

Customer Shopping Behavior Analysis for Retail Optimization

Project Overview

This project analyzes a retail company's consumer shopping data to uncover patterns in customer behavior, trends across demographics, product categories, and shipping channels. The insights aim to improve sales, increase customer satisfaction, and enhance long-term loyalty.

Business Problem

The company wants to understand which factors influence customer decisions and repeat purchases, including discounts, reviews, seasons, payment preferences, and shipping channels.

Key question:

"How can the company leverage consumer shopping data to identify trends, improve customer engagement, and optimize marketing and product strategies?"

```
In [1]: # Step 1: Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from scipy import stats
warnings.filterwarnings('ignore')

# Set display options
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 100)

# Set visualization style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (12, 6)
pd.set_option('display.max_columns', None)

# Load Dataset
df = pd.read_csv('customer_shopping_behavior.csv')
```

```
In [2]: #Initial Exploration
print(df.info())
print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3900 entries, 0 to 3899
Data columns (total 18 columns):
 #   Column           Non-Null Count  Dtype  
 --- 
 0   Customer ID      3900 non-null   int64  
 1   Age              3900 non-null   int64  
 2   Gender           3900 non-null   object  
 3   Item Purchased   3900 non-null   object  
 4   Category         3900 non-null   object  
 5   Purchase Amount (USD) 3900 non-null   int64  
 6   Location          3900 non-null   object  
 7   Size              3900 non-null   object  
 8   Color              3900 non-null   object  
 9   Season             3900 non-null   object  
 10  Review Rating    3863 non-null   float64 
 11  Subscription Status 3900 non-null   object  
 12  Shipping Type    3900 non-null   object  
 13  Discount Applied 3900 non-null   object  
 14  Promo Code Used  3900 non-null   object  
 15  Previous Purchases 3900 non-null   int64  
 16  Payment Method    3900 non-null   object  
 17  Frequency of Purchases 3900 non-null   object  
dtypes: float64(1), int64(4), object(13)
memory usage: 548.6+ KB
None
```

	Customer ID	Age	Purchase Amount (USD)	Review Rating	\
count	3900.000000	3900.000000	3900.000000	3863.000000	
mean	1950.500000	44.068462	59.764359	3.750065	
std	1125.977353	15.207589	23.685392	0.716983	
min	1.000000	18.000000	20.000000	2.500000	
25%	975.750000	31.000000	39.000000	3.100000	
50%	1950.500000	44.000000	60.000000	3.800000	
75%	2925.250000	57.000000	81.000000	4.400000	
max	3900.000000	70.000000	100.000000	5.000000	

	Previous Purchases
count	3900.000000
mean	25.351538
std	14.447125
min	1.000000
25%	13.000000
50%	25.000000
75%	38.000000
max	50.000000

```
In [3]: print(df.head())
```

```

Customer ID  Age  Gender  Item Purchased  Category  Purchase Amount (USD) \
0            1    55   Male     Blouse  Clothing        53
1            2    19   Male    Sweater  Clothing        64
2            3    50   Male      Jeans  Clothing        73
3            4    21   Male    Sandals  Footwear       90
4            5    45   Male     Blouse  Clothing        49

Location Size  Color  Season  Review Rating Subscription Status \
0  Kentucky    L     Gray  Winter    3.1      Yes
1  Maine       L     Maroon Winter    3.1      Yes
2 Massachusetts S     Maroon Spring   3.1      Yes
3 Rhode Island M     Maroon Spring   3.5      Yes
4 Oregon       M  Turquoise Spring   2.7      Yes

Shipping Type Discount Applied Promo Code Used Previous Purchases \
0  Express           Yes           Yes          14
1  Express           Yes           Yes           2
2 Free Shipping     Yes           Yes          23
3 Next Day Air     Yes           Yes          49
4 Free Shipping     Yes           Yes          31

Payment Method Frequency of Purchases
0  Venmo           Fortnightly
1  Cash            Fortnightly
2 Credit Card     Weekly
3 PayPal          Weekly
4 PayPal          Annually

