Comprehensive Data Analysis on Sale Data

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Dashboard

For seeing all the code live interactively,

Visit Dashboard

https://ayusheda-assign.streamlit.app/

Contents

1. Introduction

In this document, I will formulate how i did analysis on the data.
The data contains information about the orders, customers, products, and sales.
The goal of this analysis is to provide insights into customer behavior, sales trends, SKU performance, and other key metrics.
The analysis will be performed using Python and various data analysis libraries such as pandas, NumPy, and Matplotlib. The analysis will cover the following key areas:

- Customer behavior analysis
- Sales trends analysis
- SKU performance analysis
- Order analysis
- Cohort analysis
- Geographic analysis
- Time-based analysis
- Customer lifetime value (CLV) analysis
- Basket analysis
- Price sensitivity analysis
- And more...

Data Preparation and Overview

Loading and Inspecting the Dataset

- Load the dataset and check its structure.

	Unnamed: 0	user_id	order_date	order_id	sku_id	warehouse_name	quantity	placed_gmv
0	0	0868733	2022-09-16	262052	2567941	USA	1.0	331.60
1	1	0868733	2022-09-16	262052	434572f	USA	1.0	416.52
2	2	0868733	2022-09-16	262052	8ae8fa4	USA	2.0	45.00
3	3	0868733	2022-09-16	262052	c9932dc	USA	3.0	67.50
4	4	0868733	2022-09-16	262052	35c7c3b	USA	1.0	340.71

- Inspect data for missing values, duplicates, and correct data types. - Their are no missing values and duplicates in the dataset.

```
missing_values = df.isnull().sum()
print("Missing values in each column:\n", missing_values)
```

✓ 0.0s

```
Missing values in each column:
 Unnamed: 0        0
user_id          0
order_date       0
order_id         0
sku_id           0
warehouse_name   0
quantity         0
placed_gmv       0
dtype: int64
```

Statistical Summary

```
summary_stats = df.describe()
summary_stats
```

✓ 0.0s

	Unnamed: 0	order_id	quantity	placed_gmv
count	130000.000000	1.300000e+05	130000.000000	130000.000000
mean	64999.500000	6.822964e+05	1.591008	1336.445672
std	37527.911835	3.202138e+05	1.854480	2735.577056
min	0.000000	2.387230e+05	1.000000	4.200000
25%	32499.750000	3.236010e+05	1.000000	371.500000
50%	64999.500000	8.655470e+05	1.000000	591.900000
75%	97499.250000	9.787400e+05	2.000000	1310.490000
max	129999.000000	1.064487e+06	137.000000	216814.080000

Answer

One thing we can observe from summary is that Quantity and Placed GMV are skewed and have outliers.
As 75 percentile is 2 and 50 percentile is 1 for Quantity and 75 percentile is 1310.49 and 50 percentile is 591.90
for Placed GMV.
Whereas their Max values are 137 and 216814 which is much higher than 75 percentile.

Date Formatting

This step is essential because the date column is in string format. We need to convert it to a datetime format for further analysis.

```
df['order_date'] = pd.to_datetime(df['order_date'], errors='coerce')

print(df.dtypes)

✓ 0.0s

Unnamed: 0                    int64
user_id                      object
order_date           datetime64[ns]
order_id                      int64
sku_id                       object
warehouse_name               object
quantity                    float64
placed_gmv                  float64
dtype: object
```

Customer Behavior Analysis

Customer Purchase Frequency

Let's look at the distribution of frequency by which customers are placing orders .

```
purchase_frequency['order_count'].describe()
✓ 0.0s

count    3660.000000
mean       35.519126
std        52.486606
min         1.000000
25%         7.000000
50%        17.000000
75%        43.000000
max       833.000000
Name: order_count, dtype: float64
```

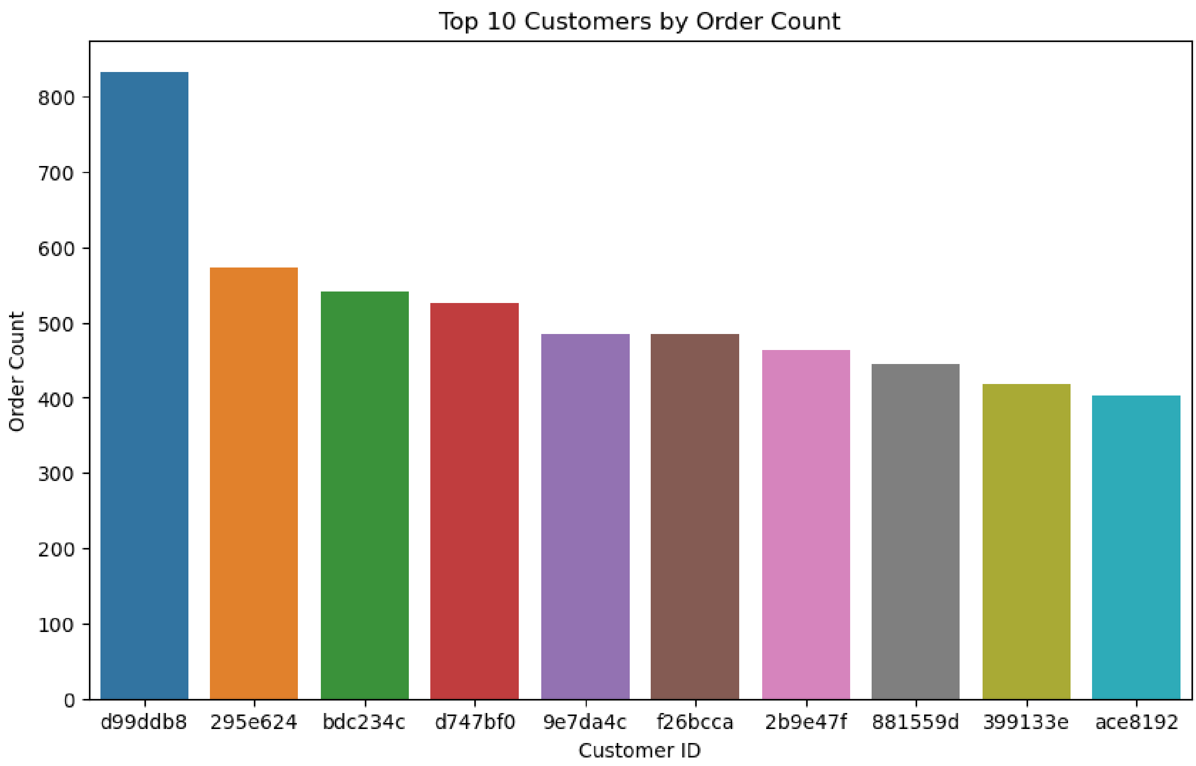
Insights

Insights:

