retailsaleseda-1

September 18, 2024

Retail Sales EDA

INTRODUCTION

In the ever-evolving retail landscape, gaining a nuanced understanding of sales dynamics and consumer behavior is essential for driving business success. This dataset provides a detailed snapshot of a fictional retail environment, capturing critical attributes that influence both retail operations and customer interactions. Specifically, the dataset includes Transaction ID, Date, Customer ID, Gender, Age, Product Category, Quantity, Price per Unit, and Total Amount. These attributes offer a rich foundation for exploring sales trends, demographic influences, and purchasing behaviors.

Purpose

The purpose of this data analysis project is to conduct a thorough examination of the dataset to reveal meaningful insights into retail operations and consumer patterns. By analyzing the interplay between transaction details, customer demographics, and product categories, we aim to identify key trends, assess the impact of demographic factors on purchasing behavior, and evaluate sales performance across different product categories. This analysis will enable us to generate actionable recommendations for optimizing inventory management, tailoring marketing strategies, and enhancing overall customer experience. Through this data-driven approach, we seek to empower stakeholders with valuable insights that drive strategic decision-making and improve operational efficiency.

About the dataset

dataset is taken from kaggle - https://www.kaggle.com/datasets/mohammadtalib786/retail-sales-dataset

Importing Libraries

[29]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore", "is_categorical_dtype")
warnings.filterwarnings("ignore", "use_inf_as_na")
warnings.filterwarnings("ignore")
```

Data Loading

[30]:
```
dataset=pd.read_csv('retail_sales_dataset.csv')
```

[31]:
```python
dataset.head(10)
```

[31]:
```
   Transaction ID        Date Customer ID  Gender  Age Product Category  \
0               1  2023-11-24     CUST001    Male   34           Beauty
1               2  2023-02-27     CUST002  Female   26         Clothing
2               3  2023-01-13     CUST003    Male   50      Electronics
3               4  2023-05-21     CUST004    Male   37         Clothing
4               5  2023-05-06     CUST005    Male   30           Beauty
5               6  2023-04-25     CUST006  Female   45           Beauty
6               7  2023-03-13     CUST007    Male   46         Clothing
7               8  2023-02-22     CUST008    Male   30      Electronics
8               9  2023-12-13     CUST009    Male   63      Electronics
9              10  2023-10-07     CUST010  Female   52         Clothing

   Quantity  Price per Unit  Total Amount
0         3              50           150
1         2             500          1000
2         1              30            30
3         1             500           500
4         2              50           100
5         1              30            30
6         2              25            50
7         4              25           100
8         2             300           600
9         4              50           200
```

[32]:
```python
dataset.shape
```

[32]:
```
(1000, 9)
```

There are 9 columns and 1000 rows in this dataset

[33]:
```python
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Transaction ID    1000 non-null   int64
 1   Date              1000 non-null   object
 2   Customer ID       1000 non-null   object
 3   Gender            1000 non-null   object
 4   Age               1000 non-null   int64
 5   Product Category  1000 non-null   object
 6   Quantity          1000 non-null   int64
 7   Price per Unit    1000 non-null   int64
 8   Total Amount      1000 non-null   int64
```

```
dtypes: int64(5), object(4)
memory usage: 70.4+ KB
```

Data Cleaning

[34]:
```python
dataset.nunique() #checking for unique values
```

[34]:
```
Transaction ID      1000
Date                 345
Customer ID         1000
Gender                 2
Age                   47
Product Category       3
Quantity               4
Price per Unit         5
Total Amount          18
dtype: int64
```

[35]:
```python
dataset.drop_duplicates(inplace=True) # dropping duplicates if any
dataset.size
```

[35]:
```
9000
```

No duplicate values. Lets explore the gender and product category column to check for any spelling mistakes.

[36]:
```python
dataset['Gender'].unique().tolist()
```

[36]:
```
['Male', 'Female']
```

[37]:
```python
dataset['Product Category'].unique().tolist()
```

[37]:
```
['Beauty', 'Clothing', 'Electronics']
```

There are 3 categories in product category

[38]:
```python
dataset.isnull().sum() #checking for null values
```

[38]:
```
Transaction ID      0
Date                0
Customer ID         0
Gender              0
Age                 0
Product Category    0
Quantity            0
Price per Unit      0
Total Amount        0
dtype: int64
```

[39]:
```
dataset.dtypes # datatypes
```

[39]:
```
Transaction ID       int64
Date                object
Customer ID         object
Gender              object
Age                  int64
Product Category    object
Quantity             int64
Price per Unit       int64
Total Amount         int64
dtype: object
```

from above we can see that Date column is of object type which needs to be changed to datetime

[40]:
```
dataset['Date']=pd.to_datetime(dataset['Date'])
dataset.dtypes
```

[40]:
```
Transaction ID               int64
Date                datetime64[ns]
Customer ID                 object
Gender                      object
Age                          int64
Product Category            object
Quantity                     int64
Price per Unit               int64
Total Amount                 int64
dtype: object
```

Descriptive Statistics

[41]:
```
dataset.describe()
```

[41]:
```
       Transaction ID                           Date         Age     Quantity  \
count     1000.000000                           1000  1000.00000  1000.000000
mean       500.500000  2023-07-03 00:25:55.200000256    41.39200     2.514000
min          1.000000            2023-01-01 00:00:00    18.00000     1.000000
25%        250.750000            2023-04-08 00:00:00    29.00000     1.000000
50%        500.500000            2023-06-29 12:00:00    42.00000     3.000000
75%        750.250000            2023-10-04 00:00:00    53.00000     4.000000
max       1000.000000            2024-01-01 00:00:00    64.00000     4.000000
std        288.819436                            NaN    13.68143     1.132734

       Price per Unit  Total Amount
count     1000.000000   1000.000000
mean       179.890000    456.000000
min         25.000000     25.000000
25%         30.000000     60.000000
```

