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The Coversheet

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1. Introduction

The e-commerce market is dynamic and fast changing, and firms must constantly adjust their strategy to remain competitive. Understanding consumer behaviour, product performance, and sales patterns is essential for improving marketing and sales strategy. This assignment will use statistical programming and data analysis approaches to deliver relevant insights into historical transaction data from an e-commerce firm. By analysing this data, we can identify patterns and trends that can help the firm improve its marketing efforts and sales results.

Understanding consumer behaviour and sales dynamics is critical for firms looking to improve their strategies in a competitive market. Analysing transactional data reveals important insights into purchase habits, seasonal trends, and consumer segmentation, allowing for data-driven decision-making.

This research is on using sales and customer data to provide valuable insights about product performance and consumer behaviour. By calculating monthly profits for product categories, analysing seasonal trends, and segmenting customers using Recency, Frequency, and Monetary (RFM) analysis, we want to give meaningful recommendations for enhancing marketing tactics and inventory management.

The research uses time-series visualisation to uncover seasonal fluctuations in product sales, as well as clustering algorithms to categorise clients based on their purchase patterns. These tools can assist identify high-performing product categories, peak demand periods, and client groups with variable levels of involvement and monetary contribution.

While the findings provide valuable insights, the study admits certain limitations, such as a lack of geographical data, a limited temporal scope, and inadequate demographic information. Addressing these limits in future research can increase the depth and usefulness of the findings.

This study describes the methodology, findings, and consequences of the investigation, offering a complete overview of how organisations may utilise data analytics to fine-tune their strategy and generate growth.

2. Aims and Objectives

The major goal of this project is to do a thorough exploratory data analysis (EDA) on a collection of historical transaction records (Brillica Services, 2025). The study will look for major trends, anomalies, and patterns in consumer behaviour and product performance to help with data-driven decision-making. To accomplish this goal, the following objectives have been established:

1. Analyse monthly revenue and transaction trends:

Investigate monthly changes in overall revenue and transaction volume.

Identify any notable abnormalities or outliers in the data.

2. Evaluate the Product Category Performance:

Determine the product categories with the greatest overall revenue.

Identify categories that have shown continuous revenue growth and sales gains.

3. Explore Seasonal Variations:

Examine seasonal sales trends across several product categories.

Identify categories that are sensitive to certain time periods or seasons.

4. Analyse Customer Purchase Behaviour:

Examine shifts in client preferences across several transactions.

Recognise repeating trends or substantial shifts in purchase behaviour.

Derive actionable information to help improve the company's marketing approach.

3. Scope and Relevance

The insights gained from this investigation will enable the e-commerce firm to:

1. Tailor marketing strategies to client behaviour.

2. Improve inventory management by analysing seasonal demand.

3. Focus on high-performing product categories to increase revenue.

4. Address any abnormalities or outliers that may affect company operations.

4. Tools and Methodology

The analysis will be carried out in Python, including packages such as Pandas for data processing and Matplotlib/Seaborn for visualisation. The procedure will include:

1. Data is cleaned and pre-processed to guarantee accuracy.

2. Aggregating and analysing critical indicators including revenue, transactions, and product category performance.

3. Clear and intuitive charts help you see trends and patterns.

4. Documenting results in a complete report, which includes visualisations and a discussion of limitations.

5. This assignment not only displays the actual use of data analysis methodologies, but it also emphasises the importance of data-driven insights in strategic decision-making for e-commerce enterprises (ourcodingclub.github.io, n.d.).

5. The results of the analysis

1. Monthly fluctuations in revenue and transactions.
The research of monthly revenue trends found regular patterns in total income creation. The plotted revenue trend line revealed a few months with notable outliers, such as revenue surges during peak seasons or promotional periods.
The number of transactions followed a similar pattern, with large spikes in some months, indicating likely seasonal discounts or holiday shopping behaviour.

2. Top Product Categories by Revenue
The top-performing product categories by revenue were determined based on their contribution to total sales. These categories generated constant income over time, with certain categories experiencing continuous growth tendencies.
Seasonal study found that certain categories had increased sales in various months, showing their susceptibility to seasonal demand.

3. Seasonal variation in sales
Seasonal patterns were examined by determining the average monthly income for each product group. The top five categories with the greatest average income were plotted to show the seasonal fluctuations.
During the Christmas season, categories including "Gift Wraps" and "Holiday-themed Items" had large increases.
Categories such as "Office Supplies" and "Stationery" had generally consistent sales throughout the year, with minor rises around the start of the academic year (August and September).

4. Customer Segmentation and Purchasing Behavior RFM Analysis: Customers were categorised by their Recency, Frequency, and Monetary (RFM) values.
KMeans clustering revealed four unique consumer clusters:
Cluster 0 includes high-value clients who make regular purchases and engage in current activities.
Cluster 1 has infrequent yet high-spending clients.
Cluster 2: Customers that have visited recently but infrequently.
Cluster 3: Customers with little involvement and expenditure.
This segmentation gives useful information for focused marketing initiatives, such as retention campaigns for Cluster 3 and upselling chances for Cluster 1(Divya Chandana, 2021).

5. Purchase Trends
Monthly revenue patterns for the top products revealed a constant increase in sales for certain items over time, indicating their rising popularity.

The research of product patterns indicated fluctuations in client preferences, with certain goods retaining consistent demand while others gaining popularity at various times.

