In [2]:
```
# Import Library
import pandas as pd
```

In [4]:
```
## Load The Datasets
df = pd.read_csv(r"D:\Customer-Order-Behaviour\Data\walmart_customer_data.csv")
```

In [5]:
```
## Preview Top 5 Rows
df.head()
```

Out[5]:

	customer_id	age	gender	city	category	product_name	purchase_date	purchase_amount	payment_method	discount_app
0	84607c1f-910c-44d5-b89f-e1ee06dd34c0	49	Female	New Cynthia	Electronics	Smartphone	2024-08-30	253.26	Cash on Delivery	
1	f2a81712-a73e-4424-8b39-4c615a0bd4ea	36	Other	Cruzport	Clothing	T-Shirt	2024-12-21	73.19	Debit Card	
2	da9be287-8b0e-4688-bccd-1a2cdd7567c6	52	Male	Jeffreytown	Beauty	Perfume	2024-12-26	125.62	Credit Card	
3	50ec6932-3ac7-492f-9e55-4b148212f302	47	Female	Jenniferburgh	Electronics	Smartwatch	2024-11-04	450.32	Credit Card	
4	8fdc3098-fc75-4b0f-983c-d8d8168c6362	43	Other	Kingshire	Electronics	Smartphone	2024-10-07	369.28	Credit Card	

In [7]:
```
# Shape of the data
df.shape
```

Out[7]:
```
(50000, 12)
```

In [8]:
```
## Column Info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Customer_ID       50000 non-null  object 
 1   Age               50000 non-null  int64  
 2   Gender            50000 non-null  object 
 3   City              50000 non-null  object 
 4   Category          50000 non-null  object 
 5   Product_Name      50000 non-null  object 
 6   Purchase_Date     50000 non-null  object 
 7   Purchase_Amount   50000 non-null  float64
 8   Payment_Method    50000 non-null  object 
 9   Discount_Applied  50000 non-null  object 
 10  Rating            50000 non-null  int64  
 11  Repeat_Customer   50000 non-null  object 
dtypes: float64(1), int64(2), object(9)
memory usage: 4.6+ MB
```

In [9]:
```
## Null Values
df.isnull().sum()
```

Out[9]:
```
Customer_ID         0
Age                 0
Gender              0
City                0
Category            0
Product_Name        0
Purchase_Date       0
Purchase_Amount     0
Payment_Method      0
Discount_Applied    0
Rating              0
Repeat_Customer     0
dtype: int64
```

In [10]:
```
# Unique values in each column
df.nunique()
```

Out[10]:
```
Customer_ID         50000
Age                    43
Gender                  3
City                25096
Category                4
Product_Name           16
Purchase_Date         366
Purchase_Amount     31378
Payment_Method          4
Discount_Applied        2
Rating                  5
Repeat_Customer         2
dtype: int64
```

In [11]:
```
# Basic stats
df.describe()
```

Out[11]:

	Age	Purchase_Amount	Rating
count	50000.000000	50000.000000	50000.000000
mean	38.945220	255.532230	2.998680
std	12.398137	141.574416	1.417956
min	18.000000	10.010000	1.000000
25%	28.000000	133.050000	2.000000
50%	39.000000	255.045000	3.000000
75%	50.000000	378.912500	4.000000
max	60.000000	499.990000	5.000000

In [12]:
```
## Check for duplicate rows
df.duplicated().sum()
```

Out[12]:
```
0
```

In [13]:
```
# Drop duplicates if any
df.drop_duplicates(inplace=True)
```

In [14]:
```
# Check again for nulls
df.isnull().sum()
```

Out[14]:
```
Customer_ID         0
Age                 0
Gender              0
City                0
Category            0
Product_Name        0
Purchase_Date       0
Purchase_Amount     0
Payment_Method      0
Discount_Applied    0
Rating              0
Repeat_Customer     0
dtype: int64
```

In [15]:
```
# Standardize column names
df.columns = df.columns.str.strip().str.lower().str.replace(" ", "_")
```