```

```
In [4]: # Renaming columns according to snake casing for better readability and document
df.columns = df.columns.str.replace(' ', '_')
```

```
In [5]: #Check columns
print(df.columns)
```

```
Index(['Customer_ID', 'Age', 'Gender', 'Item_Purchased', 'Category',
       'Purchase_Amount_(USD)', 'Location', 'Size', 'Color', 'Season',
       'Review_Rating', 'Subscription_Status', 'Shipping_Type',
       'Discount_Applied', 'Promo_Code_Used', 'Previous_Purchases',
       'Payment_Method', 'Frequency_of_Purchases'],
      dtype='object')
```

```
In [6]: df = df.rename(columns={'purchase_amount_(usd)': 'purchase_amount'})
```

```
In [7]: df = df.rename(columns={'purchase_amount': 'Purchase_Amount'})
```

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

```
Out[8]: Index(['Customer_ID', 'Age', 'Gender', 'Item_Purchased', 'Category',
       'Purchase_Amount_(USD)', 'Location', 'Size', 'Color', 'Season',
       'Review_Rating', 'Subscription_Status', 'Shipping_Type',
       'Discount_Applied', 'Promo_Code_Used', 'Previous_Purchases',
       'Payment_Method', 'Frequency_of_Purchases'],
      dtype='object')
```

```
In [12]: #Step 2: Data Cleaning & Preprocessing
```

```
#Data Quality Check
print("\nData Quality Check")
print("=*70")
```

```

#Check missing values
print("\nMissing Values")
missing = df.isnull().sum()
missing_pct = (missing / len(df) * 100).round(2)
missing_df = pd.DataFrame({'Missing Count': missing, 'Percentage': missing_pct})
print(missing_df[missing_df['Missing Count'] >0])

#Handle missing values Review Rating col (fill with median)
if df['Review_Rating'].isnull().sum() > 0:
    median_rating = df['Review_Rating'].median()
    df['Review_Rating'].fillna(median_rating, inplace=True)
    print(f"\nFilled {missing['Review_Rating']} missing Review Ratings with median: {median_rating}")

#Check duplicates
duplicates = df.duplicated().sum()
print(f"\nDuplicate Rows: {duplicates}")
if duplicates > 0:
    df.drop_duplicates(inplace=True)
    print(f"Removed {duplicates} duplicate rows")

#Clean column names (remove spaces)
df.rename(columns={'Purchase_Amount_(USD)': 'Purchase_Amount'}, inplace=True)

```

Data Quality Check

Missing Values

	Missing Count	Percentage
Review_Rating	37	0.95

Filled 37 missing Review Ratings with median: 3.8

Duplicate Rows: 0

In [13]: df.columns

Out[13]: Index(['Customer_ID', 'Age', 'Gender', 'Item_Purchased', 'Category',
 'Purchase_Amount', 'Location', 'Size', 'Color', 'Season',
 'Review_Rating', 'Subscription_Status', 'Shipping_Type',
 'Discount_Applied', 'Promo_Code_Used', 'Previous_Purchases',
 'Payment_Method', 'Frequency_of_Purchases'],
 dtype='object')

In [18]:

```

# =====
# Step 3: Feature Engineering (process of modifying features)
# =====

print("\n" + "="*70)
print("FEATURE ENGINEERING")
print("=*70")

# 1. Customer Lifetime Value metrics
customer_metrics = df.groupby('Customer_ID').agg({
    'Purchase_Amount': ['sum', 'mean', 'count'],
    'Review_Rating': 'mean'
}).round(2)

customer_metrics.columns = ['Total_Spending', 'Avg_Purchase', 'Purchase_Count',
customer_metrics.reset_index(inplace=True)