```
50%        50.000000    135.000000
75%       300.000000    900.000000
max       500.000000   2000.000000
std       189.681356    559.997632
```

[42]:
```python
dataset[['Age', 'Quantity', 'Price per Unit', 'Total Amount']].mode()
```

[42]:

	Age	Quantity	Price per Unit	Total Amount
0	43	4.0	50.0	50.0
1	64	NaN	NaN	NaN

1.The mean age of people who made transactions is 41 and median is 42 and the mode is 43 and 64 indicating people aged 43 and 64 have purchase frequently. 2. purchases are made by people aged between 18 and 64. and 75% are below 53. 3. price for per item ranges between 50 to 500 and maximum 2000 total amount.

Exploratory Data Analysis

Following set of questions to ask the data for deriving insights. 1)What are the key sales metrics we should track over time? 2)How do sales figures fluctuate across different months of the year?Are there any noticeable patterns or trends in the sales data?

1)What are the key sales metrics we should track over time?

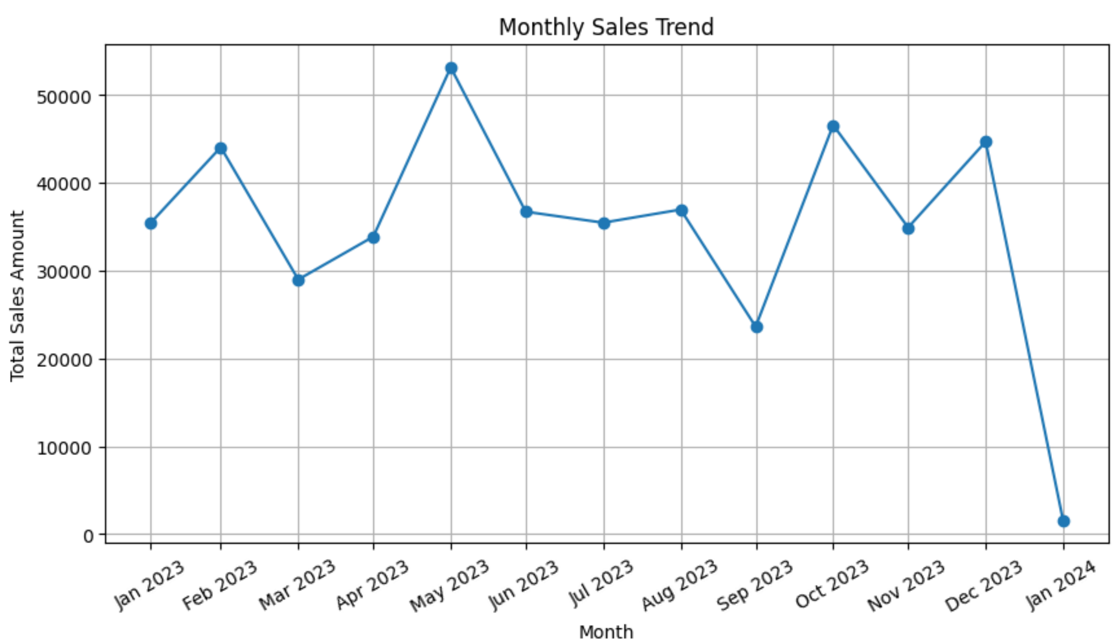
[43]:
```python
total_sales_revenue = dataset['Total Amount'].sum()
print("Total Sales Revenue Over Time:")
print(total_sales_revenue)
total_transactions=dataset['Transaction ID'].count()
print("\nTotal number of transactions:")
print(total_transactions)
total_units_sold=dataset['Quantity'].sum()
print("\nTotal Units Sold:")
print(total_units_sold)
avg_transaction_value = total_sales_revenue/total_transactions
print("\nAverage Transaction Value Over Time:")
print(avg_transaction_value)
Average_Quantity_per_Transaction = total_units_sold/total_transactions
print("\nAverage Quantity per Transaction:")
print(Average_Quantity_per_Transaction)
sales_by_category = dataset.groupby('Product Category').agg({'Total Amount':
 ↪'sum'}).reset_index()
print("\nTotal revenue per category:")
print(sales_by_category)
```

```
Total Sales Revenue Over Time:
456000

Total number of transactions:
1000
```

```
Total Units Sold:
2514

Average Transaction Value Over Time:
456.0

Average Quantity per Transaction:
2.514

Total revenue per category:
  Product Category  Total Amount
0           Beauty        143515
1         Clothing        155580
2      Electronics        156905
```

Time Series Analysis 2)How do sales figures fluctuate across different months of the year?

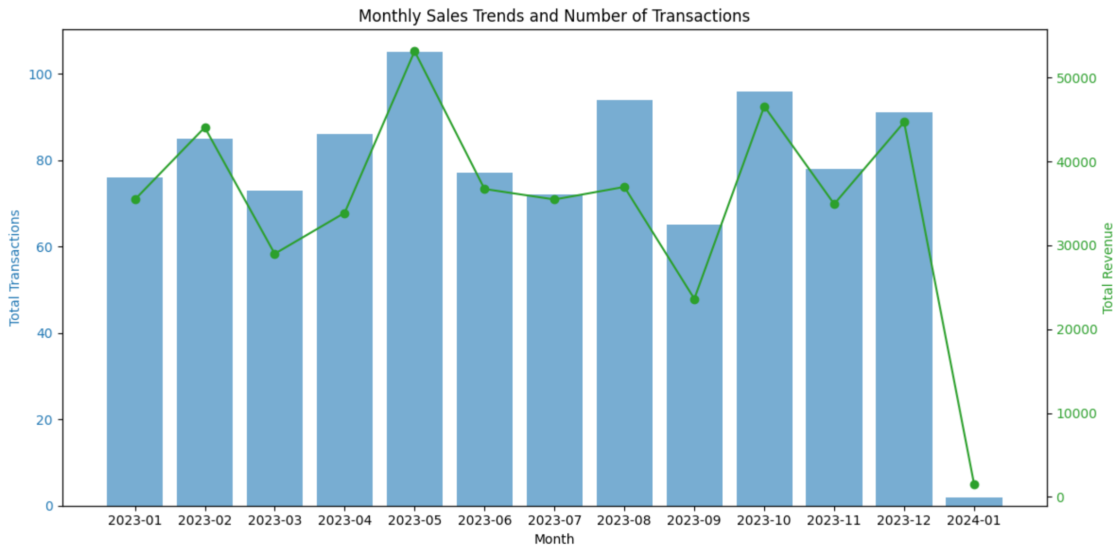
[44]:
```
monthly_sales = dataset.resample('ME', on='Date')['Total Amount'].sum()
plt.figure(figsize=(10, 5))
plt.plot(monthly_sales.index, monthly_sales.values, marker='o')
plt.title('Monthly Sales Trend')
plt.xlabel('Month')
plt.ylabel('Total Sales Amount')
plt.xticks(ticks=monthly_sales.index, labels=[month.strftime('%b %Y') for month␣
↪in monthly_sales.index], rotation=30)
plt.grid(True)
plt.show()
```



1)From the above graph we can see that revenue growth was notably recorded in February, May, October, and December, with the remaining months experienced decline.

[45]:
```
# Extract month and year from 'Date'
dataset['YearMonth'] = dataset['Date'].dt.to_period('M')