In [16]:
```
# Final shape check
df.shape
```

Out[16]:
```
(50000, 12)
```

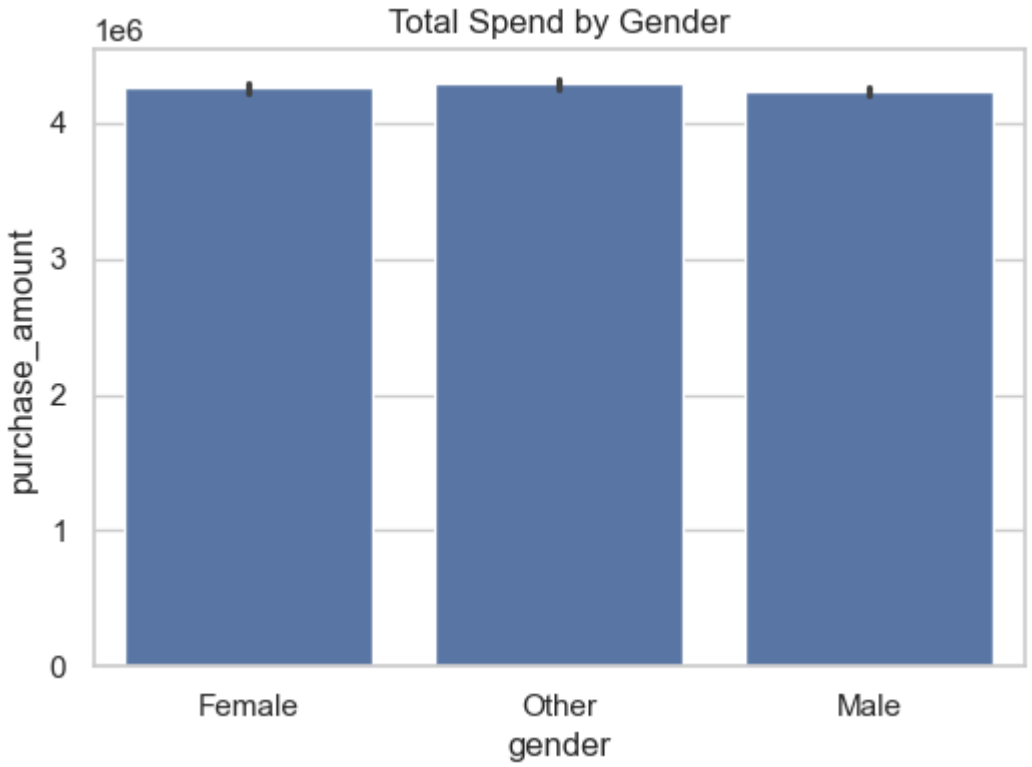
EXPLORATORY DATA ANALYSIS (EDA)

In [18]:
```
# Import Libraries
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
sns.set(style="whitegrid")
```

PART A: Categorical Analysis

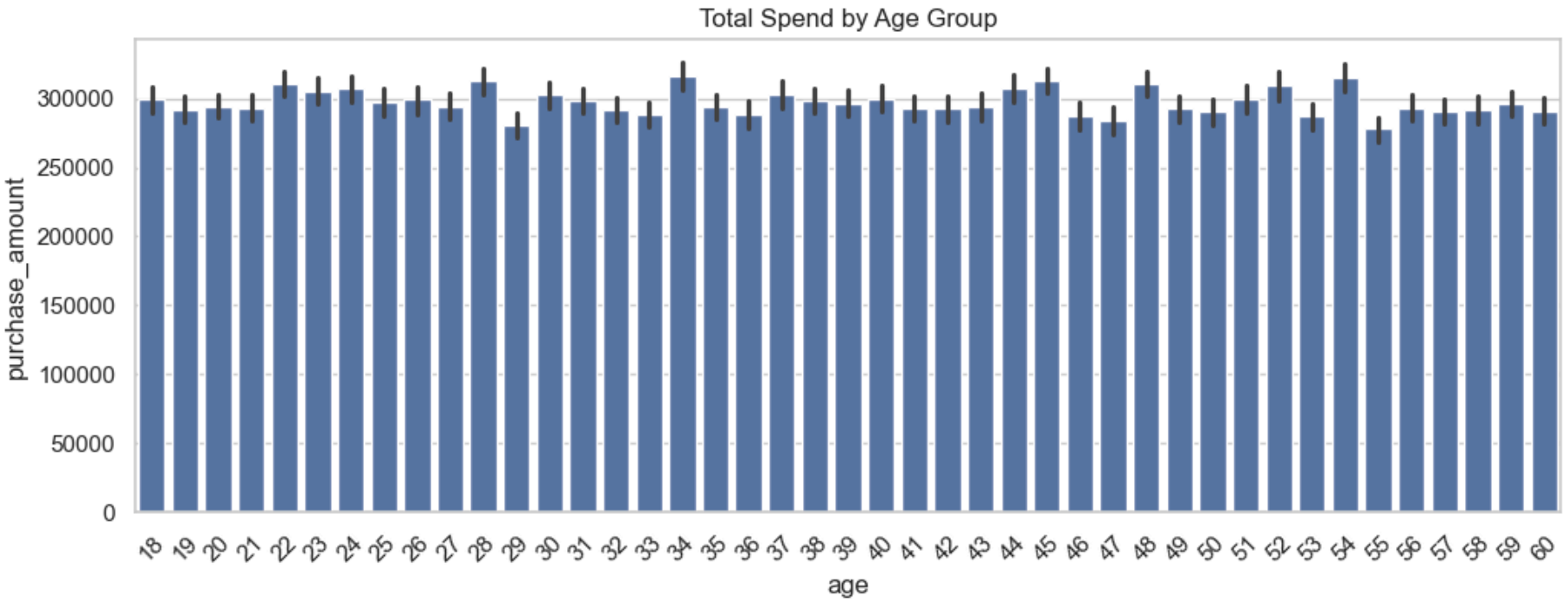
Gender-wise Spending

In [31]:
```
plt.figure(figsize=(6,4))
sns.barplot(x='gender', y='purchase_amount', data=df, estimator=sum)
plt.title("Total Spend by Gender")
plt.show()
```