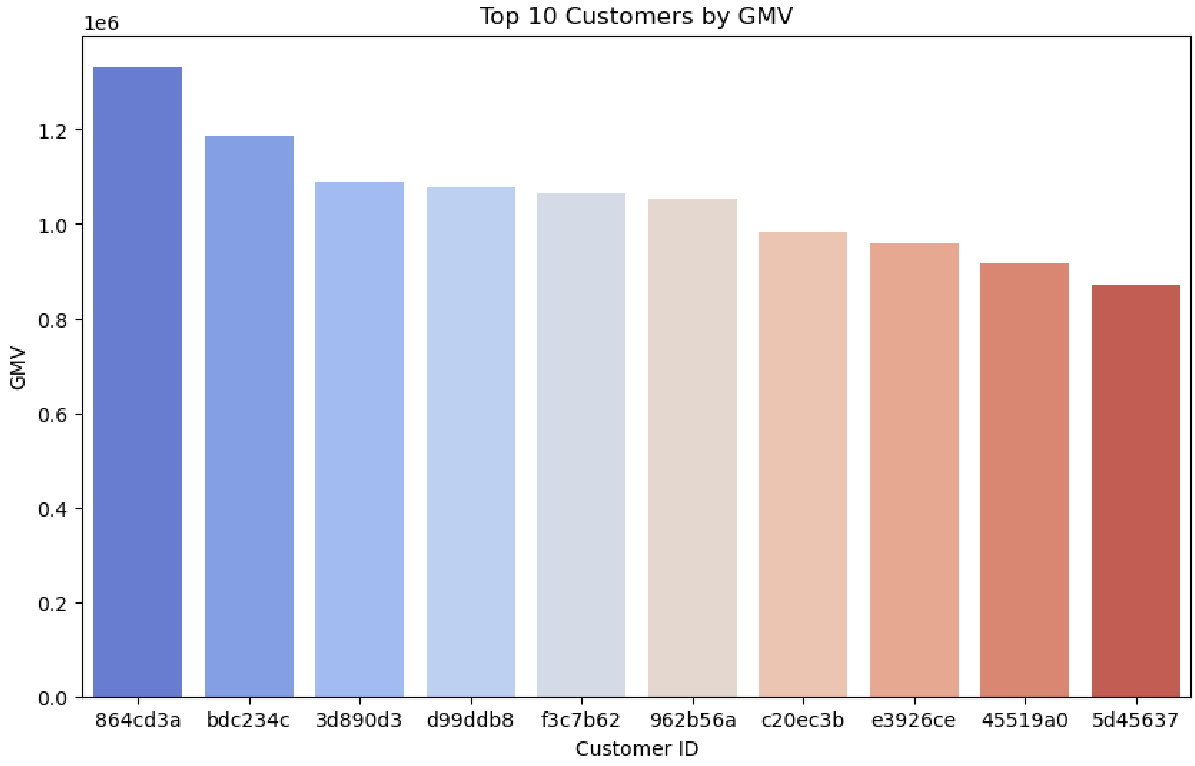
- More than 50% of customers have placed orders less than 17 times which is almost half than means
. meaning few people are buying a lot.
- And 75% of customers have placed orders less than 43 times.
- Just **293 people** out of 130000 have placed orders more than 100 times.

Top Customers

- Based on Order frequency, I am identifying the top customers.



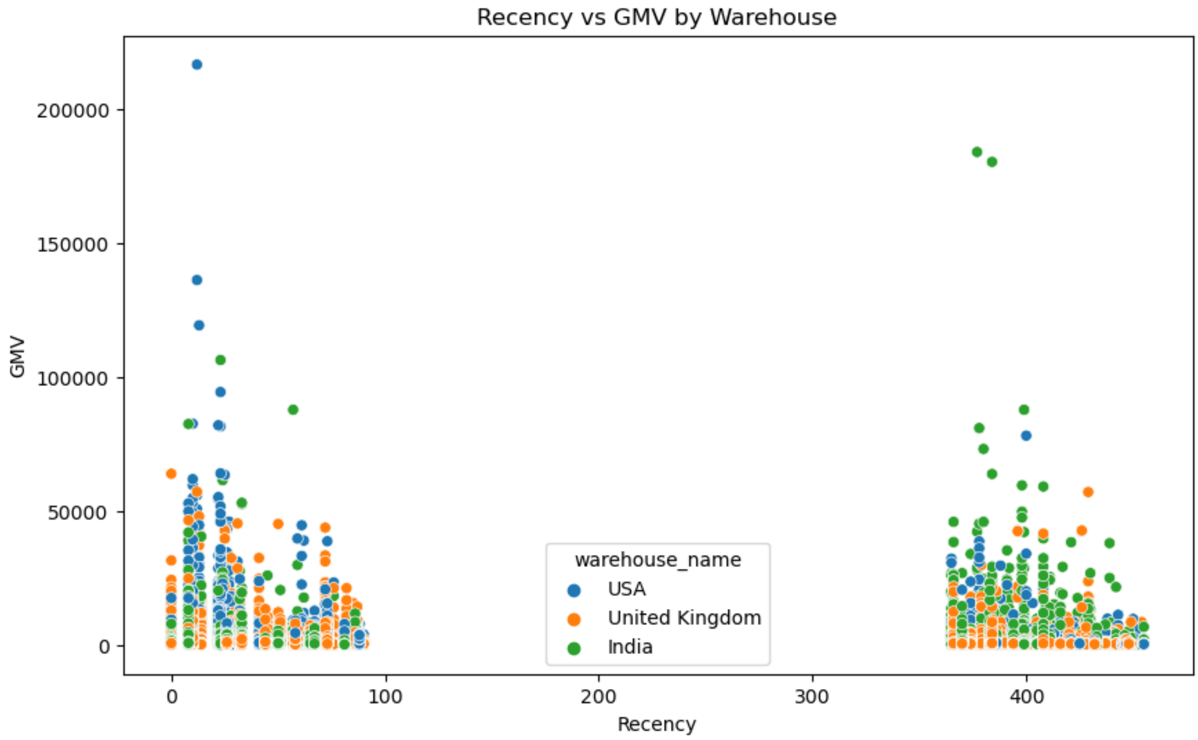
- Based on GMV, I am identifying the top customers.



RFM Analysis

RFM analysis is a powerful way to segment customers based on their behavior.

- Recency: When the customer last made a purchase. Here i am calculating the recency of the customers.

