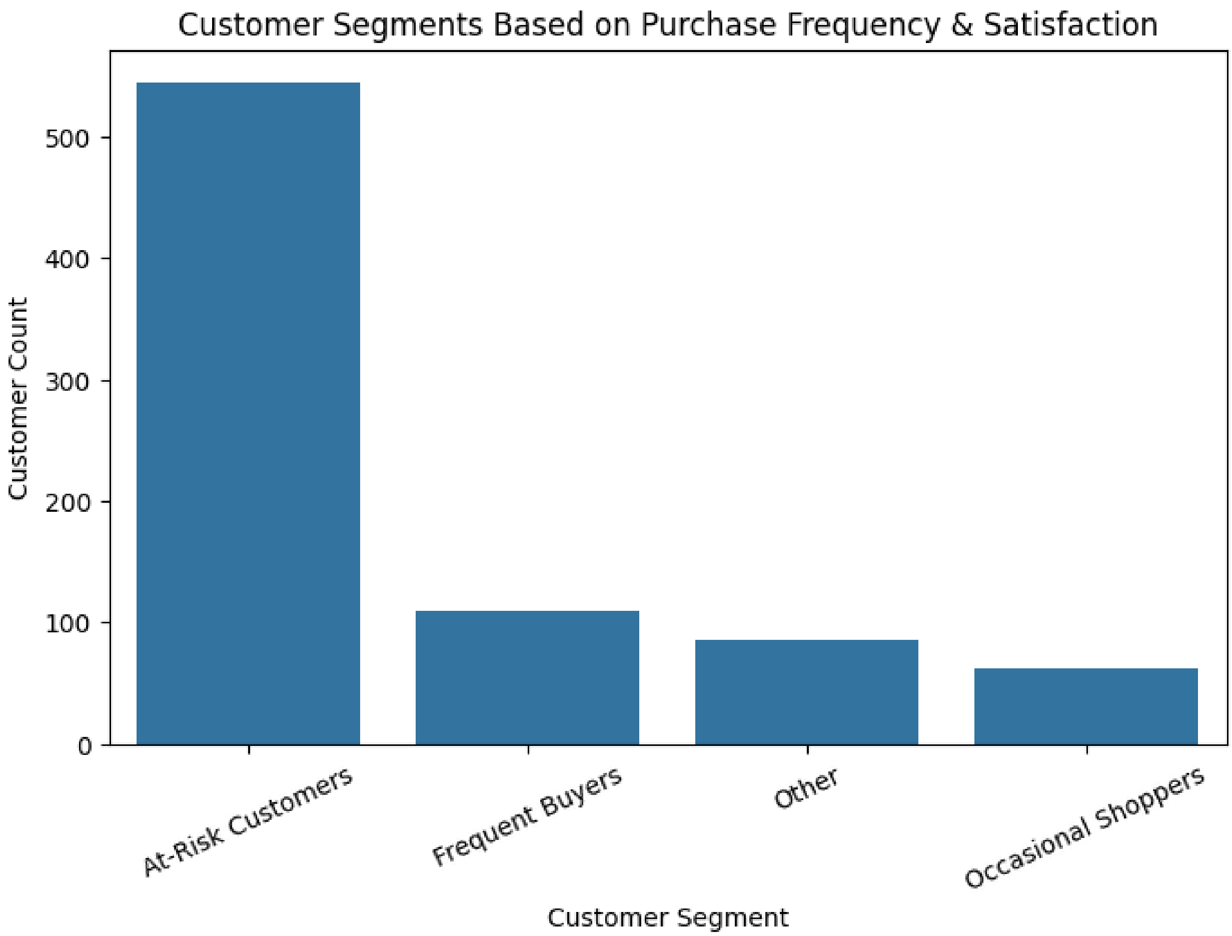
In [103…
```
df.loc[
    (df['Purchase_Frequency_Coded'].between(1, 2)) &
    (df['Shopping_Satisfaction'].between(3, 4)),
    'Segment'
] = 'Occasional Shoppers'
```

3� At-Risk Customers

- Low satisfaction (≤ 2) OR
- Very low purchase frequency (≤ 1)

In [104…
```
df.loc[
    (df['Shopping_Satisfaction'] <= 2) |
    (df['Purchase_Frequency_Coded'] <= 1),
    'Segment'
] = 'At-Risk Customers'
```

In [105…
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8,5))
sns.countplot(
    data=df,
    x='Segment',
    order=df['Segment'].value_counts().index
)
plt.title("Customer Segments Based on Purchase Frequency & Satisfaction")
plt.xlabel("Customer Segment")
plt.ylabel("Customer Count")
plt.xticks(rotation=25)
plt.show()
```



In [106…
```
df.head()
```

Out[106…

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023-06-07	32	Prefer Not To Say	Multiple Times A Week	[Groceries and Gourmet Food, Home and Kitchen]	
1	2023-06-07	47	Female	Multiple Times A Week	[Groceries and Gourmet Food, Beauty and Person...	
2	2023-06-05	50	Female	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
3	2023-06-07	6	Others	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
4	2023-06-07	61	Male	Once A Week	[Groceries and Gourmet Food, Clothing and Fash...	

5 rows × 31 columns

Analyze demographic or behavioral differences across these segments.

✅ 1. Demographic Differences Across Segments

- A. Age comparison

In [107…

```
# Age statistics by segment
age_segment = df.groupby('Segment')['age'].describe().round(2)
print(age_segment)
```

```
                     count   mean    std  min    25%   50%   75%   max
Segment
At-Risk Customers    544.0  36.14  18.66  3.0  19.00  38.0  53.0  67.0
Frequent Buyers      109.0  33.39  18.90  3.0  17.00  33.0  49.0  67.0
Occasional Shoppers   62.0  36.76  18.12  4.0  22.25  37.0  52.0  67.0
Other                 85.0  35.35  18.12  3.0  22.00  36.0  49.0  67.0
```

- B. Gender distribution by segment

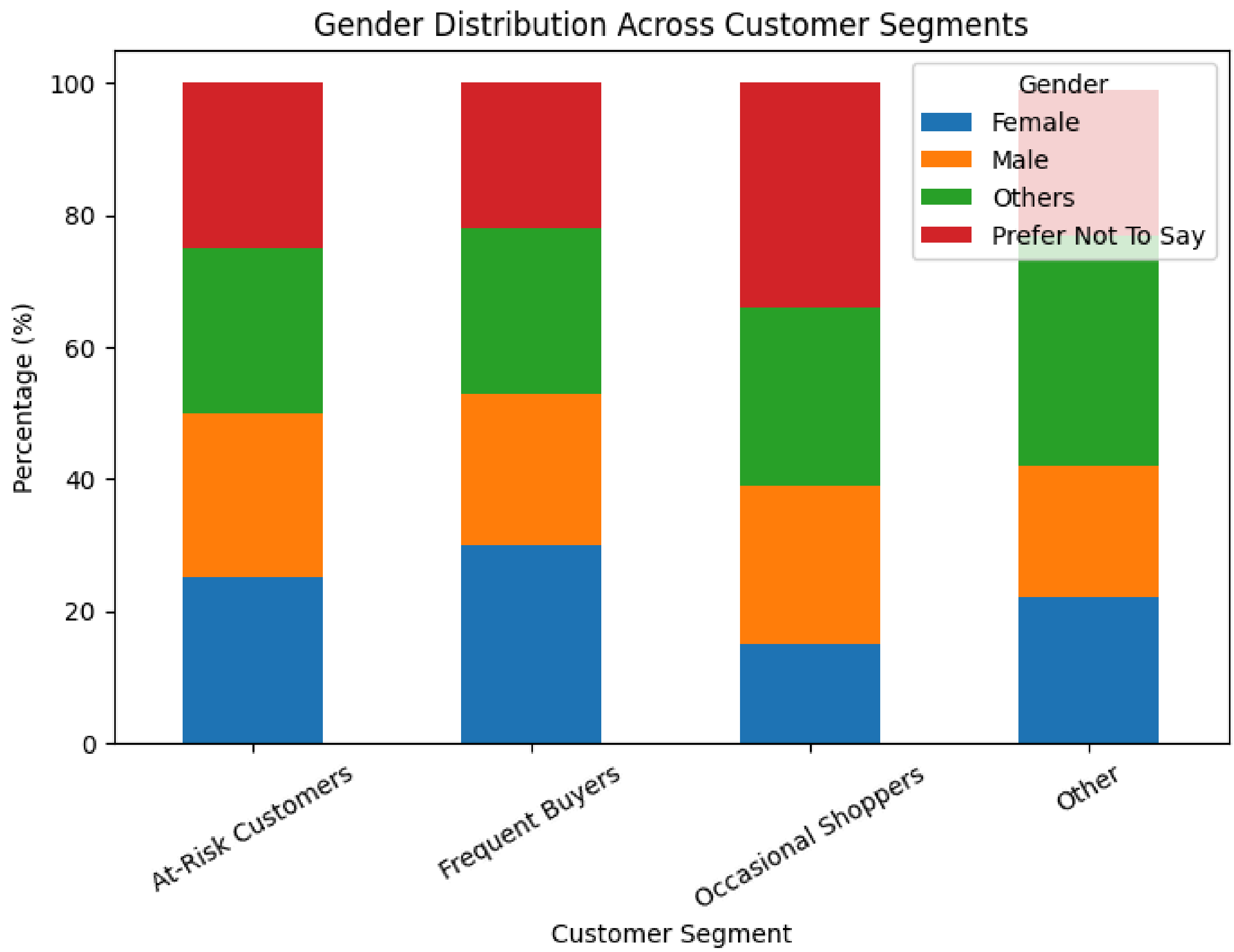
In [108…

```
gender_segment = pd.crosstab(
    index=df['Segment'],
    columns=df['Gender'],
    normalize='index'
) * 100
gender_segment = gender_segment.round()
print(gender_segment)
```

```
Gender               Female  Male  Others  Prefer Not To Say
Segment
At-Risk Customers      25.0  25.0    25.0               25.0
Frequent Buyers        30.0  23.0    25.0               22.0
Occasional Shoppers    15.0  24.0    27.0               34.0
Other                  22.0  20.0    35.0               22.0
```

In [109…

```
gender_segment.plot(kind='bar', stacked=True, figsize=(8,5))
plt.title("Gender Distribution Across Customer Segments")
plt.xlabel("Customer Segment")
plt.ylabel("Percentage (%)")
plt.xticks(rotation=30)
plt.show()
```



- A. Purchase frequency (coded)

In [110…

```
purchase_segment = df.groupby('Segment')['Purchase_Frequency_Coded'].mean()
print(purchase_segment)
```