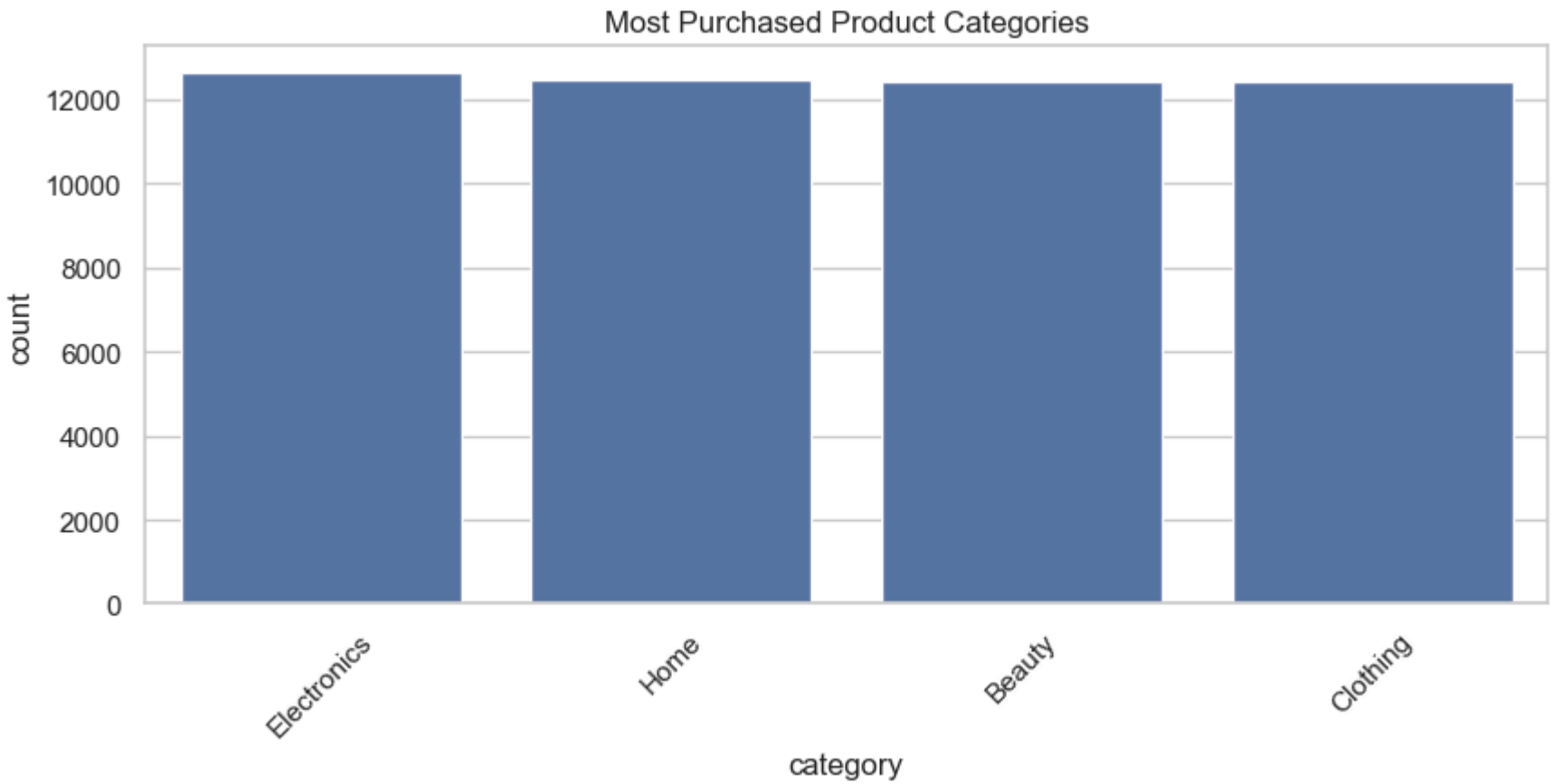
Age group Spending

In [29]:
```
plt.figure(figsize=(12,4))
sns.barplot(x='age', y='purchase_amount', data=df, estimator=sum)
plt.title("Total Spend by Age Group")
plt.xticks(rotation=45)
plt.show()
```