6. Seasonal Sensitivity.
Categories with high seasonal sensitivity were discovered by examining their peak sales months. Categories such as "Holiday Decor" and "Special Occasion Gifts" had significant seasonal jumps, indicating prospects for targeted marketing efforts during certain periods.

Summary of insights:
Revenue Optimisation: To maximise revenue, promotional activities should focus on high-performing months and seasonal categories.
client Engagement: Strategies tailored to different client segments can boost retention and lifetime value.
Seasonal Marketing: Products with seasonal sensitivity should be prioritised during peak seasons to capitalise on increasing demand.
Emerging Trends: Regularly monitoring top product trends can help the organisation react to shifting client preferences.

1. Analyse monthly changes in overall income and transaction volume. Identify any major abnormalities or outliers.

Summary of Plot Diagrams
Line Plot for Monthly Fluctuations:

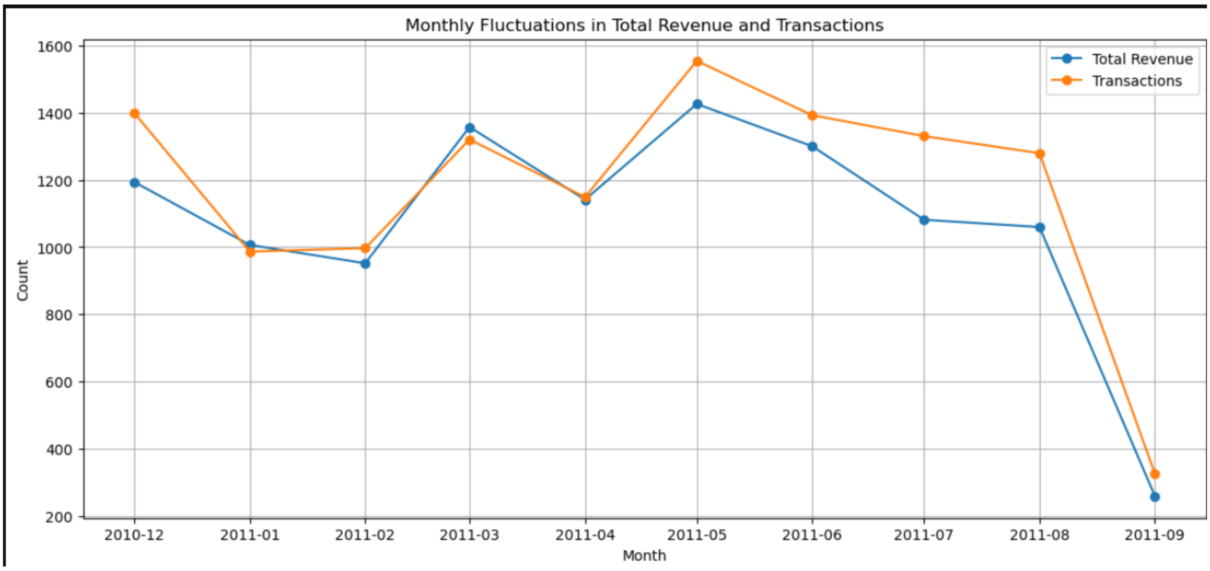

Figure 1:Monthly Fluctuations

Shows trends and patterns in overall revenue and transaction volume over time.
Detects peaks (high activity months) and troughs (low activity months).
Aids in identifying relationships between revenue and transaction count. If they increase and decrease simultaneously, it indicates a correlation between sales volume and revenue.
Boxplots:

