Data Wrangling & Processing

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme(style="darkgrid")
```

In [2]:
```
data = pd.read_csv('/mnt/data/sales_data.csv')
data = pd.DataFrame(data)
data.head(2)
```

Out[2]:

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200

In [3]:
```
data.shape
```

Out[3]:
```
(1000, 17)
```

In [4]:
```
data.columns
```

Out[4]:
```
Index(['Invoice ID', 'Branch', 'City', 'Customer type', 'Gender',
       'Product line', 'Unit price', 'Quantity', 'Tax 5%', 'Total', 'Date',
       'Time', 'Payment', 'cogs', 'gross margin percentage', 'gross income',
       'Rating'],
      dtype='object')
```

In [5]:
```
data.size
```

Out[5]:
```
17000
```

In [6]:
```
data.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   Total                    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 [7]:
```
data.describe()
```

Out[7]:

	Unit price	Quantity	Tax 5%	Total	cogs	gross margin percentage	
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	10
mean	55.672130	5.510000	15.379369	322.966749	307.58738	4.761905	
std	26.494628	2.923431	11.708825	245.885335	234.17651	0.000000	
min	10.080000	1.000000	0.508500	10.678500	10.17000	4.761905	
25%	32.875000	3.000000	5.924875	124.422375	118.49750	4.761905	
50%	55.230000	5.000000	12.088000	253.848000	241.76000	4.761905	
75%	77.935000	8.000000	22.445250	471.350250	448.90500	4.761905	
max	99.960000	10.000000	49.650000	1042.650000	993.00000	4.761905	

In [8]:
```
data.dtypes
```

Out[8]:
```
Invoice ID                 object
Branch                     object
City                       object
Customer type              object
Gender                     object
Product line               object
Unit price                float64
Quantity                    int64
Tax 5%                    float64
Total                     float64
Date                       object
Time                       object
Payment                    object
cogs                      float64
gross margin percentage   float64
gross income              float64
Rating                    float64
dtype: object
```

In [9]:
```
data['datetime'] = pd.to_datetime(data['Date'] + ' ' + data['Time'], format='%m/
data = data.drop(columns=['Date', 'Time'])
data.head(2)
```

Out[9]:

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200

In [10]:
```
data.dtypes
```

Out[10]:
```
Invoice ID                        object
Branch                            object
City                              object
Customer type                     object
Gender                            object
Product line                      object
Unit price                       float64
Quantity                           int64
Tax 5%                           float64
Total                            float64
Payment                           object
cogs                             float64
gross margin percentage          float64
gross income                     float64
Rating                           float64
datetime                  datetime64[ns]
dtype: object
```

In [11]:
```
data.isnull().sum()
```

Out[11]:
```
Invoice ID                0
Branch                    0
City                      0
Customer type             0
Gender                    0
Product line              0
Unit price                0
Quantity                  0
Tax 5%                    0
Total                     0
Payment                   0
cogs                      0
gross margin percentage   0
gross income              0
Rating                    0
datetime                  0
dtype: int64
```

Exploratory Data Analysis

A. General Sales Insights

1. **What is the total revenue for the entire dataset?**
   Analyze the overall sales performance by summing up the `Total` column.
2. **Which branch contributes the most to the total revenue?**
   Compare revenue across branches (A, B, C) to identify the top-performing branch.
3. **What percentage of revenue comes from each city?**
   Calculate each city's revenue contribution relative to the total revenue.

B. Customer Behavior

1. **What is the gender distribution of customers?**
   Count male vs. female customers to understand the primary customer demographic.
2. **How does customer type (Member vs. Normal) distribution look?**
   Determine the proportion of Members vs. Non-Members to analyze loyalty trends.
3. **What is the average customer rating based on gender and customer type?**
   Analyze how ratings vary across demographics to assess customer satisfaction.

C. Product Insights

1. **Which product line generates the most revenue?**
   Identify top-performing categories by summing revenue (`Total`) per product line.
2. **Which product line is the most profitable (Gross Income)?**
   Determine the most lucrative category by evaluating `Gross Income` .
3. **What are the average unit price and quantity sold for each product line?**
   Analyze pricing and purchasing patterns to understand customer preferences.

D. Time-Based Analysis

1. **What is the monthly revenue trend?**
   Group revenue by month to track sales performance over time.
2. **Which day of the week has the highest sales?**
   Examine daily revenue trends to identify peak shopping days.
3. **What are the peak transaction times?**
   Analyze transaction times to determine the busiest shopping hours.

E. Payment Method Preferences

1. **What is the distribution of payment methods used?**
   Count the usage of Cash, Ewallet, and Credit card to understand payment preferences.
2. **Which payment method is most popular in each branch and city?**
   Evaluate payment trends across locations to spot regional preferences.

F. Profitability Analysis

1. **What is the average gross income per branch and city?**
   Compare profitability across branches and cities to identify top performers.
2. **Which product lines have the highest and lowest gross margins?**
   Analyze profit margins to identify the most efficient categories.

G. Customer Experience

1. **How are customer ratings distributed?**
   Visualize the spread of ratings to understand customer satisfaction levels.
2. **Is there a relationship between ratings and total revenue?**
   Explore whether higher ratings correlate with higher sales.

A. General Sales Insights

O1. What is the total revenue for the entire dataset?

In [12]:
```
total_revenue = data['Total'].sum()
print(f'Total Revenue: ${total_revenue:,.2f}')
```

```
Total Revenue: $322,966.75
```

O2. Which branch contributes the most to the total revenue?

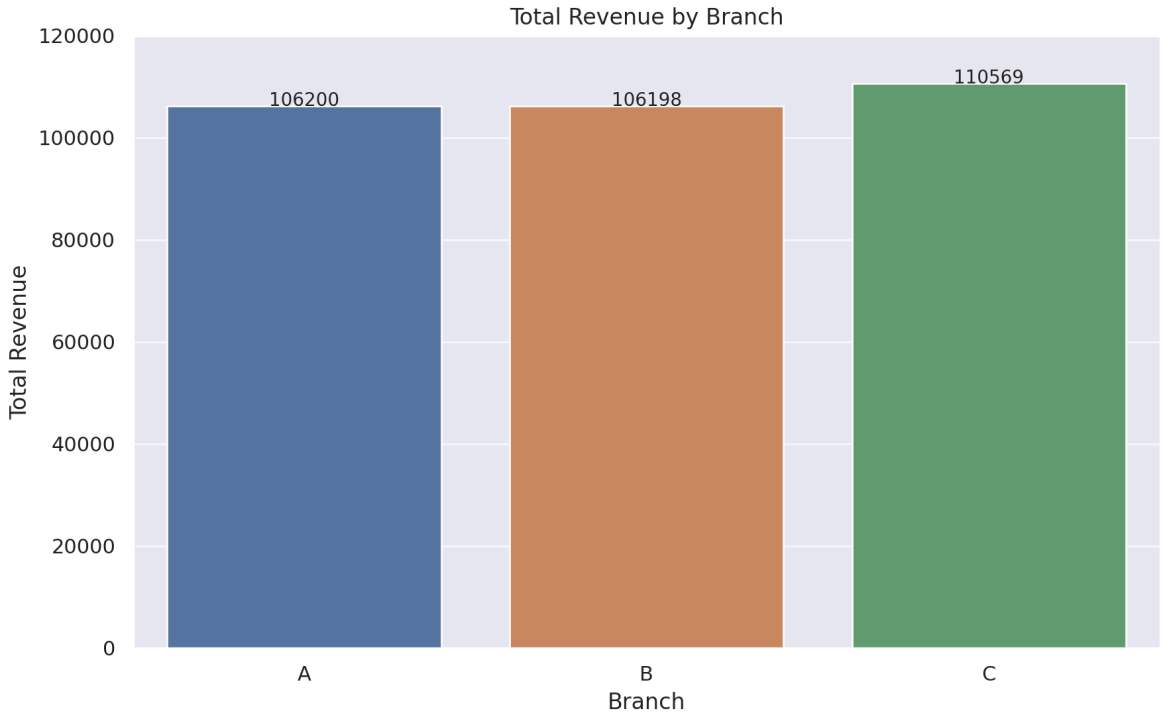
In [13]:
```
branch_revenue = data.groupby('Branch')['Total'].sum()
branch_revenue
```

Out[13]:
```
Branch
A    106200.3705
B    106197.6720
C    110568.7065
Name: Total, dtype: float64
```

In [14]:
```
highest_revenue_branch = branch_revenue.idxmax()
highest_revenue_branch_revenue = branch_revenue.max()
print(f'Highest Revenue branch is branch {highest_revenue_branch} with ${highest
```

```
Highest Revenue branch is branch C with $110,568.71 revenue
```

In [15]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x=branch_revenue.index,
            y=branch_revenue.values)

for i, value in enumerate(branch_revenue):
    plt.text(i, value, f'{value:.0f}', ha='center', fontsize=10)

plt.title('Total Revenue by Branch')
plt.xlabel('Branch')
plt.ylabel('Total Revenue')
plt.yticks(range(0, int(branch_revenue.max()) + 20000, 20000))
plt.show()
```

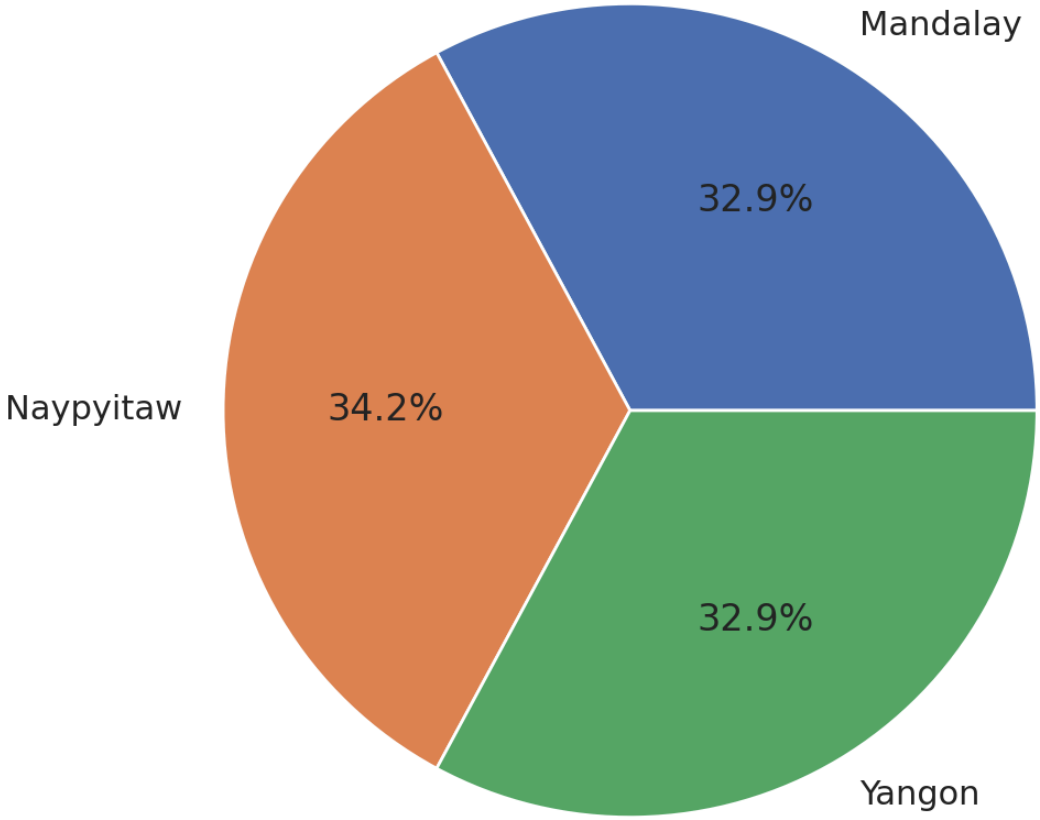


Q3. What percetage of revenue comes from each city?

In [16]:
```
city_percentage_revenue = data.groupby('City')['Total'].sum() / data['Total'].su
city_percentage_revenue.sort_values(ascending=False)
```

Out[16]:
```
City
Naypyitaw    34.235322
Yangon       32.882757
Mandalay     32.881921
Name: Total, dtype: float64
```

In [17]:
```
plt.pie (
    data=city_percentage_revenue,
    x=city_percentage_revenue.values,
    labels=city_percentage_revenue.index,
    autopct='%1.1f%%')

plt.show()
```



B. Customer Behavior

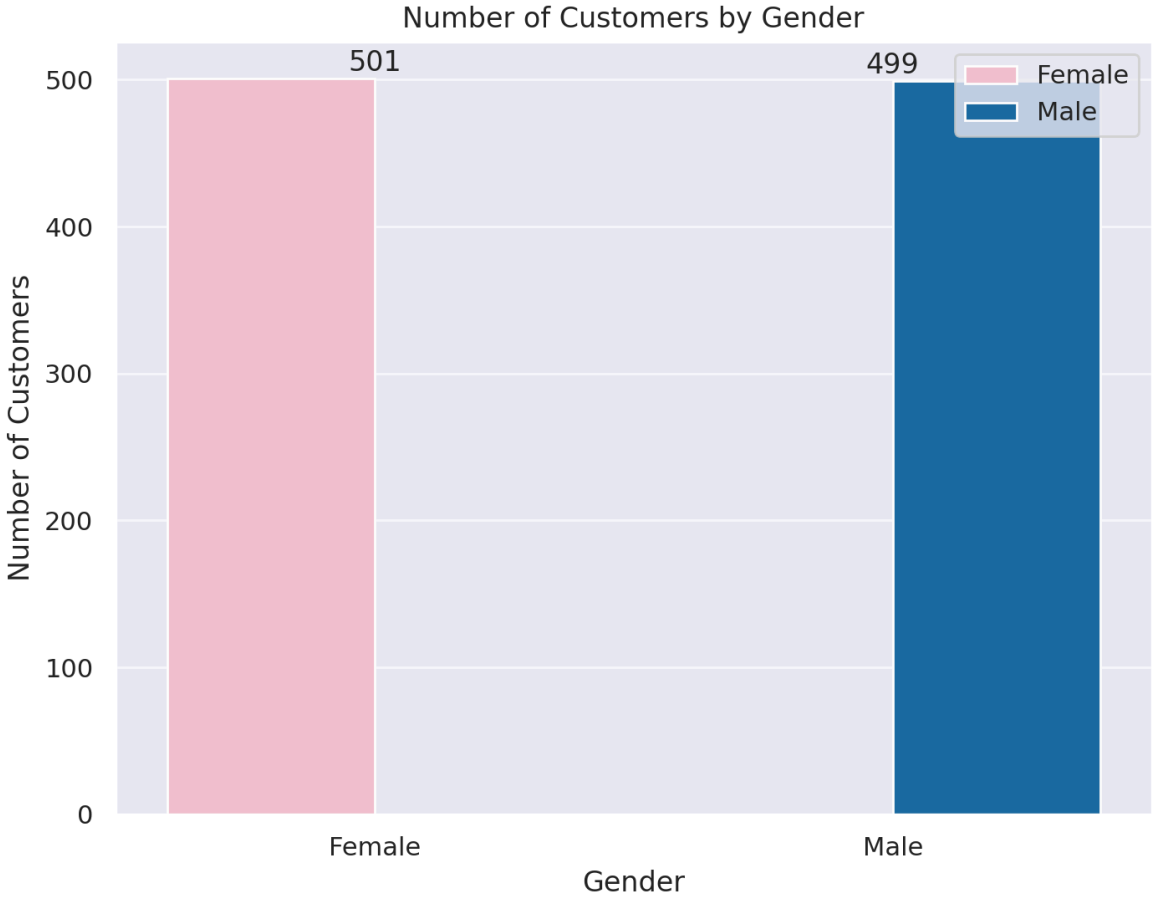
O1. What is the gender distribution of customers?

In [18]:
```
customers_gender = data['Gender'].value_counts()
customers_gender
```

Out[18]:
```
Female    501
Male      499
Name: Gender, dtype: int64
```

In [19]:
```
colors = ['#F8B7CD', '#0671B7']