Category Preference

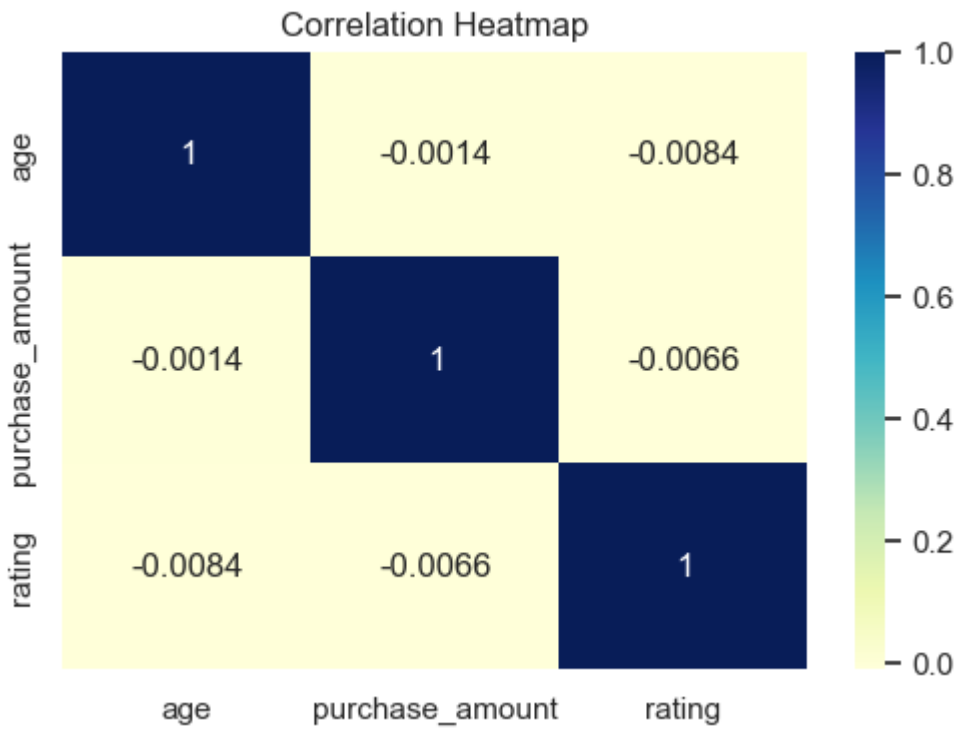
In [25]:
```
plt.figure(figsize=(10,4))
sns.countplot(x='category', data=df, order=df['category'].value_counts().index)
plt.title("Most Purchased Product Categories")
plt.xticks(rotation=45)
plt.show()
```



PART B: Correlation + Continuous Variables

Heatmap of numerical correlation

In [35]:
```
plt.figure(figsize=(6,4))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap="YlGnBu")
plt.title("Correlation Heatmap")
plt.show()
```



Average amount spent by gender

In [55]:
```
df.groupby('gender')['purchase_amount'].mean()
```

Out[55]:
```
gender
Female    256.382360
Male      254.230838
Other     255.982589
Name: purchase_amount, dtype: float64
```

Average spend by Repeat vs New Customers

In [42]:
```
df.groupby('repeat_customer')['purchase_amount'].mean()
```

Out[42]:
```
repeat_customer
No     255.043853
Yes    256.011165
Name: purchase_amount, dtype: float64
```

Which age group spends the most?

In [43]:
```
df.groupby('age')['purchase_amount'].sum().sort_values(ascending=False).head()
```

Out[43]:
```
age
34    315860.39
54    314798.58
45    312956.09
28    312606.62
48    310614.87
Name: purchase_amount, dtype: float64
```

Most profitable product categories

In [44]:
```
df.groupby('category')['purchase_amount'].sum().sort_values(ascending=False)
```

Out[44]:
```
category
Electronics    3260688.09
Home           3195217.51
Beauty         3174727.90
Clothing       3145977.98
Name: purchase_amount, dtype: float64
```

Effect of discounts on ratings

In [48]:
```
# Convert 'Yes'/'No' to 1/0
df['discount_applied'] = df['discount_applied'].map({'Yes': 1, 'No': 0})
```

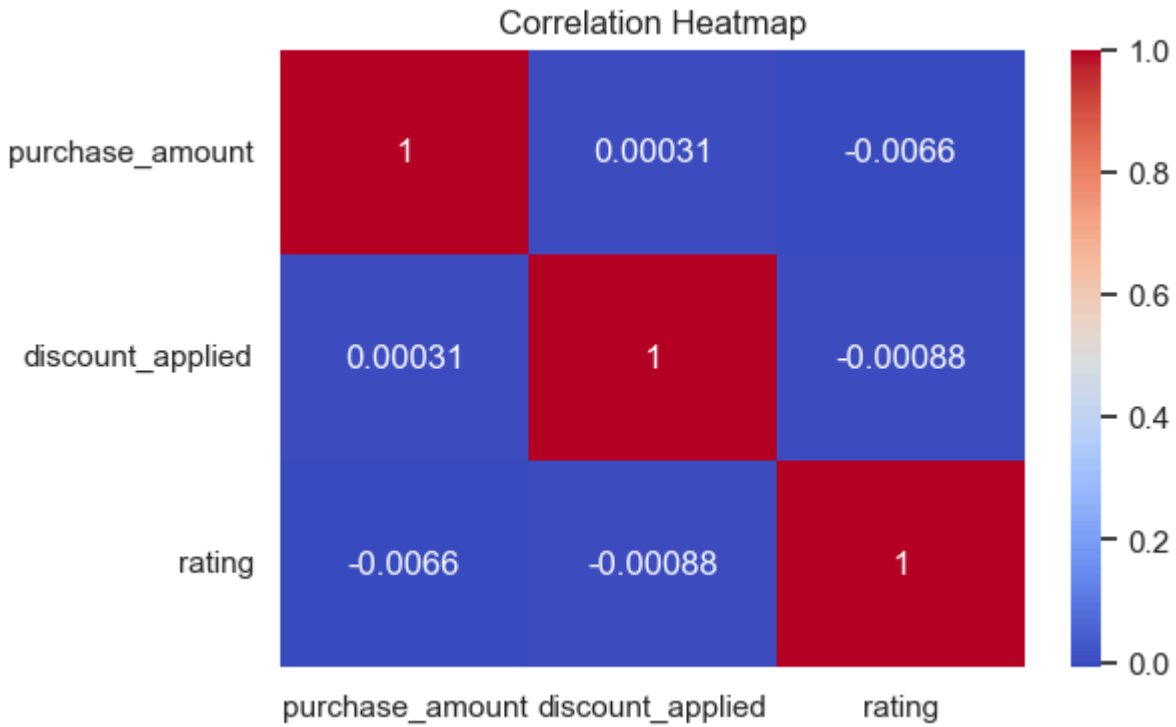
In [49]:
```
df[['discount_applied', 'rating']].corr()
```