# Calculate total number of transactions per month
transactions_per_month = dataset['YearMonth'].value_counts().sort_index()

# Calculate total revenue per month
revenue_per_month = dataset.groupby('YearMonth')['Total Amount'].sum().
↪sort_index()

# Combine results into a single DataFrame for plotting
result_df = pd.DataFrame({
    'Total Revenue': revenue_per_month,
    'Total Transactions': transactions_per_month
})

# Convert YearMonth to a readable format for plotting
result_df.index = result_df.index.astype(str)



# Plotting
fig, ax1 = plt.subplots(figsize=(12, 6))

# Plot Total Transactions as columns
color = 'tab:blue'
ax1.set_xlabel('Month')
ax1.set_ylabel('Total Transactions', color=color)
ax1.bar(result_df.index, result_df['Total Transactions'], color=color, alpha=0.
↪6, label='Total Transactions')
ax1.tick_params(axis='y', labelcolor=color)

# Create a secondary y-axis to plot Total Revenue as a line
ax2 = ax1.twinx()
color = 'tab:green'
ax2.set_ylabel('Total Revenue', color=color)
ax2.plot(result_df.index, result_df['Total Revenue'], color=color, marker='o',␣
↪label='Total Revenue')
ax2.tick_params(axis='y', labelcolor=color)

# Add titles and legends
plt.title('Monthly Sales Trends and Number of Transactions')
fig.tight_layout()
```

```
plt.show()
```



[46]:

```
dataset['YearMonth'] = dataset['Date'].dt.to_period('M')

# Calculate total number of transactions per month
transactions_per_month = dataset['YearMonth'].value_counts().sort_index()

# Calculate total revenue per month
revenue_per_month = dataset.groupby('YearMonth')['Total Amount'].sum().
↪sort_index()

result_df = pd.DataFrame({
    'Total Number of Transactions': transactions_per_month,
    'Total Revenue': revenue_per_month
})
# Reset index to use YearMonth as a column for sorting
result_df = result_df.reset_index()
result_df.rename(columns={'index': 'YearMonth'}, inplace=True)

# Sort by total revenue in descending order
result_df = result_df.sort_values(by='Total Revenue', ascending=False)

# Convert YearMonth period to a readable month name
result_df['YearMonth'] = result_df['YearMonth'].dt.strftime('%B %Y')

# Print results sorted by revenue
print(result_df)
```

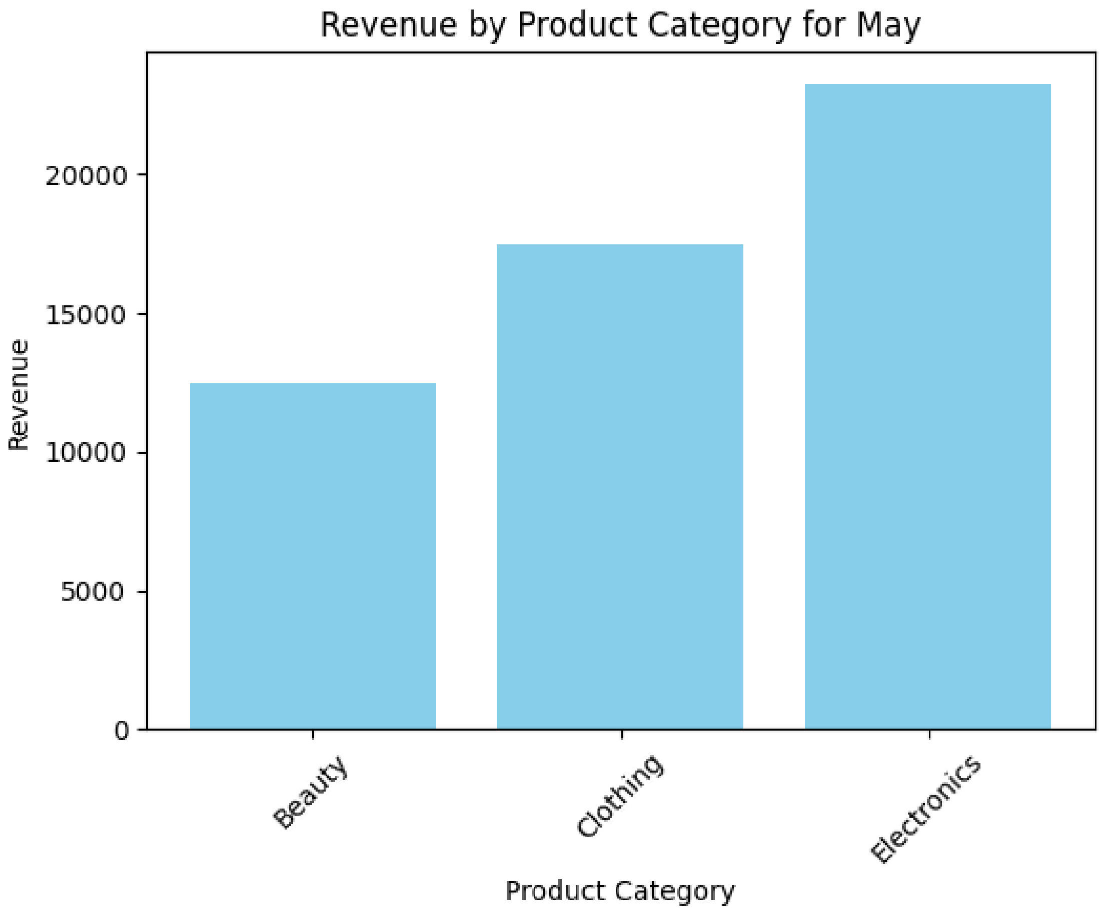
```
         YearMonth  Total Number of Transactions  Total Revenue
```