plt.figure(figsize=(8, 6))
sns.barplot(x=customers_gender.index,
            y=customers_gender.values,
            hue=customers_gender.index,
```

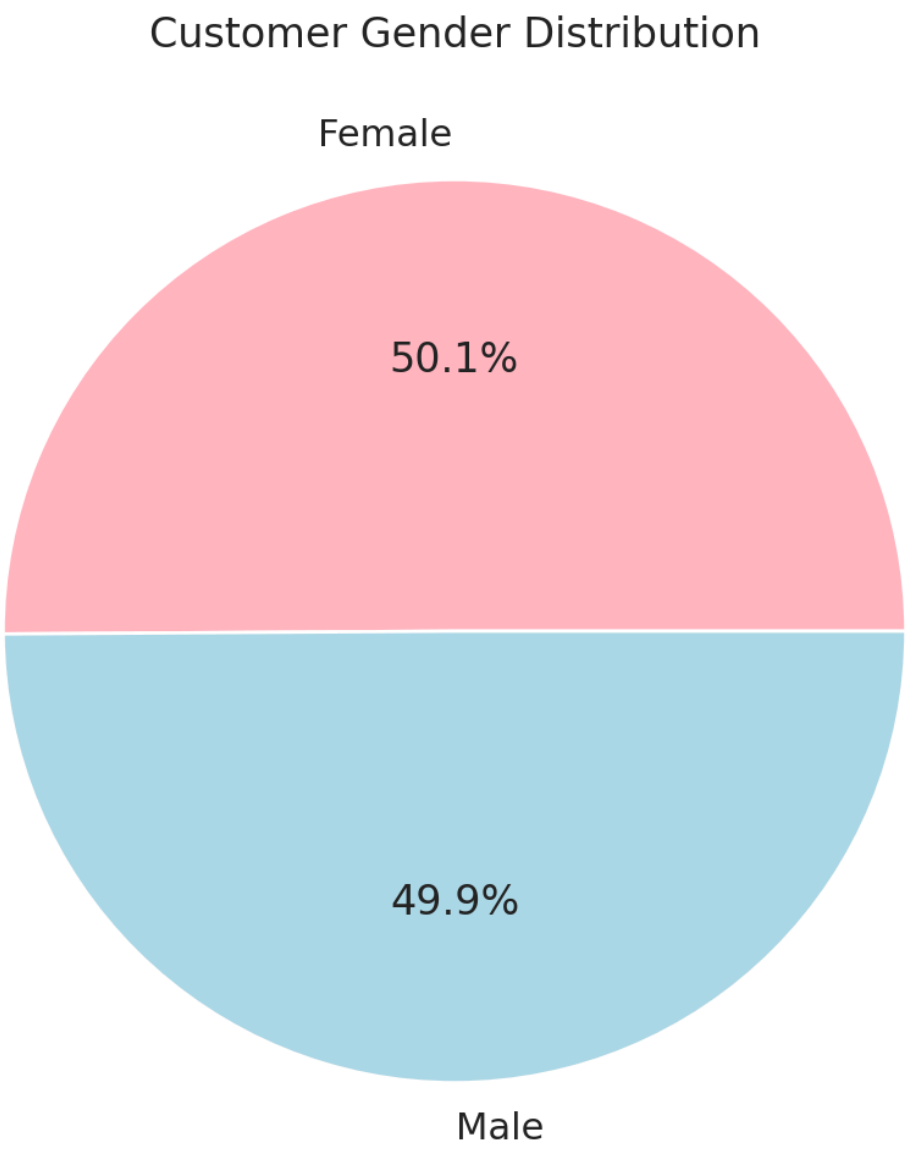
```
            palette=colors,
            )


for i, value in enumerate(customers_gender.values):
    plt.text(i, value + 5, f"{value}", ha='center', fontsize=12)

plt.title('Number of Customers by Gender')
plt.xlabel('Gender')
plt.ylabel('Number of Customers')
plt.show()
```



In [20]:
```
customers_gender_percentage = data['Gender'].value_counts() / data['Gender'].cou
customers_gender_percentage
```

Out[20]:
```
Female    50.1
Male      49.9
Name: Gender, dtype: float64
```

In [21]:
```
colors = ['#FFB6C1', '#ADD8E6']

plt.pie(customers_gender_percentage.values,
        labels=customers_gender_percentage.index,
        autopct='%1.1f%%',
        colors=colors)

plt.title('Customer Gender Distribution')
plt.show()
```



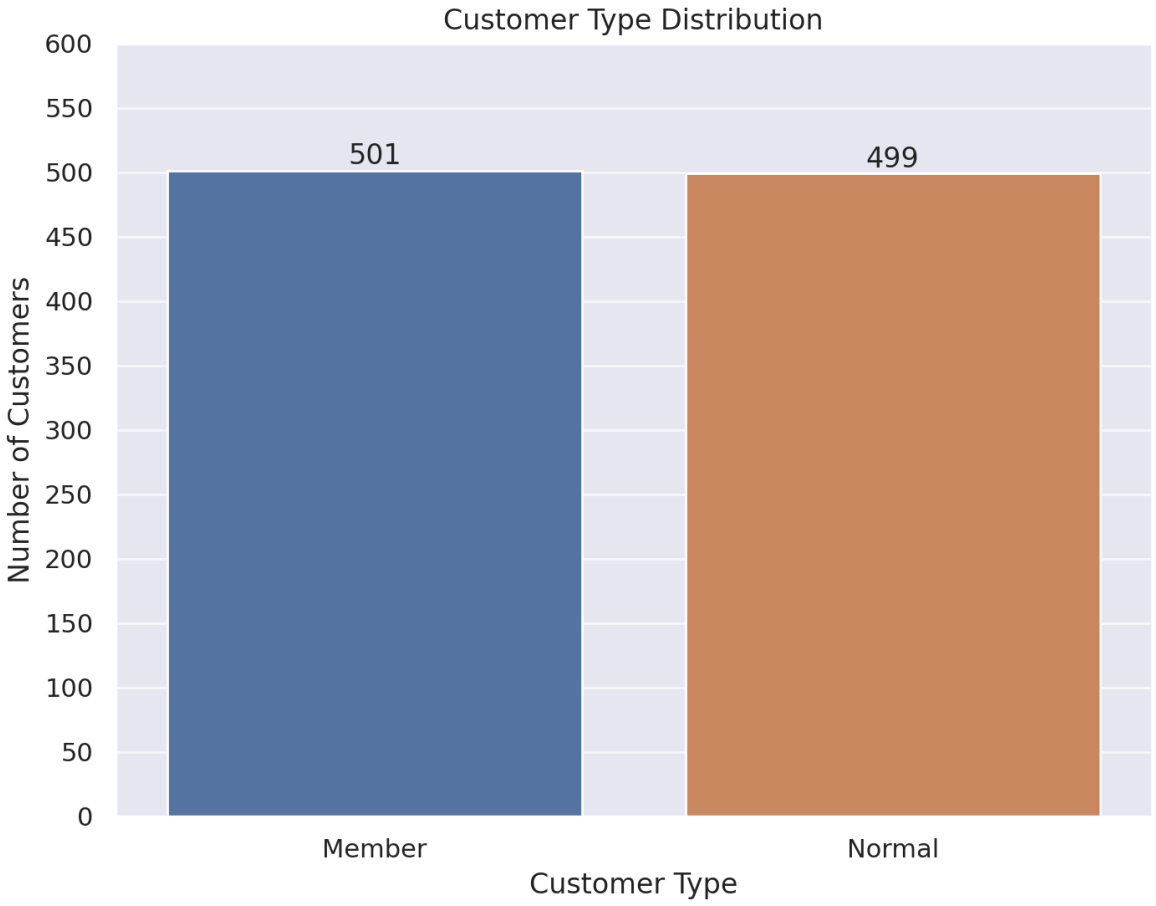
O2. How does customer type (Member vs Normal) distribution look?

In [22]:
```
customer_type_distribution = data['Customer type'].value_counts()
customer_type_distribution
```

Out[22]:
```
Member    501
Normal    499
Name: Customer type, dtype: int64
```

In [23]:
```
plt.figure(figsize=(8, 6))
sns.barplot(x=customer_type_distribution.index,
            y=customer_type_distribution.values)

for i, value in enumerate(customer_type_distribution.values):
    plt.text(i, value + 5, f"{value}", ha='center', fontsize=12)

plt.title('Customer Type Distribution')
plt.xlabel('Customer Type')
plt.ylabel('Number of Customers')
```

```
plt.yticks(range(0, customer_type_distribution.max() + 100, 50))
plt.show()
```



O3. What is the average customer rating based on gender and customer type?

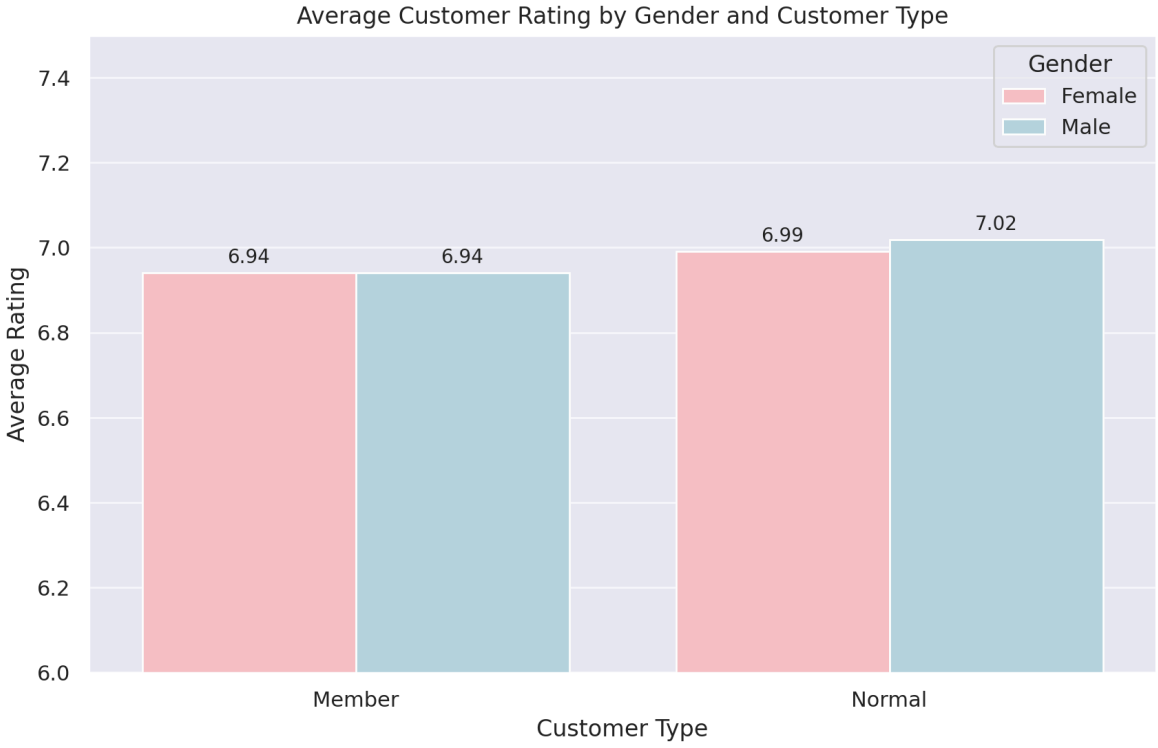
In [24]:
```
avg_customer_rating_by_gender_and_type = data.groupby(['Gender', 'Customer type'
avg_customer_rating_by_gender_and_type
```

Out[24]:

	Gender	Customer type	Rating
0	Female	Member	6.940613
1	Female	Normal	6.990417
2	Male	Member	6.940000
3	Male	Normal	7.018919

In [25]:
```
colors = ['#FFB6C1', '#ADD8E6']

plt.figure(figsize=(10, 6))
ax = sns.barplot(data=avg_customer_rating_by_gender_and_type,
                 x='Customer type',
                 y='Rating',
                 hue='Gender',
                 palette=colors)

# Add values
for container in ax.containers:
    ax.bar_label(container, fmt='%.2f', label_type='edge', padding=3, fontsize=1
```