```

```

# Remove old columns if they exist to prevent _x/_y duplicates
cols_to_drop = ['Total_Spending', 'Avg_Purchase', 'Purchase_Count', 'Avg_Rating']
df = df.drop(columns=[col for col in cols_to_drop if col in df.columns])

# Merge only the necessary new columns
df = df.merge(customer_metrics, on='Customer_ID', how='left')

# 2. Customer Segmentation based on spending
spending_quartiles = df['Total_Spending'].quantile([0.25, 0.5, 0.75])
df['Customer_Segment'] = pd.cut(df['Total_Spending'],
                                 bins=[0, spending_quartiles[0.25], spending_quartiles[0.5],
                                       spending_quartiles[0.75], df['Total_Spendi
                                       labels=['Low Value', 'Medium Value', 'High Value
                                       include_lowest=True)

# 3. Age Groups
df['Age_Group'] = pd.cut(df['Age'], bins=[0, 25, 35, 45, 55, 100],
                           labels=['18-25', '26-35', '36-45', '46-55', '55+'],
                           include_lowest=True)

# 4. Discount Effectiveness
df['Discount_Flag'] = df['Discount_Applied'].apply(lambda x: 1 if str(x).strip()
df['Effective_Price'] = df['Purchase_Amount']

# 5. High Spender Flag
median_purchase = df['Purchase_Amount'].median()
df['High_Spender'] = (df['Purchase_Amount'] > median_purchase).astype(int)

# 6. Purchase Frequency in days
frequency_mapping = {
    'Fortnightly': 14,
    'Weekly': 7,
    'Monthly': 30,
    'Quarterly': 90,
    'Bi-Weekly': 14,
    'Annually': 365,
    'Every 3 Months': 90
}

df['Purchase_Frequency_Days'] = df['Frequency_of_Purchases'].map(frequency_mappi

# Optional: rename columns to remove _x if any appear (extra safeguard)
df = df.rename(columns=lambda x: x.rstrip('_x'))

print("\nNew Features Created:")
print("- Total_Spending, Avg_Purchase, Purchase_Count, Avg_Rating (per customer")
print("- Customer_Segment (Low/Medium/High/Premium Value)")
print("- Age_Group (18-25, 26-35, etc.)")
print("- Discount_Flag (1 = Discount Applied, 0 = No Discount")
print("- Effective_Price (kept same or adjusted if discount amount known")
print("- High_Spender flag")
print("- Purchase_Frequency_Days")

```

```
=====
```

FEATURE ENGINEERING

```
=====
```

New Features Created:

- Total_Spending, Avg_Purchase, Purchase_Count, Avg_Rating (per customer)
- Customer_Segment (Low/Medium/High/Premium Value)
- Age_Group (18-25, 26-35, etc.)
- Discount_Flag (1 = Discount Applied, 0 = No Discount)
- Effective_Price (kept same or adjusted if discount amount known)
- High_Spender flag
- Purchase_Frequency_Days

In [19]: *#Step 4: Exploratory Data Analysis (EDA)*

```
print("\n" + "="*70)
print("DESCRIPTIVE STATISTICS")
print("="*70)

# Numerical summary
print("\nNumerical Variables Summary:")
print(df[['Age', 'Purchase_Amount', 'Review_Rating', 'Discount_Applied',
          'Previous_Purchases']].describe().round(2))

# Categorical summary
print("\nCategorical Variables - Value Counts:")
categorical_cols = ['Gender', 'Category', 'Season', 'Subscription_Status',
                     'Payment_Method', 'Frequency_of_Purchases']

for col in categorical_cols:
    print(f"\n{col}:")
    print(df[col].value_counts().head())
```

=====

DESCRIPTIVE STATISTICS

=====

Numerical Variables Summary:

	Age	Purchase_Amount	Review_Rating	Previous_Purchases
count	3900.00	3900.00	3900.00	3900.00
mean	44.07	59.76	3.75	25.35
std	15.21	23.69	0.71	14.45
min	18.00	20.00	2.50	1.00
25%	31.00	39.00	3.10	13.00
50%	44.00	60.00	3.80	25.00
75%	57.00	81.00	4.40	38.00
max	70.00	100.00	5.00	50.00

Categorical Variables - Value Counts:

Gender:

Gender	
Male	2652
Female	1248
Name: count, dtype: int64	

Category:

Category	
Clothing	1737
Accessories	1240
Footwear	599
Outerwear	324

Name: count, dtype: int64

Season:

Season	
Spring	999
Fall	975
Winter	971
Summer	955

Name: count, dtype: int64

Subscription_Status:

Subscription_Status	
No	2847
Yes	1053
Name: count, dtype: int64	

Payment_Method:

Payment_Method	
PayPal	677
Credit Card	671
Cash	670
Debit Card	636
Venmo	634

Name: count, dtype: int64

Frequency_of_Purchases:

Frequency_of_Purchases	
Every 3 Months	584
Annually	572
Quarterly	563
Monthly	553

```
Bi-Weekly      547  
Name: count, dtype: int64
```

```
In [20]: # Save processed dataset  
df.to_csv('customer_shopping_analysis_latest.csv', index=False)  
print("\n✓ Processed dataset saved: customer_shopping_analysis_complete.csv")  
✓ Processed dataset saved: customer_shopping_analysis_complete.csv
```