```
4          May 2023                                 105         53150
9      October 2023                                  96         46580
11    December 2023                                  91         44690
1     February 2023                                  85         44060
7       August 2023                                  94         36960
5         June 2023                                  77         36715
6         July 2023                                  72         35465
0      January 2023                                  76         35450
10    November 2023                                  78         34920
3        April 2023                                  86         33870
2        March 2023                                  73         28990
8    September 2023                                  65         23620
12     January 2024                                   2          1530
```

from the above graph and data its seen that total number of transactions during the month of march,april and august does not align with total revenue. it can be due to purchases made by customers during those months are low rate products.

The key points of discussion are the significant revenue spike in May and the noticeable revenue drop in September. Let's analyze the underlying factors contributing to these fluctuations to understand their impact on overall performance.

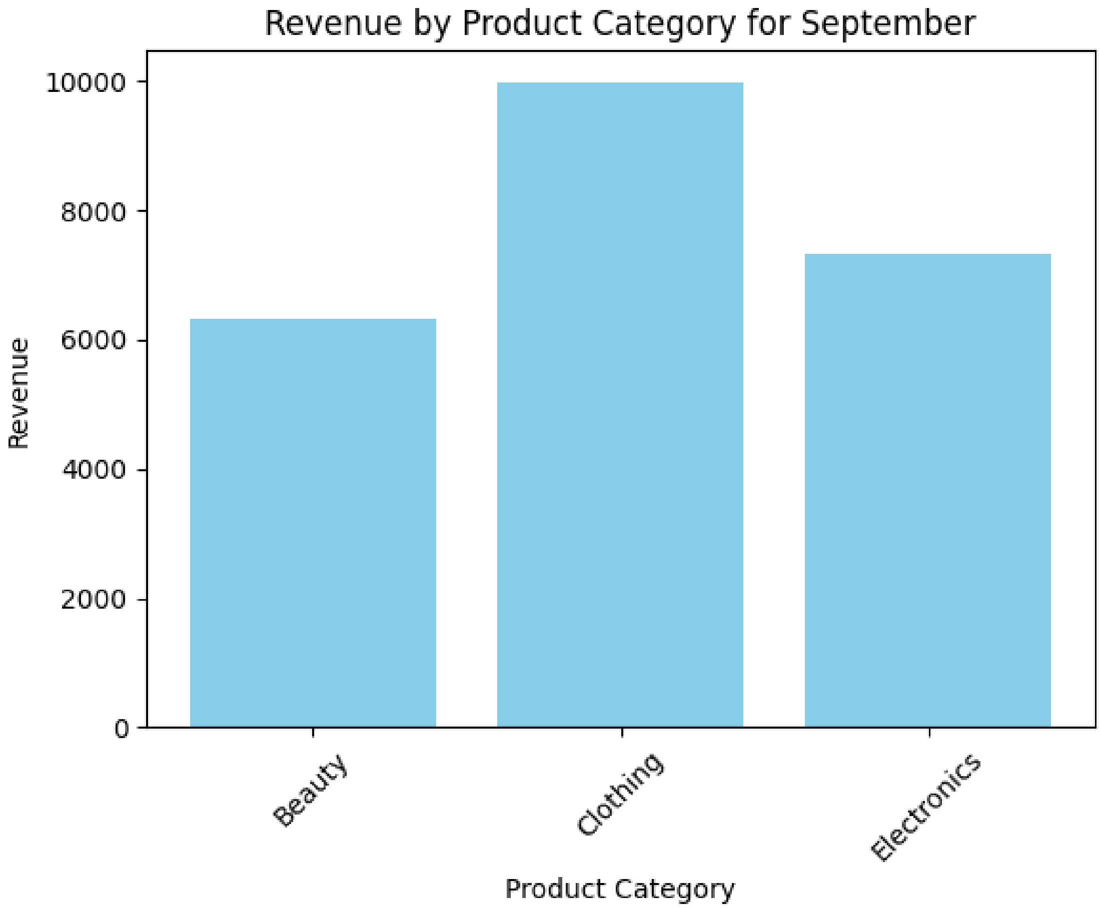
[47]:
```
dt_may = dataset[dataset['Date'].dt.month == 5]

# Group by 'Product Category' and sum 'Total Amount'
revenue_by_category = dt_may.groupby('Product Category')['Total Amount'].sum().
 ↪reset_index()

# Plotting
plt.figure(figsize=(6, 5))
plt.bar(revenue_by_category['Product Category'], revenue_by_category['Total␣
 ↪Amount'], color='skyblue')
plt.xlabel('Product Category')
plt.ylabel('Revenue')
plt.title('Revenue by Product Category for May')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



The Electronics section in the product category has generated substantial revenue, likely attributable to the summer sales period, which typically drives a higher purchase rate.

[48]:
```
dt_sep = dataset[dataset['Date'].dt.month == 9]

# Group by 'Product Category' and sum 'Total Amount'
revenue_by_category = dt_sep.groupby('Product Category')['Total Amount'].sum().
    ↪reset_index()

# Plotting
plt.figure(figsize=(6, 5))
plt.bar(revenue_by_category['Product Category'], revenue_by_category['Total␣
    ↪Amount'], color='skyblue')
plt.xlabel('Product Category')
plt.ylabel('Revenue')
plt.title('Revenue by Product Category for September')
plt.xticks(rotation=45)
plt.tight_layout()
```