```
plt.title('Average Customer Rating by Gender and Customer Type')
plt.xlabel('Customer Type')
plt.ylabel('Average Rating')
plt.ylim(6, 7.5)
plt.show()
```



C. Products Insights

O1. Which product line generates the most revenue?

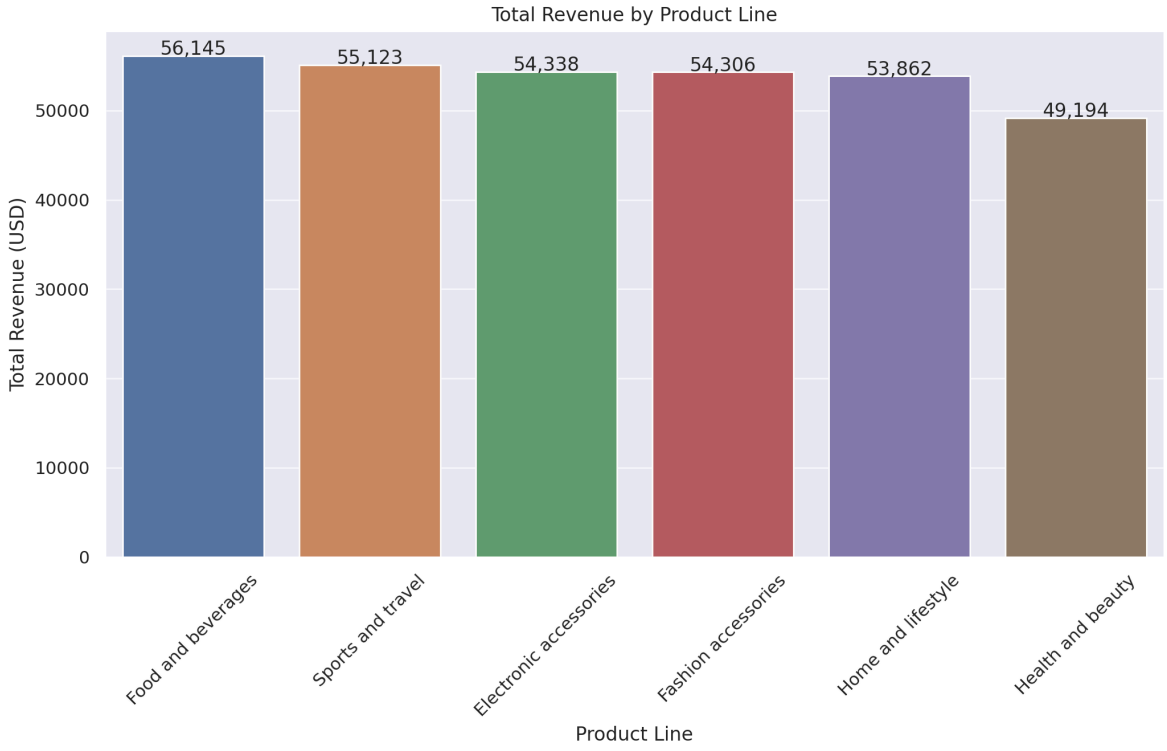
In [26]:
```
revenue_product_line = data.groupby('Product line')['Total'].sum()
print(f"Most revenue product line is {revenue_product_line.idxmax()} with ${reve

revenue_product_line.sort_values(ascending=False)
```

```
Most revenue product line is Food and beverages with $56144.844 revenue
```

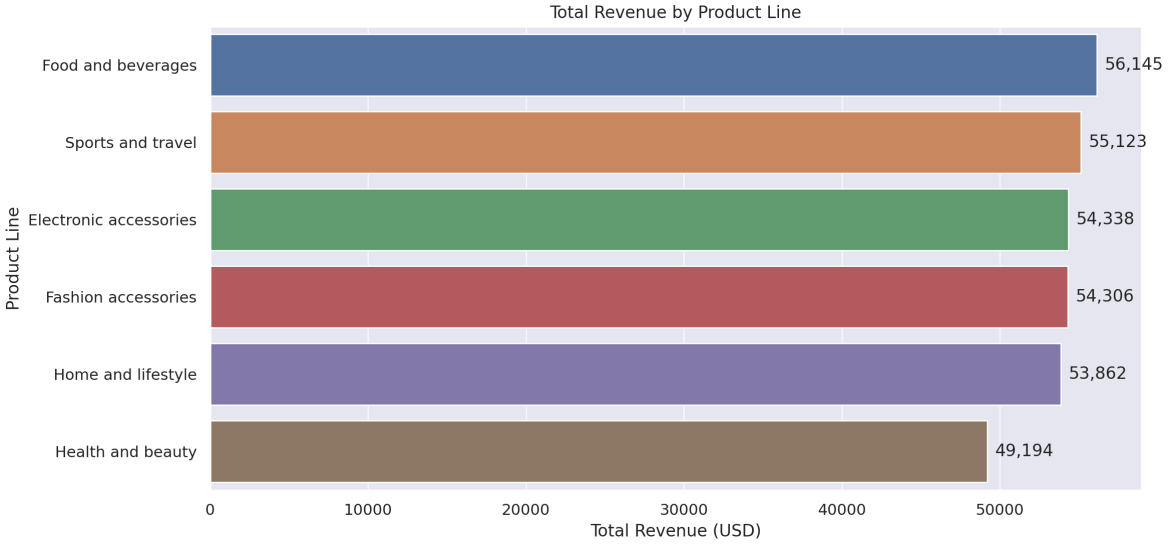
Out[26]:
```
Product line
Food and beverages        56144.8440
Sports and travel         55122.8265
Electronic accessories    54337.5315
Fashion accessories       54305.8950
Home and lifestyle        53861.9130
Health and beauty         49193.7390
Name: Total, dtype: float64
```

In [27]:
```
revenue_product_line_sorted = revenue_product_line.sort_values(ascending=False)

plt.figure(figsize=(12, 6))
sns.barplot(x=revenue_product_line_sorted.index,
            y=revenue_product_line_sorted.values)

for i, value in enumerate(revenue_product_line_sorted.values):
    plt.text(i, value + 100, f"{value:,.0f}", ha='center', fontsize=12)
```

```
plt.title('Total Revenue by Product Line')
plt.xlabel('Product Line')
plt.ylabel('Total Revenue (USD)')
plt.xticks(rotation=45)
plt.show()
```



In [28]:
```
# Horizontal Barplot

plt.figure(figsize=(12, 6))
sns.barplot(y=revenue_product_line_sorted.index,
            x=revenue_product_line_sorted.values)

for i, value in enumerate(revenue_product_line_sorted.values):
    plt.text(value + 500, i, f"{value:,.0f}", va='center', fontsize=12)

plt.title('Total Revenue by Product Line')
plt.xlabel('Total Revenue (USD)')
plt.ylabel('Product Line')
plt.show()
```



O2. Which product line is the most profitable (Gross Income)?

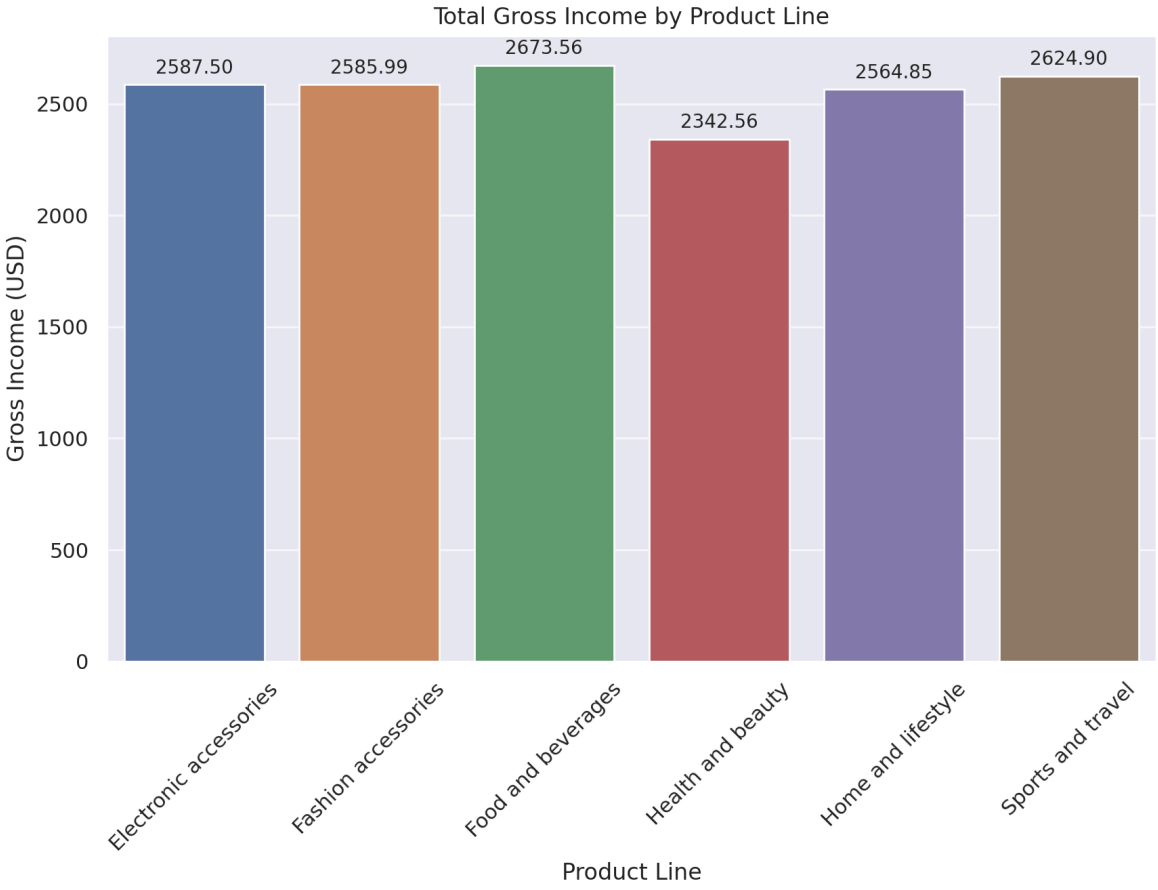
In [29]:
```
profit_product_line = data.groupby('Product line')['gross income'].sum()
print(f"Most profitable product line is {profit_product_line.idxmax()} with ${pr
```

```
Most profitable product line is Food and beverages with $2673.564 gross income
```

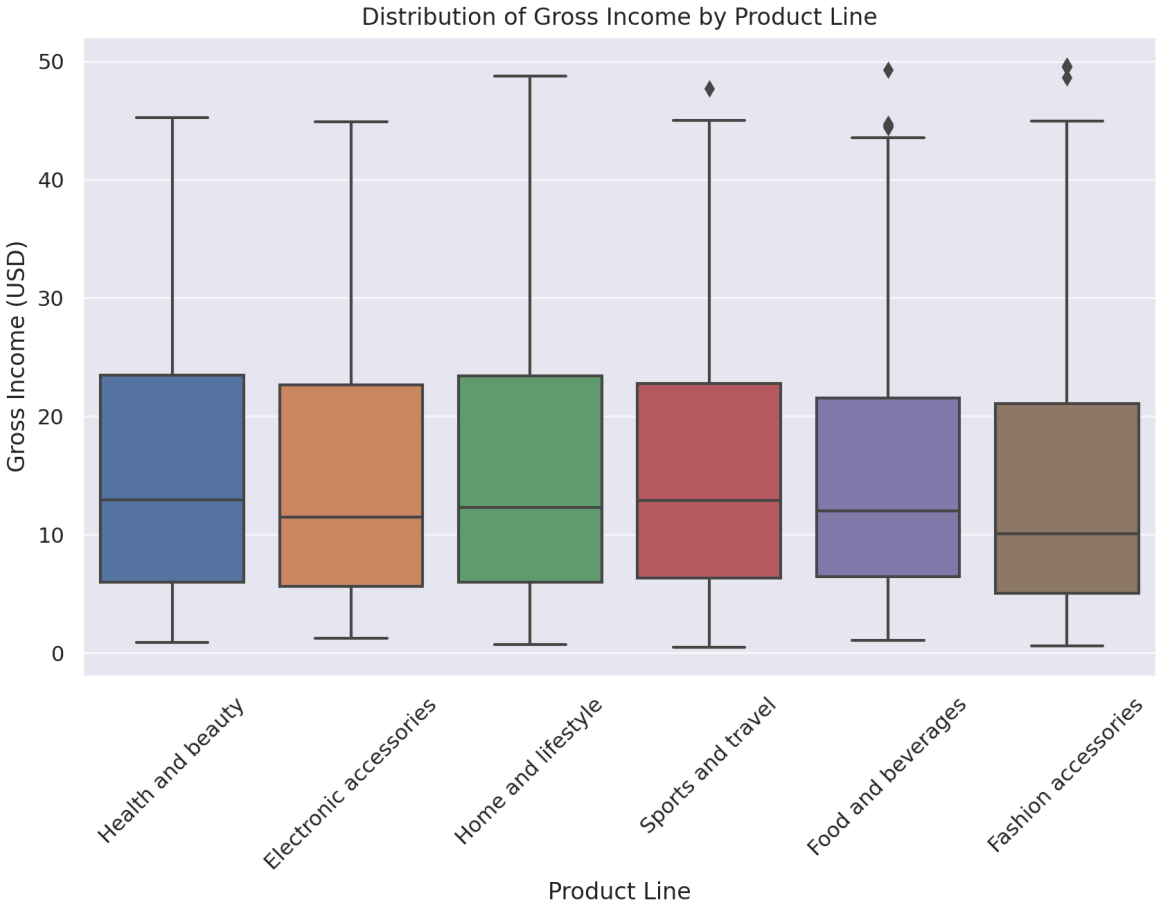
In [30]:
```
profit_product_line.sort_values(ascending=False)
```

Out[30]:
```
Product line
Food and beverages        2673.5640
Sports and travel         2624.8965
Electronic accessories    2587.5015
Fashion accessories       2585.9950
Home and lifestyle        2564.8530
Health and beauty         2342.5590
Name: gross income, dtype: float64
```

In [31]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x=profit_product_line.index, y=profit_product_line.values)

for i, value in enumerate(profit_product_line.values):
    plt.text(i, value + 50, f"{value:.2f}", ha='center', fontsize=10)

plt.title('Total Gross Income by Product Line')
plt.xlabel('Product Line')
plt.ylabel('Gross Income (USD)')
plt.xticks(rotation=45)
plt.show()
```