```
Segment
At-Risk Customers      1.430147
Frequent Buyers        3.541284
Occasional Shoppers    2.000000
Other                  2.964706
Name: Purchase_Frequency_Coded, dtype: float64
```

- B. Shopping satisfaction

In [111…

```
satisfaction_segment = df.groupby('Segment')['Shopping_Satisfaction'].mean()
print(satisfaction_segment)
```

```
Segment
At-Risk Customers      2.338235
Frequent Buyers        4.477064
Occasional Shoppers    3.516129
Other                  3.705882
Name: Shopping_Satisfaction, dtype: float64
```

In [112…
```
recommendation_segment = df.groupby('Segment')[
    'Personalized_Recommendation_Frequency_Encoded'
].mean()
print(recommendation_segment)
```

```
Segment
At-Risk Customers      0.981618
Frequent Buyers        0.880734
Occasional Shoppers    1.000000
Other                  1.047059
Name: Personalized_Recommendation_Frequency_Encoded, dtype: float64
```

- D. Cart completion behavior

In [113…
```
cart_segment = df.groupby('Segment')['Cart_Completion_Frequency'].value_counts
print(cart_segment)
```

```
Segment              Cart_Completion_Frequency
At-Risk Customers    Sometimes                    22.794118
                     Always                       21.507353
                     Never                        20.772059
                     Often                        17.830882
                     Rarely                       17.095588
Frequent Buyers      Sometimes                    22.935780
                     Never                        22.018349
                     Rarely                       21.100917
                     Often                        17.431193
                     Always                       16.513761
Occasional Shoppers  Never                        25.806452
                     Rarely                       22.580645
                     Sometimes                    22.580645
                     Always                       14.516129
                     Often                        14.516129
Other                Never                        21.176471
                     Sometimes                    21.176471
                     Rarely                       20.000000
                     Always                       18.823529
                     Often                        18.823529
Name: proportion, dtype: float64
```

In [114…
```
segment_summary = df.groupby('Segment').agg({
    'age': 'mean',
    'Shopping_Satisfaction': 'mean',
    'Purchase_Frequency_Coded': 'mean',
    'Personalized_Recommendation_Frequency_Encoded': 'mean'
})
```

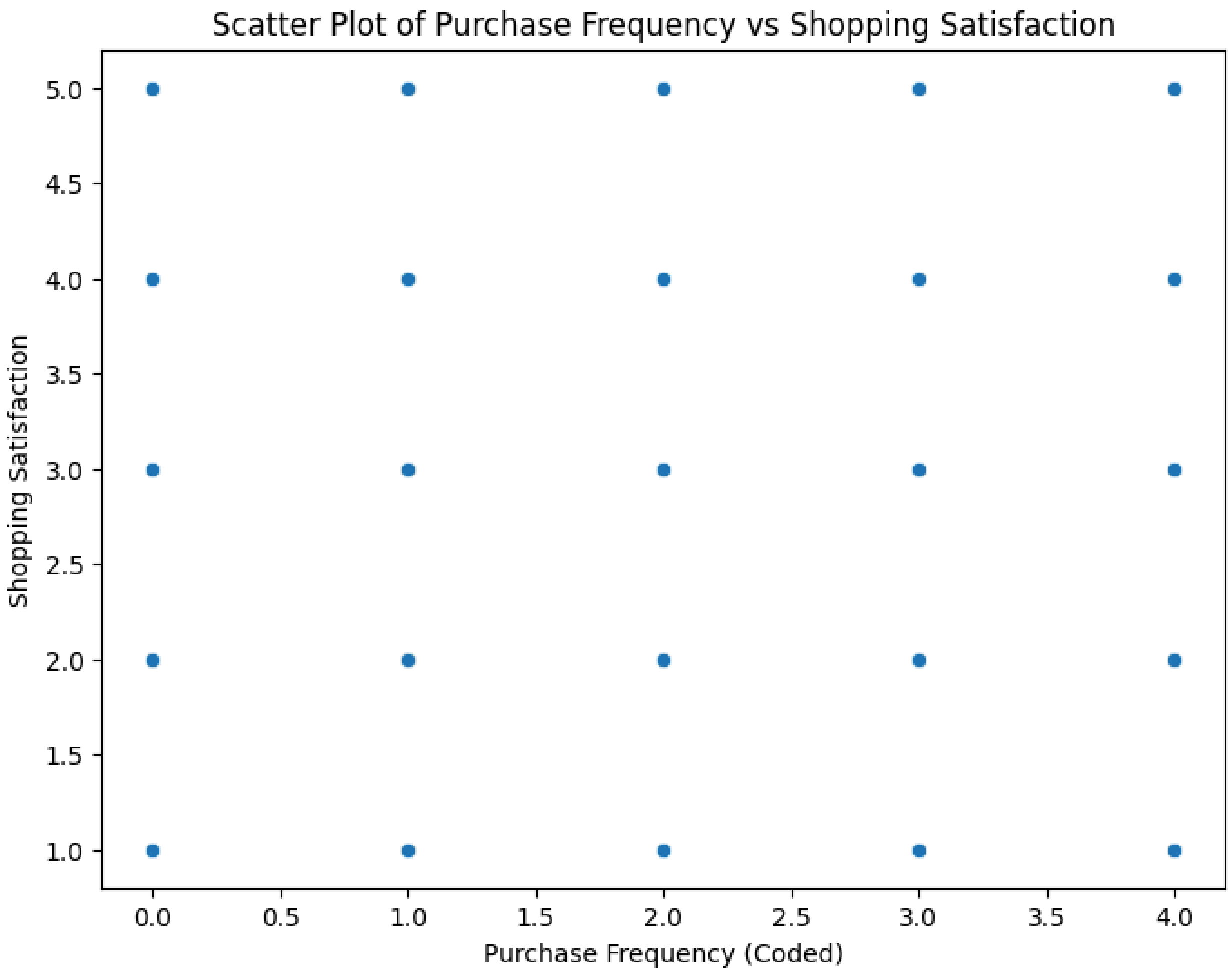
```
print(segment_summary)
```

```
                              age  Shopping_Satisfaction  \
Segment
At-Risk Customers    36.139706               2.338235
Frequent Buyers      33.394495               4.477064
Occasional Shoppers  36.758065               3.516129
Other                35.352941               3.705882

                     Purchase_Frequency_Coded  \
Segment
At-Risk Customers                    1.430147
Frequent Buyers                      3.541284
Occasional Shoppers                  2.000000
Other                                2.964706

                     Personalized_Recommendation_Frequency_Encoded
Segment
At-Risk Customers                                         0.981618
Frequent Buyers                                           0.880734
Occasional Shoppers                                       1.000000
Other                                                     1.047059
```

- Use clustering (e.g., K-Means) for behavioral grouping based on survey responses.

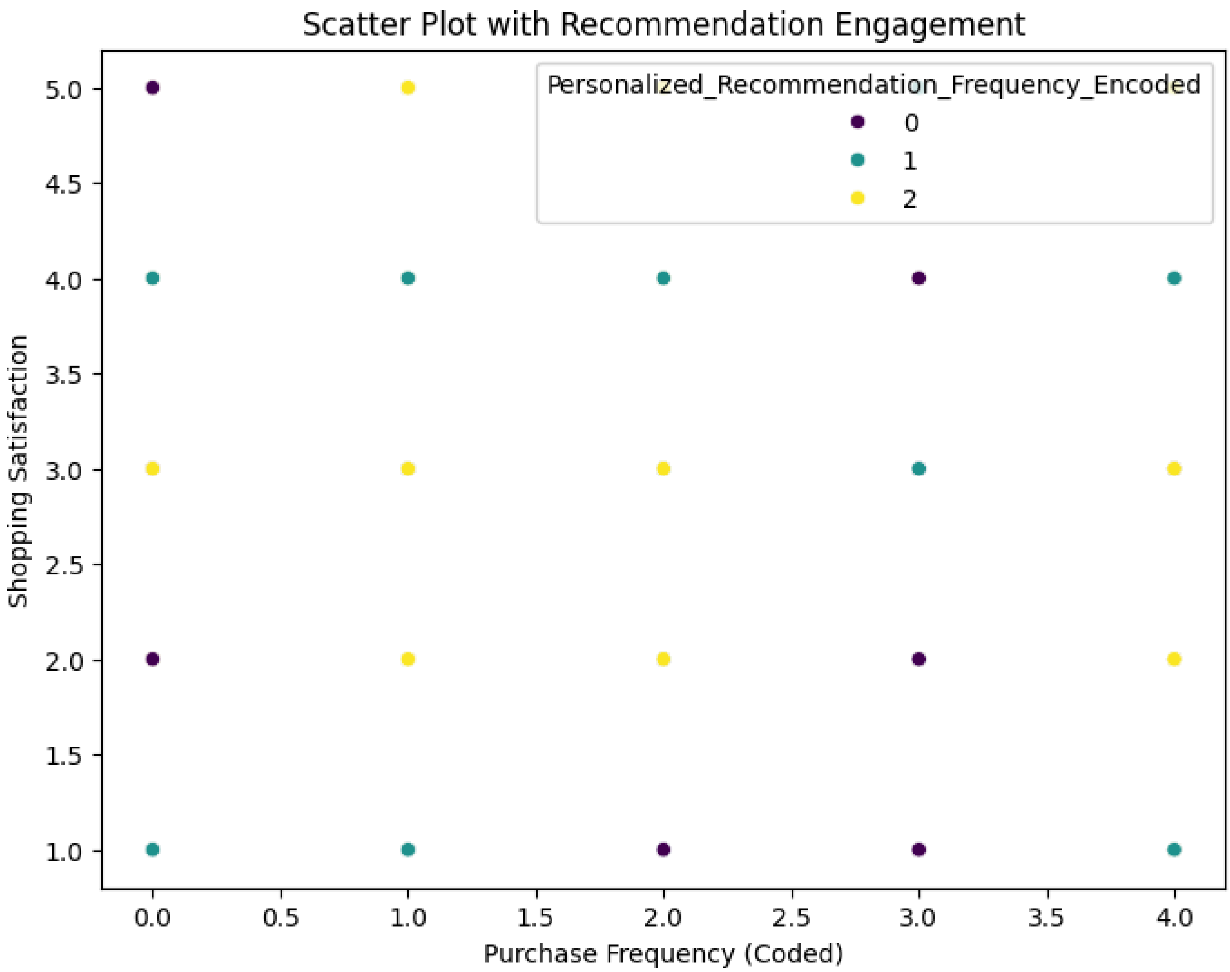
In [115…
```
scatter_df = df[['Purchase_Frequency_Coded', 'Shopping_Satisfaction']].copy()