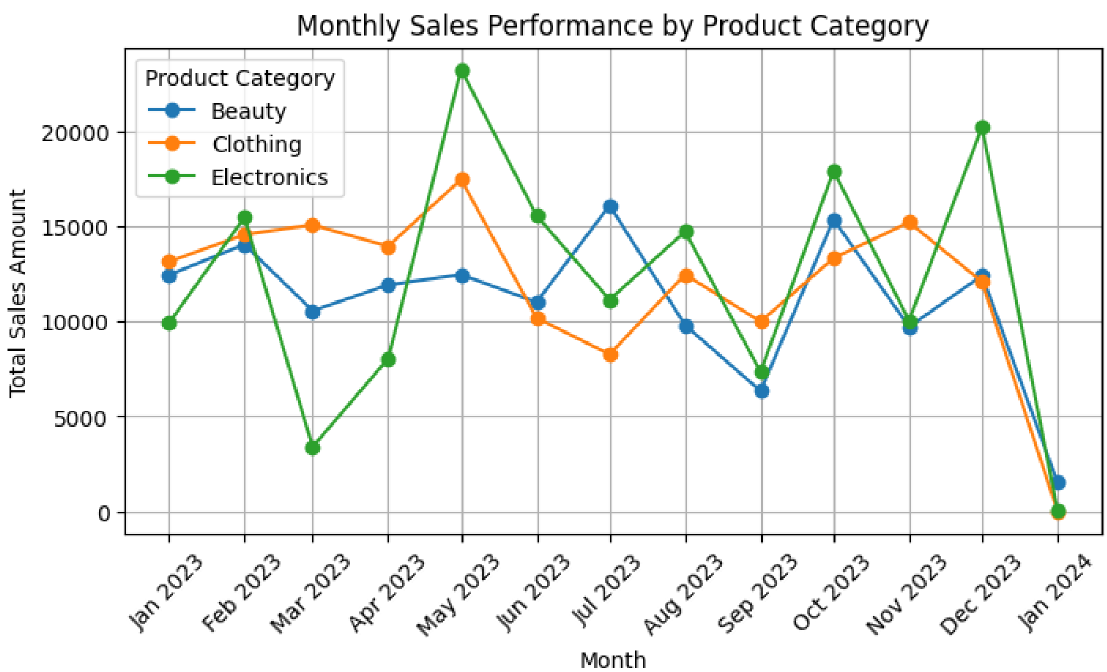
```
plt.show()
```



fall of revenue for electronics and beauty product categories with total number of transaction only 65 and revenue generated is $23620 for the month of september.

[49]:
```
category_sales = dataset.groupby([dataset['Date'].dt.to_period('M'), 'Product␣
↪Category'])['Total Amount'].sum().reset_index()

newtable = category_sales.pivot(index='Date', columns='Product Category',␣
↪values='Total Amount').fillna(0)

plt.figure(figsize=(8, 4))
for category in newtable.columns:
    plt.plot(newtable.index.to_timestamp(), newtable[category], marker='o',␣
↪label=category)  # Convert index to timestamp for better plotting

plt.title('Monthly Sales Performance by Product Category')
plt.xlabel('Month')
```

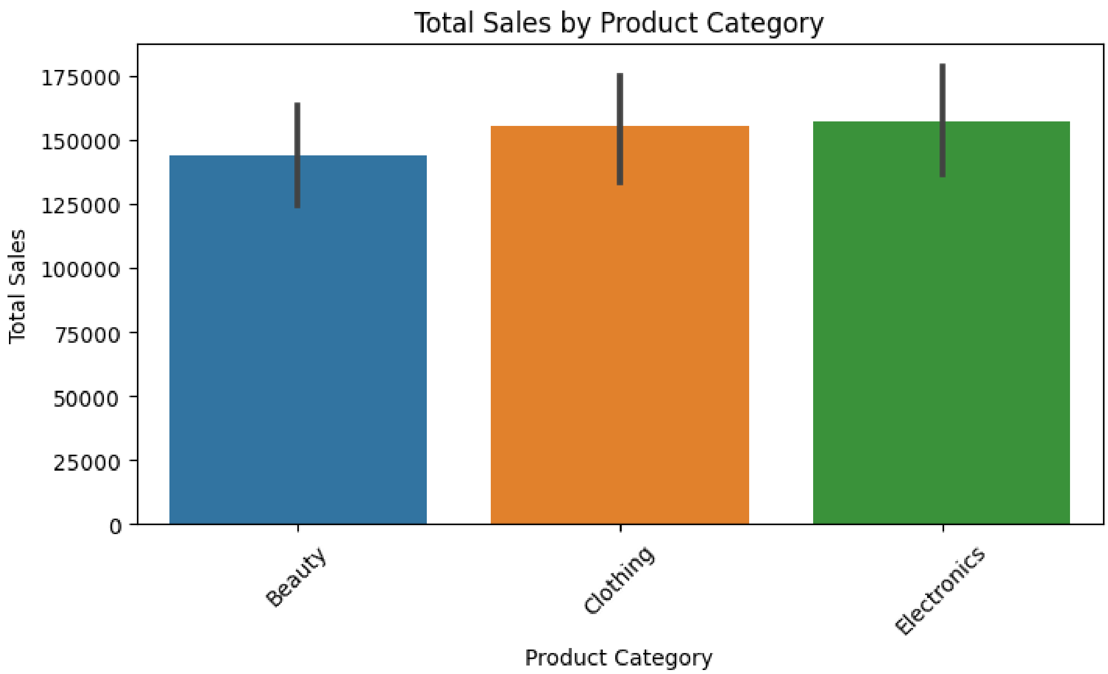
```
plt.ylabel('Total Sales Amount')
plt.legend(title='Product Category')
plt.grid(True)
plt.xticks(ticks=newtable.index.to_timestamp(), labels=[date.strftime('%b %Y')␣
↪for date in newtable.index.to_timestamp()], rotation=45)  # Convert index to␣
↪timestamp and format the labels
plt.show()
```



In May 2023, two out of three product categories saw strong sales, whereas in September 2023, all categories underperformed, with Beauty hitting an all-time low, indicating a potential issue impacting sales during that month. There is limited data available, which restricts our ability to conduct a comprehensive analysis of the decline in sales. *From the above observation its seen that Electronics experienced a sales dip in March 2023 but surged to its highest level in May 2023, while Clothing peaked in May 2023 before declining in July 2023.