In [32]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Product line', y='gross income', data=data)

plt.title('Distribution of Gross Income by Product Line')
plt.xlabel('Product Line')
plt.ylabel('Gross Income (USD)')
plt.xticks(rotation=45)
plt.show()
```



- **Food and Beverages** and **Sports and Travel** have some transactions with much higher gross income compared to others, shown by the outliers. These outliers represent exceptionally **high-profit transactions**.
- The **median gross income** is similar across most categories. However, **Fashion Accessories** has the **lowest median**, while other categories, including **Health and Beauty**, have slightly higher medians.
- The **whiskers** are of similar length for most categories, meaning the variation in gross income within each product line is **roughly the same**.

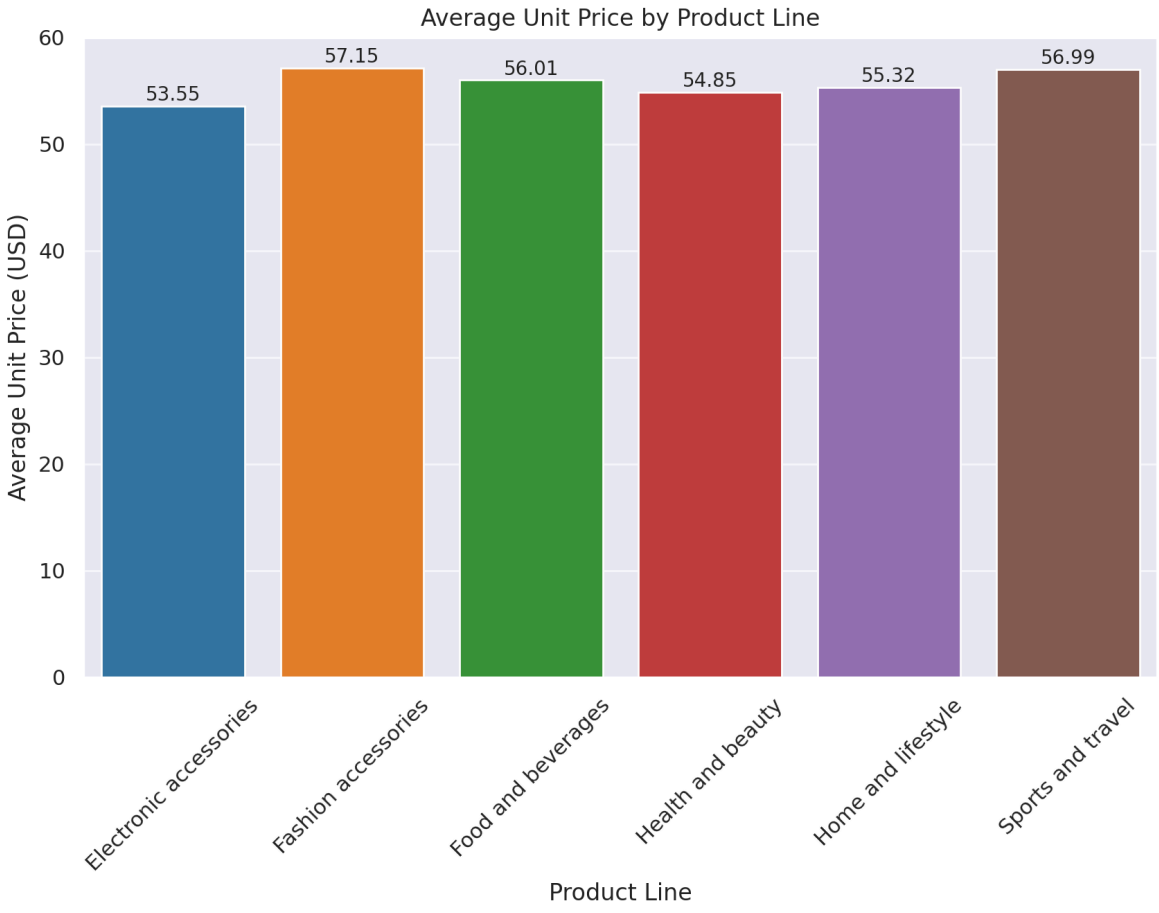
O3. What are the average unit price and quantity sold for each product line?

In [33]:
```
avg_unit_price_quantity_product_line = data.groupby('Product line')[['Unit price
avg_unit_price_quantity_product_line
```

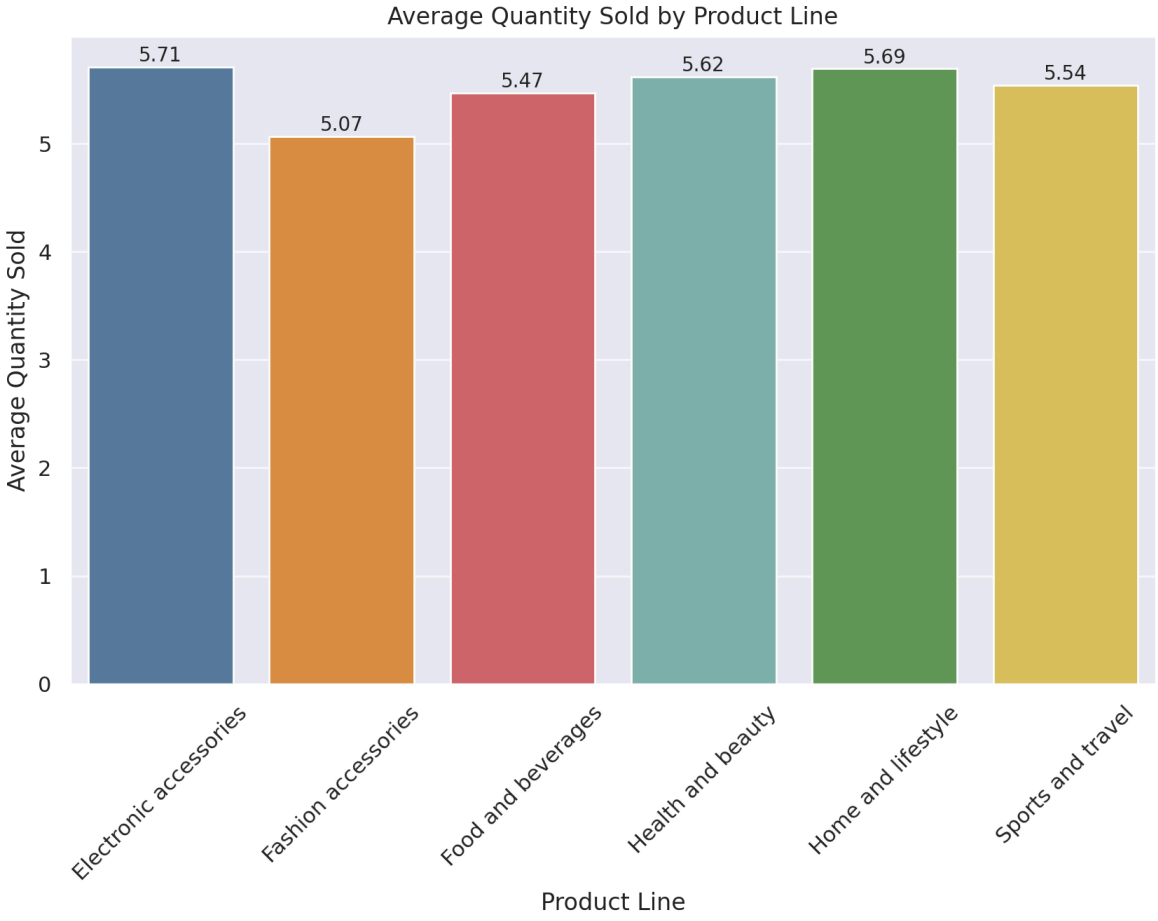
Out[33]:

Product line	Unit price	Quantity
Electronic accessories	53.551588	5.711765
Fashion accessories	57.153652	5.067416
Food and beverages	56.008851	5.471264
Health and beauty	54.854474	5.618421
Home and lifestyle	55.316937	5.693750
Sports and travel	56.993253	5.542169

In [34]:
```
colors = ['#1F77B4', '#FF7F0E', '#2CA02C', '#D62728', '#9467BD', '#8C564B']

plt.figure(figsize=(10, 6))
sns.barplot(x=avg_unit_price_quantity_product_line.index,
            y=avg_unit_price_quantity_product_line['Unit price'],
            palette=colors)

for i, value in enumerate(avg_unit_price_quantity_product_line['Unit price']):
    plt.text(i, value + 0.5, f"{value:.2f}", ha='center', fontsize=10)

plt.title('Average Unit Price by Product Line')
plt.xlabel('Product Line')
plt.ylabel('Average Unit Price (USD)')
plt.xticks(rotation=45)
plt.show()
```



In [35]:
```
colors = ['#4E79A7', '#F28E2B', '#E15759', '#76B7B2', '#59A14F', '#EDC949']

plt.figure(figsize=(10, 6))
sns.barplot(x=avg_unit_price_quantity_product_line.index,
            y=avg_unit_price_quantity_product_line['Quantity'],
            palette=colors)

for i, value in enumerate(avg_unit_price_quantity_product_line['Quantity']):
    plt.text(i, value + 0.05, f"{value:.2f}", ha='center', fontsize=10)

plt.title('Average Quantity Sold by Product Line')
plt.xlabel('Product Line')
plt.ylabel('Average Quantity Sold')
plt.xticks(rotation=45)
plt.show()
```



D. Time-Based Analysis

O1. Which is the monthly revenue trend?

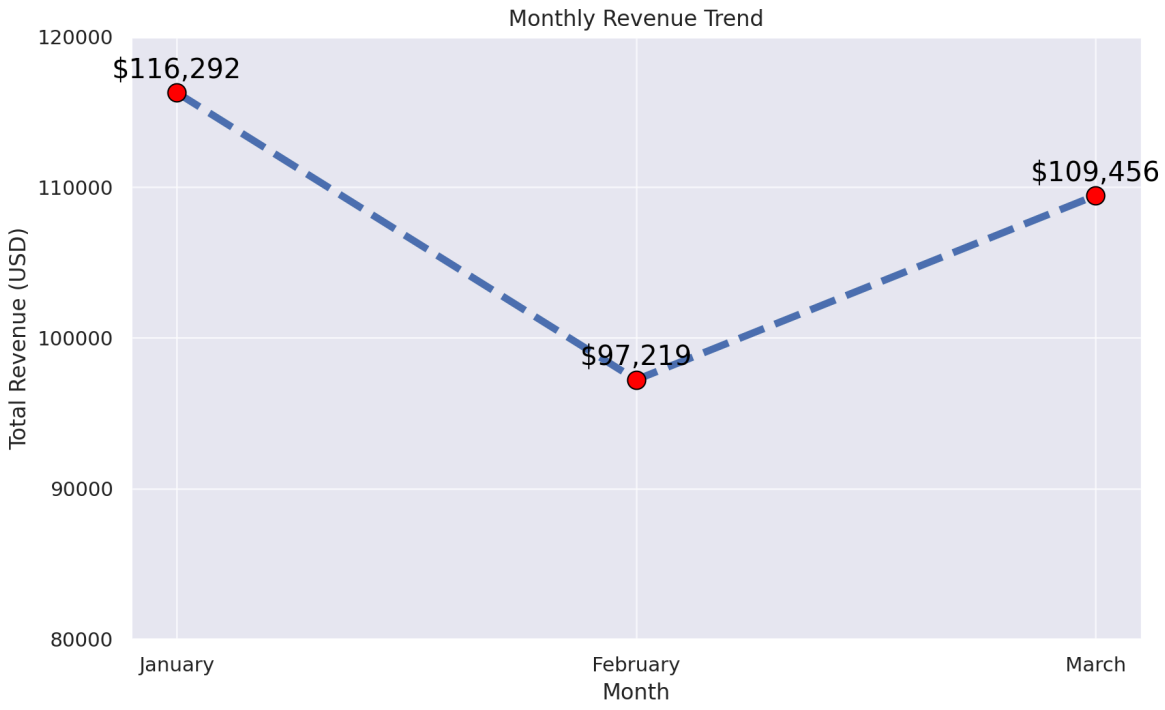
In [36]:
```
data['Month'] = data['datetime'].dt.strftime('%B')

monthly_revenue_trend = data.groupby('Month')['Total'].sum()
monthly_revenue_trend
```

Out[36]:
```
Month
February     97219.374
January     116291.868
March       109455.507
Name: Total, dtype: float64
```

In [37]:
```
month_order = ['January', 'February', 'March']
monthly_revenue_trend = monthly_revenue_trend[month_order]
monthly_revenue_trend
```

Out[37]:
```
Month
January     116291.868
February     97219.374
March       109455.507
Name: Total, dtype: float64
```

In [38]:
```
plt.figure(figsize=(10, 6))
sns.lineplot(
    x=monthly_revenue_trend.index,
    y=monthly_revenue_trend.values,
    linestyle='--', linewidth=4,
    marker='o', markersize=10,
    markerfacecolor='red', markeredgecolor='black'
)

for i, value in enumerate(monthly_revenue_trend.values):
    plt.text(i, value + 1000, f"${value:,.0f}", ha='center', fontsize=15, color=

plt.title('Monthly Revenue Trend')
plt.xlabel('Month')
plt.ylabel('Total Revenue (USD)')

max_value = monthly_revenue_trend.max()
plt.yticks(range(80000, int(max_value) + 10000, 10000))

plt.show()
```



O2. Which day of the week has the highest sales?

In [39]:
```
data['Day'] = data['datetime'].dt.strftime('%A')
daily_revenue_trend = data.groupby('Day')['Total'].sum()

# Order the day
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',
daily_revenue_trend = daily_revenue_trend.reindex(day_order)

daily_revenue_trend
```

Out[39]:
```
Day
Monday       37899.0780
Tuesday      51482.2455
Wednesday    43731.1350
Thursday     45349.2480
Friday       43926.3405
Saturday     56120.8095
Sunday       44457.8925
Name: Total, dtype: float64
```

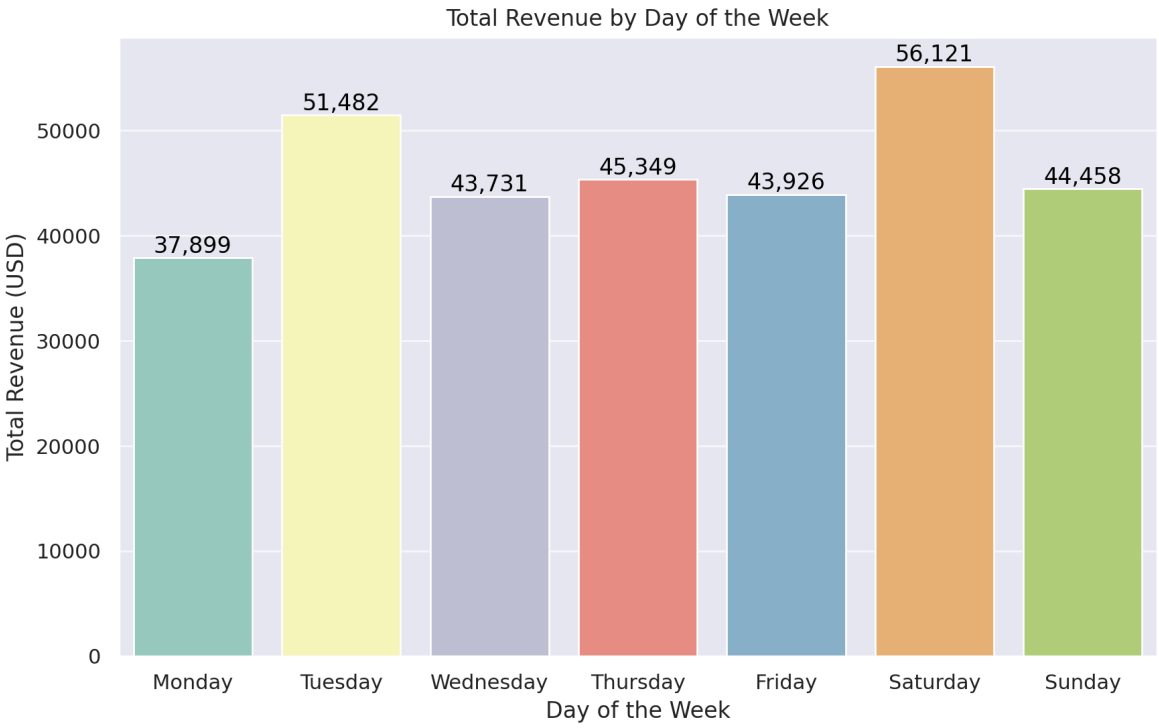
In [40]:
```
# Order the sales
daily_revenue_trend.sort_values(ascending=False)
```

Out[40]:
```
Day
Saturday     56120.8095
Tuesday      51482.2455
Thursday     45349.2480
Sunday       44457.8925
Friday       43926.3405
Wednesday    43731.1350
Monday       37899.0780
Name: Total, dtype: float64
```

In [41]:
```
print(f'The highest sales occurred on {daily_revenue_trend.idxmax()} with a reve
```

```
The highest sales occurred on Saturday with a revenue of $56,120.81
```

In [42]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x=daily_revenue_trend.index, y=daily_revenue_trend.values, palette='

for i, value in enumerate(daily_revenue_trend.values):
    plt.text(i, value + 500, f"{value:,.0f}", ha='center', fontsize=12, color='b

plt.title('Total Revenue by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Total Revenue (USD)')
plt.show()
```



O3. What are the peak transaction times?