Out[49]:

	discount_applied	rating
discount_applied	1.000000	-0.000875
rating	-0.000875	1.000000

Correlation heatmap

In [51]:
```
plt.figure(figsize=(6,4))
sns.heatmap(df[['purchase_amount', 'discount_applied', 'rating']].corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



In [ ]:

📊 Business Insights Summary

🔍 Key Questions Answered:

- Which customer segment spends the most?
- Which product categories bring in the most revenue?
- Are discounts really increasing sales or improving ratings?
- Do repeat customers spend more than new ones?
- Are there any patterns in rating vs amount spent?

🧠 Insights:

- Average spend is fairly consistent across genders, with female customers spending U256.38 on average — slightly more than others.
- Repeat customers spend marginally more (256.01) than new customers (255.04), suggesting limited loyalty-based uplift.
- Age 34, 54, and 45 are the most profitable customer groups, each contributing over 310,000 in total revenue.
- Electronics is the top-performing product category, generating over 3.26 million in revenue, followed closely by Home and Beauty.
- Discounts show no real correlation with customer ratings (correlation = -0.0008), indicating they don't directly impact satisfaction.

In [ ]:

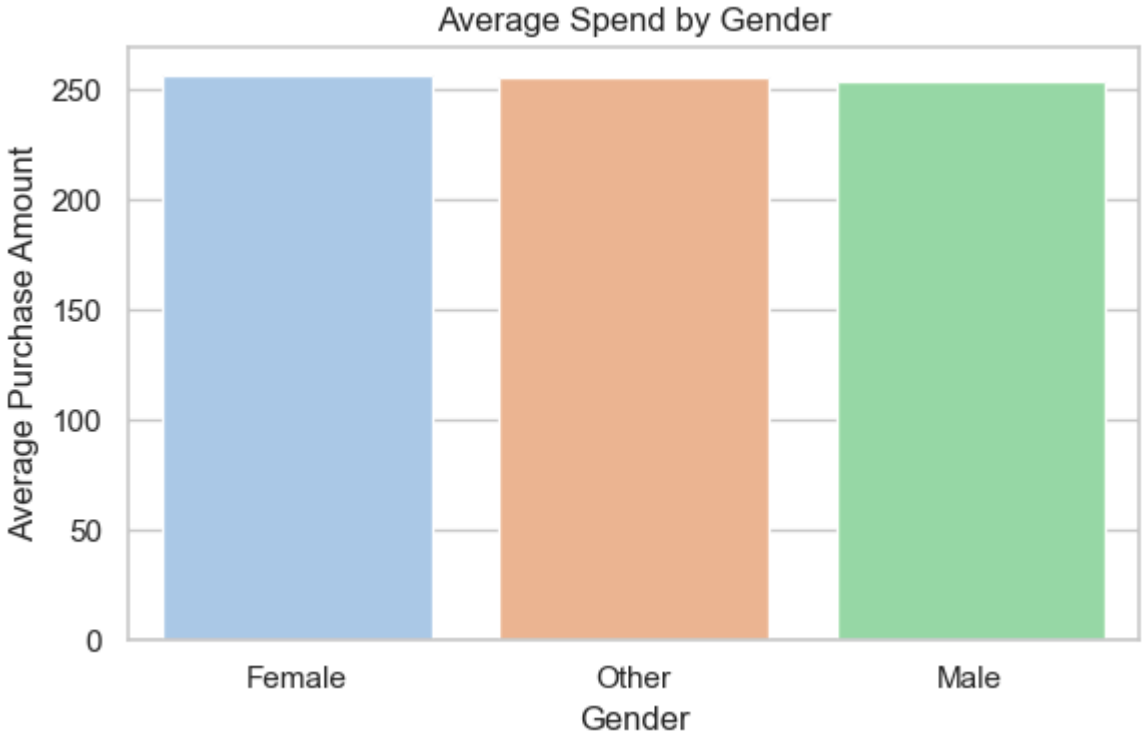
Visualization Summary

📈 Chart 1: Average Spend by Gender

This bar chart compares the average purchase amount across gender groups. Female customers show slightly higher average spending.

In [59]:
```
plt.figure(figsize=(6,4))
sns.barplot(x='gender', y='purchase_amount', data=df, estimator='mean', ci=None, palette='pastel')
plt.title("Average Spend by Gender")
plt.ylabel("Average Purchase Amount")
```

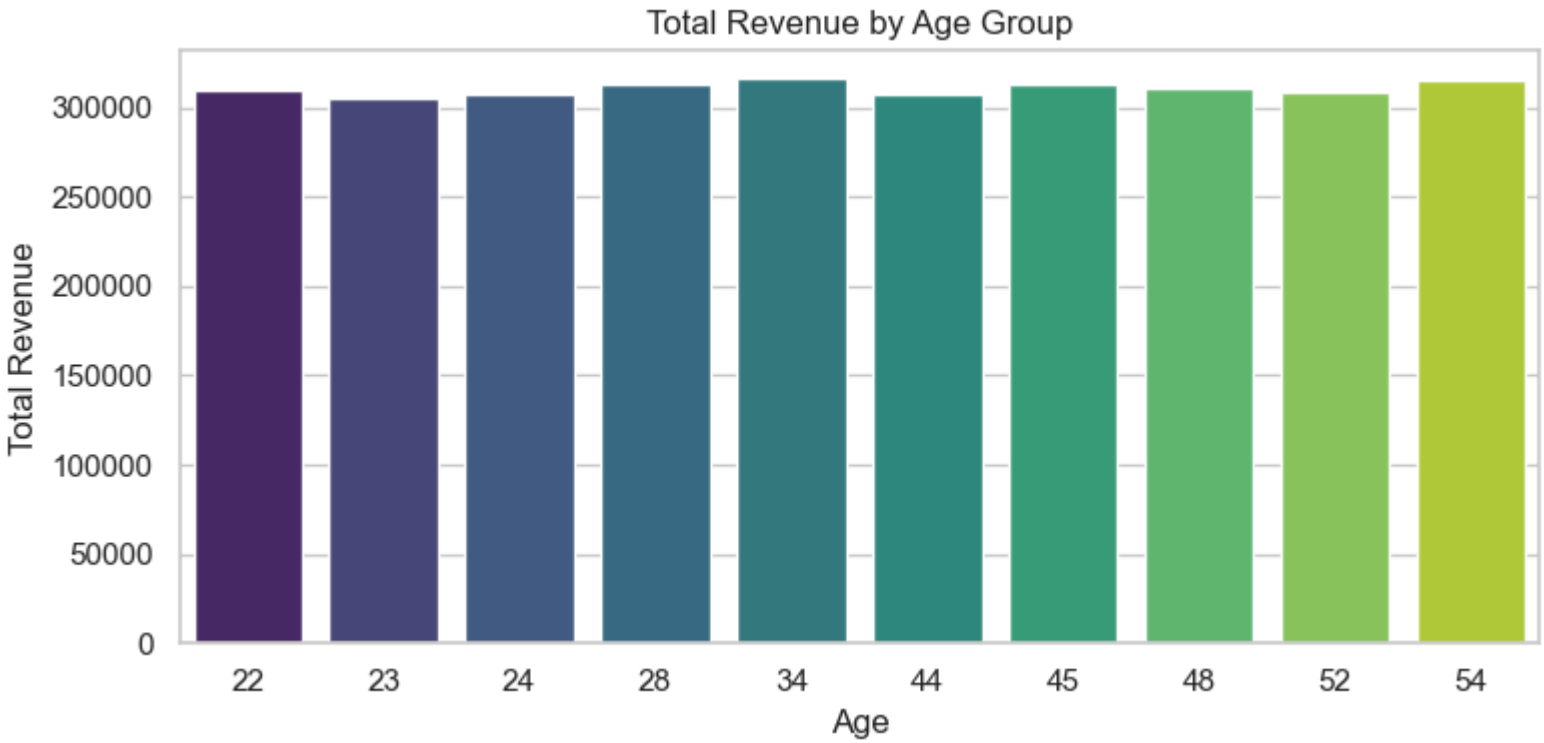
```
plt.xlabel("Gender")
plt.tight_layout()
plt.show()
```



📈 Chart 2: Total Revenue by Age Group

This chart shows the total revenue contributed by each age group. Customers aged 34, 54, and 45 are the most profitable segments.