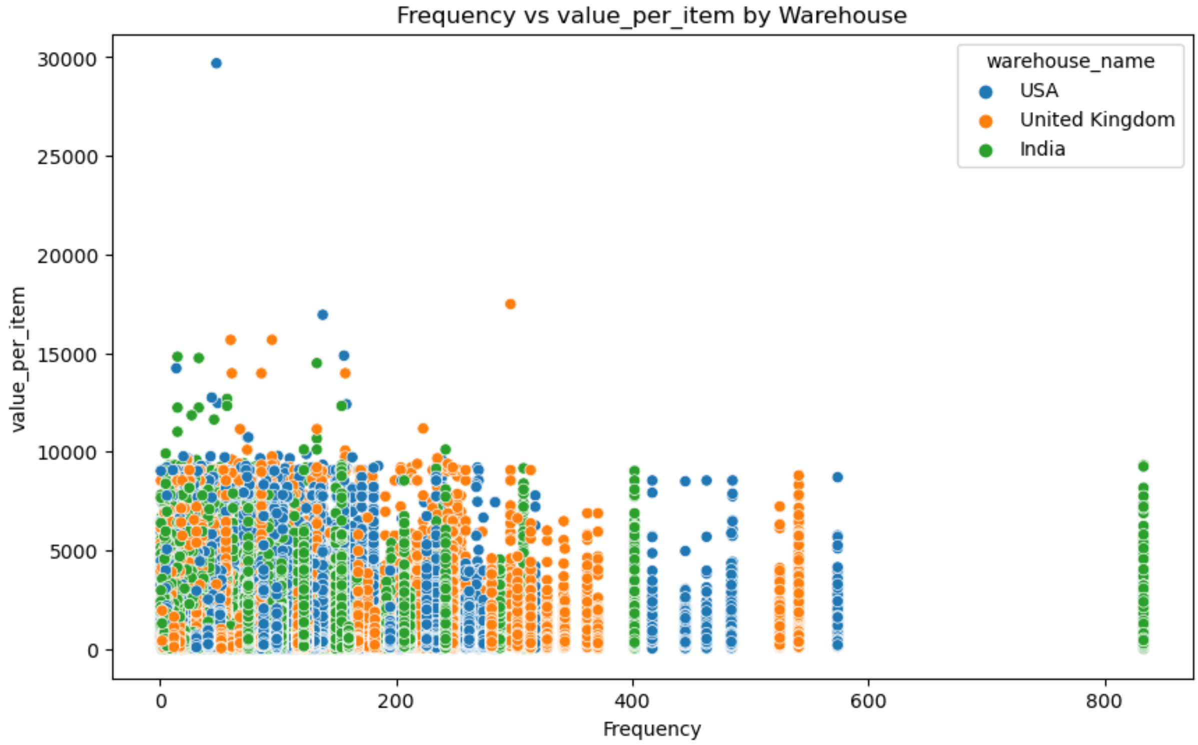


Insights

From the above graph, There are two types of custumers:-

* One who are frequent buyers and have bought recently less than 100 days.
* One who are seasonal buyers and have come to buy only after a year.

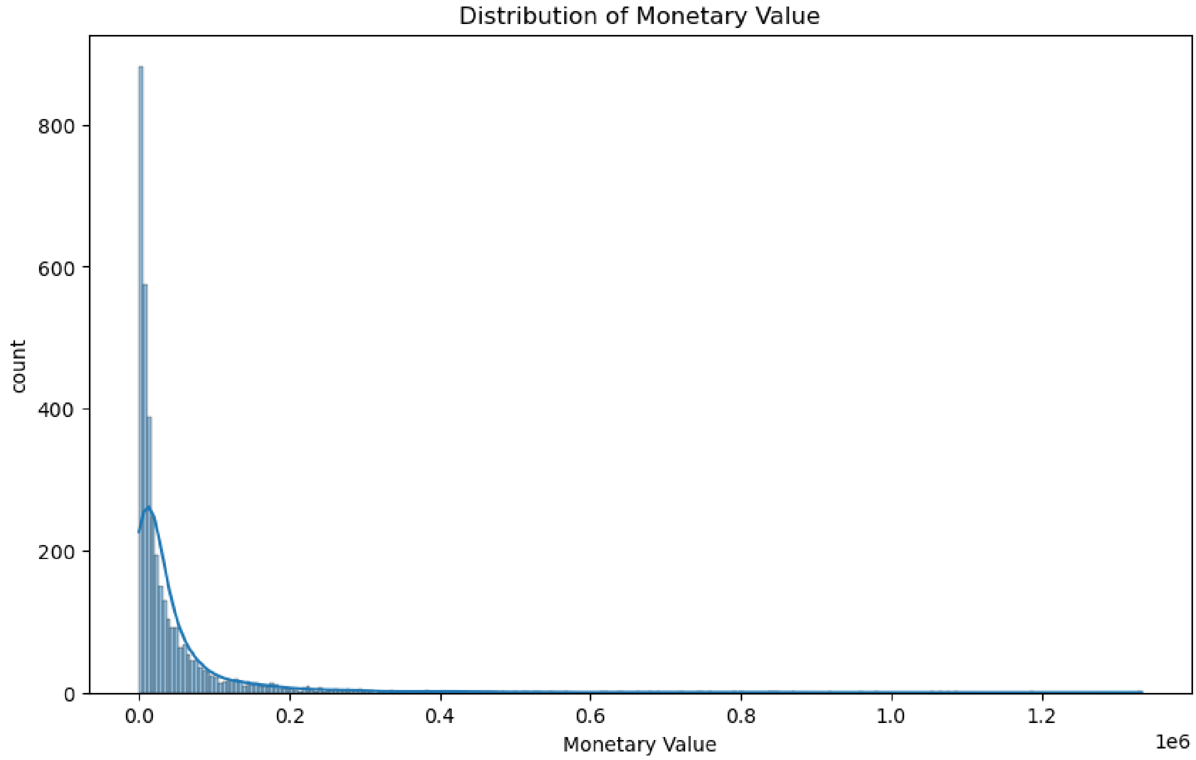
– Frequency: How often the customer made purchases. Here i am calculating the how frequent customers have come to place orders.



Insights

From the above graph, One observations is that low frequent buyers have more value_per_item than high frequent buyers.