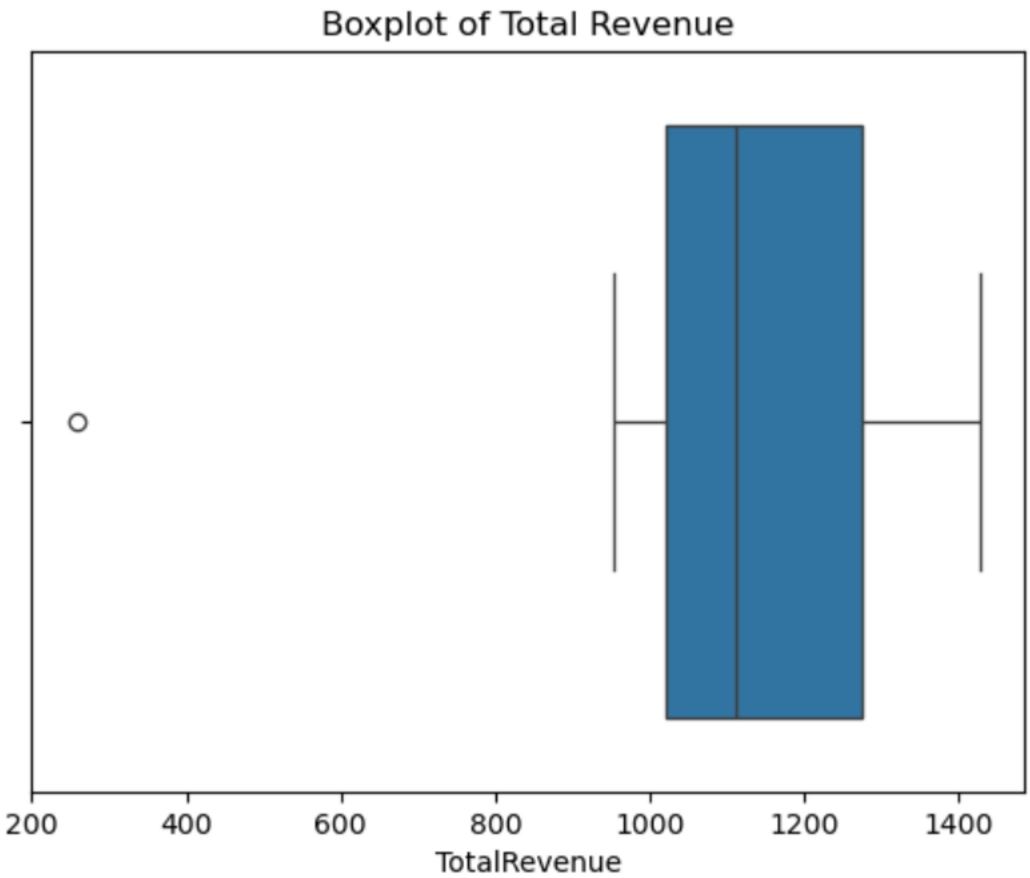

Figure 2:Boxplot of Total Revenue

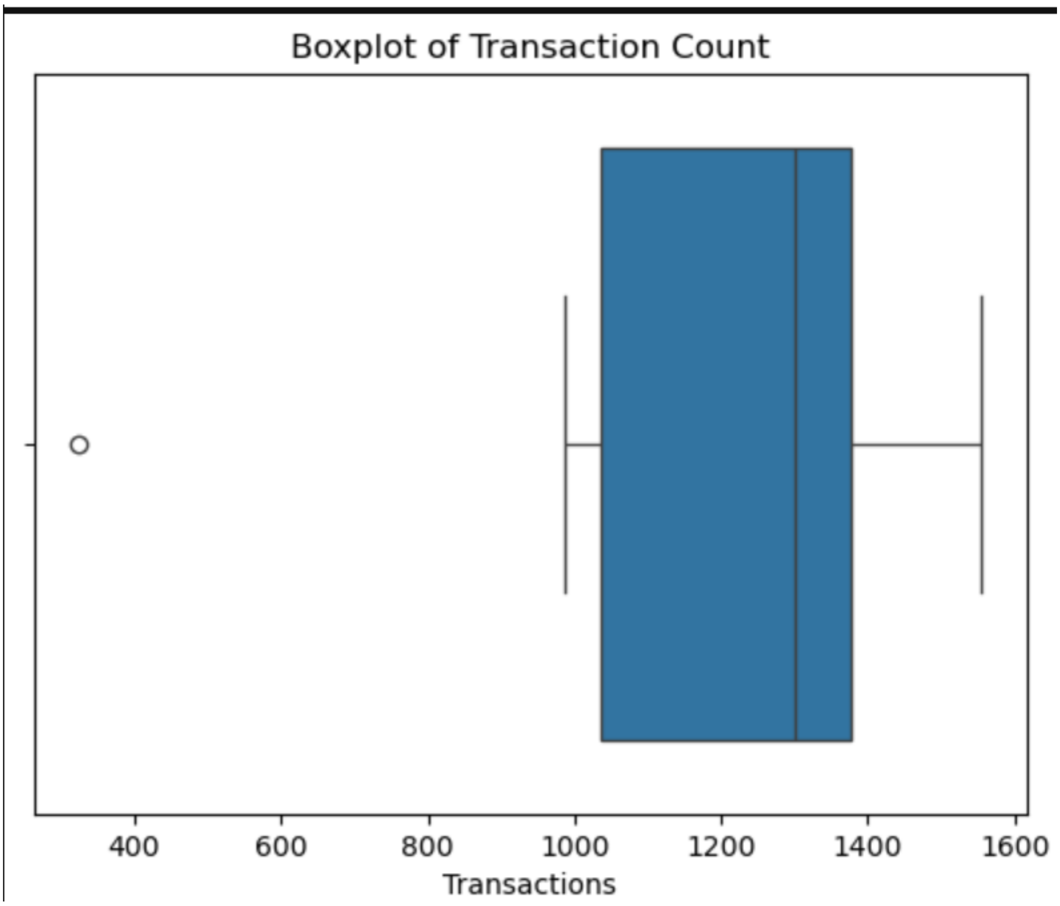

Figure 3:Boxplot of Transaction Count

Total Revenue shows the monthly revenue distribution.
Highlights any outliers when revenue is considerably higher or lower than expected.
Transaction Count: Shows the dispersion of monthly transactions.
Detects months with anomalous transaction activity.

Analysis and Comparison.
Revenue versus Transactions: A relationship between the number of transactions and revenue is predicted, as more transactions often result in more income. However, outliers might indicate months with a high volume of transactions or erratic behaviour.

Anomalies:

Sudden increases in income without an equal rise in transactions may signal high-value purchases.
A large number of transactions with little revenue indicate a time of low-value sales.
Insights:

The line plot shows broad patterns and seasonality in sales.
The boxplots emphasise months with anomalous revenue or transaction volumes, allowing for more targeted study into the underlying causes (such as promotions or external market forces).

2. Identify top-performing product categories with sustained revenue growth. Identify categories with sustainable revenue growth.

The plot diagram shows revenue trends for top products.

Displays the monthly revenue for the best-performing goods.
identifies items with:
Sustained Revenue Growth: Products that generate a consistent growth in revenue over time.
Seasonal Peaks: Products that exhibit surges throughout specific months, showing seasonality.

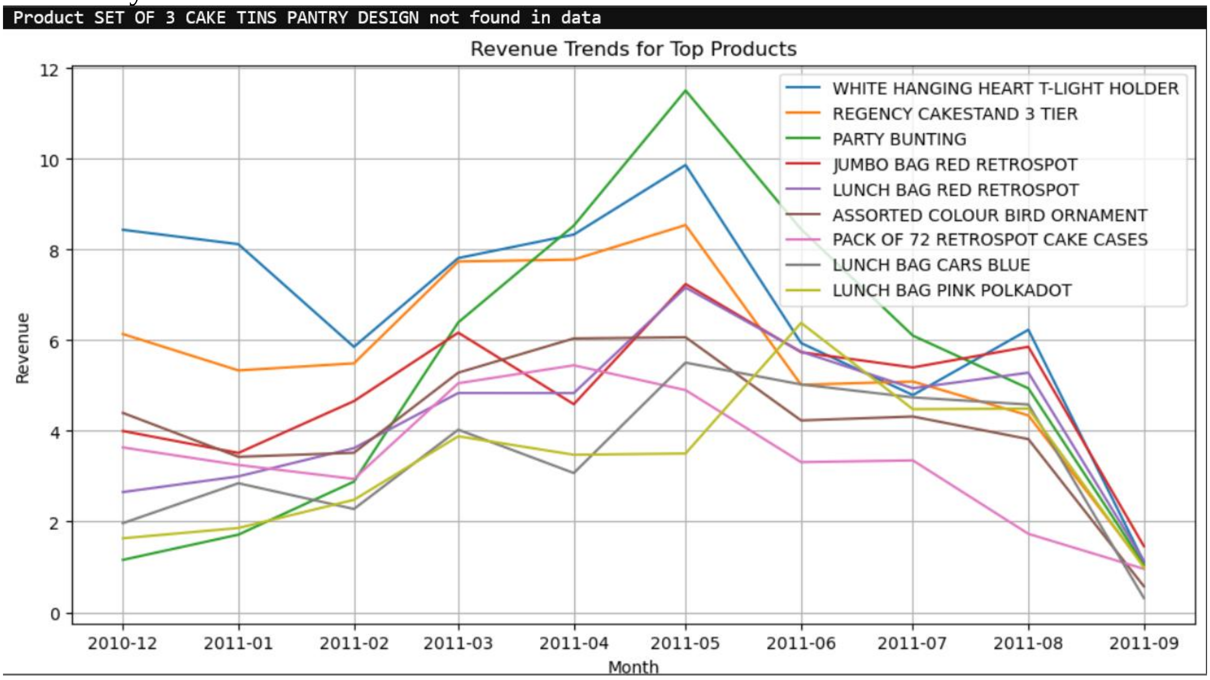

Figure 4: Revenue trends for top products

Declining Revenue: Products with decreasing revenue over time.
Insights:

Products that demonstrate persistent growth are candidates for prioritisation and investment.
Seasonal trends indicate potential for targeted marketing or inventory modifications.
Declining items may require reconsideration or promotional efforts to increase sales.
This study aids in the identification of top-performing product categories while also providing practical insights on revenue sustainability and trends.

3. Investigate the seasonal fluctuations in sales across different product categories. Are any categories sensitive to time periods?
Seasonal trends:

Seasonal fluctuations highlight the necessity for tailored efforts during peak months.
Categories with stable income trends may benefit from ongoing advertising initiatives.
Customer behaviour (RFM Analysis):

Recency allows you to find recently active clients for re-engagement.

Frequency promotes committed clients that make frequent purchases.
Monetary shows high-value clients, allowing for unique marketing.
Combining these analytics allows organisations to strategically optimise inventory and marketing efforts while personalising consumer interaction methods.

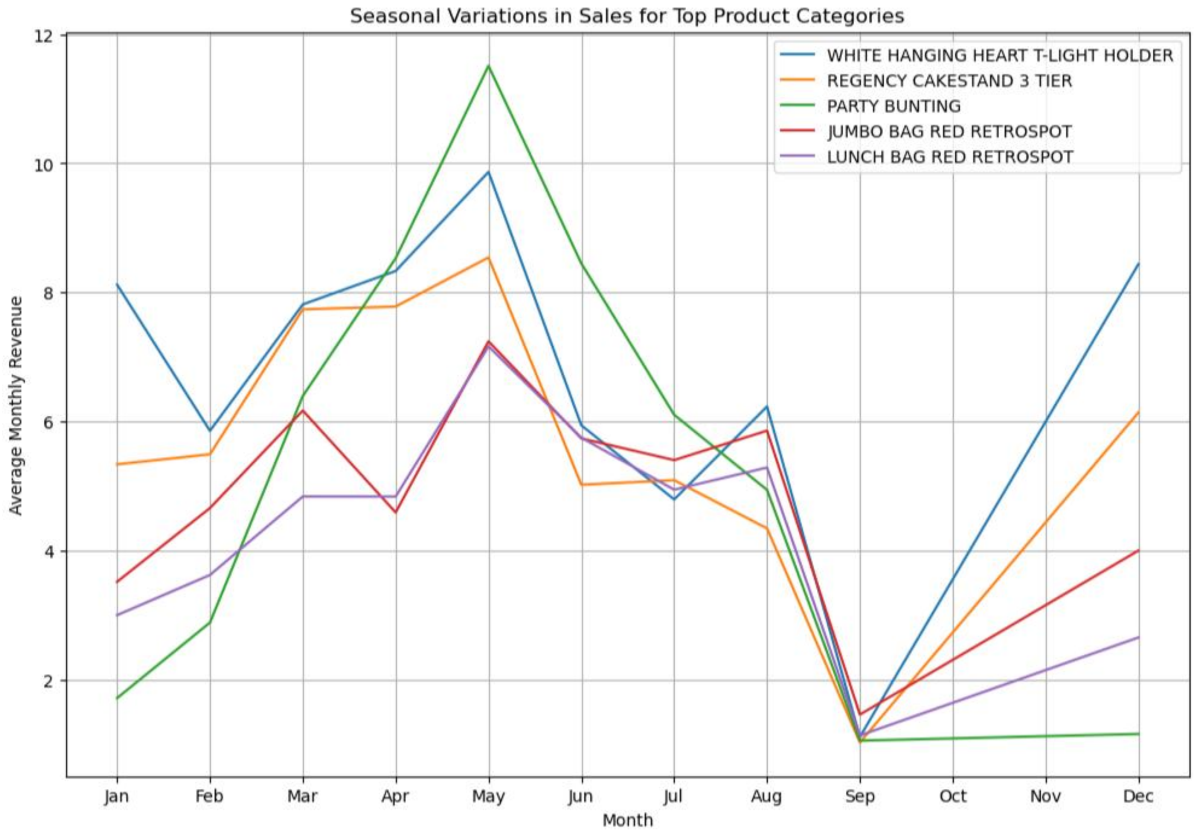

Figure 5: Seasonal Variations in Sales for Top Product Category

```
Categories Sensitive to Specific Time Periods (Peaks):
REGENCY CAKESTAND 3 TIER: Month
5    1.511888
Name: REGENCY CAKESTAND 3 TIER, dtype: float64
PARTY BUNTING: Month
4    1.617358
5    2.183147
6    1.602183
Name: PARTY BUNTING, dtype: float64
LUNCH BAG RED RETROSPOT: Month
5    1.657418
Name: LUNCH BAG RED RETROSPOT, dtype: float64
```

	CustomerID	Recency	Frequency	Monetary
0	0.000000	58	7	10.208484
1	0.000168	216	2	0.182886
2	0.000337	28	3	4.067188
3	0.000842	93	2	0.995240
4	0.001010	184	1	0.127648
...	...	...	...	...
3716	0.998822	233	1	0.549653
3717	0.998990	170	1	0.212403
3718	0.999158	9	2	0.457687
3719	0.999327	12	43	2.503026
3720	1.000000	61	2	0.222978

[3721 rows x 4 columns]

4. The study aims to identify recurring patterns in customer purchasing behavior across multiple transactions and assess if these trends can enhance the company's marketing strategy.

Monthly revenue:

Revenue data reveal both seasonal changes and prospective periods of corporate development or difficulties.

Figure 6:Monthly revenue trend

Customer Clusters:

Segmentation yields actionable insights for personalised marketing and client retention.

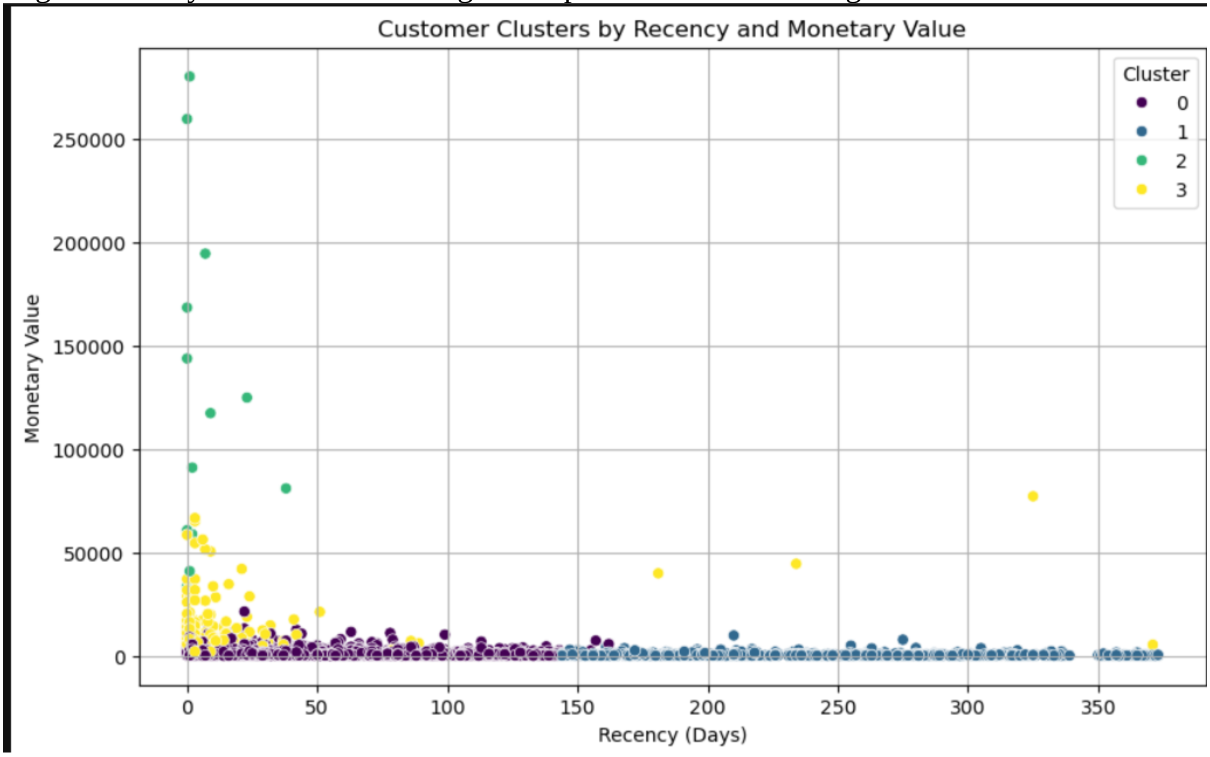

Figure 7: Customer clusters by Recency and Monetary value

Top product trends:

Key revenue drivers are recognised, allowing for more effective inventory and marketing strategies.

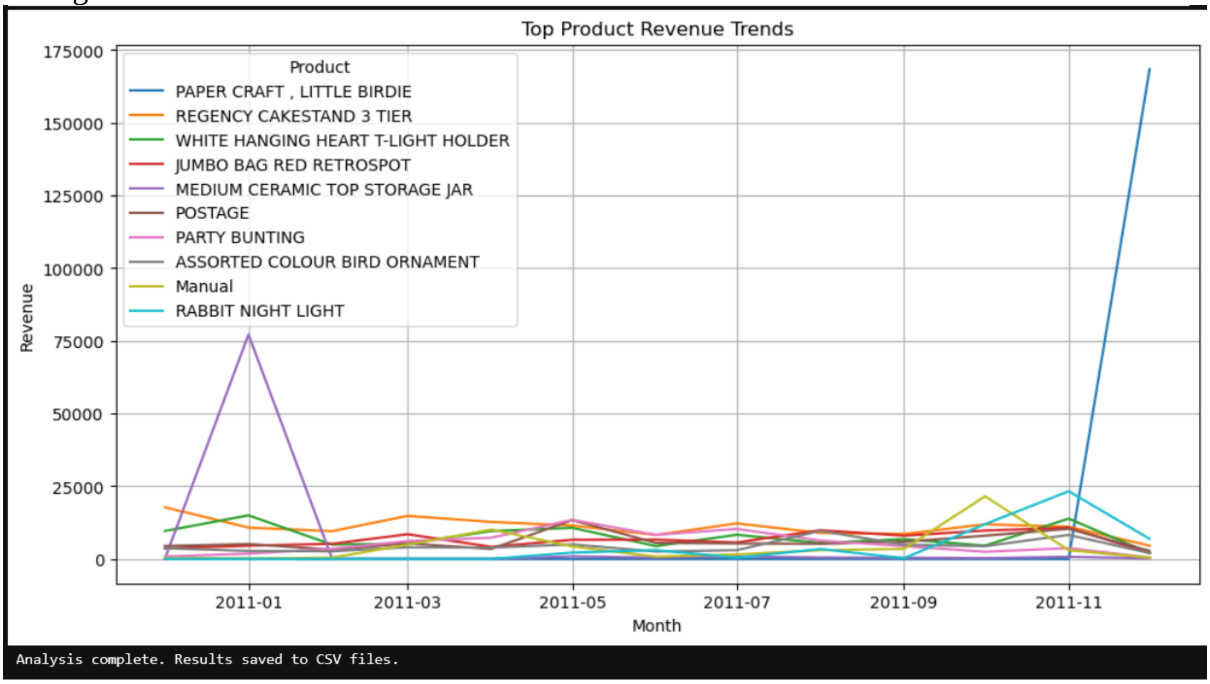

Figure 8:Top Product Revenue Trends

Business recommendations:

Align inventory and marketing strategies with recognised seasonal and product patterns. Prioritise high-value clients while researching re-engagement with inactive ones. Businesses may make more informed strategic decisions by combining revenue patterns, transaction behaviour, and product performance data.

Aspect	**Key Findings**	**Implications**
Seasonal Trends	- Certain product categories have notable revenue peaks during months.	- Targeted marketing during peak demand periods. - Make inventory modifications to match seasonal demand.
Customer Segmentation (RFM)	- High-value clients include frequent,**No table of figures entries found.** recent, and high-spending buyers.	- At-risk clients have low frequency, poor monetary value, and a long recency. - Loyalty programs for valuable clients. - Campaigns to reengage at-risk clients.
Monthly Revenue Trends	- Overall growth tendencies were observed. - Revenue drops and irregularities were discovered.	- Evaluate previous marketing initiatives and external variables that influence trends. - Address operational or market-related challenges.
Product Performance	- The top ten goods generate considerable money. - Changes in consumer demand recognised.	- Prioritise high-performing goods for marketing and inventory planning. - Adapt to changing market trends.
Limitations	- Data quality concerns. - External factor analysis is lacking. - Temporal scope and granularity restrictions. - Combine datasets to gain greater insights.	- Refresh analysis using recent data. - Conduct more detailed or external factor-driven analysis.
Recommendations	- Seasonal campaigns in critical sectors. - Customer-specific retention techniques. - Inventory optimisation. - Continuous data monitoring.	- Increase client involvement while optimising processes to achieve growth and competitiveness.

Table 1: summarizing the findings, implications, and recommendations for better strategic decision-making.

6. Discussion

The exploratory data analysis (EDA) of the e-commerce information yielded useful insights into client purchasing behaviour, seasonal trends, and product performance. These data can help make strategic decisions on how to best optimise sales and marketing efforts (Brillica Services, 2025).

Seasonal trends and Product Sensitivity

The investigation of monthly revenue patterns per product category indicated significant seasonal fluctuations. The top-performing categories showed unique revenue peaks over various months, indicating seasonal demand. For example, many categories had big revenue gains during the Christmas season, whilst others peaked at different periods of the year. These patterns suggest that some product categories are very sensitive to specific time periods, providing opportunity for targeted marketing and inventory changes (www.sciencedirect.com, n.d.).

Customer segmentation and RFM Analysis

The Recency, Frequency, and Monetary (RFM) study, along with clustering, revealed unique client groups based on their purchase habits (Wright, 2021).

For example:
High-value clients make regular purchases with significant monetary commitments and have recently completed transactions.
At-risk clients have low frequency and monetary values, as well as prolonged times between purchases. These insights enable the organisation to develop personalised marketing tactics, such as re-engagement initiatives for at-risk clients and loyalty programmes for high-value customers (Wright, 2021).

Monthly revenue trends

The examination of monthly revenue trends revealed broad growth tendencies as well as anomalies or revenue drops. Such insights are essential for understanding market trends and assessing the efficacy of previous marketing strategies. Significant variances in revenue patterns may point to external reasons, such as economic conditions or operational concerns, that should be investigated further (Optimove, n.d.).

Product Performance and Revenue Drivers

The analysis of product performance over time identified the most lucrative goods and their contribution to total income. The top ten goods regularly contributed a sizable part of sales, highlighting the necessity of prioritising these items for marketing and inventory planning. Furthermore, examination of product preferences over time indicated fluctuations in client demand, reflecting changing market trends (Handoyo et al., 2023).

Limitations and Considerations

While the study revealed useful insights, there are some constraints to consider.

Data Quality: Missing or incorrect data may impair the dependability of results. Steps were done to clean the dataset, although some abnormalities may remain.
External Factors: The analysis excludes market rivalry, economic conditions, and seasonality that is unrelated to product demand.
Temporal Scope: The insights are based on historical data, which may not completely reflect future trends or variations in customer behaviour.
Granularity: The investigation relied on aggregated measures, which may have overlooked micro-level behaviours or niche patterns (Yaoyao Fiona Zhao, Xie and Sun, 2024).

Limitation types:

1. **Geographical Analysis**: The dataset does not include geographical information, such as customer location or region. This limitation restricts the ability to analyze regional variations in sales and customer preferences, which could provide critical insights for location-based marketing strategies.
2. **Data Limits**: The dataset's scope may exclude certain relevant variables, such as marketing campaigns, competitor activity, or economic conditions, which can influence customer behavior and sales trends. Additionally, missing or inaccurate data points could lead to incomplete or biased results.
3. **Short Time Frame**: If the dataset spans only a limited time period, it may not capture long-term trends, seasonality, or changes in customer preferences. This limitation can affect the robustness of the analysis and its applicability to future periods.

7. Code Explanation

Seasonal Trends and Product Sensitivity Analysis

1. **Monthly Earnings for Each Product Category**:

```
#  Calculating monthly earnings for every product category.
monthly_category_revenue = data.groupby(['YearMonth', 'Description'])['TotalPrice'].sum().reset_index()

# Reorganizing data to simplify the analysis of seasonal patterns.
category_trends = monthly_category_revenue.pivot
(index='YearMonth', columns='Description', values='TotalPrice').fillna(0)
```

Figure 9:Monthly Earnings for Each Product Category

Groups the data by `YearMonth` and `Description`, calculating the total revenue (`TotalPrice`) for each product category per month.

2. **Reorganizing Data**:

```
#  Calculating monthly earnings for every product category.
monthly_category_revenue = data.groupby(['YearMonth', 'Description'])['TotalPrice'].sum().reset_index()

# Reorganizing data to simplify the analysis of seasonal patterns.
category_trends = monthly_category_revenue.pivot
(index='YearMonth', columns='Description', values='TotalPrice').fillna(0)

# Isolating the month component from YearMonth for seasonal analysis.
category_trends['Month'] = category_trends.index.month  # Directly extract month from PeriodIndex
```

Figure 10:Reorganizing Data

Reshapes the data into a matrix where rows represent months, columns represent product categories, and values represent revenue. Missing values are filled with 0.

3. **Extracting Month Component**:

```
# Isolating the month component from YearMonth for seasonal analysis.
category_trends['Month'] = category_trends.index.month  # Directly extract month from PeriodIndex

# Computing the average sales for each month over multiple years.
monthly_avg_sales = category_trends.groupby('Month').mean()
```

Figure 11:Extracting Month Component

Extracts the month from the `YearMonth` index for seasonal analysis.

4. **Average Sales for Each Month**:

```
# Computing the average sales for each month over multiple years.
monthly_avg_sales = category_trends.groupby('Month').mean()
```

Figure 12:Average Sales for Each Month

Calculates the average revenue for each month across multiple years.

5. **Top 5 Categories by Revenue**:

```
# Restricting the plot to the top 5 categories ranked by average monthly revenue.
top_categories = monthly_avg_sales.sum().nlargest(5).index
```

Figure 13:Top 5 Categories by Revenue

Identifies the top 5 categories based on total average monthly revenue.

6. **Seasonal Trends Visualization**:

```
# Restricting the plot to the top 5 categories ranked by average monthly revenue.
top_categories = monthly_avg_sales.sum().nlargest(5).index

# Analyzing seasonal trends for the top 5 categories.
plt.figure(figsize=(12, 8))
for category in top_categories:
    plt.plot(monthly_avg_sales.index, monthly_avg_sales[category], label=category)

plt.title('Seasonal Variations in Sales for Top Product Categories')
plt.xlabel('Month')
plt.ylabel('Average Monthly Revenue')
plt.legend()
plt.xticks(range(1, 13), ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.grid(True)
plt.show()
```

Figure 14:Seasonal Trends Visualization

Plots the seasonal trends for the top 5 categories.

7. **Categories Sensitive to Time Periods**:

```
# Identifying categories that are influenced by specific time periods.
sensitive_categories = {}
threshold = 1.5

for category in top_categories:
    seasonal_variation = monthly_avg_sales[category] / monthly_avg_sales[category].mean()
    peaks = seasonal_variation[seasonal_variation > threshold]
    if not peaks.empty:
        sensitive_categories[category] = peaks

print("Categories Sensitive to Specific Time Periods (Peaks):")
for category, peaks in sensitive_categories.items():
    print(f"{category}: {peaks}")
```

Figure 15:Categories Sensitive to Time Periods

Identifies categories with significant seasonal variations (greater than 1.5 times the average revenue).

1. **RFM Metrics Calculation**:
   - **Recency**: Days since the last purchase for each customer.
   - **Frequency**: Number of distinct invoices for each customer.
   - **Monetary**: Total revenue contributed by each customer.
2. **Clustering**:
   - The RFM metrics are normalized using `StandardScaler`.
   - KMeans clustering groups customers into segments based on their RFM scores.
3. **Cluster Analysis**:

```
# Analyze clusters
cluster_summary = customer_analysis.groupby('Cluster').agg(
    AvgRecency=('Recency', 'mean'),
    AvgFrequency=('Frequency', 'mean'),
    AvgMonetary=('Monetary', 'mean'),
    CustomerCount=('CustomerID', 'count')
).reset_index()

print("Cluster Summary:")
print(cluster_summary)
```

Figure 16:Cluster Analysis

Summarizes the characteristics of each cluster, including average RFM metrics and the number of customers in each group.

8. Recommendations

Seasonal Campaigns: Create tailored marketing campaigns that correspond to seasonal demand in sensitive product categories.
Customer Retention: Create loyalty programs and personalised offers for high-value consumers, while developing re-engagement techniques for at-risk categories.
Inventory optimisation involves adjusting inventory levels based on seasonal trends and product demand estimates in order to reduce stockouts and overstocking.
Continuous Monitoring: Update and analyse data on a regular basis to stay current with changing market circumstances and client preferences.
Finally, this study provides the e-commerce firm with practical information for improving its sales strategy, increasing consumer engagement, and optimising product offers. By harnessing these results, the organisation may position itself for long-term development and competitive advantage.

9. Conclusion

The research gave useful information about client behaviour, seasonal trends, and product performance. The key results include:

1. The analysis found substantial seasonal trends in sales for the most popular product categories. Certain categories saw peak sales in various months, demonstrating seasonal sensitivity. This information may be used to assist inventory management and targeted marketing activities during peak demand periods.

2. RFM Analysis was used to classify clients into clusters based on their recency, frequency, and monetary activity. Each cluster had distinct purchasing behaviours, such as regular consumers who made large monetary donations or clients who went inactive for extended periods of time. These categories may be used to create personalised marketing strategies that maximise client lifetime value.

3. Top-Performing items: Analysis of product trends identified top revenue-generating items and their historical performance. This information may be used to influence product development and advertising initiatives aimed at capitalising on popular goods.

4. Monthly revenue patterns show overall business success and prospective areas for improvement. Periods of diminishing revenue may signal the need for intervention, such as promotional campaigns or product diversification.

5. Actionable insights:

- Businesses in categories with high seasonal sensitivity should optimise stock levels and organise marketing efforts around peak periods.
- Customer clusters with low recency and high monetary values offer potential for re-engagement initiatives.
- Top-performing items should be prioritised for promotions to ensure constant income streams.

10.Advice for Future Work

1. Incorporate Geographical Data: Including consumer location data would allow for a more comprehensive examination of regional preferences and market trends.
2. Expand the Dataset: Analysing data over a longer time period or incorporating external factors (e.g., marketing campaigns, economic situations) might strengthen the conclusions.
3. Refine Customer Clusters: Using sophisticated clustering algorithms and new characteristics may improve customer segmentation accuracy.
4. Continuous Trend Monitoring: Regular updates to the analysis will aid in the identification of developing trends and the adaptation of plans in response.

Businesses that address the restrictions and adopt the advice can improve their decision-making processes and achieve long-term success.

11. References

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