🛒 Supermarket Sales Analysis

Tools: Python (Pandas, Matplotlib, Seaborn)
Dataset: Supermarket Sales Dataset

Objective

Analyze supermarket sales data to understand performance across product lines, branches, and time, and extract actionable business insights.

Dataset Overview

The dataset contains transactional sales data including product categories, branches, sales values, dates, customer ratings, and payment methods.

Exploratory Data Analysis (EDA)

Initial exploration was performed to understand data structure, validate data types, check for missing values, and generate statistical summaries.

In [24]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [74]:
```
df = pd.read_csv("supermarket_sales.csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Invoice ID               1000 non-null   object 
 1   Branch                   1000 non-null   object 
 2   City                     1000 non-null   object 
 3   Customer type            1000 non-null   object 
 4   Gender                   1000 non-null   object 
 5   Product line             1000 non-null   object 
 6   Unit price               1000 non-null   float64
 7   Quantity                 1000 non-null   int64  
 8   Tax 5%                   1000 non-null   float64
 9   Sales                    1000 non-null   float64
 10  Date                     1000 non-null   object 
 11  Time                     1000 non-null   object 
 12  Payment                  1000 non-null   object 
 13  cogs                     1000 non-null   float64
 14  gross margin percentage  1000 non-null   float64
 15  gross income             1000 non-null   float64
 16  Rating                   1000 non-null   float64
dtypes: float64(7), int64(1), object(9)
memory usage: 132.9+ KB
```

In [30]:
```python
df.describe()
```

Out[30]:

	Unit price	Quantity	Tax 5%	Sales	cogs	gross margin percentage	
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1.000000e+03	1000
mean	55.672130	5.510000	15.379369	322.966749	307.58738	4.761905e+00	15
std	26.494628	2.923431	11.708825	245.885335	234.17651	6.131498e-14	11
min	10.080000	1.000000	0.508500	10.678500	10.17000	4.761905e+00	0
25%	32.875000	3.000000	5.924875	124.422375	118.49750	4.761905e+00	5
50%	55.230000	5.000000	12.088000	253.848000	241.76000	4.761905e+00	12
75%	77.935000	8.000000	22.445250	471.350250	448.90500	4.761905e+00	22
max	99.960000	10.000000	49.650000	1042.650000	993.00000	4.761905e+00	49

Data Preparation

Date was converted to datetime format, and a new Month feature was created to support time-based analysis.

In [73]:
```python
df["Date"] = pd.to_datetime(df["Date"])
df["Month"] = df["Date"].dt.month
```

Visual Analysis

Visualizations were created to compare sales performance across product lines and branches, analyze monthly sales trends, and explore sales distribution.

In [48]:
```
Product_Sales = (df.groupby("Product line")["Sales"].sum().sort_values(ascending=Fa
Product_Sales
```

Out[48]:
```
Product line
Food and beverages        56144.8440
Sports and travel         55122.8265
Electronic accessories    54337.5315
Fashion accessories       54305.8950
Home and lifestyle        53861.9130
Health and beauty         49193.7390
Name: Sales, dtype: float64
```

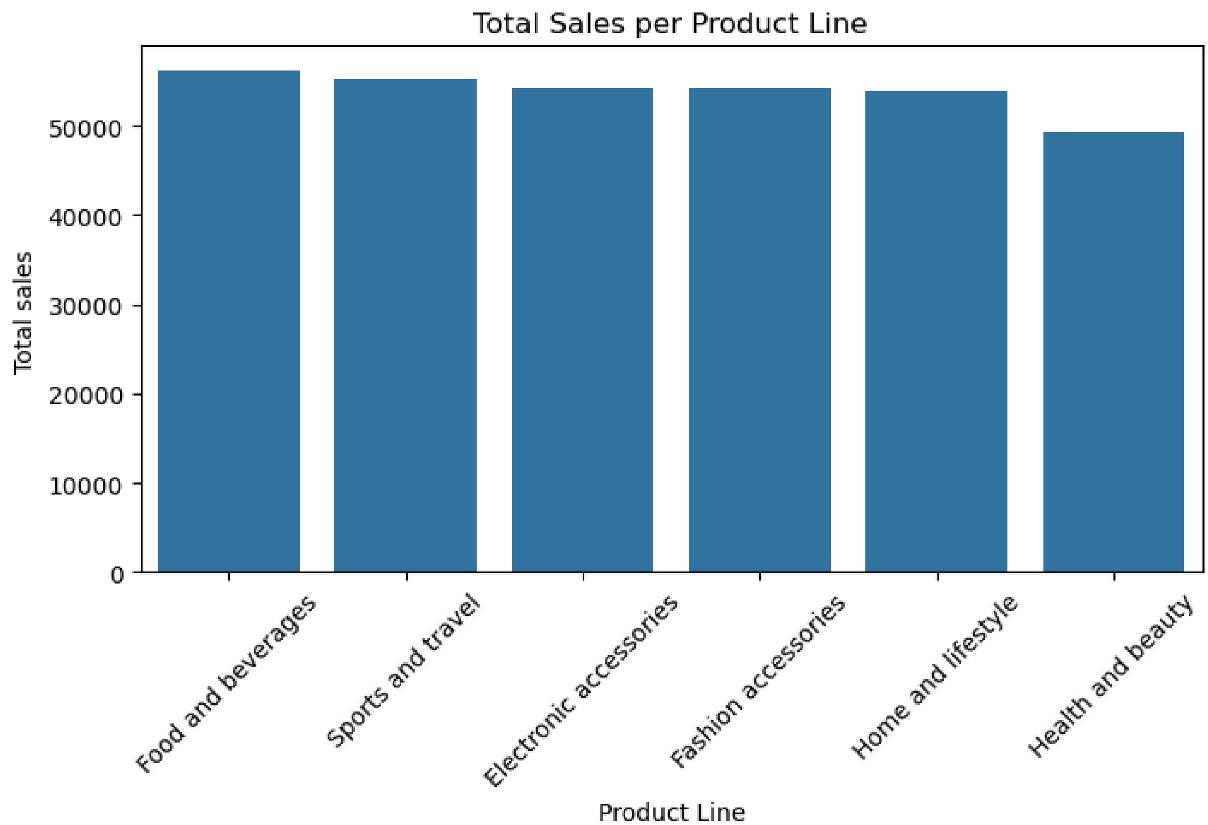
In [52]:
```
Branch_Sales = (df.groupby("Branch")["Sales"].sum().sort_values(ascending=False))
Branch_Sales
```

Out[52]:
```
Branch
Giza     110568.7065
Alex     106200.3705
Cairo    106197.6720
Name: Sales, dtype: float64
```

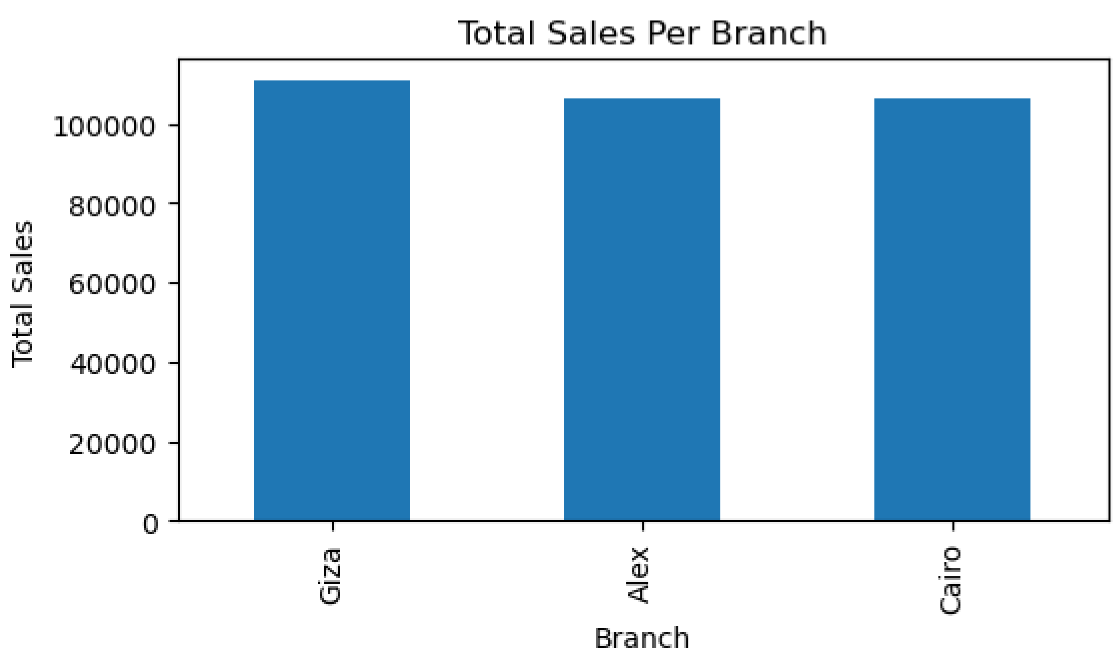
In [51]:
```
Monthly_Sales = (df.groupby("Month")["Sales"].sum())
Monthly_Sales
```

Out[51]:
```
Month
1    116291.868
2     97219.374
3    109455.507
Name: Sales, dtype: float64
```

In [60]:
```
plt.figure(figsize=(8,4))
sns.barplot(x=Product_Sales.index, y=Product_Sales.values)
plt.xticks(rotation=45)
plt.title("Total Sales per Product Line")
plt.xlabel("Product Line")
plt.ylabel("Total sales")
plt.show()
```

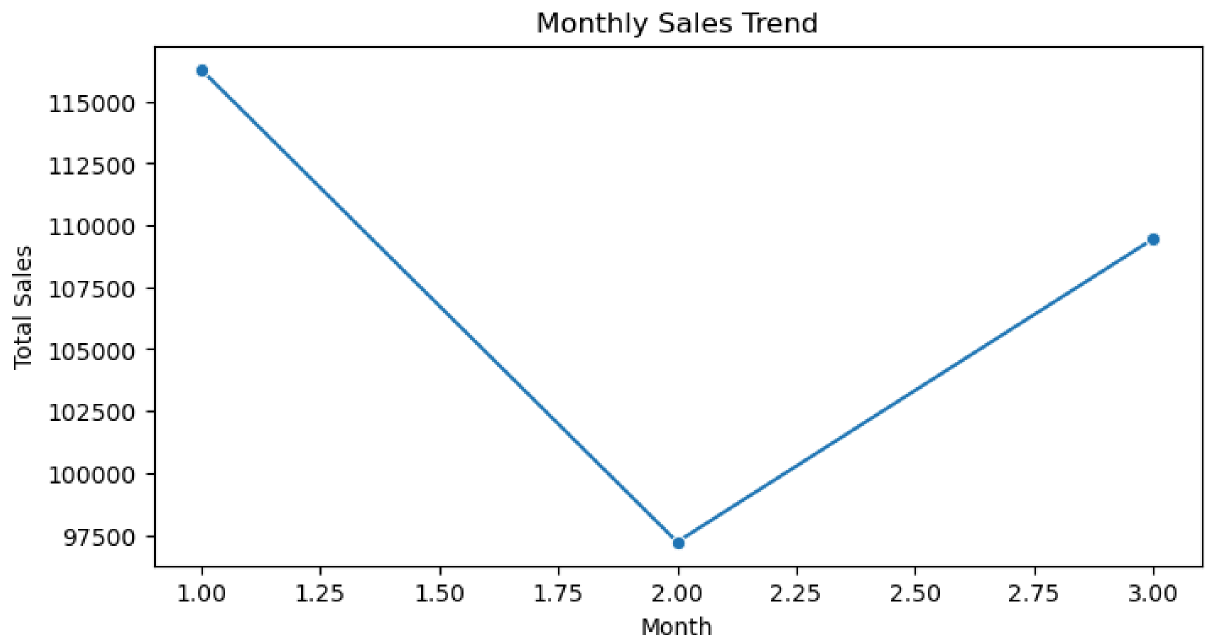


In [75]:
```
plt.figure(figsize=(6,3))
Branch_Sales.plot(kind="bar")
plt.title("Total Sales Per Branch")
plt.xlabel("Branch")
plt.ylabel("Total Sales")
plt.show()
```



In [76]:
```
plt.figure(figsize=(8,4))
sns.lineplot(x=Monthly_Sales.index, y=Monthly_Sales.values, marker="o")
```

```python
plt.title("Monthly Sales Trend")
plt.xlabel("Month")
plt.ylabel("Total Sales")
plt.show()
```



In [72]:
```python
print("Top Product Line:", Product_Sales.idxmax())
print("Top Branch:", Branch_Sales.idxmax())
print("Best Month:", Monthly_Sales.idxmax())
```

```
Top Product Line: Food and beverages
Top Branch: Giza
Best Month: 1
```

Key Insights

- Certain product lines generate consistently higher sales than others
- One branch outperforms the rest in total revenue
- Sales levels vary noticeably across different months
- Some product lines show higher sales volatility

Recommendations

- Focus marketing efforts on top-performing product lines
- Replicate successful strategies from the best-performing branch across other branches
- Prepare inventory and staffing ahead of high-sales months

Conclusion

This project highlights how exploratory data analysis and visualization can uncover meaningful patterns and support data-driven business decisions.

```
In [ ]:
```