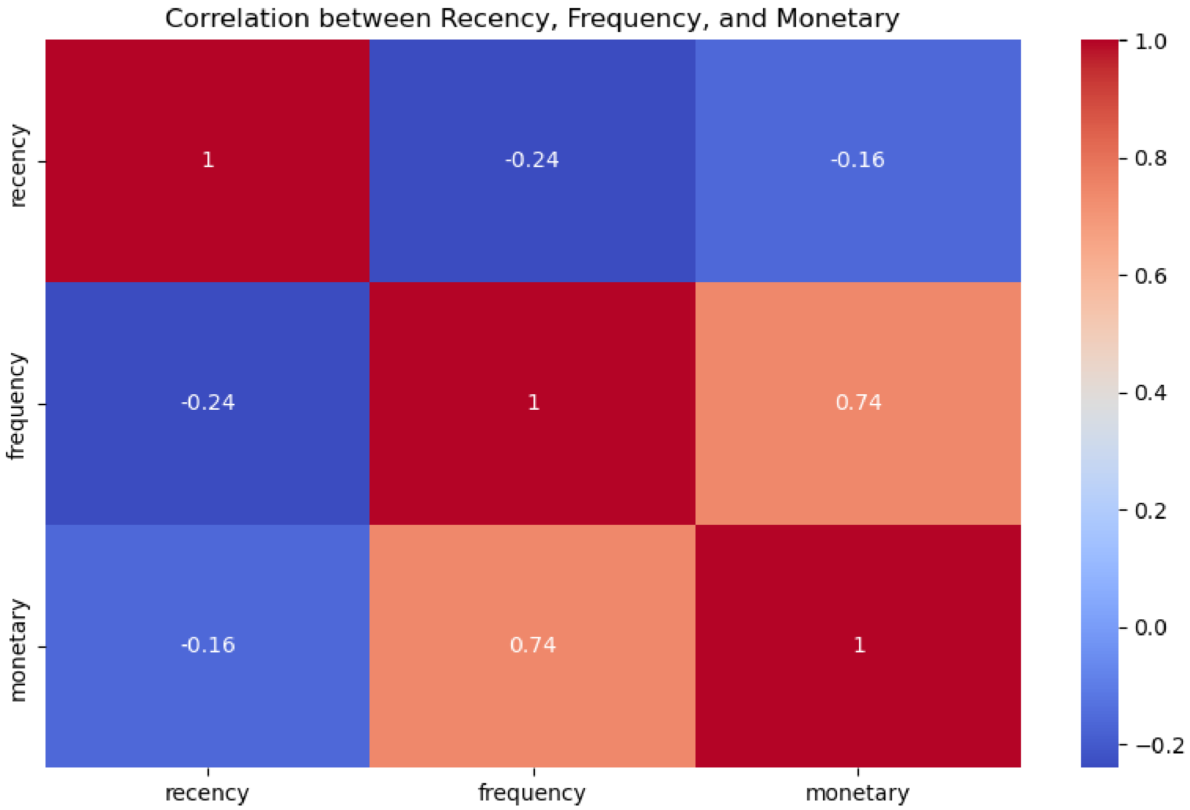
- Monetary: How much money the customer has spent. Here i am calculating the how much money customers have spent.



Insights

Majority of the people have spend less than 0.2 * 10^6.

Now let's see the relationship between recency, frequency, and monetary values.



Insights

- From the above graph, we can see that there is a positive correlation between frequency and monetary value.

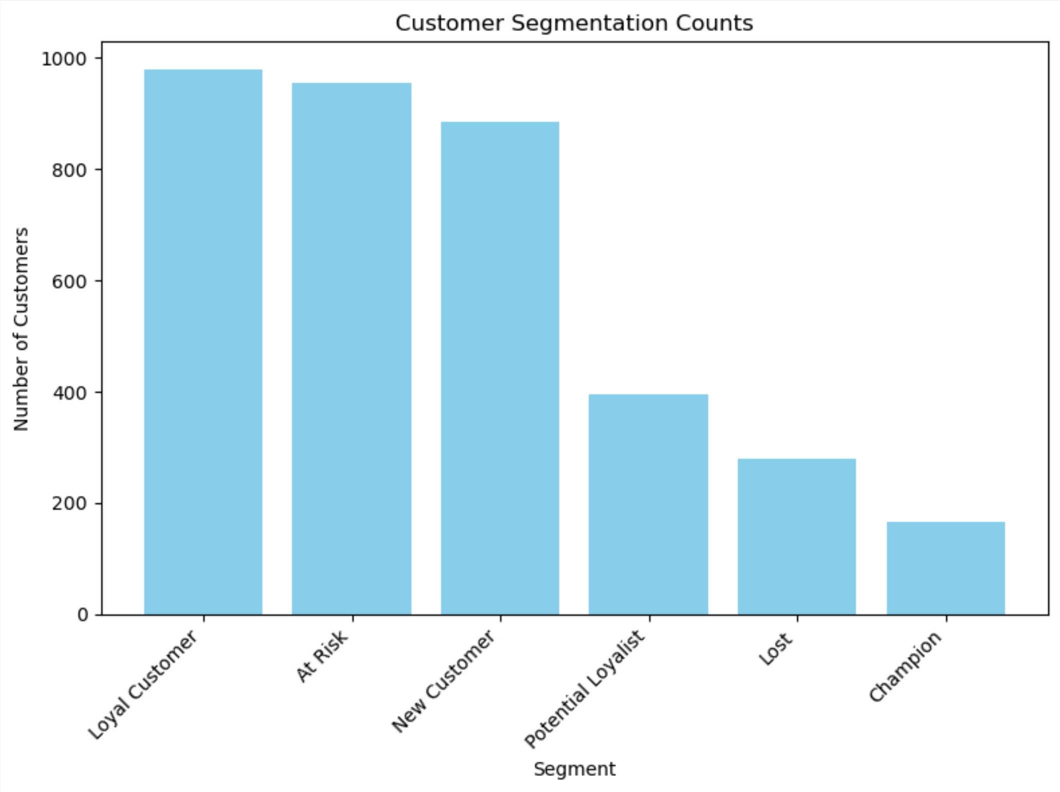
- But there is a negative correlation between recency and frequency and monetary value.

Score based on all three recency, frequency, and monetary values.

	user_id	recency	frequency	monetary	recency_score	frequency_score	monetary_score	RFM_score
0	0000e88	67	3	9491.60	2	1	2	212
1	000159a	13	98	84908.69	4	5	5	455
2	000c1b2	23	3	5304.84	4	1	2	412
3	0039abd	12	3	2098.24	4	1	1	411
4	003b0e5	76	9	2525.84	2	2	1	221

Answer

Based on this score, i segmented customers into different categories such as:

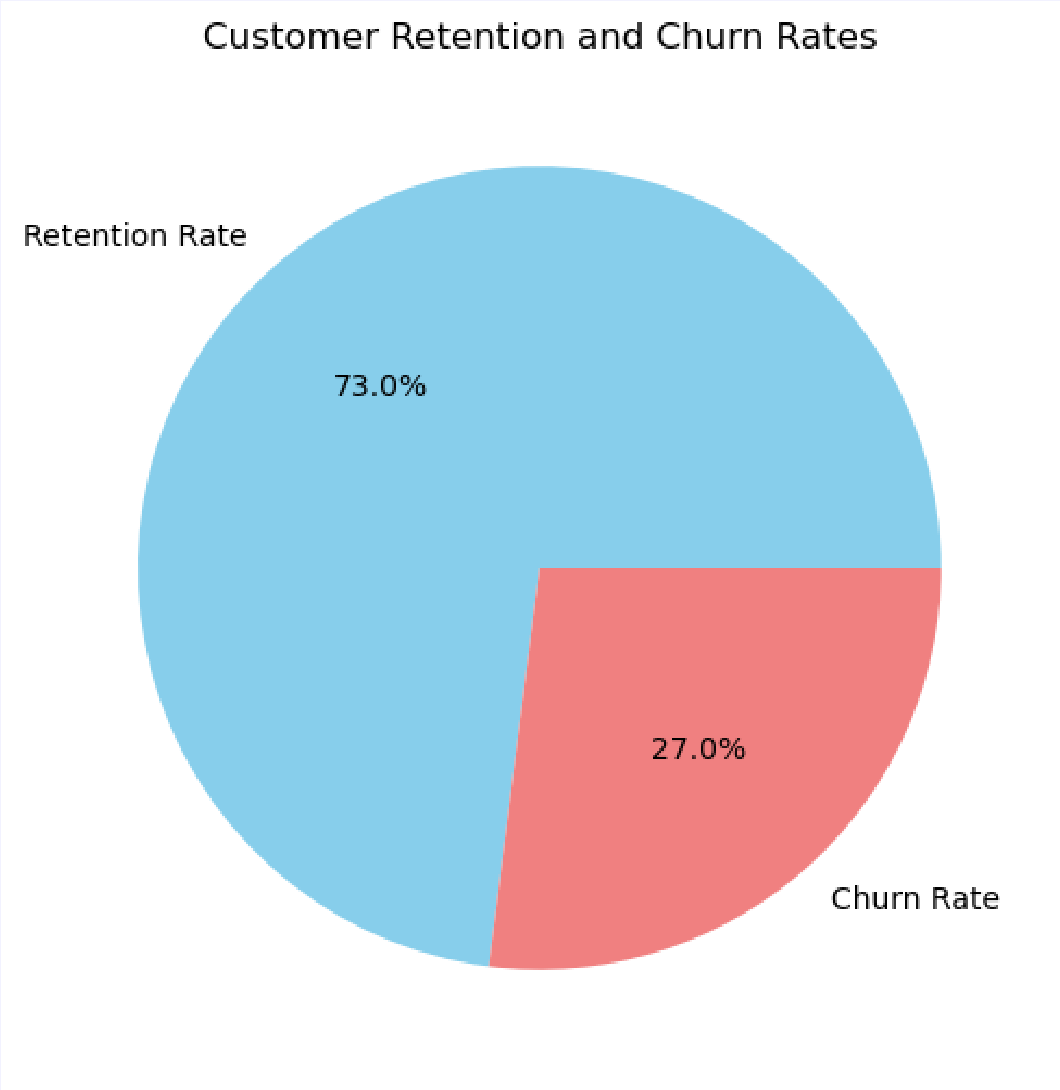


- **Champions:** Customers with high recency, frequency, and monetary scores (R = 4-5, F = 4-5, M = 4-5).
- **Loyal Customers:** Customers with high frequency and monetary scores but may have slightly lower recency (R = 3-5, F = 4-5, M = 4-5).
- **Potential Loyalists:** Customers with high recency and frequency but lower monetary value (R = 4-5, F = 3-5, M = 2-3).
- **New Customers:** High recency.
- **At Risk:** Low recency, frequency, and monetary value.
- **Lost:** Low recency, frequency, and monetary value.

Customer Retention and Churn

- Analyze customer retention rates and identify potential churn risks.

Customer Retention and Churn Rate

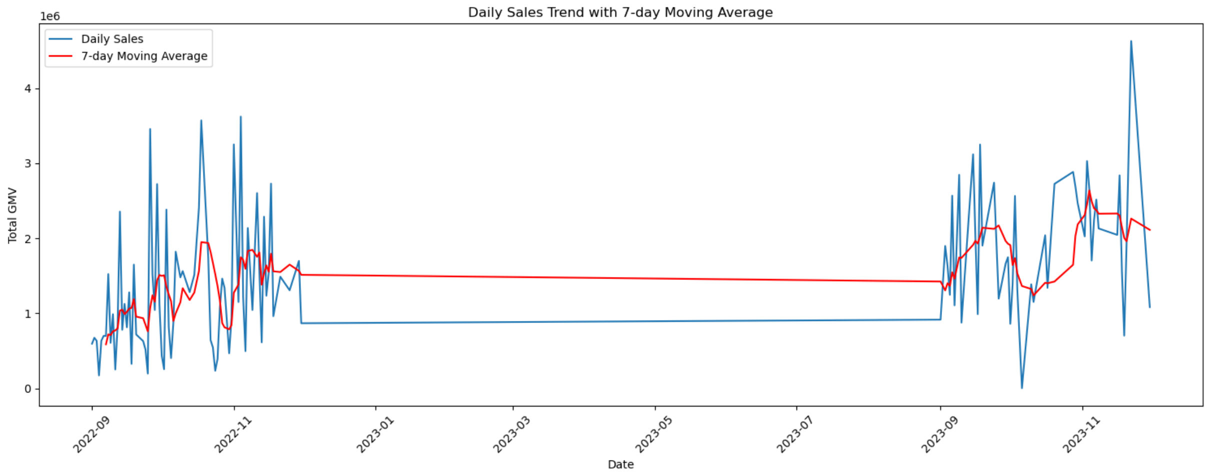


Clearly from the pie chart we can see that 73% of the customers are retained and 23% are churned.