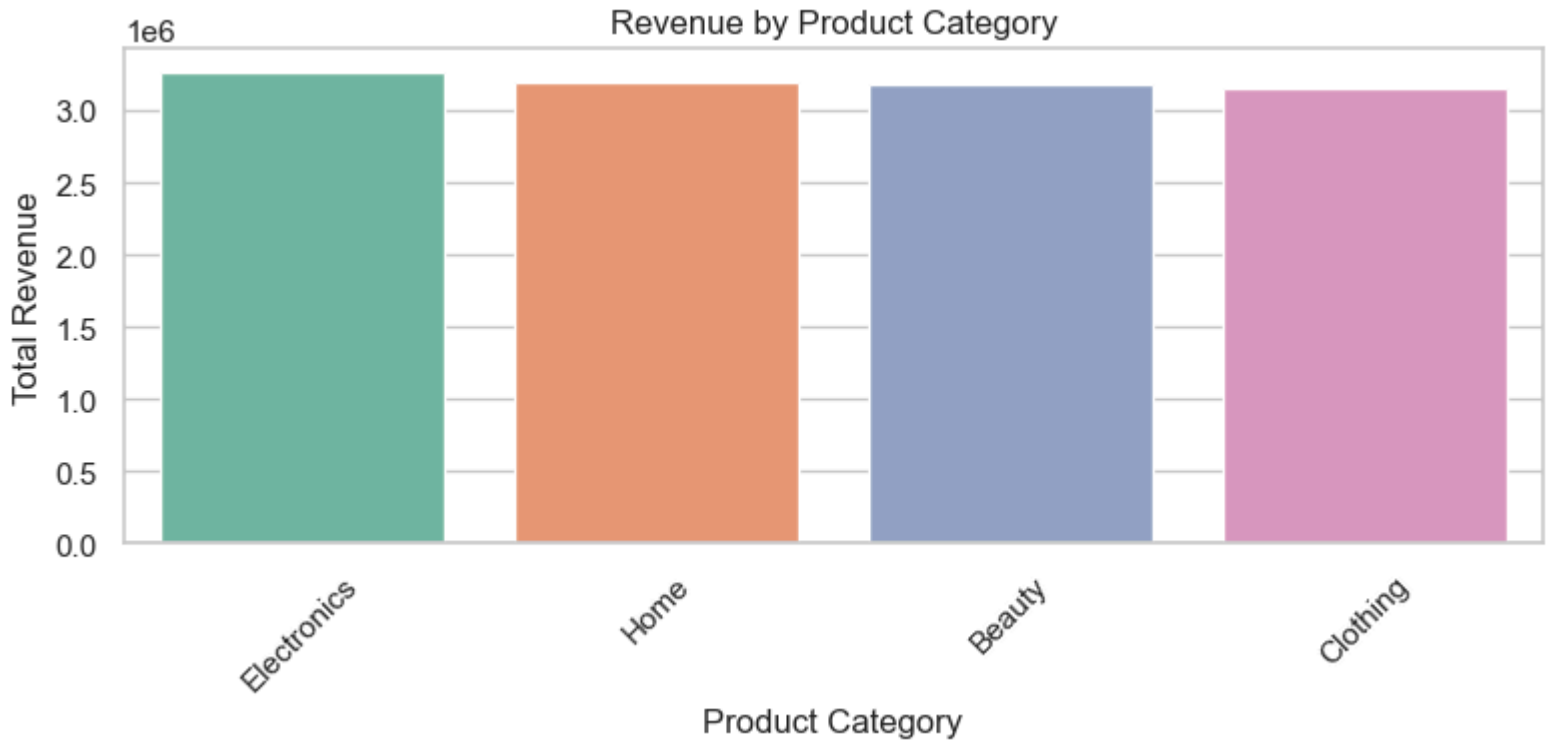
In [61]:
```
age_revenue = df.groupby('age')['purchase_amount'].sum().sort_values(ascending=False).head(10)
plt.figure(figsize=(8,4))
sns.barplot(x=age_revenue.index, y=age_revenue.values, palette='viridis')
plt.title("Total Revenue by Age Group")
plt.xlabel("Age")
plt.ylabel("Total Revenue")
plt.tight_layout()
plt.show()
```



📈 Chart 3: Revenue by Product Category

This chart highlights the top-performing product categories. Electronics leads, followed by Home, Beauty, and Clothing.

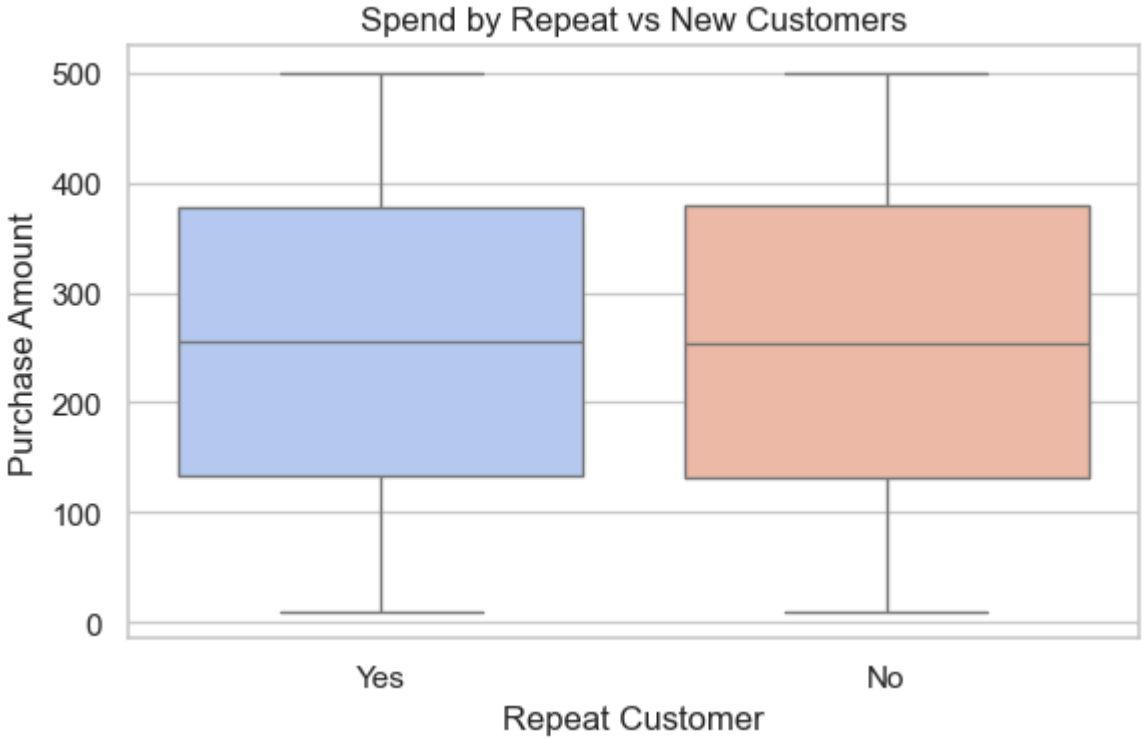
In [63]:
```
category_revenue = df.groupby('category')['purchase_amount'].sum().sort_values(ascending=False)
plt.figure(figsize=(8,4))
sns.barplot(x=category_revenue.index, y=category_revenue.values, palette='Set2')
plt.title("Revenue by Product Category")
plt.xlabel("Product Category")
plt.ylabel("Total Revenue")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