Peak Transaction Times can refer to:

1. The number of transactions per hour.
2. The total revenue per hour.

We can use line plot and heatmap.

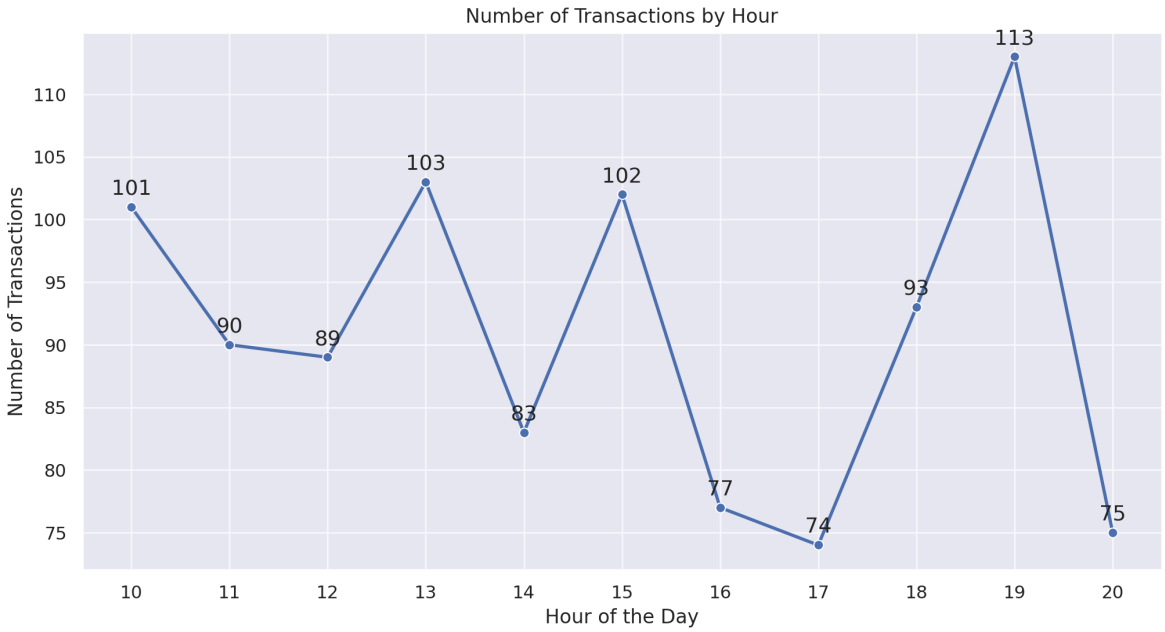
- Line Plot: shows trends over time, like peak hours for transactions or revenue.
- Heatmap: shows how transactions or revenue vary by hour and branch with color intensity.

In [43]:
```
data['Hour'] = data['datetime'].dt.hour
hourly_transaction_count = data['Hour'].value_counts().sort_index()
hourly_transaction_count
```

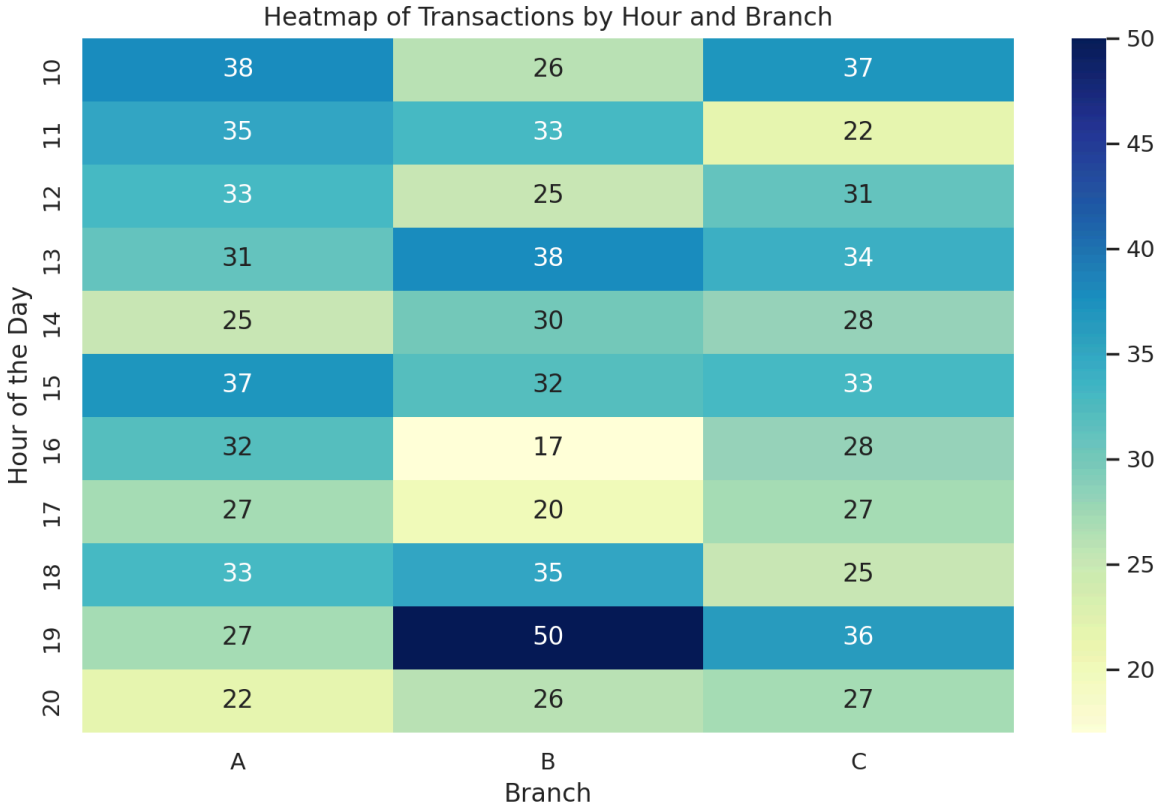
Out[43]:
```
10    101
11     90
12     89
13    103
14     83
15    102
16     77
17     74
18     93
19    113
20     75
Name: Hour, dtype: int64
```

In [44]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(x=hourly_transaction_count.index, y=hourly_transaction_count.values
```

```
for hour, value in zip(hourly_transaction_count.index, hourly_transaction_count.
    plt.text(hour, value + 1, f"{value}", ha='center', fontsize=13)

plt.title('Number of Transactions by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Transactions')
plt.xticks(range(10, 21))
plt.grid(True)
plt.show()
```



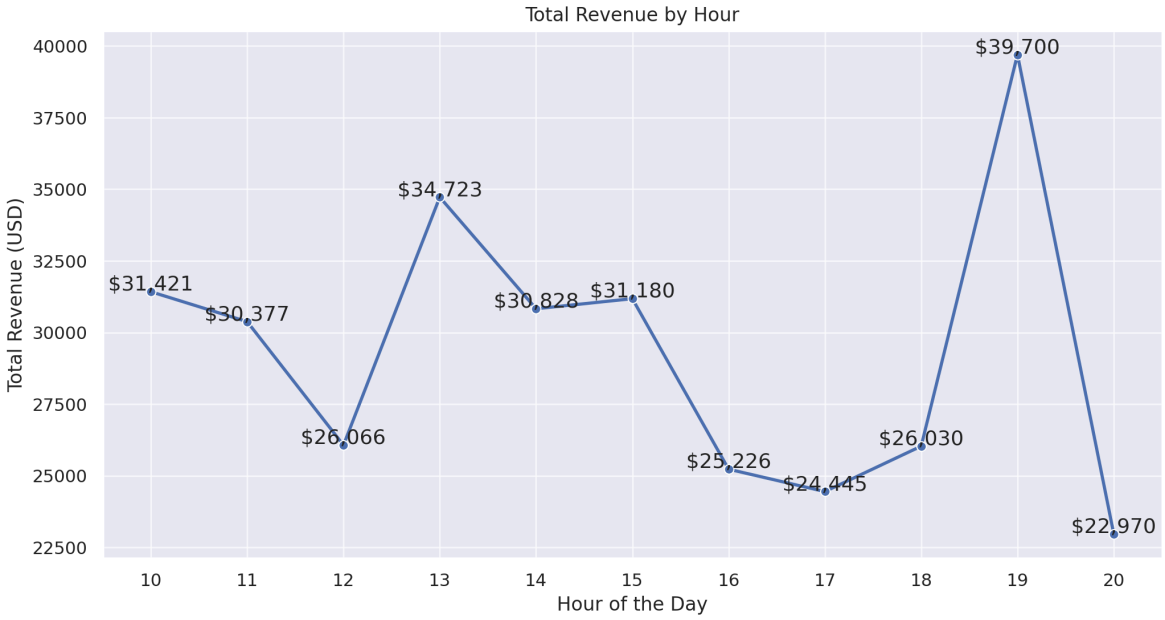
In [45]:
```
# Create a DataFrame for the heatmap
hourly_data = data.groupby(['Hour', 'Branch']).size().unstack()

plt.figure(figsize=(10, 6))
sns.heatmap(hourly_data, annot=True, cmap='YlGnBu', fmt='d')

plt.title('Heatmap of Transactions by Hour and Branch')
plt.xlabel('Branch')
plt.ylabel('Hour of the Day')
plt.show()
```



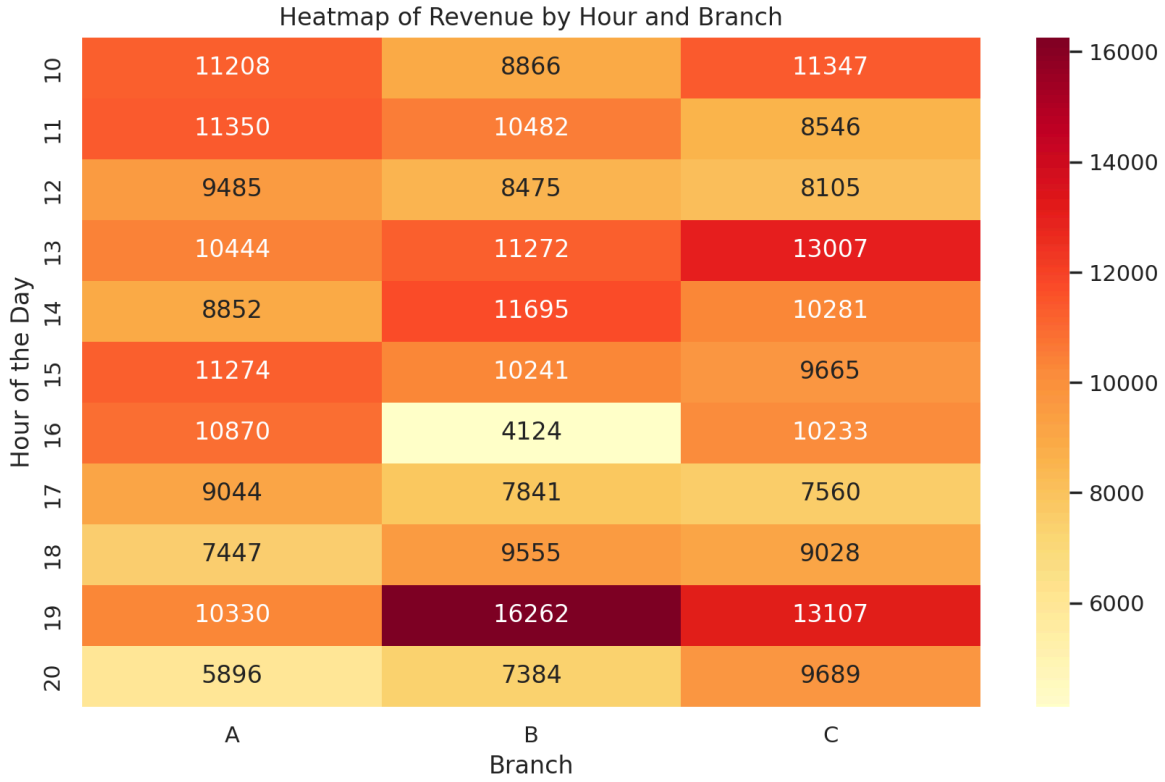
In [46]:
```
hourly_revenue_trend = data.groupby('Hour')['Total'].sum()
hourly_revenue_trend
```

Out[46]:
```
Hour
10    31421.4810
11    30377.3295
12    26065.8825
13    34723.2270
14    30828.3990
15    31179.5085
16    25226.3235
17    24445.2180
18    26030.3400
19    39699.5130
20    22969.5270
Name: Total, dtype: float64
```

In [47]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(x=hourly_revenue_trend.index, y=hourly_revenue_trend.values, marker

for hour, value in zip(hourly_revenue_trend.index, hourly_revenue_trend.values):
    plt.text(hour, value + 50, f"${value:,.0f}", ha='center', fontsize=13)

plt.title('Total Revenue by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel('Total Revenue (USD)')
plt.xticks(range(10, 21))
plt.grid(True)
plt.show()
```