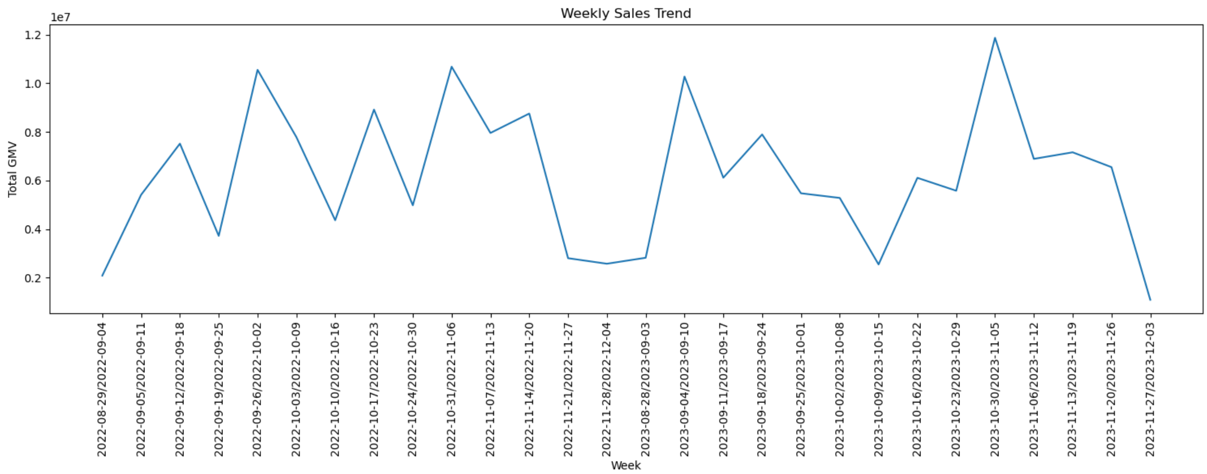
Sales Trends Analysis

Time-based Trends

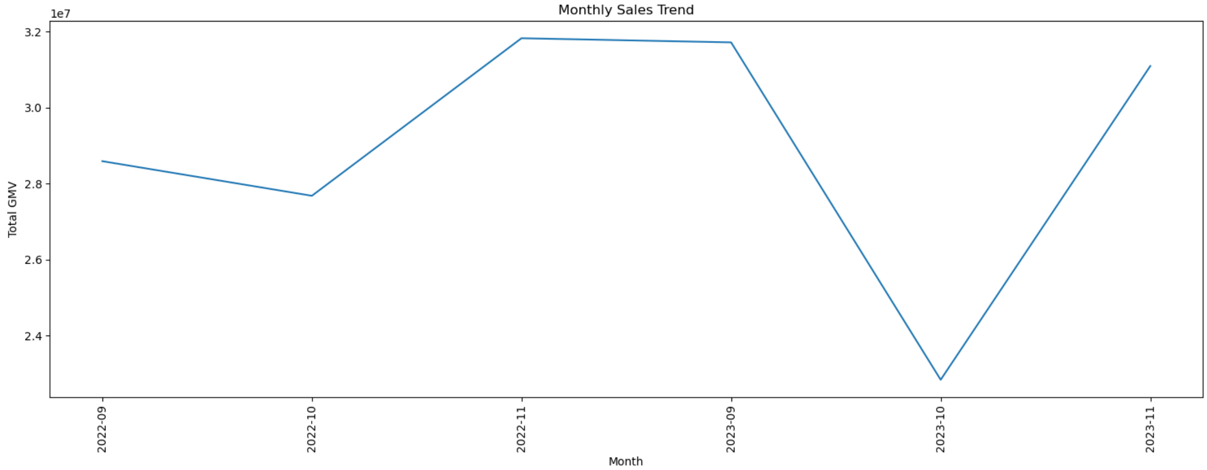
- Analyze daily, weekly, and monthly sales trends.



Daily sales trends with 7-days moving average.



Weekly sales trends.



Monthly sales trends.

Time-based sales trends.

Peak Sales Periods

Identify peak sales periods and any seasonality trends.

Peak Sales Periods by Days

Order Date	Placed GMV
2023-11-22	4,629,566.36
2022-11-04	3,623,119.11
2022-10-18	3,572,387.45
2022-09-26	3,457,606.77
2022-11-01	3,252,048.05
2023-09-18	3,250,288.29
2023-09-15	3,120,405.10
2023-11-03	3,030,412.93
2023-10-28	2,885,263.97
2023-09-09	2,846,904.68

Top 10 Peak Sales Days

Peak Sales Periods by weeks and months

Top 10 Peak

Week	Placed GMV
2023-10-30/2023-11-05	11,877,473.08
2022-10-31/2022-11-06	10,685,698.73
2022-09-26/2022-10-02	10,557,566.61
2023-09-04/2023-09-10	10,280,051.70
2022-10-17/2022-10-23	8,919,020.51
2022-11-14/2022-11-20	8,756,086.30
2022-11-07/2022-11-13	7,956,940.37
2023-09-18/2023-09-24	7,895,670.74
2022-10-03/2022-10-09	7,787,362.60
2022-09-12/2022-09-18	7,517,063.73

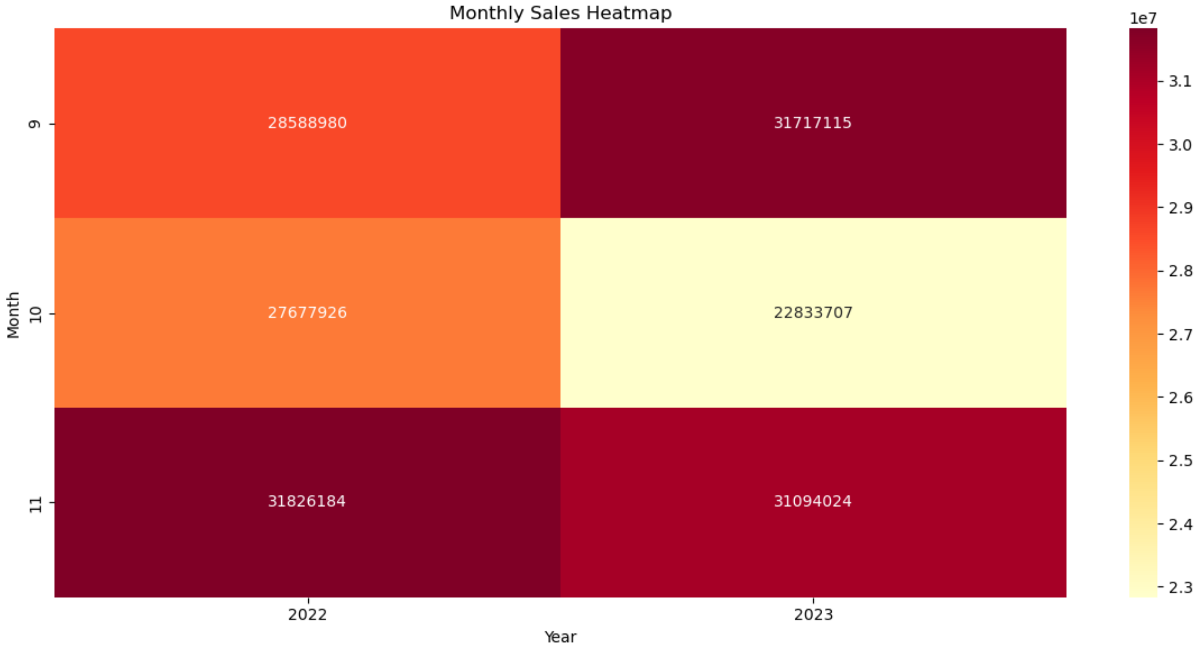
Sales Weeks

Top 10 Peak Sales Months

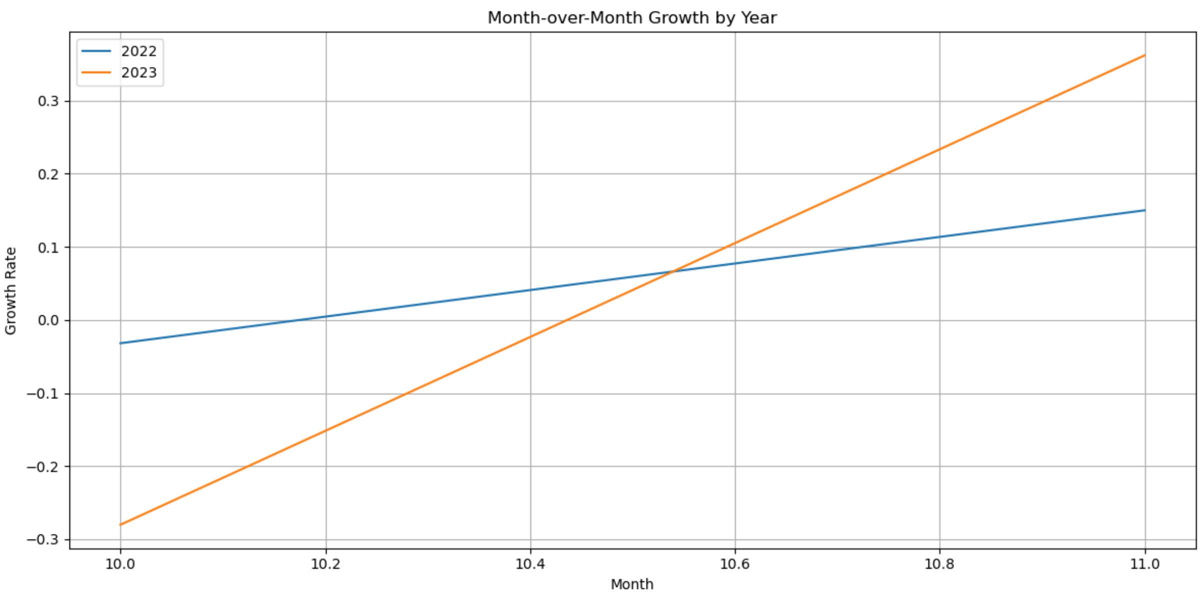
Month	Placed GMV
2022-11	31,826,184.02
2023-09	31,717,114.58
2023-11	31,094,024.46
2022-09	28,588,980.49
2022-10	27,677,926.44
2023-10	22,833,707.32

From above tables, following observations can be made:

- The top 10 peak sales days have placed GMV ranging from 2.8M to 4.6M.
- Most of the peak sales days are in the months of September, October, and November.

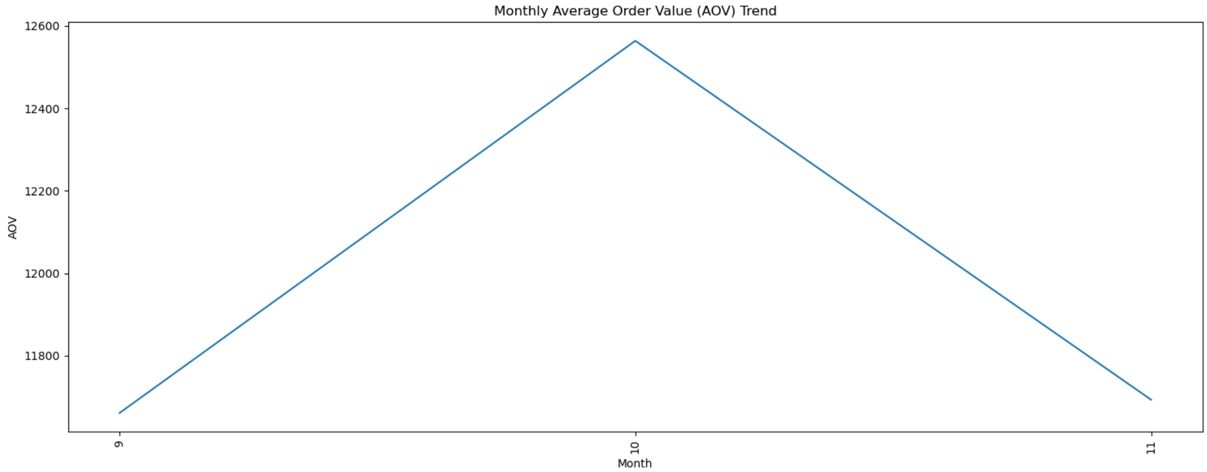


- Also we can see find month by month over year sales.



Average Order Value (AOV)

- Analyze trends in average order value over time.



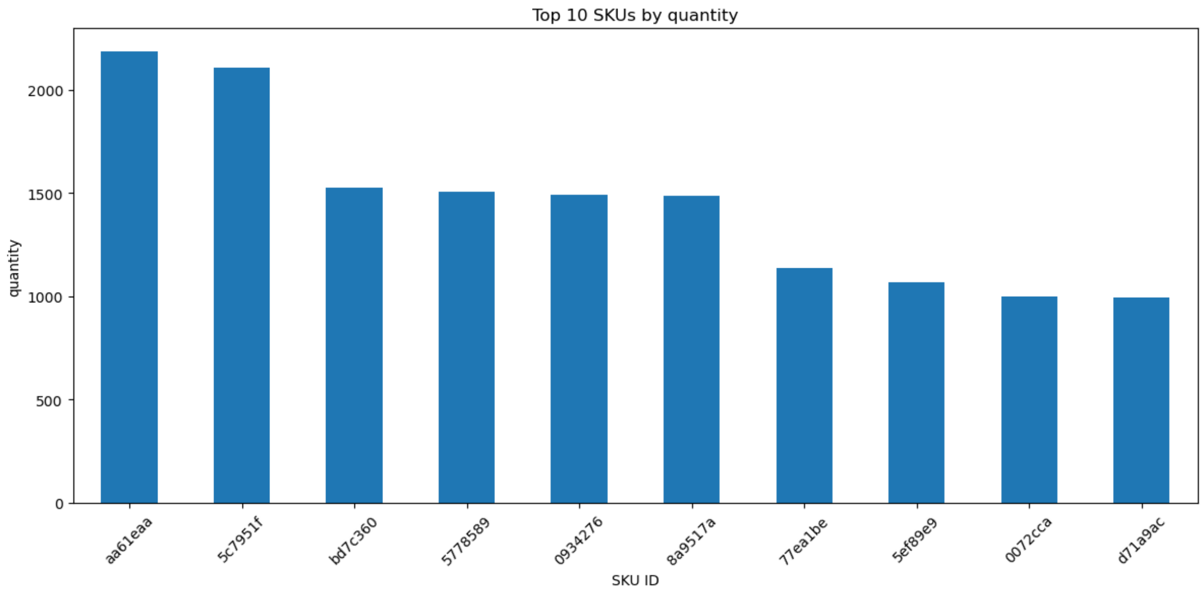
Insights:

* The aov is clearly showing an increase in sales upto october and then a decrease from there.
* It means months aroung October has higher sales and demand than other months beacuse of festivals season.

SKU Performance Analysis

Top-Selling SKUs

First lets see which are SKUs that are top selling.



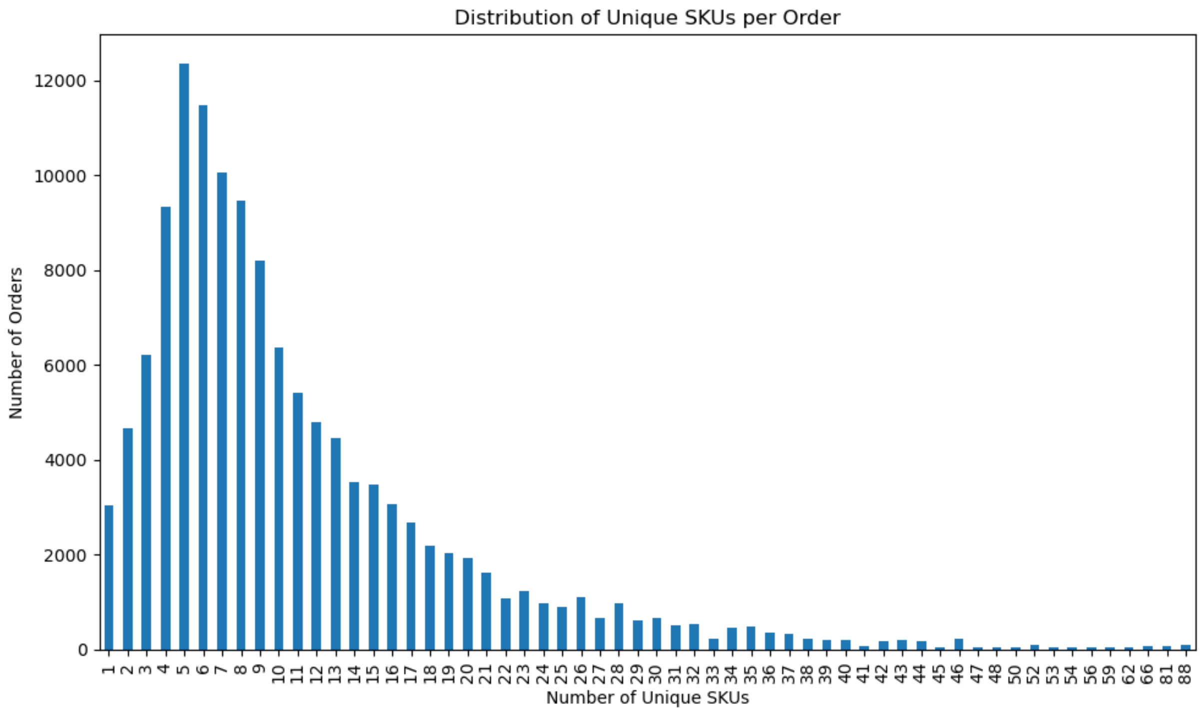
Top 10 Selling SKUs by Quantity. Also lets see the top selling SKUs by GMV.

```
Top 10 SKUs by placed_gmv:

sku_id
aa61eaa    3358729.54
bd7c360    3033729.76
5778589    2004186.77
0072cca    1818349.65
8a9517a    1770669.35
0934276    1691484.70
5c7951f    1674269.10
ee90f3e    1285239.63
be170aa    1270098.64
6323dad    1269127.86
Name: placed_gmv, dtype: float64
```

SKU Diversity

Analyze the diversity of SKUs in customer orders. What this means is that how many unique SKUS are their in any order$_I D$.



Insights

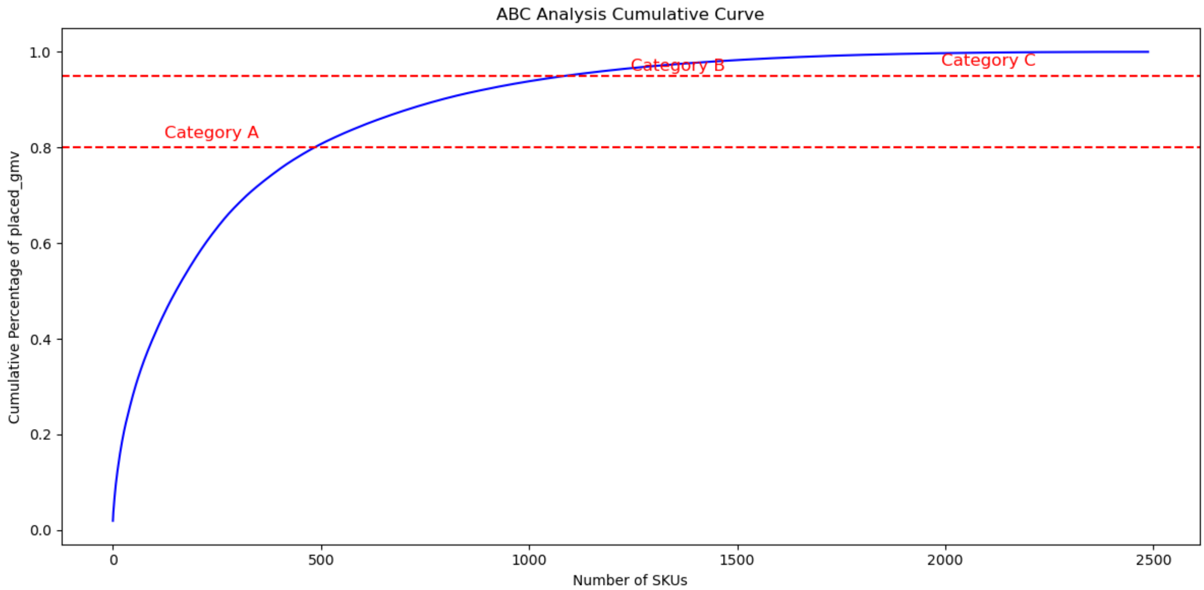
Insights:

- Majority of the orders contain 1-14 unique SKUs, meaning customers tend to buy a variety of products in a single order.
- But customers buying more than 14-15 unique SKUs are very less.
- 7 is the most common number of unique SKUs in an order.

ABC Analysis

Perform ABC analysis to categorize SKUs based on sales contribution.

- Category A SKUs (up to 80% of GMV) are the most critical for driving sales and revenue.
- Category B SKUs contribute moderately (the next 15% of GMV).
- Category C SKUs (final 5%) are the least significant for overall revenue.



One key observations that can be noticed is that **Only less than 500 unique SKU's are contributing to 80% of the GMV. Extensive results is as follows:**

```
ABC Analysis Results:
placed_gmv
A     484
B     605
C    1398
Name: count, dtype: int64

Percentage of SKUs in each category:
placed_gmv
A    19.453376
B    24.316720
C    56.189711
Name: count, dtype: float64
```

Purchase Patterns

- Examine SKU purchase patterns and correlations between items.

Order Analysis

Order Sizes

- Analyze the number of items per order.

Relationship Between Order Size and GMV

- Examine the relationship between order size and GMV.

Multi-item Orders

- Identify patterns in orders containing multiple items.

Cohort Analysis

Customer Cohorts

- Create cohorts based on the first purchase date of customers.

Cohort Retention

- Analyze retention rates and purchasing behavior over time for each cohort.

Geographic Analysis

- Analyze sales distribution across different geographic regions.
- Identify high-performing and underperforming areas.

Promotion Opportunities

- Identify potential opportunities for targeted promotions based on time-based analysis.

Customer Lifetime Value (CLV) Analysis

CLV Calculation

- Calculate customer lifetime value (CLV) for various customer segments.

CLV Influencing Factors

- Identify factors that influence CLV.

Basket Analysis

Market Basket Analysis

- Perform market basket analysis to identify frequently co-purchased items.

Product Recommendations

- Generate product recommendations based on customer purchase patterns.

Price Sensitivity Analysis

Price vs. Demand

- Analyze the relationship between price changes and demand for different SKUs.

Price Optimization Opportunities

- Identify opportunities for optimizing pricing strategies.

Advanced Analytics (Optional)

Predictive Modeling

- Develop predictive models for future sales and customer behavior.

Customer Segmentation via Clustering

- Perform clustering analysis to identify distinct customer segments.

Action Plan and Recommendations

- Based on the insights, develop actionable recommendations to improve business performance.