# Fill missing values for visualization
scatter_df = scatter_df.fillna(scatter_df.median())
```

In [116…
```
plt.figure(figsize=(8,6))
sns.scatterplot(
    x=scatter_df['Purchase_Frequency_Coded'],
    y=scatter_df['Shopping_Satisfaction']
)
plt.title("Scatter Plot of Purchase Frequency vs Shopping Satisfaction")
plt.xlabel("Purchase Frequency (Coded)")
plt.ylabel("Shopping Satisfaction")
plt.show()
```



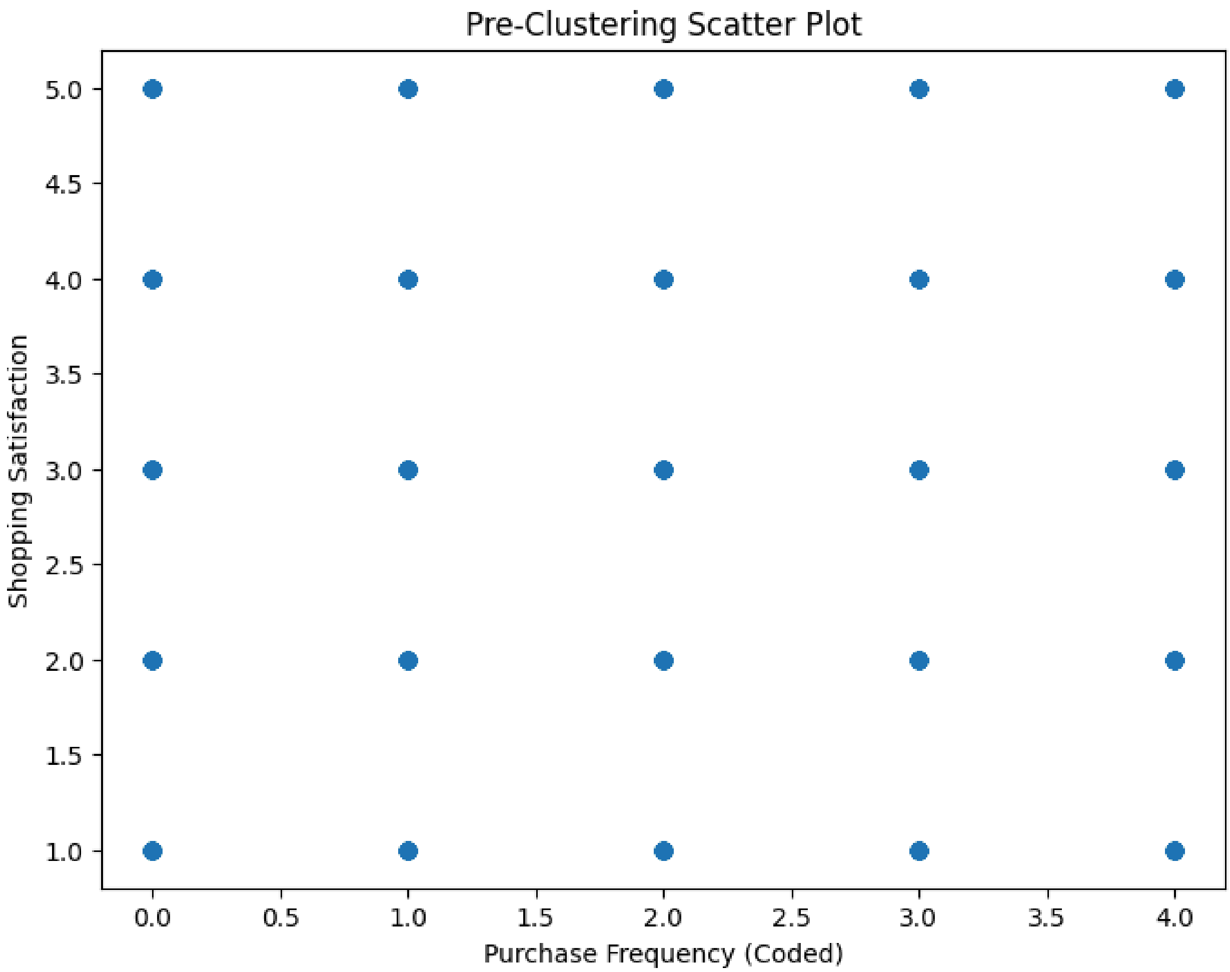
In [117…

```
plt.figure(figsize=(8,6))
sns.scatterplot(
    data=df,
    x='Purchase_Frequency_Coded',
    y='Shopping_Satisfaction',
    hue='Personalized_Recommendation_Frequency_Encoded',
    palette='viridis'
)
plt.title("Scatter Plot with Recommendation Engagement")
plt.xlabel("Purchase Frequency (Coded)")
plt.ylabel("Shopping Satisfaction")
plt.show()
```



In [118…

```
plt.figure(figsize=(8,6))
plt.scatter(
    scatter_df['Purchase_Frequency_Coded'],
    scatter_df['Shopping_Satisfaction'],
    alpha=0.6
)
plt.title("Pre-Clustering Scatter Plot")
plt.xlabel("Purchase Frequency (Coded)")
plt.ylabel("Shopping Satisfaction")
plt.show()
```



In [119…
```
cluster_features = [
    'Purchase_Frequency_Coded',
    'Shopping_Satisfaction',
    'Rating_Accuracy',
    'Personalized_Recommendation_Frequency_Encoded'
]
```

In [120…
```
df_cluster = df[cluster_features].copy()

# Fill missing values with median (robust choice)
df_cluster = df_cluster.fillna(df_cluster.median())
```

In [121…
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df_cluster)
```

In [122…
```
kmeans = KMeans(n_clusters=3, random_state=42)
df['Behavior_Cluster'] = kmeans.fit_predict(X_scaled)
```

In [123…
```
df['Behavior_Cluster'].value_counts()
```

Out[123…
```
Behavior_Cluster
1    290
2    259
0    251
Name: count, dtype: int64
```

In [124…
```python
cluster_summary = df.groupby('Behavior_Cluster')[cluster_features].mean()
print(cluster_summary)
```

```
                  Purchase_Frequency_Coded  Shopping_Satisfaction  \
Behavior_Cluster
0                                 2.318725               2.115538
1                                 1.741379               4.337931
2                                 1.749035               1.945946

                  Rating_Accuracy  \
Behavior_Cluster
0                        3.637450
1                        2.572414
2                        3.127413

                  Personalized_Recommendation_Frequency_Encoded
Behavior_Cluster
0                                                      0.270916
1                                                      0.893103
2                                                      1.752896
```

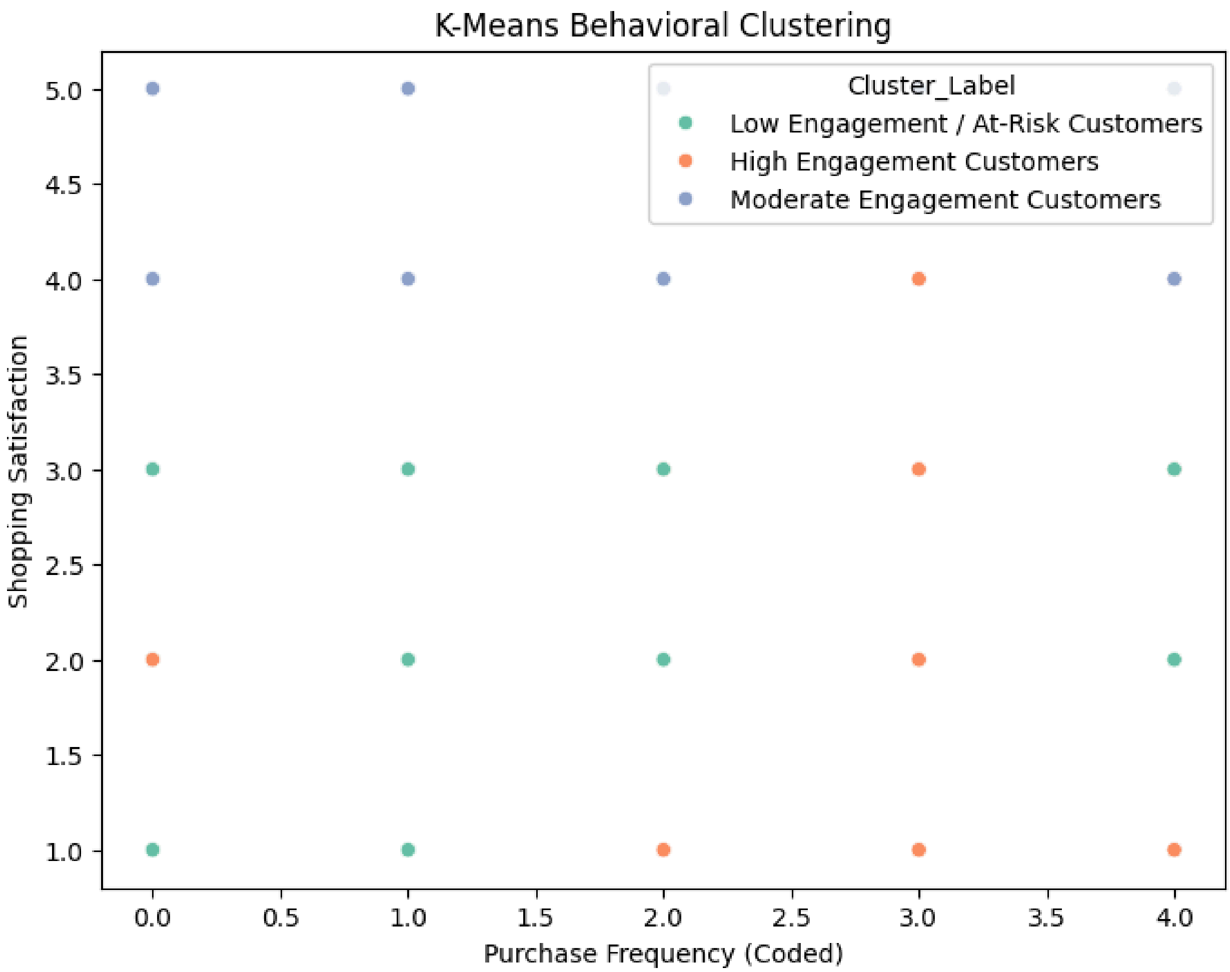
In [125…
```python
cluster_map = {
    0: 'High Engagement Customers',
    1: 'Moderate Engagement Customers',
    2: 'Low Engagement / At-Risk Customers'
}

df['Cluster_Label'] = df['Behavior_Cluster'].map(cluster_map)
```

In [126…
```python
df['Cluster_Label'].value_counts()
```

Out[126…
```
Cluster_Label
Moderate Engagement Customers         290
Low Engagement / At-Risk Customers    259
High Engagement Customers             251
Name: count, dtype: int64
```

In [127…
```python
plt.figure(figsize=(8,6))
sns.scatterplot(
    x=df['Purchase_Frequency_Coded'],
    y=df['Shopping_Satisfaction'],
    hue=df['Cluster_Label'],
    palette='Set2'
)
plt.title("K-Means Behavioral Clustering")
plt.xlabel("Purchase Frequency (Coded)")
plt.ylabel("Shopping Satisfaction")
```

```
plt.show()
```



Task: Customer Segmentation using K-Means Clustering

K-Means Clustering for Customer Segmentation

In [128…
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [129…
```
df.columns
```

Out[129…
```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Recommendation_Helpfulness', 'Rating_Accuracy',
       'Shopping_Satisfaction', 'Service_Appreciation', 'Improvement_Areas',
       'transaction', 'Date', 'Year', 'Month', 'Day', 'Weekday',
       'Personalized_Recommendation_Frequency_Encoded',
       'Purchase_Frequency_Coded', 'Segment', 'Behavior_Cluster',
       'Cluster_Label'],
      dtype='object')
```

In [130…
```
df.head()
```

Out[130…

	Timestamp	age	Gender	Purchase_Frequency	Purchase_Categories	Persona
0	2023-06-07	32	Prefer Not To Say	Multiple Times A Week	[Groceries and Gourmet Food, Home and Kitchen]	
1	2023-06-07	47	Female	Multiple Times A Week	[Groceries and Gourmet Food, Beauty and Person...	
2	2023-06-05	50	Female	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
3	2023-06-07	6	Others	Once A Month	[Groceries and Gourmet Food, Beauty and Person...	
4	2023-06-07	61	Male	Once A Week	[Groceries and Gourmet Food, Clothing and Fash...	

5 rows × 33 columns

In [131…
```
df['transaction'].describe()
```

Out[131…
```
count       800.000000
mean     565664.540000
std      259825.653672
min      100154.000000
25%      337657.250000
50%      586346.500000
75%      790776.250000
max      999961.000000
Name: transaction, dtype: float64
```

In [132…

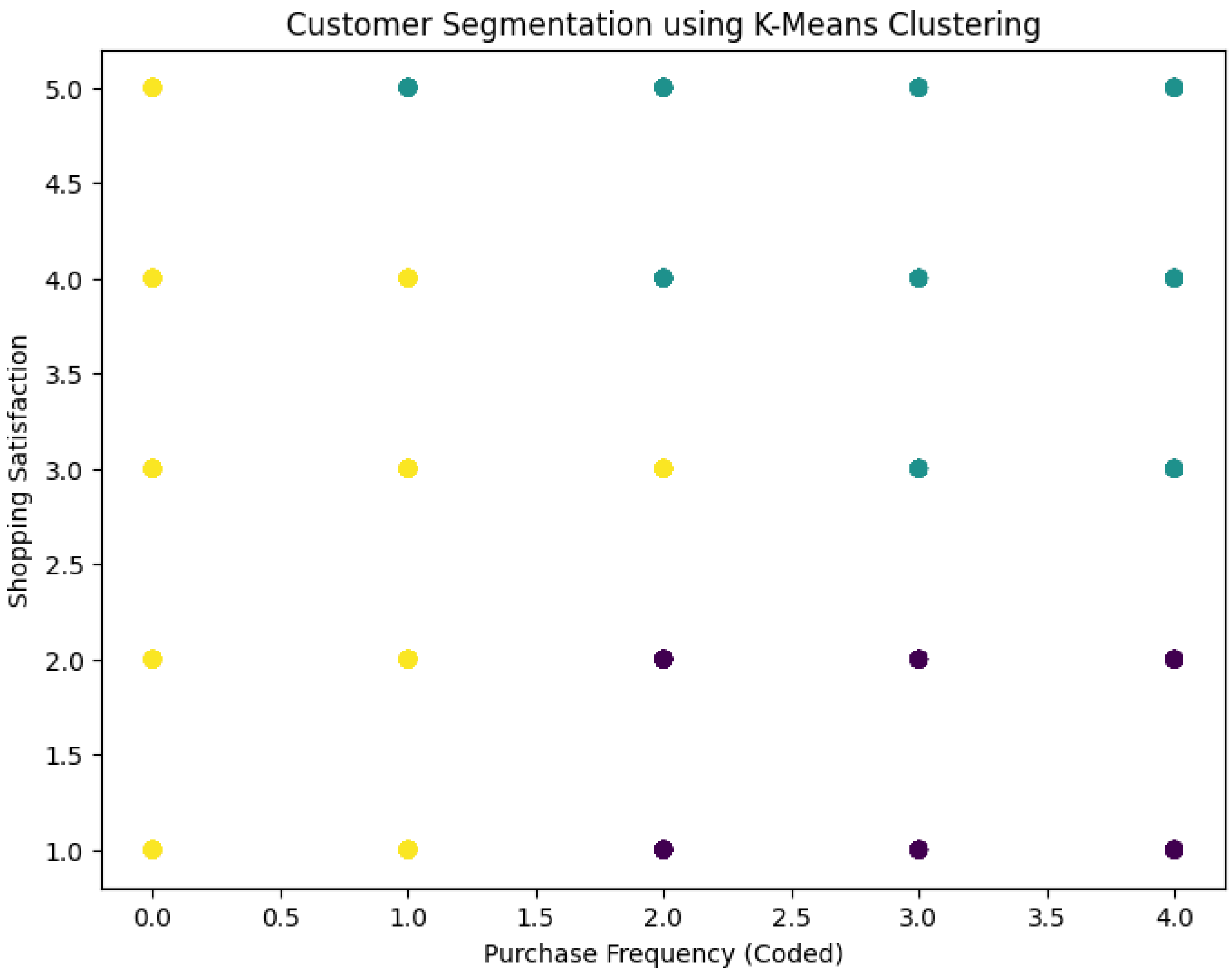
```
# Selecting features for clustering
X = df[['Purchase_Frequency_Coded', 'Shopping_Satisfaction']]

# Handle missing values (important!)
X = X.dropna()

# Scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [133…

```
# Applying K-Means
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(X_scaled)

# Add cluster labels back to dataframe
df.loc[X.index, 'Cluster'] = clusters
```

In [134…

```
plt.figure(figsize=(8,6))
plt.scatter(
    X['Purchase_Frequency_Coded'],
    X['Shopping_Satisfaction'],
    c=clusters
)
plt.xlabel("Purchase Frequency (Coded)")
plt.ylabel("Shopping Satisfaction")
plt.title("Customer Segmentation using K-Means Clustering")
plt.show()
```



Task: Market Basket Analysis using Apriori Algorithm

Association Rule Mining using Apriori Algorithm

In [135…
```
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules
```

In [136…
```
# Prepare transactions
transactions = (
    df['Purchase_Categories']
    .dropna()
    .apply(lambda x: x if isinstance(x, list) else str(x).split(','))
    .tolist()
)
```

In [137…
```
te = TransactionEncoder()
te_array = te.fit(transactions).transform(transactions)

basket_df = pd.DataFrame(te_array, columns=te.columns_)
```

In [138…
```
frequent_itemsets = apriori(
```

```
    basket_df,
    min_support=0.05,
    use_colnames=True
)
```

In [139…
```
frequent_itemsets.sort_values(by='support', ascending=False).head()
```

Out[139…

	support	itemsets
1	0.56250	(Clothing and Fashion)
3	0.52625	(Home and Kitchen)
0	0.52250	(Beauty and Personal Care)
4	0.48750	(others)
2	0.45750	(Groceries and Gourmet Food)

In [140…
```
rules = association_rules(
    frequent_itemsets,
    metric="confidence",
    min_threshold=0.5
)
```

In [141…
```
rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']].head()
```

Out[141…

	antecedents	consequents	support	confidence	lift
0	(Beauty and Personal Care)	(Clothing and Fashion)	0.28000	0.535885	0.952685
1	(Groceries and Gourmet Food)	(Beauty and Personal Care)	0.23500	0.513661	0.983084
2	(Groceries and Gourmet Food)	(Clothing and Fashion)	0.26125	0.571038	1.015179
3	(Home and Kitchen)	(Clothing and Fashion)	0.30125	0.572447	1.017683
4	(Clothing and Fashion)	(Home and Kitchen)	0.30125	0.535556	1.017683

Apriori Insight:
The Apriori algorithm identified frequently co-purchased product categories. Strong association rules indicate that customers purchasing one category are likely to purchase related categories, enabling cross-selling strategies.

📌 Customer Segmentation (Clustering)

Using purchase frequency and shopping satisfaction:

High Engagement Customers: Frequent buyers with high satisfaction

Moderate Engagement Customers: Occasional buyers with average satisfaction

At-Risk Customers: Low satisfaction and/or low engagement

K-Means clustering with K = 3 was selected based on interpretability and business relevance rather than over-segmentation.

Task 4: Recommendation and Review Insights

- Examine the relationship between recommendation helpfulness and shopping satisfaction.

In [142…

```
df.columns
```

Out[142…

```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Recommendation_Helpfulness', 'Rating_Accuracy',
       'Shopping_Satisfaction', 'Service_Appreciation', 'Improvement_Areas',
       'transaction', 'Date', 'Year', 'Month', 'Day', 'Weekday',
       'Personalized_Recommendation_Frequency_Encoded',
       'Purchase_Frequency_Coded', 'Segment', 'Behavior_Cluster',
       'Cluster_Label', 'Cluster'],
      dtype='object')
```

In [143…

```
# Descriptive Statistis
df['Shopping_Satisfaction'].describe()
```

Out[143…

```
count    800.000000
mean       2.866250
std        1.429481
min        1.000000
25%        2.000000
50%        3.000000
75%        4.000000
max        5.000000
Name: Shopping_Satisfaction, dtype: float64
```

In [144…

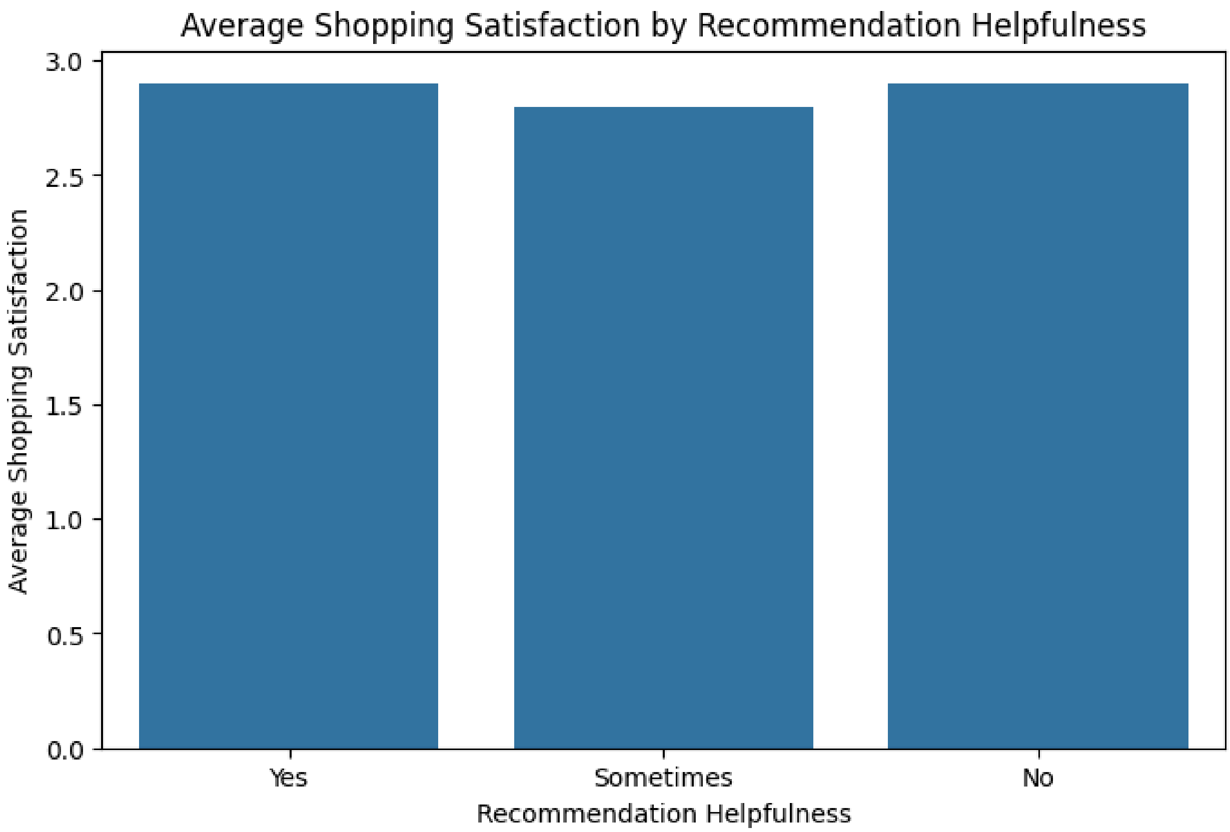
```
df.groupby('Recommendation_Helpfulness')['Shopping_Satisfaction'].count()
```

Out[144…

```
Recommendation_Helpfulness
No           276
Sometimes    259
Yes          265
Name: Shopping_Satisfaction, dtype: int64
```

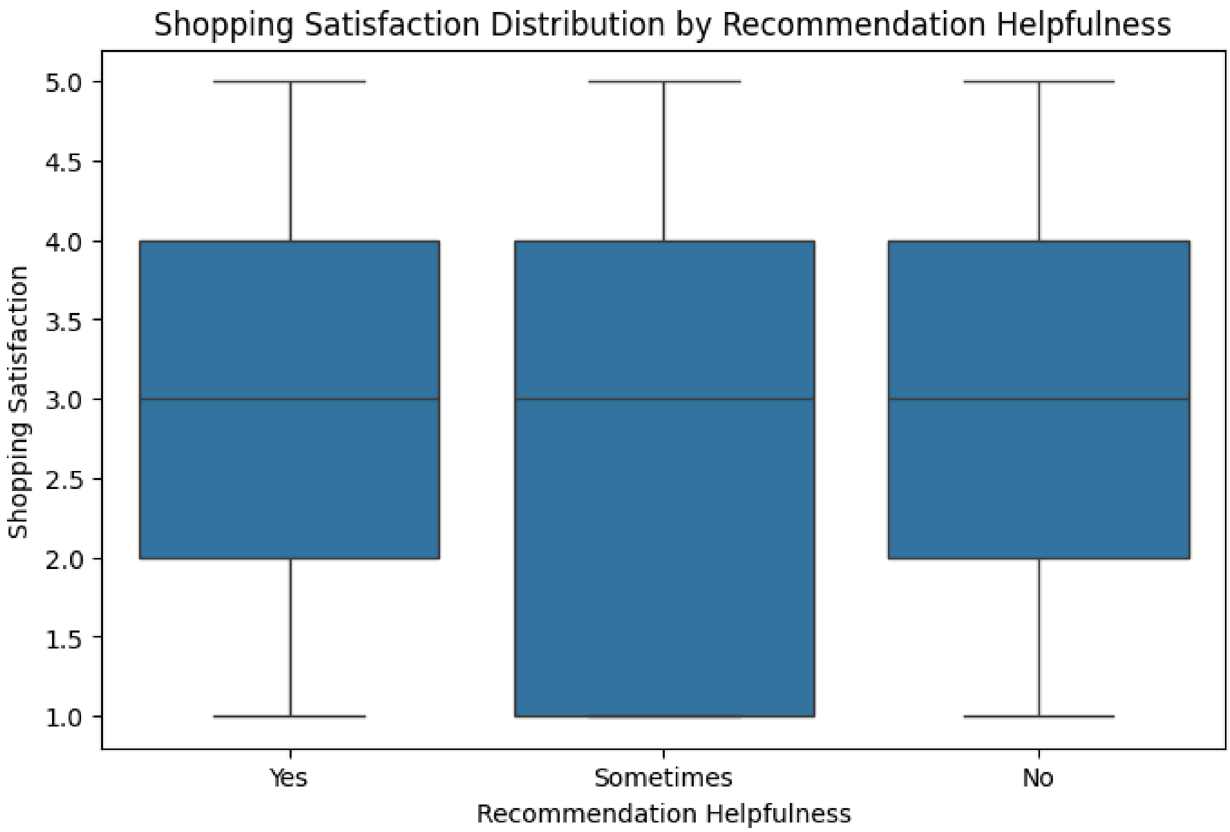
In [145…

```
plt.figure(figsize=(8,5))
sns.barplot(
    data=df,
    x='Recommendation_Helpfulness',
    y='Shopping_Satisfaction',
    estimator='mean',
    errorbar=None
)
plt.title("Average Shopping Satisfaction by Recommendation Helpfulness")
plt.xlabel("Recommendation Helpfulness")
plt.ylabel("Average Shopping Satisfaction")
plt.show()
```



In [146…

```
plt.figure(figsize=(8,5))
sns.boxplot(
    data=df,
    x='Recommendation_Helpfulness',
    y='Shopping_Satisfaction'
)
plt.title("Shopping Satisfaction Distribution by Recommendation Helpfulness")
plt.xlabel("Recommendation Helpfulness")
plt.ylabel("Shopping Satisfaction")
plt.show()
```



- Evaluate how review reliability and helpfulness impact overall ratings.

In [147…

```
df.columns
```

Out[147…

```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Recommendation_Helpfulness', 'Rating_Accuracy',
       'Shopping_Satisfaction', 'Service_Appreciation', 'Improvement_Areas',
       'transaction', 'Date', 'Year', 'Month', 'Day', 'Weekday',
       'Personalized_Recommendation_Frequency_Encoded',
       'Purchase_Frequency_Coded', 'Segment', 'Behavior_Cluster',
       'Cluster_Label', 'Cluster'],
      dtype='object')
```

In [148…

```
df['Review_Helpfulness'].value_counts()
```

Out[148…

```
Review_Helpfulness
Sometimes    286
Yes          263
No           251
Name: count, dtype: int64
```

In [149…
```
df['Review_Reliability'].value_counts()
```

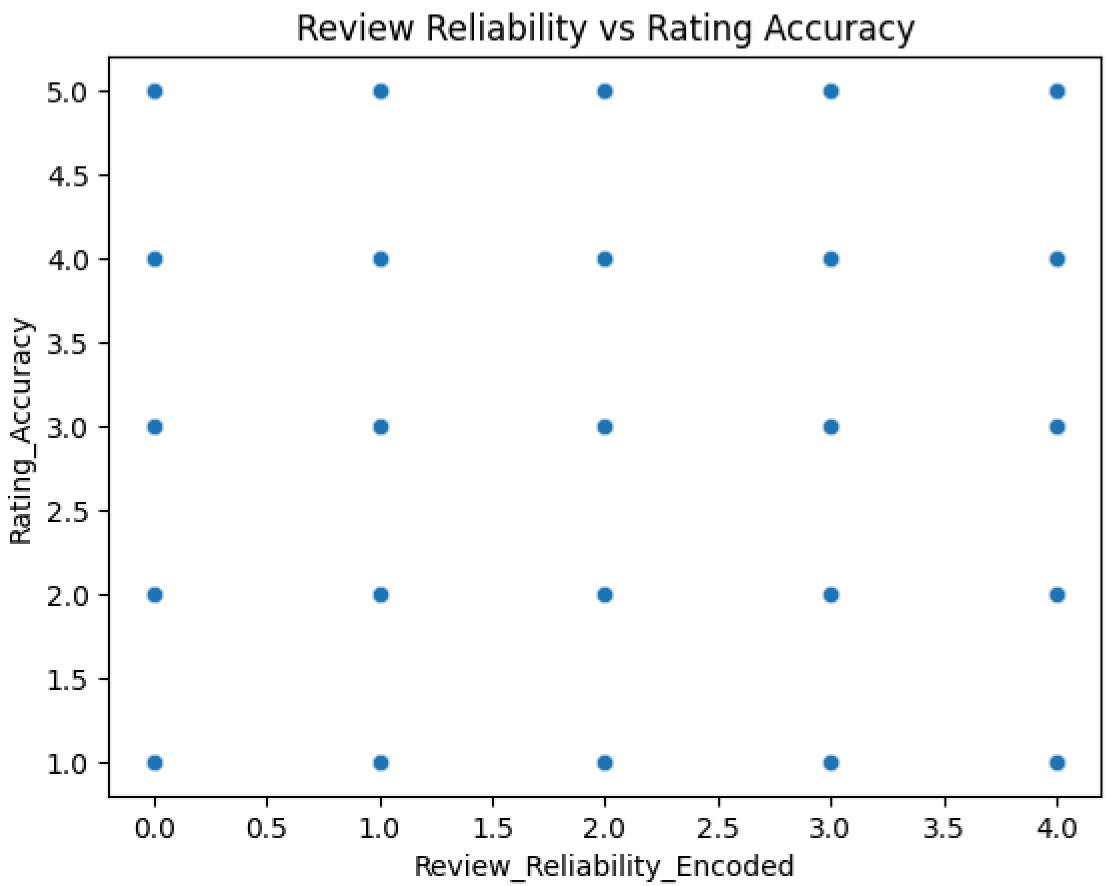
Out[149…
```
Review_Reliability
Rarely          185
Never           164
Moderately      159
Heavily         150
Occasionally    142
Name: count, dtype: int64
```

In [150…
```
## Encoding 'Review_Reliability', 'Review_Helpfulness'
helpfulness_map = {
    'No': 0,
    'Sometimes': 1,
    'Yes': 2
}