In [48]:
```
hourly_revenue_data = data.groupby(['Hour', 'Branch'])['Total'].sum().unstack()

plt.figure(figsize=(10, 6))
sns.heatmap(hourly_revenue_data, annot=True, cmap='YlOrRd', fmt='.0f')

plt.title('Heatmap of Revenue by Hour and Branch')
plt.xlabel('Branch')
plt.ylabel('Hour of the Day')
plt.show()
```



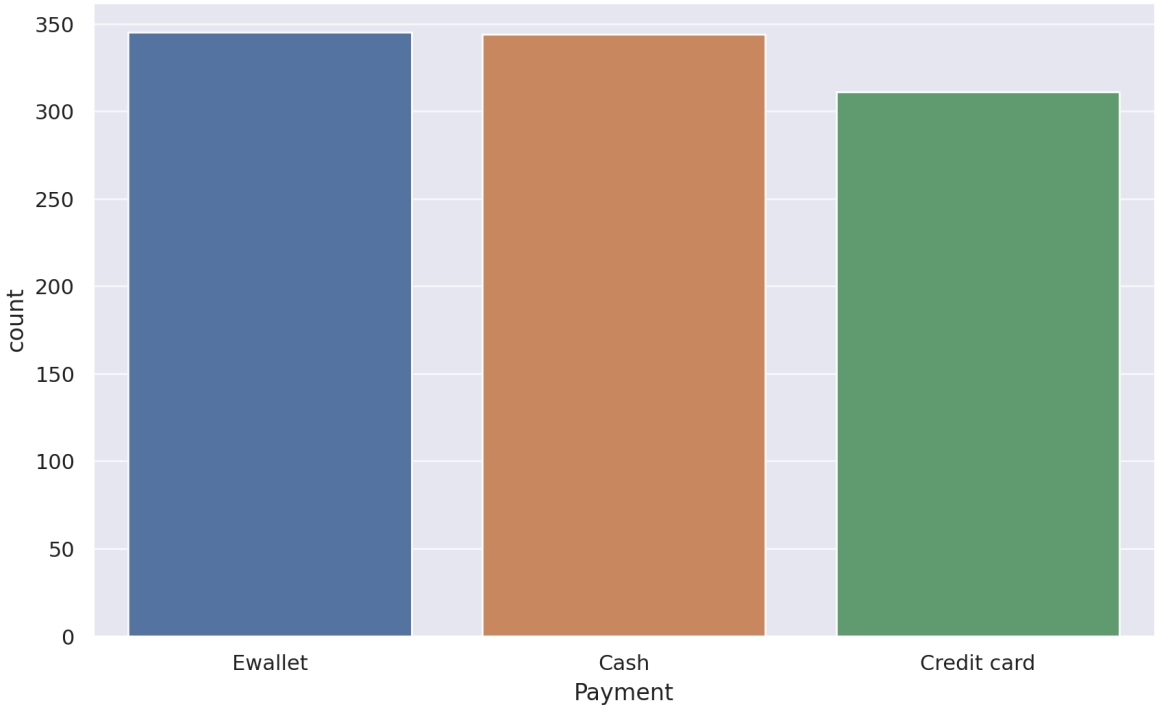
E. Payment Method Preferences

Q1. What is the distribution of payment methods used?

In [49]:
```
payment_method_distribution = data['Payment'].value_counts()
payment_method_distribution
```

Out[49]:
```
Ewallet        345
Cash           344
Credit card    311
Name: Payment, dtype: int64
```

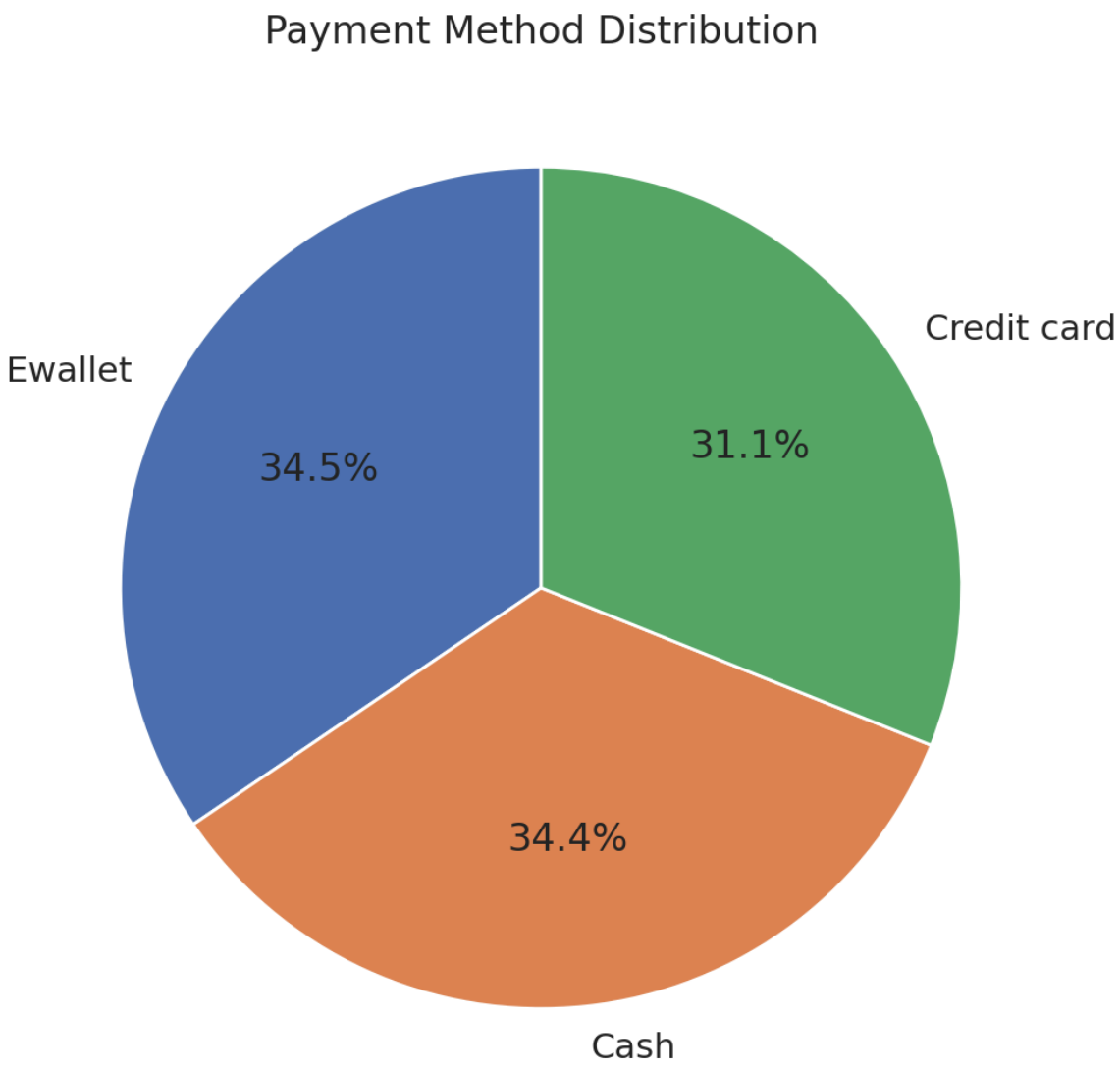
In [50]:
```
sns.countplot(data=data, x='Payment')
plt.show()
```



In [51]:
```
payment_method_percentage = data['Payment'].value_counts(normalize=True) * 100
payment_method_percentage
```

Out[51]:
```
Ewallet        34.5
Cash           34.4
Credit card    31.1
Name: Payment, dtype: float64
```

In [52]:
```
plt.figure(figsize=(8, 6))
plt.pie(
    x=payment_method_percentage.values,
    labels=payment_method_percentage.index,
    autopct='%1.1f%%',
    startangle=90
)

plt.title('Payment Method Distribution')
plt.show()
```



O2. Which payment method is most popular in each branch and city?

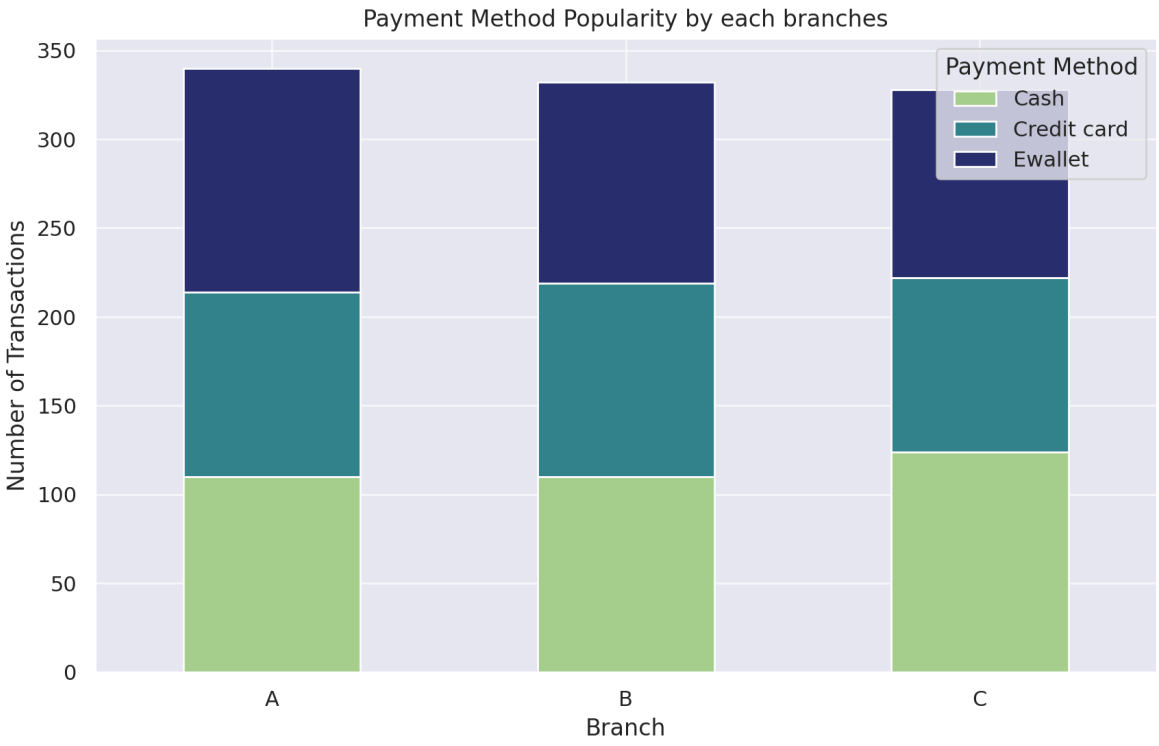
In [53]:
```
payment_method_popularity = data.groupby(['Branch', 'Payment']).size().unstack()
payment_method_popularity
```

Out[53]:

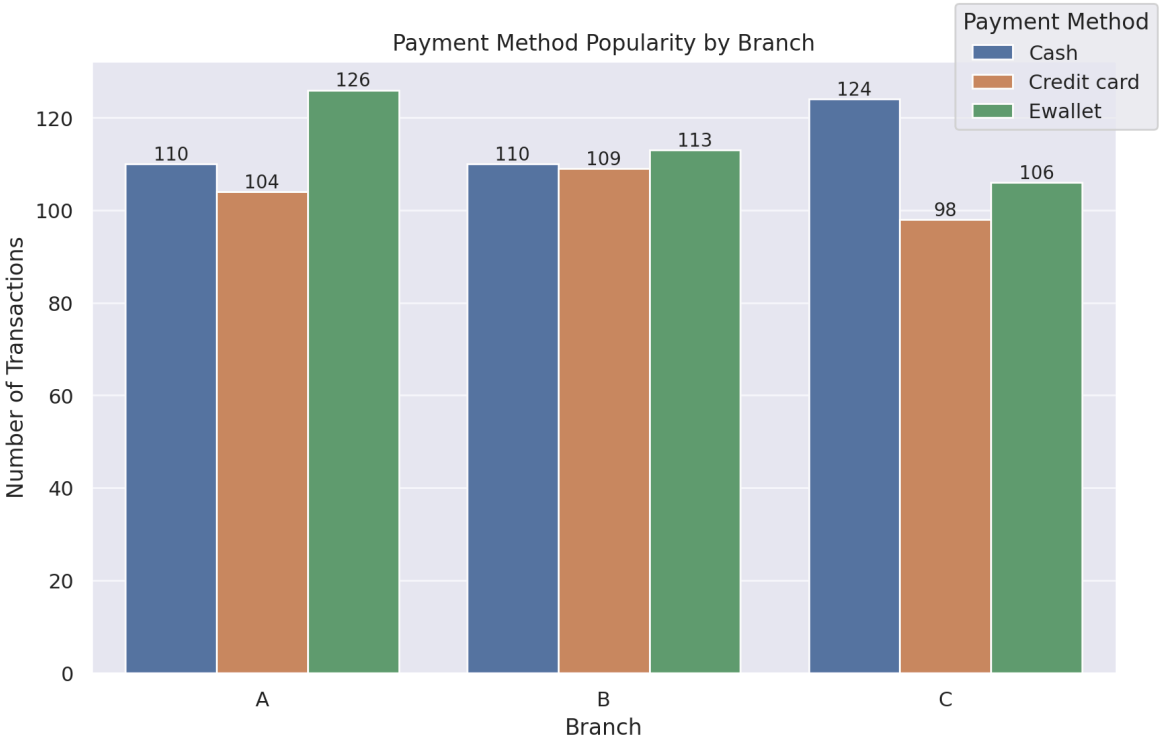
Payment	Cash	Credit card	Ewallet
Branch			
A	110	104	126
B	110	109	113
C	124	98	106

In [54]:
```
# STACKED BAR CHART
payment_method_popularity.plot(
    kind='bar',
    stacked=True,
    figsize=(10, 6),
    colormap='crest'
)
```

```
plt.title('Payment Method Popularity by each branches')
plt.xlabel('Branch')
plt.ylabel('Number of Transactions')
plt.legend(title='Payment Method')
plt.xticks(rotation=0)

plt.show()
```



In [55]:
```
# GROUPED BAR CHART
payment_method_by_branch = data.groupby(['Branch', 'Payment']).size().reset_inde

plt.figure(figsize=(10, 6))
ax = sns.barplot(data=payment_method_by_branch, x='Branch', y='Count', hue='Paym

for container in ax.containers:
    ax.bar_label(container, fmt='%d', fontsize=10, label_type='edge')

plt.title('Payment Method Popularity by Branch')
plt.xlabel('Branch')
plt.ylabel('Number of Transactions')
plt.legend(title='Payment Method', bbox_to_anchor=(1.05, 1.11), loc='upper right
plt.show()
```