3)what is the distribution of Sales by Product Category

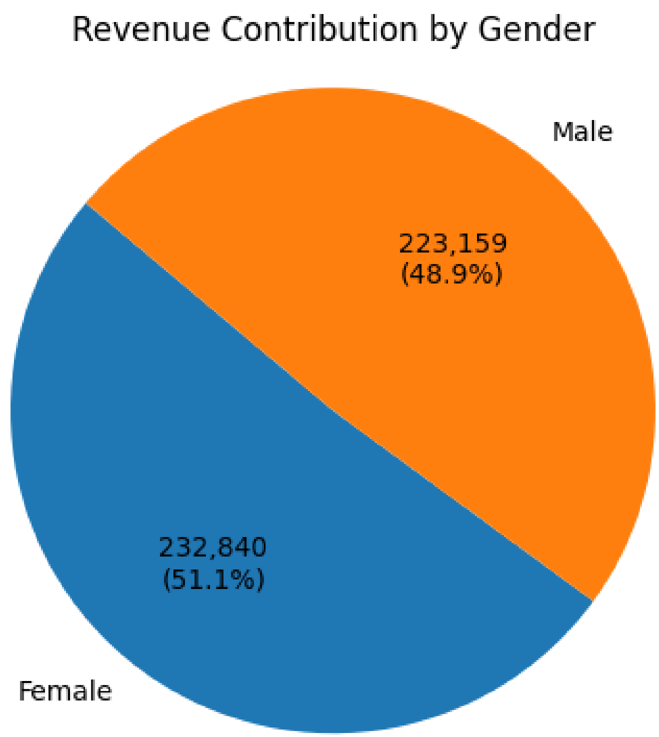
[50]:
```
plt.figure(figsize=(8, 4))
sns.barplot(x='Product Category', y='Total Amount', data=dataset, estimator=sum)
plt.title('Total Sales by Product Category')
plt.xlabel('Product Category')
plt.ylabel('Total Sales')
plt.xticks(rotation=45)
plt.show()
```



The Electronics and Clothing product categories have generated the highest revenue, indicating strong performance in these segments

4)How does revenue vary across genders?

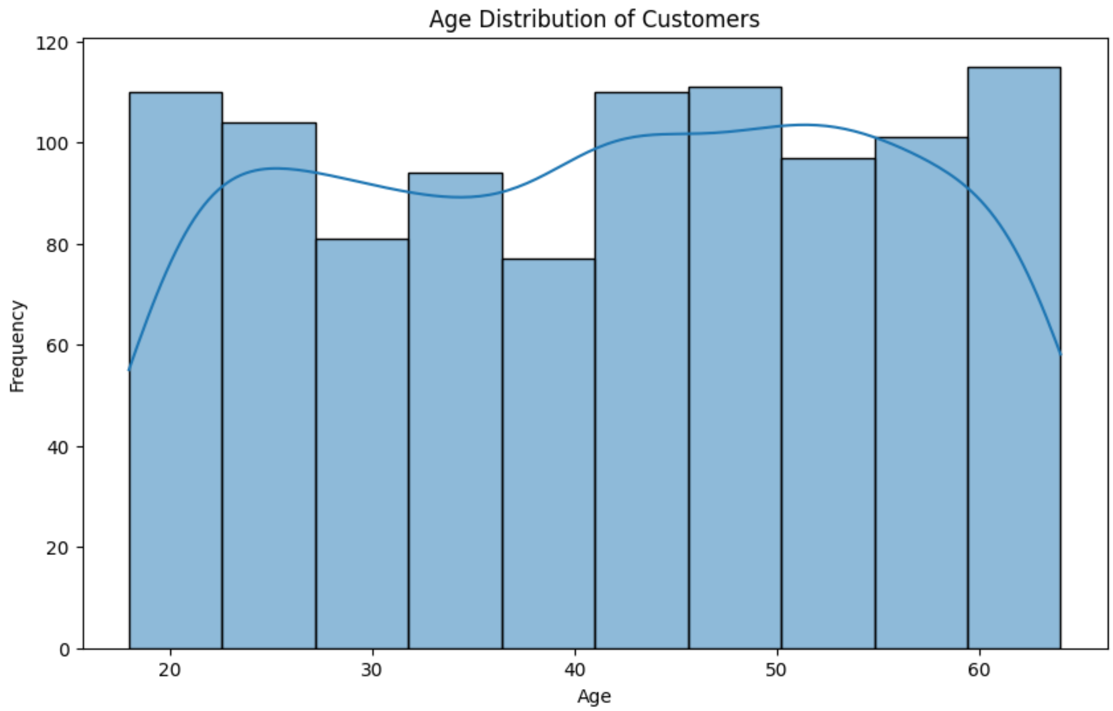
[51]:
```
revenue_by_gender = dataset.groupby('Gender')['Total Amount'].sum()

# Define a function to format the labels
def func(pct, all_vals):
    absolute = int(pct / 100.*sum(all_vals))
    return f'{absolute:,}\n({pct:.1f}%)'

# Plot pie chart
labels = revenue_by_gender.index
sizes = revenue_by_gender.values


fig, ax = plt.subplots()
ax.pie(sizes, labels=labels, autopct=lambda pct: func(pct, sizes),
 ↪startangle=140)
ax.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

plt.title('Revenue Contribution by Gender')
plt.show()
```



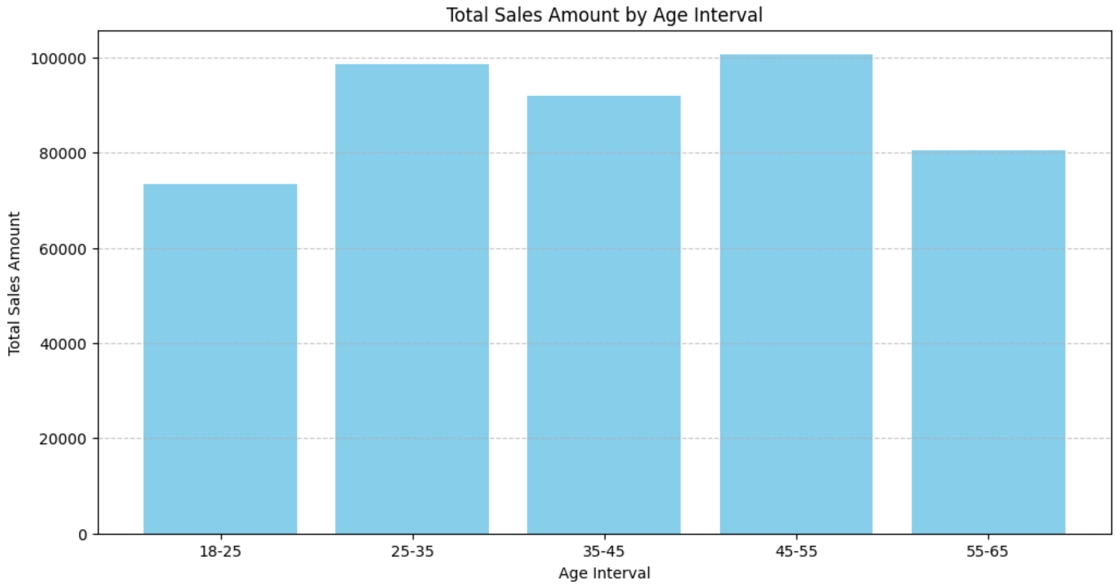
The revenue contribution by gender shows that females contributed nearly 2% more than males.