📈 Chart 4: Spend Distribution by Customer Type

This box plot compares spending patterns of repeat vs new customers. Repeat customers show slightly higher median spend.

In [65]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x='repeat_customer', y='purchase_amount', data=df, palette='coolwarm')
plt.title("Spend by Repeat vs New Customers")
plt.xlabel("Repeat Customer")
plt.ylabel("Purchase Amount")
plt.tight_layout()
plt.show()
```

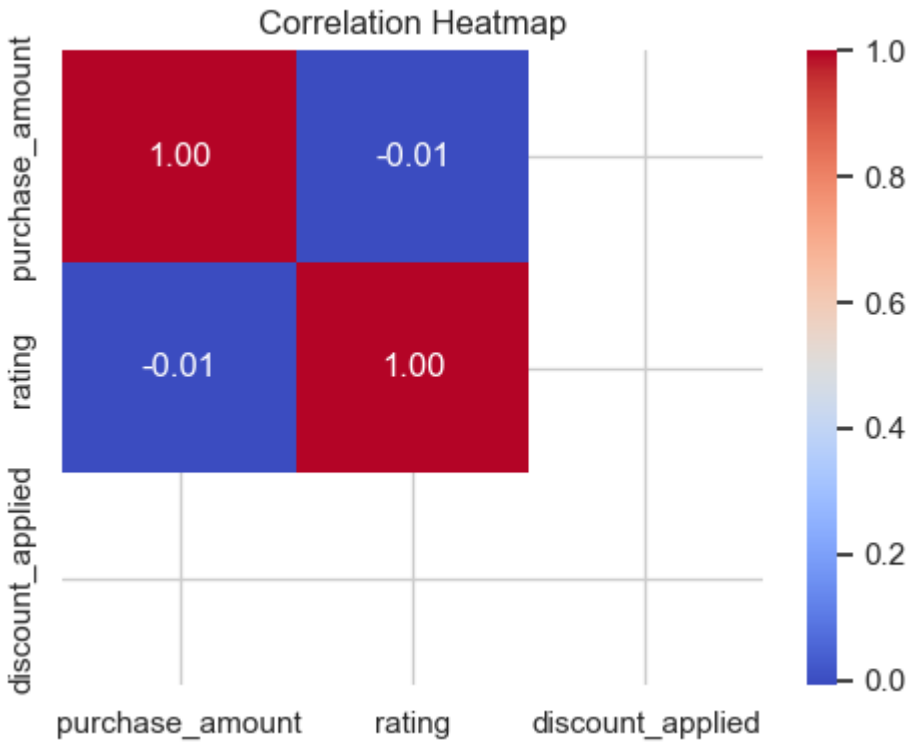


📈 Chart 5: Correlation Heatmap

This heatmap visualizes relationships between numerical variables like purchase amount, discounts, and ratings.

In [66]:
```
df['discount_applied'] = df['discount_applied'].map({'Yes': 1, 'No': 0})
corr_matrix = df[['purchase_amount', 'rating', 'discount_applied']].corr()

plt.figure(figsize=(5,4))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Heatmap")
plt.tight_layout()
plt.show()
```


Correlation Heatmap
purchase_amount
rating
discount_applied
1.00
-0.01
-0.01
1.00
purchase_amount
rating
discount_applied
1.0
0.8
0.6
0.4
0.2
0.0

In [ ]:

In [ ]: