Sales Performance Analysis

Introduction:

The following sales report is the outcome of an in-depth analysis that used RFM (Recency, Frequency, Monetary) analysis to identify loyal and at-risk clients within the given dataset. RFM analysis is a data-driven marketing method that classifies and targets clients based on their transaction history. This study provides significant insights into customer behaviour and enables focused marketing strategies by segmenting customers based on their recent purchase, frequency of buy, and monetary value of their transactions.

The dataset utilized in this research contains information regarding individual transactions, such as Order ID, Product, Quantity Ordered, Price Each, Order Date, Purchase Address, Month, Sales, City, and Hour. This dataset covers a specified time period and includes client transactions from a variety of places.

This report aims to present the findings of the RFM analysis, highlighting the identification of loyal customers, at-risk customers, and the implications for strategic decision-making. The report will delve into the characteristics of these customer segments, their purchase behaviours, and potential actionable strategies to engage and retain loyal customers, as well as mitigate the risk associated with customers at risk.

Steps:

Data Import: Retrieving and assimilating the transactional dataset, capturing crucial information such as Order ID, Product, Quantity Ordered, Price Each, Order Date, Purchase Address, Month, Sales, City, and Hour to enable comprehensive analysis.

Data Cleaning: Applying advanced data cleansing techniques to ensure the accuracy and integrity of the dataset, including addressing inconsistencies, removing duplicates, and standardizing formats for enhanced analysis.

Finding Null Values: Implementing rigorous checks to identify and rectify any null or missing values within the dataset, ensuring that the analysis is based on complete and reliable information.

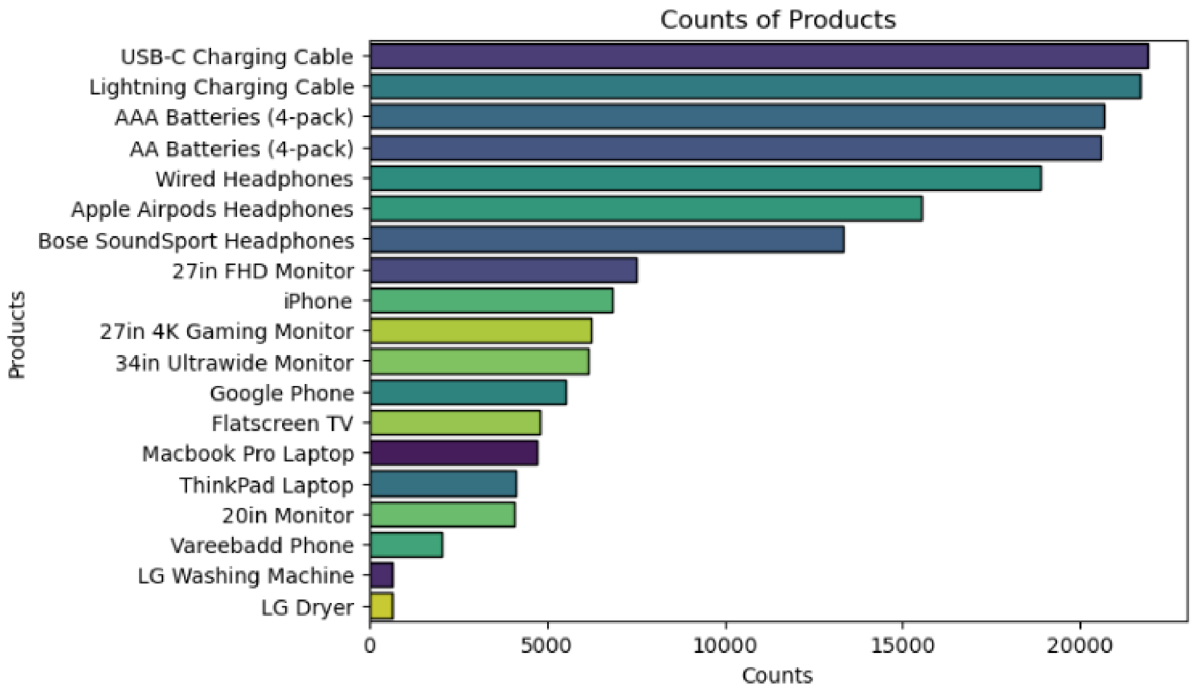
Plotting Insights: Utilizing advanced data visualization techniques to uncover key patterns, trends, and actionable insights within the dataset, creating visual representations that facilitate clear and effective communication of findings.

RFM Analysis: Employing the powerful RFM (Recency, Frequency, Monetary) analysis methodology to segment customers based on their transaction history, identifying loyal customers and those at risk, and deriving strategic insights to optimize customer engagement and retention.

Power BI Visualization: Leveraging the capabilities of Power BI to create dynamic and interactive visualizations that bring the RFM analysis to life, enabling stakeholders to gain valuable, actionable insights and make informed strategic decisions.

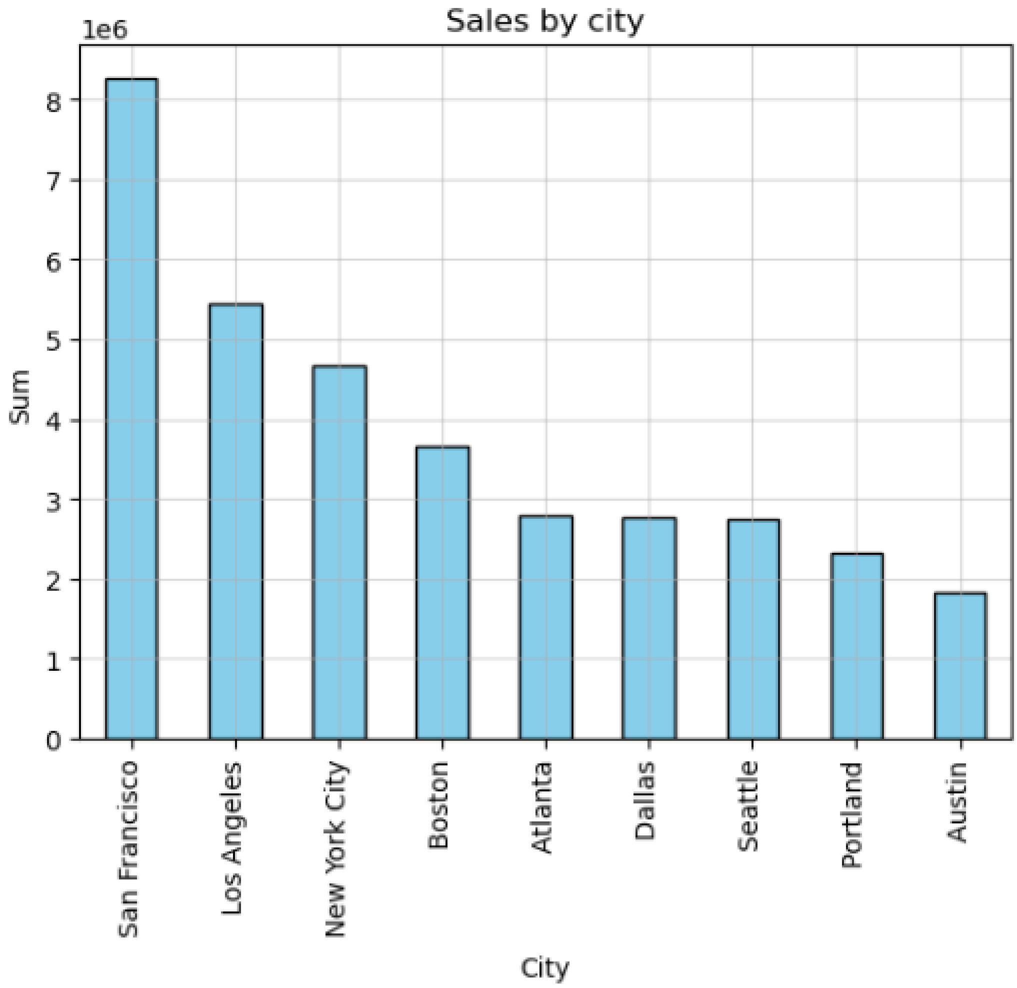
Insights:

Top Products



These insights provide a complete study of the top-selling products and their associated sales volumes, allowing for a clear picture of the market's finest performers. Identifying these products allows us to acquire significant insights about consumer preferences and demand trends. This research not only identifies the top sales drivers, but it also helps us to link these results with the dataset's sales patterns. Using this data can help firms optimize their inventory, improve marketing methods, and focus on products with the highest income potential.

Top Sales in City



The visual depiction titled "Sales by City" shows a breakdown of total sales amounts for each city. This essential insight provides a compelling view of the regional distribution of sales, allowing for a thorough understanding of income generation in each place. The bar chart depicts the total sales contribution of various cities, allowing us to identify the top performers and assess their importance in the overall sales landscape.

Sales VS Order Quantity

Scatter provides the provides the illustration between the Quantity of products and the resulting sales. The data indicates that as the quantity ordered increases, there is a corresponding increase in sales. The plotted points reveal a positively correlated trend between sales and order quantity. A linear trend is observed, demonstrating that as the quantity ordered increases, there is a linear increase in sales

The data also shows variation in sales volume for similar quantities ordered, indicating potential contributing factors such as pricing, discounts, or other variables influencing overall sales figures.

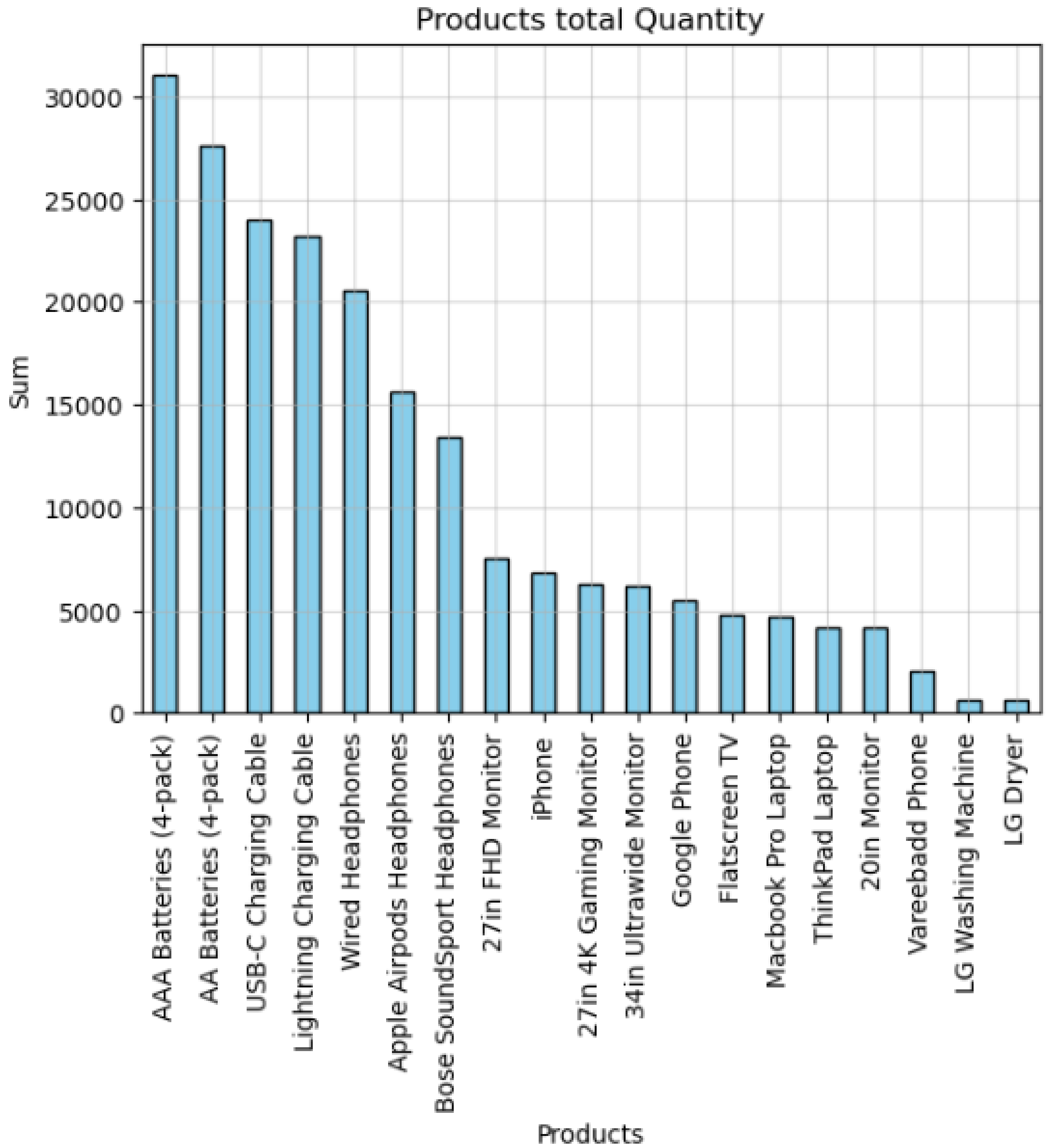
Price Distribution

The price distribution appears to be right-skewed, with the majority of products priced at the low end of the spectrum. This shows that the bulk of the things offered in the dataset are reasonably priced.

The histogram reveals that the most common price range is in the lower bins, indicating a greater frequency of low-cost products. There are fewer products in the higher price ranges, showing that high-priced items are less frequent in the dataset.

This could signal that the corporation prioritizes selling a higher volume of lower-priced things over a few high-priced items.

Products Total Quantity

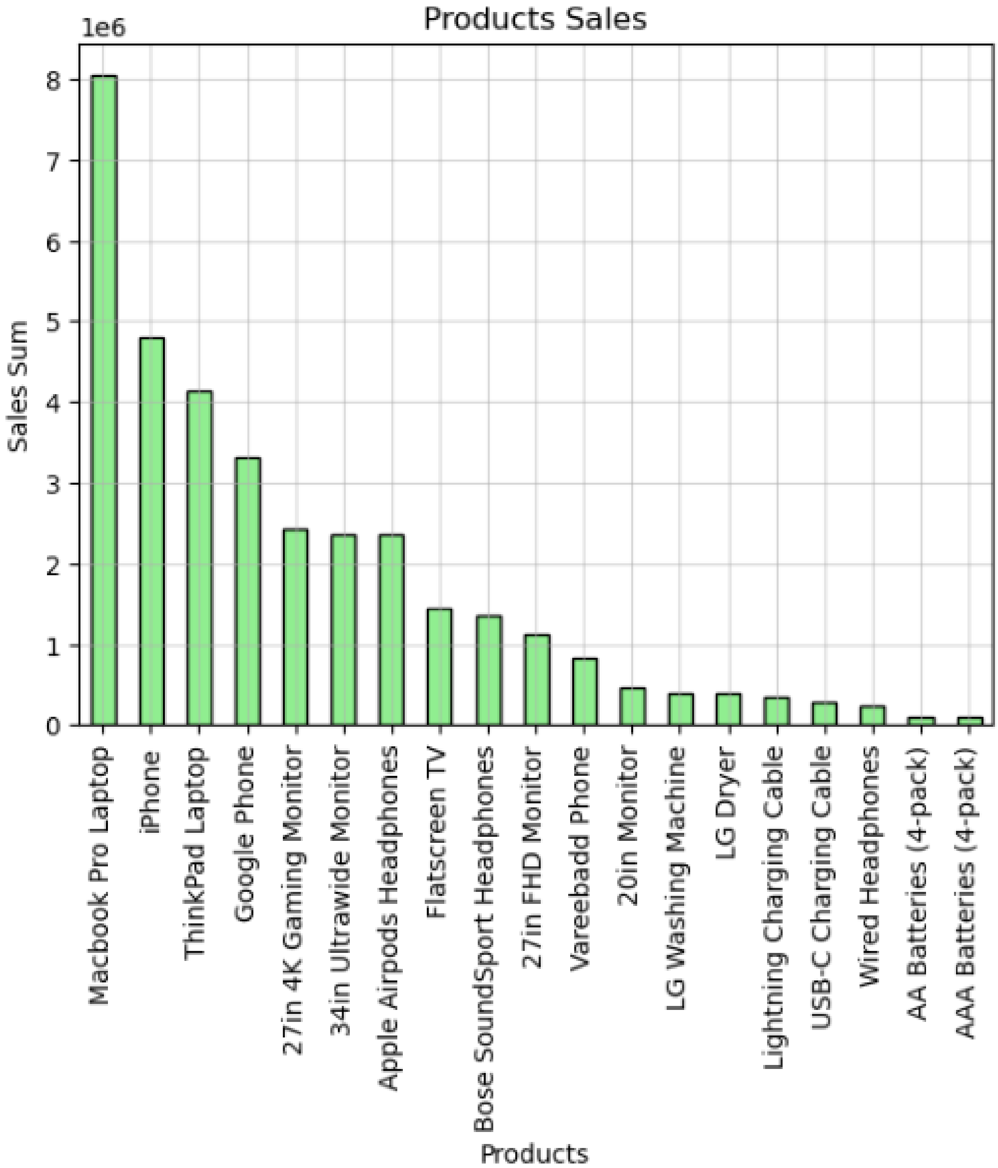


The dataset provides a comprehensive overview of sales order details for a range of products across different cities and dates. The sales information is rich with insights into the quantity ordered, price of each product, order date, and the purchase address. Through analysis of the dataset, several key findings emerge.

The Total Quantity of the products ranged from 30000 to least of 45 products

These product Quantities Depend on the Customers present in the states and the loyalty of the customer is also based on the increase in the number of products purchased in the region

Product Sales



Sales Here represent the number of quantity order * the price of each item, so the plot shows the sales of each and every item that have been purchased and stored in the dataset

The dataset shows that the MacBook laptop has the highest sales when compared to the batteries which has the lowest sales

By leveraging the insights gleaned from this analysis can guide strategic decision-making to enhance sales performance by emphasizing and promoting products with high sales

RFM Analysis and Segmentation

	Unnamed: 0	Order ID	Product	Quantity Ordered	Price Each	Order Date	Purchase Address	Month	Sales	City	Hour	Recency	Frequency	Monetary
0	0	295665	Macbook Pro Laptop	1	1700.00	2019-12-30 00:01:00	136 Church St, New York City, NY 10001	12	1700.00	New York City	0	2	1	1700.00
1	1	295666	LG Washing Machine	1	600.00	2019-12-29 07:03:00	562 2nd St, New York City, NY 10001	12	600.00	New York City	7	2	1	600.00
2	2	295667	USB-C Charging Cable	1	11.95	2019-12-12 18:21:00	277 Main St, New York City, NY 10001	12	11.95	New York City	18	19	1	11.95
3	3	295668	27in FHD Monitor	1	149.99	2019-12-22 15:13:00	410 6th St, San Francisco, CA 94016	12	149.99	San Francisco	15	9	1	149.99
4	4	295669	USB-C Charging Cable	1	11.95	2019-12-18 12:38:00	43 Hill St, Atlanta, GA 30301	12	11.95	Atlanta	12	13	1	11.95

RFM (Recency, Frequency, Monetary) analysis is a valuable method used to evaluate customer value based on their transaction history.

Recency refers to how recently a customer made a purchase, Frequency measures the number of purchases over a specific period, and Monetary represents the total amount of money a customer spent.

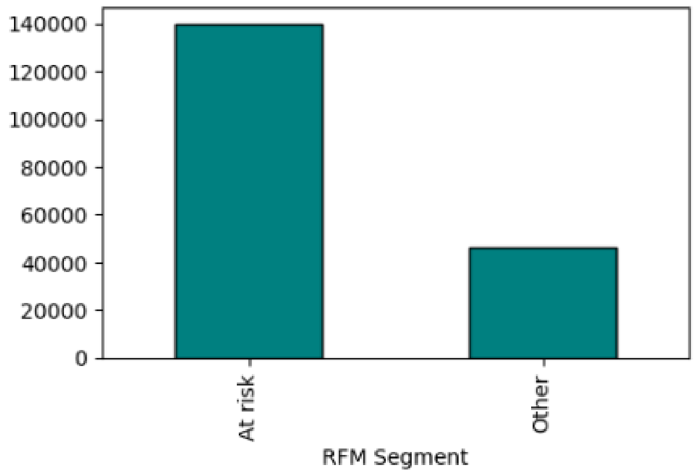
By leveraging RFM analysis, businesses can segment their customer base to identify high-value customers, re-engage lapsed customers, and tailor marketing strategies to suit the specific needs and behaviours of different customer segments.

```
## RFM Segmentation:

def segments_customer(row):
    if row['R_score'] <=1 and row['F_score'] >=2 and row['M_score'] >=2:
        return "Champions"
    elif row['R_score'] <=2 and row['F_score'] <=1:
        return "At risk"
    elif row['R_score'] <= 1 and row['F_score'] >=2:
        return 'Loyal customer'
    else:
        return "Other"
df['RFM Segment'] = df.apply(segments_customer , axis = 1)
segment_counts = df['RFM_Segment'].value_counts()
print(segment_counts)
```

Here the Customer are segmented as Champions, At-risk, Loyal Customer and others and the insights shows that there are:

- At-Risk: 139967
- Other: 45983



So, for this segmentation we have applied Marketing Strategies to improve the customer retention program and also to increase the customer sales and product sales in the company

```
# Applying Marketing Strats:

def apply_strats(row):
    if row['RFM Segment'] == ' Champions':
        return "Reward them with loyalty programs or exclusive offers.\
        Engage them with personalized emails and promotions to maintain their loyalty"
    elif row['RFM Segment'] == 'At risk':
        return "Send targeted win-back campaigns or discounts to bring them back."
    elif row['RFM_Segment'] == 'Loyal customer':
        return "Re-engage them with reminders or personalized offers to keep them active."
    else:
        return "Other"

df['Marketing_Strategy'] = df.apply(apply_strats, axis=1)
```

CONCLUSION

Finally, the entire sales performance analysis report, enhanced by the use of RFM analysis and advanced data visualization tools, provided important insights into consumer behaviour, product performance, and strategic company growth potential.

The findings highlight the need of segmenting customers based on recency, frequency, and monetary value, which enables targeted and tailored marketing techniques to improve customer engagement and retention.

Businesses can make more educated inventory decisions, better marketing methods, and nurture long-term customer connections by identifying loyal customers, at-risk clients, and top-selling products.

The report also highlights crucial patterns such as sales distribution by city, the relationship between sales and order quantity, and pricing tactics, giving a comprehensive picture of the market landscape.

Businesses may promote revenue growth, improve customer loyalty, and position themselves for long-term success in a competitive environment by implementing personalized marketing strategies for customer segments such as Champions, At-risk, and Loyal Customers.