5)What is the distribution of customers' ages, and how does it impact sales patterns?

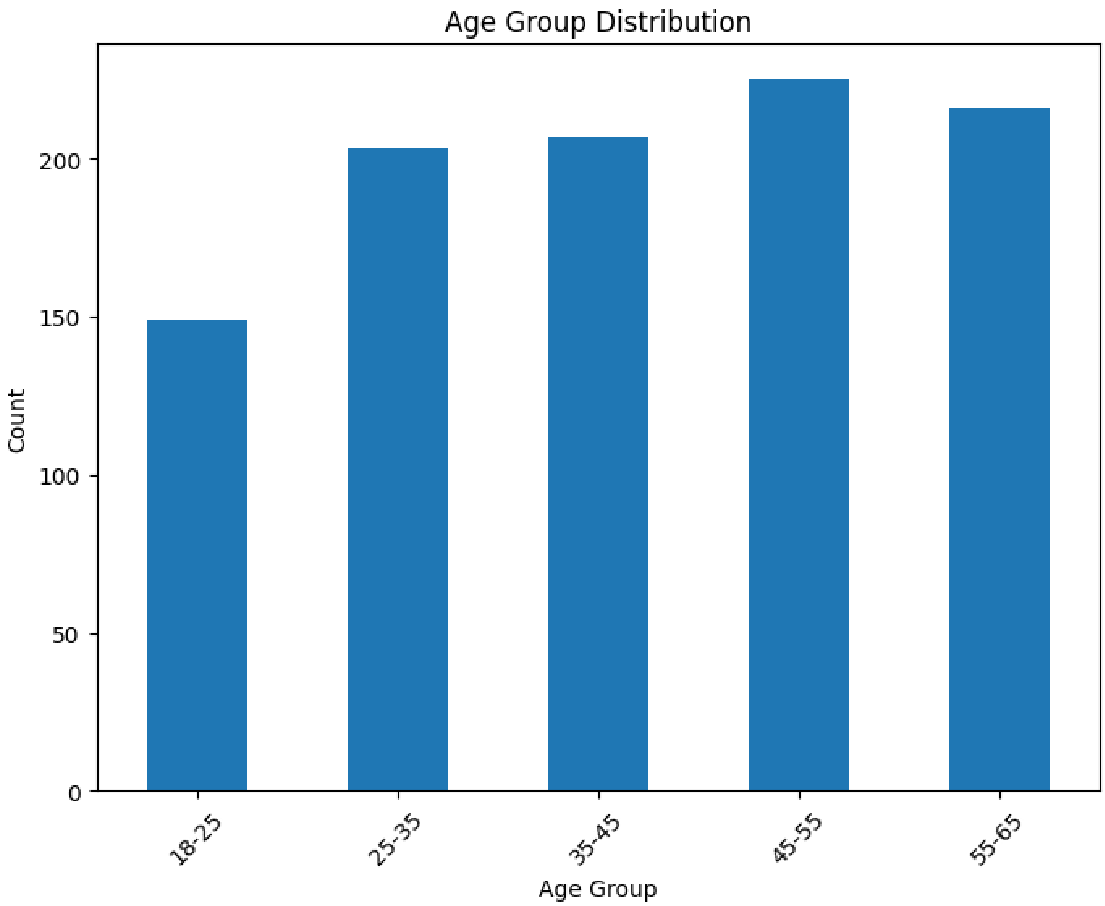
[52]:
```
plt.figure(figsize=(10, 6))
sns.histplot(dataset['Age'], bins=10, kde=True)
plt.title('Age Distribution of Customers')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



[53]:
```
bins = [18, 25, 35, 45, 55, 65]
labels = ['18-25', '25-35', '35-45', '45-55', '55-65']

# Create an 'Age Bin' column based on the defined bins
dataset['Age Bin'] = pd.cut(dataset['Age'], bins=bins, labels=labels)

# Aggregate total sales by age bin
age_bin_sales = dataset.groupby('Age Bin')['Total Amount'].sum().reset_index()

# Plot the bar graph
plt.figure(figsize=(12, 6))
plt.bar(age_bin_sales['Age Bin'], age_bin_sales['Total Amount'],␣
  ↪color='skyblue')
plt.xlabel('Age Interval')
plt.ylabel('Total Sales Amount')
plt.title('Total Sales Amount by Age Interval')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