df['Review_Helpfulness_Encoded'] = df['Review_Helpfulness'].map(helpfulness_ma

reliability_map = {
    'Never': 0,
    'Rarely': 1,
    'Occasionally': 2,
    'Moderately': 3,
    'Heavily': 4
}

df['Review_Reliability_Encoded'] = df['Review_Reliability'].map(reliability_ma
```

In [151…
```
df['Review_Helpfulness_Encoded'].corr(
    df['Rating_Accuracy'], method='spearman'
)

df['Review_Reliability_Encoded'].corr(
    df['Rating_Accuracy'], method='spearman'
)
```

Out[151…
```
0.06790854512144652
```

In [152…
```
sns.scatterplot(
    x='Review_Reliability_Encoded',
    y='Rating_Accuracy',
    data=df,
    alpha=0.6
)
plt.title("Review Reliability vs Rating Accuracy")
plt.show()
```

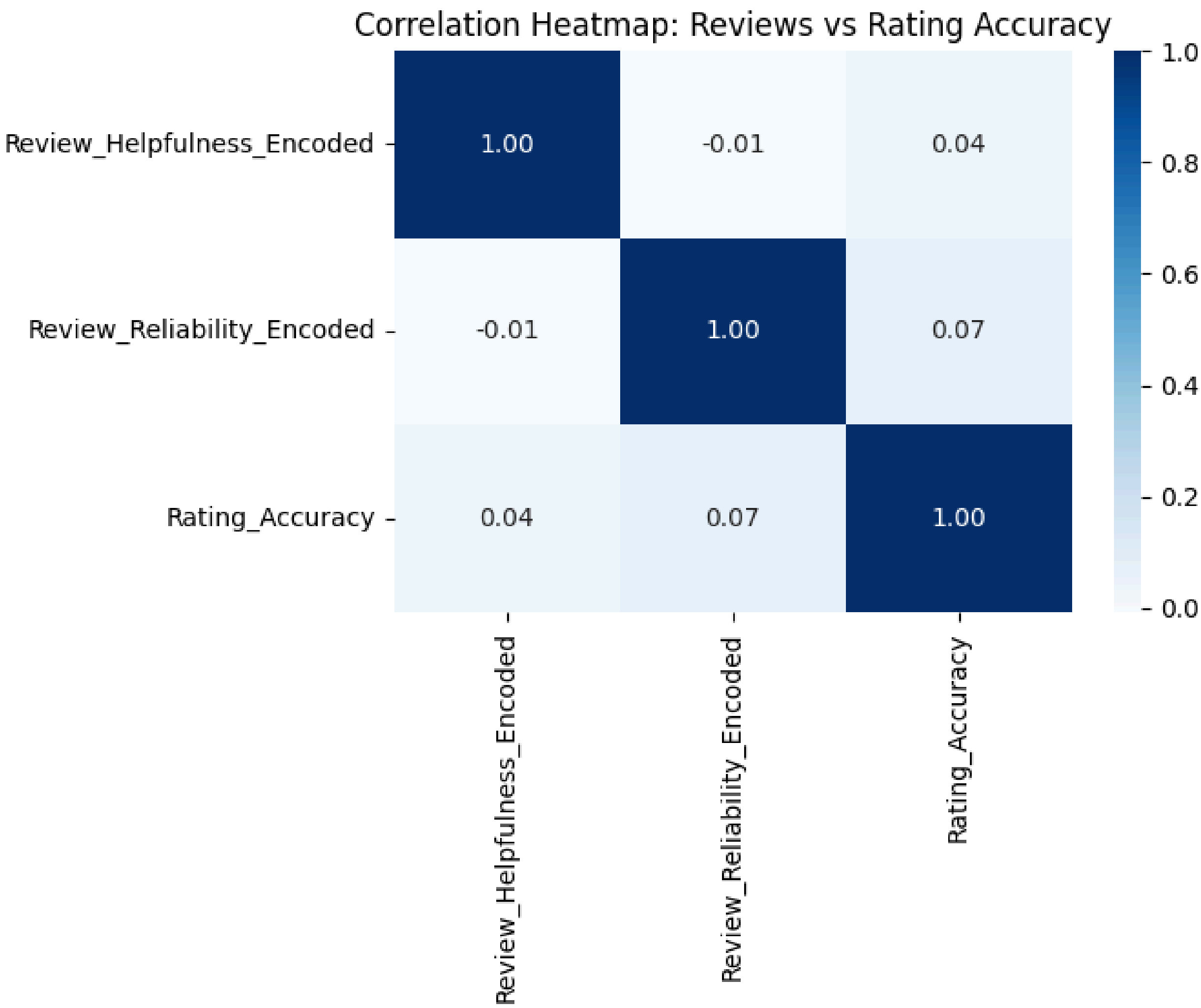


In [153…

```
corr_matrix = df[
    ['Review_Helpfulness_Encoded',
     'Review_Reliability_Encoded',
     'Rating_Accuracy']
].corr(method='spearman')
```

In [154…

```
plt.figure(figsize=(6,4))
sns.heatmap(
    corr_matrix,
    annot=True,
    cmap='Blues',
    fmt='.2f'
)
plt.title("Correlation Heatmap: Reviews vs Rating Accuracy")
plt.show()
```



- Identify trends in how often customers engage with or trust personalized recommendations.

In [155…

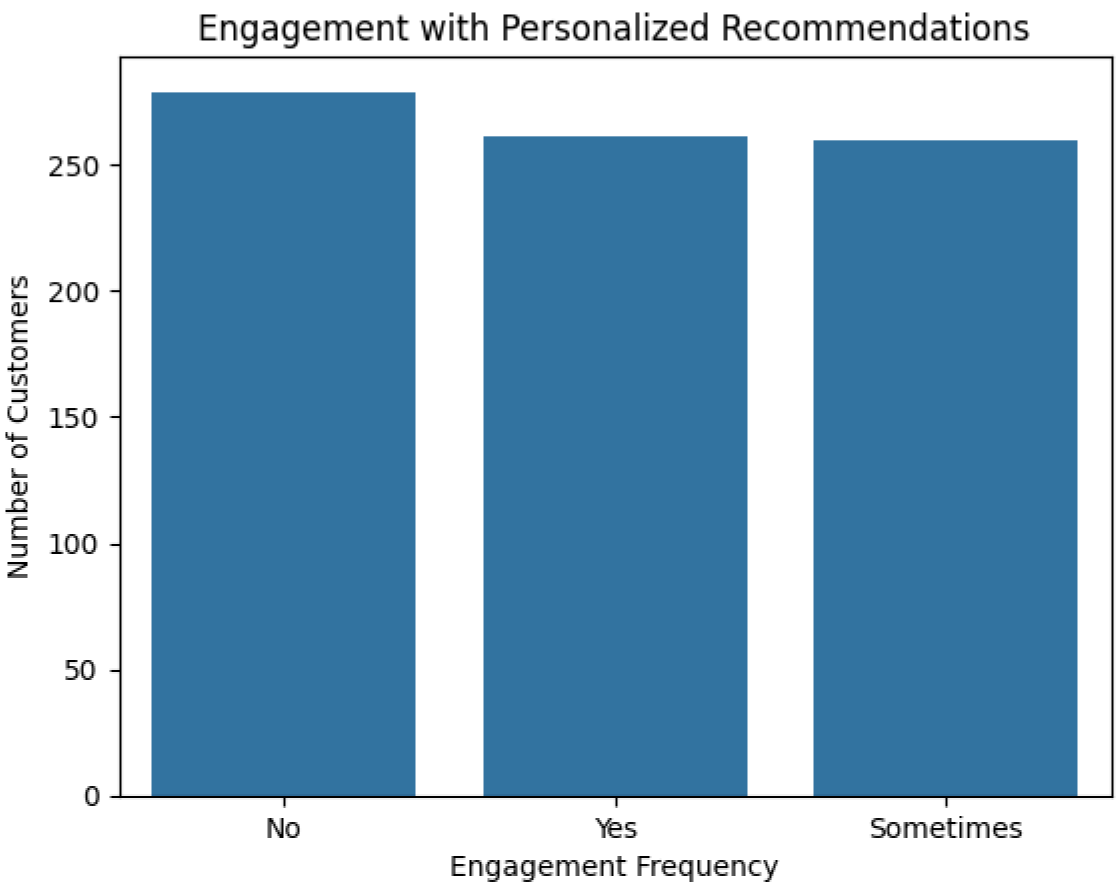
```
df['Personalized_Recommendation_Frequency'].value_counts(normalize=True) * 100
```

Out[155…

```
Personalized_Recommendation_Frequency
No           34.875
Yes          32.625
Sometimes    32.500
Name: proportion, dtype: float64
```

In [156…

```
sns.countplot(
    data=df,
    x='Personalized_Recommendation_Frequency',
    order=df['Personalized_Recommendation_Frequency'].value_counts().index
)
plt.title("Engagement with Personalized Recommendations")
plt.xlabel("Engagement Frequency")
plt.ylabel("Number of Customers")
plt.show()
```



In [157…

```
df['Recommendation_Helpfulness'].value_counts(normalize=True) * 100
```

Out[157…

```
Recommendation_Helpfulness
No           34.500
Yes          33.125
Sometimes    32.375
Name: proportion, dtype: float64
```

In [158…