F. Profitability Analysis

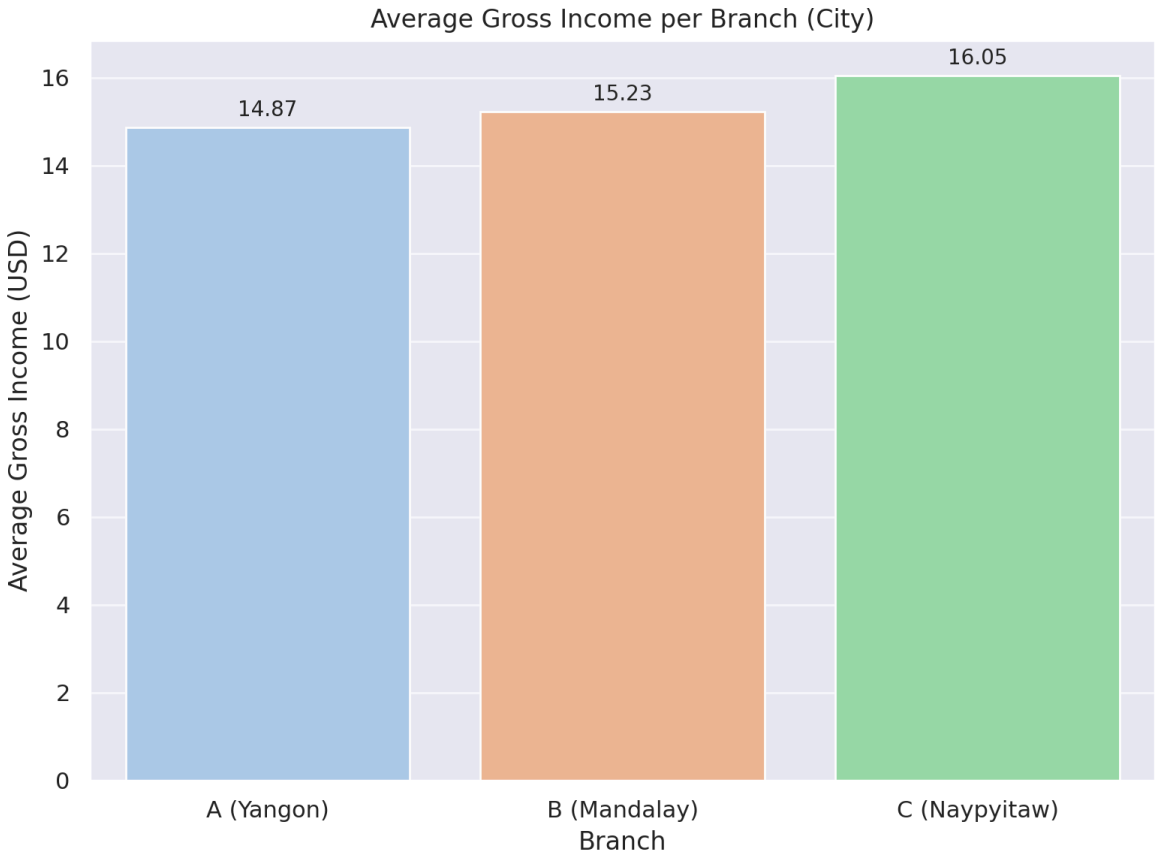
O1. What is the average gross income per branch?

In [56]:
```
avg_gross_income_by_branch_city = data.groupby(['Branch', 'City'])['gross income
avg_gross_income_by_branch_city
```

Out[56]:

	Branch	City	gross income
0	A	Yangon	14.874001
1	B	Mandalay	15.232024
2	C	Naypyitaw	16.052367

In [57]:
```
plt.figure(figsize=(8, 6))
sns.barplot(data=avg_gross_income_by_branch_city, x='Branch', y='gross income',

ax = plt.gca()
for container in ax.containers:
    ax.bar_label(container, fmt='%.2f', label_type='edge', fontsize=10, padding=

plt.title('Average Gross Income per Branch (City)')
plt.xlabel('Branch')
plt.ylabel('Average Gross Income (USD)')


branch_labels = ['A (Yangon)', 'B (Mandalay)', 'C (Naypyitaw)']
plt.xticks(ticks=range(len(branch_labels)), labels=branch_labels)

plt.tight_layout()
plt.show()
```

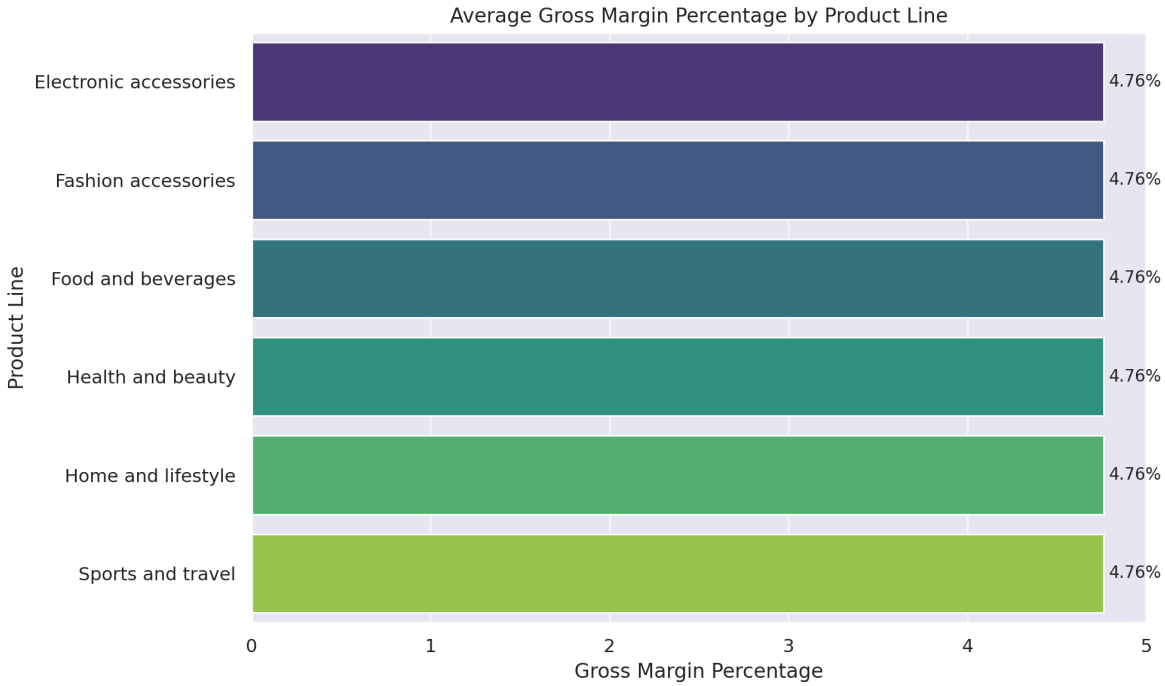


O2. Which product lines have the highest and lowest gross margins?

In [58]:
```
avg_gross_margin_by_product_line = data.groupby('Product line')['gross margin pe
avg_gross_margin_by_product_line
```

Out[58]:
```
Product line
Electronic accessories    4.761905
Fashion accessories       4.761905
Food and beverages        4.761905
Health and beauty         4.761905
Home and lifestyle        4.761905
Sports and travel         4.761905
Name: gross margin percentage, dtype: float64
```

In [59]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x=avg_gross_margin_by_product_line.values,
            y=avg_gross_margin_by_product_line.index,
            palette='viridis')

# Add labels on each bar
ax = plt.gca()
for container in ax.containers:
    ax.bar_label(container, fmt='%.2f%%', label_type='edge', fontsize=10, paddin

# Add titles and labels
plt.title('Average Gross Margin Percentage by Product Line')
plt.xlabel('Gross Margin Percentage')
plt.ylabel('Product Line')

plt.tight_layout()
plt.show()
```



Every product line has a **4.76%** gross margin, showing consistent profitability across categories.

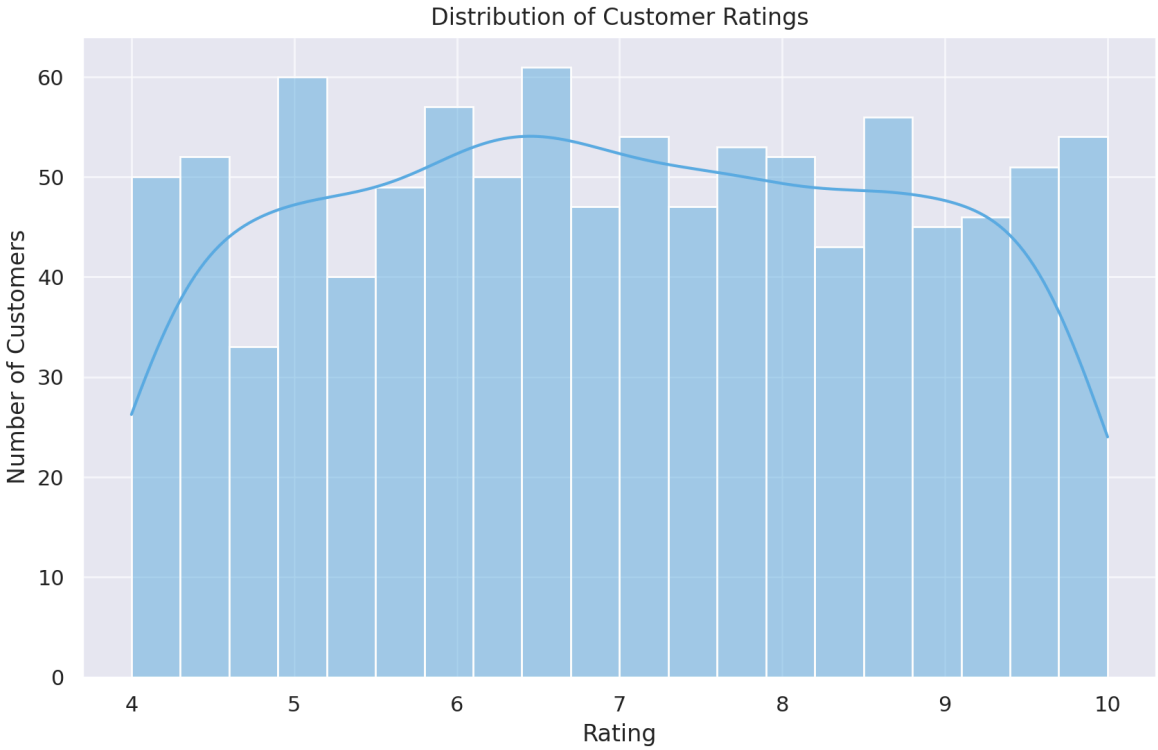
G. Customer Experience

O1. How are customer ratings distributed?

In [60]:
```
customer_rating_distribution = data.groupby('Rating')['Rating'].count()
customer_rating_distribution
```

Out[60]:
```
Rating
4.0     11
4.1     17
4.2     22
4.3     18
4.4     17
        ..
9.6     17
9.7     14
9.8     19
9.9     16
10.0     5
Name: Rating, Length: 61, dtype: int64
```

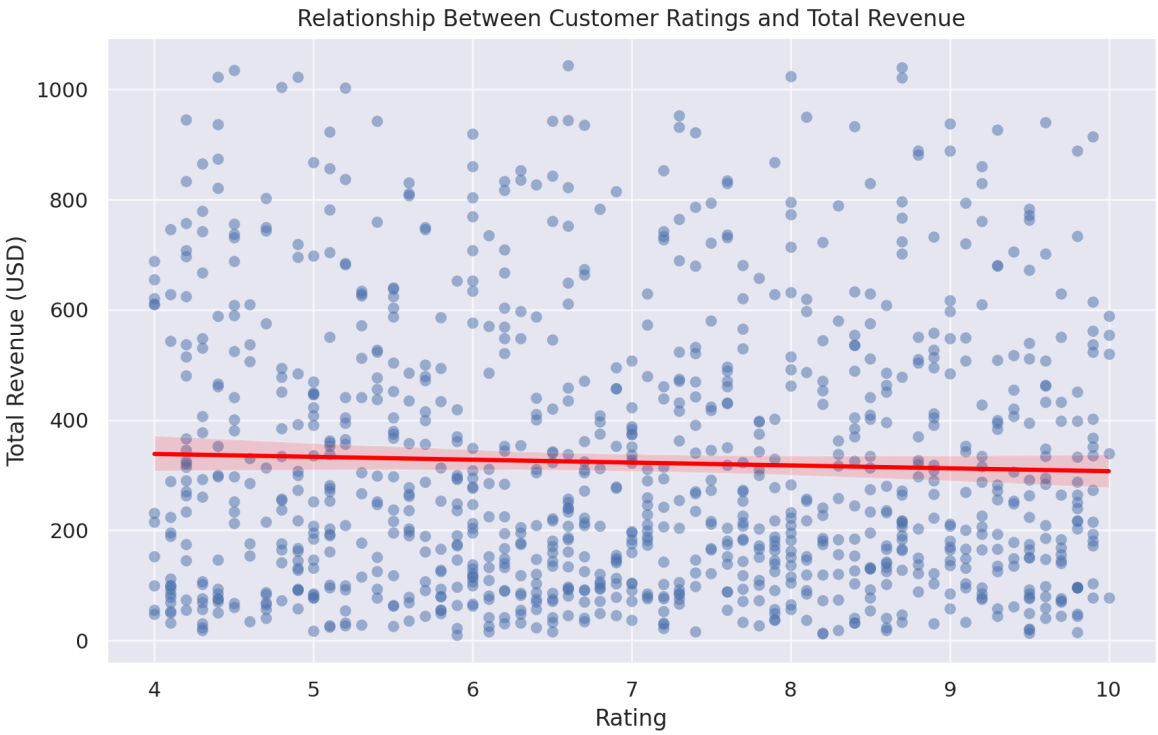
In [61]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data['Rating'], bins=20, kde=True, color='#5DADE2')

plt.title('Distribution of Customer Ratings')
plt.xlabel('Rating')
plt.ylabel('Number of Customers')

plt.show()
```



The ratings are **balanced**, ranging from 4 to 10, showing a variety of satisfaction levels. Many customers gave **frequent scores** around 5, 6, and 7. However, high ratings like 9 and 10 also appear often, suggesting a lot of positive experiences.

O2. Is there a relationship between ratings and total revenue?

