

Customer Shopping Behavior Analysis

1. Project Overview

This project analyzes customer shopping behavior using transactional data from 3,900 purchases across various product categories. The goal is to uncover insights into spending patterns, customer segments, product preferences, and subscription behavior to guide strategic business decisions.

2. Dataset Summary

- Rows: 3,900
- Columns: 18
- Key Features:
 - Customer demographics (Age, Gender, Location, Subscription Status)
 - Purchase details (Item Purchased, Category, Purchase Amount, Season, Size, Color)
 - Shopping behavior (Discount Applied, Promo Code Used, Previous Purchases, Frequency of Purchases, Review Rating, Shipping Type)
- Missing Data: 37 values in Review Rating column

3. Exploratory Data Analysis using Python

We began with data preparation and cleaning in Python:

- **Data Loading:** Imported the dataset using `pandas`.
- **Initial Exploration:** Used `df.info()` to check structure and `.describe()` for summary statistics.

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)	Location	Size
count	3900.000000	3900.000000	3900	3900	3900	3900.000000	3900	3900
unique	NaN	NaN	2	25	4	NaN	50	4
top	NaN	NaN	Male	Blouse	Clothing	NaN	Montana	M
freq	NaN	NaN	2652	171	1737	NaN	96	1755
mean	1950.500000	44.068462	NaN	NaN	NaN	59.764359	NaN	NaN
std	1125.977353	15.207589	NaN	NaN	NaN	23.685392	NaN	NaN
min	1.000000	18.000000	NaN	NaN	NaN	20.000000	NaN	NaN
25%	975.750000	31.000000	NaN	NaN	NaN	39.000000	NaN	NaN
50%	1950.500000	44.000000	NaN	NaN	NaN	60.000000	NaN	NaN
75%	2925.250000	57.000000	NaN	NaN	NaN	81.000000	NaN	NaN
max	3900.000000	70.000000	NaN	NaN	NaN	100.000000	NaN	NaN

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

- **Missing Data Handling:** Checked for null values and imputed missing values in the `Review Rating` column using the median rating of each product category.
- **Column Standardization:** Renamed columns to **snake case** for better readability and documentation.
- **Feature Engineering:**
 - Created **age_group** column by binning customer ages.
 - Created **purchase_frequency_days** column from purchase data.
- **Data Consistency Check:** Verified if `discount_applied` and `promo_code_used` were redundant; dropped `promo_code_used`.
- **Database Integration:** Connected Python script to MySQL Workbench and loaded the cleaned DataFrame into the database for SQL analysis.

4. Data Analysis using SQL (Business Transactions)

We performed structured analysis in MySQL Workbench to answer key business questions:

1. **Revenue by Gender** – Compared total revenue generated by male vs. female customers.

gender	revenue
Male	157890
Female	75191

2. **High-Spending Discount Users** – Identified customers who used discounts but still spent above the average purchase amount. Total rows: 839

customer_id	purchase_amount
2	64
3	73
4	90
7	85
9	97
12	68
13	72
16	81
20	90
22	62
24	88
29	94
32	79
33	67
35	91
37	69

3. **Top 5 Products by Rating** – Found products with the highest average review ratings.

item_purchased	average product rati...
Gloves	3.8614285714285725
Sandals	3.8443750000000003
Boots	3.8187500000000005
Hat	3.8012987012987005
Skirt	3.784810126582278

4. **Shipping Type Comparison** – Compared average purchase amounts between Standard and Express shipping.

shipping_type	average purchase amount
Express	60.48
Standard	58.46

5. **Subscribers vs. Non-Subscribers** – Compared average spend and total revenue across subscription status.

subscription_status	total_customers	avg_spend	total_revenue
Yes	1053	59.49	62645
No	2847	59.87	170436

6. **Discount-Dependent Products** – Identified 5 products with the highest percentage of discounted purchases.

item_purchased	discount_rate
Hat	50.00
Sneakers	49.66
Coat	49.07
Sweater	48.17
Pants	47.37

7. **Customer Segmentation** – Classified customers into New, Returning, and Loyal segments based on purchase history.

type	Number of Customer
loyal	3116
Returning	701
New	83

8. **Top 3 Products per Category** – Listed the most purchased products within each category.

item_rank	category	item_purchased	total_orders
1	Accessories	Jewelry	171
2	Accessories	Belt	161
3	Accessories	Sunglasses	161
1	Clothing	Pants	171
2	Clothing	Blouse	171
3	Clothing	Shirt	169
1	Footwear	Sandals	160
2	Footwear	Shoes	150
3	Footwear	Sneakers	145
1	Outerwear	Jacket	163
2	Outerwear	Coat	161

9. **Repeat Buyers & Subscriptions** – Checked whether customers with >5 purchases are more likely to subscribe.

subscription_status	repeat_buyers
Yes	980
No	2583

10. **Revenue by Age Group** – Calculated total revenue contribution of each age group.

age_group	total_revenue
Senior	55763
Adult	55978
Middle-age	59197
young Adult	62143

5. Dashboard in Power BI

Finally, we built an interactive dashboard in **Power BI** to present insights visually.



6. Business Recommendations

- **Boost Subscriptions** – Promote exclusive benefits for subscribers.

- **Customer Loyalty Programs** – Reward repeat buyers to move them into the “Loyal” segment.
- **Review Discount Policy** – Balance sales boosts with margin control.
- **Product Positioning** – Highlight top-rated and best-selling products in campaigns.
- **Targeted Marketing** – Focus efforts on high-revenue age groups and express-shipping users.