```
# Engagement vs Trust
Round_Recommendation = pd.crosstab(
    df['Personalized_Recommendation_Frequency'],
    df['Recommendation_Helpfulness'],
    normalize='index'
) * 100
Round_Recommendation.round()
```

Out[158…

Recommendation_Helpfulness	No	Sometimes	Yes
Personalized_Recommendation_Frequency			
No	34.0	33.0	33.0
Sometimes	32.0	37.0	30.0
Yes	37.0	26.0	36.0

In [159…
```
df.groupby('Personalized_Recommendation_Frequency')['Shopping_Satisfaction'].m
```

Out[159…
```
Personalized_Recommendation_Frequency
No           2.867
Sometimes    2.738
Yes          2.992
Name: Shopping_Satisfaction, dtype: float64
```

In [160…
```
df.groupby('Recommendation_Helpfulness')['Shopping_Satisfaction'].mean().rounc
```

Out[160…
```
Recommendation_Helpfulness
No           2.899
Sometimes    2.799
Yes          2.898
Name: Shopping_Satisfaction, dtype: float64
```

Actionable Insights for Improving eBay's Recommendation System:

The analysis indicates that customer engagement and trust in personalized recommendations are moderate, with many users reporting inconsistent usefulness. To improve effectiveness, eBay should enhance recommendation relevance by leveraging recent browsing behavior, purchase history, and category preferences. Segment-specific recommendation strategies can further improve engagement by tailoring suggestions for frequent buyers, occasional shoppers, and at-risk customers.

Increasing transparency by explaining why products are recommended can help build trust, while integrating review reliability and helpfulness into recommendation ranking can strengthen confidence in suggested items. Additionally, reducing inconsistency through continuous model evaluation and incorporating user feedback mechanisms can improve personalization quality. Prioritizing high-trust recommendations for at-risk customers can further enhance satisfaction and retention.

Overall, a more personalized, transparent, and feedback-driven recommendation system can significantly improve customer engagement and shopping satisfaction on eBay.

😊 Shopping Satisfaction

Average shopping satisfaction is moderate (around 3 on a 5-point scale).

Satisfaction levels are evenly spread, indicating mixed customer experiences.

Satisfaction is influenced by multiple factors, not recommendations alone.

Visual Insights Used

Bar charts for purchase categories and browsing frequency

Pie and bar charts for satisfaction distribution

Heatmaps for correlation analysis

Scatter plots for behavioral clustering and pre-cluster inspection

These visualizations made patterns easy to interpret and supported data-driven conclusions.

Task 5: Visualization and Reporting

- Create attractive visualizations (bar charts, heatmaps, pie charts) for:

- Purchase categories

In [161…
```
df.columns
```

Out[161…
```
Index(['Timestamp', 'age', 'Gender', 'Purchase_Frequency',
       'Purchase_Categories', 'Personalized_Recommendation_Frequency',
       'Browsing_Frequency', 'Product_Search_Method',
       'Search_Result_Exploration', 'Customer_Reviews_Importance',
       'Add_to_Cart_Browsing', 'Cart_Completion_Frequency',
       'Cart_Abandonment_Factors', 'Saveforlater_Frequency', 'Review_Left',
       'Review_Reliability', 'Review_Helpfulness',
       'Recommendation_Helpfulness', 'Rating_Accuracy',
       'Shopping_Satisfaction', 'Service_Appreciation', 'Improvement_Areas',
       'transaction', 'Date', 'Year', 'Month', 'Day', 'Weekday',
       'Personalized_Recommendation_Frequency_Encoded',
       'Purchase_Frequency_Coded', 'Segment', 'Behavior_Cluster',
       'Cluster_Label', 'Cluster', 'Review_Helpfulness_Encoded',
       'Review_Reliability_Encoded'],
      dtype='object')
```

In [162…
```
df['Purchase_Categories'].value_counts()
```

Out[162…

```
Purchase_Categories
[Clothing and Fashion, others]
40
[Clothing and Fashion, Home and Kitchen, others]
36
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion,
Home and Kitchen]            35
[Groceries and Gourmet Food, Home and Kitchen]
34
[Groceries and Gourmet Food, Clothing and Fashion, Home and Kitchen]
33
[Groceries and Gourmet Food, Beauty and Personal Care]
33
[Beauty and Personal Care, Clothing and Fashion, Home and Kitchen]
33
[Beauty and Personal Care, Clothing and Fashion, Home and Kitchen, others]
31
[others]
30
[Groceries and Gourmet Food, Beauty and Personal Care, others]
29
[Beauty and Personal Care, Home and Kitchen, others]
29
[Beauty and Personal Care]
29
[Beauty and Personal Care, others]
29
[Beauty and Personal Care, Clothing and Fashion]
28
[Beauty and Personal Care, Clothing and Fashion, others]
27
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion,
Home and Kitchen, others]    27
[Home and Kitchen]
26
[Home and Kitchen, others]
26
[Groceries and Gourmet Food, Clothing and Fashion]
25
[Beauty and Personal Care, Home and Kitchen]
24
[Groceries and Gourmet Food, Clothing and Fashion, others]
23
[Groceries and Gourmet Food, Clothing and Fashion, Home and Kitchen, others]
23
[Clothing and Fashion, Home and Kitchen]
23
[Clothing and Fashion]
23
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion]
23
[Groceries and Gourmet Food, Beauty and Personal Care, Home and Kitchen]
21
[Groceries and Gourmet Food, Beauty and Personal Care, Clothing and Fashion,
```

```
others]                       20
[Groceries and Gourmet Food]
20
[Groceries and Gourmet Food, Home and Kitchen, others]
20
Name: count, dtype: int64
```

In [163…

```
type(df['Purchase_Categories'].dropna().iloc[0])
```

Out[163…

```
list
```

In [164…

```
categories = (
    df['Purchase_Categories']
    .dropna()
    .explode()
    .astype(str)
    .str.strip()
)
```

In [165…

```
categories = (
    df['Purchase_Categories']
    .dropna()
    .apply(lambda x: x if isinstance(x, list) else str(x).split(','))
    .explode()
    .str.strip()
)
```

In [166…

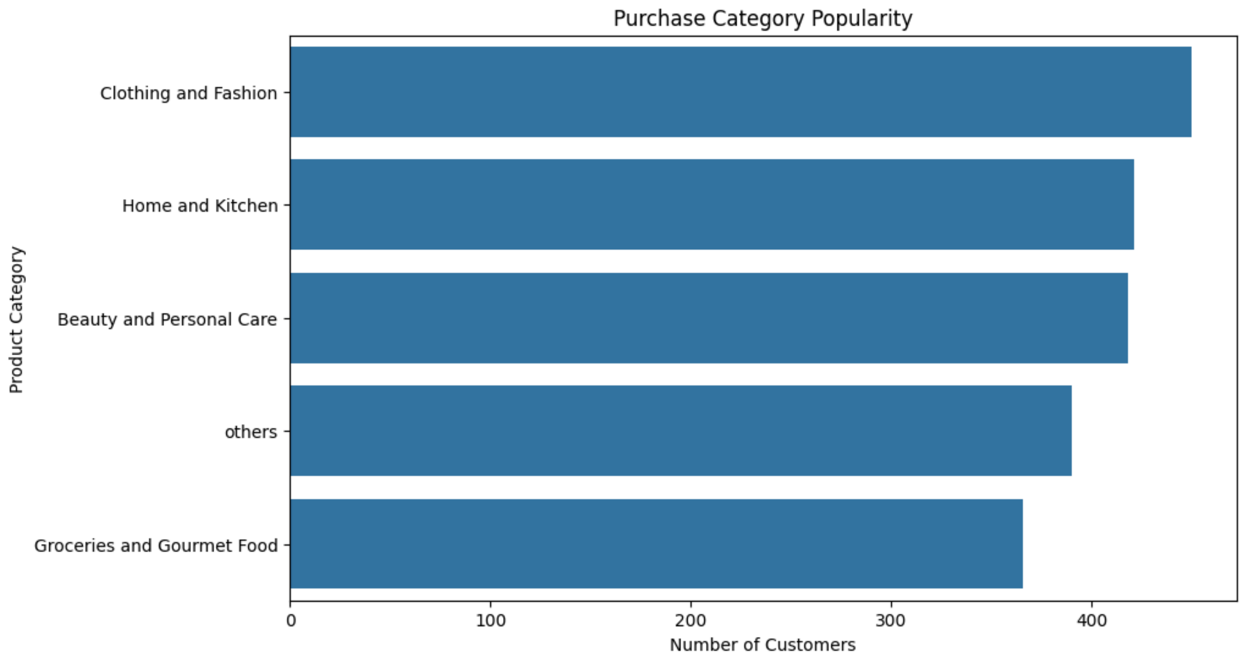
```
categories.value_counts()
```

Out[166…