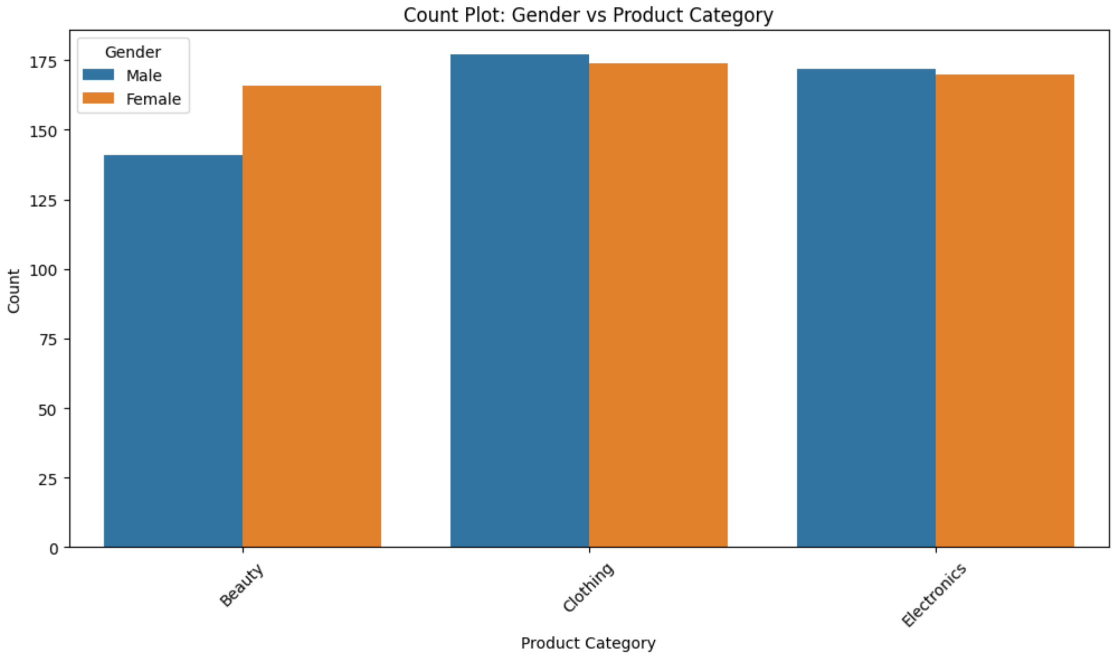


[54]:
```
bins = [18, 25, 35, 45, 55, 65]
labels = ['18-25', '25-35', '35-45', '45-55', '55-65']

dataset['Age Group'] = pd.cut(dataset['Age'], bins=bins, labels=labels,␣
 ↪right=False)

age_distribution = dataset['Age Group'].value_counts().sort_index()

age_distribution.plot(kind='bar', figsize=(8, 6), title='Age Group␣
 ↪Distribution')
plt.xlabel('Age Group')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



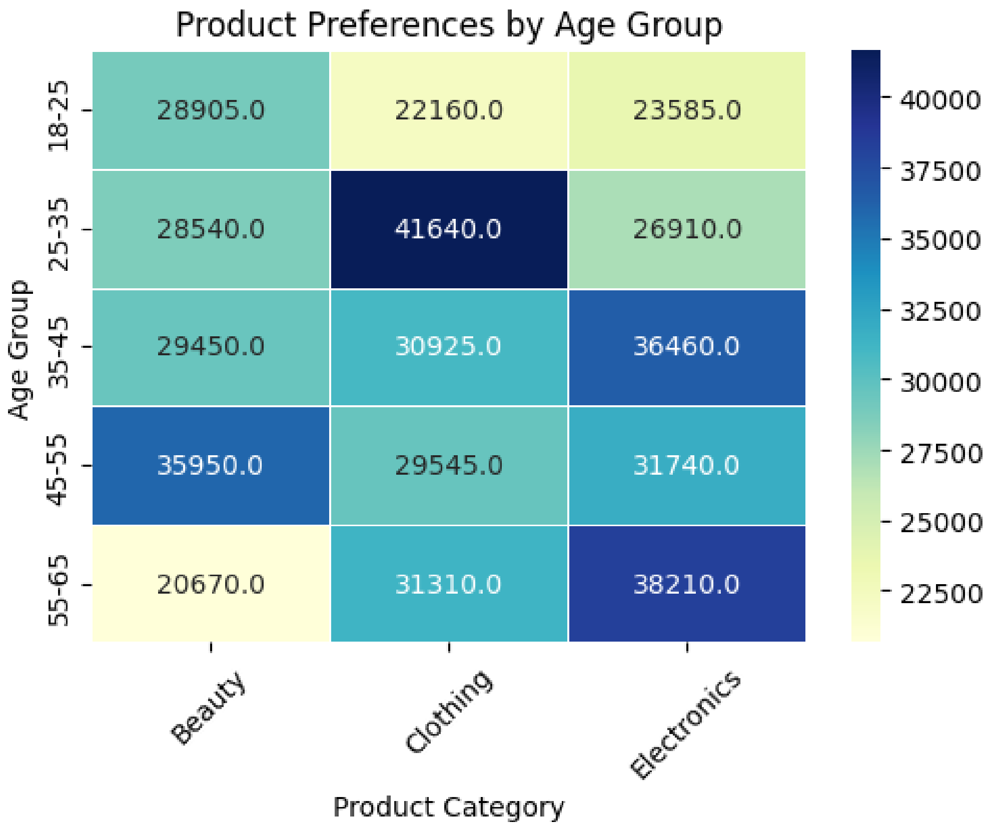
The graph reveals that the majority of shoppers fall within the 45-55 age group, whereas the 18-25 age group has the fewest shoppers.

[55]:
```
# Count Plot: Count of Gender and Product Category
plt.figure(figsize=(12, 6))
sns.countplot(data=dataset, x='Product Category', hue='Gender')
plt.title('Count Plot: Gender vs Product Category')
plt.xlabel('Product Category')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Gender')
plt.show()
```



Males purchase clothing products more frequently than females, while females buy beauty products more often than males.

[56]:
```
age_group_product_sales = dataset.groupby(['Age Group', 'Product␣
↪Category'])['Total Amount'].sum().unstack()

plt.figure(figsize=(6, 4))
sns.heatmap(age_group_product_sales, annot=True, fmt=".1f", cmap="YlGnBu",␣
↪linewidths=.5)
plt.title('Product Preferences by Age Group')
plt.xlabel('Product Category')
plt.ylabel('Age Group')
plt.xticks(rotation=45)
plt.show()
```



Recommendations

1)The shop should focus on customers aged 25-55, with specific subsegments for targeted marketing. For the 25-35 age group, prioritize Clothing products, which generate notably higher revenue in this category. For the 35-55 age group, target all product categories since revenue differences between them are minimal.Consider a targeted marketing campaign for all product categories aimed at the emerging 45-54 age group, aligning with the overall business strategy. 2)Given that females frequently purchase Beauty products but spend less per transaction, the shop should introduce higher-value Beauty items to increase revenue from female customers. This strategy aims to capitalize on their buying frequency by offering premium options. 3)The trend shows a decline in Clothing sales, necessitating strategic action to reverse this trend. Additionally, the sales dip in September requires thorough investigation and appropriate measures to address the issue. 4)May is the peak sales period, with Electronics leading. To maximize revenue during this time, explore additional marketingopportunities for Electronics and follow up with Clothing products. 5)These customers represent potential churn risks and should be targeted with personalized marketing strategies tailored to their preferred product categories.