In [62]:
```
plt.figure(figsize=(10, 6))
sns.regplot(x='Rating', y='Total', data=data, scatter_kws={'alpha': 0.5}, line_k

plt.title('Relationship Between Customer Ratings and Total Revenue')
plt.xlabel('Rating')
plt.ylabel('Total Revenue (USD)')

plt.show()
```



We can see that:

- **Downward Trend**: The regression line slightly slopes downward, showing no strong link between high ratings and increased revenue.
- **Wide Spread**: The data points are widely scattered across the rating axis, with most transactions having lower revenue (below $400). This means high ratings don't always lead to high revenue.
- **Mid-Range Ratings**: Most transactions are clustered around ratings of 6 to 8, though revenue still varies.

Therefore, The relationship between **Customer Rating** and **Total Revenue** seems **weak**. Higher ratings don't always mean higher revenue, because other factors (like the number of items bought or the price of items) likely have a bigger impact on revenue.

Summary

1. **General Sales Insights**:
    - The total revenue generated is $322,966.75, with branches contributing nearly equal amounts. This indicates **balanced performance across regions**, suggesting no specific geographical dominance.
    - The cities show almost equal revenue contributions, reflecting a consistent market presence.
2. **Customer Behavior**:
    - Gender and customer type distributions are nearly balanced, suggesting an even market segmentation. However, **Normal (non-member) customers could**

be explored further to understand purchasing frequency and conversion potential.

3. **Product Insights**:
    - Revenue and gross income are fairly evenly distributed across product lines, with **Food and Beverages** leading slightly in both metrics.
    - While the gross margin percentage is consistent at 4.76% for all product lines, **average unit price and quantity vary slightly**, suggesting room for pricing strategy adjustments or promotions.
4. **Time-Based Analysis**:
    - **Saturday** is the most revenue-generating day, with Tuesday surprisingly coming second. Peak transaction times occur closer to closing hours (5 PM to 7 PM), which could reflect after-work shopping habits or promotional effects.
5. **Payment Preferences**:
    - Payment methods are evenly distributed across branches, showing no clear preference, which reflects **effective accessibility of payment options**.
6. **Profitability Analysis**:
    - Gross income and revenue are evenly distributed across branches and product lines, suggesting **no standout area for profitability maximization**.
7. **Customer Experience**:
    - Customer ratings are fairly balanced, with no ratings below 4. This reflects **high overall satisfaction**, though ratings don't strongly correlate with revenue.

Recommendations

1. **Boost Customer Loyalty**:
    - Investigate customer preferences and purchasing habits to **convert Normal customers into Members**, focusing on frequent non-member buyers.
2. **Enhance Time-Based Strategies**:
    - Leverage peak transaction hours by **introducing time-limited offers** or special closing-hour deals to further drive revenue during high-traffic periods.
3. **Regional Promotions**:
    - Given the balanced branch performance, **local promotions or events tailored to specific cities** could tap into unexplored potential and differentiate revenue contributions.
4. **Product Line Optimization**:
    - Perform a deeper analysis to identify potential high-margin product bundles or **introduce strategic discounts** on underperforming lines to boost sales.
5. **Improved Analytics for Ratings**:

- Correlate customer ratings with specific transaction details (e.g., product lines, staff interaction, or payment methods) to identify actionable insights for improving overall satisfaction.

In [ ]:

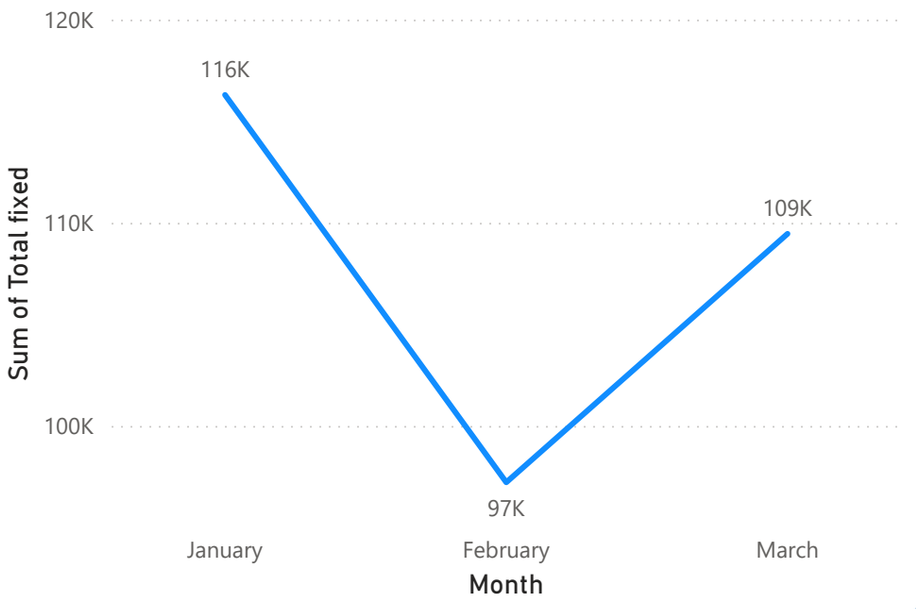
Main Overview

Total Transactions	Total Gross Income	Total Revenue	Top-Selling Product Line
1000	$15.38K	$322.97K	Food and beverages

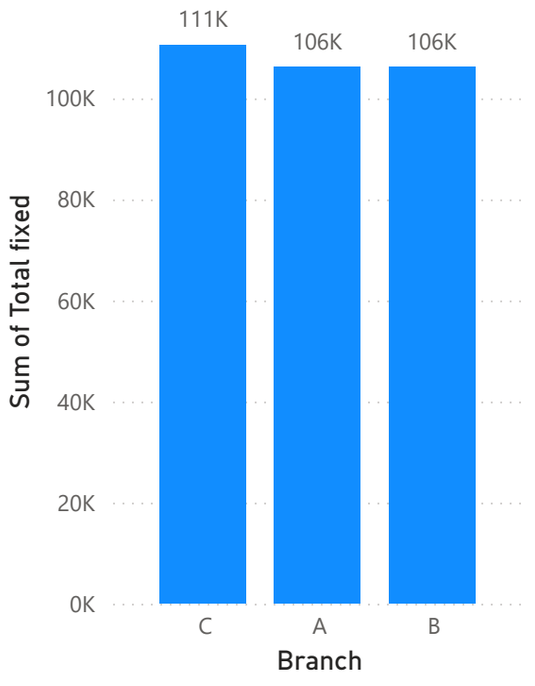
Month

All

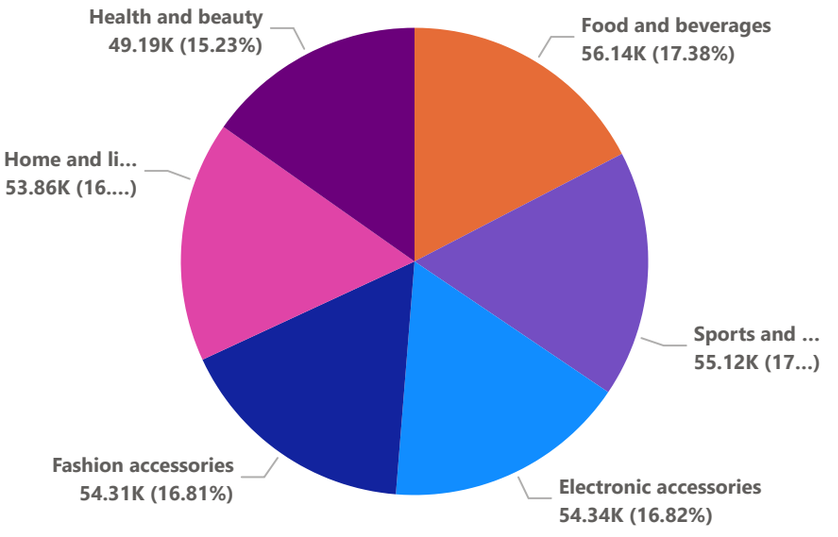
Monthly Revenue Trend



Revenue by Branch



Revenue by Product Line



Sales Analysis

Total Quantity Sold

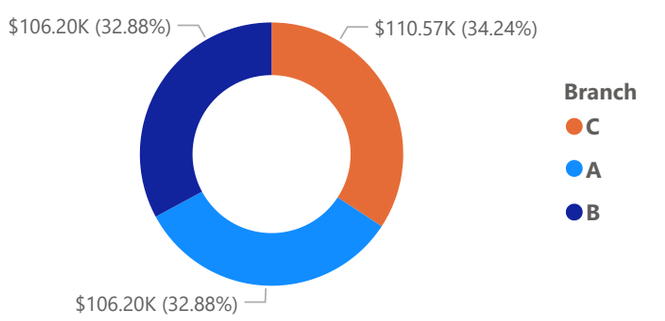
5510

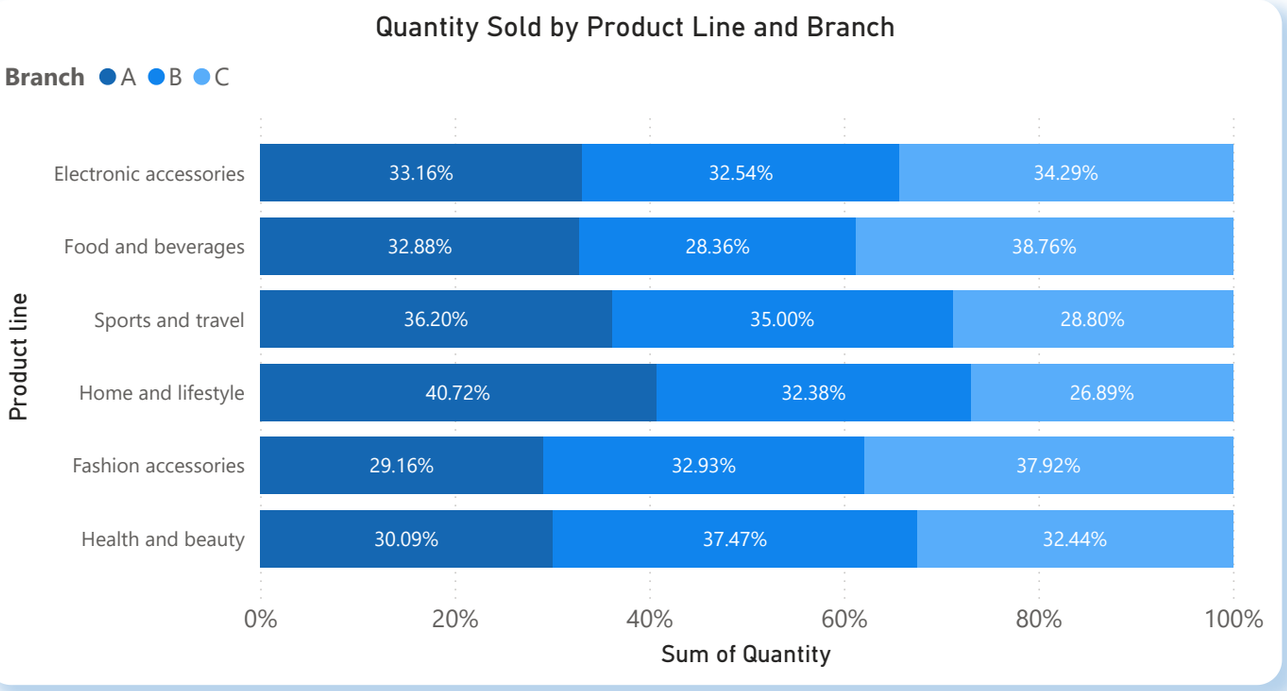
Average Sales per Transaction

$322.967

Branch, Month

All





Customer Insight

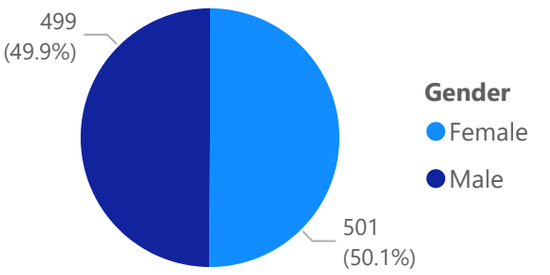
Total Transactions

1000

Average Rating

6.97

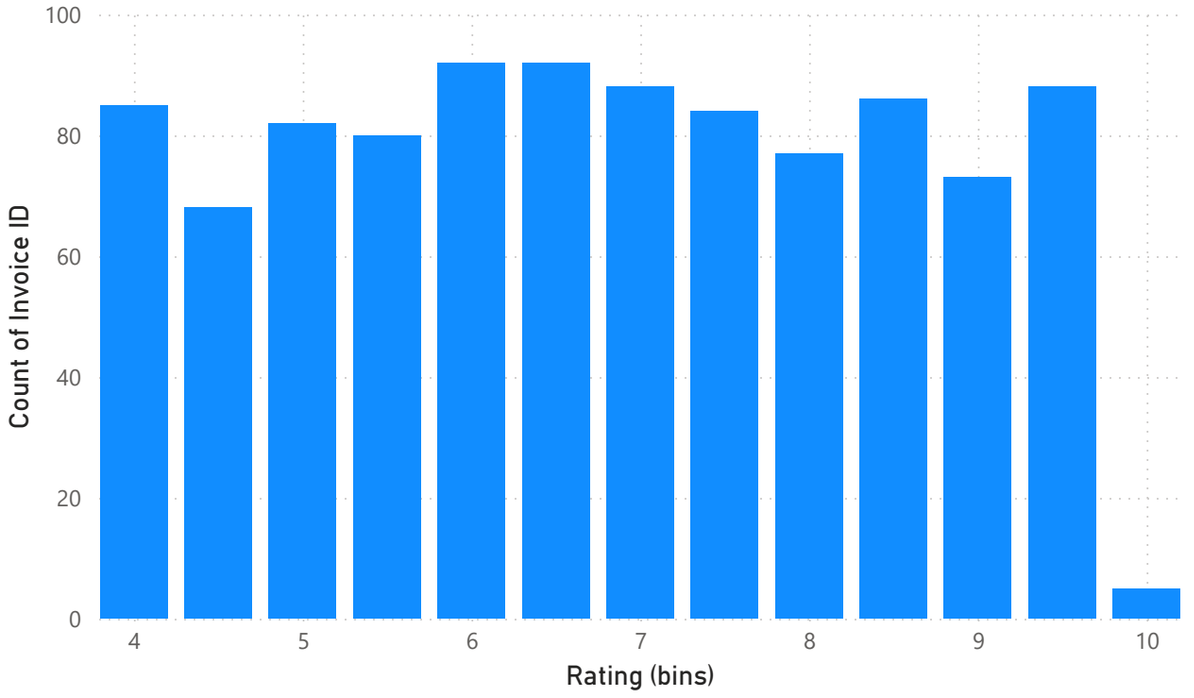
Quantity Sold by Product Line



Branch, Month

All

Rating Distribution



Quantity Sold by Branch