```
Purchase_Categories
Clothing and Fashion          450
Home and Kitchen              421
Beauty and Personal Care      418
others                        390
Groceries and Gourmet Food    366
Name: count, dtype: int64
```

In [167…

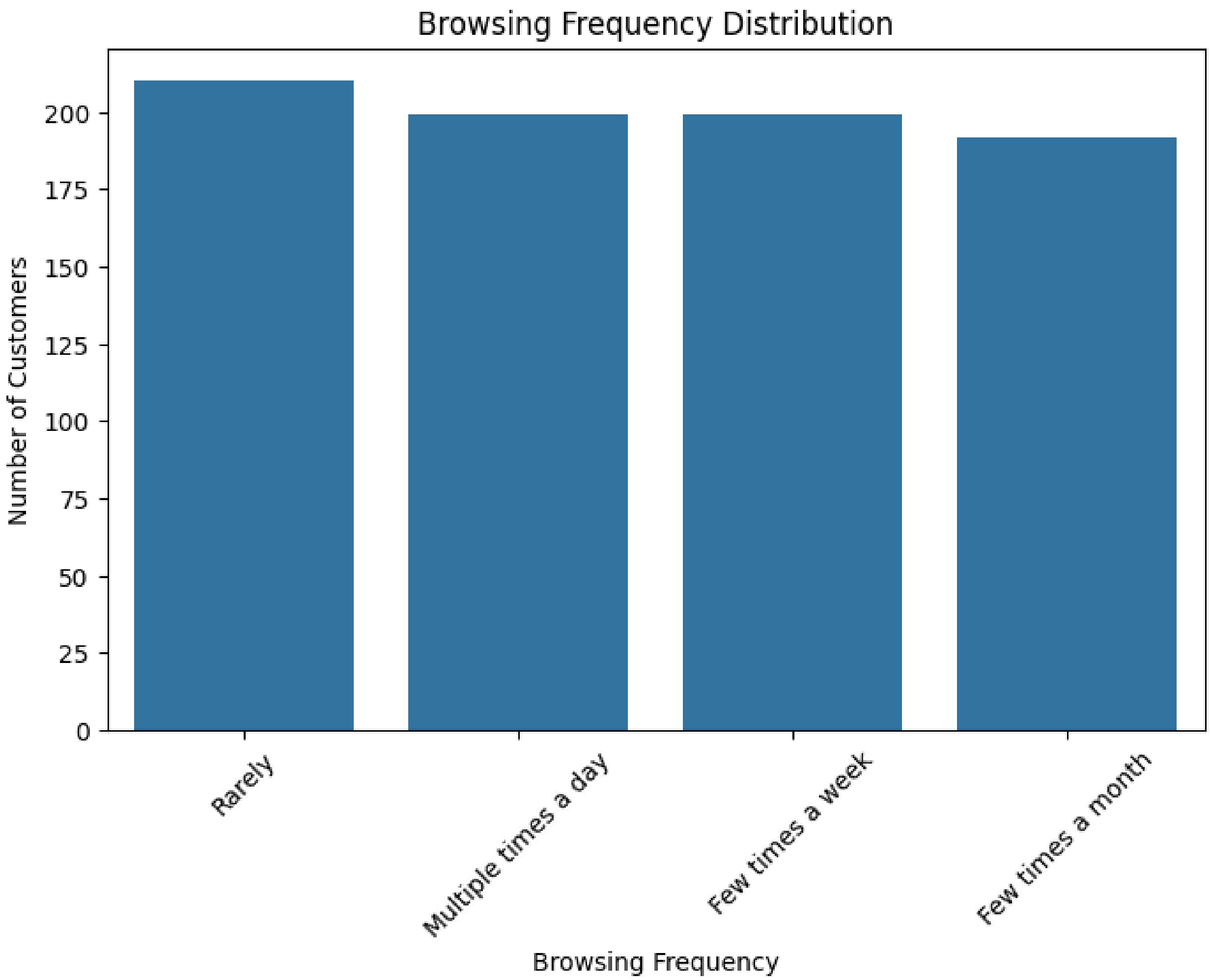
```
plt.figure(figsize=(10,6))
sns.countplot(
    y=categories,
    order=categories.value_counts().index
)
plt.title("Purchase Category Popularity")
plt.xlabel("Number of Customers")
plt.ylabel("Product Category")
plt.show()
```



- Browsing Frequency Distribution (Bar Chart)

In [168…

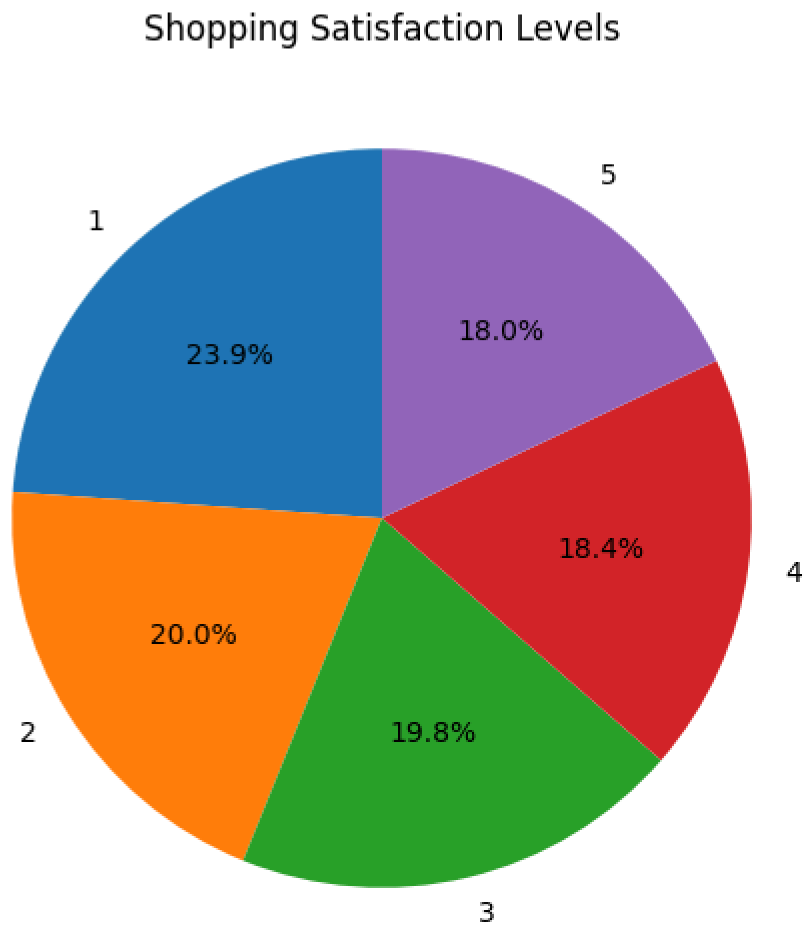
```
plt.figure(figsize=(8,5))
sns.countplot(
    data=df,
    x='Browsing_Frequency',
    order=df['Browsing_Frequency'].value_counts().index
)
plt.title("Browsing Frequency Distribution")
plt.xlabel("Browsing Frequency")
plt.ylabel("Number of Customers")
plt.xticks(rotation=45)
plt.show()
```



- Satisfaction Levels (Pie Chart + Bar Chart)

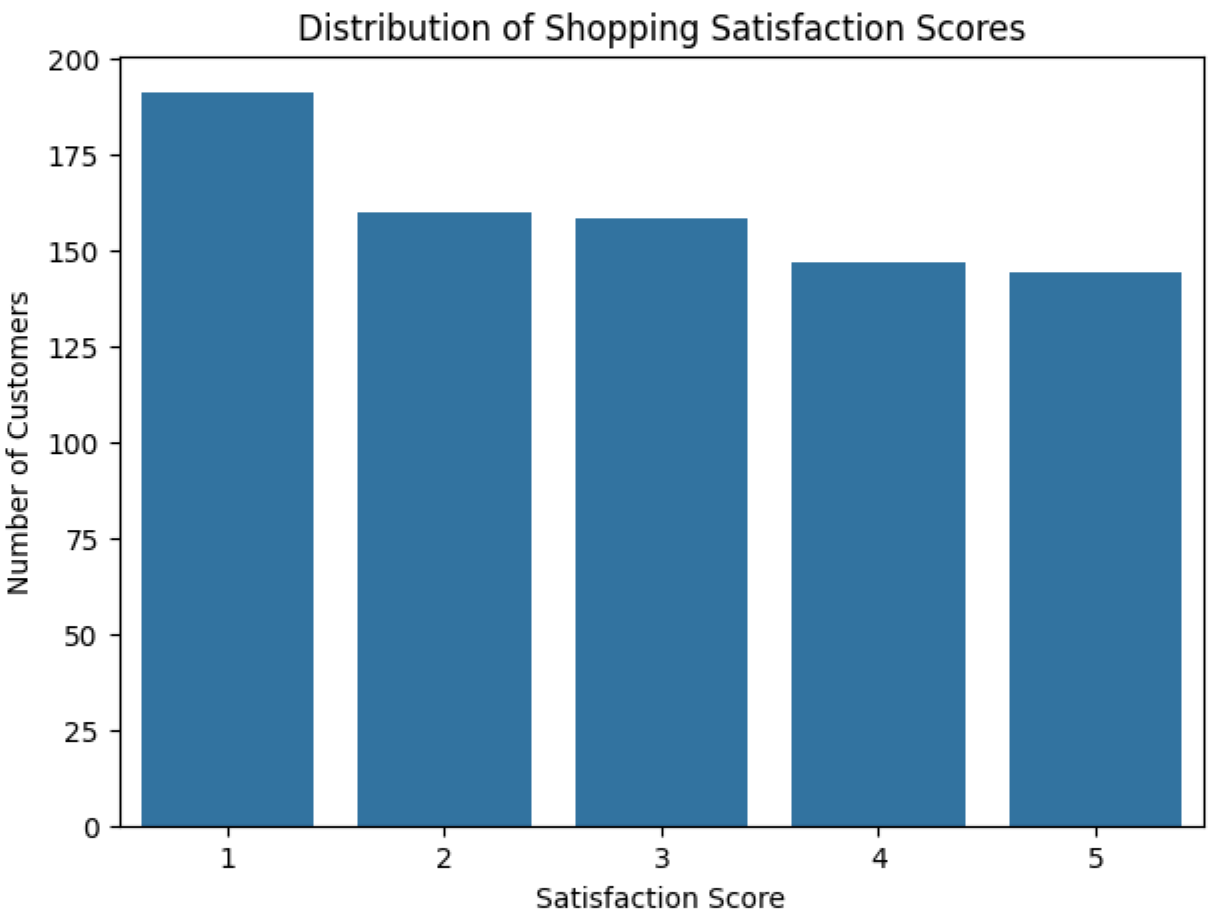
In [169…

```
satisfaction_counts = df['Shopping_Satisfaction'].value_counts().sort_index()

plt.figure(figsize=(6,6))
plt.pie(
    satisfaction_counts,
    labels=satisfaction_counts.index,
    autopct='%1.1f%%',
    startangle=90
)
plt.title("Shopping Satisfaction Levels")
plt.show()
```



In [170…

```
plt.figure(figsize=(7,5))
sns.countplot(
    data=df,
    x='Shopping_Satisfaction',
    order=sorted(df['Shopping_Satisfaction'].unique())
)
plt.title("Distribution of Shopping Satisfaction Scores")
plt.xlabel("Satisfaction Score")
plt.ylabel("Number of Customers")
plt.show()
```



- Correlation Between Recommendation Usefulness & Satisfaction (Heatmap)

In [171…
```
df['Recommendation_Helpfulness'].value_counts()
```

Out[171…
```
Recommendation_Helpfulness
No           276
Yes          265
Sometimes    259
Name: count, dtype: int64
```

In [172…
```
# Encoding the Data
helpfulness_map = {
    'No': 0,
    'Sometimes': 1,
    'Yes': 2
}

df['Recommendation_Helpfulness_Encoded'] = df['Recommendation_Helpfulness'].ma
```

In [173…
```
corr_data = df[
    ['Recommendation_Helpfulness_Encoded', 'Shopping_Satisfaction']
].corr(method='spearman')
```

In [174…

```
plt.figure(figsize=(5,4))
sns.heatmap(
    corr_data,
    annot=True,
    cmap='Blues',
    fmt='.2f'
)
plt.title("Correlation Between Recommendation Helpfulness & Satisfaction")
plt.show()
```

📌 Actionable Recommendations for eBay

Improve Recommendation Relevance

Leverage browsing history, recent purchases, and category preferences.

Segment-Based Personalization

Tailor recommendations for frequent, occasional, and at-risk customers.

Increase Transparency

Explain why products are recommended to build trust.

Leverage Review Reliability

Prioritize products with trustworthy and verified reviews.

Reduce Inconsistency

Improve recommendation consistency to convert “Sometimes” users into “Yes”.

Use Feedback Loops

Allow users to provide quick feedback on recommendations.

📌 Conclusion

The analysis reveals that while personalized recommendations contribute positively to customer experience, their current impact is limited by inconsistent relevance and moderate trust. Improving recommendation quality, transparency, and review credibility—combined with segment-specific strategies—can significantly enhance customer engagement, satisfaction, and retention on the platform.